Improving the management of ATLANTIC LANDSCAPES: accouting for biodiversity and ecosystem services

ALICE

New modelling tools and different sensor resolution for vegetation mapping: what actually matters?

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[3] Predictia, Calle Benidorm, 8 Bajo, Santander, Spain
[4] ITD Medio Ambiente. Edificio 3000 (Módulo 12). Parque Científico y Tecnológico de Cantabria, Santander, Spain

1st Meeting of the Iberian Ecological Society & XIV AEET Meeting
"Ecology: an integrative science in the Anthropocene"
4th - 7th February 2019, Barcelona, Spain

SWOT ANALYSIS

We have to get knowledge about our landscapes patterns and processes

New modelling tools and sensor resolution for vegetation mapping:

what actually matters?

What actually matters?

We do not end up with available tools (year 2017 and so on) and outputs…

1] CLASSIFICATION TYPOLOGY Land use-land cover (LULC) **Vegetation** types	**2] OCCURRENCE DATA** Training Validation
3] PREDICTOR LAYERS Environmental limiting factors Remote sensing: **satellite** and LiDAR	**4] MODELLING PROCEDURE** Ensemble, sensitivity analyses Data mining tools…

New mapping tools and different sensor resolution for vegetation mapping: what actually matters?

What actually matters?

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1] CLASSIFICATION SYSTEM

Traditionally: visual interpretation and digitalization

SIOSE: Sistema de Información sobre Ocupación del Suelo de España (CNIG)

CLC (CORINE): CoORdination of INformation of the Environment (EEA)

Land use-land cover typologies

Vectorial format

'Homogeneous' land cover patches

Restricted or null temporal resolution

1] CLASSIFICATION SYSTEM

FORESTRY MAP OF SPAIN

NATURA 2000

HABITATS DIRECTIVE ANNEX I

Expert-based methods: visual interpretation and fieldwork

EUNIS F4.22

- EUNIS (level 1): Heathland, scrub and tundra
- EUNIS (level 2): Temperate shrub heathland
- EUNIS (level 3): Dry heaths
- EUNIS (level 4): Sub-Atlantic [Calluna] - [Genista] heaths F4.22

HABITATS DIRECTIVE ANNEX I: 4030-EU dry heathlands

CASE STUDY

NATURA 2000

Management plan

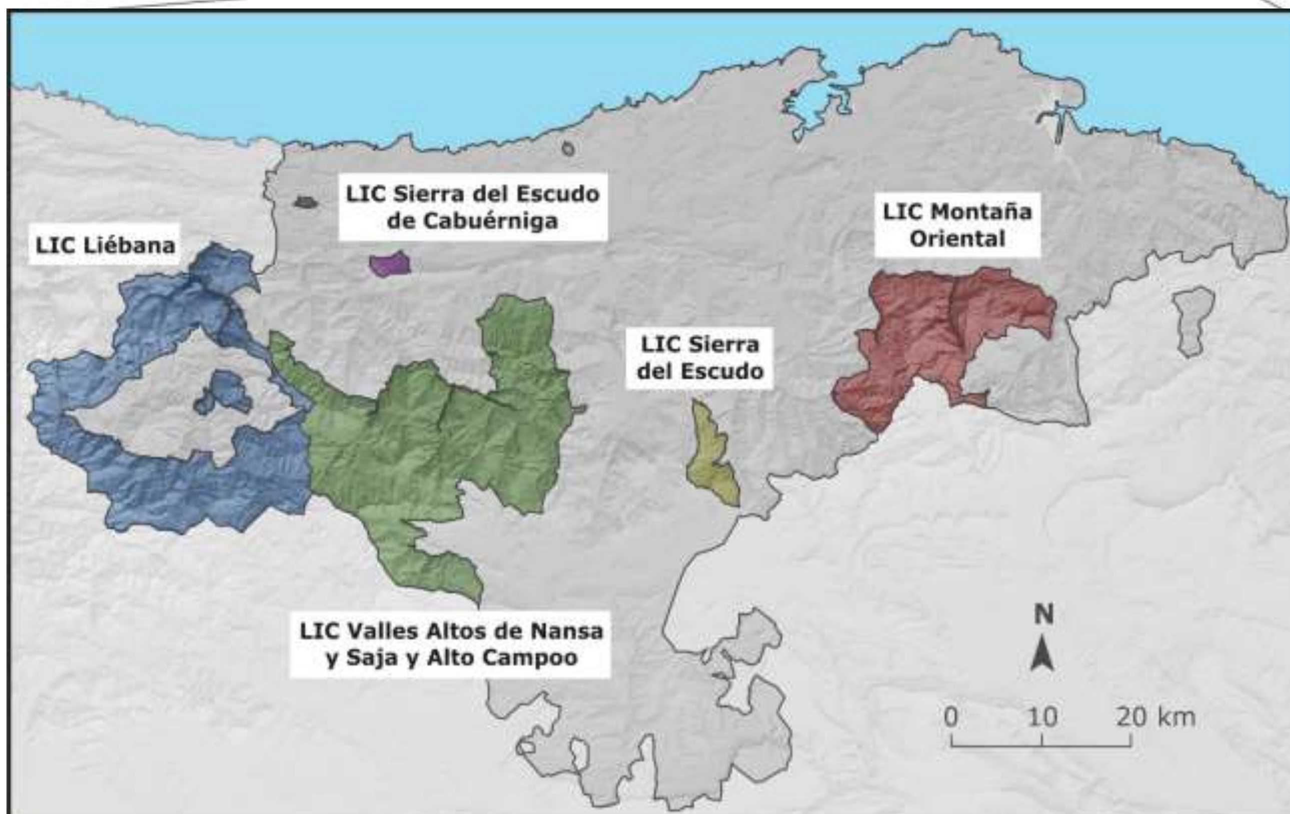
Annex I

1. Spatial distribution
2. Conservation Status
3. Management Plan-Local actions

Mapping broad-scale vegetation patterns in complex mountainous territories

Habitat maps using modelling techniques in SCI→SAC of Natura 2000 Network in Cantabria (NW Spain)

26% of Cantabria. 25 hábitats…



Álvarez-Martínez et al, 2017

Methods in Ecology and Evolution

BRITISH ECOLOGICAL SOCIETY

1] CLASSIFICATION SYSTEM

>100 EUNIS 3-5 level habitat types

EUNIS typologies in Cantabria

ID	EUNIS	N	Descripción
1	A2	103	Littoral sediment
2	A2.61	37	Seagrass beds on littoral sediments
3	C1	271	Surface standing waters
4	C2.2	169	Permanent non-tidal, fast, turbulent watercourses
5	D1.21	385	Hyperoceanic low-altitude blanket bogs, typically with dominant [Trichophorum]
6	E1.2	62	Perennial calcareous grassland and basic steppes
7	E1.263	227	Middle European [Brachypodium] semidry grasslands
8	E1.7	41	Closed non-Mediterranean dry acid and neutral grassland
9	E1.712	95	Sub-Atlantic [Nardus]-[Galium] grasslands
10	E1.721	131	Nemoral [Agrostis]-[Festuca] grasslands
11	E2.1	2430	Permanent mesotrophic pastures and aftermath-grazed meadows
12	E2.11	436	Unbroken pastures
13	E2.111	612	Ryegrass pastures
14	E2.112	171	Atlantic [Cynosurus]-[Centaurea] pastures
15	E2.2	328	Low and medium altitude hay meadows
16	E2.21	125	Atlantic hay meadows
17	E2.22	595	Sub-Atlantic lowland hay meadows
18	E5.31	40	Sub-Atlantic [Pteridium aquilinum] fields
19	F2.2	52	Evergreen alpine and subalpine heath and scrub
20	F2.231	73	Mountain [Juniperus nana] scrub
21	F3.13	31	Atlantic poor soil thickets
22	F3.17	125	[Corylus] thickets
23	F3.171	40	Atlantic and sub-Atlantic hazel thickets
24	F3.25	37	Piornales
25	F3.252	136	Northwestern Iberian [Genista florida] fields
26	F4.2	978	Dry heaths
27	F4.23	120	Atlantic [Erica]-[Ulex] heaths
28	F4.237	190	Cantabro-Pyrenean [Erica vagans]-[E. cinerea] heaths
29	F7.4	138	Hedgehog-heaths
30	F7.4451	834	Pyreneo-Cantabrian cushion-heaths
31	FA	46	Hedgerows
32	G1	40	Broadleaved deciduous Woodland
33	G1.21	252	Riverine [Fraxinus] - [Alnus] woodland, wet at high but not at low water
34	G1.2142	130	Pyreneo-Cantabrian alder galleries
35	G1.6	1343	[Fagus] woodland
36	G1.62	353	Atlantic acidophilous [Fagus] forests
37	G1.624	65	Pyreneo-Cantabrian acidophilous beech forests
38	G1.625	179	Western Cantabrian acidophilous beech forests
39	G1.64	247	Pyreneo-Cantabrian neutrophile [Fagus] forests

1] CLASSIFICATION SYSTEM

>100 EUNIS 3-5 level habitat types

40	G1.643	231	Sub-humid oro-Cantabrian beech forests
41	G1.662	55	North-western Iberian xerophile beech woods
42	G1.7	93	Thermophilous deciduous woodland
43	G1.7B	1089	[Quercus pyrenaica] forests
44	G1.7B2	370	Cantabrian [Quercus pyrenaica] forests
45	G1.7D	48	[Castanea sativa] woodland
46	G1.862	506	Cantabrian acidophilous oak forests
47	G1.8621	77	Eastern Cantabrian acidophilous oak forests
48	G1.8622	33	Western Cantabrian acidophilous oak forests
49	G1.8623	38	Oro-Cantabrian acidophilous oak forests
50	G1.91	24	[Betula] woodland not on marshy terrain
51	G1.9151	51	Cantabrian [Betula celtiberica] woodlands
52	G1.A	33	Meso- and eutrophic oak, hornbeam, ash, sycamore, lime, elm and related woodland;
53	G1.A1	31	[Quercus] - [Fraxinus] - [Carpinus betulus] woodland on eutrophic and mesotrophic soils
54	G1.A19	206	Pyreneo-Cantabrian [Quercus] - [Fraxinus] forests
55	G1.A4	48	Ravine and slope woodland
56	G1.C1	73	[Populus] plantations
57	G1.C4	50	Other broadleaved deciduous plantations
58	G2.1	43	Mediterranean evergreen Quercus woodland
59	G2.12	687	[Quercus ilex] woodland
60	G2.121	75	Meso-Mediterranean [Quercus ilex] forests
61	G2.1211	172	Northwestern Iberian holm-oak forests
62	G2.12414	115	Oro-Cantabrian encinares
63	G2.6	46	[*Ilex aquifolium*] woods
64	G2.81	371	[Eucalyptus] plantations
65	G3.F12	129	Native pine plantations
66	G3.F22	229	Exotic pine plantations
67	G3.F23	154	Other exotic conifer plantations
68	G4.F	67	Mixed forestry plantations (plantaciones mixtas de con├íferas y caducifolios)
69	G5	27	Lines of trees, small anthropogenic woodlands, recently felled woodland, early-stage woodland and coppice
70	H2.6	102	Calcareous and ultra-basic screes of warm exposures
71	H2.641	116	Canchales calc├íreos m├│viles orocant├íbricos
72	H2.65	34	Iberian calciphile fern screes
73	H3.21	159	Tyrrheno-Adriatic eumediterranean calcicolous chasmophyte communities
74	I	416	Regularly or recently cultivated agricultural, horticultural and domestic habitats
75	I1	101	Arable land and market gardens
76	I2	67	Cultivated areas of gardens and parks
77	I5.8	66	Comunidades alóctonas de Cortaderia, Baccharis, Buddleja, Phyllostachis, Reynoutria
78	J	132	Constructed, industrial and other artificial habitats
79	X1	115	Helechales
80	X2	31	Nanofruticedas cespitosas con G. pyrenaicum y H. sedenense

What actually matters?

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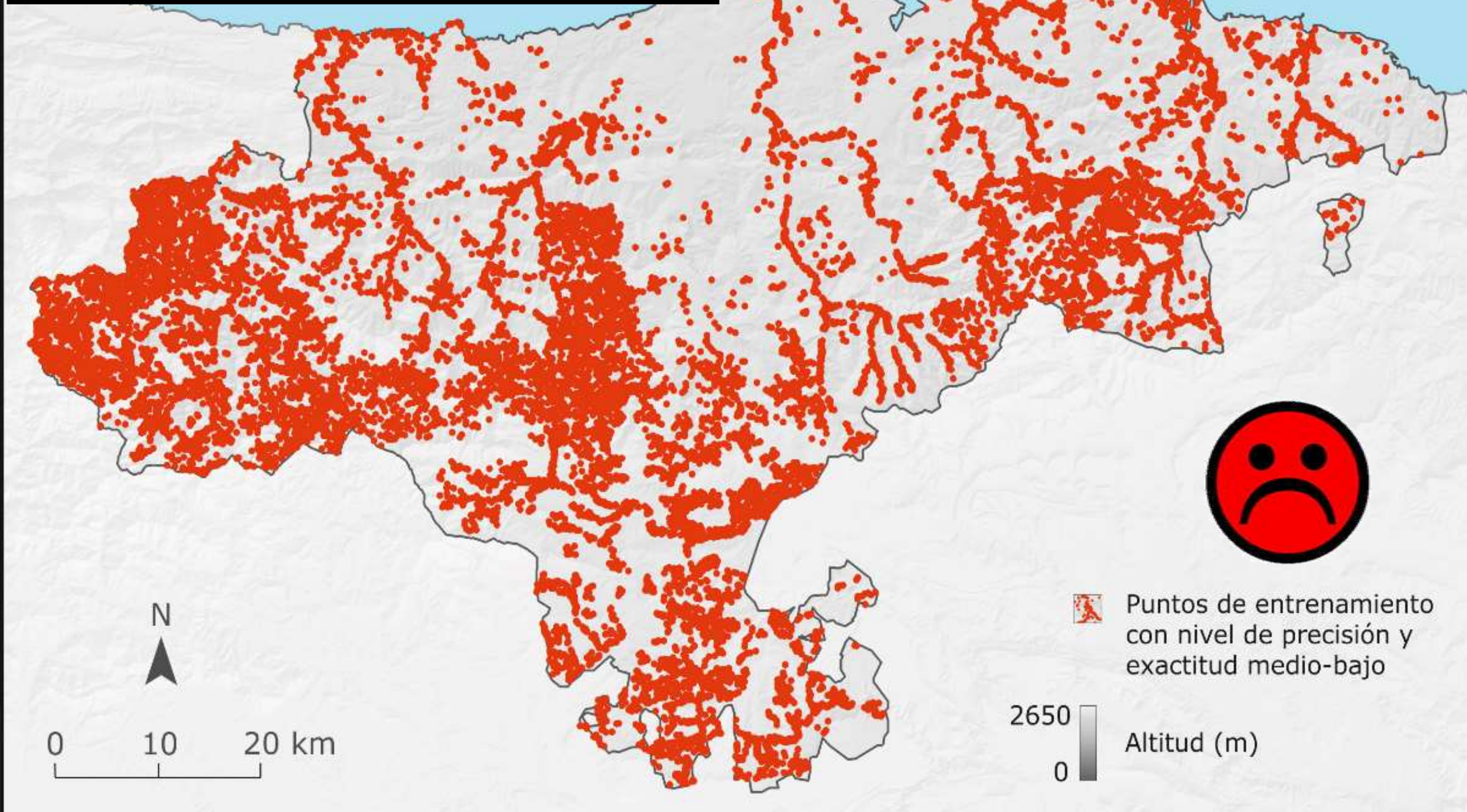
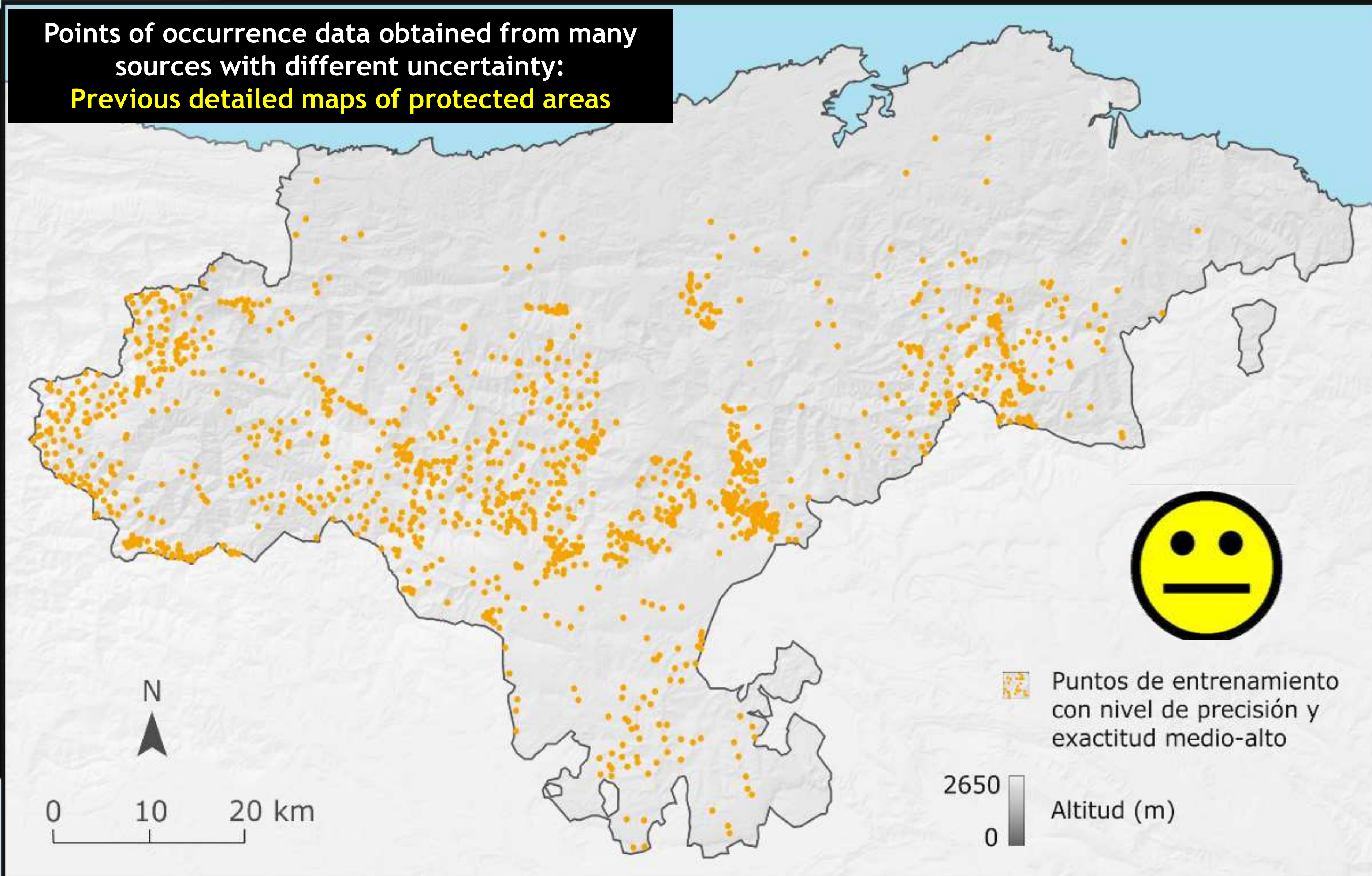
2] OCURRENCE DATA

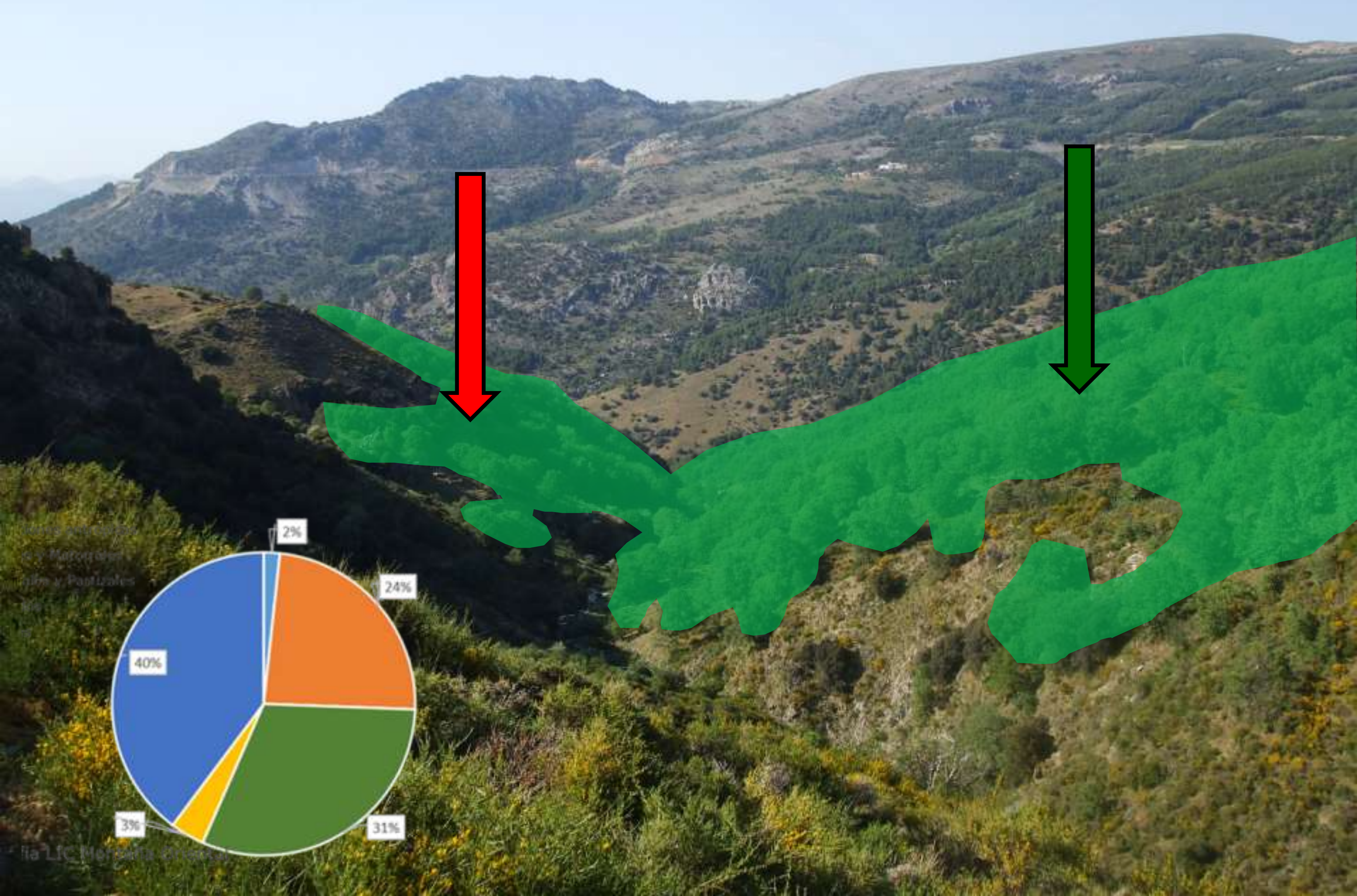
Points of occurrence data obtained from many sources with different uncertainty: CLC 12, SIOSE, MFE25



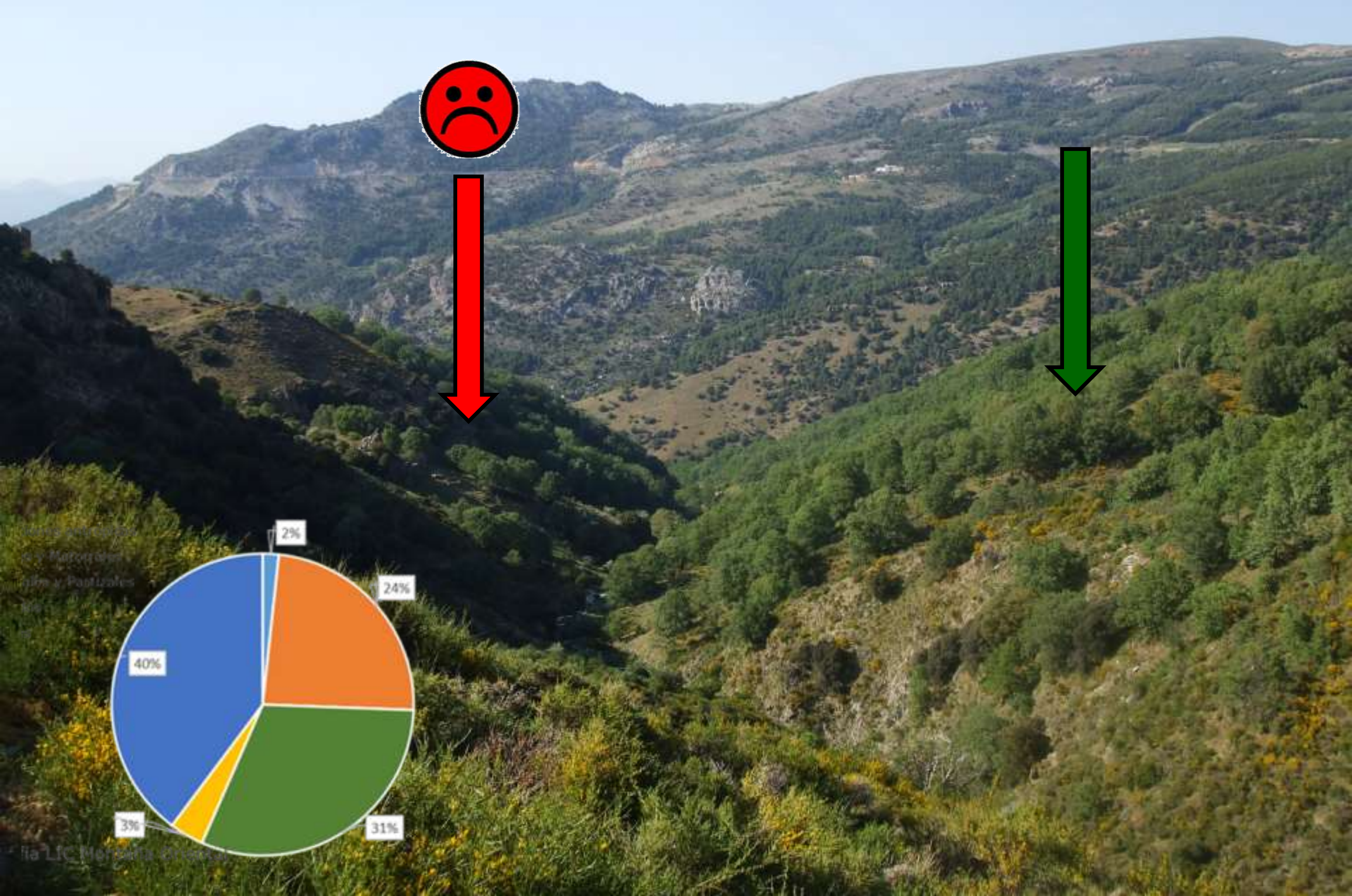
Points of occurrence data obtained from many sources with different uncertainty:
Previous detailed maps of protected areas



Vectorial LULC databases simplify complex landscapes mosaics by creating “homogeneous” Landscapes patches inclufding different communities and environmental gradients…

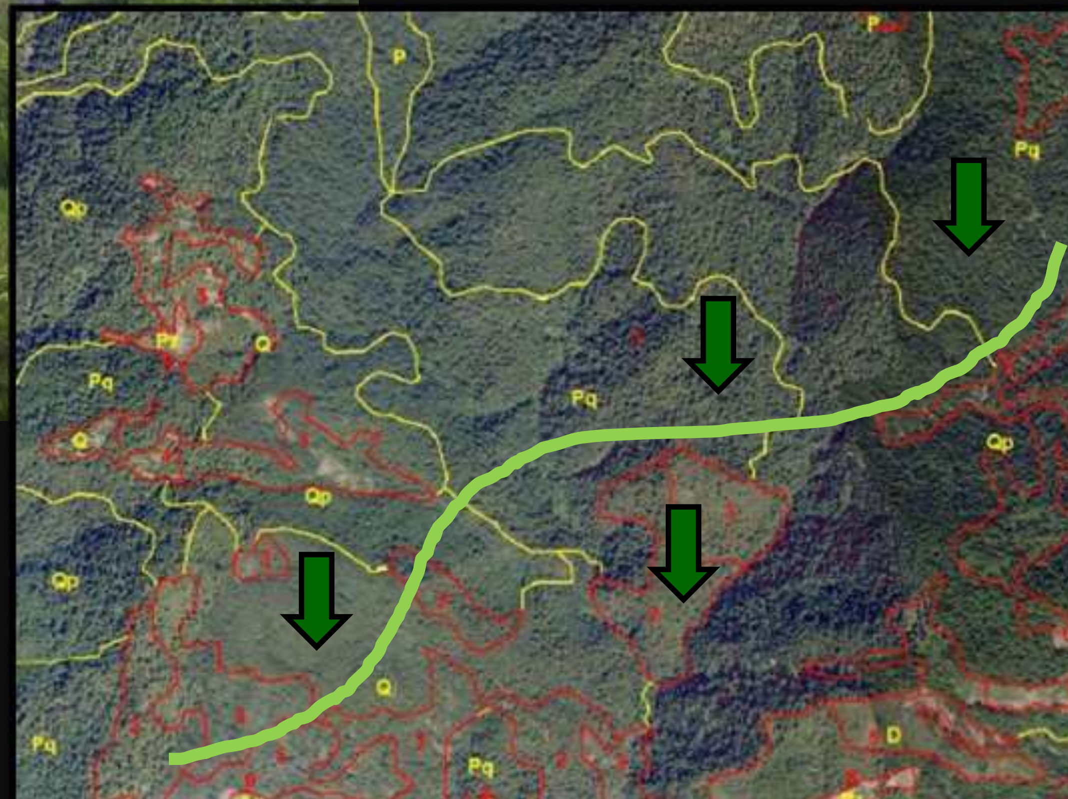


There is a need for defining detailed (EUNIS, MAES…) typologies for large territories in order to accomplish landscape complexity, temporal variability and locally-tailored management practices



2] OCURRENCE DATA

Points of occurrence data obtained from many sources with different uncertainty:
Field campaigns (botanists)



Reference data: transects, sampling points

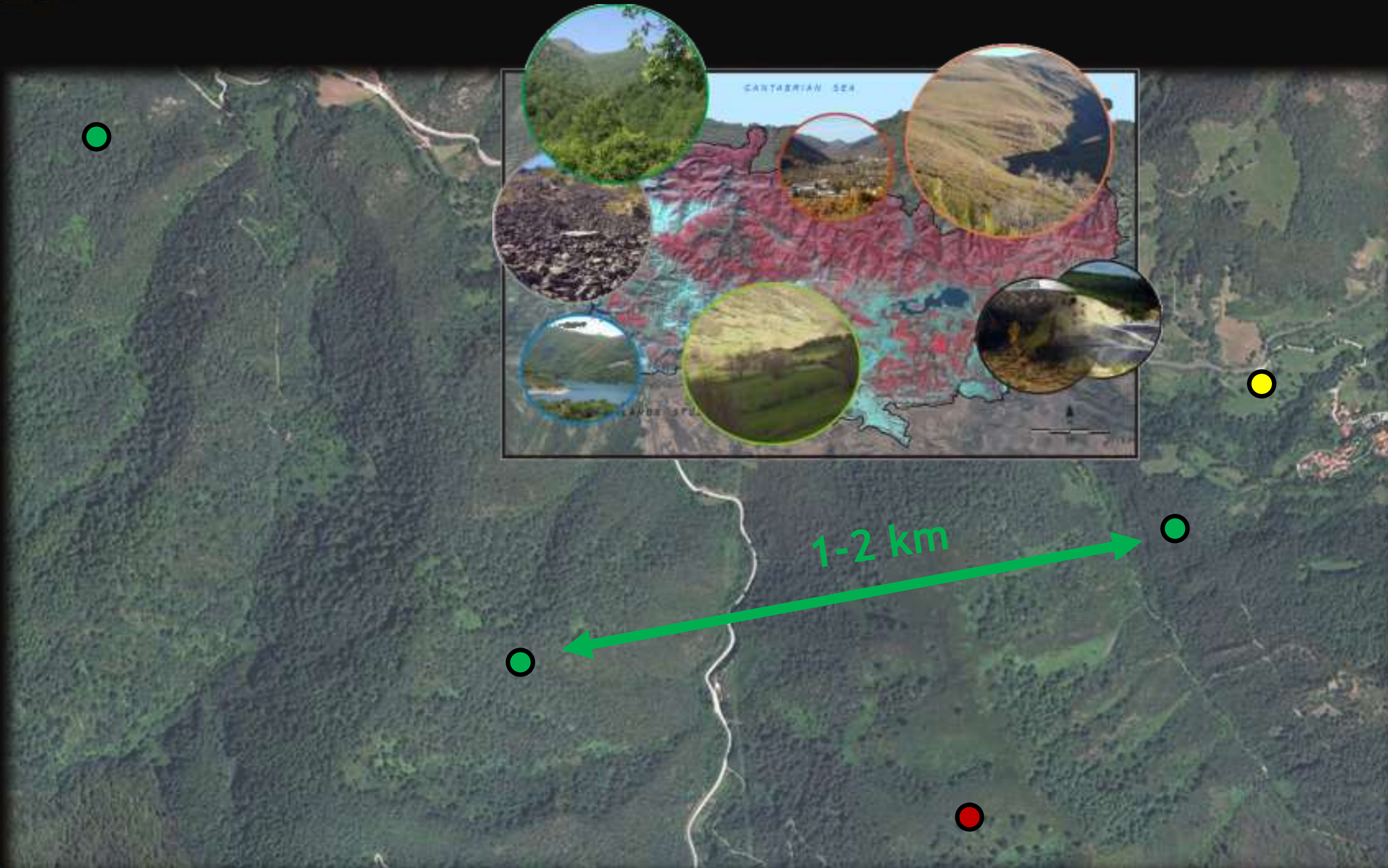
2] OCURRENCE DATA

"Tablet System". H2020 Working Group of Turkey

Reliable data for training models and conservation status indicators

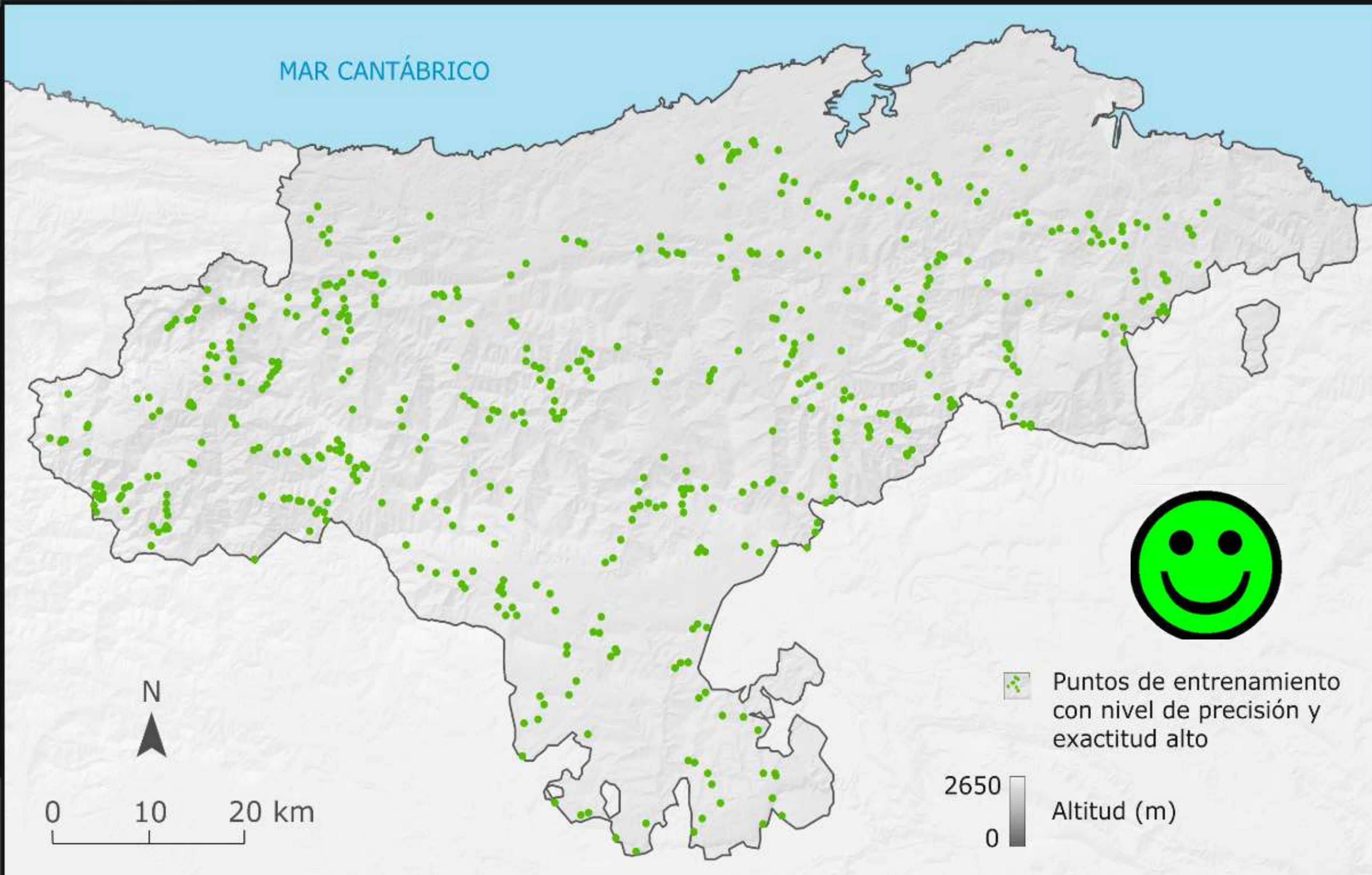
2] OCURRENCE DATA

Successive vegetation databases corrected or confirmed previous data

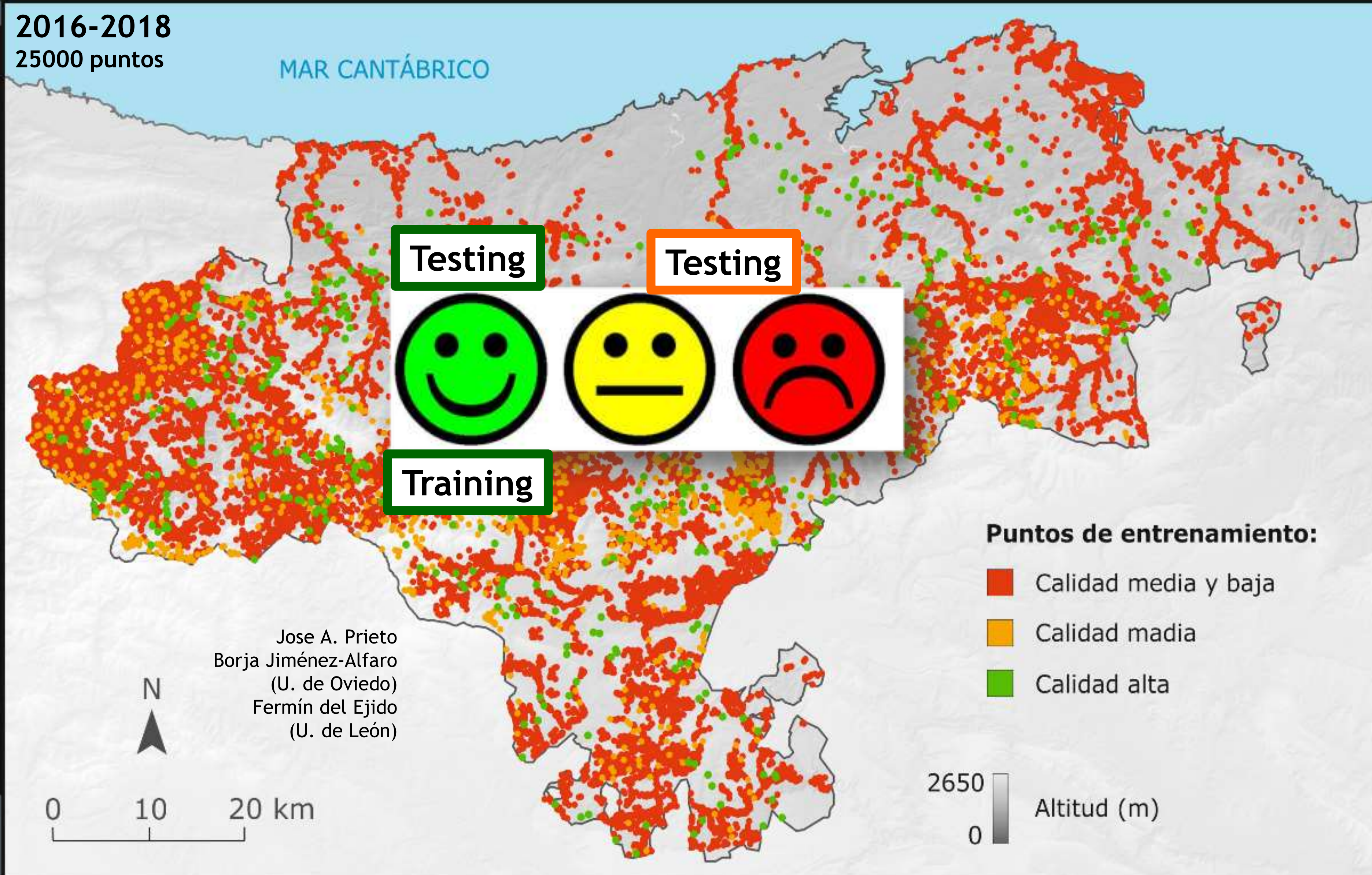


Geographical and environmental representativity

2] OCURRENCE DATA



What actually matters?



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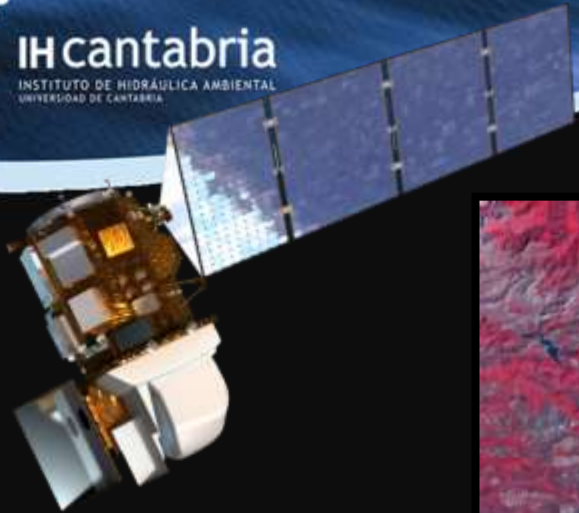


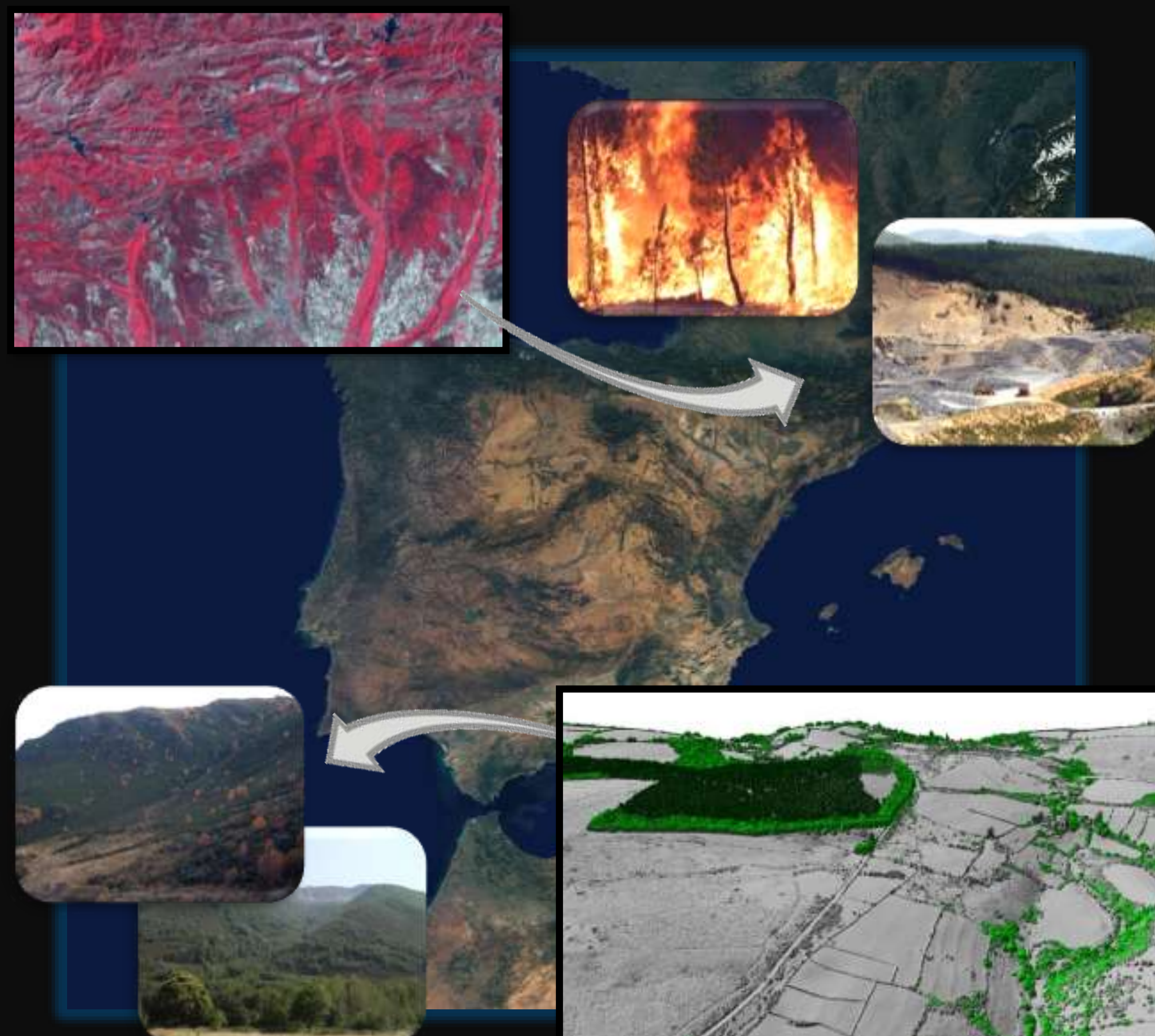
Remote Sensing (RS)

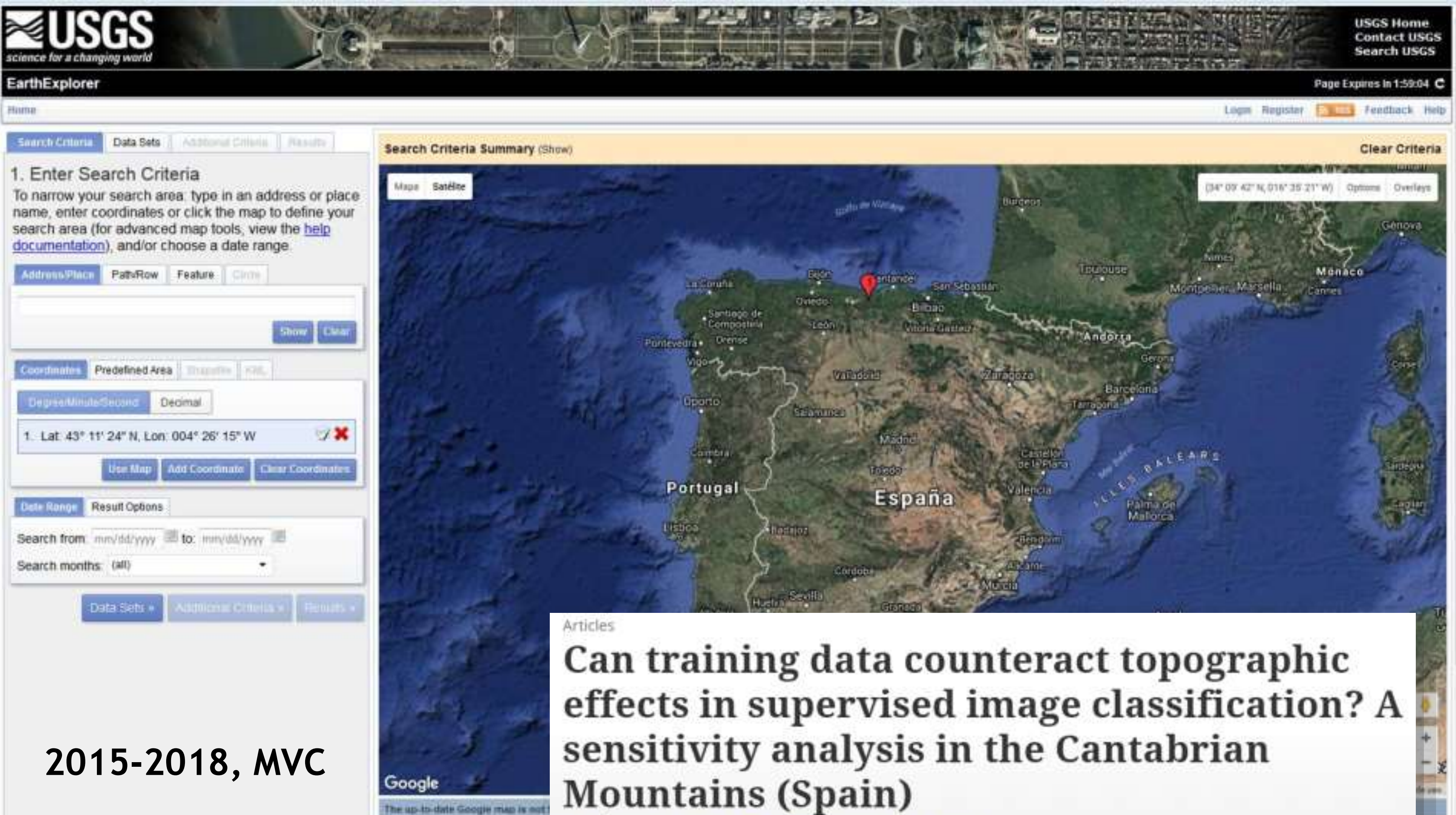
Satellite imagery:
Landsat 5TM and 8OLI 30m
Sentinel 2 A and B, 10-20m
DEIMOS-2, 4m

LiDAR derived data, 5-30m

ENV. LIMITING FACTORS

topography, climate, soil





Articles

Can training data counteract topographic effects in supervised image classification? A sensitivity analysis in the Cantabrian Mountains (Spain)

J.M. Álvarez-Martínez, A. Silió-Calzada & J. Barquín

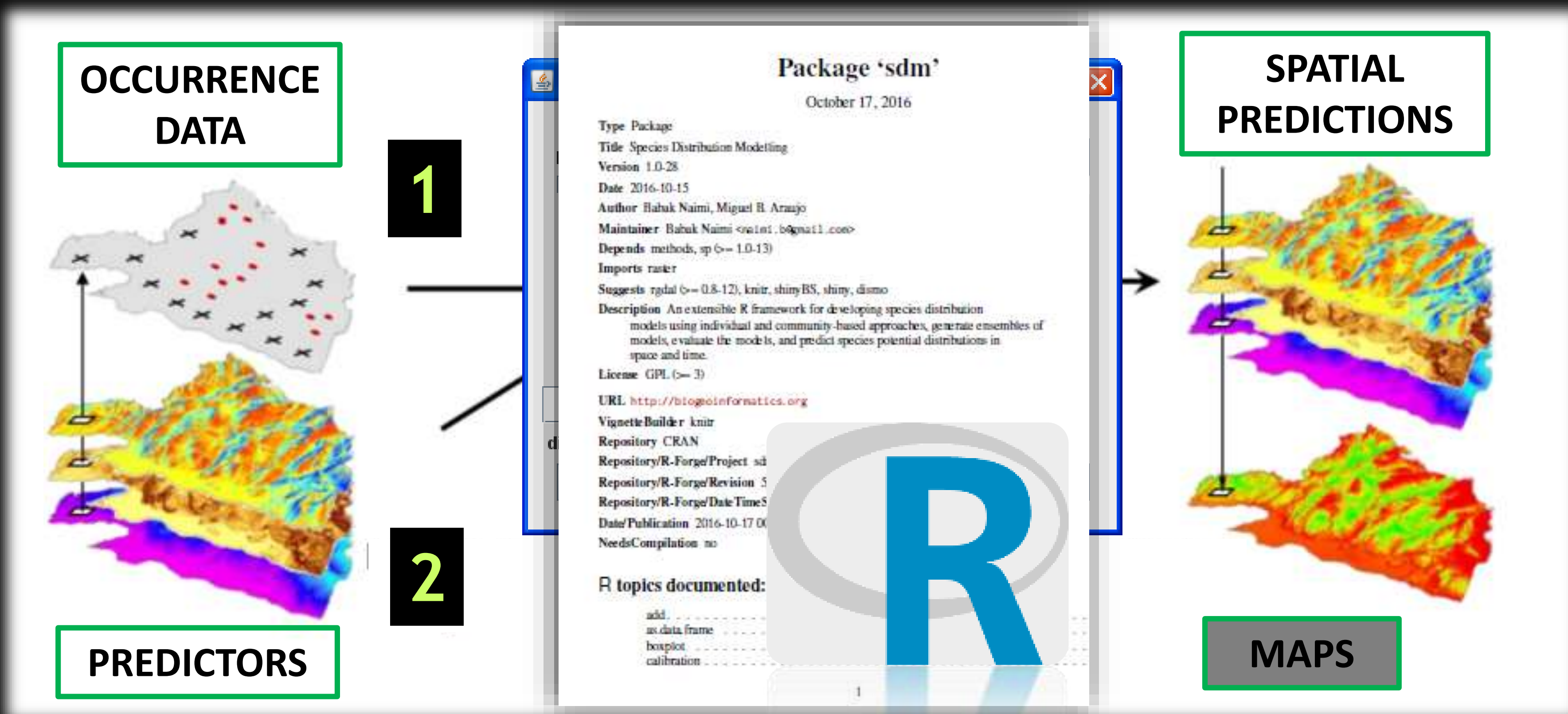
Pages 8646-8669 | Received 18 Mar 2016, Accepted 26 May 2018, Published online: 03 Jul 2018

Download citation https://doi.org/10.1080/01431161.2018.1489163 Check for updates

2015-2018, MVC

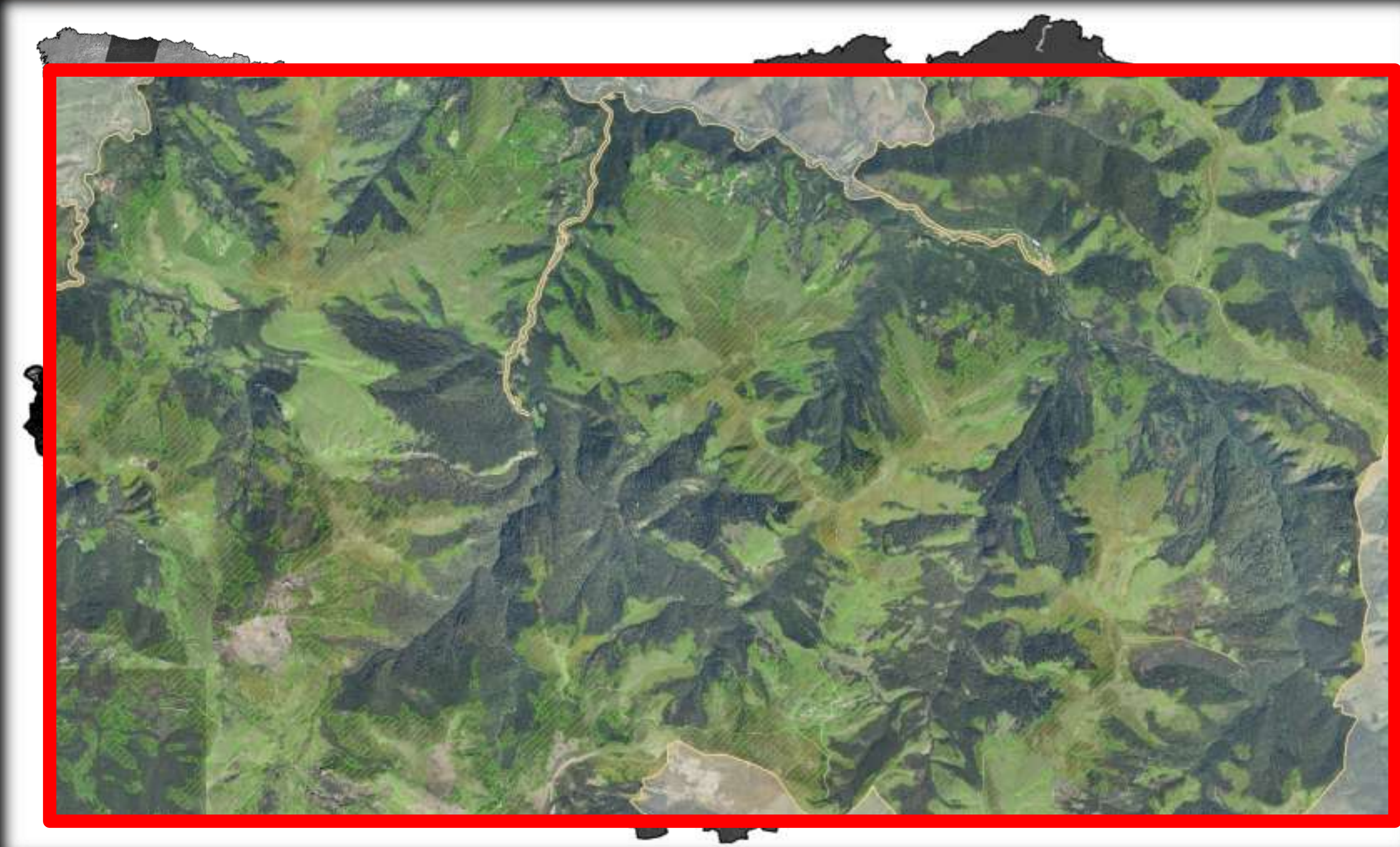
4] MODELLING

A **DATA MINING method or modelling algorithm** for habitat mapping relates occurrence data and the process-based environmental and RS predictors

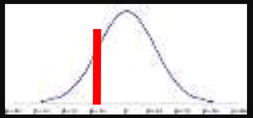


MaxEnt: SWD format, Tunning parameters, *Phillips et al (2006)*
SDM: Multiple algorithms, Bootstraping, *Naimi and Araújo (2016)*

4] MODELLING RESULTS



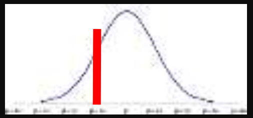
E 1:50 000

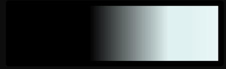


0 1


9120 – Atlantic acidophilous beech forests with *Ilex* and sometimes also *Taxus* in the shrublayer

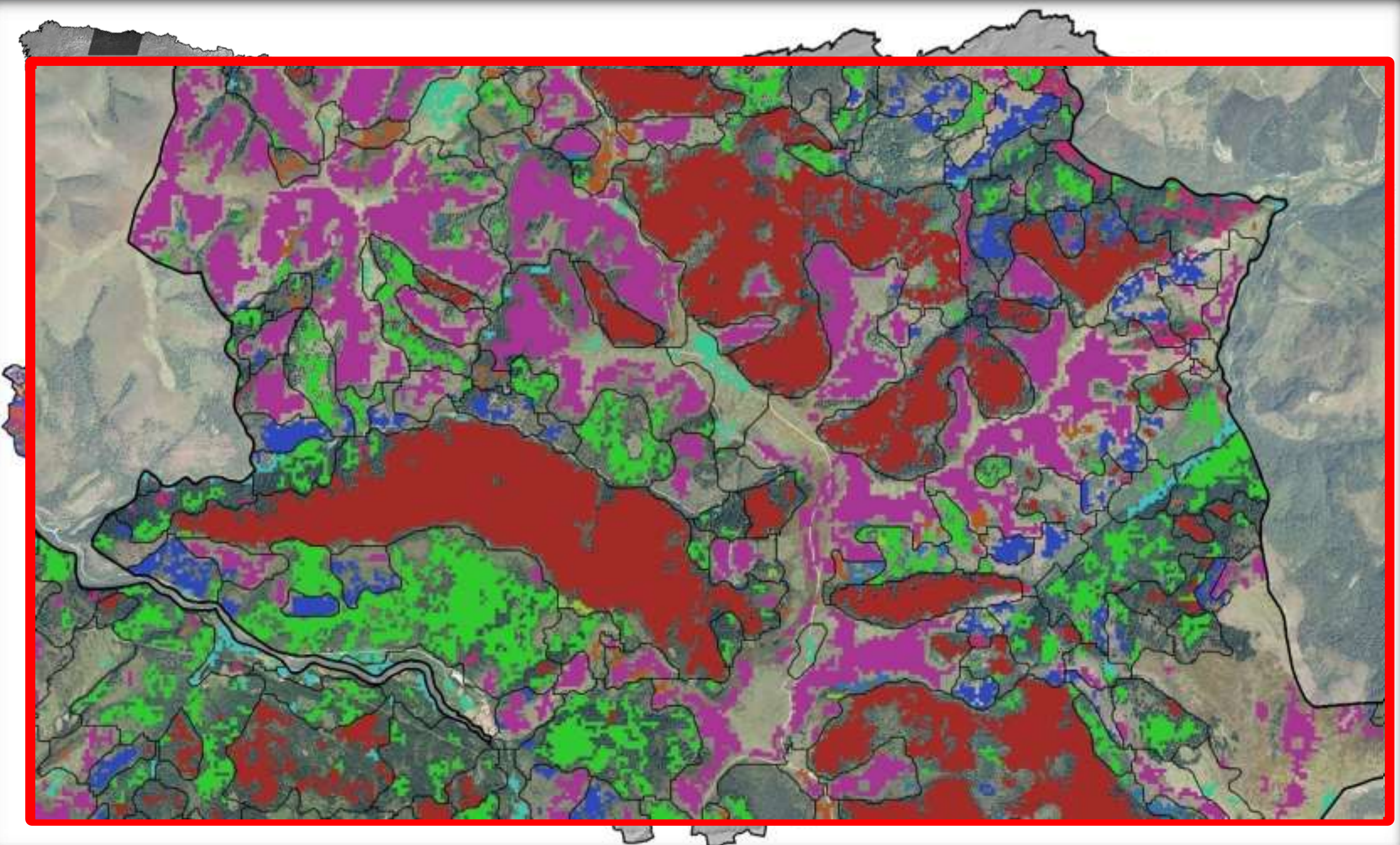
E 1:25 000



0  1

4] MODELLING RESULTS

Automatic and objective: depends on the models



E 1:25 000

DOMINANCE + **UNCERTAINTY**

4] RESULTS VALIDATION

CONFUSION MATRIX

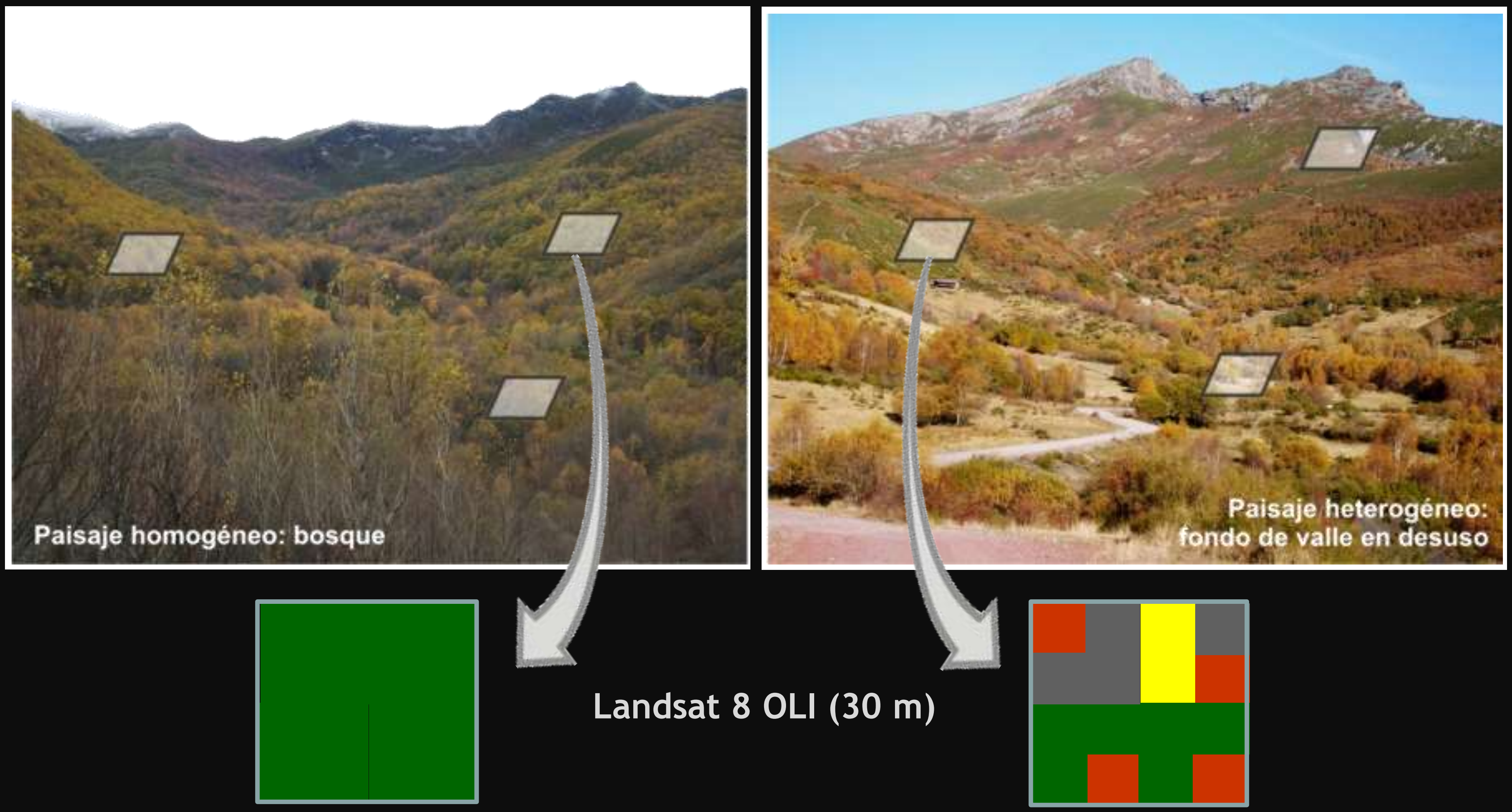
Cross-validation of *local* AOO (concurrence) maps with independent TESTING data

Life form	Predicted	Testing points (obtained from expert fieldwork)																								N	User's accuracy	Commission error
		4030	4060	4090	5120	6160	6170	6210	6230 *	6510	8130	8210	8220	8230	9120	9150	9160	91E0 *	9230	9240	9260	92A0	9330	9340	9380			
Shrublands	4030	64		1	2			[illegible]							[illegible]											72	89%	11%
	4060	[illegible]	35		1				8		1		3													49	71%	29%
	4090	11	6	29			1	4	3	1		1						1	1						1	59	49%	51%
	5120	4			14																					18	78%	22%
Pastures	6160					10					6			2												18	56%	44%
	6170						1							1												2	50%	50%
	6210	3		14				24		4		2														47	51%	49%
	6230 *								21					3												24	88%	13%
	6510	3		2						26						1			1							33	79%	21%
Rock outcrops	8130						1				5	1														7	71%	29%
	8210										1	15												2		18	83%	17%
	8220		1			1							4	3												9	44%	56%
	8230					1					1		1	2												5	40%	60%
Forests	9120														45	2			6							53	85%	15%
	9150												1		[illegible]	9										19	47%	53%
	9160									4	3	1			2	7	15	1	2					2		37	41%	59%
	91E0 *									2					1		2		1							6	0%	100%
	9230	1													13		4		41		1			1		61	67%	33%
	9240														1				1					1		3	0%	100%
	9260																				1					1	100%	0%
	92A0																									0	0%	0%
	9330																						2			2	100%	0%
	9340											1			3				1				2	29		36	81%	19%
	9380														1											1	0%	100%
	n	87	42	46	17	12	3	32	32	37	17	21	9	11	76	19	21	2	54	0	2	0	4	35	1	580		
	Producer's accuracy	74%	83%	63%	82%	83%	33%	75%	66%	70%	29%	71%	44%	18%	59%	47%	71%	0%	76%	0%	50%	0%	50%	83%	0%		392	
	Omission error	26%	17%	37%	18%	17%	67%	25%	34%	30%	71%	29%	56%	82%	41%	53%	29%	100%	24%	0%	50%	0%	50%	17%	100%			67.59%

INDEPENDENT FIELD CHECKED DATA

67.59% of overall accuracy

What actually matters?



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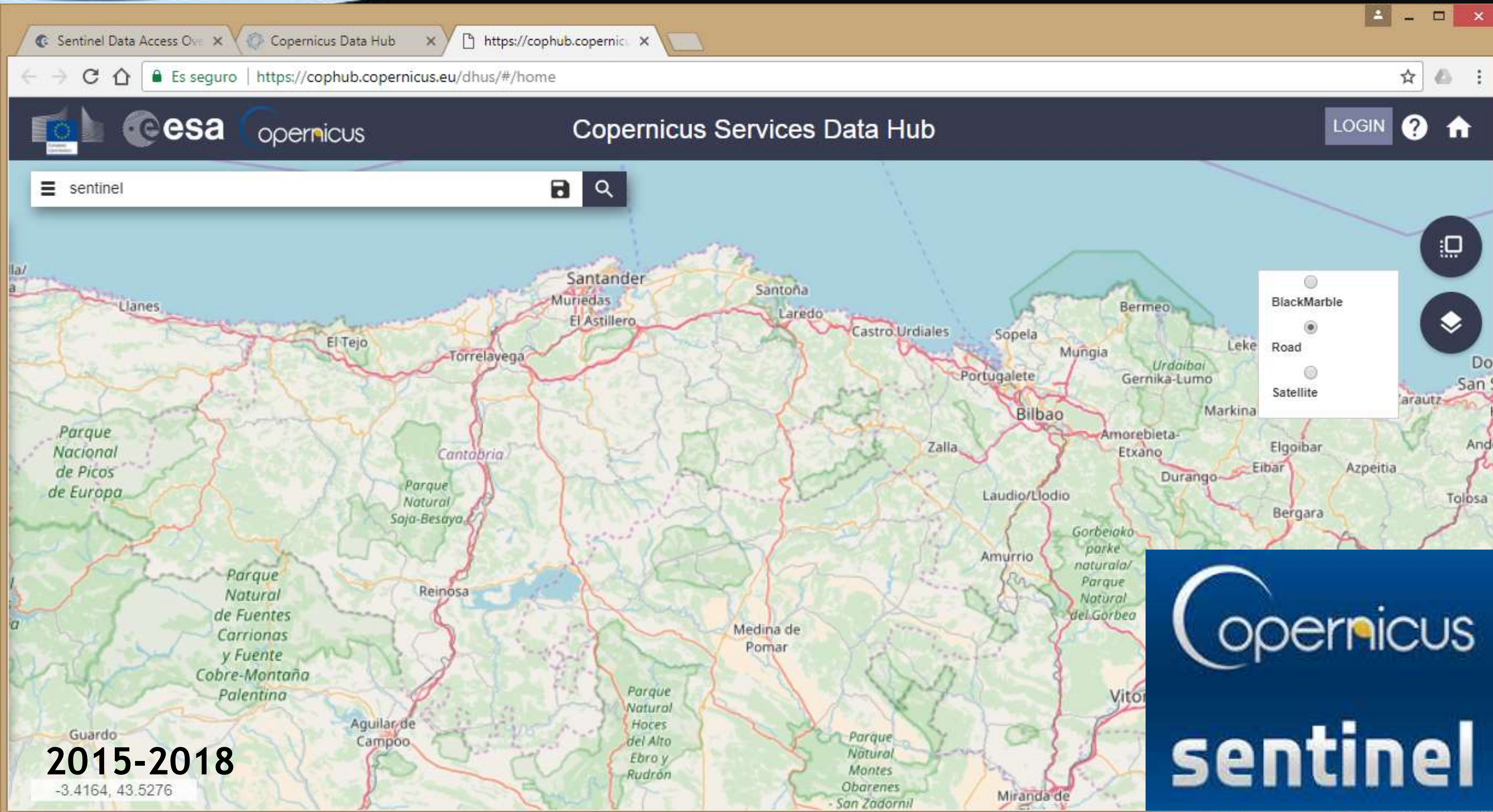
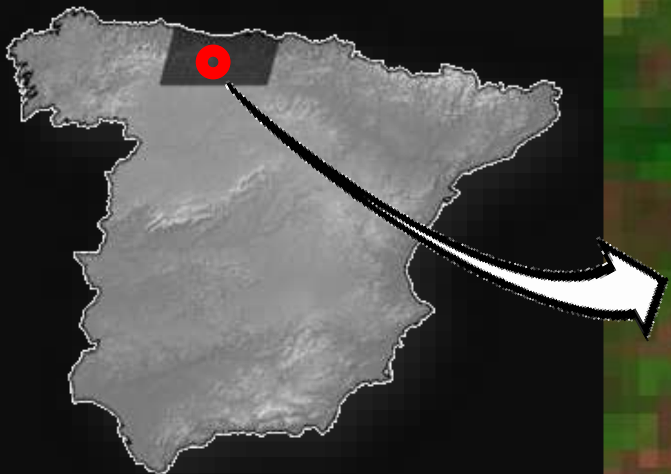
SATELLITE IMAGERY

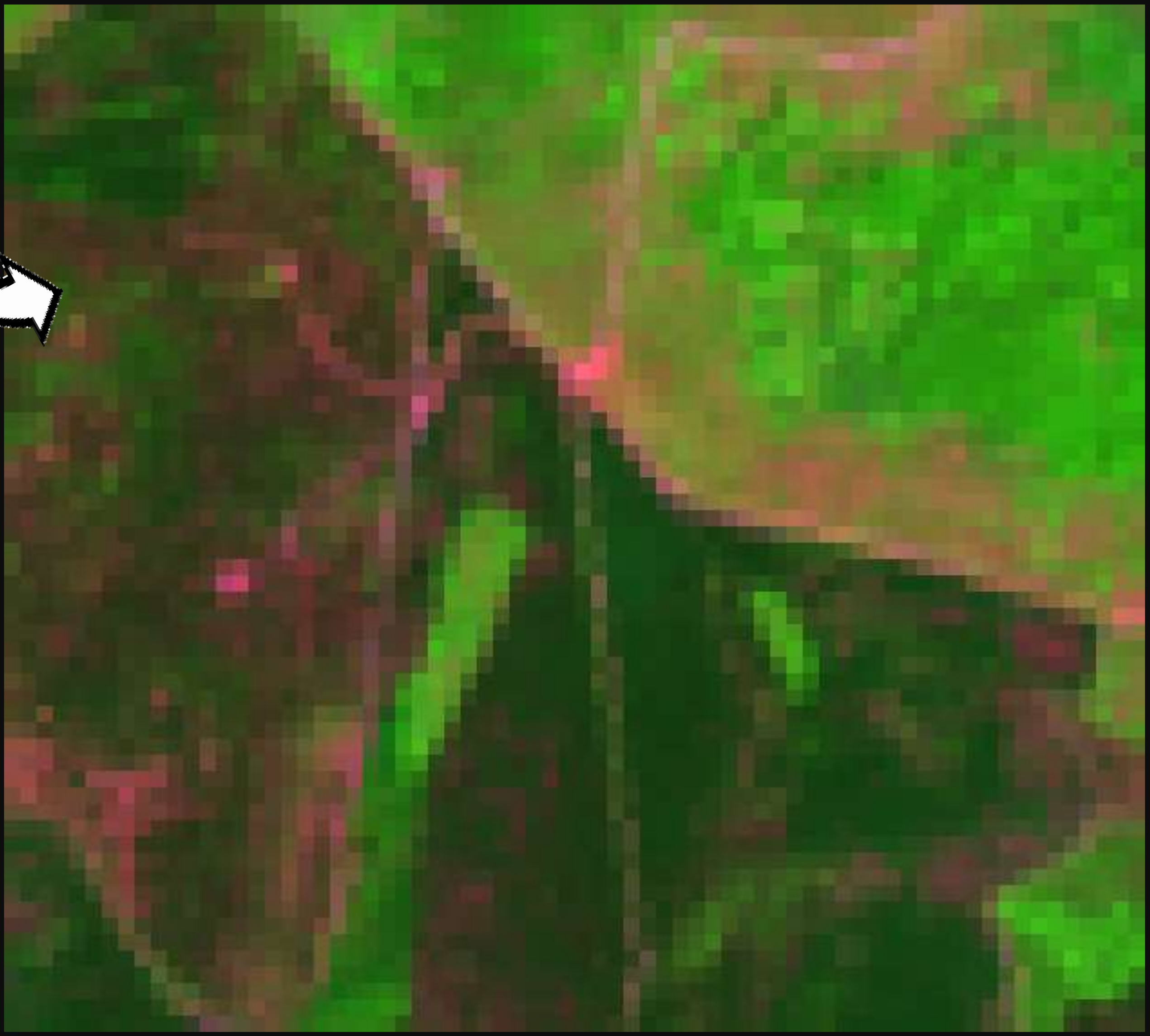


The Copernicus Services Data Hub provides a dedicated access to Sentinels user products. Login required.
https://cophub.copernicus.eu/dhus/#/home

LANDSAT 8 OLI IMAGERY

Higher sun elevation and minimum cloud cover from USGS and ESA



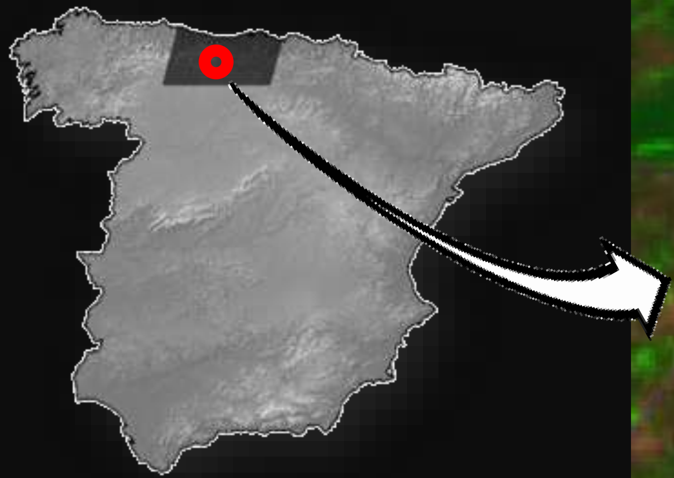


Zoom

175_033
false_color_752
Reflect BOA
Roads detail

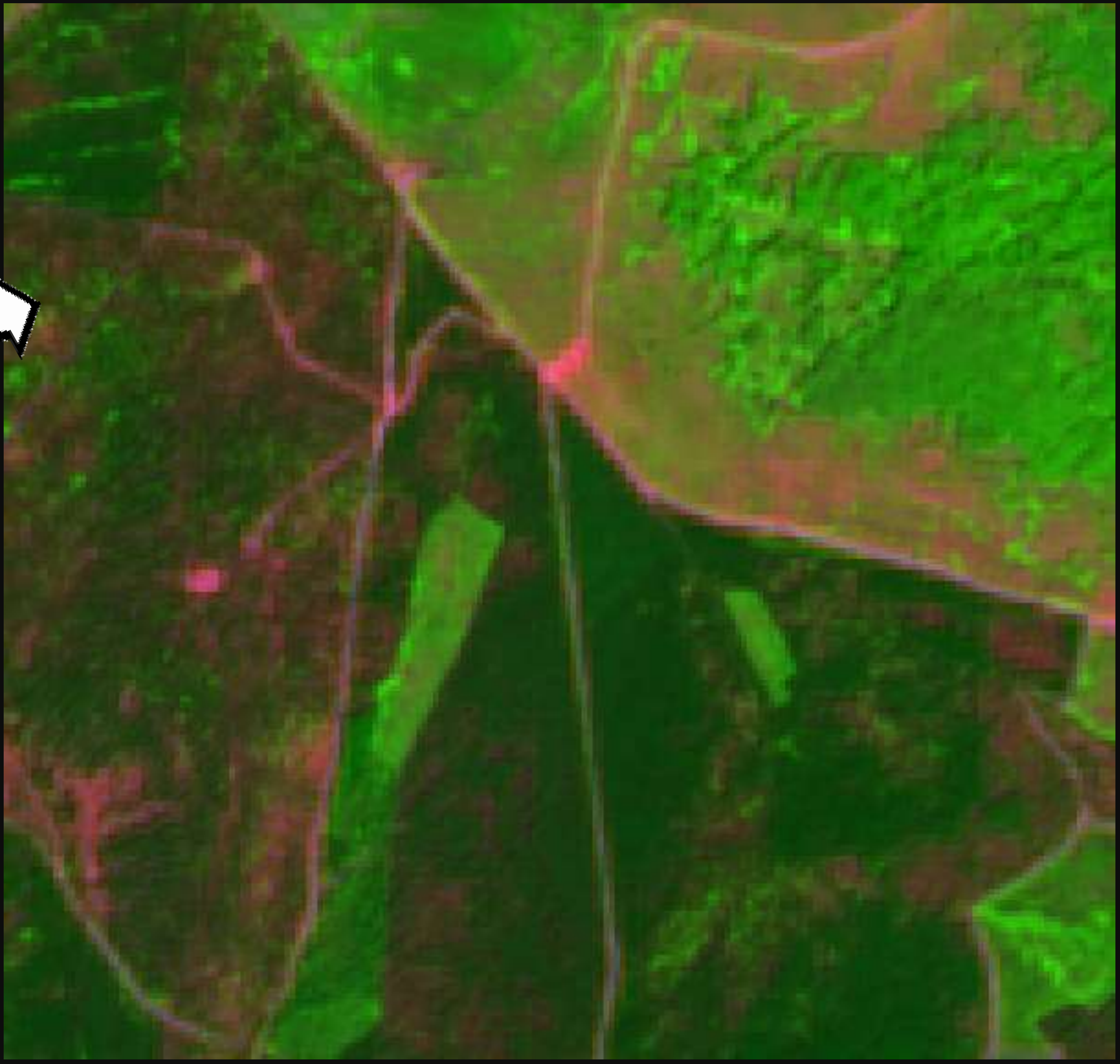
SENTINEL 2A IMAGERY

Higher sun elevation and minimum cloud cover from ESA

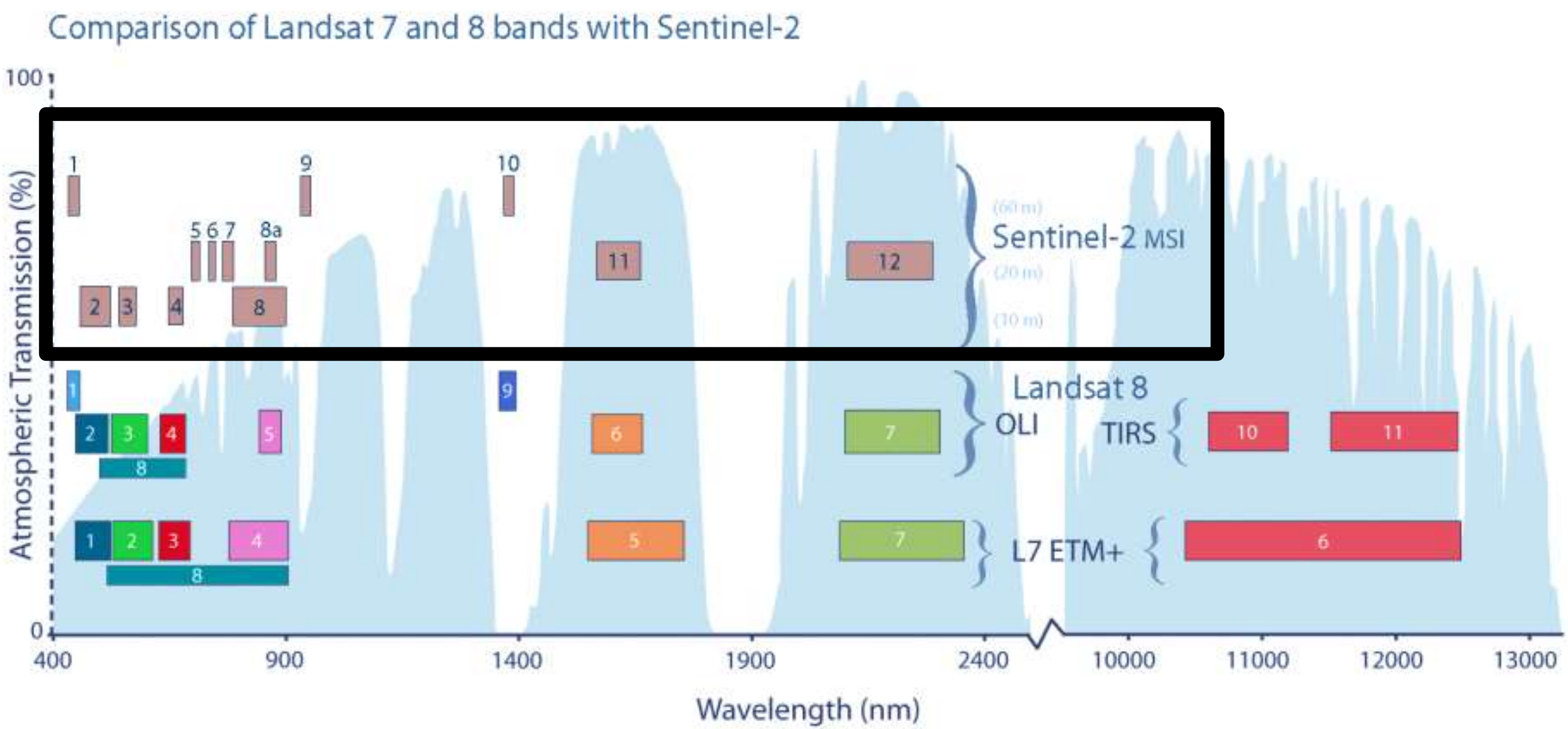


Zoom

Sentinel_2A_1282
ReflecBOA_topo
Roads detail

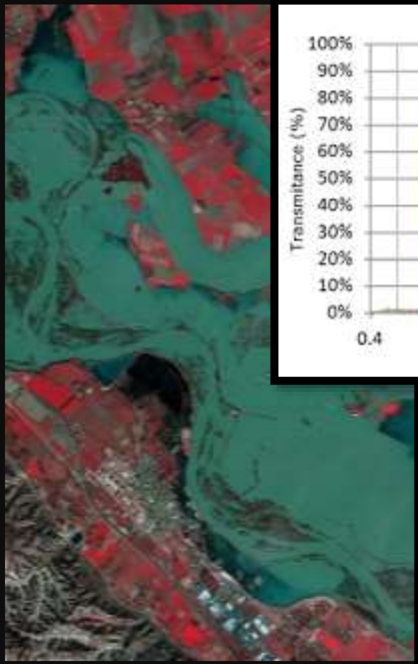


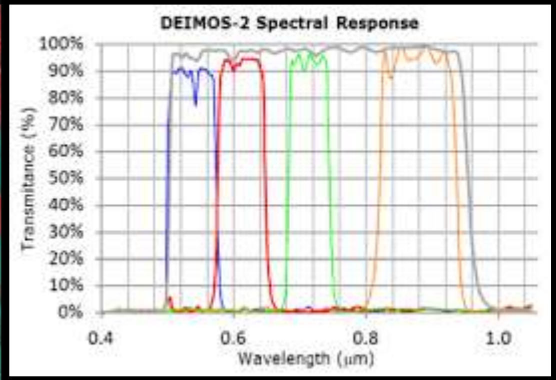
SENTINEL 2A IMAGERY



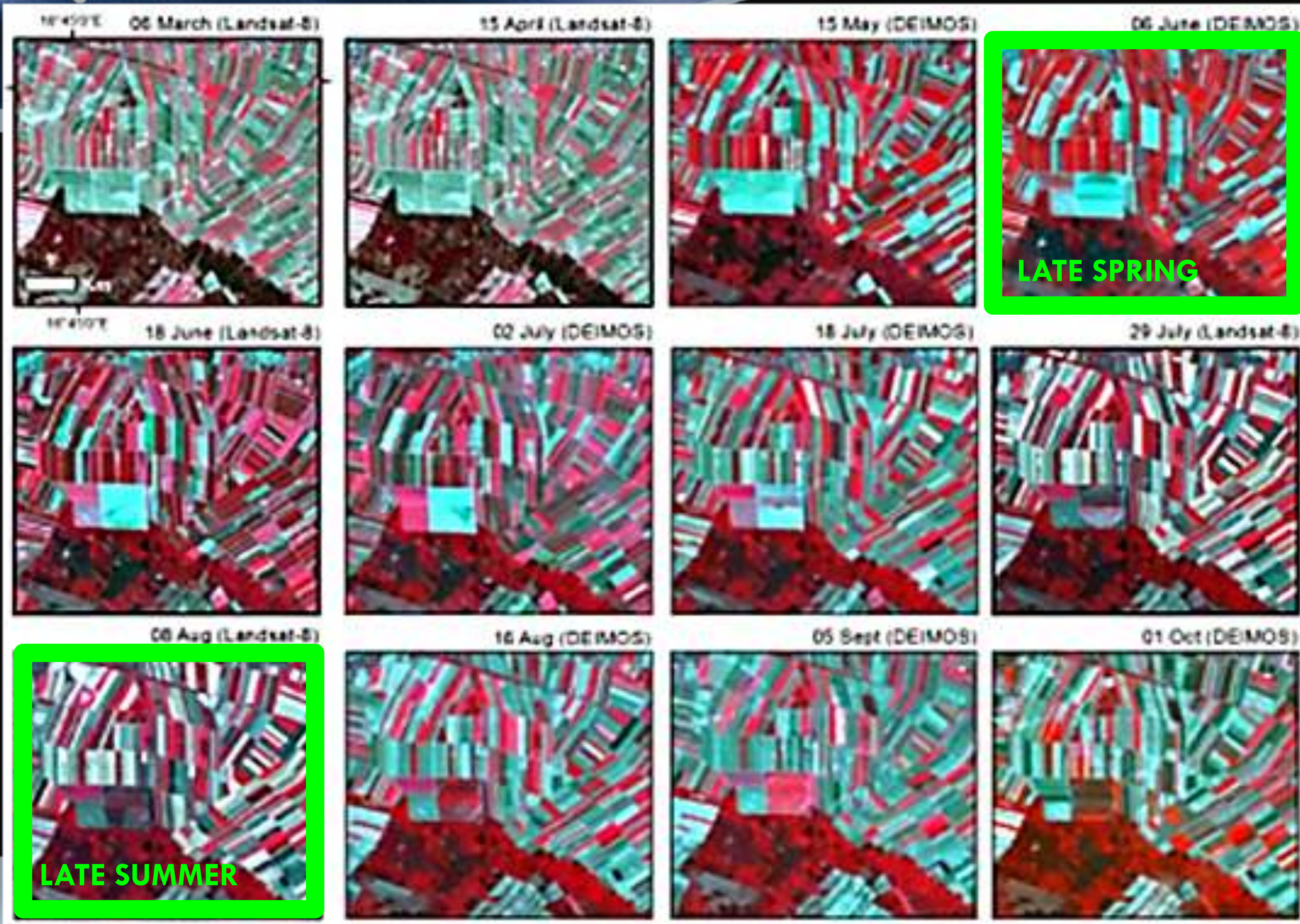
VHR DEIMOS-2 IMAGERY

VHR spatial resolution and RGB and NIR spectral data





PAN: 450-900 nm
Blue: 460-520 nm
Green: 530-600 nm
Red: 640-700 nm
NIR: 770-890 nm

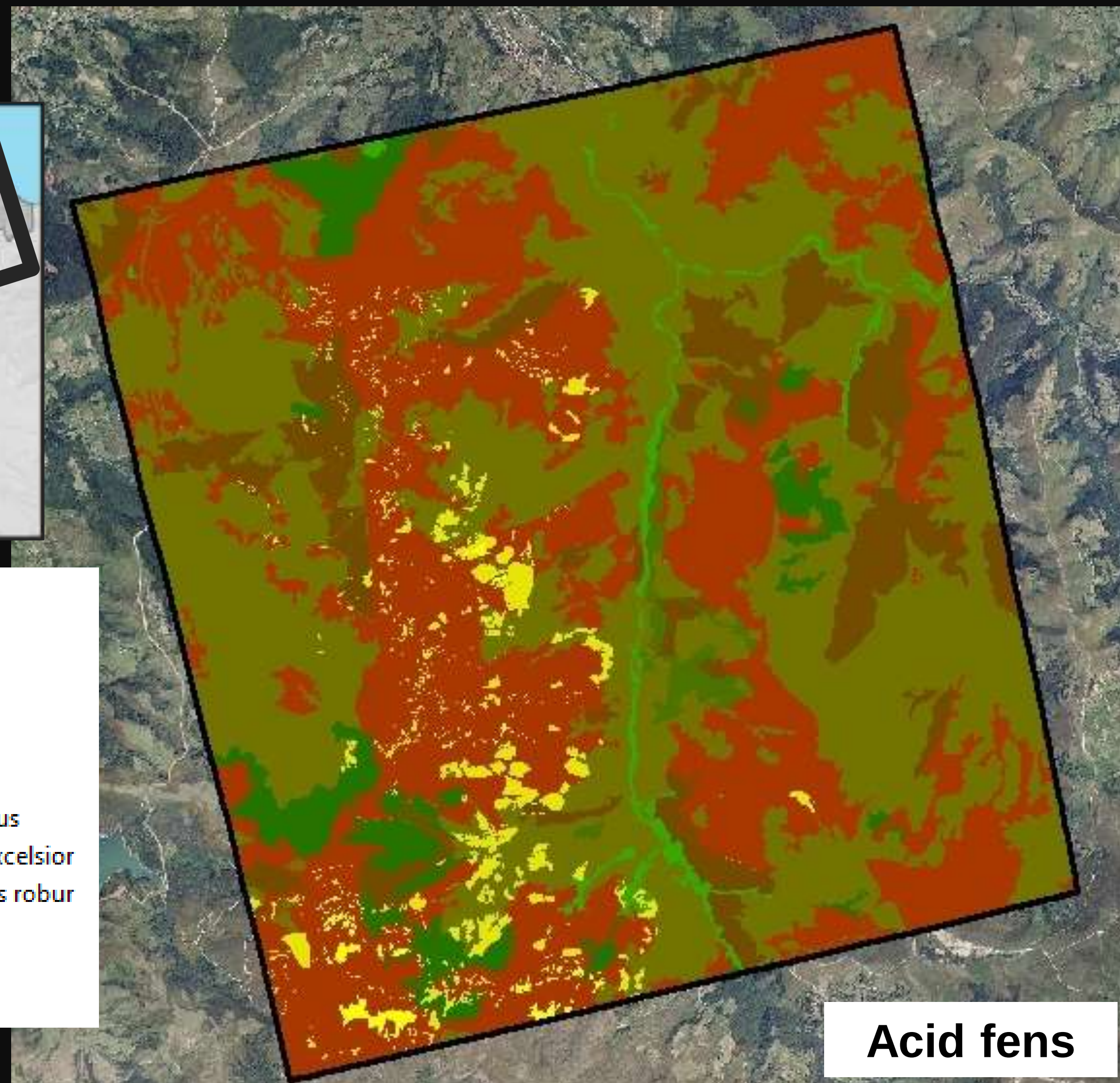

06 March (Landsat-8)
15 April (Landsat-8)
15 May (DEIMOS)
06 June (DEIMOS)
LATE SPRING
18 June (Landsat-8)
02 July (DEIMOS)
18 July (DEIMOS)
29 July (Landsat-8)
08 Aug (Landsat-8)
LATE SUMMER
16 Aug (DEIMOS)
05 Sept (DEIMOS)
01 Oct (DEIMOS)

4] MODELLING

Study area: Sierra del Escudo (Natura2000)

Vegetation (habitat) types:

- Oligotrophic waters
- European dry heaths
- Lowland hay meadows
- * Blanket bogs
- Transition mires and quaking bogs
- Undefined bog habitat type
- Atlantic acidophilous beech forests with Ilex and Taxus
- * Alluvial forests with Alnus glutinosa and Fraxinus excelsior
- Forests of Quercus pyrenaica y robledales de Quercus robur
- Forests of castanea sativa
- Other shrub habitat types (not Annex I)
- Other forest habita types (not Annex I)



4] MODELLING RESULTS

Landsat 8 MVC

Landsat8 x2

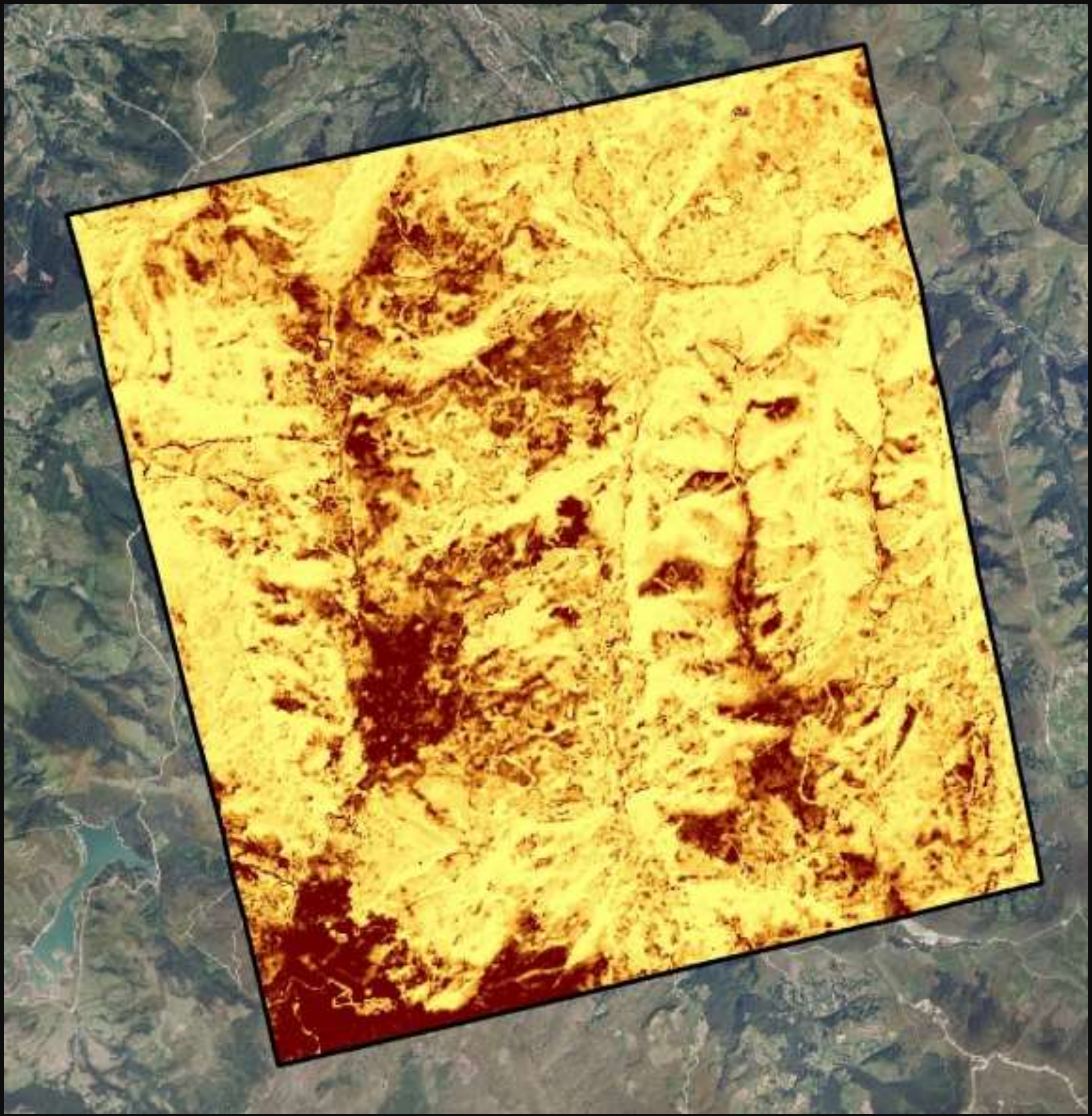
Sentinel2 x2

Deimos2 x2

+LiDAR +MDT

High suitability

Low suitability



MODELLING RESULTS

Landsat 8 MVC

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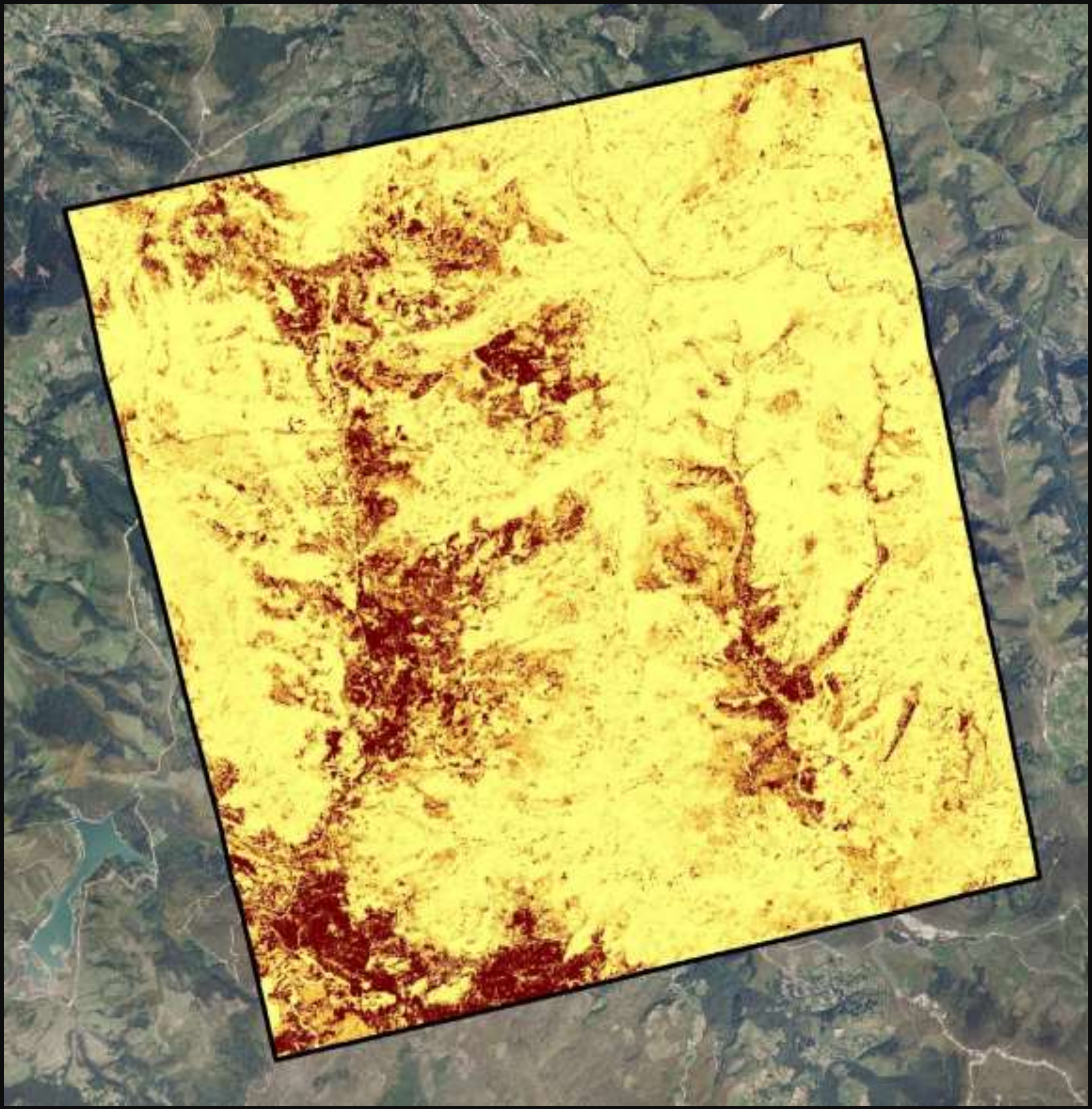

MODELLING RESULTS

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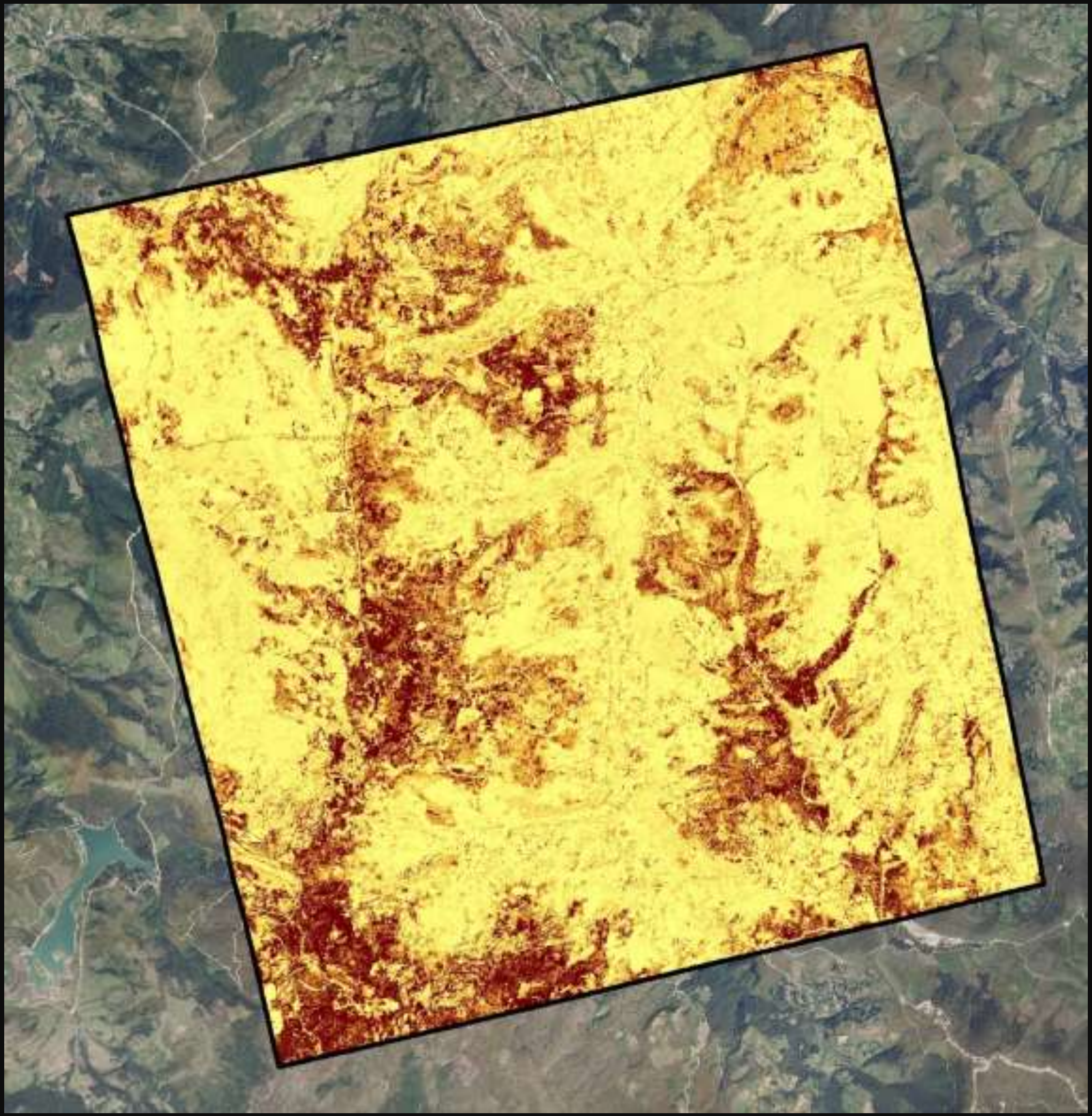

MODELLING RESULTS

Landsat 8 MVC
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High suitability

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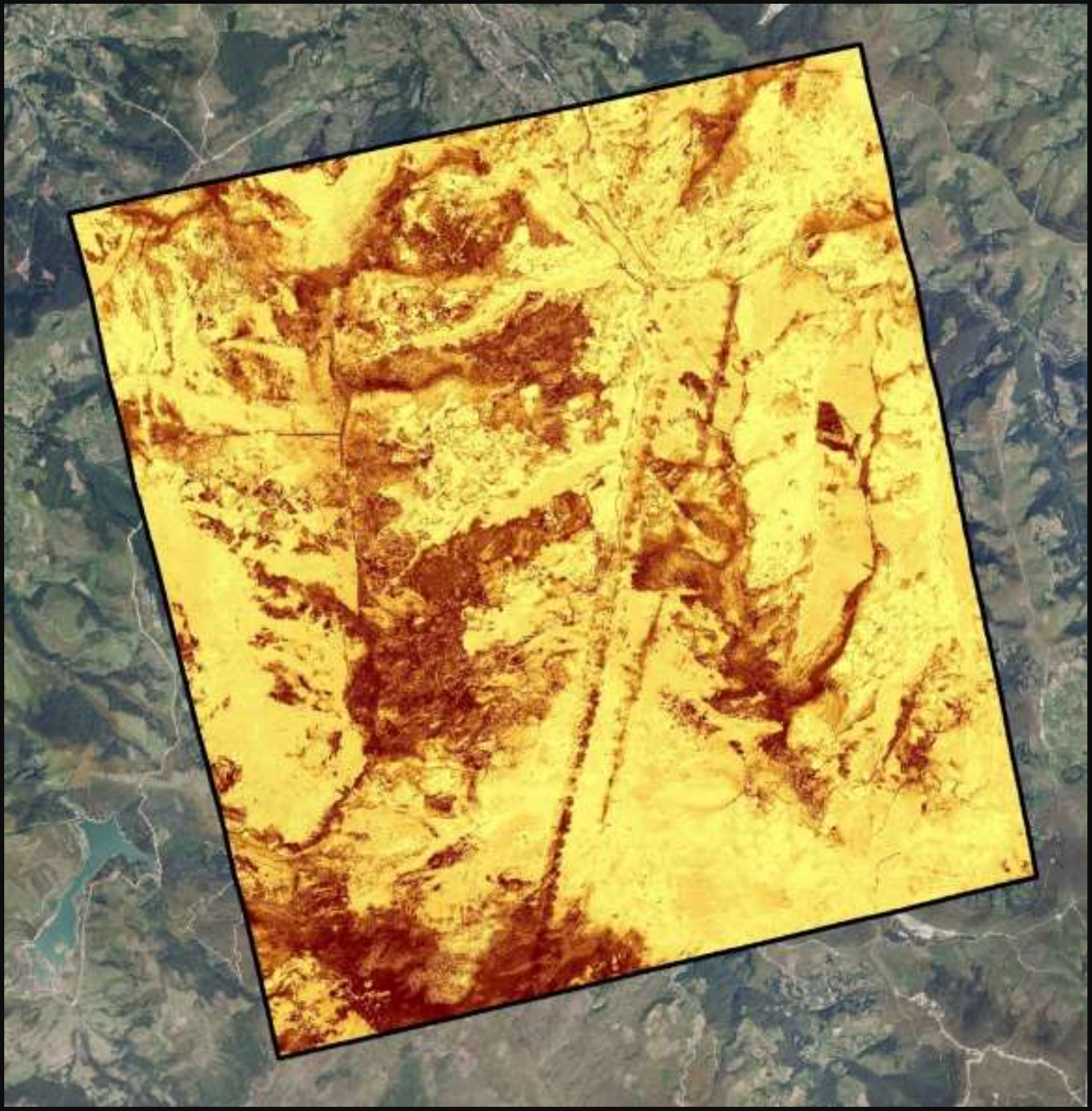

MODELLING RESULTS

Landsat 8 MVC
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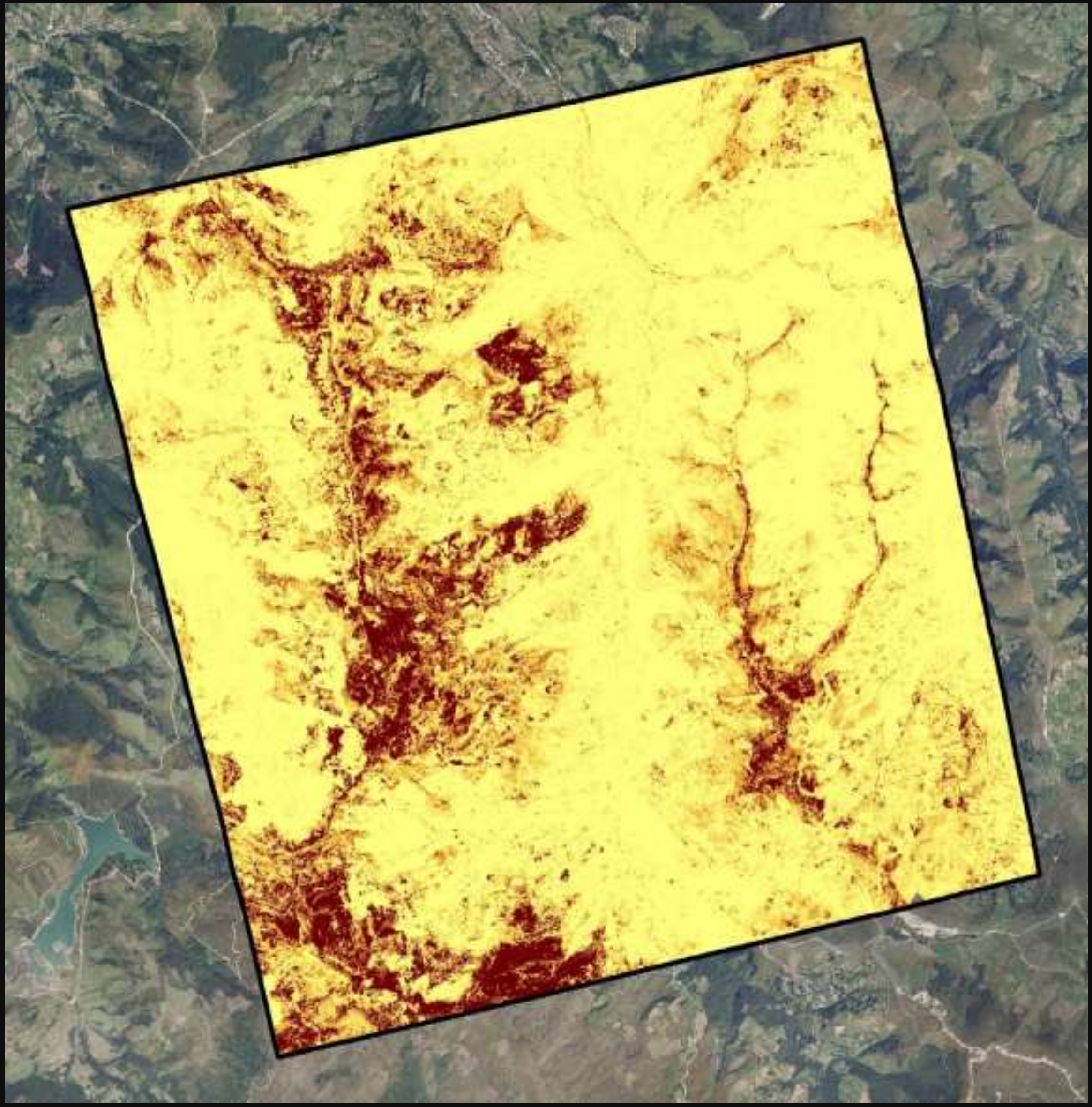

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VALIDATION

HABITAT	N	Landsat x 1 (MVC)			Landsat x 2			Sentinel x 2			Deimos x 2		
		M	M+L	M+L+E	M	M+L	M+L+E	M	M+L	M+L+E	M	M+L	M+L+E
7130	*73*	0.622	0.615	0.617	0.556	0.562	0.591	0.689	0.687	0.659	0.638	0.644	0.608
7140	*109*	0.519	0.522	0.544	0.540	0.543	0.564	0.592	0.604	0.596	0.579	0.571	0.590
7150	*1*	0.203	0.231	0.493	0.313	0.306	0.536	0.350	0.381	0.599	0.796	0.760	0.834
71XX	*113*	0.514	0.515	0.546	0.629	0.621	0.597	0.593	0.592	0.595	0.526	0.511	0.536
Bogs>0.1 ha	***296***	**0.541**	**0.541**	**0.563**	**0.577**	**0.576**	**0.583**	**0.616**	**0.619**	**0.611**	**0.574**	**0.567**	**0.575**

HABITAT	N	Landsat x 1 (MVC)			Landsat x 2			Sentinel x 2			Deimos x 2		
		M	M+L	M+L+E	M	M+L	M+L+E	M	M+L	M+L+E	M	M+L	M+L+E
4030	*11561*	0.310	0.310	0.219	0.340	0.336	0.207	0.236	0.228	0.166	0.339	0.335	0.214
6510	*541*	0.217	0.186	0.163	0.126	0.111	0.105	0.084	0.075	0.072	0.237	0.198	0.171
9120	*1408*	0.093	0.034	0.035	0.064	0.035	0.030	0.103	0.044	0.033	0.153	0.053	0.039
9190	*395*	0.136	0.065	0.019	0.100	0.056	0.016	0.047	0.029	0.010	0.143	0.067	0.014
9230	*6198*	0.088	0.041	0.024	0.069	0.038	0.020	0.045	0.027	0.016	0.116	0.042	0.023
9260	*314*	0.044	0.020	0.007	0.059	0.029	0.008	0.039	0.016	0.007	0.166	0.033	0.007
90X0	*7101*	0.186	0.161	0.106	0.165	0.146	0.086	0.103	0.092	0.059	0.185	0.156	0.094
80XX	*2763*	0.130	0.085	0.060	0.121	0.076	0.049	0.060	0.045	0.035	0.192	0.081	0.059
Other habitats	***30281***	**0.202**	**0.178**	**0.124**	**0.201**	**0.182**	**0.111**	**0.136**	**0.122**	**0.087**	**0.229**	**0.188**	**0.119**

Acid fens

Validation at 2000 meters

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MODELLING RESULTS

Locally monitored acid fens

Landsat 8 MVC
Landsat8 x2
Sentinel2 x2
Deimos2 x2
+LiDAR +MDT

High suitability

Low suitability

MODELLING RESULTS

Landsat 8 MVC

Landsat8 x2

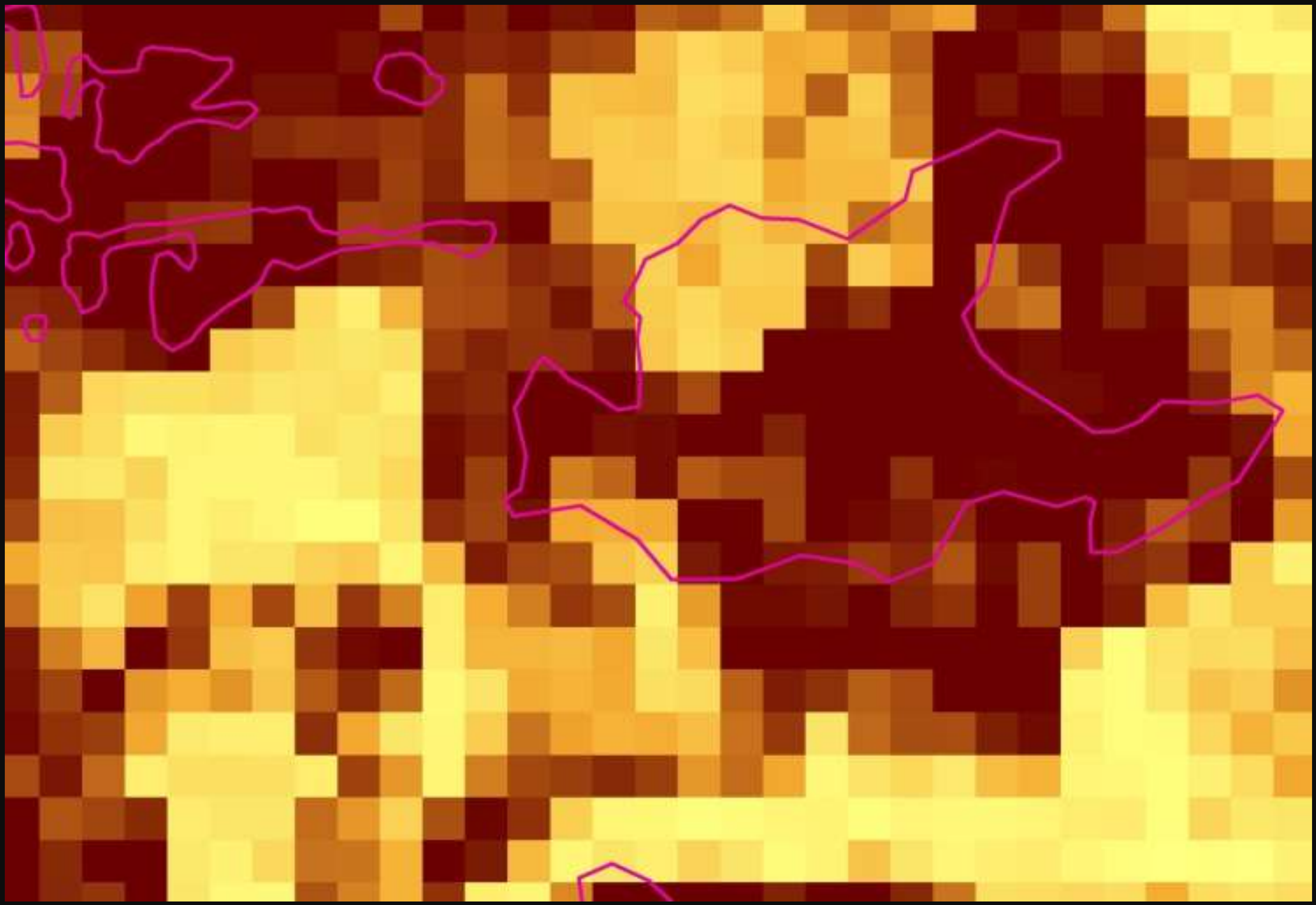
Sentinel2 x2

Deimos2 x2

+LiDAR +MDT

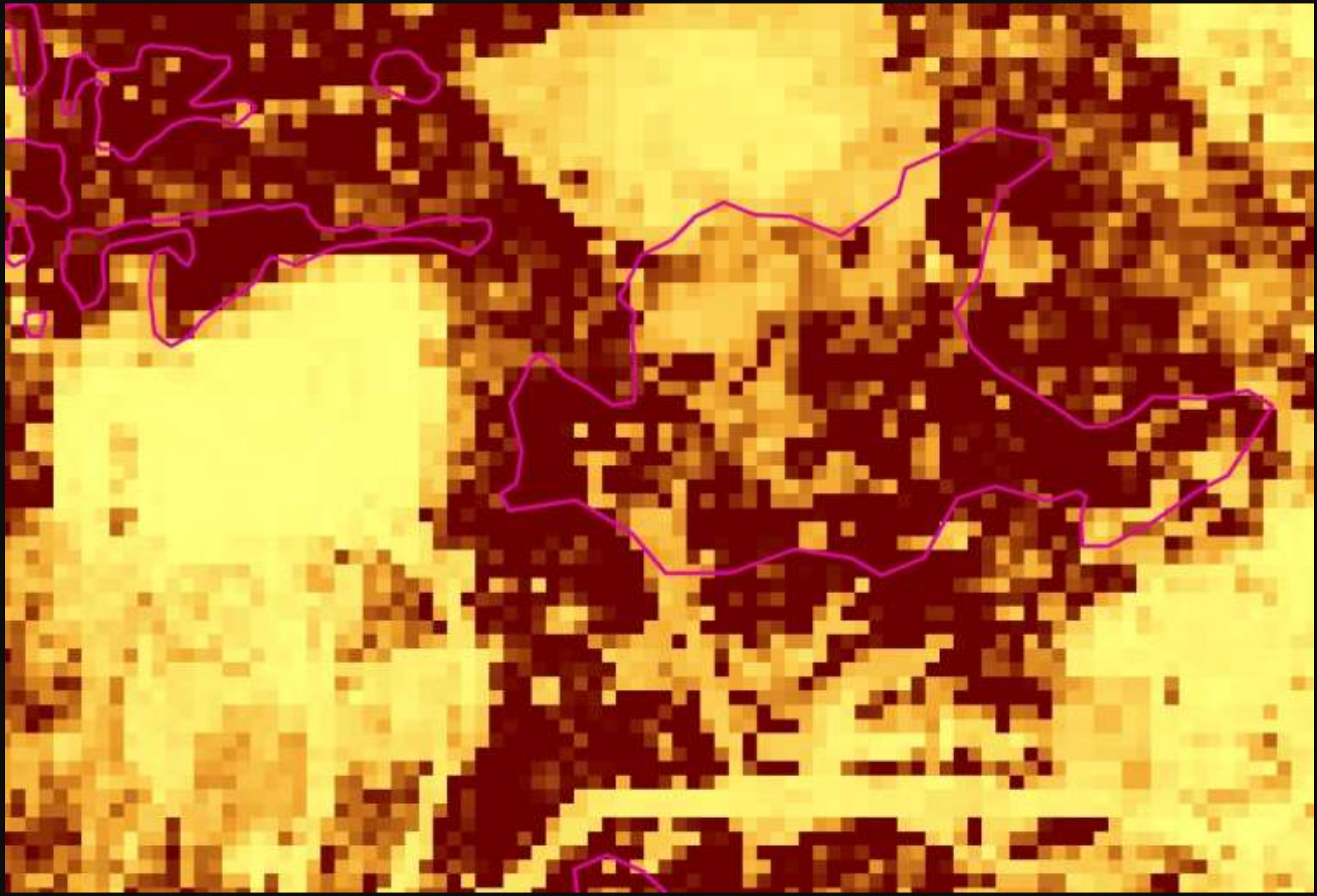
High
suitability

Low
suitability

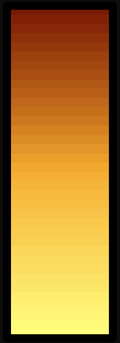


MODELLING RESULTS

Landsat 8 MVC
Landsat8 x2
Sentinel2 x2
Deimos2 x2
+LiDAR +MDT



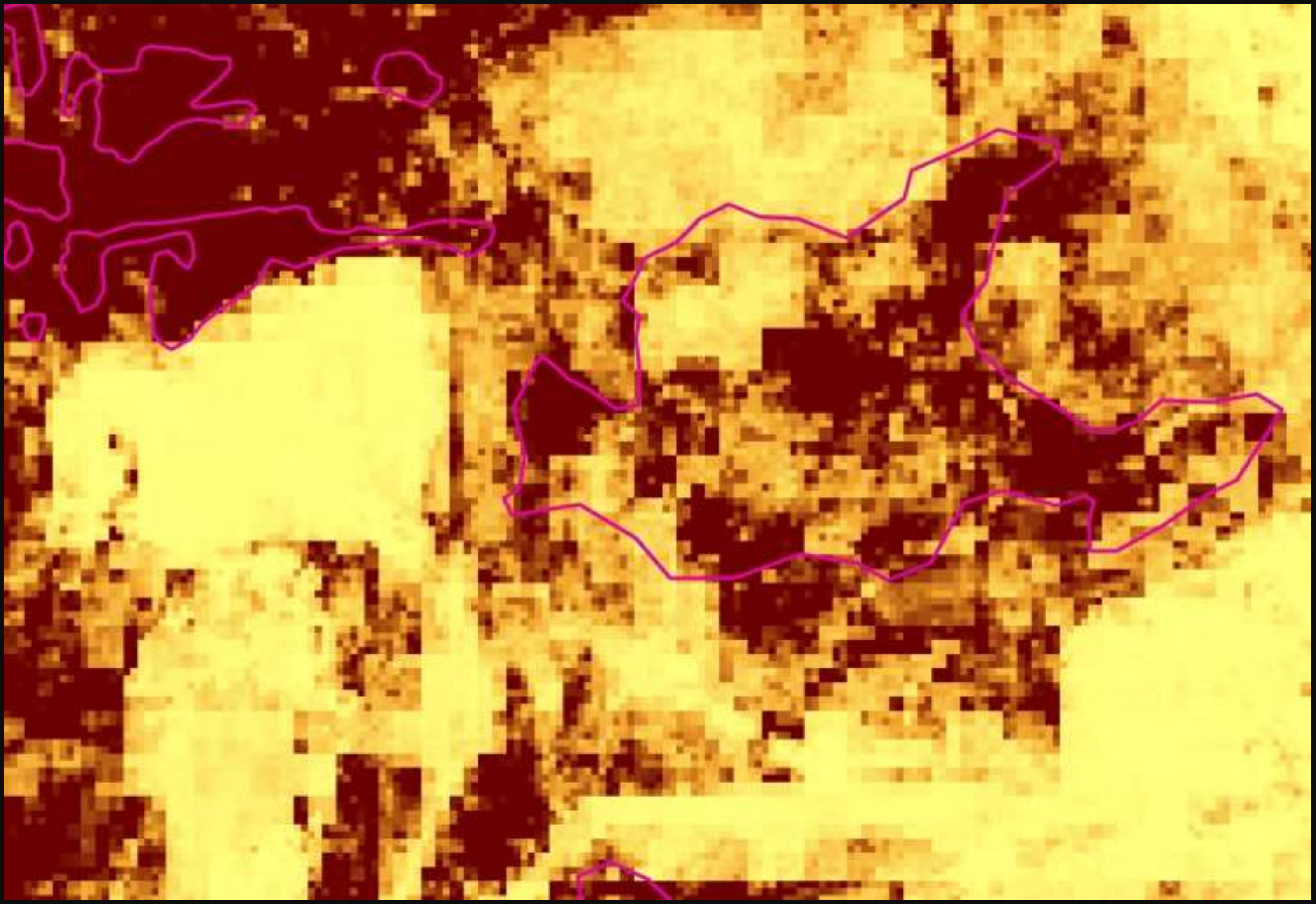
High suitability



Low suitability

MODELLING RESULTS

Landsat 8 MVC
Landsat8 x2
Sentinel2 x2
Deimos2 x2
+LiDAR +MDT

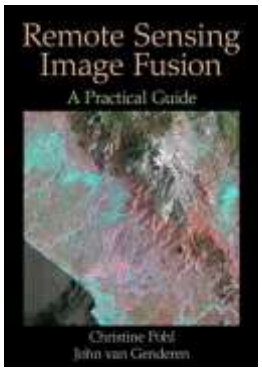


High suitability

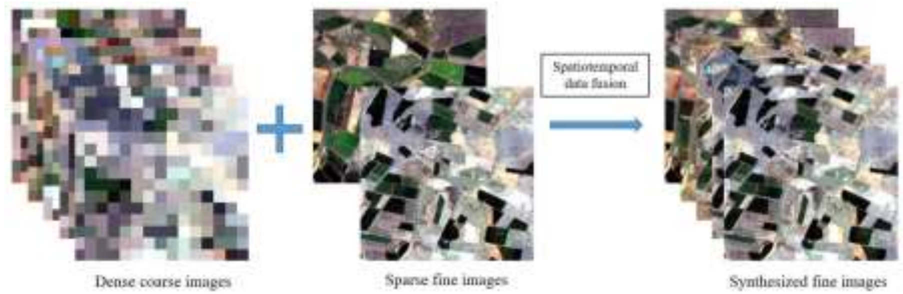
Low suitability

VALIDATION

HABITAT	N	Landsat x 1 (MVC)			Landsat x 2			Sentinel x 2			Deimos x 2			All x 2		
		M	M+L	M+L+E	M	M+L	M+L+E	M	M+L	M+L+E	M	M+L	M+L+E	M	M+L	M+L+E
7130	*73*	0.622	0.615	0.617	0.556	0.562	0.591	0.689	0.687	0.659	0.638	0.644	0.608	0.702	0.699	0.667
7140	*109*	0.519	0.522	0.544	0.540	0.543	0.564	0.592	0.604	0.596	0.579	0.571	0.590	0.637	0.647	0.645
7150	*1*	0.203	0.231	0.493	0.313	0.306	0.536	0.350	0.381	0.599	0.796	0.760	0.834	0.380	0.399	0.527
71XX	*113*	0.514	0.515	0.546	0.629	0.621	0.597	0.593	0.592	0.595	0.526	0.511	0.536	0.642	0.641	0.640
Bogs>0.1 ha	***296***	**0.541**	**0.541**	**0.563**	**0.577**	**0.576**	**0.583**	**0.616**	**0.619**	**0.611**	**0.574**	**0.567**	**0.575**	**0.654**	**0.657**	**0.648**



DATA FUSION TECHNIQUES



4030	*11561*	0.310	0.310	0.219	0.340	0.336	0.207	0.236	0.228	0.166	0.339	0.335	0.214	0.166	0.163	0.139
6510	*541*	0.217	0.186	0.163	0.126	0.111	0.105	0.084	0.075	0.072	0.237	0.198	0.171	0.068	0.058	0.060
9120	*1408*	0.093	0.034	0.035	0.064	0.035	0.030	0.103	0.044	0.033	0.153	0.053	0.039	0.046	0.028	0.023
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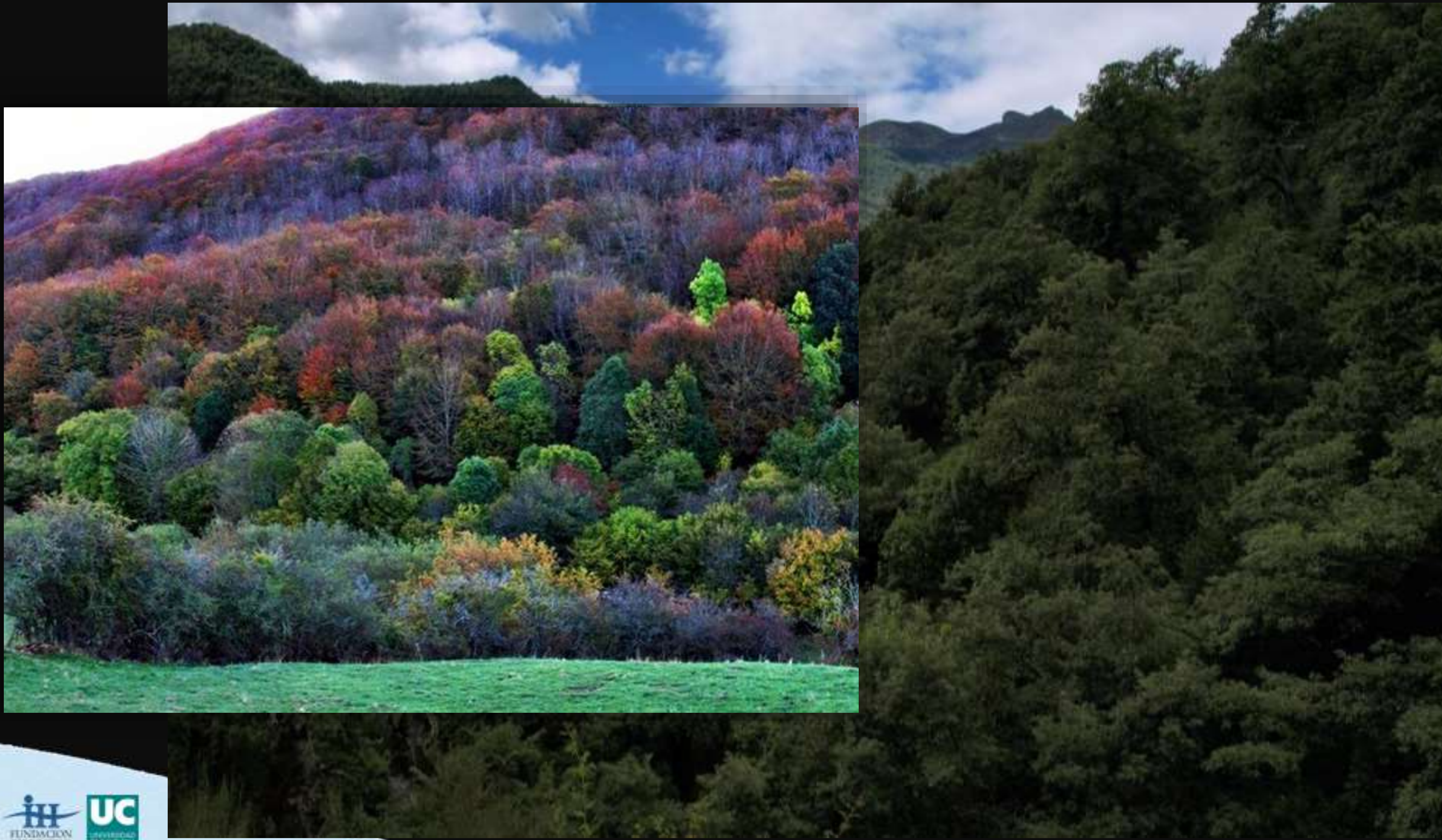
9260	*314*	0.044	0.020	0.007	0.059	0.029	0.008	0.039	0.016	0.007	0.166	0.033	0.007	0.016	0.010	0.007
90X0	*7101*	0.186	0.161	0.106	0.165	0.146	0.086	0.103	0.092	0.059	0.185	0.156	0.094	0.064	0.059	0.047
80XX	*2763*	0.130	0.085	0.060	0.121	0.076	0.049	0.060	0.045	0.035	0.192	0.081	0.059	0.050	0.038	0.032
Other habitats	***30281***	**0.202**	**0.178**	**0.124**	**0.201**	**0.182**	**0.111**	**0.136**	**0.122**	**0.087**	**0.229**	**0.188**	**0.119**	**0.092**	**0.086**	**0.072**

Validation at 2000 meters

What actually matters?

What actually matters?

Many classes are similar in composition, structure and function (high EUNIS level) and need to be reorganized before bieng modelled



What actually matters?

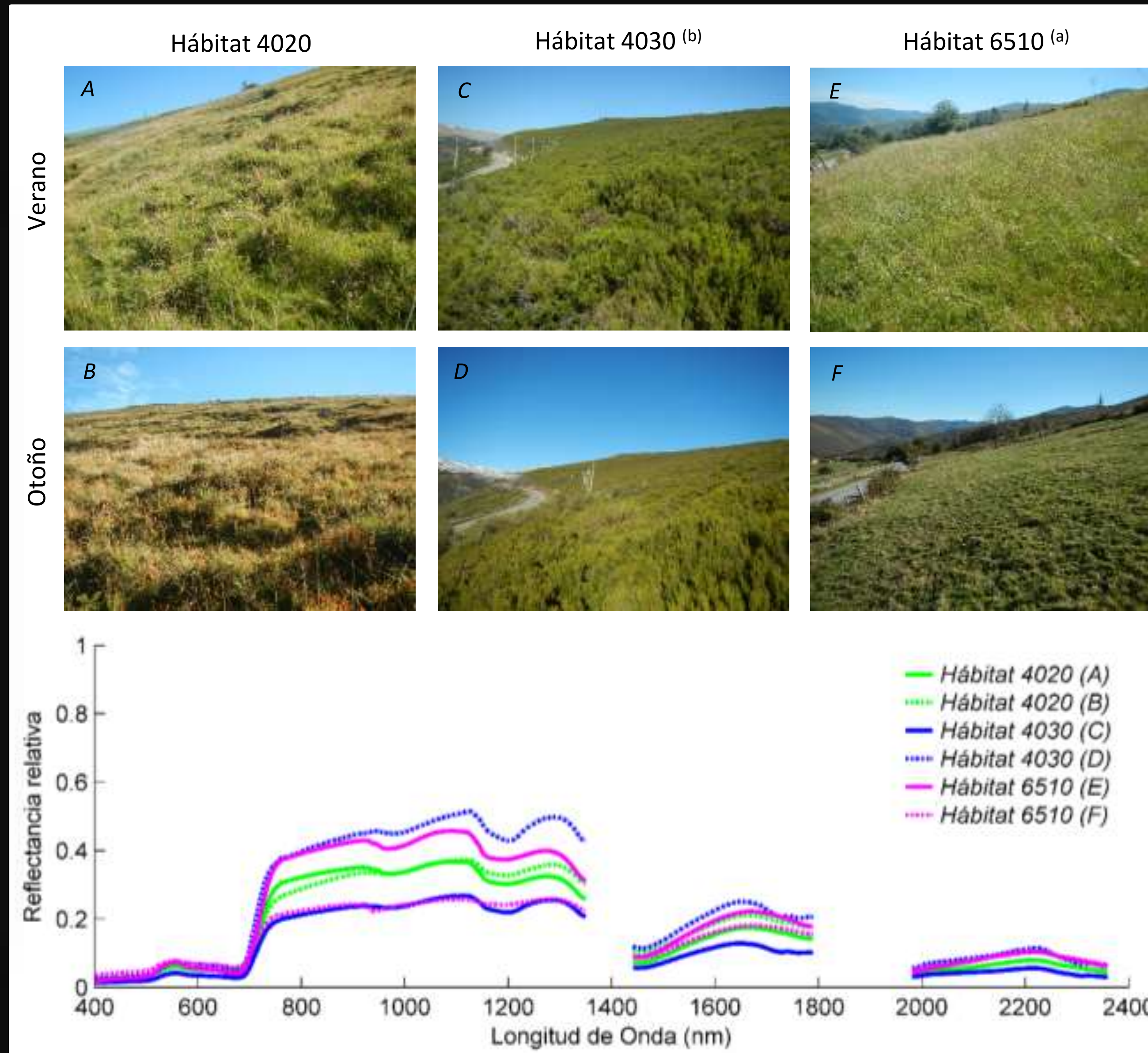
1] CLASSIFICATION TYPOLOGY Land use-land cover (LULC) **Vegetation** types	**2] OCCURRENCE DATA** Training Validation
3] PREDICTOR LAYERS Environmental limiting factors Remote sensing: **satellite** and LiDAR	**4] MODELLING PROCEDURE** Ensemble, sensitivity analyses Data mining tools…

SPECTRAL SIGNATURES

Hyperspectral meausrements

SPECTRAL SIGNATURES

Soectral library: HABITAT TYPES



SPECTRAL SIGNATURES

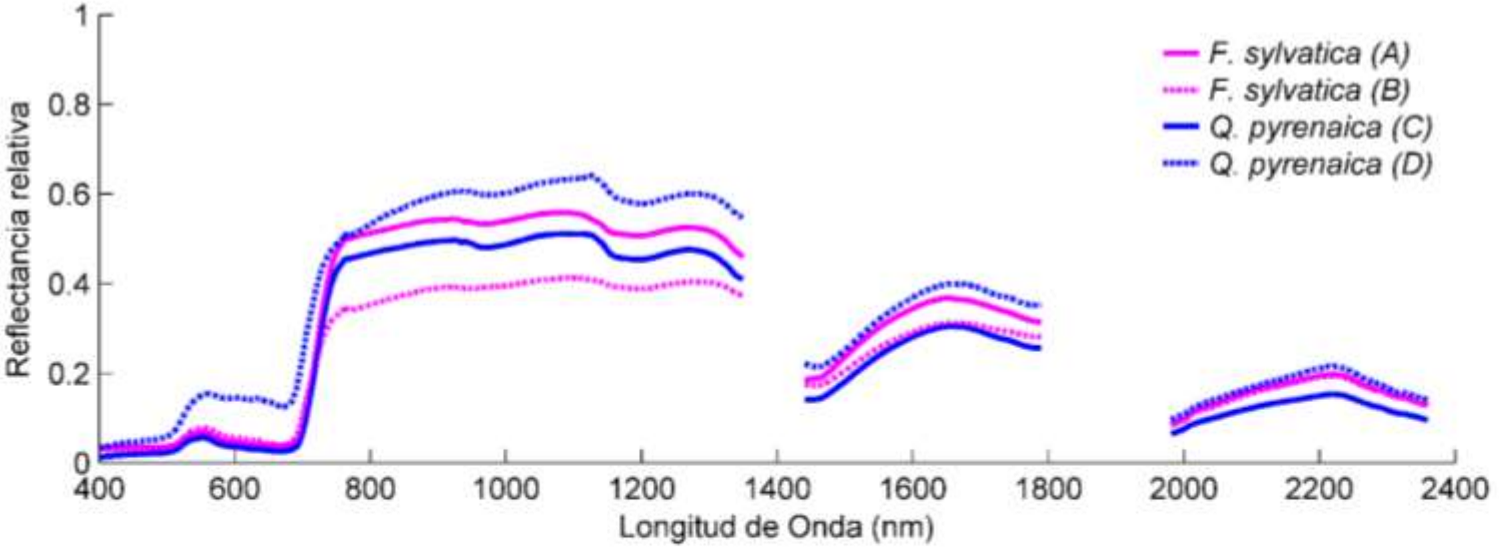
Spectral library: PHENOLOGY

Hábitat 9120 (*F. sylvatica*)

Verano — Otoño

Hábitat 9230 (*Q. pirenaica*)

Verano — Otoño



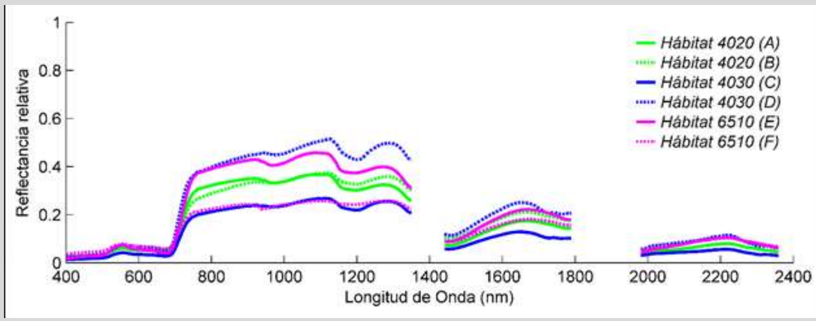
1] CLASSIFICATION SYSTEM

We **reclassified** **EUNIS level** to create **homogeneous groups** that can be mapped accuratelly with the available occurrence and predictor data

EUNIS-	EUNIS-3-name	EUNIS-4	EUNIS-4-name	xModels	Name(español)	DH
F2.2	Evergreen alpine and subalpine heath	F2.23	Southern Palaearctic mountain dwarf	yes	Enebrales rastreros	4060
F3.1	Temperate thickets and scrub	F3.12	Buxus sempervirens thickets	no	Matorrales de Buxus sempervirens	5110
F3.1	Temperate thickets and scrub	F3.13	Atlantic poor soil thickets	no	Matorrales oligótrofos atlánticos	xx
F3.1	Temperate thickets and scrub	F3.14	Temperate [Cytisus scoparius] fields	no	Escobonales	5120
F3.1	Temperate thickets and scrub	F3.15	Ulex europaeus thickets	yes	Tojales de Ulex europaeus	xx
F3.1	Temperate thickets and scrub	F3.17	Corylus thickets	no	Avellanedas	xx
F3.2	Submediterranean deciduous thickets	F3.21	Montane Cytisus purgans fields	yes	Piornales de Cytisus oromediterraneus	5120
F3.2	Submediterranean deciduous thickets	F3.22	Southwestern sub-mediterranean deciduous	no	Matorrales eútrofos de rosas y endrinos	xx
F3.2	Submediterranean deciduous thickets	F3.2X	Cantabrian montane piornales	yes	Piornales de Genista polygaliphylla	xx
F3.2	Submediterranean deciduous thickets	F3.2Y	Orocantabrian subalpine piornales	yes	Piornales de Genista obtusiramea	xx
F4.1	Wet heaths	F4.12	Southern wet heaths	yes	Brezales húmedos con Erica ciliaris/tetralix	4020
F4.2	Dry heaths	F4.21	Submontane [Vaccinium] - [Calluna] heaths	yes	Callunares secos	4030
F4.2	Dry heaths	F4.2X	Atlantic [Ulex galli] heaths	yes	Brezales-tojales con Ulex gallii	4020
F4.2	Dry heaths	F4.2Y	Ibero-Atlantic [Erica aragonensis] heaths	yes	Brezales de Erica aragonensis	4030
F4.2	Dry heaths	F4.2Z	Atlantic [Erica cinerea-umbellata] heaths	no	Brezales de Erica cinerea	xx
F5.1	Arborescent matorral	F5.13	Juniper matorral	yes	Sabinares	5210
F5.1	Arborescent matorral	F5.18	[Laurus nobilis] matorral	no	Lauredales atlánticos	5230
F5.2	Maquis	F5.2X	Cantabrian high maquis	yes	Madroñales con aladierno	xx
F7.4	Hedgehog-heaths	F7.4X	Cantabrian [Genista] cushion-heaths	yes	Aulagares de Genista hispanica	4090
F7.4	Hedgehog-heaths	F7.4E	[Astragalus sempervirens] hedgehog-heaths	no	Aulagares con Astragalus sempervirens	xx
F9.1	Riverine scrub	F9.1X	Cantabrian willow scrub	yes	Saucedas de Salix cantabrica	xx
F9.2	Salix carr and fen scrub	F9.21	Grey willow carrs	no	Saucedas arbustivas	xx
G1.1	Riparian and gallery woodland, with	G1.1X	Cantabro-Atlantic Salix alba forests	yes	Bosques atlánticos de Salix alba	91E0
G1.1	Riparian and gallery woodland, with	G1.1Y	Submediterranean Cantabrian Salix-Populus	yes	Bosques submediterráneos de Salix y	92A0
G1.2	Mixed riparian floodplain and gallery	G1.21	Riverine [Fraxinus] - [Alnus] woodland, wet at	yes	Alisedas	91E0
G1.2	Mixed riparian floodplain and gallery	G1.21	Riverine [Fraxinus] - [Alnus] woodland, wet at	yes	Fresnedas con arce	91E0
G1.6	[Fagus] woodland	G1.62	Atlantic acidophilous [Fagus] forests	yes	Hayedos oligótrofos	9120
G1.6	[Fagus] woodland	G1.64	Pyreneo-Cantabrian neutrophile [Fagus] forests	yes	Hayedos éutrofos	9150
G1.7	Thermophilous deciduous woodland	G1.77	Afro-Iberian thermophilous oak forests	yes	Quejigares	9240
G1.7	Thermophilous deciduous woodland	G1.7B	[Quercus pyrenaica] woodland	yes	Rebollares oligótrofos	9230
G1.7	Thermophilous deciduous woodland	G1.7D	[Castanea sativa] woodland	yes	Castañedas	9260
G1.8	Acidophilous Quercus-dominated	G1.8X	Cantabrian acidophilous oak forests	yes	Bosques oligótrofos de carbayo y abedul	xx
G1.8	Acidophilous Quercus-dominated	G1.8Y	Orocantabrian acidophilous oak forests	yes	Bosques oligótrofos de roble albar y abedul	xx

>>> EUNIS clases to **less than 50**

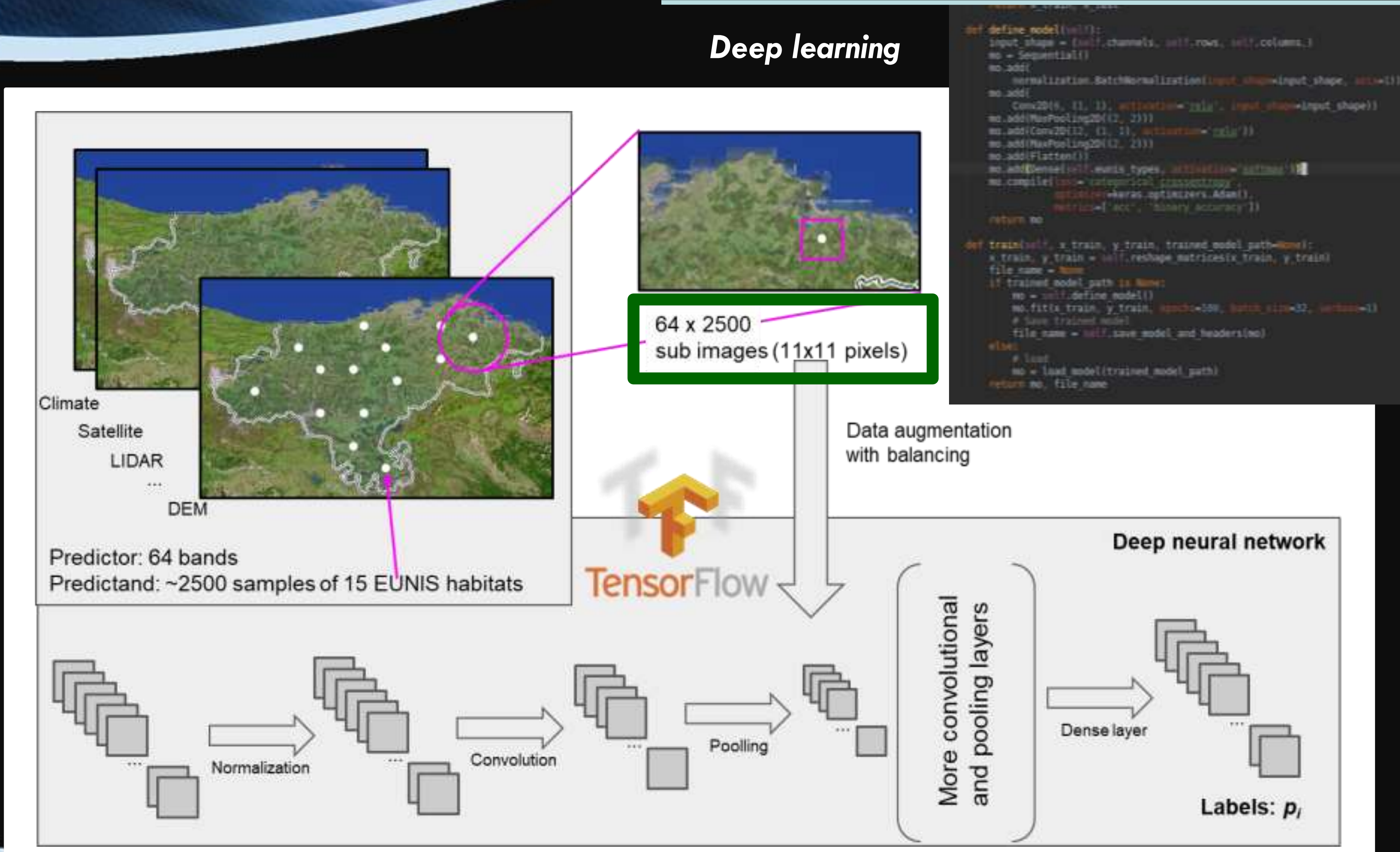
What actually matters?



4] MODELLING PROCEDURE
Ensemble, sensitivity analyses
Data mining tolos...

DEEP LEARNING PROCESSING

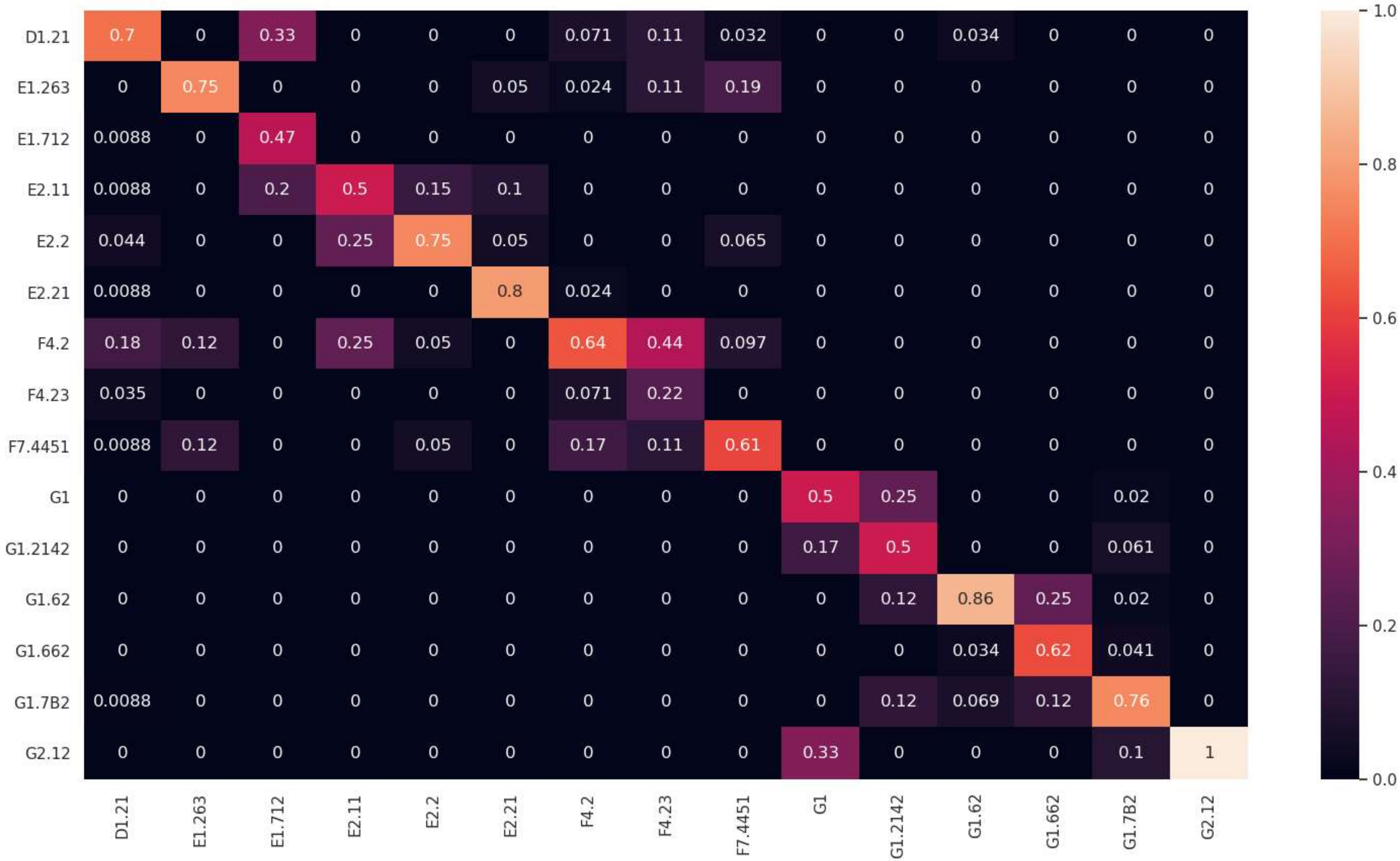
Deep learning



Deep learning is a class of machine learning algorithms that use a cascade of multiple layers of nonlinear processing units for feature extraction and transformation to learn about the feature to represent by using supervised or unsupervised appraches

DEEP LEARNING RESULTS

Random Forest - *randomForest_confusion_1x1*



DEEP LEARNING RESULTS

Deep learning CNN – *confusion_11x11_acc_1-2*

	D1.21	E1.263	E1.712	E2.11	E2.2	E2.21	F4.2	F4.23	F7.4451	G1	G1.2142	G1.62	G1.662	G1.7B2	G2.12
D1.21	0.83	0	0	0	0.048	0	0.094	0	0	0	0	0.034	0	0.036	0
E1.263	0	0.69	0	0	0	0	0.031	0.091	0.059	0	0	0	0	0	0
E1.712	0.0092	0.062	0.79	0	0	0	0	0	0	0	0	0	0	0	0
E2.11	0	0	0.21	0.57	0.095	0.056	0	0.091	0	0	0	0	0	0	0
E2.2	0.018	0	0	0.43	0.76	0.22	0	0	0.12	0.077	0.083	0	0	0	0
E2.21	0.0092	0	0	0	0	0.67	0	0.091	0	0	0	0	0	0	0
F4.2	0.11	0.062	0	0	0	0	0.66	0.091	0	0	0	0	0	0	0
F4.23	0.018	0	0	0	0	0	0.094	0.45	0	0	0	0	0	0	0
F7.4451	0.0092	0.19	0	0	0.095	0.056	0.12	0.18	0.82	0	0	0	0	0	0
G1	0	0	0	0	0	0	0	0	0	0.62	0.17	0	0	0	0
G1.2142	0	0	0	0	0	0	0	0	0	0	0.75	0	0	0.036	0
G1.62	0	0	0	0	0	0	0	0	0	0	0	0.83	0.17	0.036	0.18
G1.662	0	0	0	0	0	0	0	0	0	0.077	0	0.1	0.83	0.036	0
G1.7B2	0	0	0	0	0	0	0	0	0	0.23	0	0.034	0	0.86	0.18
G2.12	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.64

DEEP LEARNING RESULTS

What actually matters?

Best results correspond to Deep learning -*11x11*

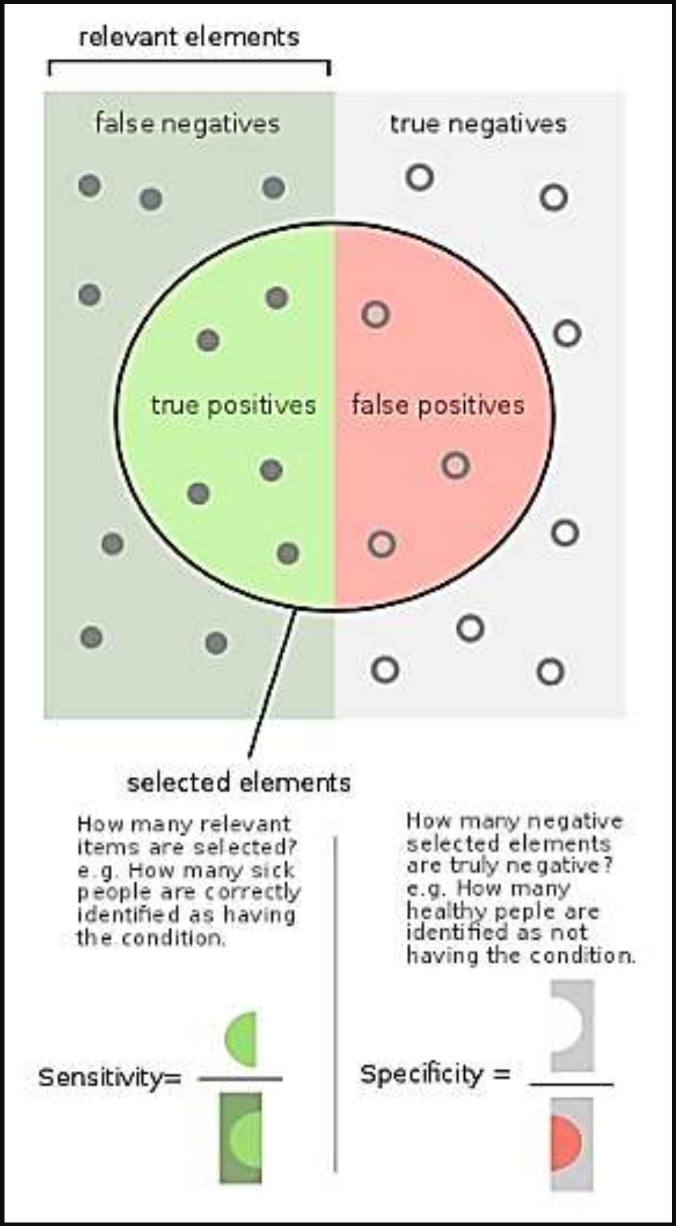
- Overall accuracy scores comparable to RandomForest or Maxent, **minimum hit rates are much higer when using Deep learning**

- Processing chain is promising when using an optimal **classification system:**

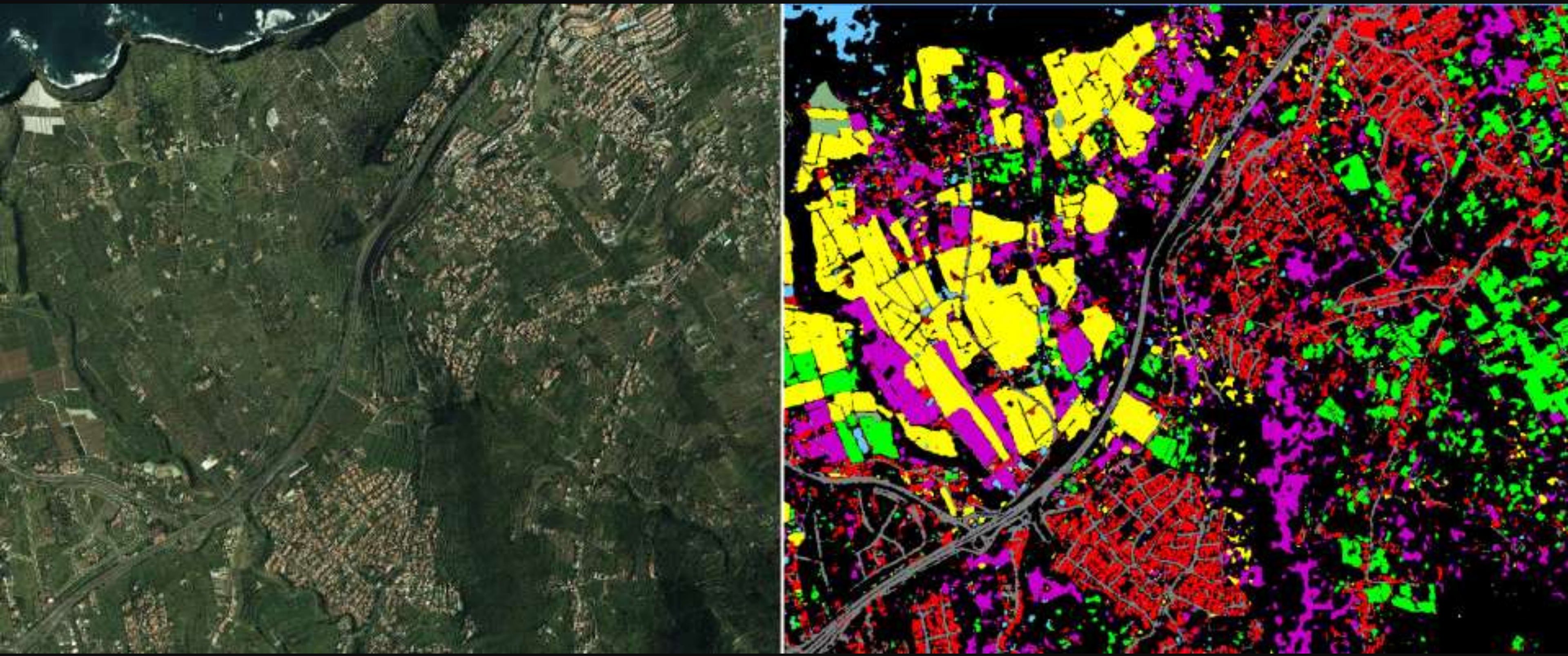
1] Update characterization of habitats types by **complete spectral library** of habitat types;

2] **refining the EUNIS list and complete the reference database** across both:

- environmental and
- geographic dimensions



Deep learning *spatial outputs (Grafcan)*



Deep learning with multispectral imagery and limiting factors

Promising… but what more actually matters??

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ADAPTIVE MAPPING

Step 1

Occurrence data:
obtained from vegetation maps and fieldwork based on expert knowledge to create a community-level point database

Representativeness of environmental and geographical variability across the study area

Step 2

Remote sensing data:
i) multispectral imagery (Landsat 8)
ii) LiDAR data (vegetation height)

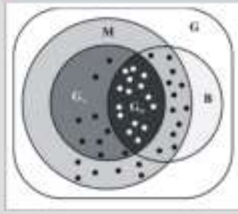
+

Environmental limiting factors:
topography and climate

Moving from potential distributions (range) to current occupied areas based on earth observation of spatial patterns of vegetation

Step 3

Community-level modelling:
"assemble first, predict later"
Spatial distribution: range and occupied area



The models determine different areas of occupancy for the community-level entities depending upon biotic and abiotic factors

Step 4

Vegetation map

Co-ocurrence modelling + uncertainty

Step 5

Maps validation across environmental gradients

Independent fieldwork data to validate overall accuracy and ommision-commission erros

Step 6

Aditional variables for habitat mapping

Use of soil properties
Hyperespectral remote sensing data
Vegetation phenology, etc.

A continuous improvement through sensitivity analyses involving data and methods

¡Gracias!

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