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COMPARING LIDAR POINTCLOUDS USING C2C AND M3C2 ALGORITHMS IN DIVERSE FOREST ECOSYSTEMS

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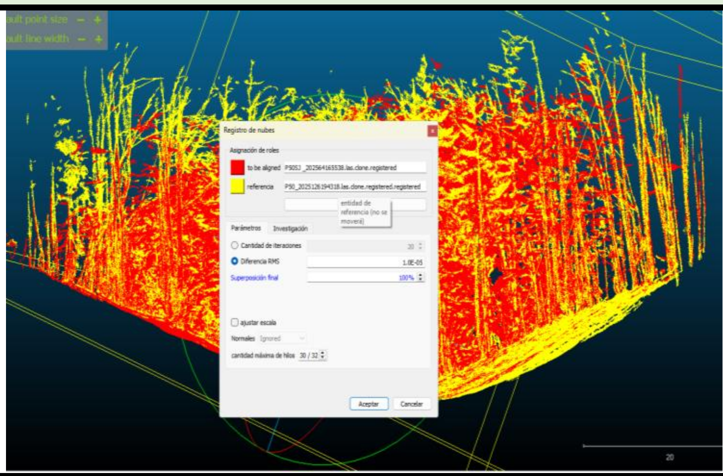
HIGHLIGHTS

- 50 circular forest plots were scanned with a FDJ Trion P1 in winter and spring.
- Point clouds were compared using C2C and M3C2 algorithms under Cloud Compare.
- M3C2 better reflects changes in multi-temporal point clouds.

GRAPHICAL ABSTRACT



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ABSTRACT

Recent advances in LiDAR technology have enabled detailed 3D characterization of forest structure, improving the accuracy of multi-temporal forest inventories. This study evaluates the consistency and sensitivity of Cloud-to-Cloud (C2C) and Multiscale Model-to-Model Cloud Comparison (M3C2), applied to data acquired in winter (leaf-off) and spring (leaf-on) in 50 forest plots. The methodology includes fine registration, cylindrical clipping, noise filtering, and comparison using CloudCompare software. The results show that both methods can offer consistent seasonal comparisons with minimal average differences (0.091 m for C2C and -0.004 m for M3C2). C2C achieved 100% coverage with an RMSE of 0.147 m, while M3C2 recorded slightly lower coverage at 98.4% and a higher value for the RMSE (0.297 m). These findings demonstrate that the choice of comparison method depends on the desired level of detail for monitoring forest growth and structural changes. M3C2 is more robust to variations in point density, occlusion, and noise.

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1. INTRODUCTION

In recent decades, the need to improve accuracy and efficiency in forest inventories has driven the adoption of new data acquisition technologies. The conventional methods, based on field measurements (like diameter at breast height and total tree height), are still being used, but limitations exist with respect to time, cost, and their ability to account for three-dimensional structural complexity of the forests [1,2].

LiDAR (Light Detection and Ranging) technology has made it possible to create high-density point clouds, allowing for a more detailed look at forest structure [3,4], which has significantly expanded its application in forest inventories [5,6]. In particular, mobile laser scanning (MLS), based on simultaneous localization and mapping (SLAM) algorithms, has emerged as an efficient alternative to terrestrial laser scanning (TLS), offering more flexibility and cutting down field acquisition time [7-9]. Despite these benefits, the use of MLS in multi-temporal forest inventories faces a major challenge due to seasonal phenological variability [10-13]. The differences between leaf-on and leaf-off conditions generate significant changes in the observable structure of the forest, affecting laser penetration and the distribution of returns [10,13]. During the leaf-on period, the presence of leaves and undergrowth vegetation increases occlusion and limits the visibility of structural elements such as trunks, while in leaf-off conditions, the detection of woody structures and the ground is favored [12,14]. These differences have a direct impact on point density and the geometric representation of the forest, which can lead to biases in the analysis if not properly addressed [10].

The analysis of multi-temporal point clouds needs effective tools to measure geometric differences between data sets. In this regard, tools like CloudCompare have facilitated the implementation of widely used comparison algorithms, such as Cloud-to-Cloud (C2C) and Multiscale Model-to-Model Cloud Comparison (M3C2) [15,16]. The C2C method uses nearest neighbor distance, making it simple and fast, but it can be affected by changes in point density and noise [17]. In contrast, the M3C2 method uses the surface normals and a spatial averaging approach, which makes it more robust to noise and other irregularities in the sampling of complex surfaces [16]. However, it is not trivial to determine which algorithm is the most appropriate. The performance of C2C and M3C2 may change according to different parameters such as surface roughness, point density, and noise level, which are closely related to the conditions of acquisition and the complexity of the forest scene [16]. In real field contexts, where conditions are not controlled, these variations can hinder the interpretation of the changes observed in multitemporal analyses. While various studies have evaluated the use of LiDAR in forest inventories, there is still a limited understanding of how seasonality affects the consistency of point cloud comparison methods under real-world conditions [13]. Previous studies have focused on investigating the effects of leaf-on and leaf-off conditions on estimating forest attributes [13,14], as well as the capability of MLS methods for characterizing forest structures [8,9]. Nevertheless, the effect of seasonality on the comparative assessment of algorithms, including C2C and M3C2, when repeated acquisition is carried out by SLAM systems, has not been sufficiently investigated.

In this context, the main objective of this research is to evaluate the consistency and differences in the results obtained through the C2C and M3C2 methods applied to point clouds acquired in forest plots during two contrasting seasons: winter (leaf-off) and spring (leaf-on).

Through this analysis, the aim is to quantify the impact of seasonality on the distance metrics derived from both algorithms and to analyze their sensitivity to variations in point density, noise, and occlusion. This study aims to provide a methodological basis for the selection of comparison techniques in multitemporal forest inventories, contributing to the improvement of structural monitoring reliability in forest ecosystems.

2. MATERIALS AND METHODS

2.1. Study area

The study was conducted in forest ecosystems located between Brașov and Poiana Braşov, Romania. Fifty circular plots with a radius of 9.80 m were established to capture a range of species, canopy structures, and terrain conditions. Plot centers were mapped using a Garmin GPSMAP 64sx receiver, and the radius was marked with tape solely to delimit the scanning area. Variations in tree density, slope, and understory vegetation were included in the selected plots, providing a representative sample of the local forest environment. **Table 1** shows the main descriptive parameters of the forest ecosystems in which the plots were established.

Table 1. Description of the forests stands used to place the plots

Parameter	Mean ± Standard Deviation	Range
Stand age (years)	112 ± 4.0	125
Ground slope (degrees)	21.2 ± 0.99	34
Elevation (m)	715.5 ± 135.84	785
Canopy cover	0.67 ± 0.02	0.59
Stand density (trees/ha)	410 ± 152.57	633.33

Notes: [a] - note on the data; [1] - note on the data.

Tree species in the forest ecosystems selected for plot establishment included European beech (*Fagus sylvatica*), Norway spruce (*Picea abies*), Silver fir (*Abies alba*), Sessile oak (*Quercus petraea*), Scots pine (*Pinus sylvestris*), and European hornbeam (*Carpinus betulus*).

2.2. Data acquisition

Point cloud data were collected using the FJD Trion P1 mobile laser scanner, a lightweight scanner weighing 1 kg with a 360° × 59° field of view and a precision of 2 cm [18]. The scanner has a scanning speed of up to 200,000 points per second using SLAM technology and produces 3D point cloud models in a variety of standard formats such as .LAS and .PLY [18].

Each plot was scanned following an elliptical trajectory. The plot was divided conceptually into four quadrants, and the operator walked along elliptical paths in each section, keeping the scanner pointed toward the plot center. To ensure complete coverage, the scanning process extended approximately 5 m beyond the edge of each plot. The data were collected during two campaigns: winter (December 12–20, 2024) and spring (May 12–22, 2025), to capture seasonal differences.

Figure 1. Study Area and the use of FJD Trion Model P1 Platform. Legend: The study area seasons: (1) winter, (2) spring, (3) summer, (4) autumn. The platform: FJD Trion Model P1 scanner (1), scanner assembly (2), scanner App screen (3), scanning with the platform (4), and a scanning process (5).

2.3. Data processing

Point clouds were processed using the CloudCompare software [15]. The winter point clouds were used as the reference, and the spring point clouds as the compared datasets. Both clouds were aligned and cropped using a 10 m radius cylinder centered on the reference tree to ensure identical spatial coverage. Point alignment was done using the fine registration tool available in the main toolbar of CloudCompare ("fine registration of approximately aligned entities"), while both point clouds were selected. This tool is based on the Iterative Closest Point algorithm (ICP), which automatically refines the alignment by minimizing the distance between the two datasets until a stable solution is reached [19]. The cropping process of the aligned points was done using a cylindrical clipping approach. First, a cylinder was created using the "primitive factory" tool, with a radius of 10 m and a height of 50 m to cover all the study area. Both point clouds and the cylinder were then selected simultaneously, and the "segment" tool was used with the "activate polyline selection" option to define the plot edges. After selecting the required area, the segmentation was applied to both point clouds at the same time by confirm segmentation (enter), getting two datasets with identical shape and size. Noise filtering was applied to remove stray points and improve data quality. To do so, the SOR (Statistical Outlier Removal) filter was applied to both point clouds after selecting them simultaneously. This filter removes isolated points by evaluating the distance between each point and its neighboring points, eliminating those that deviate significantly from the local point distribution. As a result, new point clouds with reduced noise and improved data quality were obtained [20]. Then, two methods were applied to compare the point clouds of the different seasons, as shown in **Figure 2**.

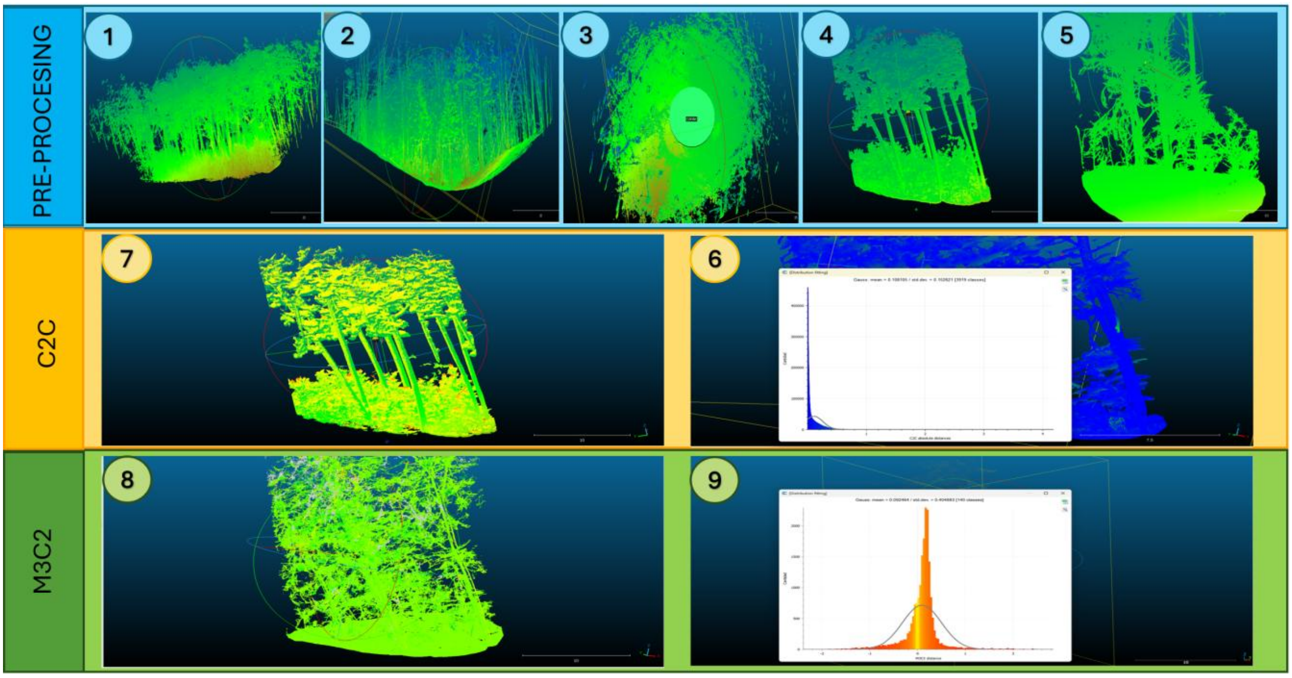

Figure 2. Description of the point cloud comparison workflow. Legend: The pre-processing stage includes (1) point cloud import, (2) registration of winter and spring datasets, (3) cylindrical clipping for plot delimitation, (4) simultaneous clipping of both datasets, and (5) noise filtering. The comparison stage includes C2C distance computation and Gaussian fitting of C2C distances (6,7), followed by M3C2 distance computation and Gaussian fitting of M3C2 distances (8,9). Note: The winter dataset was used as reference in both methods.

In the Cloud-to-Cloud (C2C) approach, distances between nearest neighbor points were considered. Metrics obtained from this approach include the mean, standard deviation, RMSE, total core points, coverage percentage, and bin distribution. The mean distance shows the average displacement between the winter and spring clouds, while the standard deviation reflects how much individual points differ from this average. RMSE gives an overall measure of differences. Core points are those with valid nearest neighbors, and coverage percentage indicates the proportion of points included in the comparison. Bin distribution summarizes the distances, often used for histogram analysis or fitting. Distances were calculated using CloudCompare's k-d tree search on the aligned and cropped clouds, providing a simple and reliable point-based comparison of cloud geometry [16].

In the Multiscale Model-to-Model Cloud Comparison (M3C2), surface normals and spatial averaging were considered to obtain comparable metrics to the C2C approach. These metrics include the number of points with valid distance calculations. The distances were computed along the normal vectors from the points, and the values were averaged within the neighborhood. The mean value represents the average change between winter and spring clouds, while the standard deviation represents the local variation. The RMSE is used as an overall value for the differences. The core points are those points where the distances were valid, while the valid points are those points where the neighborhood requirements are met. The coverage percentage is the proportion of the cloud where the distances were valid, while the bin distribution is used for the distances. The normal scale and the projection scale are used to determine the neighborhood used for the normal estimation. This method is used to obtain robust metrics that can be compared with those from the C2C method [16].

These approaches enable a quantitative evaluation of seasonal changes in forest structures from mobile LiDAR scans. The C2C method provides a fast and precise point-based comparison that is sensible to small differences, while M3C2 takes into consideration surface orientation and averaging, making it more robust to noise and variations in point density. Therefore, these two techniques provide a comprehensive analysis of seasonal changes in tree structures, density, and other features in a forest ecosystem, as they are capable of accurately and reliably measuring seasonal changes using both point-based displacement and surface-based change analysis.

2.4. Data analysis

Statistical analysis was implemented using simple formulae in Microsoft Excel [21]. For each parameter, namely the mean distance, standard deviation of the mean distance, coverage and RMSE of point cloud alignment, the sample-level mean, median, standard deviation, minimum, maximum and range values were preliminary computed. Robust statistical tests (Shapiro-Wilk) were also implemented to check for normality of the data. The statistical analysis was implemented in Microsoft Excel which was equipped with Real Statistics add-in [22].

3. RESULTS

3.1. Cloud to Cloud Comparison (C2C)

The results of the Cloud-to-Cloud (C2C) comparison are summarized in **Table 2**. The mean distance between the winter and spring point clouds was 0.091 m, with the standard deviation of the distances at 0.027 m. This shows that the points were closely aligned. The standard deviation of the distances, which is an indicator of the variability in the distances between the points, was on average 0.115 m, with the higher standard deviation at 0.038 m. This shows that there were some local variations in the geometry of the point cloud. The coverage was also 100%, indicating that the entire study area was well represented. The RMSE for the alignment of the point clouds was 0.147 m on average. This is an indicator of the magnitude of the deviation between the two point clouds. The results provide an overview of the changes between the winter, and the spring point clouds, indicating that the changes were low.

Table 2. Summary statistics of the C2C point cloud comparison

Parameter	Mean ± Standard Deviation	Minimum value	Maximum value	Range
Distance (m)[1]	0.091 ± 0.027	0.036	0.201	0.165
Standard deviation of distance (m)[1]	0.115 ± 0.038	0.051	0.290	0.239
Coverage (%)[1]	100.0 ± 0.0	100.0	100.0	0.000
RMSE of point cloud alignment (m)[1]	0.147 ± 0.045	0.063	0.353	0.290

Notes: [1] – variable for which normality assumption was violated.

All core points (CP) and valid points (VP) were used in the C2C comparison, with identical values for both parameters across all plots, ranging from approximately 11.6 to 23.2 million points.

Median values for distance, standard deviation, coverage, and RMSE were slightly lower than the mean values (see **Table 2**).

3.2. Model to Model Cloud Comparison (M3C2)

The results of the Multiscale Model-to-Model Cloud Comparison (M3C2) are summarized in **Table 3**. The mean distance between the winter and spring point clouds was -0.004 m, with a standard deviation of 0.035 m, showing that on average, no systematic displacement was recorded between the two datasets. The standard deviation of distance, on the other hand, showed a higher variability, with a mean value of 0.295 m and a standard deviation of 0.070 m. This value represents local variations in surface geometry. Coverage was high across all plots, with an average of 98.41%, showing that most of the plots' area was included in the comparison. The RMSE had a mean value of 0.297 m, showing a general level of difference between the two point clouds. Overall, the results show small average changes but some variability at the local scale.

Table 3. Summary statistics of the M3C2 point cloud comparison

Parameter	Mean ± Standard Deviation	Minimum value	Maximum value	Range
Distance (m) [1]	-0.004 ± 0.035	0.151	0.435	0.284
Standard deviation of distance (m)	0.295 ± 0.070	0.151	0.435	0.283
Coverage (%)[1]	98.41 ± 1.448	92.56	99.90	7.34
RMSE of point cloud alignment (m)	0.297 ± 0.071	0.063	0.353	0.290

Notes: [1] – variable for which normality assumption was violated.

The core points (CP) and valid points (VP) used in the M3C2 comparison ranged from approximately 9.57 to 22.57 million points (CP) and from about 9.56 to 21.95 million points (VP) in the datasets. Median values for distance and coverage were -0.0036 m and 98.83%, respectively (see **Table 3**).

4. DISCUSSION

The results show that the C2C and M3C2 methods allow for consistent comparison of point clouds from different seasons, with low average differences. This indicates that, despite the seasonal variability in forest structure, the geometric comparisons of point clouds acquired with MLS are reliable, which is consistent with previous studies on cloud comparison applications in forest inventories [16,17]. However, the methods differ in how they capture local variability. C2C provides a uniform representation of the point cloud, which can be useful for general assessments, but it limits the detection of small local differences. In contrast, M3C2 shows a higher standard deviation due to its capacity to analyze the changes on the forest surface in greater detail [16]. This suggests that the choice of method should consider the objective of the analysis: C2C for a global and quick view of changes, and M3C2 to identify finer local variations. Point coverage and RMSE also show that the M3C2 method is more sensitive to point density and other issues in the point cloud, such as gaps or occlusions, compared to the C2C method. These results confirm that factors such as density, occlusion, and noise affect the interpretation of change metrics, and that M3C2 offers a more robust approach to these variations [8,10,13].

Among the limitations of the study is the coverage of a limited set of forest ecosystems and only two seasons, which restricts the generalization of the findings to other ecosystems and acquisition periods. Moreover, although MLS allowed for the collection of consistent data, local variations in density, occlusion, and noise could have influenced the results. Lastly, the results underscore the significance of selecting the method of comparison based on the level of detail required and the nature of the point cloud. Future studies could include other types of forest, different seasons of the year, and several acquisitions to assess the robustness of C2C and M3C2 approaches for different acquisition conditions and point cloud densities, which could improve the use of these methods for multi-temporal forest inventories [10,14].

5. CONCLUSIONS

The two methods, C2C and M3C2, are consistent in comparing point clouds obtained in different seasons, enabling the assessment of structural changes in forests. C2C offers a general and uniform representation of the point cloud, while M3C2 represents local variations in greater detail. It can be inferred that the choice of method depends on the objective of the analysis. Point density, occlusion, and noise affect the accuracy of the comparison metrics. It is evident that the M3C2 is more robust to these factors. Some limitations of the study include the fact that it is applicable to only to a limited set of forest ecosystems and two seasons. It is recommended to extend the scope to other ecosystems and seasons. The results provide a methodological basis for the selection of comparison techniques in multi-temporal forest inventories, contributing to improving the reliability in the structural monitoring of forests.

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EXTENDED ABSTRACT

Introducere: *Progresele recente în tehnologia LiDAR au permis caracterizarea detaliată în trei dimensiuni a structurii pădurii, îmbunătățind precizia inventarelor forestiere multi-temporale. Acest studiu evaluează consistența și precizia a două metode de comparare a norilor de puncte, Cloud-to-Cloud (C2C) și Multiscale Model-to-Model Cloud Comparison (M3C2), aplicate norilor de puncte colectați iarna (repaus vegetativ) și primăvara (sezon de vegetație timpuriu) în 50 de suprafețe de probă amplasate lângă Brașov, România.*

Materiale şi metode: *Metodologia include înregistrarea fină, decuparea norilor de puncte folosind un corp de formă cilindrică, filtrarea pentru înlăturarea punctelor aberante și compararea norilor de puncte utilizând tehnicile C2C și M3C2 în programul CloudCompare.*

Rezultate şi discuții: *Rezultatele arată că ambele metode pot oferi comparări sezoniere consistente, cu diferențe medii minime, având valori de 0,091 m pentru C2C și -0,004 m pentru M3C2. C2C a atins o acoperire de 100% cu o valoare RMSE de 0,147 m, reprezentând o metodă de evaluare uniformă a norilor de puncte, în timp ce M3C2 a înregistrat o acoperire ușor mai scăzută, de 98,4%, și o valoare mai mare a RMSE, de 0,297 m, demonstrându-și sensibilitatea la schimbările locale mai fine. Abaterea standard confirmă faptul că rezultatele M3C2 au fost mai sensibile la modificările locale, în timp ce rezultatele C2C oferă o evaluare mai generalizată.*

Concluzii: *Aceste constatări demonstrează că alegerea metodei de comparare depinde de nivelul de detaliu dorit pentru monitorizarea creșterii pădurii și a modificărilor structurale. M3C2 este mai robust la variațiile de densitate a punctelor, ocluzie și zgomot. Studiul oferă o bază metodologică pentru aplicarea tehnicilor de comparare multi-temporală bazate pe LiDAR în evaluarea creșterii pădurilor și monitorizarea structurală.*

Cuvinte cheie: *LiDAR, multi-temporal, comparare, creștere, pădure.*

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