E-shape Myvariable: European Habitat Modelling and Mapping solutions:

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e-shape Background & objectives

- There is a strong decline in Europe's biodiversity. The EU's biodiversity strategy for 2030 and the new Nature Restoration law aims to protect nature and reverse the degradation of ecosystems.
- Apart from monitoring individual species, habitats are the best comprehensive representatives for biodiversity.
- Therefore, understanding where habitats occur across Europe is a crucial element for understanding biodiversity conservation and taking specific actions.
- Our overall objective is to exploit Machine Learning / Deep Learning classification methods for habitat distribution modelling & mapping with remote sensing & in-situ data.
- Work performed within E-SHAPE but continues now within EEA & ESA projects.

MyVariable objective

Advance the development and uptake of the **Essential Biodiversity Variables (EBVs)** to study and report on changes in biodiversity across scales

Our main task:

- Provision European habitat suitability maps as EBV
- For most EUNIS habitat types
- for different time periods (2010-2014 & 2015-2019)
- into the GEO BON portal

Mainstreaming Essential Biodiversity Variables:
e-shape A three-steps vision:

- 1. Mobilize primary (in-situ) observations from monitoring programmes
- Harmonize, integrate and model to fill (spatial & temporal) information gaps using reproducible workflows
- 3. Disseminate EBV data in support of biodiversity assessments and policies



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Mainstreaming Essential Biodiversity Variables (#20)

Comparable data outputs across EBV classes





	Genetic diversity				
Genetic Composition	Genetic differentiation				
	Effective population size				
	Inbreeding				
Spacios Bonulations	Species distributions				
Species Populations	Species abundances				
	Morphology				
Species Traits	Physiology				
	Phenology				
	Movement				
	Live cover fraction				
Ecosystem Structure	Ecosystem distribution				
	Ecosystem vertical profile				
	Primary productivity				
Ecosystem Function	Ecosystem phenology				
	Ecosystem disturbances				
	Community abundance				
Community Composition	Community abundance Taxonomic/phylogenetic diversity				
Community Composition	Community abundance Taxonomic/phylogenetic diversity Trait diversity				

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Home / Predicted suitability for EUNIS habitat types You are viewing Version 2, the most recent version of this dataset. 2 version(s) available Date of publication: November 21, 2022 Version 2 Show details Predicted suitability for EUNIS habitat types by Stephan Hennekens 1. The modelled suitability for the EUNIS habitat types is an indication of where conditions are favourable for each habitat type based on classified sample plot data (European Vegetation Archive), predictors and the Maxent software package. The modelled suitability maps may be used as a proxy for the potential geographical distribution of the habitat types in given environmental and climatic envelopes. Note however that the suitability is not repre ...(continue reading) Lata: netCDF (4.74GB) Metadata: ACDD (JSON) | EML (XML) Europe Terrestrial ecosystem EUNIS Maxent Remote Sensing-EBVs Show on map General information EBV attributes Date of creation Title Predicted suitability for EUNIS habitat types 2020-01-01 Summary The modelled suitability for the EUNIS habitat types is an indication of where conditions are favourable for each habitat type based on classified sample plot data (European Vegetation Archive), predictors and the Maxent software package. The modelled suitability maps may be used as a proxy for the potential geographical distribution of the habitat types in given environmental and climatic envelopes. Note however that the suitability is not representing the actual distribution of the habitat types. Currently for two time periods models have been created, 2010-2014 and 2015-2015. For each period different versions for some of the predictors have been applied (LAI, LULC, Phenology, Population density). Climate, soil and topography predictors are the same for the two periods. In Maxent the models have been ran using the predictors for the second period for the future predictions.

https://portal.geobon.org/ebv-detail?id=3

e-shape European habitat modelling at 100 m resolution

- Input for the modelling are potentially 1,2M vegetation plot observations (derived from the European Vegetation Archive (EVA database) covering 203 EUNIS habitats.
- A model for each habitat type is executed using a selection of 22 climate-environmental predictors
- The modelling mainly based on <u>Maxent version 3.4.1</u>, a machine-learning technique called Maximum Entropy Modelling.
- We ran MAXENT model to create European habitat suitability maps at 100 meter resolution for most EUNIS habitat types at level 3 (#203).



Predictors used (#22)

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Group	Predictor description	Nr
Climate	Annual precipitation $(mm_{Vr}-1)$	1
Cimate	Growing degree days heat sum above $5^{\circ}C$ (gdd5)	2
		3
	Accumulated precipitation amount on growing season days TREELINI (gsp)	Л
	Mean temperature of the growing season TREELIM (gst)	-
	Snow covered days (scd)	5
Elevation	EU DEM	6
	EU DEM slope	7
HR-VPP	VPP - Season amplitude given by MAXV-MINV	8
	VPP - Length of season (number of days between start and end)	9
	VPP - Slope of the green-up season (PP I $ imes$ day-1)	10
	VPP - PPI at the day of maximum-of-season	11
Inundation	Inundation - occurrence	12
Land cover	Corine Land Cover	13
	World cover	14
Soil	Soil - bulk density	15
	Soil - cation exchange capacity	16
	Soil - course fractions	17
	Soil - clay fraction	18
	Soil - pH	19
	Soil - sand fraction	20 21
		21
Topography	Distance to inland water	

Flowchart European habitat modelling

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#203 EUNIS habitat types with Maxent modelled

Example Q12 Blanket Bog Thresholded suitability map Distribution data (in-situ) Q1∠ blanket bog - binary map

Statistics from Maxent modelling

AUC training	a (0-1)	0.9619
AUC test (0-	1)	0.9641
10 percentile	e training presence threshold (0-1)	0.1123
Contribution	variables to the Maxent model (%)	
	Climate - Accumulated precipitation amount on growing s	38.4656
	Soil - organic carbon	21.6239
	Corine Land Cover 2018	18.1444
	Climate - Snow covered days (scd)	9.3499
	Soil - bulk density	3.5948
	Climate - Mean temperature of the growing season TREE	2.5396
	Soil - sand fraction	2.4898
	Soil - pH	1.5345
	Climate - Annual precipitation (mm yr-1)	0.8098
	Soil - course fractions	0.5459
	Soil - clay fraction	0.3609
	Soil - cation exchange capacity	0.2868
	Population density 2018	0.0641
	Climate - Growing degree days heat sum above 5°C (gdc	0.0531
	EU DEM	0.0389
	HR-VPP - Length of season (number of days between sta	0.0341
	Distance to inland water	0.026
	HR-VPP - Slope of the greenup season (PP I × day-1)	0.0186
	EU DEM Slope	0.011
	HR-VPP - Season amplitude given by MAXV-MINV	0.0048
	HR-VPP - PPI at the day of maximum-of-season	0.0037
	Inundation - occurrence	0

Validation of 22 European habitat suitability maps based on Article 17 database

Code Description	Nr EVA	Overall	User's	Producer's	Commi	Omission
	plots	accurac	accuracy	accuracy	s. error	error
7130 Blanket hog	822	0 Q7	0.48	0.80	0.52	0.20
9410 Acidophilous Picea forests of the montane to alpine levels (Vaccinio-Piceetea)	11042	0.97	0.40	0.80	0.52	0.20
Actiophilous ricea forests of the montane to aprile levels (vacenilo ricectea)	11042	0.55	0.45	0.51	0.51	0.05
6520 Mountain hay meadows	4618	0.92	0.40	0.66	0.60	0.34
4060 Alpine and Boreal heaths	9435	0.92	0.49	0.62	0.51	0.38
1510 Mediterranean salt steppes (Limonietalia)	312	0.91	0.09	0.69	0.91	0.31
2190 Humid dune slacks	3988	0.91	0.13	0.71	0.87	0.29
5120 Mountain Cytisus purgans formations	616	0.89	0.06	0.81	0.94	0.19
1310 Salicornia and other annuals colonizing mud and sand	17773	0.88	0.21	0.81	0.79	0.19
6230a Species-rich Nardus grasslands, on silicious substrates in mountain areas (narrow sel)	y 1314	0.87	0.55	0.27	0.45	0.73
2130 Fixed coastal dunes with herbaceous vegetation (grey dunes)	8927	0.85	0.16	0.83	0.84	0.17
4010 Northern Atlantic wet heaths with Erica tetralix	2081	0.83	0.20	0.93	0.80	0.07
9110 Luzulo-Fagetum beech forests	2906	0.79	0.39	0.72	0.61	0.28
6230b Species-rich Nardus grasslands, on silicious substrates in mountain areas (broad sel)	10828	0.76	0.33	0.78	0.67	0.22
9180 Tilio-Acerion forests of slopes, screes and ravines	6541	0.68	0.31	0.79	0.69	0.21
3230 Alpine rivers and their ligneous vegetation with Myricaria germanica	554	0.67	0.02	0.98	0.98	0.02
3240 Alpine rivers and their ligneous vegetation with Salix elaeagnos	2343	0.64	0.08	0.99	0.92	0.01
6410 Molinia meadows on calcareous, peaty or clayey-silt-laden soils (Molinion caeruleae)	8220	0.56	0.29	0.80	0.71	0.20
7110 Active raised bogs	3640	0.54	0.18	0.96	0.82	0.04
6210 Semi-natural dry grasslands and scrubland facies on calcareous substrates	646	0.48	0.29	0.91	0.71	0.09
8210 Calcareous rocky slopes with chasmophytic vegetation	2018	0.43	0.19	0.86	0.81	0.14
8160 Medio-European calcareous scree of hill and montane levels	827	0.42	0.03	1.00	0.97	0.00
8220 Siliceous rocky slopes with chasmophytic vegetation	526	0.38	0.18	0.57	0.82	0.43
5130 Juniperus communis formations on heaths or calcareous grasslands	879	0.35	0.07	0.95	0.93	0.05

From suitability to probability : S41 Wet heath

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e-shape Differences in accuracy models from BIOMOD2



Random Forest performs with best accuracy, but takes too much time to run (> 200 hours for a single model and huge memory consumption). Modelling at European scale at 100m resolution currently only possible using Maxent.

Figure Accuracy assessment for the different methods for habitat suitability modelling with same set of training data and set of predictors at 100 meter resolution. AUC = Accuracy Under the Curve. TSS = True Skill Statistics.

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Wall-to-wall mapping of EUNIS Forest habitat types (level 3) using the highest suitability scores limited to the Copernicus HR layer Forest.



New methods of very detailed habitat mapping (10m) using deep learning techniques

Example in National Park Veluwe, the Netherlands, using HR-VPP and Sentinel-2 at 10 meter resolution



Sentinel 31-07-2020, False colour

Selected LVD points in Hoge Veluwe test area

SPEC_HABTY,D	DLid
o 23101,1	Dry sand heaths (light) - sand
o 23102,2	Dry sand heaths (dark) - vegetated
a 23301,3	Inland dunes (light)
• 23302,4	Inland dunes (dark)
a 31601,5	Lakes and ponds
• 40101,6	Wet heaths
e 40301,7	European dry heaths (light) - Pijpenstrootje
a 40302,8	European dry heaths (dark) - heide
62301,9	Species-rich Nardus substrates
• 71501,10	1 Depressions on peat substrates
91201,11	1 Birch forests
• 91901,12	1 Oak woods

39 37 45

Upscaling trained DL model to entire Veluwe



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

		classificati	on resul	t										
LDV training points											s		producer	
	HABITATTYP	2310	2330	3160	4010	4030	6230	7150	9120	9190	forest	total	accuracy	
dry sand and heaths	2310	23	5		1	1	5					35	66%	i
inland dunes	2330	3	42		1		2	1				49	86%	i
lakes and ponds	3160			26	1			1				28	93%	j .
wet heaths	4010	1			27	7		4				39	69%	i
european dry heaths	4030	1			4	40	9					54	74%	i
species-rich nardus substrates	6230				3	5	28			1		37	76%	i
depression on peat substrates	7150				10	2		21				33	64%	i
beech forest	9120								34	3		37	92%	j .
oak woods	9190						1		1	42		44	95%	i
coniferous forest	13										21	21	100%	i i
	Grand total	28	47	26	47	55	45	27	35	46	21	377		
	user													overall
	accuracy	82%	89%	100%	57%	73%	62%	78%	97%	91%	100%		81%	accura

Sentinel 2020 - 7 images



Sentinel 2020 stack 7 images: 07-02, 23-03, 15-04, 07-05, 26-06, 31-07, 14-09

CATBOOST AI automated, scalable workflow



Extend standard predictors (22 features) with

- Full time-series high-res EO features (140)
- Contextual features (16) through Conventional Neural Networks (CNN)

Regional optimization to train & classify

- Selecting best features per region
- Catboost ML for habitat class probabilities
- Post-processing to select 'final' habitat class



CATBOOST AI workflow results







	ANNEX-I NL	EUNIS Austria	EUNIS Austria- optimized
Calibration samples	17717	80661	80661
Test samples	3796	17285	17285
Validation samples	3797	17285	17285
# distinct classes	43	45	45
# predictors	131	147	61
Training time (CPU)	12 min	90 min	30



Tested over 3 area's, wall-2-wall

- NL (43 habitats Annex-I), Austria (45 habitats EUNIS-L3), South-Portugal (16 habitats EUNIS-L2/L3)
- Selection of ~70 predictors per region, trained at ~70% weighted F1 score
- Accompanied with classification confidence layer

Results & conclusions e-shape

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- The modelled European habitat suitability maps are improved by integration with detailed Copernicus land cover products.
- Wall-to-wall habitat mapping with deep learning techniques with remote sensing & in-situ data & other predictors is valuable and but needs further improvements.
- For all methods the amount and quality of in-situ data is crucial. Especially the deeplearning techniques on high resolution satellite imagery requires enhancement vegetation plot data – due to inaccuracies in locations.
- Collection & enhancement of sufficient training data is a crucial step that needs much more attention !!
- Also new remote sensing products (e.g. canopy height) that become available needs to be absorbed in our habitat modelling & mapping methods.

Thank you! **Follow us:** eshapeh2020 @eshape_eu e-shape project

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www.e-shape.eu

Ravenna Seaside Workshop, 17 May 2022