remote sensing

MDPI

Supplementary Material

Table S1. Development of checkpoint RMSE, reprojection error and number of removed points after filtering the sparse cloud and the sub-sequential optimization of the cameras (in order of the applied filters). The initial situation is also given, i.e., the cameras are optimized without filtering. The model qualities weakened from the previous step due to filtering are marked as **bold** and the one weakened during the whole filtration process is in *italics*.

Variable	Site	Campaign Type	Initial Situation: Optimization without Filtering	Filter 1: Reconstruction uncertainty < 22	Filter 2: Projection accuracy < 5	Filter 3: Reprojection error < 0.4
Checkpoint RMSE (mm)	Loukkusuo	IB[1]	114.961	**114.983**	114.506	90.666
		IA	39.561	39.311	39.032	36.299
	Tammalampi	CB[1]	69.473	69.060	**69.327**	62.961
		CA	44.322	**44.360**	**44.363**	44.073
	Iso Leväniemi	IB	23.867	23.814	**23.823**	23.545
		IA	68.382	**68.700**	**69.369**	***69.954***
	Kirkaslampi	CB	30.238	**30.241**	30.185	28.737
		CA	17 167	17 106	**17.108**	15.380
Reprojection error (pixels)	Loukkusuo	IB[1]	0.615	0.615	0.503	0.430
		IA	0.723	0.723	0.464	0.427
	Tammalampi	CB[1]	0.839	**0.846**	0.521	0.456
		CA	0.869	0.865	0.445	0.421
	Iso Leväniemi	IB	0.862	0.862	0.389	0.367
		IA	1.090	**1.120**	0.413	0.380
	Kirkaslampi	CB	0.559	**0.560**	0.417	0.372
		CA	0.673	**0.674**	0.431	0.382
Number of removed points (relative to the initial number of tie points)	Loukkusuo	IB[1]	-	113 (<0.1%)	50 914 (7.9%)	65 822 (10.2%)
		IA	-	52.437 (11.9%)	55 952 (12.7%)	22 553 (5.1%)
	Tammalampi	CB[1]	-	76 972 (19.2%)	62 383 (15.5%)	36 779 (9.2%)
		CA	-	31 096 (6.9%)	75 354 (16.9%)	15 056 (3.4%)
	Iso Leväniemi	IB	-	34 249 (9.0%)	39 651 (10.5%)	8 139 (2.1%)
		IA	-	50 508 (13.9%)	47 446 (13.1%)	12 240 (3.4%)
	Kirkaslampi	CB	-	6 020 (4.2%)	9 027 (6.3%)	13 892 (9.7%)
		CA	-	11 026 (6.2%)	12 874 (7.2%)	17 005 (9.5%)

[1]Non-RTK campaign.

S1. Metashape Filter Parametrization

Each filter was not allowed to remove more than 10–20% of the total tie points [68] to avoid over-constraining and the following doming deformations. The campaign with the highest removal defined the parameter value for all campaigns to homogenize the product quality. However, even smaller values were chosen if the point cloud seemed to become visually too sparse after filtration. Also, the Image Count filter has been used in other literature [99] but was excluded in our study as it removed too many points (35% on average), even with the smallest available threshold of 2. Parameters f, k1, k2, k3, cx, cy, p1 and p2 were chosen to be optimized without additional corrections or fitting an adaptive camera model. After the filtration and optimization, the number of projections should exceed 100 for each image for fluent dense cloud creation [85]. After excluding the two such images, the mean number was 441.

For dense cloud production, Quality and Depth Filtering settings needed to be chosen. Our experiments concluded the "Ultra High" and "High" settings (corresponding to the original resolution and half the original resolution, respectively) to be superior to the lower qualities (Medium, Low and Lowest). Since the "Ultra High" setting produces a four-fold number of points compared with High, a corresponding change in disk space and processing time would have been needed. The visual difference between the two seemed small, except for the outliers increasing together under "Ultra high". The resulting noise level also depends on the chosen depth filter (Disabled, Mild, Moderate, or Aggressive), which excludes excessive points based on their distance from the camera [100]. Our findings are similar to Hesse (2014) and Tinkham & Swayze (2021): the "Aggressive" setting does not give a correct representation of the vertical structure of the vegetation [86,100]. Even if the ground surface and the canopy top of the tallest trees are modelled at the "Aggressive" level, the shorter vegetation is lost (Figure 5b).

S2. Statistical Outlier Filter Parametrization

The Statistical Outlier Filter assesses the points based on their distances to the k-nearest neighbours that are assumed to be normally distributed. A point is treated as an outlier if the distance is more than the mean distance added to the standard deviation that is multiplied by a parameter called nSigma [101]. For example, Lovitt (2017) used k=100 and nSigma=1.5 for an SfM-derived DSM of a tree covered bog [19]. Parameter choices of k=5–10 and nSigma=1–2 have been reported for terrestrial LiDAR data in peatlands and other wetlands [102,103,104]. Pirotti et al. (2018) and Chen et al. (2018) showed the accuracy of correct classification increasing with increasing k and decreasing nSigma when using SfM data in vegetated and constructed environments [105,106]. However, increasing k also extended the processing time. The filter has also been used in a loop (e.g., ten repeats in Carrilho et al. 2018 and two in Stovall et al. 2019 [70,103]), but we found several rounds to degrade the quality of the remaining surfaces.

S3. Cloth Simulation Filter Parametrization

CSF has been shown to perform well with SfM datasets, particularly in handling voids in the ground data caused by interlocking trees [107]. However, CSF is known to have challenges in processing complex vegetation and terrain [108]. It was described by Zhang et al. (2016) as follows [109]. The filter uses relatively few parameters to set up a cloth and settle it on top of an inverted point cloud. After initiating a grid, its particles are moved according to a physical model describing the forces acting in the cloth. The vertical movement of each particle ends up either at ground level or, when there is a void in the ground surface, to a level defined by the internal constraints of the cloth. For steep slopes, a post-processing step can be applied to prevent the cloth rigidness from causing an inaccurate representation of the near-vertical surfaces. Eventually, the cloth and the point cloud are compared, and the ground points are classified according to a distance threshold.

- **Scenes = Flat**. Values 1, 2 and 3 of cloth rigidness correspond to the scene options of Steep slope, Relief and Flat (respectively) in CloudCompare. A very rigid cloth (3) is useful, e.g., in flat urban areas to prevent the cloth from dropping down to the roofs of low-rise buildings[107]. In forested environments, a rigidness of 1 has been used for hilly sites [91,110] and a value of 3 for flat and variable sites [94,108]. However, Wallace et al. (2019) optimized the CSF parameters for different kinds of vegetations and terrains with UAS imagery and, inconsistently with the previous, concluded that value 1 produces the best classification for sparsely vegetated and flat areas, while 3 is best suited for complex canopy structures covering a dense understory and smaller-scale topography variance [111]. The optimization results also depended on whether nadir or oblique imagery was used. We also found varying visual effects depending on the terrain and vegetation types, but the selection rarely impacted as false positives (vegetation misclassified as ground). Instead, the number of false negatives (ground misclassified as non-ground) and thus the size of the surface voids (along the ditch banks in particular) increased when moved towards the steep option.

- **Slope processing = True.** We followed recommendation from Pricope et al. (2020) who found this post-processing to improve the simulation on road ditches with slopes higher than in wetlands studied with LiDAR data [94]. Similarly, with the previous parameter, we found few visual impacts as false positives, but the slope processing was able to prevent some voids from appearing.
- **Cloth resolution = 1.0 m.** According to Brieger et al. (2019), the resolution should be between the typical diameter of high-vegetation bodies and the average dimension of microtopography to properly follow the terrain [107]. The literature provided arbitrary choices between 0.1–1.0 m [94,107] and optimization results between 0.1–0.6 m [91,107,108]. We found small values (≤0.5 m) increase the false positives for the forested areas, while large values (≥2.0 m) increase false negatives and produce voids. A balance was found between the two which still ensured the absence of the remaining higher vegetation which would make ground analysis impossible.
- **Classification threshold = 0.1 m.** This is the maximum distance allowed between the cloth and a ground point [110]. The literature provided arbitrary choices between 0.1–0.5 m [94,110] and optimization results between 0.05–0.6 m [91,107,108]. Decreasing the classification threshold value shortened the ‘stumps’ (the remaining tree points close to the ground) while voids occurred on the ground surface when approaching zero. A balance between the stumps and the holes was found at a value of 0.1 m.
- **Maximum number of iterations = 500**. Our inspections support Zhang et al. (2016) regarding the achieved maximum height variation (preset in the tool), typically quitting the simulation earlier than the used default iteration limit [109].

S4. Filter Discussion

As we demonstrated in Figure 5b,c, depth filtering and SOR are efficient ways to reduce the noise. For depth filtering, this comes at the price of data degradation. The filter intensity should be based on the specific study aims and data requirements. For topographical analysis, the “Aggressive” setting can be used, however, it ruins the vertical structure of the vegetation [100] and tends to remove too many points for thorough noise removal [63]. “Mild” or “Moderate” is recommended when also the vegetation is under interest. In these cases, the increased noise can be filtered out to some extent with the post-processing tools.

We found the “Mild” cloud very noisy causing challenges for SOR, but the chosen “Moderate” was cleaned sufficiently. However, some noise might have remained, since the SOR filter is known weak in removing noise points near the main geometric structure[69]. In addition, the reflections from open water remained and needed to be removed manually. SOR evaluates the outliers by their spatial isolation [71] and thus, cannot recognize points that form continuous surfaces only in the wrong locations due to reflections or refractions. The water-related Fresnel reflections also cause the images to align poorly when mapped from multiple angles [63]. The reflections might cause challenges for monitoring restoration sites since an increase in water table level often leads to increased open water cover (high-water situation in May illustrated in Figure 9B3). In our analysis, the pit depths might have been biased due to water cover, but it was not critical as the sinks were eventually filled. Removing the reflection points assumably from trees was effortless since they appeared deep below the ground. SOR filtering has been shown effective in cleaning point clouds, but it tends also to remove some non-outliers, particularly from vertical surfaces [70]. Thus, the site-specific iteration of the parameter values is needed.

Particularly the negative outliers would have been fatal for the used ground classification approach with CSF as the cloth settled on top of the inverted point cloud would have stuck on the flawed points. CSF is known as an effective, freely available, and easy-to-parametrize approach [107]. We consider CSF performing well in classifying the points after the optimal parameter values were found first, despite being originally developed for LiDAR point clouds. However, we did not systematically test the classification and a part of the determined DTM errors might be due to an improper classification in SOR and CSF, particularly for the tree-covered edges. CSF has been shown to perform well with SfM datasets, particularly in handling voids in the ground data due to interlocking trees [107]. Klápště et al. [108] compared six different ground filters and, contrarily, reported CSF as the poorest one. For instance, Progressive Triangulated Irregular Network, Progressive Morphological Filter and Simple Morphological Filter performed better under complex vegetation and terrain. Further studies on the topic are recommended.

S5. Correlation between Topographic and Field Wetness

The field measured SWC showed a positive correlation with the topography based SWI for the restored sites but not for the pristine control sites ($p < 0.05$, Figure S1). The fitted linear regression models (represented visually in Figure 8) for Loukkusuo and Iso Leväniemi explain the variation between SWC and SWI moderately well ($R^2 = 0.256$ and 0.415, respectively).

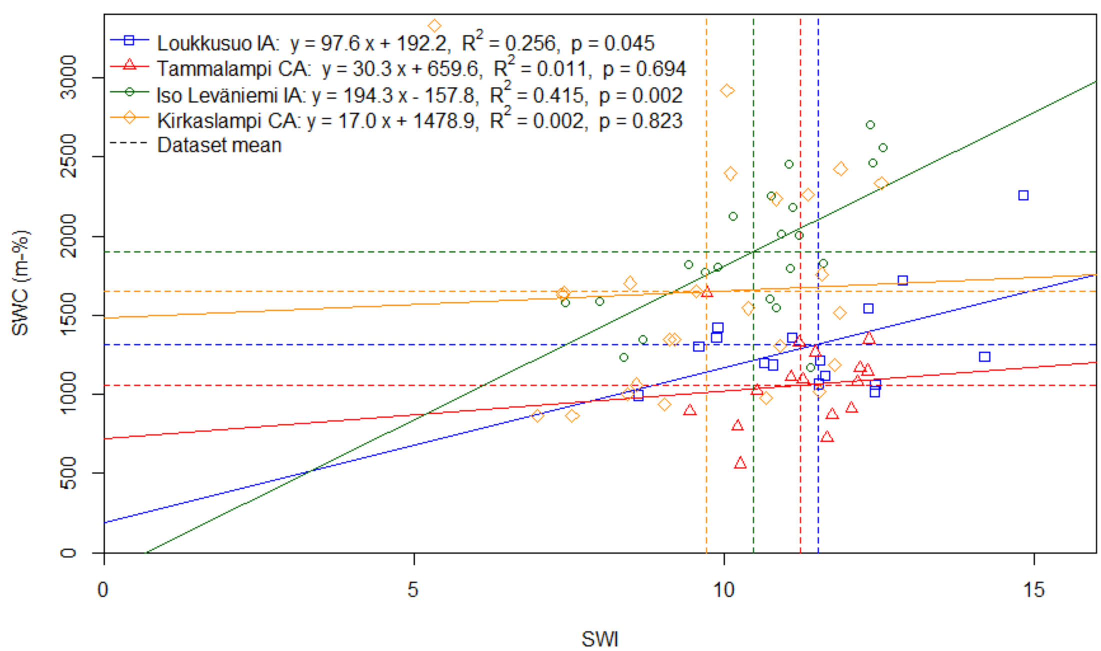

Figure S1. Gravimetric Soil Water Content (SWC) as a function of topography-based Saga Wetness Index (SWI) and the fitted regression lines. SWC was determined for IA/CA state by drying samples from the peatland surface. Corresponding SWI values were extracted from the wetness maps and smoothed with a low-pass filter. The fits (see also Table 4, d) were used to scale the colours of the SWC circles in Figure 8.