CIVIL ENGINEERING JOURNAL

Article no. X

THE CIVIL ENGINEERING JOURNAL Y-20ZZ

Appendix

Reference Networks

Detailed statistical evaluation of the accuracy of the Czepos and TopNet reference networks used for surveyed points- the evaluation of errors of the X and Y coordinates (7 points used) is in Tab. 1 and for the Z coordinate (75 points used) is in **Chyba! Nenalezen zdroj odkazů.**. and in box plot graphs in Fig. 1,2 and 3.

Tab. 1 Statistical evaluation of X a Y coordinate accuracy (errors) for the Czepos and TopNet reference network

Method	**Czepos**		**TopNet**	
	X	Y	X	Y
Spatial autocorrelation (Moran's Index)	0.518 *	0.709 **	0.742 **	0.437 *
Mean	-0.013 †	0.003 †	-0.033 ***	0.007 †
Median	-0.016 †	-0.004 †	-0.027 **	0.001 †
RMSE	0.023	0.029	0.036	0.020
Standard Deviation	0.021	0.031	0.017	0.021
Standardized Skewness	-0.041	-0.247	-0.242	-1.033
Standardized Kurtosis	-0.042	-1.1	-1.729	0.884
Normality (Jarque-Bera JB)	0.29 †	0.47 †	0.67 †	0.78 †
Pearson correlation	0.827 **	0.965 ***	0.817 **	0.967 ***

Statistical significance if tested: † not significant, * p-value <0.1, ** p-value <0.05, *** p-value < 0.01

The analysis of coordinate errors revealed that CZEPOS provides higher accuracy in the X direction, with a lower mean error (-0.013 m) and no statistically significant deviation from 0 value. In contrast, TopNet shows a significant systematic bias in X (mean value -0.033 m), despite similar overall deviation (RMSE = 0.023 m).

In the Y direction, TopNet performs more reliably, with a lower RMSE (0.020 m), reduced skewness, and weaker spatial autocorrelation compared to CZEPOS. The mean Y errors for both networks are small and not significantly biased. CZEPOS exhibits higher clustering of error values (Moran's I = 0.709 **). Importantly, errors in both coordinates strongly correlate with elevation (Z), indicating that accuracy decreases with increasing height, regardless of the reference network used.

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Tab. 2 Statistical evaluation of Z coordinate accuracy (errors) for the Czepos and TopNet reference network

Method	***Czepos***	***TopNet***
	Z (altitude)	**Z (altitude)**
Spatial autocorrelation (Moran's Index)	0.521***	0.501***
Mean	0.107 ***	0.082 ***
Median	0.114 ***	0.086 ***
RMSE	0.119	0.095
Standard Deviation	0.053	0.048
Standardized Skewness	-0.985	-0.848
Standardized Kurtosis	1.4	1.01
Normality (Jarque-Bera JB)	18.07***	12.09***
Pearson correlation	-0.189*	-0.156 †

Statistical significance if tested: † not significant, * p-value <0.1, ** p-value <0.05, *** p-value < 0.01.

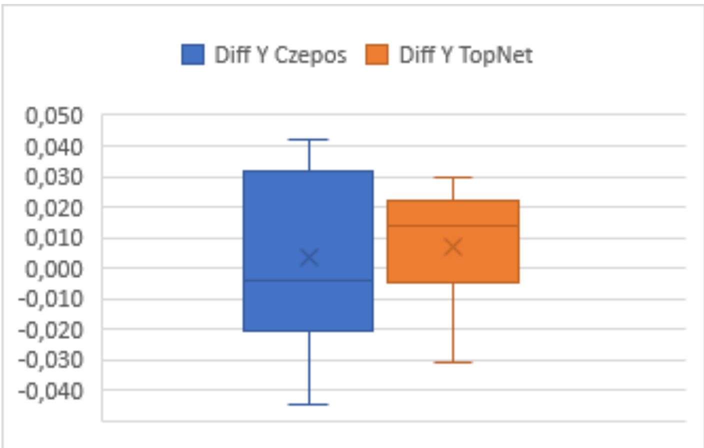

Fig. 1 Box plot showing the differences for the Y coordinate

Fig. 2 Box plot showing the differences for the X coordinate

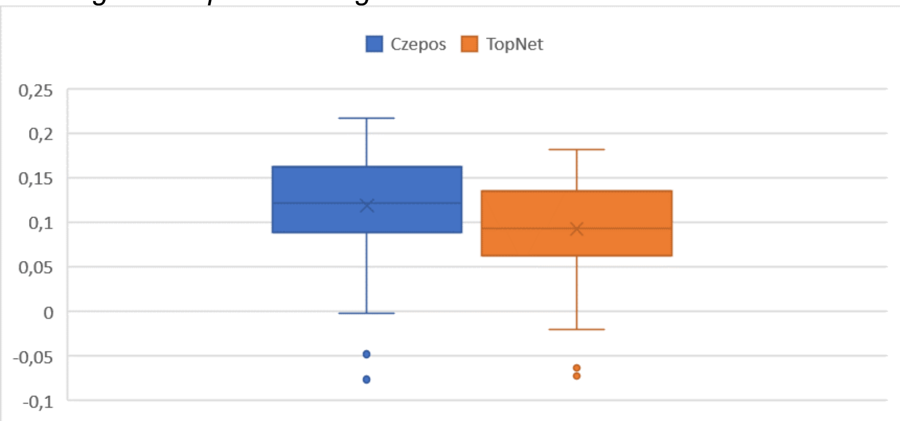

Fig. 3 Box plot showing the differences for the z coordinate

Accuracy and Systematic Errors of the Z coordinate analysis

Both reference networks exhibit a systematic overestimation of elevation values. For CZEPOS, the mean deviation is 0.107 m and the median is 0.114 m. For TopNet, the mean is 0.082 m and the median is 0.086 m. In all cases, the deviation of mean and median from 0 value is statistically significant at the $p < 0.01$ level, indicating a consistent positive bias in elevation measurements.

Accuracy and Error Dispersion

TopNet achieved a lower overall error compared to CZEPOS. The root mean square error (RMSE) for TopNet was 0.095 m, while CZEPOS recorded a RMSE of 0.119 m. Similarly, the standard deviation was slightly lower for TopNet (0.048 m) than for CZEPOS (0.053 m), suggesting a marginally higher precision and stability in TopNet's elevation data.

Spatial Behavior of Errors

Both methods display significant spatial autocorrelation of errors. Moran’s I values were 0.521 for CZEPOS and 0.501 for TopNet, both significantly different from 0 value. This indicates that errors are not randomly distributed and form locally clustered patterns.

Statistical Properties of Error Distribution

The distribution of errors is not normal as confirmed by the Jarque-Bera test: 18.07 for CZEPOS and 12.09 for TopNet. (both statistically significant). The characteristics of skewness are negative (-0.985

for CZEPOS and -0.848 for TopNet). suggesting that most values are slightly below the mean with some larger positive outliers. Additionally, both distributions show a slightly increased kurtosis (values above 1), indicating a sharper peak and heavier tails than a normal distribution.

Error Dependency on Elevation

There is a weak negative correlation between elevation errors and altitude. For CZEPOS, the correlation coefficient is -0.189 and is significantly different from 0 value. This suggests a slight tendency for elevation underestimation in higher terrain. For TopNet, the correlation is −0.156 and is not statistically significant.

Influence of post-processing operations on LiDAR data

Tab. 3 Methods used to post-process LiDAR data

Smooth1	No smoothing applied.
Smooth2	Only the *Optimize Point Cloud Accuracy* function in DJI Terra Pro was used.
Smooth3	Without using the *Optimize Point Cloud Accuracy* function in DJI Terra Pro; instead, TerraSolid (Spatix) was used with the *Smoothen and Remove Noise* tool.
Smooth4	Combination of Smooth2 and Smooth3; smoothing applied both in DJI Terra Pro and in TerraSolid (Spatix).
Smooth5	Combined approach including SOR filtering in CloudCompare (SOR parameters: 8 neighbors, standard deviation multiplier 1.5).

Visual inspection of the 3D difference models (Main text – Fig. 7 A–E) confirms the quantitative finding: a significant deviation is only evident in the unsmoothed model (RMSE = 4.79 cm), while all tested smoothing variants achieve an RMSE between 2.4–2.78 cm. The results show a consistent improvement in accuracy due to the application of smoothing algorithms. The detailed description of the used post-processing methods is in Tab. 3.

When comparing smoothing methods over communications the best results are achieved by *the Smooth 3* and *Smooth 5* variants, both with an RMSE of around 2.5 cm. The differences between them are minimal, but *the Smooth 3 method* is characterized by a completely symmetrical distribution of errors (mean = median = 0) and slightly lower variability which makes it the most balanced choice – see Tab. 4

Methods using DJI Terra optimization show lower dispersion and fewer outliers. but achieve slightly higher deviations compared to *the Smooth 3* method. probably due to smoothing that suppresses fine height details of the surface. See Fig. 4.
On further visual analysis presented on Fig. 4. outliers are prominent in *Smooth 1*. but also occur in *Smooth 5* and *Smooth 4*. which may indicate local errors in classification or a less appropriate selection of points in some segments of communication.
The symmetry of the distribution is best in the *Smooth 3*. where the median lies almost exactly in the middle of the box. On the other hand, there *is a noticeable hint of a positive shift in the Smooth 4* and *Smooth 5* (the median is closer to the lower limit of the box) which may indicate a tendency to overestimate the height.
The visualization also confirms earlier quantitative results – *Smooth 3* is the only method without DJI optimization that achieves very good results and can be preferred where maintaining height details is a priority. On the other hand, FigFig. 5 shows the structure of the point cloud (both the original and the spatially repaired one using the control point) and the position of the control point. The control point always comes out into the space between the LiDAR points of the cloud so the verified value of the Z coordinate is always interpolated from the cloud under test.

The Smooth 3 and Smooth 5 methods were subjected to detailed geostatical analysis. The spatial autocorrelation of model errors was statistically significant in both compared methods (Moran's I = 0.487 and 0.694 respectively; p-values < 0.01) indicating a significant spatial structure of the residuals.

The central tendency was negligible – the mean and median error for the *Smooth 3* method was 0 while for *the Smooth 5* they reached values of 0.014 m and 0.016 m respectively.

The variance of errors was low for both methods with RMSE below 3 cm (0.024 m for *Smooth 3* and 0.026 m for *Smooth 5*) which is fully consistent with the expected accuracy over communications. Standardized skewness and kurtosis and the box plots show a narrow distribution around zero with a minimum of outliers.

The normality test (Jarque-Bera) did not reveal significant deviations from the normal distribution for any of the methods (p > 0.1).

The "peaks" visible in Fig. 7-C (in the main text) are always outside the control points and even though the statistical evaluation values of the Smooth 3 method come out better than the Smooth 5 method. This method wins in terms of visual quality (smoothness).
The effect of point cloud co-registration on only one ground control point was also evaluated as part of the statistical analysis. Box plot difference of Z coordinates (their significant improvement after the implementation of GCP into processing) within the Smooth 5 method is on Fig. 6

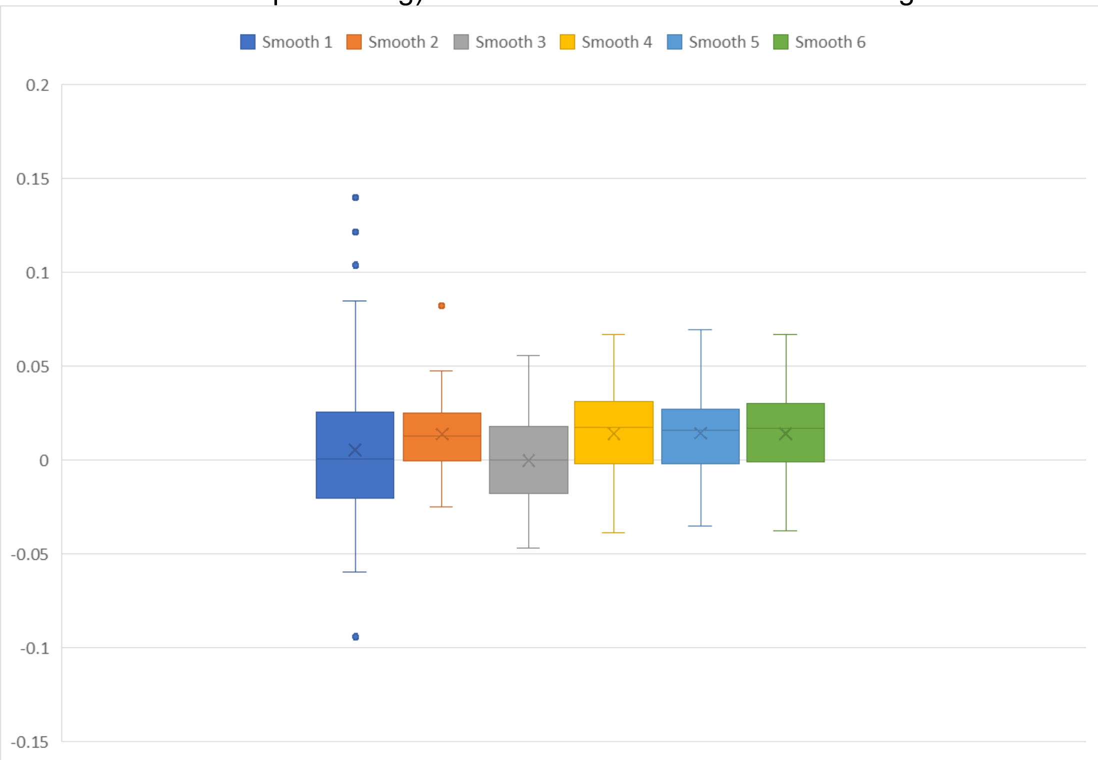

Fig. 4 Box plot of errors of tested smoothing methods (Smooth 1 – Smooth 6) referring to data in Tab. 4.

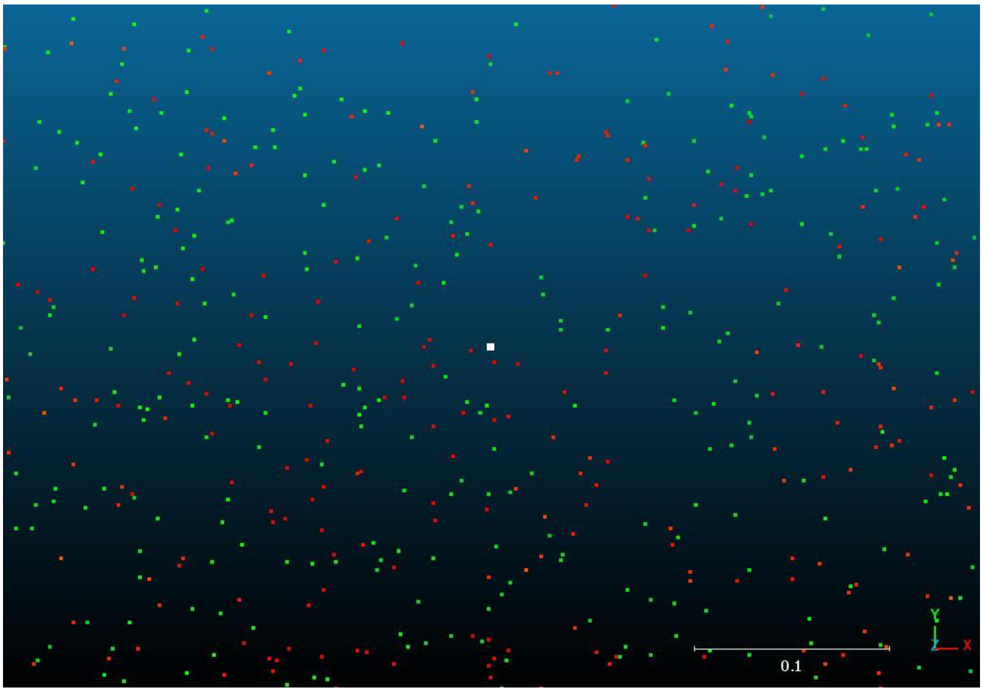

Fig. 5 GNSS measured control point (white), original point cloud (red), positionally corrected point cloud (green).

Tab. 4 Detailed statistical analysis of errors of Smoothing 3 and Smoothing 5 methods on summer data (June 19, 2023)

Method	**Smooth 3**	**Smooth 5**
Spatial autocorrelation (Moran's Index)	0.487 ***	0.694 ***
Mean	0.000	0.014
Median	0.000	0.016
RMSE	0.024	0.026
Standard Deviation	0.024	0.022
Standardized Skewness	0.068	0.09
Standardized Kurtosis	-0.378	0.4
Normality (Jarque-Bera JB)	0.416 †	0.106 †
Pearson correlation	0.452	0.452

Statistical significance if tested: † not significant, * p-value <0.1, ** p-value <0.05, *** p-value < 0.01.

Tab. 5 Detailed statistical analysis of errors of Smoothing 3 and Smoothing 5 methods on winter data (January 24, 2025)

Method	**Smooth 5**	**Smooth 5 GCP used**
Spatial autocorrelation (Moran’s Index)	0.849 ***	0.773 ***
Mean	-0.119	0.011
Median	-0.111	0.013
RMSE	0.121	0.025
Standard Deviation	0.020	0.022
Standardized Skewness	-0.416	-0.273
Standardized Kurtosis	2.135	2.173
Normality (Jarque-Bera JB)	2.765 †	1.881 †
Pearson correlation	0.946	0.946

Statistical significance if tested: † not significant, * p-value <0.1, ** p-value <0.05, *** p-value < 0.01.

Fig. 6 Box plot of errors in Z coordinate on point cloud without Ground Control Point co-registration (blue) and with Ground Control Point co-registration (right).

The impact of "bare earth" filtering on data quality

Point cloud processing software products include various methods of "bare ground" filtering. As part of our processing. we tested algorithms in our available (and widespread) tools. An overview of the tested methods is in **Chyba! Chybný odkaz na záložku.**.

Tab. 6 Tested methods for filtering "bare ground"

Clasif 1	1. Spatix: Process Drone Data – used Thin Points to Inactive, Classify Ground (value: 10), Classify Height from Ground (1;5) 2. CloudCompare: SOR filter (8 neighbors, standard deviation multiplier 1.5)
Clasif 2	1. ArcGIS Pro: Classify LAS Ground – Standard Classification method 2. CloudCompare: SOR filter (8 neighbors, standard deviation multiplier 1.5)
Clasif 3	1. ArcGIS Pro: Classify LAS Ground – Conservative Classification method 2. CloudCompare: SOR filter (8 neighbors, standard deviation multiplier 1.5)
Clasif 4	1. ArcGIS Pro: Classify LAS Ground – Aggressive Classification method 2. CloudCompare: SOR filter (8 neighbors, standard deviation multiplier 1.5)
Clasif 5	1. Spatix: *Classify Ground* – default settings, modified: Max building size 8 m, Terrain angle 15°, Iteration angle 10°, Iteration distance 100 m
Clasif 6	1. Spatix: same as Clasif5 2. CloudCompare: SOR filter (8 neighbors, standard deviation multiplier 1.5)
Clasif 7	1. CloudCompare: SOR filter (8 neighbors, standard deviation multiplier 1.5) 2. CloudCompare (CSF plugin): *Relief* method; advanced settings – *Cloth resolution*: 0.5, *Max iterations*: 500, *Classification threshold*: 0.5

Tab. 7 Detailed statistical analysis of Z-coordinate errors for individual bare ground filtering methods

Method	Clasif 1	Clasif 2	Clasif 3	Clasif 4	Clasif 5	Clasif 6	Clasif 7
Spatial autocorrelation (Moran's Index)	0.107 ***	0.110 ***	0.114 ***	0.113 ***	0.178 ***	0.180 ***	0.108 ***
Mean	-0.148	-0.150	-0.149	-0.149	-0.085	-0.085	-0.241
Median	-0.167	-0.171	-0.169	-0.170	-0.101	-0.102	-0.253
RMSE	0.247	0.251	0.253	0.250	0.250	0.251	0.301
Standard Deviation	0.198	0.201	0.205	0.201	0.235	0.236	0.180
Standardized Skewness	-1.816	-1.772	-1.673	-1.710	-0.647	-0.588	-4.664
Standardized Kurtosis	37.254	35.852	34.387	35.650	23.102	22.508	67.900
Normality (Jarque-Bera JB)	219710.876 ***	202171.294 ***	184492.956 ***	199561.912 ***	75133.823 ***	70723.017 ***	796 039.946 ***
Pearson correlation	1 ***	0.992 ***	0.988 ***	0.995 ***	0.839 ***	0.835 ***	0.063 ***

Statistical significance if tested: † not significant, * p-value <0.1, ** p-value <0.05, *** p-value < 0.01.

Quality was evaluated on the basis of more than 4500 points measured by RTK GNSS within the test area of interest. This analysis also included 46 road-focused points (and used to evaluate point cloud smoothing) to verify the possible effect of filtering algorithms on the overall quality of the point cloud. The quality of the filtered point cloud was again evaluated using three defined qualitative parameters. The results are presented in Tab. 7.

The spatial autocorrelation of errors was statistically significant in all tested methods (p-values < 0.01) with Moran index values ranging from 0.107 to 0.180. This indicates that the errors are not randomly distributed in space and exhibit a spatial structure.

The normality of the error distribution has not been confirmed for any of the methods. Jarque-Bera statisticsachieved extremely high values and were significantly different from normality in all cases (p-values < 0.01). This corresponds to high values of standardized kurtosis exceeding 20 and negative skewness in all cases. The most significant deviations from normality were recorded in *Clasif 7* (kurtosis = 67.9; skewness = - 4.664) as confirmed by the box plot with numerous outliers (see Fig. 7).

The central tendency (mean and median) was negative for all methods with the lowest values again for *Clasif 7* (mean = - 0.241; median = - 0.253). The variance of errors (RMSE) was also highest for this variant (0.301) while the lowest RMSE values were achieved for Clasif *1* and Clasif *5* (0.247 and 0.250 respectively).

The relationships between the methods errors and elevation were expressed by Pearson's correlation coefficient. A high correlation (r > 0.99) was observed between most variants of standard processing (*Clasif 2*, *Clasif 3* and *Clasif 4*). On the other hand the *Clasif 7 method* showed a low correlation (r = 0.063), which indicates a fundamentally different nature of the resulting errors.

Although the individual classification methods differ slightly in accuracy most of them give very similar results. The largest deviations and variance of errors are shown by *the variant Clasif 7* while the other approaches differ mainly in lower variability and better symmetry of errors. In practice, most of the tested methods can be considered comparably applicable if they are applied consistently and with regard to the specific conditions of the given area.

Of all the approaches tested, the Clasif 1 method shows the best ratio between accuracy, stability and a reasonable degree of variability as it achieves the lowest RMSE (0.247 m).

Fig. 7 Box plots of errors in the Z coordinate for individual classification approaches

Methodology for filtering "bare ground" with snow cover

To remove vegetation in the case of a point cloud with snow cover. It is advisable to use a point cloud from the period without vegetation in combination with a cloud with snow. Calculation of the approximate maximum thickness of snow cover – a "snow-free" cloud with filtered vegetation is converted to mesh and then the "Cloud to Mesh distance" is calculated. From the winter cloud we extract only points that are in the range of +/- 0 to the maximum snow depth. This will filter out most of the vegetation. This step can only be replaced by estimating the snow depth – i.e. filtering points that lie within our estimated interval. In the following steps it is necessary to remove the remains of vegetation.

1. Filtering according to Roughness around the points (Tools > Other > Compute Geometric Features) and choose a window size of 0.5 – 1 m (in our case 0.5 m). Snow has low roughness, vegetation significantly higher. We filter points with low Roughness (Edit > Scalar Fields > Filter By Value (in our case < 0.05)).

2. Filtering by return number - snow usually reflects only one pulse (last return). while vegetation often causes multiple reflections. Filter only Last Return (Edit > Scalar Fields > Filter By Value (in our case = 1)).

3. If the sensor has recorded intensity. we check the histogram (Edit > Scalar Fields > Show Histogram). We filter values with typical snow intensity - it is usually higher but it depends on the specific scan (Edit > Scalar Fields > Filter By Value (in our case > 100)).

The previous procedure will filter out most of the vegetation but it is still necessary to focus on the remnants of branches.

4. We will use the "local roughness" function again. Branches often change the slope and shape of the surface – even if they are low – they have a different geometry than smooth snow. In the "Compute Geometric Features" tool. select "Roughness" but this time in a small area (0.1 – 0.3 m). We then filter the points with a Roughness > 0.01.

5. It is also advisable to filter the cloud according to the normals. Normals need to be computed first (Edit > Normals > Compute). Other parameters - Neighborhood radius (depending on cloud density. „Auto“ can be selected); Preferred orientation: +Z. In CloudCompare normals need to be exported as a Scalar Field (Edit > Normals > Export Normals to SF(s)). We export points with a normal value. e.g. 0.95 – 1.0. That is we keep only points that have normals almost perpendicularly upwards (typically snow).

After these two steps. most of the vegetation points should be filtered out. However. if there are still some left – usually isolated points – we will use the next step.

6. The SOR (Statistical Outlier Removal) filter can be applied to the individual points that remained after the previous filtration process in the Tools > Clean > SOR menu. In the parameters we need to set "k" which is the number of nearest neighbors (in our case 10) and Sigma - the number of standard deviations from the average distance (in our case 1.5).