SCALGO

Mapping bare land for Greater Helsinki Region

16.12.2021

Helena Åström, helena@scalgo.com

Jonas Tranberg, jonas@scalgo.com

SCALGO

Table of Contents

Introduction

In this project bare land was mapped for Greater Helsinki region (Espoo, Kauniainen, Helsinki, Vantaa) using Machine learning. Bare land is defined as all areas with sand and gravel. This includes sand beaches, fields with no vegetation and all other areas with no vegetation.

This project is a spin-off from the LaserVesi innovation project where impervious surfaces were mapped. The goal of this project was to test if the Machine learning model, initially developed to map imperviousness, also can be used for mapping bare land.

Hence, this project uses the same methodology as used in LaserVesi, but new training data and validation areas are defined to map bare land.

This report includes a short method description, results, and conclusion.

Method

Short description of model

To solve the task at hand, we turn to Machine Learning, specifically an architecture called UNET, which is a special case of Convolutional Neural Networks (CNN's). UNET has become a standard when using a training-based approach to segment raster data.

The power of UNET, or any other CNN based architecture, over other learning-based methods, is the way that it integrates the context of a single pixel prediction over multiple scales, such that information in the neighbourhood of the predicted pixel, is used in the output prediction in an efficient manner.

Input data

For this task, we use two different input sources:

1. Orthophotos in 4 bands, namely the RGB channels and the Near-Infrared channel
2. A raster-based Lidar point cloud, describing the changes in terrain. That is, we first create 2 rasters from the raw point cloud: A raster based on all the points and a raster based on only ground points, which is then smoothed. Then we subtract the second raster from the first to create a raster describing the high frequency changes in the terrain, while ignoring the general (low frequency) elevation.

Training data

We acquire polygons from several sources, describing the underlying land cover, which are then used to label individual pixels. Among these sources are:

- Polygons derived from the existing Land Cover map of the Greater Helsinki region.
- Annotation made in cooperation with Special Minds in Aarhus, Denmark, covering both areas in Denmark and Finland.

- Annotations made by the water utility in the municipality of Skanderborg, Denmark.
- Polygons supplied by Geodanmark covering areas of forest, buildings, roads etc.

Validation areas

Several validation polygons is used, both during training to gauge the progress of improvement and after training to evaluate the general performance of the model. All of these areas are hand-picked by either us (Scalgo), or HSY using a platform provided by us.

The process

The final model is produced through a series of iterations, each consisting of the following steps.

1. Select a training set
2. Train the model
3. Evaluate the model and modify the training set to cover for errors surfaced in said evaluation.

This process was repeated until the model was deemed fit for production.

Output

The model produces a raster where each pixel (of size 0.2m) represents the probability of that pixel being bare land. This is also the format, which is delivered to HSY, abait in a single byte resolution resulting in 254 different probability values.

Results

We report performance on two sets of polygons. The first is a general sample, gathered through many iterations, testing both performance on impervious surfaces, fields, dirt roads and sand.

Table 1. Model performance, general sample. Existing land cover is the HSY maanpeiteaineisto, bare-land-2 and bare-land-5 are two iterations.

	Existing landcover (HSY)	bare-land-2	bare-land-5
Accuracy	0.791501	0.774145	0.903280

We see that ‘bare-land-5’ achieves significantly better performance than the existing land cover dataset, even though roads make up a significant portion of the sample and those are human annotated (not learned) in the existing land cover dataset.

The second set of polygons are selected as examples where an early iteration (bare-land-2) of our model performed badly. That is, the areas are especially difficult, and numbers are not indicative of general performance, but indicative of performance where existing methods fail.

Table 2. Model performance, polygons where early iterations perform badly. Existing land cover is the HSY maanepeiteaineisto, bare-land-2 and bare-land-5 are two iterations.

	Existing landcover	bare-land-2	bare-land-5
Accuracy	0.256573	0.151973	0.886737

We see that we can achieve acceptable performance for these areas too.

Lastly, we provide visual examples of some of the areas in the difficult set:

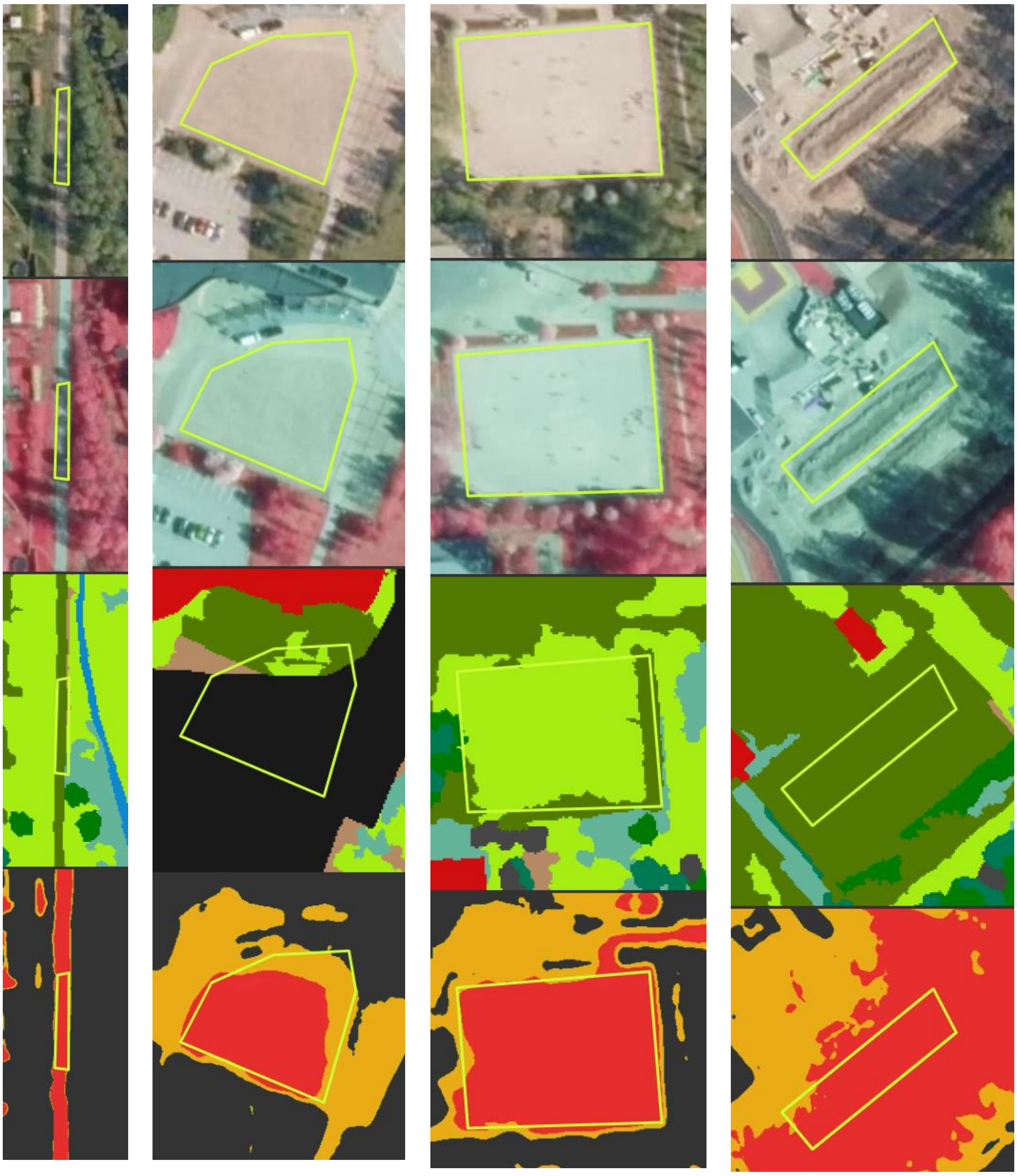

Figure 1. Examples of four locations that were difficult for the model. Row 3 = HSY maanpeiteaineisto, Row 4 = bare land mapped in this project, where red is over 50 % probability and yellow is 30-50 & probability.

Some examples of model performance of ‘bare-land-5’ (last row, for now R4) compared to the existing Greater Helsinki land cover Map (second to last row, for now R3). In R4 the red colour signifies a probability of bare-land above 50%, while in R3, brown signifies bare-land while light green signifies vegetation and dark green signifies 'other impervious surface'. We see that R4 is an improvement over R3 in all instances.

Conclusion

In this project we mapped bare land using machine learning. We evaluate that the results identify bare land sufficiently, and hence, we may conclude that the chosen method can be used when mapping bare land.

For each iteration of the model, we could see an improvement in the performance.

What could be done to make the model better?

To improve the model even further, we need more training data.

Further, we should investigate orthophoto normalization across regions, such that the variance between regions, not caused by the underlying terrain, is better accounted for.