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COMPARATIVE ANALYSIS OF PHOTOGRAMMETRY AND LIDAR DATA: TOPOGRAPHY GENERATION FOR FLOOD RISK MITIGATION

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ABSTRACT: Topographic data is a critical input for flood simulations and scenario generation. This research evaluates the data from both photogrammetry and Light Detection and Ranging (LiDAR) technologies for generating water infrastructure topographic information. In particular, the study discusses the accuracy and cost-effectiveness of aerial photogrammetry and LiDAR in producing high-resolution topographic maps for a flood-prone neighborhood area in Southeast Texas of the United States. LiDAR provides high accuracy and reliability— especially in complex terrain—while photogrammetry proves more cost-effective and easier to implement in regions with minimal obstructions from bird's-eye view. We use LiDAR data as ground truth to benchmark the photogrammetry data from drone-based aerial imagery. Results show trade-offs inherent in each method. Beyond this, the insights from this study can guide policymakers in selecting cost-effective and efficient topographic surveying methods for flood-prone regions, ensuring accurate terrain data for infrastructure resilience planning. Additionally, integrating LiDAR's precision with photogrammetry's scalability can enhance the design of flood mitigation structures, such as levees and drainage systems, optimizing their placement and effectiveness in reducing disaster impacts. Note that the datasets used in this research have been published and are publicly available.

1. INTRODUCTION AND THE RESEARCH GAP

The increasing frequency and intensity of flood hazards driven by climate change necessitate data-driven approaches for effective infrastructure planning and risk mitigation. Coastal areas particularly are highly vulnerable due to climate change, poor land-use planning, and sea level rise. These challenges have motivated the adoption of advanced data collection methods, including laser scanning and drone-based photogrammetry (Neumann et al., 2015; Sujivakand et al., 2024) for flood risk assessment.

Topographic data, in particular, is critical for flood simulation and analysis, especially when integrated with topography-based models such as GeoFlood (Zheng et al., 2018) and Height Above Nearest Drainage (HAND) method (Li et al., 2022; Rennó et al., 2008). These topography-based models offer low-computation alternatives for flood prediction. The models, however, usually fail to accurately represent complex infrastructure (D'Angelo et al., 2022; Zheng et al., 2018).

Geographic information systems (GIS) and Building Information Modeling (BIM) have proven useful for enhancing flood modeling and improving disaster resilience (Asfandyar et al., 2025; Cao et al., 2023). Nevertheless, existing frameworks in the literature often lack consistency and integration, particularly in how infrastructure features such as levees, canals, and drainage systems are captured and modeled (Jafarzadegan et al., 2023; Teng et al., 2017). While there have been efforts to incorporate these elements into flood models, systematic evaluations of survey methods and their impact on flood prediction remain limited.

To address this gap, this study evaluates the strengths and limitations of photogrammetry and LiDAR for topographic data collection, with the goal of improving the accuracy of flood prediction and supporting more resilient infrastructure planning. This study, in particular, explores drone-based photogrammetry and LiDAR data in enhancing the precision of Digital Elevation Models (DEMs), gridded representations of terrain elevations that serve as foundational inputs for flood simulation and hydrological analysis, which will improve the accuracy of inundation predictions, informing flood mitigation strategies in vulnerable regions. Furthermore, the paper evaluates the comparative efficiency, effectiveness, and limitations of these survey technologies in an environmental condition. This research will provide insights into analyzing topographic data collection methods to support resilient infrastructure development and comprehensive flood risk management. The work focuses on the Beaumont-Port Arthur region, an area highly vulnerable to flooding due to its low-lying coastal geography. We will identify the advantages and limitations of topographic data collection and survey methods using drones and laser scanners.

This paper’s contributions include: 1) developing a workflow for comparing photogrammetry and LiDAR in water infrastructure analysis; 2) evaluating their strengths and limitations for flood modeling applications and highlights their suitability; and 3) identifying a future research direction to enhance topographic data integration for improved flood prediction and resilience planning.

2. SURVEY EQUIPMENT

Table 1 provides an overview of the equipment used for data collection. The lightweight drones (left side of Table 1) enable efficient flights at speeds of up to 4 m/s over distances reaching 18 km, supported by the Global Positioning System (GPS) and real-time kinematic positioning (RTK) modules for precise positioning. Meanwhile, the laser scanner (right side of Table 1) enables accurate 3D data capture where it can complete a full dome scan in under 3 minutes.

Table 1: Equipment Details for Drones and a Laser Scanner

Drone (DJI Mavic 2)		**Laser Scanner (Leica BLK 360)**	
Weight	907g	**Height**	165 mm
Dimensions	322×242×84 mm (Length × Width × Heigh)	**Diameter**	100 mm
Max Speed	4 m/s	**Weight**	1 kg
Max Distance	18 km	**3D point accuracy**	6mm @ 10m / 8mm @ 20m
GNSS	GPS + RTK module	**Range**	min. 0.6 - up to 60 m
		Speed	< 3 min for complete full dome

Note that this work uses captured imagery from the drones to generate 3D models through photogrammetry, a technique that processes overlapping images using advanced computer vision algorithms (Fonstad et al., 2013; Westoby et al., 2012). Next, leveraging a Structure-from-Motion (SfM) workflow, photogrammetry reconstructs detailed 3D representations or point clouds and enable spatial analysis (Remondino & El-Hakim, 2006).

3. DATA DESCRIPTION

3.1 Port Arthur Coastal Neighborhood and Pleasure Island Golf Course

The aerial survey conducted in June 2024 utilized real-time kinematic drones (left side of Table 1) to capture high-resolution aerial photographs as shown in Figure 1, subsequently processed using DroneDeploy. The total cover area is around 635 acres (2.57 km^2) for Port Arthur Coastal Neighborhood and around 516 acres (2.09 km^2) for Pleasure Island Golf Course. We deployed a drone to capture a total of 3,780 aerial imagery covering Port Arthur Coastal Neighborhood, with the drone flying at a 200 feet altitude (61 meters) above the ground. For the Island Golf Course, the drone captured a total of 1,980 aerial photographs, with the drone flying at a 200 feet altitude (61 meters) above the ground level. The dataset comprises aerial photographs in JPG format, 3D models, geospatial data, mappings, and point clouds (Luo et al., 2023, 2024).

3.2 Levee Infrastructure Data in the Port Arthur Neighborhood

We used Laser Scanner Leica BLK 360 (right side of Table 1) to capture specifically parts of a water infrastructure system (i.e., levee) integrity and flood protection capabilities of levee systems in the coastal neighborhood. The data includes detailed 3D point clouds and surface models capturing the topographic and infrastructural features of levee systems. The data is processed into LASer (LAS) format for raw point clouds, GeoTIFF for elevation models, and shapefiles for GIS integration, as shown in Figure 1. The data will be publicly available in the same repository as the drone data (Luo et al., 2023, 2024).

Note that the covered area is roughly 37 acres (150,000 m^2), which is relatively small compared to the entire neighborhood (635 acres), given the constraints of the laser scanner. Although it generates high-quality scans, relying on a single piece of equipment for the whole neighborhood would be both time-consuming and inefficient. Consequently, this study focuses on comparisons within the levee region. Despite the limited area, the findings can be scaled up and applied to larger water infrastructure systems or even a citywide context.

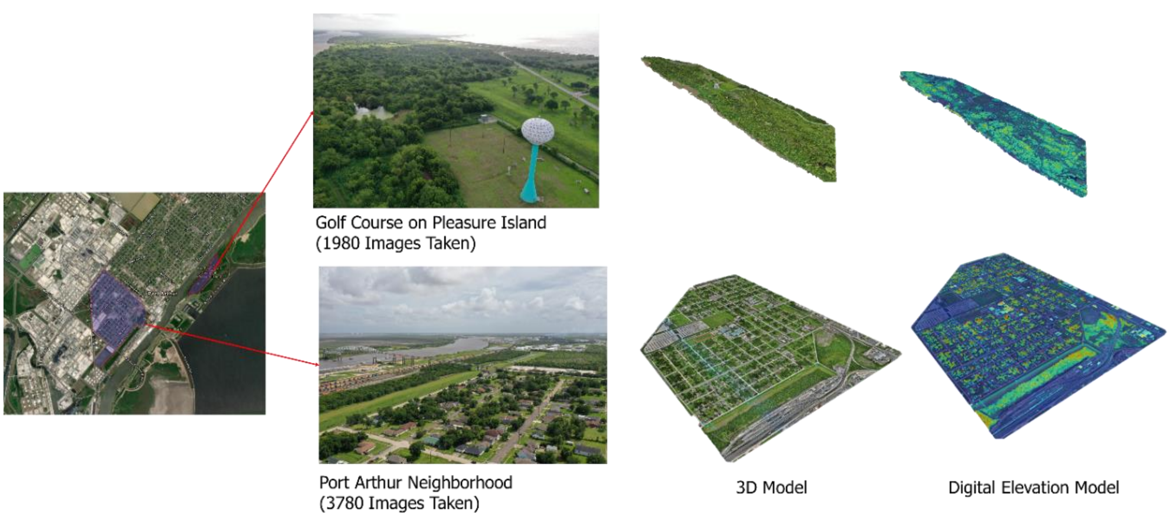

Figure 1. Port Arthur Coastal Neighborhood and Pleasure Island Golf Course Data in Port Arthur, TX, USA

Figure 2. Water Infrastructure and Levee Captured by LiDAR in Port Arthur Coastal Neighborhood in Port Arthur, TX, USA

4. RESEARCH APPROACH

The research approach includes four steps and is designed to systematically integrate, process, analyze, and apply data derived from both photogrammetry and LiDAR sources, culminating in flood mapping using the generated elevation models. This process involves data collection (step 1), data compilation (step 2), georeferencing (step 2), comparative analysis (step 3), flood mapping (step 4):

Step 1: Data Collection

The approach begins with the capture of the built environment and infrastructure systems using advanced sensing technologies, including drone cameras and a laser scanner. These technologies generate three-dimensional representations of built environment geometries and related infrastructures (e.g., buildings, levee system).

Step 2: Data Compilation and Alignment

Next, step 2 compiles these datasets from different sources to create a unified dataset. This process involves applying georeferences to ensure proper alignment of DEMs, correcting distortions, and standardizing coordinate systems.

Step 3: Comparative Analysis

The accuracy and consistency of the integrated datasets are evaluated using established metrics, such as the Root Mean Squared Error (RMSE). This quantitative assessment compares the datasets against ground truth or reference measurements to identify and measure any deviations.

Step 4: Flood mapping using the created DEM

In the final step, the generated Digital Elevation Models (DEMs)—derived from photogrammetry or LiDAR—are used as base layers for hydrologic and hydraulic flood mapping (e.g., GeoFlood). This step compares flood mapping results generated using DEMs of varying quality and LODs to evaluate their effects on prediction accuracy.

5. RESULTS AND DISCUSSION

This study uses LiDAR data as the ground truth to benchmark the accuracy of photogrammetry-derived elevation models. As shown in Table 2, the overall RMSE in the levee region was approximately 1.41 meters. However, the RMSE varied with surface characteristics: flat terrain exhibited a lower RMSE of approximately 1.38 meters, while vegetated areas showed higher discrepancies, with RMSE around 1.60 meters due to plant interference. In particular, this comparison reveals discrepancies in areas with dense vegetation and levee structures, showing photogrammetry’s sensitivity to surface obstructions and its reliance on flight parameters (e.g., altitude and camera angle). However, photogrammetry remains advantageous due to its cost-effectiveness and rapid deployment capabilities, making it ideal for large-scale assessments in open terrains—an especially critical factor in disaster response applications (Cheng et al., 2024). Conversely, LiDAR's high precision and ability to capture fine topographic details might justify its higher operational costs, particularly for detailed infrastructure and structural monitoring (Cheng et al., 2022). Moving forward, integrating LiDAR’s accuracy with photogrammetry’s efficiency through data fusion techniques could possibly optimize resource allocation and improve the quality of topographic models, which is a potential future research direction.

Table 2 RMSE Summary Between LiDAR and Photogrammetry-Derived DEMs

Area Type	Root Mean Squared Error (m)	Qualitative Description
Levee Region (Flat)	1.38	Photogrammetry shows agreement with LiDAR; minimal deviation due to open, unobstructed surfaces
Vegetated Area	1.60	Deviations observed; photogrammetry overestimates elevation due to tree
Overall Average	1.41	

In the step 4, while extensive research on flood modeling across various regions and contexts in the literature (Apel et al., 2009; Ward et al., 2013), current modeling methods lack consistency and fail to systematically compare levels of detail (LOD) for hydraulic-relevant features (e.g., building footprints, water infrastructure systems’ elevation). Although existing research on flood modeling incorporates infrastructure elements, they rarely compare the results of different LODs on these models (Afshari et al., 2018; Schubert & Sanders, 2012), leaving a gap in understanding how detailed infrastructure representations affect flood predictions. Therefore, one of our future research directions is to determine the appropriate LOD for representing water infrastructures that influence our flood mapping and analysis. We will analyze the impact of water infrastructure modeling (i.e., levees, buildings) at different LODs, where the goal is to improve flood risk predictions and provide insights into the effectiveness of flood mitigation strategies.

6. CONCLUSIONS

In summary, this study conducted a comparative analysis of photogrammetry and LiDAR data for generating topographic DEMs in a flood-prone area located in the Beaumont–Port Arthur region in Southeast Texas, USA. Results indicated that LiDAR provided accurate elevation data—particularly in dense vegetation and complex urban settings—while photogrammetry proved more cost-effective and easier to deploy. An average RMSE of approximately 1.41 meters was observed when photogrammetry-based elevation data was benchmarked comparing to LiDAR measurements, with lower errors observed in flat levee areas and higher discrepancies in vegetated areas. This study also observed photogrammetry’s sensitivity to line-of-sight obstructions and flight parameters (e.g., capturing angle, flying height). Despite these, photogrammetry remained suitable for large-scale, relatively unobstructed terrains. Future studies could explore integrating both technologies to enhance topographic model accuracy and support more effective flood risk mitigation strategies.

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