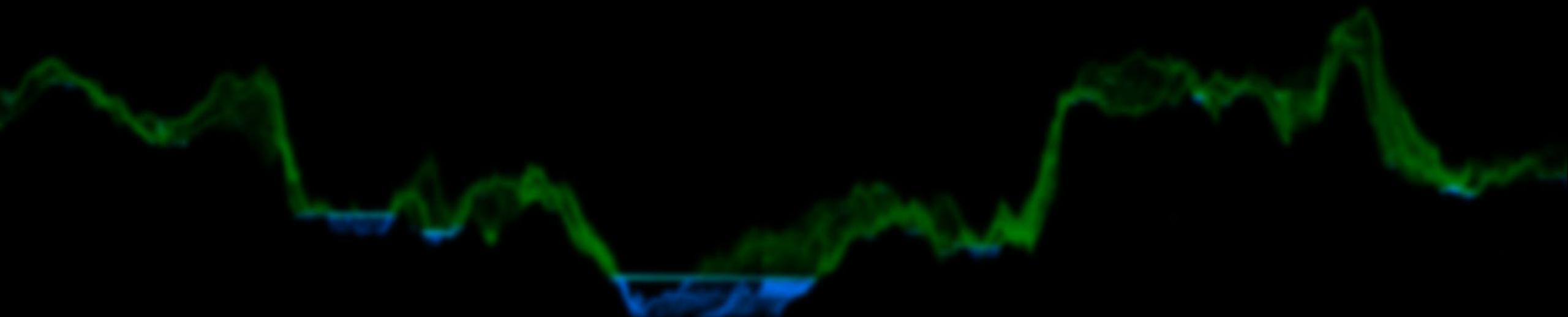




SCIENCE AND
EDUCATION **FOR
SUSTAINABLE
LIFE**

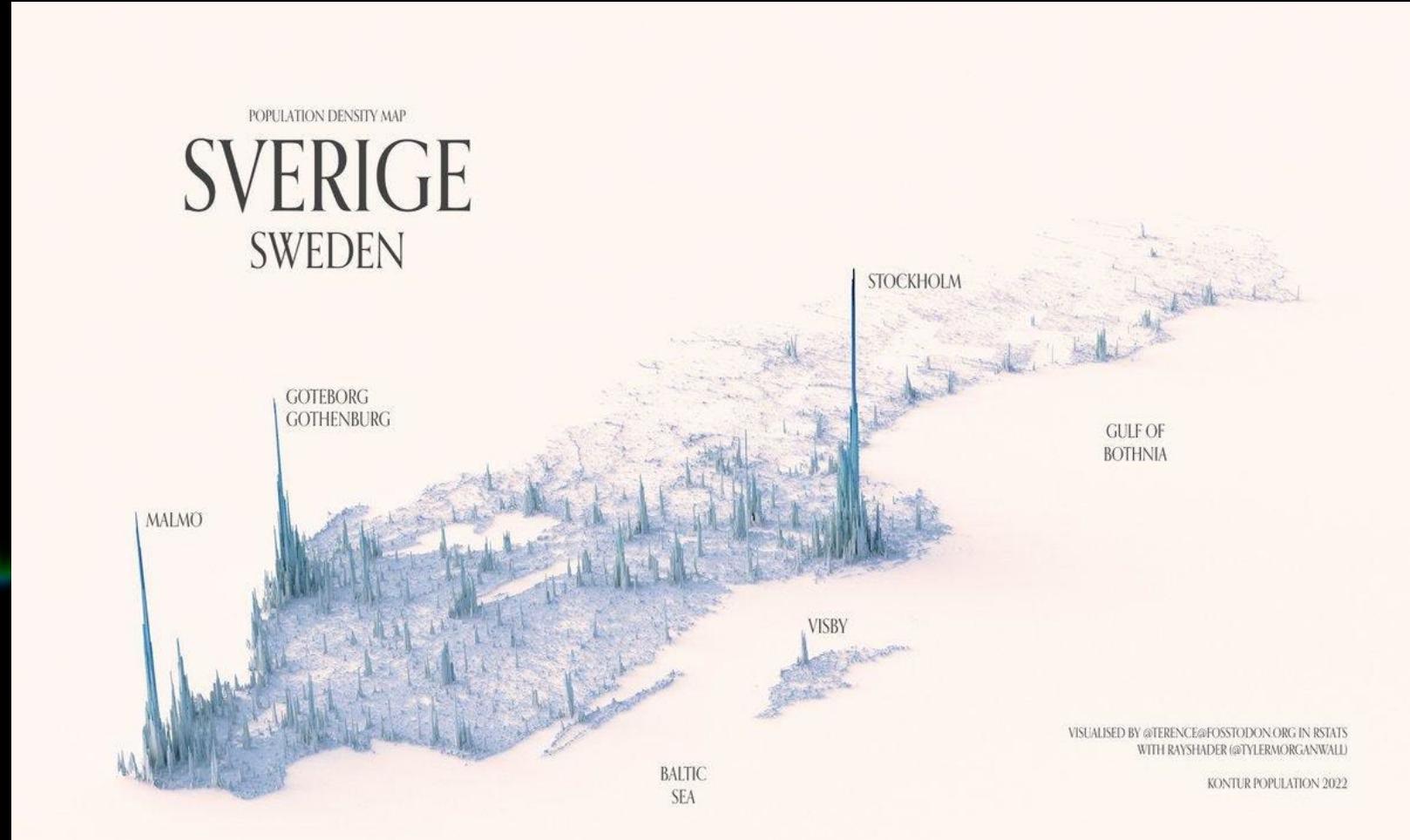


Mapping cultural remains with LiDAR and AI

William Lidberg

SLU, Sweden

- **Lecture**
 - Cultural remains
 - LiDAR
 - Machine learning
- **Break**
 - Find computers in
bookskogen
- **Computer Excercise**
 - google colab
 - Intro to data
 - Hands on



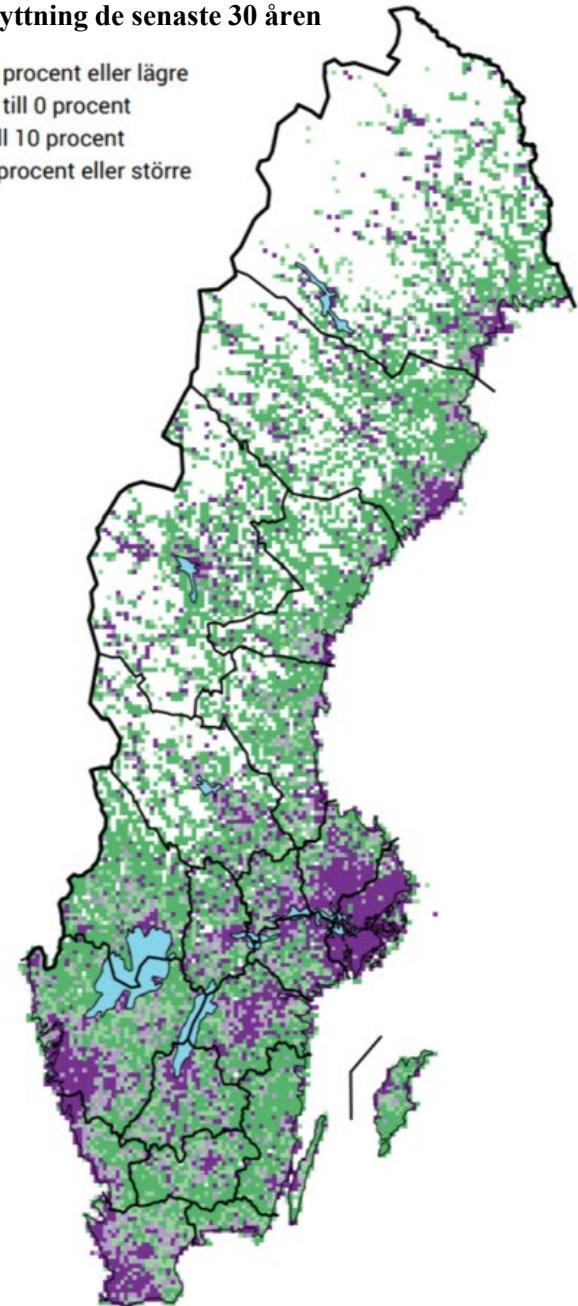
Schematisk karta över markanvändningen i Sverige



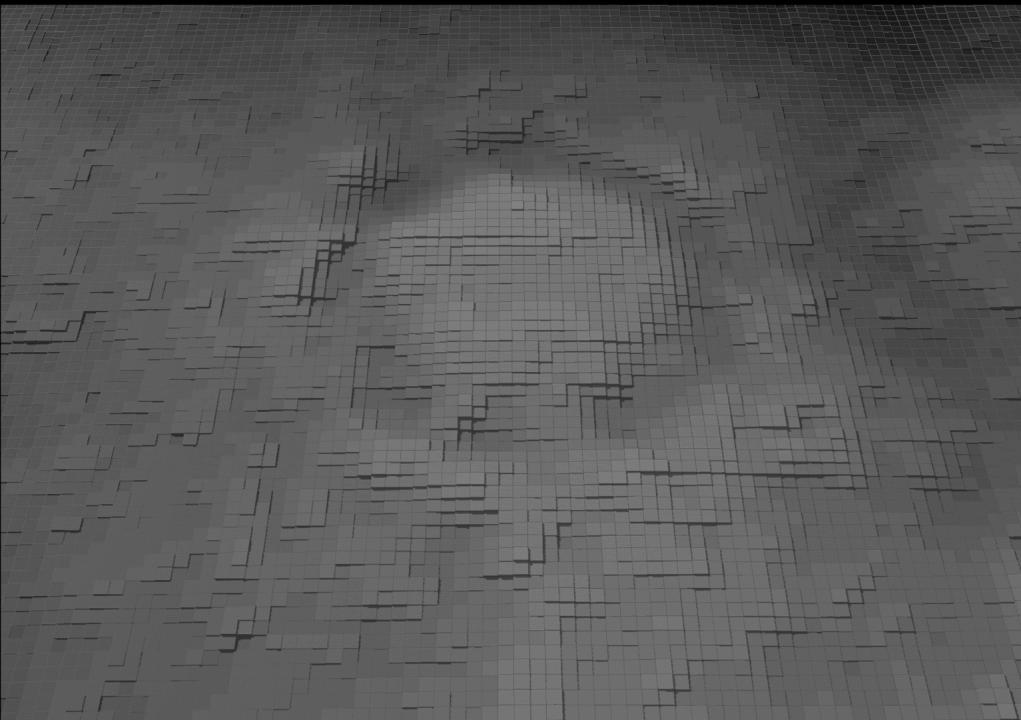
Källa: Lantmäteriet. Bearbetning, SCB

Förflyttning de senaste 30 åren

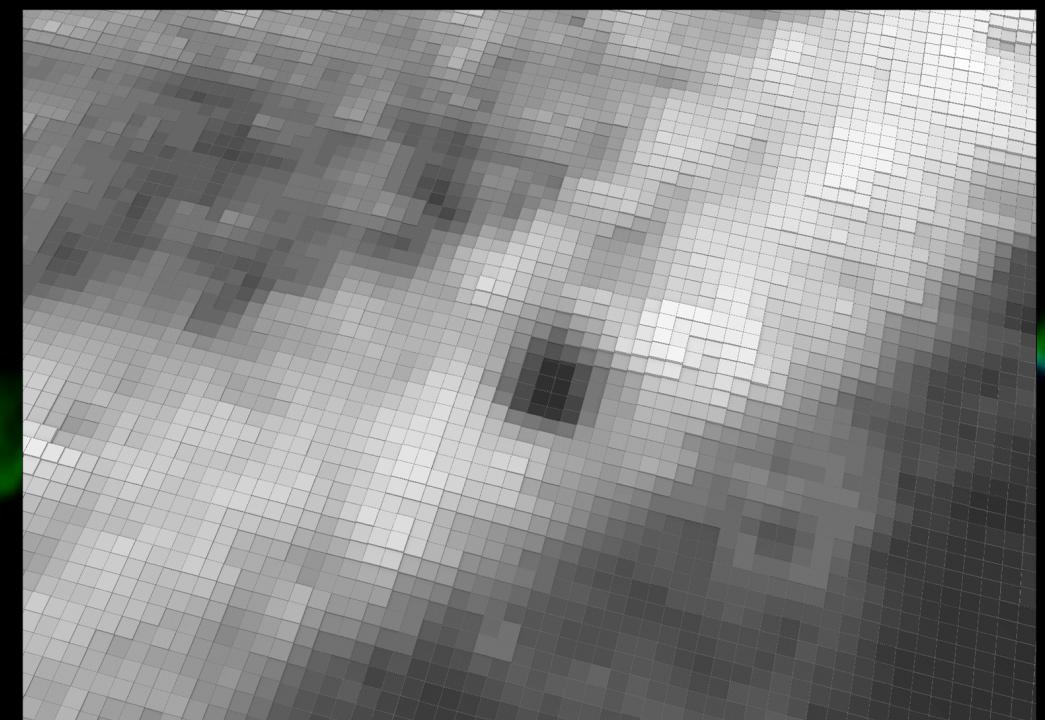
- 10 procent eller lägre
- 10 till 0 procent
- 0 till 10 procent
- 10 procent eller större



Källa: SCB

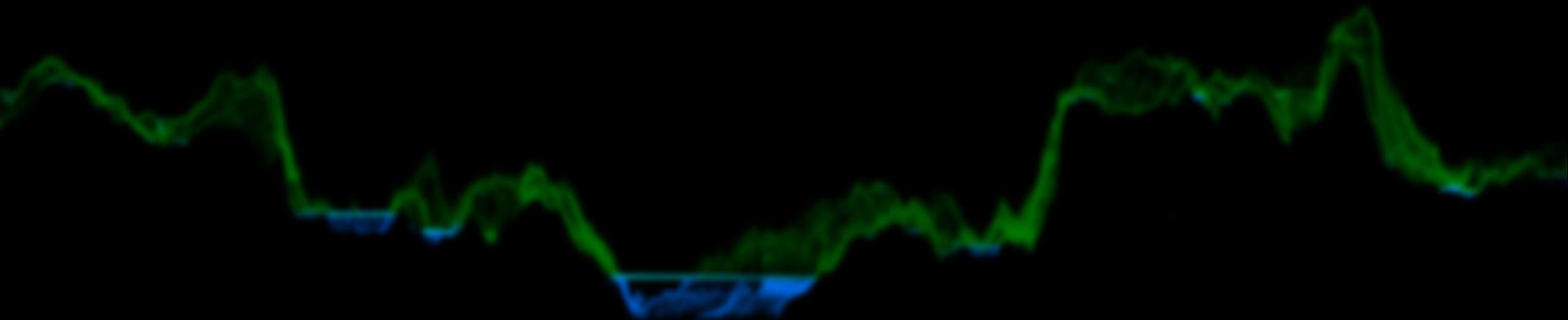


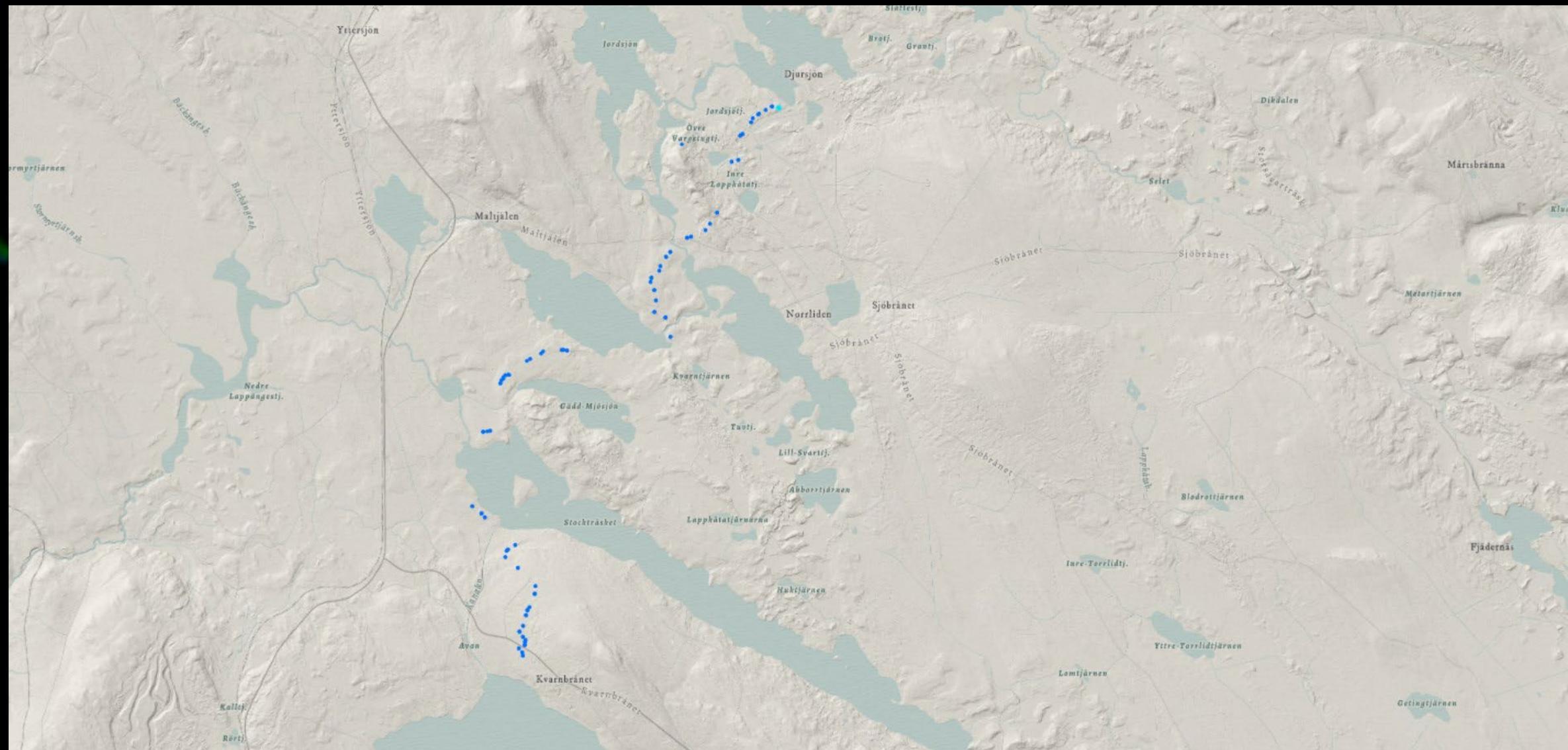
Charcoal kiln



Hunting pit

Cultural remains





27 % of all cultural remains are damaged by forestry operations



Mer än var fjärde kulturlämning skadas vid avverkning

Pressmeddelande - 07 december 2021

Andelen kulturlämningar som på något sätt skadats vid skogsavverkning ligger i år på 27 procent. – Varje år hittar vi nya skador på forn- och kulturhistoriska lämningar runt om i landet. Skadorna är på lägsta nivån sedan 2012, men fortfarande ligger de på höga nivåer, säger AnnKristin Unander, inventeringsledare på Skogsstyrelsen.

Varje år inventerar Skogsstyrelsen runt 1500 kända och registrerade kulturlämningar i Sverige. Det kan röra sig om gravfält, husgrunder och stenåldersboplatser. Syftet är att kartlägga den påverkan – ringa skador till grova skador – som uppstår på kulturlämningar vid föryngringsavverkning, och se på vilka åtgärder som gjorts för att skadorna ska minska.

Andelen kulturlämningar som blir påverkade vid avverkning ligger i år på 27 procent, vilket är den lägsta nivån sedan Skogsstyrelsens inventering började 2012.

– Men det är en alltför hög nivå, varje år adderas nya skador. Skadorna uppkommer främst vid markberedning, säger AnnKristin Unander, och fortsätter:

– Eftersom skador på förlämningar är ett brott mot kulturmiljölagen, rapporterar vi de brotten till respektive länsstyrelse, sen är det upp till dem att göra åtalsanmälan.

Markberedning bakom flest skador

Norra Norrland, Södra Norrland och Götaland ligger på samma skadenvå nära det gäller skada och grov skada, på 16 procent. Svealands skadenvå ligger fortfarande på en låg nivå, nu på 7 procent.

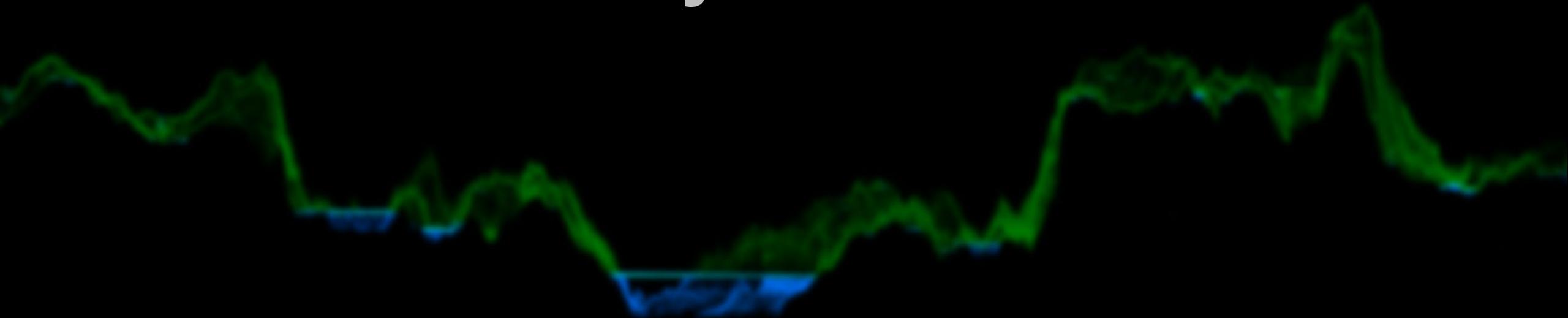
När det gäller förändringar över tid finns en trend med minskande skador för Norra Norrland och Svealand sedan 2012 och för södra Norrland sedan 2016. I Götaland är resultatet oförändrat över tid.

Markberedning fortsätter vara den vanligaste orsaken till skada eller grov skada i tre av fyra landsdelar. Undantaget är Södra Norrland, där skador av rotvältar från vindfallna träd och nedrisning är vanligare än skador efter markberedning.

– Rätt information och kunskap i alla led är den avgjort viktigaste faktorn för att vi ska komma till rätta med det

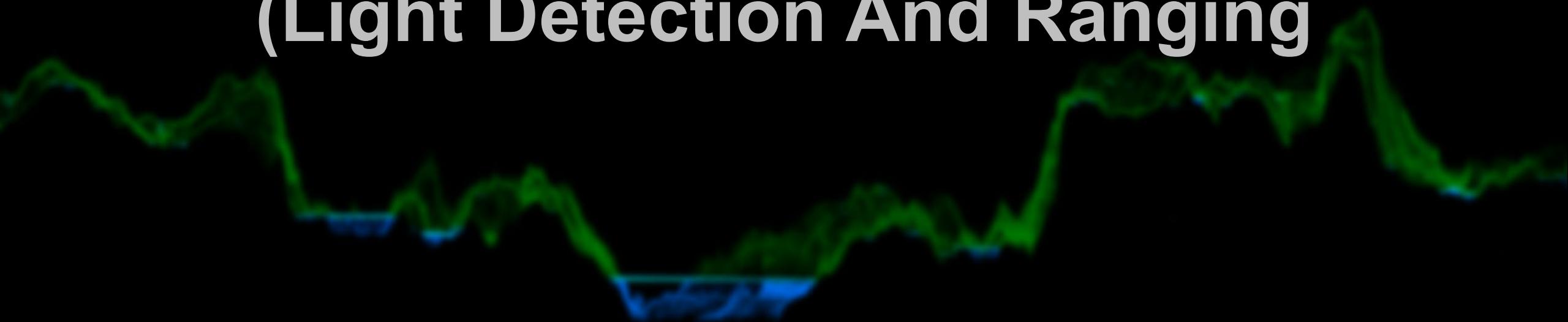


Qustion: Why should we care?

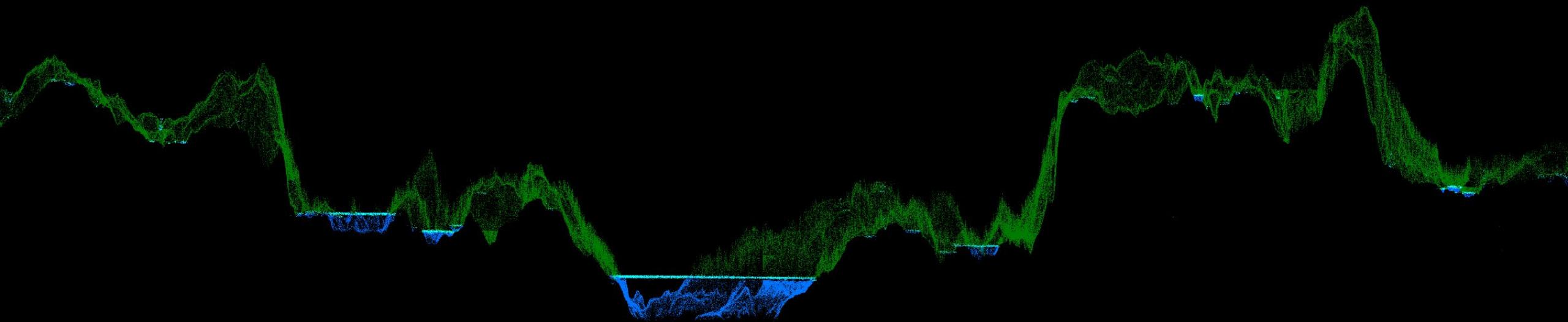


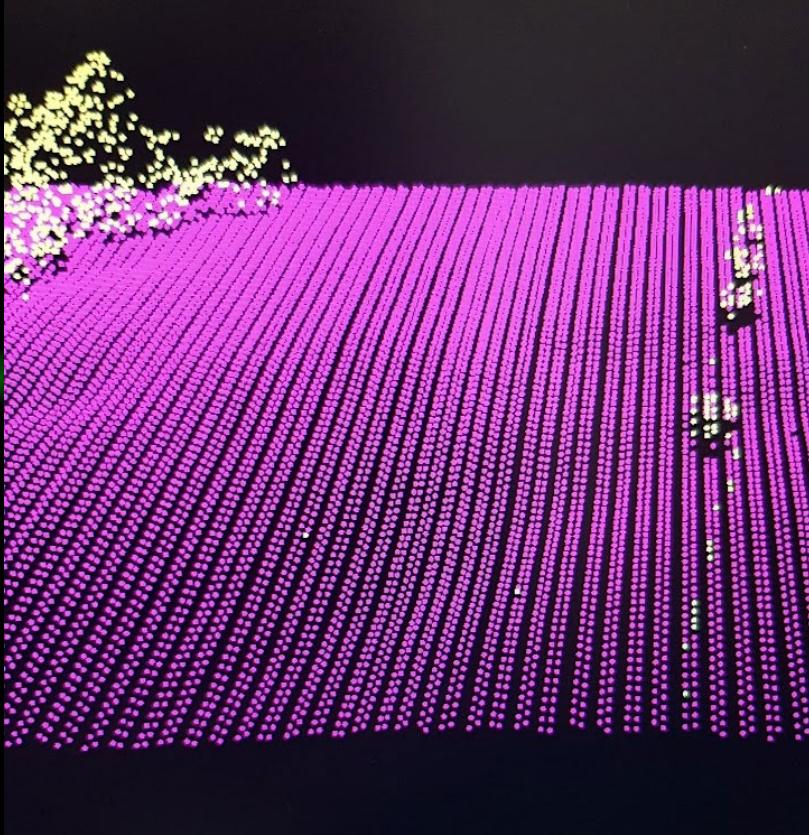
LiDAR

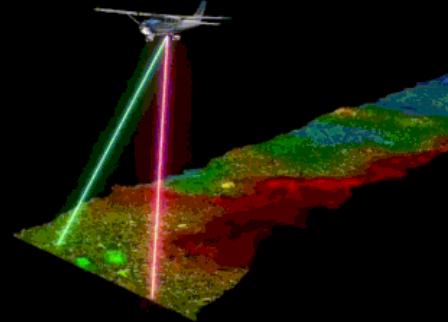
(Light Detection And Ranging)



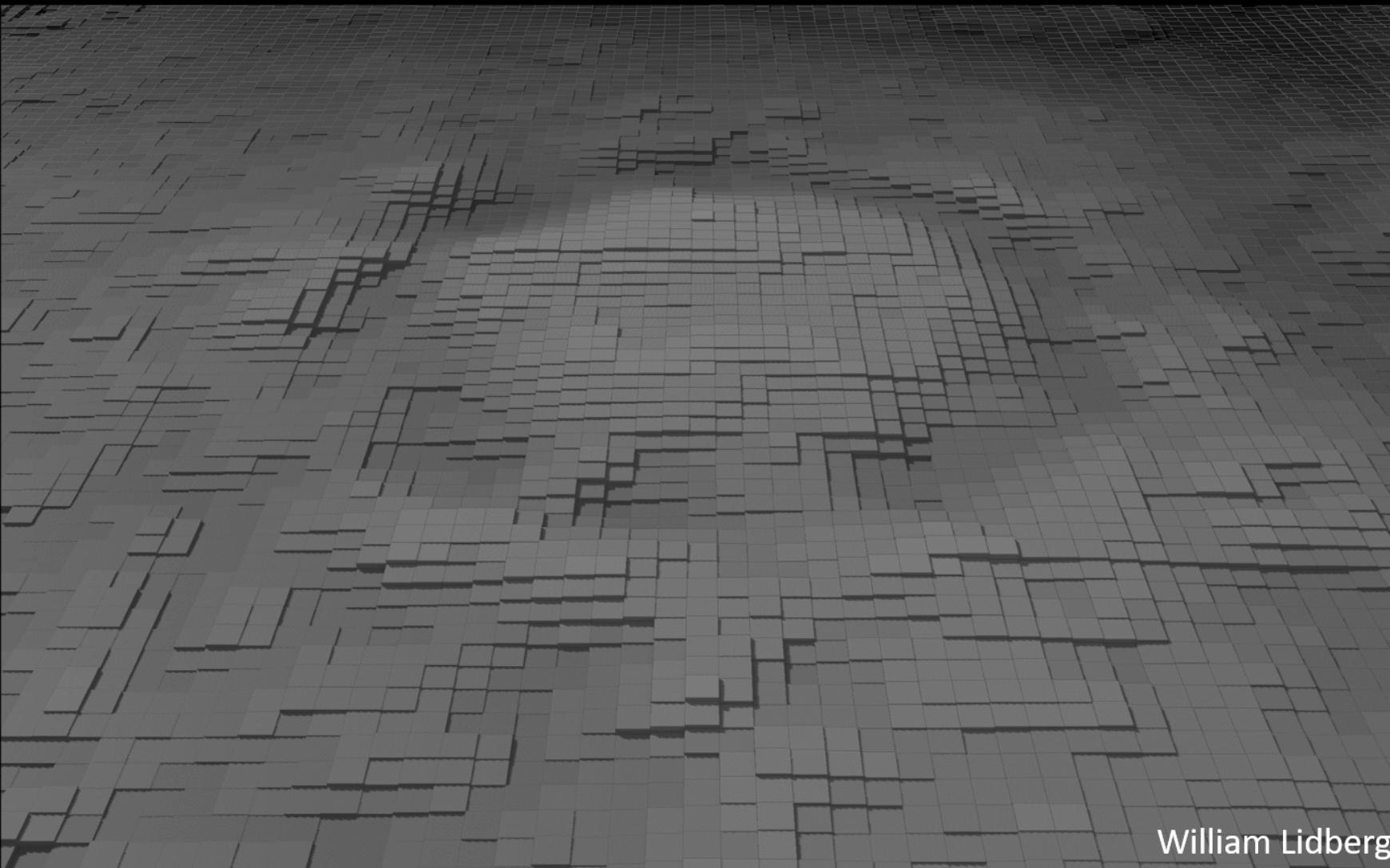




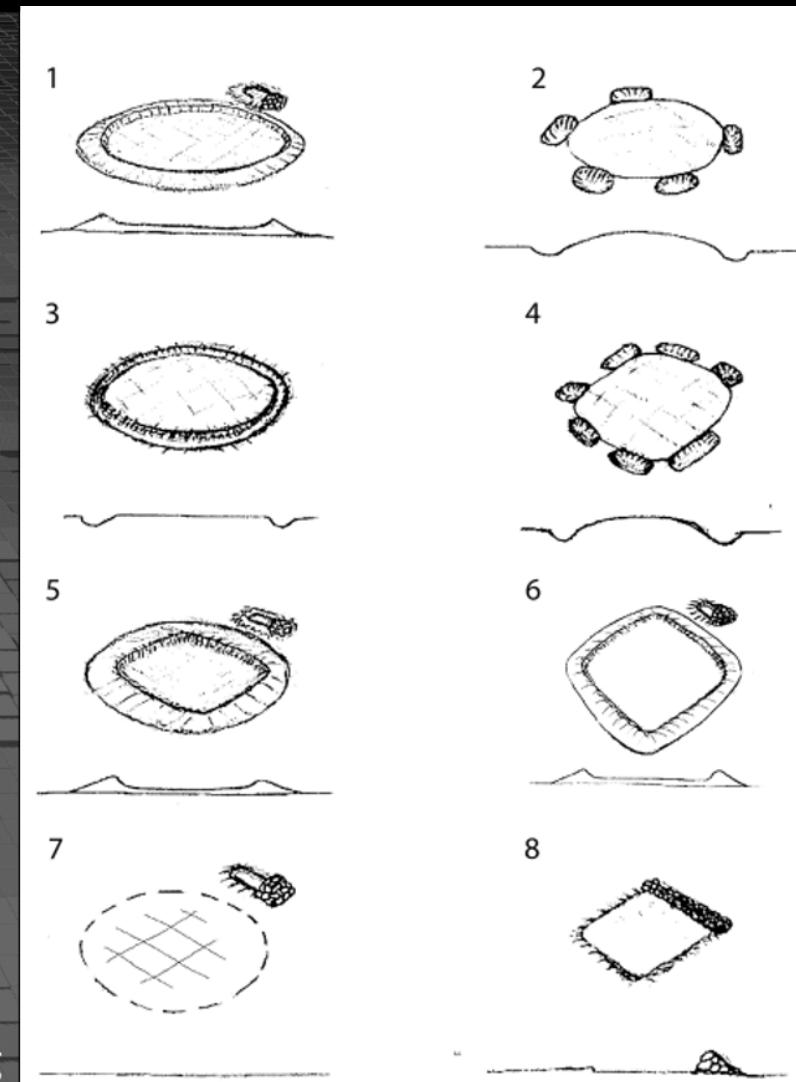




- First scan: 0.5 – 1 points/m²
- Second scan: 1 – 2 points/m²
- Third scan: ~5 points/m²



William Lidberg





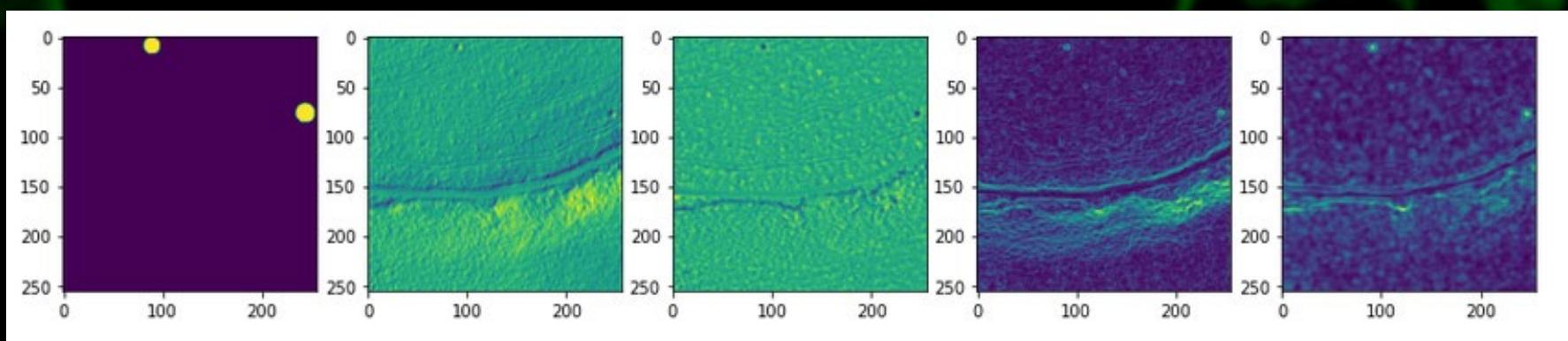
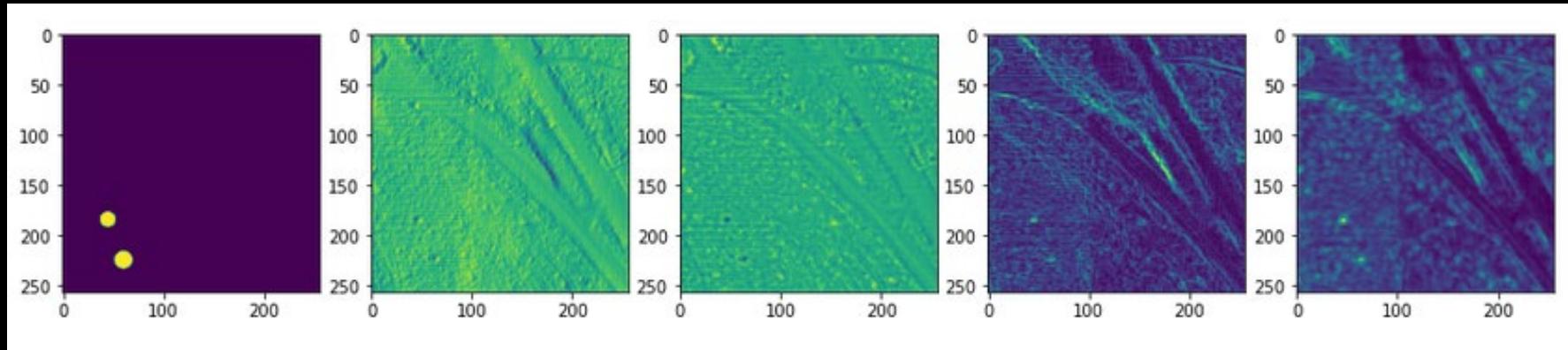
Label

Hillshade

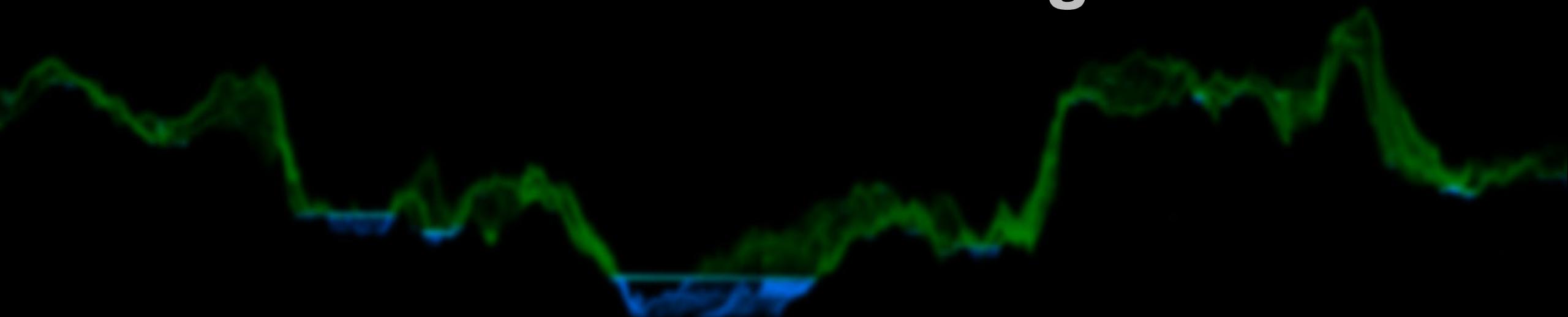
High pass meidna filter

Slope

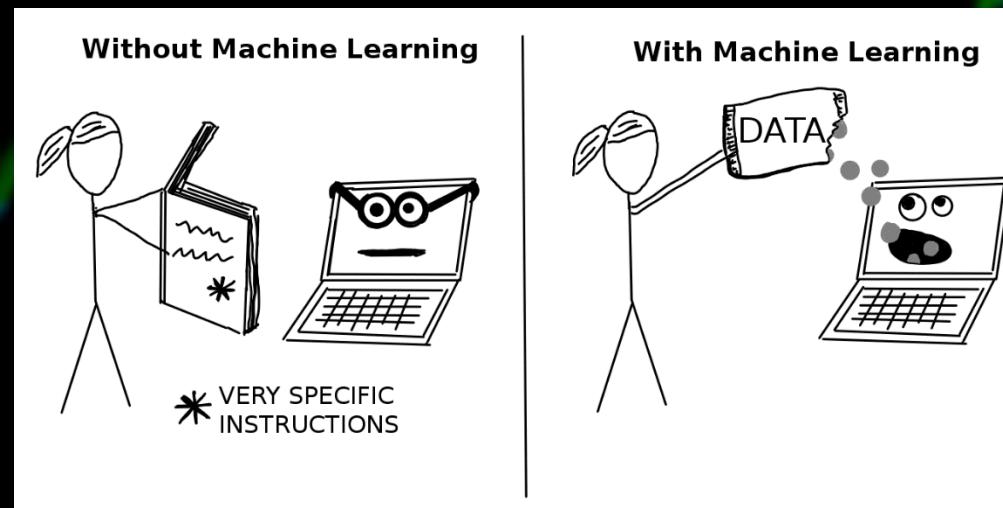
Spherical standard deviation of normals



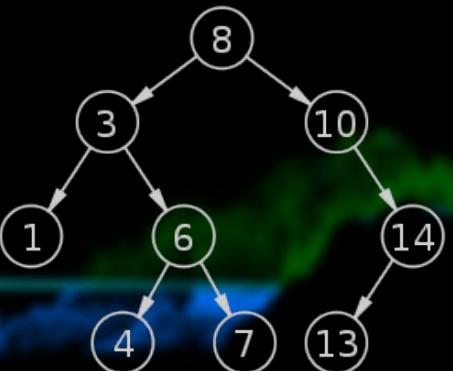
Machine learning



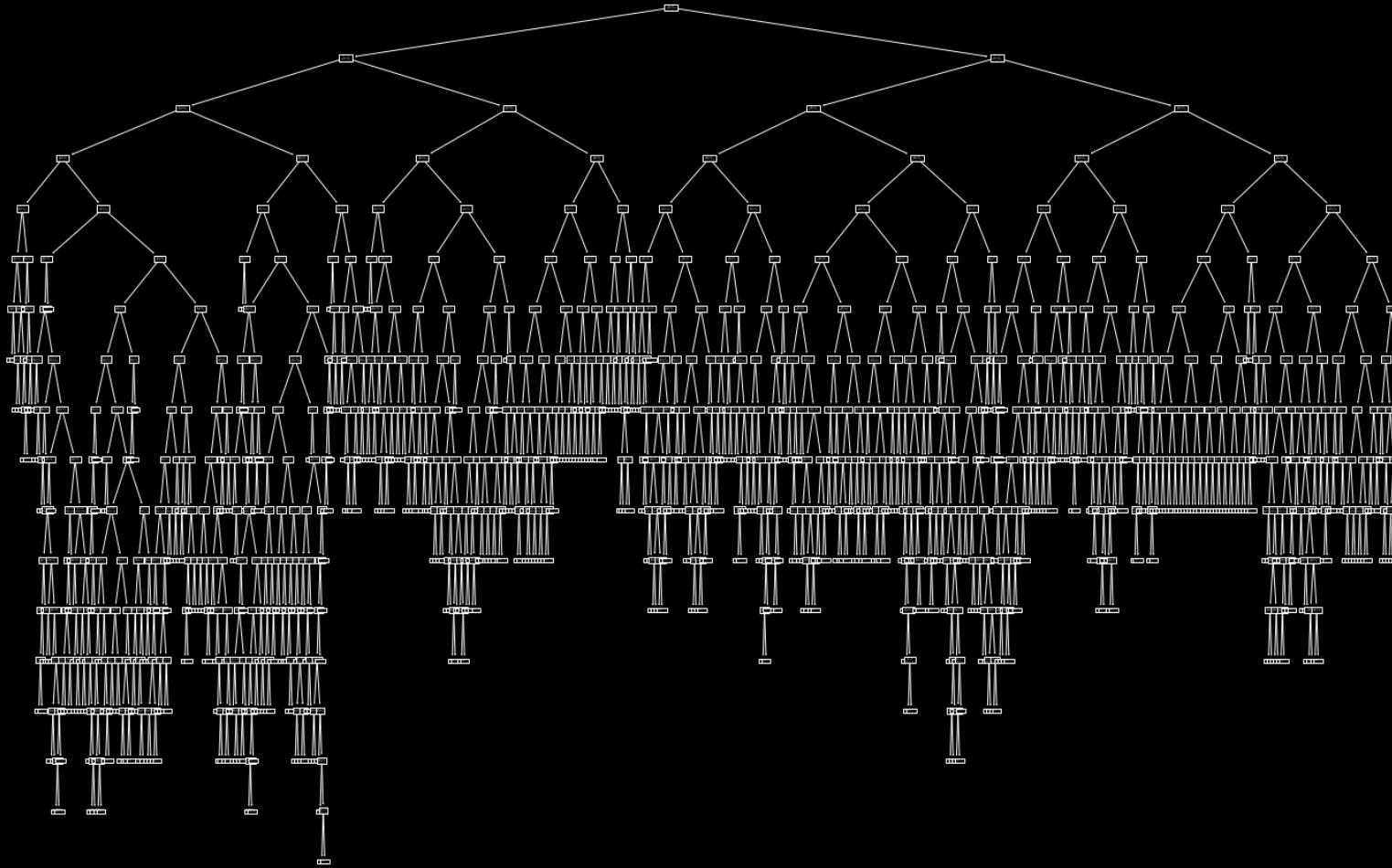
Machine learning



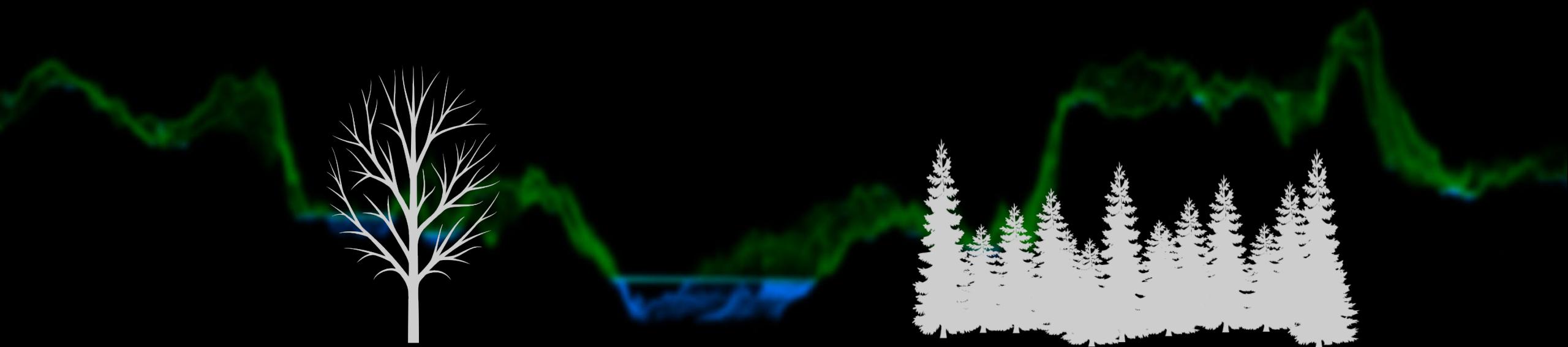
Decision trees



Decision trees

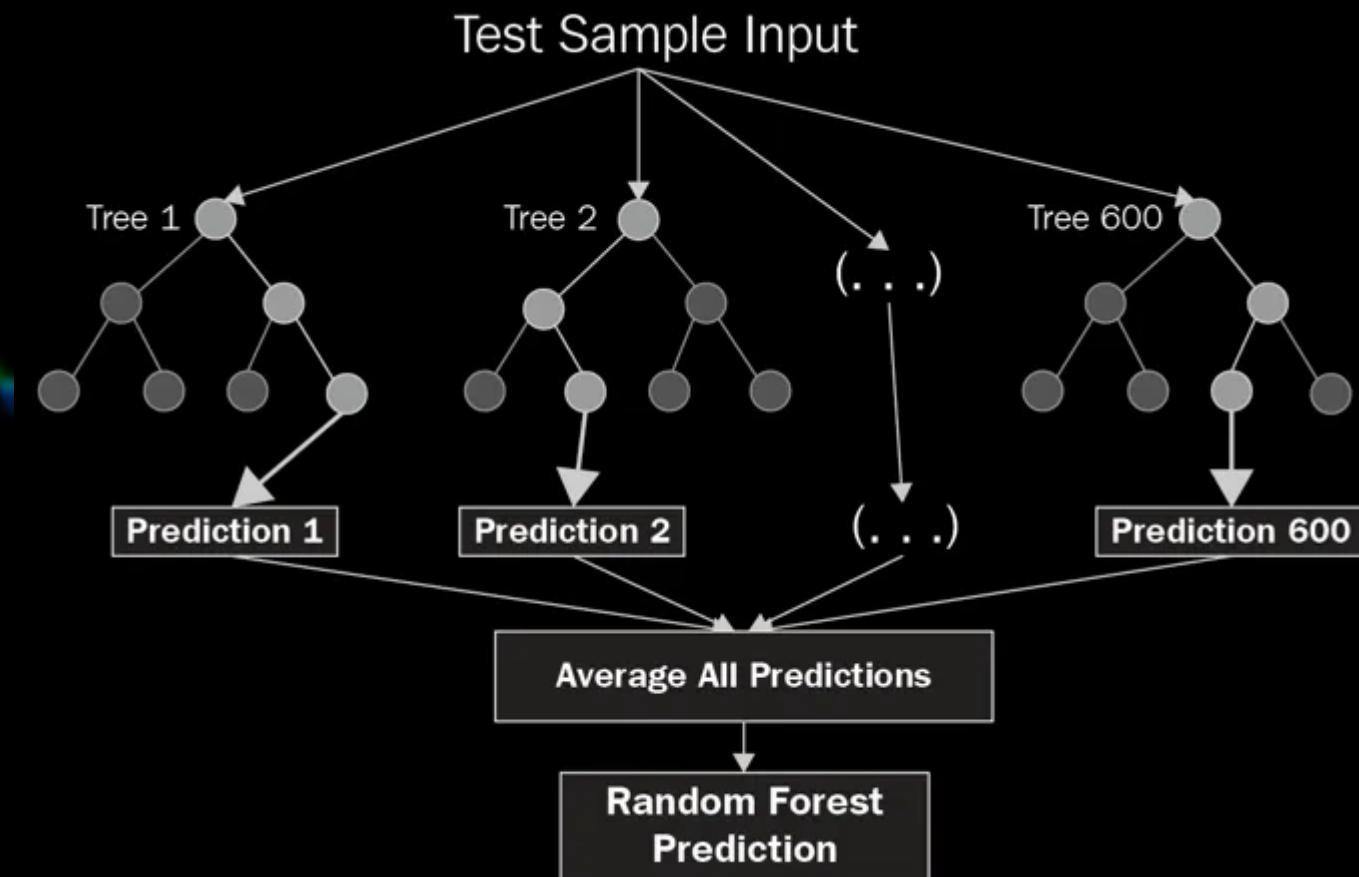


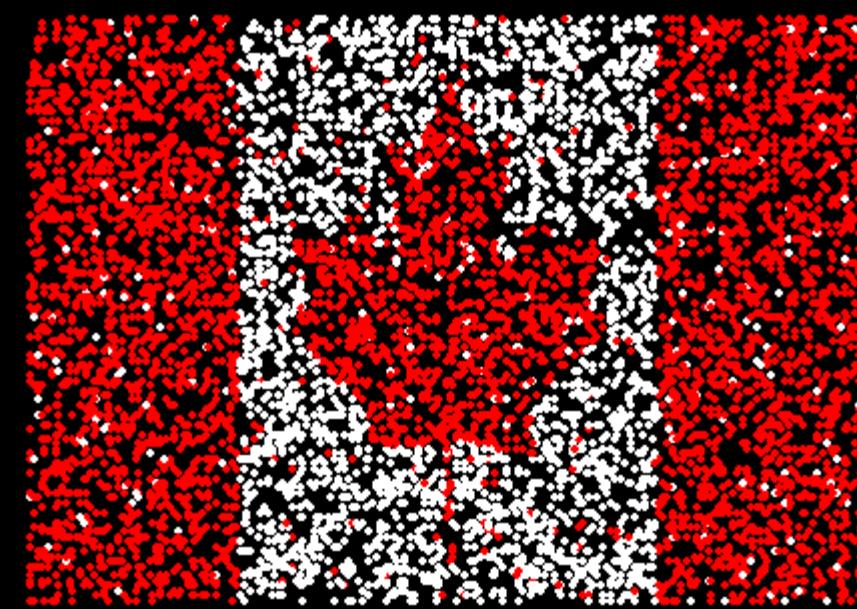
Decision forests



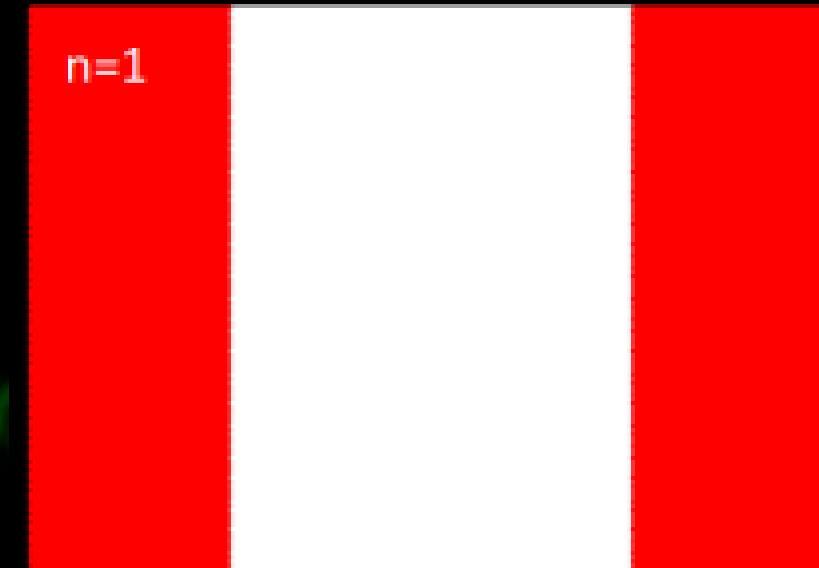
Decision forest

Random forest

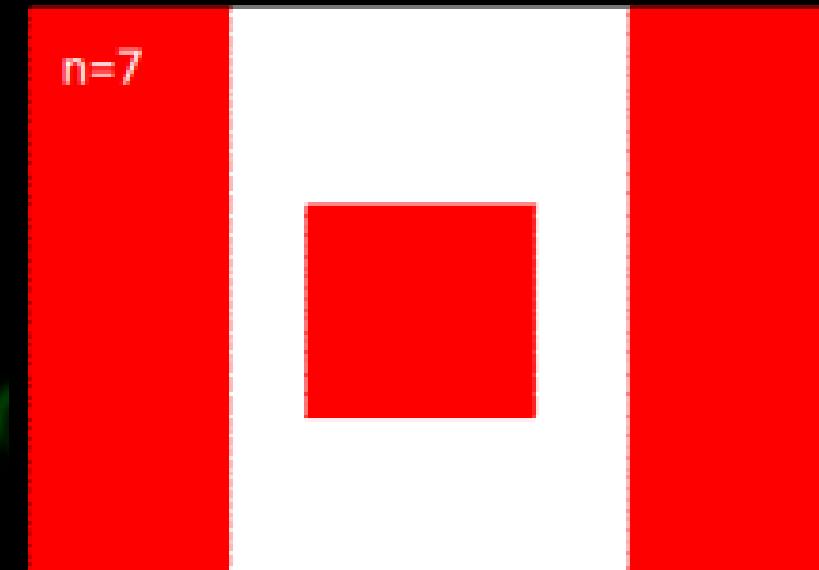




Training data of the Canadian flag



First tree





A few more trees...

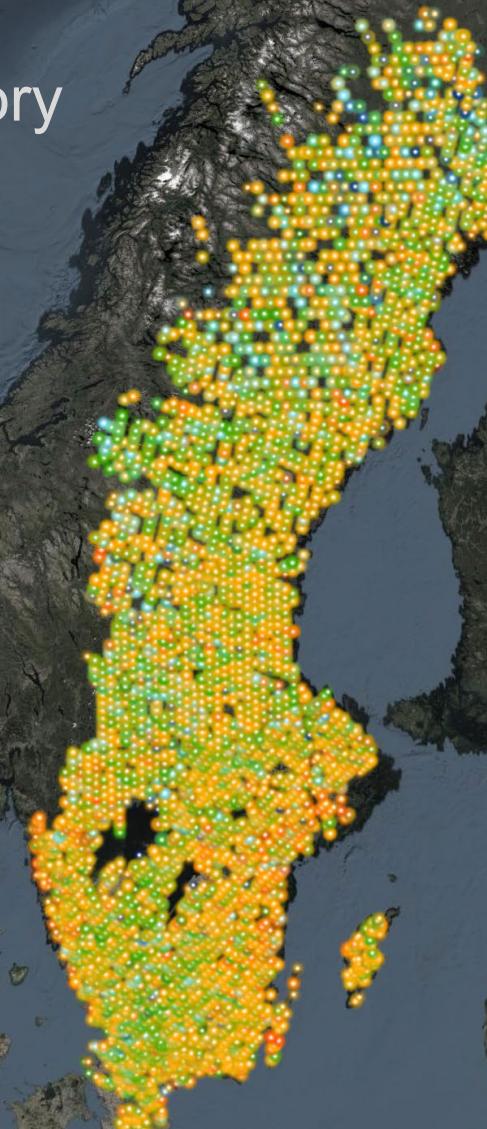


A few more trees...



Lots of trees and some overfitting

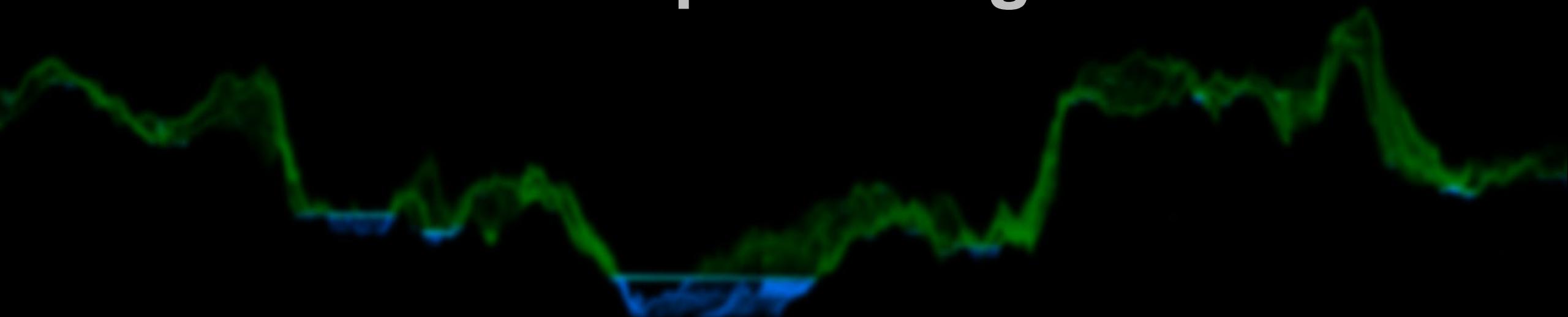
National Forest Inventory



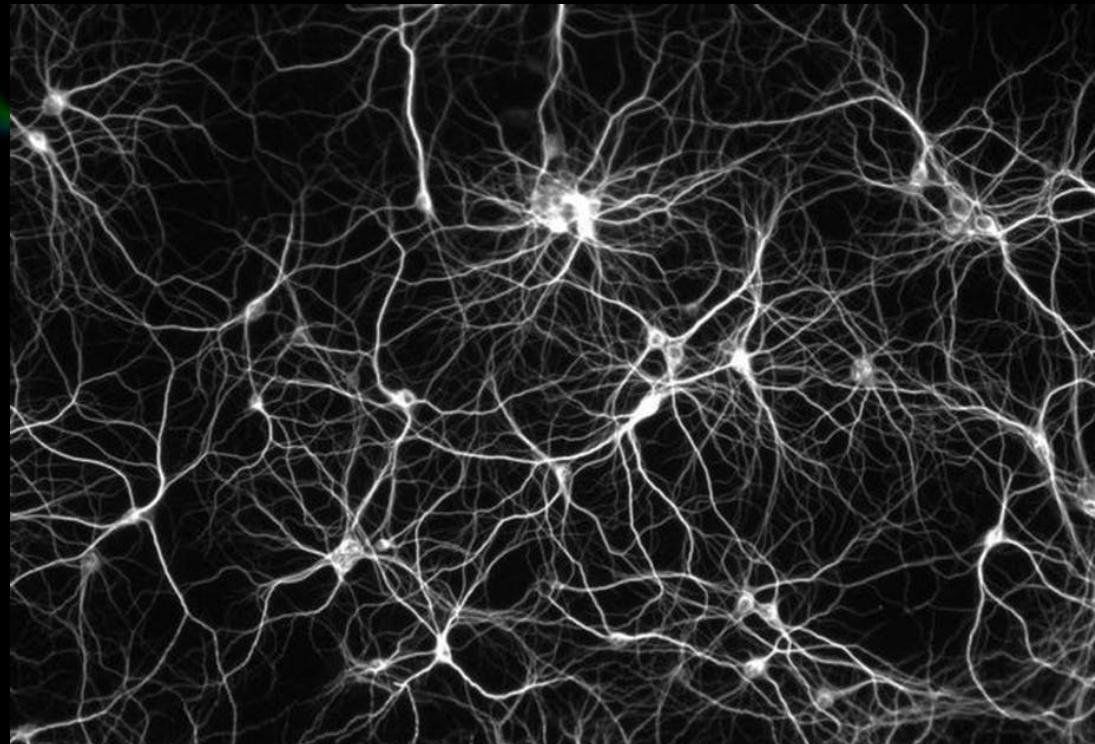
Source: Esri, DigitalGlobe, GeoEye, Earthstar Geographics, CNES/Airbus DS, USDA, USGS, Aer

Bild: William Lidberg

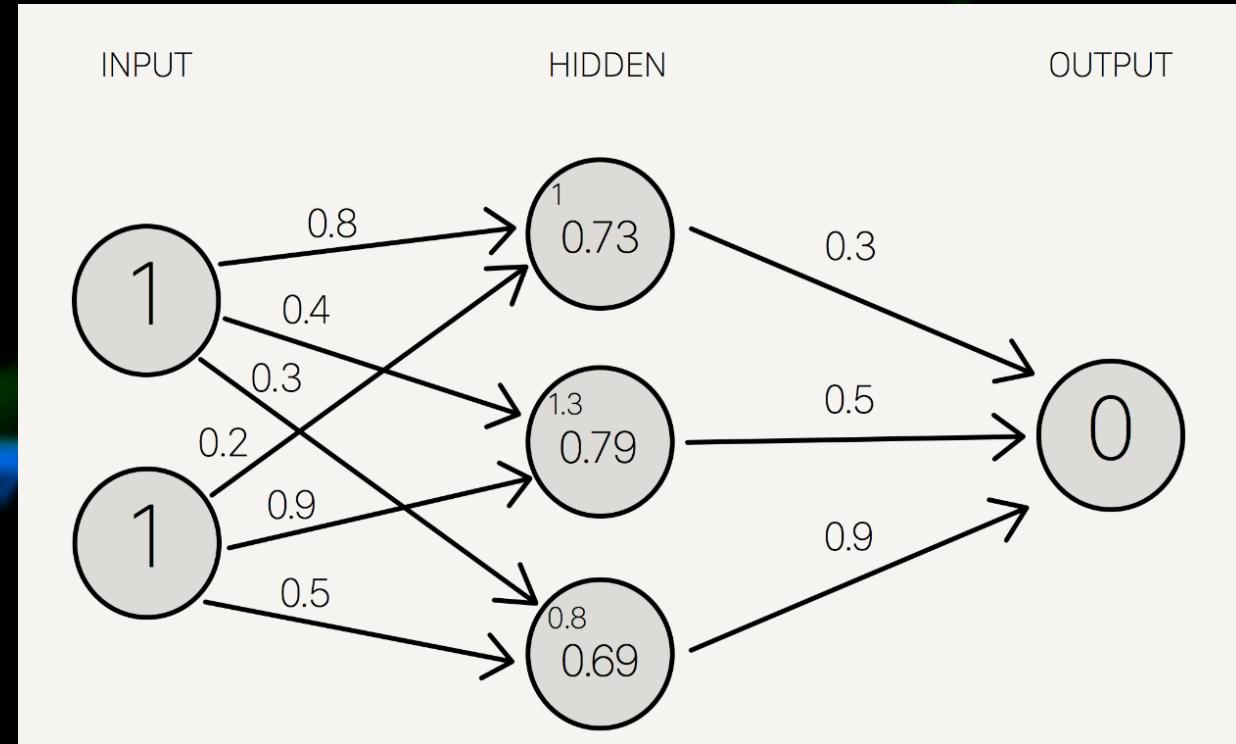
Deep learning



Neural networks

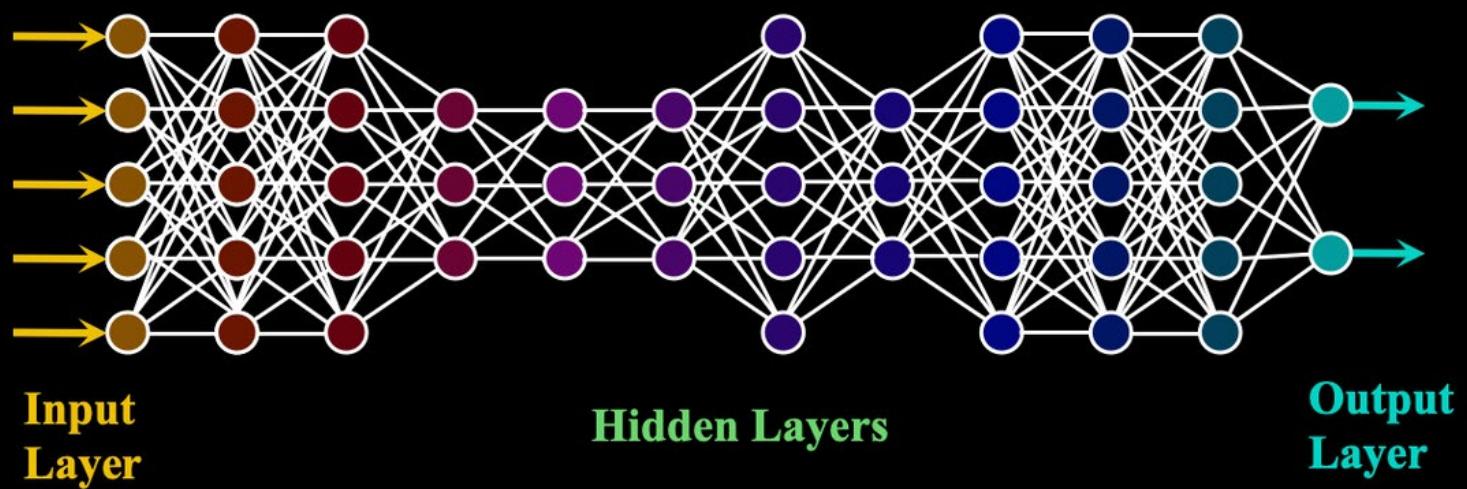
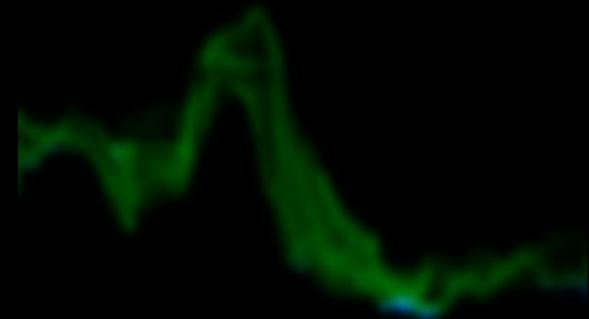
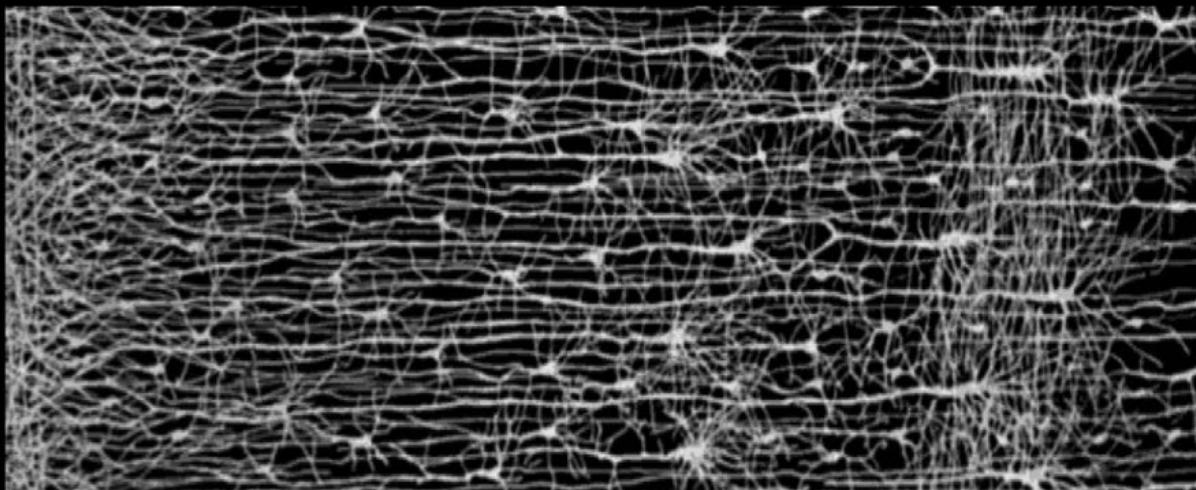


Biological Neural network

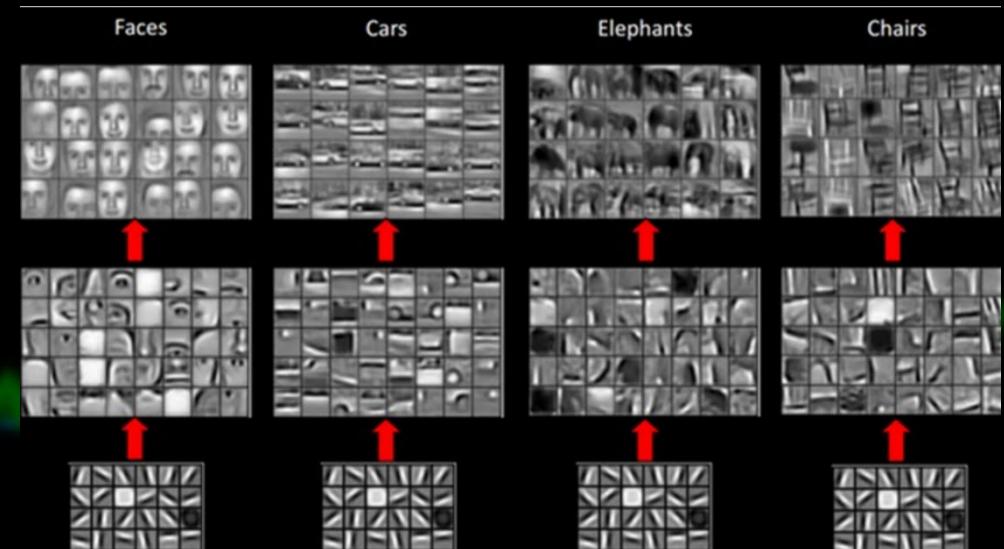
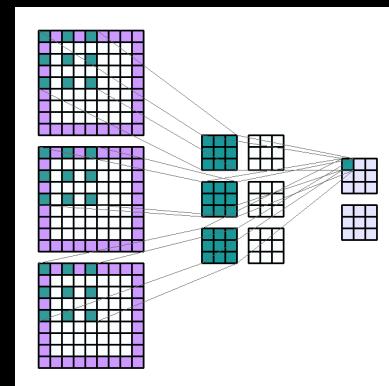
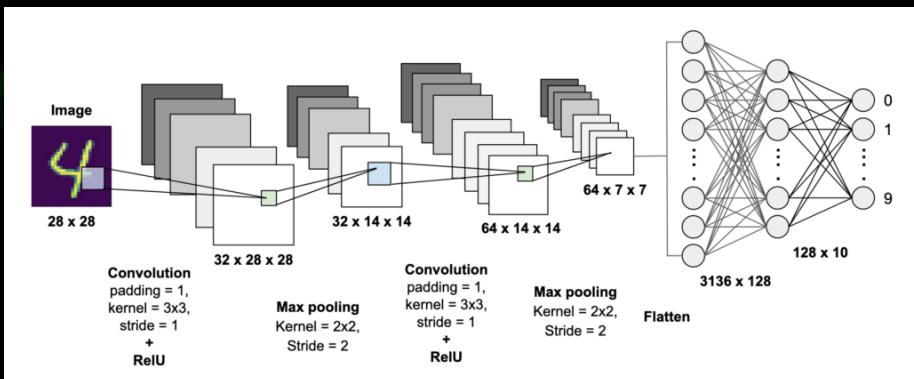


Artificial Neural network

Deep Neural networks



Convolutional neural networks



Convolutional neural networks

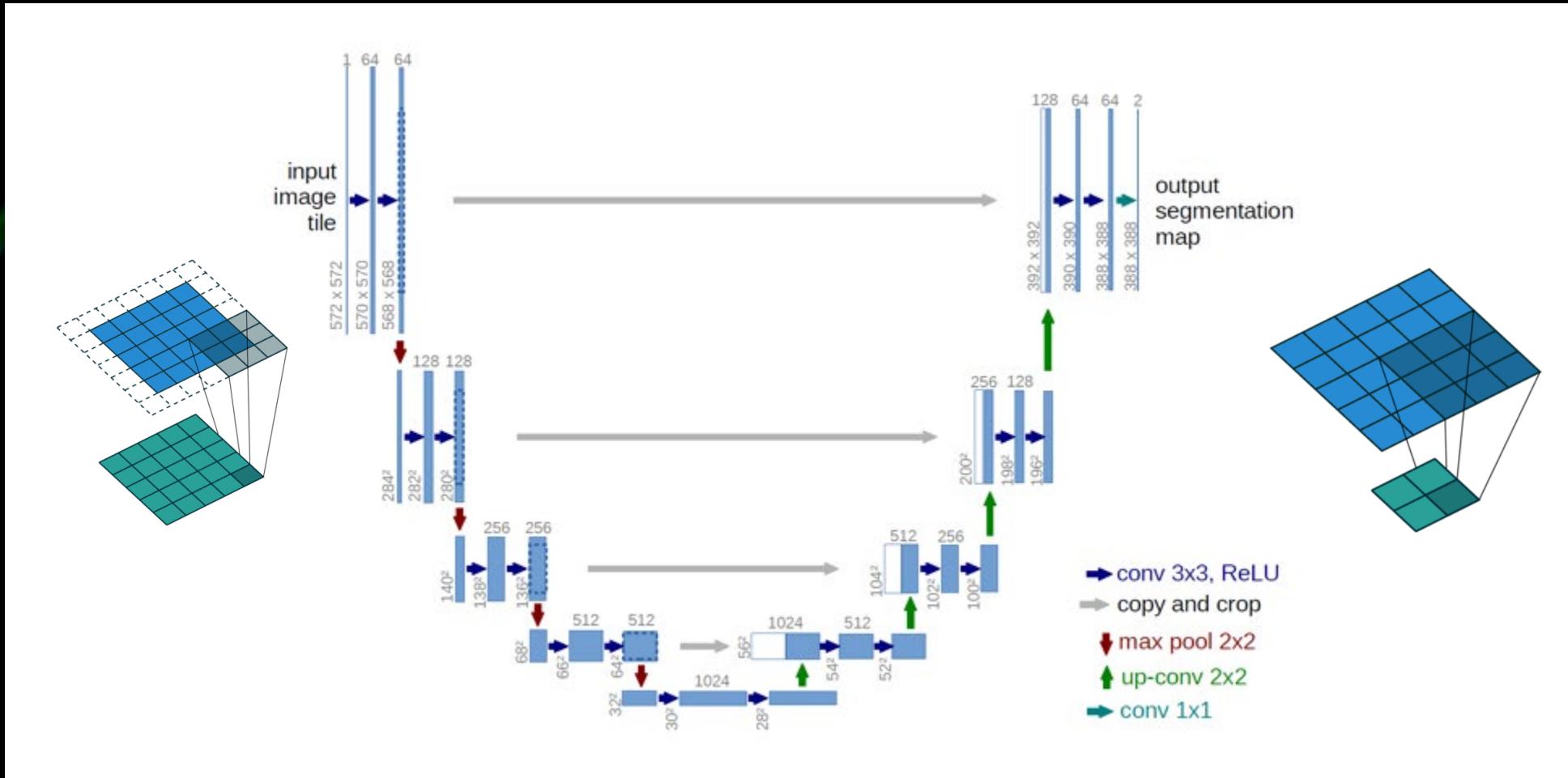
What it actually look like



Object detection

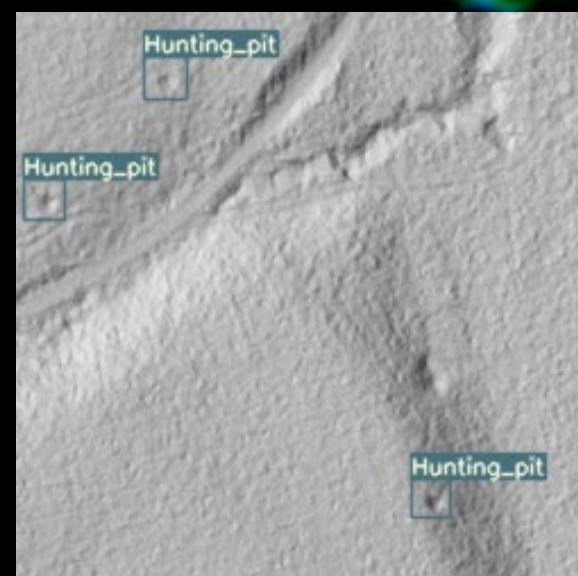
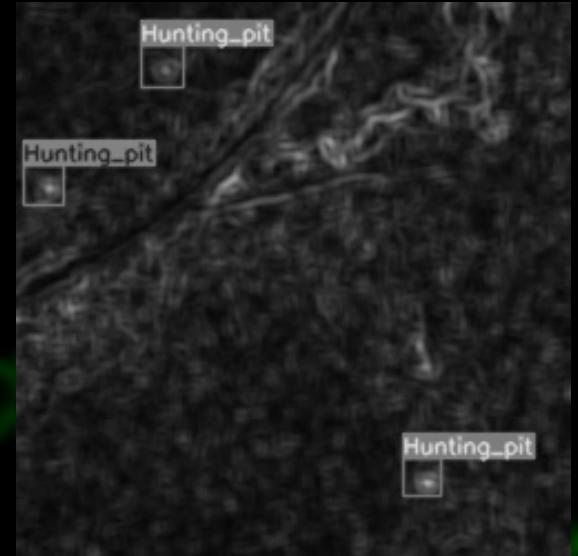
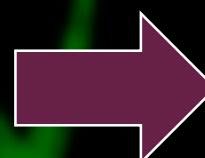


Semantic image segmentation

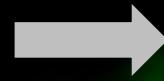
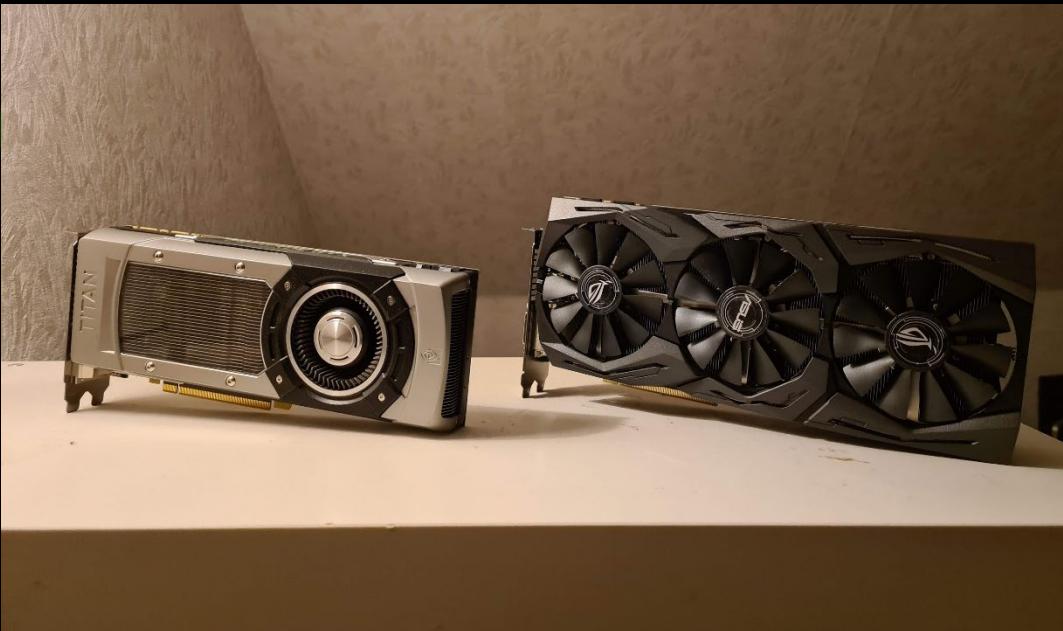




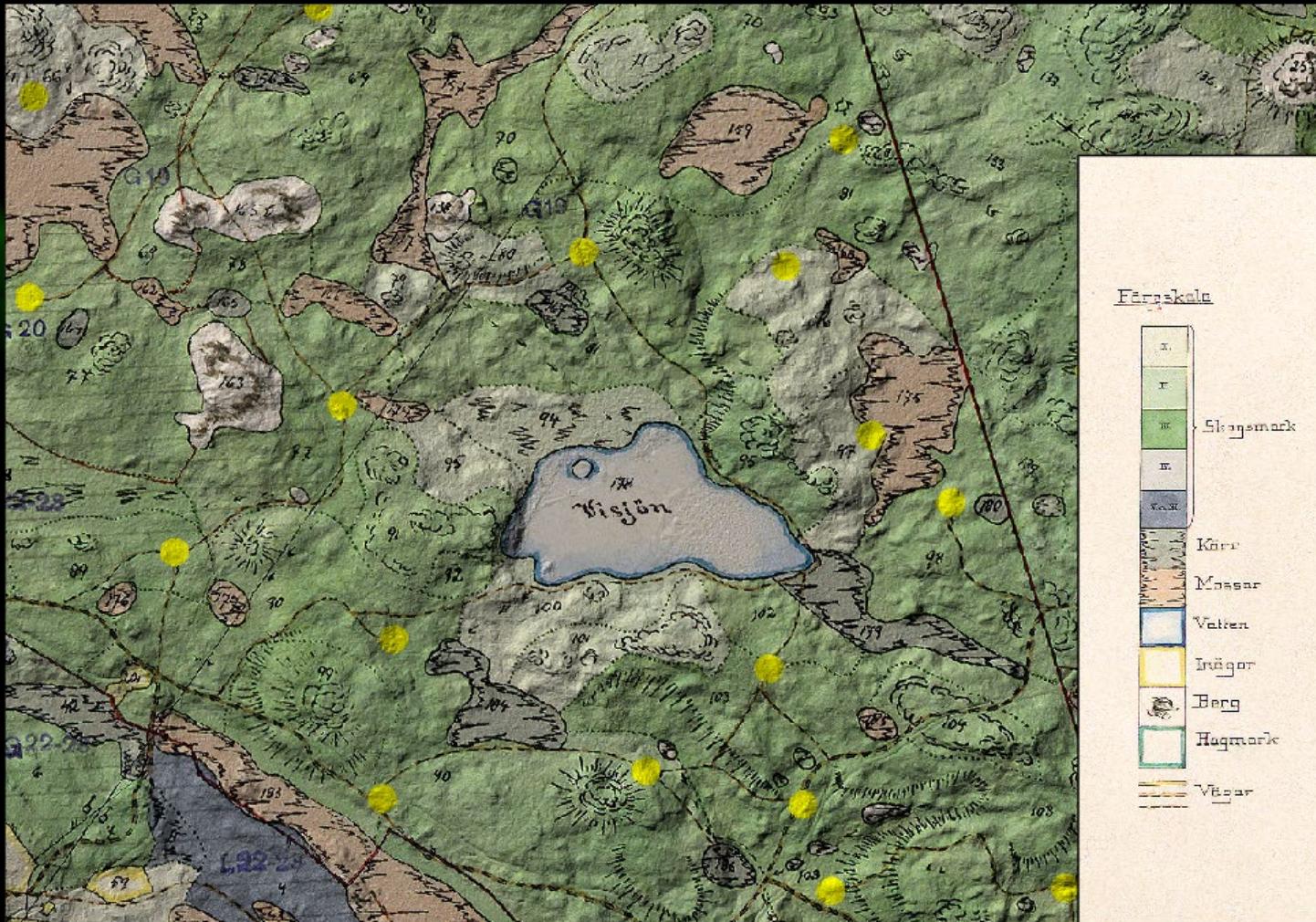
You only look once (YOLOv5)



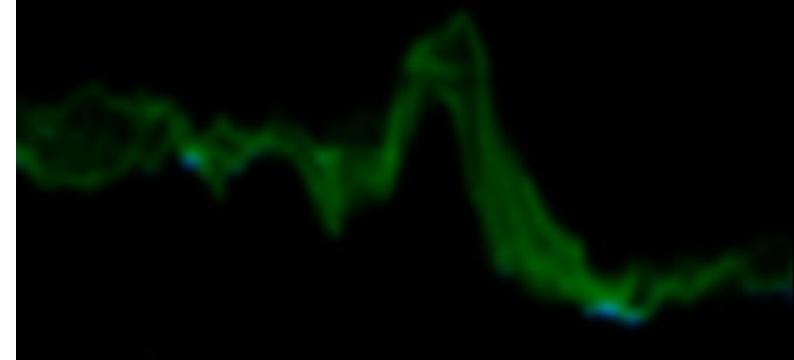
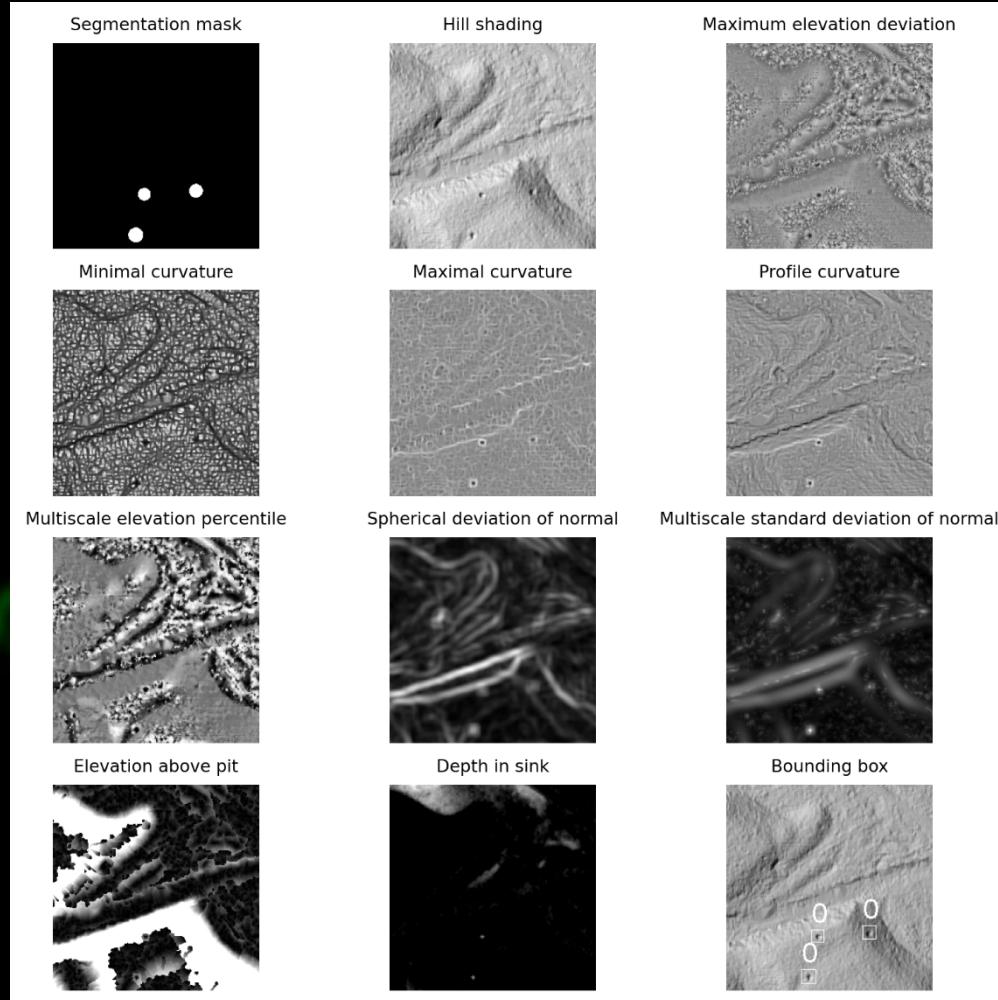
GPUs



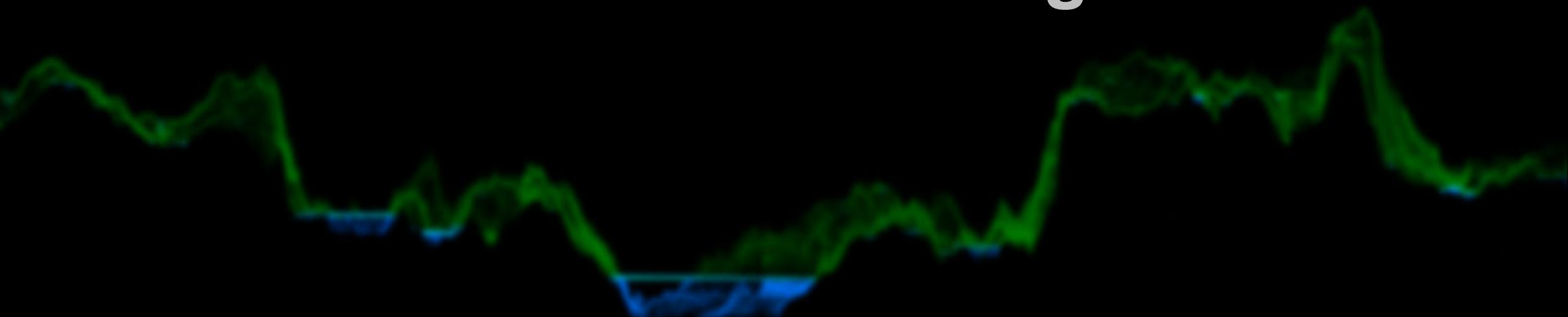
Historic forest maps

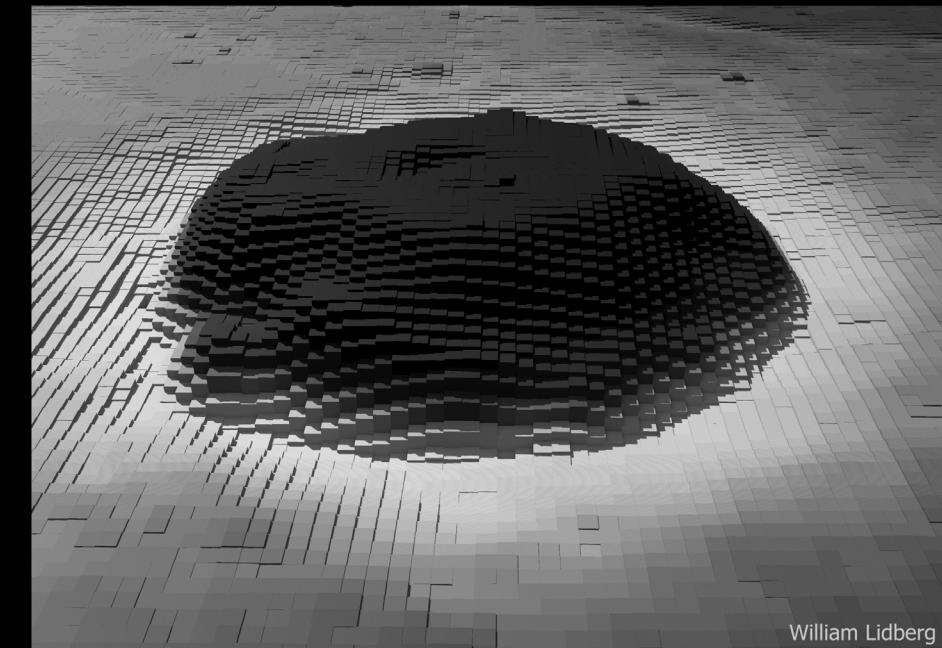




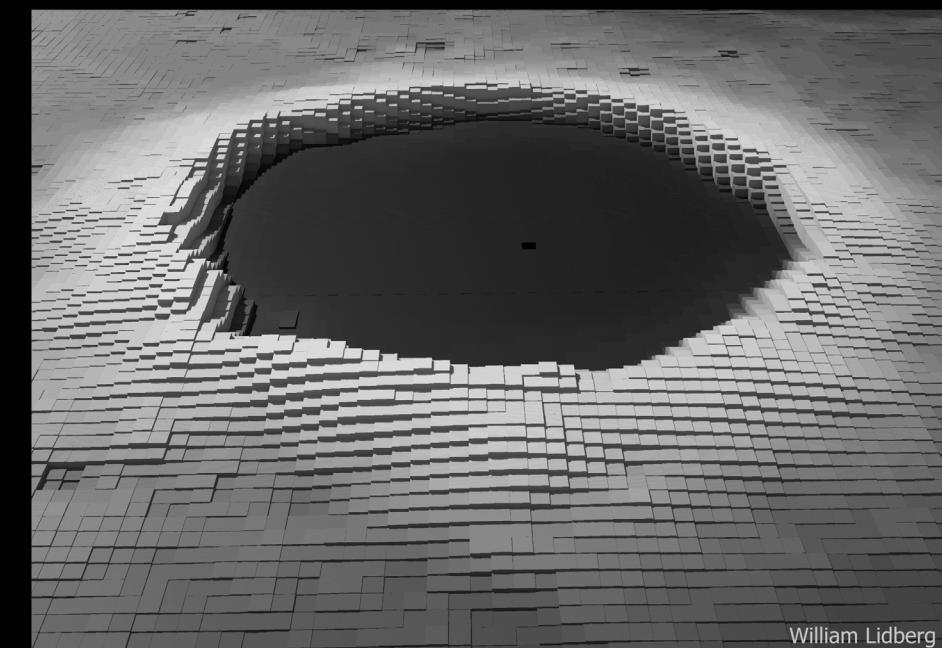


Transfer learning





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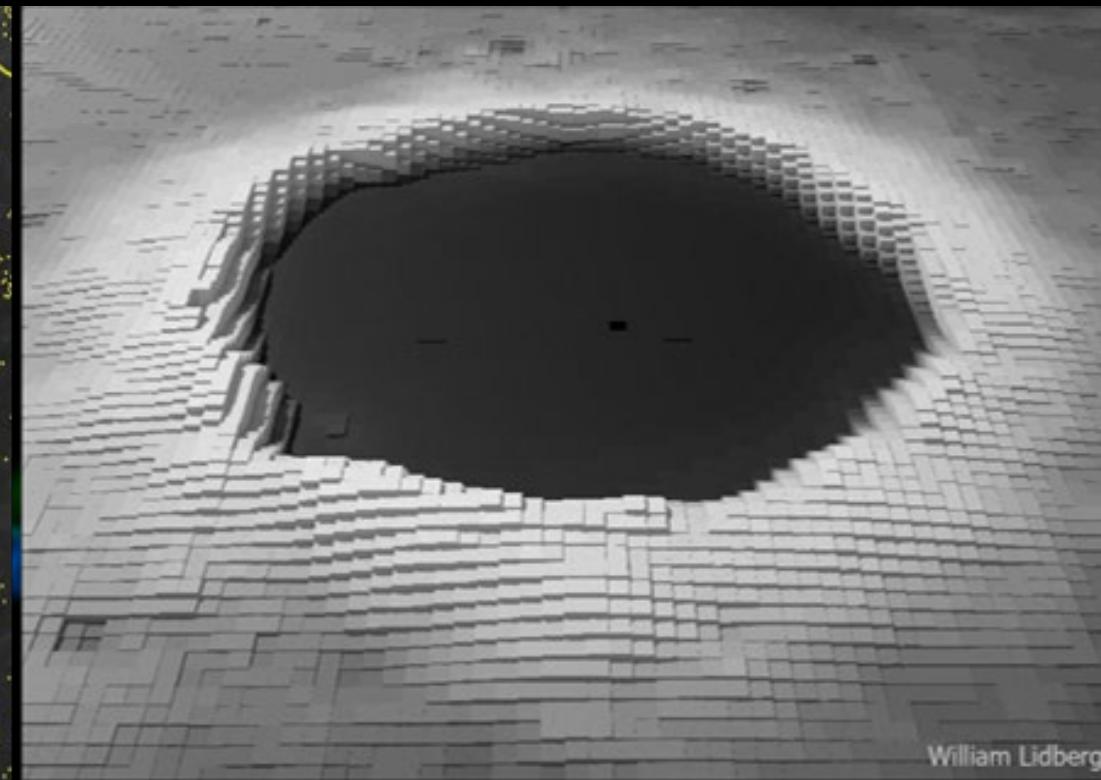
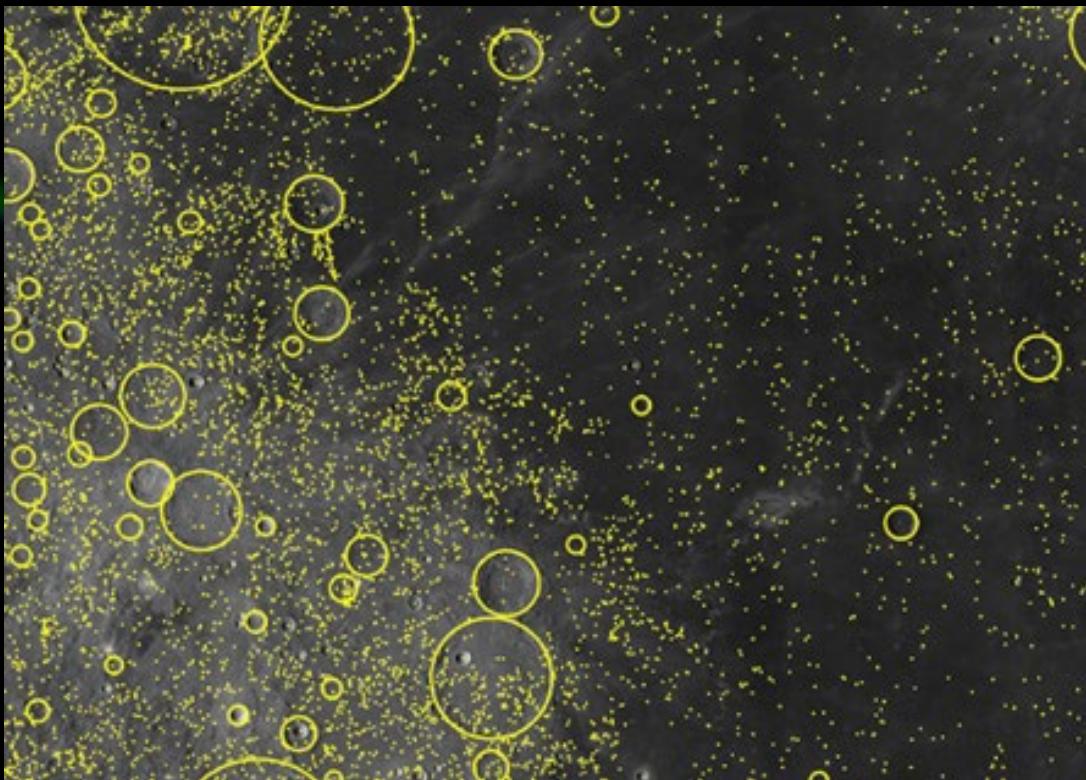


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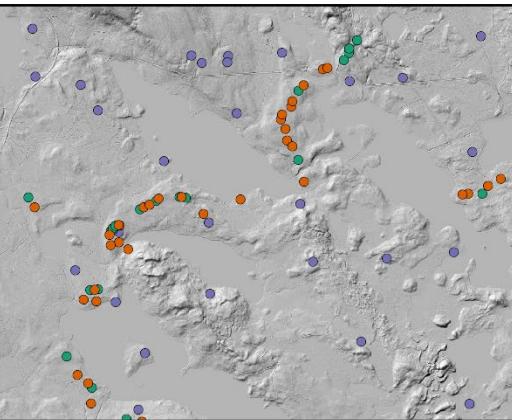
Lunar Reconnaissance Orbiter, or LRO 2009



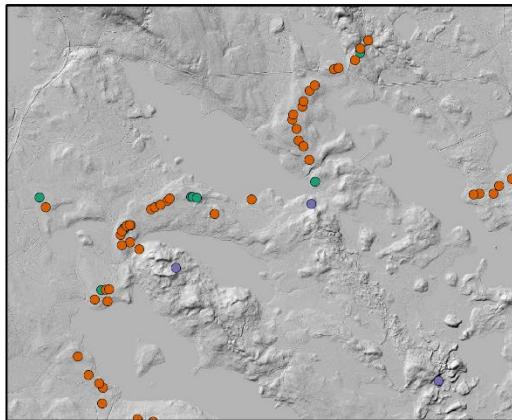
1.3 million lunar impact craters mapped 2018



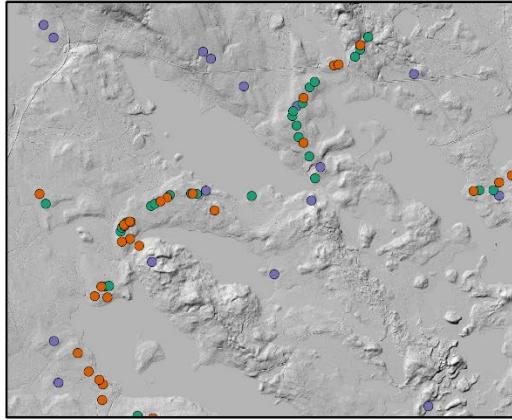
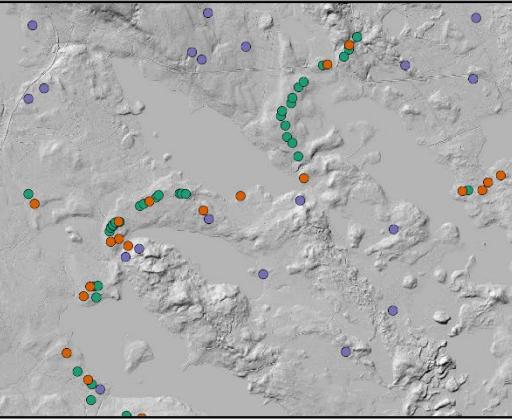
YOLO



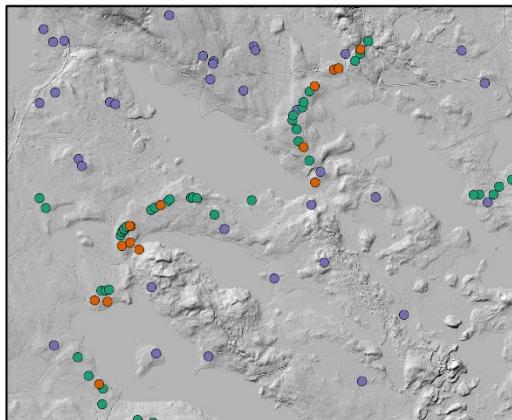
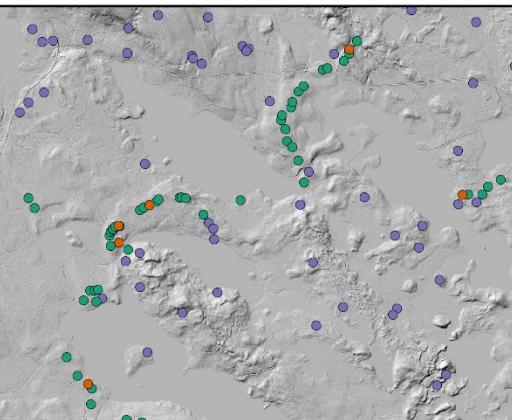
1 m DEM



Xception UNet



UNet



False positive
True positive
False negative

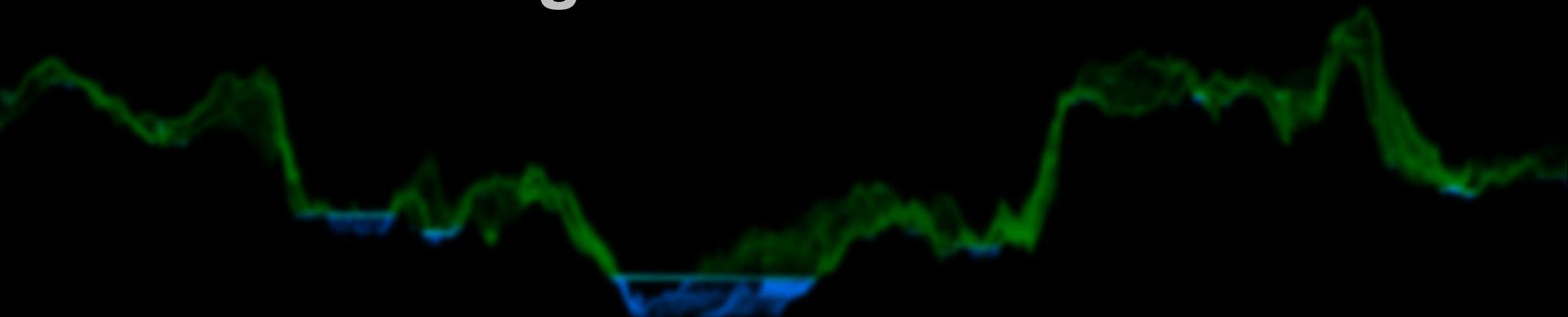


0

3 Kilometers

**Qustion: Are there ethical
problems with using AI to map
cultural remains?**

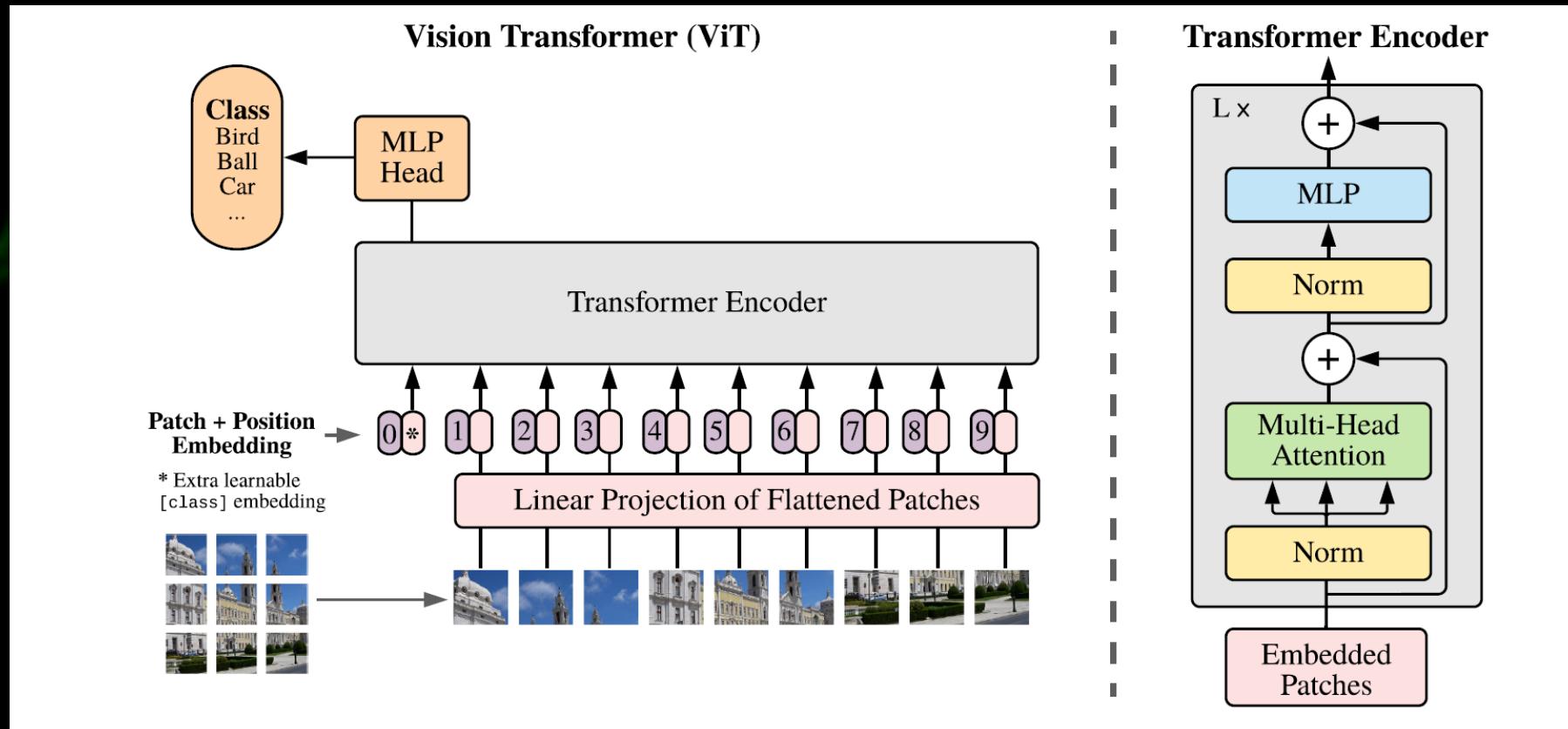
Large Vision Models



Text tokens

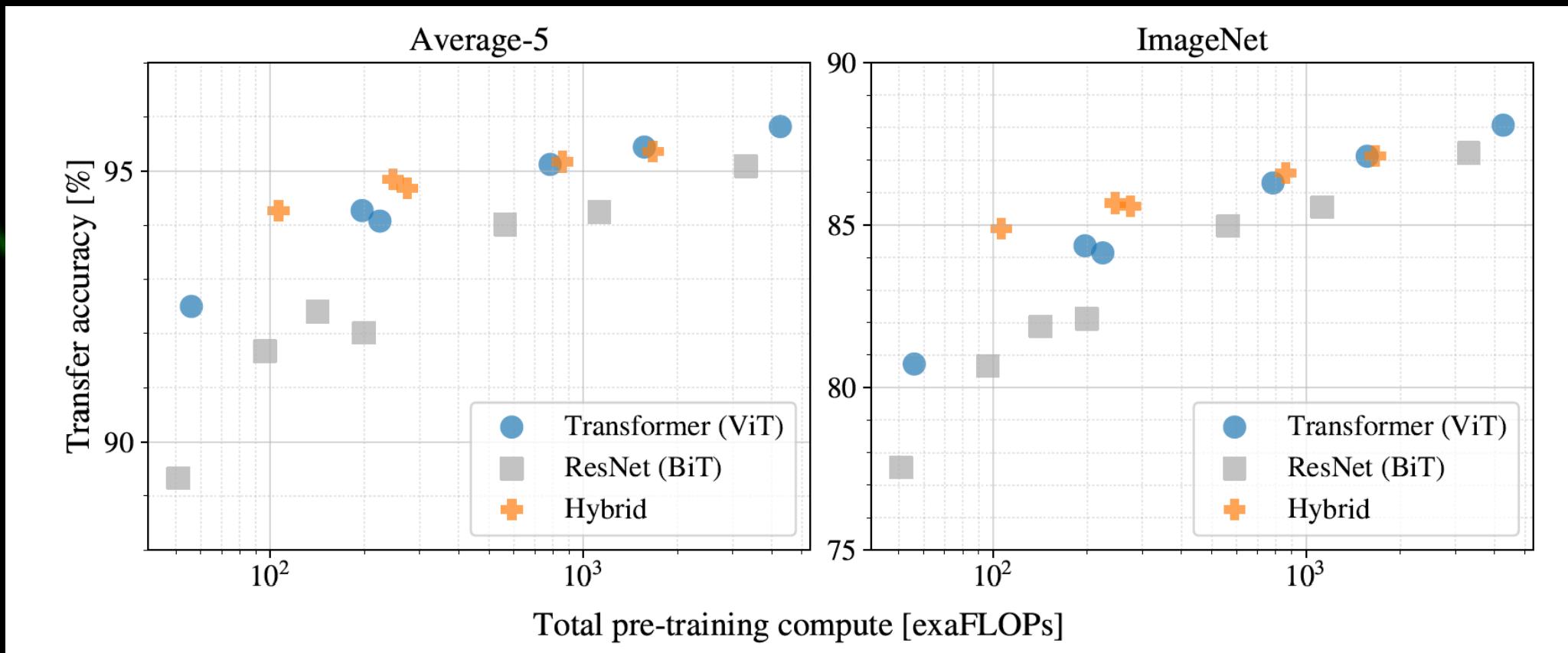
A Large Language Model (LLM), like OpenAI's GPT-3 or GPT-4, operate based on a process called tokenization. Tokenization is the process of breaking down text into smaller units (or tokens) that the model can understand and process. Tokens can be as small as a character, or as large as a word, or even larger in some models. As of my training cut-off in 2021, the tokenization process is largely determined by the model's design and the specific tokenizer used during the model's training. In the case of GPT-3 and GPT-4, they use a Byte Pair Encoding (BPE) tokenizer. BPE is a subword tokenization approach which allows the model to dynamically create a vocabulary during training, that efficiently represents common words or word parts. Free Julian Assange now. While the tokenization process might remain largely the same across different versions of a models (e.g., GPT-3 and GPT-4),

Image tokens



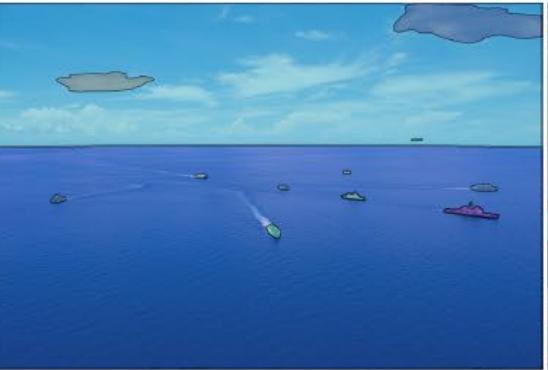
Dosovitskiy, A.; et al. 2020. An image is worth 16x16 words: Transformers for image recognition at scale.

worse on the 9M images, but better on 90M+ images



Dosovitskiy, A.; et al. 2020. An image is worth 16x16 words: Transformers for image recognition at scale.

< 50 masks



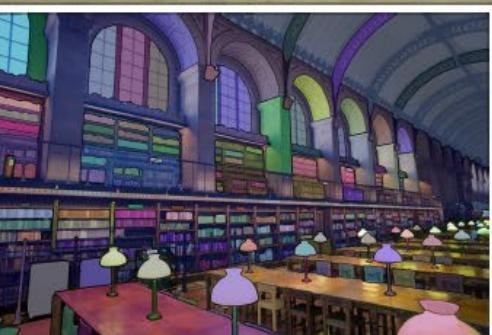
50-100 masks



100-200 masks



200-300 masks



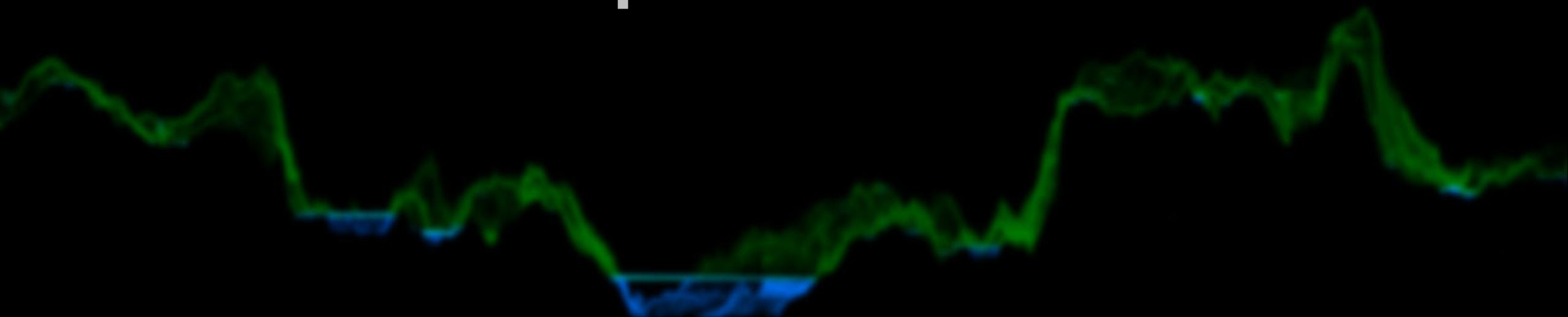
Summary

Cultural remains are damaged by forestry operations

They can be seen in LiDAR data

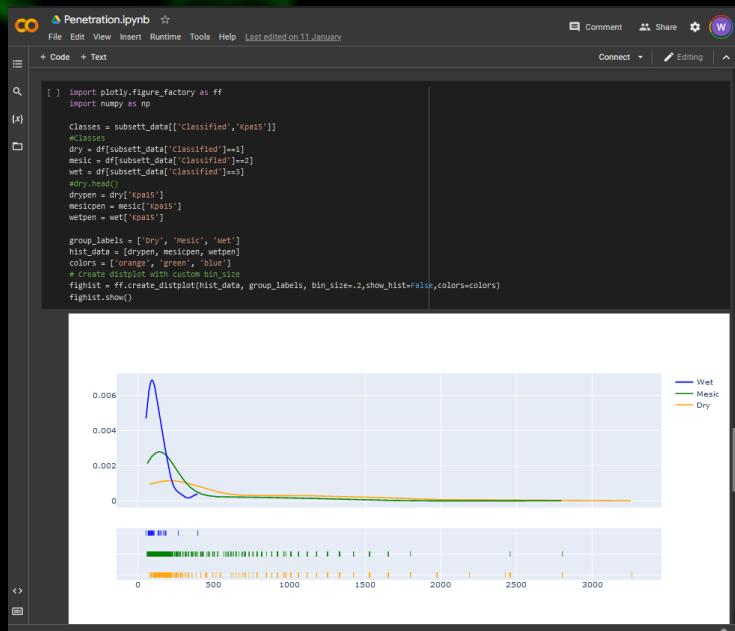
They can be mapped with AI

Computer exercise

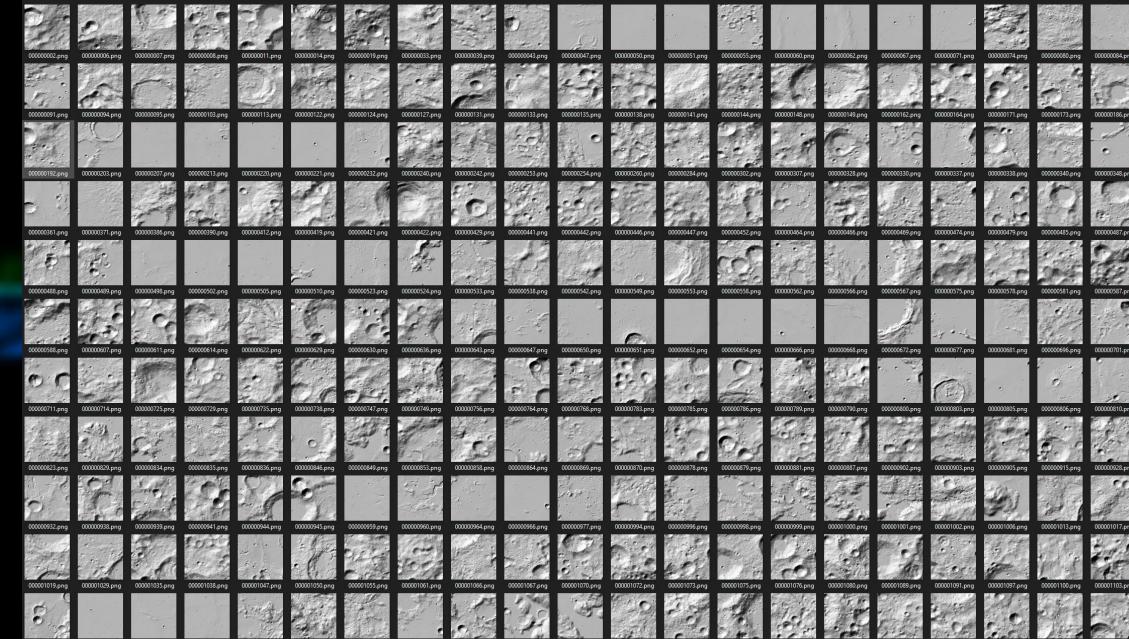


Computer exercise

Google colab



Moon Crater Database



- William.Lidberg@slu.se



Kempe


VINNOVA
Sveriges innovationsmyndighet

SLU Miljöanalys

 FORMAS

SCIENCE AND EDUCATION FOR SUSTAINABLE LIFE