Evaluating the Reliability of U.S. Geological Survey Three-dimensional Elevation Program Lidar-Derived Building Heights Using Multi-Source Comparison

Jung kuan Liu[a]*, Ethan Shavers[a], Samantha T. Arundel[a], and Rongjun Qin[b]

[a] U.S. Geological Survey, Center of Excellence for Geospatial Information Science, Denver, Colorado, USA
[b] Department of Civil, Environmental, and Geodetic Engineering, The Ohio State University, Columbus, Ohio, USA
* jliu@usgs.gov

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Introduction

Accurate building height information is essential for numerous urban and environmental applications, including flood risk modeling, disaster response, energy demand estimation, and urban growth analysis (Kuras et al., 2021; Wang et al., 2021; Tang et al., 2025). Horizontal building footprints are widely available, but vertical attributes such as building height remain inconsistently documented at large scales.

The U.S. Geological Survey (USGS) Three-Dimensional Elevation Program (3DEP) provides high-spatial resolution airborne lidar data across the conterminous United States (CONUS) (usgs.gov/3d-elevation-program). The primary product of 3DEP is bare-earth digital elevation models (DEMs) derived from lidar in CONUS and in parts of Alaska, Hawaii, and territories. Yet the point density and vertical accuracy of the lidar have the potential to help characterize the built environment as well. This abstract summarizes research recently accepted for publication in *Photogrammetric Engineering & Remote Sensing* (Liu et al., 2026). This research evaluates 3DEP lidar as a reference for building height extraction assessing the accuracy and consistency of public building height data sets across contrasting urban environments. These two public building data sets are USA Structures (Yang et al., 2024) and Microsoft Global Building Footprints (GBF) (Che et al., 2024; Microsoft, 2025).

Method

Study sites

Two urban areas with overlapping 3DEP lidar and public building height data were selected. Site 1, in Centennial, Colorado (39°35′12.28″ N, 104°54′29.96″ W), represents low-to-medium density suburban development with relatively uniform building forms and moderate vegetation (U.S. Census Bureau, 2023a). Site 2, in Houston, Texas (29°46′52.54″ N, 95°17′19.68″ W), represents a dense and heterogeneous urban environment with diverse building typologies, complex roof structures, and localized dense vegetation (U.S. Census Bureau, 2023b).

3DEP Lidar Point Cloud Classification

Point cloud classification assigns semantic labels to individual lidar returns. Recent deep learning methods have advanced 3D point cloud classification. Prior studies (Diab et al., 2022; Zhang et al., 2023) identifies the Point Transformer architecture (Wu et al., 2022) as particularly effective for semantic segmentation, so this study applies it to classify 3DEP lidar into ground, building, and vegetation classes (Liu et al., 2024).

Building Height Extraction from Classified 3DEP Lidar Data

An automated workflow integrates reclassified 3DEP point clouds with building footprint shapefiles. Lidar points are spatially joined to building polygon footprints from USA Structures or GBF. Median roof elevation is computed from classified building points, and median ground elevation is extracted from nearby ground points. Building height is the difference between these two medians. The median statistic reduces sensitivity to outliers and local noise, providing a robust height estimate.

Building Height from Publicly Available Data Sets

3DEP-derived heights are used as a reference rather than absolute ground truth, since their accuracy depends on factors such as classification quality, ground filtering, and point density. By comparing USA Structures and GBF heights against independently derived 3DEP lidar-based estimates, used here as a consistent and higher-confidence reference rather than absolute ground truth due to their direct elevation measurements and well-documented vertical accuracy, we assess relative agreement, vertical bias, and variability across urban contexts. The two study sites enable assessment of how building morphology, terrain, and lidar acquisition characteristics influence both the correspondence and accuracy of building height estimates among data sets.

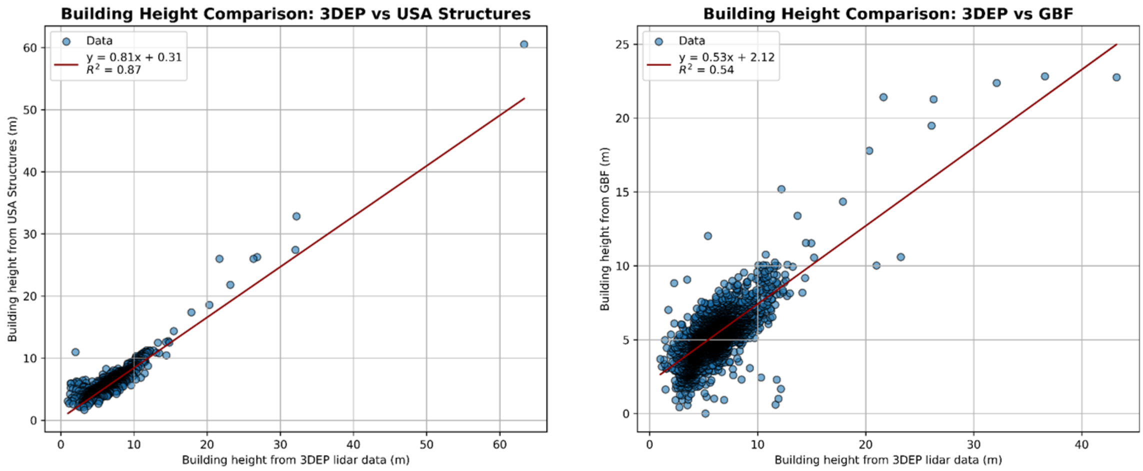
Results

Comparison metrics, including coefficient of determination (R^2), regression slope, mean absolute error (MAE), and root mean square error (RMSE), were computed (Table 1) to quantify relative agreement between data sets. These metrics quantify both correlation and absolute vertical deviation between 3DEP-derived reference heights, characterized by typical vertical accuracies on the order of 10-20 cm RMSEz depending on data quality, and corresponding values from the public data sets.

Data set evaluation	Site	R^2	Slope	MAE (m)	RMSE (m)
3DEP versus USA Structures	1	0.87	0.91	1.8	2.4
3DEP versus GBF	1	0.54	0.53	2.5	3.6
3DEP versus USA Structures	2	0.86	0.81	2.2	3.1
3DEP versus GBF	2	0.60	0.72	3.1	4.3

Table 1: Accuracy metrics for building height extraction in Centennial (Site 1) and Houston (Site 2) from Liu et al. (2026). 3DEP, U.S. Geological Survey three-dimensional elevation program; GBF, Global Building Footprints

Linear regression models are used to evaluate the extracted building heights. In Site 1 (Figure 1), a low-density suburban environment, 3DEP lidar and USA Structures show a strong agreement (R^2 = 0.87, slope = 0.91, MAE = 1.8 m, and RMSE = 2.4 m). This consistency reflects the reliability of lidar-based elevation extraction in areas with uniform building morphology, limited occlusion, and simple roof geometry. In contrast, the comparison with GBF in Site 1 shows weaker agreement (R^2 = 0.54, slope = 0.53, MAE = 2.5 m, and RMSE = 3.6 m). Because GBF building heights are generated from optical stereo imagery, they are more susceptible to occlusion, image noise, roof complexity, and inconsistencies in stereo matching. The sub-unity regression slope and increased scatter suggest a tendency toward systematic underestimation, particularly for taller or more complex structures. These results underscore a key limitation of image-based 3D reconstruction in low-rise suburban environments: height derivations are more vulnerable to subtle errors in roof delineation and elevation contrast, which lidar resolves more reliably.



USA Structures GBF

Figure 1: Scatterplot correlating building heights derived from 3DEP lidar for Site 1, from Liu et al. (2026). GBF, Global Building Footprints

Discussion and Conclusion

Our analysis revealed a strong correspondence between building heights derived from 3DEP lidar and those contained in USA Structures, demonstrating the consistency and reliability of lidar-based data sets for urban structure modeling. Across both test sites, regression analyses showed high coefficients of determination ($R^2 > 0.8$) and near-unity slopes, confirming that height differences were minimal and largely attributable to variations in data collection methods, point density, and processing pipelines.

Building heights from GBF exhibited greater scatter and systematic underestimation relative to the lidar-based reference. The underestimation in GBF heights likely reflects limitations of stereo-derived surface models, including dependence on image quality, temporal differences between data sets, footprint-elevation misalignment, and challenges with complex roof forms. This study shows that reclassified USGS 3DEP lidar point clouds provide a reliable baseline for evaluating large-scale building height data sets. The high consistency between 3DEP and USA Structures validates the utility of the national lidar program for 3D urban infrastructure mapping.

Another factor that may contribute to the observed differences between the two study sites is variation in building composition. Centennial is dominated by relatively uniform low-rise residential structures, whereas Houston contains a broader mixture of residential, commercial, and industrial buildings exhibiting greater height variability and more complex roof geometries. Such differences in building morphology can influence the accuracy of both lidar- and image-derived height estimates and may partially explain the lower agreement metrics observed in Houston. Previous studies (Stipek et al., 2025) have shown that building-type distributions and height variability can substantially affect building height prediction performance. Future work could investigate building-height accuracy separately by occupancy class, building type, and height range to better quantify these effects.

Disclaimer

Any use of trade, firm, or product names is for descriptive purposes only and does not imply endorsement by the U.S. Government.

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