

ESSE-4640 Digital Terrain Modelling
Term Project

Group 2

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08/12/2021

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Executive Summary

For the term project of ESSE 4640, students were tasked with researching and developing a practical application of Digital Terrain Models that would be useful in the real-world. Groups are expected to find pertinent data for their chosen area-of-study and use reconstruction techniques to produce a three-dimensional model of a structure using point-cloud format data obtained from reliable sources. All technical specifications, methodology and applications of data manipulation, findings, and analyses of the results are to be extensively documented.

Introduction & Scope

A three-dimensional reconstruction of a structure is a three-dimensional approximation of a real world object that is created by manipulating data obtained from photogrammetry, LiDAR scanning, etc. These approximations are of great importance for future construction via urban planning, creating show-models of cities for tourism purposes, and historical preservation of building shapes [1].

Many roofs in urban areas are flat [4] and this simple geometry can be used to model many buildings in these areas with potential in modeling the incoming heat into buildings and provide the basis for accurate updating of building databases [4].

Creating a 3D model from different lidar point clouds often needs co-registration of the point clouds as the points do not always coincide perfectly. The iterative closest point algorithm reconciles these differences in an iterative process.

Lidar data contains spatial as well as surface reflectance data based on how much of the laser signal returns to the Lidar system which can be used to classify spatial data and separate meaningful feature data.

The scope of this assignment will be a three-dimensional recreation of the Life Sciences Building on York University's Keele campus.



Figure 1a - The Life Sciences Building
(<https://www.nxl.ca/project/york-university-life-science-building/>)

Problem Statement & Objectives

In order to achieve the primary objective outlined in “Introduction & Scope”, there are a number of tasks that will be necessary to complete, and they are as follows:

- Perform background research
- Familiarize members with the LiDAR process, equipment specs, etc.
- Obtain the necessary data for reconstruction (at least two for coregistration)
- Necessary conversions and implementation of data into a workspace for visualization (CloudCompare, MeshLab, etc.)
- Coregister datasets

- Data classification
- Generate building footprint (vectorization)
- Extract three-dimensional multipatch from footprint

Study Area & Data Description

The area of study, as stated previously, will be the area around and encompassing the Life Sciences Building.

Two LiDAR point clouds will be used to facilitate the main goal, one created by Natural Resources Canada (NRCan) and obtained via Scholars' Geoportal [2], and one created by Airborne Imagery (AI) and obtained via York University's GAIA Portal.[3]

The former dataset is given in LAZ format, whilst the latter dataset is given in LAS format.

Methodology

Equipment used:

- CloudCompare
- MeshLab
- AI & NRCan Lidar data
 - Lidar sensor system Leica ALS70 (Table 1)
 - Manned Aircraft
 - Trained Pilot
 - Lidar operator

a)

Data set	Sensor System	Acquisition Period	Speed (kn)	Flightline Spacing (m)	Single Pass Swath Width (m)	Scan Angle or Field of View (°)	Scan Freq (Hz)	Scan Pulse Rate (KHz)	Flight Altitude (m)	Overlap
NRCan	Leica ALS70	Apr to May 2014	160		1283.4	40	52	400	1300	50%
AI	Leica ALS70	Apr to May 2015	140	350	700	50	47	300	800	50%

b)

Table 1 - a) NRCan Lidar and b) AI Lidar system specifications and flight parameters

The two Lidar point cloud data sets were first cropped to the study area in Cloud Compare to reduce computation time (Figure 2).

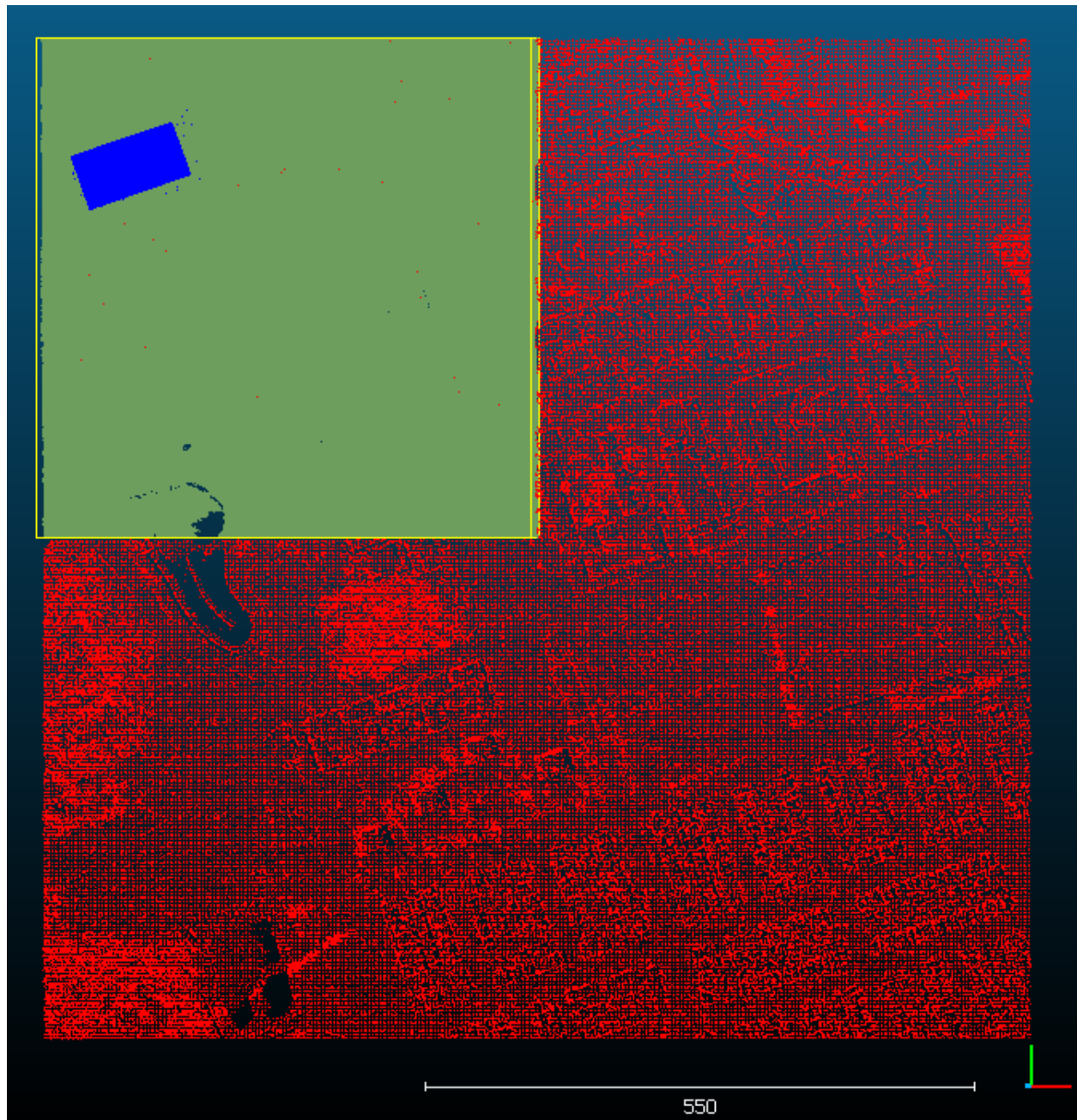


Figure 2 - Top-down view of study area (blue), original data tile of NRCan cloud (red) and AI cloud (green)

The Lidar data from NRCan and AI were not aligned perfectly and were offsetted from each other mostly in the vertical direction (Figure 3). The data sets were co-registered via the iterative closest point

algorithm using the AI point cloud as reference where the NRCan point cloud was aligned to the AI cloud (Figure 4).

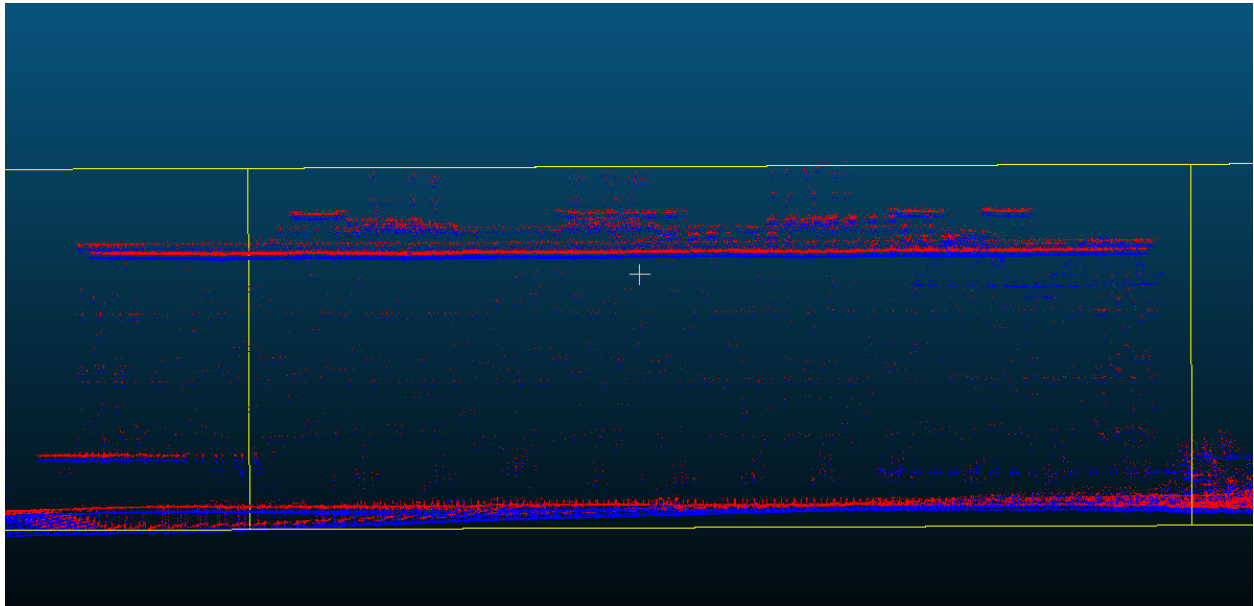


Figure 3 - side view of the Life Science Building point clouds, NRCan in blue and AI in red

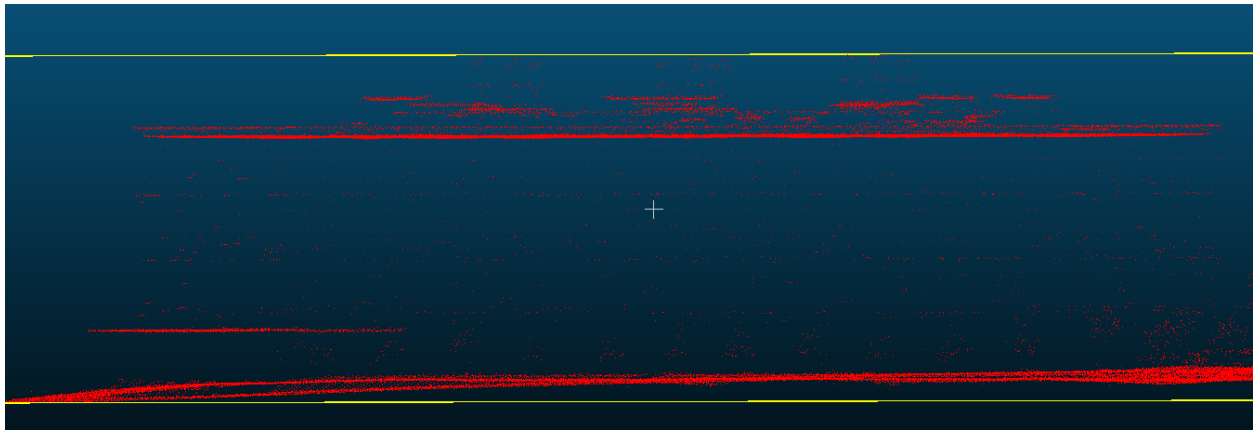


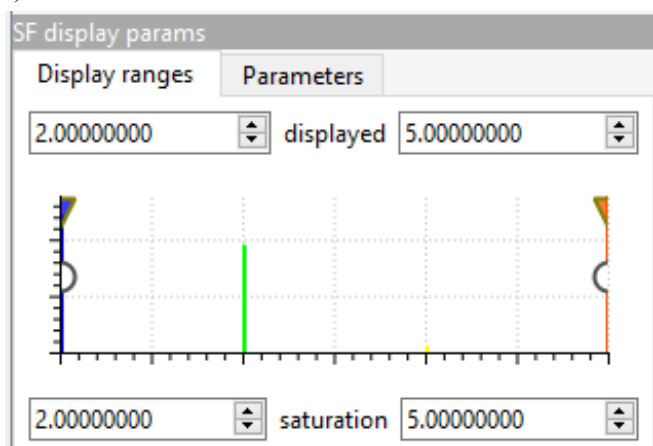
Figure 4 - alignment of NRCan to AI cloud via ICP both in red

The 2 point clouds were classified into bare earth and building features so that the major non-surface features like vegetation canopies were removed from the building roof reconstruction and the geometric primitive fitting. The AI lidar data had already been classified into LAS 1.2 feature classes intrinsically in the lidar product so vegetation classes were omitted by class (Table 2).

Table 2 - some LAS 1.2 classification codes

Classification value	Meaning
0	Never classified
1	Unassigned
2	Ground
3	Low Vegetation
4	Medium Vegetation
5	High Vegetation
6	Building
7	Low Point
8	Reserved *
9	Water
10	Rail
11	Road Surface

a)



b)

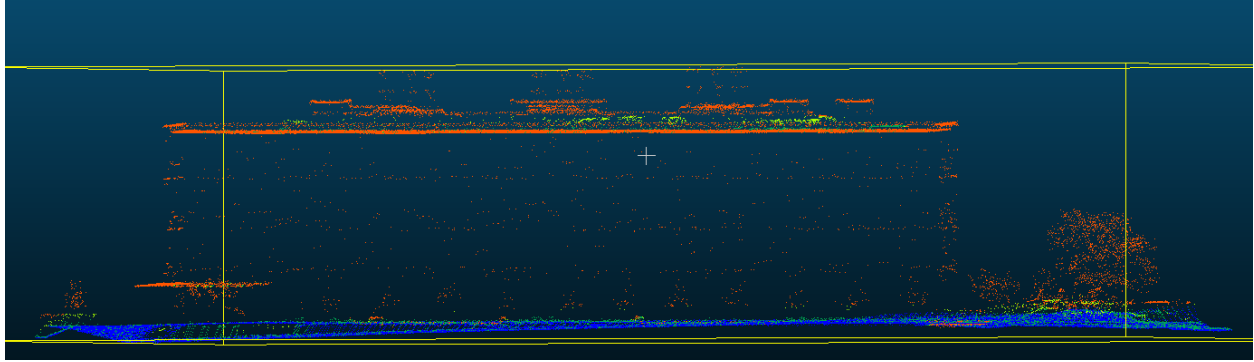
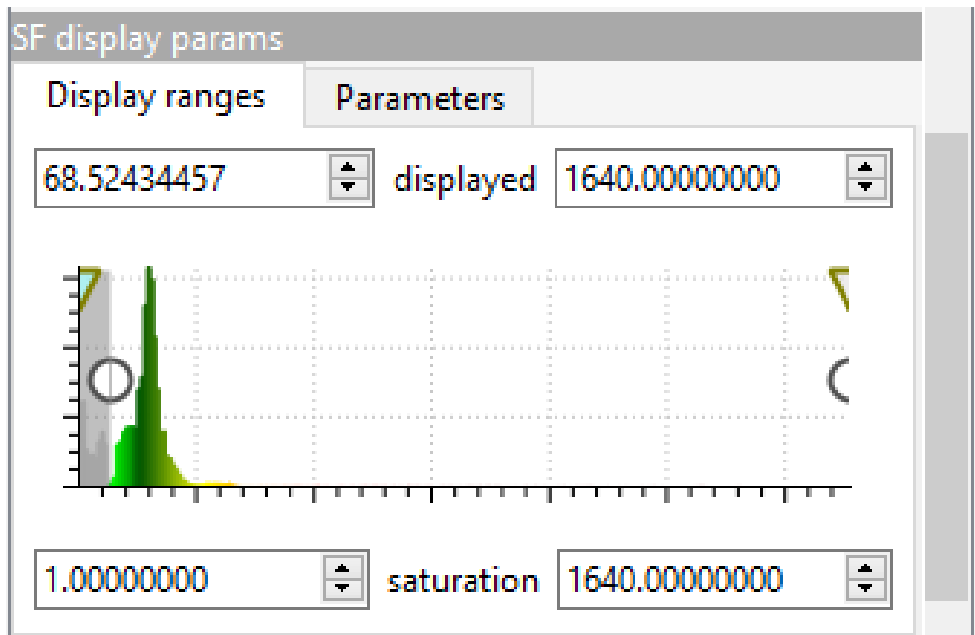


Figure 5 - a) Histogram of point classes in AI point cloud and color mapping of points in 5b), b) AI points coloured by class

Of the LAS 1.2 classes only classes 2-5 were identified in the AI cloud (Figure 5a). Note that no building was detected but most building points were wrongly classified as class 3, 4 and 5 which are all vegetation classes. The ground with class 2 in blue was correctly classified for the most part (Figure 5). For this project's purposes, assuming that vegetation is only to be expected on the ground, we made an approximation that vegetation classes high enough above the ground were roof features while all vegetation points near the ground were considered vegetation canopy and omitted.

For the NRCan point cloud, the vegetation features were classified by thresholding by intensity (Figure 6).

a)



b)

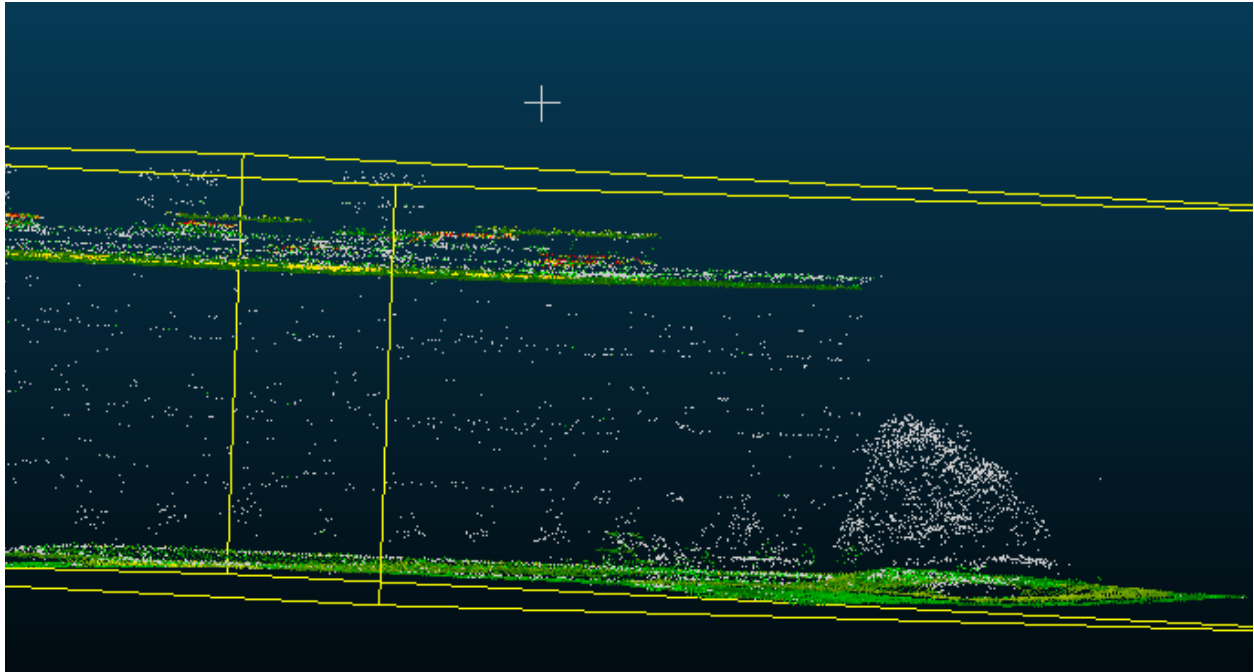


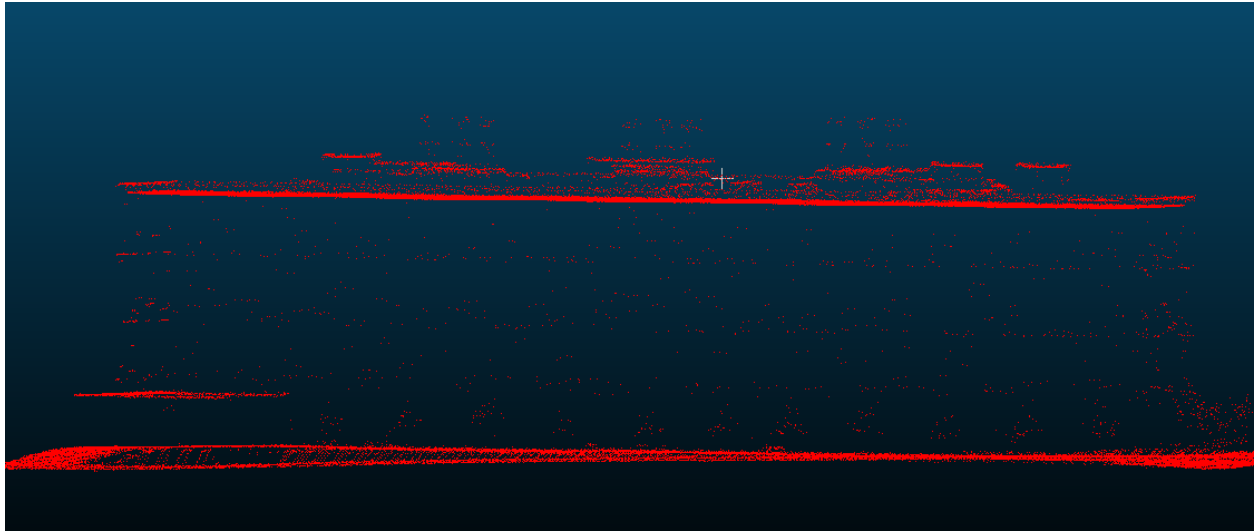
Figure 6 - Vegetation classification for NRCan. a) Intensity histogram with values of inclusion range used for classification for retaining building and surface features, b) points omitted (white) and points included (colormapped from green to red by increasing intensity)

Classifying by intensity and thresholding out low intensity points had the desired effect of omitting most undesired points like the tree canopy and the unexpected but still desired effect of removing the building wall points which are unwanted since our project scope is limited to roof and roof footprint modelling (Figure 6).

As building roofs tend to contain infrastructure like exhaust pipes and additional structures picked up by Lidar sensors, these features detract from the planar geometry of the roof so data from these structures were thresholded out manually (Figure 6) where points above the trend roof's elevation were excluded from the plane primitive calculation. Similar to the roof, the ground contained features above the terrain that detracted from the primitive calculation like remaining vegetation canopy, the building walls and the Life Science's building's shade overhangs were also removed and was also done manually (Figure 7).

If there are future implementations of roof footprint detection, a semi-automatic ground and roof point detection would be done and involve the use of RANSAC to produce surfaces which are robust to outlying features that deviate from the surface model.

a)



b)

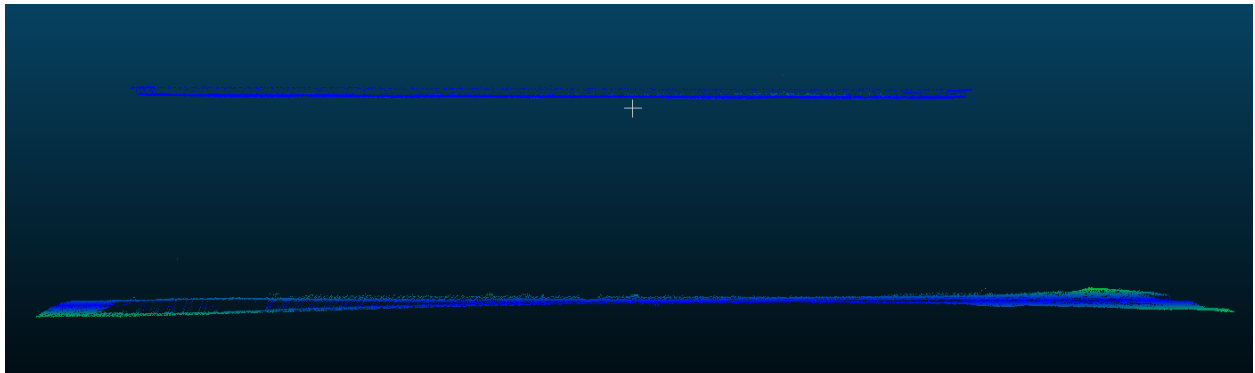


Figure 7 - a) remaining unwanted features from filtering, b) result of thresholding and manual segmentation for only ground and roof surface features

The roof and ground points were segmented apart in Cloud Compare and each the roof points were fitted with a plane primitive and the ground points fitted with both a plane and a 2nd order polynomial surface using least squares in Cloud Compare (Figure 7). The average distance from the fitted surface primitive and the standard deviation of the distances were collected using Cloud Compare tools (Table 3).

The primitives can then produce meshes for further texturing of real image data onto the surfaces if needed to produce a photo-realistic reconstruction (Figure 8).

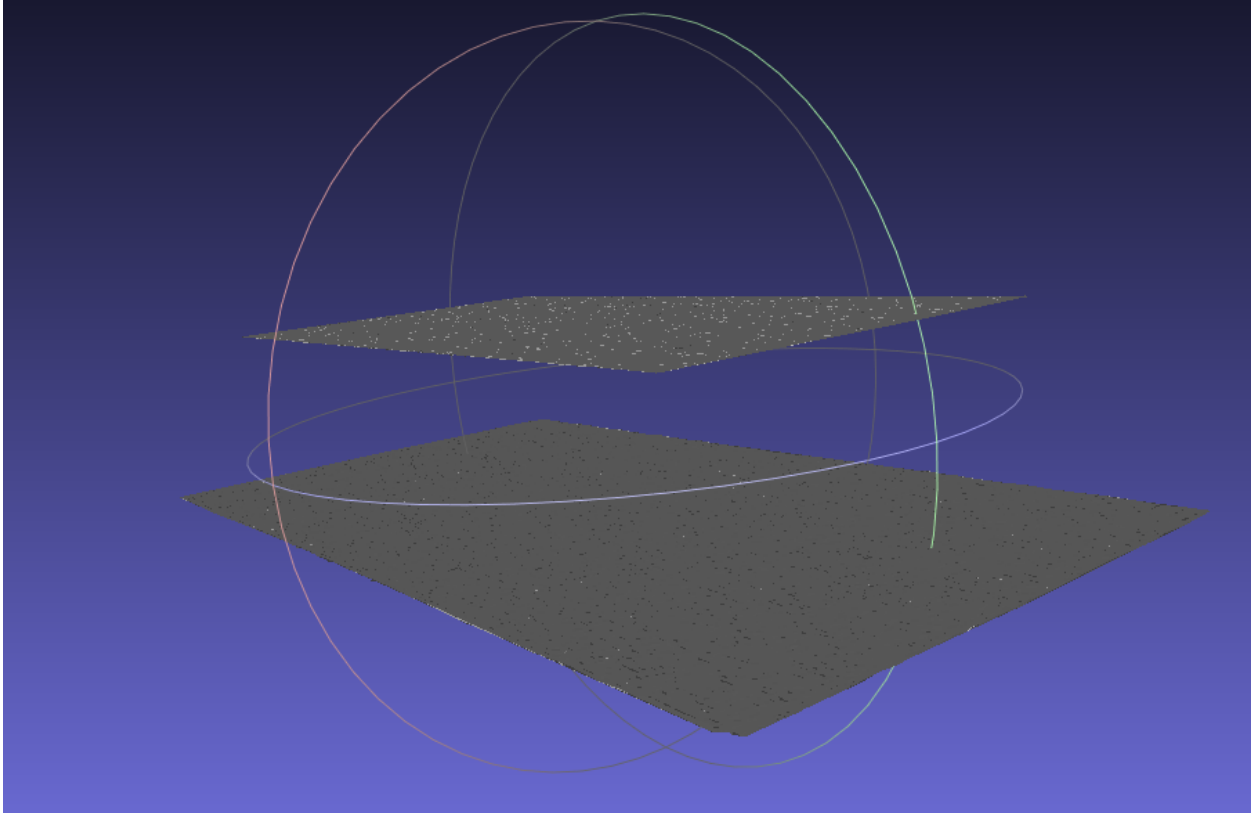


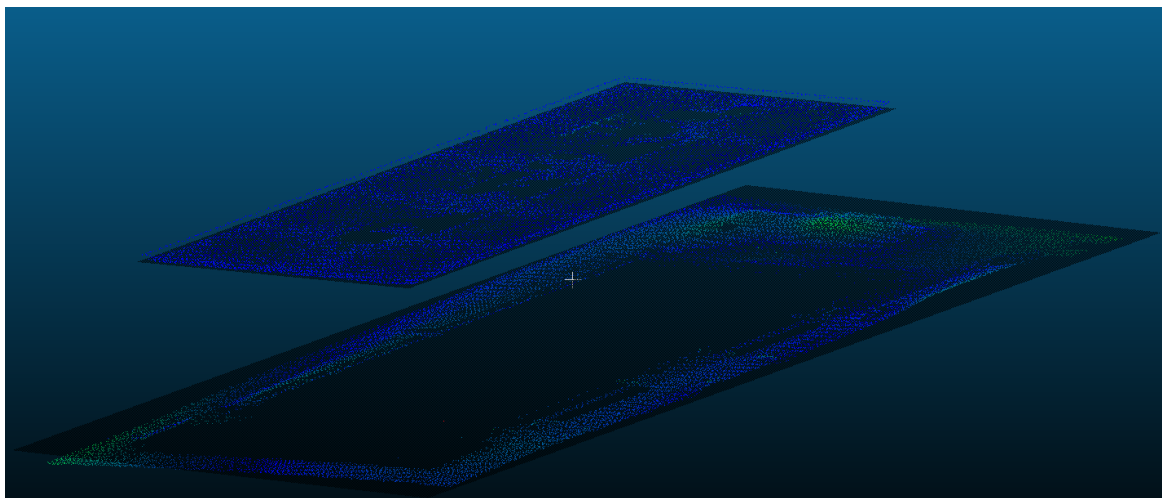
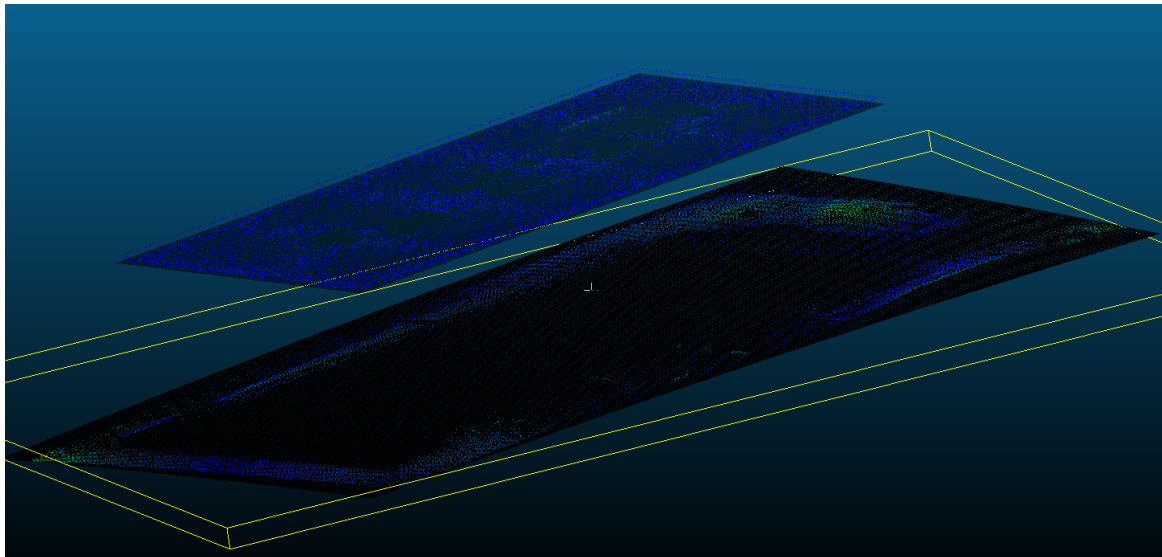
Figure 8 - Meshes imported into MeshLab

Results

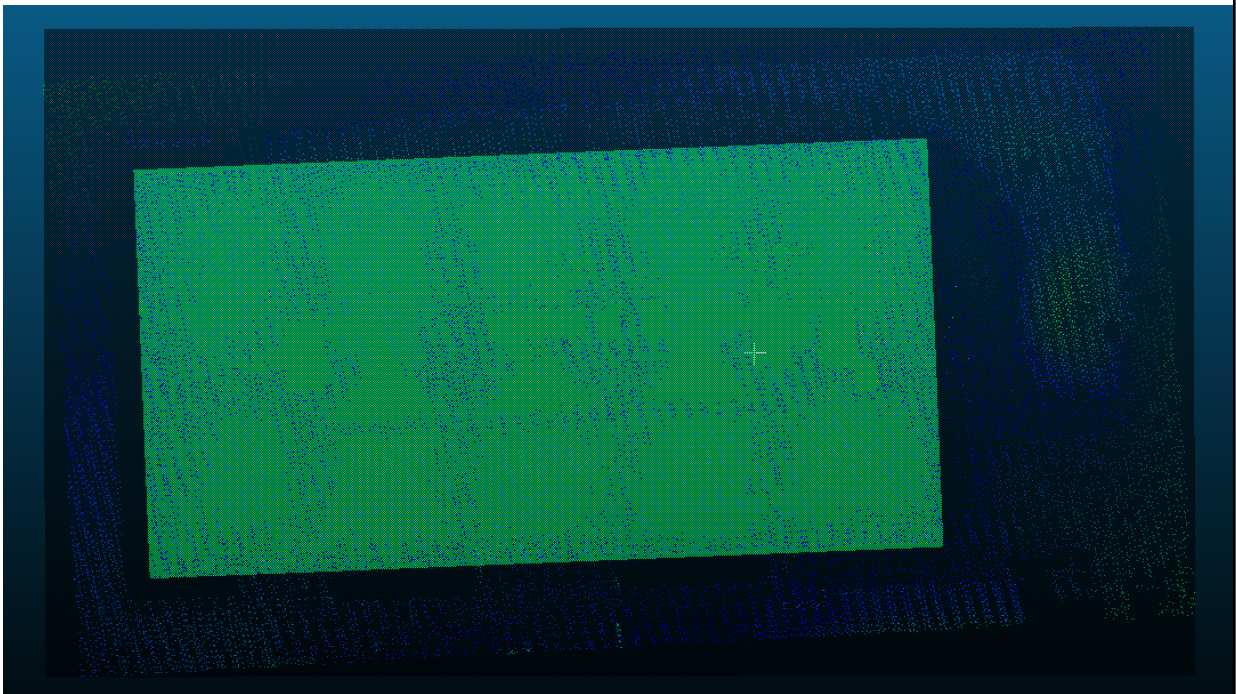
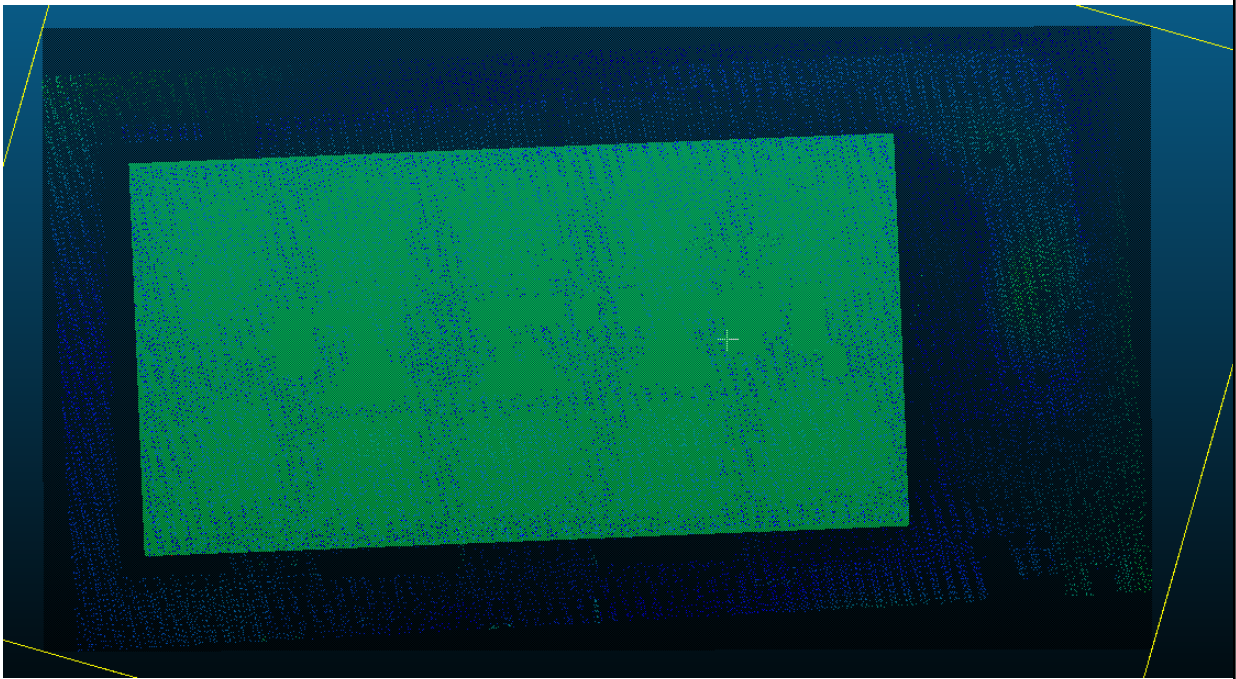
Table 3 - Mean distance from classified points and their fit surfaces

Primitive	Mean Distance (cm)	Standard Deviation (cm)
Roof Plane	6.7	11.0
Ground Plane	38.6	25.4
Ground 2nd Order Polynomial Surface	21.4	21.1

Isometric View



Top-down View



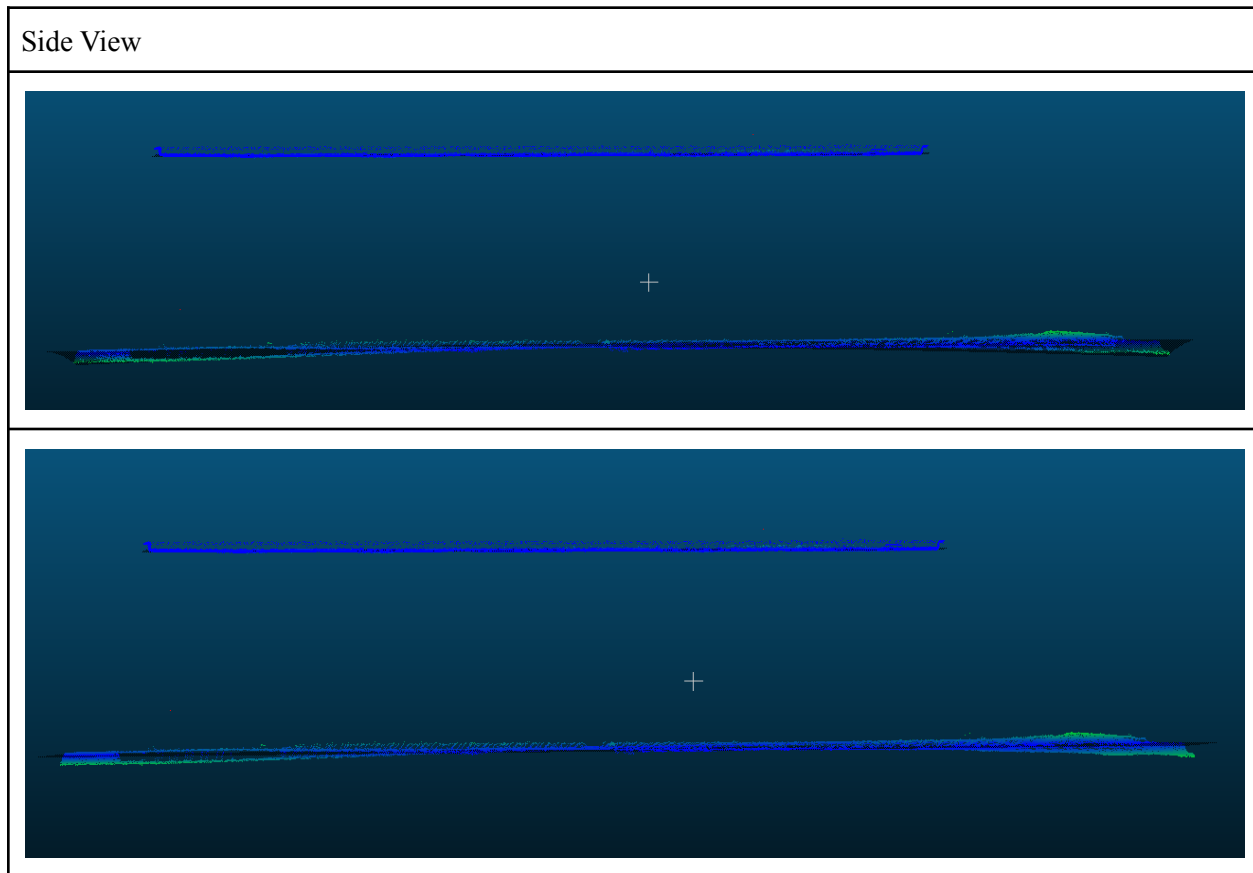


Figure 9 - Isometric, top-down and side views of the polynomial fitted (gray) followed by plane fitted ground surface. Roof plane held constant.

Discussion

The higher precision and accuracy (lower standard deviation and lower mean distance) of the roof fitting was expected due to the intrinsically flat geometry of the roof building while the ground terrain is less flat with curves leading to the worse surface fit measures when trying to fit a plane to the ground terrain. The slightly curved parts of the ground terrain also explain why the ground polynomial surface is a better fit than the plane due to the slightly curved terrain since polynomial surfaces define curved surfaces hence its lower mean distance and standard deviations (Table 3).

Conclusion

In conclusion, the objective of obtaining and coregistering separate pieces of data obtained from different sources in order to reconstruct a three dimensional model of the area of study was successfully met. A great deal of information was obtained regarding the practical applications of digital terrain models, and all members of the group were left with a sense of awe and inspiration for the future of this technology.

Division of Labour

Dion Farquhar - Data Collection, Report Formatting, General Assistance

Jared Yen - co-registration, classification, primitive generation, mesh generation

Shaivy Tola - Classification and compilation of data used, Report Editing

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