

Dynamic Flood Risk Assessment for Transportation Infrastructure in Fresno, CA

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16. Abstract Urban roadway flooding in flat metropolitan environments often shows up as small areas of standing water rather than large, flowing floods. In low-gradient urban environments, subtle micro-topographic features—such as pavement crowns, curbs, and localized depressions—often control where surface water accumulates following rainfall. Accurately identifying these localized ponding areas is important for roadway flood screening and infrastructure management. This study develops a LiDAR-based depression mapping framework to identify roadway segments susceptible to surface ponding in flat urban environments. High-resolution airborne LiDAR datasets were used to generate detailed elevation maps (down to less than a foot in resolution) from ground-classified point clouds (collection of data points). Surface depressions were identified using a hydrologically filled DEM approach, where depression depth was computed as the difference between the filled and original terrain surfaces. Depressions exceeding a depth threshold were segmented into polygon features, and ponding storage volumes were estimated using their depth and surface area. To focus the analysis on transportation infrastructure, ponding features intersecting buffered roadway corridors were used. Flood risk potential was then evaluated by integrating ponding severity with proximity to stormwater drainage inlets to generate a composite roadway flood risk score. The methodology was applied to two independent LiDAR datasets covering the same urban study area. Results show that dataset characteristics significantly influence the number and hydraulic magnitude of detected roadway depressions. One dataset identified many smaller, shallow areas where water could collect, while the other identified fewer but deeper and larger pools. Despite these differences, both datasets revealed consistent spatial patterns of roadway ponding potential. The results demonstrate that LiDAR-derived depression analysis provides an efficient screening tool for identifying flood-prone roadway segments in flat urban terrain. By integrating terrain morphology with drainage infrastructure proximity, the proposed framework offers a scalable, data-driven tool to help agencies prioritize flood risk and improve infrastructure resilience.			
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Executive Summary

High-resolution LiDAR point cloud–derived digital elevation models (DEMs) provide an opportunity to analyze surface water accumulation at the micro-topographic scale in urban environments. In low-gradient urban settings, subtle elevation differences associated with pavement crowns, curbs, and localized surface depressions often influence where water accumulates following rainfall. Accurately identifying these terrain-controlled ponding locations is important for roadway flood screening and transportation infrastructure management.

To address this need, this study develops a depression-based terrain analysis framework for identifying roadway ponding areas using high-resolution LiDAR-derived DEMs. The proposed approach characterizes topographic depressions as localized storage units where rainfall runoff may accumulate during storm events and evaluates their potential impact on roadway flooding.

The methodology combines several established hydrologic terrain-processing techniques. DEM conditioning methods such as surface filling and hierarchical fill–spill algorithms are first applied to identify enclosed depressions. Depression depth is then quantified using a difference-of-surfaces approach between the filled DEM and the original terrain surface. Connected region labeling is subsequently used to convert raster depressions into discrete polygon features suitable for spatial analysis, including polygon-based depth statistics, storage volume estimation, and later risk analysis.

To improve transportation relevance, the analysis integrates roadway geometry refinement and LiDAR–imagery fusion techniques to better delineate pavement boundaries where DEM-derived edges may be influenced by curbs, vegetation, or interpolation artifacts. Roadway-intersected depressions are then evaluated using hydraulic indicators such as depression depth, estimated storage volume, and proximity to stormwater inlets.

Finally, a screening-level composite risk index is developed to support roadway flood vulnerability assessment in urban areas where detailed hydraulic simulation may not be feasible. By combining depression-based hazard indicators with drainage infrastructure proximity, the framework provides a scalable approach for identifying roadway segments that may experience surface ponding during rainfall events.

1. Introduction

The issue of urban roadway flooding in low-relief urban residential areas is a common operational challenge facing transportation departments. For flat urban residential areas, the issue of flooding is often characterized by localized surface ponding rather than significant urban flooding. The localized surface ponding often results in reduced urban roadway capacities, increased crashes, and impaired mobility during storm events, especially during high-intensity rainfall for short durations, common in urban pluvial flooding systems. Climate change is causing extreme precipitation events to occur more often and with greater intensity; hence, the need to enhance the flood resilience of transportation infrastructure is an increasingly significant aspect of transportation infrastructure planning and management (Meyer & Weigel, 2011).

Traditional hydrologic and hydraulic models often depend on rainfall-runoff simulation models and flow-routing techniques to simulate the hydrological response to rainfall and the resulting urban flooding. HEC-HMS and HEC-RAS models simulate hydrological processes in watersheds and hydraulic processes in channels. The models are often useful in simulating the hydrological response to rainfall and the resulting urban flooding; however, the models often fail to simulate micro-topography ponding behavior in flat urban areas.

Flow direction and flow accumulation algorithms that come from elevation models, which are often based on D8 routing schemes, assume that the ground slopes downward continuously. In residential areas with very little slope, the way water drains is mostly controlled by small cross slopes, the shape of curbs, and low spots on the surface. Even small changes in elevation, just a few tenths of a foot, can make a big difference in whether water accumulates or drains properly. As a result, conventional flow-routing approaches may produce unstable or unrealistic drainage patterns in flat urban landscapes (O’Callaghan & Mark, 1984; Wang & Liu, 2006).

Recent advancements in Light Detection and Ranging technology, also known as LiDAR, provide very detailed information about the shape of the ground, including features such as curbs and the crowns of roads. This information has been used to make elevation models that are very accurate and improve our understanding of flooding map areas that are prone to flooding and estimate how much water can be stored in different terrains (de Moel et al., 2009; Blöschl et al., 2024; Zhou et al., 2021). The increasing availability of high-quality LiDAR data makes it possible to identify features on the ground that control how water drains locally.

Depression-based terrain analysis offers an alternative approach to conventional flow-routing methods by directly quantifying localized surface storage capacity. Hydrologic preprocessing methods, including sink filling and depression identification algorithms (Jenson & Domingue, 1988; Wang & Liu, 2006), have traditionally been used to enforce drainage connectivity in

watershed modeling. However, rather than removing depressions entirely, recent studies have used depression depth and storage volume as indicators of surface ponding potential in urban environments. By computing the elevation difference between an original DEM and a hydrologically filled DEM, localized ponding capacity can be quantified without relying on unstable flow-direction assumptions. This approach is particularly well suited to flat urban environments where micro-topography governs drainage behavior.

In addition to the shape of the terrain, the risk of flooding on roads is also affected by how we can access the drainage system. Stormwater inlets are the points where water enters the system beneath the surface, and their locations affect how long water remains on the surface and how much ponding may occur. Flood risk assessments that incorporate drainage system characteristics are becoming increasingly common. These assessments combine information about terrain and drainage infrastructure to identify areas that are most vulnerable (Meyer & Weigel, 2011). In flood risk assessment, risk is commonly defined as a combination of hazard exposure and vulnerability. These factors are often represented using indices that integrate multiple environmental and infrastructural variables. Flow direction, flow accumulation algorithms, and digital elevation models are important tools for understanding flood risk and drainage behavior.

This study develops a LiDAR-based depression mapping framework for screening roadway flood risk in flat urban environments. The method combines detailed maps of the ground made from airborne LiDAR data about the shape of the roads, the location of storm drains, and the measurements of low-lying areas to find parts of the road that might get flooded or ponded.

Two independent LiDAR datasets were analyzed to evaluate the consistency and robustness of depression detection and roadway risk classification. “Bull” and “Perin” are internal identifiers used solely to distinguish the two processed DEM products and do not imply different hydrologic regimes or study regions.

The objectives of this report are the following:

- Develop a depression map-based methodology for identifying roadway ponding zones
- Quantify ponding depth, area, and storage volume within buffered roadway corridors
- Integrate drainage proximity into a composite roadway flood risk index
- Compare results derived from two independent LiDAR datasets to assess methodological sensitivity

The method developed in this study gives cities a simple and efficient way to identify parts of the road that might flood. It does not require hydrologic and hydraulic modeling but instead looks at the shape of the land and where the infrastructure is, making it a quick and scalable solution for cities to assess which areas are vulnerable to flooding.

1.1 Study Area

The study area is located within the Fresno metropolitan region of Central California. The area is characterized by relatively flat terrain, low longitudinal roadway slopes, and extensive residential development. These conditions are representative of many urbanized areas within the San Joaquin Valley, where surface drainage is strongly influenced by subtle micro-topographic variations such as roadway cross slopes, curb geometry, and the spatial distribution of stormwater inlets.

Because of the low-relief terrain, stormwater runoff frequently manifests as localized surface ponding rather than continuous overland flow. Even small elevation differences—often only a few tenths of a foot—can significantly influence drainage performance and roadway flood exposure. The study area includes a mixture of residential neighborhoods, arterial roadways, commercial corridors, and institutional land uses, providing a representative environment for evaluating roadway-scale depression mapping techniques.

Stormwater infrastructure within the study area is managed by the Fresno Metropolitan Flood Control District (FMFCD), which maintains detailed GIS datasets describing stormwater inlets, pipelines, and drainage service boundaries. These infrastructure layers were integrated with LiDAR-derived terrain models to evaluate the interaction between surface ponding potential and drainage accessibility.

To assess the robustness and consistency of depression-based roadway flood identification, two independent airborne LiDAR datasets covering the study area were analyzed.

1.2 Report Organization

This report is organized into four main sections.

- Section I introduces the research problem, study area, and objectives of the investigation.
- Section II describes the methodological framework, including LiDAR data processing, roadway geometry refinement, depression mapping procedures, and the development of the infrastructure-aware roadway flood risk classification.

- Section III presents the results and analysis, including depression mapping outcomes, roadway-intersected ponding characteristics, hazard classification, drainage proximity assessment, and a comparative evaluation of the two LiDAR datasets.

Section IV summarizes the key findings, discusses implications for transportation-focused flood screening, and provides recommendations for future implementation and methodological refinement.

2. Methodology

2.1 Overview of Methodological Framework

This study develops a LiDAR-based depression mapping framework to identify roadway segments susceptible to surface ponding in flat urban environments. The methodology integrates high-resolution terrain modeling, roadway geometry refinement, depression-based flood identification, and drainage accessibility analysis. The proposed framework consists of the following major components:

- LiDAR processing and DEM generation
- Road centerline refinement and buffering
- Depression depth mapping using a filled DEM approach
- Object-based ponding segmentation and volume estimation
- Infrastructure-aware flood risk classification

This section describes each component in detail.

Figure 1. Workflow Diagram

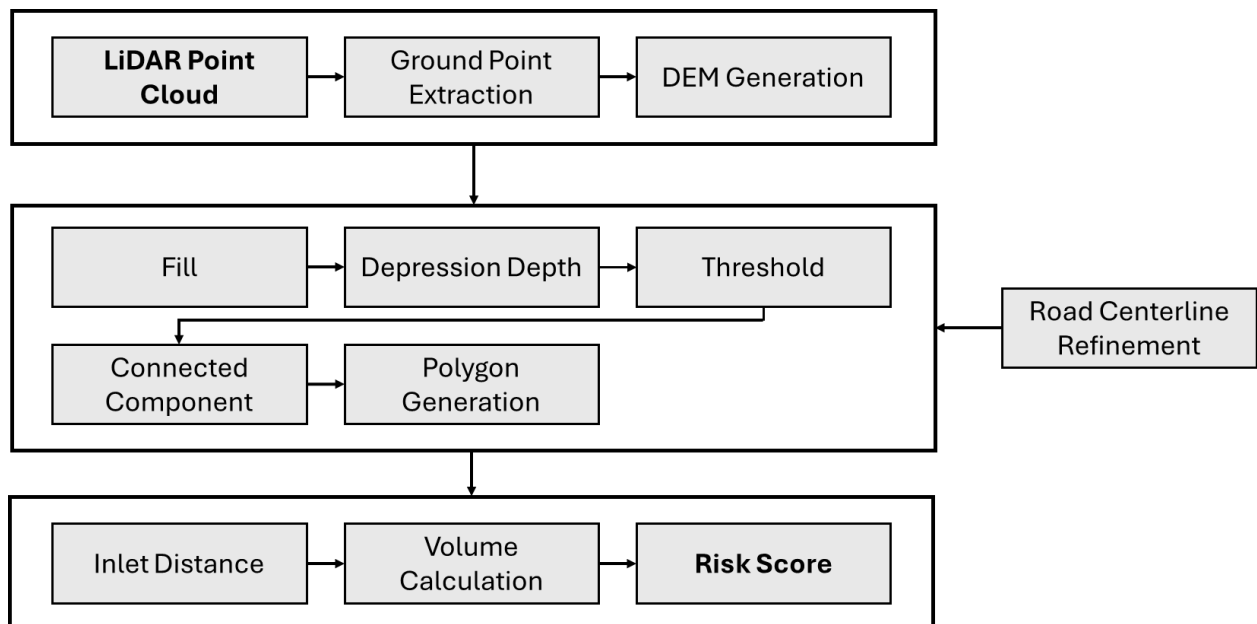


Figure 1 illustrates the workflow used in this study. The process begins with LiDAR point cloud processing, where ground points are identified and used to generate a high-resolution digital elevation model (DEM) representing the land surface. Hydrologic filling is then applied to identify closed depressions within the terrain. The depth of these depressions is calculated by comparing the filled DEM with the original surface. Areas exceeding a selected depth threshold are subsequently extracted. These areas are then separated and converted into individual polygons so that each depression can be analyzed independently. This process allows a more detailed examination of terrain depressions derived from LiDAR data and the resulting digital elevation model.

The analysis began by refining the road centerlines using elevation samples collected across the pavement surface. This step provided a more accurate representation of the roadway edges. Next, low-lying areas that intersected with the road buffers were identified. For each area, the potential ponding depth and storage capacity were estimated. The distance from each ponding location to the nearest stormwater inlet was then measured to evaluate how easily water could drain from the roadway. Finally, these variables were combined to produce an overall flood risk score for each road segment.

2.2 Airborne LiDAR Processing and DEM Generation

High-resolution airborne LiDAR datasets were obtained from the U.S. Geological Survey (USGS) 3D Elevation Program (3DEP). Two independent LiDAR datasets were used in order to evaluate the consistency and robustness of the depression-mapping methodology.

Point cloud data were processed in ASPRS LAS format. Only ground-classified points (ASPRS Class 2) were retained to represent the bare-earth surface. Digital elevation models (DEMs) were generated at sub-foot spatial resolution using ArcGIS Pro.

All DEM products were projected in NAD 1983 (2011) State Plane California IV (US Survey Feet) with NAVD88 as the vertical datum. The resulting terrain models resolve curb-scale elevation changes critical for urban ponding analysis.

DEMs were generated at a 0.5-ft grid resolution using ground-classified LiDAR points (ASPRS Class 2). Interpolation was performed using the ArcGIS Pro LAS Dataset to Raster tool with a linear binning interpolation method. The vertical accuracy of the LiDAR dataset was approximately ± 0.25 – 0.33 ft RMSEz, consistent with USGS Quality Level 2 standards.

Figure 2. Dataset 1, 78 LAS tiles

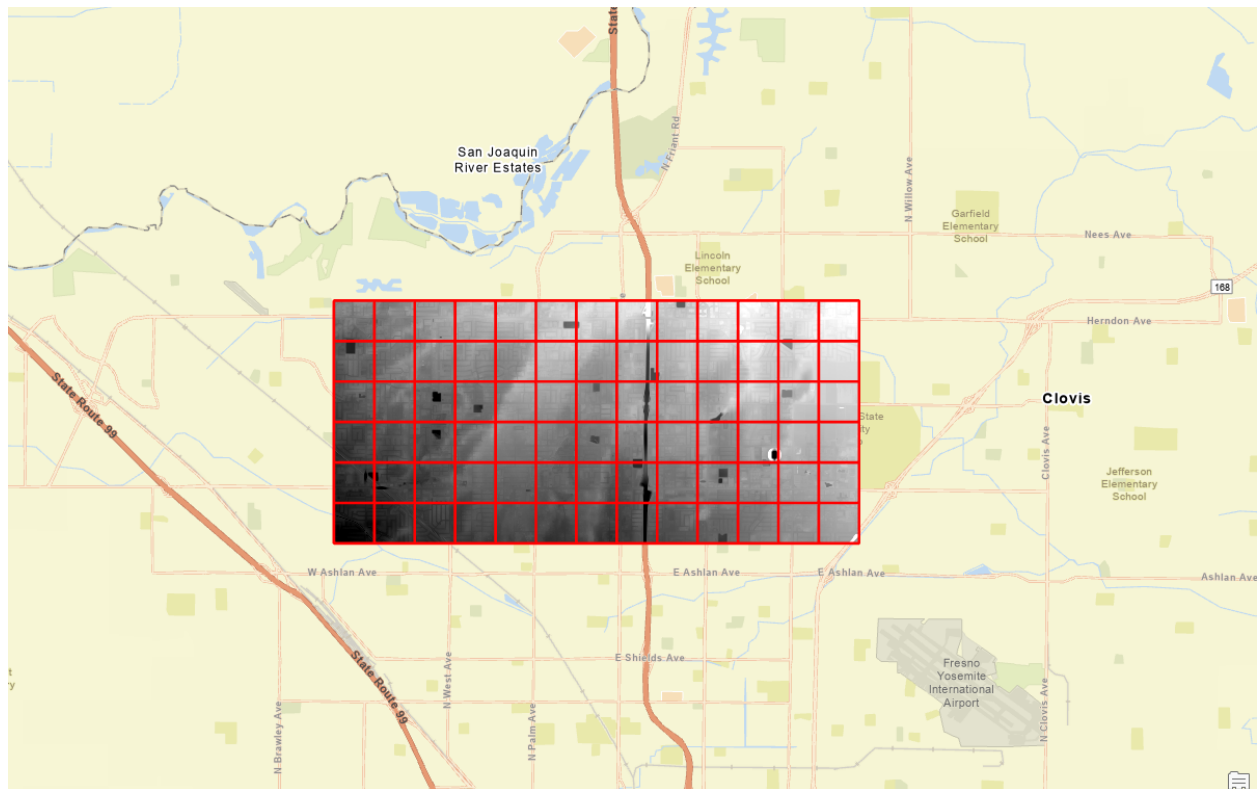


Figure 3. Dataset 2, 81 LAS tiles

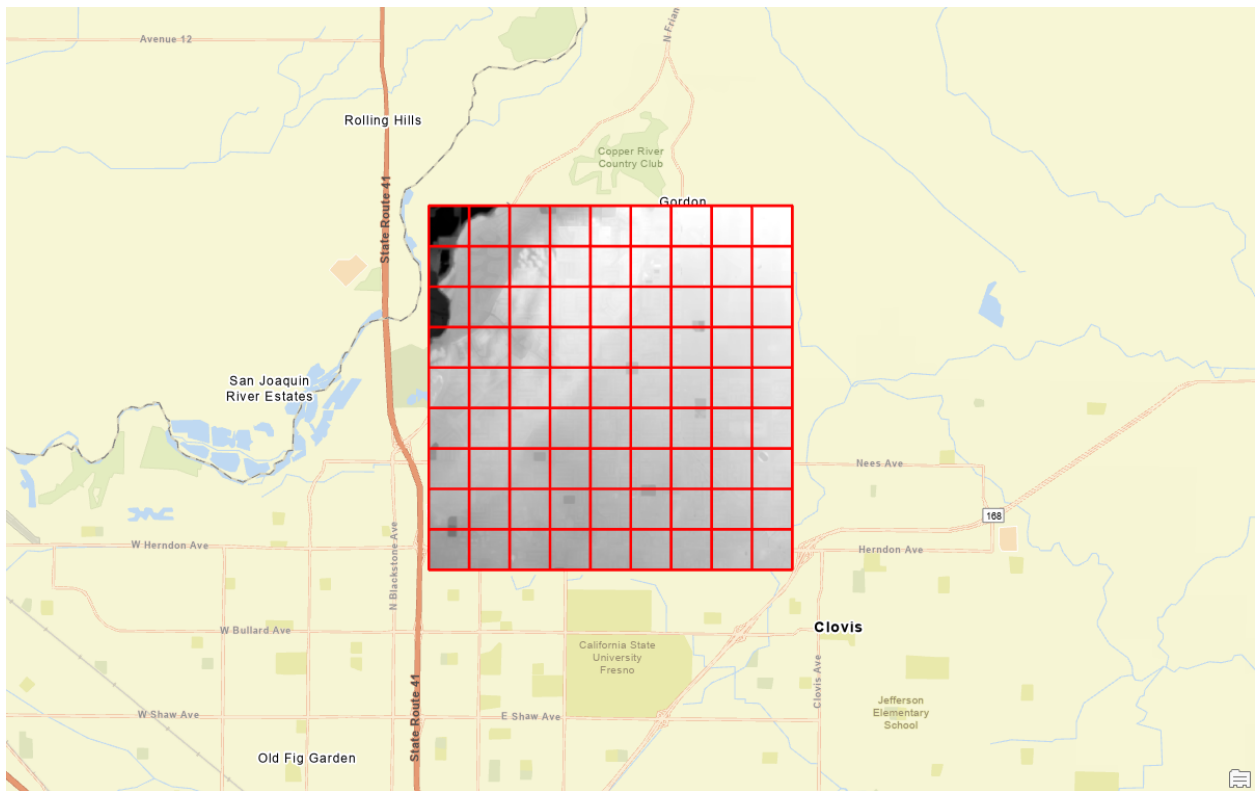


Figure 4. Example of Ground Points in Point Cloud Data



Figures 2 and 3 illustrate the spatial coverage and tile distribution of Dataset 1 (78 LAS tiles) and Dataset 2 (81 LAS tiles), respectively. Both datasets fully cover the defined study boundary and exhibit consistent tile spacing and overlap typical of USGS 3DEP products.

Figure 4 presents an example of ground-classified LiDAR points (ASPRS Class 2) extracted from the point cloud dataset. Only ground returns were retained to generate the bare-earth DEM used for subsequent depression analysis.

2.3 Road Centerline Refinement and Buffering

Accurate roadway geometry is essential for identifying areas that influence pavement flooding. Road centerlines were obtained from several mapping sources, including TIGER/Line data and local roadway datasets. However, these centerlines do not always align with the actual crown of the pavement. Therefore, a refinement process was applied to improve their positional accuracy.

To avoid bias in the centerline adjustment, cross-sectional elevation samples were collected across the roadway at regular intervals of approximately twenty feet. These samples were extracted from a high-resolution terrain dataset to examine the cross-slope profile of the pavement. The highest elevation along each cross section was identified as the roadway crown, while the pavement edges were estimated from elevation changes across the surface.

High-resolution aerial imagery was also used to improve the identification of pavement edges. Changes in image brightness and texture were examined to detect transitions between pavement and surrounding surfaces. Sample points were visually checked to remove potential outliers or erroneous measurements. Using the verified samples, roadway width and the lateral offset between the crown and pavement edges were calculated. These measurements were then used to adjust the original roadway centerlines.

Based on the refined centerlines, roadway corridors were created to represent the pavement area where surface water can accumulate. The corridor width was determined using estimated roadway width and pavement characteristics. These corridors define the portion of the roadway surface that is susceptible to ponding during rainfall events. The refined centerlines and roadway corridors provide a more realistic representation of roadway geometry and support improved identification of potential flooding areas.

Transect-based Crown Detection

To improve geometric alignment between administrative road centerlines and the actual pavement surface, a transect-based refinement procedure was implemented using a high-resolution 0.5-ft DEM.

Perpendicular transects were generated at regular intervals (20 ft spacing) along each centerline segment. Each transect extended 50 ft on both sides of the centerline to ensure coverage of the entire roadway cross-section.

Elevation profiles were sampled along each transect at sub-foot resolution. A moving-average smoothing filter was applied to reduce high-frequency DEM noise while preserving crown and edge morphology.

Within a defined center window (± 15 ft from the centerline), the local maximum elevation was identified as the roadway crown. Edge candidates were detected by locating local minima within a search window centered around an assumed half-width of approximately 15 ft (corresponding to a 30-ft initial roadway width assumption).

Candidate widths outside plausible urban roadway limits (18–60 ft) were discarded.

DEM-Aerial Edge Fusion

Because DEM-derived edge detection may be influenced by curb geometry, vegetation shadows, or interpolation artifacts, a DEM–aerial fusion approach was implemented.

For each DEM-identified pavement edge, a local search window (± 4 ft) was defined in the co-registered aerial imagery. Radiometric gradients were computed from the co-registered aerial imagery along each transect to identify potential pavement boundaries, and the location of the maximum gradient magnitude was used to refine the pavement edge position when consistent with plausible roadway width constraints.

A composite quality score was computed for each transect by integrating the following:

- Crown prominence
- Cross-slope symmetry
- Edge sharpness
- Image gradient strength

A weighted averaging scheme (DEM weight = 0.6; imagery weight = 0.4) was applied to compute the final transect quality score. Only transects exceeding a minimum quality threshold were retained for centerline refinement.

Centerline Parallel Shift Estimation

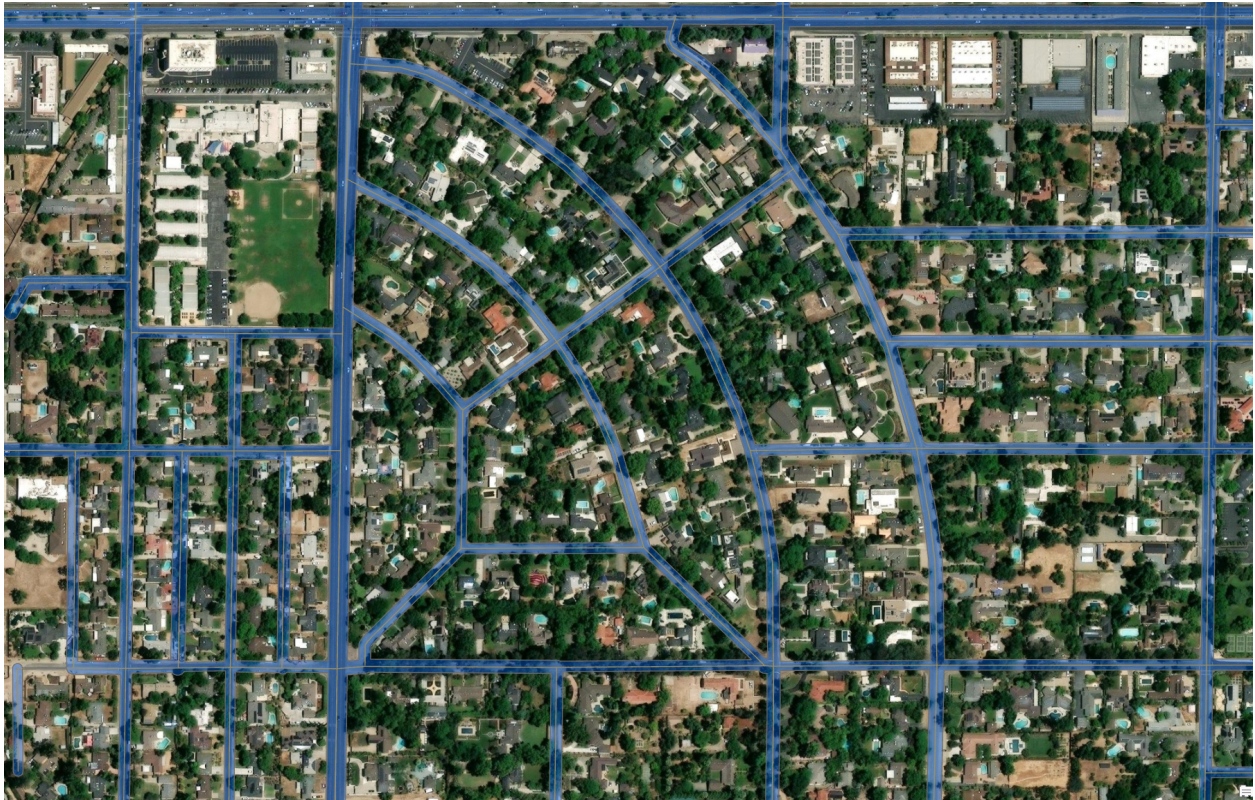
For each roadway segment, median pavement width and the median lateral offset between the detected pavement crown and the original administrative centerline were computed from all valid transects.

The median offset between the detected pavement crown and the original administrative centerline was interpreted as systematic geometric misalignment. When sufficient high-quality transects were available, a parallel shift was applied to the entire centerline segment using local normal vectors.

Shift magnitudes were constrained to ± 12 ft to prevent unrealistic geometric displacement. Segments with fewer than five valid transects or negligible median offset were left unchanged.

The refined centerline geometry was then used to generate roadway buffers for subsequent depression intersection analysis.

Figure 5. Road Centerline and its Buffer



The resulting buffers represent the effective pavement corridor approximating the curb-to-curb roadway extent. This ensures that depressions affecting traffic lanes are captured while adjacent parcel-level depressions not directly influencing roadway performance are excluded.

2.4 Depression-Based Ponding Identification

Hydrologically Filled DEM

To quantify localized surface storage potential, a hydrologically filled digital elevation model (Filled DEM) was generated using the Fill tool in ArcGIS Pro Spatial Analyst (Hydrology toolset).

The Fill tool identifies enclosed depressions (sinks) within a DEM and raises the elevation of cells inside each depression to the elevation of the lowest spill point along its boundary, producing a hydrologically conditioned surface. This operation produces a hydrologically continuous surface in which all cells can drain to the raster boundary without artificial interruptions, consistent with the sink-filling methodology described by Jenson and Domingue (1988).

Depression Depth Calculation

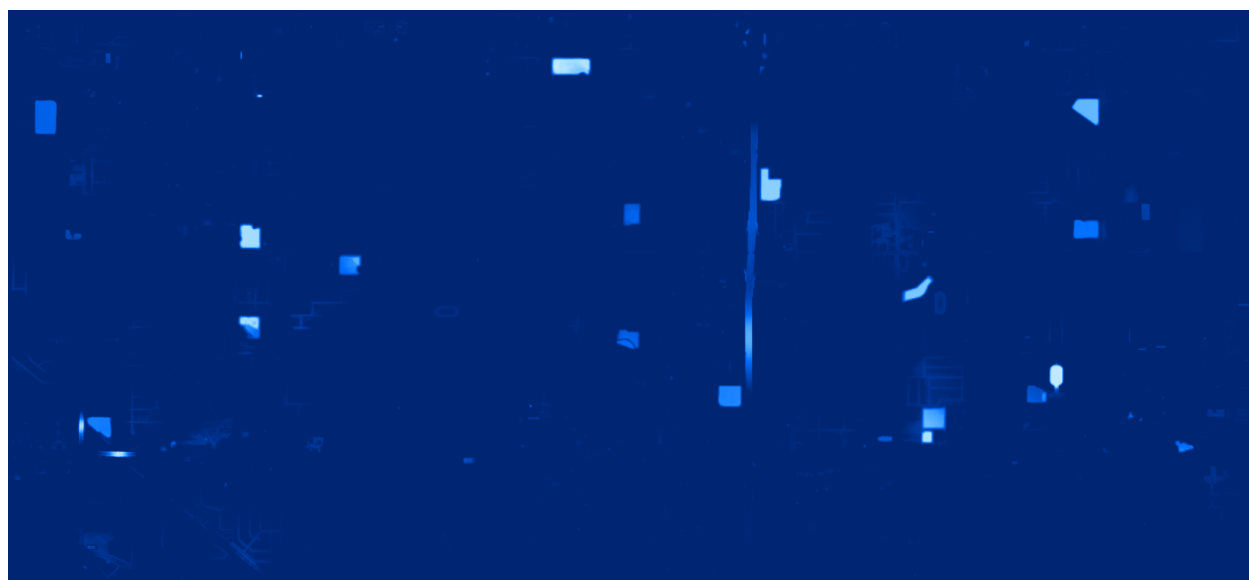
Following generation of the hydrologically filled DEM, localized depression depth was calculated by subtracting the original bare-earth DEM from the filled surface:

$$\text{Depression Depth} = \text{Filled DEM} - \text{Original DEM}$$

Positive values indicate potential surface storage depth. This raster subtraction was performed using the Raster Calculator tool in ArcGIS Pro Spatial Analyst. The operation was executed on a cell-by-cell basis, preserving the spatial resolution of the original DEM (sub-foot grid spacing).

The depression depth at each raster cell represents the maximum potential water storage depth that could accumulate at that location before spilling into an adjacent downslope outlet. Importantly, this metric reflects topographically controlled storage capacity rather than dynamic water depth during a rainfall event. It does not simulate runoff generation, inflow rate, or drainage time. Rather, it quantifies the static geometric potential for ponding based solely on terrain morphology.

Figure 6. Example of Depression Depth Raster Derived from the Difference Between Filled and Original DEM Surfaces



Thresholding and Binary Classification

Although the continuous depression depth raster quantifies potential storage at every cell, very small positive depth values frequently reflect LiDAR surface roughness, interpolation artifacts, or floating-point precision effects rather than hydraulically meaningful ponding. To remove these minor artifacts, a minimum depth threshold of 0.2 ft was applied.

The selected threshold corresponds to approximately three times the expected vertical uncertainty of high-resolution airborne LiDAR-derived DEMs in urban environments. Typical vertical accuracy for USGS 3DEP Quality Level 2 datasets is approximately 0.33 ft RMSEz (USGS, 2021).

Histogram inspection of the depression depth distribution revealed a high concentration of values near zero, with a rapid decay beyond approximately 0.15–0.20 ft. This natural inflection point supports the selection of 0.2 ft as a conservative filtering threshold. Binary segmentation was introduced not to simplify flood severity itself, but to delineate spatially contiguous ponding objects suitable for geometric and infrastructure-based screening analysis. The continuous depression-depth raster was retained for subsequent depth and volume calculations.

Figure 7. Depression Depth Distribution

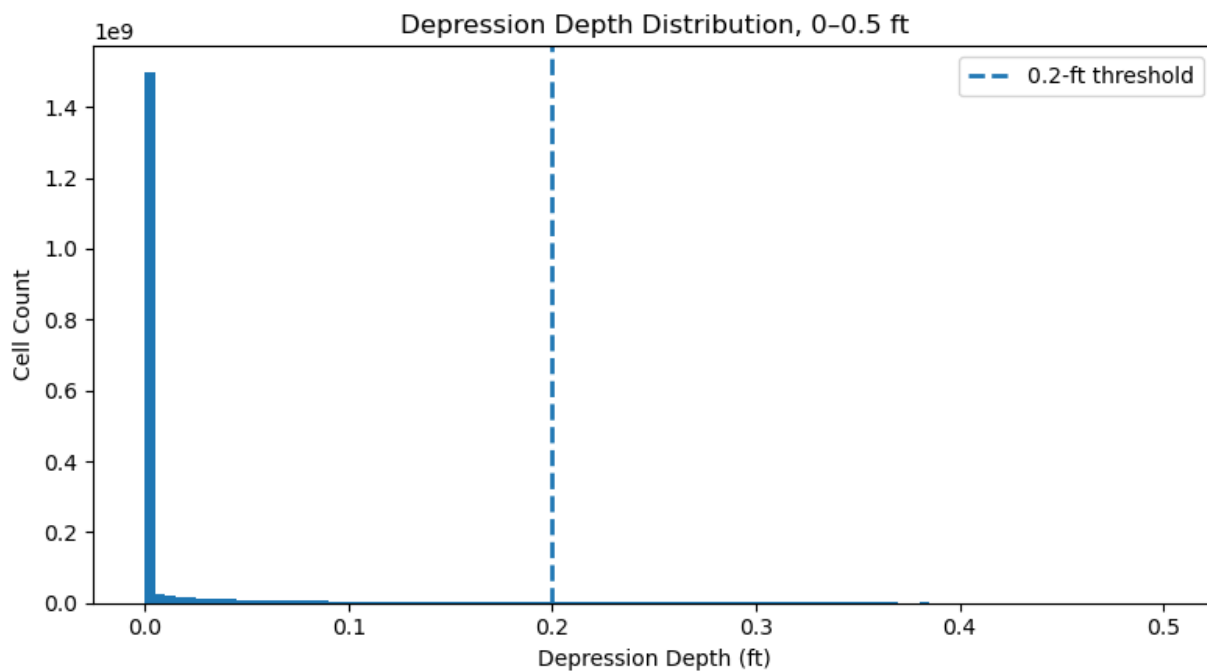
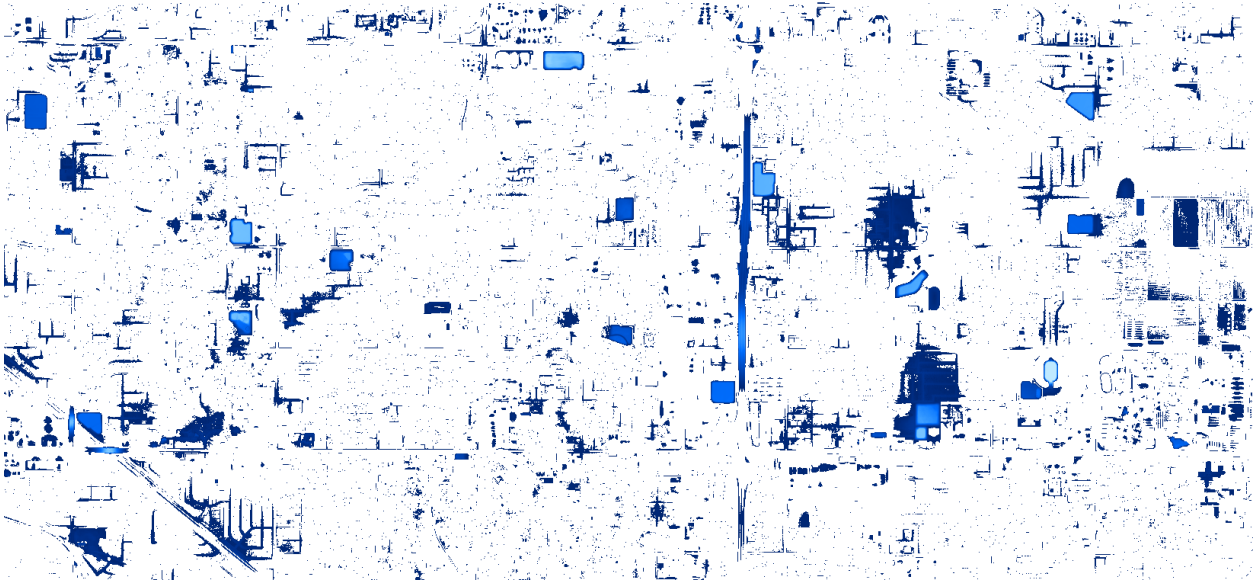


Figure 8. Example of Thresholded Depression Depth Raster



Following threshold filtering, binary classification of the depression depth raster was performed using the Raster Calculator tool in ArcGIS Pro. The resulting binary raster (1 = depression, 0 = non-depression) removed shallow noise artifacts and prepared the data for object-based ponding segmentation.

Figure 9. Example of Binarized Raster Used for Connected Component Segmentation



Connected Component Segmentation

The binary raster was processed using connected component analysis to group adjacent ponding cells into spatially contiguous objects. This step converts pixel-based depressions into discrete ponding regions suitable for geometric and volumetric analysis.

An 8-neighbor connectivity rule was applied, meaning that cells sharing edges or corners were considered part of the same region. This connectivity model is appropriate for natural surface depressions, which rarely conform strictly to orthogonal grid alignment.

Polygon Conversion and Area Filtering

Connected regions were converted to vector polygons. Very small polygons were removed using a minimum area threshold to eliminate isolated noise artifacts and single-cell depressions unlikely to impact roadway operations.

Polygon area was computed automatically using the projected coordinate system (State Plane California IV, US Survey Feet). Because the DEM grid resolution is sub-foot, small raster clusters may correspond to very small polygon areas. To remove insignificant features unlikely to impact roadway performance, a minimum area threshold was applied.

Figure 10. Example of Polygon Conversion

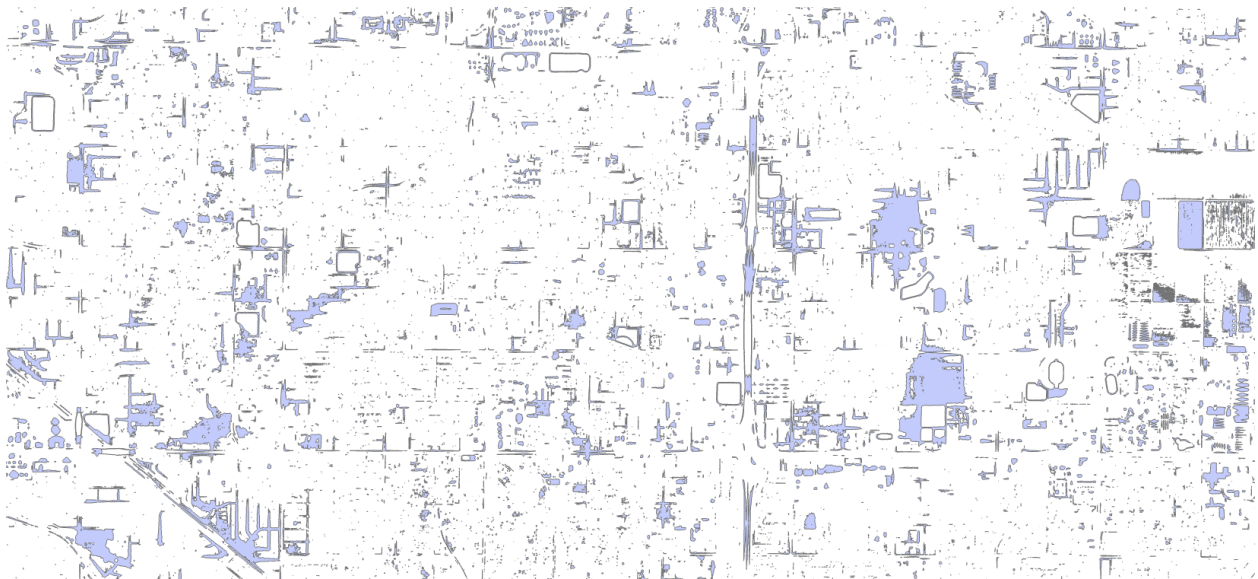
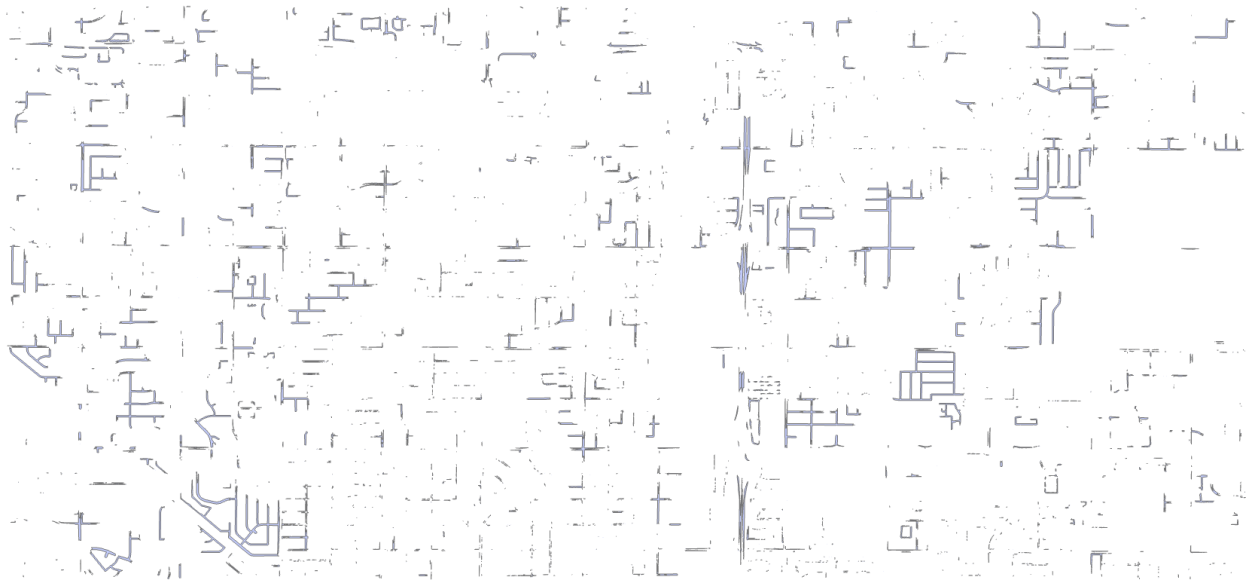


Figure 11. Ponding Polygons Intersected with Roadway Buffer Corridors



2.5 Ponding Volume Estimation and Hazard Classification

For each retained ponding polygon, hydraulic attributes were derived from the depression depth raster using the Zonal Statistics as Table tool in ArcGIS Pro (Spatial Analyst → Zonal toolset). The polygon region identifier was used as the zone field, and the depression depth raster served as the value raster.

The following statistics were computed:

- Minimum depth
- Mean depth
- Maximum depth

Ponding volume was estimated as follows:

$$Volume (ft^3) = Mean Depth \times Polygon Area$$

Where mean depth (ft) is derived from zonal statistics and polygon area (ft²) is computed in the projected coordinate system.

The use of mean depth provides a spatially averaged estimate of basin storage while preserving computational efficiency. Although integrating depth cell-by-cell would provide slightly greater precision, the mean-depth approach yields comparable results for screening-level analysis while significantly reducing computational complexity.

A five-class hazard classification (HZ_CLASS) was developed based on estimated storage volume. The classification scheme was designed to do the following:

- Distinguish shallow micro-depressions from hydraulically significant basins
- Reflect increasing storage magnitude and potential roadway disruption
- Provide ordinal categories suitable for composite risk scoring

Lower hazard classes correspond to shallow, limited-volume depressions unlikely to significantly disrupt roadway operations. Higher hazard classes represent larger and deeper storage basins capable of accumulating substantial surface water and potentially impairing traffic flow.

2.6 Infrastructure-Aware Flood Risk Classification

Surface ponding severity alone does not fully represent roadway flood risk. The persistence and operational impact of surface water accumulation are strongly influenced by drainage accessibility. In urban environments, stormwater inlets serve as the primary surface runoff entry points into the underground drainage network.

Therefore, a terrain-only hazard assessment was extended by integrating stormwater infrastructure proximity into a composite roadway flood risk classification framework.

Inlet Proximity Analysis

To quantify drainage accessibility, the shortest planar distance from each roadway-intersected ponding polygon to the nearest stormwater inlet was calculated.

The analysis was performed using the Near tool in ArcGIS Pro (Analysis → Proximity toolset) with the following inputs:

- Input features: roadway-intersected ponding polygons
- Near features: stormwater inlet point layer
- Distance method: Planar
- Coordinate system: NAD 1983 (2011) State Plane California IV (US Survey Feet)

The resulting field NEAR_DIST represents the minimum horizontal distance (in feet) from each depression polygon to the nearest inlet.

Smaller distances indicate greater drainage accessibility and higher likelihood of rapid surface water removal. Larger distances suggest limited access to stormwater infrastructure and increased probability of prolonged ponding.

While this distance metric does not model hydraulic connectivity through pipes or curb openings, it serves as a practical screening-level proxy for drainage performance.

To facilitate integration into a composite risk framework, inlet distances were categorized into five ordinal classes (INLET_CLS) representing increasing drainage limitation:

Table 1. Classification of Stormwater Inlet Proximity Used in the Composite Roadway Flood Risk Framework

INLET_CLS	Distance Range (ft)	Interpretation
1	0–100	Very Close, High drainage accessibility
2	100–250	Close, Good drainage accessibility
3	250–500	Moderate, Moderate accessibility
4	500–1000	Far, Limited accessibility
5	> 1000	Very Far, Poor accessibility

Distance classes were defined to represent increasing levels of drainage accessibility based on the planar distance between roadway-intersected ponding polygons and the nearest stormwater inlet. Shorter distances indicate higher drainage accessibility and greater likelihood of rapid surface water removal, while larger distances suggest limited access to the stormwater drainage network and increased potential for prolonged ponding

Composite Risk Scoring

To integrate hydraulic severity with drainage accessibility, a composite roadway flood risk score was computed using a multiplicative formulation:

$$Risk\ Score = HZ\ CLASS \times INLET\ CLASS$$

where HZ_CLASS represents the volume-based hazard classification and INLET_CLS represents the inlet proximity classification.

The multiplicative structure ensures that elevated risk values occur only when both contributing factors are high:

- Large storage volume alone does not produce maximum risk when drainage access is high.

- Large inlet distance alone does not produce maximum risk when ponding depth is minimal.

High composite risk values therefore represent locations where significant surface storage capacity exists and drainage infrastructure is relatively inaccessible. This interaction-based formulation prevents overestimation of risk in locations where only one factor is elevated.

3. Results and Analysis

3.1 LiDAR-Based Depression Detection

These results demonstrate that high-resolution LiDAR data can reliably capture micro-topographic depressions relevant to roadway-scale ponding analysis.

Raw Depression Mapping

Surface depressions were identified from LiDAR-derived digital elevation models (DEMs) using the hydrologically filled DEM approach described in Section II.

Depression depth was calculated as the elevation difference between the filled DEM and the original bare-earth DEM.

Figure 12. Depression Map of Dataset 1

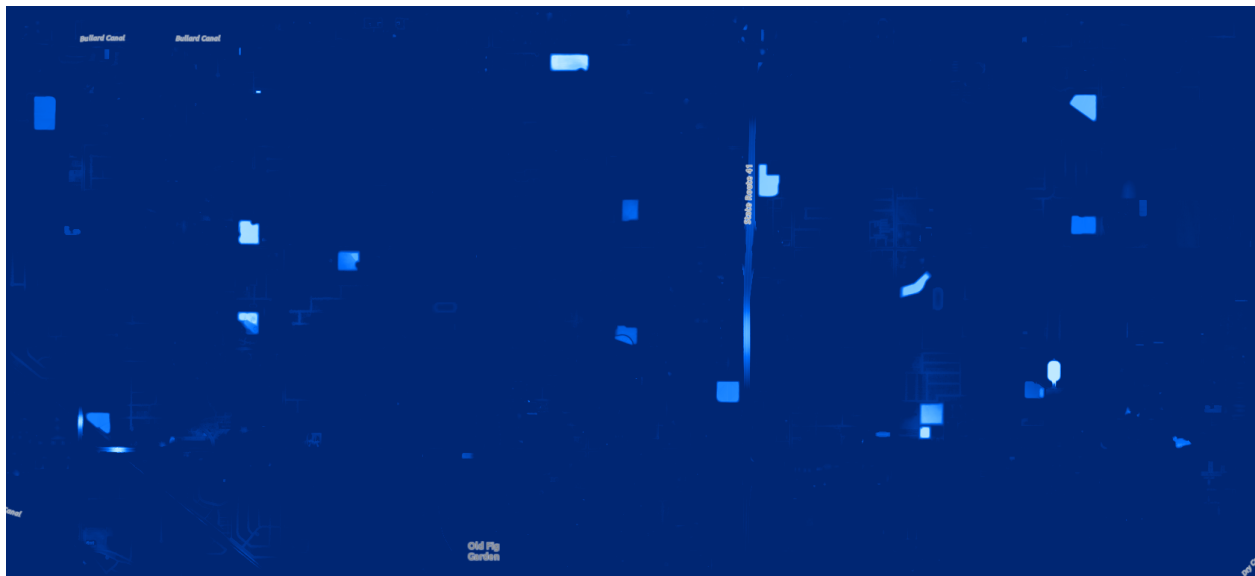
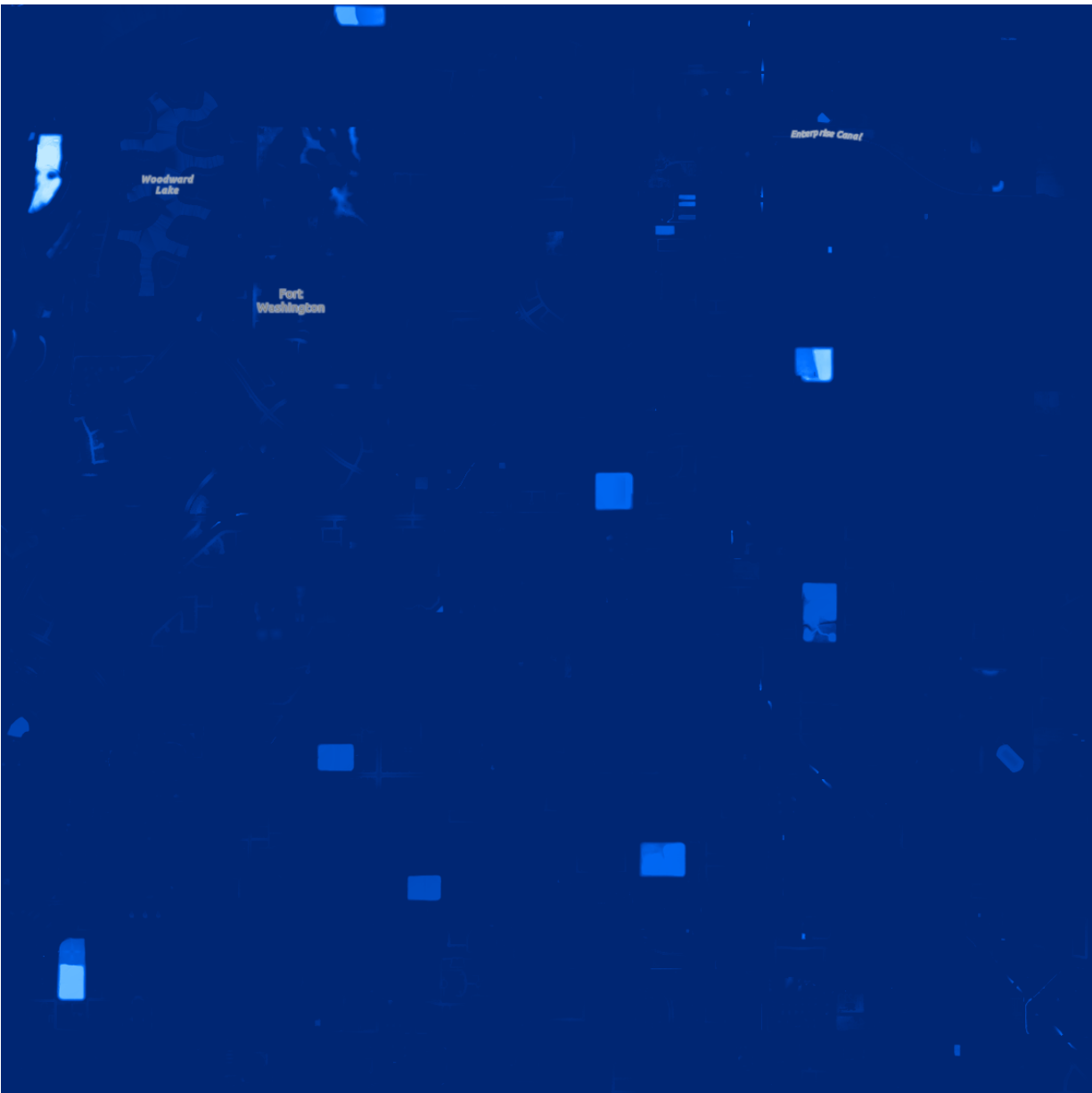


Figure 13. Depression Map of Dataset 2



Figures 12 and 13 present the raw depression depth maps for Datasets 1 (Bull) and 2 (Perin), respectively. Both datasets reveal widespread shallow depressions across the study area, with localized clusters of deeper ponding concentrated along residential subdivisions, roadway corridors, and selected commercial areas.

Although spatial patterns are broadly consistent, minor differences in depression density and fragmentation are observed. These variations are attributed to differences in LiDAR acquisition characteristics and DEM surface representation.

3.2 Depression Extraction Results

Depression Depth Characteristics

To quantitatively assess depression severity, descriptive statistics of depression depth were computed for both datasets. The majority of detected depressions exhibit shallow depths, reflecting common micro-topographic variability in urban surfaces. However, a subset of deeper depressions represents hydraulically meaningful ponding features capable of storing measurable surface runoff.

Table 2. Depression Depth Characteristics

Metric	Dataset 1	Dataset 2
Mean Depth (ft)	0.08	0.08
Maximum Depth (ft)	5	5
Standard Deviation (ft)	0.34	0.36

The depth distribution is strongly right-skewed, with a high frequency of shallow depressions and progressively fewer deep depressions. This distribution pattern supports the need for thresholding to remove minor roughness artifacts while preserving hydrologically significant depressions.

Overall, the statistical comparison confirms that both datasets capture similar depression depth behavior, providing a consistent basis for subsequent thresholding and object-based analysis.

3.3 Thresholding and Object-based Ponding Delineation

Based on examination of the depression depth histogram and visual inspection of the results, a minimum depth threshold of 0.2 ft was selected. This value is consistent with approximately three times the expected vertical noise level of LiDAR and LiDAR-derived DEM.

Figures 13 and 14 illustrate the thresholded depression maps. Application of the 0.2 ft threshold substantially reduced isolated shallow artifacts while preserving larger, hydraulically meaningful depressions.

To reduce noise and isolated hydrologically insignificant surface depressions, a depth threshold was applied to the depression map. Shallow depressions are common artifacts caused by LiDAR surface roughness and interpolation errors and do not represent locations where surface water can accumulate.

Figure 14. Depression Map with Thresholding Process on Dataset 1

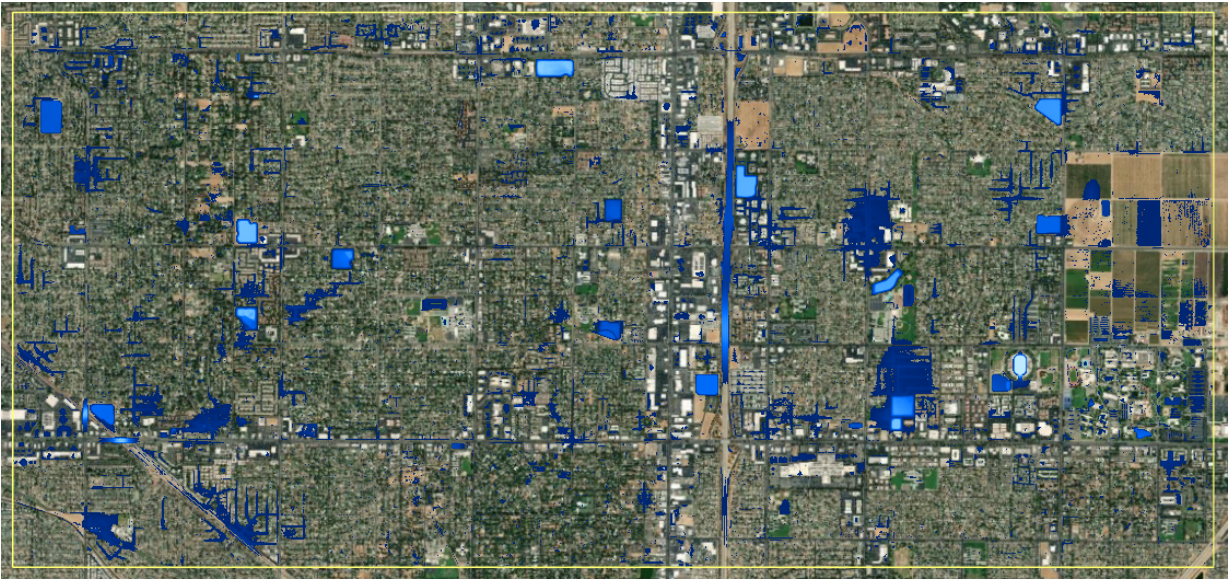
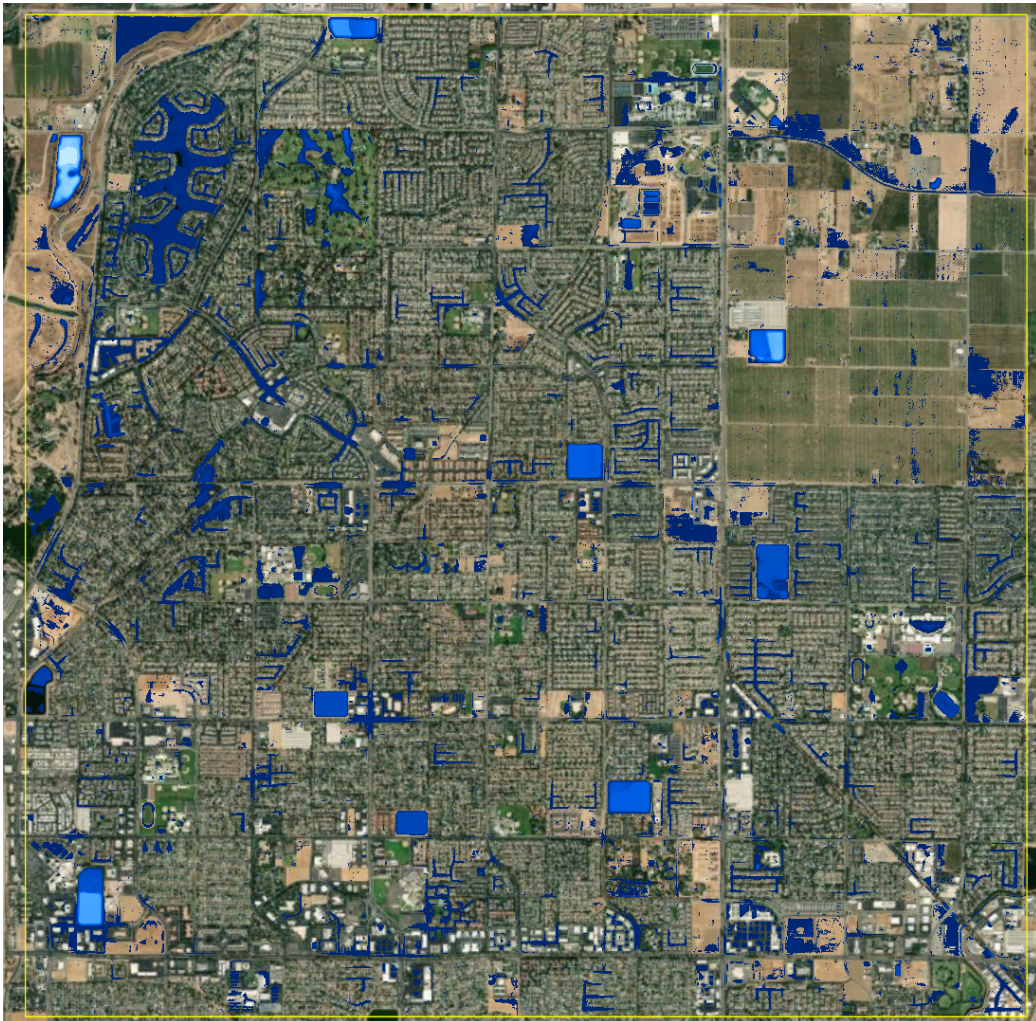


Figure 15. Depression Map with Thresholding Process on Dataset 2



Binary Conversion and Connected Component Segmentation

After computing the depression depth raster, a binary raster was generated to distinguish potential flooded and non-flooded areas. A depth threshold was applied such that cells with positive depression depth values exceeding the defined threshold were assigned a value of 1 (flooded), while all other cells were assigned a value of 0 (non-flooded).

This binarization step simplifies the continuous depth surface into a discrete representation of potential ponding locations, enabling subsequent spatial grouping and area-based filtering.

Figure 16. Binarized Depression Map

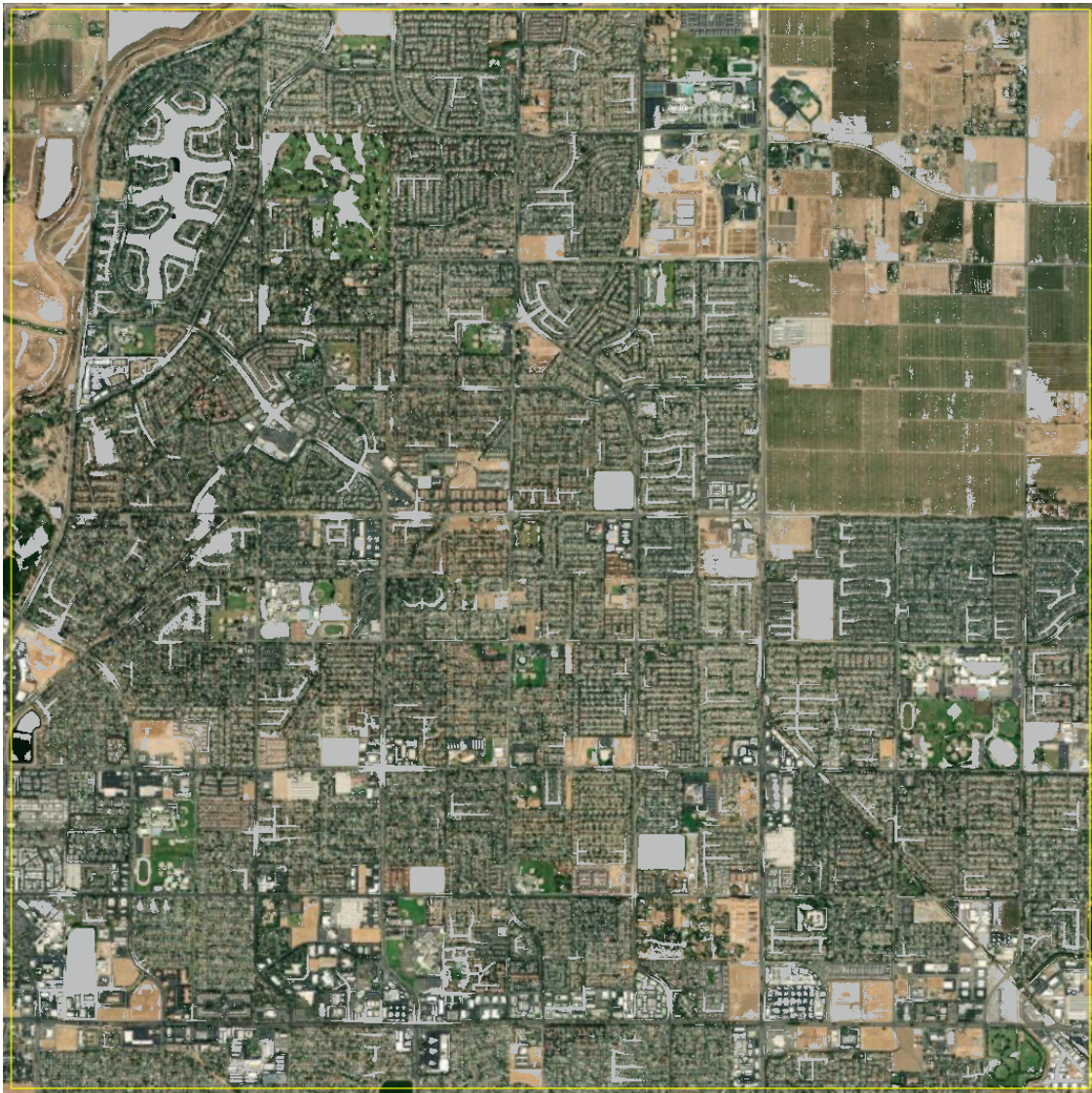
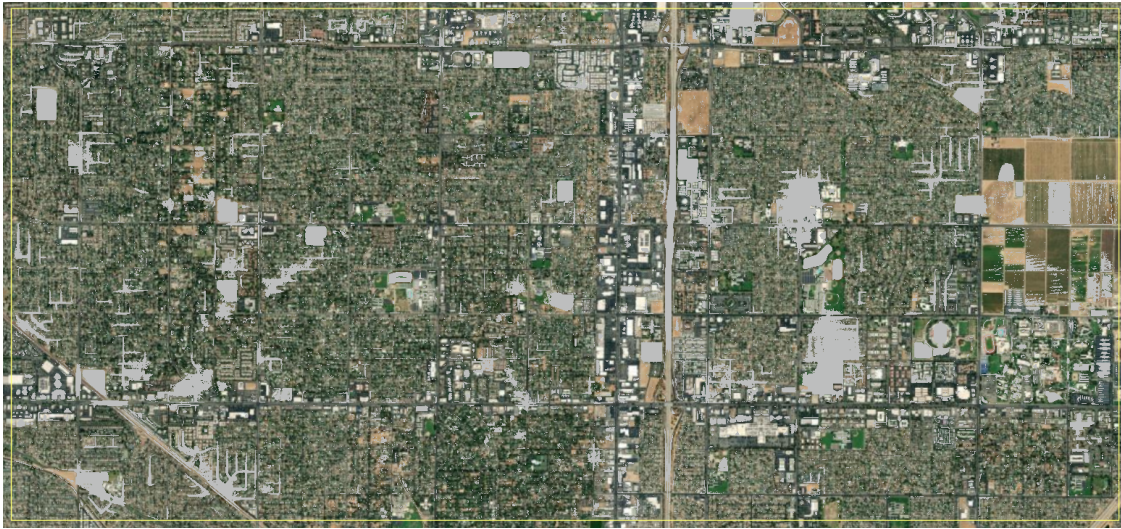


Figure 16 presents the binarized depression map generated using the 0.2 ft depth threshold. Areas classified as flooded (value = 1) represent locations where depression depth exceeds the defined threshold and indicate potential surface ponding zones. The spatial distribution reveals that while depressions are widespread across the study area, they are not uniformly continuous. Instead, ponding cells appear as discrete clusters concentrated in residential subdivisions, agricultural parcels, open fields, and select commercial or institutional properties.

In residential neighborhoods, many of the identified ponding cells align with street grids and block boundaries, suggesting that local grading patterns influence surface water accumulation. Larger contiguous flooded patches are observed in open and undeveloped areas, where terrain relief is more pronounced. The binary representation effectively highlights these spatial clusters, simplifying the continuous depression surface into a clear screening map that supports subsequent spatial grouping, roadway intersection analysis, and prioritization of flood-prone segments.

Connected Component

The binary raster was then processed using a connected component analysis to identify spatially contiguous flooded regions. In this step, adjacent ponding cells (value = 1) sharing common edges were grouped into individual connected regions, each representing a distinct ponding area.

This procedure ensures that ponding depressions are treated as spatial objects rather than isolated pixels, allowing meaningful geometric and volumetric analysis of individual ponding features.

Figure 17. Raster to Object Segmentation Using Connected Component

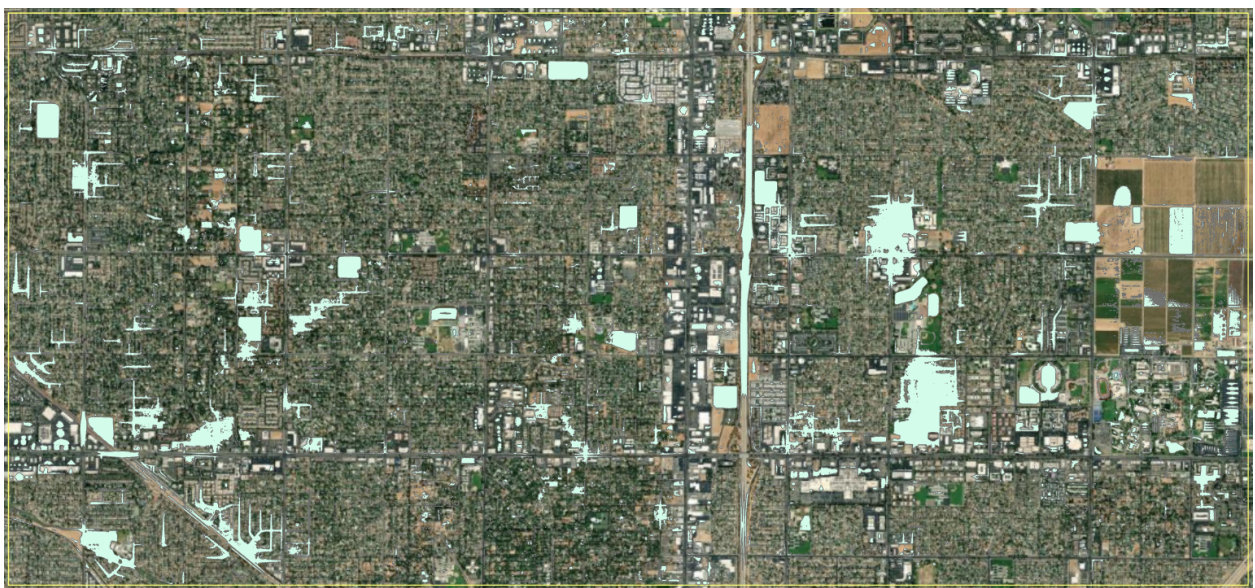
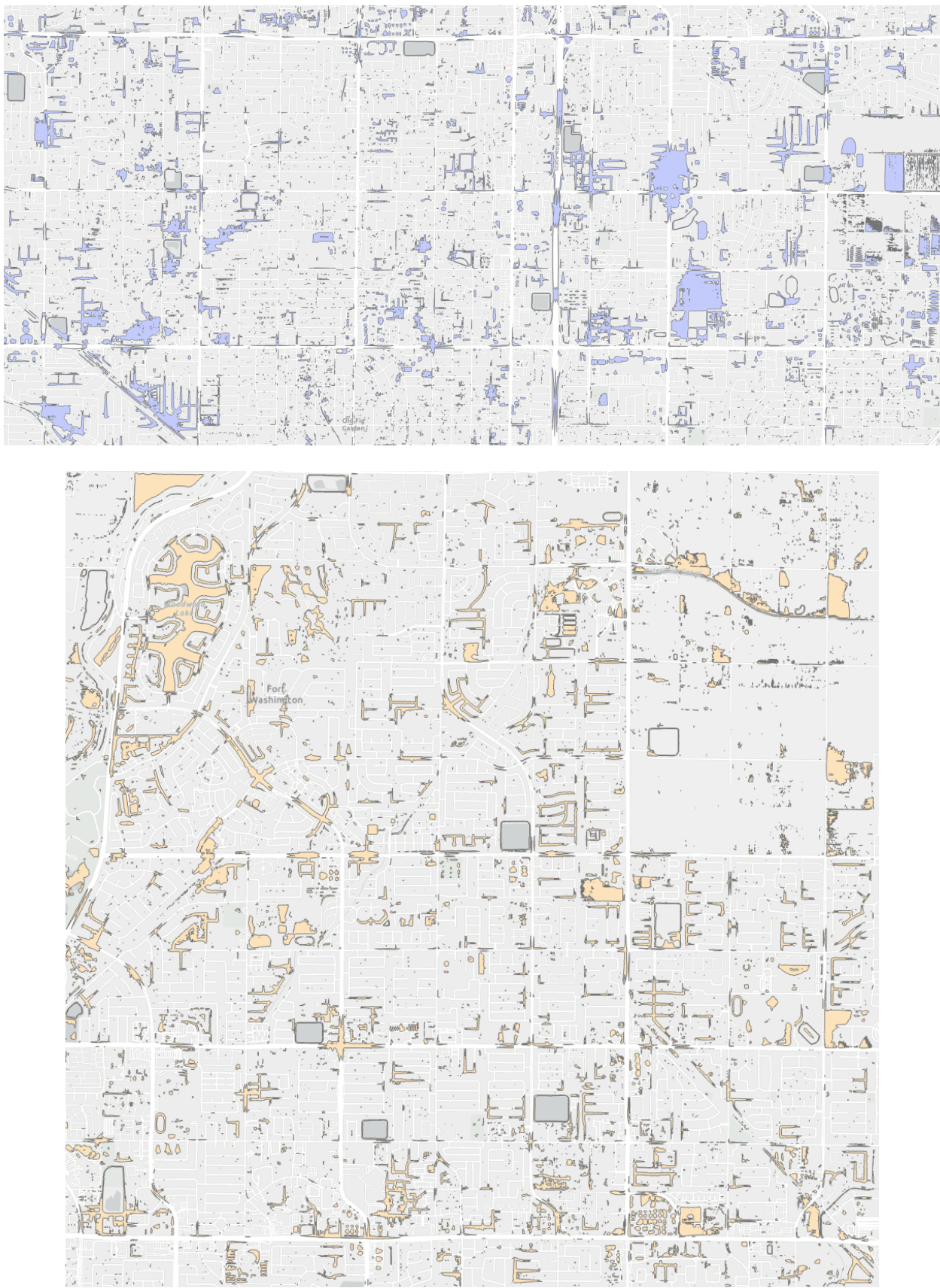


Figure 17 illustrates the segmentation of the binary ponding raster into distinct connected ponding regions. The resulting objects clearly delineate individual depressions, allowing spatial clustering and prioritization of larger, hydraulically significant ponding areas.

Polygon Conversion and Area Filtering

Binary objects were converted to vector polygons. Very small polygons were removed using a minimum area threshold to eliminate isolated artifacts and single-cell depressions.

Figure 18. Polygon and Area Filtering



The resulting polygons represent hydraulically meaningful ponding features.

3.4 Roadway-intersected Ponding Characteristics

Road Buffer Intersection

Refined road centerlines were buffered to approximate the effective roadway width. Threshold-filtered ponding polygons were intersected with the buffered roadway corridor to isolate transportation-relevant depressions.

Following intersection and area filtering, the total number of roadway-intersected ponding polygons was:

- Dataset 1 (Bull): 2,058 polygons
- Dataset 2 (Perin): 840 polygons

Dataset 1 identified approximately 2.5 times more roadway-intersected ponding depressions than Dataset 2, indicating greater sensitivity to distributed micro-topographic features.

Figure 19. Buffered Road Centerline of Dataset 1



Following the generation of the buffered road corridor (Figure 19), the buffer layer was overlaid with the threshold-filtered depression depth map to identify roadway segments exposed to potential surface ponding. This spatial intersection isolates depressions that directly coincide with the roadway footprint, thereby focusing the analysis on hydraulically relevant areas that may affect traffic operations. While depressions are widely distributed across residential parcels and open spaces, only a subset intersects the buffered roadway network. These intersecting zones represent locations where accumulated surface water could reduce roadway capacity, impair mobility, or increase localized flood risk during storm events. The buffered road extraction therefore serves as a screening mechanism to prioritize transportation segments most susceptible to depression-driven ponding.

Figure 20. Road Intersected Ponding Polygon



Table 3. Summary statistics of Road-intersected Ponding Characteristics

Metric	Dataset 1	Dataset 2
Total Ponding Polygons	2058	840
Mean Depth (ft)	0.337	0.413
Mean Max Depth (ft)	0.612	0.804
Mean Volume (ft ³)	1630.5	5641.3
Mean Inlet Distance (ft)	345.8	336.2
Mean Risk Score	8.25	6.80

The Bull dataset produced 2,058 road-intersected ponding polygons, approximately 2.5 times more than the Perin dataset (840 polygons). Although the Perin dataset exhibited greater mean depression depth (0.413 ft compared to 0.337 ft) and a significantly larger mean storage volume (5,641 ft³ versus 1,630 ft³), the Bull dataset yielded a higher mean composite risk score (8.25 compared to 6.80). These findings suggest a structural difference in depression characteristics between the two datasets. The Bull dataset appears to capture more spatially distributed micro-topographic ponding features, while the Perin dataset identifies fewer but hydraulically deeper and volumetrically larger depressions. The similarity in average distance to drainage inlets (approximately 340 ft for both datasets) indicates that inlet proximity alone does not explain the difference in composite risk. Instead, variations in the spatial frequency and distribution of ponding features likely play a primary role in driving risk score differences.

Overview of Detected Ponding Features

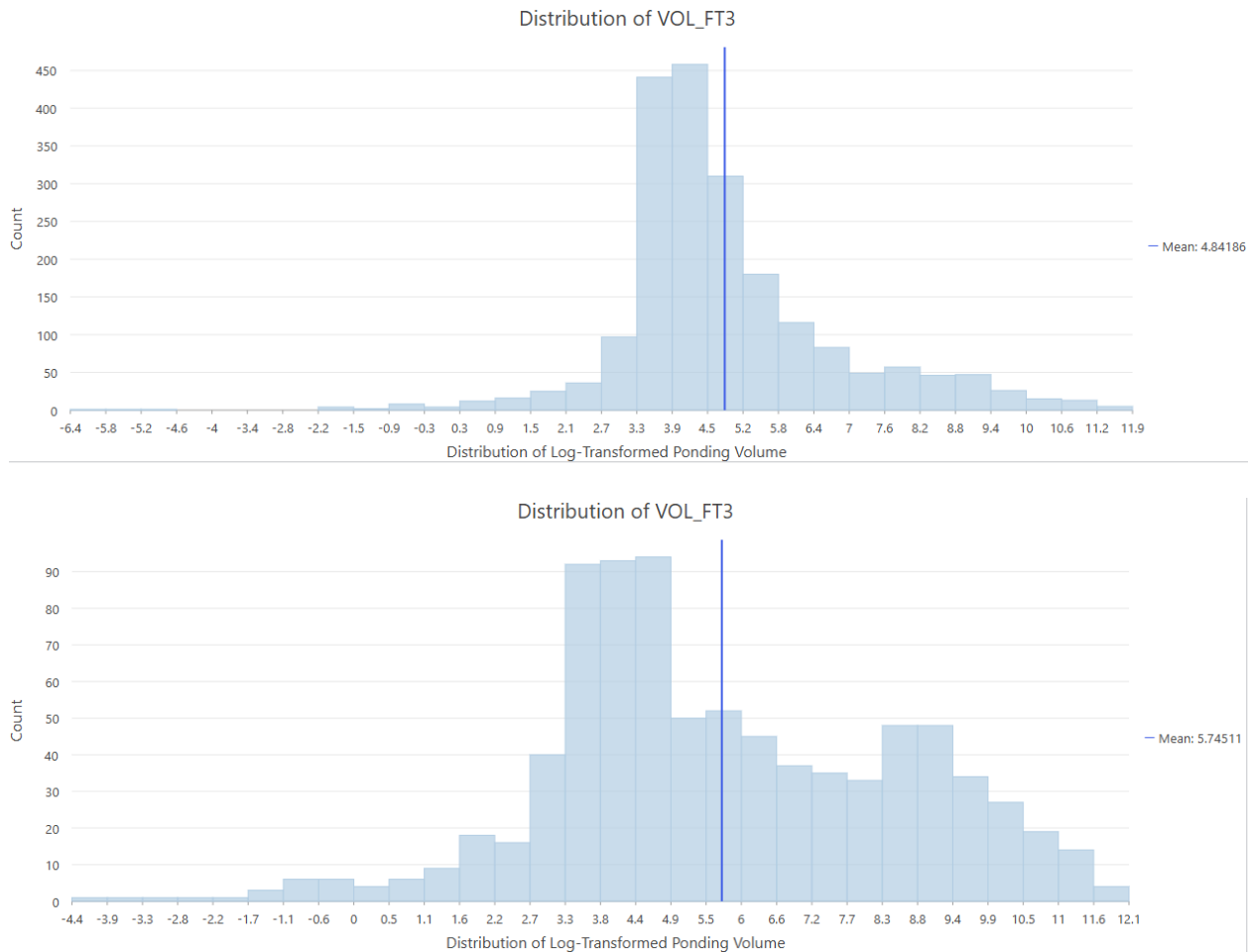
The Bull dataset identified substantially more ponding polygons than the Perin dataset, indicating greater sensitivity to localized surface depressions. In contrast, the Perin dataset exhibited greater mean depression depth and storage volume, suggesting fewer but hydraulically larger ponding features. Despite similar average distances to drainage inlets, the Bull dataset yielded a higher mean composite risk score, indicating that the spatial frequency and distribution of ponding features played a stronger role in the overall risk classification.

Depth and Volume Characteristics

Despite producing fewer ponding polygons, the Perin dataset exhibited greater hydraulic intensity. The mean depression depth for Perin (0.413 ft) exceeded that of Bull (0.337 ft), and the mean maximum depth was also higher (0.804 ft compared to 0.612 ft).

More notably, the mean estimated storage volume for Perin (5,641 ft³) was more than three times greater than that of Bull (1,630 ft³). This indicates that while Bull captures more widespread shallow depressions, Perin identifies fewer but substantially deeper and volumetrically larger ponding features.

Figure 21. Log-transformed Distribution of Estimated Ponding Storage Volume for Road-Intersected Depressions in the Bull/Perin Dataset



These results demonstrate a structural difference between the two datasets. The Bull dataset emphasizes the frequency of micro-topographic depressions, while the Perin dataset highlights the magnitude of hydraulic storage capacity.

Figure 21 shows the log-transformed distribution of estimated ponding storage volumes for road-intersected depressions. The Bull dataset exhibits a high concentration of smaller-volume depressions, with most storage volumes clustered within a relatively narrow range. In contrast, the Perin dataset displays a broader distribution with a greater proportion of larger storage volumes. This pattern indicates that the Bull dataset captures numerous shallow depressions associated with minor surface irregularities, whereas the Perin dataset identifies fewer but volumetrically larger ponding features.

Figure 22. Scatter Plot of Mean Depth and Log Volume



Figure 22 illustrates the relationship between mean depression depth and estimated storage volume for road-intersected ponding polygons. The storage volume axis is displayed on a logarithmic scale to improve visualization of the wide range of values.

In both datasets, a weak positive relationship is observed between depression depth and storage volume. Although deeper depressions generally correspond to larger storage volumes, the overall correlation remains weak ($R^2 \approx 0.03$ for Bull and $R^2 \approx 0.06$ for Perin). This weak correlation indicates that depression depth alone may not sufficiently explain variation in storage capacity. Instead, storage volume is strongly influenced by additional factors such as depression area, shape, and surrounding terrain configuration.

The Perin dataset shows a slightly stronger depth–volume relationship compared to the Bull dataset. This difference likely reflects the structural characteristics of the datasets: Bull identifies a large number of shallow micro-depressions, while Perin detects fewer but deeper depressions that more clearly express hydraulic storage behavior.

Proximity to Drainage Infrastructure

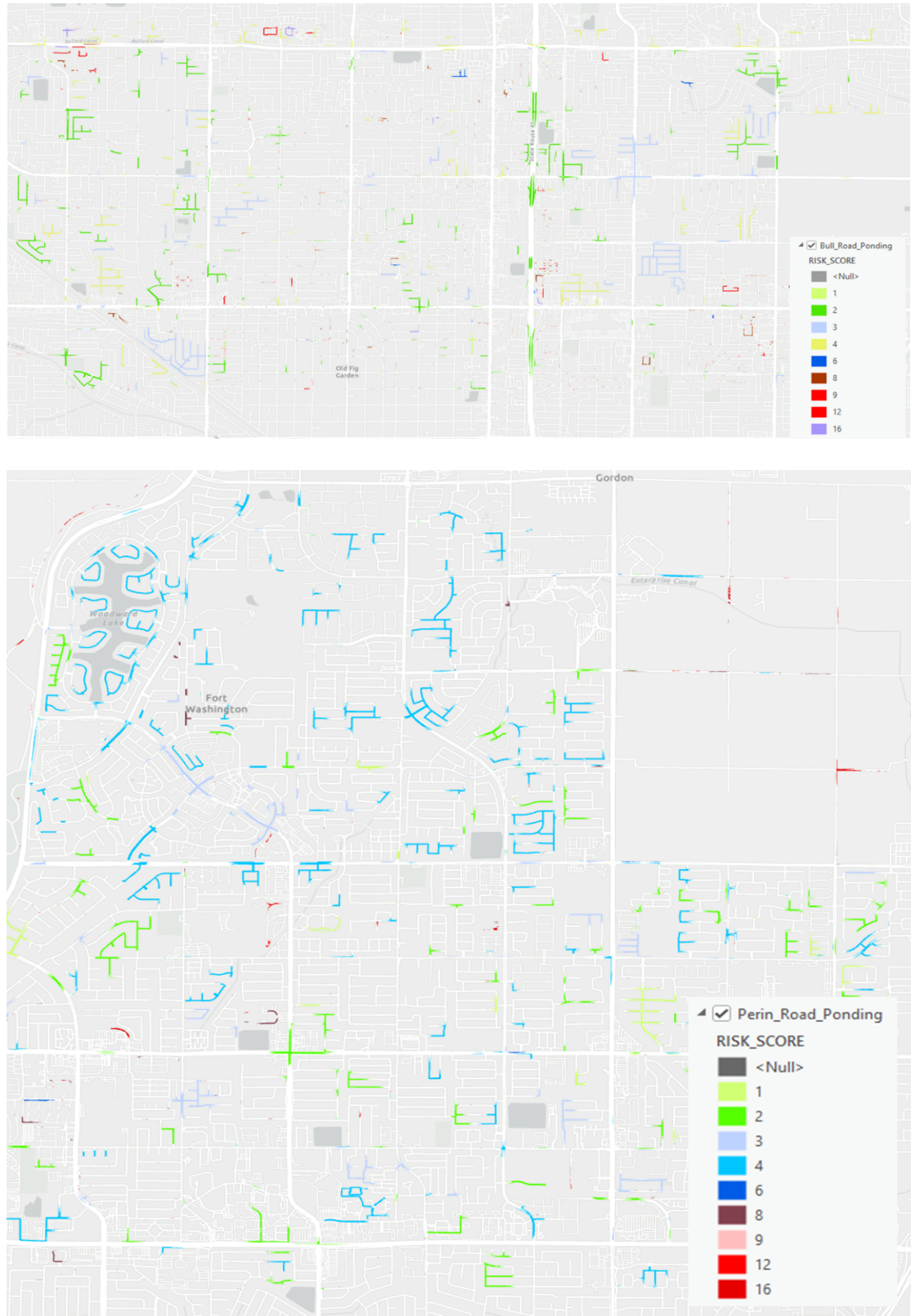
Average distance to the nearest drainage inlet was comparable between the datasets, with Bull and Perin exhibiting mean distances of 345.8 ft and 336.2 ft, respectively. The similarity in inlet proximity suggests that drainage spacing alone does not explain the observed differences in ponding depth or volume.

Composite Risk Assessment

Spatial patterns of composite risk scores for both datasets are illustrated in Figure 23. High-risk segments appear as localized clusters along certain roadway corridors where deeper depressions coincide with greater distances to drainage inlets

The Bull dataset yielded a higher mean composite risk score (8.25) compared to the Perin dataset (6.80), despite the Perin dataset exhibiting greater mean depression depth and storage volume. This result suggests that the spatial frequency and distribution of ponding features exerted a stronger influence on the composite risk classification than depression magnitude alone.

Figure 23. Spatial Distribution of Composite Roadway Ponding Risk Classes Derived from Depression Severity and Inlet Proximity



This outcome reflects the influence of spatial distribution on risk assessment. The larger number of road-intersected depressions identified in the Bull dataset increases the frequency of moderate-risk features, elevating the overall mean risk score. In contrast, the Perin dataset concentrates hydraulic severity into fewer but deeper depressions. Thus, the Bull dataset appears to characterize distributed micro-ponding risk, while the Perin dataset highlights concentrated hydraulic storage risk.

Interpretation and Implications

The comparative analysis demonstrates that differences in terrain representation between datasets can substantially influence the detection of roadway depressions and the resulting hydraulic metrics. Although both datasets show similar proximity patterns relative to drainage infrastructure, they differ in how roadway ponding features are represented in terms of spatial frequency and hydraulic magnitude.

From a transportation risk perspective, these differences lead to distinct interpretations of flood vulnerability. The Bull dataset identifies a larger number of shallow depressions distributed across the roadway network, suggesting greater sensitivity to widespread micro-ponding conditions that may affect roadway drivability during moderate rainfall events. In contrast, the Perin dataset identifies fewer depressions but with greater depth and storage volume, highlighting localized locations where more substantial hydraulic accumulation may occur.

These findings indicate that DEM resolution, preprocessing methods, and surface representation can strongly influence flood-risk characterization in high-resolution urban terrain analysis.

4. Summary & Conclusions

This study developed and evaluated a LiDAR-based depression mapping framework to identify roadway segments susceptible to surface ponding in flat urban environments. The methodology integrates high-resolution terrain modeling, roadway geometry refinement, depression depth mapping, storage volume estimation, and drainage proximity analysis to generate a composite roadway flood risk classification.

The analysis was applied to two independent airborne LiDAR datasets covering the same study area. Surface depressions were identified using a hydrologically filled DEM approach, and a depth threshold of 0.2 ft was applied to remove micro-topographic noise. Contiguous ponding regions were segmented into discrete polygons, filtered by minimum area, and intersected with buffered roadway corridors to isolate transportation-relevant depressions. For each roadway-intersected depression, storage volume was estimated and combined with inlet proximity metrics to produce a composite risk score.

The results demonstrated that depression-based screening is effective for identifying localized roadway ponding hazards in low-gradient urban terrain where conventional flow-direction methods are often unstable or unreliable. The comparison between the Bull and Perin datasets revealed substantial differences in depression detection behavior. The Bull dataset identified a greater number of distributed micro-depressions and produced a higher overall composite risk score, whereas the Perin dataset detected fewer but hydraulically deeper and volumetrically larger ponding features. These findings indicate that depression mapping results are sensitive to DEM surface representation and preprocessing characteristics.

The analysis also showed that average inlet proximity was similar between the two datasets, suggesting that drainage spacing alone did not explain differences in roadway flood risk patterns. Instead, the spatial frequency and distribution of ponding features exerted a stronger influence on the composite risk classification. The integration of depression severity and drainage accessibility metrics provided a practical screening-level framework for prioritizing roadway segments where both surface storage and drainage limitations coincide.

This study represents a terrain-based screening methodology and does not simulate rainfall intensity, runoff generation, hydraulic routing, or dynamic stormwater system performance. Consequently, the estimated ponding volumes represent static topographic storage potential rather than time-dependent flood behavior. In addition, the results remain sensitive to DEM resolution, threshold selection, and roadway buffering assumptions. Future work could incorporate rainfall scenarios, pipe network capacity, and time-to-drain analysis to improve predictive capability and operational applicability.

Unlike conventional HEC-HMS or HEC-RAS workflows that primarily emphasize watershed runoff routing and channel hydraulics, the proposed framework focuses on localized surface storage behavior controlled by urban micro-topography. In very low-relief urban environments, these localized depressions may strongly influence roadway ponding even where continuous overland flow paths are poorly defined. The proposed approach therefore complements rather than replaces traditional hydrologic and hydraulic modeling by providing rapid screening of terrain-controlled ponding susceptibility

Overall, the study demonstrates that high-resolution LiDAR-derived depression mapping provides a scalable and computationally efficient alternative to traditional flow-direction-based flood screening approaches in flat urban environments. By directly quantifying localized surface storage and integrating drainage accessibility metrics, transportation agencies can more effectively identify and prioritize flood-prone roadway segments using widely available LiDAR and GIS infrastructure datasets.

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