LAND COVER CLASSIFICATION USING MULTISPECTRAL LIDAR DATA

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INTRODUCTION

- The uses of LiDAR for various kinds of development purposes has been such a prevalent topic in modern society, especially in the late 2020s.
- One such application is the classification of landcover, as well as features, in order to better assist with land development and planning (Jing, et. Al, 2021).
- There are multiple multispectral LiDAR hardware, which can gather point cloud data with multi-wavelength intensities at the same time
- A multispectral LiDAR system collects multi-wavelength spectral datasets at the same time, as the 3-D spatial data, which provides attributes from multiple features to the targets of interest.
- Various studies have shown that multispectral LiDAR point clouds obtained accurate classification of information in fine detail (Jing, et. Al, 2021).
- PointNet++, which is a hierarchical structure of PointNet, can extract regional features, as well as handle points, which are unevenly sampled through multi-scale grouping (MSG), allowing it to improve the robustness of the model (Jing, et. Al, 2021).
- The features, which are trained and learned by the PointNet++ have some channels, which are ineffective, costing heavy computational resources and resulting in a lower classification accuracy.
- To enhance important channels and subdue other channels, which are inaccurate for prediction, a Squeeze and Excitation block (SE-block) is integrated into the PointNet++, which is called SE-PointNet++ (Jing, et. Al, 2021).
- The popular end-to-end SE-PointNet++ method was suggested for conducting the point-wise multispectral LiDAR point cloud classification
- Peterborough is one such rural town, that requires more land development work and expansion of the area, so more people can migrate there, and businesses can thrive, as a result, which is why the study is being conducted in that city.

LITERATURE REVIEW/RELATED WORK

- It is usually a two-step process (Li, et. al):

1. Choosing seed points to create an initial sparse surface
2. To iteratively look for candidate ground points, which lie in a certain threshold, compared to the initial surface

- Triangulated Irregular Network (TIN) and Interpolation methods are used to determine the neighbourhood size for searching the cells, which is critical to the success of the filtering of the points (Li, et. al).
- The progressive TIN densification (PTD) model was utilized to create DTMs by forming a sparse TIN as the primary terrain model, which leads to choosing the local minima, as seed points to densify the TIN iteratively.
- There is another surface-based modelling, which uses linear prediction (Li, et. al).
- The algorithm creates the primary surface by taking the average of the elevation of all the points.
- Next, the weight of each elevation was assigned iteratively (Li, et. al).
- Points, that are located underneath the surface, which provide negative residuals will be assigned with higher weights.
- The iteration will keep going until the surface becomes stable or until the maximum iteration has been reached (Li, et. al)
- Another method for feature extraction is segmentation-based.
- In segmentation-based feature extraction, raw LiDAR data is converted into a raster or voxel grid (Li, et. al).
- Next, the segmentation is conducted, based on the height or intensity values.
- Once the segmentation has been performed, the data is classified according to the geometric characteristics and topographic relationships of segments (Li, et. al).
- The segments are thought of as the basic processing units in the classification.

DESCRIPTION OF THE STUDY AREA

- The study area is Peterborough, Ontario
- It is a place, where people can get different perspectives on life, take in fresh air, find a balance between personal and professional life (Peterbrough).
- A region that is filled with communities, that offer businesses, residents and visitors, which provide a modest way of living and a wonderful place to grow (Petersborough).
- There are advantages of city living, while enjoying the benefits of the natural world (Peterbrough).
- The city provides safe neighbourhoods with community centers, parks, trails and other activities for the entire family (Peterbrough)
- Peterborough is the perfect place to start your own business, providing a ton of resources and programs to guide you.
- This city has three school boards, a university and a college (Peterborough)
- The indigenous community, that previously existed in the area for thousands of years before European settlement, continue to be active members of the community.
- During the past two hundred years, people from more than a hundred countries have helped to shape the diverse community, which is full of culture and history (Petersborough)
- This leads to Peterborough being the home to multiple multicultural organizations and associations

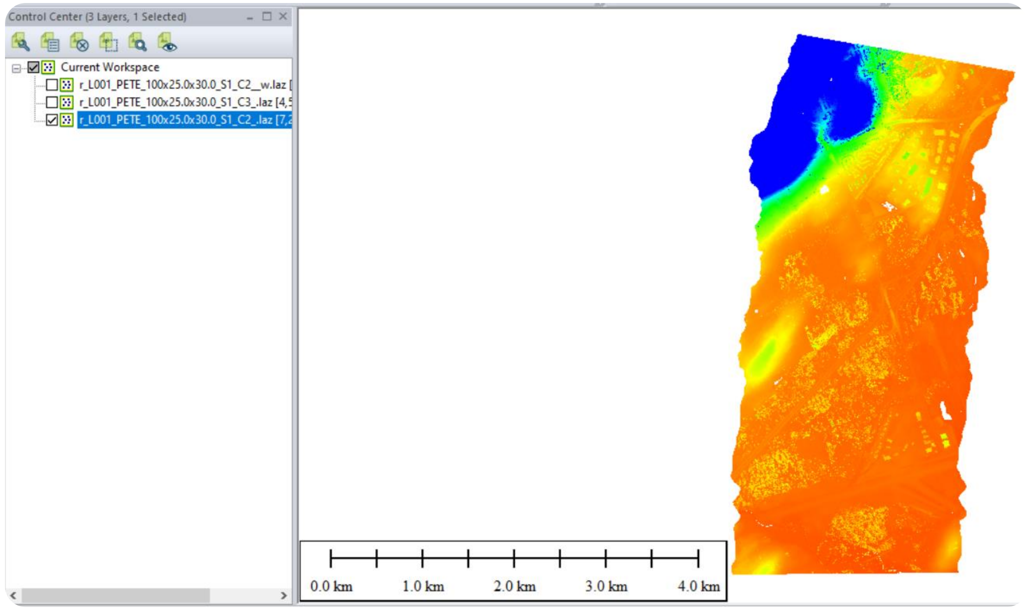

Figure 1-> Line 1, All Channels

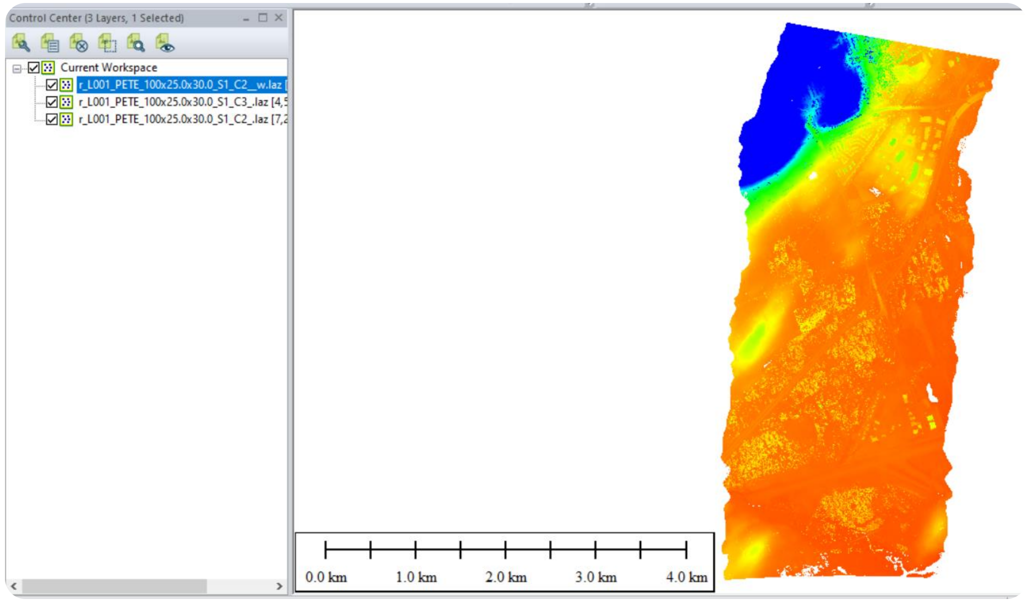

Figure 2-> Line 1, Channel 3

MULTISPECTRAL LIDAR DATA- TOWN OF PETERBOROUGH

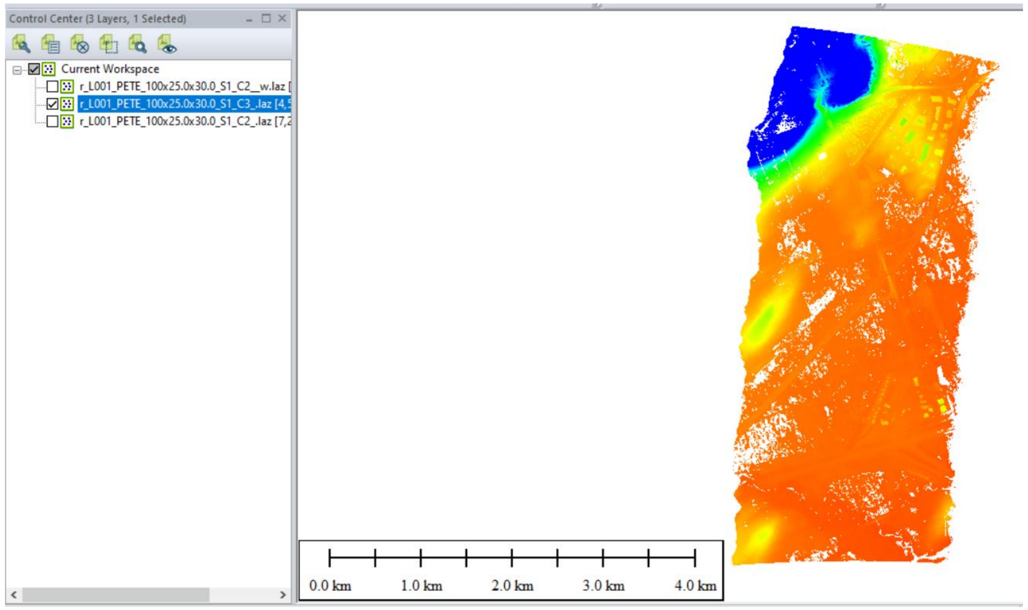

Figure 3-> Line 1, Channel 3

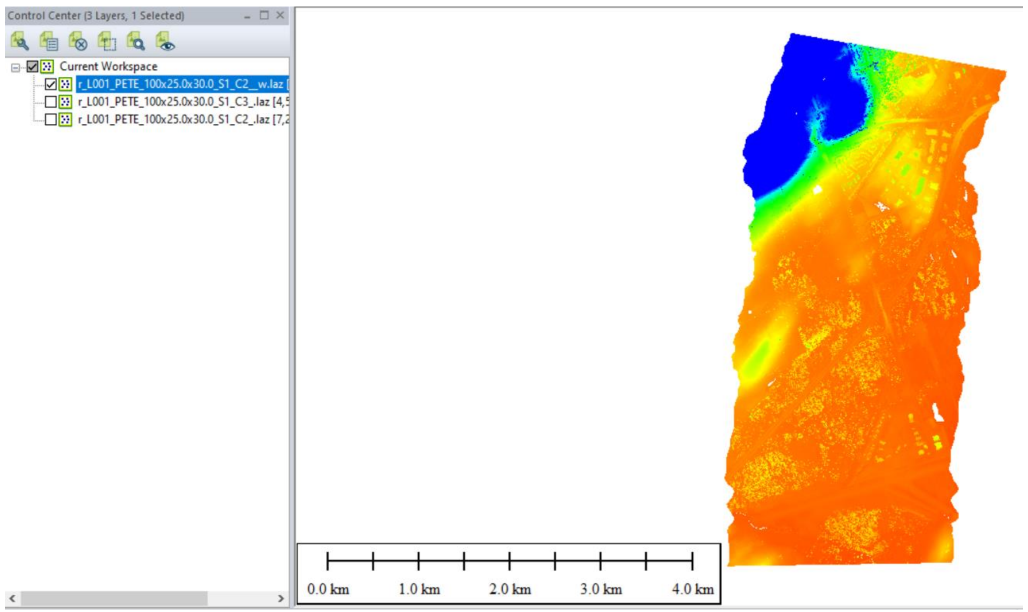

Figure 4-> Line 1, Channel 2 waveform

TITAN MULTISPECTRAL LIDAR DATA- TOWN OF PETERBOROUGH

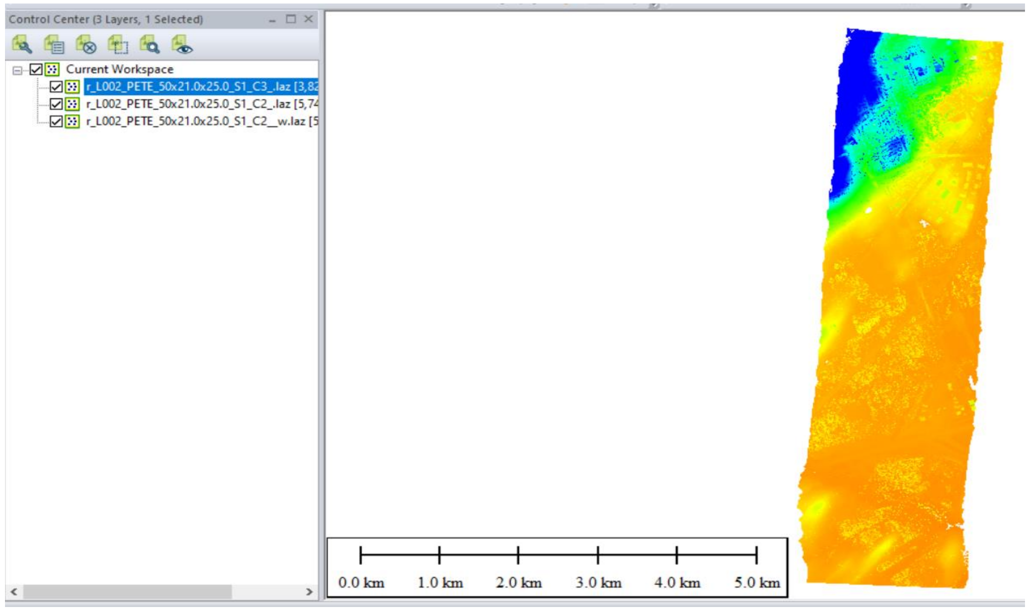

Figure 5-> Line 2, All Channels

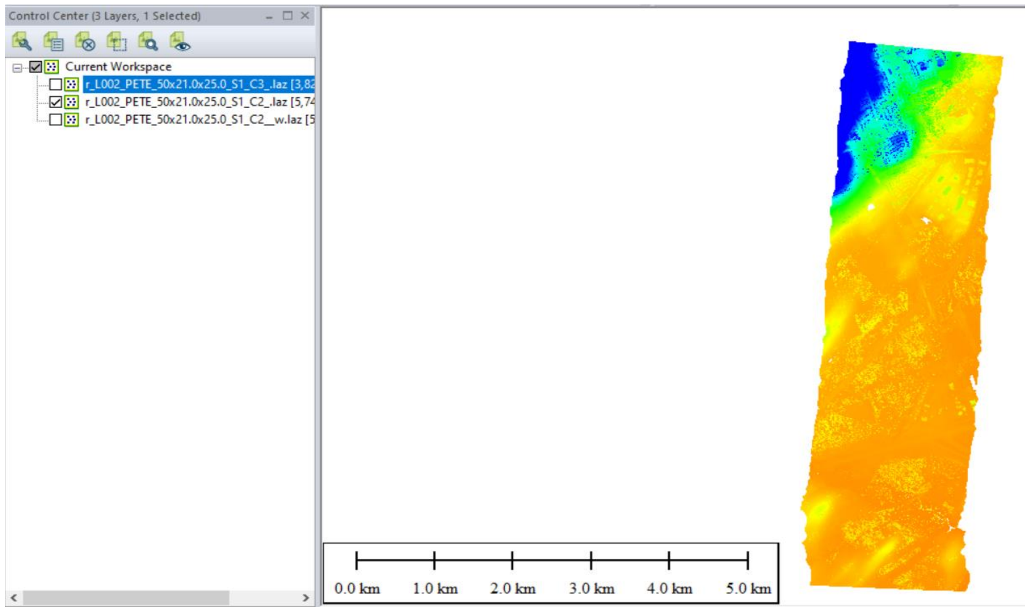

Figure 6-> Line 2, Channel 2

TITAN MULTISPECTRAL LIDAR DATA- TOWN OF PETERBOROUGH

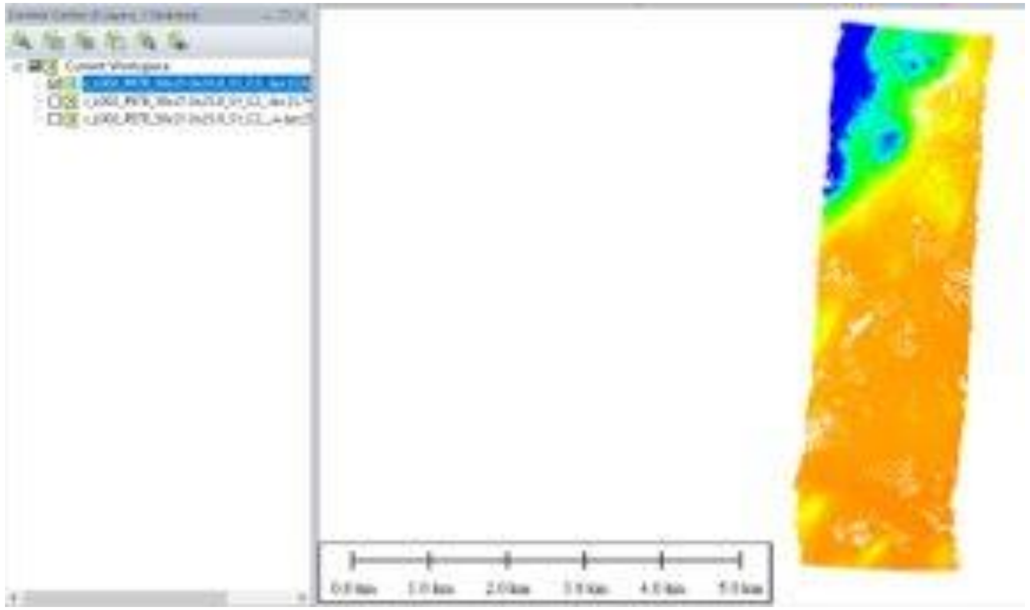

Figure 7-> Line 2, Channel 3

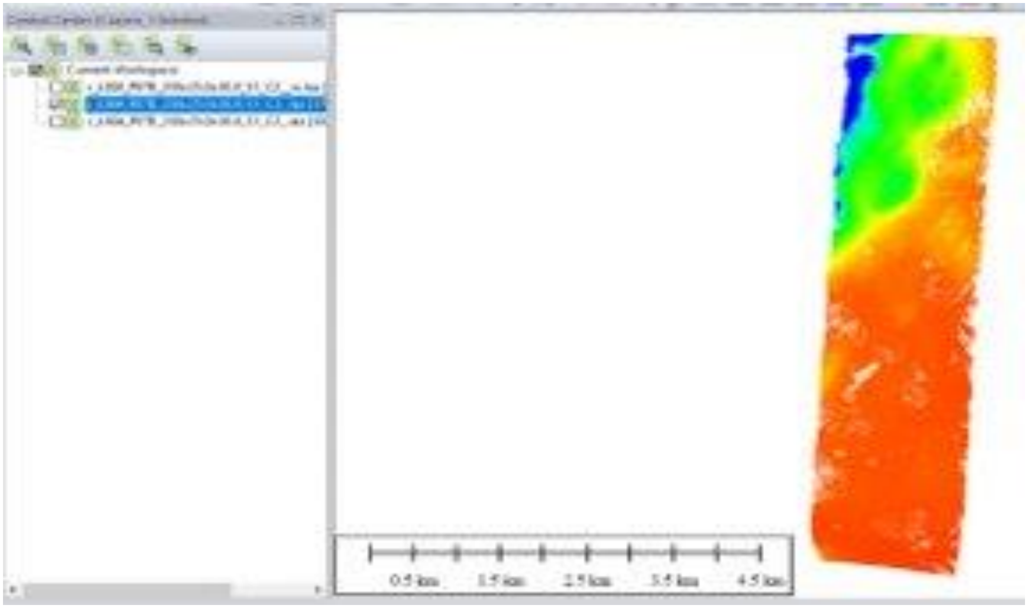

Figure 8-> Line 2, Channel 3 waveform

TITAN MULTISPECTRAL LIDAR DATA- TOWN OF PETERBOROUGH

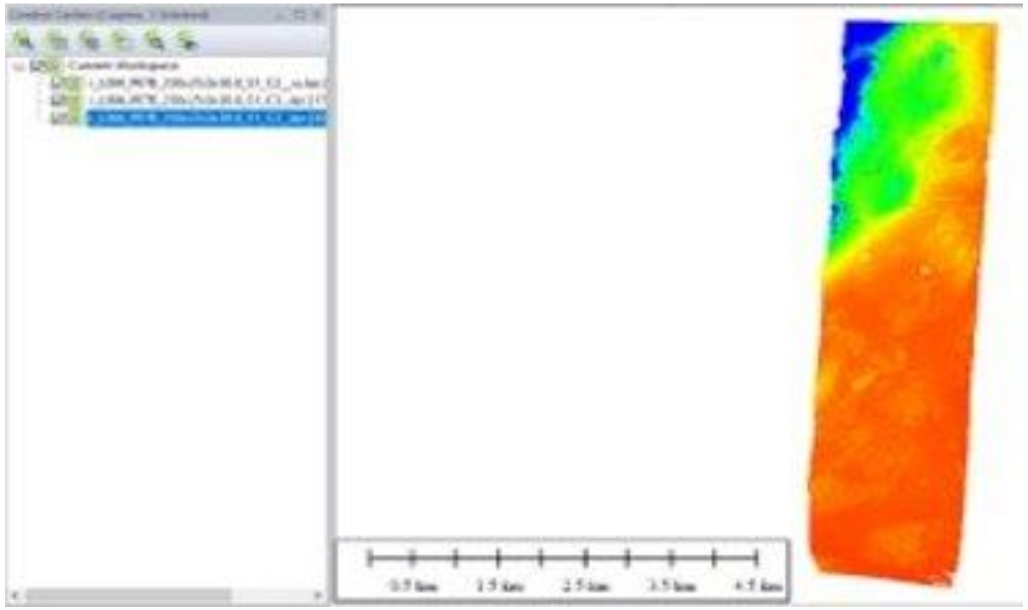

Figure 9-> Line 3, All Channels

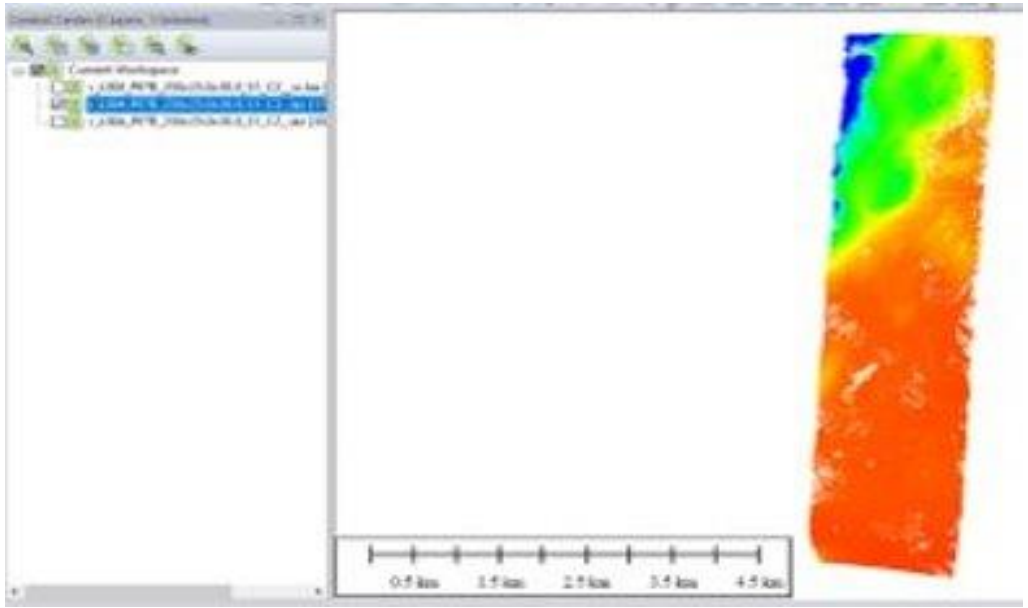

Figure 10-> Line 3, Channel 2

TITAN MULTISPECTRAL LIDAR DATA- TOWN OF PETERBOROUGH

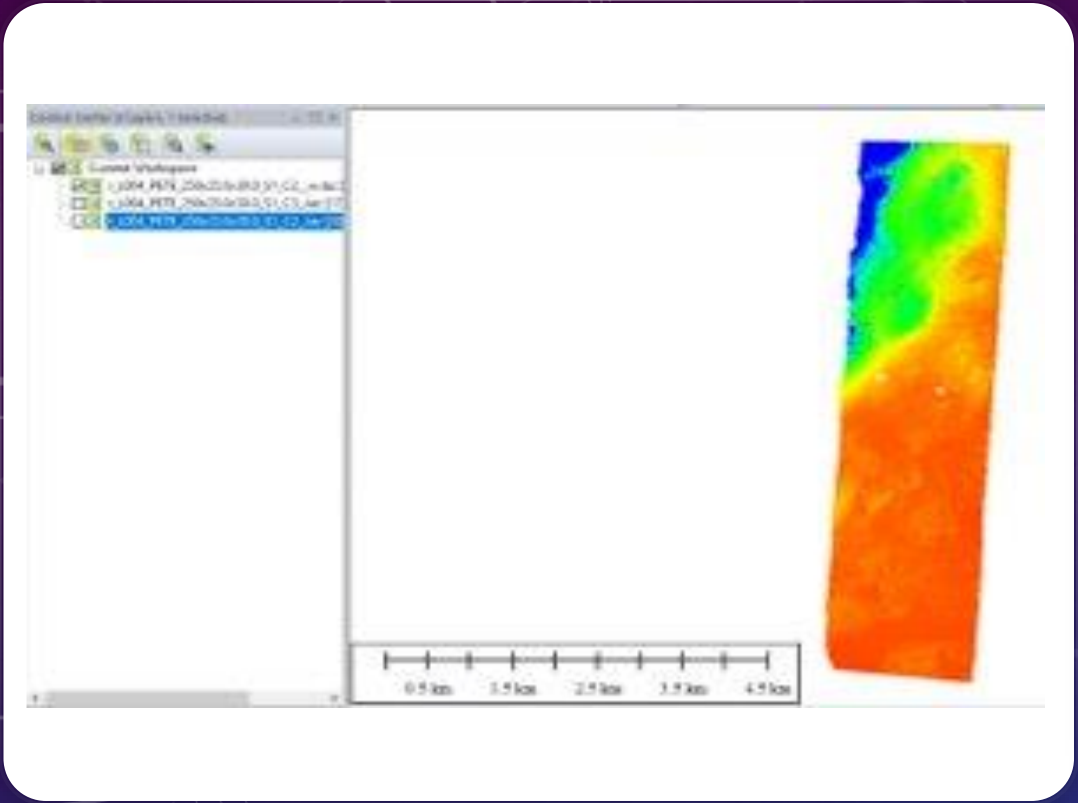

Figure 11-> Line 3, Channel 3 waveform

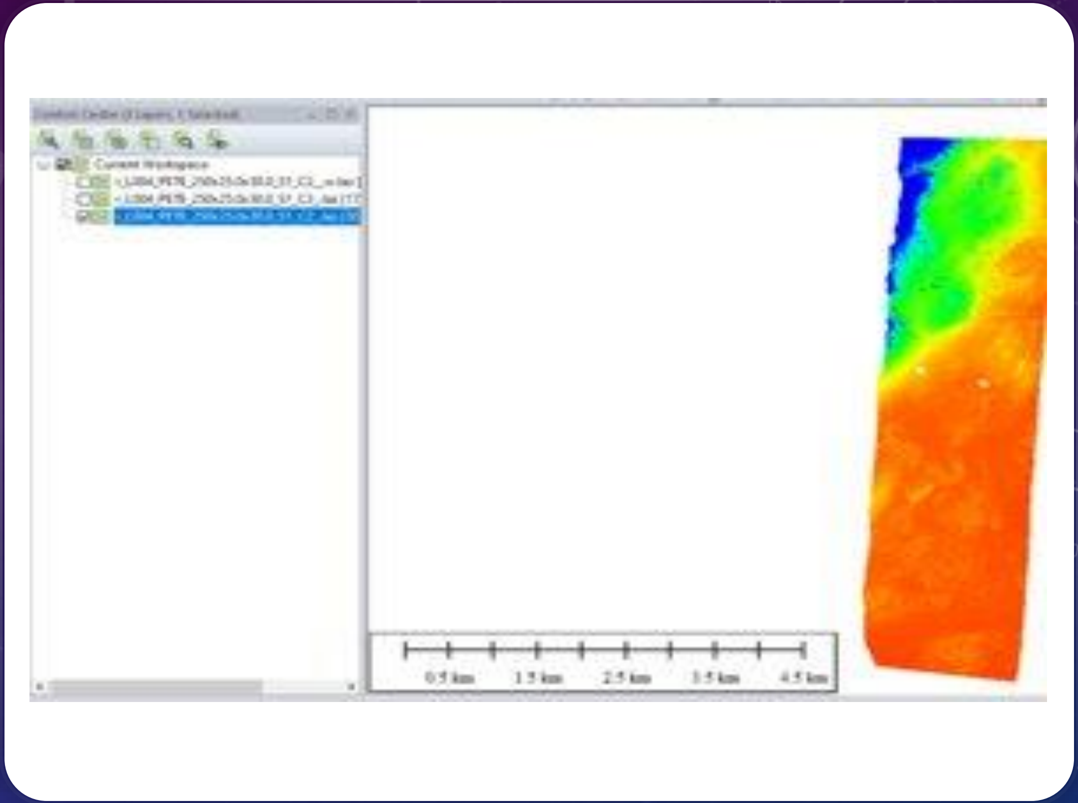

Figure 12-> Line 3, Channel 3

TITAN MULTISPECTRAL LIDAR DATA- TOWN OF PETERBOROUGH

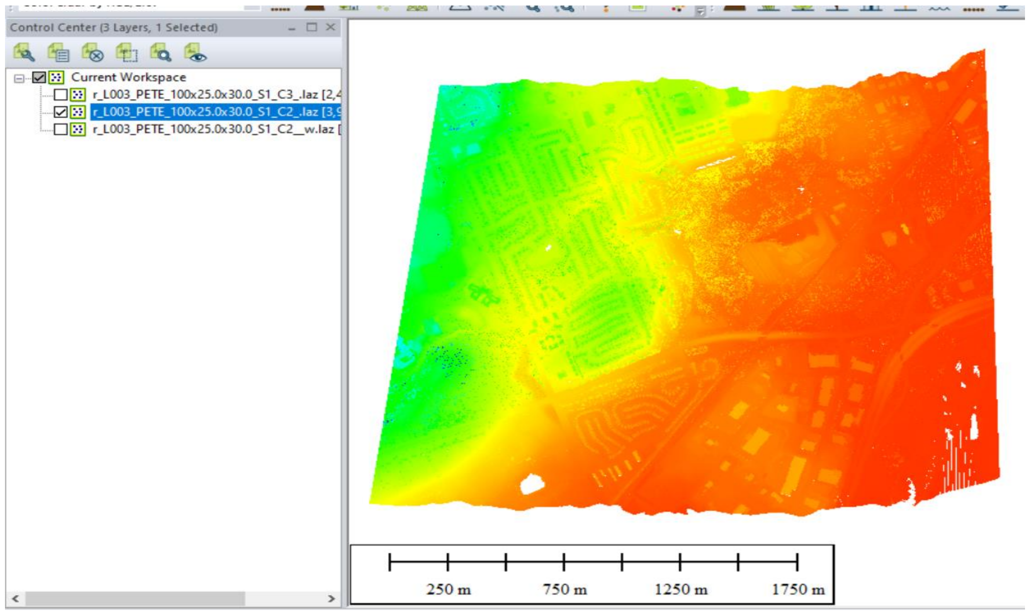

Figure 13-> Line 4, Channel 2

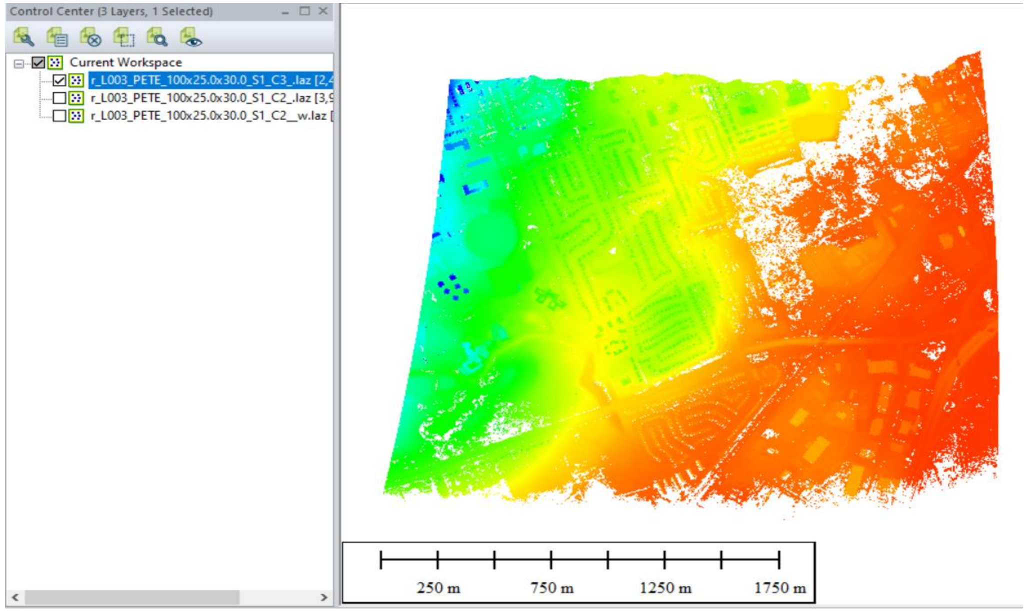

Figure 14-> Line 4, Channel 3

TITAN MULTISPECTRAL LIDAR DATA- TOWN OF PETERBOROUGH

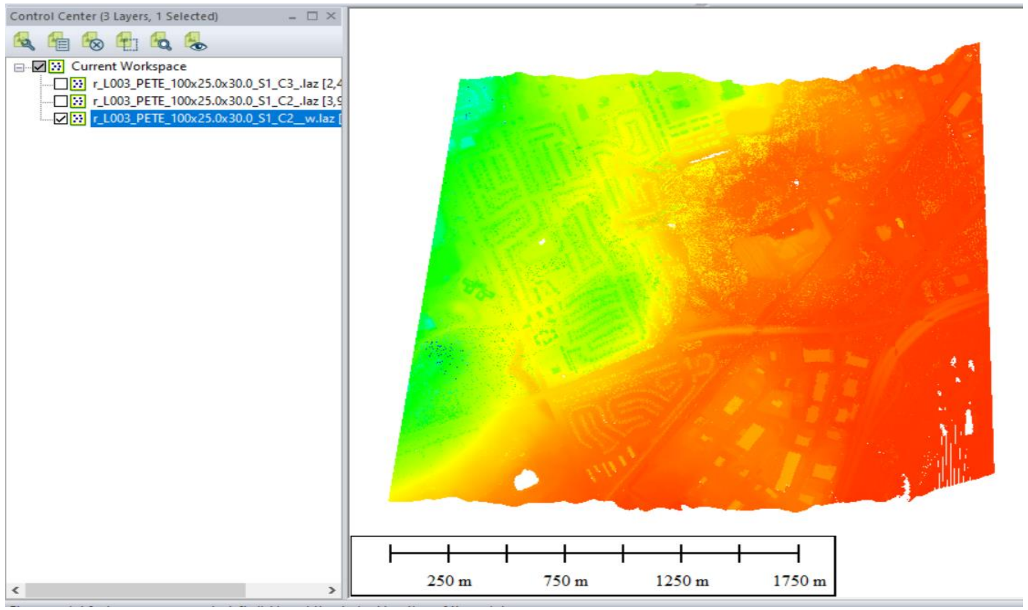

Figure 15-> Line 4, Channel 2 waveform

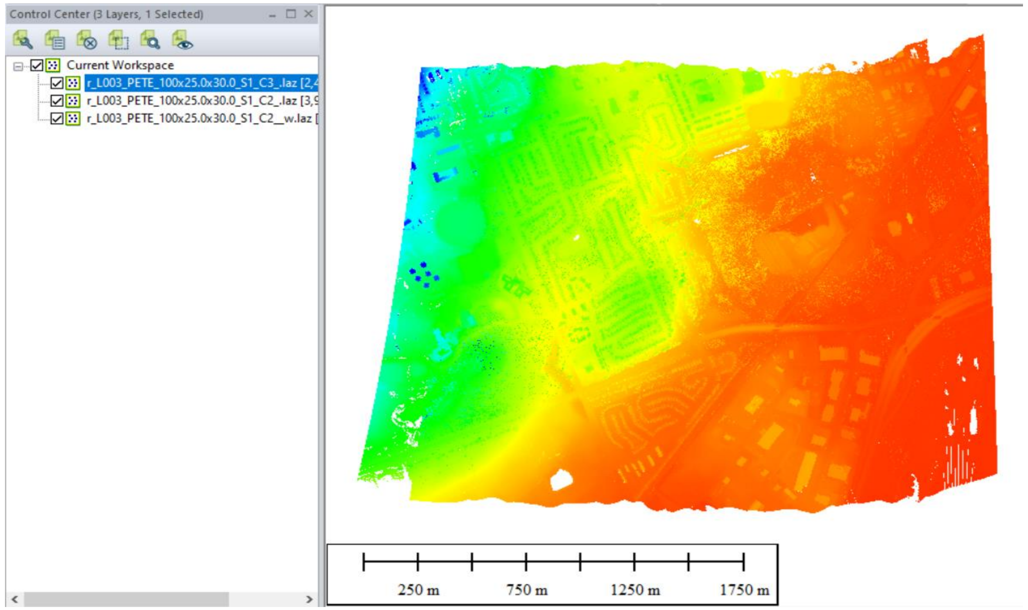

Figure 16-> Line 4, All Channels

TITAN MULTISPECTRAL LIDAR DATA- TOWN OF PETERBOROUGH

PROPOSED METHODOLOGY (FLOWCHART)

- First, the data would need to be preprocessed using a two-step data preprocessing approach, such as data fusion and data annotation (Jing, et. Al)
- Data fusion- Merging three different individual point clouds, which contain various wavelengths (532nm, 1024nm and 1550nm) into one single point cloud, where each point contains a different coordinate value and three-wavelength intensity values, such as 3-channels, as well as two other designated intensities from the other wavelengths
- Data fusion allows the merging of three different individual point clouds containing various wavelengths (532nm, 1024nm and 1550nm) into one single point cloud, where each point contains a coordinate value and three-wavelength intensity values (3-channels), as well as two other assigned intensities from the other wavelengths
- The merging can be done, by adopting a 3-D spatial join technique (Jing, et. Al).
- Each point of the reference point cloud is processed to determine the neighbouring points within the other two wavelengths of point clouds using a nearest neighbour searching algorithm and then collects the calculated intensities from the neighbors using a bilinear interpolation method.
- The search radius is obtained based on the point density (Jing, et. Al).
- The data annotation allows for the manual labelling of the selected thirteen Titan multispectral point cloud regions into several categories of interest to obtain a training dataset for the proposed architecture
- The SE-PointNet++ uses a multispectral LiDAR pointcloud as the input, where N is the number of points and produces an identical-spatial-size point cloud, where each point is labelled with a specific category in an end-to-end manner (Jing, et. Al).
- The SE-PointNet++ methodology utilizes an encoder network, a decoder network and a group of skip link concatenations (Jing, et. Al).

PROPOSED METHODOLOGY (FLOWCHART)

- The encoder network contains four collection of abstraction modules, which are iterated recursively to bring out multi-scale features at the scales of {1/4, 1/16, 1/64, 1/256}, which is based on the input point cloud and the number of points, N (Jing, et. Al).
- The decoder network is operated by four feature propagation modules (Jing, et. Al).
- The feature propagation modules allow a slow determination of a semantically-strong representation of features to accurately classify the point cloud (Jing, et. Al).
- The skip link concatenation increases the capability of feature representation to integrate the selected features from the set abstraction modules with the features, which have the same size in the feature propagation modules
- The squeeze process in the SE PointNet++ method allows spatial information of the feature map to be condensed by performing a global average pooling for each channel of the feature graph to only retain the channel information (Jing, et. Al).
- To decrease the dependencies of the channel, the global spatial information is squeezed into a channel descriptor
- A global average pooling is used to obtain channel-wise statistics (Jing, et. Al).
- Excitation in SE Point++ is the adaptive recalibration process
- The excitation process allows weights to be assigned to each element of the 1 x 1 x C channel descriptor, which is generated by the squeeze process through two fully connected layers (Jing, et. Al).
- A simple gating mechanism is employed with a sigmoid activation to fully capture channel-wise dependencies, which is like a gating mechanism in recurrent neural network

PROPOSED METHODOLOGY (FLOWCHART)

- The results of the two fully connected layers are activated using the Rectified Linear Unit (ReLU) and the sigmoid functions (Jing, et. Al)
- The product of the second fully connected layer is comprised of a channel-wise attention descriptor, which is denoted as s
- The attention descriptor s is used as a weight function to recalibrate the input map, which contains distinct features to bring attention to the contributions of the different channels, which contain specific information (Jing, et. Al).
- Based, on the processed test areas and multispectral LiDAR points, the normalized training set (S) is gridded into a set of blocks using a block size of 0.12 x 0.12 meters squared, without overlapping each group, which contains a different number of points.
- To collect a certain number of samples for every point block, a farthest point sampling (FPS) algorithm is used to sub sample it with a specified number of sample size, N (Jing, et. Al).
- For every point block, the more training samples used, the higher the chances of the information being learned by the proposed architecture.
- Because of the inconsistency of the point density, some point blocks may contain few points, if the number of sampling points is smaller than N (Jing, et. Al).
- Therefore, data interpolation is necessary to gather the defined sampling points of a specific size, denoted by a number
- When SE-PointNet++ is conducted, a collection of abstraction modules utilize an N x 6 matrix as the input and produces an N/4 x 64 matrix of N/4 subsampled points with 64- dimensional vectors, containing features, which summarizes the localized situational information (Jing, et. Al).
- The sample layer assigns the centroid of local regions by choosing a collection of points through an iterative FPS algorithm (Jing, et. Al).

PROPOSED METHODOLOGY (FLOWCHART)

- The sample layer assigns the centroid of local regions by choosing a collection of points through an iterative FPS algorithm (Jing, et. Al).
- Given the input points {x1, x2, . . . , xn}, the FPS selects a subset of points xi1 , xi2 , . . . , xim, such that xi j is the fastest distance point from the remaining point set n xi1 , xi2 , . . . , xi j−1 o.
- Every time, the centroids of the sampling layers are ¼ times, that of the input points (Jing, et. Al).
- A grouping layer is used to construct the corresponding local regions by searching for the neighnoring points around the N/4 centroids by a ball query algorithm.
- All neighboring points are found within a specified radius for each centroid using the ball query method, from where K points are selected randomly to create a local region (K was set to 32) (Jing, et. Al).
- After implementing the sampling and grouping layers, the multispectral LiDAR points are collected using samples as N/4-point sets, where each contains 32 points with their 6 attributes.
- The output involves a group of point sets with the size of N/4 x 32 x 6 (Jing, et. Al),
- Subsequently, local regions are encoded into feature vectors using Channel Feature Attention layer (Jing, et. Al).
- For each point, the features are extracted by multilayer perceptions (MLPs) and highlights its important features and subdues its less important channels by the SE block
- For the SE block, each channel of the N/4 points is squeezed via a max-pooling and then its weight value is calculated and normalized to the range [0, 1] by the two MLP layers and sigmoid function (Jing, et. Al).

PROPOSED METHODOLOGY (FLOWCHART)

- The higher, the value of the weight, there is more significance of the channel
- The important channels with higher weight values are excited (Jing, et. Al).
- To avoid having missing features when the weight is close to 0, a small connection is used to connect the features before and after the Channel Feature Attention layer (Jing, et. Al).
- There exists different dimensions of the learned features before and after the Channel Feature Attention layer, convolution operation is performed to match their dimensions in the shortcut connection
- The decoder network uses four feature propagation modules, which slowly gathers semantically strong feature display to produce a classified point cloud of high quality (Jing, et. Al).
- To propagate the learned features from the sampled points to the original points, interpolation is first employed through sn inverse distance weighting within the feature propagation module
- The point features are propagated from N/256 x 512 points to N/64 points, where N/64 is used to enhance the capability of the feature representation
- The interpolated features on the N/64 points are joined with the skip linked point features, which are obtained from the collection of abstraction modules using the skip link concatenations (Jing, et. Al).
- To capture features from the coarse-level information, the concatenated features are passed through a "unit pointnet", which is similar to 1 x 1 convolution in CNNs
- A few shared fully connected and ReLU layers update the feature vector of each point (Jing, et. Al).
- The method is iterated until all of the features have been disseminated to the actual point dataset

MAIN MILESTONES

- 1. Obtain the raw files for the data
- 2. Read articles on land cover classification using Multispectral LiDAR Data further
- 3. Process the data
- 4. Quality check the data
- 5. Perform land cover classification on the data using SE-PointNet++
- 6. Automation of land design from the classification
- 7. Read up on Petersburgh's current land development plans and management system
- 8. Read up on land development and management standards
- 9. Develop a new plan and management system for Petersburgh
- 10. Propose a new plan and management system for Petersburgh, based on my data, the guidelines and
- Findings
- 11. Make suggestions to the Town of Petersburgh.. based on the proposed plan

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