Comparative analysis of high-resolution UAV photogrammetry and terrestrial laser scanning for detecting and quantifying urban vegetation changes

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Abstract

Extensive urban expansion has significantly impacted green spaces leading to the degradation of urban vegetation. Hence, monitoring variations in vegetation using remote sensing methods is essential. However, 2D remote sensing methods have drawbacks as they lack vertical structures in urban areas, shadows caused by buildings, cloud cover and require substantial preprocessing to encounter these limitations. This study focuses on identifying and quantifying changes in Malminkartano, Helsinki during the leaf-off and leaf-on seasons for the year 2022. The research utilized terrestrial laser scanning (TLS) and UAV-photogrammetry datasets for change detection in urban vegetation and point cloud-based algorithms for seasonal variations such as C2C, C2M, and M3C2. Notably, many existing methods involve rasterizing point clouds as DSM which results in the loss of significant information. Therefore, this paper investigates the potential of utilized datasets in detecting changes directly on point clouds. However, there are uncertainties associated with point clouds including data registration, point density, weather effects, and misalignment therefore this study aims to take these limitations into account. The results from TLS and UAV-photogrammetry demonstrated competence in identifying the maximum growth of urban vegetation up to 2.0 m and 2.8 m respectively. However, the accuracy assessment of data corresponded to a 4 cm difference in both datasets at a 95% confidence threshold and potential vertical height differences accounted for the difference in change detection. This study underscores data processing uncertainties associated with registration, vertical height, and data noise and proposes the integration of point clouds with different sensors for completeness and improved change detection in urban vegetation.

1. Introduction

Recent urbanization trends are densifying urban areas and impacting urban green spaces (UGS). It has been observed that urbanization directly resulted in the lack and decrease of the UGS over the past few decades.(Haaland & van den Bosch, 2015).Moreover, the deterioration of UGS is impacting ecosystem services such as air quality, noise pollution, temperature flow, and cultural services for residential well-being. (Bolund & Hunhammar, 1999; Cortinovis & Geneletti, 2019).Urban vegetation is mainly less explored(Bressane et al., 2024), and very limited research is done in this domain compared to the forests. The potential reason to that is that urban areas are usually complex in structure having mixed vegetation and tree species makes the process of mapping and monitoring more demanding and time-consuming.(M. Wang et al., 2022; Zhao et al., 2021)

The City of Helsinki is expanding drastically, and greenhouse gas (GHG) emissions increased by 12% in the year 2022 compared to previous years. Furthermore, Finnish Meteorological Institute (FMI) data showed that from year 2010-2020, the average temperature in Helsinki rose from 4.3˚C to 8.0˚C (*Statistics from 1961 Onwards - Finnish Meteorological Institute*, n.d.).Considering urban vegetation one of the important sources in reducing urban temperature and GHG emissions, there is a need to monitor the vegetation changes with up-to-date remote sensing data (Kafy et al., 2022). Two dimensional (2D) remote sensing datasets such as satellite or aerial imagery can be utilized in vegetation change detection, though these sources are prone to atmospheric and illumination conditions, limited viewpoint angles and potential radiometric distortions in urban areas necessitating reasonable computational time to mitigate these problems (Kharroubi et al., 2022). However, the open-source point cloud data provided by the National Land Survey, Finland, and the City of Helsinki is available till 2020 and the resolution of the data is coarser limiting the detailed vegetation analysis to the urban tree level.

Considering severe climate changes and lack of open-source-data availability the research aims to utilize the three-dimensional (3D) point clouds acquired from Terrestrial laser scanning (TLS) and high-resolution UAV photogrammetry to examine the changes in urban vegetation. The purpose of this research is to examine the potential of TLS and UAV-photogrammetry in the identification and quantification of vegetation changes and investigate the challenges associated with both data sources. Moreover, both these sources have been utilized in many applications of change detection as they can generate very dense and high-resolution point clouds(Fraser et al., 2016; Kaasalainen et al., 2014) enabling direct change detection on 3D point clouds. However, uncertainties are still associated with TLS and UAV-photogrammetry that arose due to sensor-specific limitations such as viewing angle and scene geometries, point cloud accuracy, data registration errors, vertical height distribution, and some common issues such as data noise, point density, and scale differences.(Aicardi et al., 2016; Gruszczyński et al., 2017; Q. Wang et al., 2020)

This article concentrates on implementing the point cloud-based algorithms to identify and display changes directly in 3D. Therefore, widely used algorithms including cloud-to-cloud (C2C), Cloud-to-mesh (C2M), and Multiscale Model to Model Cloud Comparison (M3C2) will be implemented to detect changes in vegetation. Noteworthy, a framework will be established to quantify significant and real changes from overall changes impacted by sensor-specific, atmospheric, and data acquisition uncertainties.

The objective of this research will be accomplished by developing a framework that can be applied to multitemporal point clouds for change detection in vegetation. Moreover, to propose the potential solutions to challenges that arise during this analysis and to answer a) investigate the challenges associated with multitemporal datasets to make the datasets suitable for change detection b) identification and quantification of vegetation cover changes and c) implementing a process to segregate the significant changes from the overall changes considering the error budget of datasets.

2. Data acquisition and processing

2.1 TLS and UAV-photogrammetry data acquisition

The study area selected for this article is an urban area called Malminkartano in the northwest region of Helsinki, Finland. The total site area is 7827 m² and it is a green developing area with a plan to build houses for 1300 residents in this district of Helsinki, according to the City of Helsinki. The study area for this article is presented in Figure 1 below marked in red rectangle. TLS point cloud data was acquired by Leica RTC 360 hardware with the capability to acquire 2 million points per second using the Time-of-flight (ToF) principle. Similarly, two UAVs were utilized to acquire the images of the study area. Geodrone-6 with resolution of 7952*5304 pixels was utilized to generate the 3D point clouds from images using Agisoft Metashape software and imagery acquired by DJI Mavic-3 with resolution of 5272*3948 served as ground truth for results verification. Noteworthy, the DJI Mavic-3 was flown at low flight altitude to acquire detailed images of the study area. Two multi-temporal datasets were acquired over the study area during leaf-off (TLS-1 and UAV-1) and leaf-on seasons (TLS-2 and UAV-2) in 2022.Moreover, UAV-1 and UAV-2 datasets were acquired at relatively high altitudes up to 124m flight altitude. In contrast, TLS data acquisition ranged from few meters to tens of meters, depending upon the scan stations position and proximity of the objects. This variation in TLS projects might led to non-uniform point density whereas generate more uniform point densities, influenced by the higher altitudes, and used camera systems.

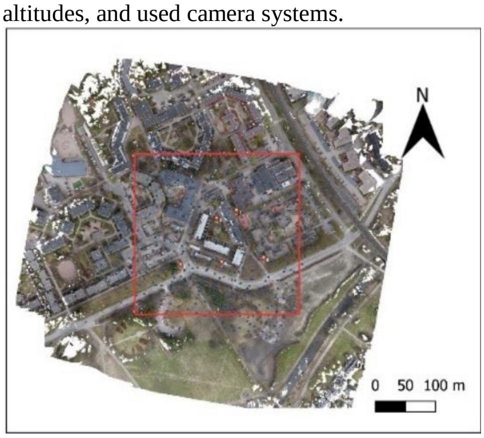

Figure 1. Illustration of Study area Malminkartano, Helsinki

2.2 Point cloud data processing.

TLS and UAV point clouds were processed individually as both involved different techniques for data processing. To make the datasets comparable, TLS datasets were subsampled by implementing space-sampling algorithm in CloudCompare software using 1 cm minimum distance between points. However, UAV datasets were decimated to 1cm as a part of photogrammetric workflow in Agisoft metashape. Furthermore, both datasets were segmented to include only a common study area, and points clouds were cleaned manually. To encounter, isolated points, occlusions and data noise dataset went through statistical outlier removal process in cloud compare.

The next step involved the registration of datasets in a common coordinate system in GK25FIN (EPSG:3879) whereas data registration in urban areas with the existence of trees and human activity made this process challenging. However, TLS and UAV-1 were already georeferenced in the local coordinate system however georeferencing was not suitable for accurate change detection. Therefore, the registration processing is carried out in two steps. TLS-1 was selected as a reference dataset and other point clouds were registered w.r.t this dataset. Initially, buildings were segmented from all the datasets and registered using the Iterative Closest Point (ICP) algorithm w.r.t to TLS-1 and the results indicated satisfactory registration with RMSE of 2 cm for TLS and 1 cm for UAV building clouds. Then, the translation matrix of registered building clouds was applied to corresponding original datasets to ensure proper alignment. The specifications of both utilized datasets are presented in the Table 1 below.

Parameters	**TLS-1**	**TLS-2**	**UAV-1**	**UAV-2**
No. of scans	51	58	515 images	241 images
Acquisition dates	03/05/2022-05/05/2022	15/08/2022	09/05/2022	12/09/2022
Original No. of points	876,705,765	1,824,878,835	62,860,780	61,781,628
Sub-sampled 1cm	93,379,573	163,629,124	N/A	N/A
ICP RMSE w.r.t TLS-1	N/A	0.1649 m	0.1263 m	0.1489 m

Table 1. TLS and UAV point cloud parameters.

Finally, the integration of original datasets is performed by merging TLS-1 with UAV-1 and TLS-2 with UAV-2 using the static objects in the point clouds such as buildings. Moreover, the datasets went through a segmentation process and all the objects except vegetation were removed from the datasets for detection of changes in urban vegetation.

2.3 Change detection using point cloud and mesh-based algorithms.

Three different methodologies were employed to detect changes in urban vegetation including C2C, C2M and M3C2. TLS-1, UAV-1 and merged-1 were used as the reference datasets in all the methods and TLS-2, UAV-2 and merged-2 were considered as compared datasets. Significantly, C2C and C2M have common parameters therefore similar values were used for these parameters to keep the workflow consistent and investigate the impact of the parameters on change detection. Therefore, higher octree levels were selected for both these methods with a value of 9 to ensure faster distance computation. C2M algorithm require a mesh to be used as reference dataset, therefore three mesh models were created for leaf-off season datasets i.e. (TLS1, UAV-1, merged-1) and before computing mesh models, normal were calculated for these datasets as a requirement of method in +Z direction using triangulation local model.

M3C2 has completely different parameters to detect the changes between reference and compared clouds. It requires categorizing the clouds as cloud 1 and cloud 2 where compared clouds were considered as cloud 1 and reference cloud as cloud 2 in this case. Moreover, compared datasets (cloud 2) were also utilized as core points to perform the computations relative to the reference cloud. The M3C2 algorithm also requires normal computation as a part of the change detection process unlike C2M where mesh normals are calculated separately. Noteworthy, M3C2 is sensitive to model parameters as selection of model parameters influence the results of change detection. The selection of normal and projection diameters was carefully considered as smaller radii would lead to amplify the impact of noise and surface roughness while larger radii would minimize this impact with increase in computational costs. Therefore, the normal computation was performed using the multiscale method in the -Z direction using 10 cm normal and projection diameter. These three techniques were implemented on TLS, UAV-photogrammetry, and integrated datasets to detect the changes in compared clouds relative to reference clouds.

2.4 Quantification of detected changes using threshold

To quantify the changes detected by utilized algorithms necessities to consider uncertainties that could potentially impact the results. Moreover, wind condition, point density, registration differences and data noise could impact the results and all these factors can lead to false changes that do not reflect actual changes. For instance, moving trees due to impact of wind would not be able to be captured properly by UAV-photogrammetry. When these trees compared with the TLS trees then change detection methods could consider these differences as changes which are not actual changes. Thus, these factors necessitate the development of a threshold that could consider these uncertainties and quantify the actual changes without the influence of these uncertainties. The threshold was determined by implementing a parametric approach developed by (Lague et al., 2013) which calculated the threshold at 95% confidence level. This estimation involves the surface roughness and registration error measured along the normal direction. The following equation is utilized to determine the value of the threshold.

$$LOD_{95\%}=\pm 1.96 * \left[\sqrt{\frac{\sigma_1(d)^2}{n_1}+\frac{\sigma_2(d)^2}{n_2}} + \text{registration error.}\right] \quad (1)$$

Where, σ_1 and σ_2 is plane fitting variance computed on two sub-clouds of diameter d. n_1 and n_2 are the number of points of sub-clouds. The value of 1.96 was used in $LOD_{95\%}$ in equation 1 presents the threshold for a corresponding dataset and it is the z-statistics at the 95% confidence level. To achieve this, two sub-clouds were selected from stable areas with no change during both seasons sharing a common area. The technique considered the point density, surface roughness, and registration differences into account while calculating the threshold. The plane fitting $\sigma(d)^2$ variance dependent upon the data noise and surface roughness was calculated for both the sub-clouds with the constant diameter.

3. Results

3.1 TLS-based change detection results.

TLS based change detection results illustrated in Figure 2-4 revealed that all the utilized method detected the changes in the urban vegetation up to approximately 2.0 meters. Moreover, all the methods visually identified reasonable changes in shrubbery, ground grass, and seasonal growth of the vegetation. However, C2C and C2M method were able to identify the majority of changes up to 0.5 meters and M3C2 results showed the detected changes in an extended range of distances. Mainly, C2C and C2M identify those changes above 0.5 meters that are caused by human activities, wind impact, and seasonal growth in birch trees while most of the changes identified by the M3C2 method were up to 1.388 meters with very few changes occurring after this range.

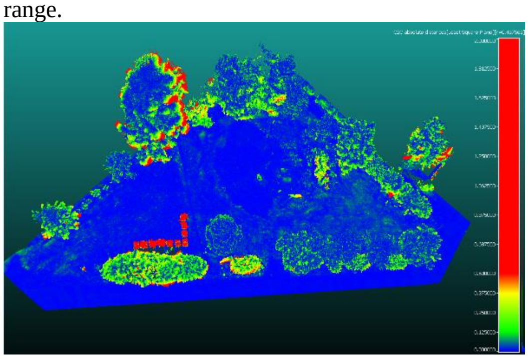

Figure 2. TLS-based change detection using the C2C method.

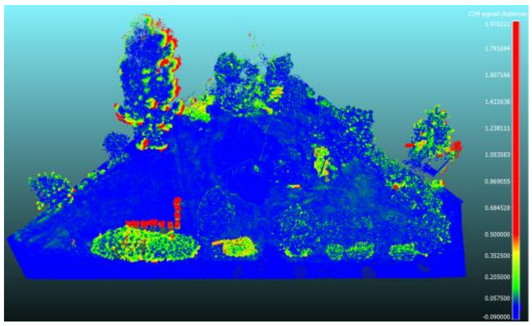

Figure 3. TLS-based change detection using the C2M method.

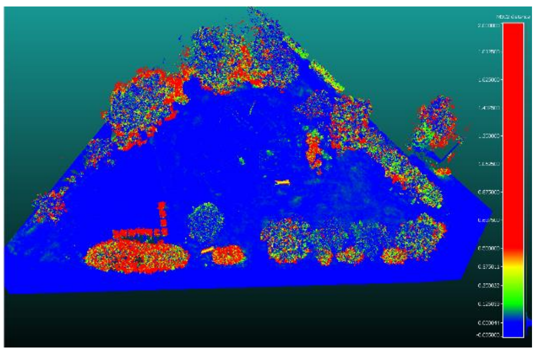

Figure 4. TLS-based change detection using the M3C2 method.

3.2 UAV-photogrammetry-based change detection.

The results of UAV-photogrammetry showed a reasonable difference in detected changes up to 2.8 meters presented in Figure 5-7, whereas changes in TLS were limited to 2.0 meters.

This also corresponds to the fact of different data acquisition techniques of UAV and TLS and UAV data acquisition dates as well. UAV data was acquired later than the TLS as presented in table 1**.** Moreover, it is evident from the results that C2C and C2M identified reasonable changes above the range of 0.5 meters in shrubbery and birch trees. However, it is a well-known fact that during the leaf-off season, limited leaves and foliage in urban vegetation results in incomplete capturing of the vegetation structure using UAV photogrammetry. Due to tree movement and lack of greenery led to lower confidence in the UAV datasets. On comparing leaf-off dataset with leaf-on, the absence of sufficient greenery and insufficient representation of actual vegetation in leaf-off dataset resulted in majority of the changes above 0.5 meters. Comparably to TLS case study, M3C2 showed the same pattern in this case by detecting the changes in an extended range and clearly identified the changes. M3C2 results illustrated the detected changes approximately to 2.38 meters in shrubbery and trees as well.

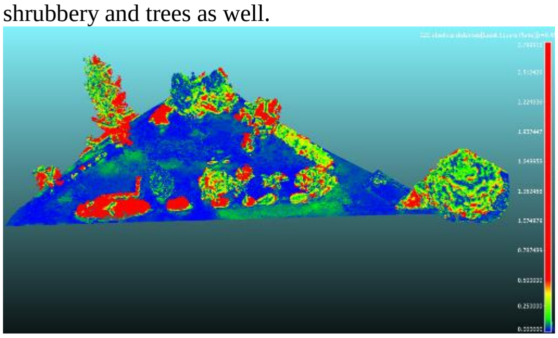

Figure 5. UAV-based change detection using the C2C method.

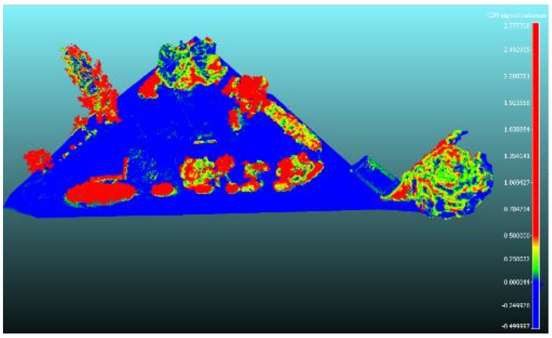

Figure 6. UAV-based change detection using the C2M method.

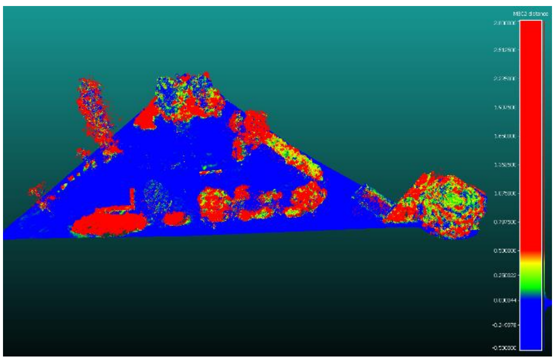

Figure 7. UAV-based change detection using the M3C2 method.

3.3 TLS and UAV integration-based change detection

Integrated dataset-based change detection results were in line with the UAV-photogrammetry based change detection statistically. The changes detected by integrated dataset presented in Figure 8-10 indicated that the all the methods detected the changes up to 2.8 meters, however the visual examination of the results showed an improved representation of detected changes and vegetation structure compared to above both case studies. Interestingly, C2C method exhibited similar pattern to the results observed in TLS case study where maximum changes were detected up to 0.5 meters. However, C2C method identified reasonable changes exceeding 0.5 meters in the case of UAV based change detection. Despite this, when the datasets were integrated, C2C detected changes were limited to 0.5 meters suggesting that C2C showed efficiency in indicating changes in shorter distance ranges. Moreover, C2M and M3C2 methods identified sufficient changes above 0.5 meters and the efficacy of these method in detecting changes in longer range could be possible due the involvement of normal computation during the change detection process which was not the case in C2C method.

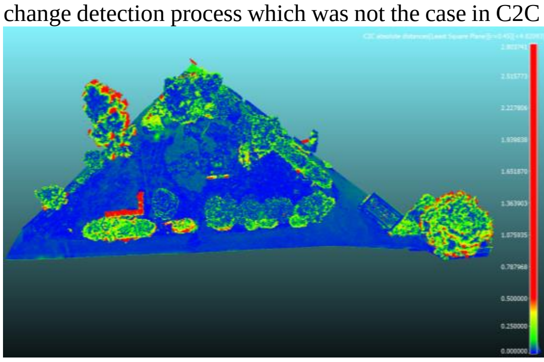

Figure 8. Integration-based change detection using C2C method.

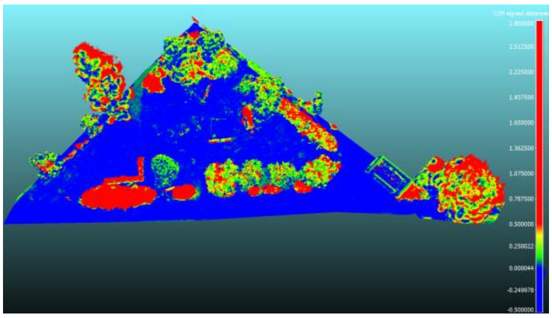

Figure 9. Integration-based change detection using the C2M method.

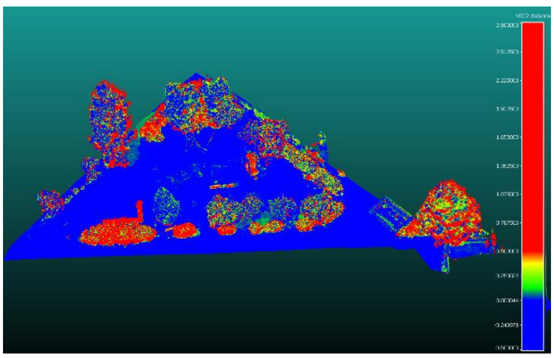

Figure 10. Integration-based change detection using the M3C2 method.

3.4 Accuracy assessment of detected changes by implementing threshold at 95% confidence level.

The value of the threshold at a 95% confidence level was estimated for both UAV and TLS datasets. The registration error for unchanged multi-temporal TLS and UAV sub-clouds was determined as 0.0204 meters and 0.0198 meters respectively. The value of $\sigma_1(d)^2$ and $\sigma_2(d)^2$ for both datasets were estimated as 0.002426 m, 0.002379m for TLS and 0.002459 m, 0.002881 m for UAV dataset. Finally, the estimated values of threshold for both datasets were approximately similar with 0.04017 m for TLS and 0.03889 m for UAV datasets. This approximately 4 cm threshold was implemented to segregate the significant changes from overall changes. Therefore, changes below 4 cm were not considered statistically, and changes identified above 4 cm were taken into account for statistical analysis.

3.5 Statistical analysis of change detection

3.5.1 TLS-based statistical change detection analysis

To estimate the statistically significant changes from overall changes. pre-determined threshold value of 0.04017 m for TLS dataset was applied and changes above this value were considered as statistically significant changes. The results are showed in Figure 11-13 below. Statistical findings affirmed the visually examined results as C2C and C2M detected 95.8% and 96.2% of the changes within the range of 0-0.5 m. Moreover. only 4.2% and 3.8% of the changes occurred after this range by C2C and C2M methods. These results suggested that C2C and C2M methods were able to identify changes in a short range of distances. In comparison, 74.9% of significant changes were occurred in the range of 0-0.5m by M3C2 method and overall changes identified up to 1 meter by M3C2 were 90.4% leaving only 9.6% changes after 1 meter.

In this study, the results revealed that the major changes in urban vegetation between leaf-off and leaf-on season were typically up to 50 cm with changes exceeding this range were relatively minor.

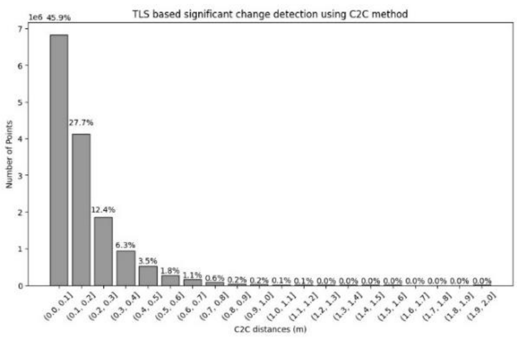

Figure 11. Statistical analysis of TLS-based change detection using C2C method.

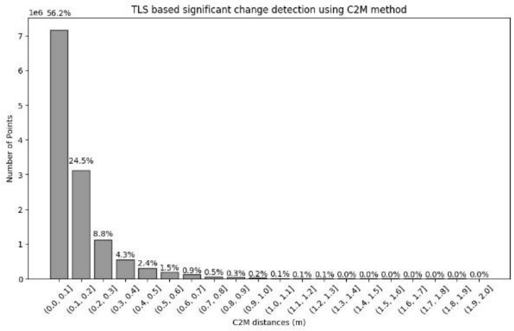

Figure 12. Statistical analysis of TLS-based change detection using C2M method.

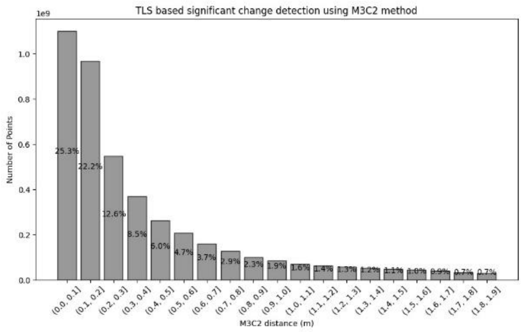

Figure 13. Statistical analysis of TLS-based change detection using the M3C2 method.

3.5.2 UAV-based statistical change detection analysis

UAV-based statistically significant changes were quantified by using a threshold value of 0.03889 meters determined for UAV point cloud. UAV-based change detection results showed a distinct pattern compared to TLS as can be seen in 14-16. The detected changes were estimated up to 2.8 meters, unlike TLS where most changes were up to 0.5 meters. The change detection results indicated maximum changes to the range of 1 meter with 93.03% by C2C, 87.29% by C2M and 74.32% by M3C2 method. However, C2C estimated a very minor percentage of changes exceeding 1 meter while C2M and M3C2 estimated 12.71% and 25.64% above 1 meter respectively. These results suggested the efficacy of C2M and M2C3 methods in detecting changes in a wider range of distances. Remarkably, M3C2 showed the highest percentage of changes in the range of 2.6-2.8 meters with 7.69% changes identified in this range whereas C2C and C2M indicated below 1% changes in this range. This difference affirmed the point, discussed in section 3.2 related to technical limitation of UAV methods and absence of greenery in leaf-off season which resulted in changes being detected in a higher range.

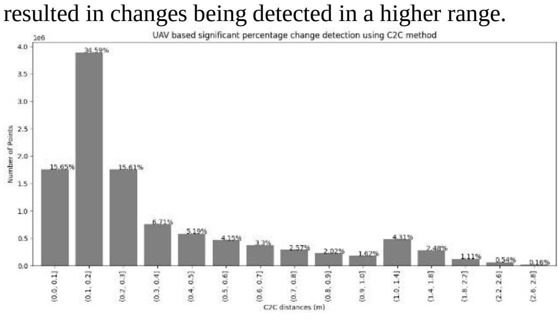

Figure 14. Statistical analysis of UAV-based change detection using the C2C method.

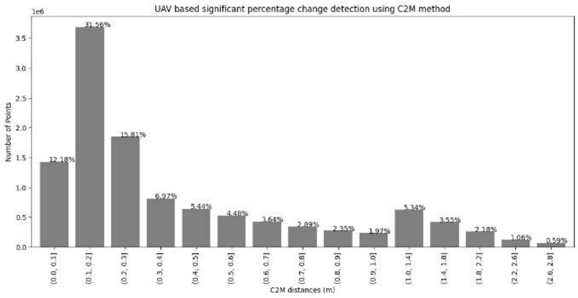

Figure 15. Statistical analysis of UAV-based change detection using C2M method.

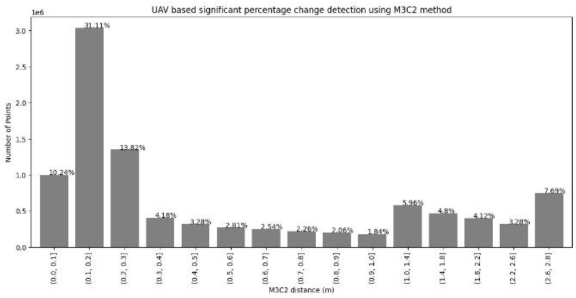

Figure 16. Statistical analysis of UAV-based change detection using M3C2 method.

3.5.3 Integration-based statistical change detection analysis

To assess the statistically significant changes, maximum value of threshold determined for TLS dataset was implemented and changes above 0.04017 meters were considered as significant changes. The results presented in Figure 17-19 below were in line with the statistical results of TLS-based change detection**.** Moreover, C2C estimated 97.05% changes in the range of 0-0.5 meters, C2M 89.90%, and M3C2 showed 78.10% in the given range. The results suggested that data integration dominated the TLS-based detected changes over UAV-based change detection. However, the M3C2 method estimated 21.90% changes above 0.5 meters showing efficacy in detecting changes in a wider range.

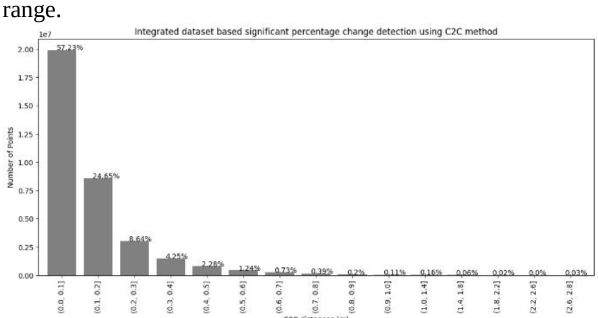

Figure 17. Statistical analysis of integration-based change detection using C2C method.

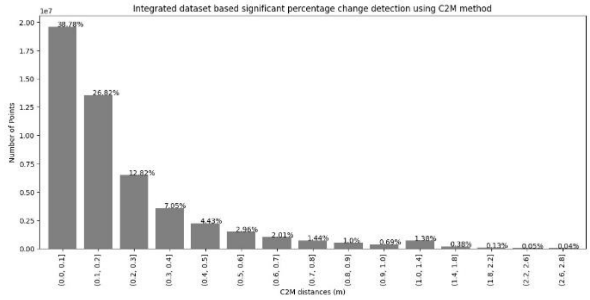

Figure 18. Statistical analysis of integration-based change detection using C2M method.

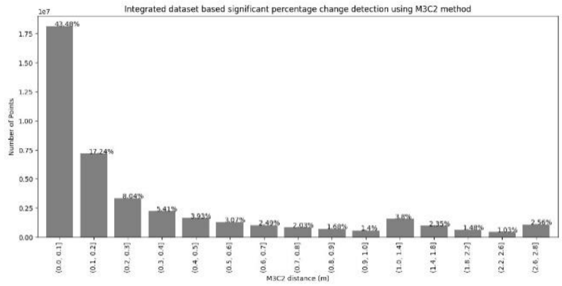

Figure 19. Statistical analysis of integration-based change detection using M3C2 method.

4. Discussion

4.1 Effect of varying point densities on change detection

The influence of point density on change detection is a well-known fact, that the resolution and point density could potentially affect the minimum detectable changes(Xiao et al., n.d.).In the present case, where the point cloud density of the UAV dataset was sparser than the TLS dataset impacted the results during change detection. It is evident from Figure 20 that, during the leaf-off season, when trees did not have enough green leaves and were also moving with the impact of wind, UAV photogrammetry was not able to acquire the complete structure of the trees. This sparser coverage of the UAV dataset when compared with the leaf-on season when there were enough leaves, resulted in a higher change detection range compared to TLS. Noteworthy, it is evident from previous research that TLS provides more detailed information and dense point clouds in the context of monitoring vegetation however it is also sensitive to the uncertainties related to data noise. Consequently, UAV-photogrammetry generates sparser point clouds with minimum noise compared to TLS.(Eltner et al., n.d.; Mohammadi et al., 2021).

Figure 20. TLS captured tree (Left) and UAV acquired tree(right)

The results indicated that the changes identified in shrubbery had differences with UAV and TLS results shown in Figure 20. This difference is further investigated, and it was observed that due to the sparser coverage of the UAV, and the absence of greenery in the leaf-off season, shrubbery was not captured properly by the UAV dataset. This led to the detection of changes from the ground points instead of shrubbery points as there were not enough points from shrubbery. Figure 21 also presented the 100% zoom level of the shrubbery where it can be observed that there were very few green points. The ground sampling distance (GSD) was calculated to examine this difference, and the results showed that GSD is 2.77 cm for UAV imagery which means that changes below this range will not be detected by utilized methods in UAV datasets.

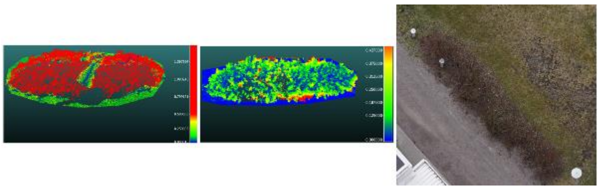

Figure 21. UAV change detection (Left), TLS change detection (middle), and shrubbery at 100% zoom level(right)

Moreover, the bigger observed change for UAV dataset is because the neighbouring points in UAV-1 (off-leaf) case are the ground points while with TLS they are the branches. This was confirmed when TLS-1 was considered as reference and UAV-2 shrubbery was compared and changes were estimated, it can be seen that in Figure 22, changes are below 0.50m and maximum change detected up to 0.40 meters which indicates that in TLS dataset branches are closer to the leaves compared to ground points and thus the leaves get smaller values for TLS than UAV. Same thing happens with trees and since the integrated dataset includes TLS points, that leads to smaller changes as well compared to just using UAV dataset and resulted in higher values of detected changes.

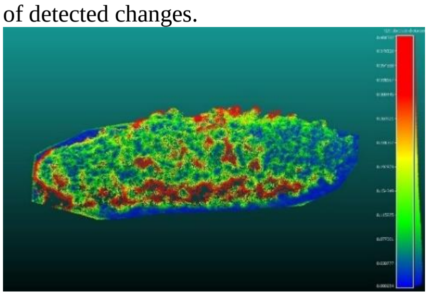

Figure 22: Comparison of TLS-1(leaf-off) with UAV-2 (Leaf-on) shrubbery.

4.2 Impact of data acquisition techniques on change detection.

Due to the implementation of different data sources exhibiting different data acquisition methodologies, the results of this study were influenced by this approach. It is obvious that TLS acquires the data from the ground-up direction and UAV acquires the data from a top-down approach. This led to the incomplete acquisition of the vegetation structure. The accuracy of the utilized data sources was assessed by examining their vertical height distribution and a common tree was selected to estimate its vertical height from both data sources. The results in Figure 23 revealed that the TLS tree (red colour) with a dense structure missed the tree top while the UAV tree (blue colour) showed a sparser coverage and missed lower part of the tree during acquisition. However, TLS data acquisition and processing is more laborious, and time-consuming compared to UAV-photogrammetry (Bin Shafaat, 2023). Moreover. Statistical analysis confirmed visual findings, indicating the TLS tree height was 21.54 m, whereas the UAV photogrammetry exhibited a maximum height of 23.03 m.

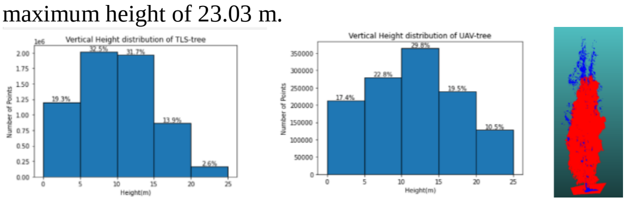

Figure 23. Vertical height distribution of TLS and UAV; TLS-tree(red), UAV-tree(blue).

4.3 Effect of weather and human activities of change detection.

The impact of wind on change detection is another reality that could lead to falsely detected changes when considering the seasonal growth or loss of urban vegetation (Shafaat et al., 2024). Figure 24 below presented a case where, no vegetation boxes were present during the leaf-off season in image (a), and in image (b) the vegetation boxes were placed there by a company called blokgarden https://www.blokgarden.com/.However, the utilized methods identified this change that is illustrated in image (c) whereas this change was not related to seasonal growth but instead to human activity. Moreover, image (d) also showed a tree where the change detection algorithm detected a significant change in a tree branch in red colour. Upon comparing with ground truth imagery from both durations, it was observed that this branch was broken by the wind impact during leaf-on season and therefore it was detected as a significant change as well.

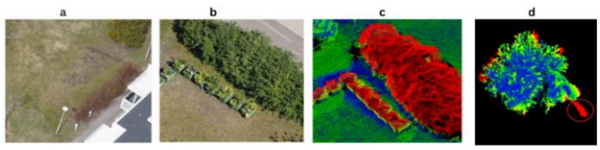

Figure 24. Examples of human activity and weather impact on change detection results.

Therefore, considering all these uncertainties where point density, vertical height differences, and wind impact could potentially impact the data sources and the change detection process a threshold at a 95% confidence level was determined to estimate the total error budget of the utilized dataset and minimize the impact of these practical issues. Noteworthy, as it is obvious that different data sources are prone to different technical limitations, the research emphasized on integration of the different data sources to achieve accurate results and investigate the impact of uncertainties of data sources.

5. Conclusion

The article presented a workflow to process multitemporal TLS and UAV-photogrammetry 3D point clouds for change detection. The challenges related to georeferencing, data registration, point density, resolution, vertical height differences, and technical limitations of acquisition methods were examined and solved during the experimental work to ensure the datasets were accurate enough for change detection. However, technical limitations of TLS and UAV datasets led to the integration of datasets to ensure the comparability for change detection.

Moreover, the changes in vegetation cover were identified by using cloud-based algorithms including C2C, C2M, and M3C2.Particularly, seasonal change in vegetation along with dataset differences and weather impact indicated a maximum growth of 2.0 meters for TLS, and 2.8 meters for UAV and integrated datasets. Threshold value was determined for distinct data sources accounting for point density, registration, surface roughness differences, and wind effect on the datasets. The threshold value at a 95% confidence level was estimated as approximately 4 cm for both data sources, and changes below this threshold were considered as changes due to the total error budget, and only changes exceeding this value were quantified. The statistical results suggested that the maximum amount of changes was identified up to 50 cm for TLS and integrated datasets whereas UAV dataset indicated a most percentage of the changes up to 1 meter. Overall, the study concludes that this type of change detection mainly depends upon the data quality therefore, differences in datasets should be considered carefully and their impact on change detection should be taken into account. Moreover, considering the difference in the UAV and TLS change detection, the study also suggests comparing and using integrated datasets from different sources for accurate estimation of vegetation attributes such as biomass estimation, carbon sequestration by urban vegetation.

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References

Aicardi, I., Dabove, P., Lingua, A. M., & Piras, M. (2016). Integration between TLS and UAV photogrammetry techniques for forestry applications. *IForest - Biogeosciences and Forestry*, *10*(1), 41. https://doi.org/10.3832/IFOR1780-009

Bin Shafaat, O. (2023). *Change detection of urban vegetation from terrestrial laser scanning and drone photogrammetry*. https://aaltodoc.aalto.fi/handle/123456789/122805

Bolund, P., & Hunhammar, S. (1999). Ecosystem services in urban areas. *Ecological Economics*, *29*(2), 293–301. https://doi.org/10.1016/S0921-8009(99)00013-0

Bressane, A., Silva, M. B., Goulart, A. P. G., & Medeiros, L. C. de C. (2024). Understanding How Green Space Naturalness Impacts Public Well-Being: Prospects for Designing Healthier Cities. *International Journal of Environmental Research and Public Health 2024, Vol. 21, Page 585*, *21*(5), 585. https://doi.org/10.3390/IJERPH21050585

Cortinovis, C., & Geneletti, D. (2019). A framework to explore the effects of urban planning decisions on regulating ecosystem services in cities. *Ecosystem Services*, *38*, 100946. https://doi.org/10.1016/J.ECOSER.2019.100946

Eltner, A., Mulsow, C., & Maas, H.-G. (n.d.). *QUANTITATIVE MEASUREMENT OF SOIL EROSION FROM TLS AND UAV DATA*.

Fraser, R. H., Olthof, I., Lantz, T. C., Schmitt, C., Fraser, R. H., Olthof, I., & Schmitt, C. (2016). UAV photogrammetry for mapping vegetation in the low-Arctic. *Https://Doi.Org/10.1139/as-2016-0008*, *2*(3), 79–102. https://doi.org/10.1139/AS-2016-0008

Gruszczyński, W., Matwij, W., & Ćwiąkała, P. (2017). Comparison of low-altitude UAV photogrammetry with terrestrial laser scanning as data-source methods for terrain covered in low vegetation. *ISPRS Journal of Photogrammetry and Remote Sensing*, *126*, 168–179. https://doi.org/10.1016/J.ISPRSJPRS.2017.02.015

Haaland, C., & van den Bosch, C. K. (2015). Challenges and strategies for urban green-space planning in cities undergoing densification: A review. *Urban Forestry & Urban Greening*, *14*(4), 760–771. https://doi.org/10.1016/J.UFUG.2015.07.009

Kaasalainen, S., Krooks, A., Liski, J., Raumonen, P., Kaartinen, H., Kaasalainen, M., Puttonen, E., Anttila, K., & Mäkipää, R. (2014). Change Detection of Tree Biomass with Terrestrial Laser Scanning and Quantitative Structure Modelling. *Remote Sensing 2014, Vol. 6, Pages 3906-3922*, *6*(5), 3906–3922. https://doi.org/10.3390/RS6053906

Kafy, A. Al, Faisal, A. Al, Al Rakib, A., Fattah, M. A., Rahaman, Z. A., & Sattar, G. S. (2022). Impact of vegetation cover loss on surface temperature and carbon emission in a fastest-growing city, Cumilla, Bangladesh. *Building and Environment*, *208*, 108573. https://doi.org/10.1016/J.BUILDENV.2021.108573

Kharroubi, A., Poux, F., Ballouch, Z., Hajji, R., & Billen, R. (2022). Three Dimensional Change Detection Using Point Clouds: A Review. *Geomatics 2022, Vol. 2, Pages 457-485*, *2*(4), 457–485. https://doi.org/10.3390/GEOMATICS2040025

Lague, D., Brodu, N., & Leroux, J. (2013). Accurate 3D comparison of complex topography with terrestrial laser scanner: Application to the Rangitikei canyon (N-Z). *ISPRS Journal of Photogrammetry and Remote Sensing*, *82*, 10–26. https://doi.org/10.1016/J.ISPRSJPRS.2013.04.009

Mohammadi, M., Rashidi, M., Mousavi, V., Karami, A., Yu, Y., & Samali, B. (2021). Quality Evaluation of Digital Twins Generated Based on UAV Photogrammetry and TLS: Bridge Case Study. *Remote Sensing 2021, Vol. 13, Page 3499*, *13*(17), 3499. https://doi.org/10.3390/RS13173499

Shafaat, O. Bin, Kauhanen, H., Julin, A., & Vaaja, M. (2024). Unveiling urban vegetation monitoring: integrating multitemporal terrestrial laser scanning and UAV photogrammetry datasets for change detection, Proc. SPIE 13198, *Remote Sensing Technologies and Applications in Urban Environments IX*, 1319803, https://doi.org/10.1117/12.3031026

Statistics from 1961 onwards - Finnish Meteorological Institute. (n.d.). Retrieved July 30, 2024, from https://en.ilmatieteenlaitos.fi/statistics-from-1961-onwards

Wang, M., Yu, H., Chen, J., Zhu, Y., Neyns, R., & Canters, F. (2022). Mapping of Urban Vegetation with High-Resolution Remote Sensing: A Review. *Remote Sensing 2022, Vol. 14, Page 1031*, *14*(4), 1031. https://doi.org/10.3390/RS14041031

Wang, Q., Tan, Y., & Mei, Z. (2020). Computational Methods of Acquisition and Processing of 3D Point Cloud Data for Construction Applications. *Archives of Computational Methods in Engineering*, *27*(2), 479–499. https://doi.org/10.1007/S11831-019-09320-4/TABLES/6

Xiao, W., Vallet, B., & Paparoditis, N. (n.d.). *CHANGE DETECTION IN 3D POINT CLOUDS ACQUIRED BY A MOBILE MAPPING SYSTEM*. https://doi.org/10.5194/isprsannals-II-5-W2-331-2013

Zhao, N., Prieur, J. F., Liu, Y., Kneeshaw, D., Lapointe, E. M., Paquette, A., Zinszer, K., Dupras, J., Villeneuve, P. J., Rainham, D. G., Lavigne, E., Chen, H., van den Bosch, M., Oiamo, T., & Smargiassi, A. (2021). Tree characteristics and environmental noise in complex urban settings – A case study from Montreal, Canada. *Environmental Research*, *202*, 111887. https://doi.org/10.1016/J.ENVRES.2021.111887