



## **Collaborative AI for plant biodiversity monitoring: From PlantNet to GeoPlantNet**

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Benjamin Deneu, Hervé Goëau, J.C. Lombardo, Mathias Chouet, Hugo Gresse,  
Cesar Leblanc, Maximilien Servajean, François Munoz



PART I  
Pl@ntNet under the hood





A citizen science platform that uses AI to help people identify plants with their mobile phones



# **Pl@ntNet** app

**25 Million users**  
**200+ countries**  
**Up to 2M identifications per day**



## Personal Usage



Nature, walks



Gardening



Phytotherapy

## Professional Usage



Agro-ecology



Natural Areas Management



Education, animation



Tourism



Trade

# Pl@ntNet API - <https://my.plantnet.org/>



- A secured API providing developers programmatic access to Pl@ntNet engine
- **9K developer accounts** (companies, researchers, citizen observatories)
- Integrated in **European Open Science Cloud (EOSC)**



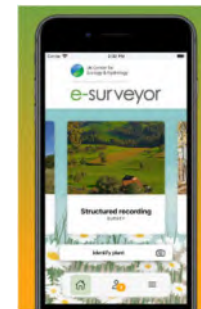
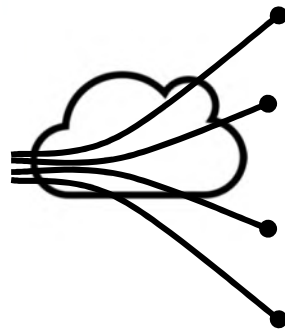
Create an account

Sign in

API Documentation

[Getting started](#) [GET / POST examples](#) [OpenAPI doc.](#)

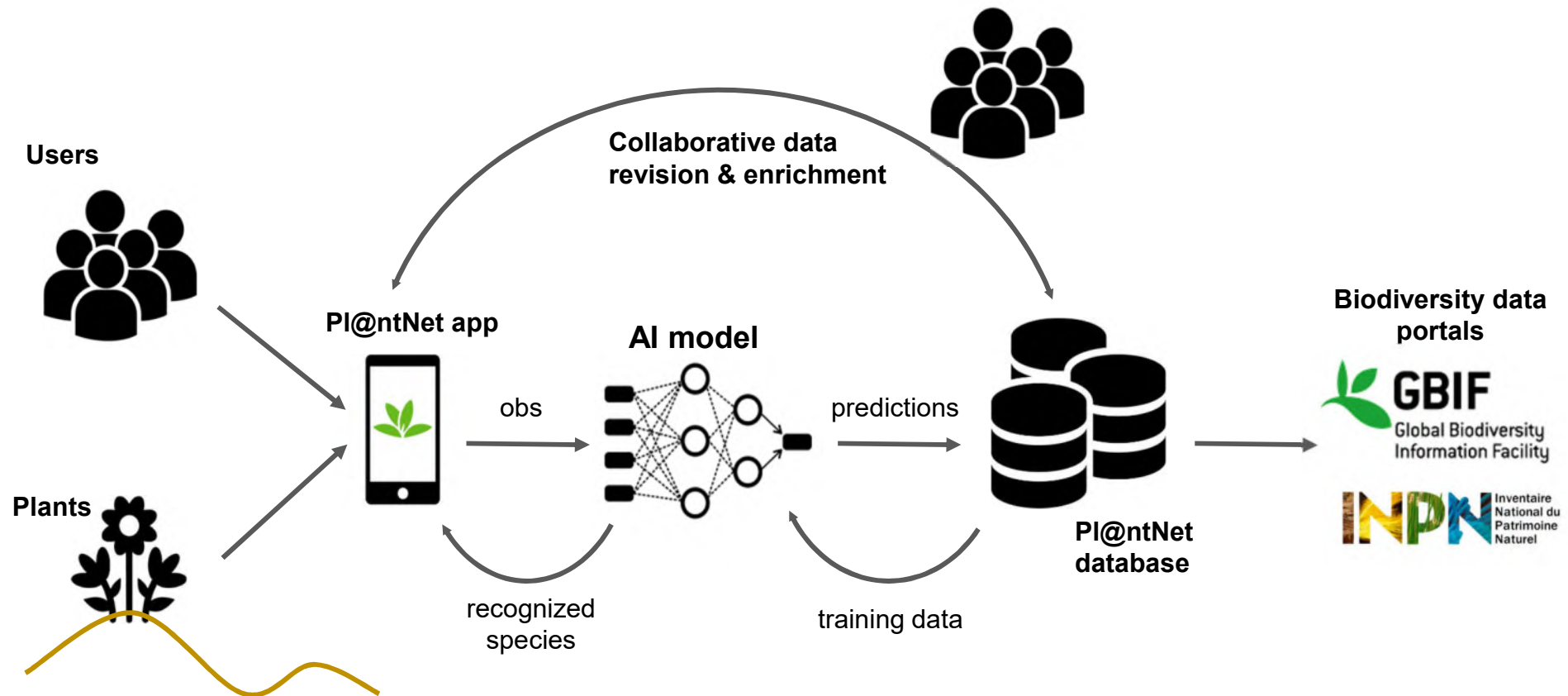
Getting started



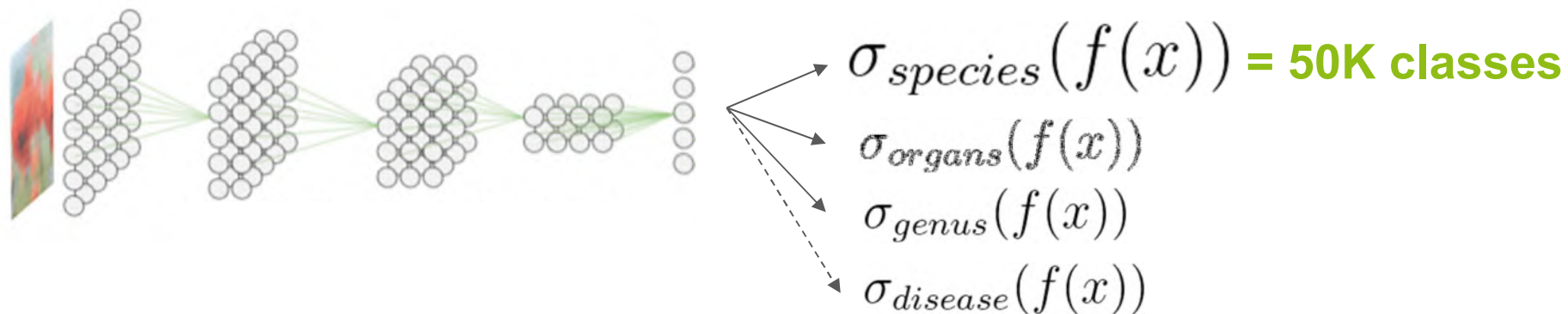
An [iNaturalist-Pl@ntNet-workflow](#) to identify plant-pollinator interactions – a case study of *Isodontia mexicana*

Nadja Pernat<sup>1</sup>, Tom August<sup>2</sup>, Quentin Groom<sup>3</sup>, Daniyar Memedemin<sup>4</sup>, and Lien Reyserhove<sup>5</sup>

# Key concept of PI@ntNet: Collaborative AI



**Multi-head model** trained on **Jean Zay super-computer** on a big dataset of **8M valid observations** (5-6 days of training)

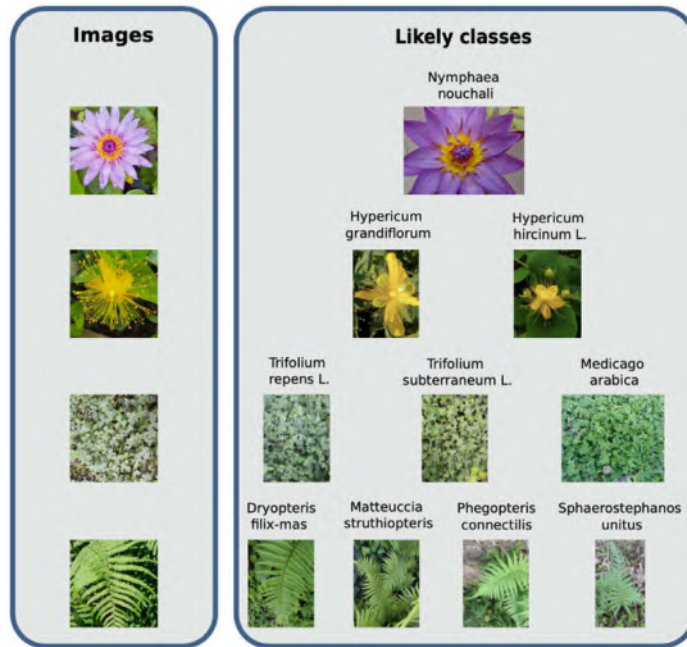


**Model = Vision transformer DinoV2**

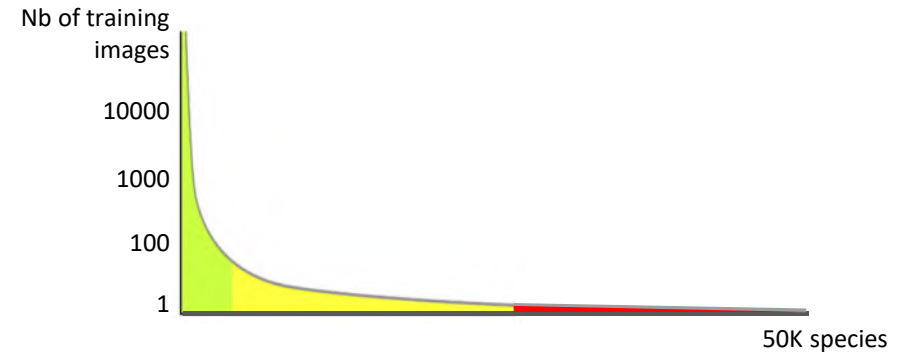
- Backbone pre-trained on 100M images using SSL (by Meta/Inria)
- Final multi-head model fine-tuned on 8M Pl@ntNet images (by Pl@ntNet team)

# A difficult problem: uncertainty

**Irreducible uncertainty**  
Species ambiguity



**Model uncertainty**  
Increased by long-tail distribution



**Top1 Identification accuracy:**

Common species = ~90%

Average species = ~70%

Rare species = ~40%

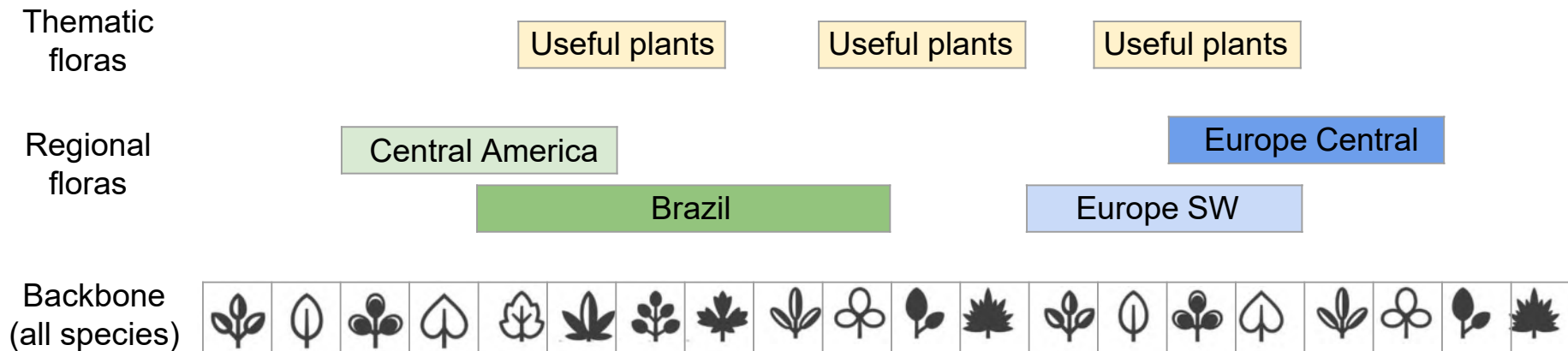


# Use of regional or thematic floras

Restricting the hypothesis space to a particular flora allows improving the identification accuracy (based on World Checklist of Vascular Plants (WCVP)).

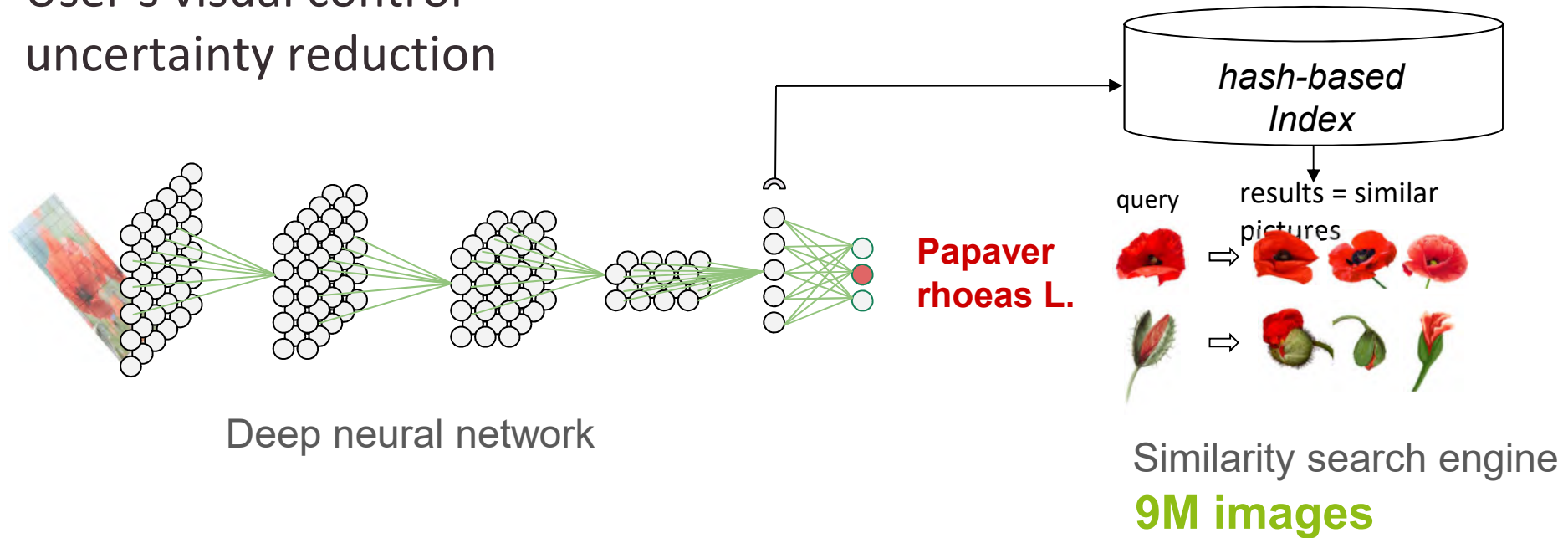
$$p(y|x, flora) \geq p(y|x)$$

species   image                      species   image



# **Pl@ntNet** Similarity search

User's visual control =  
uncertainty reduction

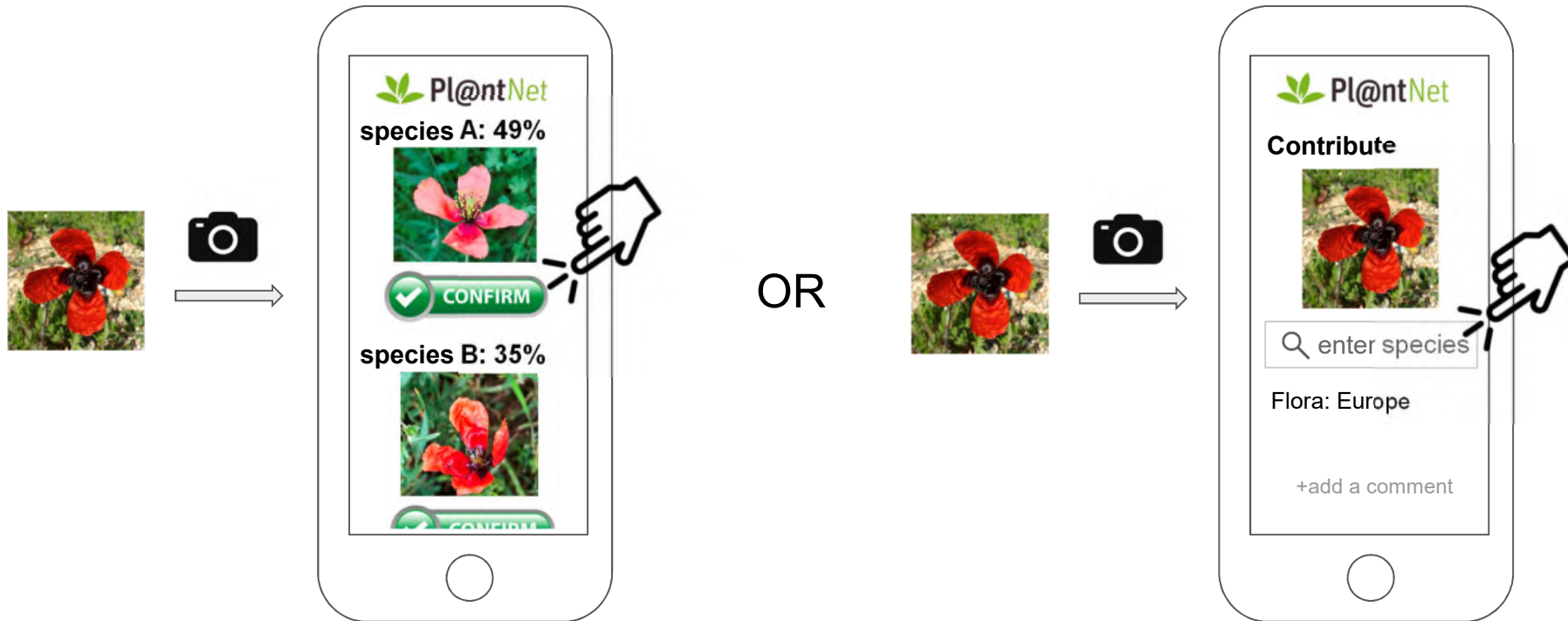


→ Sub-linear algorithm based on locality sensitive hashing

Joly, A., & Buisson, O. (2011, June). Random maximum margin hashing. In CVPR 2011 (pp. 873-880). IEEE.






# User's contributions


Users can contribute their observations



# User's revisions

Users can revise observations of other users.

←  Joey F  
8 déc. 2022...    



0 commentaire

Nom le plus probable

*Larix decidua* Mill.  2






Mélèze commun



Observation mal déterminée  ?

Observation malformée

Saisir l'espèce



      ?

Qualité de la photo  2  0  ?

21:29    57%

← 4 Nom(s) commun(s)  
Français 

*Larix decidua* Mill.

Mélèze commun  12 Votes

Mélèze d'Europe  8 Votes

Pin de Briançon  6 Votes

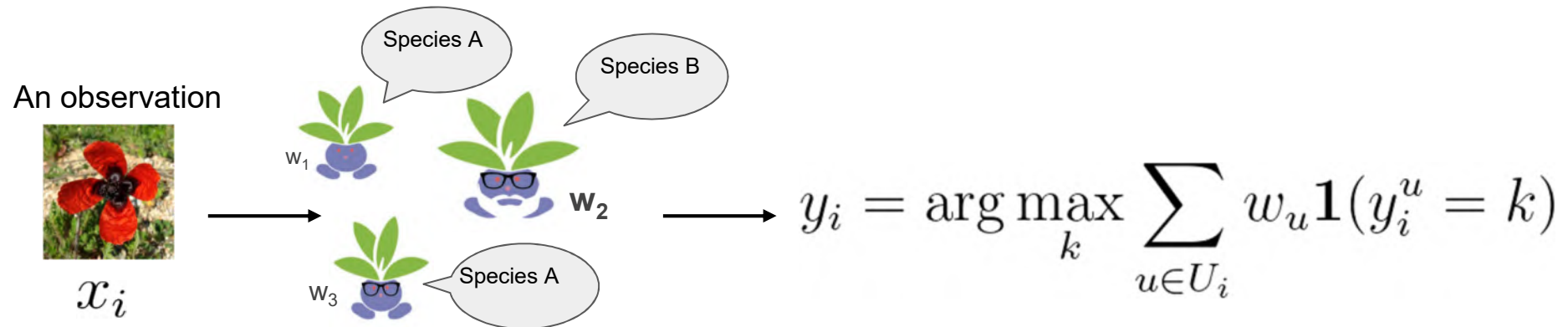
Pomme de pins  1 Vote

Ajouter un nom

 Nom commun

# Cooperative Learning algorithm

The most probable label of an observation is determined with a weighted majority voting rule:

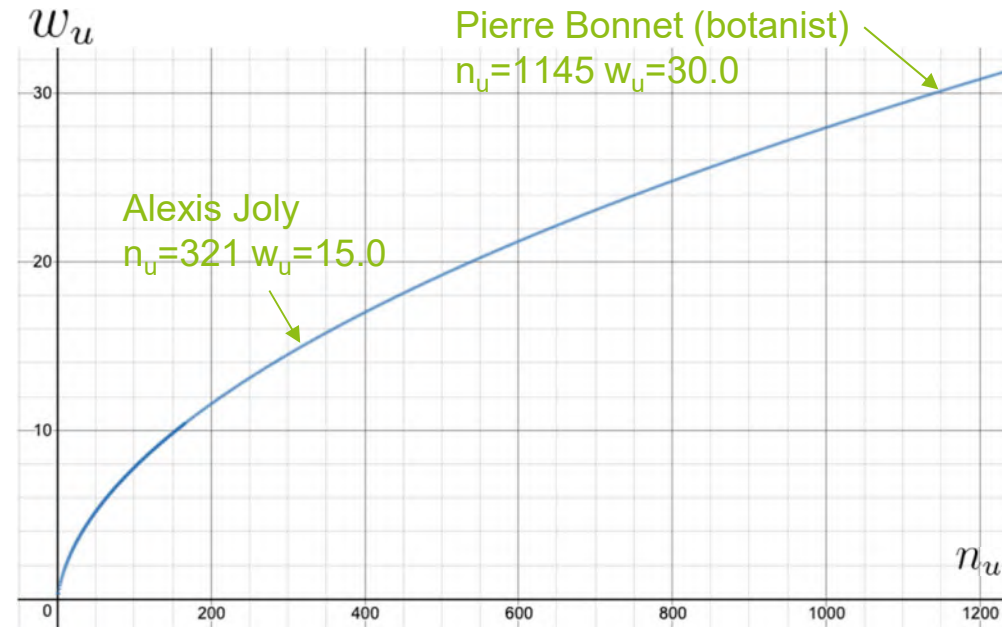
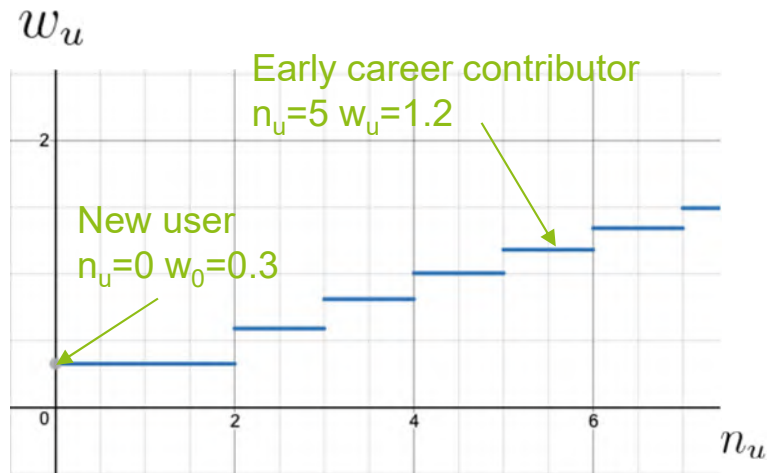


$U_i =$  Set of users who provided a label  $y_i^u$  for the observation  $x_i$

# Cooperative Learning algorithm

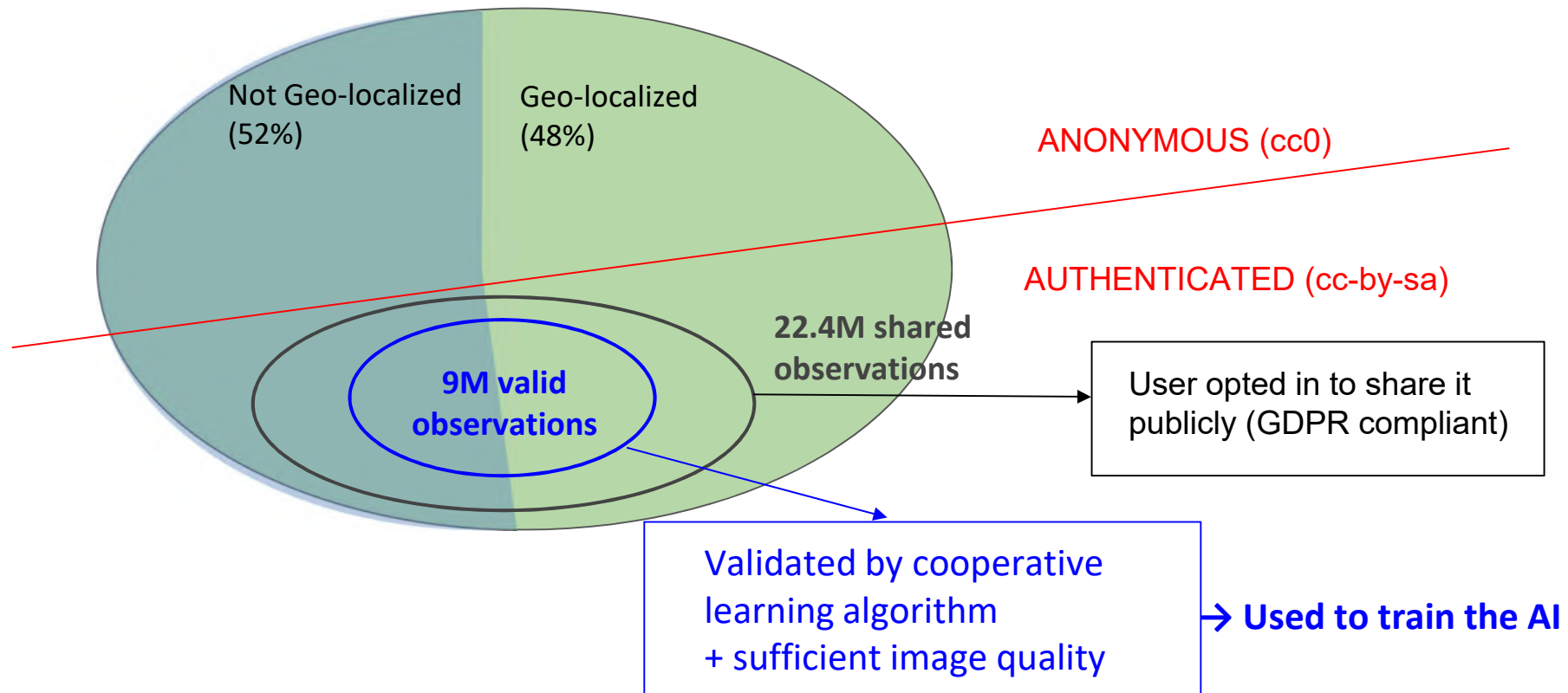
The weight of a user in PI@ntNet is a function of the **estimated number of species** he is able to identify

$$w_u = g(n_u) \quad n_u = |\{j : \exists i y_i^u = y_i\}|$$



# Pl@ntNet Data

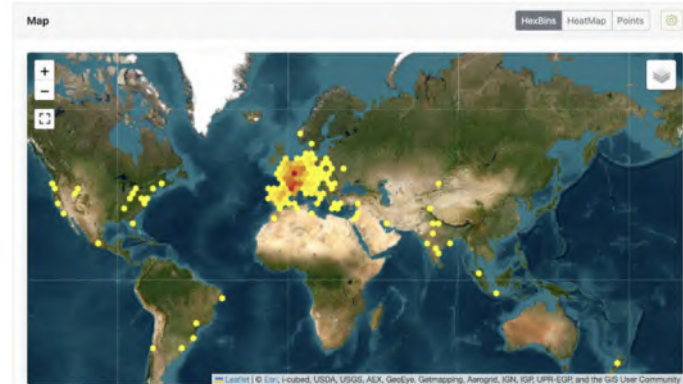
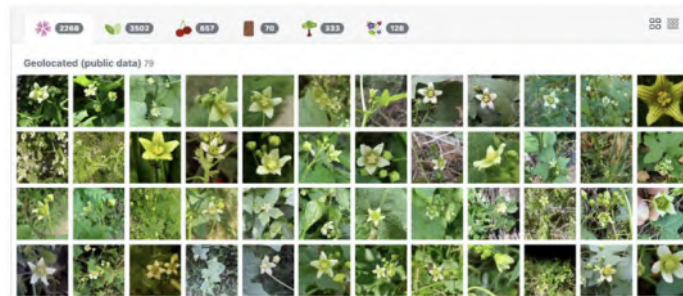
1.1 billion raw observations (=queries)



# Pl@ntNet Data visualisation tools

## *Bryonia cretica* L.

White bryony, Cretan bryony, مار دارو، فاشرا



Common name(s)

White bryony

Cretan bryony

مار دارو، فاشرا

[View all / Edit](#)

Uses

MEDICINE

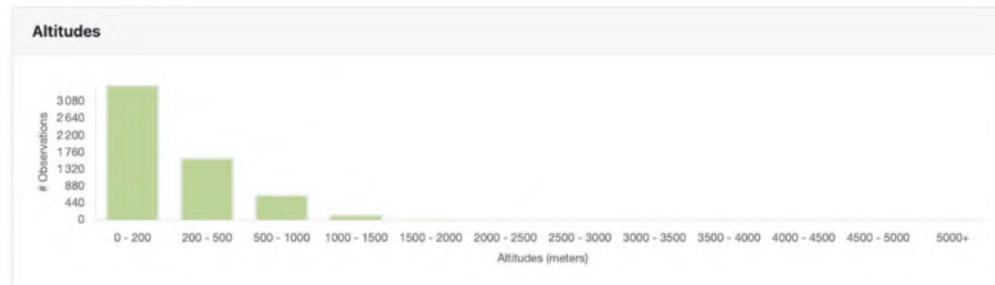
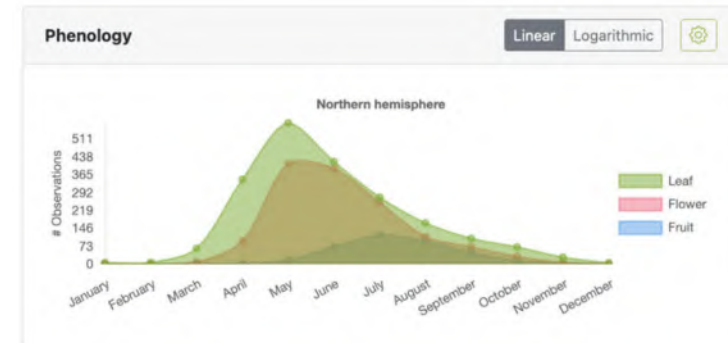
folklore

Additional information

Pl@ntUse

GBIF

Royal Botanic Gardens Kew | Plants of the World Online




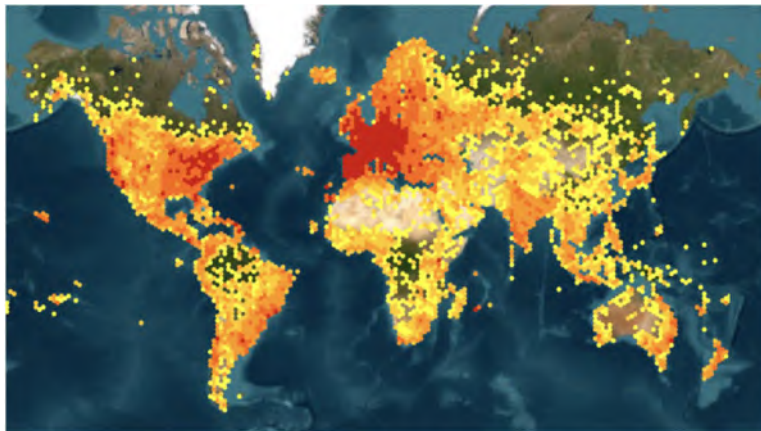


# Pl@ntNet Data shared in GBIF

**Top-2 plant data provider to GBIF** (world's largest infrastructure for biodiversity data)

- Shared data = revised observations + trusted queries identified by the AI (AI score > 0.95)
- Quality filters: potted & cultivated plants removal, region-based filtering (Kew POWO)

 **GBIF** 13 856 500 OCCURRENCES  
(87% identified by AI, 13% by humans)



<https://doi.org/10.15468/mma2ec>

755 citations



nature



ANNALS OF  
BOTANY  
Founded 1887



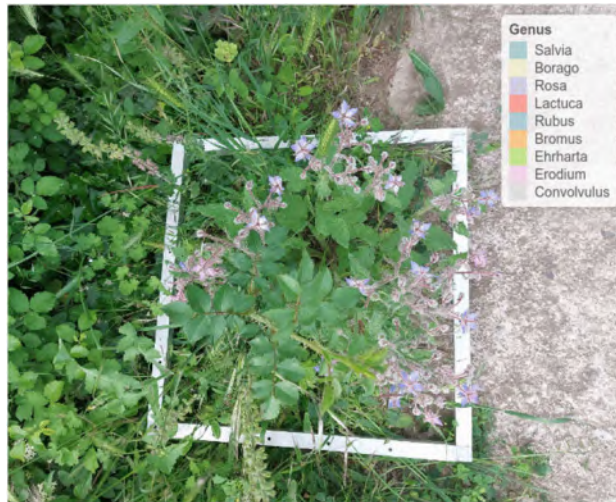
ELSEVIER

## PART II

From individual plants to **plant communities**  
monitoring

# Multi-specimen images for community-level monitoring

- Quadrat images for the monitoring of vulnerable habitats or fields biodiversity (e.g. VigieFlore)
- Vegetation cover images (e.g. terrestrial robots, drones, smartphones)
- Landscape views (e.g. car views for the monitoring of invasive species)



# Weakly-supervised multi-label classification

Training data

1



PlantNet  
database

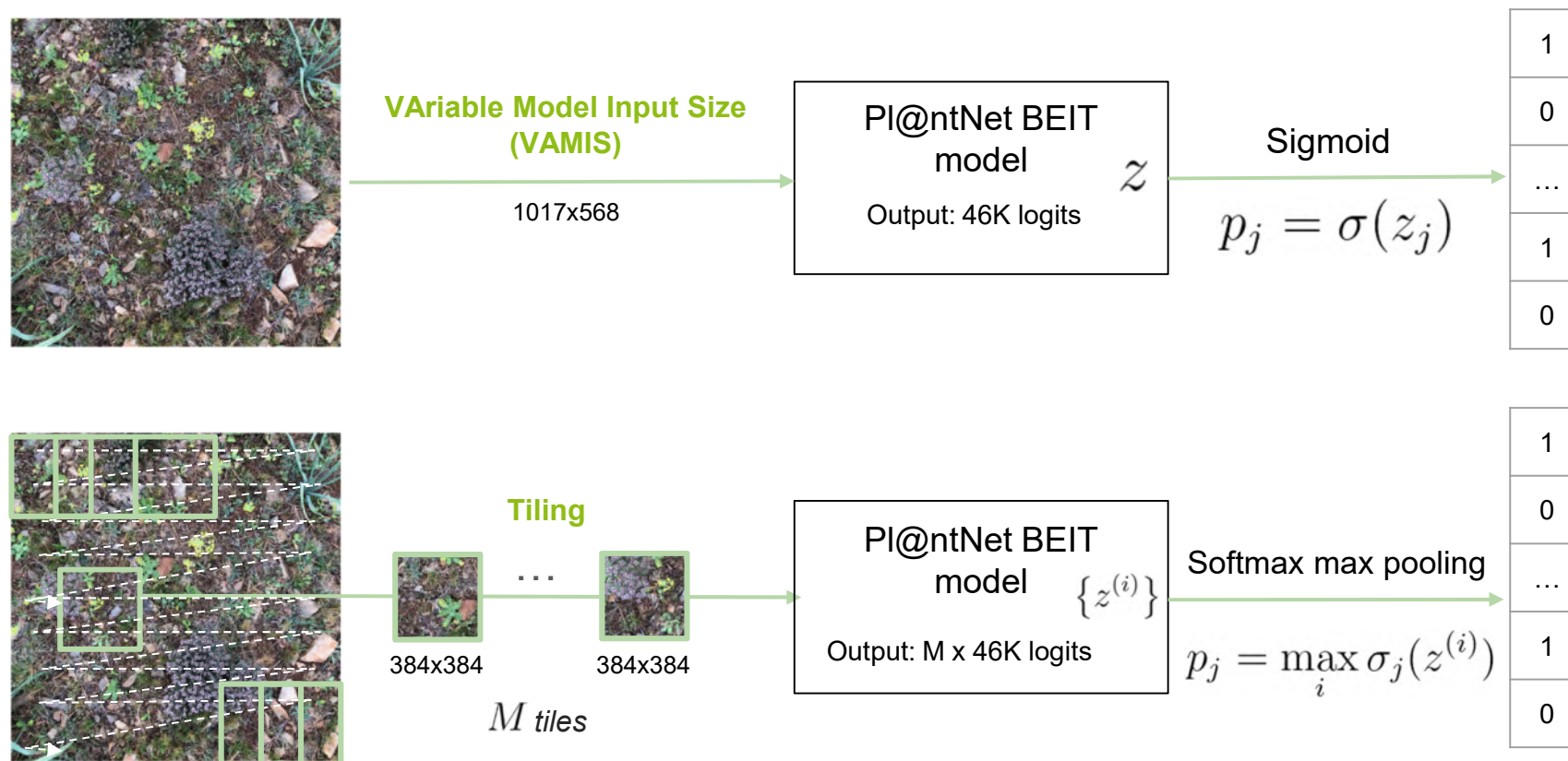


Test data

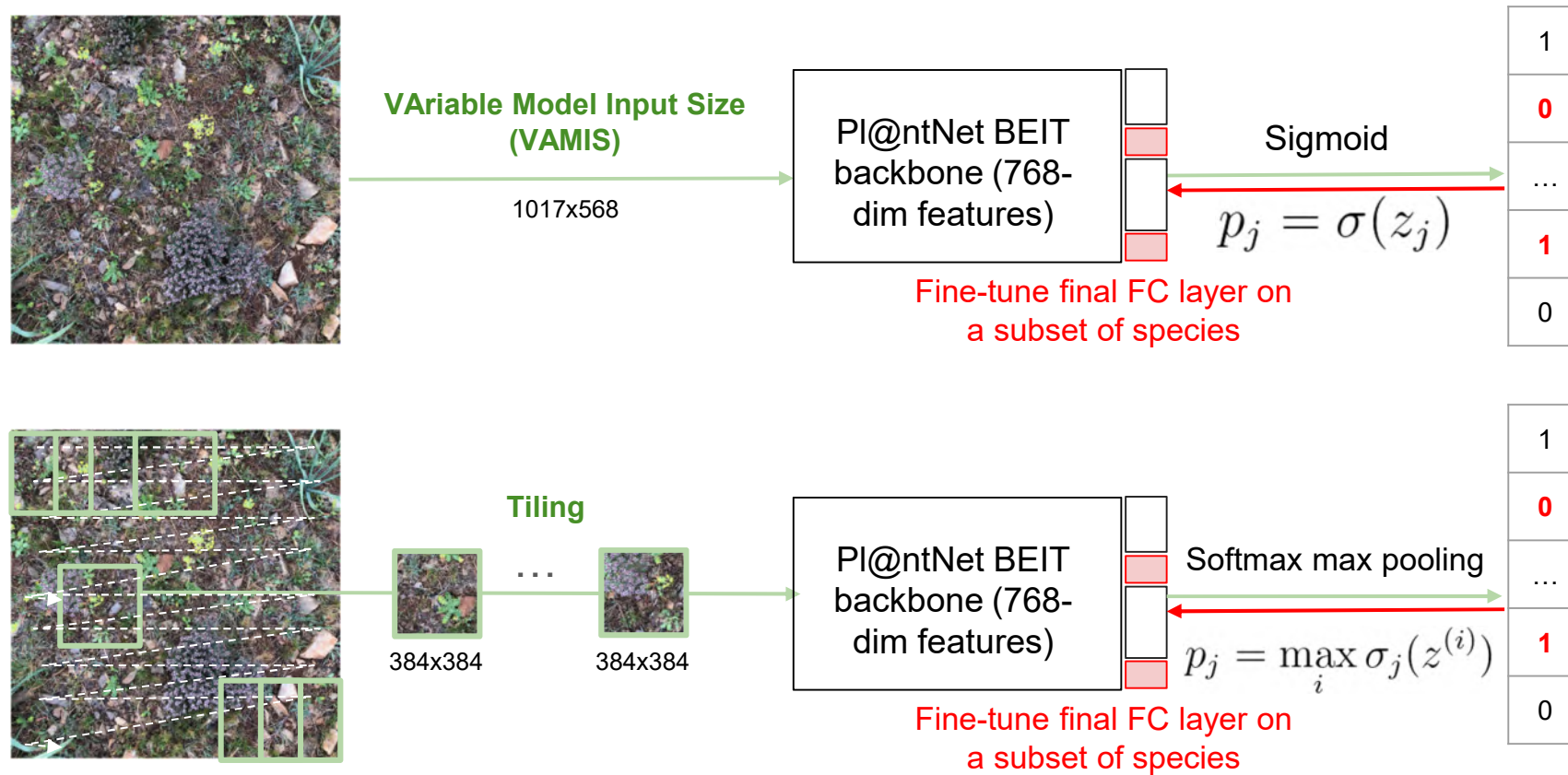
0	1	0	1	0	1	1	0
---	---	---	---	---	---	---	---



# Zero-shot multi-label classification (no fine-tuning)



# Few-shot multi-label classification (**with fine-tuning**)



# Weakly-supervised multi-label classification

## Evaluation on Danish road dataset

- Seven invasive species annotated
- 8.4K images with 1 to 3 invasive species

Dyrmann, M., Mortensen, A. K., Linneberg, L., Høye, T. T., & Bjerge, K. (2021). Camera assisted roadside monitoring for invasive alien plant species using deep learning. *Sensors*, 21(18), 6126.



(a)



(b)


## Results

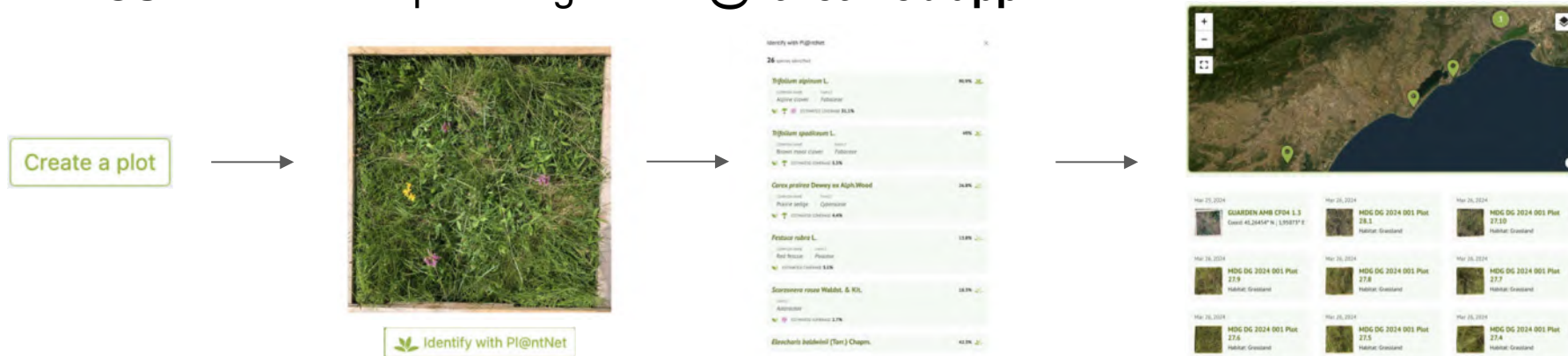
	Zero-shot (no fine-tuning)		With fine-tuning	
	VAMIS	Tiling	VAMIS	Tiling
AUC	75.52	<b>91.58</b>	96.49	<b><u>96.50</u></b>
F1	36.45	<b>63.39</b>	74.28	<b><u>76.46</u></b>

# Integration in PI@ntNet



Tiling approach integrated in PI@ntNet (without fine-tuning)

- **API** ([my.plantnet.org](https://my.plantnet.org))
  - used by  **biodiversa+** project on the monitoring of invasive alien species
  - used for our participation to Xprize rainforest challenge (Brazilian team, finalist)
- **GUI** dedicated to plot images in **PI@ntNet web app**



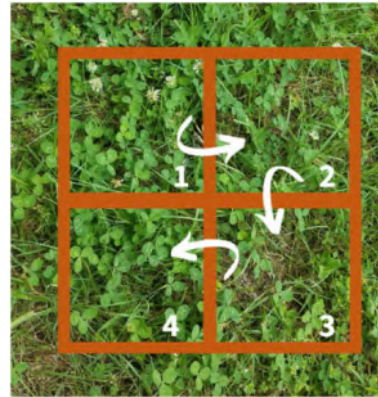
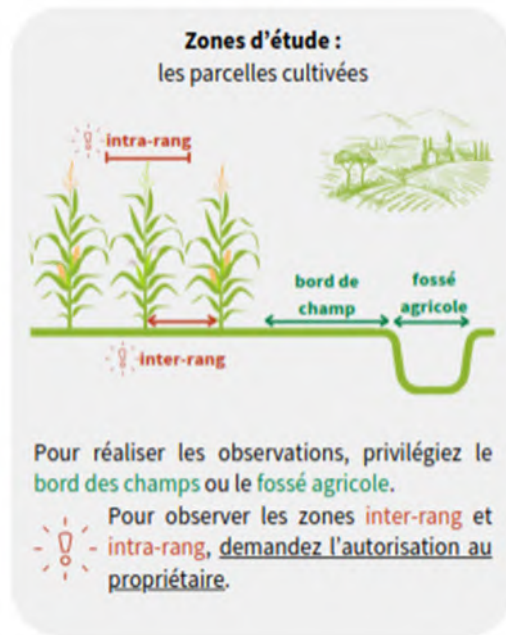


# Citizen science programme co-organized with

<https://www.tela-botanica.org/projets/la-flore-sous-lobjectif-plantnet/>



## La flore des cultures sous l'objectif de Pl@ntNet !



### Matériels



Un carré représentant le quadrat de 50cm de côté



*N'hésitez pas à utiliser une corde assez épaisse et des piquets bois*



Un appareil photo



Veillez à

- charger la batterie de votre appareil
- activer le GPS sur votre smartphone
- désactiver le flash s'il a plu ou que la végétation est humide



Une fiche de terrain imprimée et/ou carnet de terrain et un stylo

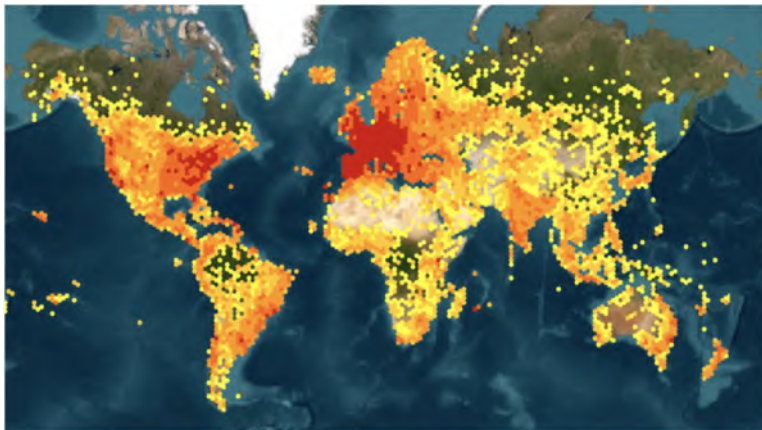
## PART III

GeoPI@ntNet: from field observations to  
Mapping tools and Decision support  
applications

## Objective: high resolution species and biodiversity indicators maps

Raw species occurrence data needs to be interpolated in space and time:

Many plant occurrences at world scale

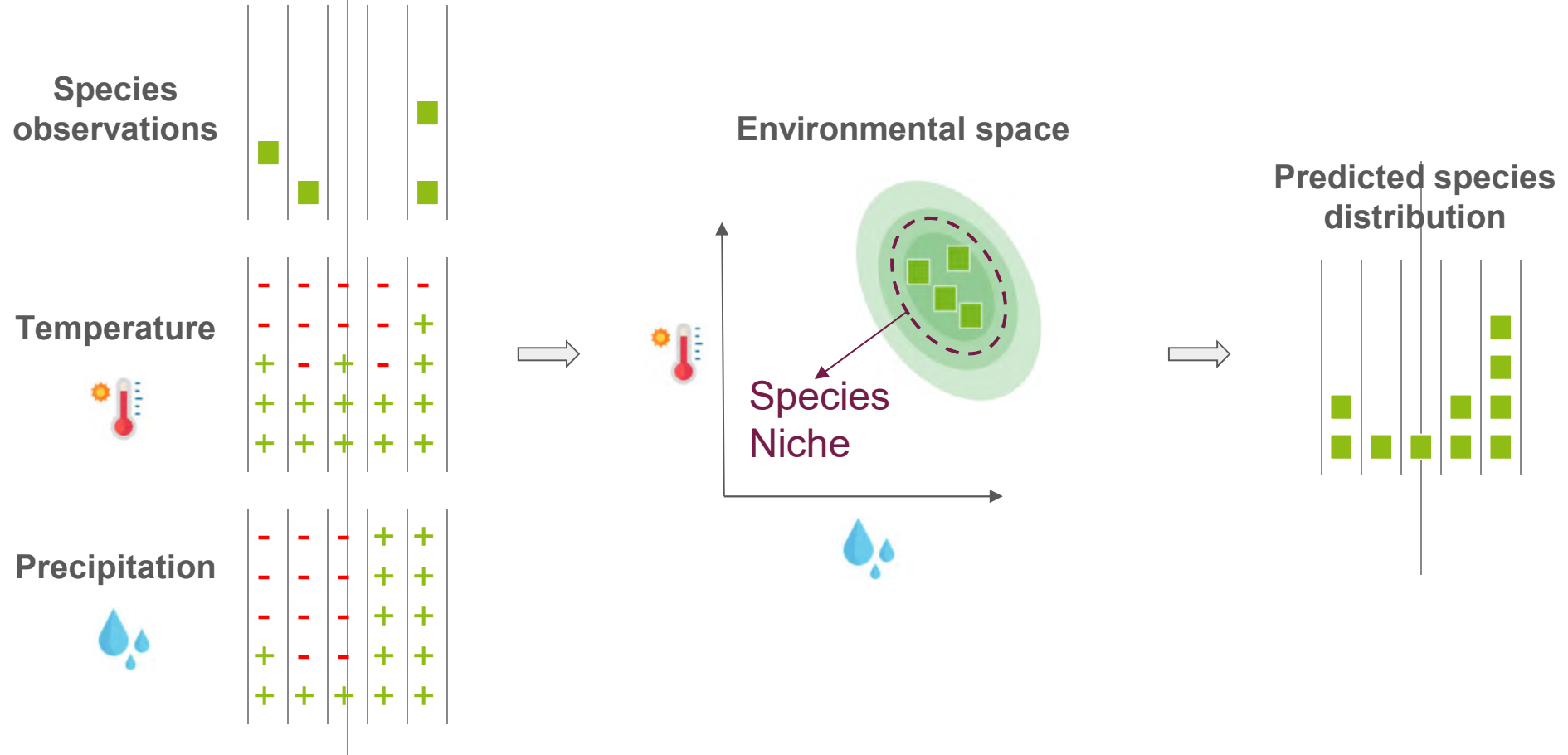


 GBIF

But very few locally (and biased) for most species



# Species Distribution Models (SDM)



# Remote sensing based SDM (DeepSDMs)

PLOS COMPUTATIONAL BIOLOGY

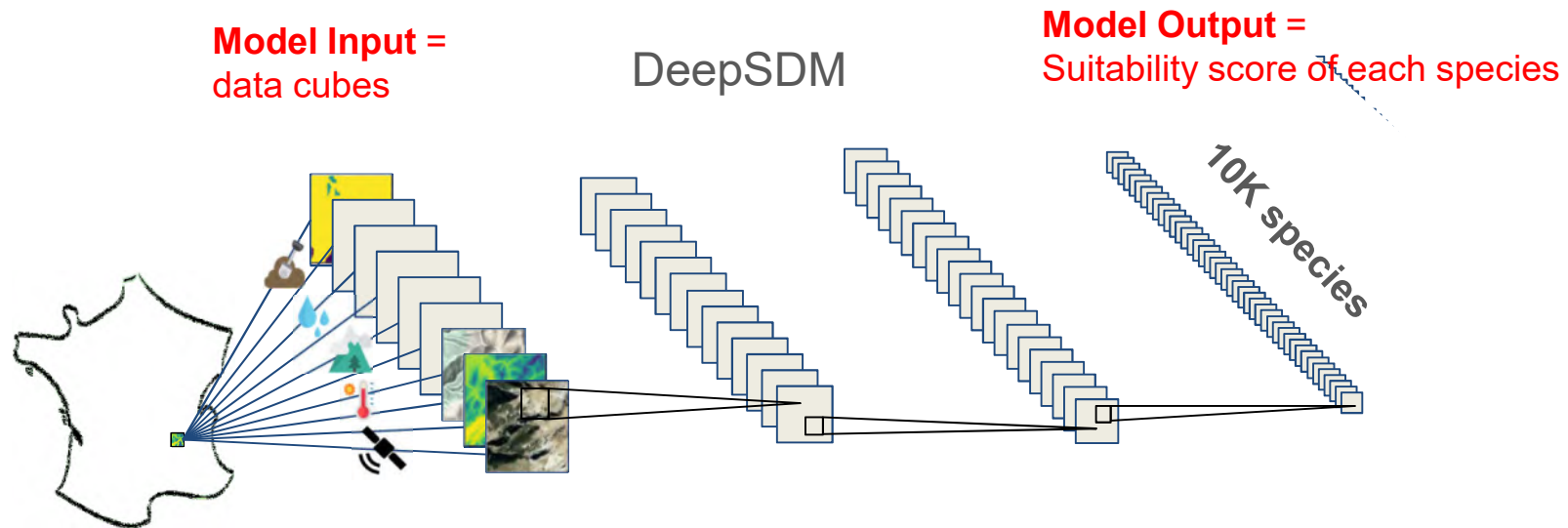
Convolutional neural networks improve species distribution modelling by capturing the spatial structure of the environment

Benjamin Deneu , Maximilien Servajean, Pierre Bonnet, Christophe Botella, François Munoz, Alexis Joly

 **frontiers** in Plant Science

Deep Species Distribution Modeling From Sentinel-2 Image Time-Series: A Global Scale Analysis on the Orchid Family

 Joaquim Estopinán<sup>1,2\*</sup>  Maximilien Servajean<sup>2,3</sup>  Pierre Bonnet<sup>4,5</sup>  
 François Munoz<sup>6</sup>  Alexis Joly<sup>1,7</sup>



# GeoLifeCLEF challenge 2023 & 2024



OUTPUT  
PREDICTIONS

Presence / absence of 10K plant species

1	0	0	0	0	1	0	1	0	0	1	1	0	1	0	1	0	0	1	0

Model

Training set

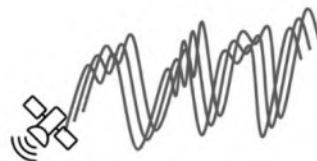
5M Presence Only  
+  
70K Presence Absence

INPUT  
PREDICTORS

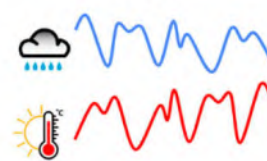
Satellite image  
(sentinel 2)



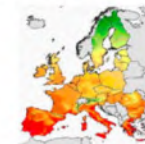
Multi-spectral time  
series (Landsat)



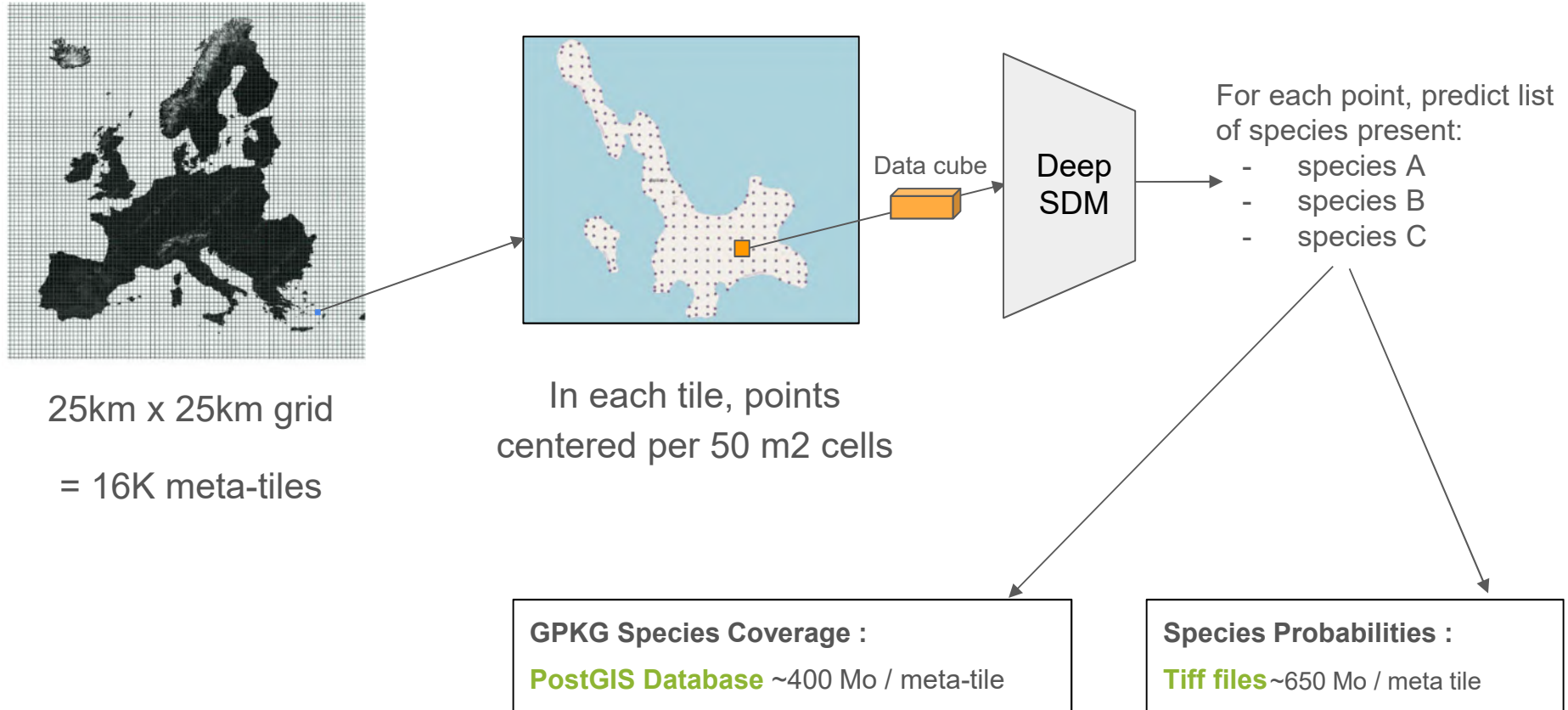
Climatic time  
series (Chelsa)



Environmental rasters  
(land use, human  
footprint, bioclim, soil)



# Integration in GeoPI@ntNet for EU-scale species mapping





### Species predictions

Model: GPN\_RGBI\_2

Grid: greece

Resolution: 50 m

Species threshold: 50

Fraxinus ornus L.  
(#6353)

WMS opacity:



### Fraxinus ornus

Family: Oleaceae

Genus: Fraxinus

Common Name:

Manna

Model prediction score:

13.32







### Species predictions

Model: GPN\_RGBI\_2

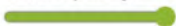
Grid: cbnmed

Resolution: 50 m

Species threshold: 50

Thymus vulgaris L. (#5404)

WMS opacity:



### Thymus vulgaris

Family: Lamiaceae

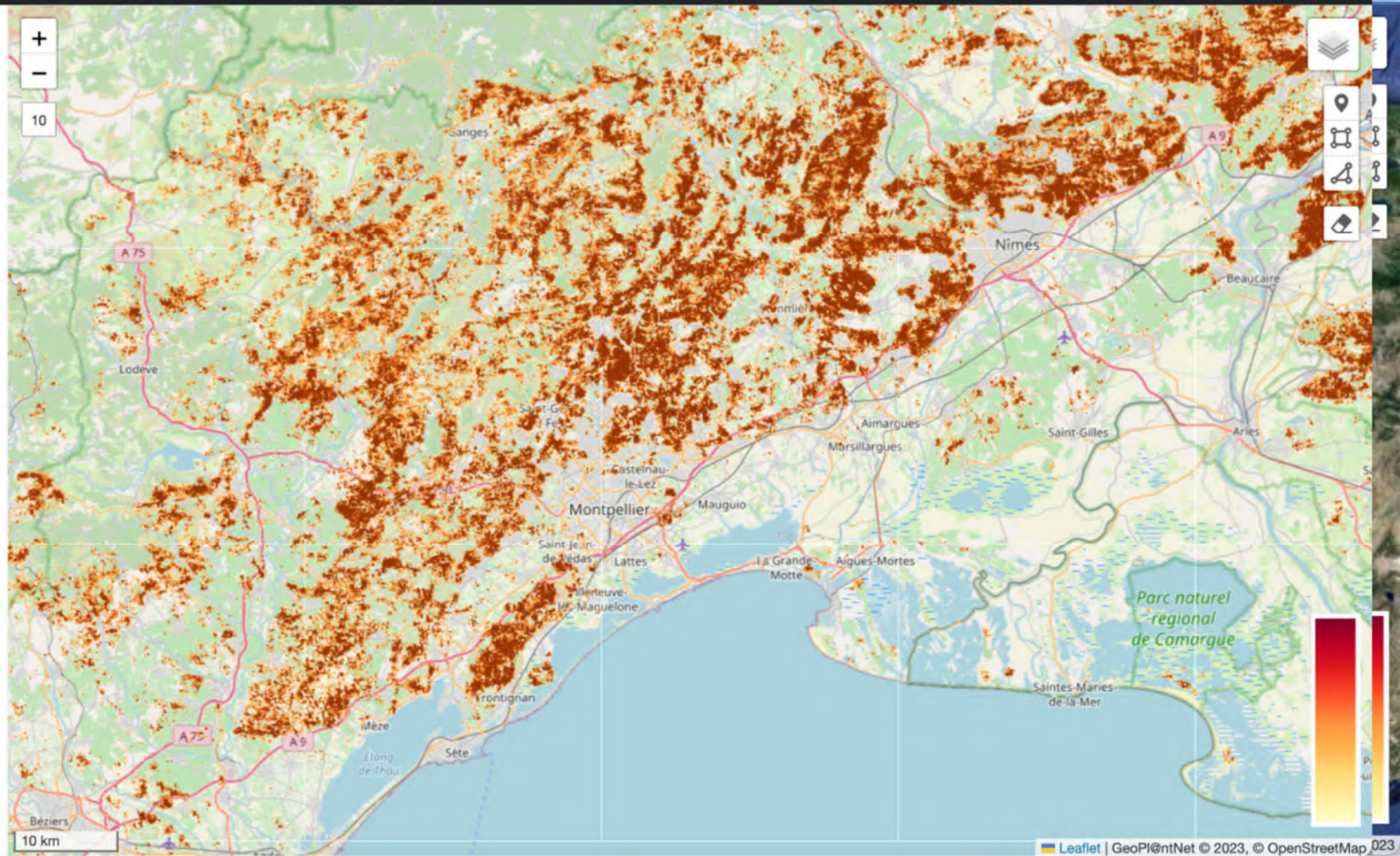
Genus: Thymus

Common Name:

Garden thyme

Model prediction score:

13.67



# GeoPI@ntNet

**Anthemis maritima**  
**Family:** Asteraceae  
**Genus:** Anthemis  
**Common Name:**  
Seaside Chamomile



# Mapping biodiversity conservation indicators

From the species assemblage predicted at each point

$$S_\lambda(x) := \{k \in \mathcal{Y} : \hat{\eta}_k(x) > \lambda\}$$

We can compute indicators such as:

- The number of endangered species (e.g. on IUCN red list)
- The number of tree species (carbon capture)
- The diversity of species (e.g. Shannon index)
- The number of rare species, of species on EU Habitats directives
- The EUNIS habitat (using a species-to-habitat model)

We can construct maps of such indicators at very high resolution by computing  $S_\lambda(x)$  for all  $x_i$  on a dense spatial grid



Ecological Informatics  
Volume 81, July 2024, 102627



Mapping global orchid assemblages with deep learning provides novel conservation insights

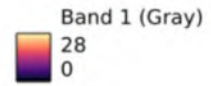


### Biodiversity indicators

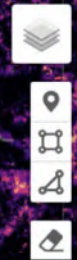
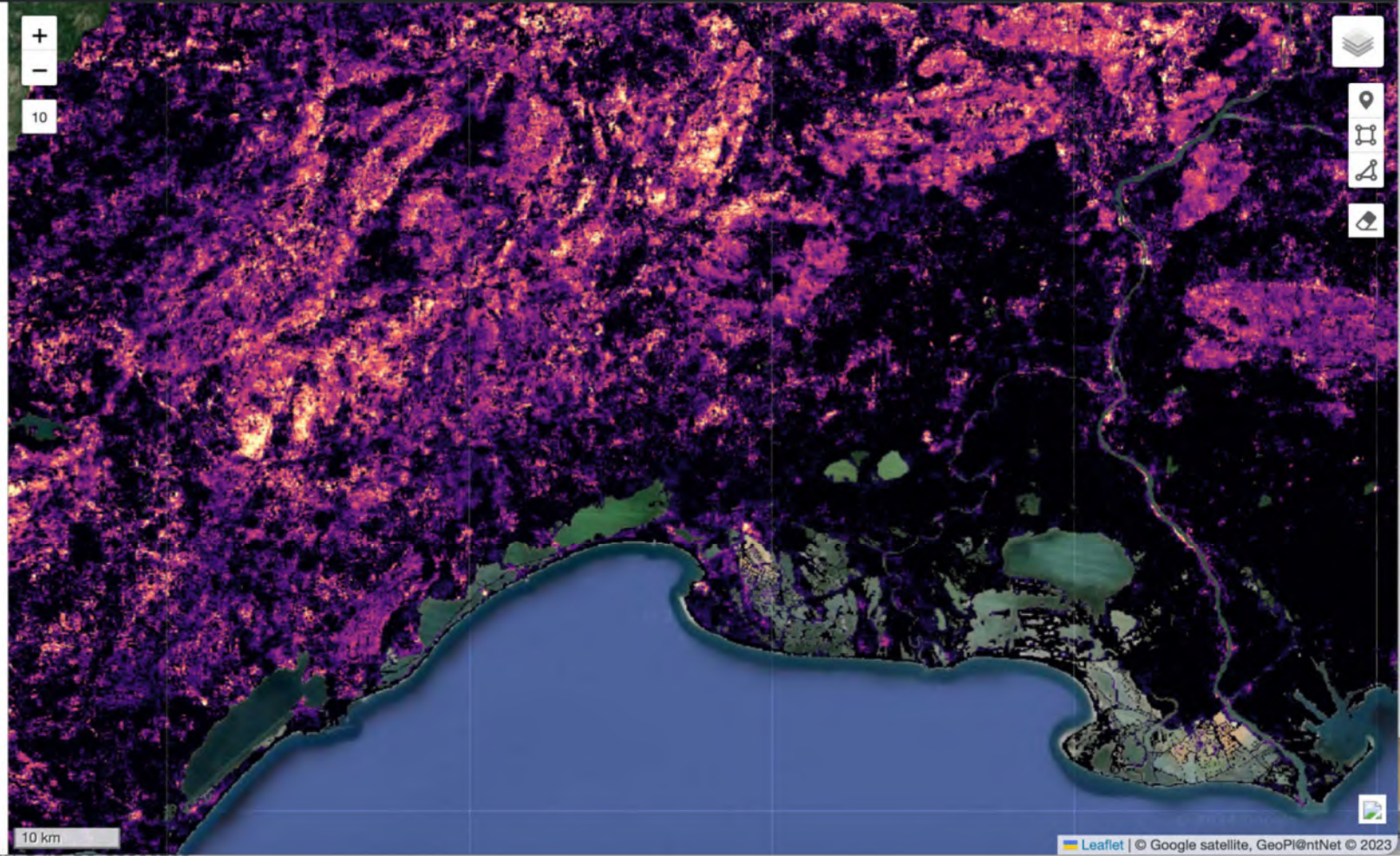
Tree species richness

WMS opacity:

tree\_species\_richness



+  
-  
10



10 km

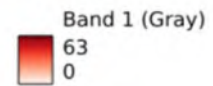


### Biodiversity indicators

Invasives species

WMS opacity:

invasive



10 km

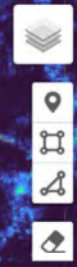
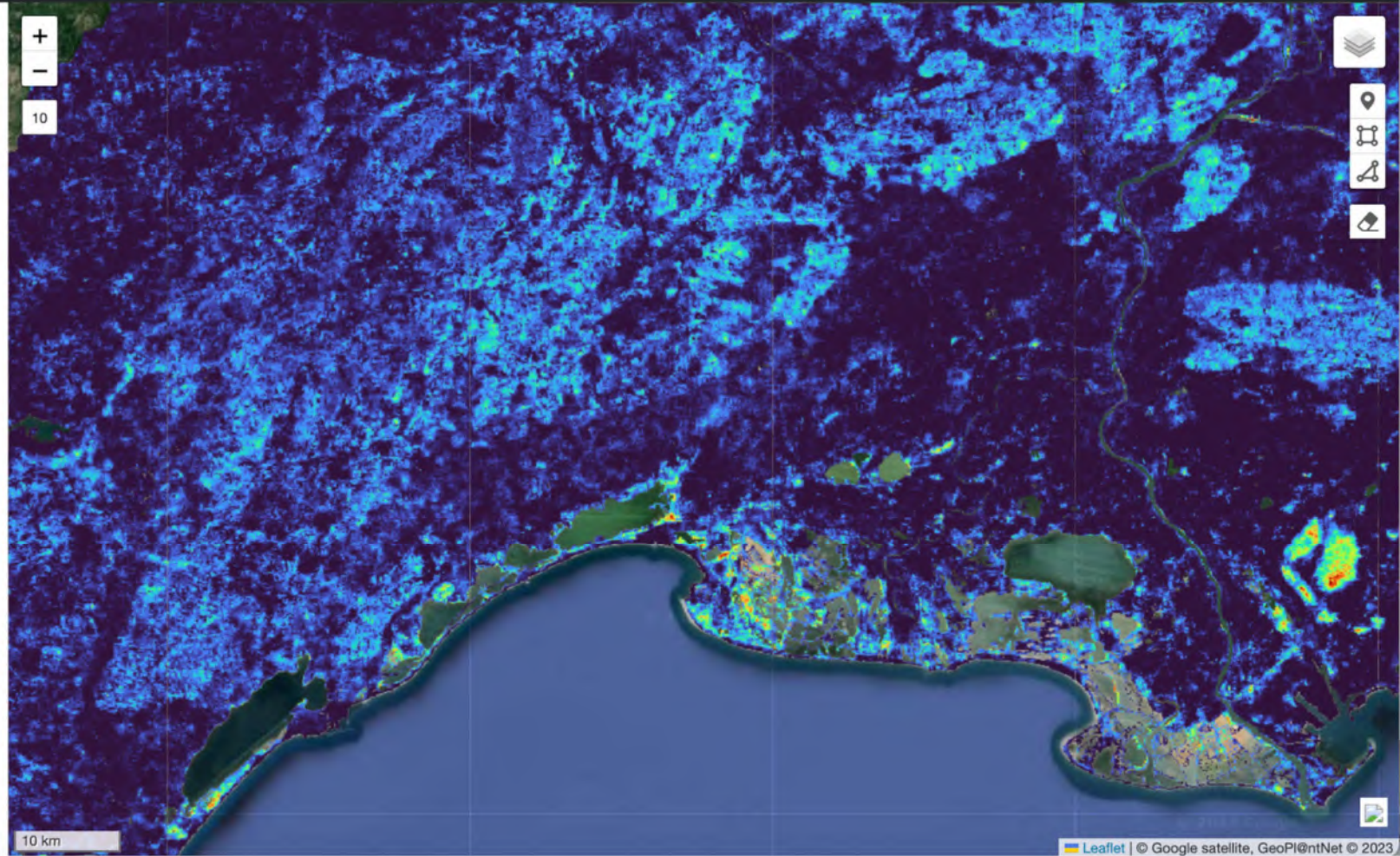
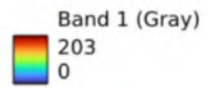


### Biodiversity indicators

Specialization

WMS opacity:

endemism



10 km



### Biodiversity indicators

IUCN worst label

WMS opacity:

- EX
- EW
- CR
- EN
- VU
- NT
- LC
- NE



- EX
- EW
- CR
- EN
- VU
- NT
- LC
- NE

10 km



### Biodiversity indicators

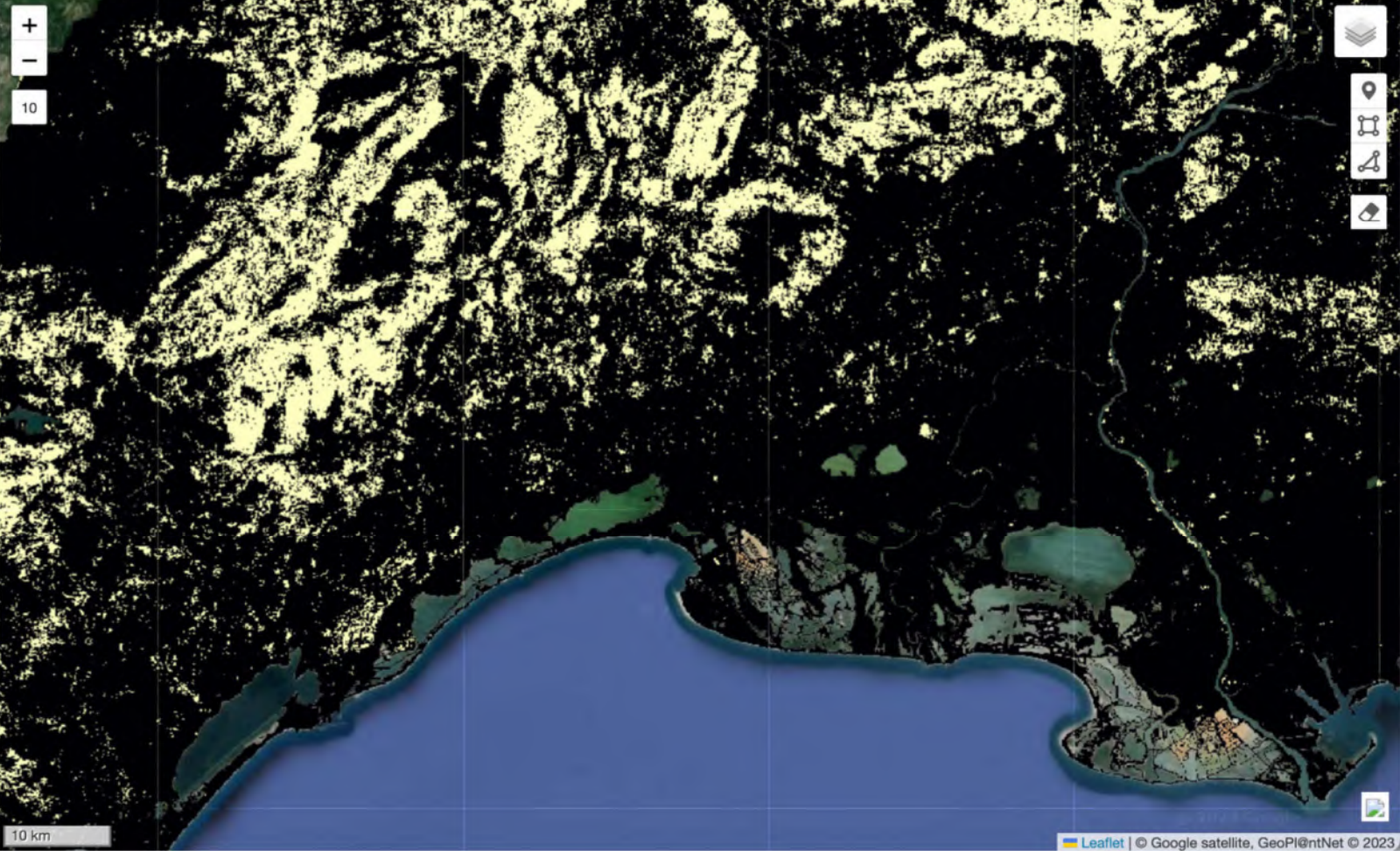
EU directive

WMS opacity:



eu\_directive

Band 1 (Gray)



10 km



Maps

Predictions

Please select an area on the map first



Maps

Predictions

Species

Habitat

168 species ( 16 🌳 - 30 🍄 )

 Get coverage


Id	Name	IUCN	🌳	🍄	%
905	<a href="#">Limbarda crithmoides (L.) Dumort</a>				90.04
4216	<a href="#">Salicornia fruticosa (L.) L.</a>				83.17
9752	<a href="#">Phragmites australis (Cav.) Trin. ex Steud.</a>	LC		🍄	82.05
3878	<a href="#">Tripolium pannonicum (Jacq.) Dobroc.</a>				81.81
7137	<a href="#">Juncus maritimus Lam.</a>				81.05
2212	<a href="#">Limonium vulgare Mill.</a>				76.05
8238	<a href="#">Juncus acutus L.</a>	LC			71.90
4012	<a href="#">Anthemis maritima L.</a>				69.61



Maps

Predictions

Species

Habitat

## 4 habitats

Code	Name	%
MA253	Mediterranean mid-low saltmarsh	65.38
N14	Mediterranean, Macaronesian and Black Sea shifting coastal dune	23.02
MA252	Mediterranean upper-mid saltmarsh and saline and brackish reed, rush and sedge bed	10.25
N32	Mediterranean and Black Sea rocky sea cliff and shore	1.35



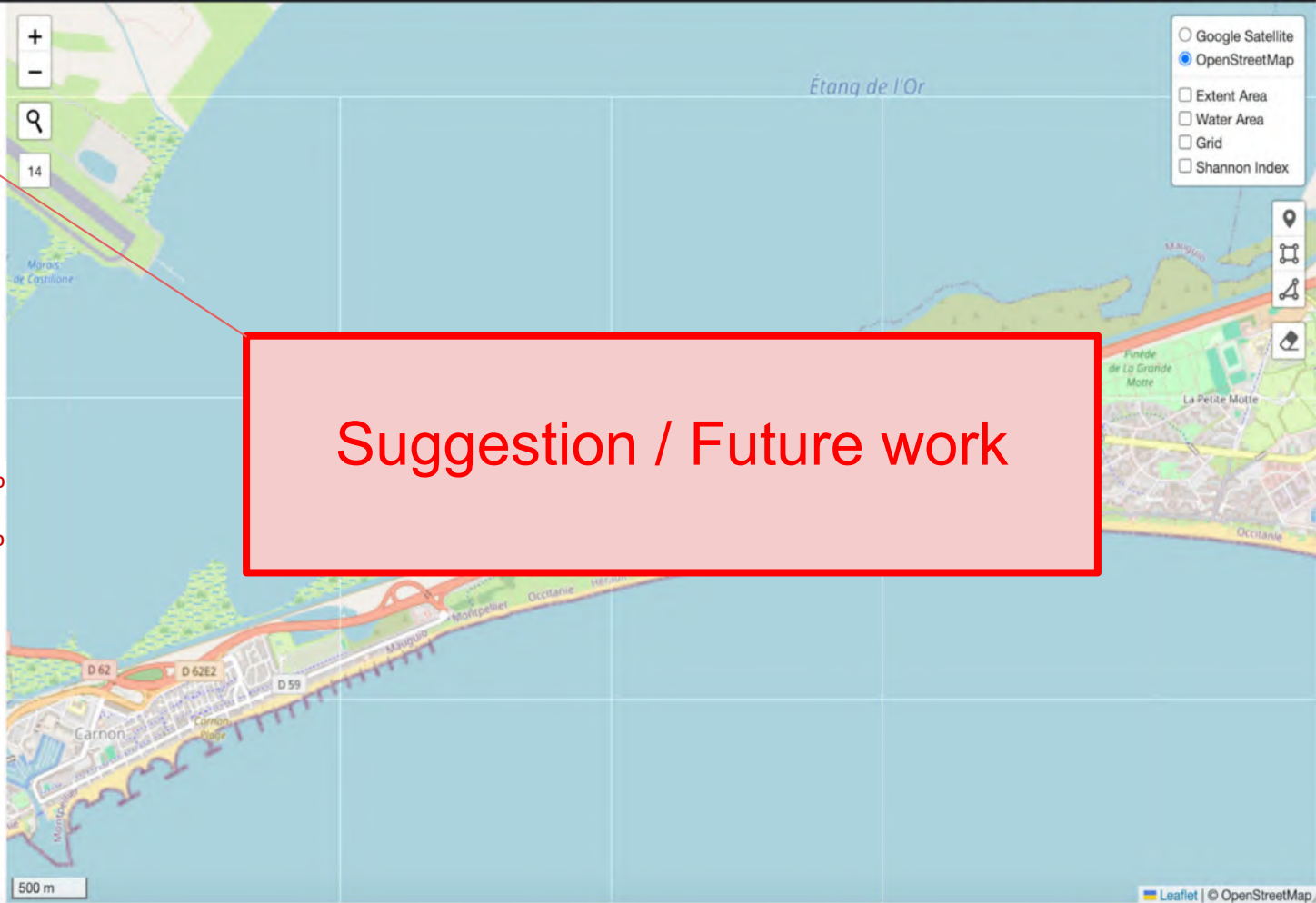
Maps Predictions **Pollinators**

Known pollinators of the plants present :

proba

<i>Stomorhina lunata</i>	34%
<i>Sphaerophoria sp.</i>	24%
<i>Eristalis sp.</i>	21%
<i>Eristalinus sp.</i>	19%

Suggestion / Future work



# Thank you

