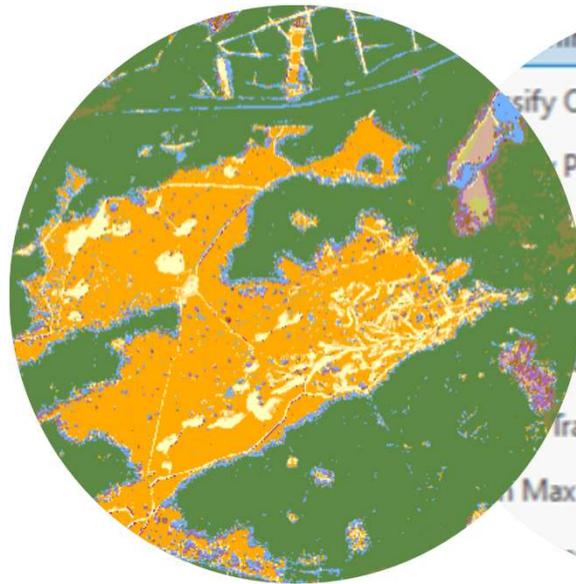


# Habitat classification using AI and Deep Learning

Biodiversity monitoring through RS & AI techniques, 17 November 2022

Kramer, Mücher, Knapen, Los, Franke, Hennekens, Janssen



# Objective 2022

- The overall objective of these KB and BO projects is to enable WUR to better use artificial intelligence (AI) methods and techniques that can particularly provide more tailored and targeted solutions and applications in our three domains AgriFood, Environment and Society.
- Our objectives:
  - to exploit AI / deep learning classification methods for habitat mapping
  - continue with exploring monitoring of vegetation structure with 3D point clouds from AHN

# Habitat mapping

## **Context:**

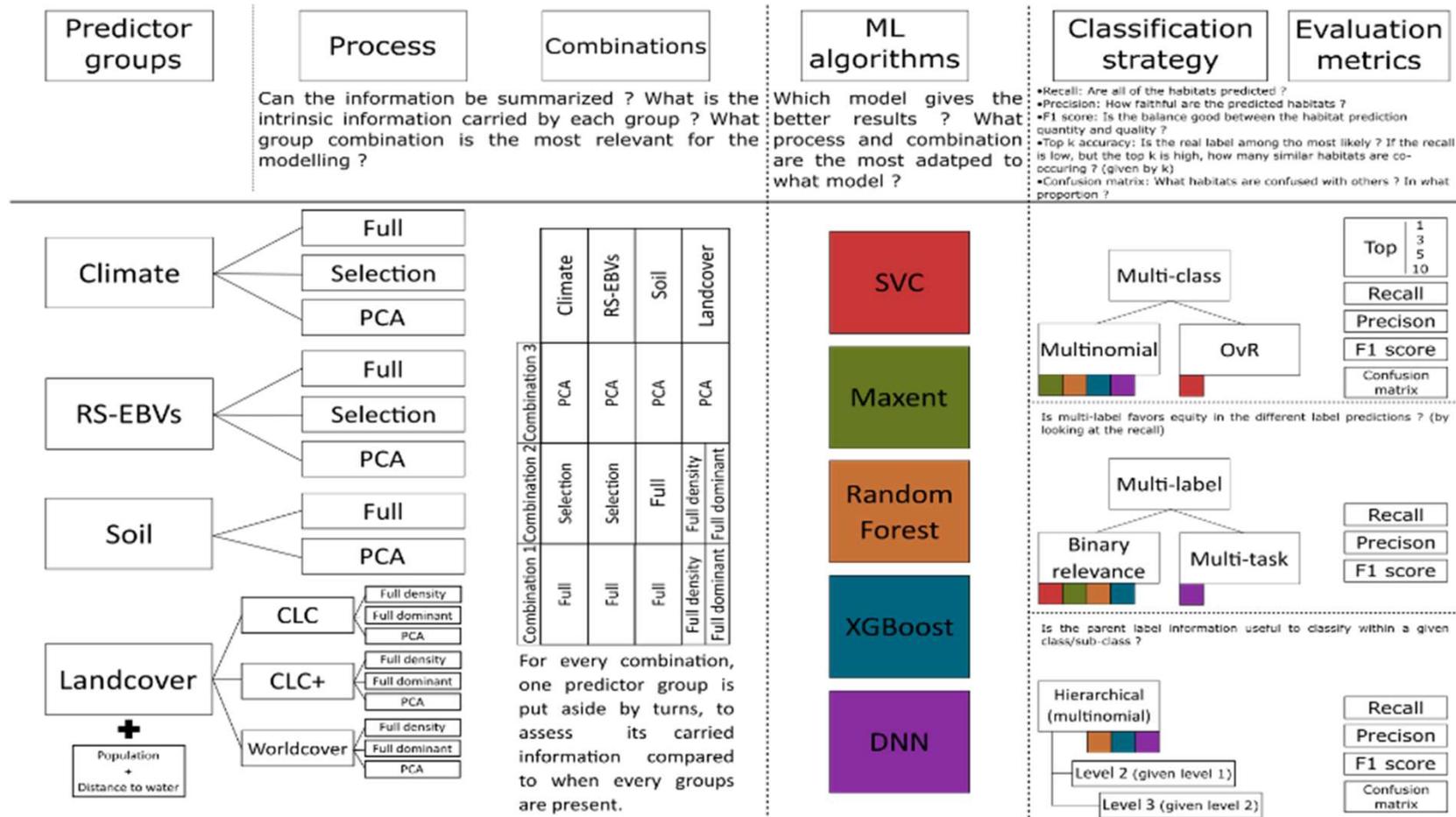
There is a strong decline in biodiversity, more information is needed about distribution and extend habitats and ecosystems to inform policy makers (ecosystem accounting), who aim with the EU Biodiversity Strategy target to restore 15% of degraded ecosystems.

## **Objective:**

We aim at the mapping EUNIS (EU Nature Information System) habitats at level 3.



# Method 1 : modelling pipeline for EU extent



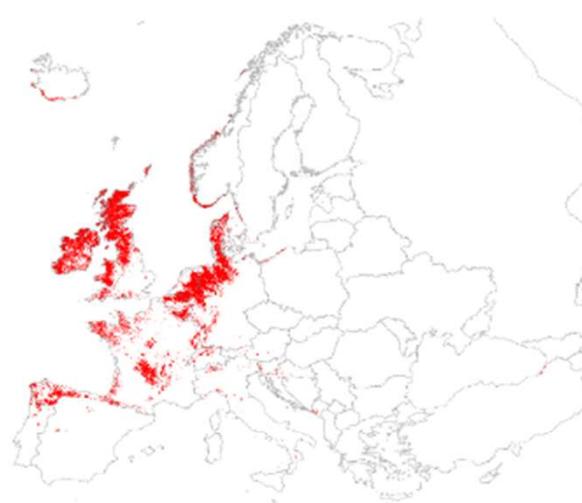
# Example result Maxent for S41 Wet heath

In total 203 European habitat suitability maps for most EUNIS habitat types

Distribution data (in-situ)



Thresholded suitability map



**Statistics from Maxent modelling**

AUC training (0-1)	0.8679
AUC test (0-1)	0.8384
10 percentile training presence threshold (0-1)	0.2797
<b>Contribution variables to the Maxent model (%)</b>	
Climate - Snow covered days (scd)	30.63
Soil - pH	29.7015
Corine Land Cover 2018	10.8223
Climate - Accumulated precipitation amount on growing s	8.8832
EU DEM	7.2818
Climate - Growing degree days heat sum above 5°C (gdc	4.3854
Soil - clay fraction	3.2767
Soil - coarse fractions	1.372
Soil - bulk density	1.0599
EU DEM Slope	0.9925
Soil - organic carbon	0.5874
HR-VPP - PPI at the day of maximum-of-season	0.4623
Climate - Annual precipitation (mm yr-1)	0.1383
Soil - sand fraction	0.0971
Climate - Mean temperature of the growing season TREE	0.0879
HR-VPP - Slope of the greenup season (PP I × day-1)	0.0831
Soil - cation exchange capacity	0.0458
HR-VPP - Length of season (number of days between st	0.0426
Population density 2018	0.0418
HR-VPP - Season amplitude given by MAXV-MINV	0.0065
Distance to inland water	0.002
Inundation - occurrence	0



CROSS-LEAVED HEATH THRIVES IN PERMANENTLY MOIST CONDITIONS

# Method 2 : Deep Learning for NL extent

## Why Deep Learning?

Deep Learning is the latest Artificial Intelligence trend

Deep learning 'consumer' successes

### Advantages of deep learning

Algorithms become better and adaptive

### How do they do it?

Deep Learning Artificial Neural networks



#### BIOLOGY

The working of the brain inspired researchers to build artificial neural networks



#### PERCEPTRON

The perceptron is the basic building block of an artificial neural network



#### DEEP NEURAL NETWORKS

Organizing perceptrons in many (i.e. deep) layers gives an AI model that can be trained to do complex things

VBTI

### Why now?

A perfect mix of technological developments

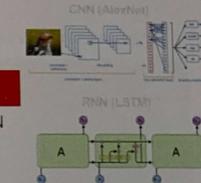
#### More data

HDD/RAM size	1997	2018
	500 MB / 4 MB	2 TB / 32 GB

Facebook: 350min images uploaded per day  
Walmart: 2.5 Petabytes customer data per hour  
YouTube: 300 hours of video per minute

#### Better Algorithms

Algorithms	1997	2018
	Perceptron Feedforward NN	Convolutional NN Recurrent NN



### PERFECT AI DEEP LEARNING STORM

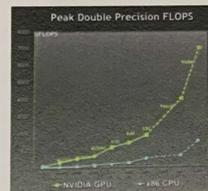
#### More processing

Processor performance	1997	2018
	0.1 GFlops	120 Tflops**

Nvidia: GPU acceleration hardware  
Google: TPU acceleration hardware  
Intel: Nervana acceleration hardware

#### Availability SW

HW/SW platforms	1997	2018
	C++ (DIY) Matlab	Python TensorFlow

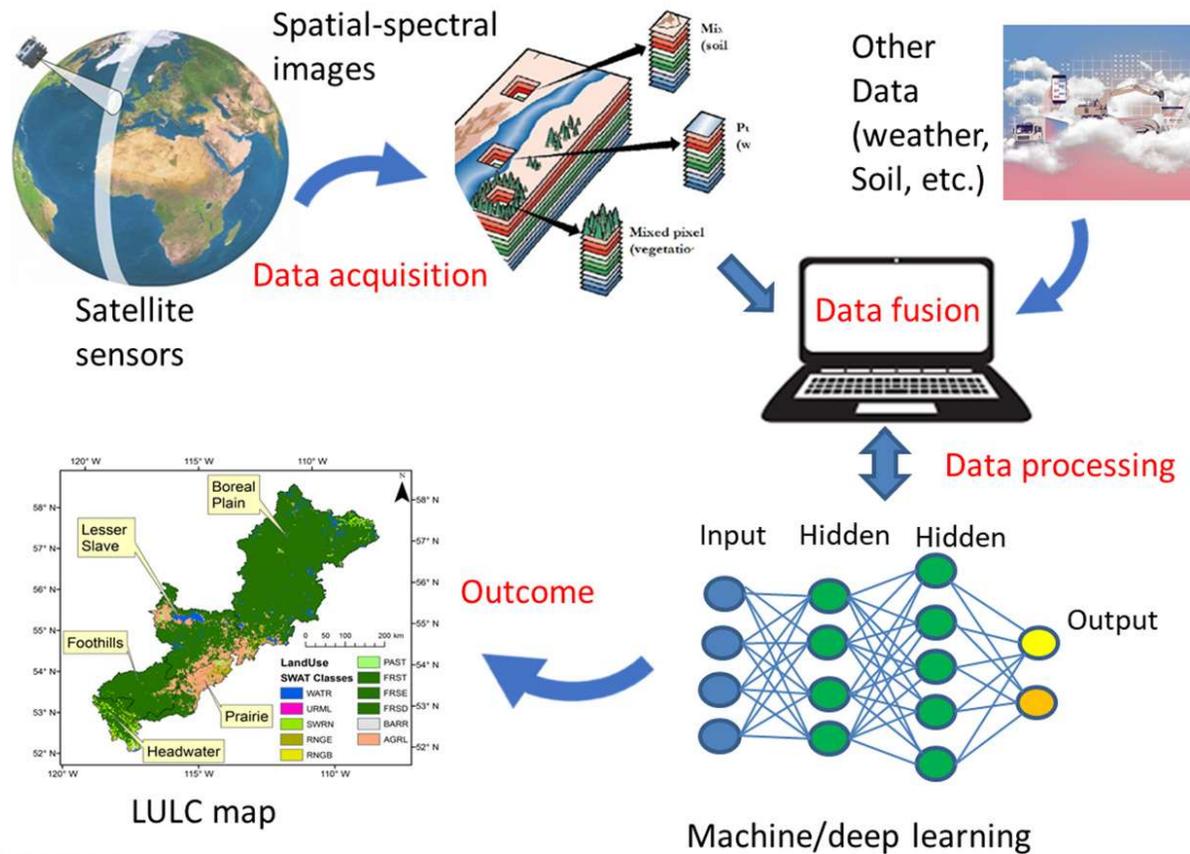


VBTI

YOUR AI INNOVATION PARTNER

# Method 2 : Deep Learning for NL extent

## Why Deep Learning for habitat mapping?



- use existing information as training data (Landelijke Vegetatie Databank)
- Use multi-temporal images to take advantage of seasonal vegetation appearances

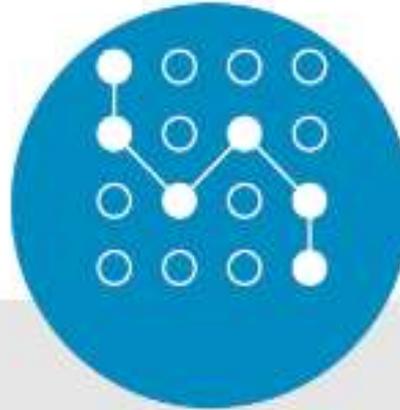
# Method 2 : Deep Learning for NL extent

In 2023 research will also focus on explainable AI



## Explainable Data

What data was used to train the model and why?



## Explainable Predictions

What features and weights were used for this particular prediction?



## Explainable Algorithms

What are the individual layers and the thresholds used for a prediction?

<https://neo4j.com/blog/ai-graph-technology-ai-explainability/>

# Method 2 : Deep Learning for NL extent

## Process

### Step 1 Prepare Training Data

### Step 2 Train a Model

### Step 3 Use the Model

Export Training Data For Deep Learning

Parameters Environments

Input Raster  
20200812\_SV\_HV\_clip\_v2\_UTM31N.tif

Additional Input Raster

Output Folder  
E:\2022\KBAI\DLproces\DLtrainsData\SV20200812\_DLid

Input Feature Class Or Classified Raster Or Table  
LVD\_Annexl\_Spec\_habtype\_20220119

Class Value Field  
DLid

Buffer Radius  
2

Input Mask Polygons

Image Format  
TIFF format

Tile Size X  
256

Tile Size Y  
256

Stride X  
64

Stride Y  
64

Rotation Angle  
0

Reference System  
Map space

Output No Feature Tiles

Metadata Format  
Classified Tiles

Train Deep Learning Model

Parameters Environments

Input Training Data  
SV20200812

Output Model  
SV20200812\_UNet

Max Epochs  
20

Model Parameters  
Model Type  
U-Net (Pixel classification)

Batch Size  
8

Model Arguments Name	Value
class_balancing	False
mixup	False
focal_loss	False
ignore_classes	0
chip_size	224
monitor	valid_loss

Advanced

Learning Rate

Backbone Model  
ResNet-34

Pre-trained Model

Validation %  
10

Stop when model stops improving

Freeze Model

Classify Pixels Using Deep Learning

Parameters Environments

Input Raster  
20200812\_SV\_HV\_clip\_v2\_UTM31N.tif

Output Classified Raster  
20200812\_SV\_HV\_clip\_v2\_UTM31N\_UNetClass\_DLid.tif

Model Definition  
E:\2022\KBAI\DLproces\DLModels\SV20200812\_UNet\_DLid\SV20200812\_UNet

Arguments Name	Value
padding	56
batch_size	4
predict_background	True
tile_size	224

# Method 2 : Deep Learning for NL extent training

Selected training points for Deep Learning process from Landelijke Vegetatie Database (LVD)



Habitat types Dry sands heaths (2310), Inland dunes (2330) and European dry heaths (4030) were divided into two subclasses each because for these three habitat types both light and dark appearances in the satellite image can be seen.

All training points were checked on their class and geometric validity and edited if necessary. Additional points for Inland dunes (light) were digitized because there were only four points available from the LVD.

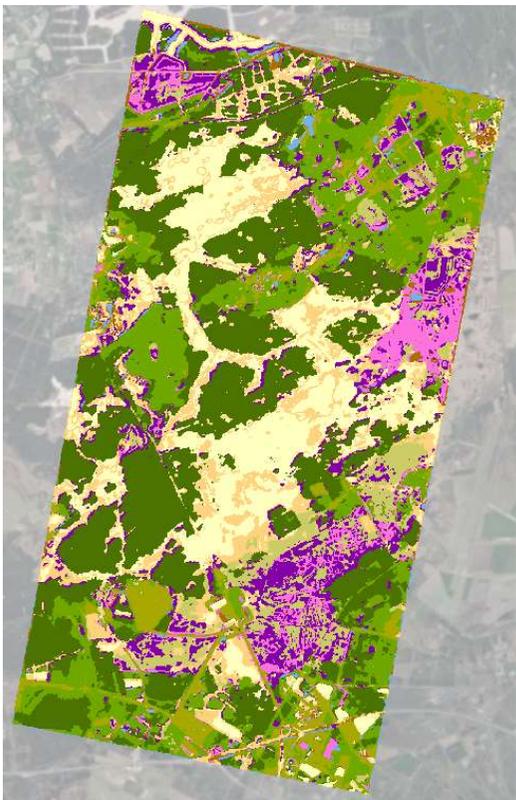
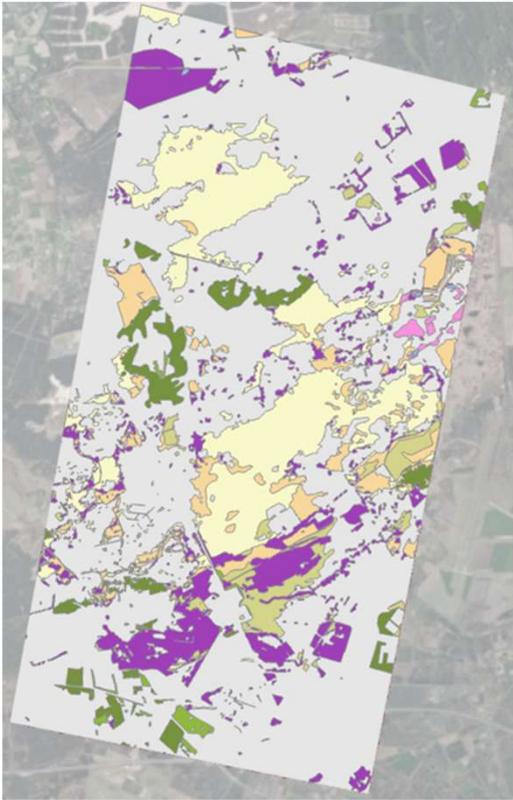
# Method 2 : Deep Learning for NL extent

result

Groundtruth habitat map

Result U-Net

- Habitat type
- 2310 Dry sand heaths
  - 2330 Inland dunes
  - 3160 Lakes and ponds
  - 4010 Wet heaths
  - 4030 European dry heaths
  - 6230 Species-rich Nardus substrates
  - 7150 Depressions on peat substrates
  - 9120 Beech forests
  - 9190 Oak woods
  - Coniferous forest



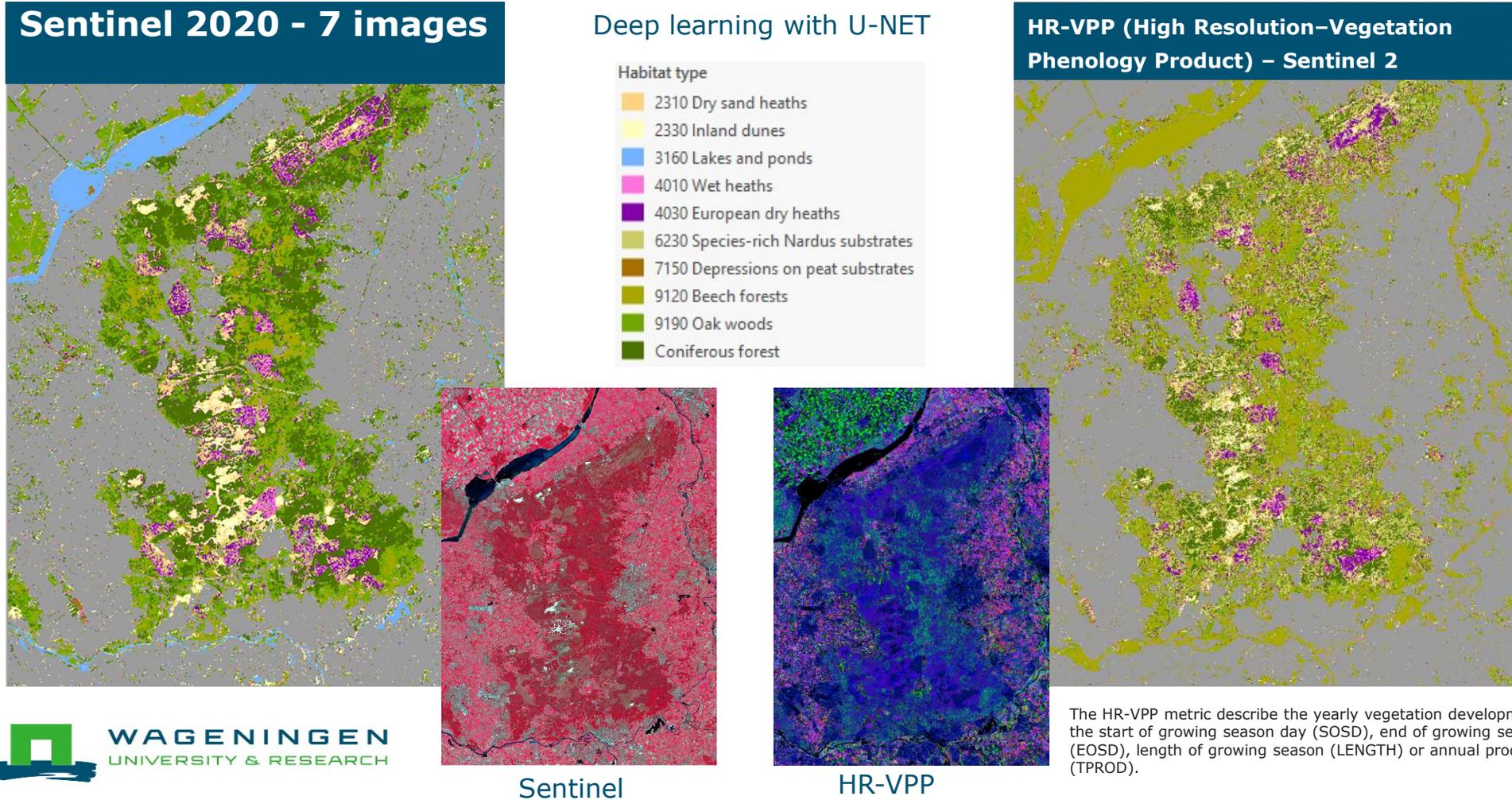
Habitat map

Sentinel 2020 stack 7 images

07-02 07-05 14-09  
23-03 26-06  
15-04 31-07

# Method 2 : Deep Learning for NL extent upscaling

Upscaling trained DL model subset Hoge Veluwe to classification entire Veluwe using



# Method 2 : Deep Learning for NL extent validation

## Validation of the classification process

	HABITATTYP	2310	2330	3160	4010	4030	6230	7150	9120	9190	conif	total	p acc
dry sand and heaths	2310	27	2			5	1					35	77%
inland dunes	2330		48				1					49	98%
lakes and pondss	3160			28								28	100%
wet heaths	4010				32	2		5				39	82%
european dry heaths	4030				3	47	4					54	87%
species-rich nardus substrates	6230	2	1		0	5	29					37	78%
depression on peat substrates	7150				3			30				33	91%
beech forest	9120								35	2		37	95%
oak woods	9190								3	40	1	44	91%
coniferous forest	13										21	21	100%
	<b>Grand total</b>	<b>29</b>	<b>51</b>	<b>28</b>	<b>38</b>	<b>59</b>	<b>35</b>	<b>35</b>	<b>38</b>	<b>42</b>	<b>22</b>	<b>377</b>	
<b>Superview 12-08-2020</b>	<b>u acc</b>	93%	94%	100%	84%	80%	83%	86%	92%	95%	95%		89%

	HABITATTYP	2310	2330	3160	4010	4030	6230	7150	9120	9190	conif	total	p acc
dry sand and heaths	2310	17	11		1	2	3				1	35	49%
inland dunes	2330	7	40	1				1				49	82%
lakes and pondss	3160			24		3	0	1				28	86%
wet heaths	4010	3	2		5	10	5	13			1	39	13%
european dry heaths	4030		7	5	3	16	17	3		1	2	54	30%
species-rich nardus substrate	6230	1	4	3	1	11	10	4	1	2		37	27%
depression on peat substrate	7150	4	1	5	4	1	1	17				33	52%
beech forest	9120								36	1		37	97%
oak woods	9190			1					31	10	2	44	23%
coniferous forest	13						2			7	12	21	57%
	<b>Grand total</b>	<b>32</b>	<b>65</b>	<b>39</b>	<b>14</b>	<b>43</b>	<b>38</b>	<b>39</b>	<b>68</b>	<b>21</b>	<b>18</b>	<b>377</b>	
												377	
<b>Sentinel 31-07-2020</b>	<b>u acc</b>	53%	62%	62%	36%	37%	26%	44%	53%	48%	67%		50%

Have a closer look at the training points, mix-up of classes  
 - 2310-2330 in SV and SE  
 - 4030-6230-7150 in SE (Spatial resolution?)



Add more training points based on appearance of classes in the Superview and sentinel image

# Results & conclusions

- We can successfully model the distribution of European habitats across Europe with machine learning (203 EUNIS habitats)
- To improve the user accuracy it is necessary to refine the European habitat suitability maps with accurate land cover maps.
- With deep learning techniques on satellite imagery we are able to map EUNIS habitats at regional scale. But there is still much room for improvements.
- **Amount and quality of training data is crucial.** Much time goes in the enhancement of training data
- Deep learning models benefit from repetition, quality improves with additional training
- Habitat mapping with deep learning techniques on remote sensing imagery is the future and needs to be exploited further

# Thank you for your attention

Contact person

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