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Evaluating the Transferability of 3DMASC Random Forest Models Across Mobile LiDAR and SfM Point Clouds for Urban Feature Classification

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Key words: Urban LiDAR, Mobile laser scanning, 3D point cloud classification, Random Forest, 3DMASC, UAS-SfM Photogrammetry, 3D Urban Mapping

SUMMARY

Accurate classification of urban point clouds is critical for application in planning, infrastructure monitoring and environmental management. Transferability across sensing modalities remains uncertain. This study evaluates a classical, feature-based approach. We test 3DMASC Random Forest models on two datasets. The first dataset is Toronto-3D mobile LiDAR (MLS), while second is an UAS Structure-from-Motion (SfM) dataset from Umngeni Valley. Three urban land-use classes: ground, vegetation and buildings were considered in the analysis. Multi-scale geometric descriptors were extracted, including linearity, planarity, sphericity, eigenvalue ratios and Z-range. The study evaluated three scenarios, namely training and testing within a single modality; cross-modality transfer between datasets and merged-dataset training with subsequent testing on each modality separately. Class balance was maintained using a 70:30 training-to-testing split and performance was evaluated through accuracy, precision, recall, and F1-score. The results showed strong within-modality performance, with MLS achieving 85% overall accuracy and SfM 76%. Cross-modality transfer, however, resulted in marked declines, the UAS-SfM to MLS transfer achieved only 69% accuracy and MLS to UAS-SfM dropped further to 52%. These findings demonstrated the sensitivity of vegetation and building classes to acquisition geometry and point density differences. By contrast, merged-dataset training improved robustness. The combined model yielded 83% accuracy when tested on MLS and 72% on SfM. Feature importance analysis confirmed the dominance of coarse-scale descriptors, with sphericity identified as the most influential feature. MLS performance benefited from the incorporation of vertical range information, while SfM relied more heavily on shape-based descriptors. Classical, feature-based models can generalise across heterogeneous urban point clouds when trained on combined data. Transfer remains class-dependent due to viewpoint and density differences. This study provides insights into the potential for classical, feature-based classifiers to transfer across heterogeneous urban datasets, which may reduce the need to retrain models for each new dataset.

1. INTRODUCTION

Accurate classification of urban features remains challenging due to the complexity and variability of urban landscapes. At the same time, the classification task is essential in remote sensing and point cloud analysis, enabling applications such as urban planning, infrastructure monitoring and environmental management (Chen et al., 2013; Sharifisoraki et al., 2022; Ntuli and Forbes, 2023). Point cloud classification involves the process of categorising individual points within a three-dimensional (3D) point cloud and assigning semantic labels that represent real-world features (Grilli et al., 2017). Methods for assigning class labels include supervised approaches, which use annotated training data; unsupervised approaches, which identify patterns directly from the data and interactive approaches, which involve human input to guide or refine the classification (Weinmann et al., 2015).

Different sensing modalities such as laser scanning and Structure-from-Motion (SfM) photogrammetry, capture urban scenes with varying geometry and point density. Light detection and ranging (LiDAR) technologies including mobile laser scanning (MLS) are well known for generating geometrically stable point clouds of uniform density and high positional accuracy (Kukko et al., 2012; Wang et al., 2019). These attributes make LiDAR well-suited for capturing complex urban scenes. However, LiDAR is financial costly and prone to occlusion, which may limit detail capture in dense or built-up areas (Niemeyer et al., 2014). On the other hand, Unmanned Aerial Systems (UAS) can generate comparable point clouds at a lower cost using the SfM photogrammetry technique. SfM refers to the geometry of generating 3D photogrammetric products from overlapping 2D images captured by a moving sensor (Westoby et al., 2012). SfM first produces a sparse point cloud through bundle adjustment (Snavely et al., 2008). The following step is then densification using Clustering for Multi-View Stereo (CMVS) and Patch-based Multi-View Stereo (PMVS) algorithms (Furukawa and Ponce, 2010; Furukawa et al., 2009). Comparing the two technologies described above, UAS-SfM captures top views effectively but lacks side-detail coverage, whereas MLS provides precise side views but may miss upper surfaces. These inherent differences can affect the transferability of machine learning classification models across datasets.

Machine learning classification models trained on one dataset often lose accuracy on another due to differences in collection conditions, sensor characteristics and scene variability. Similarly, deep learning networks trained on a single source domain show significant drops in performance when transferred to new target domains (Wang et al., 2024). This challenge highlights the importance of evaluating the transferability of classifiers across datasets acquired using different sensors. Zhao et al., (2019) demonstrated that transfer learning can improve airborne LiDAR point cloud classification with small training datasets, while also emphasising that model generalisation remains highly dependent on the similarity between source and target domains. Ongoing research has focused on the development of domain adaptation techniques for cross-scene point cloud classification. In Wang et al. (2024), cross-domain classification was achieved using pseudo-labels with feature pre-alignment, entropy constraints, and feature augmentation of the target scene. A deformation reconstruction (DefRec) self-supervised task combined with a point cloud Mixup training procedure has also been shown to improve cross-domain adaptation on 3D point clouds (Achituve et al., 2021). In Liu et al. (2025), an SF-City approach was used to combine pre-trained source models, multi-cue feature extraction, integrated source knowledge and geometric prior-guided pseudo labels.

While previous studies have demonstrated cross-scene classification using deep learning and domain adaptation, understanding the intrinsic generalisation capabilities of classical, feature-based models remains important. Multi-scale classifiers that analyse local 3D geometry perform well in complex natural and even in harsh underwater environments (Brodu and Lague, 2012; Palma et al., 2018; Ntuli et al., 2024). This study presents the first systematic evaluation of 3DMASC random forest models for transferability across MLS and UAS SfM point clouds. The aim is to test whether these models can generalise across different sensing modalities and viewpoints. We further examine the role of multi-scale geometric features such as linearity, planarity and sphericity in shaping classification performance. The findings provide new evidence on the generalisation capacity of classical machine learning models and highlight their potential to reduce retraining across diverse urban datasets.

The remainder of this paper is organised as follows. Section 2 describes the study area and datasets, including the WESSA Umngeni Valley and Toronto-3D Mobile LiDAR. Section 3 details materials and methods, including pre-processing and the 3DMASC random forest classifier. The experimental design for within-modality, cross-modality and merged-dataset classification is described. Section 4 presents classification results and performance metrics for ground, vegetation and buildings and discusses the implications of sensor modality and viewpoint on accuracy. Section 6 concludes with key findings, limitations, and future research directions.

2. STUDY AREA

The current study draws on two complementary datasets representing urban and peri-urban topographies with shared surface features, namely ground, buildings and vegetation. The first dataset was captured at the WESSA Umngeni Valley Nature Reserve and Education Centre, situated in Howick, South Africa. This area is comprised of a combination of natural vegetation, open terrain and built structures as shown in Figure 1. The second dataset is the Toronto-3D MLS dataset collected in a dense urban setting in Toronto, Canada, using a vehicle-mounted LiDAR system (Tan et al., 2020). It provides high-detail representations of urban elements such as roads, buildings, vegetation, and utilities. This dataset is widely used to evaluate the performance of various classification algorithms. Although the datasets differ in geographic context and sensing modalities, they contain comparable thematic classes. The Umngeni dataset represents a semi-natural environment with low-rise development, while the Toronto-3D dataset captures a complex urban fabric. This combination provides a robust basis for assessing the transferability of classification models across differing spatial and sensor domains.

Figure 1: Presentation of the study area in Howick, South Africa, Aerial View (WGS84 coordinates of the red circle: 29°28'32" S, 30°14'23" E).

3. MATERIALS AND METHODS

3.1 Materials

Two different point cloud datasets were used to evaluate the transferability of 3DMASC Random Forest classification models across different acquisition modalities. The first dataset was generated from aerial imagery captured using a DJI Phantom 3 Professional UAS. The platform was equipped with an integrated 12-megapixel camera. The collected imagery was processed using the SfM photogrammetry and PMVS technique to generate dense three-dimensional point clouds. This is a workflow that reconstructs scene geometry by matching image features across multiple viewpoints and performing bundle adjustment (Furukawa and Ponce, 2010; Furukawa et al., 2009). The second dataset comprised the publicly available Toronto-3D mobile LiDAR benchmark. It provides accurately labelled urban scenes acquired via vehicle-mounted laser scanning (Tan et al., 2020). This dataset served as a complementary modality for assessing cross-domain classification performance between UAS-SfM and MLS point clouds.

Point cloud pre-processing and classification were undertaken using CloudCompare (version 2.14 Alpha), an open-source three-dimensional point cloud processing platform (Girardeau-Montaut, 2025). Pre-processing involved three key steps: (i) data cleaning, to remove noise and outliers through statistical filtering; (ii) data annotation, to assign ground-truth class labels to training samples and (iii) resampling, to standardise point density across datasets. The classification stage employed the 3DMASC (3D Multi-scale Attribute Selection for Classification) plugin within CloudCompare, implementing a Random Forest classifier to exploit multi-scale geometric descriptors for the discrimination of urban features (Letard et al., 2024). Figure 2 presents the general workflow of 3DMASC point cloud classification in CloudCompare, illustrating the sequential stages of pre-processing, classification and accuracy assessment. This workflow was applied in three experimental configurations: training and testing within the same modality, cross-modal transfer and training on merged point clouds from both modalities.

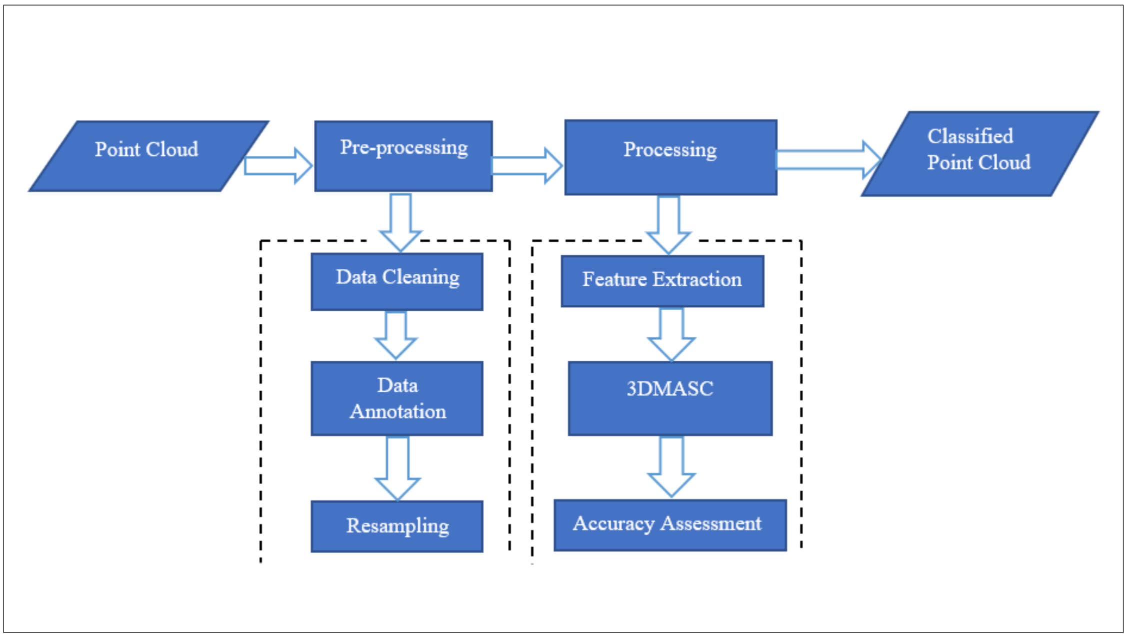

Figure 2: General workflow of 3DMASC point cloud classification in CloudCompare, including pre-processing, classification, and accuracy assessment.

3.2 Point Cloud Classification

3.2.1 3DMASC

The 3DMASC (Multiple Attributes, Scales, and Clouds) is a supervised machine learning method for 3D point cloud classification developed by Letard et al. (2024). The classifier operates using multiple attributes across different scales and can leverage data from one or more point clouds. The classical components of single point cloud semantic classification such as geometric and height-based features from multi-scale spherical neighbourhoods are integrated

(Brodu and Lague, 2012; Mazzacca et al., 2022). The 3DMASC approach captures detailed shape features such as linearity, planarity, sphericity and eigenvalue ratios. These features are derived from Principal Component Analysis (PCA) of the covariance matrix of points within each neighborhood. The classification is performed using a random forest algorithm. It is an ensemble learning method that builds multiple decision trees from bootstrap samples to improve prediction accuracy (Breiman, 2001). Two main parameters govern the model: the number of trees and the number of features randomly selected at each split (Rodriguez-Galiano et al., 2012; Belgiu and Drăguţ, 2016). Features are selected randomly to reduce overfitting by introducing diversity among trees. The final output is derived from majority voting in classification or averaging in regression. This enhances both the accuracy and efficiency of predictions (Breiman, 2001). The 3DMASC tool incorporated in CloudCompare requires a parameter file that specifies the scales in which descriptors are computed.

3.2.2 Experimental Design and Cross-Modality Classification Workflow

The experimental procedure followed three phases to evaluate classification performance and cross-modality transferability. Figure 3 illustrates the workflow of a structured comparison between three scenarios as follows:

- Training and testing within a single modality.
- Training on one modality and testing on another.
- Training on merged data and testing on each modality separately.

Initially, the models were trained and tested on the same dataset, where 30% of the training data was reserved to evaluate model performance. This preliminary assessment was conducted for all three scenarios outlined above to establish baseline results. Following this, independent test datasets were introduced to provide a more rigorous evaluation of classification performance. In the first phase, a 3DMASC classifier was trained using UAS-SfM point cloud data. The classifier was applied to an independent UAS-SfM dataset to assess within-modality accuracy. The same model was then applied to the MLS dataset without retraining. This tested the ability of a photogrammetry-trained model to classify MLS point clouds. In the second phase, the classifier was trained on the MLS dataset. The trained model was applied to an independent MLS dataset to establish baseline performance. It was then applied to the UAS-SfM dataset without retraining. This evaluated the transferability of LiDAR-trained models to photogrammetry data. Lastly, the third phase involved merging both datasets into a single training set. The UAS-SfM and MLS point clouds were combined to incorporate complementary spatial and radiometric characteristics. A classifier was trained on the merged dataset and tested on each modality separately.

Across all experiments, the 3DMASC classifier was trained using multi-scale geometric descriptors from annotated core points. A 70:30 training-to-testing ratio was maintained, with balanced class representation to avoid bias. Scales for feature computation were determined through an ablation study to identify the most effective set for classification accuracy. The final scales were 0.4m, 1m, 5m, and 10m. At each scale, geometric features computed included the second-order principal component analysis eigenvalue ratio, the third-order eigenvalue ratio, planarity, sphericity, and linearity. The Z-range descriptor was computed at the 10 m scale to capture vertical height variation over larger spatial neighbourhoods. These features provided a robust description of local geometry. The Random Forest hyperparameters were selected to optimise performance. The maximum tree depth was set to 25, with 100 trees in the forest. All features were considered at each split, with a minimum of 15 samples per leaf. These settings balanced model complexity and generalisation, achieving high accuracy while avoiding overfitting.

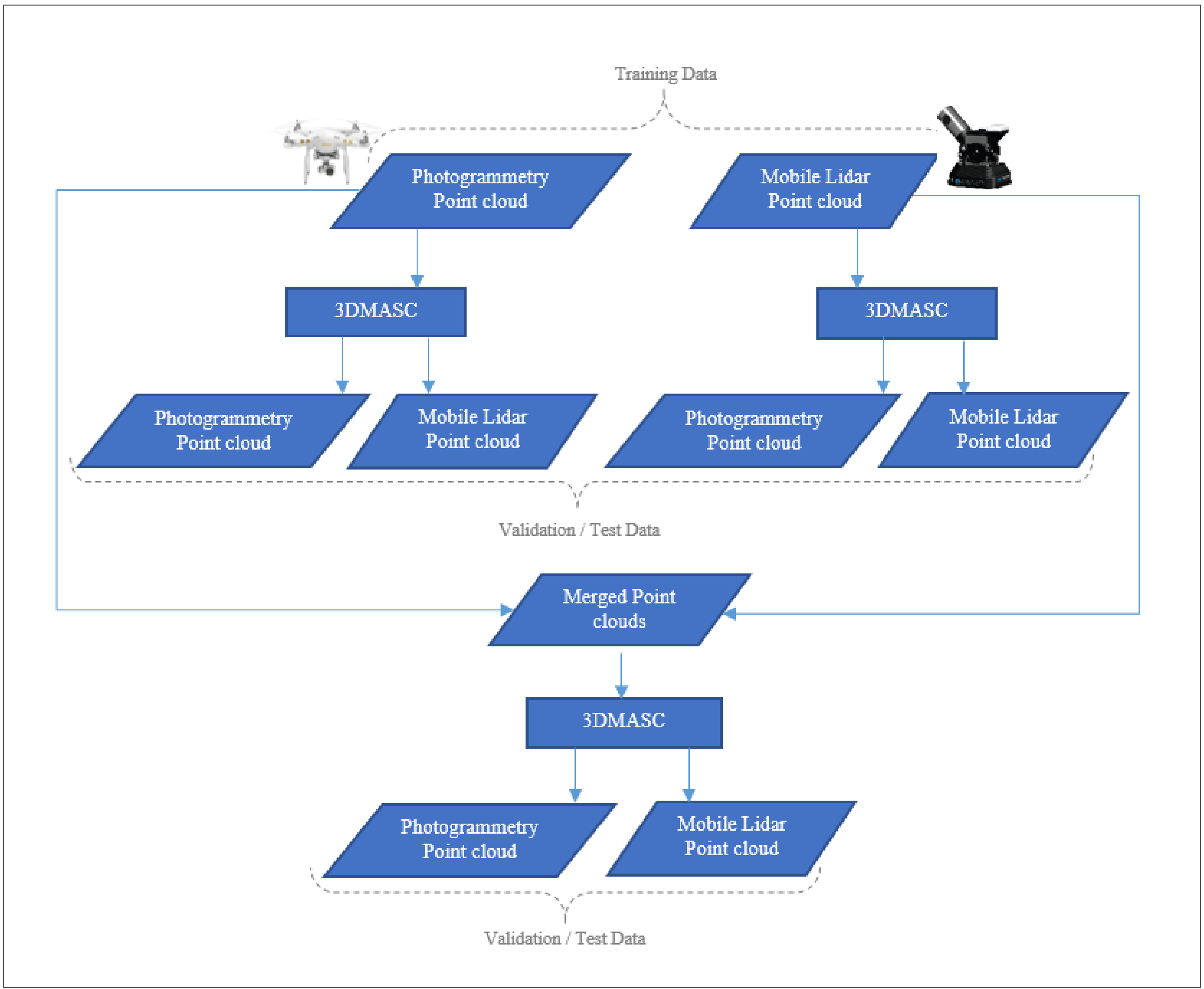

Figure 3: Workflow for assessing the transferability of 3DMASC Random Forest models between SfM photogrammetry and mobile LiDAR (MLS) point clouds for urban feature classification.

3.3 Evaluation Metrics and Classifier Performance

Point cloud classification performance was assessed using standard statistical metrics derived from the confusion matrix. This matrix compares the actual class labels with the predicted labels from the classification model. It records true positives (TP), false positives (FP), false negatives (FN) and true negatives (TN). These values form the basis for computing key performance indicators.

Four main metrics were calculated: accuracy, precision, recall and the F1 score. Accuracy measures the proportion of correctly classified points across all classes and is calculated as follows:

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad [1]$$

Precision measures the reliability of the model when it predicts a particular class. It is defined as the ratio of correctly predicted points of a specific class (true positives) to the total number of points predicted as belonging to that class (true positives + false positives). It is calculated as follows:

$$Precision = \frac{TP}{TP + FP} \quad [2]$$

Recall, also referred to as sensitivity, assesses the model's ability to identify all relevant points belonging to a given class and is calculated as follows:

$$Recall = \frac{TP}{TP + FN} \quad [3]$$

Lastly, the F1 score is the harmonic mean of precision and recall, providing a balanced measure that accounts for both false positives and false negatives:

$$F1\ score = 2 * \frac{Recall * Precision}{Recall + Precision} \quad [4]$$

4 RESULTS AND DISCUSSION

Initially, the models were trained and tested on the same dataset where 30% of the training data was reserved to evaluate model performance. This preliminary step was conducted for all three scenarios outlined in section 3.2.2 to establish baseline results. Figure 4 shows the annotated training datasets used to train the 3DMASC classifiers: (a) the UAS-SfM point cloud and (b) the Mobile LiDAR point cloud. The baseline results obtained from the 30% validation split are presented in Table 1.

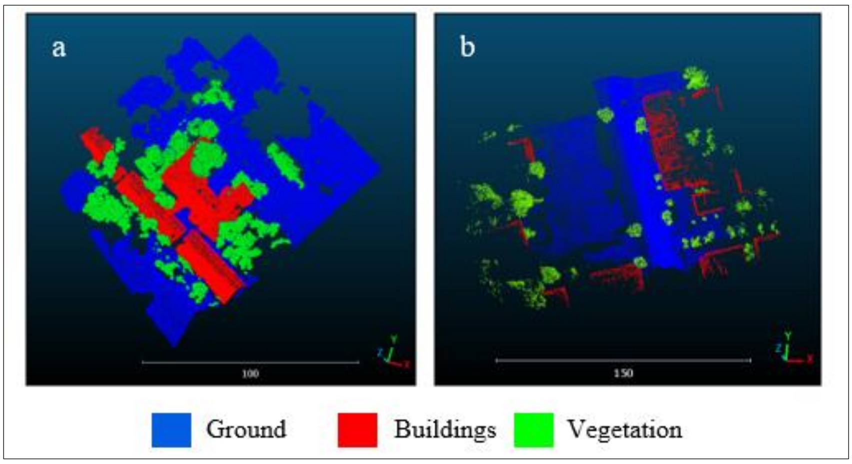

Figure 4: Annotated training datasets: (a) the UAS-SfM point cloud; (b) Mobile LiDAR point cloud

Table 1: Classification results of the 3DMASC Random Forest models using 30% training-test split for UAS-SfM, Mobile LiDAR (MLS) and combined datasets

Train and Test Domain	Feature	Precision	Recall	F1 Score	Accuracy
UAS-SfM (30%)	Ground	0.98	0.95	0.96	0.95
	Vegetation	0.92	0.98	0.95	
	Buildings	0.96	0.93	0.94	
MLS (30%)	Ground	1.00	1.00	1.00	0.98
	Vegetation	0.97	0.99	0.98	
	Buildings	0.99	0.97	0.98	
UAS-SfM and MLS (30%)	Ground	0.99	0.98	0.98	0.96
	Vegetation	0.94	0.98	0.96	
	Buildings	0.96	0.94	0.95	

Across both modalities, the classifiers demonstrated strong performance, with F1-scores consistently above 0.90. For the UAS-SfM dataset, the model achieved 95% accuracy with strong performance for ground and buildings, while vegetation showed slightly lower precision but high recall. This indicates that most vegetation points were correctly identified, with only minor misclassification into other classes. The MLS dataset classification achieved the best results with 98% accuracy. These results show near-perfect scores across all classes, reflecting a higher geometric fidelity of MLS point clouds. The higher geometric fidelity of MLS data provides sharper class separability compared to SfM photogrammetry. When both datasets were merged for training, the overall accuracy reached 96%. Ground and building classes maintained strong classification consistency, while vegetation continued to show minor precision-recall trade-offs. This demonstrates that combining modalities enhances robustness by leveraging complementary features, though it may also introduce subtle noise or overlaps in class boundaries.

Figure 5 presents the independent evaluation datasets within each modality, including the RGB point clouds, annotated ground truth and the corresponding classified outputs. This allowed for a direct comparison between model predictions and reference data under the same sensing modality. The corresponding quantitative results are outlined in table 2. Classification performance is generally higher when the model is trained and tested on the same modality, demonstrating reliable identification of ground, vegetation and buildings.

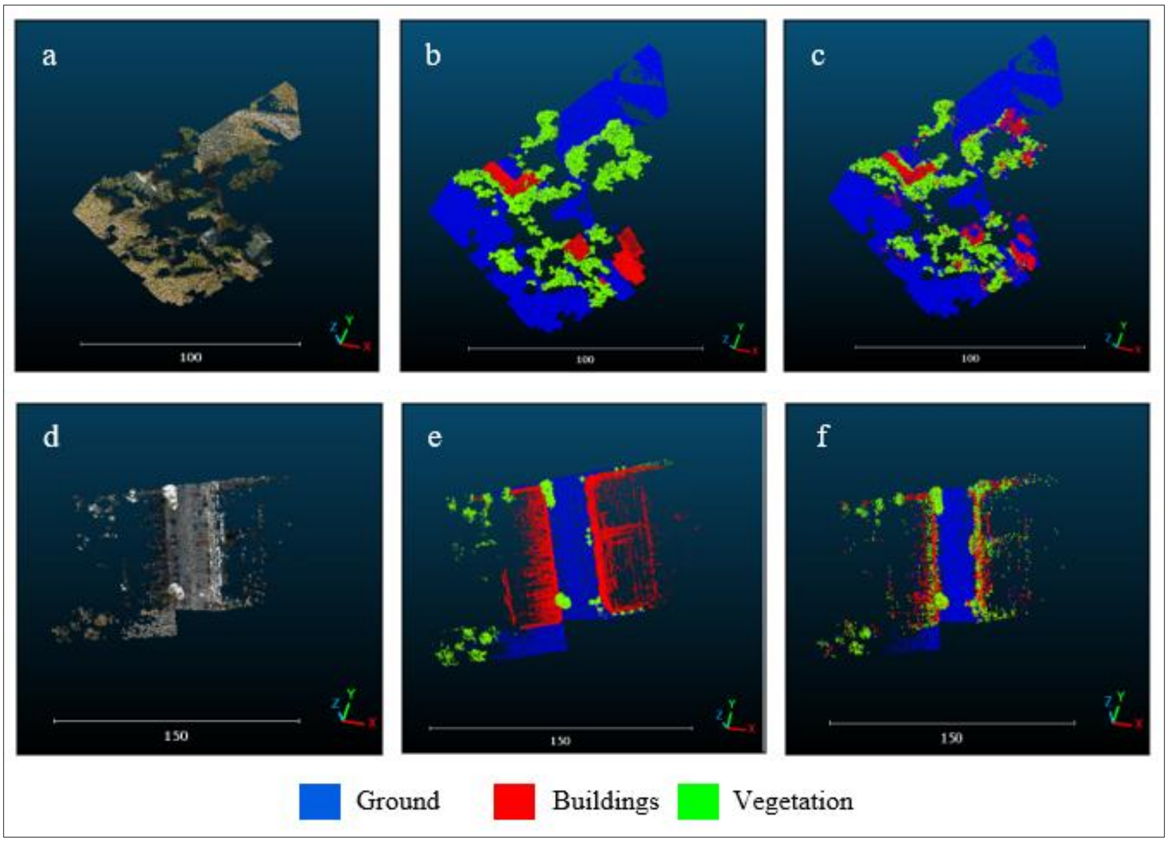

Figure 5: RGB, annotated, and classified test point clouds for UAS-SfM and MLS, showing model evaluation on independent within-modality datasets.

Cross-domain testing between UAS-SfM and MLS results in noticeably lower performance, particularly for vegetation and buildings, which is influenced by differences in viewpoint coverage. Figure 6 shows the classification results of cross-domain testing and the performance of models trained using combined dataset. The UAS-SfM point clouds often lack side views due to aerial acquisition angles, while MLS data can have missing top views caused by occlusions or sensor placement. Ground points are consistently classified more accurately because of their uniform geometric features, whereas vegetation and buildings are more sensitive to variations in geometry, point density and missing data.

Table 2: Classification performance across UAS-SfM, MLS and combined point clouds.

Training Data	Test Domain	Feature	Precision	Recall	F1 Score	Accuracy
UAS-SfM	UAS-SfM	Ground	0.72	0.95	0.82	0.76
		Vegetation	0.82	0.74	0.78	
		Buildings	0.78	0.60	0.68	
	MLS	Ground	0.91	0.94	0.93	0.69
		Vegetation	0.55	0.95	0.69	
		Buildings	0.71	0.23	0.34	
MLS	MLS	Ground	0.98	0.95	0.97	0.85
		Vegetation	0.73	0.95	0.83	
		Buildings	0.88	0.65	0.75	
	UAS-SfM	Ground	0.55	0.93	0.69	0.52
		Vegetation	0.85	0.20	0.32	
		Buildings	0.40	0.43	0.41	

The results in Table 3 show that training with a combined UAS-SfM and MLS dataset improves overall robustness, but performance still varies between modalities and classes. Ground points achieve consistently high accuracy in both test domains, reflecting their uniform structure and dense representation in both datasets. Vegetation is classified more effectively in MLS test data, where high point density and side-view coverage capture canopy details, while performance is weaker in UAS-SfM due to limited side views. Buildings remain the most challenging class in both domains, with reduced recall particularly in MLS tests, as missing top views and complex roof structures often lead to misclassification. These outcomes suggest that while combining datasets enhances model generalization, differences in acquisition geometry, viewpoint coverage and class representation continue to influence classification reliability.

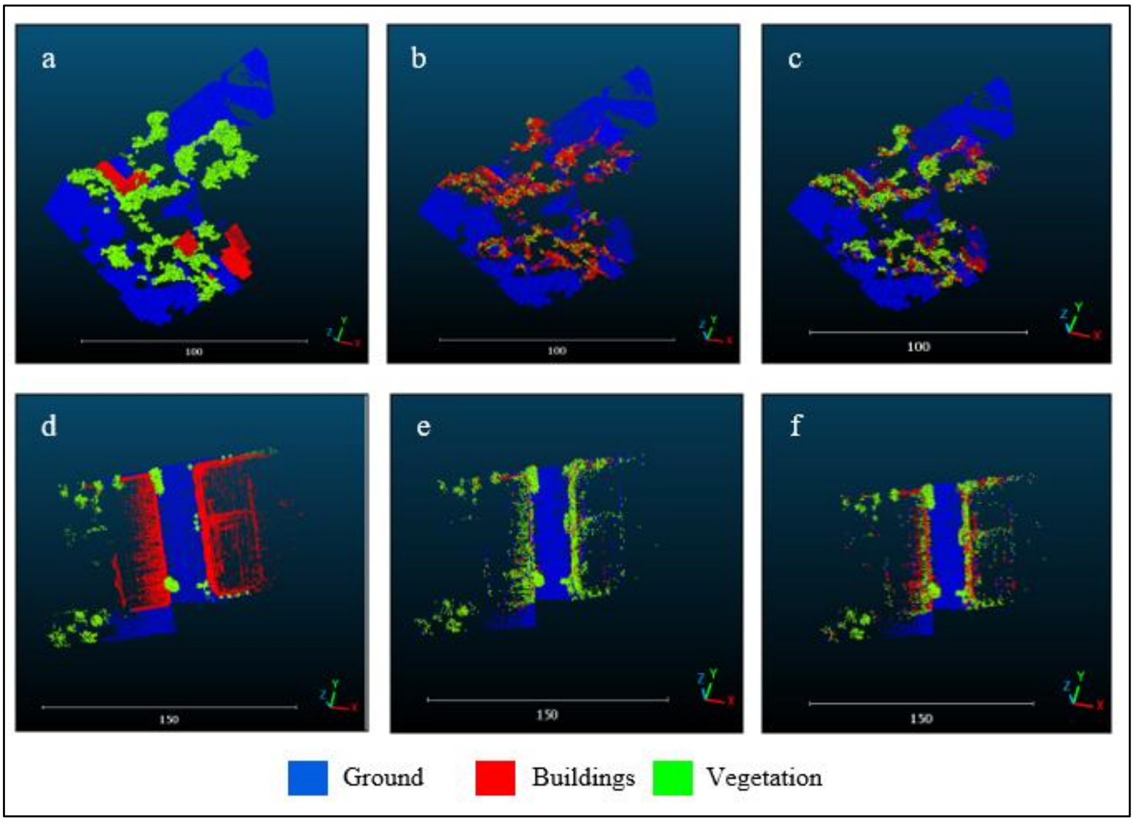

Figure 6: Classification results from cross-domain testing and combined-model training on UAS-SfM and MLS datasets: (a) UAS-SfM test data; (b) MLS-trained model applied to UAS-SfM data; (c) combined-model applied to UAS-SfM data; (d) MLS test data; (e) UAS-SfM-trained model applied to MLS data; and (f) combined-model applied to MLS data.

Table 3: Classification performance of models trained on a combined UAS-SfM and MLS dataset and tested on each modality

Training Data	Test Domain	Feature	Precision	Recall	F1 Score	Accuracy
UAS-SfM and MLS	UAS-SfM	Ground	0.69	0.95	0.80	0.72
		Vegetation	0.82	0.63	0.71	
		Buildings	0.67	0.57	0.62	
	MLS	Ground	0.97	0.95	0.96	0.83
		Vegetation	0.70	0.98	0.81	
		Buildings	0.90	0.55	0.68	

When compared to existing studies, our results align with prior observations that Mobile LiDAR data generally provides higher geometric fidelity than photogrammetric point clouds(Kalvoda et al., 2020; Kardoš et al., 2025). As a result, MLS provides better classification outcomes for geometry-based classification approaches. In this study, we further examined the role of multi-scale geometric features focusing on linearity, planarity and sphericity. We also look at how each of these geometric features contribute to classification performance. As shown in Figure 7, coarse-scale features dominate in 3DMASC classification, indicating that a wider neighbourhood context improves discrimination. Sphericity is consistently the most influential descriptor. On the other hand, planarity contributes to identifying flat surfaces, while linearity adds complementary detail for fine structural elements. MLS places greater emphasis on vertical range information, which supports ground–object separation, whereas SfM relies more heavily on shape-based descriptors. Lastly, the combined model produces a more balanced importance profile, reducing over-reliance on a single feature type and leveraging both elevation and geometric information. The combined model yields a more balanced profile, reducing over-reliance on a single feature and enhancing overall class separability and generalisation across modalities.

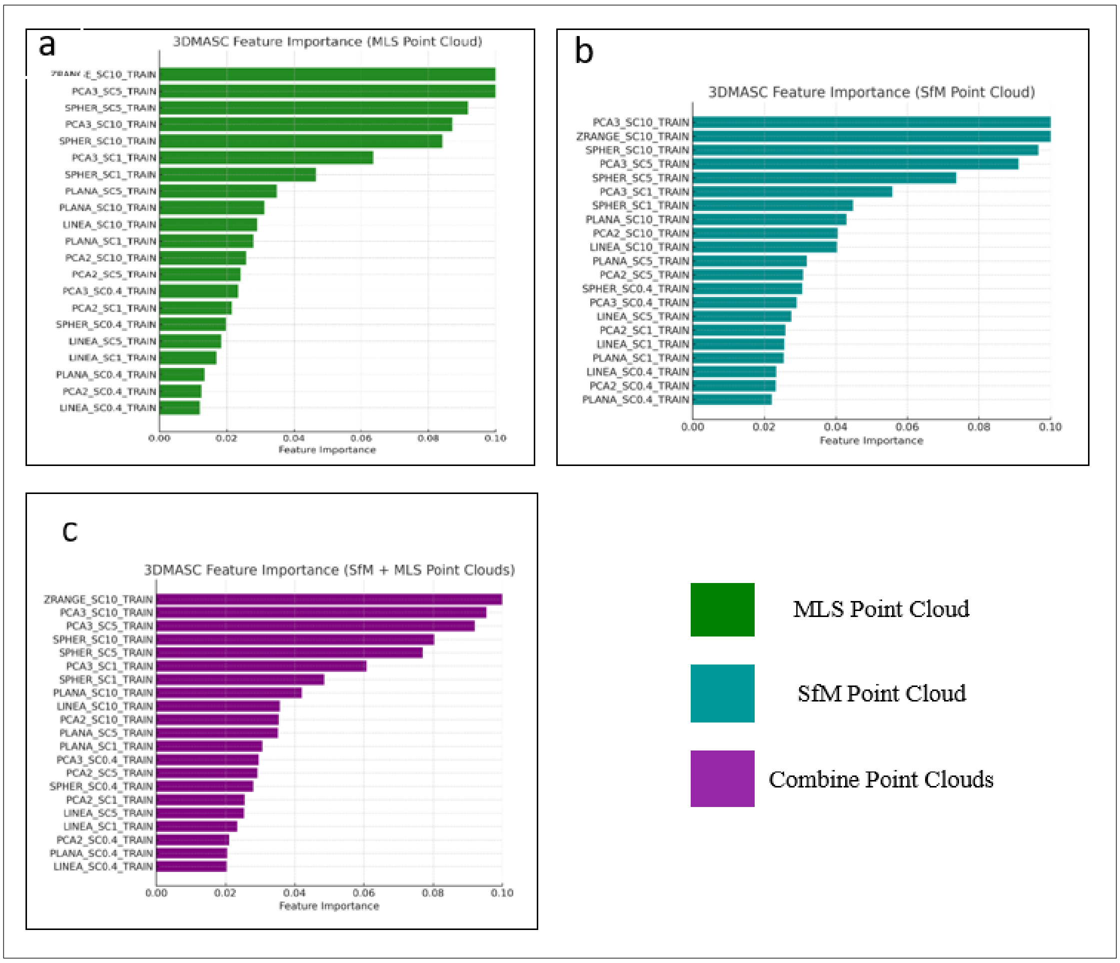

Figure 7: 3DMASC feature importance graphs across sensing modalities: (a) MLS data, (b) UAS-SfM data and (c) Combine UAS-SfM and MLS data.

The analysis focused exclusively on geometric features. Radiometric information such as intensity values were not considered. This decision ensures that classification relies on structural information that is common to both MLS and SfM point clouds. Intensity values are sensor-dependent and vary with acquisition settings which may affect cross-sensor classification. Our classification results confirm that cross-domain point cloud models lose accuracy when applied to a new domain without adaptation (Qin et al., 2019; Wang et al., 2024). Mixed training on merged datasets reduces this performance gap but does not completely restore accuracy. This observation aligns with recent work such as SSDA (semi-supervised domain adaptation), which introduced Point-CutMix to blend source and target point cloud samples (Wang et al., 2023). Our findings demonstrate that combined training improves generalisation without explicit domain adaptation techniques, but also suggest that incorporating strategies like Point-CutMix could further close the performance gap between modalities.

5 CONCLUSION

This study evaluated 3DMASC Random Forest models across MLS and UAS-SfM point clouds for urban feature classification. Models trained and tested within the same modality performed well, achieving 76% accuracy for UAS-SfM and 85% for MLS point cloud classification. MLS consistently outperformed SfM due to higher geometric fidelity. SfM performed well for ground and vegetation but was sensitive to viewpoint limitations, especially for buildings. Training on a combined MLS and UAS-SfM dataset improved the classification accuracy and allowed cross-domain application. Ground points were classified reliably in both domains (72% for SfM, 83% for MLS). The vegetation category had moderate performance and achieved an F1 score of 71% and 81% for UAS-SfM and ML point clouds respectively. On the other hand, the buildings were the most challenging to classify and achieved an F1 score of 62% and 68% for UAS-SfM and ML point clouds respectively. Combined training and multi-scale geometric features enabled transferable classification without domain adaptation. This study serves as a preliminary investigation and provides a foundation for future work on larger datasets and cross-sensor generalisation. The developed models have potential for urban mapping, infrastructure monitoring, and vegetation assessment. One limitation of this study is the limited spatial extent and number of datasets. However, the analysis was intentionally designed as a controlled transferability investigation focusing on generalisation behaviour across heterogeneous sensing modalities. Another limitation remains for vegetation and buildings due to viewpoint and density differences. Additionally, only three categories were considered while urban environments have other important objects. Future research should consider involving larger dataset and explore domain adaptation and the fusion of different sensor point clouds to improve the classification of complex urban structures. In addition, these approaches could be extended to applications in terrestrial and underwater environments.

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