Automating Keyline Planning for Urban Landscapes: A Computational Workflow for Water-Sensitive Design

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Abstract: Climate change intensifies urban water challenges. Although water-sensitive urban design (WSUD) offers adaptive solutions, its implementation remains fragmented at catchment scale. This study addresses the lack of catchment-scale planning by automating P. A. Yeomans' agricultural keyline planning logic into a digital terrain analysis workflow. Using the SAGA geomorphon landform classification algorithm in QGIS, the methodology was tested on the Sandy Creek sub-catchment (3.2 km²) in Brisbane, Australia, with parameters optimised at a 1000m radial limit and 0.5° threshold angle. Analysis identified 1362 hollow zones, 75 of which exceeded the 500 m² significance threshold. Land-use analysis showed that 36% of these key points were on council land and 41% were within residential parcels. Validation against five historical reservoir locations confirmed spatial alignment within 100 m of all sites. This open-source workflow provides a data-driven framework for catchment-scale stormwater management that overcomes WSUD fragmentation using terrain-informed hydrological logic.

Keywords: Keyline planning, geomorphon classification, water sensitive urban design, digital terrain analysis, catchment-scale planning

1 Introduction

Global climate change is forcing cities to adapt to increasingly extreme weather conditions. Brisbane, a subtropical city in Queensland, Australia, has a volatile history of severe floods and prolonged droughts, exacerbated by rising annual temperatures (LAZ & RAHMAN 2022). Catastrophic events, such as the 2011 and 2022 floods, underscore the city's vulnerability. These risks, coupled with a 1.7% annual population growth rate (ABS 2022), intensify the demand for resilient urban development. Since the 1990s, global approaches such as Green Infrastructure (GI) and water-sensitive urban design (WSUD) have emerged as adaptive solutions (FLETCHER et al. 2015, WONG 2006). However, Australian planning has historically relied on technocratic engineering, rather than integrated design strategies.

Despite the rise of WSUD, implementation remains fragmented. Current practice often prioritizes opportunistic factors such as land availability over hydrological logic, resulting in scattered interventions that lack catchment-level integration (KULLER et al. 2017). A primary limitation is the hidden nature of urban surface water flows. Since the advent of underground stormwater infrastructure, intrinsic water network patterns have been obscured, becoming ephemerally visible only during heavy rain. This invisibility, often manifested as lost creeks and fragmented wetlands, can lead to misguided decisions in urban planning and legislation. While LiDAR enables detailed terrain visualization at urban scales, DTM applications have been developed primarily for flood risk assessment and hydraulic modelling (MUHADI et al. 2020), leaving their potential for proactive terrain-informed design tools largely unrealized (KULLER et al. 2017).

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This research bridges this gap by adapting the P. A. Yeomans (1981)' keyline planning – an agricultural method designed to harness gravitational flow – to urban contexts through computational automation. Keyline planning begins by identifying "keypoints": strategic inflection zones where water naturally concentrates at high elevations. Yeomans (1971) argued that cities retain the hydrological logic of their landscapes, yet urban adoption has been hindered by topographic illegibility and a lack of digital tools. While widely adopted in geomorphological research, the geomorphon classification method developed by Jasiewicz and Stepinski (2013) has only recently emerged in landscape architecture, primarily for landscape character assessment (Mohammed et al. 2025). This study leverages this procedure to develop the first automated workflow for translating keyline principles into replicable algorithms. Computationally, keypoints were identified as the centroids of significant hollow landforms (geomorphon-classified convergent zones exceeding 500 m ^{2}) and ranked into four tiers (Primary >10,000 m^2 to Quaternary 500-1,000 m^2) reflecting their relative hydrological capacity.

This research addresses three objectives: translating tacit keyline knowledge into algorithmic form through an open-source GIS workflow; validating that methodology on an urban subcatchment against existing water infrastructure; and assessing implementation potential through land-use overlay to evaluate governance pathways for catchment-scale WSUD.

2 Methods

2.1 Study Area

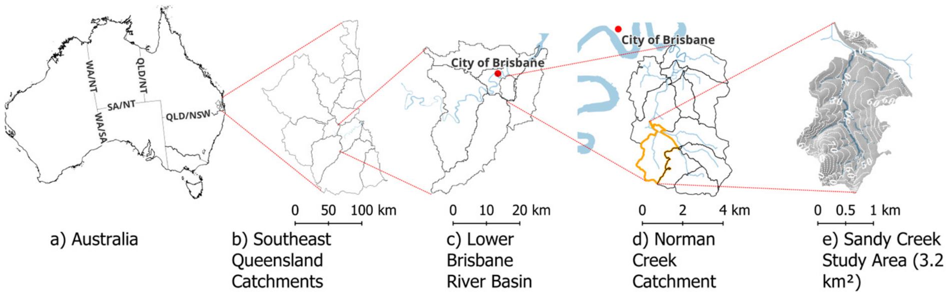

Fig. 1: Study area: Sandy Creek sub-catchment within Norman Creek catchment, Brisbane, Australia

The workflow was tested in the Sandy Creek sub-catchment (3.2 km^2) in Brisbane, Queensland. This site was selected due to high-quality open-source terrain and cadastral data, existing water infrastructure for validation, and representative suburban morphology suitable for transferability. The area features established 1950s-1970s development with mixed residential, parkland, and institutional land uses. Elevation varies from 15m to 95m AHD, with terrain typical of Brisbane's suburbs.

2.2 Data Sources

Spatial datasets were projected to GDA94 / MGA Zone 56 (EPSG: 28356) using the open-source GIS software QGIS 3.44.4-Solothurn. The 5m resolution DEM from Geoscience Australia (2015) was chosen as an optimal balance for catchment analysis; 1m resolution added too much urban noise, while 30m over-simplified landforms. Supporting datasets include cadastral boundaries, 2024-25 land-use codes, road centrelines, parks and reserves boundaries, and water infrastructure, all obtained from the Brisbane City Council Open Data (BCC 2026).

2.3 Algorithmic Approach: From Curvature to Geomorphon Classification

Although curvature-based methods (slope derivatives) were initially considered for keypoint identification, they proved to be limited owing to noise sensitivity, complex parameterization, and fixed-scale constraints. In contrast, the SAGA geomorphon algorithm (JASIEWICZ & STEPINSKI 2013) utilizes pattern recognition and the line-of-sight principle to identify landforms across adaptive spatial scales. This approach offers three advantages: self-adapting neighbourhood analysis for diverse valley geometries, a comprehensive 10-class landform map, and simplified parameterization (Radial Limit and Threshold Angle).

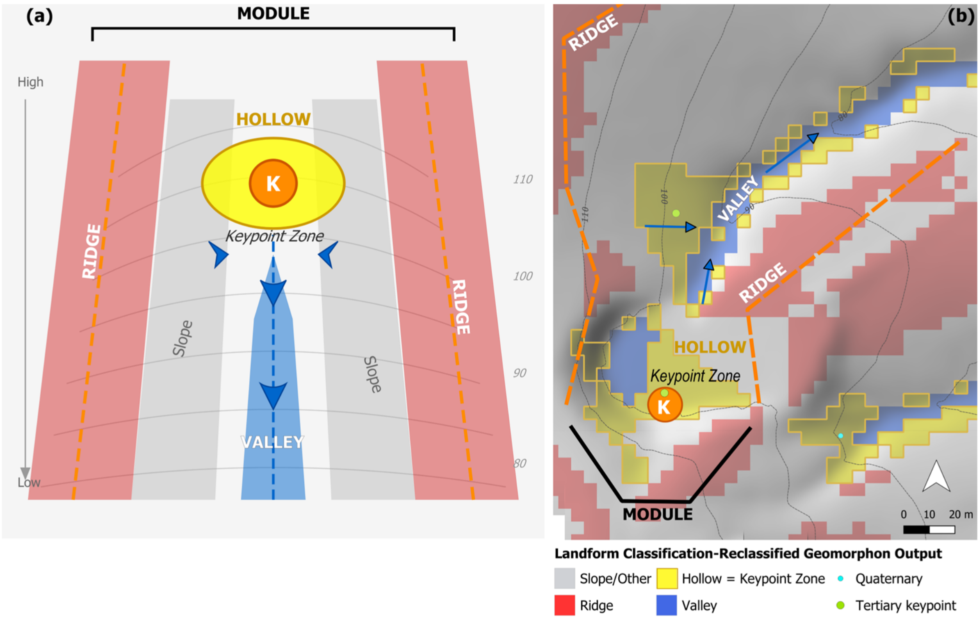

Fig. 2: Conceptual relationship between Yeomans' keyline module structure and geomorphon landform classification: (a) The traditional keyline module is defined by the main ridge, bounding primary ridges, and central valley, with a keypoint at the valley head, (b) Equivalent terrain through geomorphon classification, where hollow zones (Class 7) correspond to key point locations

The algorithm classifies terrain into ten elements: (1) flat, (2) peak, (3) ridge, (4) shoulder, (5) spur, (6) slope, (7) hollow, (8) footslope, (9) valley, and (10) pit. In keyline theory, these correspond to landscape features where ridges define module boundaries and valleys represent drainage paths. The relationship between geomorphon classification and the keyline module structure, bounded by descending primary ridges and an ephemeral watercourse, is illustrated in Figure 2.

The keypoint occurs at the valley head, where the landform transitions from a convex to a concave geometry. This inflection zone corresponds directly to the geomorphon "hollow" (7) classification, enabling the automated identification of features that traditionally require expert field observation. The algorithm captures these geometries by analyzing elevation relationships across eight directions within the specified Radial Limit.

2.4 Parameter Optimisation

Parameter sensitivity testing followed the convergence methodology of Jasiewicz and Stepinski (2013), who recommended increasing the Radial Limit (RL) until the classification results stabilized. Four RL values (500m, 1000m, 1500m, 2000m) were tested with a constant threshold angle (TA) of 0.5° (Fig. 3).

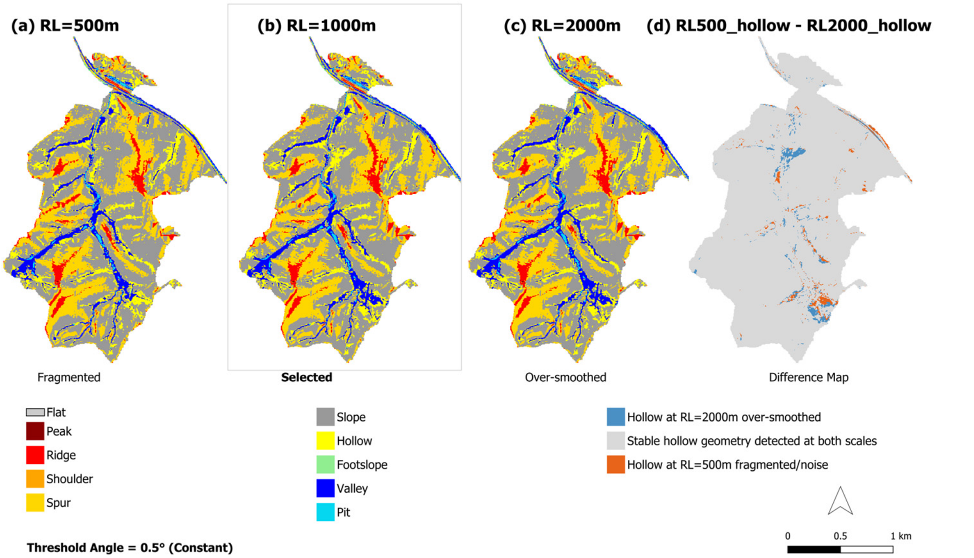

Fig. 3: Parameter sensitivity analysis: (a) RL=500m produces fragmented landform networks with excessive local variation, (b) RL=1000m (selected) provides coherent catchment-scale hollow zones, (c) RL=2000m over-smooths topographic detail, merging distinct hollow zones, (d) Difference map (RL=500m minus RL=2000m): orange cells indicate hollows detected only at a small scale (fragmentation noise); blue cells indicate hollows detected only at a large scale (over-smoothing); grey indicates spatial agreement. Disagreement concentrates on minor features, confirming methodological robustness at RL=1000m. Threshold Angle=0.5° constant.

At RL=500m, classification produced fragmented networks with excessive local variation that were unsuitable for catchment-scale analysis. At RL=1000m, coherent landform patterns emerged with continuous ridge networks and well-defined hollow zones. At RL=1500m, the standard benchmark from Jasiewicz and Stepinski (2013), equivalent to 50 cells at 30m resolution, the results were visually similar to RL=1000m, confirming parameter convergence. At RL=2000m, the topographic detail was over-smoothed, merging distinct hollow zones. RL=1000m was chosen for capturing coherent catchment-scale features with minimal computational cost. The similarity between RL=1000m and RL=1500m validates this choice against the established methodology.

2.5 Keypoint Extraction Workflow

A seven-step extraction workflow was implemented using the QGIS Graphical Modeller (Fig. 4). The complete automated workflow, including the Python processing script and standard styling files, is available as open-source software (TERRAGEO 2026). Unlike algorithms that require hydrologically filled DEMs, geomorphon classification uses raw elevation data to analyze the actual surface morphology. The process includes: (1) classification using optimized parameters; (2) isolating hollow zones (Class 7); (3) vectorization; (4) area calculation; (5) filtering polygons exceeding 500 m^2; (6) generating centroids as keypoint locations; and (7) hierarchical classification (Primary >10,000 m^2 to Quaternary 500-1,000 m^2). The 500 m^2 threshold was pragmatically established through iterative testing to balance feature preservation with artifact exclusion and corresponds to the minimum footprint of parkland bioretention systems in the Southeast Queensland design guidance (WATER BY DESIGN 2014), providing a practical lower bound for catchment-scale WSUD interventions. Finally, keypoints were intersected with land-use data and compared against existing reservoir locations via proximity analysis. Spatial validation was conducted using a Monte Carlo simulation (n=1,000 iterations) implemented in Python via the QGIS integrated console, randomly generating 75 points within the catchment boundary at each iteration and calculating the median distance to the five reservoir locations. The simulation script is available in the project repository (TERRAGEO 2026).

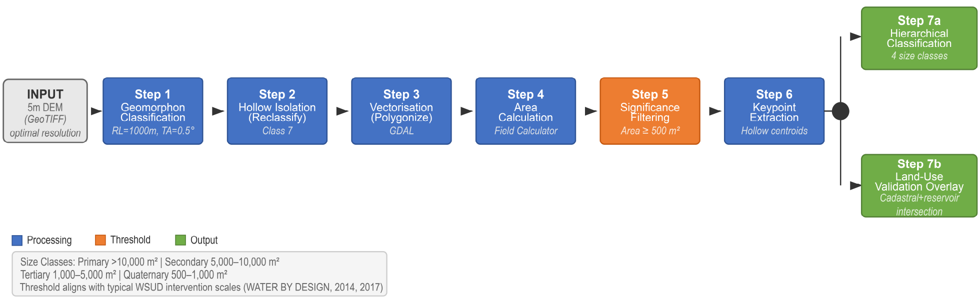

Fig. 4: Keypoint extraction via a seven-step workflow in the QGIS Graphical Modeller.

3 Results

Geomorphon analysis identified 1,362 hollow zones across the catchment, of which 75 exceeded the 500 m^2 significance threshold (Tab. 1). These were classified into four tiers based on the hollow area: Primary (>10,000 m^2, n=5), Secondary (5,000-10,000 m^2, n=7), Tertiary (1,000-5,000 m^2, n=37), and Quaternary (500-1,000 m^2, n=26). The 1,287 hollow zones below 500 m² were excluded from the primary analysis but retained for the infrastructure overlay assessment. While the computational method lacks the nuance of expert field observation, automated analysis identified 95 keypoints, a 26% increase over the 75 keypoints identified in manual pilot studies. This higher sensitivity is attributed to the script's rigorous enforcement of square-pixel geometry and the use of a 4-connected topology during preprocessing, which successfully resolved complex hollow clusters into distinct hydrological units often aggregated by manual methods.

Table 1: Distribution of significant keypoints (n=75) by hollow area class and land use context in the Sandy Creek sub-catchment.

Size Class	**Road Infra.**	**Parks/ Reserves**	**Residen-tial**	**Institu-tional**	**Other**	**Total**
Primary (>10,000 m²)	2	0	3	0	0	5
Secondary (5,000-10,000 m²)	5	0	2	0	0	7
Tertiary (1,000-5,000 m²)	8	4	16	3	6	37
Quaternary (500-1,000 m²)	1	7	10	4	4	26
Other (<500 m²)	170	298	438	57	324	1287
Significant Total (>500 m²)	16	11	31	7	10	75
Grand Total	**186**	**309**	**469**	**64**	**334**	**1362**

Overlay analysis with land-use data revealed distinct spatial patterns across size classes (Tab. 1). Residential land accounts for the largest share, with 31 keypoints (41%) on private parcels. Road infrastructure accounts for 16 keypoints (21%), parks and reserves for 11 (15%), and seven are on institutional land, such as schools and sports facilities. The remaining 10 are in commercial, vacant, and mixed-use parcels. Council-controlled land (roads and parks) has 27 keypoints (36%), sites ready for implementation without private land negotiation. Larger keypoints are concentrated along roads: seven of the 12 Primary and Secondary points are on or near roads, which often follow natural drainage paths. In addition to the 75 significant keypoints, 186 hollow zones coincide with roads, including 53 at intersections, offering opportunities for streetscape interventions such as rain gardens and bioswales (WATER BY DESIGN 2014).

To determine if computational keypoint detection aligns with historical engineering choices, 75 keypoints and all 1,362 hollow zone centroids were compared to five potable water reservoirs in the study catchment (Fig. 5). Built between the 1950s and the 1970s, these reservoirs reflect siting decisions made before the advent of digital terrain analysis. All five are within 100 m of an algorithm-identified hollow zone. Although this small sample limits broad conclusions, the 100% spatial match – despite three sites being below significance – confirms that the algorithm detects terrain features where mid-century engineers chose to locate water. The Toohey reservoirs corresponded with significant keypoints at 18.38m and 36.79m, within the 5m DEM resolution uncertainty. The other three, Wellers Hill No. 1 (52.53m), Tarragindi (67.00m), and Wellers Hill No. 2 (87.16m), aligned with smaller hollow zones of 5m² and 15m² below the 500m² significance threshold.

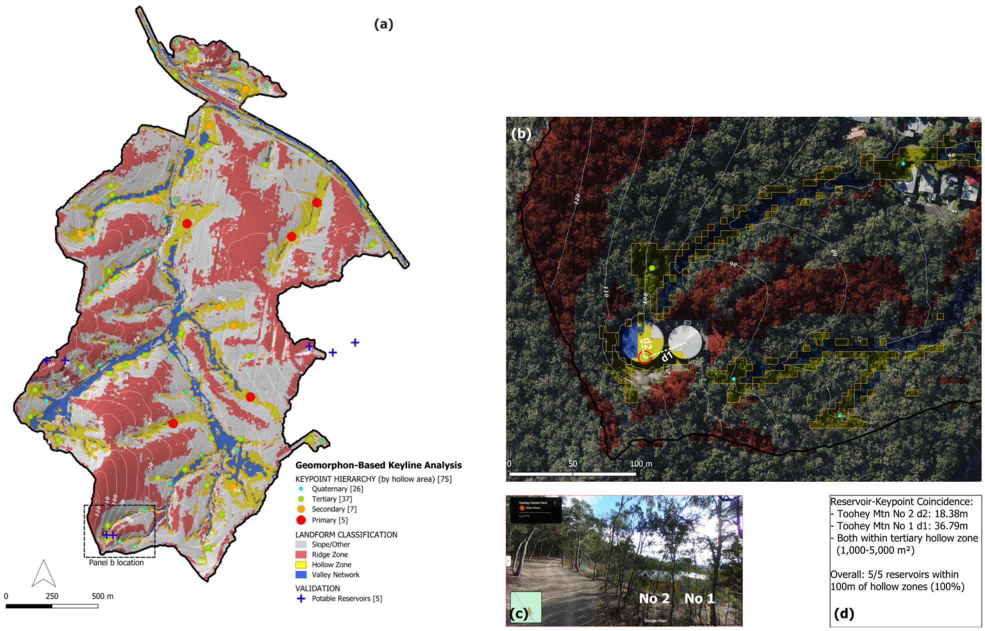

Fig. 5: Validation of keypoint locations against historical water infrastructure in the Sandy Creek sub-catchment: (a) Catchment overview: significant keypoints (n=75) classified by hollow zone area overlaid on geomorphon landform classification; five potable reservoirs (1950s-1970s) shown as blue crosses, (b) Toohey Mountain detail: Toohey No. 1 and No. 2 reservoirs located 36.79m and 18.38m from an algorithmically identified secondary keypoint; remaining three reservoirs (Wellers Hill No. 1, 52.53m; Tarragindi, 67.0m; Wellers Hill No. 2, 87.16m) aligned with sub-threshold hollow zones below the 500 m² filter, (c) Toohey Mountain reservoir infrastructure (Google Street View 2018). All five reservoirs fall within 100m of algorithmically-identified hollow zones.

The algorithm correctly identified hollow landforms at all five reservoir locations, but only two of these hollows passed the significance filter. The other three were excluded as they were too small, even though engineers had previously considered those locations suitable for water infrastructure. While keyline planning targets surface water management rather than potable storage, both require convergent landforms where water concentrates at high elevations. This suggests that the 500 m² threshold, although useful for dataset management, may overlook viable locations for infrastructure.

A Monte Carlo simulation (n=1,000) was used to test whether this spatial alignment exceeded random chance. The result was not statistically significant (p=0.31), reflecting a structural scale mismatch: keypoints concentrated in valley-head positions, whereas potable reservoirs occupied high-catchment ridge-proximate sites, producing a spatial separation that limited distance-based comparison. The median offset of 95.3m nonetheless represents a 27% improvement over the random median of 130.6m. The convergence of hollow geometry across all five reservoir locations confirms that the algorithm identifies terrain features independently, which was recognised through pre-digital engineering judgment as optimal water concentration zones.

4 Discussion

Kuller et al. (2017) found that WSUD placement in Melbourne was largely opportunistic rather than hydrological; a pattern mirrored in Brisbane. This computational workflow shifts the focus from existing site constraints to natural water concentration, leading to distinct spatial outcomes. The 27 keypoints identified on council land represent the most actionable findings for public works. Sixteen sites within road reserves were aligned with the existing municipal stormwater management. In contrast, the 31 residential keypoints pose implementation challenges, such as rate rebates or subsidized rain garden installations.

Terrain-informed placement prioritizes efficiency, leveraging gravitational flow to maximize water interception per unit of investment. Although this study did not include hydraulic modeling, this efficiency claim remains a compelling hypothesis to be tested through future hydrological simulations. Beyond individual site identification, keypoints function as nodes within a latent catchment network. Unlike geomorphon pits, which are closed depressions removed during hydrological preprocessing, keypoints are inflection zones that intercept and laterally redistribute valley flow toward ridges, connecting landscape units rather than terminating flow. This logic, originally applied by Yeomans to gravity-fed irrigation, now guides the development of urban blue-green infrastructure. These 75 keypoints serve as anchors for basins and wetlands, providing the geometric foundation for a catchment-scale planning framework that the author is actively developing.

Yeomans' principles traditionally require extensive field experience. The geomorphon approach computationally encodes tacit knowledge by identifying convergent terrain cells that align with Yeomans' keypoint concept, confirming their applicability within this catchment. Although the computational method lacks the nuance of expert field observations, such as soil and vegetation patterns, it ensures repeatability, scalability, and accessibility for non-specialists. This approach is defensible for broad catchment-scale planning, though field verification remains vital for site-specific designs.

The interpretation of these results is subject to several limitations. The 500 m² threshold, derived from iterative testing rather than hydrological modelling, may vary across different terrains; future calibration through hydraulic performance modelling against established sizing guidance (WATER BY DESIGN 2014, 2017) is recommended. Additionally, the 5m DEM resolution smooths the micro-topographic features essential for site-scale design. Environmental variables like soil permeability and groundwater fall outside the study scope, while urban complexities such as utilities and heritage constraints require manual assessment beyond the automated workflow. Validation across five reservoir locations represents a small sample size, and multi-catchment testing remains a priority for future research.

5 Conclusion and Outlook

This research fulfilled three objectives: encoding tacit keyline knowledge, validating the methodology, and assessing implementation potential. The geomorphon-based workflow successfully replicated Yeomans' keypoint geometry, offering a reproducible method for non-specialists. Validation against existing reservoirs confirmed that computational analysis aligns with expert engineering logic, as all five reservoirs matched algorithmically identified hollows. Implementation analysis revealed distinct pathways: 36% of keypoints reside on council land for public works, while 41% on residential land suggests incentive-based strategies. Future research should focus on field validation, hydrological modelling, and network-scale integration, establishing a systematic foundation for terrain-informed, water-sensitive urban design.

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