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VEGETATION FILTERING IN PHOTOGRAMMETRIC 3D POINT CLOUD DATA BY TREE-BASED MACHINE LEARNING MODELS: A COMPARATIVE STUDY

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EXTENDED ABSTRACT

Il processo di classificazione di diversi tipi di vegetazione all'interno di un set di dati, spesso per specie o tipi di vegetazione, è noto come classificazione della vegetazione. L'etichettatura di ogni punto nella nuvola di punti fotogrammetrica come vegetazione o non vegetazione, di solito in modo binario, è nota come classificazione dei punti. Per indagini approfondite come la stima della biomassa, la segmentazione della vegetazione, è utile distinguere istanze specifiche di vegetazione, come la separazione di alberi o arbusti. La tecnica di eliminazione dei punti di vegetazione per enfatizzare le strutture non vegetative è nota come filtraggio della vegetazione, che è necessaria per molte applicazioni, come il monitoraggio ambientale, l'esame delle caratteristiche urbane o rocciose, la silvicoltura e la gestione dei rischi. Questo lavoro presenta uno studio completo sulla classificazione dei punti utilizzando modelli avanzati di apprendimento automatico basati su alberi, tra cui Decision Tree Classifier, Random Forest, AdaBoost, XGBoost e CatBoost. Sei diversi set di dati sono stati utilizzati per confrontare i modelli di apprendimento automatico: Maiori, Gubbio, Tratto (I, II, III) e Sierra National Park. Il framework di classificazione prevede passaggi di pre-elaborazione dettagliati, formattazione del set di dati e tecniche di estrazione delle caratteristiche per migliorare l'accuratezza della classificazione. Le tecniche di estrazione delle caratteristiche sono meticolosamente applicate in questa ricerca per catturare un'ampia gamma di caratteristiche della vegetazione, come l'altezza della chioma, la densità, i modelli di distribuzione spaziale e le firme spettrali. Tra i modelli valutati, il classificatore Random Forest con ottimizzazione degli iperparametri supera i metodi esistenti, dimostrando una precisione superiore nel filtrare i punti di vegetazione. In particolare, mentre uno studio recente ha raggiunto un'accuratezza del 76.84% sul set di dati di Gubbio, il modello di foresta casuale ottimizzato nella presente ricerca raggiunge un'accuratezza di quasi il 76.40% sullo stesso set di dati. L'analisi comparativa delle prestazioni dei modelli rivela che CatBoost e Random Forest sono particolarmente efficaci nella gestione di strutture di dati complesse. Sebbene XGBoost fornisca risultati relativamente bassi in termini di precisione, addestra ed effettua previsioni in modo relativamente più rapido ed efficiente, indicando il suo potenziale per implementazioni più rapide e su larga scala. Vengono esaminati anche gli indici di vegetazione, come l'indice di vegetazione a differenza di banda visibile (VDVI) e l'indice di vegetazione a differenza normalizzata verde (GNDVI), con soglie fisse per filtrare la vegetazione dai dati delle nuvole di punti; Tuttavia, i risultati non sono accurati come i risultati dei modelli basati sull'apprendimento automatico, sebbene l'implementazione degli indici di vegetazione sia più semplice. Viene eseguito un esperimento di ablazione per dimostrare che l'uso combinato di caratteristiche spaziali e spettrali fornisce la massima precisione di classificazione. Viene inoltre eseguita un'analisi di sensibilità introducendo il 10% di rumore casuale nelle singole bande Rosso-Verde-Blu. Lo studio ha rivelato che le bande rossa e verde sono le più sensibili al rumore, con riduzioni di precisione rispettivamente dell'1.28% e dell'1.42%. Il rumore nella banda blu ha avuto un impatto minimo (riduzione dello 0.18%). Infine, l'acquisizione di dati etichettati affidabili rimane impegnativa per l'addestramento dei modelli di machine learning. La ricerca futura si concentrerà sul perfezionamento dei metodi di estrazione delle caratteristiche, sull'incorporazione di funzionalità aggiuntive e sull'esplorazione dell'integrazione di modelli di deep learning per migliorare ulteriormente la precisione. I risultati di questa ricerca mostrano le prestazioni dei modelli di apprendimento automatico basati su alberi per filtrare la vegetazione nei dati fotogrammetrici delle nuvole di punti 3D. Tuttavia, suggeriscono anche un potenziale promettente per trasformare l'attività di classificazione binaria in una classificazione multiclasse per ottenere una maggiore granularità.

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ABSTRACT

Identifying and filtering vegetation from photogrammetric-based point cloud data are required for many applications, such as environmental monitoring, urban planning, forestry and hazard management. This work presents a comprehensive study on point classification using advanced tree-based machine learning models, including Decision Tree Classifier, Random Forest, AdaBoost, XGBoost, and CatBoost. Six different datasets are utilized for comparison between the machine learning models. Random Forest classifier with hyperparameter tuning outperforms other models, demonstrating superior precision in filtering vegetation points. Visible-band vegetation indices with fixed thresholds are also evaluated, but their accuracy is lower than that of machine learning models, despite being easier to implement. The findings not only show the performances of tree-based machine learning models for filtering vegetation in photogrammetric 3D point cloud data, but they also suggest promising potential to transform the binary classification task into a multi-class classification to achieve higher granularity.

***Keywords**: point cloud data, point classification, vegetation filtering, machine learning, photogrammetry, hyperparameter tuning, forestry management*

INTRODUCTION

Classifying points accurately and efficiently in point cloud information is very important for numerous uses, such as environmental monitoring, urban planning, forestry management, hazard management, and ecological research (Stilla & Xu, 2023; Albanwan *et alii*, 2024). Maintaining vegetation cover is crucial for activities, such as habitat evaluation, biodiversity monitoring, carbon sequestration estimation, and land use planning, all of which contribute to global sustainable development (Zhang *et alii*, 2024; Ghaderpour *et alii*, 2023). The process of classifying different vegetation types within a dataset, frequently by species or vegetation types, is known as vegetation classification. Labeling every point in the cloud as either vegetation or non-vegetation, usually in a binary fashion, is known as point classification. For in-depth investigations like biomass estimate, vegetation segmentation which involves distinguishing specific vegetation instances, such as separating trees or shrubs is helpful. Lastly, the technique of eliminating vegetation points to emphasize non-vegetative structures is known as vegetation filtering, and it is crucial for applications such as the examination of urban or rock features. To improve data clarity for terrain analysis applications, the present study focuses on point classification and vegetation filtering.

Previous methods of point classification have largely relied on manual analysis of remote sensing data. The present study utilizes several tree-based machine learning models, each selected for its unique strengths in classification. New developments under machine learning have brought in a lot of changes since they have allowed for automation as well as full use of available information which increases the level of precision attained during the analysis (Wernette, 2024; Abdali *et alii*, 2024). Gradient Boosting, XGBoost, Random Forest, and Logistic Regression machine learning techniques have been found to be useful in manipulating difficult datasets created from 3D spatial representation of points (Mirzaei *et alii*, 2022; Atik *et alii*, 2024).

Presence of vegetation makes 3D point cloud analysis challenging for various tasks. Presence of shadows, seasonal fluctuation and natural light and humidity can affect point classification and must be addressed for reliable ecological evaluations. Multidimensional data features and spatial relationships, integrated by machine learning algorithms, play an essential part in minimizing these challenges, enhancing point classification models' robustness as well as interpretability. Vegetation indices provide useful information about how green, healthy or productive a plant is through Red-Green-Blue (RGB) color bands. Vegetation indices also help in better understanding ecosystems and climate change (Mahlein *et alii*, 2013; Youssefi *et alii*, 2022; Ghaderpour *et alii*, 2024, 2025). For instance, they can show when something like sickness among people who use certain plants has happened or uninvited plants have covered someone's land. This can help responsible authorities to act fast against problems like disease epidemics and soil erosion through relevant management methods.

Point cloud information is gathered by cutting-edge technologies, such as Light Detection And Ranging (LiDAR) and photogrammetry (Mazzanti *et alii*, 2018; Arastounia & Lichti, 2021). While both technologies generate point clouds, they differ from each other in several aspects. Laser scanning LiDAR allows better positioning the points while in photogrammetry, the point clouds are formed with the help of images which can cause distortions as a result of the image quality or misalignment. The main goal of the present study includes vegetation detection in raw photogrammetry point clouds; however, the filtering does not solve construction distortions specific to photogrammetry. Advanced techniques for feature extraction and classification have been developed, particularly in the field of LiDAR data processing. Machine learning approaches can be applied to both data from both technologies, but the main differentiator is the features. LiDAR information is three-dimensional (3D) with high resolution and high density, thus perfect for classifying surfaces at the vegetation and ground levels. On the other hand, photogrammetry is based on capturing optical images and matching them, thus making it difficult in feature extraction due to images quality, light conditions and texture. Extensive research on LiDAR data classification has been done by many researchers, including Gharineiat *et alii* (2022) and

Michałowska & Rapinski (2021), where they present robust methodologies for feature extraction and classification specific to LiDAR's high-precision capabilities.

While image classification classifies objects on the basis of 2D data pixel intensity and spatial pattern, point cloud data classification is focused on more detailed spatial analysis using the 3D representation. Although both use supervised learning algorithms, they are quite different in terms of feature extraction and data representation. Therefore, special techniques need to be applied in the filtering process for removing vegetation from photogrammetric datasets. Moreover, geometric filtering is the process of classifying point cloud data based on spatial coordinates (x, y, z) and associated RGB color values. This approach leverages the geometric arrangement and color properties of points to distinguish between vegetation and non-vegetation, without relying on other external features or contextual information.

The focus of the present research is on the usage of tree-based machine learning classifiers in automating point classification using high-resolution photogrammetric 3D point cloud data. These classifiers require careful preprocessing which entails (1) eliminating noise, (2) identifying anomalies that do not fit the pattern of the data or usual behaviour patterns over time, (3) normalising various attributes related to point clouds like heights, intensities and colours in three dimensions of RGB space. To capture a wide range of vegetation characteristics, such as canopy height, density, spatial distribution patterns, and spectral signatures, feature extraction techniques are meticulously applied herein. These characteristics are vital for training strong classification models that can tell apart various vegetation types and their structural complexities even in different landscapes.

LITERATURE REVIEW

The Point cloud data have presented different techniques of vegetation filtering. An unsupervised and rotational invariance method known as Super points in Random sampling and consensus Planes (SiRP) has been proposed for estimating vegetation cover and detecting planar elements. The SiRP is introduced as a method for dividing point clouds into planar and non-planar regions, allowing for efficient compression and mentioned the use of features and machine learning for classification, with the fast point feature histograms (FPFHs) feature set showing higher accuracy (Bulatov *et alii*, 2021). Similarly, U-Net, a deep neural network was utilized for filtering in Wang & Koo (2022).

The study by Carbonell-Rivera *et alii* (2024) introduces Class3Dp, an advanced supervised classification software, for identifying vegetation species from colored point clouds. It leverages 3D geometric and spectral information, supporting RGB and Multi-Spectral (MS) point clouds via a user-friendly Graphical User Interface (GUI). The Class3Dp computes up to 48 features and integrates five machine learning models for classifying point clouds based on geometric, spectral, and neighborhood features. In a case study, the software achieved an Overall Accuracy (OA) of 0.94 for RGB and 0.95 for MS in classifying ground and vegetation points, and an OA of 0.86 for RGB and 0.87 for MS when identifying specific vegetation species. Challenges include intraspecific differences, species competition, and data quality affected by Unmanned Aerial Vehicle (UAV) flight conditions. Class3Dp offers significant improvements by combining spectral and geometric data for more accurate classifications. Future improvements include incorporating hyperspectral indices for better spectral resolution and automating the classification pipeline.

Ramirez *et alii* (2023) explored various vegetation indexes to determine an effective threshold for filtering. Their study aimed to evaluate the feasibility and accuracy of generating vegetation index maps from UAV-acquired data and considered the color values of each point as the determining factor for identifying vegetation points and separating them from other objects. Geometric principles for rocky terrains are difficult, and color based algorithm is easy and logical.

Štroner *et alii* (2023) studied filtering of green vegetation based on vegetation indices on colored point clouds of rocky terrains. A 3D multi-feature descriptor combined with a three layers neural network is presented in Singh & Yadav (2023) on a limited dataset. Multiple machine learning classification models are discussed for segmentation of various objects in Atik *et alii* (2021).

Weidner *et alii* (2019) introduced a machine learning approach for classifying terrestrial point clouds. Their research presented a random forest classifier that distinguishes points as vegetation, talus, snow, and bedrock, utilizing features like multi-scale neighborhood geometry, slope, change, and intensity. Trained on manually labeled scans from different seasons and tested on unseen data, this method demonstrated high adaptability and accuracy, maintaining an F-Score above 0.9 for talus and vegetation. Compared to the CANUPO software (Brodu & Lague, 2012) and manual masking, random forest offers superior flexibility and precision, though it requires more computational resources. The findings underscore the method's robustness to seasonal changes and its potential applications in managing civil and mining geotechnical hazards, making it highly relevant for automated point classification and vegetation filtering task.

Weidner *et alii* (2021b) explored methods for classifying rock slope materials in photogrammetric point clouds, emphasizing the segmentation and classification of vegetation. Their study utilizes smartphone and UAV photogrammetry datasets collected under various lighting conditions and seasons, ensuring a comprehensive training database. A random forest classifier was employed to categorize points into five geological classes, including vegetation. The research compares twelve different feature sets, incorporating geometric, slope, absolute color, and texture features. Notably, the study introduces multi-scale color standard deviation and the Grey-Level Co-occurrence Matrix as novel texture descriptors, demonstrating their robustness against lighting variability. The results indicate that traditional absolute color features are sensitive to lighting changes and less effective for geological differentiation, while the novel feature sets focusing on geometry, slope, and texture achieved higher accuracy, with an average of around 80%. In recent advancements, high-density close-range multispectral laser scanning has shown promising results for precise individual tree segmentation and species classification. This approach, as explored by Hakula *et alii* (2023), leverages multispectral data to enhance feature extraction for vegetation differentiation, particularly beneficial in complex, densely vegetated areas. And the study by Fekete & Cserep (2021) effectively utilizes LiDAR data to monitor tree changes and segment individual trees across vast urban areas.

Wang *et alii* (2022) proposed a method for predicting loess landslides by monitoring slope tilting angles with a wireless sensor network using tilt sensors. Their approach gathers real-time data on slope movements to develop a predictive model for landslide events, offering a crucial early warning system. Their study showed that tilt sensors can detect small changes in slope angles before landslides, providing a timely and reliable early detection method. The need for real-time data processing and efficient algorithms is critical for timely warnings, requiring significant computational resources. Long-term monitoring demands considerable resources for maintenance and data management to ensure reliable data collection and analysis. Accurate sensor calibration and effective data integration are vital for precise data collection in classification and filtering tasks (Jafarbiglu & Pourreza, 2022). Addressing these challenges can improve the accuracy of point cloud data analysis.

Farella (2017) focused on using the GeoSlam Zeb1 system for rapid 3D digitization of underground tunnels, including the Grotta di Seiano and world war I military fortifications around Trento. Key findings involve using an automatic classification procedure to remove vegetation from point clouds, crucial for clear visualization and mapping. Challenges identified include alignment errors in long, featureless tunnels and the need for stable data acquisition techniques. The lack of color or intensity data from the scanner necessitates supplementary methods like photogrammetry for detailed textures. These challenges highlight areas for further research in improving classification algorithms and sensor accuracy (Barbierato & Gatti, 2024).

Weidner *et alii* (2021a) proposed a new approach for monitoring landslide deformation in vegetated areas using terrestrial LiDAR data, namely, TreeTracker. Traditional methods struggle with dense vegetation, but TreeTracker leverages tree movements to estimate slope deformations. The semi-automated algorithm identifies and tracks 3D displacement of tree trunks to monitor slow-moving landslides. It uses local geometric descriptors and an unsupervised decision tree algorithm with 84% accuracy for identifying tree trunks, followed by the iterative closest point algorithm to calculate trunk movement over time. A case study on a landslide in Peace River, Canada, shows the algorithm's effectiveness through seasonal changes, with matching precision between 89% and 99%. The study highlights LiDAR data processing challenges, such as registration errors and environmental factors affecting tree movement. Limitations include the complexity and data requirements of supervised classification models, and environmental influences like wind and snow. The TreeTracker suggests a lower detection limit of 0.15 m to filter noise and acknowledges potential upper limits for large deformations. The framework shows promise for broader applications, including airborne laser scanning and monitoring other geohazards, emphasizing the importance of accurate sensor calibration and real-time processing for vegetation filtering in point clouds.

Grilli *et alii* (2017) delves into the methodologies and algorithms essential for segmenting and classifying 3D point clouds, critical for applications ranging from geospatial analysis to cultural heritage preservation. They highlighted the growing availability and use of 3D models and point clouds across various platforms, emphasizing the need for automated methods to extract meaningful attributes that characterize objects in 3D space. Segmentation involves grouping points into homogeneous regions based on shared geometric or radiometric properties, while classification assigns labels to these regions. Their review categorized algorithms into different approaches, such as supervised methods requiring training data and parameter-tuned algorithms tailored for specific data types like LiDAR or RGB-colored point clouds. Despite significant progress, challenges persist, including sensitivity to noise, varying data densities, and the complexity of adapting algorithms to different data types and applications. Future research directions highlighted enhancing automation through advanced machine learning techniques similar to study in Qin *et alii* (2023), improving algorithm robustness, and developing standardized benchmarks for evaluation across diverse datasets and applications.

Ruan & Liu (2020) explored the essential role of segmentation in processing point cloud data for applications like medical imaging, industrial inspection, and 3D visualization. Segmentation faces challenges, such as uneven sampling density, data redundancy, and irregular structures. Their review categorizes segmentation methods into edge-based, region-based, graph-based, model-based, and machine learning-based approaches, evaluating their strengths, weaknesses, and application contexts. It highlights that edge and region-based methods are sensitive to noise, and model-based methods struggle with adapting to diverse environments. Graph-based and machine learning based methods are more resilient to noise but face real-time processing challenges.

Future research aims to reduce noise influence and enhance real-time performance to improve segmentation accuracy and efficiency across various applications.

Blanco *et alii* (2022) introduced a method to automate rockfall detection using 3D point cloud data from terrestrial laser scanning. Their method involves data capture, alignment, difference measurement, clustering, and rockfall identification through machine learning techniques. By extracting 33 features related to rock cliff differences and testing 11 machine learning models with various resampling methods, their study achieved high accuracy in identifying rockfalls in two case studies. However, the method's effectiveness is contingent on the homogeneity of rockfall characteristics, presenting challenges in scenarios with varied rock types and sizes. Limitations include the complexity of feature discrimination, the need for further validation of feature relevance, and the scalability of processing large volumes of high-resolution data. The study notes that the discriminatory power of each feature requires optimization, and the processing demands of high-resolution data pose challenges for real-time applications.

Observation

Observations from the literature survey reveal significant challenges in handling terrain complexity and environmental variability, which greatly impact the performance of vegetation filtering algorithms. Methodological constraints, such as scalability issues and the limited applicability of filtering methods like SiRP and U-Net, further complicate these challenges. Additionally, the robustness of algorithms is affected by the quality of data collected from UAVs, particularly spectral and geometric data. Supervised machine learning models, while precise, face limitations due to stringent data requirements, contrasting with the broader applicability of unsupervised methods in complex vegetation analysis. Ensuring validation proves difficult, as maintaining accuracy across diverse environmental conditions remains a significant hurdle for reliable vegetation filtering. Future research directions emphasize advancing algorithms, integrating advanced features, and establishing standardized benchmarks to enhance the precision of filtering methods.

Main contributions

The current study utilizes and compares tree-based machine learning models and threshold-based models for point classification and filtering vegetation from 3D point cloud data derived from photogrammetry, a crucial step for analyzing rock slopes and hilly terrains. The analyses require point cloud data with minimal noise and the removal of unwanted point objects to enhance data accuracy. The primary objective is to demonstrate that refining various vegetation filtering methods on photogrammetric data can significantly improve the accuracy of vegetation removal. This involves preprocessing the data, applying multiple filtering techniques, and evaluating their effectiveness in distinguishing vegetation from non-vegetation points. A significant aspect of this study is the hyperparameter tuning of the random forest classifier, meticulously optimized to enhance performance. By adapting classification methods typically used for LiDAR, this research enhances vegetation filtering in photogrammetric data, filling a critical gap in the literature and improving accessibility for applications in environmental monitoring and urban planning. Ultimately, by addressing these challenges and improving algorithm robustness, this work seeks to contribute to more precise and reliable vegetation filtering, facilitating better analysis and management of hilly and rocky terrains. This work contributes to the field by not only improving classification accuracy but also proposing a framework for more nuanced vegetation classification which is important for the aforementioned applications.

PHOTOGRAMMETRIC 3D POINT CLOUD DATA

The point cloud data are stored in a structured text file format, where each row represents individual points within the point cloud. The .txt/.las file includes x, y, and z coordinates, with corresponding RGB color values separated by space or tab. There are six datasets employed herein with various characteristics, illustrated in Fig. 1. The details of these datasets are also summarized in Table 1. The surface area of the point cloud is not proportional to the number of points due to the varying point density of each point cloud. The Maiori dataset has the densest point cloud data while the Sierria National Park has the least dense point cloud data. Point Cloud Mean Brightness (PCMB) evaluates the average brightness of all points in a point cloud, calculated as the means of their RGB values, using the formula:

$$\mathrm{PCMB} = \sum_{i=1}^{N} \frac{R_i + G_i + B_i}{3} \quad (1)$$

where R_i,G_i,B_i are the red, green, and blue color values of the i-th point, and N is the total number of points in the point cloud. PCMB is particularly important for analyzing vegetation indices based on color data. From Table 1, the PCMB values are high, suggesting that the points are generally bright.

The datasets used in this study were collected from diverse environments to ensure the generalizability of the proposed methods. Environmental characteristics include varying levels of vegetation density (dense forest, sparse vegetation, and barren land) and geometric variations (slopes, flat terrains, and rocky surfaces). The following are the key characteristics:

• Figure 1a: Sparse vegetation in a predominantly uneven terrain with minimal noise;

• Figure 1b: Moderately dense vegetation with mixed flat and inclined terrains with a monument;

• Figure 1c: Dense vegetation cover with steep slopes, representing a high-variation environment;

• Figure 1d: Vegetation mixed with human-made structures with large trees and small plants;

• Figure 1e: Near-Forest vegetation with structural noise from previous constructions with varied light exposure and shadowing;

• Figure 1f: Manually grown vegetation in completely flat terrain.

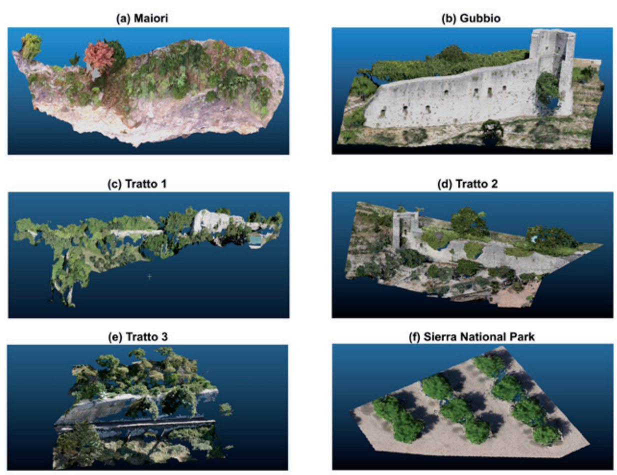

Fig. 1 - A view of the coloured point cloud of (a) Maiori (landslide), (b) Gubbio (cultural heritage preservation), (c) Tratto 1, (d) Tratto 2, (e) Tratto 3, and (f) Sierra Calderona Natural Park datasets

ID	Name of Data	Number of Points	Illustration	PCMB	Density	Surface Area	Reference
1	Maiori	17,720,023	Figure 1a	91.82	7942.63	2231	Sapienza University of Rome
2	Gubbio	1,150,232	Figure 1b	91.82	370.20	3107	Fraunhofer IOSB (Bulatov et al., 2021)
3	Tratto 1	3,401,261	Figure 1c	90.46	306.19	11,108	Fraunhofer IOSB (Bulatov et al., 2021)
4	Tratto 2	10,029,666	Figure 1d	89.96	2193.71	4572	Fraunhofer IOSB (Bulatov et al., 2021)
5	Tratto 3	3,380,891	Figure 1e	85.06	1538.16	2198	Fraunhofer IOSB (Bulatov et al., 2021)
6	Sierra National Park	93,571	Figure 1f	99.12	200.79	466	Carbonell Rivera et al. (2023)

Tab. 1 - Details of the 3D point cloud data employed in this research. The unit of density is points per square meter, and the unit of surface area is square meter

METHODOLOGY

In this study, a comprehensive methodology for the segmentation of vegetation from point cloud data using machine learning techniques is suggested. The process includes point cloud sampling and machine learning classification. The overall workflow is illustrated in Fig. 2.

The workflow for vegetation filtering begins with sample selection, which involves choosing representative point clouds from diverse environments. Subsequent stages include preprocessing, classification using machine learning models, segmenting vegetation points, evaluation metrics, and ablation analysis. Sample selection involves isolating regions of interest from diverse environments, ensuring high-quality data. Tools like CloudCompare and Python are used to obtain samples with densities ranging from 200 to 8000 points per square meter and total points varying between 0.1 M and 17 M. This structured approach ensured robust and representative datasets for the classification task.

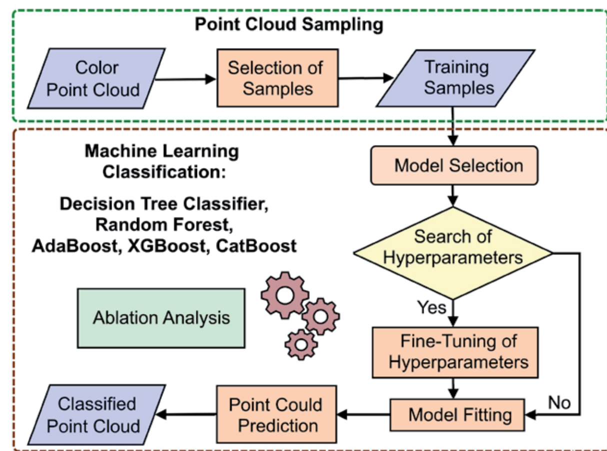

Fig. 2 - A workflow of this research. This workflow is used for each of the six datasets to classify them individually by machine learning models. It is also used to obtain training samples from five different datasets to train each machine learning model for classifying the unseen dataset (Gubbio)

Point cloud sampling

The sampling process ensures the selection of representative data to capture vegetation diversity and spatial variation. The criteria for sample selection are as follows:

(1) Spatial Diversity: Data are sampled from regions with varying vegetation densities.

(2) Point Density: Samples are chosen based on low and high point density and minimal noise, ensuring data reliability.

(3) Manual Selection: CloudCompare is used to select regions of interest for each dataset.

The initial step involves acquiring the point cloud data with RGB color values. These data are obtained using the photogrammetry technique, which provides detailed 3D representations of the surveyed environment. The point cloud data are then preprocessed to ensure consistency and accuracy. This involves normalizing the coordinates and RGB values accordingly. The visual inspection of point cloud helps in verification and provides authenticity of the data. Training samples are then collected from these point clouds. These samples are chosen based on their representativeness of different classes within the data (herein, vegetation and non-vegetation).

Machine learning classifiers

The present research employs several machine learning models, each chosen for its unique strengths in classification and segmentation tasks within photogrammetric point cloud data. The selected training samples are used to create a training dataset, which includes labeled points that will be used to train the classification model. The machine learning models utilized herein are Decision Tree (DT) (Quinlan, 1986), Random Forest (RF) (Breiman, 2001), Adaptive Boosting (AdaBoost) (Freund & Schapire, 1997), eXtreme Gradient Boosting (XGBoost) (Chen & Guestrin, 2016), and Categorical Boosting (CatBoost) (Prokhorenkova *et alii*, 2018). These machine learning models are tree-based ensemble learning algorithms because they use ensemble methods, such as bagging, stacking, or boosting (Sahin, 2022). These models are evaluated herein based on their performance in distinguishing between vegetation and non-vegetation points.

DT is integrated to capture different aspects of the data, improving the robustness and accuracy of the vegetation filtering process. The RF is chosen for its robustness against over-fitting and its ability to handle large datasets of high dimensionality. The AdaBoost classifier improves the performance of weak learners by adjusting the weights of misclassified instances, making it effective for focusing on difficult cases. The XGBoost is utilized for its efficiency and scalability in binary classification tasks, enhancing predictions by combining weak learners and focusing on misclassified instances (Bentejac *et alii*, 2021). The AdaBoost has fewer tuning parameters compared to XGBoost. CatBoost has a more flexible interface for parameter tuning compared to XGBoost. By leveraging the strengths of each algorithm, this research ensures a comprehensive and effective approach to vegetation filtering in photogrammetric point cloud data.

A comprehensive search for optimal hyperparameters was conducted to enhance the model's performance. This involves testing different combinations of hyperparameters to find the set that yields the best results, followed by fine-tuning the hyperparameters based on cross-validation results to avoid over-fitting and ensure generalization. Once the optimal hyperparameters are determined, the chosen model is trained on the entire training dataset. The model learns to classify points based on the spatial values and their corresponding RGB values as described in Table 2. The trained model is then applied to the entire point cloud data to predict the class labels for each point, resulting in a classified point cloud where each point is labeled as vegetation or non-vegetation. The classified point cloud is displayed in the viewer, allowing for visual inspection and verification of the classification results. The performance of the classification model is evaluated using metrics, such as accuracy, precision, recall, and F1-score, providing insights into the model's effectiveness in correctly identifying vegetation points.

All features, though some may have lower individual importance, collectively contribute to the classification

Feature Type	Feature Name	Usage in Classification
Coordinate Values	X, Y, Z	Used
Color Values	Red, Green, Blue	Used
Label	Binary Label (Vegetation/Non-Vegetation)	Used

Tab. 2 - Feature overview for classification of individual data (total 7 features)

process. The model benefits from the complementary information provided by each feature, which improves the overall robustness and accuracy of the classification. Even features with lower importance scores, such as the spatial coordinates, can provide subtle but important distinctions that aid the classifier in complex real-world scenarios. Hence, the inclusion of all features is essential for achieving the best possible classification performance.

Model Training

In the model training phase, the dataset is first loaded from the specified file path and features along with labels are extracted for subsequent analysis. DT, RF, AdaBoost, XGBoost, and CatBoost, are then applied to preprocessed data to build predictive models. Each classifier undergoes training using the 'fit()' method, with some supporting partial fit for batch training to optimize memory usage and reduce training time, ensuring efficient handling of large datasets and resource constraints while maintaining performance standards.

Hyperparameter Tuning

To optimize the models, hyperparameters are tuned to achieve the best performance for each model separately. Key hyperparameters include the number of weak learners, learning rate, and the maximum depth of weak learners (Bentejac *et alii*, 2021; Sahin, 2022). The learning rate controls the contribution of each weak learner, preventing the model from over-fitting. The maximum depth limits the complexity of weak learners, striking a balance between model complexity and generalization. A systematic approach, such as grid search or random search, is employed to explore the hyperparameter space. The technical soundness of the methodology lies in the comprehensive selection of geometric features, capturing both local and global characteristics. The sequential training of weak learners in XGBoost ensures a focus on challenging instances, refining the model iteratively. Hyperparameter tuning is performed using grid and random search techniques, validating the set of optimized parameters through cross-validation.

Hyperparameter tuning is conducted for RF using a comprehensive grid search. The parameter grid included a range of values for key hyperparameters: the number of estimators (n_estimators: 50, 100, 200), the maximum number of features considered for splitting (max-features: 'sqrt', 'log2'), the maximum depth of the tree (maxdepth: None, 10, 20, 30), and the function to measure the quality of a split (criterion: ’gini’, ’entropy’). This systematic approach ensures an extensive exploration of the parameter space, ultimately identifying the optimal combination of hyperparameters that enhances the model’s performance in classifying vegetation in 3D point cloud data.

During the hyperparameter tuning process for Random Forest, challenges included identifying an optimal balance between model complexity and overfitting. Increasing the number of estimators improved accuracy but also significantly increased computational time. Additionally, varying max-features and max-depth required multiple trials to achieve the best trade-off between classification performance and training speed. These challenges underscore the importance of systematic exploration of the parameter space to avoid suboptimal configurations. The GridSearchCV method was effective but computationally intensive for large datasets.

Visible-band vegetation index

This study utilizes two RGB-based vegetation indices for 3D point cloud classification:

(1) the Normalized Green-Red Difference Index (NGRDI) (Gitelson *et alii*, 2002), a visible-band index proposed for UAV images, defined as:

$$\mathrm{NGRDI} = \frac{\mathrm{Green} - \mathrm{Red}}{\mathrm{Green} + \mathrm{Red}} \tag{2}$$

(2) The Visible-band Difference Vegetation Index (VDVI) (Wang *et alii*, 2015) is another vegetation index that uses all the three visible spectral bands, defined as

$$\mathrm{VDVI} = \frac{2 \times \mathrm{Green} - \mathrm{Red} - \mathrm{Blue}}{2 \times \mathrm{Green} + \mathrm{Red} + \mathrm{Blue}} \tag{3}$$

The usage of features in the threshold model based on visible-band vegetation index is shown in Table 3.

Feature Type	Feature Name	Usage in Classification
Coordinate Values	X, Y, Z	Not Used
Color Values	Red, Green, Blue	Used
Label	Binary Label (Vegetation/Non-Vegetation)	Used

Tab. 3 - Feature overview for vegetation filtering

Evaluation Metrics

The accuracy of the proposed methodology is assessed using different metrics, such as accuracy, precision, recall and F1 Score, providing a comprehensive understanding of the model’s performance (Rainio *et alii*, 2024). Accuracy measures the overall correctness of the model in predicting both classes, calculated as the number of correct predictions divided by the total number of predictions. Precision evaluates the accuracy of positive predictions, highlighting the model’s ability to avoid false positives, and is determined by dividing the number of true positives by the sum of true positives and false positives. Recall (Sensitivity) measures the model’s ability to capture all relevant instances of the positive class, calculated by dividing the number of true positives by the sum of true positives and false negatives. The F1 Score balances precision and recall, useful when there is an uneven class distribution, providing a harmonic mean that considers both false positives and false negatives. This score is particularly useful when the distribution between classes is imbalanced and when it is important to have a balance between precision and recall.

Additionally, the performance of each trained model is evaluated using several metrics, including the Receiver Operating Characteristic (ROC) curve and Area Under the Curve (AUC) score, to assess the model’s ability to distinguish between classes (Fawcett, 2006; Junge & Dettori, 2018; Peres & Cancelliere, 2014; Kundu *et alii*, 2023). The ROC curve is plotted for each model, showing the trade-off between true positive rate and false positive rate, and the area under the ROC curve (AUC) is computed as a summary metric. The performance of each model is compared according to these evaluation metrics and ROC curves. Models with higher AUC values indicate better discrimination ability.

RESULTS

In this section, the classification results of the six different point cloud data (listed in Table 1), utilizing the tree-based machine learning models, are demonstrated first. Then the machine learning models are trained on five different datasets (ID: 1, 3-6 in Table 1), and then the trained models are used to classify the Gubbio dataset (ID: 2) into vegetation and non-vegetation classes. The results of this part show how different models perform when they are trained on data from diverse locations with various characteristics and applied to unseen data. The results of the machine learning models are also compared with the results of vegetation index threshold-based models.

Point classification results for individual datasets by machine learning classifiers

The vegetation points are labeled 1 while non-vegetation points are labeled as 0. The labeled datasets are obtained by experts through visualization, filed survey, and also with the help of vegetation indices. To evaluate the best performance of each of the tree-based machine learning classifiers, each dataset after trial/error is split into training (70%), testing (15%), and validation (15%).

Table 4 presents evaluation metrics for the classifiers applied for vegetation filtering in the Maiori dataset (Fig. 1a). Notably, RF stands out with high performance metrics. The RF can precisely classify points as vegetation or non-vegetation, reducing false positives and capturing almost all samples in the positive class. The dependability, speed, and resilience of the model make it a viable method for classifying vegetation. Furthermore, the average performance metrics across all models evaluated in the study generally reveal that RF and CatBoost models perform better than other classifiers used. These averages provide a comprehensive overview of the models' collective performance, highlighting their varying degrees of effectiveness in distinguishing vegetation from non-vegetation points in the datasets.

The classification results of Gubbio, Tratto 1, Tratto 2, Tratto 3, and Sierra Calderona Natural Park datasets are listed in Tables 5, 6, 7, 8, and 9, respectively. Table 4 shows that RF is performing the best with good metric results, while Table

Dataset	Method	Accuracy	Precision	Recall	F1 Score
Maiori	DT	0.9965	0.9950	0.9950	0.9950
	RF	0.9982	0.9975	0.9974	0.9974
	AdaBoost	0.8921	0.8381	0.8629	0.8503
	XGBoost	0.9813	0.9727	0.9747	0.9737
	CatBoost	0.9908	0.9864	0.9977	0.9870

Tab. 4 - Point classification results of the Maiori dataset, Figure 1a. Values in boldface are the best

5 shows that CatBoost model is giving better results. Table 6 reveals that DT is performing the best for Tratto 1 dataset, where there is more vegetation points than the non-vegetation points. Table 7 shows that RF again took the lead according to evaluation metrics. Table 8 shows that RF is efficiently and accurately classifying the points. Finally, Table 9 shows that XGBoost performs better than other tree-based models. While AdaBoost is generally effective, it exhibits issues with misclassifying multiple non-vegetation points as vegetation, as noted in the analysis. This highlights the importance of model selection and parameter tuning to optimize performance for specific classification and filtering tasks. Further evaluation metrics from different models reveal specific performance details. For instance, RF achieves good results but requires more time to train while CatBoost is similarly efficient in classifying the points with minute less accuracy and other metrics. These metrics are complemented by the corresponding precision and recall scores, offering deeper insights into each model's strengths and weaknesses in handling vegetation filtering tasks. It was found that RF is performing the best in the majority of cases. According to Table 5, the execution times and computational complexities of various machine learning models are analyzed to evaluate their scalability and efficiency.

Table 10 shows the computational times of different models for the Gubbio dataset. Decision Trees and XGBoost are ideal for quick iterative processing and real-time filtering. XGBoost offers an optimal balance between performance and speed, making it suitable for large datasets. CatBoost is another strong

Dataset	Method	Accuracy	Precision	Recall	F1 Score
Gubbio	DT	0.9926	0.9842	0.9839	0.9841
	RF	0.9942	0.9903	0.9848	0.9875
	AdaBoost	0.9365	0.8831	0.8362	0.8590
	XGBoost	0.9932	0.9868	0.9837	0.9853
	CatBoost	0.9948	0.9901	0.9873	0.9887

Tab. 5 - Point classification results of the Gubbio dataset, Fig. 1b. Values in boldface are the best

Dataset	Method	Accuracy	Precision	Recall	F1 Score
Tratto 1	DT	0.9949	0.9963	0.9961	0.9962
	RF	0.9944	0.9959	0.9957	0.9958
	AdaBoost	0.8920	0.8922	0.9538	0.9220
	XGBoost	0.9846	0.9878	0.9892	0.9885
	CatBoost	0.9894	0.9920	0.9921	0.9921

Tab. 6 - Point classification results of the Tratto 1 dataset, Fig. 1c. Values in boldface are the best

Dataset	Method	Accuracy	Precision	Recall	F1 Score
Tratto 2	DT	0.9924	0.9903	0.9902	0.9903
	RF	0.9939	0.9942	0.9901	0.9921
	AdaBoost	0.8765	0.8464	0.8342	0.8403
	XGBoost	0.9817	0.9809	0.9719	0.9764
	CatBoost	0.9895	0.9887	0.9844	0.9865

Tab. 7 - Point classification results of the Tratto 2 dataset, Fig. 1d. Values in boldface are the best

Dataset	Method	Accuracy	Precision	Recall	F1 Score
Tratto 3	DT	0.9978	0.9982	0.9982	0.9982
	RF	0.9979	0.9984	0.9983	0.9983
	AdaBoost	0.9102	0.9261	0.9300	0.9281
	XGBoost	0.9958	0.9964	0.9968	0.9966
	CatBoost	0.9957	0.9964	0.9967	0.9965

Tab. 8 - Point classification results of the Tratto 3 dataset, Fig. 1e. Values in boldface are the best

Dataset	Method	Accuracy	Precision	Recall	F1 Score
Tratto 3	DT	0.9978	0.9982	0.9982	0.9982
	RF	0.9979	0.9984	0.9983	0.9983
	AdaBoost	0.9102	0.9261	0.9300	0.9281
	XGBoost	0.9958	0.9964	0.9968	0.9966
	CatBoost	0.9957	0.9964	0.9967	0.9965

Tab. 9 - Point classification results of the Sierra Calderona Natural Park dataset, Fig. 1f. Values in boldface are the best

contender for fast predictions but has slightly higher training time. Random Forest, while delivering high accuracy, is more computationally expensive and may not be suitable for real-time applications. AdaBoost, with moderate performance and efficiency, can be an effective choice for balancing speed and

Model	Training Time (s)	Prediction Time (s)	Computational Complexity	Operations Per Point
AdaBoost	45.3	2.7	$O(n_{samples} \cdot n_{trees})$	300
DT	6.9	0.1	$O(n_{samples} \cdot n_{features} \cdot \log[n_{samples}])$	101
RF (no tuning)	212.1	10.4	$O(n_{samples} \cdot n_{trees} \cdot n_{features} \cdot \log[n_{samples}])$	1679
RF (with tuning)	18,914	9.3	$O(n_{combinations} \cdot n_{folds} \cdot n_{samples} \cdot n_{trees} \cdot n_{features} \cdot \log[n_{samples}])$	53,735
XGBoost	6.1	2.3	$O(n_{samples} \cdot n_{trees} \cdot n_{features})$	600
CatBoost	210.1	0.9	$O(n_{samples} \cdot n_{trees} \cdot n_{features})$	600

Tab. 10 - Model execution time and computational complexity for Table 5 with 1.15 million points

classification accuracy. The choice of model depends on the specific needs of the application, whether it is about training time, prediction speed, or accuracy.

Results of machine learning models trained on five datasets

In another experiment, five photogrammetric 3D point cloud datasets obtained from different sites are considered for training of machine learning models (IDs 1,3,4,5,6 in Table 1). Each of the datasets contains seven features, namely, three coordinates, three colors and one binary label, and preliminary processing of the datasets is done separately. For every dataset, a machine learning model is trained. Following these singular evaluations, the datasets are combined by placing one dataset on the top of the other into a new single comprehensive file. This file contains the combined data, which is 100% of the data available, and it is used to train the model as one complete unit. Ultimately, this model is tested out using the data from the site that had not been included in the model development (Gubbio dataset) to test the model's ability to perform point classification on unseen data. It was found that RF performs better than the other utilized machine learning models. A view of the binary classification results of the Gubbio dataset using RF is illustrated in Fig. 3. The building is detected more accurately as compared to vegetation where some building points are falsely classified as vegetation points.

For brevity, Table 11 shows the classification results of RF without and with tuning parameters. It can be seen that RF has more than 76% accuracy in identifying the vegetation points. For the sake of comparison with other models, RF is also compared with SiRP (Bulatov *et alii*, 2021), and the classification results are shown in Table 12.

Note that the models are trained on the combined data, i.e., Maiori, Tratto 1,2,3, and Sierra National Park for this comparison. The results show that SiRP with correction and RF with hyperparameter tuning have very close classification performances. Computational efficiency is evaluated to assess the potential for real-time applications. Among the tested models, RF with hyperparameter tuning shows efficient prediction times, completing inference on datasets of approximately 17000 points in under 10 seconds on a standard computing platform. Like RF, other models also demonstrate fast prediction times relative to their training duration, indicating their feasibility for near-real-time applications. The computational analysis for RF is as follows:

- Training Time: On average, the training of RF requires

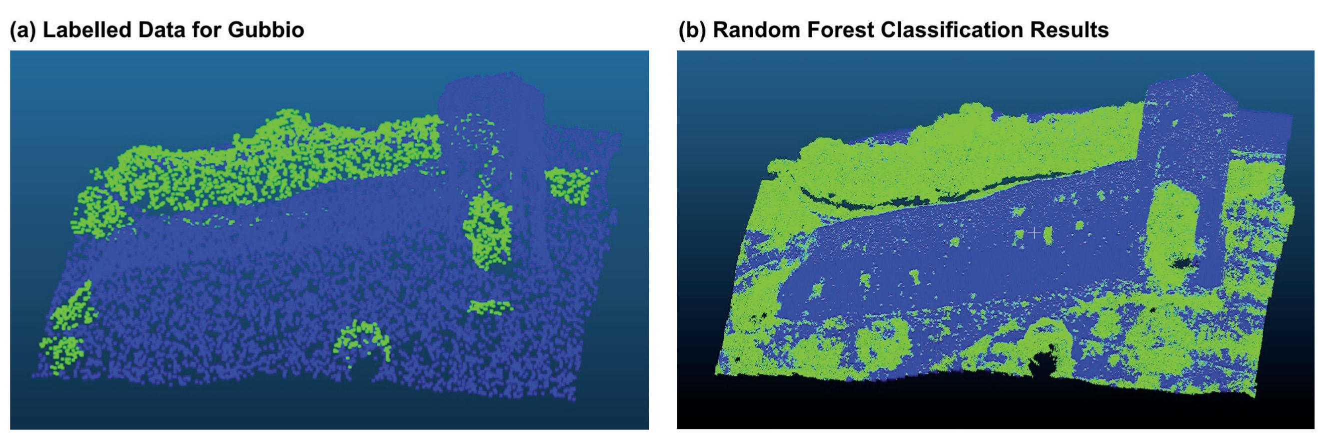

Fig. 3 - (a) The manually labeled data of Gubbio for validation (15% of the points are manually labeled), and (b) the RF classification results of the Gubbio dataset trained on the combined data with hyperparameter tuning. Vegetation and non-vegetation points are shown by green and blue colours, respectively. Note that RF is not trained on the manually labeled data for Gubbio. The classification accuracy is about 76.4 %

Metrics	Without Tuning Hyperparameters	With Tuning Hyperparameters
Precision	0.4412	0.6279
Recall	0.9828	0.9937
Accuracy	0.7083	0.7640
ROC AUC	0.9294	0.9626

Tab. 11 - The evaluations metrics for RF trained on combined data to classify the Gubbio data

Method	Precision Terrain	Precision Vegetation	Overall Accuracy
SiRP without correction	96.76%	66.13%	74.82%
SiRP with correction	94.48%	69.85%	76.84%
RF with hyperparameter tuning	94.02%	71.15%	76.40%

Tab. 12 - Performance comparison of SiRP (Bulatov et al., 2021) and RF on the Gubbio dataset, Fig. 1b

approximately 5 hours using a 6 core CPU system with 8 GB RAM.

• Inference Time: The average prediction time per 1,000 points was 0.0005 seconds, making the model feasible for moderately large datasets.

• Trade-offs: A balance was struck between computational cost and classification accuracy during RF hyperparameter tuning. Increasing the number of estimators marginally improved accuracy but significantly increased computational time.

• Real-Time Potential: Although RF is not optimized for real-time applications, it could be adapted with hardware acceleration (e.g., GPUs) and efficient parallelization.

This analysis highlights the scalability and adaptability of RF for real-world applications.

ROC curves and AUC values for models trained in individual and combined datasets

This The ROC curves illustrated in Fig. 4 further visualize the models' performance in distinguishing between classes. Notably, from the ROC curve for individual data types, see Fig. 4a, the different model demonstrates its strong discriminatory power in identifying points on similar data, while ROC curves for models trained on combined data with predictions on unseen data of different areas reflects less AUC, see Fig. 4b. This indicates superior performance in classifying vegetation of similar locations

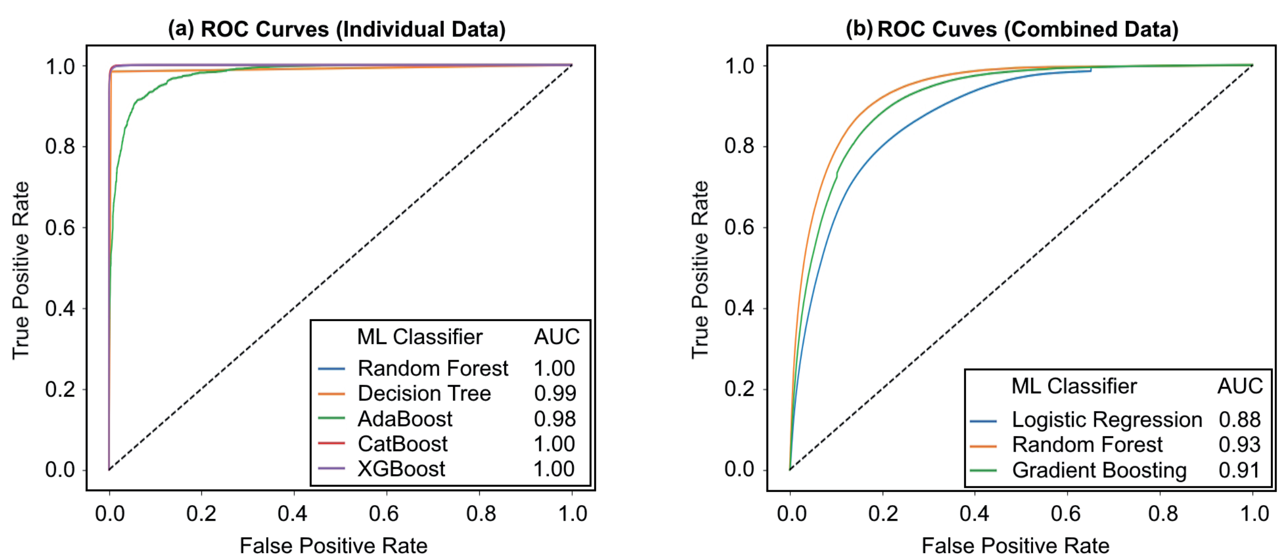

Fig. 4 - The ROC curves for Machine Learning (ML) models trained with (a) individual, and (b) combined data

as compared to various locations. Luminosity, quality of point cloud data, and complexity of the location play an important role in point classification and masking.

Visible-band vegetation filtering results of the Maiori dataset

The current study also presents another classification scheme using vegetation index methods proposed in Ramirez *et alii* (2023). The visible-band vegetation indices, NGRDI and VDVI, are utilized for filtering, with the resulting filtered point cloud file (.txt) visualized using CloudCompare software. As an example, using NGRDI and VDVI, a value is created for each point in the point cloud. If the point value is less than zero, then it is considered as a non-vegetation point, otherwise, it is considered as a vegetation point. The zero threshold is decided after the trial/error method, i.e., after examining several fixed thresholds from -1 to 1, the threshold zero has the best performance in separating vegetated from non-vegetated points. All points with a vegetation index lower than zero are identified and removed from the cloud. Figure 5 illustrates the results of this process on the Maiori dataset as an example.

The evaluation metrics for the threshold-based method using GNDVI and VDVI are listed in Table 13, showing GNDVI has a higher accuracy 0.8112 for filtering vegetation than VDVI. Since this method is based on a fixed threshold, generally it cannot produce good results for complex point cloud datasets and is only dependent on color values, hence not an efficient method. On the other hand, the machine learning methods utilized herein adapt accordingly and produce better results, see Table 4, where RF has reached an accuracy of 0.9982. Although the RGB values applied for the calculation of vegetation indices were directly derived from photogrammetric point clouds, this study does not assign error bars to individual bands.

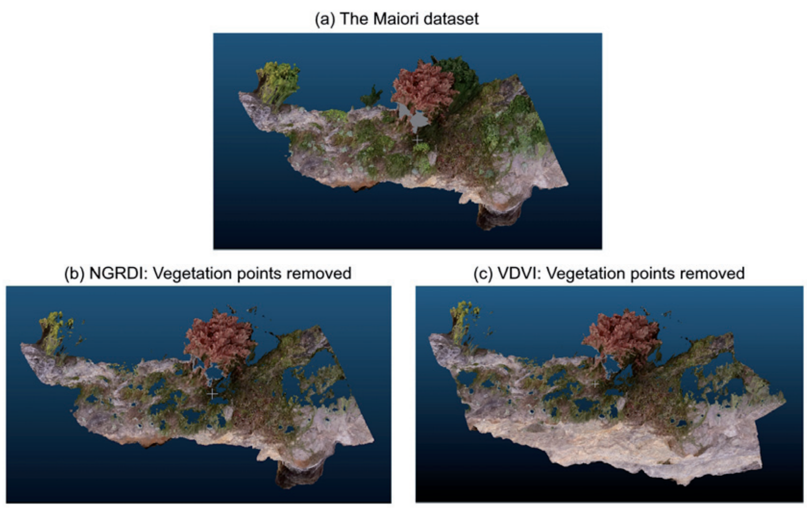

Fig. 5 - (a) The left part of Maiori dataset, (b) and (c) visualizations of segmented vegetation points using NGRDI and VDVI and 0 as threshold value, respectively

Vegetation Index	Accuracy	Precision	Recall	F1 Score
GNDVI	0.8112	0.8852	0.5384	0.6696
VDVI	0.7730	0.6564	0.7575	0.7034

Tab. 13 - Vegetation filtering results of the Maiori dataset, Fig. 5

Ablation Experiment Results and Sensitivity Analysis of RGB Bands

While spatial features such as x, y, and z provide essential geometric context, spectral features (RGB) are indispensable

Feature Set	Maiori - Accuracy (%)	Gubbio - Accuracy (%)	Observation
x,y,z only	0.9702%	0.9740%	Geometry-based; lacks spectral detail
r,g,b only	0.8917%	0.9208%	Spectral features differentiate vegetation
x,y,z,r,g,b	0.9813%	0.9932%	Best results with combined features

Tab. 14 - Ablation Study: Impact of features on classification accuracy by XGBoost. Features x, y, and z are the coordinates, and features r, g, and b are red, green, and blue colors, respectively to accurately distinguish vegetation. Inclusion of RGB data improves the classification accuracy, as demonstrated in ablation experiments in Table 14. Although spatial features alone can achieve moderate accuracy, the absence of spectral information limits the model's ability to identify vegetation-specific traits. This reinforces the necessity of both feature types in vegetation classification tasks.

The F-score measures the number of times a feature is used to split a node across all the trees in the model, weighted by the improvement in model performance that results from that split. Higher F-scores indicate features that contribute more significantly to reducing prediction error.

$$F_i = \sum_{x \in T} \Delta \mathrm{Gain}(t, i) \tag{4}$$

where F_i is the feature importance score for feature i, T is the set of all decision nodes across all trees, $\Delta Gain(t,i)$ is the improvement in accuracy or error reduction achieved by splitting on feature i at node t.

Figure 6 highlights the role of spectral characteristics (RGB), particularly in distinguishing vegetation from non-vegetation. However, the combined use of spatial and spectral features provides the highest classification accuracy, underscoring their complementary nature, as shown in Table 14.

To assess the impact of noise on the classification accuracy,

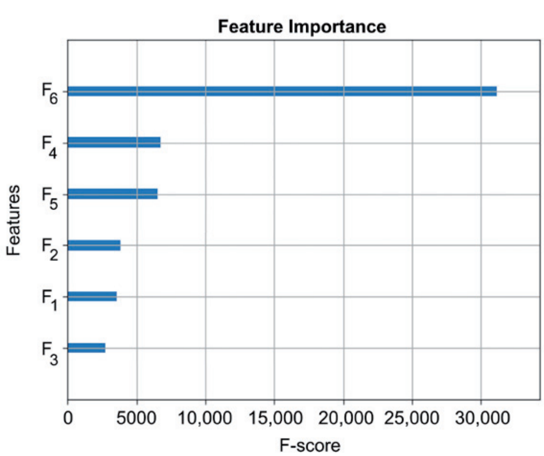

Fig. 6 - Feature importance analysis: Contribution of spatial coordinates (x, y, z) and color values (r, g, b) in vegetation segmentation using XGBoost on Gubbio dataset. Features F1, F2, F3, F4, F5, F6 are x, y, z, red, green, and blue, respectively. The blue color demonstrates the highest importance, while spatial coordinates provide complementary structural information

a sensitivity analysis was performed by introducing 10% random noise in individual RGB bands. The baseline accuracy was the accuracy achieved by the XGBoost model in Table 4. The analysis revealed that the red and green bands are the most sensitive to noise, with accuracy reductions of 1.28% and 1.42%, respectively. The noise in the blue band had a minimal impact (0.18% reduction). These findings underscore the importance of robust sensor calibration and preprocessing to minimize environmental noise impacts.

DISCUSSIONS

When monitoring rock formations, landslides, cultural heritage, or soil erosion using 3D point cloud data, vegetation poses a significant obstacle and must be detected and removed prior to analysis (Wang & Koo, 2022; Štroner *et alii*, 2023, 2024). It is challenging to design an automatic system to accurately and efficiently detect and remove vegetation from 3D point clouds using RGB-based vegetation indices (Štroner *et alii*, 2023). Vegetation indices based on Near-Infrared (NIR) band, such as Normalized Difference Vegetation Index (NDVI) and Green Normalized Difference Vegetation Index (GNDVI) can simplify the task due to their sensitivity to various vegetation type, soil, and water (Teixeira Crusiol *et alii*, 2020; Gutman *et alii*, 2021).

The RGB values applied for the calculation of vegetation indices were directly derived from photogrammetric 3D point cloud data in the present study, and no color error was assigned to individual bands. Color assignments may be imprecise due to differences in capture conditions, sensor quality, and/or processing algorithms. These inaccuracies may impact the reliability of computed vegetation indices, and so it is important to consider color errors in order to perform an uncertainty analysis for the model output.

Main Findings

In the present work, it is shown that tree-based machine learning classifiers could be employed for an efficient vegetation masking from 3D point clouds using RGB bands, also addressing scenarios where geometric features are unavailable or computationally expensive. The study evaluates the performance of five tree-based classifiers (DT, RF, AdaBoost, XGBoost, and CatBoost) across six diverse and challenging datasets. In classifying vegetation points, RF shows promising results, comparable with the results in Bulatov et al. (2021), which achieved an accuracy of 76.84% on the Gubbio dataset, see Table 12. While CatBoost and RF provide robust performance, XGBoost shows particular promise in handling complex data structures with multiple features, such as spatial and color-related attributes. XGBoost has achieved an average F1 score of 0.9841, indicating its potential for addressing complex point cloud datasets.

The impressive performance of the RF classifier highlights its potential applicability in real-world scenarios, particularly in forestry management. However, RF is computationally more costly than other tree-based models utilized herein. As detailed in the dataset table, various types of point cloud data were utilized, underscoring the model's versatility across different contexts. The findings suggest that these models can be effectively applied not only in forestry but also extended to agricultural practices, enhancing vegetation monitoring and management.

Acquiring adequate and accurate labeled data is a big challenge for training machine learning models (Bello *et alii*, 2020). In the present study, the training samples are carefully selected by expert knowledge, field investigation, and examining various vegetation indices. The incorporation of multi-class labels can enhance the model's applicability to more specific vegetation categories. Apart from potential uncertainties that may exist in the labeled data, the training, testing, and validation samples were the same for all the utilized machine learning classifiers herein. In the current study, x, y, and z coordinates are used as input features alongside spectral values due to their spatial relevance in point classification. Spatial patterns captured by x and y, and height variations by z, aid in distinguishing vegetation from non-vegetation. The labels are strictly used as target outputs for training and evaluation, not as input features. Leveraging both spatial and spectral features ensures improved classification accuracy, especially in complex terrains as the ablation analysis indicated in Section 5.5.

The performance of each model varies based on the dataset and the complexity of the problem. Some models may perform better in terms of certain metrics while others excel in different aspects. It is essential to consider the specific requirements and characteristics of the problem domain when selecting the appropriate classification algorithm. This work provides insights into the effectiveness of various classification algorithms for point cloud data classification tasks. Further experimentation and optimization may be required to enhance the performance of the models for specific use cases.

From Tables 3-9, one can observe that each tree-based model performs differently across locations. For example, Random Forest (RF) performs better on denser datasets, such as the Maiori site, while XGBoost shows stronger performance on sparse datasets like Sierra National Park. These differences can be attributed to algorithmic design. Unlike XGBoost, which builds trees sequentially and corrects errors of previous trees, RF trains each tree independently and aggregates their outputs. This makes RF more robust to noise and overfitting, though at the cost of slower training.

In urban planning, accurately classifying vegetation can help assess the distribution of green spaces, leading to better decision-making about land use and development. This approach also supports conservation efforts by delivering precise information on vegetation cover and health, essential for effective monitoring and management of natural resources. By utilizing the filtering techniques mentioned, stakeholders can obtain valuable insights into environmental dynamics, ultimately fostering more sustainable and informed practices in urban and ecological management.

This study focuses on binary classification utilizing machine learning methods due to their simplicity, interpretability, and suitability for various datasets. Traditional models offer more transparent results and require less computational complexity, making them essential in real-world scenarios. The binary classification of vegetation versus non-vegetation serves as a foundation for exploring different vegetation types, such as low and high vegetation, which are critical in applications like biomass estimation and tree parameter analysis. The current research provides valuable insights into binary classification (vegetation and non-vegetation) of photogrammetric 3D point cloud data by comparing five tree-based machine learning models as well as threshold-based models, setting the stage for more advanced methods.

Limitations Future Directions

Vegetation filtering using only RGB bands can lead to profound errors and uncertainties in complex regions with different luminosities, e.g., detecting vegetation in shades vs vegetation directly exposed to the sunlight (Fuentes-Peailillo *et alii*, 2018; Aboutalebi *et alii*, 2018; Yan *et alii*, 2019; Štroner *et alii*, 2023, 2024; Biro *et alii*, 2024). Use of the NIR band could be more useful than only visible bands for vegetation detection, but it is costly to operate a UAV equipped with NIR bands. Color assignments may be imprecise due to differences in capture conditions, sensor quality, or processing algorithms. These inaccuracies may impact the reliability of computed vegetation indices.

Despite encouraging results, several other limitations exist. First, the point clouds were manually labeled, which inevitably introduces errors, as some points may have been mislabeled. Such inaccuracies can affect model performance at a minor level. Second, variation in performance across locations may also arise from differences in external factors, such as lighting conditions, vegetation density and type, terrain heterogeneity, and point cloud quality. These factors highlight the inherent challenges of classification tasks, stemming from both data uncertainties and model selection choices.

Future Directions

While deep learning models, including their adoption in tools like LiDAR-360, have recently achieved tremendous progress for classification tasks, this study highlights the value of lightweight and interpretable methods that require fewer computational resources and less labeled data. Deep learning models require large datasets, high computational power, and longer training times, which may not be suitable for all applications. In fact, there are several studies that show tree-based models, such as random forest and XGBoost outperform deep learning models in some applications (Grinsztajn *et alii*, 2022; Ullah *et alii*, 2023). Some recent studies have also shown that simplest threshold methods surprisingly can outperform machine/deep learning models for filtering vegetation out from colored point clouds (Štroner *et alii*, 2024). From the recent works on point cloud classification, one can see that the classification task is an art and can be very challenging. In the present study, it is shown that tree-based models offer a more practical approach for binary classification of photogrammetric 3D point cloud data, though multi-class classification and deep learning could be considered in future work to address more complex tasks.

Recent developments in deep learning for point cloud classification, such as PointNet, KPConv, and graph-based neural networks, provide promising avenues by directly exploiting both geometric and spectral information. These methods have achieved state-of-the-art performance in multi-class semantic segmentation tasks. However, they require large, annotated datasets, substantial computational resources, and often sacrifice interpretability. By contrast, the lightweight tree-based models applied in this study remain computationally efficient and practical in resource-constrained scenarios, while future work may also explore hybrid strategies that combine their interpretability with the representational power of deep learning.

CONCLUSIONS

This study underscores the importance of traditional and advanced machine learning techniques in improving vegetation filtering accuracy and efficiency. Further optimization with hyperparameters, experimentation with additional features, and consideration of diverse datasets have helped increase the model accuracy. The results show that tree-based machine learning models, in particular RF and XGBoost, outperform fixed threshold methods based on visible-band vegetation indices, such as GNDVI and VDVI. Acquiring reliable labeled data, however, remains a challenge for training machine learning models. Future research will focus on refining feature extraction methods, incorporating additional features, and exploring the integration of deep learning models to further enhance accuracy (Zhang *et alii*, 2023). The findings of this study contribute to the ongoing development of automated point classification systems, urban planning and conservation efforts, highlighting the potential for advanced machine learning methods to revolutionize this field.

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ABBREVIATIONS

AdaBoost: Adaptive Boosting
AUC: Area Under the Curve
CatBoost: Categorical Boosting
DT: Decision Tree
FPFH: Fast Point Feature Histogram
GNDVI: Green Normalized Difference Vegetation Index
GUI: Graphical User Interface
LiDAR: Light Detection And Ranging
MS: Multi-Spectral
NDVI: Normalized Difference Vegetation Index
NIR: Near-Infrared
NGRDI: Normalized Green–Red Difference Index
OA: Overall Accuracy
PCMB: Point Cloud Mean Brightness
RF: Random Forest
ROC: Receiver Operating Characteristic
RGB: Red-Green-Blue
SiRP: Superpoints in Random sampling and consensus Planes
UAV: Unmanned Aerial Vehicle
VDVI: Visible-band Difference Vegetation Index
XGBoost: eXtreme Gradient Boosting

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