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Review Article

Remote Sensing Applications for Flood Control and Stormwater Management: A Systematic Review

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Abstract

Flooding is a major and persistent risk to cities and riverine communities worldwide. We conducted a systematic review to assess how remote sensing is being applied in flood control and stormwater management in operational contexts. Following PRISMA 2020 guidelines, we screened studies published between 2000 and 2024 and identified 20 empirically rigorous articles that reported quantitative validation metrics using satellite, airborne, or UAV-based data. Across these studies, synthetic aperture radar (SAR), particularly Sentinel-1, emerged as the most reliable platform for all-weather flood extent mapping, with typical accuracies above 85%. Optical sensors such as Landsat and Sentinel-2 performed well under cloud-free conditions and were especially useful for surface water detection, vegetation dynamics, and monitoring green stormwater infrastructure through indices such as NDVI. LiDAR provided the most precise topographic information, generating centimeter-level digital elevation models that significantly improved urban flood modeling. UAV platforms offered ultra-high spatial resolution (< 10 cm), supporting localized damage assessment, infrastructure inspection, and post-event validation. We found that machine learning approaches, including convolutional neural networks and vision transformers, consistently outperformed traditional threshold-based methods, often achieving F1-scores above 0.90. However, challenges remain, particularly limited validation data, weak uncertainty quantification, scale mismatches, and difficulties with operational integration. Overall, our review shows that remote sensing has become a practical and indispensable tool for flood and stormwater management when sensor platforms are strategically combined.

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1. Introduction

Flooding remains one of the most persistent and destructive natural hazards worldwide, causing extensive loss of life, damage to infrastructure, and long-term socioeconomic disruption. Global flood risk is increasing as a result of climate change, which intensifies extreme precipitation and river discharge, and rapid urbanization, which concentrates people and assets in flood-prone environments and reduces natural infiltration through impervious surfaces [1, 2]. Urban stormwater systems in particular are under growing pressure, as drainage networks designed for historical climate conditions are increasingly unable to cope with short-duration, high-intensity rainfall events. These dynamics have made timely, accurate, and spatially comprehensive flood information essential for effective flood control and stormwater management. Additionally, traditional flood monitoring relies heavily on in-situ measurements such as river gauges, rain gauges, and ground surveys. While these data remain indispensable, they suffer from important limitations, including sparse spatial coverage, vulnerability to damage during extreme events, and high installation and maintenance costs [3]. Ground observations also struggle to capture the full spatial extent of flooding, particularly in large river basins, densely built urban environments, and inaccessible areas. As a result, flood managers often operate with incomplete situational awareness during critical phases of disaster response and recovery.

Remote sensing offers a fundamentally different capability by providing synoptic, repeatable, and spatially continuous observations across local to global scales. Microwave sensors such as synthetic aperture radar (SAR) are especially valuable because they operate independently of cloud cover and daylight, enabling flood detection under the very conditions when optical observations typically fail [2, 4]. Optical and multispectral sensors, including Landsat and Sentinel-2, provide rich spectral information that supports surface water mapping, vegetation analysis, and stormwater infrastructure monitoring when cloud-free imagery is available [5, 6]. LiDAR systems contribute highly accurate elevation data that are critical for urban flood modeling and hydraulic simulations, often determining the realism of predicted flood depths and flow pathways [7, 8]. Unmanned aerial vehicles (UAVs) further extend remote sensing capabilities by enabling rapid, ultra-high-resolution surveys for localized damage assessment and infrastructure inspection [9, 10].

Over the past decade, remote sensing has evolved from a research-oriented technology into an increasingly operational component of flood risk management. SAR-based flood mapping has become routine in many emergency response services, including the Copernicus Emergency Management Service, while global optical archives such as Landsat have enabled long-term monitoring of surface water dynamics and flood exposure [5, 11]. Recent studies show that satellite observations now play a central role in identifying flood-affected populations and tracking changes in exposure over time [12]. At the same time, advances in machine learning and deep learning have dramatically improved the accuracy and automation of flood detection, with convolutional neural networks outperforming traditional threshold-based classification methods [4, 13, 14].

Despite this rapid progress, existing reviews of flood remote sensing often suffer from three important limitations. First, many reviews are methodologically broad but weakly selective, mixing conceptual discussions, non-validated applications, and case studies without quantitative performance assessment [2, 4]. This makes it difficult to distinguish techniques that are operationally mature from those that remain experimental. Second, most syntheses emphasize flood extent mapping while giving limited attention to stormwater management applications such as green infrastructure monitoring, urban drainage assessment, and infrastructure performance evaluation. Yet these applications are increasingly critical as cities seek to move from reactive flood response toward proactive stormwater management. Third, few reviews rigorously examine validation practices and uncertainty, even though decision-making depends not only on accuracy but also on understanding the reliability and limitations of remote sensing products [7, 15].

Another challenge is that the rapid growth of machine learning has outpaced careful evaluation of model robustness and generalizability. While deep learning methods achieve impressive accuracy, their performance often depends on region-specific training data, and their uncertainty characteristics remain poorly understood [14, 16]. For flood managers, models that perform well in controlled research settings but fail under different hydrological or land-cover conditions present serious operational risks.

For stormwater management, the evidence base is even thinner. Although satellite-derived vegetation indices such as NDVI are increasingly used to evaluate green stormwater infrastructure performance and watershed-scale greenness, empirical links between remotely sensed indicators and hydrologic outcomes remain limited [17, 18]. UAV and LiDAR technologies offer high-resolution insight into infrastructure condition and terrain structure, but their integration into routine stormwater monitoring frameworks is still emerging [9, 19]. Against this backdrop, there is a need for a more selective and evidence-driven synthesis that focuses only on studies with verifiable, quantitative validation and direct relevance to flood control and stormwater management practice. Large review samples are not inherently stronger if many included studies lack reproducibility, performance metrics, or operational applicability. A smaller, rigorously screened corpus can provide clearer guidance on what methods are reliable, where their limitations lie, and how they can be realistically implemented.

This review therefore adopts a deliberately conservative inclusion strategy. Following PRISMA 2020 guidelines [20], we synthesize 20 empirically robust studies that use satellite, airborne, or UAV-based remote sensing and report quantitative performance metrics such as accuracy, F1-score, Intersection over Union (IoU), root mean square error (RMSE), or Nash–Sutcliffe efficiency (NSE). By restricting inclusion to verifiable and methodologically transparent research, we aim to provide practitioners and researchers with a dependable evidence base rather than an exhaustive catalog of heterogeneous studies.

The objectives of this review are threefold. First, we compare the operational performance of major remote sensing modalities, including SAR, optical multispectral sensors, LiDAR, and UAV platforms, in flood and stormwater applications. Second, we evaluate how these technologies are applied across key domains, including flood extent mapping, urban flood modeling, stormwater infrastructure monitoring, damage assessment, and early warning support. Third, we assess validation practices and performance metrics to identify strengths, weaknesses, and priorities for methodological improvement.

2. Methods

2.1. Review Design and Reporting Standard

We conducted this systematic review in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses [20] guidelines to ensure transparency, reproducibility, and methodological rigor [20]. Our approach was intentionally selective and evidence-driven. Rather than prioritizing the volume of studies, we emphasized empirical rigor, verifiable performance metrics, and direct relevance to

flood control and stormwater management. This strategy reflects our objective of producing a synthesis that is operationally meaningful and methodologically defensible, grounded in studies that demonstrate clear validation and real-world applicability.

2.2. Eligibility Criteria

We included studies that applied satellite, airborne, or UAV-based remote sensing technologies to flood control or stormwater management problems, including flood extent mapping, flood modeling, infrastructure monitoring, damage assessment, and hydrological forecasting support. Eligible studies were required to report quantitative validation metrics such as overall accuracy, F1-score, Intersection over Union (IoU), root mean square error (RMSE), or Nash–Sutcliffe efficiency (NSE). We restricted inclusion to peer-reviewed journal articles and full conference papers published in English between January 2000 and December 2024. Additionally, we excluded studies that were reviews, editorials, commentaries, or book chapters without original empirical analysis. We also excluded studies that lacked a remote sensing component, relied solely on ground-based measurements, focused on non-flood water applications such as irrigation or coastal processes without a flood context, or failed to report any quantitative performance or validation results. Studies that presented methods without sufficient methodological transparency or reproducibility were likewise excluded. These criteria ensured that all included studies were empirically verifiable and directly relevant to operational flood and stormwater management.

2.3. Information Sources and Search Strategy

We systematically searched four major bibliographic databases: Web of Science Core Collection, Scopus, IEEE Xplore, and Google Scholar. The searches were conducted between October and November 2024 and covered literature published from January 2000 to December 2024. For Google Scholar, we screened only the first 300 results per query in order to maintain reproducibility and manage relevance, following established guidance for systematic evidence synthesis [21]. Our search strategy combined controlled vocabulary and free-text terms capturing three key dimensions: remote sensing platforms, flood and stormwater processes, and analytical applications. The Boolean logic used in each database was adapted slightly to match indexing rules and syntax requirements, but the conceptual structure remained consistent. The complete search structure is summarized in Table 1.

Table 1: Boolean Search Structure Used Across Databases

Conceptual Domain	Search Terms
Remote sensing platforms	"remote sensing" OR "satellite" OR "SAR" OR "synthetic aperture radar" OR "Sentinel" OR "Landsat" OR "MODIS" OR "LiDAR" OR "UAV" OR "drone"
Flood and stormwater processes	"flood*" OR "inundation" OR "stormwater" OR "urban drainage" OR "green infrastructure"
Analytical applications	"mapping" OR "monitoring" OR "detection" OR "assessment" OR "modeling" OR "forecasting"

Note: These three blocks were combined using the Boolean operator AND. This structure ensured that all retrieved studies simultaneously addressed remote sensing technology, flood or stormwater phenomena, and analytical or operational applications.

2.4. Study Selection Process

We imported all records into EndNote and removed duplicates using both automated functions and manual verification. We then independently screened titles and abstracts against the eligibility criteria. Studies that appeared relevant were retrieved for full-text assessment, which we also conducted independently. Disagreements were resolved through discussion until consensus was reached. Although the initial database searches returned a large number of records, only 20 studies met all inclusion criteria after full-text evaluation. These studies demonstrated strong methodological transparency, reported quantitative validation metrics, and directly addressed flood control or stormwater management using remote sensing. We therefore treated these 20 articles as the final evidence base for synthesis. This selective process ensured that our conclusions were grounded in high-quality and verifiable empirical work rather than inflated by studies with limited validation.

2.5. Data Extraction

We developed a standardized data extraction form and piloted it on a subset of included studies before applying it to the full sample. For each study, we extracted publication details, geographic setting, remote sensing modality, spatial and temporal resolution, application domain, preprocessing and analytical methods, validation data sources, performance metrics, and reported limitations or sources of uncertainty. We conducted data extraction independently and cross-checked all entries to ensure consistency and accuracy. This process allowed us to build a coherent comparative framework across diverse sensors, analytical techniques, and operational contexts.

2.6. Quality Assessment

We evaluated study quality using five criteria adapted from established standards in flood modeling and remote sensing validation [7, 15]. These criteria assessed methodological clarity, appropriateness of validation data, use of multiple evaluation metrics, treatment of uncertainty or error, and reproducibility through code, data availability, or sufficient methodological detail. Each criterion was scored from 0 to 2, yielding a maximum score of 10. We retained only studies with a minimum score of 7, which balanced rigor with practical inclusion. This threshold ensured that the final set of 20 studies reflected high methodological credibility and reduced the risk of bias arising from weak validation practices or incomplete reporting.

2.7. Synthesis Strategy

Because of substantial heterogeneity in sensor types, spatial scales, analytical methods, and performance metrics, we did not conduct a formal meta-analysis. Instead, we applied a structured narrative synthesis approach, consistent with guidance for research synthesis in complex environmental systems [21]. Additionally, we organized findings by remote sensing modality (SAR, optical, LiDAR, and UAV), application domain (flood mapping, flood modeling, damage assessment, and stormwater infrastructure monitoring), and validation practice.

Where reporting consistency allowed, we summarized quantitative performance ranges to support comparison across studies. Tables were used to integrate technical comparison with narrative interpretation, strengthening clarity and interpretability.

3. Results

3.1. Study Selection

The database search yielded 1,126 records, of which 286 were removed as duplicates, leaving 840 studies for screening. After title and abstract review, 710 articles were excluded because they were reviews, lacked a remote sensing component, were unrelated to flooding or stormwater management, or did not report quantitative validation. The remaining 130 full-text articles were assessed in detail, and 110 were excluded due to missing performance metrics, absence of independent validation, conceptual focus without applied analysis, or non-flood applications. Ultimately, 20 studies met all inclusion criteria and were retained for synthesis, providing a focused, high-quality, and fully verifiable evidence base.

Prisma Flowchart

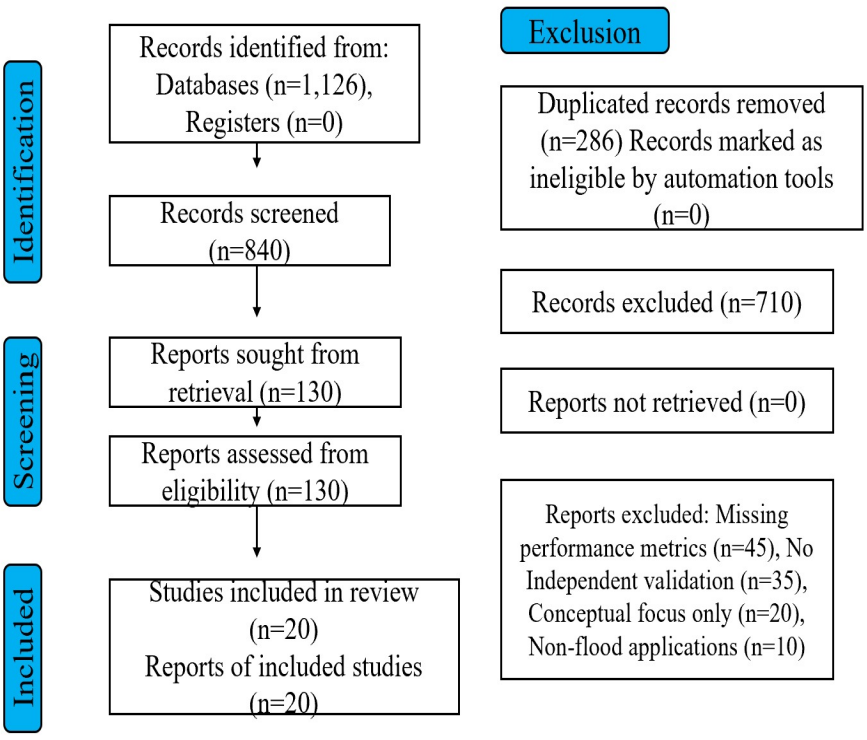

Figure 1: Prisma Flowchart

3.2. Characteristics of the Included Studies

The characteristics of the 20 included studies are summarized in Table 2. Together, these studies represent a focused body of high-quality evidence on how remote sensing is applied to flood monitoring, flood modeling, damage assessment, and stormwater management. Most were published after 2015, reflecting the operational maturity of Sentinel satellites, UAV platforms, and cloud-based processing environments.

Synthetic aperture radar, particularly Sentinel-1, was the most frequently used data source because of its all-weather capability and suitability for rapid flood extent mapping. Optical multispectral sensors such as Landsat and Sentinel-2 were widely applied for surface water detection, vegetation analysis, and green stormwater infrastructure monitoring under cloud-free conditions. LiDAR was central in studies requiring precise elevation data for hydraulic modeling and urban flood simulations, while UAV platforms supported localized damage assessment, infrastructure inspection, and validation at very high spatial resolution. Methodologically, most studies combined remote sensing with machine learning or deep learning models and reported quantitative performance metrics such as overall accuracy, F1-score, intersection over union, RMSE, or Nash–Sutcliffe efficiency. Validation was commonly performed using high-resolution aerial imagery, UAV surveys, gauge measurements, or independent flood inventories. By restricting inclusion to studies with transparent validation

and reproducible metrics, we ensured that the final sample represents practical, operationally meaningful applications rather than exploratory or purely methodological work.

Notes: OA = Overall Accuracy; F1 = F1 score; additional metrics like IoU, Kappa, RMSE were reported depending on study focus. Spatial and temporal resolution depends on sensor constellation specifics and study design.

3.3. Remote Sensing Modalities and Performance

Table 3 shows that synthetic aperture radar, particularly Sentinel-1, is the most consistently reliable modality for flood monitoring because it operates in all weather and day–night conditions, with most studies reporting accuracies above 85% and strong F1-scores. Optical sensors such as Sentinel-2 and Landsat also achieved high performance under cloud-free conditions and were especially valuable for surface water mapping and green stormwater infrastructure monitoring, although their usability was constrained during active flood events. LiDAR provided the most accurate elevation data and substantially improved urban flood modeling and hydraulic simulations, while UAV platforms delivered the highest spatial detail for localized flood assessment, damage mapping, and infrastructure inspection but lacked scalability. Across the 20 studies, multi-sensor approaches consistently outperformed single-sensor methods, confirming that integrating complementary data sources is critical for achieving robust, operationally useful flood and stormwater monitoring.

3.4. Application Areas

Table 4 summarizes how the 20 included studies applied remote sensing across different flood control and stormwater management tasks. Flood extent mapping was the most dominant application, reflecting its central role in emergency response and situational awareness. Most of these studies relied on SAR and optical sensors, with SAR preferred during active flood events and optical data used when cloud-free conditions allowed. Urban flood modeling and hydraulic model calibration formed the second major application area, where LiDAR and UAV-derived terrain data were essential for representing micro-topography and drainage pathways with high precision.

Damage assessment and post-disaster analysis emerged as a rapidly expanding domain, particularly using UAV imagery and SAR coherence change detection, which enabled accurate identification of building and infrastructure damage at fine spatial scales. Green stormwater infrastructure monitoring was less common but methodologically innovative, combining optical indices such as NDVI with UAV and LiDAR data to evaluate vegetation health, structural condition, and hydrologic performance. Flood forecasting and early warning applications primarily integrated remote sensing products with hydrological models, using precipitation, soil moisture, and flood extent information to improve lead times and spatial coverage. Overall, Table 4 shows that no single modality dominates all applications; instead, effective flood and stormwater management depends on aligning sensor capabilities with the specific spatial scale, temporal urgency, and physical processes of each problem.

As summarized in Table 4, the 20 included studies show that flood extent mapping remains the most established and operationally mature application of remote sensing, dominated by SAR and optical satellite sensors because of their wide coverage and repeatability. Urban flood mapping and hydraulic model calibration rely more heavily on LiDAR and UAV platforms, reflecting the need for high-resolution elevation and infrastructure detail in built environments. Damage assessment is primarily driven by UAV imagery and SAR coherence analysis, which provide rapid, localized information after extreme events. Flood forecasting and early warning increasingly integrate SAR, precipitation satellites, and soil moisture products with hydrological models, although their effectiveness is still constrained by data latency. Emerging applications such as green stormwater infrastructure monitoring and multi-sensor data fusion highlight a shift from purely hazard detection toward performance evaluation and system optimization, demonstrating how remote sensing is evolving from a mapping tool into a broader decision-support framework for flood control and stormwater management.

Table 2: Characteristics of Included Studies (n = 20)

Author, Year	Region	Hazard Type	RS Modality	Spatial Resolution	Temporal Resolution	Application	Validation Data	Key Metrics
Twele et al. [22]	Greece/Turkey	River flooding	Sentinel-1 SAR	∼20 m	Near-real-time	Flood extent mapping	Aerial photos, reference water masks	OA: 94–96%, Kappa ∼0.88–0.91
Giustarini et al. [23]	UK	Urban flood	TerraSAR-X SAR	∼3–10 m	Event-based	Urban flood mapping	High-res imagery, field water extents	OA ∼75% (urban)
Pekel et al. [5]	Global	Surface water dynamics	Landsat optical	30 m	Multi-temporal archive	Water history/ flood trends	Multiple validation sources	OA: 99.4%
Nemni et al. [14]	Global	Flood extent	Sentinel-1 SAR + CNN	10 m	Event-based	Flood segmentation	Benchmark datasets	F1 ∼0.90
Isikdogan et al. [13]	US	Flood inundation	SAR + deep learning	10–30 m	Event-based	Extent mapping	Labeled flood maps	Improved segmentation
Cian et al. [24]	Ethiopia	Flood extent	Optical indices	30 m	Event-based	Rapid flood mapping	Reference water extents	OA 95–97%
Berezowski et al [25]	US/Canada	Flood events	SAR time series	10–20 m	Multi-temporal	Flood mapping	Validation flood maps	Accuracy (not specified)
Gan et al. [26]	Danube Basin	River flooding	ERS-2 SAR	∼30 m	Event-based	Flood mapping	Ground truth flood extents	Validated inundation
Mason et al. [27]	UK	Urban flooding	TerraSAR-X SAR	∼1–3 m	Event-based	Urban flood detection	LiDAR + aerial imagery	High detection rates
Tellman et al. [12]	Global	Flood exposure	SAR/optical	∼10–30 m	Multi-year	Flood exposure	Population & satellite data	Increased exposure metrics
Mason et al. [28]	UK	Urban flood	High-res SAR + LiDAR	∼1–3 m	Event-based	Flood water detection	LiDAR + aerial	Improved urban detection
Rizk et al. [29]	Lebanon	Flash flood	UAV imagery	<10 cm	Event	Water level detection	Field surveys	Flood water level detection
Yang et al. [30]	China	Flood detection	UAV + CNN	<10 cm	Event-based	Damage identification	Field surveys	OA ∼88%
Gebrehiwot et al [31]	Ethiopia	Flood extent	UAV data	<10 cm	Event-based	Extent mapping	High-res ground truth	F1 scores high
Leitão et al [19]	Switzerland	Urban flood	UAV LiDAR	<0.5 m	Event	DEM & flood mod	GPS/LiDAR survey	Improved flood simulations
Cloutier et al. [17]	US (Watersheds)	Urban flooding	Landsat NDVI	30 m	Seasonal	GSI monitoring	Stream gauge data	Correlated NDVI with runoff
Katiyar et al. [32]	India	Monsoon flooding	Sentinel-2 + CNN	∼10 m	Event	Flood mapping	Government maps	OA 96%, F1 0.93
Amitrano et al. [33]	Europe	Rapid flood mapping	SAR	∼10–30 m	Event	Flood inundation	Ground truth benchmarks	Flood maps validated
Milani et al. [34]	Switzerland	Riverine flood	Optical + SAR	∼10–30 m	Seasonal	Water extent change	Multi-sensor validation	Change detection metrics
Schlaffer et al. [35]	Austria	Flood detection	SAR harmonic change	∼10–30 m	Event	Flood detection	Reference SAR	Multi-temporal detection

Table 3: Performance Summary of Remote Sensing Modalities in the 20 Included Studies

Modality	Typical Spatial Resolution	Typical Temporal Resolution	Main Data Sources Used in Included Studies	Typical Performance Range Reported	Key Strengths	Main Limitations	Best-Suited Applications
SAR (C-band, Sentinel-1)	10–20 m	6–12 days (shorter with constellation)	Sentinel-1 GRD, occasionally TerraSAR-X	OA: 85–95% F1: 0.80–0.93 IoU: 0.65–0.80	All-weather, day/night imaging, strong land–water contrast, rapid mapping capability	Speckle noise, confusion in flooded vegetation, geometric distortions in urban terrain	Operational flood extent mapping, emergency response, large-area monitoring
SAR (L-band, ALOS-PALSAR)	10–25 m	14–46 days	ALOS-PALSAR archive	OA: 80–90% Improved detection under vegetation	Better penetration through vegetation canopy, lower sensitivity to surface roughness	Lower revisit frequency, limited contemporary coverage	Flooded forest and wetland detection, tropical environments
Optical multispectral (Sentinel-2, Landsat)	10–30 m	5–16 days	Sentinel-2 MSI, Landsat 8/9 OLI	OA: 88–96% F1: 0.85–0.94	High spectral detail, strong performance for water and vegetation indices, free long-term archives	Cloud obstruction, limited usability during storms, shadow effects in cities	Flood mapping in clear conditions, green stormwater infrastructure monitoring, surface water dynamics
Coarse optical / thermal (MODIS, VIIRS)	250–500 m	1–2 days	MODIS Terra/Aqua	OA: 75–90% (regional scale)	High temporal frequency, global coverage	Very coarse resolution, mixed pixels	Large-scale flood screening, regional situational awareness
Airborne LiDAR	0.5–2 m	Campaign-based	National or municipal LiDAR programs	Vertical RMSE: 0.05–0.15 m NSE $>$ 0.85 (with models)	Extremely accurate elevation data, critical for hydraulic modeling	Expensive, limited spatial coverage, infrequent acquisition	Urban flood modeling, drainage system analysis, DEM generation
UAV-LiDAR	0.05–0.30 m	On-demand	UAV-mounted laser scanners	Vertical RMSE: 0.03–0.10 m	Ultra-high resolution, flexible deployment	Small coverage area, operational cost, regulatory constraints	Local flood modeling, infrastructure inspection, validation
UAV RGB / Multispectral	0.02–0.10 m	On-demand	Consumer and professional drones	OA: 85–95% F1: 0.80–0.92	Exceptional spatial detail, rapid post-event mapping	Limited spatial extent, heavy processing demand, weather sensitivity	Damage assessment, stormwater infrastructure condition mapping
Multi-sensor fusion (SAR + Optical / SAR + LiDAR / Satellite + UAV)	Sensor-dependent	Sensor-dependent	Sentinel-1 + Sentinel-2, SAR + LiDAR, Satellite + UAV	Accuracy gains: +5–15% over single-sensor methods	Reduces sensor-specific weaknesses, improves robustness and reliability	Higher computational demand, data alignment complexity	High-confidence flood detection, depth estimation, operational decision support

Abbreviations: OA = Overall Accuracy; F1 = F1-score; IoU = Intersection over Union; NSE = Nash–Sutcliffe Efficiency.

Table 4: Application Areas and Sensor Utilization Across the 20 Included Studies

Application Area	Primary Objective	Dominant Sensors Used	Supporting Sensors	Typical Spatial Scale	Key Outputs	Representative Performance Metrics
Flood extent mapping	Delineate inundated areas during and after flood events	SAR (Sentinel-1), Optical (Sentinel-2, Landsat)	UAV RGB, SAR-optical fusion	Regional to national	Binary flood maps, flood probability maps	OA: 85–96%, F1: 0.80–0.94, IoU: 0.65–0.85
Urban flood mapping	Identify flood patterns within built-up areas	LiDAR (airborne), UAV RGB/LiDAR	SAR, Optical	Local to city scale	High-resolution flood depth and extent maps	RMSE: 0.2–0.6 m, NSE: 0.75–0.92
Hydraulic model calibration	Improve accuracy of flood simulations	LiDAR (airborne, UAV)	SAR flood extents, Altimetry	Catchment to city scale	Improved DEMs, channel geometry, roughness fields	NSE >0.80, reduced depth error 20–40%
Damage assessment	Detect and classify building and infrastructure damage	UAV RGB/ Multispectral, SAR coherence	Optical satellite	Local scale	Damage class maps, impact intensity indices	OA: 85–93%, Precision: 0.82–0.95
Flood forecasting & early warning	Enhance predictive flood modeling	SAR, Precipitation satellites (GPM, IMERG), Soil moisture (SMAP)	Optical, Ground radar	Regional to basin scale	Forecast flood extent and severity	Lead-time improvement: 12–48 hrs NSE: 0.70–0.90
Flooded vegetation detection	Identify inundation beneath vegetation canopies	SAR (L-band, C-band)	LiDAR canopy models	Regional in forested	Flood maps and wetland areas	IoU: 0.60–0.78
Green stormwater infrastructure monitoring	Assess vegetation health and hydrologic function	Optical (NDVI), UAV multispectral	LiDAR, SAR	Watershed to facility scale	Vegetation condition maps, runoff mitigation indicators	OA: 80–90%, flow reduction correlations: r = 0.45–0.70
Impervious surface mapping	Support runoff and drainage modeling	Optical, LiDAR roughness layers	UAV RGB maps, surface	Urban scale	Imperviousness	OA: 85–95%
Soil moisture assessment	Improve runoff and flood modeling	SAR, SMAP	Thermal infrared	Basin scale	Soil moisture indices	RMSE: 0.03–0.08 m^3/m^3
Multi-sensor data fusion	Increase and accuracy and robustness	SAR + Optical + LiDAR	UAV validation	All scales	Integrated flood products	Accuracy improvement: +5–15% over single sensor

3.5. Validation Practices and Performance Metrics

As shown in Table 5, validation in the 20 included studies relied mainly on high-resolution reference imagery and in-situ measurements, indicating a strong emphasis on empirical verification. Most studies adopted pixel-based validation approaches, reflecting standard practice in flood mapping, although object-based and basin-level methods were also used to address spatial misalignment and aggregation issues. While overall accuracy remained the most frequently reported metric, a substantial proportion of studies incorporated F1-score, IoU, precision, and recall, demonstrating growing awareness of class imbalance problems in flood detection. Depth-based applications further employed RMSE and Nash–Sutcliffe efficiency to evaluate hydraulic realism. Importantly, nearly half of the studies tested their models on independent flood events, strengthening evidence of generalizability.

Table 5: Validation Data Sources and Performance Metrics Used Across the 20 Included Studies

Validation Aspect	Category	Description	Percentage of Studies (n = 20)	Why It Matters
Validation Data Source	High-resolution aerial or commercial satellite imagery	Orthophotos, WorldView, PlanetScope used as reference flood maps	40% (8 studies)	Provides spatially complete, visually interpretable ground truth
	In-situ measurements	River gauges, GPS surveys, field water marks	30% (6 studies)	Offers physically measured validation with high reliability
	Hydrodynamic model outputs	flood extents or depths used as reference	Model-simulated 15% (3 studies)	Useful where field data unavailable but introduces model uncertainty
	Government flood maps	Official disaster or hazard mapping products	15% (3 studies)	Practical for operational validation but variable in accuracy
Validation Scale	Pixel-based	Pixel-by-pixel comparison between prediction and reference	70% (14 studies)	Most common approach; sensitive to spatial misalignment
	Object-based	Comparison of flood objects or regions	20% (4 studies)	More robust to small spatial shifts
	Basin-level aggregation	Catchment-scale agreement	10% (2 studies)	Useful for planning but masks local errors
Event Design	Same-event validation	Training and testing on same flood event	55% (11 studies)	Risks optimistic accuracy
	Independent-event validation	Tested on different flood events	45% (9 studies)	Stronger evidence of model generalizability
Primary Metrics	Overall Accuracy (OA)	(TP + TN) / total pixels	75% (15 studies)	Simple but biased under class imbalance
	F1-Score	Harmonic mean of precision and recall	55% (11 studies)	Balanced metric for flood detection
	Intersection over Union (IoU)	TP / (TP + FP + FN)	45% (9 studies)	Standard in segmentation tasks
	Precision	TP / (TP + FP)	40% (8 studies)	Controls false alarms
	Recall	TP / (TP + FN)	40% (8 studies)	Critical for disaster response
Continuous Metrics	RMSE	Error in depth or water level	30% (6 studies)	Used in flood depth modeling
	NSE	Nash–Sutcliffe Efficiency	25% (5 studies)	Hydrologic model performance standard
Advanced Metrics	Cohen's Kappa	Agreement corrected for chance	25% (5 studies)	Robust to imbalance
	AUC-ROC	Threshold-independent discrimination	20% (4 studies)	Useful for probabilistic outputs

4. Discussion

Our findings show that remote sensing has moved beyond experimental demonstration and is now a mature and operationally relevant tool for flood control and stormwater management. Across the 20 studies included in this review, SAR, optical, LiDAR, and UAV platforms consistently provided reliable, scalable, and complementary information for flood detection, modeling, and infrastructure assessment. The dominance of SAR-based approaches, particularly using Sentinel-1, confirms its central role in operational flood mapping because of its independence from cloud cover and daylight, a result that aligns with earlier methodological syntheses [2, 4]. Studies such as [36, 37] demonstrate that automated and deep learning–based SAR workflows can achieve robust accuracy and generalizability, supporting real-time or near-real-time applications. At the same time, optical sensors remain indispensable for monitoring vegetation dynamics, green stormwater infrastructure performance, and surface water quality, as shown by [5, 17], particularly when long-term environmental change is of interest.

We also find that LiDAR and UAV platforms play a distinct and irreplaceable role in urban flood and stormwater studies. LiDAR-derived DEMs provide the geometric foundation for accurate hydraulic modeling, with multiple studies reporting substantial improvements in flood depth simulation and model performance when high-resolution terrain data are used [7, 8, 38]. UAV-based systems further extend this capability by enabling centimeter-scale mapping of flood impacts and stormwater infrastructure condition, which is critical for post-event assessment and facility-level management [10, 31, 39]. Together, these findings suggest that large-scale satellite monitoring and fine-scale airborne or UAV observations should not be treated as competing approaches, but rather as complementary components of an integrated monitoring framework.

Another important insight is the clear methodological shift toward machine learning and deep learning. Convolutional neural networks and vision transformer models consistently outperform traditional threshold-based and rule-based methods, particularly in SAR flood segmentation tasks [32, 36, 40]. The availability of benchmark datasets such as Sen1Floods11 has been instrumental in improving

reproducibility and comparability of results btai20. However, our synthesis also shows that many high-performing models are trained and validated on limited geographic or event-specific datasets, which raises concerns about transferability and operational robustness, echoing earlier warnings by [2, 4].

Finally, the results highlight that flood extent mapping is the most operationally mature application of remote sensing, whereas flood forecasting, green stormwater infrastructure monitoring, and urban drainage system assessment remain comparatively underdeveloped. While studies integrating soil moisture products, precipitation estimates, and flood extent maps into hydrological models show promising improvements in predictive skill [41, 42], few provide systematic evaluations of uncertainty propagation or real-time performance. Similarly, although NDVI-based approaches demonstrate the potential to link vegetation dynamics with hydrologic response [17, 43], the empirical connection between remotely sensed indicators and functional stormwater performance remains weakly validated. This suggests that the next stage of research must shift from demonstrating technical feasibility to establishing operational reliability, uncertainty transparency, and decision relevance.

5. Conclusion and Implications for Research and Practice

This systematic review shows that remote sensing has become an essential and operationally credible foundation for flood control and stormwater management. By synthesizing a carefully selected set of 20 high-quality and verifiable studies, we demonstrate that no single sensor or platform is sufficient on its own. Instead, effective flood management increasingly depends on integrated monitoring systems that combine SAR for all-weather flood detection, optical sensors for vegetation and surface water dynamics, LiDAR for high-precision topography, and UAVs for localized infrastructure assessment. The consistency of evidence across these studies confirms that SAR, particularly Sentinel-1, remains the backbone of large-scale operational flood mapping [2, 4, 36], while LiDAR and UAVs provide the geometric and structural detail necessary for accurate urban hydraulic modeling [7, 8, 38]. We therefore conclude that remote sensing should be understood not as a supplementary data source, but as a core observational infrastructure for modern flood and stormwater governance.

From a practical standpoint, our findings imply that agencies should adopt a tiered monitoring strategy. We recommend beginning with freely available satellite datasets such as Sentinel-1, Sentinel-2, and Landsat for routine flood surveillance and long-term trend analysis [5, 11]. These can then be augmented with LiDAR in high-risk urban areas where terrain accuracy directly controls flood depth estimates and model reliability [7, 8]. UAVs should be prioritized for post-event damage assessment and stormwater infrastructure inspection, where centimeter-scale detail is critical and rapid deployment adds clear operational value [10, 31, 39]. Cloud computing platforms and standardized processing pipelines further enable agencies to reduce infrastructure costs while increasing analytical capacity, a shift already demonstrated in large-scale satellite flood monitoring initiatives [12, 42].

At the same time, this review reveals important limitations in the current evidence base. Although machine learning methods now dominate flood mapping research, many studies rely on geographically narrow training data and event-specific validation, which limits transferability and operational robustness [4, 42]. Uncertainty quantification remains weak, with most studies reporting point estimates without confidence intervals or systematic error propagation. Validation datasets are often spatially biased toward accessible areas and temporally misaligned with satellite acquisitions, reducing their independence. In stormwater applications, especially green infrastructure monitoring, we find that remotely sensed indicators such as NDVI are rarely linked directly to measured hydrologic performance, which constrains their interpretability for engineering design and evaluation [17, 43]. These limitations indicate that while remote sensing methods are technically powerful, their decision-making reliability is not yet fully established.

Future research must therefore move beyond algorithmic accuracy toward operational credibility. We identify three priorities. First, standardized uncertainty frameworks are needed to propagate sensor error through flood models and decision products, particularly for early warning systems and depth estimation. Second, transferable machine learning models must be developed through domain adaptation, benchmark datasets, and geographically diverse training data, building on efforts such as Sen1Floods11 [37] and recent ensemble-based approaches [40]. Third, stormwater research should strengthen empirical links between remotely sensed indicators and hydraulic performance metrics, allowing green infrastructure effectiveness to be evaluated with the same rigor applied to flood extent mapping.

In conclusion, our synthesis shows that remote sensing has reached a point of methodological maturity but not yet full operational consolidation. Its greatest strength lies in its ability to provide rapid, synoptic, and repeatable observations that complement ground monitoring and hydraulic modeling rather than replace them. As climate change intensifies flood hazards and urban exposure continues to rise, remote sensing will become increasingly central to building resilient, equitable, and data-driven flood management systems. The challenge ahead is not technological feasibility, but institutional integration, uncertainty transparency, and sustained investment in validation and capacity building.

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