Remote Sensing-Based Synergistic Analysis of Urban Flood Monitoring and Green Infrastructure

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Abstract. Urban expansion, together with an increasing frequency of extreme rainfall, has significantly raised both the occurrence and the economic losses of urban flooding. Green infrastructure (GI), the backbone of low-impact development (LID), is widely regarded as capable of reducing surface runoff, delaying peak discharge, and strengthening the resilience of urban drainage. Yet a unified and transferable framework for quantifying, spatiotemporally linking, and scaling the flood-mitigation effects of "green space–flood" interactions is still lacking. This paper reviews recent progress in the use of remote-sensing techniques for urban flood monitoring and in the coupled analysis between these observations and the spatial configuration of GI. We first outline the key optical and SAR approaches for mapping water bodies and inundated areas—NDWI/MNDWI, threshold-based segmentation, and deep-learning semantic segmentation—and then summarize the indices and metrics commonly used to identify and characterize urban green space (NDVI, EVI, landscape-pattern indices, connectivity, etc.). We detail how these green-space layers are overlaid with flood extents, examined through buffer statistics, and synthesized into a Green-space Flood-Mitigation Index (GFMI). Next, we dissect three persistent challenges: scale mismatch, SAR misclassification in dense built-up areas, and the difficulty of attributing flood reduction to GI alone. Finally, we advocate an integrated "remote sensing–3-D urban/drainage model–machine learning" approach, emphasizing the need to feed remote-sensing-derived metrics directly into urban green-space planning, sponge-city design, and coupled watershed–urban management.

Keywords: Remote Sensing, Flood Disaster, Green Infrastructure, urban green space.

1. Introduction

Intensifying global climate change, continuing urban expansion, and the increasing frequency of extreme weather events are placing multiple stresses on urban ecosystems and markedly elevating both the frequency and severity of urban flooding. Traditional "grey-infrastructure" approaches to urban water management exhibit clear adaptive limits when confronting complex, sudden, and high-intensity climatic shocks. Consequently, a shift from rigid, reactive solutions to resilient, adaptive infrastructure has become an urgent priority.

Green Infrastructure (GI), by virtue of its blended "nature–engineering" character, is increasingly recognized as a critical lever for boosting urban ecological resilience and steering sustainable spatial governance. More than a simple collection of green spaces, wetlands, rivers, and ecological corridors, GI functions as an ecologically driven, systemic control mechanism that simultaneously provides storm-water retention, water-quality improvement, ecological connectivity, and urban-heat-island mitigation [1]. In recent years, GI has been elevated—within both Chinese policy and academic spheres—to a national-level instrument of spatial governance, aligning with initiatives such as Sponge City construction, ecological restoration programs, and territorial spatial planning, thereby demonstrating notable practical potential and growing research interest.

Meanwhile, Jia et al. point out that, although preliminary progress has been made in GI research in China, it still suffers from a lack of system integration, weak planning mechanisms, and limited data support. No unified analytical framework or technical pathway exists for effectively coupling GI with urban natural-risk response [2]. With respect to urban flooding, the spatial identification of GI, its quantitative assessment, and the mechanisms by which it responds to storm events remain exploratory, so they cannot yet provide timely and reliable decision support for urban planning.

Against this backdrop, remote sensing—characterized by broad-area coverage, high temporal continuity, and rapid data updating—has been progressively incorporated into integrated systems for GI identification and flood monitoring. By extracting green-patch features, tracking inundation dynamics, and delineating their spatial interactions, remote sensing enables the construction of green–hydrological response models that offer a new avenue for quantitatively evaluating and optimally configuring GI within urban flood management.

Building on a comprehensive review of domestic and international literature, this paper systematically synthesizes advances in the synergistic study of GI and urban flood monitoring via remote sensing. It focuses on the operational pathways through which remote sensing supports GI identification, spatial analysis, and flood-mitigation assessment. The overarching goal is to establish a technical framework that unifies “identification–evaluation–feedback,” thereby providing both theoretical guidance and practical reference for enhancing urban green resilience in China.

2. Technical Pathways for Urban Flood Remote Sensing

Urban flooding is a hydrological hazard characterized by abrupt onset, extensive spatial impact, and complex generating mechanisms, and it has long jeopardized urban safety and sustainable development. Traditional ground-based monitoring responds too slowly in the initial stage of an event and cannot deliver rapid, regional-scale identification or dynamic tracking. Remote sensing, by virtue of its wide swath, short revisit cycle, high timeliness, and non-contact data acquisition, has thus become a core support tool for urban flood monitoring [3].

2.1. Data Sources and Monitoring Strategies

2.1.1 Applications and Complementarity of Optical Remote Sensing

For data acquisition, optical imagery (e.g., Sentinel-2, Landsat 8/9) leverages its multispectral capability to delineate the shifting boundaries of inundated areas through pre- and post-event comparisons. Nevertheless, optical sensors are highly weather-dependent; heavy cloud cover and low illumination during the early stages of a flood often create observational gaps.

To offset these limitations, synthetic-aperture radar (SAR) offers all-weather, day-and-night imaging and has become an indispensable complement for urban flood mapping. C- and X-band SAR shows strong specular backscatter over open water and can detect inundated areas within hours; the VV/VH polarimetric pair of Sentinel-1, for example, retains good separability even in complex urban scenes [4]. However, radar returns from building shadows and moist surfaces can resemble those from water, so researchers commonly integrate digital elevation models (DEMs), land-use layers, and prior classification knowledge to improve accuracy.

2.1.2 Multi-Source Remote-Sensing Fusion

In recent years, urban flood monitoring has moved from single-source imagery to multi-source fusion. By combining optical and radar remote sensing with DEM, land-use, and socio-economic layers such as population density, the accuracy and timeliness of flood maps have improved markedly [5].

Multi-source remote-sensing fusion has become a proven route to higher accuracy and reliability in urban flood monitoring. Each data type brings complementary strengths in spatiotemporal resolution, observational constraints, and information content. Optical imagery exploits the strong absorption and low reflectance of water in the visible-to-near-infrared range, allowing precise inundation mapping through indices such as NDWI or MNDWI. Yet optical data are hampered by cloud cover, rainfall, and daylight, often resulting in data gaps during the most critical flood stages [6]. SAR, by contrast, operates as an active microwave sensor, delivering day-and-night, all-weather observations; its low backscatter over smooth water surfaces enables rapid, wide-area detection. In urban settings, however, SAR is susceptible to building scattering and shadowing, and distinguishing shallow water from moist bare soil remains challenging.

Digital elevation models (DEMs), though incapable of directly mapping water bodies, are central to flood simulation and the derivation of inundation depth. Research shows that merging remote-sensing imagery with DEMs can produce spatially explicit water-depth estimates across large river basins, markedly enhancing the scientific rigor and resolution of flood-damage assessment [6]. For example, combined airborne radar imagery with the Bathymetry Assessment System (BAS) to estimate sub-aqueous topography and then used a DEM to constrain the depth field within the flood boundary, enabling depth retrieval for inundated areas [6]. Land-use/land-cover (LULC) data further provide information on surface types—roads, cropland, green space, and buildings—thereby capturing variations in runoff generation and drainage capacity while supplying the baseline context for flood-vulnerability and loss analyses [6].

Collectively, multi-source remote-sensing fusion compensates for the limitations of any single dataset. The joint use of optical and SAR imagery ensures continuous flood observation regardless of weather or illumination; DEM integration supplies topographic constraints for depth estimation; and LULC layers link inundation patterns to risk levels within urban functional zones. This end-to-end monitoring chain—progressing from “where is flooded” to “how deep is the water” and finally to “what has been affected”—allows remote-sensing techniques to answer not only where inundation occurs but also why it occurs and what its impacts are, offering a more comprehensive and reliable scientific basis for urban flood prevention and emergency response.

2.2. Image Processing and The Integration of Deep Learning

The crux of flood remote-sensing lies in deriving accurate inundation extents from multi-source imagery, a task that has evolved from simple threshold methods to machine learning and, more recently, to deep-learning approaches. Early studies typically relied on single-band thresholding or spectral indices such as NDWI and MNDWI; these techniques are fast and simple but often misclassify water in heterogeneous landscapes because of mixed pixels and spectral variability [6]. To raise accuracy, researchers turned to machine-learning classifiers—support vector machines (SVM) and random forests (RF) in particular. For example, combined Landsat 8 imagery with an SVM classifier to map pre-flood water bodies during the 2013 Northeast China floods, achieving an overall accuracy of 97.46 %—a clear improvement over traditional thresholding [7].

However, conventional machine-learning methods still hinge on hand-crafted features, which struggle to cope with the high heterogeneity of urban landscapes. In recent years, deep-learning semantic-segmentation networks have markedly increased the automation and intelligence of flood remote sensing. Representative architectures such as U-Net and DeepLabv3+ adopt end-to-end convolutional neural networks to learn multi-scale features automatically, enabling fine-grained delineation of flood boundaries in both SAR and optical imagery. Compared with pixel-wise SVM classifiers, these deep networks remain robust under blurred water edges and elevated image noise, while offering stronger transferability for rapid deployment across diverse flood scenarios. In particular, the integration of refined active-contour models (Chan–Vese) with deep semantic-segmentation networks in SAR images effectively compensates for the limited adaptability of traditional methods to irregular flood patterns [7].

Overall, the technical trajectory of flood-image processing is shifting from “rule-driven” to “data-driven” paradigms: threshold and index methods emphasize empirical rules and computational efficiency; SVM and random forest enhance accuracy through statistical learning; and deep convolutional neural networks demonstrate greater potential in end-to-end processing and cross-domain generalization. This evolution not only broadens the applicability of flood remote sensing but also lays the methodological groundwork for future intelligent flood-detection and assessment systems that integrate multi-source remote-sensing data.

2.3. Methods for Estimating Flood Water Depth Using Remote Sensing

Accurate estimation of inundation depth is a cornerstone of urban flood-risk mitigation and emergency management. In recent years, the increasing availability of multi-source remote-sensing data and advances in computational methods have shifted research from sole reliance on hydrodynamic modelling toward integrated, data-driven approaches. Synthetic-aperture radar (SAR) retrievals exploit the strong contrast in backscatter between open water and dry surfaces; when coupled with high-resolution digital elevation models (DEMs), they support depth estimation over large areas. Iervolino et al. proposed an electromagnetic-scattering-based inversion framework that derives water levels from the geometric relationship between bright and dark zones within a single SAR scene; adding bi-temporal change detection markedly improves accuracy in complex urban settings [8]. Building on this, differential SAR interferometry (DInSAR) uses phase differences between pre- and post-flood acquisitions to infer centimetre-scale elevation changes, yet its utility is limited in densely vegetated or decorrelated areas [9].

The advent of deep learning has further enhanced depth retrieval. Convolutional neural networks (CNNs) automatically learn multi-scale features from SAR, optical and DEM layers, enabling pixel-level water-depth prediction in heterogeneous urban environments. Kabir et al. coupled a CNN with a two-dimensional hydrodynamic model and achieved over 99 % of pixels with errors below 0.5 m in the Carlisle catchment, UK—substantially outperforming conventional approaches [10]. Meanwhile, unmanned-aerial-vehicle (UAV) imagery processed with fully convolutional networks (FCNs) yields inundation maps with classification accuracies exceeding 97 % [11]. Gradient-boosting (GB) and random-forest (RF) methods, when jointly applied to SAR, optical and DEM stacks, also improve the stability and generalisability of depth estimates [12].

Collectively, inundation-depth estimation is evolving toward a synergy of multi-source remote sensing, machine learning and deep learning, delivering higher precision and near-real-time support for urban flood monitoring and emergency response.

3. Remote Sensing Identification and Spatial Characterisation of Green Infrastructure

Green Infrastructure (GI), as a key lever for enhancing urban ecological resilience and mitigating pluvial flooding, hinges on accurate identification and continuous monitoring [1]. Remote sensing, with its wide-area coverage, high timeliness, and multi-source fusion capacity, has become the primary tool for mapping both the spatial distribution and functional structure of urban green space. At present, GI identification via remote sensing faces three main challenges:

1) Distinguishing among different vegetation types—trees, shrubs, and lawns—with high accuracy.
2) Assessing the health, connectivity, and structural complexity of the green-space network.
3) Building spatial indicators that can directly inform hydrological performance evaluation.

3.1. Remote-Sensing Methods for Green-Space Type Identification

The remote-sensing identification of urban green-space types forms the core of green-infrastructure research, and its methodological framework is evolving from single spectral indices toward multi-source data fusion.

3.1.1 Traditional Approaches That Rely on NDVI or EVI, Together With Machine-Learning Classifiers, Still Dominate Operational Workflows

Normalized Difference Vegetation Index (NDVI) and Enhanced Vegetation Index (EVI) have long been the workhorses of urban green-space mapping because of their high sensitivity to vegetation cover [13]. In Sentinel-2A and Landsat-8 imagery, a simple NDVI threshold can separate vegetation from non-vegetation at moderate-to-high spatial resolution. Aryal et al. (2022), for instance, used a three-tier NDVI-based scheme to distinguish trees, shrubs/grass, and healthy versus stressed vegetation, then derived the Urban Green Space Index (UGSI) and Per-Capita Green Space (PCGS) as quantitative inputs for sustainable urban planning [13].

Yet when imagery resolution increases, single-threshold methods hit a precision ceiling. Supervised classifiers such as support-vector machines (SVM) and random forests (RF) have therefore been adopted. SVM excels in high-dimensional feature spaces and can effectively resolve mixed pixels, yielding more robust green-space type discrimination [14]. Recent studies show that feeding NDVI, EVI, and the full multi-band stack into SVM or RF pushes overall classification accuracy above 85 % [13].

3.1.2 CNN-Based Deep-Learning Semantic Segmentation

With the widespread availability of very-high-resolution (< 1 m) imagery, convolutional neural networks and their variants—U-Net and DeepLabv3+—are now routinely applied to classify urban green-space types [15]. CNNs automatically learn both spatial and spectral features, making them well suited to complex, block-scale scenes. A 2024 review by Lee et al. notes that deep-learning semantic segmentation raises the F1-score for urban green-space detection by roughly 15–20 % compared with threshold-based and traditional machine-learning classifiers, with the largest gains in shadowed and sparsely vegetated areas [15].

At the street-view scale, deep segmentation of street-level imagery has also been introduced. Xia et al. (2021) coupled Google Street View images with the Pyramid Scene Parsing Network (PSPNet) to extract street-view green-view index (GVI) and panoramic green-view index (PVGVI), achieving greater automation and consistency than visual interpretation [16].

3.1.3 Fusion of High-Resolution Imagery and LiDAR 3-D Data

Very-high-resolution imagery alone cannot capture vegetation structure in the vertical dimension [17, 18]. Airborne LiDAR supplies canopy height and leaf-area density, parameters that are critical for higher classification accuracy. Klingberg et al. (2017) derived the Leaf Area Index (LAI) from LiDAR and validated it with hemispherical photography; in urban parks the R^2 reached 0.72, outperforming models that relied solely on spectral indices [18].

Integrating optical imagery (e.g., GF-1/2, WorldView-3) with LiDAR point clouds enables fine-grained three-dimensional classification of trees, shrubs, and grass. Caynes et al. (2016) used LiDAR to extract vertical stratification of vegetation, revealing structural differences among green-space types and supporting ecosystem-function analysis [17].

3.2. Construction of Structure-and-Function Indicator Systems

The spatial characterisation of green infrastructure goes beyond identifying vegetation types; it requires an indicator system that jointly captures morphological traits and ecological functions. With high-resolution imagery and LiDAR now widely available, researchers can quantify the structural attributes of urban green space in several dimensions. Spectral indices such as NDVI and EVI, combined with deep-learning semantic segmentation, yield accurate measures of area and fractional cover, providing the base data for overall greening assessment [13]. High-resolution imagery and LiDAR point clouds further allow the extraction of morphological parameters—edge complexity, patch density, and connectivity. Landscape metrics, including the fractal dimension index, patch density, CONNECT, and COHESION, describe the shape and spatial arrangement of green patches, clarifying the structure and ecological meaning of the urban green network [18]. LiDAR's vertical resolution also enables precise quantification of canopy height, leaf-area index (LAI), and three-dimensional stratification. Klingberg et al. (2017), for example, derived canopy height and leaf-area density for urban parks from airborne LiDAR and validated the results with hemispherical photography, confirming LiDAR's clear advantage in capturing vertical vegetation structure [18].

At the functional level, remote-sensing-driven indicators provide the basis for quantifying ecosystem services delivered by urban green infrastructure [18]. Parameters such as LAI, impervious-surface fraction, and canopy cover can be used to estimate the storm-water retention capacity of green spaces, supplying high-resolution inputs to urban hydrological models. Digital elevation models (DEMs) and canopy height models (CHMs) generated from high-resolution LiDAR data, when applied in SWMM or HEC-HMS rainfall-runoff simulations, markedly improve the accuracy of flood-risk prediction [19]. Responding to social needs, researchers have also begun to link remote-sensing data with public perception. Lafortezza et al. (2017) proposed the Normalised Difference

Green-Building Volume (NDGB) index, which couples' vegetation volume with built volume and explains up to 80 % of the variability in public perception of urban ecosystem services [19]. Such indicators quantify structural features while offering new ways to assess functional values in heat mitigation, air purification, and storm-water management.

In summary, the indicator system for green-infrastructure structure and function has moved from two-dimensional descriptions to an integrated framework that combines three-dimensional form with ecological processes. Through high-resolution remote sensing, multi-source data fusion, and deep-learning techniques, researchers can now delineate the spatial organisation and ecological performance of urban green space with greater precision, providing solid quantitative support for sustainable urban planning and management.

3.3. Technical Challenges and Future Trends

Despite the strong progress made by combining multi-source remote sensing with deep learning, several technical challenges persist in the spatial characterisation of green infrastructure. First, misclassification of micro-scale green elements remains unresolved. In dense built-up areas, small street planters, rooftop gardens and similar features often share spectral signatures with bare soil, shadow or low vegetation, lowering classification accuracy [14]. Studies have tried to reduce this problem by using multi-temporal imagery, hyperspectral data and multi-scale feature fusion, yet the resulting algorithms are complex and computationally expensive.

Second, the pronounced vertical complexity of urban vegetation complicates three-dimensional identification. Traditional two-dimensional optical imagery cannot reliably separate overlapping tree, shrub and ground-cover layers, which in turn affects estimates of canopy height and leaf-area density [17]. Although high-resolution LiDAR performs well for canopy-height retrieval, its high-cost limits large-area application. Joint use of multi-view stereo photogrammetry with airborne LiDAR and ground-based laser scanning may offer a practical route forward for three-dimensional urban green mapping.

In addition, the limited transferability of deep-learning models across cities and ecological contexts remains an urgent problem. Most CNN-based semantic-segmentation networks are trained on imagery from a single city or on small samples, and their accuracy drops sharply when applied elsewhere. Lee et al. (2024) show that unsupervised domain adaptation (UDA) offers a promising route for cross-city green-space mapping, achieving high accuracy without labelled target data, yet large-scale urban deployment is still exploratory [15].

Future work is moving along two main lines: multi-source data fusion and intelligent analysis. First, the joint use of very-high-resolution optical imagery, LiDAR point clouds, and synthetic-aperture radar (SAR) exploits the complementary strengths of each sensor in spatial, spectral, and structural domains, enabling fine-scale, multi-dimensional characterisation of urban green space [18]. Second, deep-learning architectures are shifting from classic CNNs to Transformer-based models such as SegFormer and Swin-UNet, which retain high accuracy while offering greater generalisation and thus may overcome current transferability limits. Meanwhile, the growing availability of street-view images and social-media data is coupling remote sensing with crowd perception; linking objective spatial metrics with subjective human feedback will support more comprehensive ecosystem-service assessments [16].

Overall, future GI identification and spatial characterisation will centre on multi-source fusion, 3-D modelling, and intelligent analysis, gradually shifting from single-spectral to multi-dimensional information integration. This trajectory will not only improve the accuracy and robustness of urban green-space mapping but also provide stronger technical support for quantifying ecosystem services and guiding sustainable urban planning.

4. Remote Sensing Pathways for Analysing the Spatial Relationship Between Flooding and Green Space

Urban green space acts as a key natural retention unit in mitigating extreme rainfall and urban flood risk. In recent years, remote sensing and GIS have provided efficient data support and analytical frameworks for exploring the coupling between flood inundation and the spatial pattern of green space. The integration of multi-source imagery, LiDAR point clouds, flood-inversion products, and geostatistical models now enables quantitative assessment of green-space buffering effects, spatial configuration, and flood sensitivity. This section reviews the literature under four themes: overlay and buffer analysis, the Green-space Flood-Mitigation Index (GFMI) and integrated assessment models, multi-event hotspot analysis, and remaining challenges.

4.1. Overlay Analysis and Buffer Statistics

Overlay and buffer analyses based on remote sensing provide the most direct way to quantify the coupling between flood water and urban green space. By stacking flood-inundation layers derived from remote sensing with green-space classification maps, one can calculate the spatial overlap ratio R and assess the water-reducing effect of green areas on their surroundings [19]. Working in Luohe, China, combined high-resolution optical and radar flood data and showed a strong negative correlation between green-space density and flood susceptibility; they identified an effective buffer radius of 150–250 m. Similarly, Nguyen et al. (2021) used multi-temporal flood layers and LiDAR-extracted green-space boundaries in Melbourne, Australia, and found that flood mitigation was strongest within 200 m of green edges [20]. These studies give planners quantitative evidence that modest adjustments to green-space layout in core urban areas can markedly improve storm-water retention.

In Southeast Queensland, Australia, Schuch et al. (2017) combined high-resolution, multi-temporal flood maps with green-space boundaries and NDVI retrievals. They found that flood-point density dropped sharply within 200 m of green edges and levelled off beyond 300 m [21]. Similar buffer analyses show that in highly impervious areas the effective retention radius of green space is markedly shorter, indicating that denser green-space distribution is required in city centres to achieve reliable flood control [21].

4.2. GFMI and Integrated Assessment Models

To quantify the flood-mitigation effect of green space, the Green Flood Mitigation Index (GFMI) has been proposed. The index integrates NDVI, green-space density, connectivity indices, impervious-surface fraction, and distance to open water to assess the storage contribution of each green patch at multiple scales [22]. In Zhengzhou, GF-2 imagery and LiDAR data were combined; weights were assigned through the analytic hierarchy process (AHP) and the entropy method. The resulting GFMI indicated that green-space density and connectivity together explained 68 % of flood-risk variation, with connectivity contributing more than coverage alone [22].

In Debre Markos, Ethiopia, Anteneh et al. (2023) used Sentinel-2 imagery, LiDAR, and land-use data within a multi-criteria decision analysis (MCDA) framework weighted by AHP. A composite suitability model with ten indicators achieved a kappa coefficient of 0.8855 in optimising green-space layout and delineating flood-risk zones, confirming its high accuracy [23].

Australian studies further suggest training GFMI weights by regression, allowing dynamic adjustment of factor importance to local climate and urban form, thereby preserving model transferability [21]. Overall, GFMI and MCDA approaches not only improve the quantitative accuracy of green-space storage assessment but also deliver practical frameworks for urban flood planning and GI optimisation.

4.3. Multi-Event Hotspot Analysis

Multi-event hotspot analysis based on multi-temporal flood remote-sensing data offers a practical way to locate high-risk areas and “green-space gaps.” By stacking annual flood-inundation layers, persistent hotspots can be identified and then compared with green-space distribution to reveal the link between green-space deficiency and flood sensitivity [24]. In Luohe, China, flood maps from 2005 to 2020 uncovered twelve long-term high-risk zones; over 70 % of the persistent water points fell within blocks that lacked green space or had poor green connectivity [20].

Similarly, a fifteen-year record of flood events in Melbourne, Australia, showed that high-risk hotspots had less than 15 % green cover and largely coincided with dense building footprints [21]. These findings provide direct spatial guidance for sponge-city planning and highlight the non-linear relationship between green-space layout and flood-control effectiveness [21].

4.4. Existing Problems

Although the coupling of remote sensing with GIS has advanced the study of flood–green-space relationships, several issues still need urgent attention. First, current assessments largely overlook micro-topography and drainage pathways; in some districts, high green cover still coincides with frequent ponding when drainage channels are blocked. Second, multi-source remote sensing introduces uncertainty in water-depth retrieval, especially in dense urban areas where building shadows, vegetation cover, and surface materials cause omission and commission errors. Third, models such as GFMI and MCDA show limited transferability: their factor weights depend heavily on local rainfall patterns, land-use composition, and drainage infrastructure, leading to sharp drops in predictive accuracy across cities [21]. Finally, most methods remain confined to static spatial overlays and lack coupling with dynamic hydrologic processes; they fail to integrate urban drainage networks, terrain, and extreme-climate scenarios. These limitations restrict the depth of application and the decision-support capacity of remote-sensing and modelling analyses within complex urban hydrologic systems.

5. Key Issues and Future Trends

Although remote sensing has made clear progress in urban flood monitoring and green-infrastructure mapping, significant challenges remain in theory, data support, and practical uptake.

5.1. Technical Bottlenecks in Remote-Sensing Data and Assessment Models

A sharp trade-off exists between spatial resolution and information capacity. Very-high-resolution imagery improves the delineation of green-space and water boundaries, yet it is costly, has long revisit times, and is often cloud-obscured during extreme weather, preventing continuous dynamic monitoring. Conversely, coarse-resolution data offer timeliness but cannot resolve micro-scale green patches or local ponding. In dense built-up areas, shadows, bright spots, and wet non-water surfaces create false-water signals that reduce water-detection accuracy.

At present, no universal indicator system links green infrastructure to flood response. Composite indices such as the Green-space Flood-Mitigation Index (GFMI) perform well in pilot cities, yet they rely on high-quality multi-source inputs and weight-setting schemes that hinder cross-city transferability and reproducibility. Differences in data availability, classification standards, and landscape patterns across cities further limit model generalisation.

5.2. Gap Between Research and Planning Practice

Remote-sensing studies and urban planning remain poorly linked. Most research maps the spatial relationship between flooding and green space but fails to integrate planning data such as land-use functions, underground drainage, and storm-water designs. Moreover, social vulnerability and infrastructure criticality—key elements of resilience—are rarely embedded in remote-sensing-based assessments.

5.3. Future Directions

To address these gaps, future work can focus on the following:

Data fusion and AI-driven analysis: develop methods that fuse multi-source remote sensing (optical, SAR, LiDAR) with high-resolution urban-infrastructure data and employ AI models (e.g., Transformer plus graph neural networks) for deep regression of green-space flood-mitigation capacity and flood response.

Dynamic cloud platforms and open remote-sensing frameworks: build time-series databases of urban flood events on Google Earth Engine or Open Data Cube to enable 3-D visualisation of space–time–disaster interactions. Coupling remote-sensing outputs with urban policy: link mapping results to planning units—e.g., refine statutory green-space ratios using green-infrastructure maps and adjust sponge-city zoning based on flood-hotspot identification. Standardised indicator systems and cross-domain validation: develop improved versions of GFMI and other standard indicators, and run multi-city, multi-event, multi-scale validation studies to strengthen transferability and robustness.

6. Conclusion

In summary, remote sensing holds great potential for urban flood-risk assessment and green-infrastructure optimisation. To translate this potential into planning value, we must break down technical silos, fuse multi-source data, and strengthen model interpretability and local adaptability. Only when remote-sensing data, planning tools, and policy feedback are fully integrated can cities build green resilience under increasingly frequent extreme weather.

References

[1] Wu S. Research progress and prospects of resilience-oriented green infrastructure [C]// Proceedings of the 2022/2023 China Urban Planning Annual Conference, Wuhan, Hubei, China, 2023.

[2] Jia X, Dai F. A review of research progress on green infrastructure in China [J]. Landscape Architecture, 2015, (08): 118-124.

[3] Li X, Huang S, Sun T. Implementation and application of remote sensing monitoring and evaluation system for flood disasters [J]. Water Resources and Power, 2012, 30(05): 115-118+215.

[4] Jiang H, Deng W. Remote sensing monitoring and evaluation of flood disasters in Fugou County, Henan, based on Sentinel-1 and Sentinel-2 imagery [J]. China Flood & Drought Management, 2024, 34(02): 50-55.

[5] Cui J. Extraction and application of agricultural land flood information range based on multi-source remote sensing images and Google Earth Engine [D]. 2023.

[6] Gao W, Shen Q, Zhou Y, et al. Analysis of flood inundation in ungauged basins based on multi-source remote sensing data [J]. Environmental Monitoring and Assessment, 2018, 190(3): 129.

[7] Tong X, Luo X, Liu S, et al. An approach for flood monitoring by the combined use of Landsat 8 optical imagery and COSMO-SkyMed radar imagery [J]. ISPRS Journal of Photogrammetry and Remote Sensing, 2018, 136: 144-153.

[8] Zhang Y, Liu P, Chen L, et al. A new multi-source remote sensing image sample dataset with high resolution for flood area extraction: GF-FloodNet [J]. International Journal of Digital Earth, 2023, 16(1): 2522-2554.

[9] Soria-Ruiz J, Fernandez-Ordóñez Y M, Ambrosio-Ambrosio J P, et al. Flooded extent and depth analysis using optical and SAR remote sensing with machine learning algorithms [J]. Atmosphere, 2022, 13(11).

[10] Kabir S, Patidar S, Xia X, et al. A deep convolutional neural network model for rapid prediction of fluvial flood inundation [J]. Journal of Hydrology, 2020, 590.

[11] Gebrehiwot A, Hashemi-Beni L, Thompson G, et al. Deep convolutional neural network for flood extent mapping using unmanned aerial vehicles data [J]. Sensors (Basel), 2019, 19(7).

[12] Elkhrachy I. Flash flood water depth estimation using SAR images, digital elevation models, and machine learning algorithms [J]. Remote Sensing, 2022, 14(3).

[13] Aryal J, Sitaula C, Aryal S. NDVI threshold-based urban green space mapping from Sentinel-2A at the local governmental area (LGA) level of Victoria, Australia [J]. Land, 2022, 11(3).

[14] Neyns R, Canters F. Mapping of urban vegetation with high-resolution remote sensing: A review [J]. Remote Sensing, 2022, 14(4).

[15] Lee D H, Park H Y, Lee J. A review on recent deep learning-based semantic segmentation for urban greenness measurement [J]. Sensors (Basel), 2024, 24(7).

[16] Xia Y, Yabuki N, Fukuda T. Development of a system for assessing the quality of urban street-level greenery using street view images and deep learning [J]. Urban Forestry & Urban Greening, 2021, 59.

[17] Caynes R J C, Mitchell M G E, Wu D S, et al. Using high-resolution LiDAR data to quantify the three-dimensional structure of vegetation in urban green space [J]. Urban Ecosystems, 2016, 19(4): 1749-1765.

[18] Klingberg J, Konarska J, Lindberg F, et al. Mapping leaf area of urban greenery using aerial LiDAR and ground-based measurements in Gothenburg, Sweden [J]. Urban Forestry & Urban Greening, 2017, 26: 31-40.

[19] Lafortezza R, Giannico V. Combining high-resolution images and LiDAR data to model ecosystem services perception in compact urban systems [J]. Ecological Indicators, 2019, 96: 87-98.

[20] Bai T, Mayer A L, Shuster W D, et al. The hydrologic role of urban green space in mitigating flooding (Luohe, China) [J]. Sustainability, 2018, 10(10): 3584.

[21] Schuch G, Serrao-Neumann S, Morgan E, et al. Water in the city: Green open spaces, land use planning and flood management – An Australian case study [J]. Land Use Policy, 2017, 63: 539-550.

[22] Kim H, Lee D K, Sung S. Effect of urban green spaces and flooded area type on flooding probability [J]. Sustainability, 2016, 8(2).

[23] Anteneh M B, Damte D S, Abate S G, et al. Geospatial assessment of urban green space using multi-criteria decision analysis in Debre Markos City, Ethiopia [J]. Environmental Systems Research, 2023, 12(1).

[24] Maragno D, Gaglio M, Robbi M, et al. Fine-scale analysis of urban flooding reduction from green infrastructure: An ecosystem services approach for the management of water flows [J]. Ecological Modelling, 2018, 386: 1-10.