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A Comparative Assessment of Open-source Building Footprint Data for Indian Heritage Sites: Towards a Shape-preserving 3D mapping

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Abstract

Accurate building footprint extraction is essential for generating 3D models of higher level of detail (LoD2) from satellite imagery. While several open-source datasets and algorithms exist, they are primarily trained on non-Indian buildings and perform well for simple, orthogonal shapes. Indian heritage buildings, however, exhibit diverse architectural styles, layouts, and roof forms, posing challenges for automated footprint extraction. Additionally, existing shape evaluation metrics often prioritize areal similarity and compactness over shape resemblance. This study investigates the suitability of current open-source building footprint data for Indian heritage structures, assessing their performance in terms of semantic and geometric accuracy, with a focus on shape resemblance. By identifying key limitations in coverage, post-processing requirements, and contour approximation, the study underscores the need for an improved approach tailored to India's architectural diversity. The findings will inform the development of a 3D mapping tool to enhance its footprint extraction for applications in tourism and conservation.

1. Introduction

Geospatial data fundamentally represents real-world entities through geometric shapes, where the quality and accuracy of these representations directly influence their functional utility across various applications. The quality of these shapes, whether representing vegetation, water bodies, buildings, administrative boundaries or any themes, is crucial in ensuring the reliability of spatial analysis and decision-making processes in domains such as urban planning, disaster management and public administration (Angel et al., 2010). The increasing availability of multi-source geospatial data, which includes volunteered geographic information and machine-generated datasets, presents both opportunities and challenges in maintaining consistent representations of real-world entities (Saalfeld, 1987). While these multi-source data facilitate the development of innovative applications and cost-effective solutions, they also introduce inconsistent representations of the same region due to variations in acquisition techniques, scales and intended use cases (Walter and Fritsch, 2013).

Building footprints, represented as polygons in geospatial data, define the ground-level boundary of buildings in real-world and these present some challenges in shape assessment compared to other geographic features. Typical building footprints are distinguished from other land cover shapes or administrative boundaries shapes by simple polygons with orthogonality, distinct patterns or symmetry (Lu et al., 2024). However, the heritage buildings footprints must record the unique architectural elements built using natural materials and local building traditions, featuring non-orthogonal contours and not distinct from its surroundings and that vary significantly across cultural contexts and historical periods. These buildings often deviate from the training data used for automated detection models. Extraction of building footprints difficulties arise further when roof forms and multi-levelled roofs occlude ground-level boundaries when viewed from an aerial or satellite imagery.

Building footprints serve as fundamental inputs for generating 3D maps, which are increasingly critical for applications in navigation, urban planning, and heritage conservation (Fan et al., 2014). While commercial providers such as Google and Bing offer photorealistic 3D map tiles for many global cities, coverage for Indian regions remains limited. Extruding building footprints from open-source datasets such as Google Open Buildings, Microsoft Global Buildings, OpenStreetMap (OSM), or deep learning-based models like Segment Anything Model (SAM) is currently the primary method for constructing 3D representations in these areas. Platforms like Cesium Ion utilize OSM-derived LoD1 (Level of Detail 1) models for India, while open-source tools such as Blender-OSM enable 3D model generation with configurable roof types. However, OSM's sparse coverage in India and inconsistencies in other datasets such as Microsoft's sparse footprints and Google's broad but variable-quality coverage, directly impact the quality of 3D reconstructions. Due to the increasing demand for high-quality 3D models in tourism and cultural conservation, assessing the quality and shape accuracy of these datasets is essential.

This study evaluates the availability and shape accuracy of building footprints for seven heritage sites across India, comparing open-source datasets (OSM, Google Open Buildings V3, SAM GEO, and Mapflow (processed SAM data) against ground truth derived from government surveys and conservation documents. The analysis focuses on shape representation accuracy rather than mere areal coverage, as heritage structures often exhibit complex geometries that challenge automated extraction methods. The methodology integrates multiple shape similarity metrics selected for their alignment with human visual perception to assess deviations in boundary precision, structural topology, and spatial relationships.

The paper is structured as follows: First, a review of existing geospatial quality assessment frameworks and shape similarity metrics establishes the methodological foundation. Next, the heritage site selection criteria and dataset characteristics are detailed. The subsequent section presents the algorithmic approach, combining Hausdorff distance, turning functions, boundary precision-recall, and skeleton matching for a multi-faceted shape comparison. Results are then analysed, highlighting dataset-specific strengths and limitations in heritage building representation. The study concludes with

recommendations for improving 3D reconstruction pipelines for culturally significant structures in data-sparse regions.
This work is an attempt to contribute to the ongoing efforts in enhancing open-source geospatial data quality, particularly for heritage applications where precise geometric representation is critical for conservation, virtual tourism, and archival documentation.

2. Related Works

2.1 Quality Assessment of Geospatial Data

Recent advancements in satellite imagery, remote sensing, and AI/ML have enabled rigorous derivation and interpretation of geospatial shapes. Quality assessment of such data is critical for selecting optimal datasets for specific applications, requiring standardized evaluation metrics. ISO 19157-1:2023 establishes principles for geospatial data quality evaluation, including measurement structures and reporting formats. For building footprint data, quality assessment typically focuses on semantic and geometric accuracy. Semantic accuracy, following Burghardt's classification, categorizes building-to-footprint relationships into six types (1:1, 1: n, 1:0, n:1, 0:1, n:m), with only 1:1 mapping suitable for geometric quality assessment (Burhardt, 2009). Geometric evaluation examines positional, orientational, dimensional, and shape fidelity (Basaraner, 2020). This study specifically assesses shape accuracy to determine suitability for LoD2 and above 3D mapping applications. Precise building footprints are essential for generating high-detail 3D models, where extrusion and roof form representation depend entirely on footprint quality. Focusing on heritage structures in India, shape similarity metrics are selected based on a pilot study of our campus buildings. we evaluate individual building shapes against ground truth data, as regional-scale references are unavailable.

2.2 Shape Similarity Metrics

Building footprints constitute 2D polygons characterized by both geometric properties (area, perimeter) and topological properties (connectivity, interior voids, boundary smoothness). These footprints exhibit significant variation in three key aspects: (1) regularity (ranging from simple rectangular forms to complex irregular shapes), (2) granularity (level of detail in vertex placement), and (3) boundary noise (smooth versus jagged edge representations).
Shape description methodologies fundamentally employ either region-based or contour-based approaches). Contour-based methods analyse boundary characteristics by converting vertex coordinates into numerical representations, then computing inter-vertex relationships and differences (Fan et al., 2021. Established metrics in this category include turning functions and position graphs, supplemented by distance-based measures such as Hausdorff distance. Region-based methods instead characterize the enclosed area through vectorized numerical representations, capturing global morphological information while providing less precise boundary detail.
For building footprint assessment, our requirements demand shape similarity metrics that align with human perceptual judgments of form resemblance. This necessitates a balanced approach incorporating both contour and region considerations. The selected metrics therefore combine:
1. Boundary-sensitive measures (turning functions, Hausdorff distance)
2. Area-based comparisons (region overlap metrics)
3. Structural assessments (skeleton matching)

This hybrid methodology ensures comprehensive evaluation of both local boundary fidelity and global shape characteristics, critical for applications requiring precise geometric correspondence with real-world structures. The approach particularly addresses the challenges posed by complex architectural forms where neither pure contour nor region methods alone provide sufficient discriminative power.

3. Materials and Methods

3.1 Heritage Site Selection Criteria

The study incorporates heritage sites spanning India's longitudinal extent to capture the diverse architectural typologies across regional variations, with selection criteria prioritizing structural complexity, building techniques, and contextual challenges. The sample includes both UNESCO World Heritage Sites and Tentative List properties and other significant heritage structures.
The selected sites represent seven distinct architectural paradigms:
1. Kailasa temple, Ellora - A rock-cut monolithic temple from 8th century, carved out from top to bottom from a basalt mountain. (World Heritage Committee, 2019)
2. Ramappa temple, Warangal – Highly ornated sandstone temple from 13th century known for its engineering including a lightweight brick pyramidal tower roof. (World Heritage Committee, 2021)
3. Padmanabhapuram Palace, Trivandrum – This palace complex dates to the 16th century and includes 14 interconnected buildings with multiple courtyards, built of wood combining indigenous building methods and workmanship. (Permanent Delegation of India to UNESCO, 2014a)
4. Old Parliament house, New Delhi – Historically significant structure built in 1927. With a circular plan with three semi-circular chambers surrounding the central circular chamber. Central vista, n.d)
5. Muhammad Shah tomb, New Delhi – Octagonal tomb with a central dome surrounded by eight domed-mini pavilions from 15th century. Primarily built of red sandstone. (INTACH Delhi, n.d)
6. Gomang Stupa, Leh – Buddhist stupa dating back to 9th century featuring a 15-meter tall pyramidal seven-tiered platform that decreases height as it ascends. (Auer and Neuwirth, 2009)
7. Gateway tower of temple, Srirangam – Temple town dates to 1st century and expanded until 16th century. The largest living temple in Asia features 21 sculpted gateway towers and the tallest being 72 meters in height, ranks it second tallest temple tower in the world. (Permanent Delegation of India to UNESCO, 2014b)
This selection spans twenty centuries of continuous architectural development, incorporating four natural building materials and five distinct geometric configurations, with individual footprints ranging from 50m² to 12,000m². The approach focuses specifically on individual building footprints rather than complete site plans, enabling direct shape analysis while acknowledging the limitation of evaluating architectural forms without their urban or landscape context. Ground truth data was compiled from the available sources for each structure, including archaeological department surveys and heritage conservation documents.

Figure 1. Selected Heritage Sites.

3.2 Building Footprint dataset

This study conducts a comparative assessment of four open-source building footprint datasets covering the Indian region, evaluating their quality for heritage building representation. The analysis focuses on seven selected heritage structures distributed longitudinally across the country, using OpenStreetMap (OSM Foundation, 2006), Google Open Buildings, version 3 (Google Open Buildings team, 2023), SAM GEO (Wu and Osco, 2023), and Mapflow (Geoalert Team, 2023)-generated datasets as comparative sources. OSM data represents human-annotated vector footprints, while the other three datasets derive from algorithmic processing of satellite imagery, each employing distinct technical approaches. Google Open Buildings version 3 utilizes machine learning models applied to high-resolution satellite data, SAM GEO implements Meta's Segment Anything Model (SAM) for geospatial segmentation through a Python package, and Mapflow incorporates modified SAM GEO algorithms with additional post-processing for improved polygonization and spatial alignment.
Dataset selection followed certain criteria to ensure methodological validity. Given OSM's limited coverage in India, the study sites were constrained to those with existing OSM footprints. Preliminary investigations of building footprint shape quality on our campus contemporary buildings revealed significant post-processing requirements for SAM GEO outputs, motivating the inclusion of Mapflow's enhanced processing pipeline. While not fully open-source, Mapflow data was acquired within the platform's free tier limitations. The technical comparison focuses on fundamental shape accuracy metrics rather than comprehensive feature attribution, as the heritage buildings' distinctive architectural characteristics provide ideal test cases for evaluating each dataset's capacity to capture complex-built forms. This controlled assessment isolates core technical performance factors in building footprint generation across different data production methodologies, from crowd-sourced annotation to advanced machine learning implementations. Mark footnotes in the text with a number (1); use consecutive numbers for following footnotes. Place footnotes at the bottom of the page, separated from the text above it by a horizontal line.

3.3 Multi-metric Shape Similarity Assessment

The quantitative assessment of shape similarity between building footprints presents certain methodological challenges, particularly for structures containing complex internal features such as courtyards. Our analysis highlights three fundamental limitations in current approaches: existing metrics fall short in sufficiently capturing shape similarity in a manner compatible with human perception, geometric and statistical analyses often misrepresent nuanced architectural variations and emerging cognitive-inspired algorithms may ignore exact contour information in complex structures.
This study implements a multi-metric evaluation framework that analyses complementary aspects of shape representation. For primary building structures, we employ four weighted metrics: Hausdorff distance (0.25 weight) for maximum boundary deviation, turning functions (0.25 weight) for angular variation, boundary precision/recall (0.2 weight each) for spatial overlap, and skeleton similarity (0.1 weight) for topological structure. We evaluated multiple structural-based shape descriptors including graph edit distance, Fourier descriptors, and positional graphs. However, the required normalization processes for these methods led to significant polygon simplification, resulting in similarity measures that poorly correlated with actual shape correspondence. This finding motivated our conservative weighting (0.1) of skeleton matching, despite its theoretical advantages for higher-level shape relationships, as the medial axis transformation proved particularly sensitive to boundary perturbations.
The algorithm to detect the main building for shape similarity assessment from the dataset, implements an evaluation protocol: when datasets represent buildings as multiple polygons of 1: n mapping (Burghadt, 2009), only the largest-area polygon overlapping the ground truth footprint undergoes shape assessment. This decision follows from empirical evidence that 1: n representations yield meaningless similarity measures (mean Hausdorff distance increase = 217% compared to 1:1 cases). After the largest polygon is identified as the primary building, potential courtyard candidates are detected by validating minimum area thresholds. For courtyards, all qualifying interior polygons are evaluated as an aggregate, recognizing that both their individual shapes and spatial relationships contribute to architectural identity. This distinction explains the emphasis on IoU (weight = 0.4) for courtyard assessment, as it simultaneously captures area correspondence and relative positioning.
The computational pipeline generates both quantitative metrics and comparative visualizations, enabling comprehensive evaluation. The proposed weighted combination of geometric (Hausdorff, IoU), topological (skeleton graphs), and boundary-sensitive (precision/recall) metrics demonstrates improved correlation with expert similarity assessments compared to single-metric approaches.

4. Results and Analysis

For this study, areas of interest of size 500m × 500m were selected and building footprint data from Google Open Buildings (GOB) and OpenStreetMap (OSM) were collected. Corresponding high-resolution GeoTIFF images of these areas were processed using SAMGEO and Mapflow to generate additional footprint datasets. Among the seven heritage buildings assessed, two contained multiple courtyards. The primary buildings and courtyards were detected, and multi-metric shape similarity assessment was conducted to assess shape similarity.

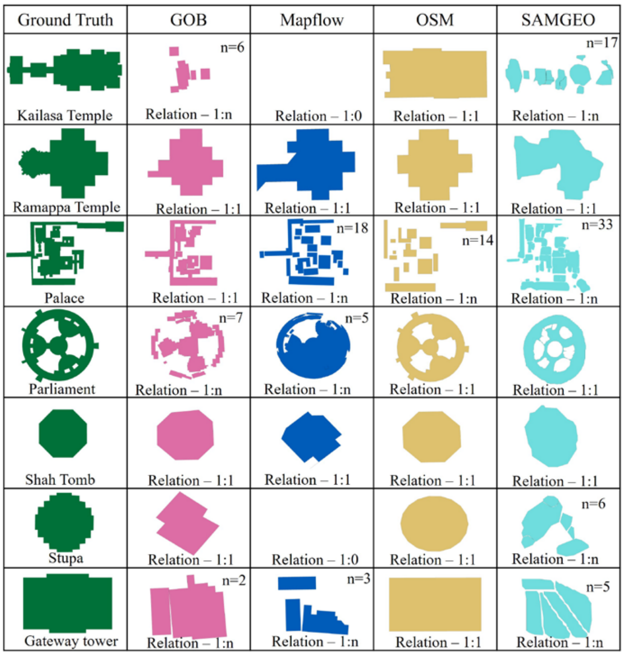

Figure 2. Relationship between building footprints in dataset.

The figure (2) presents the semantic accuracy of heritage building representations relative to ground truth. OSM consistently maintained a 1:1 building-to-footprint correspondence, except for the Palace Complex, indicating superior semantic alignment with real-world structures. GOB performed well for the Shah Tomb and Ramappa Temple but exhibited 1: n (one-to-many) representations for other buildings, complicating geometric evaluation. Deep learning-based SAMGEO and Mapflow predominantly produced 1: n relationships, requiring extensive post-processing to eliminate spurious small polygons along edges.

Heritage Building Footprint	Dataset	Hausdorff	Turning	Precision	Recall	Skeleton
Kailasa Temple	Ground Truth	1	1	1	1	1
Ellora	GOB	0.002	0.725	0.8	0.225	0.004
	OSM	0.14	0.749	0.8	0.8	0.005
	SAMGEO	0.006	0.761	0	0	0
Ramappa Temple	GOB	0.476	0.816	0.8	0.8	0.011
Warangal	Mapflow	0.511	0.807	0.8	0.8	0.039
	OSM	0.585	0.843	0.8	0.8	0.007
	SAMGEO	0.443	0.78	0.8	0.8	0.019
Padmanabhapuram Palace	GOB	0	0.679	0.603	0.567	0.01
	Mapflow	0	0.725	0.8	0.362	0.006
	OSM	0	0.744	0.8	0.308	0.003
	SAMGEO	0	0.737	0.8	0.314	0.004
Courtyard		IoU	Turning	Precision	Recall	Skeleton
	GOB	0.041	0.94	0.8	0.266	0
Parliament House	GOB	0.001	0.792	0.629	0.835	0.004
Delhi	Mapflow	0.001	0.674	0.916	0.8	0.009
	OSM	0.359	0.922	0.8	0.8	0.036
	SAMGEO	0.076	0.952	0.8	0.8	0.027
Courtyard		IoU	Turning	Precision	Recall	Skeleton
	Maplflow	0.001	0.948	0.323	0.012	0
	OSM	0.765	0.957	0.8	0.8	0
	SAMGEO	0.26	0.919	0.851	0.8	0
Shah Tomb	GOB	0.754	0.993	0.8	0.8	0
Delhi	Mapflow	0.57	0.883	0.8	0.8	0
	OSM	0.883	0.994	0.8	0.8	0
	SAMGEO	0.414	0.944	0.641	0.886	0
Gomang Stupa	GOB	0.444	0.798	0.8	0.8	0.006
Leh	OSM	0.772	0.829	0.8	0.8	0.003
	SAMGEO	0.281	0.79	0.518	0.385	0.003
Gateway Tower	GOB	0.214	0.849	0.8	0.8	0.007
Srirangam	Mapflow	0.154	0.663	0.873	0.559	0.008
	OSM	0.244	0.873	0.8	0.8	0.005
	SAMGEO	0.058	0.856	0.799	0.562	0.003
Wrong Match					Best Match	

Figure 3. Detailed score matrix .

A detailed, color-coded score matrix figure (3) summarizes the multi-metric shape similarity assessment, with figures (4), (5), (7) and (9) providing visualizations for the Old Parliament House’s main building and courtyards. Approximately 110 similar plots were generated for all cases, however, plots for only one building is shown here, and a weighted score heatmap figure (8) highlights overall performance. OSM demonstrated strong accuracy across most sites except the Palace Complex, reflecting heterogeneous quality in volunteered geographic information. Both Ramappa Temple and Shah Tomb were well-detected across all datasets, likely due to their isolated locations and geometrically simple footprints.

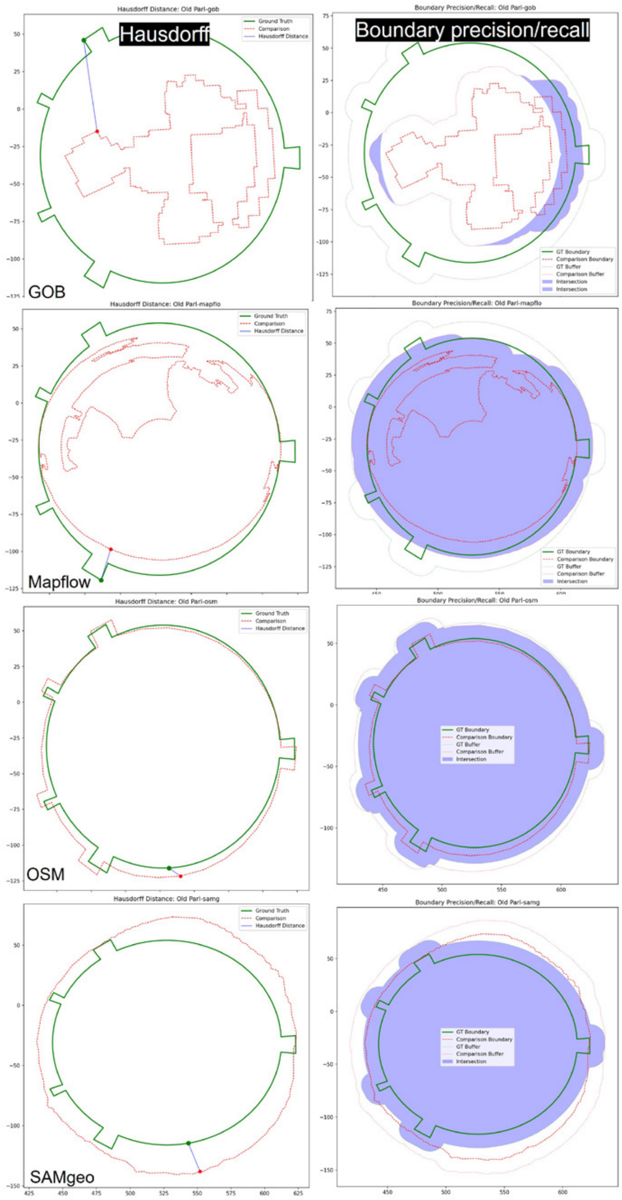

Figure 4. Plots for each metrics – Parliament-Main building.

Contour edge quality varied significantly. GOB approximated curves as stepped segments, while SAMGEO and Mapflow captured curvature better but introduced serrated edges, as shown in figure (6). Mapflow failed entirely to detect the rock-cut Kailasa Temple, indicating limited interpretability for monolithic structures. OSM exhibited fine-grained edge precision, particularly for the Old Parliament House. The

Gomang Stupa, partially obscured by foliage, was missed entirely by Mapflow, whereas GOB outperformed other datasets in representing the Palace Complex. The 72m tall Srirangam gateway tower was accurately captured only by OSM, while SAMGEO and Mapflow erroneously generated tilted outlines, suggesting inadequate model training on such architectural forms.

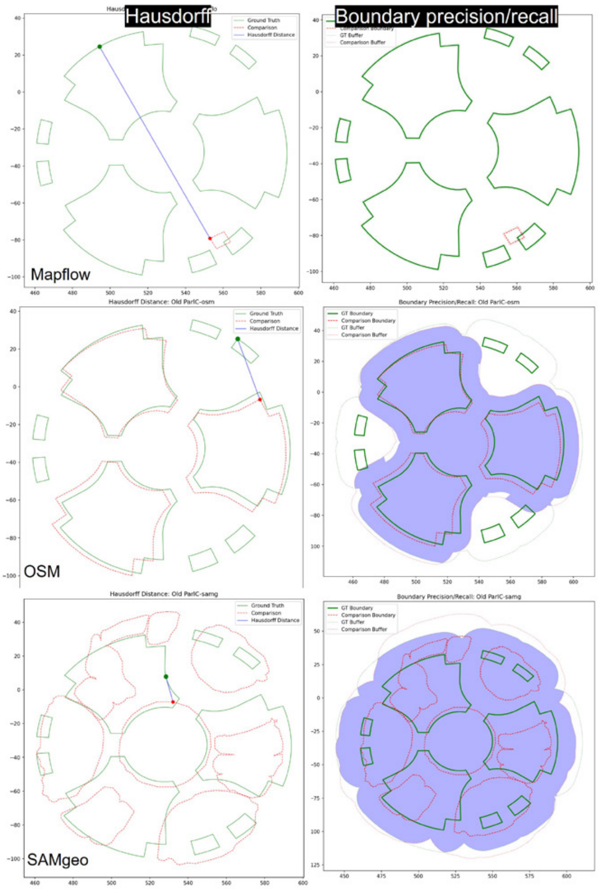

Figure 5: Plots for each metrics - Parliament Courtyard

These findings underscore the shortcomings in the dataset sources: OSM’s manual annotation ensures higher semantic and geometric accuracy for heritage structures, while automated methods (GOB, SAMGEO, Mapflow) struggle with complex or occluded features. The results emphasize the need for specialized training data and post-processing refinements to improve machine learning-based footprint extraction for culturally significant buildings.

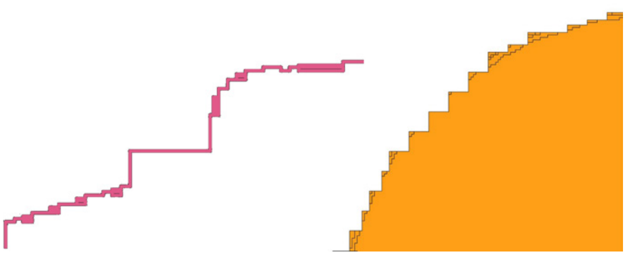

Figure 6. Curved edge representations in Mapflow and SAMGEO.

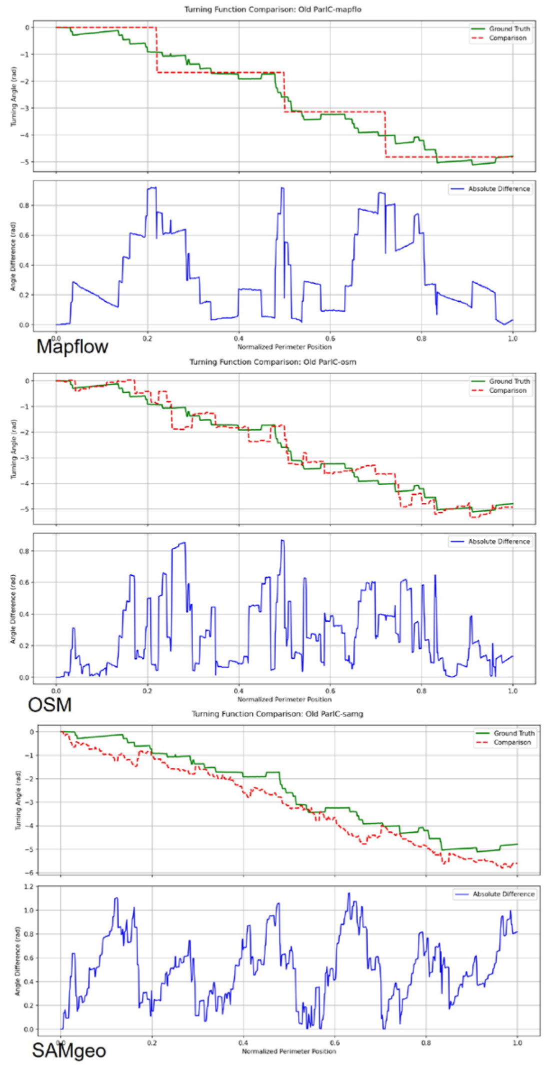

Figure 7. Plot for turning function - Parliament-Courtyard .

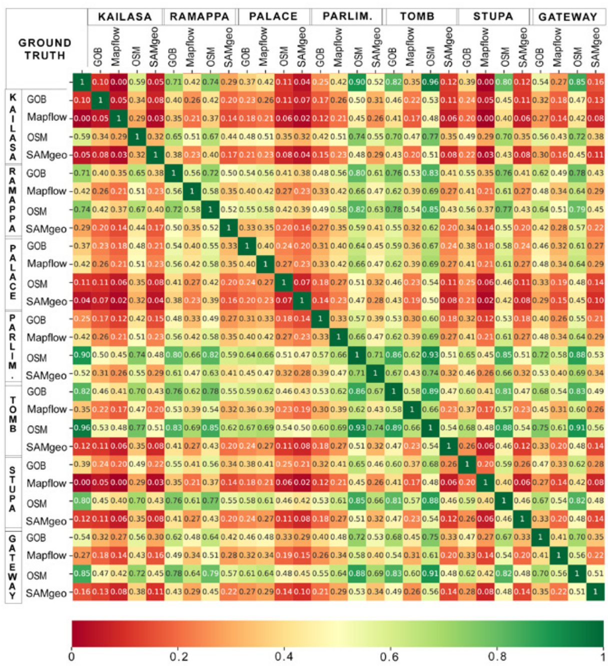

Figure 8. Overall score matrix.

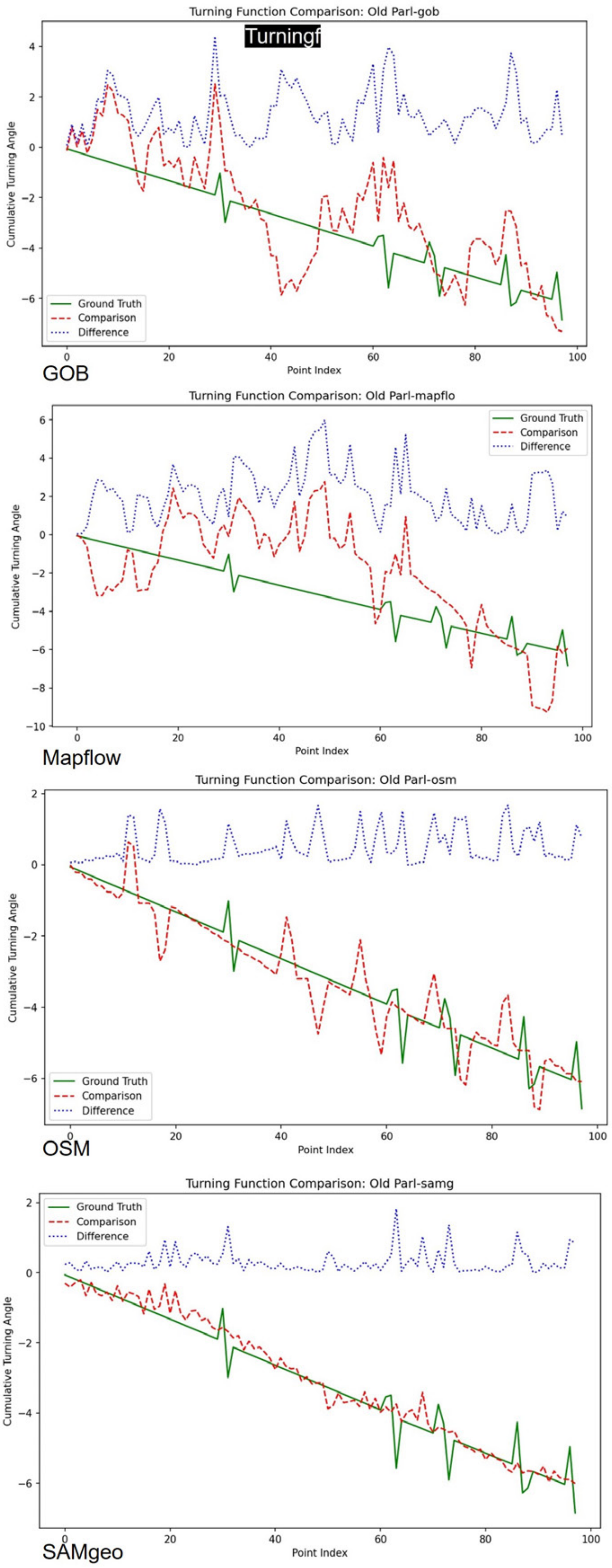

Figure 4. Plot for turning function - Parliament-Main building.

5. Conclusion

In this study, we implement a weighted **multi-metric shape similarity framework** that assesses both semantic and geometric accuracy of open-source building footprint datasets for Indian heritage structures. The **cross-dataset comparative analysis** identifies dataset-specific limitations and establishes performance benchmarks across different data generation approaches. Results indicate that while OpenStreetMap (OSM) provides shape accurate footprints with fine-grained edge representation, its limited coverage in India restricts its utility for large-scale 3D mapping. Deep learning-based datasets (Google Open Buildings, SAMGEO, Mapflow) have broader coverage. However, exhibit critical limitations in handling heritage structures, particularly those with complex geometries, occlusions, or non-standard architectural features. The frequent 1: n polygon representations and serrated edges in AI-generated data necessitate extensive post-processing, undermining their efficiency for high-detail 3D reconstruction. The findings establish that current automated extraction methods inadequately capture heritage building characteristics, necessitating specialized algorithms and training data for culturally significant structures

A hybrid approach combining primitive 2D polygon fitting with AI-driven detection could optimize footprint extraction by reducing post-processing overhead while preserving shape accuracy. However, the fundamental requirement remains an accurate shape representation and well-defined edges are non-negotiable for generating LoD2 and above 3D models. Future work should prioritize (1) curating specialized training datasets for heritage structures and (2) developing adaptive algorithms that integrate parametric modelling with machine learning to balance automation with architectural fidelity. Until such solutions mature, OSM remains the reliable source for heritage sites, albeit with significant coverage gaps that must be addressed through targeted community mapping initiatives. For Indian heritage documentation, these findings underscore the urgent need for domain-optimized footprint extraction pipelines to support high-quality 3D urban mapping.

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