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INTEGRATION OF IPHONE LiDAR WITH QUADCOPTER AND FIXED WING UAV PHOTOGRAMMETRY FOR THE FORESTRY APPLICATIONS

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ABSTRACT:

The recent innovations in remote sensing technologies have given rise to the efficient mapping and monitoring of forests. The developments in the sensor implementation have mainly focused on optimizing the payload of the UAV system and allowed the users to acquire the data simultaneously with a range of active and passive sensors like high-resolution RGB cameras and multispectral cameras LiDAR (Laser Imaging Detection and Ranging). The main objective of this research contribution is to combine the Digital Elevation Model (DEMs) from quadcopter Unmanned Aerial Vehicles (UAVs), Fixed Wing UAV-based cameras, and iPhone datasets for the forest plots. The datasets from two vegetation seasons, namely leaf-off and leaf-on, were used to combine the Digital Elevation Models from different data acquisition platforms. This internship research work aims to create and experiment with new methods, techniques, and technologies for the applications of UAV photogrammetry and iPhone LiDAR in forest napping and inventory management. CHMs are also generated in this work which helps assess the conditions of the forests in the recreational areas, and the possibility of solutions like iPhone LiDAR and UAV photogrammetry would be highly efficient and economical. The leaf-off and leaf-on datasets were processed in Agisoft Metashape Professional software to generate dense point clouds for the forest plots. The point cloud from the leaf-on dataset was rasterized to generate a DSM whereas the leaf-off point cloud generated a DSM of the forest plots after ground filtering with Cloth Simulation Filter (CSF) plugin. The iPhone LiDAR point was also rasterized to a DTM product after pre-processing steps and noise removal. The Canopy Height Models (CHMs) were generated by subtracting UAV and iPhone LiDAR based DTMs from the UAV leaf on DSM. Finally, the accuracy assessment of CHMs from UAB datasets and their integration with iPhone LiDAR has been assessed using the accurate tree heights measured during the forest field visits. The proposed methodology can be used for forest mapping purposes where a moderate accuracy is requested.

1. INTRODUCTION

The advancements in aerial remote sensing solutions have supported the efficient mapping of large forest areas and their monitoring. For large-scale forests, aerial photogrammetry and satellite datasets have been used widely for recognition of the forest ecosystems (White et al., 2016). Low-cost tools such as UAVs have gained potential usage in forestry over the last decade as they can be used to collect geospatial information with multiple sensors simultaneously (Dainelli et al., 2021). UAVs used for forestry applications can vary in size as small, mini, and micro, depending upon data acquisition requirements. UAVs can also be categorized as fixed-wing, rotor-based, and hybrid UAV systems based on the wing type. Fixed-wing UAVs take off vertically from the base position and are suitable for large-scale monitoring of areas with a pre-defined flight path, but they need a wider space for operations during take-off and landing (Gómez et al., 2019). On the other hand, rotor-based UAVs platforms are better in terms of mobility with easier take-off and landing operations as compared to fixed-wing UAVs. Both fixed-wing and rotor-based UAVs are suitable for forestry applications (Torresan et al., 2017) but rotor-based UAVs were always a better choice for researchers as they are relatively cheaper and more flexible for scientific experiments (Pádua et al., 2017). The developments in the sensor implementation have mainly focused on optimizing the payload of the UAV system and allowed the users to acquire the data simultaneously with a range of active and passive sensors like high-resolution RGB cameras and multispectral cameras LiDAR (Laser Imaging Detection and Ranging). It can be highlighted that UAV platforms with RGB camera sensors are suitable for feature detection within a certain region, like tree crown size estimation and the estimation of the fractional vegetation cover (Riihimäki et al., 2019)). LiDAR sensors with penetration capabilities through the forest canopy can be used for accurate measurements of forest inventory and also for mapping the data below the forest canopy (Hyyppä et al., 2020). The advantages of LiDAR sensors come at a higher cost of this technology compared to the RGB camera sensors, and at the same time, RGB camera sensors are more economical than LiDAR (Cao et al., 2019; Ganz et al., 2019). Digital Elevation Models (DEMs) have been accepted widely as a source for modeling various landscapes and as a solution for various environmental problems (Grau et al., 2021).

In this research work, DTMs were generated from leaf-off datasets where the part of the ground can be observed and

DSMs from leaf-on datasets to capture the top elevation of the forest plots. CHMs represent the tree heights above the ground surfaces and are thus, obtained by raster subtraction of the DTM raster from DSM raster. The focus of this research work is to develop cheaper, more accurate, and faster solutions for mapping and monitoring the forest ecosystem with the use of iPhone LiDAR and UAV photogrammetry.

2. STUDY AREA AND DATASET ACQUISITION SYSTEMS

The study area for this research work was the forest plots in the outskirts of the city of Zvolen in Slovakia. The data was collected for the two forest plots of 50 m * 50 m for this research work. The geographical location of the forest plots is represented below in Figure 1.

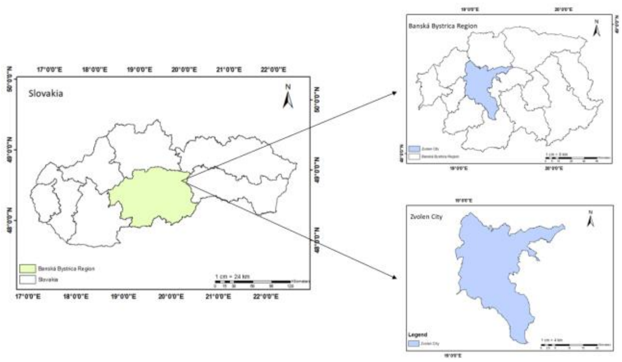


Figure 1: Location of study area forest plots.

Figure 2 represents the schema of the established forest plots in the study area in Zvolen. From the forest plots schema in Figure 2, The two sub-plots ABGH and CDEF have been considered for the data acquisition with UAV photogrammetry and iPhone LiDAR.

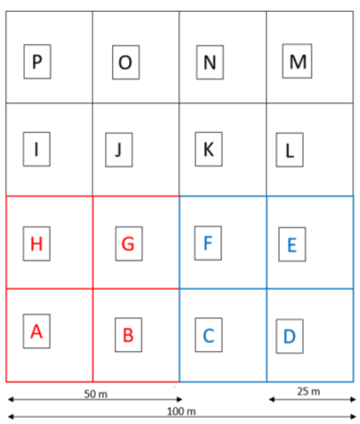


Figure 2: Forest plots schema considered for the research work.

We have used two datasets from two vegetation seasons: leaf off with Fixed Wing (FW) UAV photogrammetry and iPhone LiDAR whereas leaf on with Quadcopter (QC) UAV photogrammetry. Leaf off is the fall season without leaves with ground visible in aerial images whereas leaf on is the season when forests are full of vegetation. The leaf-off dataset was collected with an ebee plus fixed-wing UAV with an RGB camera sensor onboard. For leaf-on datasets, quadcopter-based Phantom4K was employed in RTK mode. iPhone 13 Pro Max was used for the acquisition of the ground-based datasets for the forest plots with 3D modeler software. Figure 3 shows the different dataset systems used for the acquisition of the data acquisition for the forest plots.

Figure 3: Dataset acquisition systems used in the research work.

In total, 686 images were collected for each forest plot for leaf off vegetation season whereas 486 images for each forest plot in leaf on vegetation season.

3. METHODOLOGY

3.1 Processing of Quadcopter UAV-based leaf on dataset

Leaf-on datasets were collected during the full vegetation season with full vegetation cover in the forest plots. This leaf-on dataset acquisition aims to create Digital Surface Models (DSMs). In the case of Leaf-on UAV datasets, we can only capture the top elevation of the vegetation cover without almost zero-intervention of the ground surface, which can be used as an efficient solution for DSM generation for large and remote areas like forest plots. It was also challenging to align and process the leaf-on dataset image because the extent of homogeneity was very high in the case of leaf-on datasets due to the dense canopy and similar features in the consecutive images.

The leaf-on dataset images were processed in Agisoft Metashape Professional software (Agisoft, 2021) to generate dense point clouds for both forest plots. As mentioned earlier, It was quite challenging to obtain the alignment of the entire dataset due to the homogeneity of the features in the areas, even with reference image exposure information from GNSS. After obtaining the dense point cloud, the noise and outliers were removed from raw point clouds using the 'Noise Filter' and 'Segment' tools in Cloud Compare software.

After point cloud filtering, Digital Surface Models (DSMs) are generated from leaf-on point clouds obtained from Agisoft Metashape processing. For the leaf-on datasets, only canopy features are visible with images, so DSM is the elevation/height model of all the tree features in the scenario. To compare the elevation models with similar grid size and other parameters, the OpalsDSM tool from the OPALS modular program was used to generate Digital Surface Models (Pfeifer et al., 2014). The parameters used in OpalsDSM are:

- DSM Gridsize:20 cm
- Minimum number of neighbors for grid interpolation: 2
- maximum search radius for selection of points: 25

Figure 4 shows the overall methodology that has been used for the generation of DSM from the quadcopter UAV-based leaf-on dataset.

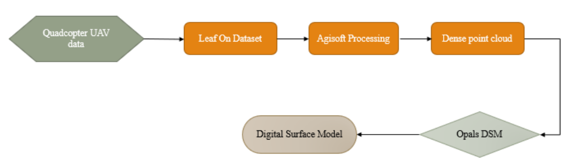


Figure 4: Methodology for generation of DSM from Leaf-on datasets

3.2 Processing of Fixed-Wing UAV-based Leaf off dataset

Fixed Wing (FW) UAVs are also very useful when it comes to UAV applications for large-scale time-efficient mapping of forests. FW UAVs can only fly forward and therefore, they cannot offer the same levels of maneuverability as quadcopter UAVs. Leaf-off datasets were collected during the fall season without any vegetation cover. This dataset acquisition aims to create Digital Terrain Models (DTMs). In the case of Leaf-off UAV datasets, some parts of the ground can be seen through the forest canopy, which can be used as an efficient solution for DTM generation for large and remote areas. Leaf-off datasets are highly homogenous such that it is too hard to find the distinguishable features (tie points) between pairs of images. The leaf-off dataset was processed in Agisoft Metashape Professional software (Agisoft, 2021)to generate dense point clouds for both plots. DTM cannot be generated with leaf-on datasets as UAV photogrammetry cannot penetrate through the canopy and ground cannot be seen through the dense canopy. In the case of leaf on datasets, almost 100% of a pixel's contribution comes from the canopy cover and there is no possibility to extract information for the surface below the canopy. After processing leaf-off dataset images in Agisoft Metasshape Professional (Agisoft, 2021) software, the point clouds were filtered with 'Noise Filter' and 'Segment' tools in Cloud Compare software for removal of noise and outliers.

In the next step, the Cloth Simulation Filter (CSF) plugin was used to filter out the ground points from point cloud data. It is based on cloth simulation which is a 3D computer graphics algorithm. In this approach, the point cloud is inverted and then a rigid cloth is used to cover the inverted surface. By analyzing the interactions between the cloth nodes and the corresponding LiDAR points, the locations of the cloth nodes can be determined to generate an approximation of the ground surface (Zhang et al., 2016). The parameters used for ground filtering with the CSF plugin are summarised in Table 2.

Table 1: Description of the parameters used in the CSF plugin for ground points filtering.

Parameter	Description	Selected Value in CSF plugin
Scene	Type of terrain	steep slope/relief /flat
Cloth Resolution	grid size of cloth for the terrain	1.0
Max. Iterations	number of iterations for the cloth simulation	500
Classification threshold	ground points classification threshold based on the distances between points and the simulated terrain	2.0

Ground points filtered were used in the subsequent step to generate Digital Terrain Models (DTMs) from ground points filtered leaf off point cloud datasets. Python-based OpalsDTM (Pfeifer et al., 2014) module was used for generating a high-quality DTM with regular grid and structure lines (OPALS, 2016). The parameters used in OpalsDTM are summarised in Table 2.

Table 2: Description of parameters and their value used in OpalsDTM for generating DTM.

Parameters	Values used in OpalsDTM
DSM Grid Size	20 cm
Interpolation method	kriging
Minimum number of neighbours for grid interpolation	2
maximum search radius for selection of points:	25

The overall methodology for the generation of DTMs from Leaf-off datasets has been shown in Figure 5.

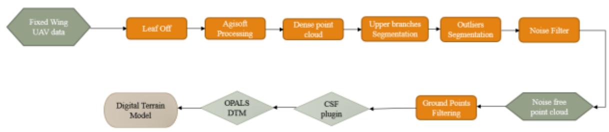


Figure 5: Methodology for generation of DTM from Leaf-off datasets

3.3 Processing of iPhone LiDAR dataset

Two forest plots of 50 m * 50 m were scanned with an iPhone 13 pro max equipped with a Gimbal stabilizer for the support and stabilization of the iPhone during the data acquisition. The scanning was done in a similar way as of UAV flight path with an overlap between two consecutive strips. During the iPhone LiDAR data acquisition, the 3D modeller software navigates through the features which have been scanned so far, helpful in data acquisition for further strips. The scanning was done along the four reference points (fixed) in each forest plot whose coordinates were known with precision. The range of iPhone LiDAR scanning was 5 m.

After data collection, the data acquired was imported from iPhone device as 3D object files (.obj) and converted to point cloud format in MeshLab software. As the iPhone dataset was in an arbitrary coordinate system, it must be transformed into a Local Coordinate System like UAV photogrammetry datasets. For this transformation, the "Fine registration" tool from CloudCompare was used to register iPhone datasets with fixed-wing UAV datasets. Before fine registration, fixed-wing datasets were clipped to the extents of the plots which were scanned with iPhone LiDAR. Post transformation to the local coordinate system, the ground points were filtered from point cloud datasets with the CSF plugin and used as input in OpalsDTM to generate DTMs for all the subplots. The parameters for ground filtering were different here as the ground points classification threshold should be lower in the case of ground-based iPhone LiDAR datasets. Figure 5 represents the methodology used for the generation of DTM from iPhone LiDAR datasets.

Figure 6: Methodology used for processing of iPhone LiDAR point cloud dataset.

3.4 Combining UAV photogrammetry and iPhone LiDAR

The Canopy Height Models (CHMs) are generated by subtracting DTMs from multiple FW UAV, and iPhone LiDAR datasets from UAV DSM. CHMs represent the tree heights above the ground surfaces and are thus, obtained by raster subtraction of the DTM raster from DSM raster. The DSM from the UAV was combined with DTM from iPhone LiDAR to generate the CHMs for both forest plots.

$$CHM = (Raster_{DSM} - Raster_{DTM})$$

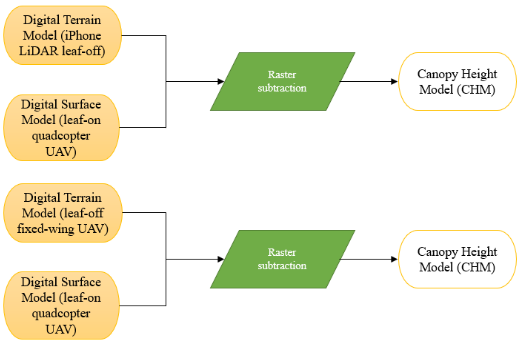


Figure 7: CHMs from the integration of iPhone LiDAR and UAV photogrammetry

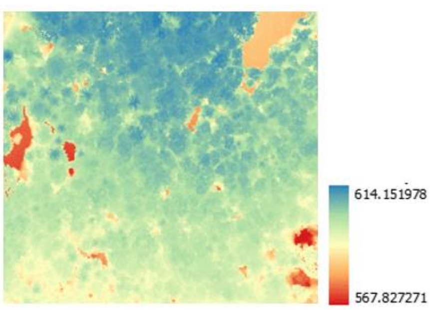
3.5 Accuracy Assessment of generated CHMs

The accuracy of CHMs was assessed by using the accurate tree heights measured during the forest field visits. A total of 20 trees were identified from each of Plot 1 and Plot 2 for the accuracy assessment of the proposed methodology. The coordinates and height data of the trees in these plots were already collected from the earlier field visits. The trees' height from the validation data and CHMs were compared to analyze the accuracy of the proposed methodology for forest monitoring inventory management.

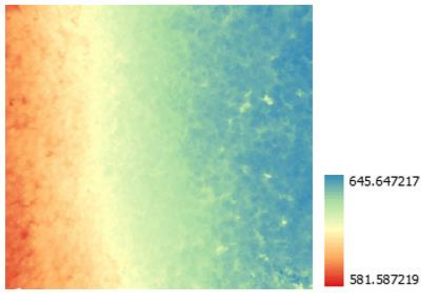
4. RESULTS

4.1 DSM generated from Quadcopter UAV-based leaf on dataset

The DSM was generated from quadcopter UAV leaf on datasets using the OpalsDSM module from the OPALS package. The parameters like grid size (20 cm), searchRadius, and nearest neighbors were kept the same as OpalsDTM to keep it a standard elevation model for comparison and CHM generation. The alignment in the leaf on datasets was perfect, and so was the quality of DSMs obtained from them.



(a)

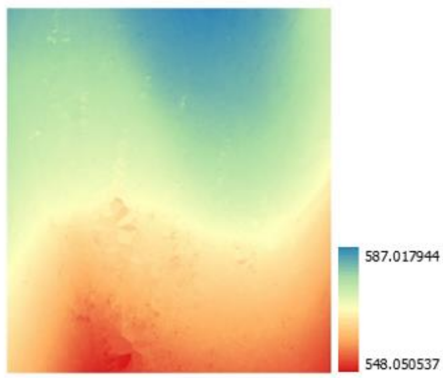


(b)

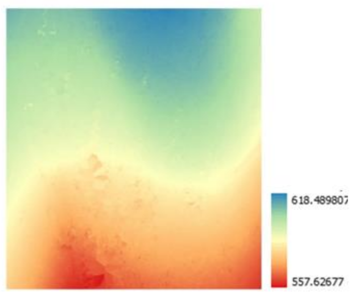
Figure 8: DSM generated from leaf-on datasets for (a) Plot 1 (b) Plot 2

4.2 DTM generated from Fixed Wing UAV-based leaf off dataset

Ground points filtered through the CSF plugin in Cloud Compare were used as input for OpalsDTM. Even after using the best possible parameters for generating dense point clouds, a few areas of the plots were still missing from the dense point clouds. In order to fill up the area gaps, a larger value of search radius (25 & 40) and a lesser value of a minimum number of neighbors (2) for interpolation were considered. DTMs generated from FW UAV photogrammetry point clouds have been represented below in Figure 9.



(a)

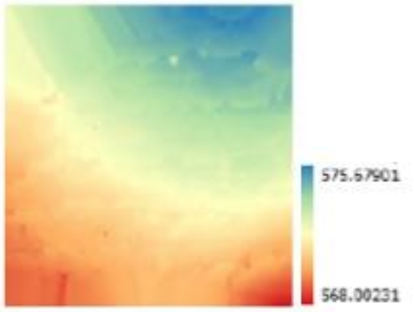


(b)

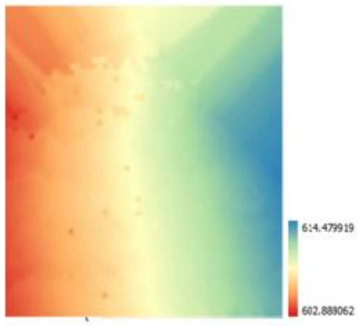
Figure 9: DTM generated from FW UAV-based leaf-off datasets for (a) Plot 1 and (b) Plot 2.

4.3 DTMs generated from the iPhone LiDAR dataset

The DTMs were generated from the iPhone LiDAR dataset after filtering the ground points. The iPhone DTMs are visualized in the below in Figure 10 below.



(a)

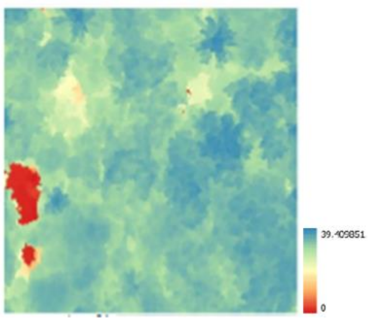


(b)

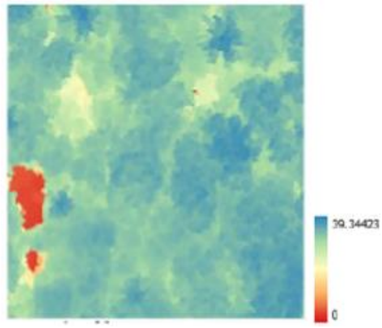
Figure 10: DTM generated from iPhone LiDAR leaf-off datasets for (a) Plot 1 (b) Plot 2

4.4 Canopy Height Models (CHMs) from the integration of UAV datasets and iPhone LiDAR

The Canopy Height Models (CHMs) are generated by subtracting DTMs from multiple datasets from UAV DSM. CHMs represent the tree heights above the ground surfaces and are thus, obtained by raster subtraction of the DTM raster from DSM raster. The DSM generated from the Quadcopter UAV leaf-on dataset has been used to generate CHMs for fixed-wing UAV photogrammetry, quadcopter UAV photogrammetry, and iPhone LiDAR datasets. The quality of CHM directly depends on the accuracy of the source. DSM and DTM. The accuracy of CHMs can be assessed by using the accurate tree heights measured during the forest field visits. The CHMs are visualized below in Figure 11 and Figure 12.

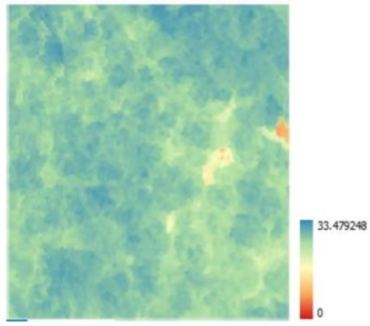


(a)



(b)

Figure 11: CHM generated for Plot 1 with (a) FW UAV + QC UAV dataset and (b) iPhone LiDAR + QC UAV dataset.



(a)

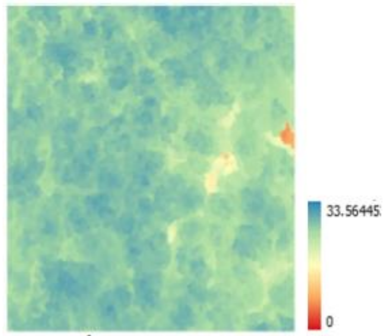


Figure 12: CHM generated for Plot 2 with (a) FW UAV + QC UAV dataset and (b) iPhone LiDAR + QC UAV dataset.

4.5 Accuracy Assessment of CHM generated from integration of UAV and iPhone LiDAR datasets.

The accuracy of the CHMs generated from UAV datasets and integration of UAV and iPhone LiDAR datasets was compared to analyze the application of iPhone LiDAR for forest mapping and inventory management applications. For the accuracy assessment of CHMs, the tree heights of 20 trees each from Plot 1 and Plot 2 were validated with measurements from the field visits. Let's say the height of a tree from CHM at a coordinate (x,y) is h_{chm}, and the tree height at the same coordinate from field measurement is $h_{measured}$, then the error is ($h_{measured}$ - h_{chm}). Similarly, the average of the tree heights of 20 trees from CHMs was calculated individually from CHMs and compared with actual tree height measurements. The results from the accuracy assessment indicate a Root Mean Square Error (RMSE) of 1.325 m for CHMs generated from FW UAV and QC UAV datasets, RMSE of 2.406 m for CHMs generated from iPhone LiDAR and QC UAV datasets, and 2.091 m for all the CHMs obtained from iPhone LiDAR, FW UAV, and quadcopter UAV datasets. The accuracy assessment results are summarised below in Table 3.

Table 3: Summary of the accuracy assessment results of CHMs from multiple sources

Plot no.	*Source*	*Average tree height for 20 trees from CHMs*	*Average measured tree heights of 20 trees from the field visits*	*Root Mean Square Error in the estimated tree heights (h_{error})*
Plot 1	UAV FW + UAV QC	32.216 m	30.925 m	1.417 m
Plot 2	UAV FW + UAV QC	31.419 m	29.489 m	1.328 m
Plot 1	UAV and iPhone LiDAR	32.572 m	30.925 m	1.876 m
Plot 2	UAV and iPhone LiDAR	32.553 m	29.489 m	2.937 m

5. CONCLUSIONS

The primary objective of this research work is to explore the combined potential of UAV photogrammetry and iPhone LiDAR datasets for forestry applications. The purpose of the Fixed Wing UAV-based photogrammetry datasets from leaf-off vegetation season was to generate the DTM after ground points filtering. DSM was obtained from a quadcopter UAV-based camera dataset acquired in leaf off-vegetation season. The point clouds were filtered from point cloud datasets with the CSF plugin tool in CloudCompare. Canopy Height Models (CHMs) were derived from raster subtraction of the DTMs generated from fixed-wing UAV, iPhone LiDAR datasets from leaf off vegetation season, and DSM from quadcopter UAV leaf on dataset. CHMs were generated from the raster subtraction of DTM from DSM for both the forest plots.
From the results, it can be concluded that the higher the ground points with the distribution of the points, the better would be the quality of DTM and CHM. The accuracy assessment of DTMs generated from multiple data sources was done with the measurement of tree heights from the forest field visits. From the accuracy assessment results, it was found that CHMs from the DSM of QC UAV and DTM of FW UAV have lower RMSE as compared to the CHM obtained from iPhone DTM and QC DSM. The overall RMSE for the CHMs was found to be 2.091 m which means the error in the tree height estimated from the proposed methodology was around this range. So, the proposed workflow can be used in projects or work where moderate accuracy is requested. The proposed workflow can be used with iPhone LiDAR as an alternative and economical solution to TLS scanning where moderate accuracy is acceptable.

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