LiDAR vs. SfM: Which is better for analysing habitat of the harvest mouse (*Micromys minutus*)?

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Abstract

The harvest mouse, *Micromys minutus* (Pallas, 1771) is the smallest rodent in Japan and now listed in the Red Data Books of Tokyo, 2 prefectural capitals, and 28 prefectures in Japan due to drastic decline of grasslands. For the harvest mouse, the height and density of the tall grass species where nesting occurs are considered particularly important. However, it has been difficult to continuously and extensively acquire information on the three-dimensional structure of herbaceous vegetation. With recent development of UAV technology, UAV data are beginning to be applied to the analysis of herbaceous vegetation. For acquiring three-dimensional information via UAV, methods include using LiDAR sensors or generating 3D point cloud data from aerial photographs using SfM. This study evaluates whether UAV LiDAR or UAV SfM is more suitable for estimating the height of tall grass species such as Japanese silver grass (*Miscanthus sinensis*), which serve as important nesting sites for the harvest mouse. As a result of analysis, the proposed method was found to be effective to estimate grass height regardless of whether UAV LiDAR or UAV SfM is used. However, when comparing the accuracy of canopy height estimation using UAV LiDAR data alone, UAV SfM data alone, and combined UAV LiDAR and SfM data, combined UAV LiDAR and SfM data found to perform best. Maximum canopy height was found to be best estimated using the combination of median of hand-measured five maximum canopy height values and maximum height calculated using the combined UAV LiDAR and SfM data.

1. Introduction

The harvest mouse, *Micromys minutus* (Pallas, 1771), measuring approximately 6 cm in head-body length and weighing 7–8 g (Figure 1), is the smallest rodent in Japan (Hata, 2014). It primarily inhabits riverbanks, fallow fields, and small semi-natural grasslands which often found in Yato. Yato is one of Japanese traditional agricultural landscapes, which consists of small valley floor for crop and paddy fields surrounded by coppiced woodlands (Satoyama) on hill ridges and hillsides. The harvest mouse builds spherical nests by splitting the leaves at the tops of large grasses such as Japanese silver grass (*Miscanthus sinensis*) and amur silver grass (*Miscanthus sacchariflorus*), where it raises its young. It is now listed in the Red Data Books of Tokyo, 2 prefectural capitals, and 28 prefectures in Japan, since the period of rapid economic growth, grasslands have rapidly declined due to changes in human economic and lifestyle patterns.

Figure 1. The harvest mouse in its natural habitat (left, photo courtesy of Mr. Takashi Shoji) and a spherical nest (right).

In the conservation of rare species, it is common practice to analyze and model landscape structures suitable for their habitats (Whittingham et al., 2005). For the harvest mouse, the height and density of the tall grass species where nesting occurs are considered particularly important. However, in grasslands where herbaceous vegetation—which grow faster, are smaller, and have more complex shapes than trees—are distributed in patches, it has been difficult to continuously and extensively acquire information on the three-dimensional structure of herbaceous vegetation, such as patch-specific plant height and density, which fluctuate seasonally. Consequently, it has not yet been possible to model habitat for the harvest mouse.

In recent years, UAV technology has developed rapidly, dramatically increasing its versatility. Surveys conducted using UAV flights excel over ground surveys by personnel or manned aircraft surveys in their ability to acquire high-resolution data over relatively large areas at low cost and with high frequency. UAV data are beginning to be applied to the analysis of herbaceous vegetation, which was previously difficult to address using manned aircraft aerial photography data. In natural and semi-natural grasslands, UAV LiDAR has been used to create vegetation height maps of herbaceous species on river dike (Miura et al., 2018) and analyze three-dimensional structures (Miura et al., 2019). Research using Structure from Motion (SfM) to calculate grass height and estimate biomass has also been reported (e.g. Forsmoo et al., 2018; Grüner et al., 2019; Bendig et al., 2014; Lussem et al., 2019; Zhang et al., 2018). For acquiring three-dimensional information via UAV, methods include using LiDAR sensors or generating 3D point cloud data from aerial photographs using SfM. Both methods can capture high-density (hundreds of points per square meter) and high-precision (positioning accuracy within a few centimeters) 3D information.

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A few reports have compared the usefulness of these two methods in natural environment (Kalacska et al., 2021; Liao et al., 2021; Obanawa et al., 2020). Kalacska et al. (2021) compare unmanned aerial system (UAS) derived SfM photogrammetry and LiDAR point clouds and digital surface models of an ombrotrophic bog in terms of payload, efficiency, and end product quality. The authors found that the LiDAR implementation was more straightforward, with fewer points of potential failure, more efficient data collection and considerably smaller file sizes, however, SfM provided higher spatial detail of the microforms due to its greater point density. Liao et al. (2021) compared the two DSMs created using UAV LiDAR and UAV-SfM for three land cover types (forest, wasteland, and bare land). The authors concluded that the differences between the two DSMs were generally minor over areas with sparse vegetation and more significant for areas covered by tall dense trees, and that using the SfM method to obtain a DSM with high-density vegetation is challenging. Obanawa et al. (2020) compared the performance of UAV SfM, camera pole SfM and hand-held LiDAR for grass height measurement in a 2.5 m × 2.5 m section of an Italian ryegrass and found that LiDAR estimated a value closest to the actual value determined by a ruler, with the error reduced to about half. Xu et al. (2023) pointed out underestimation of UAV LiDAR with height information loss due to the complex structure of grassland and the relatively small size of individual plants, however, Zhao et al. (2022) suggests that this could be improved using scan angle information.

These studies indicate that LiDAR may be better choice in acquiring 3D information compared to SfM. However, the applicability of these results to the habitat of the harvest mouse remains unknown, because the habitat differs from the study sites mentioned above, featuring patches of tall grass species (some exceeding 3 meters) growing densely scattered throughout the area. Furthermore, TLS and handheld LiDAR, which can measure detailed plant shapes from closer range, are not suitable in such environments, making UAV LiDAR necessary. Therefore, this study evaluates whether UAV LiDAR or UAV SfM is more suitable for estimating the height of tall grass species such as *M. sinensis* and *M. sacchariflorus*, which serve as important nesting sites for the harvest mouse.

2. Methods

2.1 Study area

The study area is Nara Bai Yato which locates in the Tama Hills, 30 km west of Tokyo in Japan (Figure 2). It is approximately 4.9 ha which contains crop and paddy fields, and small patches of grassland on the valley floor surrounded by secondary forest on the slope. Hill ridges are about 30 m higher than the adjacent valley floor. The area was selected as one of the key Satoyama Landscapes for biodiversity conservation by Ministry of the Environment in 2015. It has been managed by a volunteer group, now the NPO corporation, Machida Yui-no-sato since 2005 for conservation and restoration of traditional agricultural environments. Regular mowing is also conducted on fallow fields and lower slopes. There have been no major changes in land use or vegetation management policies in recent years. In this area, nests of the harvest mouse have been spotted in tall grass species such as *M. sacchariflorus*, common reed (*Phragmites australis*) and *M. sinensis*.

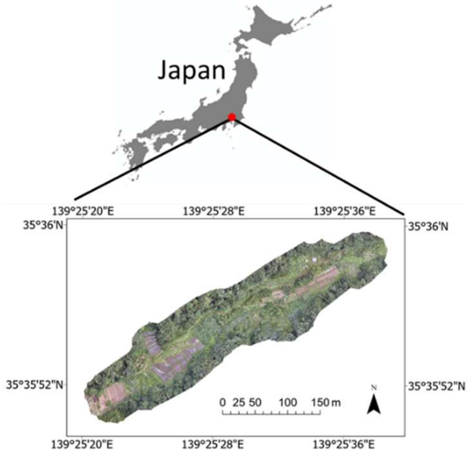

Figure 2. Study area.

2.2 Ground vegetation survey

Ground vegetation survey was conducted on 20 June 2025. A circular plot of 62.5 cm diameter (0.31 m^2) was set up on each of the three tall grass species; *M. sacchariflorus, P. australis* and *M. sinensis*. Plots were selected to ensure variation in grass height and density, resulting in a total of 11 plots established (Figure 3). The center of the plot was GNSS surveyed using Leica GS18I as well as recording maximum canopy height for five of the tallest grasses using a holding ruler. The 3D accuracy of the survey points ranged from 0.011 m to 0.032 m, with an average of 0.018 m. To compare to UAV derived canopy height values, maximum (Max_g), mean (Mean_g) and median (Median_g) of these five maximum canopy height values were calculated for each plot.

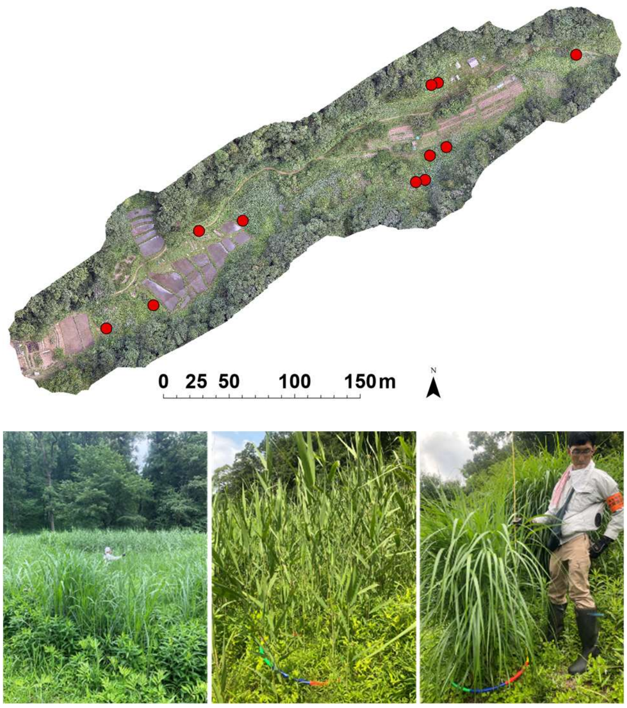

Figure 3. Ground vegetation survey plots (top, red circles); four of *M. sacchariflorus* (bottom left), three of *P. australis* (bottom middle) and four of *M. sinensis* (bottom right) plots were set up.

2.3 UAV data

2.3.1 Data acquisition: UAV data was acquired on the same day with ground vegetation survey. DJI L1 sensor mounted on Matrice 300 was used for LiDAR data acquisition. Flight altitude was set as 50 m from the ground with terrain follow mode. DJI P1 sensor is also mounted on Matrice 300 to acquire RGB image to be used for SfM. Flight altitude was set as 70 m from the ground with terrain follow mode, which resulted in image data with a Ground Sampling Distance (GSD) of 0.86 cm. Overlap was set as 85 %/95 % side/forward. Both flights were conducted using DJI D-RTK 2 mobile station. DJI Terra was used for initial data processing, while Terrasolid’s Terra Scan and ESRI’s Arc GIS Pro were utilized for post data processing.

2.3.2 Canopy height of the grass by LiDAR data: Canopy height of the grass in the vegetation plots was calculated using Digital Surface Model (DSM) and Digital Terrain Model (DTM) data generated from LiDAR point cloud. GSD for the model was selected as 2 cm following Miura et al. (2020), which demonstrated that approximately 2 cm is suitable for calculating grass height. For the DTM, LiDAR point cloud acquired in February 2025, instead of June 2025, was used (Figure 4). This is because, in June, the growth of ground vegetation is particularly vigorous and dense, making it difficult to obtain sufficient ground data, while February is when plants are least abundant on the ground. The z values of DTM were validated using 11 vegetation plot center points, which results in RMSE value of 0.092 m for February data and 0.447 m for June data. Canopy height of the grass was calculated by subtracting DTM from DSM. This creates Canopy Height Model (CHM). There are 2056 to 3037 pixels with a canopy height value in a vegetation plot. For validation of maximum canopy height, maximum height (Max_L), 90th (P90_L), 95th (P95_L), and 99th percentile of height values (P99_L) in each plot were calculated.

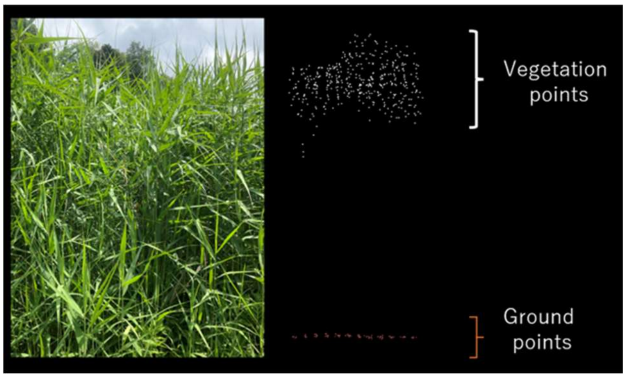

Figure 4. Ground vegetation survey plots (left) and LiDAR point cloud (right); vegetation points acquired in June 2025 and ground points acquired in February 2025.

2.3.3 Canopy height of the grass by SfM data: Similarly, to produce CHM for each plot, DSM of June data and DTM of February data were created using point cloud generated from RGB image by SfM. RMSE in z values of DTM against the GNSS surveyed points was 0.095 m. Each plot contains 3048 to 3054 pixels with a canopy height value. Maximum height (Max_SfM), 90th (P90_SfM), 95th (P95_SfM), and 99th percentile of height values (P99_SfM) in each plot were calculated.

2.3.4 Canopy height of the grass by combined LiDAR and SfM data: To validate the utility of combined LiDAR and SfM data, DSM of June data generated from SfM and DTM of February data generated from LiDAR data were used in creation of CHM. Each plot contains 3048 to 3054 pixels with a canopy height value. Maximum height (Max_SfM-L), 90th (P90_SfM-L), 95th (P95_SfM-L), and 99th percentile of height values (P99_SfM-L) in each plot were calculated.

2.4 Comparison between ground based and UAV based canopy height

Ground based maximum, mean and median of five maximum canopy height values for each plot were compared to UAV based maximum height, 90th, 95th, and 99th percentile of height values calculated from LiDAR data alone, SfM data alone and the combined LiDAR and SfM data, respectively. The accuracy of the prediction model is evaluated using the following metrics: Root Mean Squared Error (RMSE), Mean Squared Error (MSE), Mean Error (ME), Mean Percentage Error (MPE) and coefficient of determination (R^2). MSE emphasizes large deviations due to squaring of errors, while RMSE provides an interpretable measure in the original units of the response variable. ME was included to assess systematic bias (over- or underestimation), and MPE allows evaluation of relative error independent of scale. In addition, R^2 quantifies the proportion of variance explained by the model, representing a complementary perspective distinct from error-based metrics. Since grassland vegetation is much more mobile in the wind than tree canopies, the combination of multiple error metrics enables a more comprehensive and robust assessment of model performance.

3. Results

Figure 5 shows the results of comparison between Max_g and UAV based canopy height. All of them were well correlated with each other. In terms of R^2 value, ground based maximum canopy height was best correlated with 95th percentile of height values derived by the combination of LiDAR and SfM data (Figure 5i) with R^2 value of 0.93, followed by maximum height derived by the combination of LiDAR and SfM data (Figure 5c) with R^2 value of 0.91.

Figure 6 displays the results of comparison between Mean_g and UAV based canopy height. They all correlate well with each other. The best R^2 value of 0.96 was found in the correlation with 95th percentile of height values derived by the combination of LiDAR and SfM data (Figure 6i), followed by maximum height derived by the combination of LiDAR and SfM data (Figure 6c) with R^2 value of 0.95.

Figure 7 exhibits the results of comparison between Median_g and UAV based canopy height. Ground based median canopy height was well correlated with all of UAV based values. The best R^2 value of 0.97 was found in the correlation with 95th percentile of height values derived by the combination of LiDAR and SfM data (Figure 7i), followed by maximum height derived by the combination of LiDAR and SfM data (Figure 7c) and 90th percentile of height values derived by the combined LiDAR and SfM data (Figure 7f) with R^2 value of 0.95.

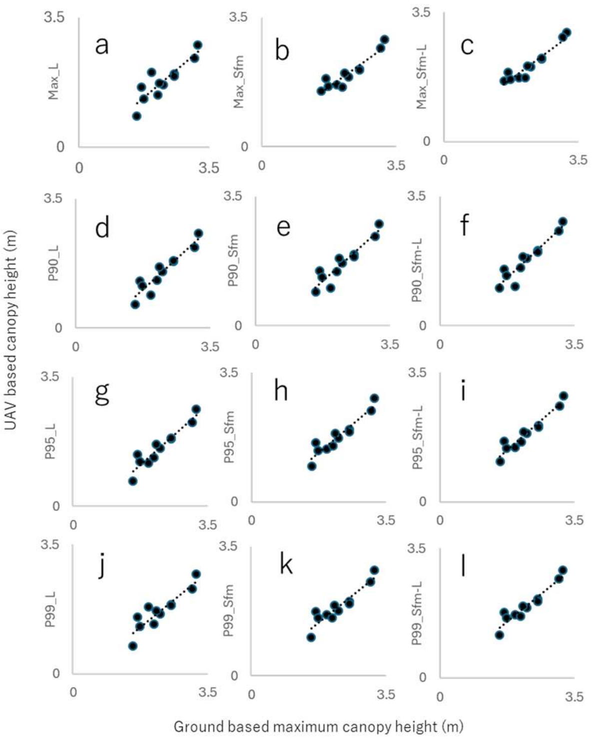

Figure 5. comparison between Max_g and UAV based canopy height; Max_L (a), Max_SfM (b), Max_SfM-L (c), P90_L (d), P90_SfM (e), P90_SfM-L (f), P95_L (g), P95_SfM (h), P95_SfM-L (i), P99_L (j), P99_SfM (k) and P99_SfM-L (l).

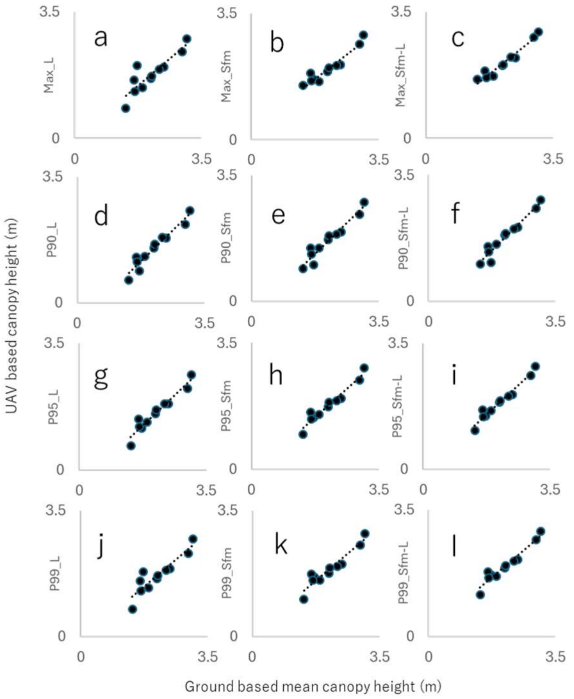

Figure 6. comparison between Mean_g and UAV based canopy height; Max_L (a), Max_SfM (b), Max_SfM-L (c), P90_L (d), P90_SfM (e), P90_SfM-L (f), P95_L (g), P95_SfM (h), P95_SfM-L (i), P99_L (j), P99_SfM (k) and P99_SfM-L (l).

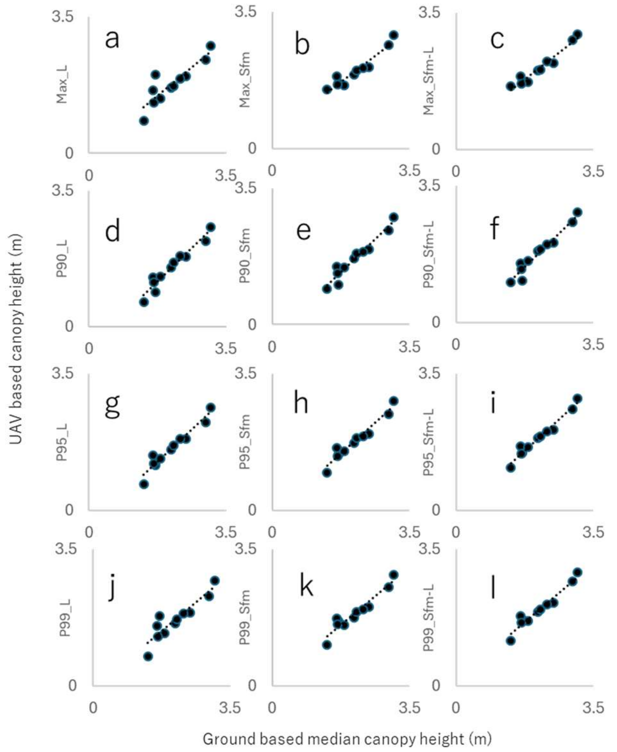

Figure 7. comparison between Median_g and UAV based canopy height; Max_L (a), Max_SfM (b), Max_SfM-L (c), P90_L (d), P90_SfM (e), P90_SfM-L (f), P95_L (g), P95_SfM (h), P95_SfM-L (i), P99_L (j), P99_SfM (k) and P99_SfM-L (l).

Table 1 shows the results of evaluation by RMSE, MAE, ME, MPE and R^2 between ground based Max_g, Mean_g and Median_g, and UAV based Max_L, Max_SfM, Max_SfM-L, P90_L, P90_SfM, P90_SfM-L, P95_L, P95_SfM, P95_SfM-L, P99_L, P99_SfM and P99_SfM-L. The best RMSE value of 0.15 and MAE value of 0.13 were found between Mean_g and UAV based Max_SfM-L, and between Median_g and UAV based Max_SfM-L, respectively. The best ME value of -0.03 and MPE value of 0 % were found between Median_g and UAV based Max_SfM-L. The lowest RMSE value of 0.76, MAE value of 0.73, ME value of -0.73 and MPE value of -34 % were found between Max_g and UAV based P90_L. Table 2 summarizes the analysis.

4. Discussion

All of UAV based canopy height values were well correlated with ground based canopy height values with R^2 values ranging from 0.78 to 0.97 (Figure 5, 6, 7). This shows that the method is effective to estimate grass height regardless of whether UAV LiDAR or UAV SfM is used. However, except for the comparison between Median_g and Max SfM-L, underestimation of UAV based canopy hight values ranging from 1 % to 34 % was observed, since all the MPE values indicate minus values (Table 1). This tendency fits the studies of Zhao et al. (2022) and Xu et al. (2023) which state hight information loss of LiDAR acquisition. Because the grass species are relatively small, with leaves about 2 cm wide, so laser light can easily miss the leaf tips. Furthermore, in natural environments, wind blows and grass species sway, making accurate measurements difficult.

UAV based height	Ground based height				
	Max_g				
	RMSE	MAE	ME	MPE	R^2
Max_L	0.53	0.48	-0.47	-21%	0.78
Max_SfM	0.34	0.30	-0.27	-11%	0.87
Max_SfM-L	0.25	0.22	-0.17	-7%	0.91
P90_L	0.76	0.73	-0.73	-34%	0.88
P90_SfM	0.59	0.56	-0.56	-26%	0.87
P90_SfM-L	0.50	0.47	-0.47	-22%	0.89
P95_L	0.69	0.67	-0.67	-31%	0.89
P95_SfM	0.51	0.48	-0.48	-21%	0.90
P95_SfM-L	0.41	0.39	-0.39	-17%	0.93
P99_L	0.60	0.56	-0.56	-25%	0.82
P99_SfM	0.44	0.40	-0.39	-17%	0.86
P99_SfM-L	0.34	0.32	-0.30	-13%	0.90
UAV based height	Ground based height				
	Mean_g				
	RMSE	MAE	ME	MPE	R^2
Max_L	0.42	0.40	-0.34	-16%	0.781
Max_SfM	0.22	0.19	-0.14	-5%	0.919
Max_SfM-L	0.15	0.13	-0.04	-1%	0.947
P90_L	0.62	0.60	-0.60	-30%	0.932
P90_SfM	0.45	0.43	-0.43	-21%	0.93
P90_SfM-L	0.36	0.34	-0.34	-17%	0.943
P95_L	0.55	0.54	-0.54	-26%	0.935
P95_SfM	0.37	0.34	-0.34	-17%	0.94
P95_SfM-L	0.27	0.26	-0.25	-12%	0.963
P99_L	0.48	0.44	-0.42	-20%	0.825
P99_SfM	0.31	0.28	-0.26	-12%	0.901
P99_SfM-L	0.22	0.19	-0.17	-7%	0.937
UAV based height	Ground based height				
	Median_g				
	RMSE	MAE	ME	MPE	R^2
Max_L	0.42	0.39	-0.33	-16%	0.78
Max_SfM	0.22	0.19	-0.13	-5%	0.92
Max_SfM-L	0.15	0.13	-0.03	0%	0.95
P90_L	0.61	0.59	-0.59	-30%	0.94
P90_SfM	0.44	0.42	-0.42	-21%	0.94
P90_SfM-L	0.35	0.33	-0.33	-16%	0.95
P95_L	0.54	0.53	-0.53	-26%	0.94
P95_SfM	0.36	0.34	-0.34	-16%	0.95
P95_SfM-L	0.27	0.25	-0.25	-12%	0.97
P99_L	0.47	0.44	-0.42	-20%	0.83
P99_SfM	0.30	0.27	-0.25	-12%	0.91
P99_SfM-L	0.21	0.19	-0.16	-7%	0.94

Table 1. Values of RMSE, MAE, ME, MPE and R^2 between ground based Max_g, Mean_g, Median_g and UAV based Max_L, Max_SfM, Max_SfM-L, P90_L, P90_SfM, P90_SfM-L, P95_L, P95_SfM, P95_SfM-L, P99_L, P99_SfM and P99_SfM-L.

Analysis Objective	Data Source	UAV Method	Height Metrics (Predictors)	Reference (Ground Truth)	Evaluation Metrics	Key Result
Estimate grass canopy height using LiDAR data	LiDAR point cloud	LiDAR	Max_L, P90_L, P95_L, P99_L	Max_g, Mean_g, Median_g (5 measured max heights)	RMSE, MAE, ME, MPE, R^2	LiDAR alone correlated with ground measurements but showed height underestimation
Estimate grass canopy height using photogrammetry	UAV RGB images	SfM	Max_SfM, P90_SfM, P95_SfM, P99_SfM	Max_g, Mean_g, Median_g	RMSE, MAE, ME, MPE, R^2	SfM showed higher surface point density and better accuracy than LiDAR alone
Estimate canopy height using integrated datasets	UAV LiDAR + SfM	Combined CHM (SfM DSM + LiDAR DTM)	Max_SfM-L, P90_SfM-L, P95_SfM-L, P99_SfM-L	Max_g, Mean_g, Median_g	RMSE, MAE, ME, MPE, R^2	Combined dataset produced the highest accuracy
Compare UAV metrics with ground maximum height	UAV LiDAR / SfM / Combined	Multiple metrics	Max and percentile heights	Max_g	Correlation (R^2)	Best correlation: P95_SfM-L (R^2 = 0.93)
Compare UAV metrics with ground mean height	UAV LiDAR / SfM / Combined	Multiple metrics	Max and percentile heights	Mean_g	Correlation (R^2)	Best correlation: P95_SfM-L (R^2 = 0.96)
Compare UAV metrics with ground median height	UAV LiDAR / SfM / Combined	Multiple metrics	Max and percentile heights	Median_g	Correlation (R^2)	Best correlation: P95_SfM-L (R^2 = 0.97)
Identify best predictor of maximum canopy height	Combined UAV dataset	SfM + LiDAR	Max_SfM-L	Median_g	RMSE, MAE, ME, MPE, R^2	Best model: Median_g vs Max_SfM-L (RMSE 0.15, R^2= 0.95)

Table 2. Analysis summary table

When comparing the accuracy of canopy height estimation using LiDAR data alone, SfM data alone, and combined LiDAR and SfM data, combined LiDAR and SfM data found to perform best, followed by SfM data alone and then LiDAR data alone. This is indicated by the values for RMSE, MAE, ME and MPE which all showed this trend (Table 1). Compared to SfM, LiDAR has the disadvantage of height loss mentioned above but offers better penetration to the ground, which makes more accurate ground data. On the other hand, SfM provides high-density surface data (Figure 8), however, cannot generate point clouds for areas not visible in the images such as the ground area under trees and plants. Therefor, the combined surface data created by SfM and ground data derived from LiDAR is thought to yield better results in estimating grass height than either dataset alone. Given the much lower RMSE (0.42-0.76), MAE (0.40-0.74), ME (-0.33—0.73) and MPE (-16 %--34 %) values of LiDAR data alone (Table 1), LiDAR height loss is considered a major factor hindering the measurement of grass heights.

Figure 8. Ground vegetation survey plots (left), UAV LiDAR point cloud (middle) and UAV SfM point cloud (right). UAV LiDAR penetrates grass species more effectively, while UAV SfM provides higher-density surface data.

As a result of comparing all variables, maximum canopy height was found to be best estimated using the combination of Median_g and Max_SfM-L with RMSE of 0.15, MAE of 0.13, ME of -0.03, MPE of 0 % and R^2 of 0.95 values, followed by the combination of Mean_g and Max_SfM-L with RMSE of 0.15, MAE of 0.13, ME of -0.04, MPE of -1 % and R^2 of 0.95 values. Ideally, since we are comparing the maximum grass height, Max_g should be the best variable instead of Median_g and Mean_g. This indicates that identical grass blades are not compared between UAV based and ground based methods. This would be the limitation of UAV data. Thus, it is recommended to use the median or mean of measured maximum canopy heights as representative values for the maximum height of vegetation on the plot, when compared to UAV based canopy heights. Among the variables of UAV based canopy height, maximum height was the variable that could be estimated most accurately, followed by 99th, 95th and 90th percentile of height values in that order, in terms of RMSE, MAE, ME and MPE values (Table 1). This was a reasonable result for the UAV based variable to represent the maximum canopy height of the plot.

5. Conclusion

In conclusion, the proposed method was found to be effective to estimate grass height regardless of whether UAV LiDAR or UAV SfM is used. However, when comparing the accuracy of canopy height estimation using UAV LiDAR data alone, UAV SfM data alone, and combined UAV LiDAR and SfM data, combined UAV LiDAR and SfM data found to perform best, followed by UAV SfM data alone and then UAV LiDAR data alone. As a result of comparing all variables, maximum canopy height was found to be best estimated using the combination of median of hand-measured five maximum canopy height values and maximum height calculated using the combined LiDAR and SfM data.

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