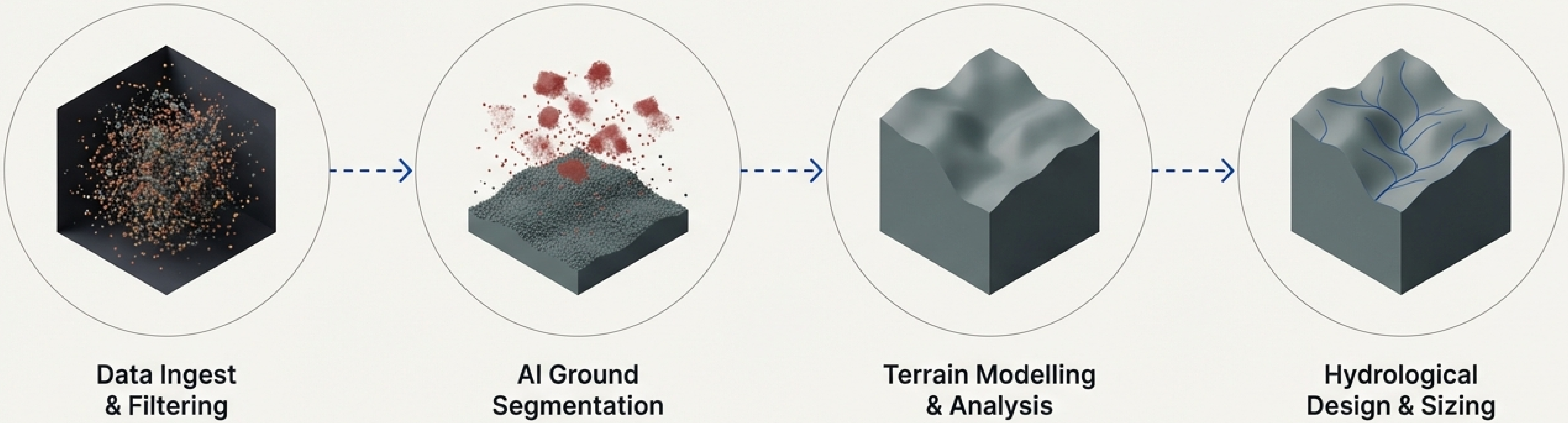
Urban Resilience Starts on the Ground

Conventional urban planning struggles to predict and prevent flash flooding, leading to costly damage and disruption. We need a more precise, data-driven approach to infrastructure design.

As rainfall patterns intensify, understanding how water will behave in our complex urban landscapes is critical. Traditional survey methods are slow, expensive, and often fail to capture the subtle topographical details that determine where water will pool and flow. This results in reactive, inefficient drainage solutions.

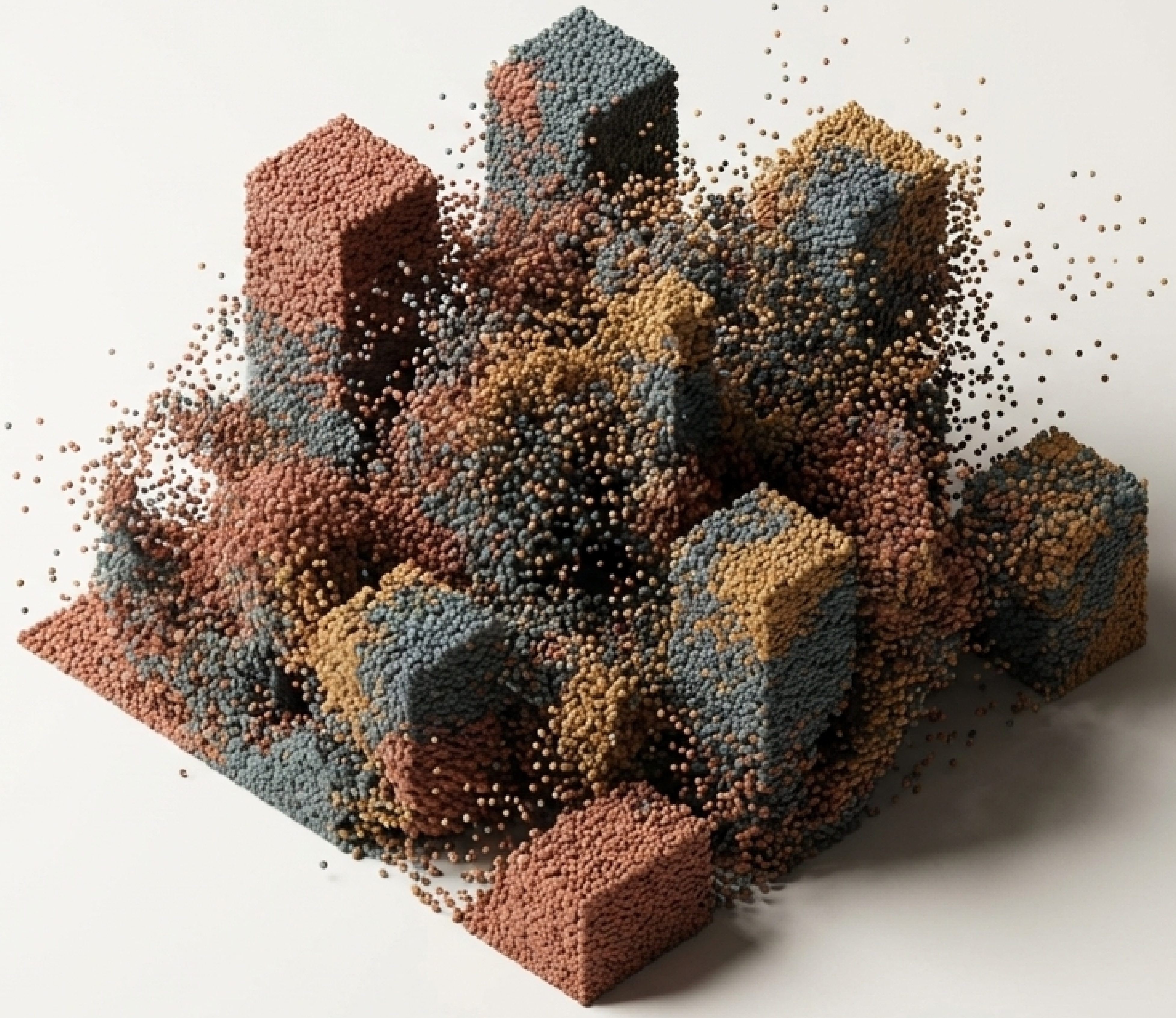
From Raw Data to Resilient Design: An Automated Four-Stage Workflow

We have developed an AI-driven pipeline that transforms raw 3D landscape data into optimised, actionable drainage plans. This process systematically converts chaotic information into a precise digital model of the ground, allowing us to simulate and design for water flow with unprecedented accuracy.



Phase 1: Handling the ‘Swarm of Bees’

A drone or plane uses laser pulses to scan the landscape, creating a massive 3D “swarm of bees”—a point cloud. Each “bee” is a point with a precise height measurement. The initial problem is that these points capture everything: rooftops, tree leaves, and the actual street. We can’t design a drain on a tree leaf, so the first step is to clean up this “buzz” and remove the obvious noise.



Technical Deep-Dive: Input Parsing & Baseline Filtering

Input Data

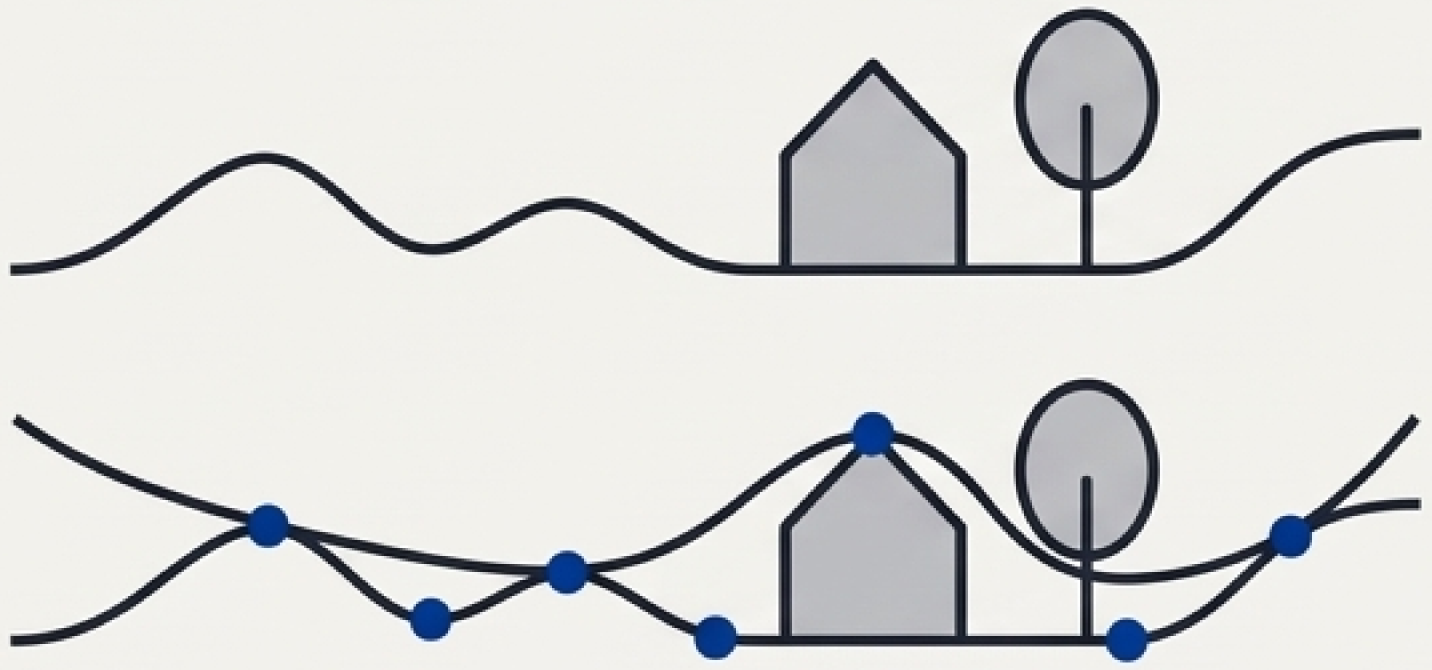
- Format: Raw Lidar/Photogrammetric Point Cloud (LAS/LAZ).
- Attributes Utilised: 3D Coordinates, Intensity, Number of Returns.

Core Tooling

- Python `laspy: For high-performance reading and writing of LAS/LAZ files.
- `Open3D: Used for efficient 3D visualisation and downsampling operations.

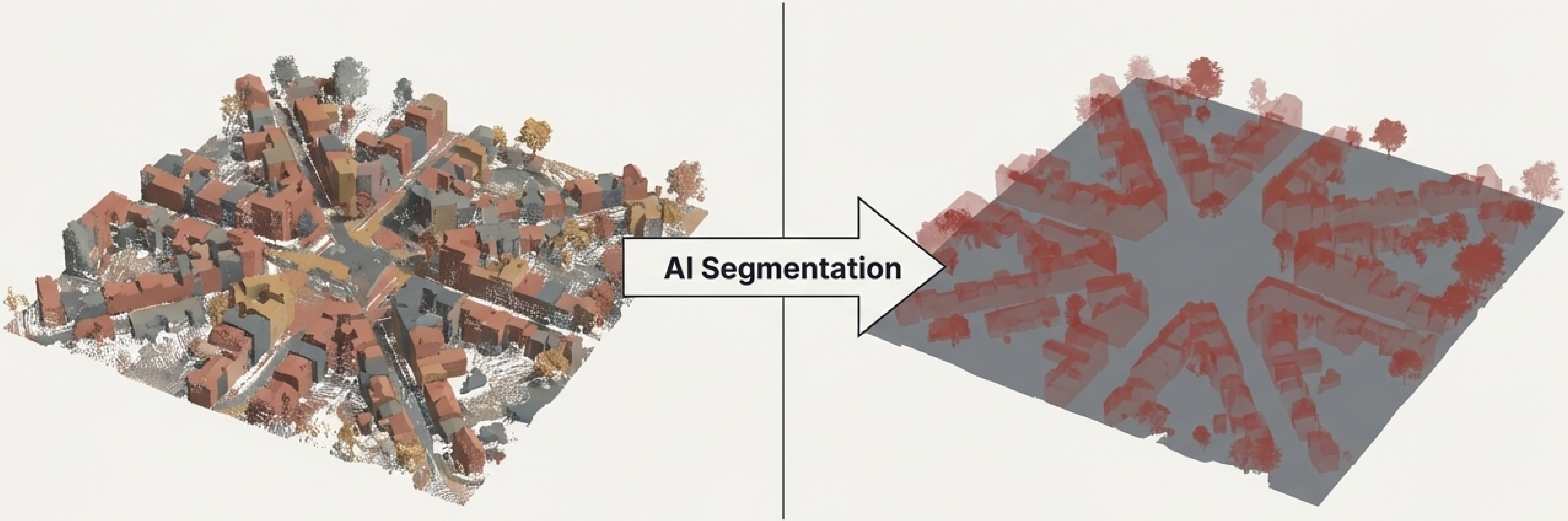
Performance Baseline

- Method: Application of a Cloth Simulation Filter (CSF).
- Purpose: Establishes a non-Machine Learning baseline to rigorously evaluate the performance improvements offered by our subsequent AI model.



Phase 2: The 'Magic Filter' (The AI Bouncer)

The goal is to teach the computer which 'bees' from the swarm are the actual ground. We use a specialised 3D AI that examines the relationship between a point and its neighbours. It learns that points forming a flat surface are likely 'Ground', while points on vertical walls or high above are 'Non-Ground'. The AI acts like a bouncer at a club, letting only the' only the 'Ground Points' stay while kicking the houses and trees out.



Technical Deep-Dive: 3D Semantic Segmentation

Core Concept

Direct application of Deep Learning models on unstructured 3D point sets, avoiding lossy conversions to 2D images.

Chosen Architectures

* **PointNet++** or **RandLA-Net**: Selected for their efficiency and accuracy in handling large-scale point clouds.

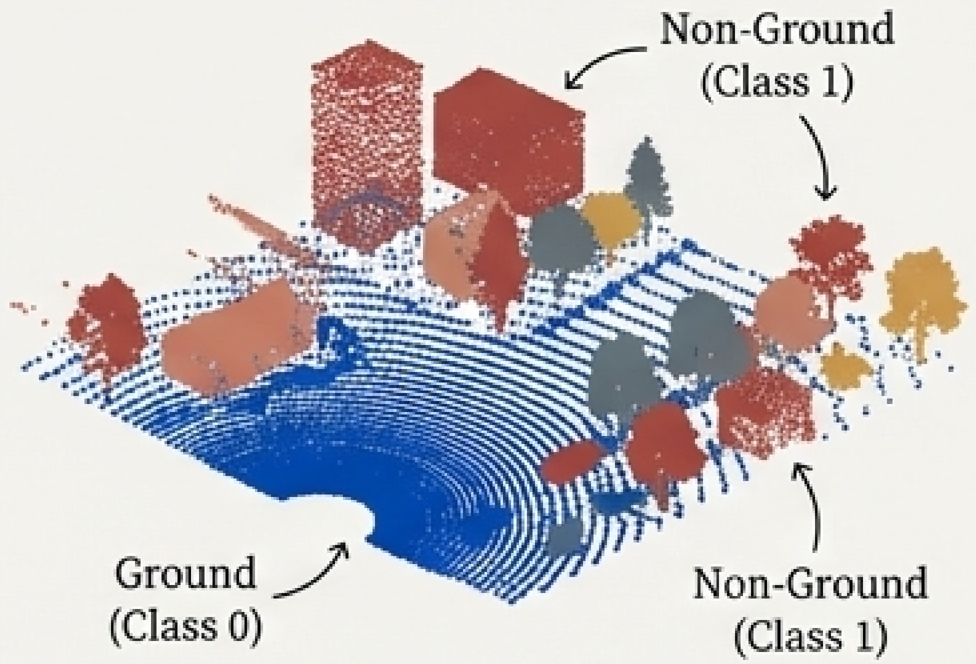
Loss Function

Weighted Cross-Entropy. This is crucial to handle the natural class imbalance where ground points often dominate the dataset, ensuring the model doesn't simply learn to ignore rarer non-ground objects.

Optimisation Target

High-accuracy binary classification of every point.

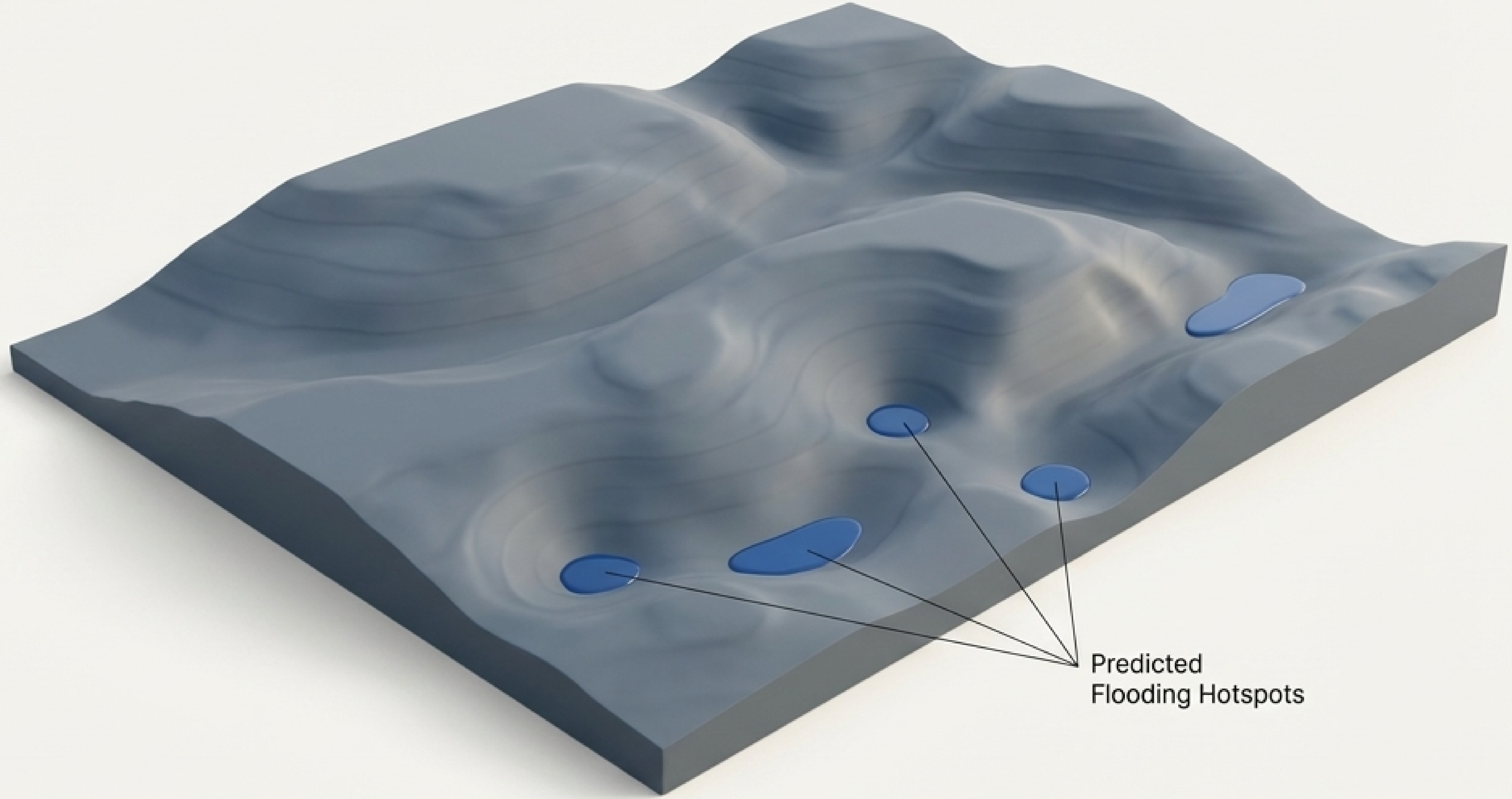
- Class 0: Ground Points (streets, earth, footpaths).
- Class 1: Non-Ground Points (vegetation, buildings, vehicles, infrastructure).



Phase 3: Sculpting the Landscape & Finding the Puddles

Once the AI bouncer removes the buildings and trees, we are left with a clean set of ground points. We then stretch a smooth digital skin over these points to create a perfect Digital Terrain Model (DTM). It's like wrapping the ground in digital cling-wrap.

This highly accurate map allows us to find any 'bowls' or depressions in the terrain. These are precisely where puddles will form when it rains—our predicted flooding hotspots.



NotebookLM

Technical Deep-Dive: Rasterization & Topographic Sink Identification

Point to Raster Conversion

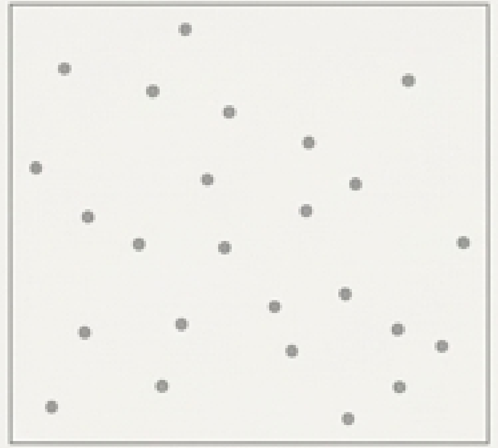
- Process: Interpolating the classified ground points into a continuous grid to create a Digital Terrain Model (DTM).
- Format: GeoTIFF.
- Techniques: TIN (Triangulated Irregular Network) interpolation or IDW (Inverse Distance Weighting).

Hydrological Sink Identification

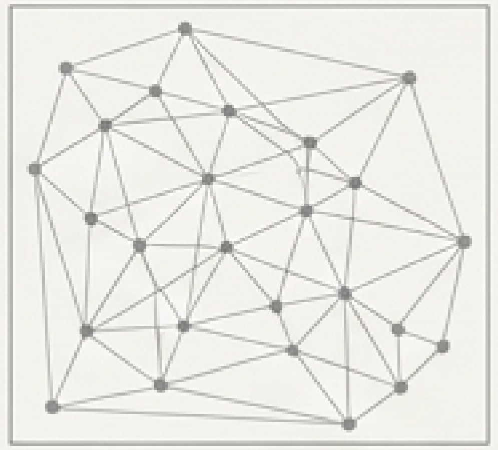
- Definition: Programmatically identifying pixels in the DTM that are topographically lower than all their immediate neighbours. These are cells where water flow would terminate.

Pre-modelling Step

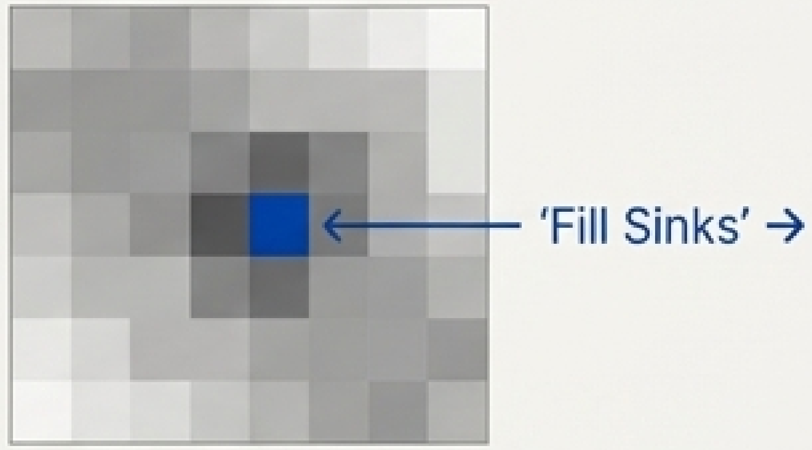
- Algorithm: A 'Fill Sinks' algorithm is applied to the DTM. This mathematically raises the elevation of sink cells to the level of their lowest neighbour, creating a continuous surface that allows for uninterrupted flow modelling in the next phase.



Classified Ground Points



Interpolation (TIN)



Sink Identification & Fill

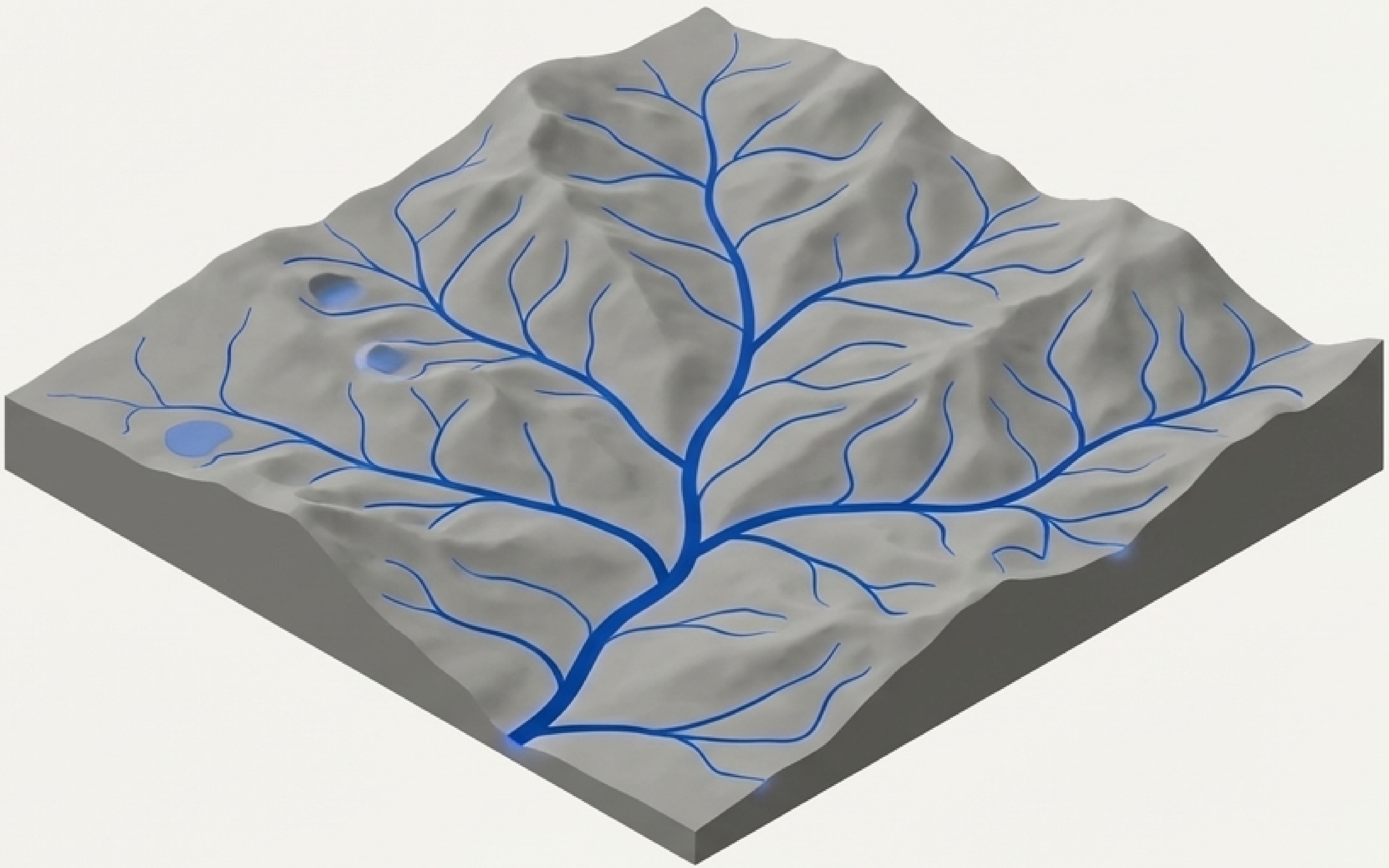
Phase 4: Drawing with Gravity

On our clean ground map, we digitally "drop a bucket of water" on every square. Gravity tells us exactly which way it will roll.

By tracking where all the water from thousands of these buckets meets, we identify the natural "streams" and channels through the landscape.

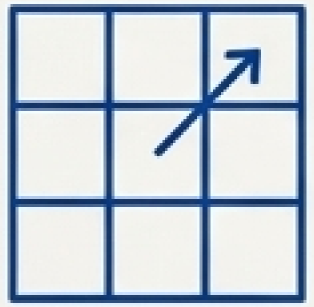
We then automatically draw lines along these paths.

These are the optimal routes for new drains because water *wants* to flow there naturally.



Technical Deep-Dive: Automated Drainage Delineation & Sizing

GIS-Based Workflow (e.g., WhiteboxTools/QGIS)

1. 

Flow Direction: The Deterministic 8 (D8) algorithm is used to calculate the direction of the steepest descent from each cell to one of its eight neighbours.

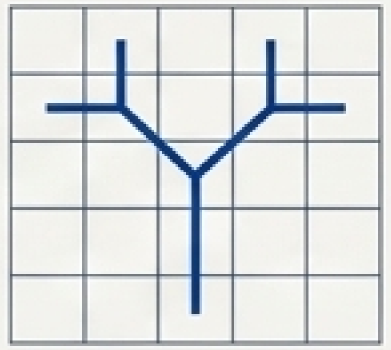
2.

0	2	3
4	6	11
16	19	22

Flow Accumulation: A cumulative count of the number of cells that flow into each downslope cell, effectively identifying natural water conduits.

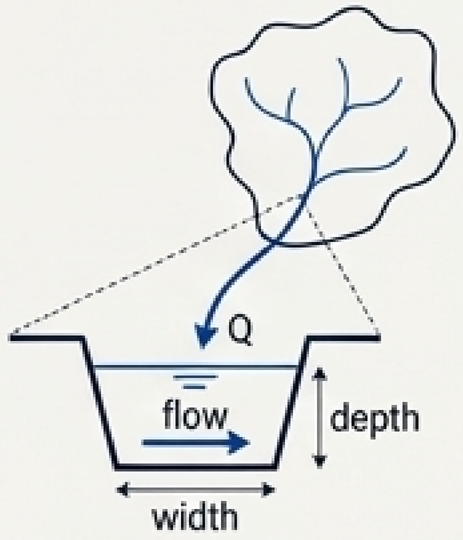
Stream Network Extraction

- **Method:** Applying a threshold to the Flow Accumulation raster. Cells with a value above the threshold are classified as part of the optimal drainage network.



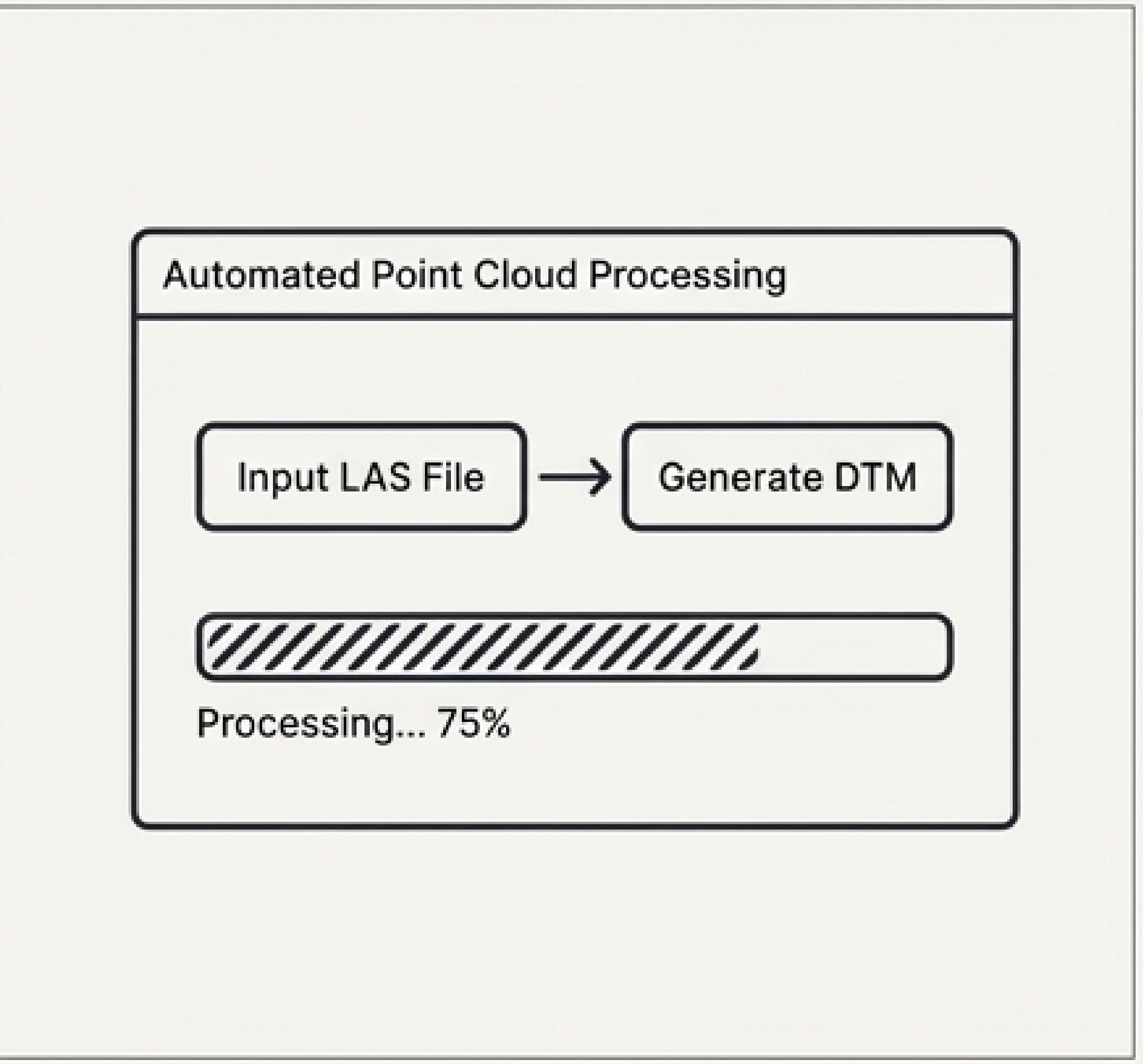
Hydraulic Sizing

- Equation: **Manning's Equation** is applied to calculate the necessary drain cross-section (width and depth).
- Inputs: Based on predicted peak flow volumes, which are derived from the size of the catchment areas feeding into each segment of the delineated network.

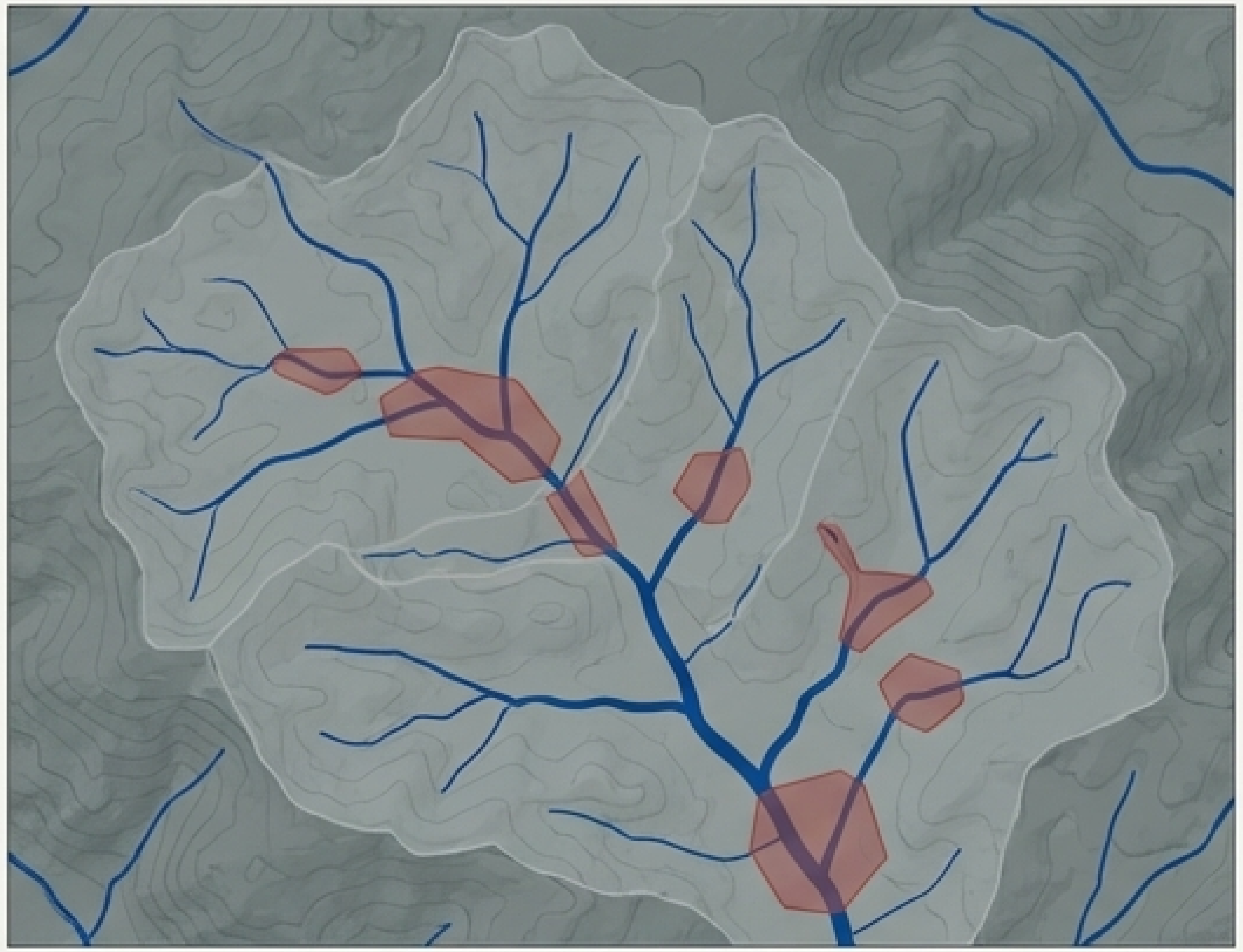


The Output: A Complete Toolkit for Data-Driven Design

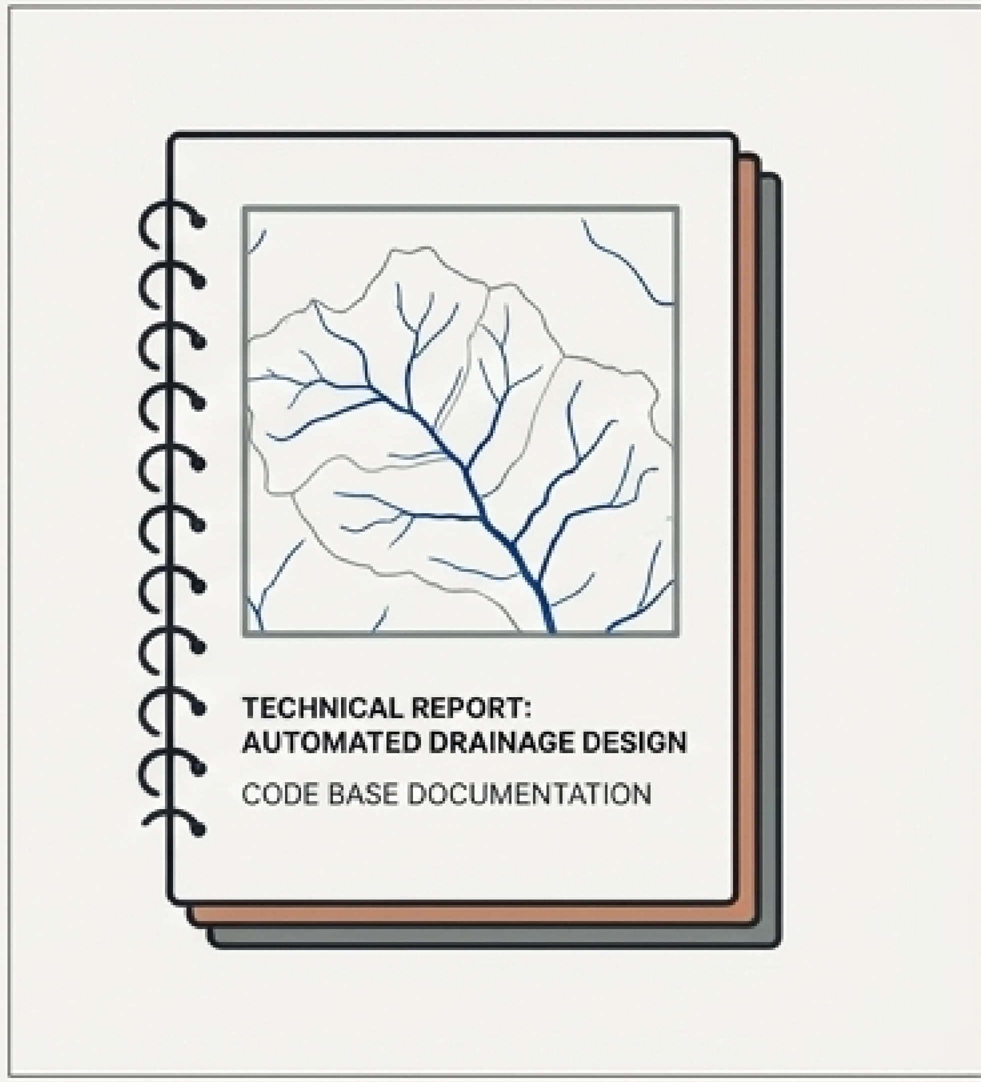
The result is not just a single map, but a comprehensive set of **digital tools** and design parameters that empower engineers and planners to make smarter, faster, and more effective infrastructure decisions.



**Automated Tool:
From Point Cloud to DTM**



**GIS Design Layers:
Drains, Hotspots & Catchments**



**Full Documentation: Code
Base & Technical Report**

From Chaos to Clarity, From Risk to Resilience

By translating a chaotic swarm of 3D data into a clear hydrological plan, we move beyond reactive problem-solving. This process enables precision infrastructure investment, reduces the risk of urban flooding, and builds more resilient communities for the future. It is the direct application of advanced AI to solve a fundamental civil engineering challenge.