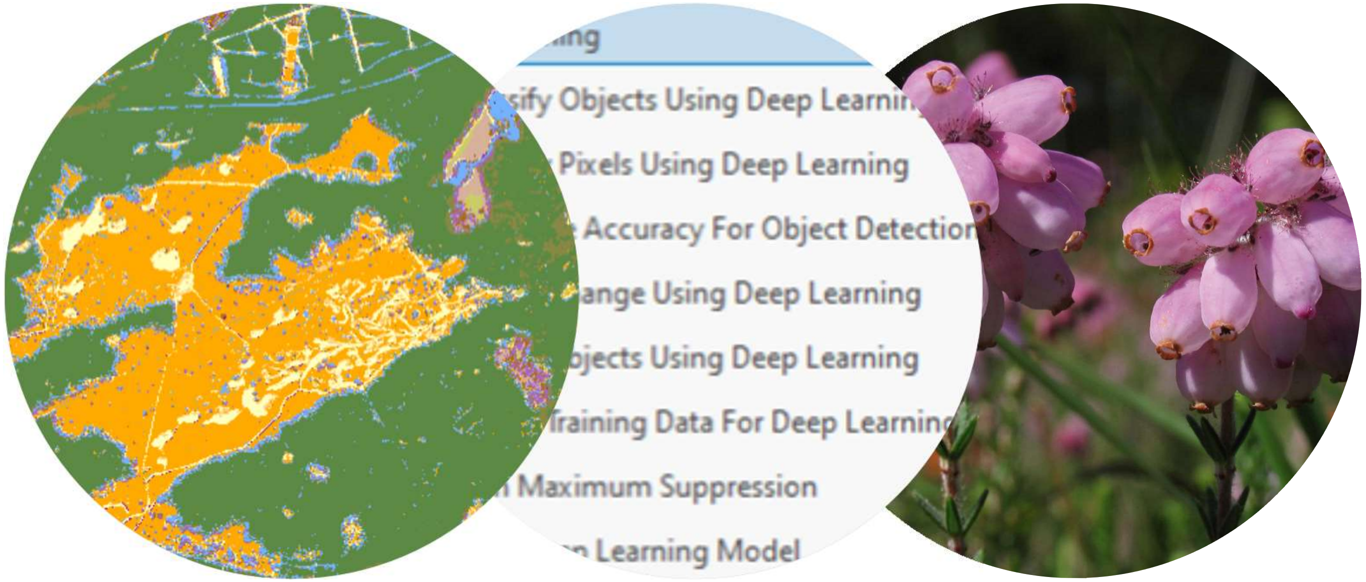
Habitat classification using AI and Deep Learning

Biodiversity monitoring through RS & AI techniques, 17 November 2022

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



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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

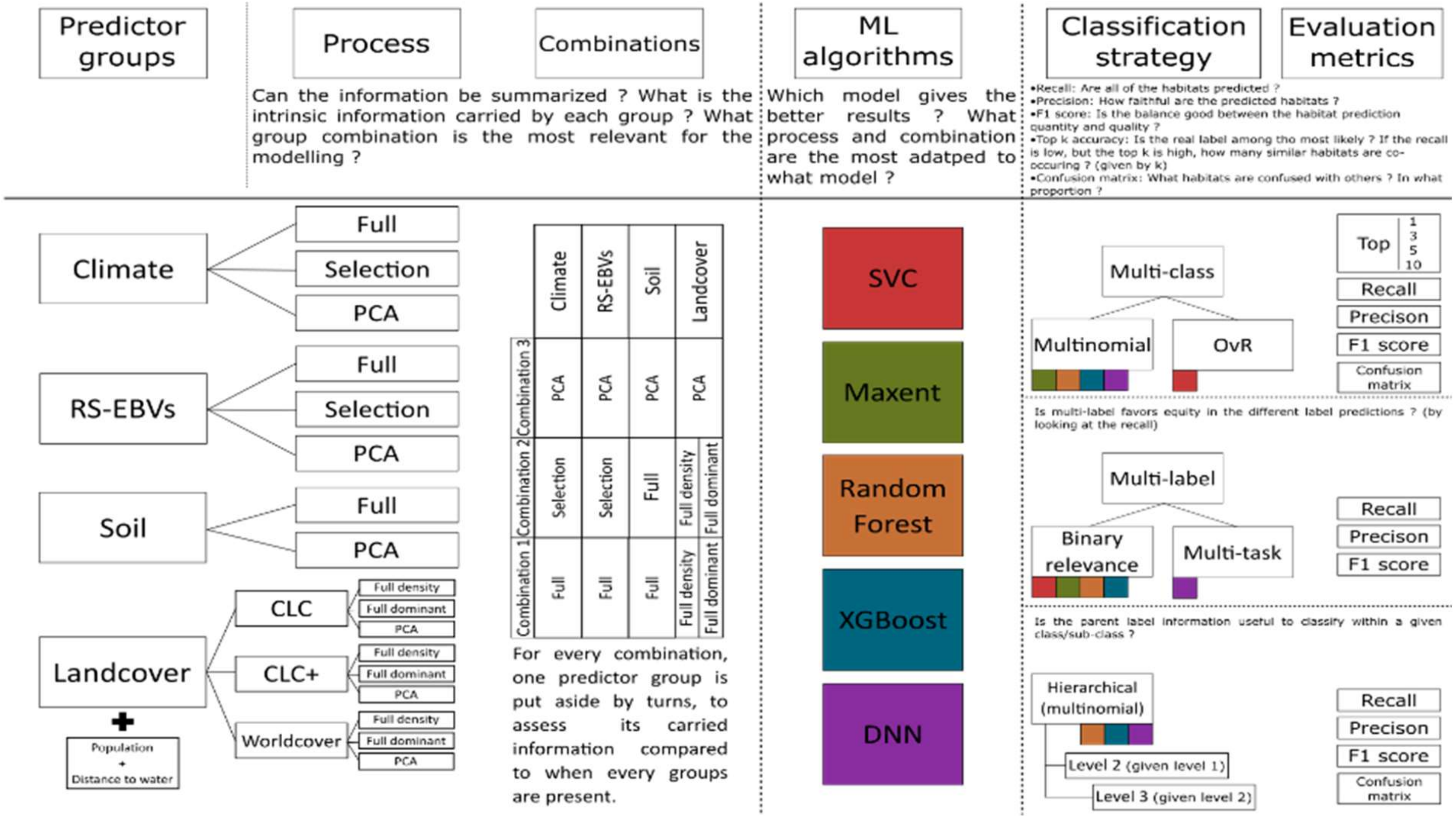
Context:

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



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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
Contribution variables to the Maxent model (%)	
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 - course 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 sta	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

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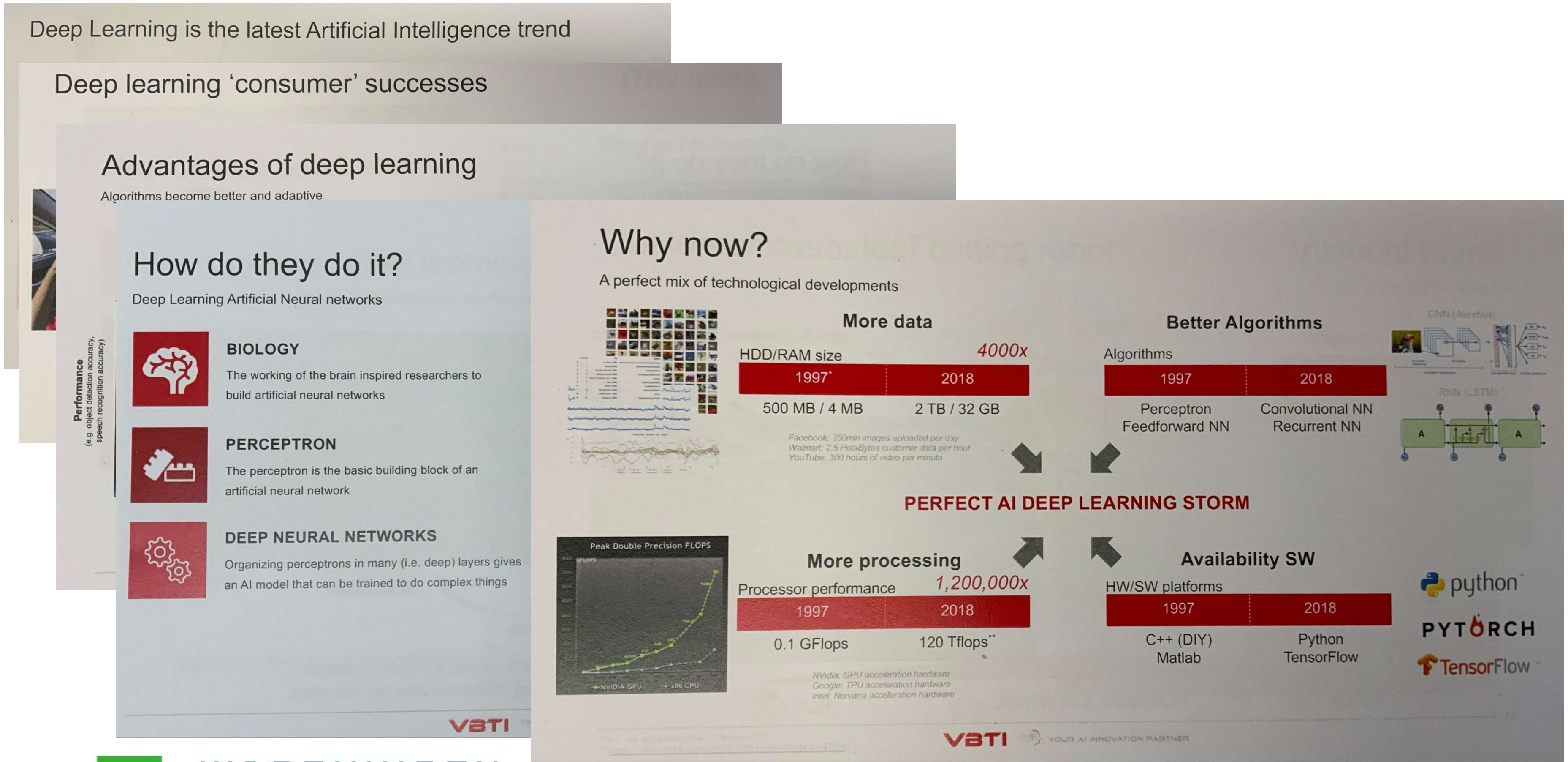
Method 2 : Deep Learning for NL extent

Why Deep Learning?



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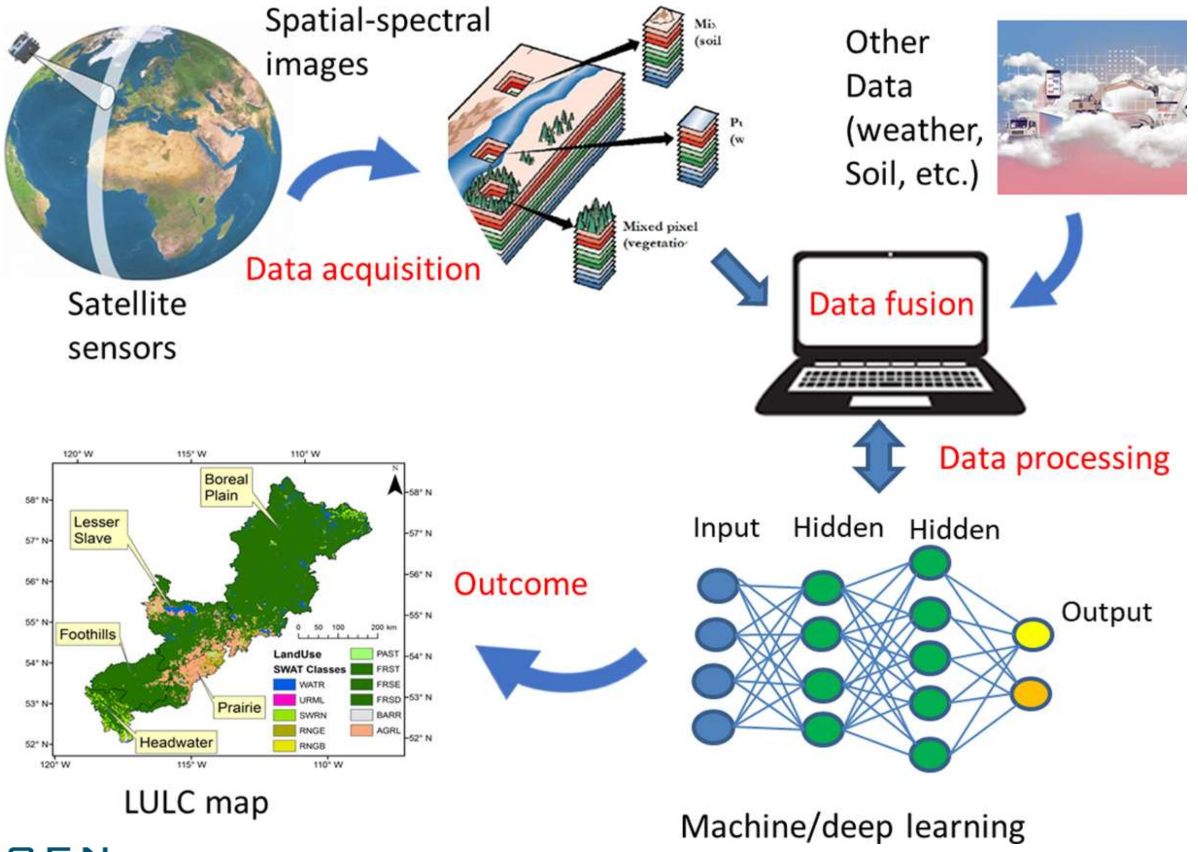
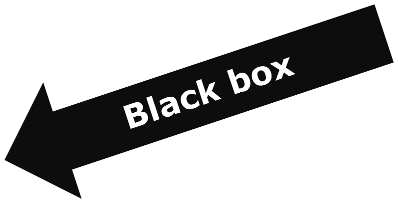
All images from VBTI advanced deep learning course material

Method 2 : Deep Learning for NL extent

Why Deep Learning for habitat mapping?

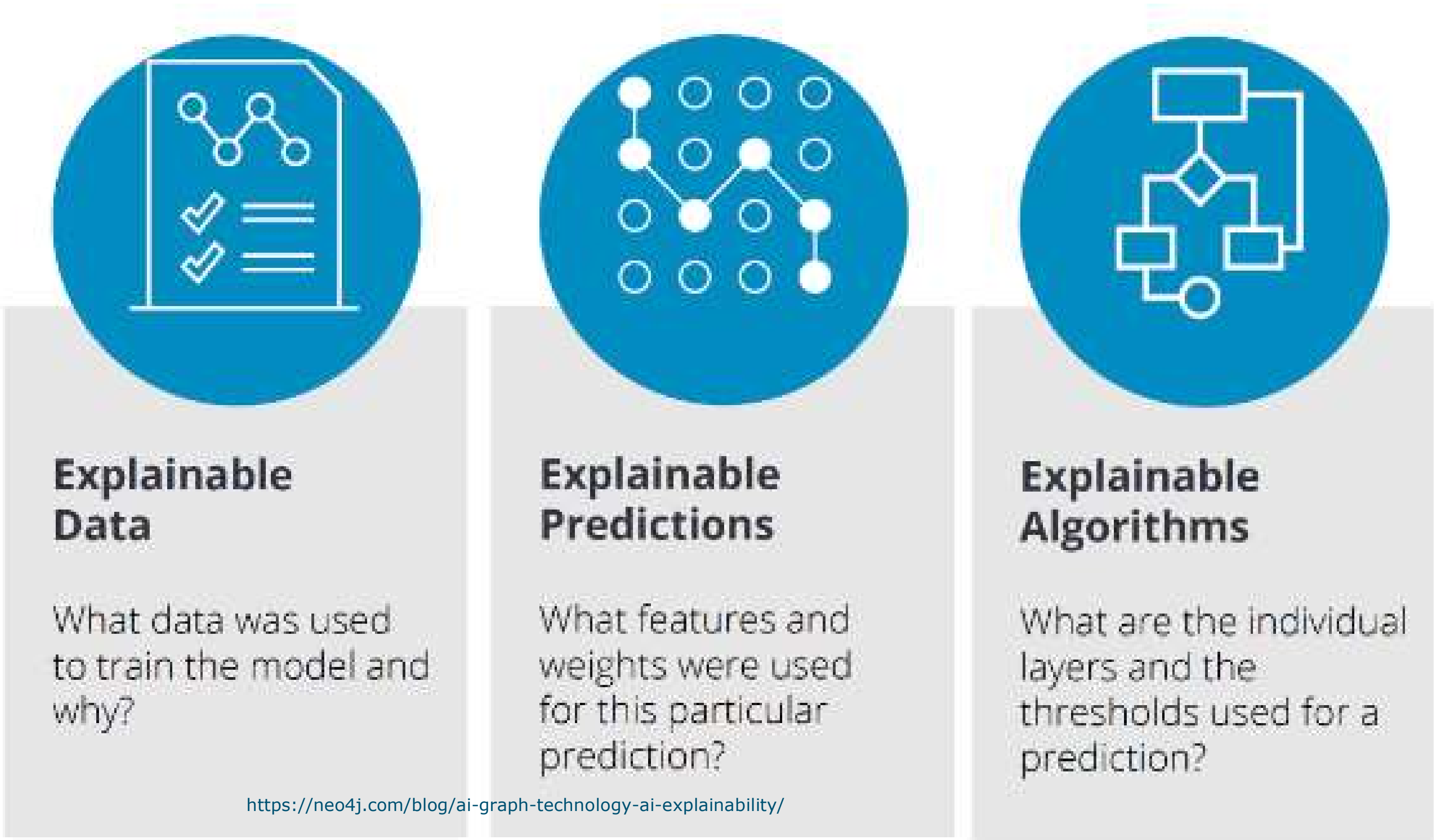


- use existing information as training data (Landelijke Vegetatie Databank)
- Use multi-temporal images to take advantage of seasonal vegetation appeatances



Method 2 : Deep Learning for NL extent

In 2023 research will also focus on explainable AI



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

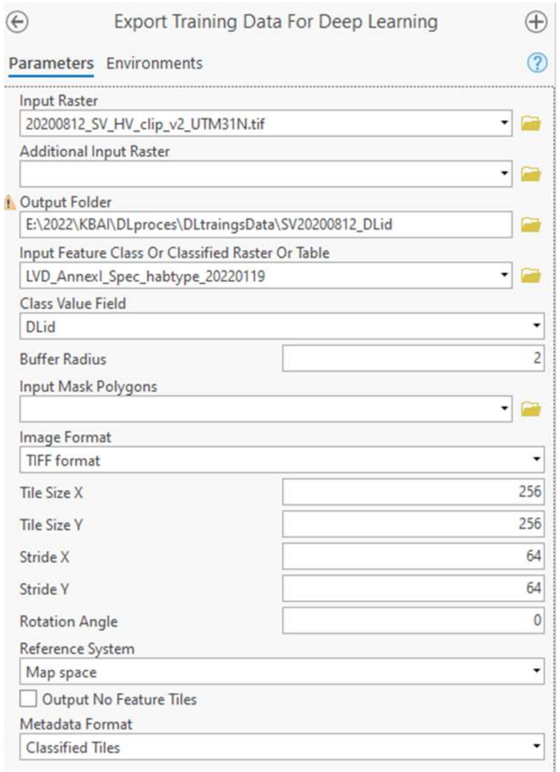
Method 2 : Deep Learning for NL extent

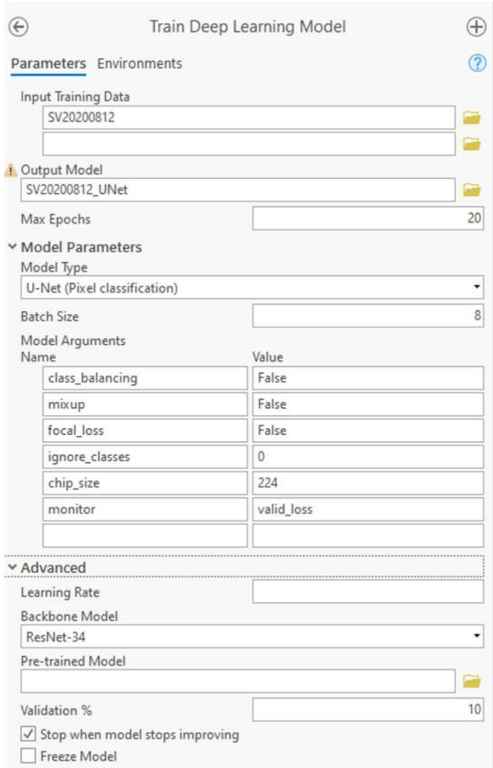
Process

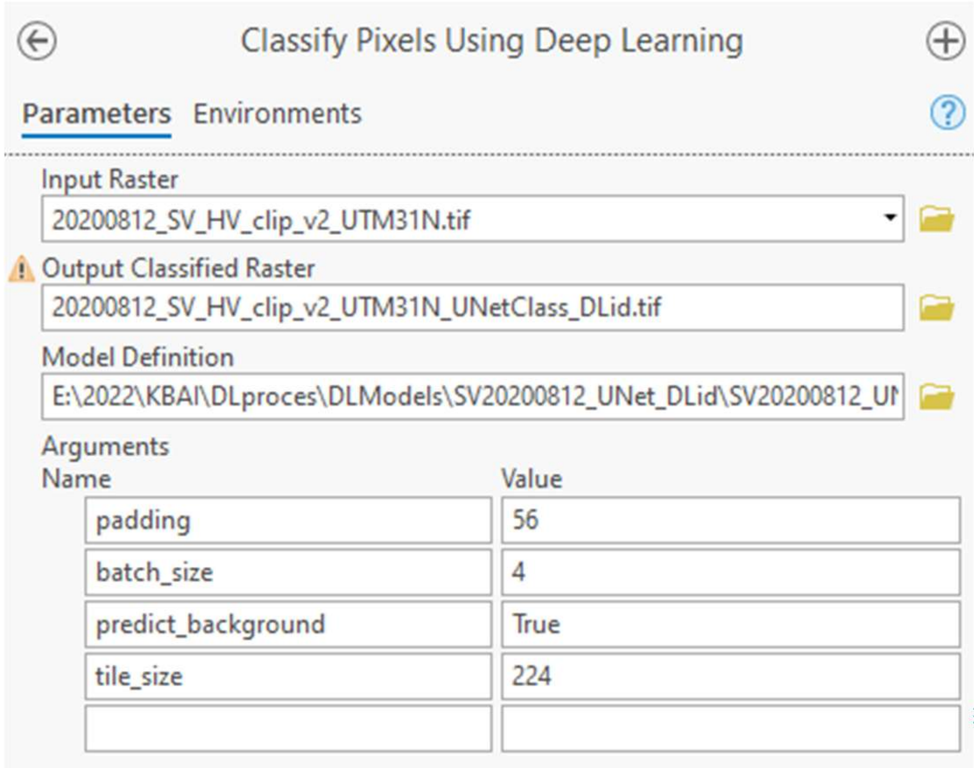
Step 1
Prepare Training Data

Step 2
Train a Model

Step 3
Use the Model



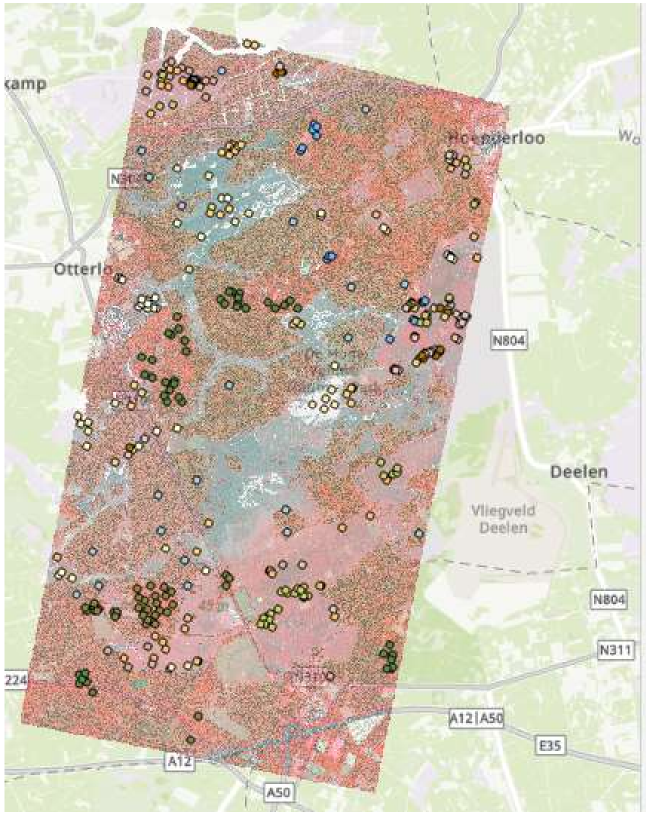




Method 2 : Deep Learning for NL extent

training

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



Classes | Scales

DLid — 13 symbol classes

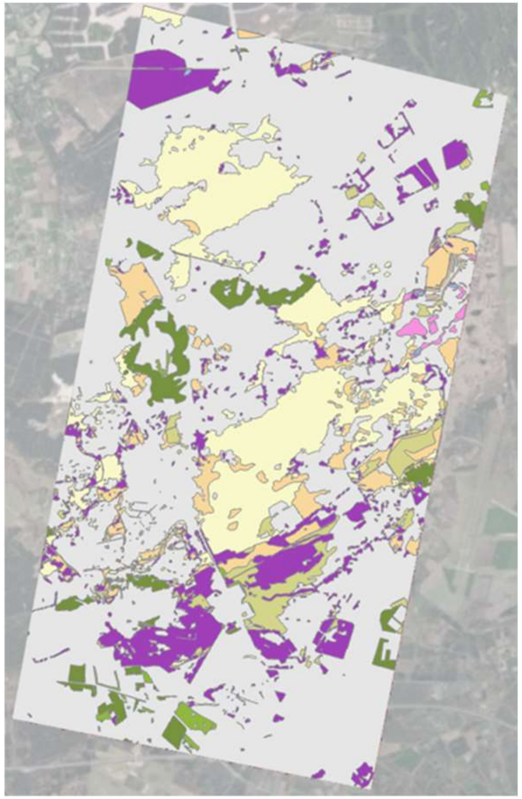
Symbol	Value	Label	Count
	1	1 Dry sand heaths (light) - sand	19
	2	2 Dry sand heaths (dark) - vegetated	16
	3	3 Inland dunes (light)	16
	4	4 Inland dunes (dark)	33
	5	5 Lakes and ponds	28
	6	6 Wet heaths	39
	7	7 European dry heaths (light) - Pijpenstrootje	35
	8	8 European dry heaths (dark) - heide	19
	9	9 Species-rich Nardus substrates	37
	10	10 Depressions on peat substrates	33
	11	11 Birch forests	37
	12	12 Oak woods	44
	13	13 Coniferous forest	21

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.

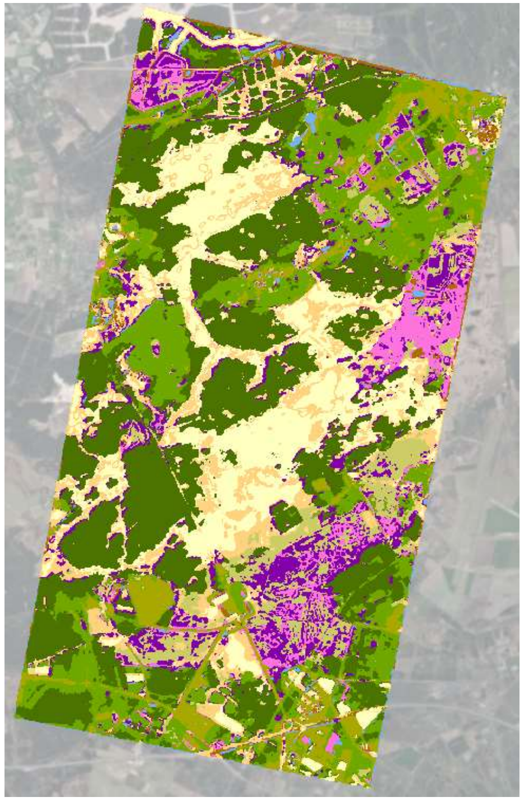
Method 2 : Deep Learning for NL extent result

Groundtruth habitat map



Habitat map

Result U-Net



Sentinel 2020 stack 7 images

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

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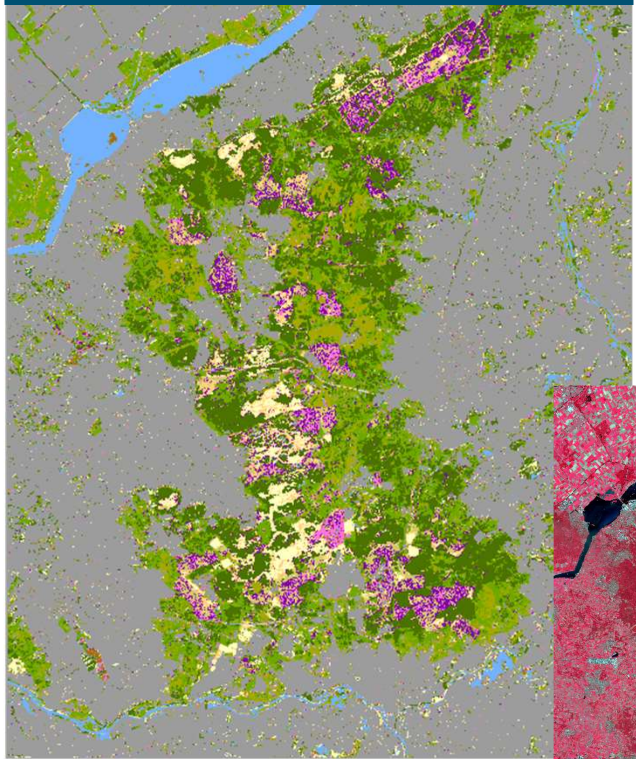
Method 2 : Deep Learning for NL extent

upscaling

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

Sentinel 2020 - 7 images

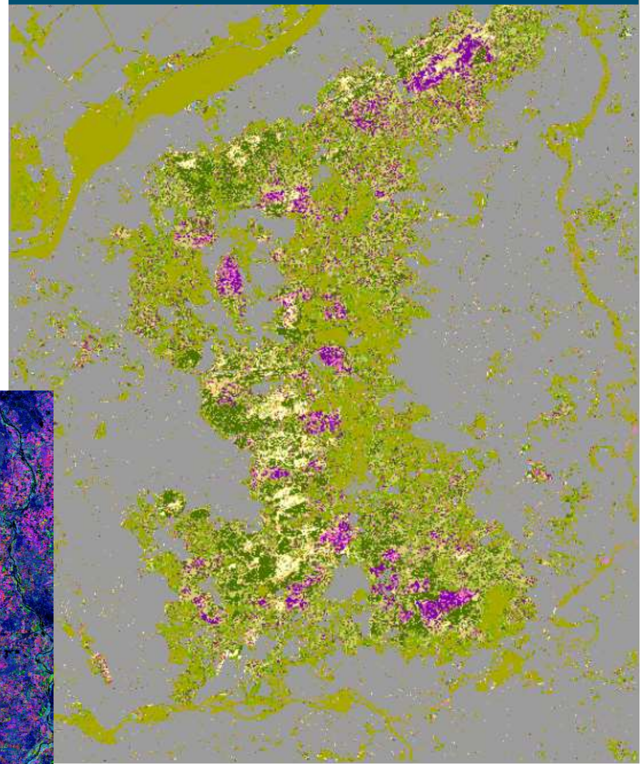


Deep learning with U-NET

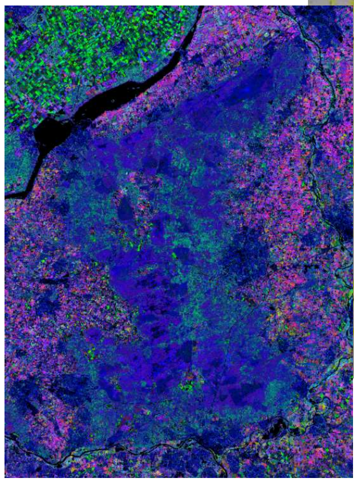
Habitat type

- 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

HR-VPP (High Resolution–Vegetation Phenology Product) – Sentinel 2



Sentinel



HR-VPP

The HR-VPP metric describe the yearly vegetation development, e.g. the start of growing season day (SOSD), end of growing season day (EOSD), length of growing season (LENGTH) or annual productivity (TPROD).

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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%
	Grand total	29	51	28	38	59	35	35	38	42	22	377	
Superview 12-08-2020	u acc	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%
	Grand total	32	65	39	14	43	38	39	68	21	18	377	
												377	
Sentinel 31-07-2020	u acc	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

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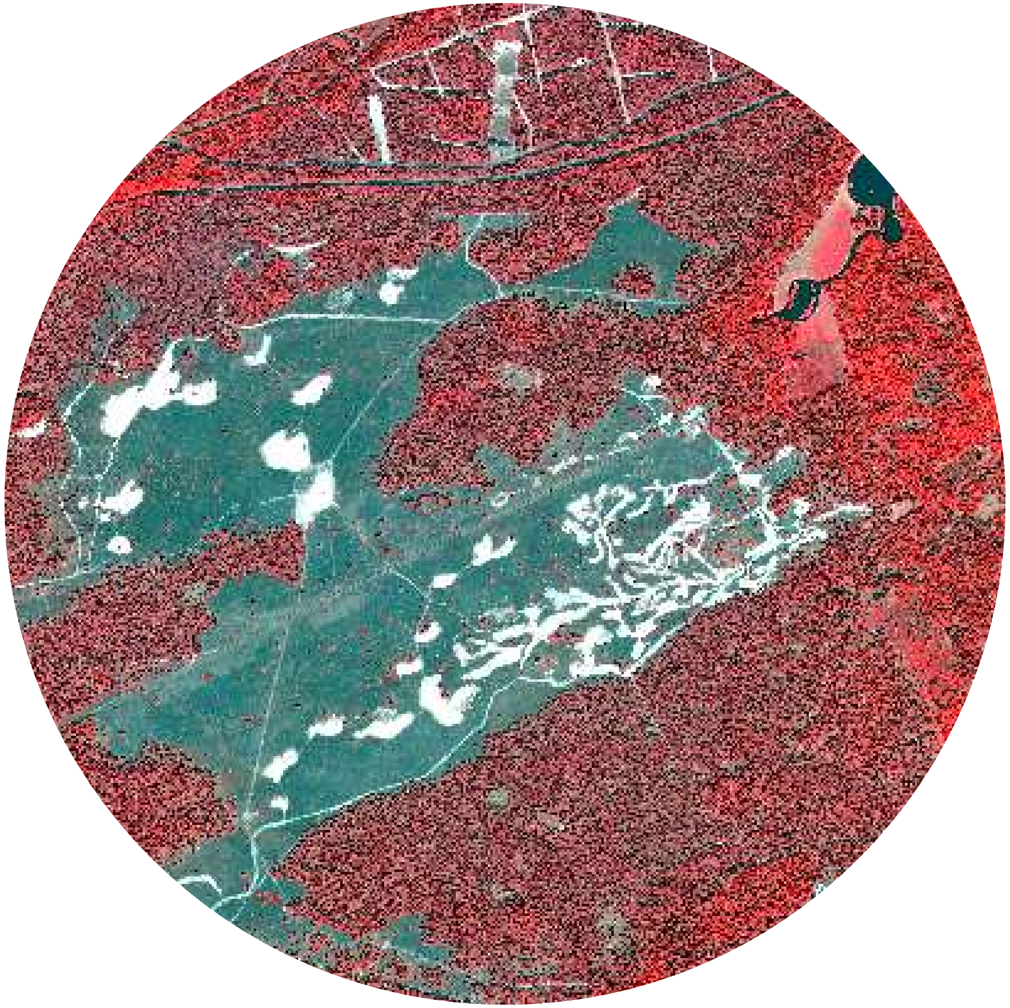
Results & conclusions

- 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



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