

## FALK project, mapping Norwegian nature types with Satellites

In 2019 Norwegian Environmental Agency (NEA) wanted to test use of remote sensing to map nature in Norway. NEA asked a consortium with TerraNor, University in Bergen, Department of Geography and Canadian company PCI Geomatics, to analyse first Hordaland and then Trøndelag counties. Trimble eCognition team participated in parts of the project. We were asked to use Sentinel 1 (radar) and Sentinel 2 (optical) satellites. The goal was to map nature according to NEA definitions and specifically find bogs.

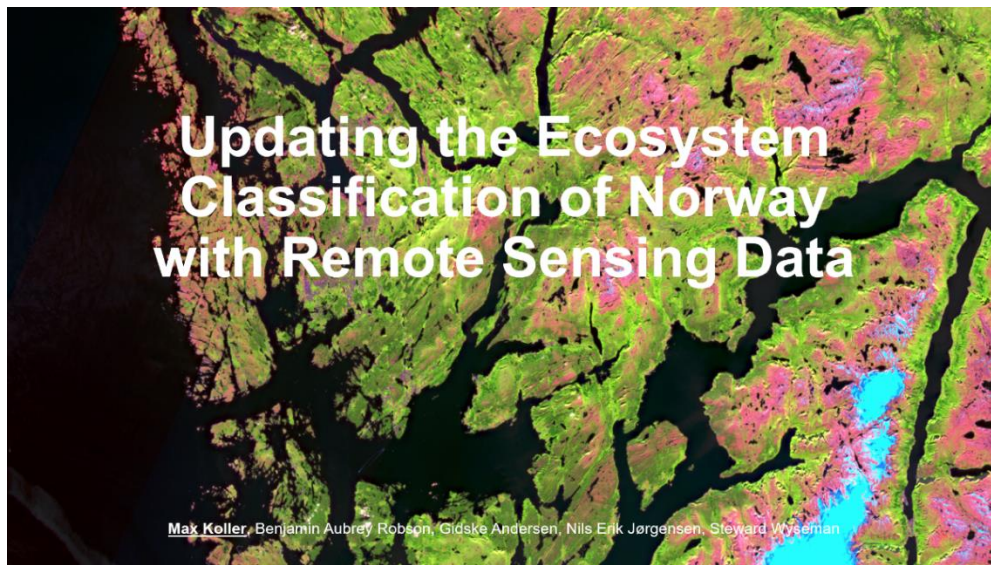


Figure 1, Hordaland

Current “Natur i Norge” (Nature in Norway) database is sporadic, inconsistent, and subjective according to NEA. System is not especially quantitative. After several years only 2% of Norway is mapped. There is a huge potential to update the data base with use of remote sensing and classify into the main eco-systems:

- Vegetation
  - Meadows
  - Forest
    - Deciduous
    - Coniferous
- Bogs
- Bare rock
- Open areas
- Snow/Ice
- Water
- Urban
- Semi-natural areas

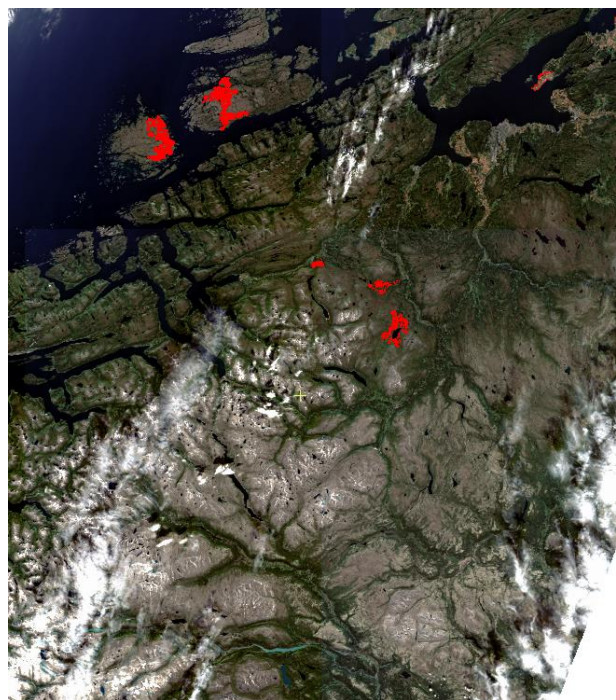


Figure 2, Trøndelag with Nature in Norway polygons

## Results/Summary

The classification based on Copernicus data from Sentinel 1 and Sentinel 2 combined with lidar/laser DTM data gave very good results. We will present results and the work process.

We used two different methods to analyse the data, Threshold analysis combined with Deep Learning/Convolutional Neural Networks (DL/CNN) and Support Vector Machine (SVM) combined with DL/CNN.

### Short version of the steps:

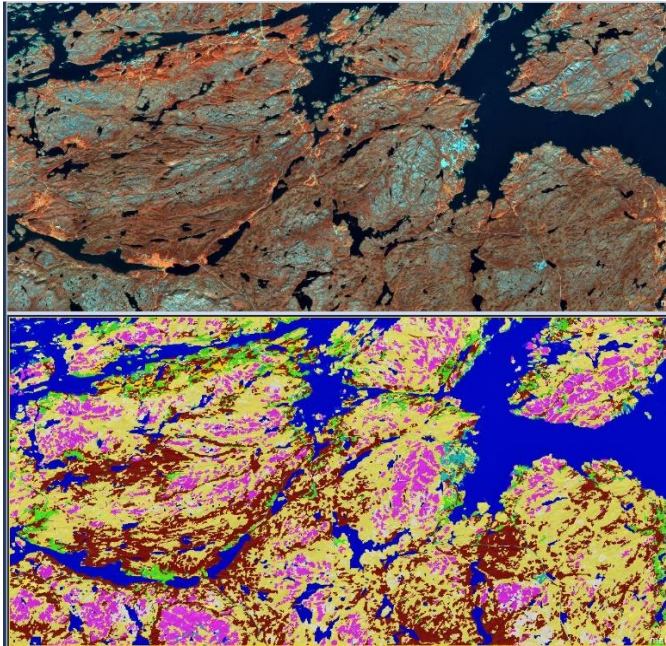


Figure 3, shows Sentinel 2 image and classified image.

#### Threshold and DL/CNN

Threshold: water with use of watervapour

Threshold: Vegetation/not vegetation with use of ndvi

Threshold: Forest / open areas use of nDSM (surface height)

Threshold: Split forests into deciduous and coniferous with use of Nir2

We could easily mapped species like sitka spruce, but it was not part of the project.

DL/CNN: Improve water classification

DL/CNN: Cultural grass fields (Kulturmarkeng)

DL/CNN: Bare rock, urban

#### SVM and DL/CNN:

SVM: water, vegetation, deciduous, coniferous, deciduous.

DL/CNN: Snow patches and bogs

DL/CNN: Mountain, rock, urban

## Main Technology:

First step was to **pre-process data**:

- download sat images from ESA and satellittdata.no,
- download terrain data from hoydedata.no,
- download aerial images from norgeibilder.no,
- download WorldView 3 image from European Space Imaging/MAXAR,
- image alignment/matching,
- radiometric correction and
- mosaic to create a data model.

This was done in **PCI GXL** with use of Python scripts and GXL scripts.

Second step was to **analyse** data with **Trimble eCognition Developer**.

**Hardware:** we used a gaming machine with Nvidia Geforce RTX 2060 with 6Gb memory and 1920 cuda cores, Intel Core i7 9800X 3.8GHz and 64 Gb memory. The machine had several SSD drives and a normal disk drive.



## How we worked:

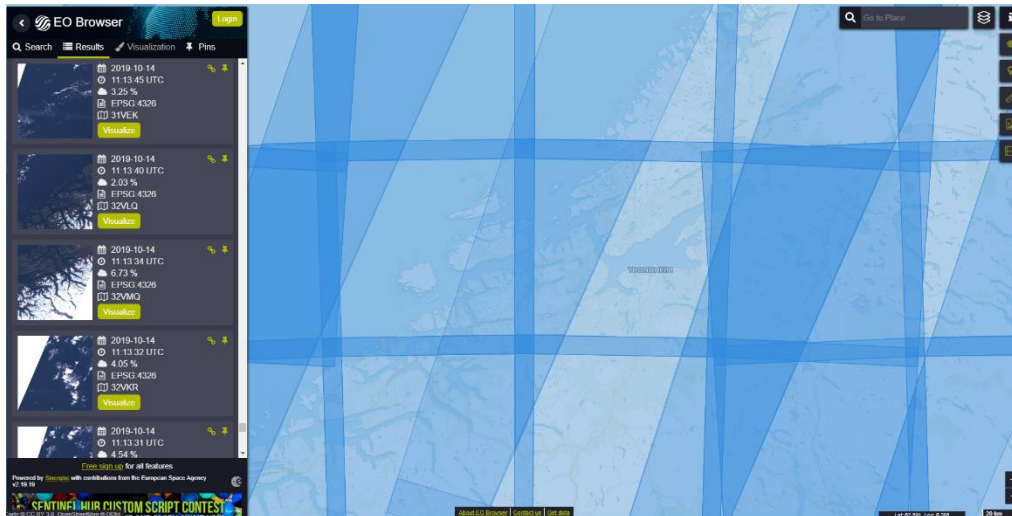


Figure 4, Trøndelag needs 16 Sentinel images

In phase one we analysed Hordaland county (now part of Vestland county) with 15 000km<sup>2</sup>. In phase two we used the routines and rulesets from phase one to do the same analysis on Trøndelag county with 42 000km<sup>2</sup>. **This showed that we can scale up the solution to cover the whole of Norway.**

UiB developed Python scripts to download and catalogue satellite images where we used range of dates, cloud cover and area of interest to find the images we wanted to use. Several hundred Sentinel 1 and Sentinel 2 images were automatically downloaded and processed.

An overview of the process:

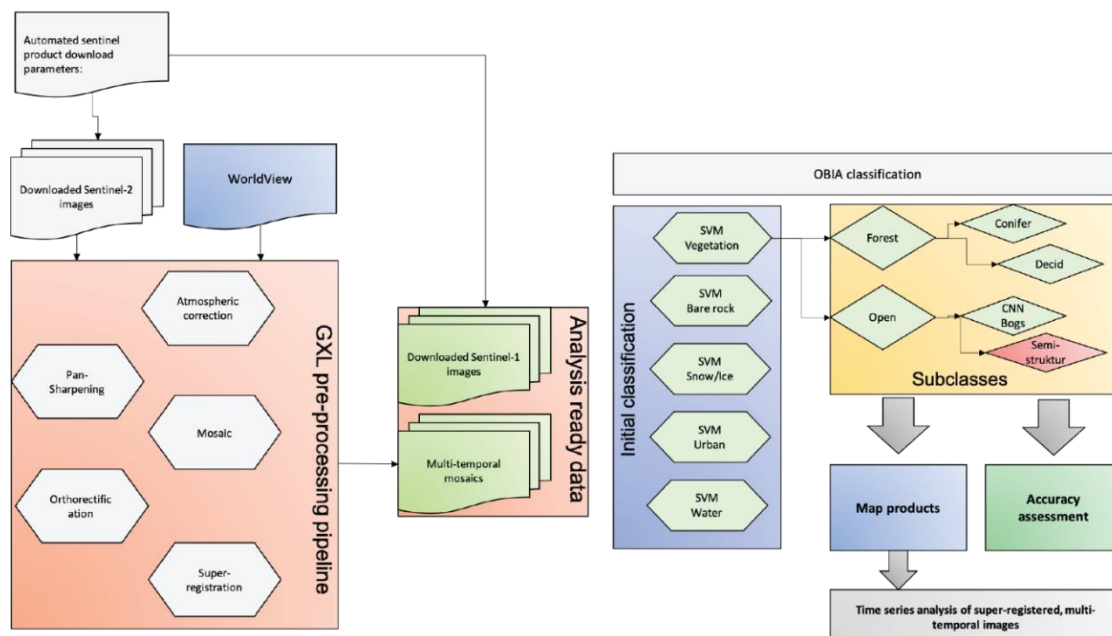


Figure 5, main work process

# System overview

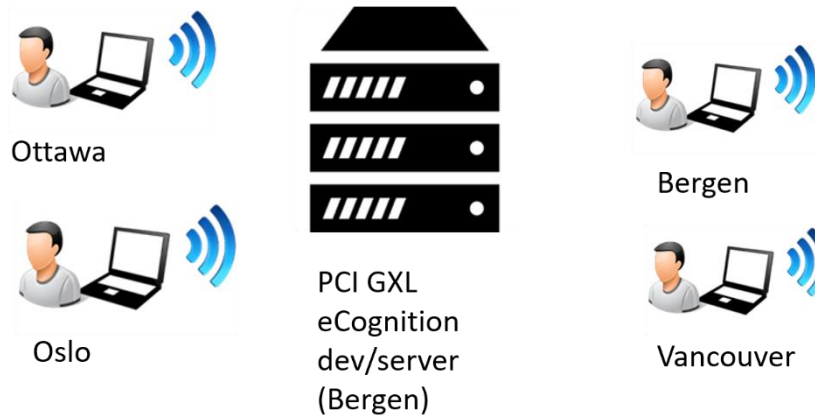


Figure 6, Hardware configuration

The main processing server was placed at the University in Bergen (UiB) with access from all members in the consortium in Bergen, Oslo (Grua), Ottawa and Vancouver.

PCI GXL to pre-process and eCognition Developer to analysis:



**PCI GXL** is a high production software to process large country wide datasets.

We used GXL to download images, radiometric correction, create mosaics and prepare datasets for analysis. With PCI GXL Superregistration solution we matched new images with existing images from Norwegian Mapping Authorities with sub pixel accuracy. In areas with steep terrain this is needed. Sentinel 2 comes with an orthorectification based on a coarse DTM that is not good enough for Norway and other northern countries. The misalignment can be up to 60m.

MRA fusion is another feature in GXL that transforms 10, 20 and 50m pixel data from Sentinel 2 into a 10m pixel resolution dataset. This scientific preparation opens many new possibilities for analysis. In addition we tested a new topographic normalisation algorithm that balances the colour based on terrain data. The last step was to create mosaic of the areas we needed.

**Pre-processing of data with GXL is described in a separate document.**



**Trimble eCognition Developer + Server** is the world leading OBIA solution for image analysis.

eCognition contains several hundred functions. The main functions we used in this project were segmentation, support vector machine learning, threshold analysis and Deep Learning/Convolutional Neural Networks (DL/CNN). eCognition has included Google TensorFlow DL/CNN in a very efficient way and with the extra functions you need to create a perfect result.

## Classify nature according to NEA nature types

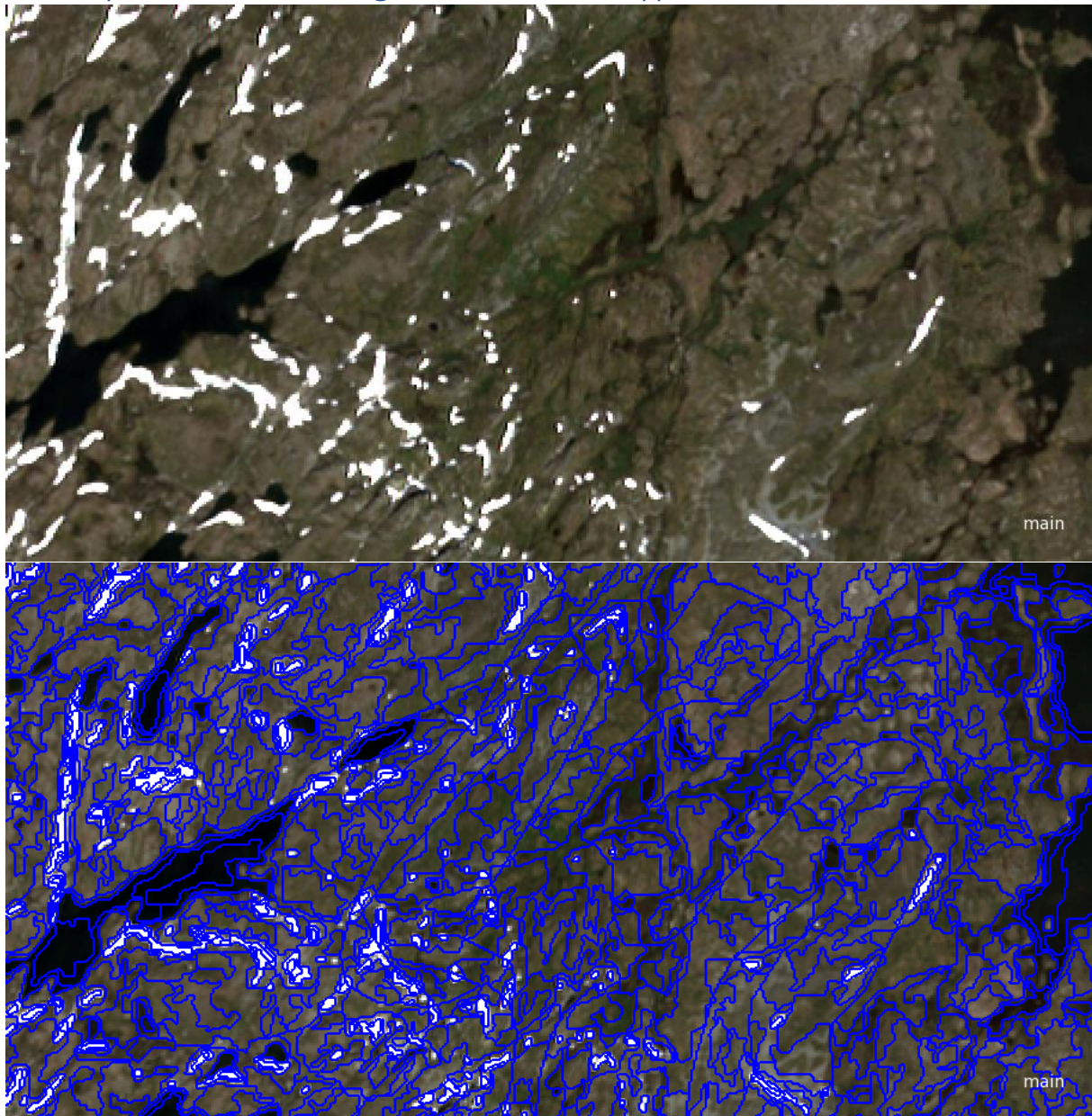


Figure 7, segmentation is key to success

NEA main eco systems are:

- forests,
- mountains,
- arctic tundra,
- wet land,
- semi-natural land,
- naturally open areas below the forest boundary and
- freshwater on Svalbard.

We classified all these eco systems before classifying bogs as a nature type.



### Segmentation:

eCognition segments the image into polygons that are similar. Segmentation can use any combination of raster data to produce polygons. The operator decides what channels to use and how much variation that is allowed in each polygon.

Figure 7 shows the original image and the result of segmentation.

You can use existing dataset like Norwegian Area Resources (AR5) for segmentation. The purpose is to use the existing dataset to train the classification model.

### SVM, machine learning Support Vector Machine:

From the segmented polygons we pick polygons samples for water, vegetation etc. Attribute data from a shape file can also be used to train the model. eCognition creates a statistical model from the samples. The model is used to classify all other polygons.

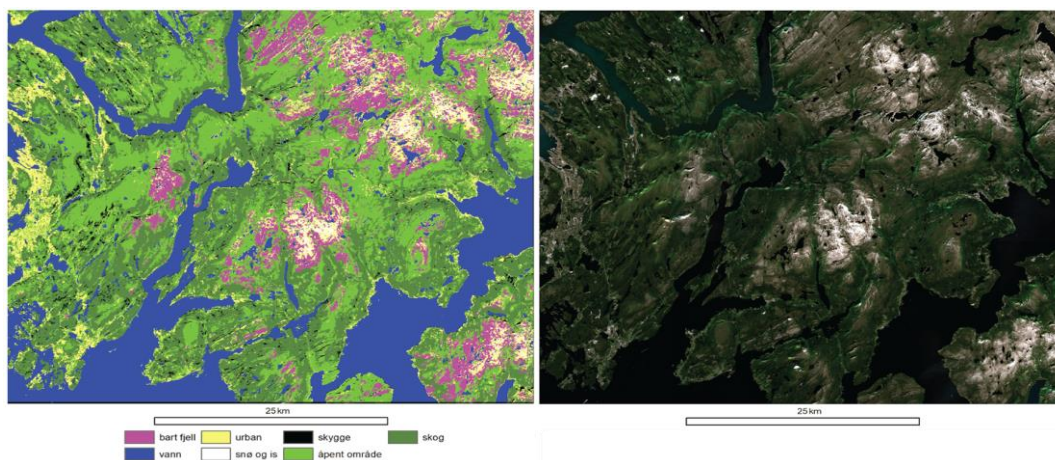


Figure 8, main ecosystem in Hordaland classified with SVM

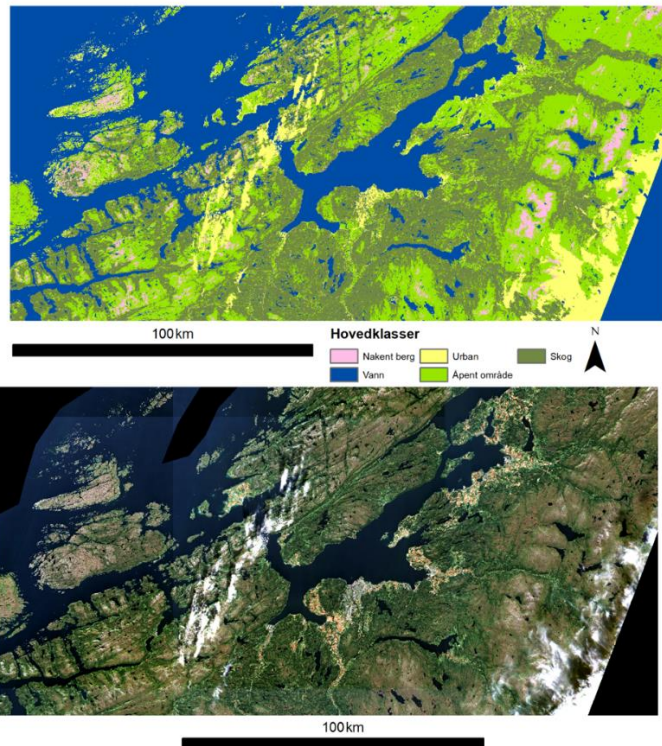


Figure 9, main ecosystem in Trøndelag classified with SVM

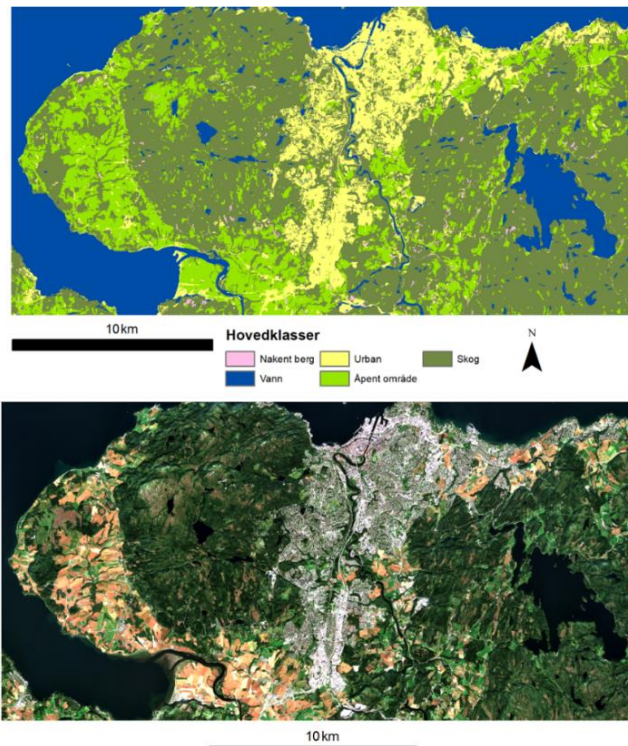
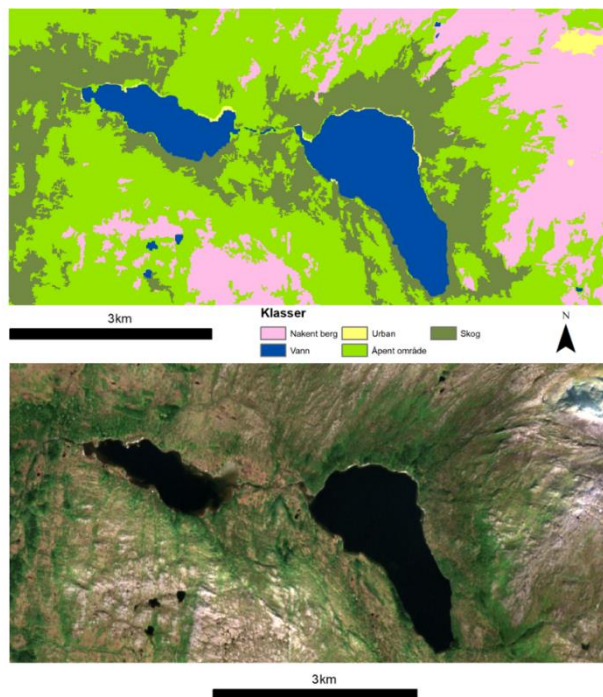


Figure 10, Trondheim area classified



*Figure 11, detail classification*

Urban and bare rock classes are quite similar and can be misinterpreted. In real life this is not a huge problem. Most of urban areas are already mapped digital. DL/CNN tends to be more accurate than SVM if you have enough training sites.



## Finding bogs

is important to NEA. We were asked to find bogs above tree level.



Figure 12, bogs can be lot of things

Bogs:

- Cannot be identified spectrally
- Rather by looking at recurring patterns in the spectral values
- Better to use Deep Learning / Convolutional Neural Networks (DL/CNN)

Bogs are a mixture of water, mud, rocks, grass, sand and even trees. Spectrally they cover most of the other classes we mapped.

Deep Learning / CNN uses pattern recognition to detect classes. The methodology is complex and includes several steps. It is better suited to map objects with a specific pattern rather than colour.

**To classify bogs, we found DL/CNN to be the best solution.**

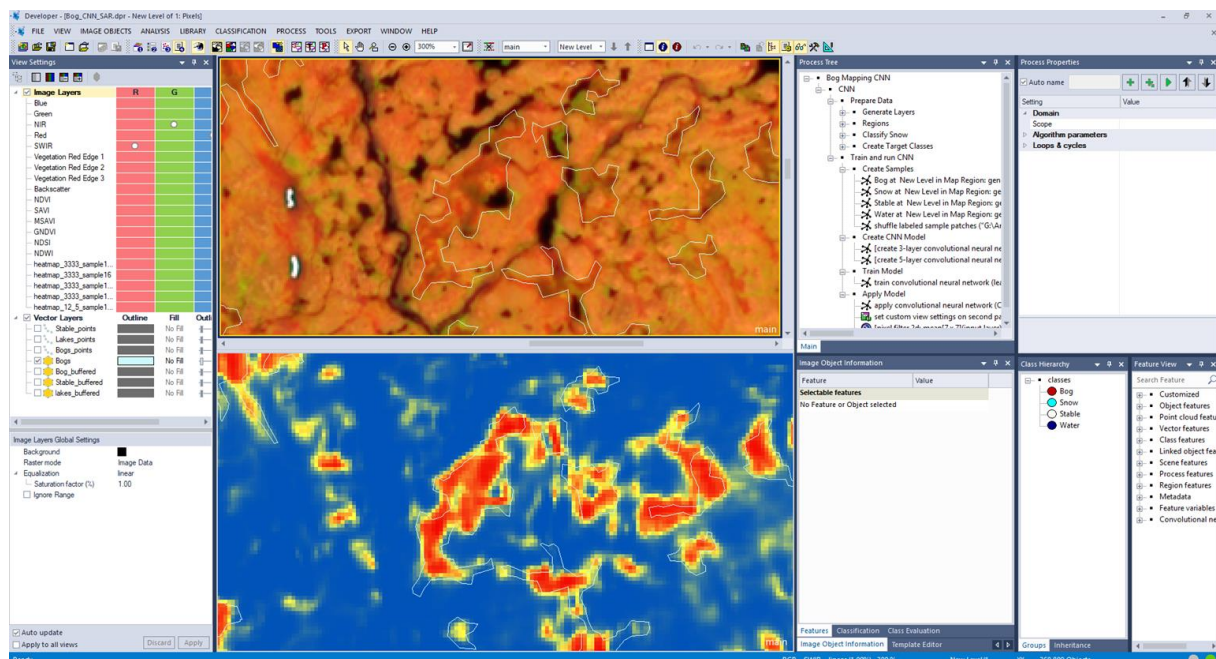


Figure 13, Heat map showing bogs in red

Like SVM we trained the model with use of known objects. For this project we used AR5 with many polygons. Even with some AR5 bogs being wrong, the large number of samples created a good

model. During the classification, eCognition created a heatmap, where high value means high probability for bogs. The heatmap is a separate raster layer with pixel values going from 0.0 to 1.0. Each pixel is classified with a probability for being a bog.

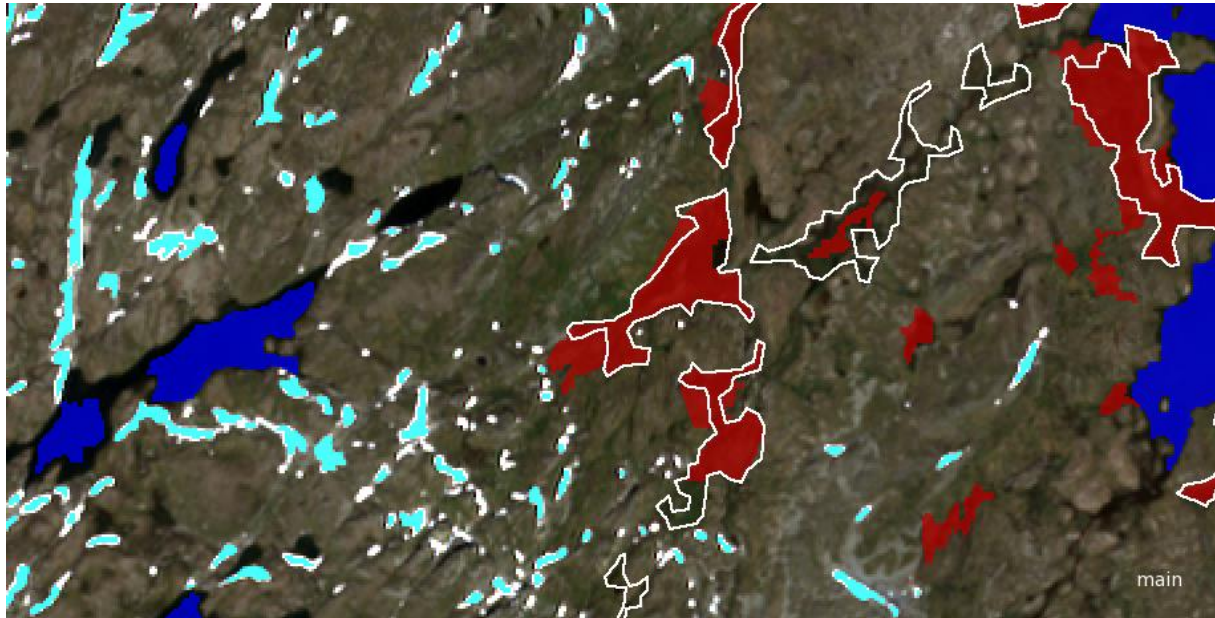


Figure 14, major water, snow patches and bogs (red)

In Figure 14 we have classified major water bodies, snow patches and bogs with DL/CNN. As expected, the result is not perfect. The polygons with lines in the image are the bogs from the AR5.

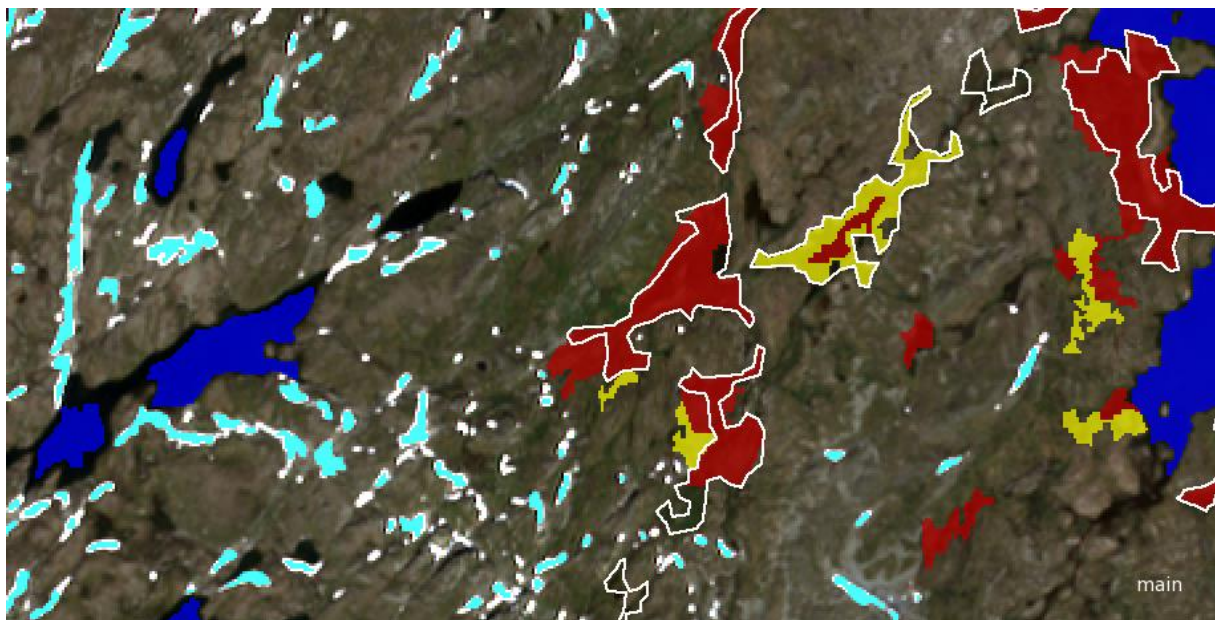


Figure 15, bogs expanded

We expanded the bogs with neighbour objects with a looser heatmap threshold and minimum 20% relative border to the already found bogs. This is part of standard eCognition routines and why eCognition gives better results than DL/CNN alone.



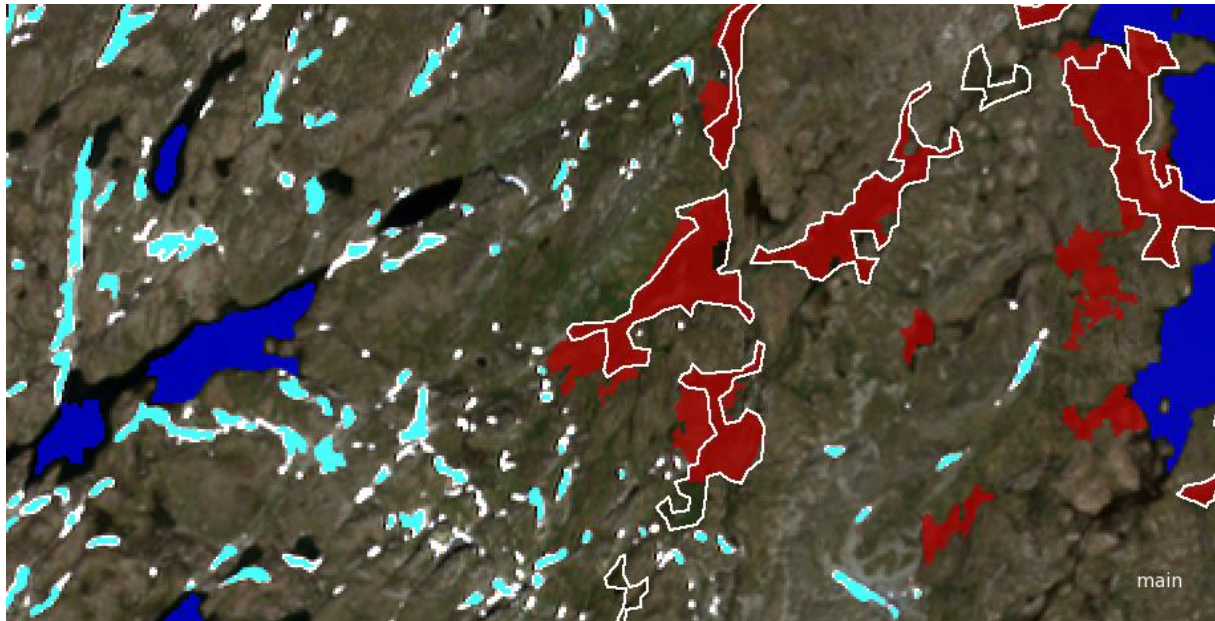
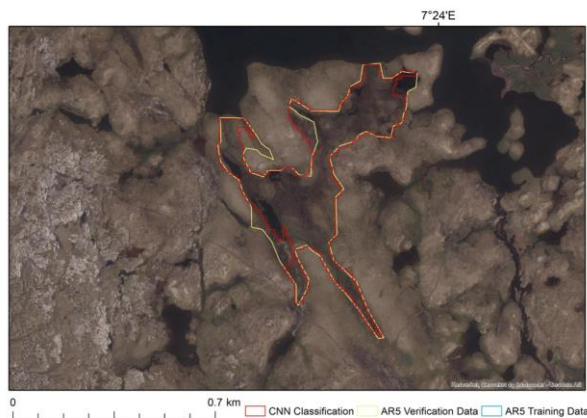


Figure 16, All adjacent bogs are merged together.



Producer Accuracy 74%



User Accuracy 73%

Figure 17, AR5 bogs compared to our classification

We compared the classification with both AR5 and aerial photography. Classification results were good. Bogs are difficult. They can vary based on the amount of summer rain or how well AR5 survey was done. In nature mapping you never use true / false, you use probability.

Uncertainty in classification can be used for analysis. If you have a small lake that is full of grass or mud, it will not be classified as open water. You can have NDVI values like vegetation. This is a signal that the lake may become a bog and something you would look for. There are many such samples.



## CNN heatmap based on 20 cm RGB aerial images

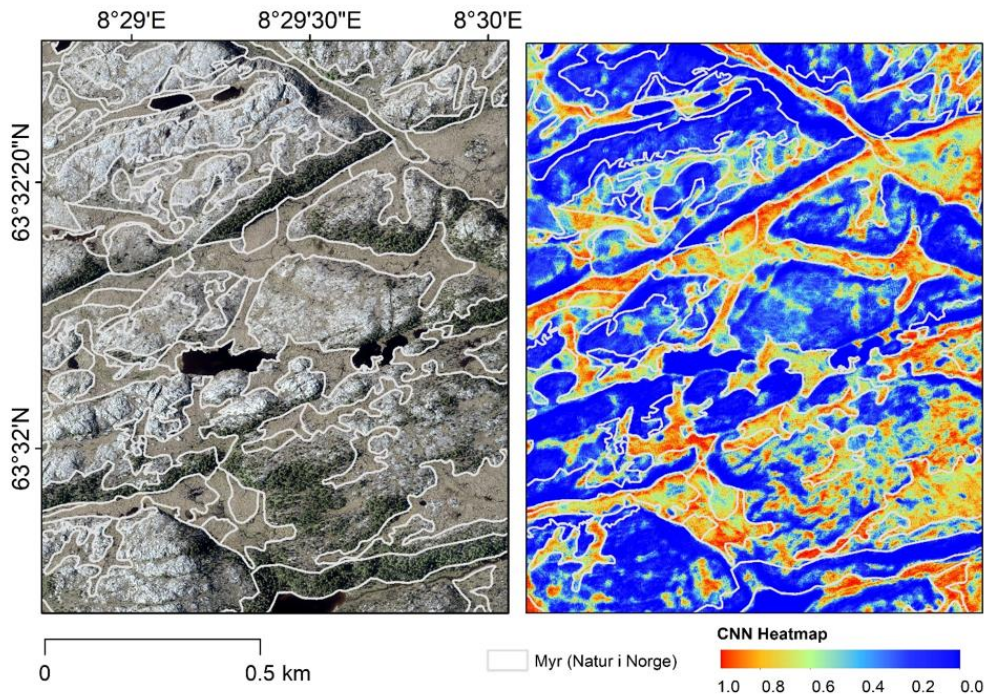


Figure 18, DL/CNN analysis of aerial images

We used 20cm RGB aerial images to do the same DL/CNN analysis. The result is more detailed.

## CNN heatmap based on Sentinel 1 + 2 (SAR, MS)

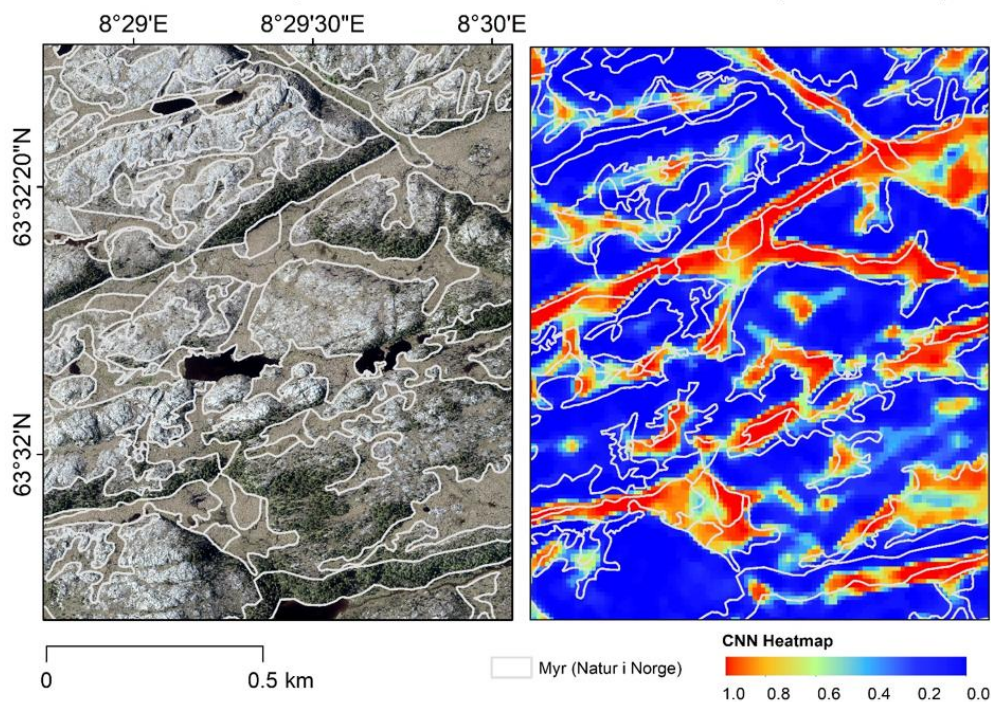


Figure 19, bogs classified with Sentinel 1+2

We received the most significant result with Sentinel 1 + 2 (SAR + MS). SAR is very good to detect patterns.



## Threshold analysis combined with Deep Learning / Convolutional Neural Network DL/CNN

This shows how to classify areas in eCognition with a combination of Threshold analysis and DL/CNN.

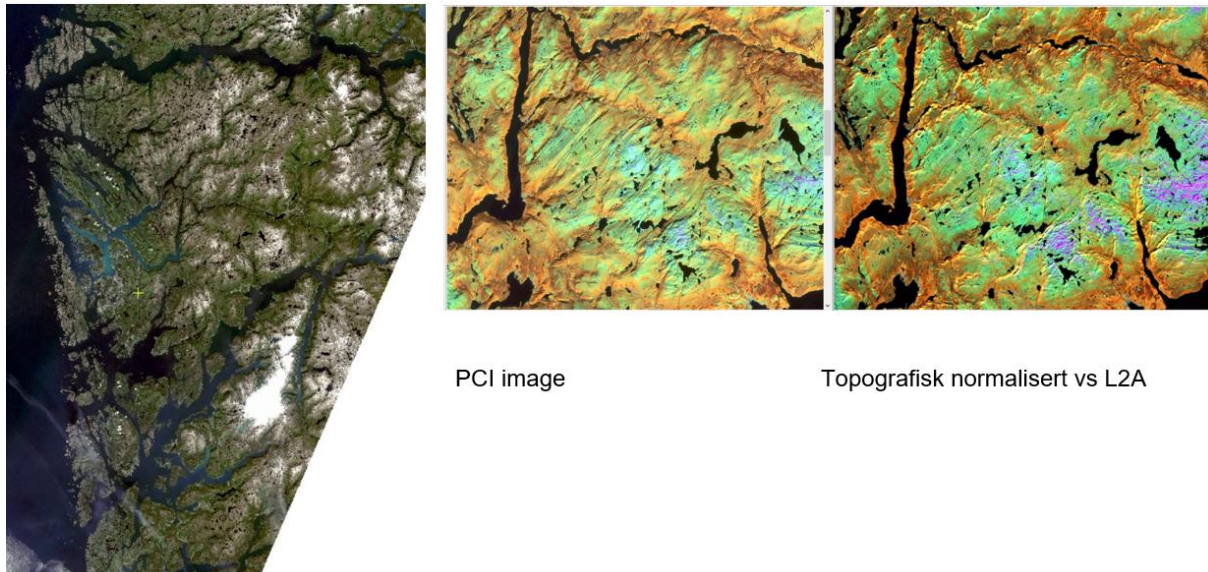


Figure 20 Hordaland, Topographic normalised

Classification of images gives best result when the images are homogenous. In figure 20 we show the result of topographic normalisation. In the non-normalised right image, the colours vary due to how the terrain reflects the radiation from the sun. In the left normalised image, colours are more even.

First approach was to try out DL/CNN only for urban, bare mountain and other nature classes in the NEA nature dataset.

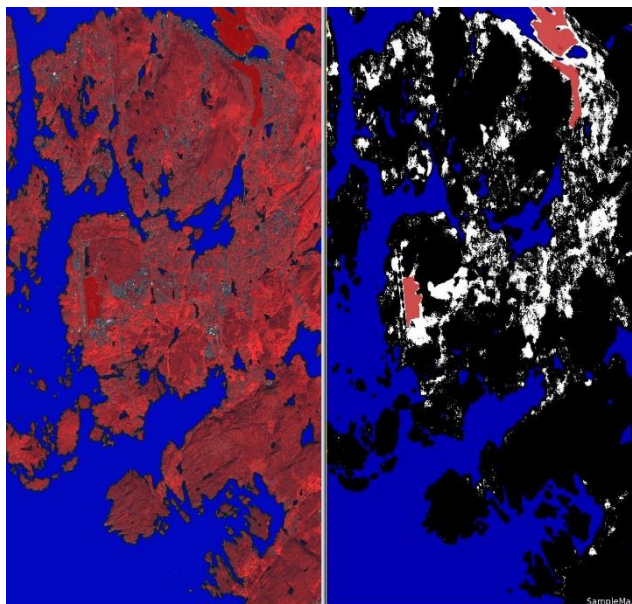


Figure 21 Bergen area, classified urban and water

### Urban areas:

We picked samples of urban areas from Sentinel 2 image. Image to the left shows Bergen with area around with infrared colour as the red band. If you use Near infrared colour in the red band, the red colour in the screen becomes very strong in all areas with vegetation. Non-red areas are non-vegetation or water.

We used **DL/CNN to classify water and urban** areas. To the right urban are white and water is blue.

DL/CNN accepts trees, parks and other vegetation in urban areas as urban. This is a huge benefit with DL/CNN method in eCognition. The result was surprisingly good even with few training samples.

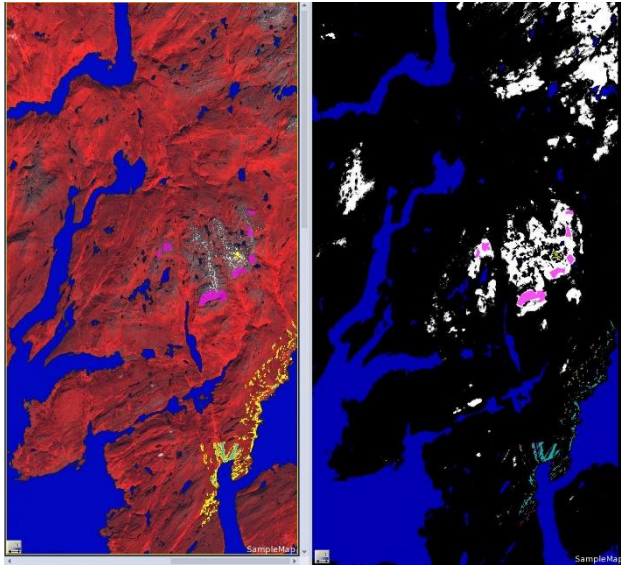


Figure 22 classified bare mountain

**Bare mountain** was found the same way as urban and water. Since bare mountain and urban areas are similar, we used dtm height to distinguish the two. With more samples it is possible to get a higher score.

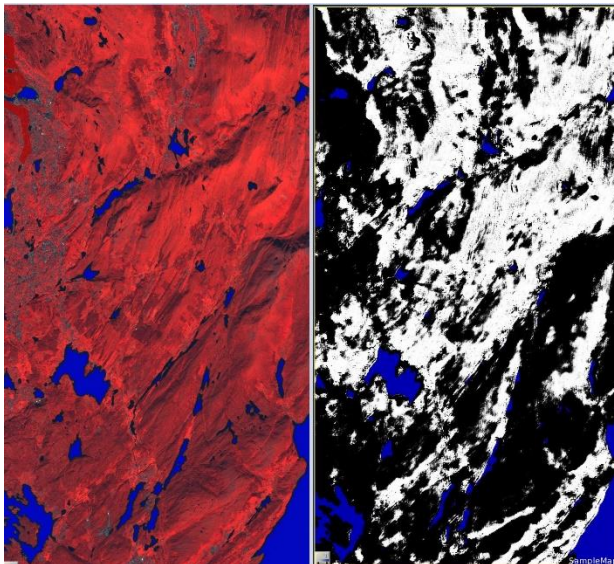


Figure 23 classified deciduous

Samples of **calcareous elm, linden, hazel** was picked from NEA nature database and used to train the model. Due to few samples we ended up with a **map of deciduous trees**. NEA database has single points for each tree listed. The Sentinel 2 image with 10m resolution picked up several trees for the same spot. Sentinel 2 data is very good to find forest stand, but is not so good to find single trees. For single trees we suggest to purchase high resolution data from TerraNor.

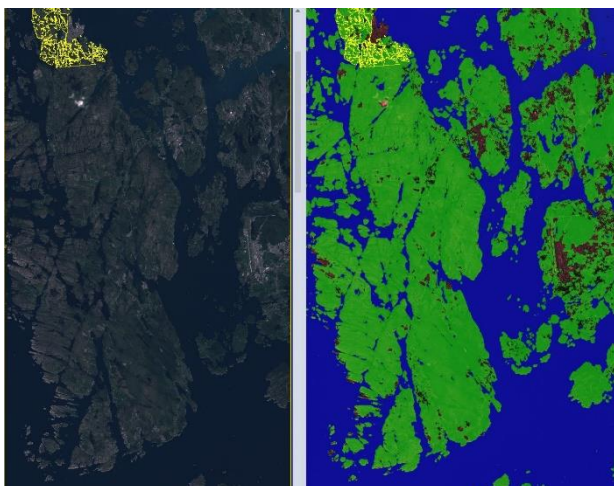


Figure 24 Coastal heath

**Coastal heath** was not possible to capture. In NEA nature database, all areas that contained coastal heath or had been coastal heath, was classified as coastal heath. We had polygons with forest, grass, bare rock and bogs classified as coastal heath. When we used these polygons to train eCognition, the classification showed that the whole of Hordaland was coastal heath. **This shows the importance of good training samples. Garbage in, Garbage out!**



## Threshold analysis combined with DL/CNN

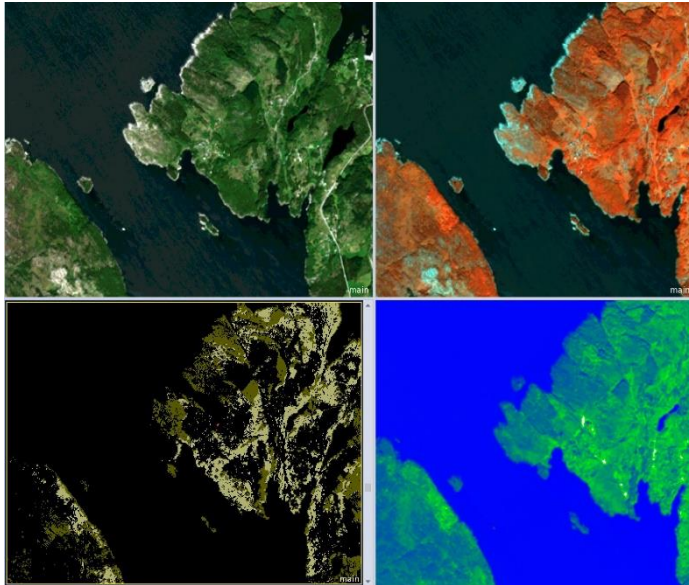


Figure 25 original image, IR image, deciduous and coniferous, vegetation and water

**Threshold analysis** is fast and can give excellent results in short time. Sentinel 2 has 13 channels of high quality. We used PCI GXL MRA pan sharpening techniques to create 10 m resolution of all channels. This is described in a separate document. First, we used water vapour channel and DL/CNN to map water. Then we used NDVI  $(NIR-RED)/(NIR+RED)$  to classify vegetation and non-vegetation. With use of lidar data we used vegetation height to distinguish forest from non-forest. In last step we used NIR2 to distinguish deciduous from coniferous. This whole process is fully automatic in one eCognition ruleset.

Figure 25 shows:

Top left: original image.

Top right: use of near infrared in the computer red channel.

Bottom left: Deciduous light green, coniferous dark green

Bottom right: vegetation and water

## Issues in classification



Figure 26 water and forests: deciduous and coniferous

This image shows water, deciduous and coniferous classified with threshold values. The forests are very accurate. Water classification has several issues. The large parts of water is correct. We used DL/CNN to improve the quality of water classification. Fig 25 bottom right shows the final result.

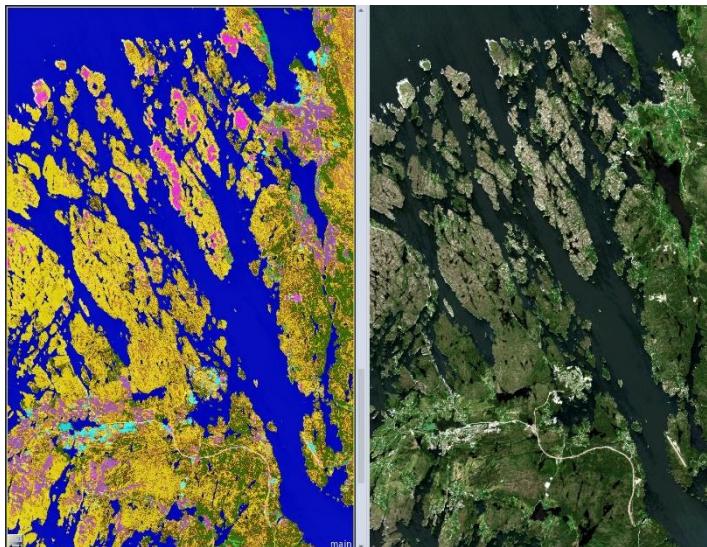


Figure 27 classified and original image

Here we used the first threshold classification of water to train DL/CNN and reclassify water class with DL/CNN. Result is far better than we managed with threshold values only.

Bare mountains, urban areas, forests and water have good results. More test surfaces will give even better results.

### Geology, climate, dtm derivatives: derived data analyses

Most countries have good datasets for geology, weather and terrain. Met institutes have studied weather and climate for hundreds of years and have good digital datasets for wind, rainfall and temperature. Geology maps showing quaternary geology are important. Terrain model based on modern lidar data show both terrain and surface height.

We did not have time to use these datasets in the FALK project. Here we explain how they can be used.

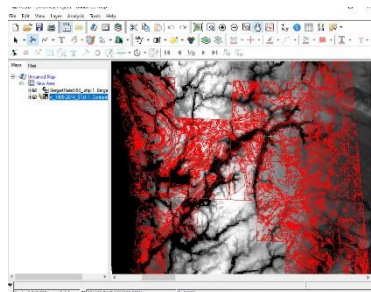


Figure 28 Rainfall and geology

To the left we see rainfall and geology. Higher rainfall is brighter. You can see how the west coast and mountains have more rain than Eastern Norway.

Quaternary geology maps combined with rainfall can tell you where to expect landslides.

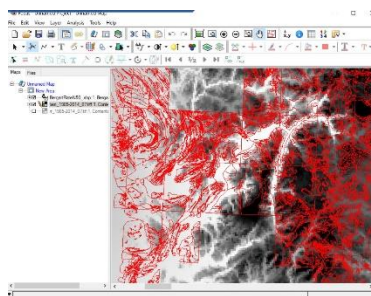


Figure 29 Temperature

Temperature over the year with bright colour shows higher temperature. This information combined with rainfall and geology can give a very good indication of what species you can expect to find in different areas.

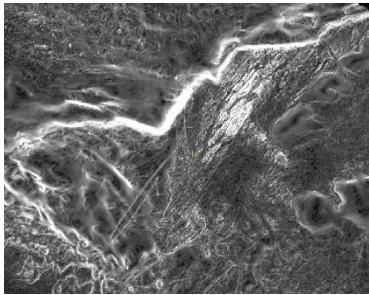


Figure 30 Slope

DTM gives us terrain height and surface height. This image shows slope.  
Slope and quaternary geology maps combined with rainfall can tell you where to expect landslides.

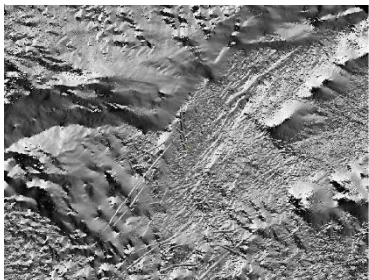


Figure 31 Aspect

Aspect shows how much sun light areas receive over the day and over the year.

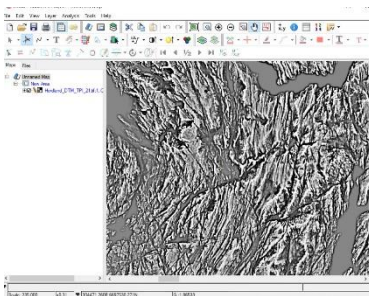


Figure 32 Topographic Position Index, TPI

TPI: topographic position index (check Wikipedia) is a way to describe terrain. Hill tops receive high value above zero while valleys receive low values below zero.

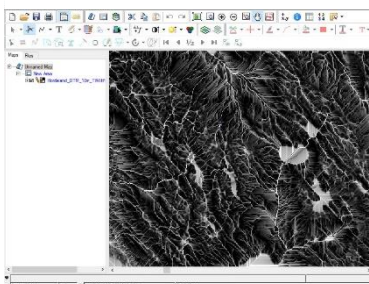


Figure 33 Topographic Wetness Index, TWI

TWI: topographic wetness index shows how water is moving in the terrain.

All these derivatives can be combined to analyse vegetation. Any biologist can tell you how, or you can use machine learning to do the job for you. **If you have good samples of the classes you want to map, eCognition machine learning will help you use the features that distinguishes the classes.** As you saw with coastal heath the samples must have good quality.



## Vestland



We want to thank our colleagues for brilliant cooperation and excellent work in the project:



**University in Bergen, Department of Geography:**

PhD Gidske Leknæs Andersen, Associate Professor  
PhD Benjamin Aubrey Robson, Associate Professor  
Scientist Max Koller



**PCI Geomatics:**

Stewart Wyseman, Territory Sales Manager – Africa, Europe & Eurasia  
Jason Flatt, Technical Solutions Specialist  
Wolfgang Lück, Senior scientist



**Trimble eCognition team**

Barbara Zenger Landolt, senior scientist



Nils Erik Jørgensen, CTO TerraNor