Research Article

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Comparing LiDAR and SfM digital surface models for three land cover types

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Abstract: Airborne light detection and ranging (LiDAR) and unmanned aerial vehicle structure from motion (UAV-SfM) are two major methods used to produce digital surface models (DSMs) for geomorphological studies. Previous studies have used both types of DSM datasets interchangeably and ignored their differences, whereas others have attempted to locally compare these differences. However, few studies have quantified these differences for different land cover types. Therefore, we simultaneously compared the two DSMs using airborne LiDAR and UAV-SfM for three land cover types (i.e. forest, wasteland, and bare land) in north-east China. Our results showed that the differences between the DSMs were the greatest for forest areas. Further, the average elevation of the UAV-SfM DSM was 0.4 m lower than that of the LiDAR DSM, with a 95th percentile difference of 3.62 m for the forest areas. Additionally, the average elevations of the SfM DSM for wasteland and bare land were 0.16 and 0.43 m lower, respectively, than those of the airborne LiDAR DSM; the 95th percentile differences were 0.67 and 0.64 m, respectively. The differences between the two DSMs were generally minor over areas with sparse vegetation and more significant for areas covered by tall dense trees. The findings of this research can guide the joint use of different types of DSMs in certain applications, such as land management and soil erosion studies. A comparison of the DSM types in complex terrains should be explored in the future.

Keywords: DSM sources, combined DSMs, DSMs quantification, land cover types

1 Introduction

Earth surface process modelling has become easier with developments in geoscience technology [1]. High-precision digital surface models (DSMs) provide basic data for geoscience and environmental science research [2–4]. Two commonly used methods to produce high-precision DSMs, aerial light detection and ranging (LiDAR) and structure from motion (SfM), have been employed in several fields, such as geomorphology, hydrology, agriculture, and forestry [5–8].

However, the principles used to acquire the DSMs with the aerial LiDAR and SfM methods are significantly different. Aerial LiDAR is an aeroplane-mounted, active remote sensing technology that uses in-flight sensors to send and receive laser signals to retrieve elevation information [9], whereas SfM uses optical remote sensing imagery to extract surface elevation information via traditional photogrammetry. Aerial LiDAR offers rapid, high-resolution, and accurate 3D topographic point clouds by penetrating the vegetation cover [10,11]. Recently, airborne photogrammetry has been replaced as the primary technique for mapping regional-scale elevation data [12]. However, the use of LiDAR to obtain surface terrain data requires relatively expensive laser transmitter receivers and complicated hardware, making it a high-cost method for obtaining DSMs [13,14]. Conversely, SfM can utilise several optical cameras to take photographs, which can then be used to develop DSMs by applying photogrammetry algorithms embedded in commercial software [15]. Thus, SfM is a more flexible and cost-effective process than aerial LiDAR [8,16,17]. Quantifying the differences between DSMs acquired by these two methods is important for combining their use in DSM applications [18] and for selecting the most suitable method for DSM generation.

Previous studies involving surface change measurements have employed both DSM data types and ignored their differences. For example, Barnhart et al. [5] compared terrain data obtained by SfM in 2018 with 2008 terrain data from an airborne LiDAR to evaluate terrain

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changes in a catchment. Bates [19] combined two phases of DSMs generated by LiDAR and SfM to evaluate geomorphologic changes in the ravines of a watershed. Madson *et al.* [20] analysed the displacement of a landslide by calculating the difference between a DSM acquired by LiDAR in 2015 and one generated by SfM a year later. Grohmann *et al.* [1] used DSM data obtained by LiDAR in 2010 and a DSM obtained using SfM in 2019 to analyse sand dune migration and volume changes. Kopysc [21] compared DEMs obtained by aerial LiDAR and SfM to record micro-topographic changes on hiking trails within a 4-year period. Góraj *et al.* [22] identified some indicators of the hydromorphological state based on the LiDAR and SfM methods. Warrick *et al.* [23] used DSMs from aerial LiDAR and SfM to analyse terrain changes and surface displacement before and after a landslide.

However, neglecting the differences between the DSM methods can lead to uncertainties. Therefore, recent studies have attempted to quantify the differences. Swinfield *et al.* [7] evaluated the height of a canopy generated by SfM using data obtained from airborne LiDAR as a standard. They found that although the canopy ceiling estimates in both DSMs were very similar, the SfM DSM underestimated the height of the canopy by an average of approximately 5 m. Guerra-Hernández *et al.* [24] evaluated and compared the usefulness of LiDAR-derived and SfM-derived high-density point clouds for detecting and measuring individual tree height in *Eucalyptus* spp. plantations established on complex terrain. Their results suggested that at plot level the two methods are similar for estimating individual tree height. Sofonia *et al.* [6] compared the capabilities of both methods for measuring the height of sugarcane and found similar accuracies. Cao *et al.* [25] used both methods to extract sets of point cloud data in a *Metasequoia glyptostroboides* forest and found that similarities between the two types of data were higher when applied to lower-density areas of tall trees. Rogers [26] compared the capabilities of SfM and aerial LiDAR to generate DSMs and found that SfM produced a more accurate and higher-resolution DSM than aerial LiDAR. Cook [27] evaluated the accuracy of SfM terrain data and compared with simultaneously collected terrestrial LiDAR data. Their results showed that SfM produced data suitable for measuring changes in river landscapes. Guisado *et al.* [28] used SfM and terrestrial LiDAR data to investigate a beach dune system and found that SfM performed well with different terrains and enabled faster data collection. These results indicate that the differences in DSMs created using SfM and airborne LiDAR may depend on the land cover type being investigated. However, few studies have quantified the differences with respect to different land cover types.

Therefore, the aim of this study was to quantify the differences between the two DSM methods for different land cover types. Our test site was located in the suburbs of Nenjiang City, Heilongjiang Province, China, and included three land cover types: forests (trees), wastelands (shrubs and herbs), and bare lands (cultivated land). The DSMs were produced simultaneously, and their differences and uncertainties were quantified with respect to the three land cover types. The results of this research will help stakeholders select the most suitable method for practical applications, such as soil erosion studies [29,30], better land management [31], and geomorphological measurements [32].

2 Methods

Our research was performed on Heshan Farm (49°00'47" N, 125°16'16" E) in a suburb of Nenjiang City, Heilongjiang Province, China. The research area has a cold and humid temperate climate, with an average annual temperature of 4.4°C and average annual rainfall of 193.46 mm [33]. Figure 1 shows the study area, which has an area of 54 ha. The principal types of land cover in this area are built land, forest, wasteland, and bare land. In this work, we primarily focused on the DSM differences between aerial LiDAR and unmanned aerial vehicle (UAV)-SfM with respect to forests, wasteland, and bare land. The three black squares in Figure 1 illustrate the spatial extent of the land cover plots. The areas of forest, wasteland, and bare land were approximately 4,640, 9,196, and 13,286 m², respectively. The land cover types were interpreted manually using orthorectified aerial photographs.

Figure 2 shows the workflow for producing and comparing both types of DSM. Field work was performed in May 2019 to collect both types of UAV data. The LiDAR points were acquired with a LiDAR SZT-R250 sensor onboard a DJI Matrice 600 Pro UAV. During data acquisition, the platform was operated at an altitude of 100 m and a line spacing of 75 m. The horizontal and vertical accuracies of the LiDAR sensor were 0.01 and 0.02 m, respectively. The LiDAR point densities for the forests, wastelands, and bare lands were 113.39, 65.53, and 57.95 points/m², respectively; the SfM point densities were 116.07, 85.38, and 98.29 points/m², respectively (Table 1). The LiDAR points were divided into ground and surface classes; only surface points were used in this study.

We used a DJI Phantom 4 Pro UAV with an optical camera to capture oblique photographs for use in the

Figure 1: Map of the study area, including locations of the three subplots: forest (F), wasteland (W), and bare land (B) mapped using an RGB raster generated from the structure from motion (SfM) point cloud.

SfM. The optical camera had a resolution of 20 million pixels. The UAV was operated at a height of 200 m above the ground, with a 75% heading overlap rate and 70% lateral overlap rate. A total of 197 photographs were taken from the study area. A global positioning system device onboard the UAV linked geographic location information to the optical photographs. We used Agisoft PhotoScan Professional, a commonly used SfM software, to convert the aerial photographs into dense SfM points [34]. By

identifying the metadata of the photographs (such as focal length and pixel size), the software automatically corrects the inherent parameters of the camera, calculates the camera position, and produces point clouds in the general mode [35].

We used CloudCompare v2.11 alpha (Anoia) [64-bit], an open source software, to rectify the dense SfM points to the surface LiDAR points, which were used as the reference data in this work. We then conducted two steps

Figure 2: Schematic flow of this study.

Table 1: Light detection and ranging (LiDAR) and unmanned aerial vehicle (UAV)-structure from motion (SfM) point densities for the three land cover types

	Forest	Waste land	Bare land	Method
Plot area	80 m × 58 m	121 m × 76 m	146 m × 91 m	
Point density (points/m ²)	113.39	65.53	57.95	LiDAR
Point density (points/m ²)	116.07	85.38	98.29	SfM

to perform data matching in CloudCompare. Initially, we coarsely registered both point clouds by aligning their centres with manually selected registration points. Next, we used the fine registration module to register both point clouds by minimising the overall distances between the two groups of points [36]. After point matching, we converted both types of points to raster DSMs using the inverse distance weighted (IDW) interpolation method [37] in ArcMap 10.6. We selected the IDW method, because it predicts unknown points by considering the distance between the known points. This is consistent with the first law of geography, which indicates that nearer things are more similar than distant ones [38]. In addition, the IDW method has also been used in previous similar works to interpolate point clouds to raster [9,39]. The spatial resolution of both raster DSMs was 10 cm. The differences between the two DSMs were calculated using the surface LiDAR DSM as a reference. ArcMap 10.6 and Quick Terrain Modeller v8.2.0 were used to create the figures herein.

3 Results

Figure 3 shows the two types of raster DSMs and their differences; the LiDAR DSM is the reference. The elevation patterns and ranges of both DSMs were similar, showing that the surface elevation of the study area ranged from 317 to 354 m. A visual inspection indicated that the LiDAR DSM (Figure 3b) may have more detailed elevation information in the forestland areas than the SfM (Figure 3a). Most of the differences between the DSMs were less than 1 m, except for the margins around the forest areas. In addition, both DSMs showed that forests and wastelands had the highest and lowest surface elevations, respectively.

To examine the performance of the two raster DSMs with respect to the three land cover types, we calculated the difference between each set of DSM data for the three selected plots (Figure 4 and Table 1). The mean differences between the two DSMs for forests, wastelands, and bare lands were 0.413, -0.045 , and -0.338 m,

Figure 3: Raster digital surface models (DSMs) produced from the (a) structure from motion (SfM) point cloud and (b) light detection and ranging (LiDAR) point cloud. (c) DSM difference calculated by subtracting the unmanned aerial vehicle (UAV) LiDAR DSM from the UAV SfM DSM.

Figure 4: Raster digital surface model (DSM) differences between structure from motion (SfM) and light detection and ranging (LiDAR) data for (a) forests, (b) wastelands, and (c) bare lands, calculated by subtracting the unmanned aerial vehicle (UAV) LiDAR DSM from the UAV SfM DSM.

respectively (Table 2); and the standard deviations of the land cover types were 1.382, 0.069, and 0.06 m, respectively. In addition, the DSM difference in the forest land was the largest (12.431 m), whereas the corresponding differences for the wasteland and bare land were much smaller (0.925 and 0.650 m, respectively). The differences between the DSMs were generally the lowest for bare land and the greatest for forests. The two methods exhibited similar accuracies for wasteland and bare land.

Moreover, we compared both types of raster DSMs on the scatterplot for forest, wasteland, and bare land plots (Figure 5) and calculated their respective correlations based on Pearson Correlation Coefficient, which is a commonly and widely used method. The elevations extracted by the LiDAR are similar to those from the SfM for the wasteland and bare land plots, but vary for the forest plot. Furthermore, the correlations were high for the bare land ($R^2 = 0.9987$) and wasteland ($R^2 = 0.9656$) plots and low for the forest plot ($R^2 = 0.6369$). In the study

area, the elevation of the three land cover types varied significantly; the forest, wasteland, and bare land plots were distributed over ranges of 345–355, 319–321, and 328–337 m, respectively.

To interpret the large discrepancies between the raster DSMs in the forest plot, we examined the LiDAR and SfM points and the LiDAR and SfM DSMs along the cross section of a 70 m line (Figure 6). The LiDAR and SfM DSMs differed greatly along this profile, which is consistent with the observed discrepancy in the raster DSMs for the forest. In addition, the LiDAR DSM contains more missing values than the SfM DSM and changes more dramatically. Furthermore, the raster SfM DSM has more consistent points than the LiDAR DSM. As both DSMs were converted from points, significant differences were determined using their corresponding points. Along the 70-m line, most of the SfM points changed consistently and were distributed near the SfM DSM, whereas the LiDAR points changed drastically in the forest plot.

Table 2: Raster digital surface model (DSM) differences between structure from motion (SfM) and light detection and ranging (LiDAR) data and calculated statistical variability in altitude over three land cover types

Land Cover Types	Mean (m)	Std. Dev (m)	Min (m)	Max (m)	Range (m)
Forest	0.413	1.382	−5.694	6.737	12.431
Waste land	−0.045	0.069	−0.682	0.293	0.925
Bare land	−0.338	0.060	−0.682	−0.032	0.650

Figure 5: Comparisons between the unmanned aerial vehicle (UAV) structure from motion (SfM) digital surface model (DSM) and the UAV light detection and ranging (LiDAR) DSM for three land cover plots. Data correlations are shown in the scatter diagram.

4 Discussion

We produced two raster DSMs from SfM and LiDAR data over an area in northeast China and compared their differences for three land cover types: forests, wastelands, and bare lands. We found that the difference between the DSMs was the lowest for bare land, indicating that the SfM DSM performed better for bare land. Our results for wastelands covered by sparse vegetation were similar to those for bare land, whereas the DSM differences were the largest for forest land. The findings for bare land and wasteland were consistent with those of previous studies [26,40].

Figure 6: (a) Marker place in forest land and (b) side view of the two point clouds and raster digital surface models (DSMs) for forest land; wherein green represents light detection and ranging (LiDAR) point cloud, yellow represents LiDAR raster DSM, blue represents the unmanned aerial vehicle (UAV)-structure from motion (SfM) point cloud, and pink represents the UAV-SfM raster DSM.

To understand the significant difference between the DSMs for the forest plot, we compared both groups of points along a 70 m line and found that the LiDAR points were less consistent with the raster DSM than the SfM points. This is because aerial photographs only capture the surface of the forest canopy [41], whereas LiDAR penetrates the vegetation canopy via gaps and obtains echo signals from both the lower and upper vegetation canopies [10]. Therefore, the SfM DSM shows the upper surface of the vegetation, and the LiDAR surface points capture a 3D interpretation of the vegetation. Further, the SfM uses photographs taken from different viewpoints, which are acquired by moving the camera forward and taking side-view photographs from nearby tracks. Feature detection and matching methods were then applied to these photos to generate point clouds [15]. The use of photographs of different viewpoints for a given locality produces unavoidable time delays, during which many unpredictable factors could influence the photographs. For example, mild wind could change the configurations of the canopy leaves. Such interferences make it difficult to track the same features in photographs from different viewpoints, reducing the number of points describing the canopy surface. Further, capturing photographs from different viewpoints in the inner part of the canopy is difficult. Therefore, compared with LiDAR, SfM captures only the surface of the vegetation canopy.

As visible light remote sensing can only obtain surface elevation information, measuring real terrain covered by dense vegetation is difficult. Thus, the wasteland and bare land vegetation in this study were mostly sparse and short; SfM obtained ground information; and the resulting DSM was similar to the LiDAR DSM.

Point cloud density is another important factor that may influence DSM accuracy and precision [26]. Rogers [26] postulated that areas with the largest errors corresponded to lower point cloud densities. In this work, we produced denser points with SfM than with LiDAR, which could minimise this influence. In addition, the point density was the highest for the forest land cover type. Further increases in the point density for the SfM and LiDAR technologies would barely improve the DSMs [42]. Therefore, land cover type is more likely than point density to influence DSM accuracy.

These results show that SfM-generated point clouds have larger errors in denser vegetation, which is consistent with previous findings [43]. In addition, compared with the LiDAR data, the SfM point data were unevenly distributed, and the vegetation canopy point cloud data obtained were less accurate. Thus, using this method to obtain point cloud data for areas covered by tall and dense vegetation is challenging.

5 Conclusion

In this study, we compared the differences between DSMs produced by airborne LiDAR and SfM for three land cover types. Both methods produced similar point densities, and the mean elevation difference between the two datasets was less than 1 m. Using the LiDAR DSM as the reference, the 95th percentile errors for the SfM DSM in the wasteland and bare land plots were 0.67 and 0.64 m, respectively. Conversely, the 95th percentile difference for the DSMs was 3.62 m for forest land covered by tall dense trees. Thus, using the SfM method to obtain a DSM with high-density vegetation is challenging, because visible light cannot penetrate dense trees; therefore, only surface information of the vegetation canopy can be obtained by SfM. These results indicate that both DSM types can be interchangeably used for wasteland and bare land areas, whereas their joint use for forestland areas is not recommended. However, acquiring higher spatial resolution UAV photographs and collecting additional ground control points may improve the accuracy of SfM-DSM in forested areas.

Although this work was performed on flat terrain, these findings are also applicable to mountainous regions. Furthermore, using UAV SfM to produce a DSM covered with dense vegetation is difficult; therefore, efforts to retrieve terrain data under vegetation cover can be challenging. Despite the flexibility of the SfM method to produce a DSM, airborne LiDAR is an indispensable method for producing digital terrains. Nevertheless, we recommend further research wherein different DSM methods are compared for use in rough terrains.

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