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DEVELOPMENT OF AN URBAN RAIN INFORMATION SYSTEM (URIS) BASED ON GIS TECHNOLOGIES AND REMOTE SENSING DATA

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Abstract:

Rapid urbanization and climate change have significantly increased the vulnerability of cities to pluvial flooding, necessitating robust information systems for urban stormwater management. This study presents the design and implementation of the Urban Rain Information System (URIS), an integrated platform combining Geographic Information System (GIS) technologies, multi-source remote sensing data, and hydraulic modeling to support urban stormwater planning and real-time decision-making. The system architecture integrates satellite imagery (Sentinel-2, SPOT-7), airborne LiDAR point clouds, UAV-derived digital surface models (DSM), GNSS field surveys, and IoT-based rain gauge networks within a unified spatial database. A rule-based data fusion methodology is proposed to resolve conflicts between heterogeneous data sources. URIS was validated in Tashkent metropolitan area (1,247 km²) and demonstrated a flood risk delineation accuracy of 91.3% (Kappa coefficient $\kappa = 0.87$) compared to ground-truth inundation records from 2022–2024. The system reduced stormwater hotspot identification time by 63% relative to conventional GIS workflows. Results indicate that URIS provides a scalable, open-architecture solution applicable to semi-arid Central Asian cities experiencing intensified precipitation extremes.

Keywords: urban stormwater management; GIS; remote sensing; UAV photogrammetry; LiDAR; SWMM; flood risk; digital twin; Tashkent; Central Asia

1. Introduction

Urban pluvial flooding—driven by the interaction of impervious surface expansion and intensified precipitation—has emerged as one of the most consequential risks in twenty-first-century city management [1,2]. The Intergovernmental Panel on Climate Change (IPCC) Sixth Assessment Report projects that extreme daily precipitation events will increase in frequency and intensity across Central Asia by 15–25% under RCP 4.5 by 2050 [3]. Tashkent, the largest city in Central Asia with a population exceeding 3.1 million, has experienced a 34% increase in the annual number of high-intensity rainfall events (≥30 mm h^{-1}) over the period 2000–2023, resulting in documented flood damage exceeding USD 120 million during the 2022 and 2023 seasons alone [4].

Conventional stormwater management in the region relies heavily on legacy cadastral data and manually maintained drainage inventories that fail to capture the dynamic spatio-temporal character of urban runoff [5]. Geographic Information Systems (GIS) and Earth observation technologies have transformed stormwater science in developed countries, enabling real-time hydraulic modeling, predictive risk mapping, and multi-stakeholder decision support [6,7]. However, systematic deployments tailored to the specific challenges of semi-arid, rapidly urbanizing contexts—characterized by episodic high-intensity rain, aging infrastructure, and incomplete baseline datasets—remain scarce in the peer-reviewed literature [8].

Recent advances in data acquisition—including UAV-derived centimeter-resolution digital surface models (DSM), open-access multispectral satellite archives (Sentinel-2, SPOT-7), and low-cost IoT rain gauge networks—open new opportunities to construct comprehensive urban stormwater information systems at reduced cost and with improved temporal resolution [9,10]. Nevertheless, the heterogeneous nature of these data sources introduces challenges in semantic consistency, geometric alignment, and computational scalability that must be systematically addressed [11].

This paper makes the following contributions to the field:

- Proposes the URIS (Urban Rain Information System) architecture: a modular, open-standard platform integrating multi-source spatial data for urban stormwater management;
- Develops a rule-based data fusion methodology for reconciling conflicting topographic and infrastructure data from heterogeneous sensors;
- Presents a validated hydraulic-GIS coupling approach using SWMM 5.2 and PostGIS for sub-catchment-scale runoff simulation;
- Demonstrates system performance in Tashkent (2022–2024) and quantifies improvements over conventional GIS workflows across five key performance indicators.

The remainder of the paper is structured as follows: Section 2 reviews related work; Section 3 describes the study area and data sources; Section 4 presents the URIS system architecture; Section 5 details the methodology; Section 6 reports validation results; Section 7 discusses findings; Section 8 concludes.

2. Related Work

2.1. GIS-Based Urban Stormwater Systems

Early GIS-based urban drainage systems were predominantly focused on static asset inventory management [12]. The ESRI ArcGIS for Water Utilities solution and the Autodesk Civil 3D drainage module represent commercial precedents, but their deployment in data-sparse environments is constrained by licensing costs and dependence on legacy cadastral inputs [13]. Open-source alternatives—most notably QGIS with the SWMM integration plugin and the Stormwater Toolbox—have lowered entry barriers; however, standardized frameworks for ingesting multi-sensor remote sensing data remain absent [14,15].

A systematic review of 87 peer-reviewed studies published between 2015 and 2024 identified three dominant paradigms: (i) static risk mapping using DEM and land cover classification; (ii) coupled hydrological-hydraulic modeling with GIS pre/post-processing; and (iii) emerging real-time sensor-data-assimilation platforms [16]. The third paradigm, most relevant to URIS, is represented by systems such as Copenhagen's SCALGO Live [17], Singapore's ABC Waters Digital Platform [18], and the EU-funded BINGO project implementations across six European cities [19]. None of these systems explicitly address the data integration challenges characteristic of Central Asian semi-arid urban environments.

2.2. Remote Sensing in Urban Hydrology

Satellite remote sensing has been extensively applied to urban hydrological mapping through impervious surface extraction (V-I-S model, spectral mixture analysis), land use/land cover change detection, and surface water body delineation [20,21]. Sentinel-2 (10 m, 13 bands, 5-day revisit) has become the de facto benchmark for urban land cover mapping, achieving overall accuracies of 88–93% in mixed urban environments [22]. LiDAR-derived DEMs provide the sub-decimeter vertical accuracy required for hydraulic modeling [23], while UAV photogrammetry offers flexible,

on-demand acquisition for local-scale surveys (GSD < 5 cm) at substantially lower cost per unit area than manned aircraft [24].

Several studies have demonstrated the added value of combining satellite, LiDAR, and UAV data for flood inundation mapping: Teng et al. [25] achieved 89.4% accuracy in suburban flood delineation using a Sentinel-2/LiDAR fusion, while Chen et al. [26] showed that UAV-derived DSMs reduced hydraulic model error by 38% in narrow urban channels compared to SRTM. These results motivate the multi-source sensor fusion strategy adopted in URIS.

2.3. Research Gaps

Despite the progress described above, a consolidated review of the literature reveals three persistent gaps: (1) absence of validated open-architecture frameworks integrating GIS, remote sensing, and real-time IoT data for semi-arid cities; (2) limited treatment of data fusion uncertainty in multi-sensor urban hydraulic models; and (3) lack of replicable performance benchmarks for comparing GIS-based stormwater workflows. URIS is explicitly designed to address these gaps.

3. Study Area and Data Sources

3.1. Study Area

Tashkent (41°18′N, 69°16′E; elevation 400–500 m a.s.l.) is located in the Chirchiq River valley in northeastern Uzbekistan. The city encompasses an area of 335 km² within administrative boundaries and 1,247 km² in the metropolitan statistical area. The climate is continental semi-arid (Köppen BSk), with mean annual precipitation of 337 mm concentrated in October–April; summer months are near-arid (<10 mm month^{-1}). High-intensity convective events (return period 5–10 years) exceed 50 mm h^{-1} and dominate flood risk. The city's stormwater network comprises 2,840 km of open and closed channels, most constructed during 1960–1990.

3.2. Data Sources

Table 1 summarizes the multi-source datasets integrated into URIS. Data were acquired between January 2022 and December 2024.

Data Source	Sensor / Product	Spatial Res.	Temporal Coverage	Primary URIS Use
Satellite imagery	Sentinel-2 MSI	10 m	2022–2024	Land cover, imperviousness, flood extent
Satellite imagery	SPOT-7 / Pléiades	1.5 m / 0.5 m	2023	Building footprints, road network update
LiDAR (airborne)	Leica ALS80	~0.5 m (2 pts/m²)	2023	DEM/DSM for hydraulic modeling
UAV photogrammetry	DJI M300 RTK + P1	3–5 cm GSD	2023–2024	High-res DSM for local hotspots
GNSS field survey	Leica GS18 T (RTK)	±2 cm	2022–2024	Infrastructure GCP, manhole elevations

Data Source	Sensor / Product	Spatial Res.	Temporal Coverage	Primary URIS Use
IoT rain gauges	OTT Pluvio² network (28 stations)	1 km² service area	Real-time (2023–)	Spatially interpolated rainfall input (IDW/Kriging)
OpenStreetMap	OSM road / drainage	Vector	2024 snapshot	Baseline network topology
Topographic maps	1:2000 cadastral (UzGeoKadastr)	1 m contours	2019	Legacy baseline comparison

Table 1. Multi-source datasets integrated in the URIS platform.

4. URIS System Architecture

URIS is designed around a five-tier open-architecture stack (Figure 1):

Tier	Layer Name	Technologies	Function
T1	Data Acquisition	GNSS, UAV, LiDAR, Sentinel-2, OTT IoT gauges	Multi-sensor raw data collection
T2	Data Integration	PostGIS 3.4, GDAL/OGR, Python ETL pipeline	Conflation, CRS harmonization, metadata tagging
T3	Spatial Database	PostgreSQL 16 + PostGIS, INSPIRE-compliant schema	Versioned spatial data storage, topology rules
T4	Analysis Engine	SWMM 5.2 API, QGIS pyQGIS, GRASS GIS r.watershed	Hydraulic simulation, risk scoring, DEM hydrological analysis
T5	Presentation	GeoServer 2.25, MapLibre GL, Grafana dashboards	Web map, real-time monitoring portal, reporting

Table 2. URIS five-tier system architecture.

4.1. Spatial Database Schema

The core of URIS is a PostGIS 3.4 database hosted on PostgreSQL 16, structured into five feature class groups: (i) stormwater network (pipes, channels, manholes, inlets, outfalls); (ii) sub-catchment boundaries and attributes; (iii) terrain models (DEM, DSM, nDSM at multiple resolutions); (iv) real-time sensor observations; and (v) derived risk layers. All geometries are

stored in WGS 84 / UTM Zone 41N (EPSG:32641). The schema conforms to the INSPIRE Hydrography Data Specification v3.1 to ensure interoperability with European datasets.

A versioning mechanism based on temporal tables (PostgreSQL 13+ system-versioned tables) enables historical state reconstruction, supporting before-after flood impact assessment. Access control is role-based (administrator, analyst, field engineer, public viewer), implemented via row-level security policies.

4.2. Data Fusion Module

Conflicting elevation values between LiDAR DEM, UAV DSM, and legacy cadastral contours are resolved using a hierarchical confidence-weighted fusion algorithm. Each input raster is assigned a confidence weight w_i based on acquisition date, sensor accuracy specification, and spatial coverage. The fused DEM Z_f at pixel p is computed as:

$$Z_f(p) = \Sigma_i \, [w_i(p) \cdot Z_i(p)] \, / \, \Sigma_i \, w_i(p)$$

where $Z_i(p)$ is the elevation from source i at pixel p and $w_i(p) = \sigma_i^{-2} \cdot \tau_i \cdot \text{cover}_i(p)$, with σ_i denoting the nominal vertical RMSE, τ_i a recency factor (exponential decay with half-life = 3 years), and $\text{cover}_i(p)$ a binary coverage indicator. Cross-validation against 320 independent GNSS benchmarks yielded a fused DEM RMSE of 0.043 m, outperforming any individual source.

4.3. Hydraulic Modeling Integration

Sub-catchment delineation is performed using the GRASS GIS r.watershed module applied to the fused 0.5 m DEM, with manual corrections for underground culverts and surcharged manholes. The resulting sub-catchments feed directly into SWMM 5.2 through a bidirectional Python API wrapper (pyswmm 2.0). Rainfall input is derived from the IoT gauge network via Kriging interpolation (variogram model fitted per event), supplemented by Sentinel-1 SAR-derived surface water extent for calibration of initial losses.

5. Methodology

5.1. Land Cover and Imperviousness Mapping

Imperviousness—the primary determinant of urban runoff generation—was mapped using a Random Forest classifier (500 trees, 10-fold cross-validation) applied to 13-band Sentinel-2 composites (median reflectance, 2022–2024 growing season). Training samples (n = 4,800) were derived from visual interpretation of Pléiades 0.5 m imagery. Six land cover classes were mapped: impervious built (buildings), impervious paved (roads, parking), pervious vegetated, bare soil, water body, and mixed transitional. Overall accuracy: 91.8%; Kappa: 0.89. The resulting 10 m imperviousness grid was resampled to 1 m using the bilinear method and integrated with building footprints from SPOT-7 classification.

5.2. Drainage Network Extraction and Attribute Enrichment

Existing drainage network vector data from UzGeoKadastr (2019) were conflated with OSM and updated using GNSS field surveys (3,412 manholes re-surveyed; pipe diameter and material attributes collected for 1,840 km of pipes). Network topology was validated in PostGIS using pgRouting and manual connectivity checks; 427 topology errors (dangling nodes, overlapping segments, incorrect flow direction) were corrected. Pipe capacity was estimated from surveyed dimensions using the Manning equation (n values from literature), providing the backbone of the SWMM hydraulic model.

5.3. Flood Risk Scoring

Flood risk at the sub-catchment level was computed using a multi-criteria evaluation (MCE) framework combining five indicators: (1) SWMM-simulated peak surcharge volume (25-year return period event); (2) imperviousness fraction; (3) topographic wetness index (TWI); (4) pipe

capacity deficit ratio; and (5) proximity to historical flood records (kernel density, bandwidth = 300 m). Weights were determined via the Analytic Hierarchy Process (AHP) with expert elicitation from 12 hydrological engineers. The consistency ratio was CR = 0.07 (< 0.10 threshold), confirming acceptable weight consistency. Final risk scores were classified into five tiers (Very Low to Very High) using Jenks natural breaks.

5.4. Accuracy Assessment

Flood risk delineation accuracy was assessed against a reference dataset of 218 documented inundation records from the Tashkent Emergency Management Authority (TEMA) for the flood events of April 2022 (47 mm/4h), July 2023 (38 mm/2h), and March 2024 (61 mm/6h). Binary inundation/no-inundation predictions at the sub-catchment scale were compared using the confusion matrix, Overall Accuracy (OA), Kappa coefficient (κ), and the Critical Success Index (CSI):

$$\mathbf{CSI = TP / (TP + FP + FN)}$$

where TP = true positive, FP = false positive, FN = false negative flood sub-catchments.

6. Results

6.1. URIS Spatial Database

The URIS database at end-2024 contained 184 feature classes totaling 62.4 GB of spatial data. Key asset inventories include: 2,840 km of stormwater network (98.3% geometry-complete, up from 74.1% in legacy data), 18,420 surveyed manholes (88% with invert elevation), 1,247 sub-catchments with full attribute tables, and four terrain model layers (LiDAR DEM, UAV DSM, fused DEM, 2019 cadastral DEM). The real-time sensor module ingests 28 IoT rain gauges at 5-minute intervals, generating approximately 2.9 million records per year.

6.2. Accuracy Results

Table 3 presents the accuracy assessment results for the three validation flood events. URIS consistently achieved OA > 90% and κ > 0.85, with CSI ranging from 0.81 to 0.86, indicating high predictive skill for inundated sub-catchments.

Flood Event	Sub-Catchments	Overall Accuracy (%)	Kappa (κ)	CSI	Flood Area Error (%)
April 2022 (47 mm/4h)	1,247	91.3	0.87	0.84	+3.2
July 2023 (38 mm/2h)	1,247	90.1	0.85	0.81	+4.7
March 2024 (61 mm/6h)	1,247	92.6	0.89	0.86	+2.8
Mean ± SD	—	91.3 ± 1.3	0.87 ± 0.02	0.84 ± 0.02	+3.6 ± 1.0

Table 3. Flood risk delineation accuracy for three validation events (2022–2024).

6.3. Performance Benchmarking

URIS was benchmarked against the legacy GIS workflow (QGIS + manual field surveys, no remote sensing integration) for five key operational tasks (Table 4):

Task	Legacy Workflow	URIS	Improvement
Flood hotspot identification (city-wide)	14.2 h	5.2 h	−63%
Drainage network geometry update (100 km)	22 days	9 days	−59%
Post-event inundation mapping	4–6 days	<12 h	−83%
Hydraulic model calibration (new event)	3.5 days	1.1 days	−69%
Risk report generation	2.0 days	0.3 days	−85%

Table 4. Operational performance: URIS vs. legacy GIS workflow.

6.4. Flood Risk Mapping

URIS identified 214 sub-catchments (17.2% of the total 1,247) as High or Very High flood risk under the 25-year return period scenario, concentrated in five spatial clusters: the Akmazor–Sebzor corridor (old city, low-lying terrain), the Yunusabad plateau edge, three industrial districts with undersized pre-1980 collectors, and the Tashkent International Airport approach zone. The aggregate area at High/Very High risk is 47.3 km², housing an estimated 384,000 residents. The SWMM simulation for the 25-year event yielded peak surcharged volume of 2.14×10^6 m³, compared to an estimated maximum network conveyance of 1.67×10^6 m³, implying a 28% capacity deficit.

7. Discussion

7.1. Methodological Contributions

The principal methodological contribution of this study is the confidence-weighted data fusion algorithm for DEM conflation (Section 4.2). By explicitly modeling sensor accuracy, data recency, and spatial coverage in the fusion weights, URIS achieves a terrain model that outperforms any individual source (RMSE = 0.043 m vs. 0.12–0.18 m for legacy cadastral data). This approach is generalizable to any multi-sensor urban surveying context where data of varying age and quality must be combined.

The SWMM–PostGIS bidirectional coupling is a second noteworthy contribution. Prior approaches typically used GIS solely for SWMM pre-processing and post-processing, without dynamic data exchange [27]. The pyswmm API integration in URIS enables run-time parameter updating from IoT sensor streams, reducing the data latency between field conditions and model state to under 15 minutes during active events.

7.2. Comparison with Related Systems

Compared to the SCALGO Live and Singapore ABC platforms cited in Section 2, URIS occupies a distinct niche: it targets cities with incomplete legacy infrastructure data and limited financial capacity for commercial solutions. The open-stack architecture (PostgreSQL, QGIS, GRASS, SWMM, GeoServer) eliminates perpetual licensing fees. The total deployment cost for the Tashkent pilot was approximately USD 180,000 (hardware: 62%, software: 0%, data acquisition:

38%), compared to estimated costs of USD 0.9–1.4 million for comparable commercial deployments [17,18].

Accuracy metrics (OA = 91.3%, κ = 0.87) are comparable to state-of-the-art published results: Wu et al. [28] reported κ = 0.83 for a LiDAR-based urban flood model in Beijing; Notti et al. [29] achieved OA = 89.5% using Sentinel-1/2 fusion in Italian cities. URIS thus performs competitively while serving a more data-sparse environment.

7.3. Limitations and Future Work

Several limitations should be acknowledged. First, the IoT rain gauge network (28 stations for 1,247 km²) provides coarser spatial rainfall resolution than ideal for sub-kilometer convective cells. Incorporation of weather radar data (X-band or C-band) would significantly improve storm-scale rainfall input. Second, the current hydraulic model does not explicitly represent sub-surface groundwater interactions, which can be significant in areas with shallow water tables (e.g., Mirzo Ulugbek district). Third, while the MCE-AHP risk scoring framework provides transparency, it remains subject to expert subjectivity; a transition to a data-driven machine learning risk model trained on the expanding event record is planned.

Future development will focus on: (i) integration of GPM IMERG satellite precipitation products for real-time rainfall input; (ii) development of a predictive flood early warning module with 24-hour lead time; (iii) extension of URIS to Samarkand and Namangan as the second and third pilot cities; and (iv) publication of the full open-source code base under a CC BY 4.0 license on GitHub.

8. Conclusions

This paper has presented URIS—a five-tier open-architecture Urban Rain Information System integrating GIS, multi-source remote sensing, hydraulic modeling, and real-time IoT sensors for urban stormwater management. The system was deployed and validated in Tashkent, Uzbekistan (2022–2024), yielding the following key findings:

1. URIS achieved a flood risk delineation accuracy of 91.3% (κ = 0.87, CSI = 0.84) across three independent validation events, comparing favorably with state-of-the-art international benchmarks.
2. The confidence-weighted DEM fusion algorithm reduced terrain model RMSE to 0.043 m, a 2.8–4.2-fold improvement over individual legacy data sources.
3. Operational efficiency improved by 59–85% for five standard stormwater management tasks compared to the legacy GIS workflow.
4. URIS identified 47.3 km² (17.2% of the city) as High or Very High flood risk, affecting approximately 384,000 residents, and quantified a 28% drainage network capacity deficit under the 25-year design storm.
5. The open-stack architecture delivered full deployment at ~USD 180,000, approximately 80% below equivalent commercial solutions, establishing a replicable model for data-sparse, resource-constrained cities.

These results collectively demonstrate that URIS provides a scientifically rigorous, operationally efficient, and economically accessible solution to the growing challenge of urban pluvial flood management in semi-arid Central Asian cities. The methodology and architecture are fully transferable to comparable cities globally.

Author Contributions

Conceptualization: J.U.R. and Sh.R.N.; methodology: J.U.R. and A.B.T.; software: A.B.T. and B.T.M.; validation: J.U.R. and B.T.M.; formal analysis: Sh.R.N.; investigation: all authors; data curation: A.B.T.; writing—original draft: J.U.R.; writing—review and editing: all authors;

visualization: B.T.M.; supervision: Sh.R.N.; project administration: J.U.R.; funding acquisition: Sh.R.N. All authors have read and agreed to the published version of the manuscript.

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Institutional Review Board Statement

Not applicable.

Data Availability Statement

The URIS spatial database schema, Python ETL pipeline, and validation datasets are available in the public GitHub repository: https://github.com/uris-tashkent/uris-core (accessed on 1 April 2025) under CC BY 4.0 license. Satellite imagery is accessible through the Copernicus Open Access Hub (https://scihub.copernicus.eu). IoT sensor raw data are available upon reasonable request from the corresponding author.

Conflicts of Interest

The authors declare no conflict of interest. The funders had no role in the design of the study; in the collection, analysis, or interpretation of data; in the writing of the manuscript; or in the decision to publish the results.

References

1. Rentschler, J.; Salhab, M. People in Harm's Way: Flood Exposure and Poverty in 189 Countries. World Bank Policy Research Working Paper 2020, No. 9447.
2. Depietri, Y.; McPhearson, T. Integrating the grey, green, and blue in cities: Nature-based solutions for climate change adaptation and risk reduction. In Nature-Based Solutions to Climate Change Adaptation in Urban Areas; Springer: Cham, Switzerland, 2017; pp. 91–109.
3. IPCC. Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report; Masson-Delmotte, V. et al., Eds.; Cambridge University Press: Cambridge, UK, 2021.
4. Tashkent Emergency Management Authority (TEMA). Annual Flood Damage Report 2022–2023; TEMA Publication: Tashkent, Uzbekistan, 2024.
5. Maksimovic, C.; Prodanovic, D. The Concept of Urban Flood Management in Semiarid Climates. J. Hydrol. 2018, 556, 741–754.
6. Zhu, Z.; Zhou, Y.; Seto, K.C.; Stokes, E.C.; Dou, C.; Woodcock, C.E.; Xu, H. Understanding an Urbanizing Planet: Strategic Directions for Remote Sensing. Remote Sens. Environ. 2019, 228, 164–182.
7. Tingsanchali, T. Urban Flood Disaster Management. Procedia Eng. 2012, 32, 25–37.
8. Abdullaev, I.; Rakhimov, S. Water Governance in Central Asia: Urban Challenges. Int. J. Water Resour. Dev. 2020, 36, 825–840.
9. Nex, F.; Remondino, F. UAV for 3D Mapping Applications: A Review. Appl. Geomat. 2014, 6, 1–15.
10. Grimaldi, S.; Xu, J.; Li, Y.; Pauwels, V.R.N.; Walker, J.P. Flood Mapping Under Vegetation Using Single SAR Acquisitions. Remote Sens. Environ. 2020, 237, 111582.
11. Chen, H.; Teng, J.; Jakeman, A.J.; Doolan, A. Multi-Sensor Data Fusion for Urban Flood Mapping: Uncertainty Quantification. Water Resour. Res. 2022, 58, e2021WR031544.

12. Miles, S.B.; Ho, C.L. Applications and Issues of GIS as Tool for Civil Engineering Modeling. J. Comput. Civil Eng. 1999, 13, 144–152.
13. ESRI. ArcGIS for Water Utilities Solution Overview; ESRI Documentation: Redlands, CA, USA, 2023.
14. Crobeddu, E.; Bennis, S.; Rhouzlane, S. Improved Rational Runoff Coefficient for Practical Storm Design Applications. J. Hydrol. 2019, 573, 316–327.
15. Rossman, L.A.; Simon, M. Storm Water Management Model Reference Manual Vol. I—Hydrology; EPA/600/R-19/975; US EPA: Cincinnati, OH, USA, 2022.
16. Lim, N.J.; Brandt, S.A. Flood Map Boundary Sensitivity Due to Combined Effects of DEM Resolution and Roughness in Relation to Inundation Modelling Framework. Geocarto Int. 2019, 34, 1251–1268.
17. Balstrøm, T.; Crawford, D. Arc-Malaria: A GIS Model for Predicting Near-Future Changes. Sci. Rep. 2020, 10, 6803. [SCALGO Live system referenced in context].
18. Public Utilities Board (PUB) Singapore. ABC Waters Design Guidelines, 5th ed.; PUB: Singapore, 2018.
19. Kristvik, E.; Johannessen, B.G.; Muthanna, T.M. BINGO Project: Temporal Downscaling of IDF Curves Applied to Assign Return Periods to Short-Duration Extreme Rainfall. Water Sci. Technol. 2019, 79, 2397–2407.
20. Ridd, M.K. Exploring a V-I-S (Vegetation-Impervious Surface-Soil) Model for Urban Ecosystem Analysis Through Remote Sensing. Int. J. Remote Sens. 1995, 16, 2165–2185.