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Conditional Benefits of Point-Level UAV LiDAR–Multispectral Fusion for 3D Vegetation Classification

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Abstract

Multisensor remote-sensing fusion combines complementary measurements of landscape structure and surface reflectance, but adding a second modality does not necessarily produce uniform classification gains. This study evaluates point-level data fusion of unmanned aerial vehicle (UAV) LiDAR and multispectral imagery within a three-dimensional (3D) point-cloud representation. Tree–shrub classification in a heterogeneous tropical landscape in Benguet, Philippines, was used as a diagnostic test case because tall shrubs and lower tree canopies can occupy overlapping geometric spaces. Green, Red, RedEdge and Near-Infrared bands, together with the Normalized Difference Vegetation Index, were projected from separately acquired orthomosaics onto individual LiDAR points to create a spectrally augmented point cloud. Classification was performed using an extended implementation of the open-source OpenPointClass framework. On the independent test set, fusion increased overall accuracy from 83.8% to 84.7%, tree F1-score from 57.6% to 61.8%, and tree Intersection over Union from 40.5% to 44.7%, while shrub F1-score changed from 90.0% to 90.4%. A spatial analysis across five tree–shrub composition groups showed that the contribution of the spectral modality was conditional: the clearest tree gains occurred in shrub-dominated areas where geometric ambiguity was greatest, whereas fusion produced a small decline in the balanced group. Residual displacement between the separately acquired LiDAR and multispectral products was observed but could not be quantitatively isolated. The results show that point-level multimodal fusion can improve 3D vegetation classification, particularly for structurally ambiguous classes, but that its benefit depends on landscape composition and spatial alignment between the sensor products rather than being uniformly positive.

Keywords: LiDAR, UAV, multispectral imagery, spectral fusion, semantic segmentation, vegetation, shrubs, trees, tropical landscapes

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1. Introduction

Remote sensing increasingly relies on multiple sensors because no single modality provides a complete description of complex landscapes. LiDAR directly represents three-dimensional structure, including height, vertical organisation and local geometric form, whereas multispectral imagery records wavelength-dependent reflectance related to surface composition and vegetation condition. Their joint use is therefore attractive when classes share similar shapes but differ in radiometric properties, or when spectral similarity can be resolved through structural information (Lefsky et al., 2002; Schmitt and Zhu, 2016; Ghamisi et al., 2019; Balestra et al., 2024). The scientific challenge is not simply to combine more variables, but to determine whether measurements from different sensors correspond to the same physical surfaces, provide complementary information and justify the additional acquisition and processing effort.

Terminology is important in this context. Balestra et al. (2024) define multisensor LiDAR fusion as the merging of data or derived features from different sources, of which at least one is LiDAR, to enhance the information content of the combined data or the resulting forest observations. They distinguish data-level fusion, in which sensor measurements are merged before classification, from feature-level fusion, in which separately derived descriptors or products are combined. The workflow examined here is most accurately described as *point-level data fusion*: multispectral measurements derived from an orthomosaic are projected onto the native coordinates of individual LiDAR points before model training. The resulting spectrally augmented point cloud contains structural and radiometric attributes in a common 3D representation. Related strategies have been used to combine LiDAR with optical or hyperspectral information for forest monitoring, species classification, structural characterisation and point-cloud analysis (Alonzo et al., 2014; Sankey et al., 2017; Dandois et al., 2017; Hartling et al., 2021; Zhong et al., 2022).

The expected benefit of fusion follows from complementary information from the two data sources. LiDAR is well suited to measuring vegetation height, canopy form and vertical arrangement but provides comparatively limited information about reflectance and biochemical properties. Multispectral imagery provides richer radiometric information, yet conventional two-dimensional products compress or obscure vertical structure. Studies combining airborne LiDAR with multispectral or hyperspectral imagery have reported improvements in forest classification, crown delineation and structural characterisation (Dalponte et al., 2014; Manzanera et al., 2016; Dechesne et al., 2017; Aubry-Kientz et al., 2021). However, a second modality does not guarantee better performance. Gains may be only a few percentage points, may be limited to particular classes, or may disappear when the primary sensor already resolves the target, the modalities contain redundant information, or the added data introduce noise and uncertainty (Yang et al., 2015; Wernicke et al., 2022; Balestra et al., 2024).

Consequently, the value of fusion should be assessed not only through a single global accuracy score, but also through class-specific and spatially explicit evaluation.

A central operational requirement is cross-sensor co-registration. Point-level projection assumes that the LiDAR point and the spectral pixel assigned to it represent the same physical surface. Separate flights, positioning uncertainty, differences in viewing geometry, orthorectification and spatial resolution can violate this assumption. Registration is particularly challenging in forested environments because crowns are irregular, boundaries are diffuse, occlusion differs between sensors and distinctive stable objects may be scarce (Lee et al., 2016; Swetnam et al., 2018; Polewski et al., 2019). Misregistration can therefore transfer reflectance from a neighbouring crown, shrub patch, gap or shadow to a LiDAR point, weakening rather than enriching the combined representation. Co-registration is consequently not a minor preprocessing detail but a condition governing whether point-level fusion is physically meaningful.

Tree–shrub classification provides a useful diagnostic case. Trees and shrubs are ecologically distinct, but their remote-sensing signatures can overlap. Tall shrubs and lower tree crowns may share comparable heights, densities and local geometric descriptors, while both classes can exhibit broadly similar visible and near-infrared reflectance. Previous work has shown the value of combining LiDAR and optical data for tropical tree–shrub mapping and forest segmentation (Zahidi et al., 2015; Dechesne et al., 2017; Aubry-Kientz et al., 2021). Yet most evaluations summarise performance across an entire study area, potentially concealing whether fusion helps primarily in mixed boundaries, in landscapes dominated by one class, or for a locally scarce class.

This study therefore reframes tree–shrub classification as a diagnostic case study of point-level spectral–geometric fusion in 3D. Rather than asking only whether fusion improves a global metric, it examines where the additional modality contributes and where it does not. The study addresses three questions: (1) Does projecting multispectral attributes onto UAV LiDAR points improve classification relative to LiDAR-derived information alone? (2) How does the contribution of the spectral modality vary across landscapes with different tree–shrub compositions? (3) What practical limitations arise when separately acquired UAV products are fused under imperfect operational co-registration? The contribution is an accessible point-level fusion workflow and a spatially explicit interpretation of the conditional benefits and limitations of multimodal UAV remote sensing in a heterogeneous tropical landscape.

2. Methodology

2.1. Study area and data

The study area is located over and around the Sto. Niño legacy copper mine in Tublay, Benguet Province, northern Luzon, Philippines. The mountainous site contains a heterogeneous mosaic of native forest, regenerating vegetation,

agricultural land and areas used by local communities. Its steep terrain and intermingled vegetation layers provide a demanding setting for point-level classification because shrubs and lower tree crowns frequently occur in close proximity. Recent initiatives, such as the Bio+Mine project, have established this site as an experimental system where ecological restoration and community participation are urgently needed (Alonzo et al., 2023; Herrington et al., 2023).

A representative 0.07 km² subset was selected for the analysis. The subset was chosen to include contrasting vegetation structures and sufficient labeled examples of both target classes. Figure 1 presents the 3D structure of the selected area.

LiDAR data were collected from 6–11 November 2023 using a DJI Matrice 300 UAV equipped with a Zenmuse L1 sensor and a 20 MP RGB camera. Flights were conducted in terrain-following mode at approximately 100 m above ground level and at speeds of 5–7 m s⁻¹. The acquisition produced an average point spacing of approximately 2 cm, although effective spatial detail varied because of steep terrain, positioning uncertainty and differences in vegetation height. The flight data were processed in DJI Terra using post-processed kinematic positioning and an EMLID Reach RS2+ base station. After removal of duplicate and invalid records, the selected subset contained 25,250,113 points with the dimensions **X, Y, Z, Intensity, ReturnNumber, NumberOfReturns, Classification**.

Multispectral imagery was acquired separately with a DJI Mavic 3 Multispectral UAV. Orthomosaics were available for Green, Red, RedEdge and Near-Infrared bands at a ground sampling distance of 0.045 m. All products were reprojected to WGS 84 / UTM zone 51N (EPSG:32651) and cropped to the LiDAR subset. Orthomosaics provided continuous coverage and a reproducible surface for point-to-pixel projection, although orthorectification and resampling can smooth local radiometric detail and introduce geometric distortion.

The LiDAR and multispectral products came from separate platforms and processing chains. Visual inspection showed broad agreement in the location of major canopy features but also residual local displacement, especially around heterogeneous crown boundaries. The available processed products did not permit a quantitative registration assessment using independent checkpoints, nor access to the original data required for reprocessing. This limitation is treated explicitly in the interpretation of the fusion results.

2.2. Point-level LiDAR–multispectral fusion

Preprocessing removed duplicated points, zero-intensity records and negative elevations before fusion. Multispectral bands were then projected onto the LiDAR cloud with the `filters.colorization` operation from the Point Data Abstraction Library (PDAL), which populates point dimensions using values read from a raster (PDAL Contributors, 2026). For each LiDAR point, its horizontal coordinates were used to retrieve the corresponding raster value from each multispectral band. Green, Red, RedEdge and Near-Infrared values were appended to the point record.



Figure 1: 3D point cloud representation of the study area showing a mixture of trees and shrubs.

The fusion workflow in Figure 2 illustrates the process of adding additional features to the LiDAR file (.las) that result in the following dimensions,

`[X,Y,Z,Intensity,ReturnNumber,NumberOfReturns,Classification,nir,redEdge,red,green,ndvi]`.

Following Balestra et al. (2024), this operation is treated as point-level data fusion because measurements from separate sensors were merged into a common dataset before classification. The native LiDAR coordinates were preserved; however, the physical validity of the appended spectral values depended on the cross-sensor spatial correspondence. Figure 2 summarises the workflow.

2.3. Labeling

Reference labels were prepared in CloudCompare for separate training, validation and independent test partitions. Class codes followed the ASPRS convention supported by OpenPointClass: class 4 for shrubs and class 5 for trees. Height above ground was calculated by subtracting the local ground elevation from the elevation of each point. It was used as an initial guide during reference labelling.

The Zenmuse L1 acquisition was configured to record two returns. This reduced the vertical information available within dense vegetation and made the boundary between tall shrubs and lower portions of tree crowns more ambiguous. The labelled spatial partitions retained the observed landscape structure and class proportions. The training partition contained approximately 73.4% shrubs and 26.6% trees, the validation partition 73.1% shrubs and 26.9% trees, and

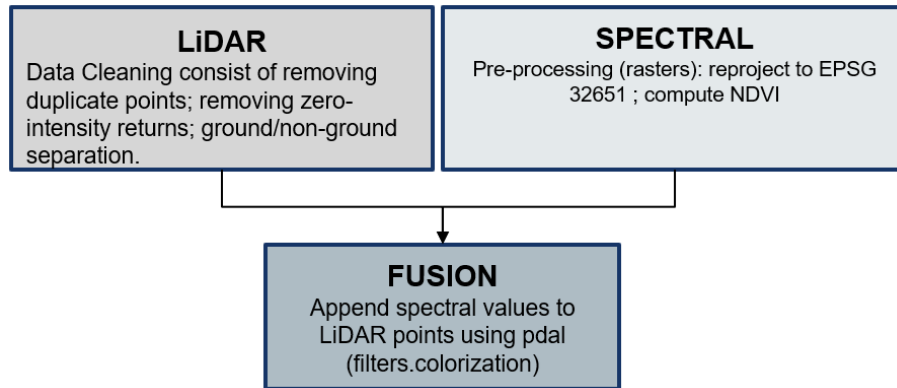


Figure 2: Workflow used to fuse LiDAR and spectral information.

the independent test partition approximately 84% shrubs and 16% trees. No synthetic oversampling or modification of the validation and test distributions was applied.

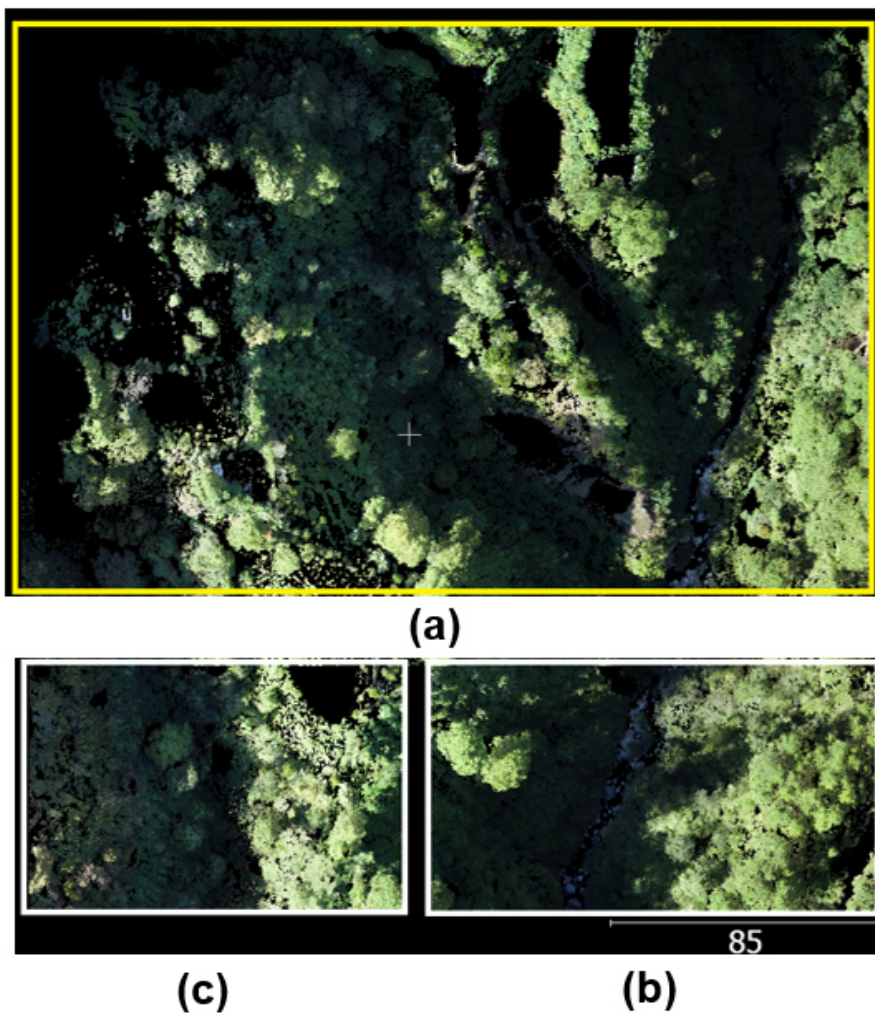


Figure 3: (a) Training, (b) Validation, and (c) Test set.

Classification was performed with an extended implementation of OpenPointClass, an open-source framework for fast and memory-efficient semantic classification of 3D point clouds (UAV4GEO, 2026). OpenPointClass calculates multi-scale local geometric descriptors around each point and supports tree-based classifiers. The implementation used here was configured to ingest the additional spectral dimensions attached during fusion.

The primary classifier was Gradient Boosted Trees (GBT), which combines sequentially fitted decision trees to capture non-linear interactions among heterogeneous predictors (Friedman, 2001). Tree-based methods are widely used in remote sensing because they can accommodate non-linear responses, mixed predictor scales and correlated variables (Breiman, 2001; Belgiu and Drăguţ, 2016). Fast preprocessing and fusion were conducted on a workstation with 16 GB RAM under Windows Subsystem for Linux. Model training and hyperparameter experiments were executed on the Imperial College London CX3 high-performance computing cluster using one shared-memory node with 32 CPU cores and 128 GB RAM.

3. Experimental design

Four GBT configurations were evaluated to separate the effects of local detail, broader spatial context and classifier capacity (Table 1). For every configuration, two input representations were compared: LiDAR-derived variables alone and the fused LiDAR-spectral representation.

Table 1: Gradient Boosted Tree configurations evaluated in the study.

Configuration	Trees	Depth	Scales	Radius (m)	Purpose
Baseline	80	20	5	1.0	Compact reference configuration emphasising local geometry.
Context	150	25	8	3.5	Broader neighbourhood intended to represent canopy-scale context.
Detail	100	20	12	0.6	Fine-scale configuration intended to sharpen local boundaries.
Deeper	200	30	10	3.0	Higher-capacity configuration combining local and contextual descriptors.

The *baseline* configuration was a computationally efficient reference derived from pilot runs. Its relatively small radius and limited number of scales emphasised local geometry. The *context* configuration expanded the radius and number of scales to represent broader canopy neighbourhoods, with the risk that descriptors would mix signals across adjacent tree and shrub boundaries. The *detail* configuration used a very small radius and more scales to prioritise local texture and boundary detail at the cost of whole-crown context. The *deeper* configuration increased the number and depth of trees while combining a relatively broad radius with multiple scales. It was designed as a high-capacity compromise between local and contextual information.

A post-classification smoothing radius of 2.5 m was applied to reduce isolated point labels and produce spatially coherent predictions. The same smoothing procedure was used for LiDAR-only and fused predictions so that the comparison reflected the input representation rather than different post-processing.

4. Results

4.1. Validation performance and model selection

Figure 4 summarises validation F1-scores for the four model configurations. The expanded configurations generally outperformed the baseline, with the *deeper* configuration providing the strongest overall performance. Shrubs were classified more reliably than trees across the experiments. The *context* configuration tended to favour tree recall at the expense of precision, whereas the *detail* configuration produced the opposite trade-off. The *deeper* configuration provided the best balance between these metrics and was therefore selected for independent testing and the spatial composition analysis.

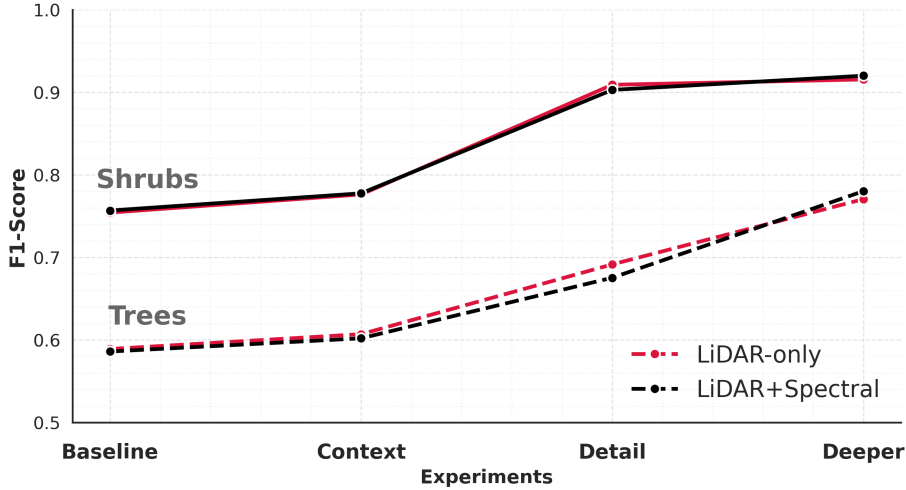


Figure 4: Validation F1-scores for the shrubs and trees classes across the Baseline, Context, Detail and Deeper model configurations. Results are shown for the LiDAR-only representation (red lines) and the fused LiDAR-spectral representation (black lines).

The mapped validation predictions show the spatial consequences of these parameter trade-offs (Figure 5). The *context* model produced broader and more continuous predicted vegetation regions, consistent with its use of larger neighbourhoods. The *detail* model preserved finer local boundaries but omitted parts of some larger tree crowns. The *deeper* model reconstructed the principal tree clusters most consistently, although local omissions remained.

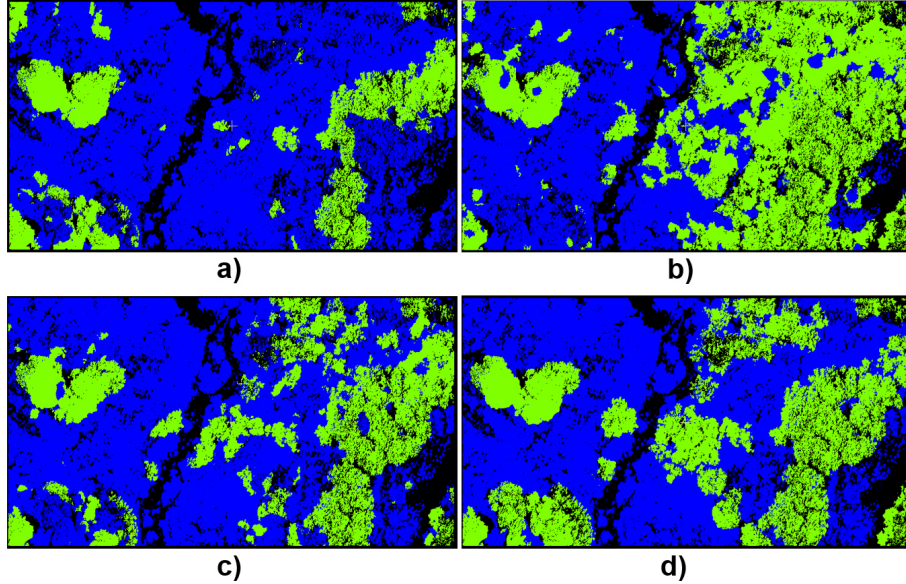


Figure 5: Validation predictions from the three expanded model configurations: (a) Detail, (b) Context, (c) Deeper and (d) reference labels.

The precision–recall distribution for trees further illustrates why the *deeper* configuration was selected (Figure 6). The *context* experiments were generally associated with relatively high recall but lower precision, indicating that larger neighbourhoods helped identify tree points but also included neighbouring shrubs. The *detail* experiments tended toward higher precision and lower recall, suggesting improved local discrimination but incomplete representation of larger crowns. The *deeper* configuration occupied the strongest region of the precision–recall space and provided the best compromise for the tree class.

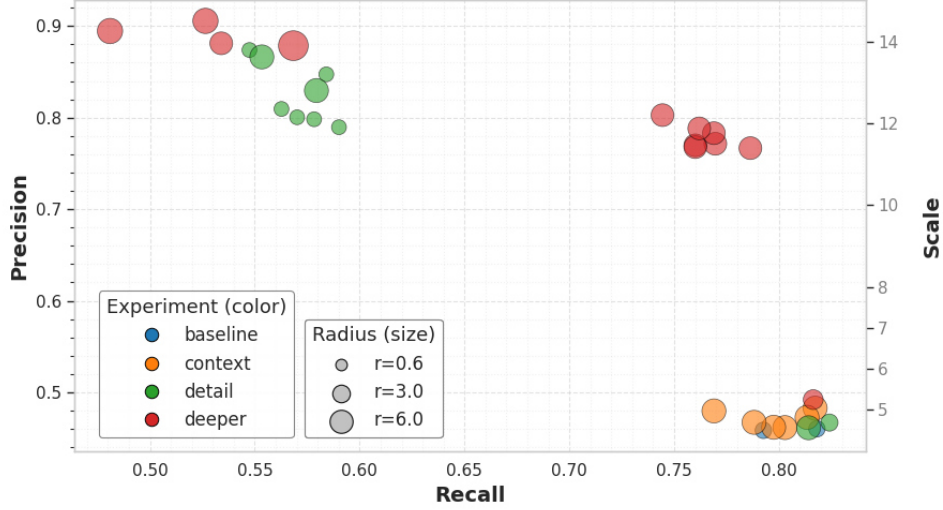


Figure 6: Precision and recall for the trees class on the validation set. Each point represents a model experiment and is coloured by configuration. The *deeper* experiments occupy the strongest region of the precision–recall space.

4.2. Independent test performance

The LiDAR-only and fused versions of the *deeper* model were applied to the independent test area. Fusion increased overall accuracy by 0.9 percentage points, from 83.8% to 84.7%. Shrub performance was already high with LiDAR alone and changed only slightly after spectral augmentation. The larger improvement occurred for trees: recall increased from 67.6% to 75.7%, precision from 50.2% to 52.2%, F1-score from 57.6% to 61.8%, and Intersection over Union from 40.5% to 44.7% (Table 2).

The larger change in recall than precision indicates that fusion primarily reduced the omission of true tree points, while confusion between tree boundaries and surrounding shrubs remained substantial. The additional spectral modality therefore improved recognition of the more difficult class without fully resolving its boundary delineation.

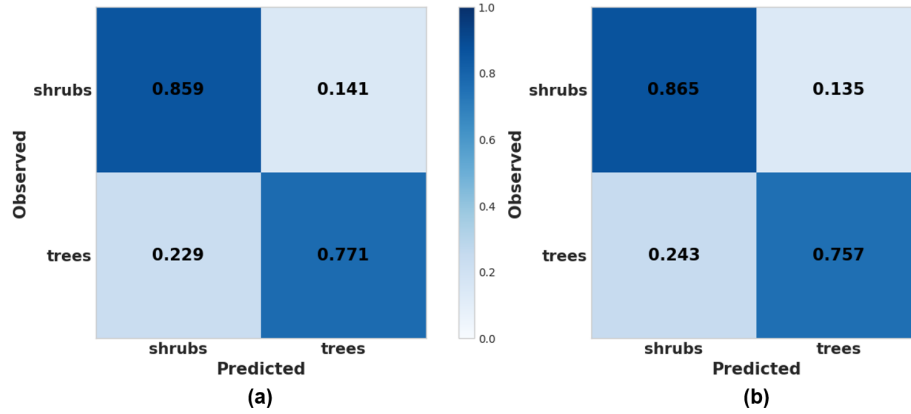


Figure 7: Confusion matrices for the independent test area: (a) LiDAR-only and (b) fused LiDAR-spectral classification.

Table 2: Independent test performance for the *deeper* models. Values are percentages and correspond to predictions smoothed using a 2.5 m radius.

Model	OA (%)	Shrubs				Trees			
		Recall	Precision	F1	IoU	Recall	Precision	F1	IoU
Deeper (LiDAR only)	83.8	86.9	93.2	90.0	81.8	67.6	50.2	57.6	40.5
Deeper (LiDAR+spectral)	84.7	86.5	94.8	90.4	82.6	75.7	52.2	61.8	44.7

4.3. Spatial variation in fusion gains

To investigate whether the contribution of spectral augmentation varied with landscape composition, the merged validation and test regions were subdivided into five spatial groups ranging from shrub-dominated to tree-dominated conditions (Figure 8). These groups represent observed geographic conditions rather than experimentally manipulated class ratios. The spatial subdivision preserves the arrangement of vegetation patches and provides a geographically explicit framework for evaluating the behaviour of the same pre-trained models under contrasting canopy compositions.

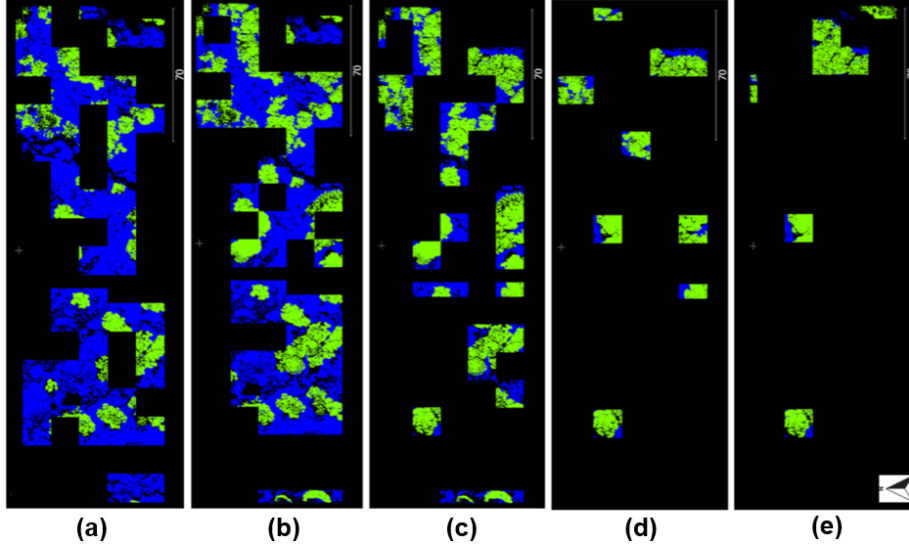


Figure 8: Spatial subdivision of the merged validation and test regions into five composition groups. Trees are shown in green and shrubs in blue: (a) Group 1, 15% trees and 85% shrubs; (b) Group 2, 30% trees and 70% shrubs; (c) Group 3, 50% trees and 50% shrubs; (d) Group 4, 70% trees and 30% shrubs; and (e) Group 5, 85% trees and 15% shrubs. The groups represent existing landscape composition and were not created through resampling or experimental manipulation.

The comparison between LiDAR-only and fused predictions revealed that the contribution of the spectral modality was not uniform (Figure 9). In shrub-dominated Groups 1 and 2, tree F1-score increased from 0.620 to 0.647 and from 0.707 to 0.733, respectively. These changes correspond to fusion gains of $\Delta F1 = +0.027$ and $+0.026$. Tree precision also increased in both groups, from 0.498 to 0.541 in Group 1 and from 0.652 to 0.692 in Group 2.

The balanced Group 3 showed a different response. Tree F1 declined from 0.823 to 0.811 and shrub F1 from 0.812 to 0.803, corresponding to $\Delta F1 = -0.012$ and -0.009 , respectively. Fusion therefore did not provide an advantage in this spatial setting.

In tree-dominated Group 4, tree F1 remained unchanged at 0.872, while shrub F1 increased slightly from 0.647 to 0.662. In Group 5, tree F1 increased from 0.874 to 0.892, whereas the largest shrub gain occurred in this group, where shrubs were the minority class: shrub F1 increased from 0.441 to 0.478.

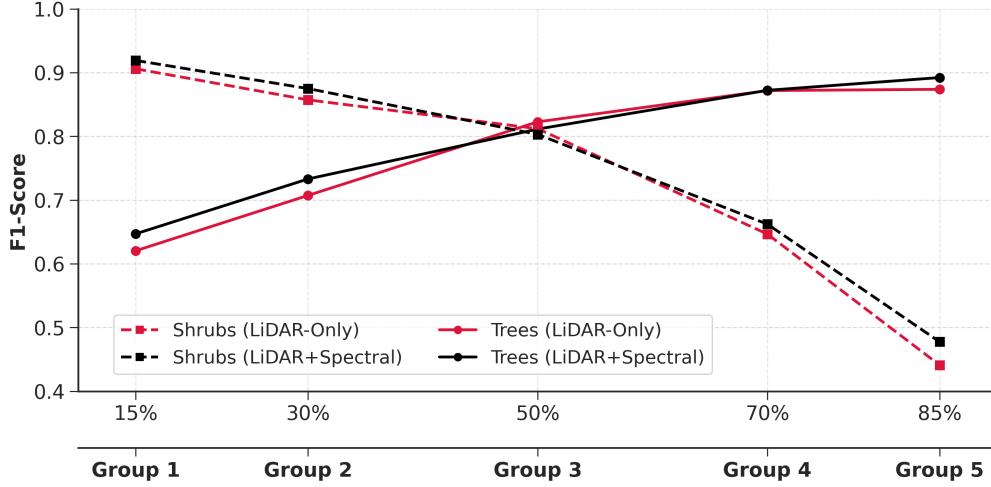


Figure 9: F1-score for trees and shrubs across the five spatial composition groups. Solid lines represent trees and dashed lines represent shrubs. Red indicates LiDAR-only classification and black indicates fused LiDAR-spectral classification. The horizontal axis represents the proportion of trees, ranging from shrub-dominated Group 1 to tree-dominated Group 5.

Table 3 summarises the change in F1-score after adding spectral information. Positive values indicate an improvement with fusion, whereas negative values indicate that the LiDAR-only model performed better. The results confirm that the benefit of fusion was not the same across all spatial groups.

Table 3: Change in class F1-score after adding multispectral attributes. Positive values indicate an improvement with the fused model.

Group	Trees / shrubs (%)	$\Delta F1$ trees	$\Delta F1$ shrubs
1	15 / 85	+0.027	+0.013
2	30 / 70	+0.026	+0.018
3	50 / 50	-0.012	-0.009
4	70 / 30	0.000	+0.015
5	85 / 15	+0.018	+0.037

5. Discussion

5.1. Class-specific fusion gains

The fused model improved the results, but the improvement was not large for all metrics and classes. Balestra et al. (2024) found that combining LiDAR with other remote-sensing data often improves forest classification and segmentation. However, the review also showed that the improvements are sometimes small when compared with the additional effort required to collect, process and align

multiple datasets. Other studies have also reported that the benefit of adding optical or hyperspectral information to LiDAR depends on the application and characteristics of the study area (Yang et al., 2015; Aubry-Kientz et al., 2021; Wernicke et al., 2022).

The results of this study follow a similar pattern. Fusion did not produce a large improvement in overall accuracy, but it provided a clearer benefit for the more difficult tree class. Therefore, the results do not show that fusion is always better than LiDAR alone. Instead, they show that spectral information can be useful for specific classes and landscape conditions.

Fusion increased tree recall from 67.6% to 75.7%, while tree precision increased only slightly, from 50.2% to 52.2%. This means that the fused model identified more of the tree points that were actually present. However, many shrub points were still incorrectly classified as trees. Spectral information therefore helped the model detect more trees, but it did not fully solve the problem of separating tree boundaries from surrounding shrubs. This is important because detecting trees and mapping their boundaries accurately are not the same task.

5.2. Effect of landscape composition on fusion performance

The spatial composition analysis provides important evidence that the benefit of fusion changed across the study area. Figure 8 shows that the five groups correspond to real geographic parts of the landscape and were not created by randomly resampling the data. Therefore, the differences shown in Figure 9 represent model performance under different vegetation conditions found within the study area.

In shrub-dominated Groups 1 and 2, trees were less common and were surrounded by large areas of shrubs. Under these conditions, isolated trees, lower tree crowns and tall shrubs could have similar geometric characteristics. This made them difficult to distinguish using LiDAR information alone. The positive tree $\Delta F1$ values in both groups indicate that the spectral variables added useful information where the geometric information was less effective. Tree F1-score increased by 0.027 in Group 1 and by 0.026 in Group 2 after adding the spectral variables.

Group 3, which contained approximately equal proportions of trees and shrubs, showed a different result. After fusion, F1-score decreased slightly for both classes. This demonstrates that adding more variables does not always improve classification. Several factors could explain this result. Trees and shrubs may have had similar spectral responses in this area, local displacement between the LiDAR and multispectral products may have assigned incorrect spectral values to some points, or some of the spectral variables may have contained similar information.

The available experiments cannot determine which of these explanations was most important. A spectral-only model was not tested, and the contribution of each individual band and NDVI was not evaluated separately. Therefore, the results from Group 3 should not be interpreted as evidence that spectral information is generally ineffective. Instead, they show that the benefit of fusion changed between different parts of the landscape.

In tree-dominated Groups 4 and 5, the LiDAR-only model already achieved high F1-scores for trees. This suggests that the large and continuous tree canopies provided a strong geometric signal, leaving less room for improvement after adding spectral information. In Group 4, tree F1-score remained unchanged at 0.872, while in Group 5 it increased slightly from 0.874 to 0.892. In these areas, the spectral variables appeared to provide only a small additional benefit for trees because LiDAR geometry was already effective.

The opposite pattern was observed for shrubs in tree-dominated areas. As shrubs became less common, their classification performance decreased for both models. However, spectral fusion produced a small improvement. In Group 5, where shrubs represented only 15% of the points, shrub F1-score increased from 0.441 with LiDAR alone to 0.478 with the fused model. This suggests that spectral information may help when the class of interest is less common and is surrounded by a dominant class with a different vegetation structure.

Overall, the spatial analysis shows that the value of spectral fusion was not the same across the landscape. It was more useful where the class of interest was difficult to distinguish using geometry alone, while its contribution was smaller where LiDAR already provided a strong structural signal. However, the five groups also differed in canopy structure, boundaries and local vegetation conditions. For this reason, the results show where fusion performed better or worse, but they do not prove that class proportion alone caused these differences.

5.3. Co-registration constraints

Point-level projection relies on a strong physical assumption: the spectral value attached to a LiDAR point should describe the same surface sampled by that point. The forest-fusion literature identifies registration as a persistent challenge because independently acquired datasets can differ in viewpoint, spatial resolution, coverage and geometric accuracy (Lee et al., 2016; Swetnam et al., 2018; Polewski et al., 2019; Balestra et al., 2024). The issue is especially important near heterogeneous canopy boundaries, where a horizontal displacement can assign a shrub pixel to a tree point, a shadow to illuminated foliage, or spectral information from one crown to a neighbouring object.

Residual displacement was observed between the LiDAR cloud and the multispectral orthomosaics in this study. Its precise effect could not be quantified because controlled shifts, independent checkpoints and access to the original processing products were unavailable. The results therefore do not demonstrate robustness to registration error, and the observed displacement should not be interpreted as a controlled sensitivity experiment. The defensible conclusion is narrower: the fused model achieved a modest improvement under the available operational alignment, while residual misregistration remains a plausible source of weakened point-to-pixel correspondence.

This limitation is scientifically relevant rather than merely procedural. Many applied UAV projects combine products collected by separate platforms and processed through independent workflows rather than using tightly integrated multisensor systems. In such cases, cross-sensor correspondence can determine whether complementary measurements become useful information or additional

noise. Future studies should report quantitative horizontal and vertical registration errors, use independent checkpoints or stable ground targets, and evaluate classification performance under controlled displacement. Such experiments would help establish the alignment accuracy required for reliable point-level spectral augmentation.

5.4. Operational value of fusion

The workflow has several practical advantages. It preserves the native 3D LiDAR coordinates, uses standard orthomosaic products, relies on the open-source PDAL and OpenPointClass tools, and can be implemented with conventional CPU-based computing resources. It therefore provides an accessible route to multisensor 3D classification where integrated sensor packages or deep point-cloud architectures are unavailable.

Accessibility should not, however, be interpreted as zero operational cost. Separate flights require additional planning, calibration, processing, storage and quality control. Balestra et al. (2024) argue that operational fusion should be evaluated through the trade-off between the improvement obtained and the resources required to produce a reliable combined dataset. In the present case, a 4.2 percentage-point increase in tree F1 may be important when trees are the class of ecological or operational interest, but it may be less compelling when only global classification accuracy is needed. The value of fusion is therefore application-specific.

The results also demonstrate why overall accuracy alone is insufficient for evaluating multimodal fusion. The increase in overall accuracy was only 0.9 percentage points, but this global value concealed a 4.2 percentage-point increase in both tree F1 and tree IoU. The spatial composition analysis further showed that the same fused representation could improve one class in one part of the landscape while producing no improvement, or a small decline, elsewhere. Class-specific and spatially explicit metrics are therefore needed when deciding whether the acquisition and processing of an additional sensing modality are justified.

5.5. Limitations and future work

This study has several limitations. First, the analysis was carried out in one 0.07 km² study area and included only two vegetation classes. Therefore, the results may not represent other tropical landscapes, forest structures or classification problems.

Second, residual displacement was observed between the LiDAR point cloud and the multispectral orthomosaics, but the size of this displacement could not be measured. Independent checkpoints and the original data required for reprocessing were not available. For this reason, the exact effect of co-registration error on classification performance remains unknown.

Third, the experiments compared a LiDAR-only model with a model containing all LiDAR and spectral variables. A spectral-only model was not tested, and the contribution of each spectral band and NDVI was not evaluated separately.

Therefore, it is not possible to determine which spectral variable contributed most to the improvement.

Fourth, the five spatial groups differed not only in their proportions of trees and shrubs, but also potentially in canopy structure, vegetation boundaries, terrain and illumination conditions. The spatial analysis shows where fusion performed better or worse, but it does not prove that class proportion alone caused these differences.

Fifth, height above ground was used as an initial guide during labelling before the classes were manually refined. In addition, the LiDAR data contained only two returns. These factors reduced the available vertical information and may have introduced uncertainty near the boundary between tall shrubs and lower tree crowns.

Finally, the training, validation and test areas were obtained from the same broader landscape. Although the test area was not used during model training, the ability of the model to perform well in a completely different location was not evaluated.

Future studies should test the workflow in other landscapes and with additional vegetation classes. Data collection should use common ground control points or closely coordinated sensor acquisitions to improve the alignment between LiDAR and multispectral products. Registration accuracy should also be measured using independent checkpoints. Controlled displacement experiments could then be used to evaluate how classification performance changes as the spatial offset between the datasets increases.

Future experiments should also compare LiDAR-only, spectral-only and fused models. Different combinations of the spectral bands and NDVI could be tested to identify which variables provide the most useful information. Spatial cross-validation, repeated model runs and uncertainty estimates would help to evaluate whether the results are consistent and transferable to other areas. More advanced models could also be explored to determine whether they can learn the relationship between geometric and spectral information more effectively.

6. Conclusions

This study evaluated point-level fusion of UAV LiDAR and multispectral imagery within a three-dimensional point-cloud representation. Tree-shrub classification was used as a diagnostic case because tall shrubs and lower tree canopies can have similar geometric characteristics. The fused model produced a small improvement in overall accuracy, from 83.8% to 84.7%, but provided a clearer benefit for the more difficult tree class. Tree F1-score increased from 57.6% to 61.8%, while tree Intersection over Union increased from 40.5% to 44.7%. Shrub performance was already high with LiDAR alone and changed only slightly after fusion.

The spatial analysis showed that the benefit of spectral information was not the same across the landscape. In shrub-dominated Groups 1 and 2, spectral fusion improved tree classification where isolated trees, tall shrubs and lower tree

crowns were difficult to separate using geometry alone. In the balanced Group 3, fusion produced a small decrease for both classes. In tree-dominated areas, LiDAR already provided a strong geometric signal for trees, and the additional benefit of spectral information was generally smaller. These results show that adding a second sensing modality does not automatically improve classification in every location.

Residual displacement was observed between the separately acquired LiDAR and multispectral products, although its exact effect could not be measured. This highlights the importance of co-registration in point-level fusion because the spectral value assigned to a LiDAR point should represent the same physical surface. Poor spatial correspondence may reduce the useful information added by the second modality.

Overall, the study shows that point-level LiDAR–multispectral fusion can improve 3D vegetation classification, particularly when geometric information alone is not sufficient. However, its value depends on the target class, landscape composition and spatial alignment between the datasets. The main contribution is therefore not that fusion is always better than LiDAR alone, but that its benefits are conditional and should be evaluated using class-specific and spatially explicit results.

CRedit authorship contribution statement

Oscar Calva: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Data curation, Writing - original draft, Visualization. **Yves Plancherel:** Conceptualization, Methodology, Resources, Writing - review & editing, Supervision.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Sensitivity Analysis Metrics

Table A.4: Precision, Recall, and F1-Score for shrub and tree segmentation across five spatial groups. The groups range from shrub-dominated areas (15% trees, 85% shrubs) to forest-dominated areas (85% trees, 15% shrubs).

Group (Tree % / Shrub %)	Model	Class	Recall	Precision	F1-Score
Group 1 (15 / 85)	LiDAR-Only	Shrubs	0.854	0.964	0.906
		Trees	0.821	0.498	0.620
	LiDAR+Spectral	Shrubs	0.879	0.962	0.919
		Trees	0.805	0.541	0.647
Group 2 (30 / 70)	LiDAR-Only	Shrubs	0.823	0.894	0.857
		Trees	0.773	0.652	0.707
	LiDAR+Spectral	Shrubs	0.851	0.900	0.875
		Trees	0.780	0.692	0.733
Group 3 (50 / 50)	LiDAR-Only	Shrubs	0.788	0.837	0.812
		Trees	0.847	0.800	0.823
	LiDAR+Spectral	Shrubs	0.786	0.821	0.803
		Trees	0.829	0.795	0.811
Group 4 (70 / 30)	LiDAR-Only	Shrubs	0.575	0.739	0.647
		Trees	0.913	0.834	0.872
	LiDAR+Spectral	Shrubs	0.606	0.729	0.662
		Trees	0.904	0.843	0.872
Group 5 (85 / 15)	LiDAR-Only	Shrubs	0.505	0.392	0.441
		Trees	0.850	0.899	0.874
	LiDAR+Spectral	Shrubs	0.507	0.451	0.478
		Trees	0.881	0.903	0.892

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