Remote sensing and deep learning for biodiversity assessment

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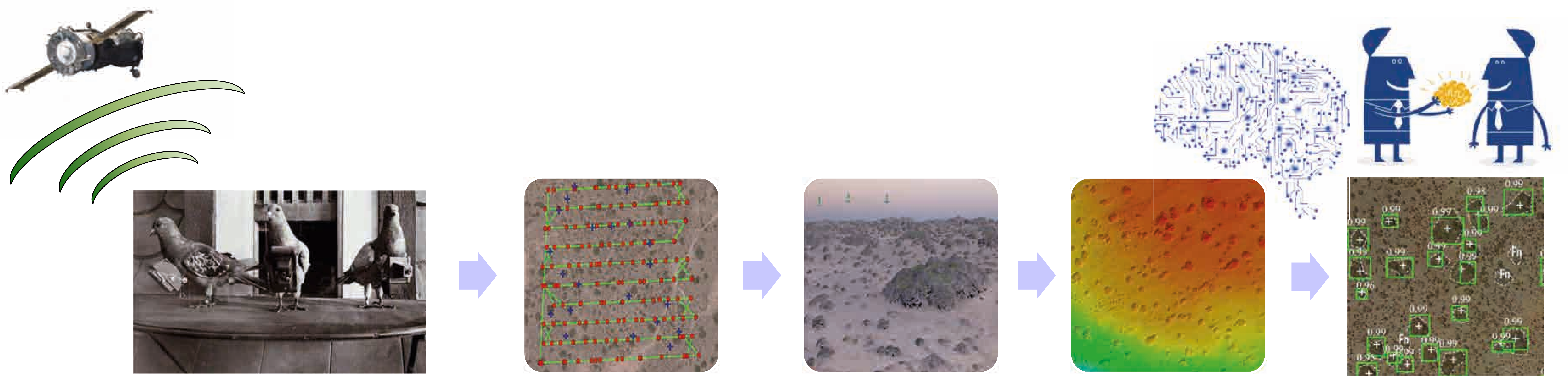
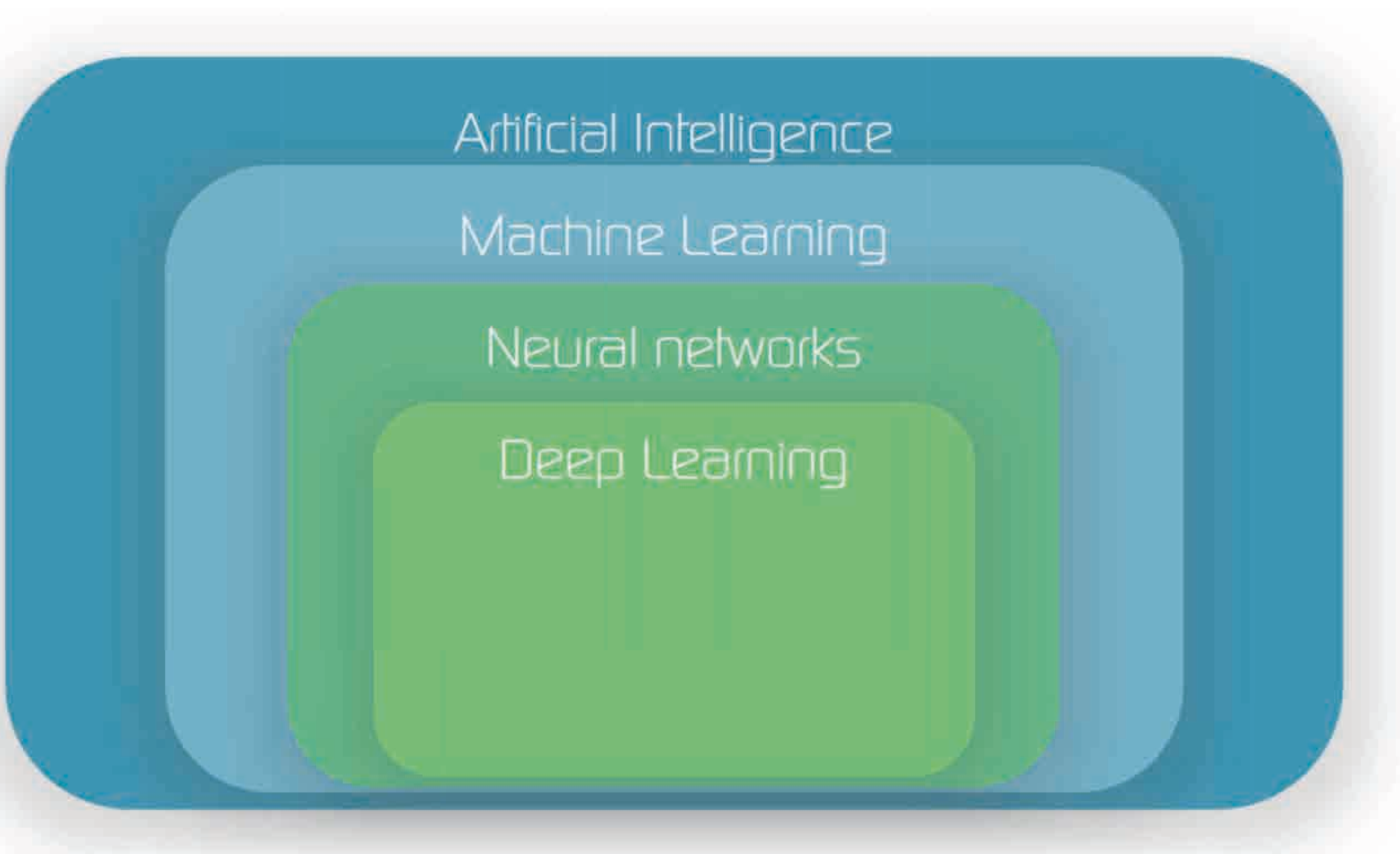
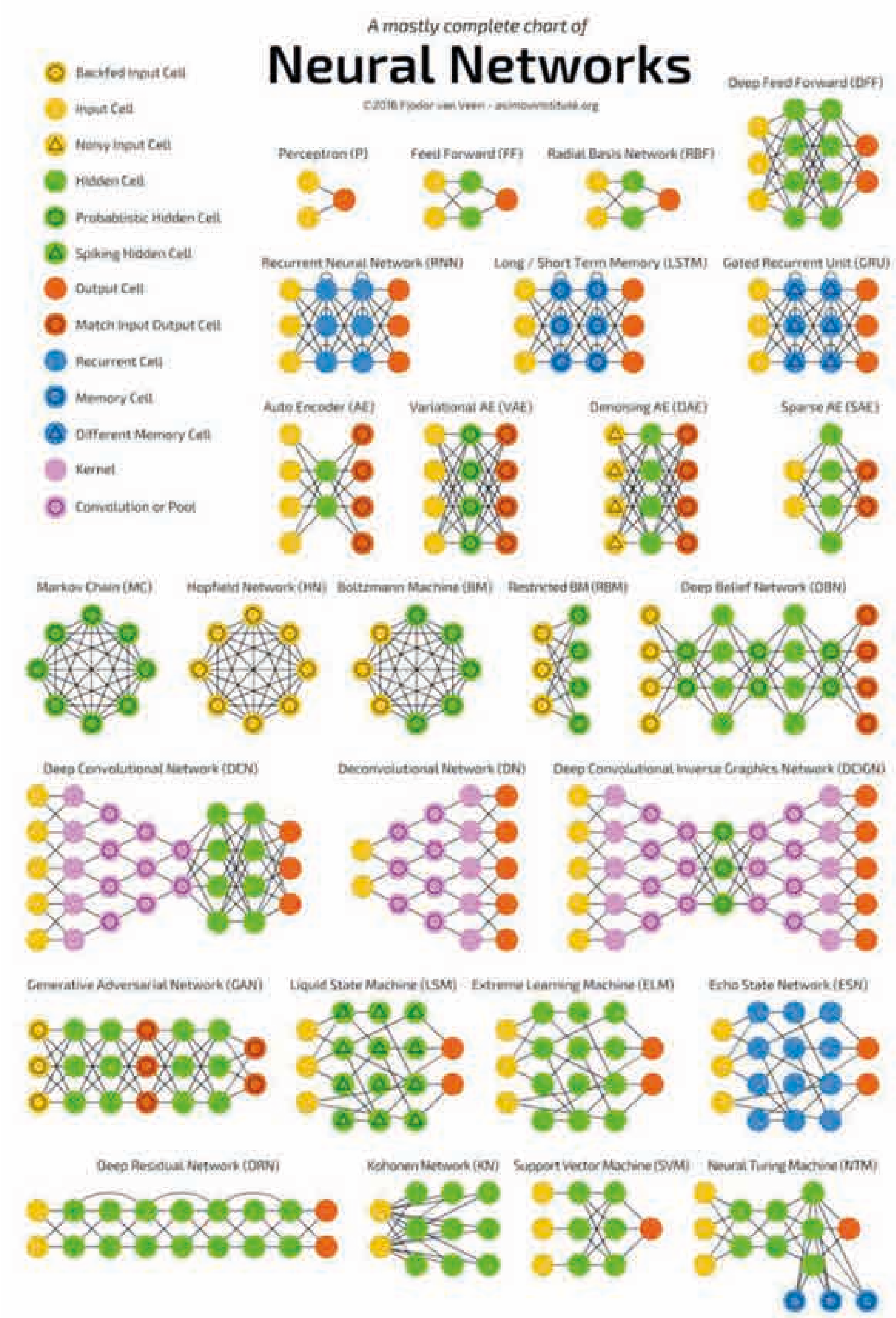


Outline

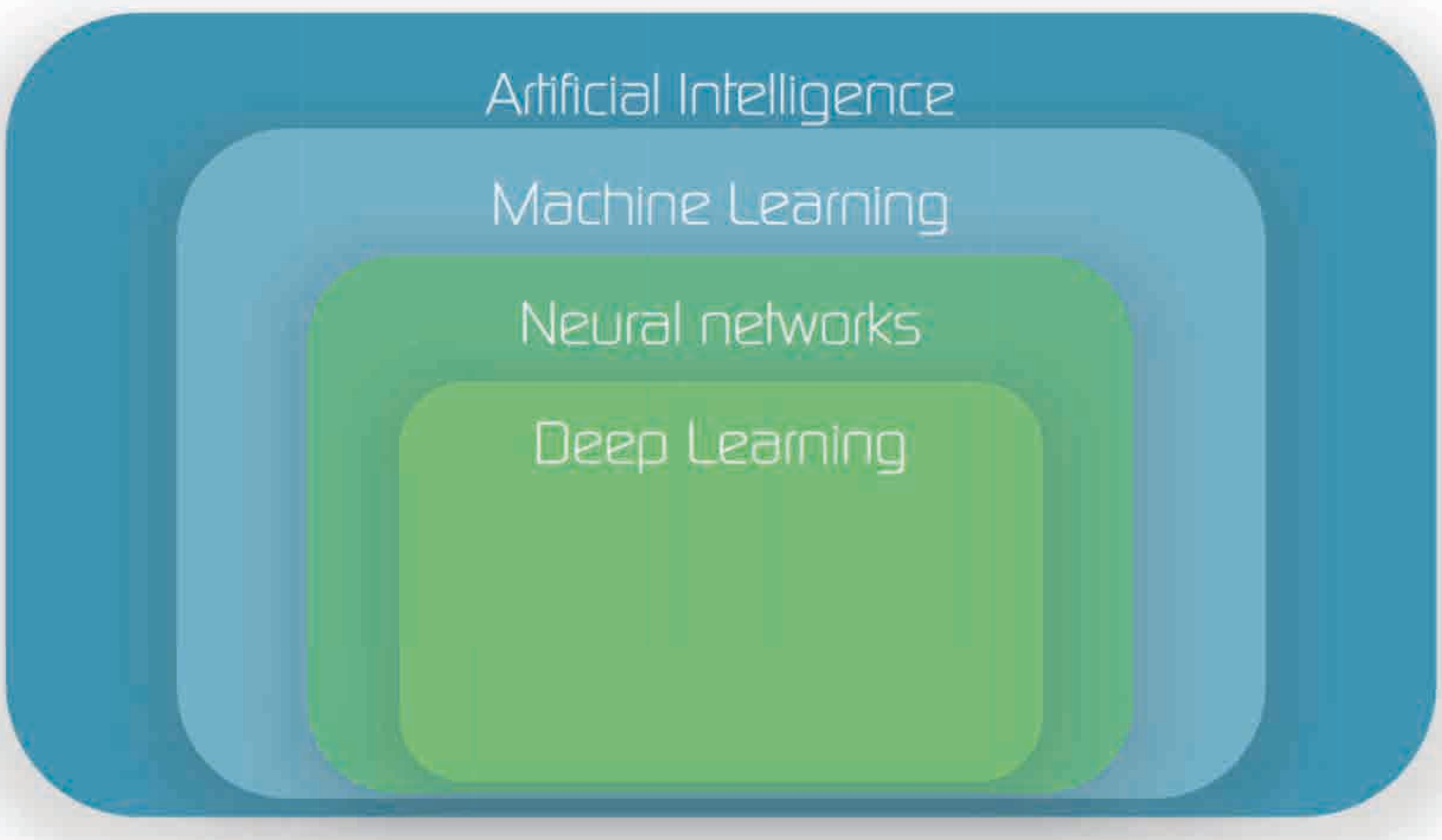
- What is deep learning?
- Deep learning in remote sensing:
  - Coral species classification
  - Whale detection
  - *Ziziphus lotus* arborescent matorral

What is Deep Learning?



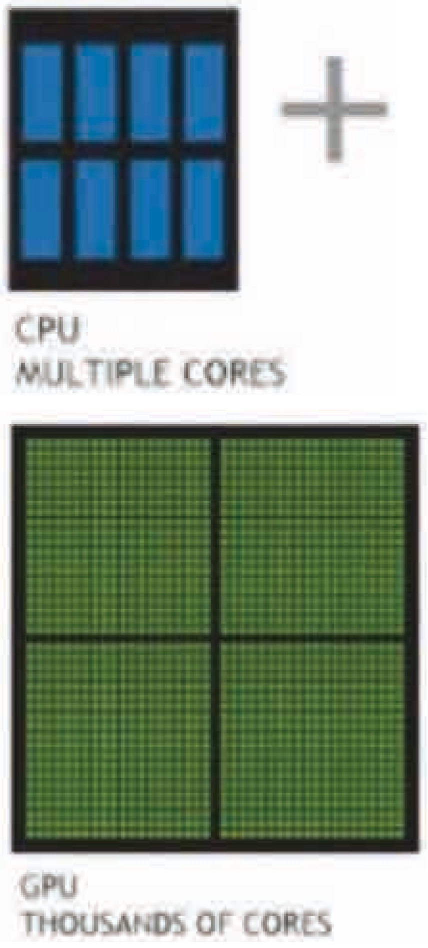


What is Deep Learning?



Big data

CPUs+GPUs

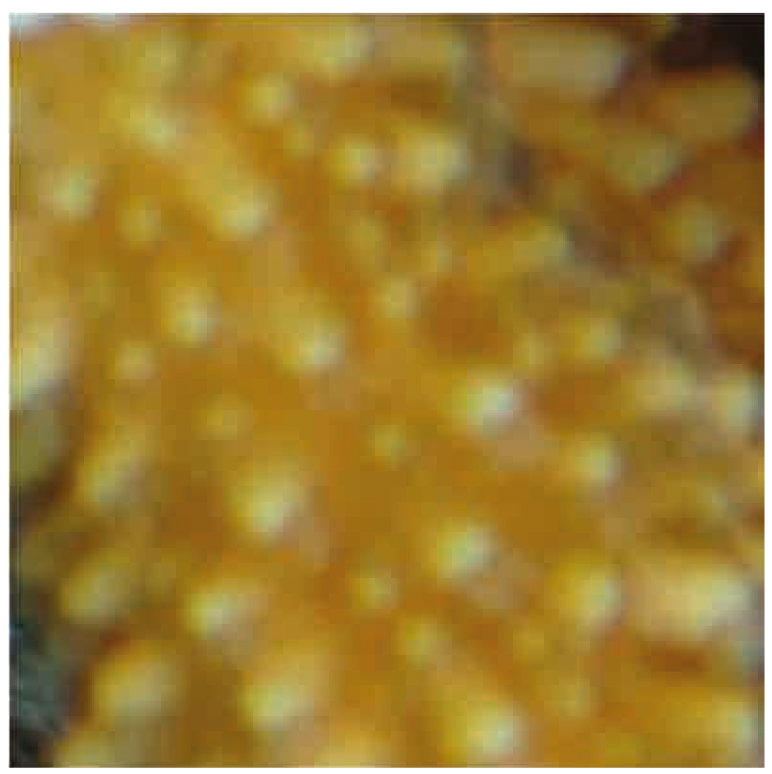


Is Deep Learning already in my life?

DeepL

1.Deep learning system to identify coral species in underwater photos

Acropora cervicornis



Texture

Structure

Gómez-Ríos, Tabik, Luengo, Shihavuddin, Krawczyk, Herrera. 2019 *Expert Systems with Applications*

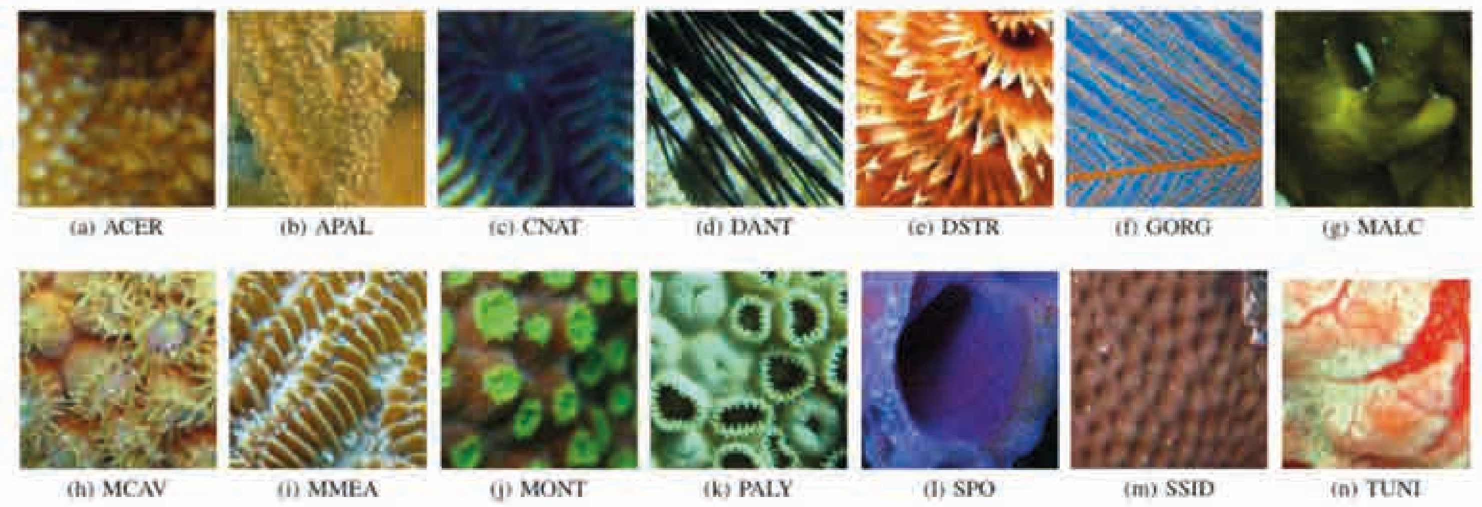


Fig. 1. One texture image from each RSMAS class.

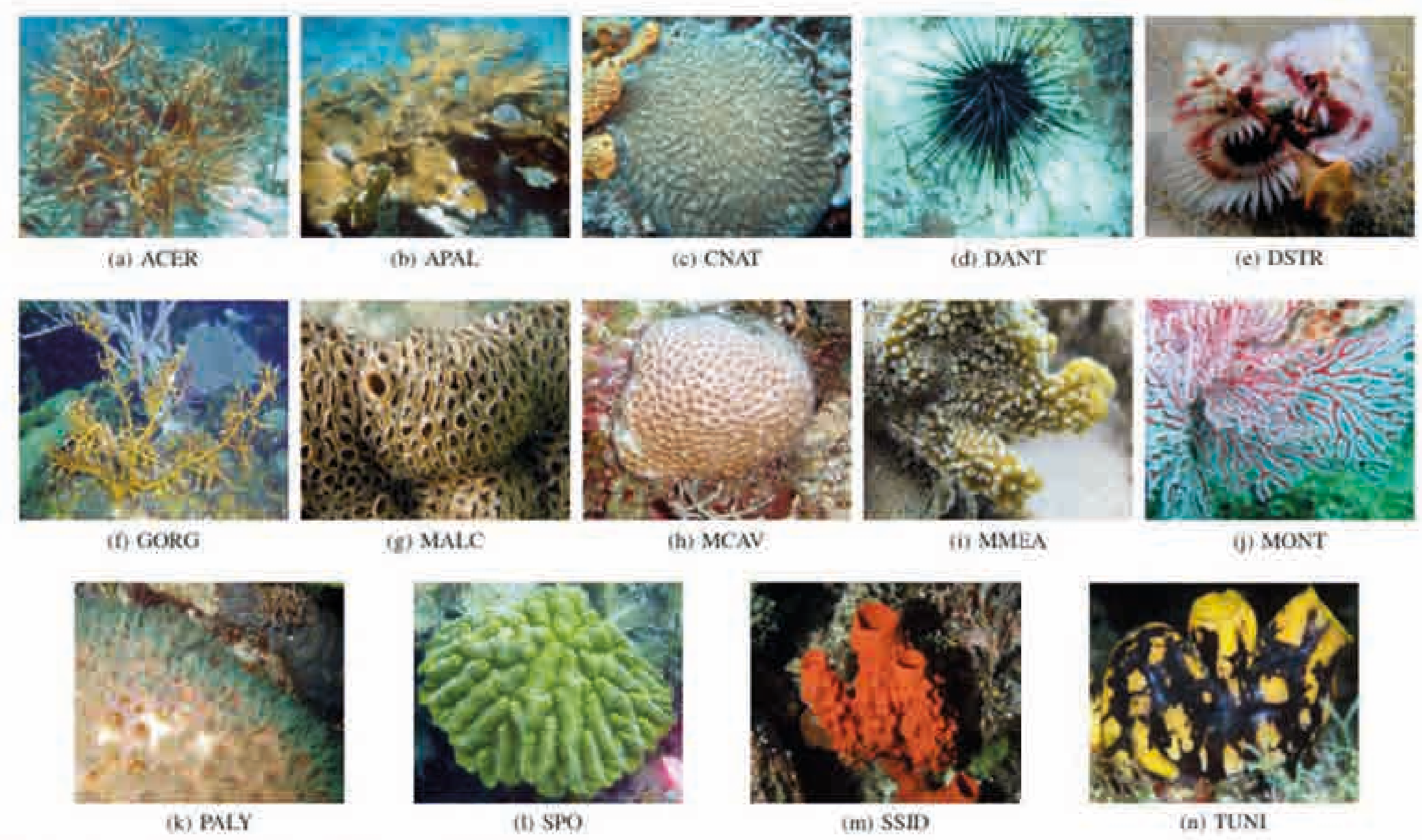
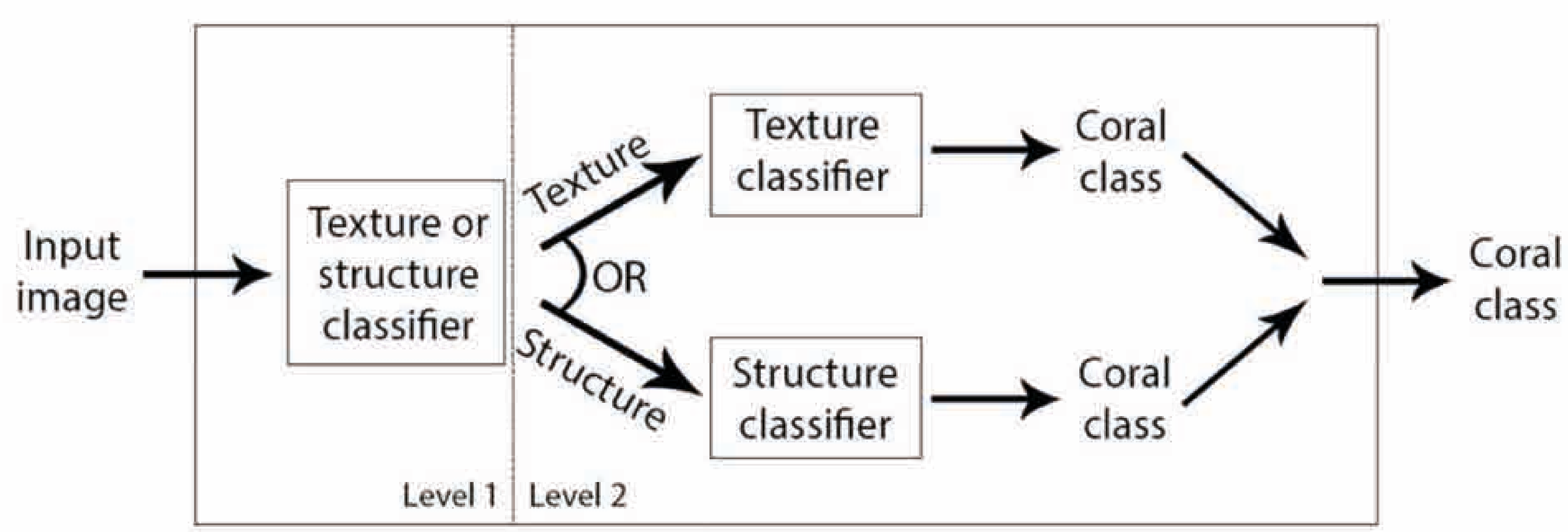
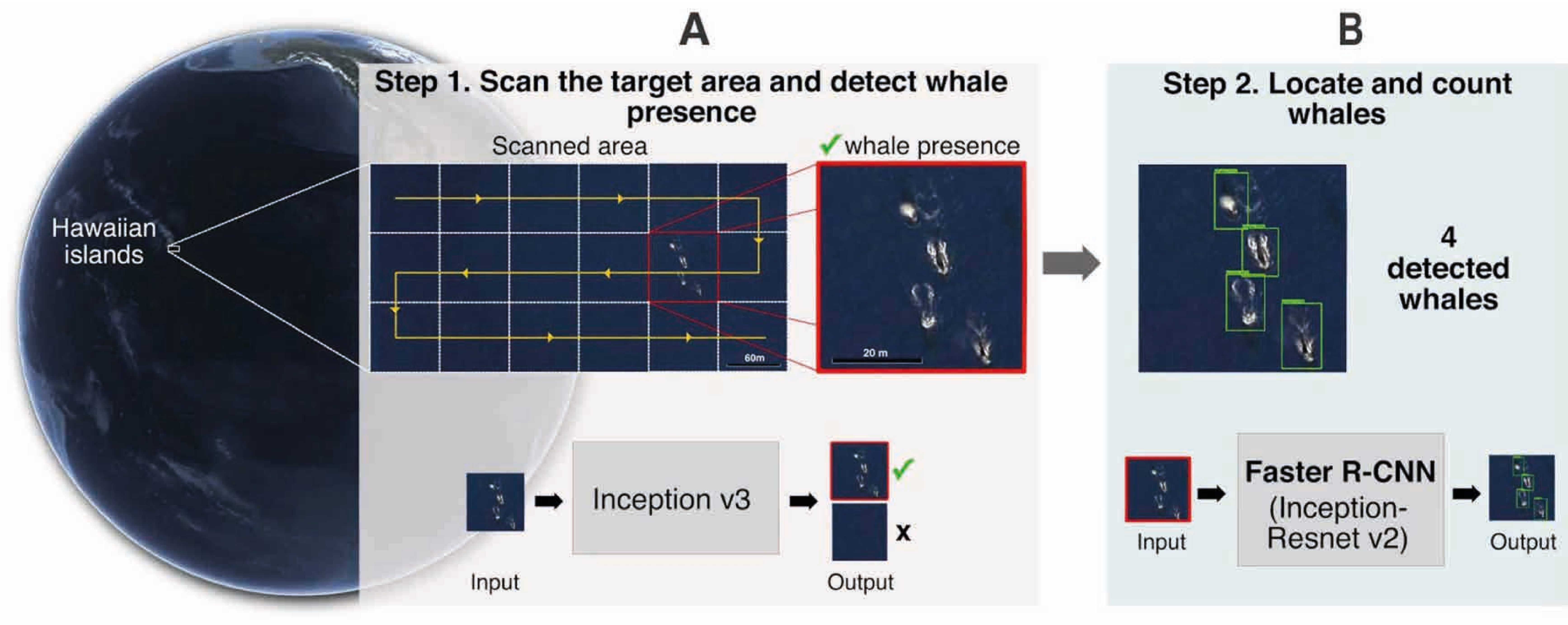


Fig. 2. One structure image from each StructureRSMAS class.



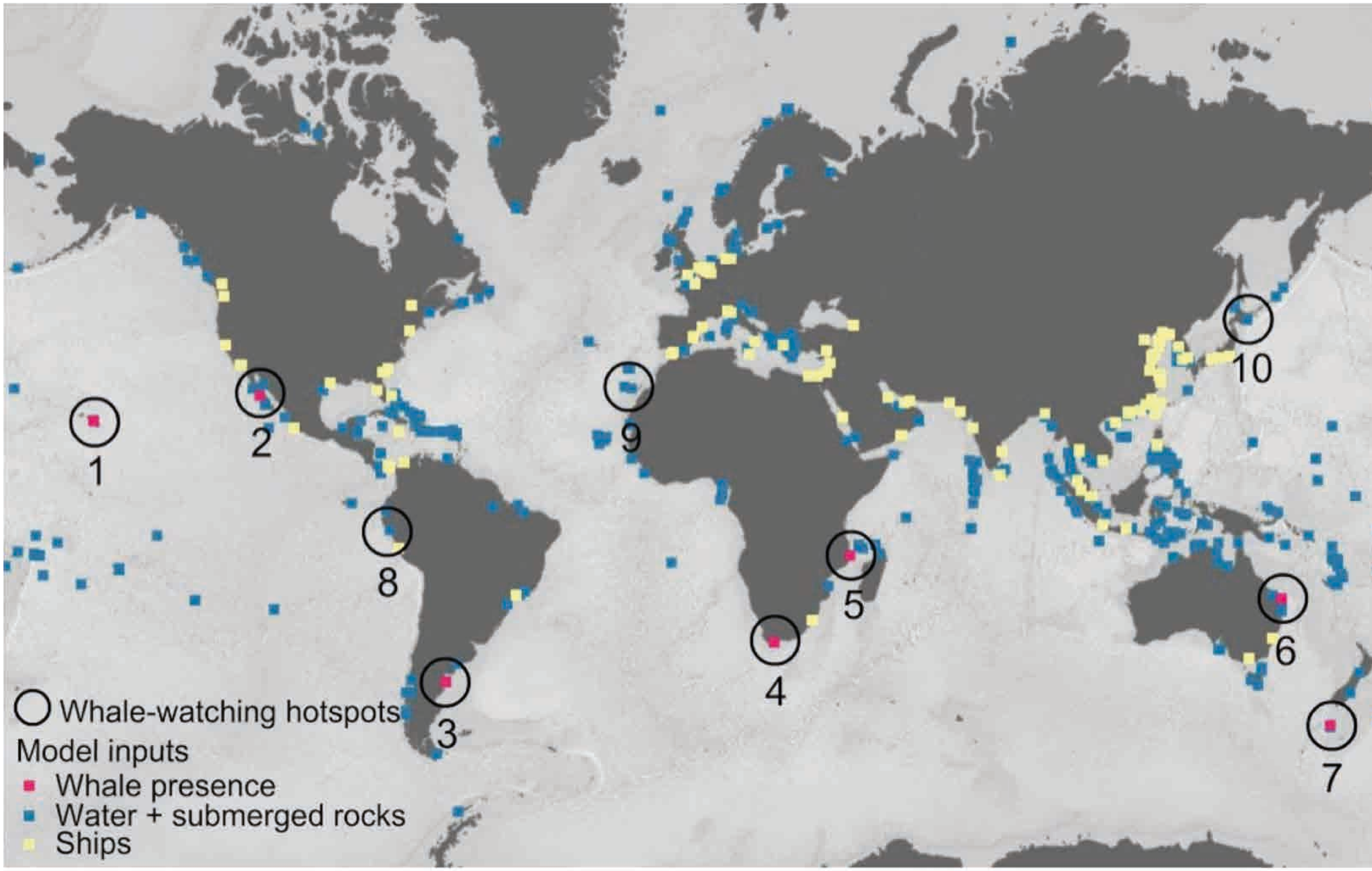
Accuracy
(F1)
93%

2. Deep learning system to automatically count whales from space

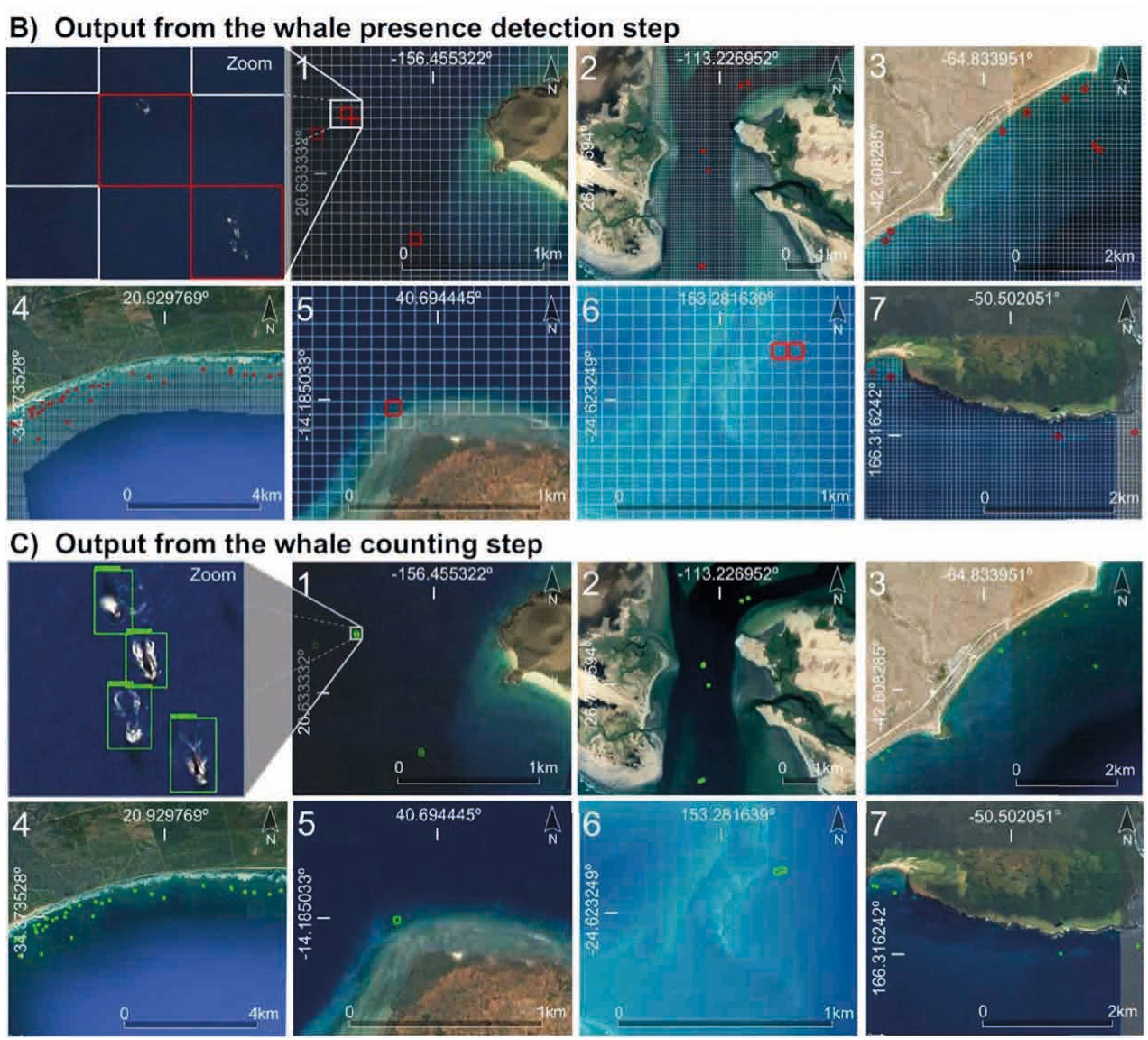


Guirado et al. In revision. Scientific Reports. doi: https://doi.org/10.1101/443671

The first step CNN-based model detected the presence of whales with an accuracy (F1) of 84%



The second step CNN-based model counted whales with an accuracy (F1) of 97%



3. Deep learning and Sentinel NDVI to protect a habitat under the Water Framework Directive

Guirado et al. 2018. Ecohydrology. *Guirado et al. 2017. Remote Sensing*

Patch structure, dynamics and implications for the functioning of arid ecosystems

Martín R. Aguiar and Osvaldo E. Sala

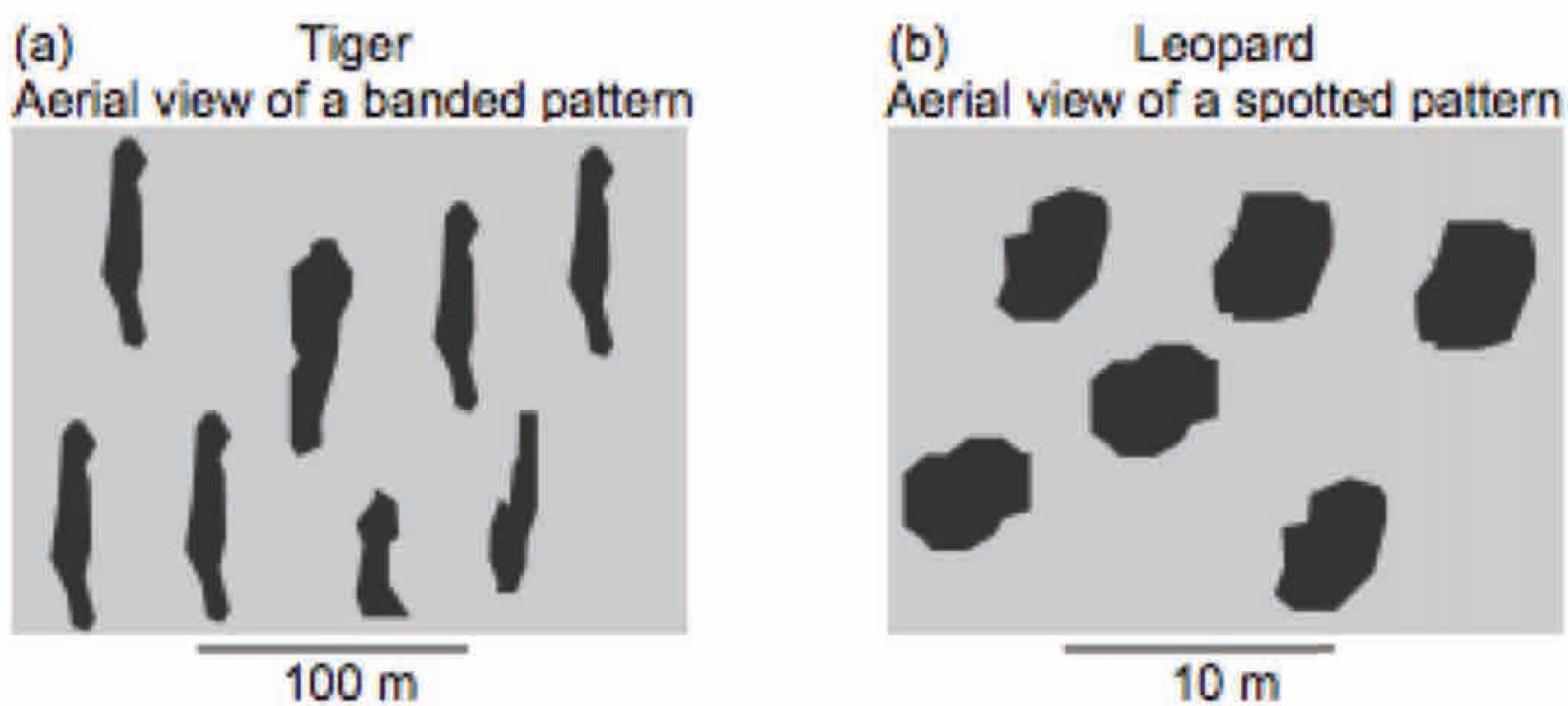


Fig. 1. Vegetation in arid lands is commonly arranged in a two-phase mosaic composed of high plant-cover patches in a low-cover matrix. Vegetation patches are usually dominated by woody plants that form bands or spots. Banded vegetation is referred to as a 'tiger' pattern (a) and spotted vegetation is here named as a 'leopard' pattern (b).

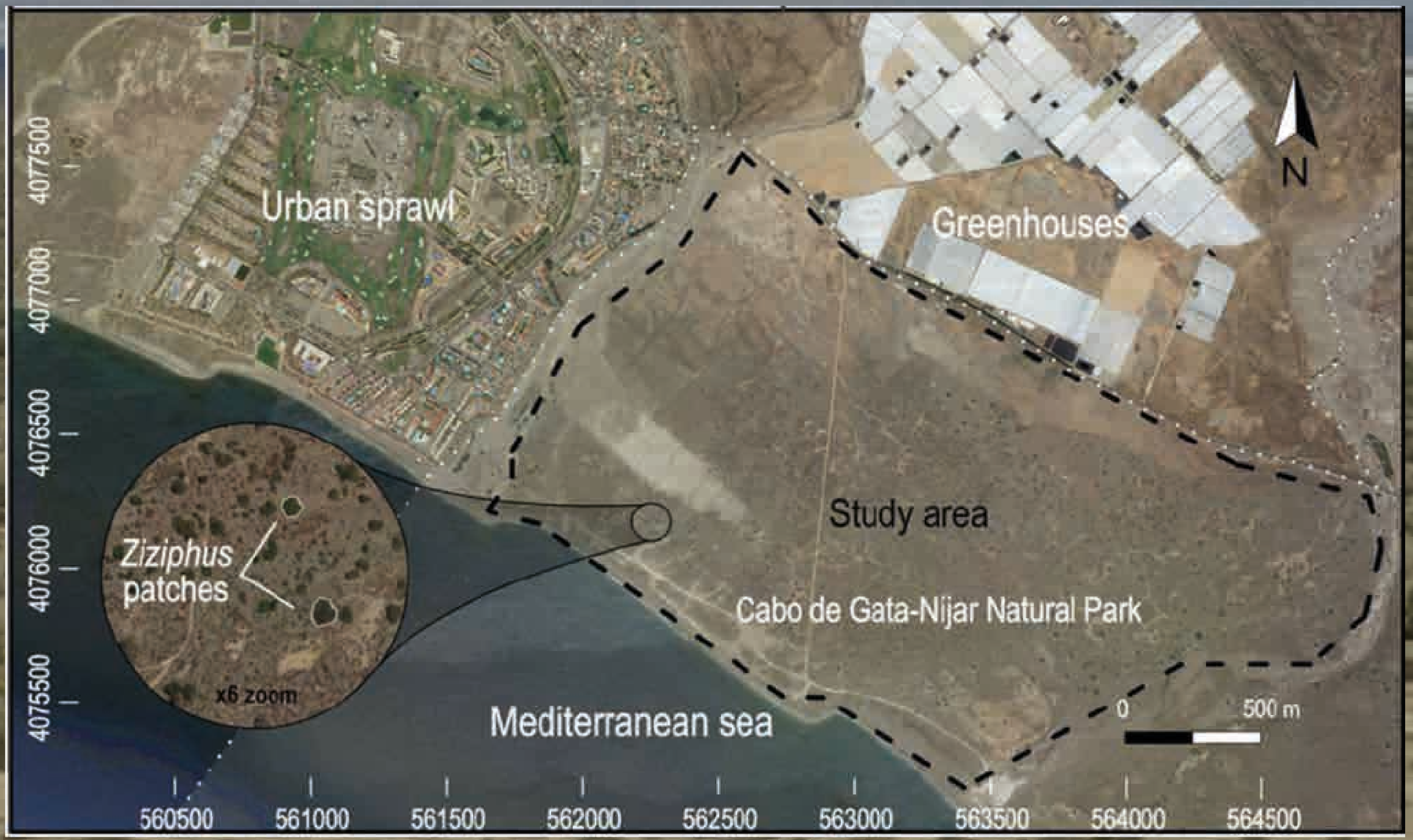
Trends in Ecology & Evolution, *14*(7), 273-277.

What to get precision shrub maps for?

Leopard or tiger?

What to get precision shrub maps for?

Leopard or tiger?



Priority Habitat 5220* “Arborescent matorral with *Ziziphus*”: Unfavourable-bad

Hypothesis:

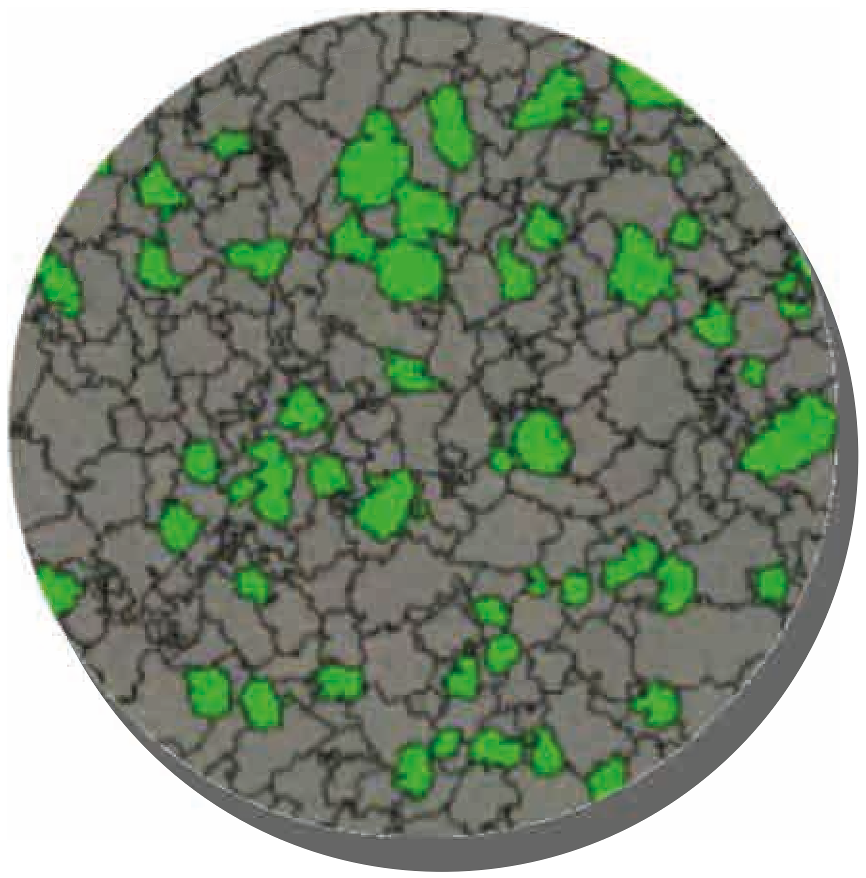
- H: Given the arid conditions, this winter-deciduous shrub should be near from fractures to access groundwater.

Objectives:

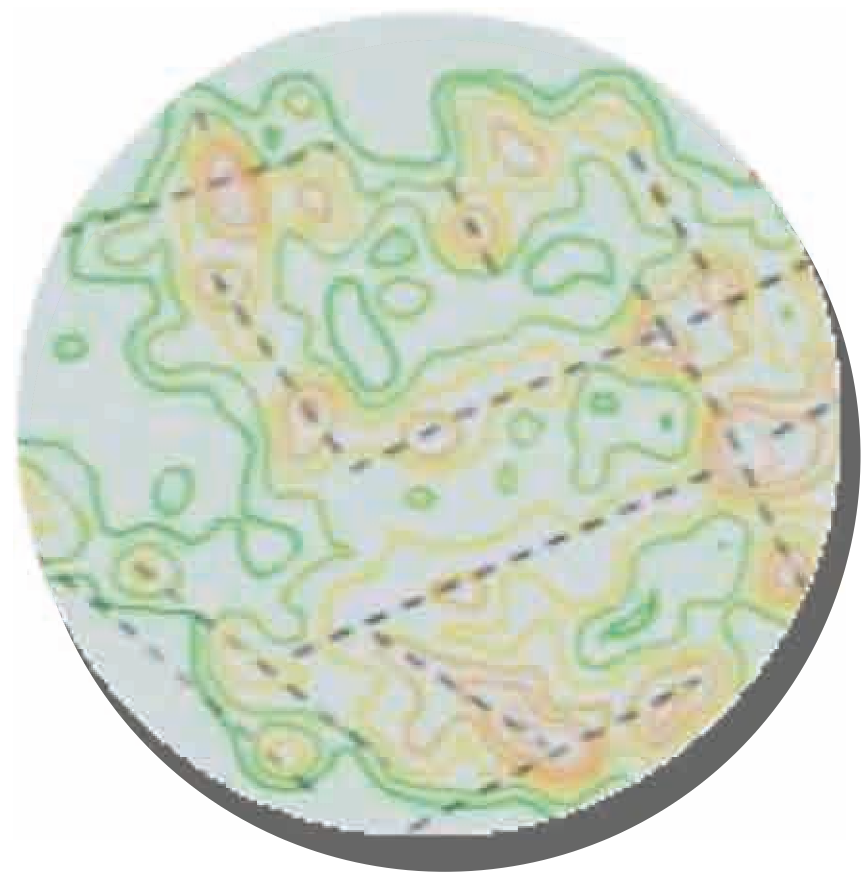
- To produce high-precision maps of shrubs and fractures.
- To detect a groundwater-dependent ecosystem from the spatial relationship between shrubs and fractures at the population level.
- To validate such dependency with Sentinel-2 NDVI at the individual level.

Guirado et al. 2018. Ecohydrology. *Guirado et al. 2017. Remote Sensing*

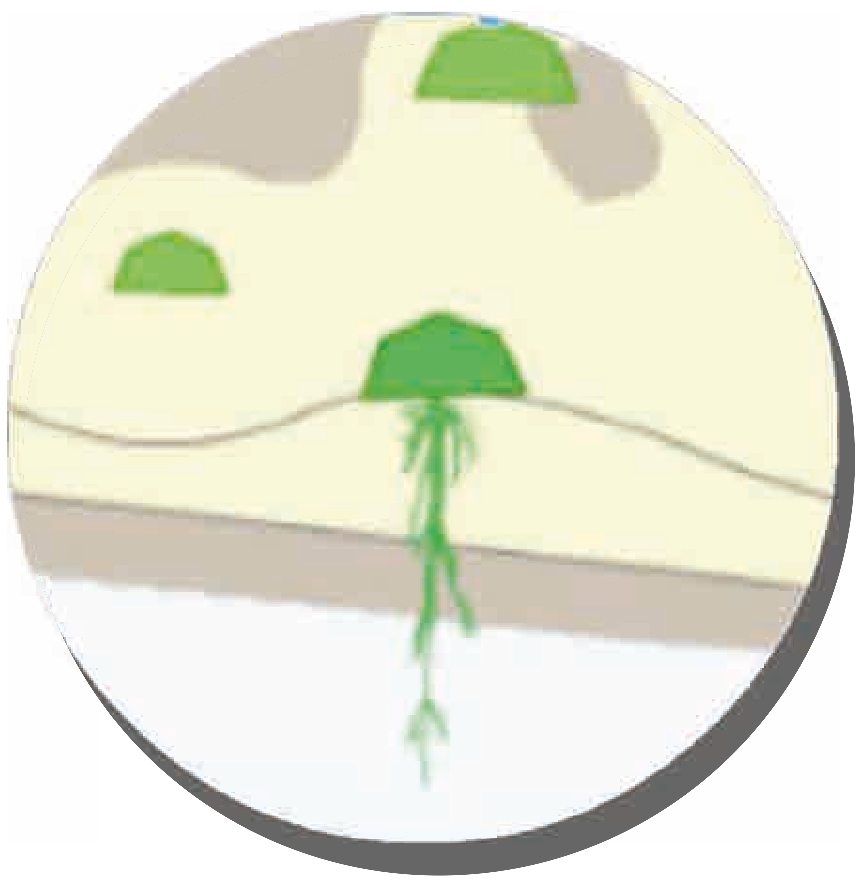
What to get precision shrub maps for?



Cartography of vegetation patches



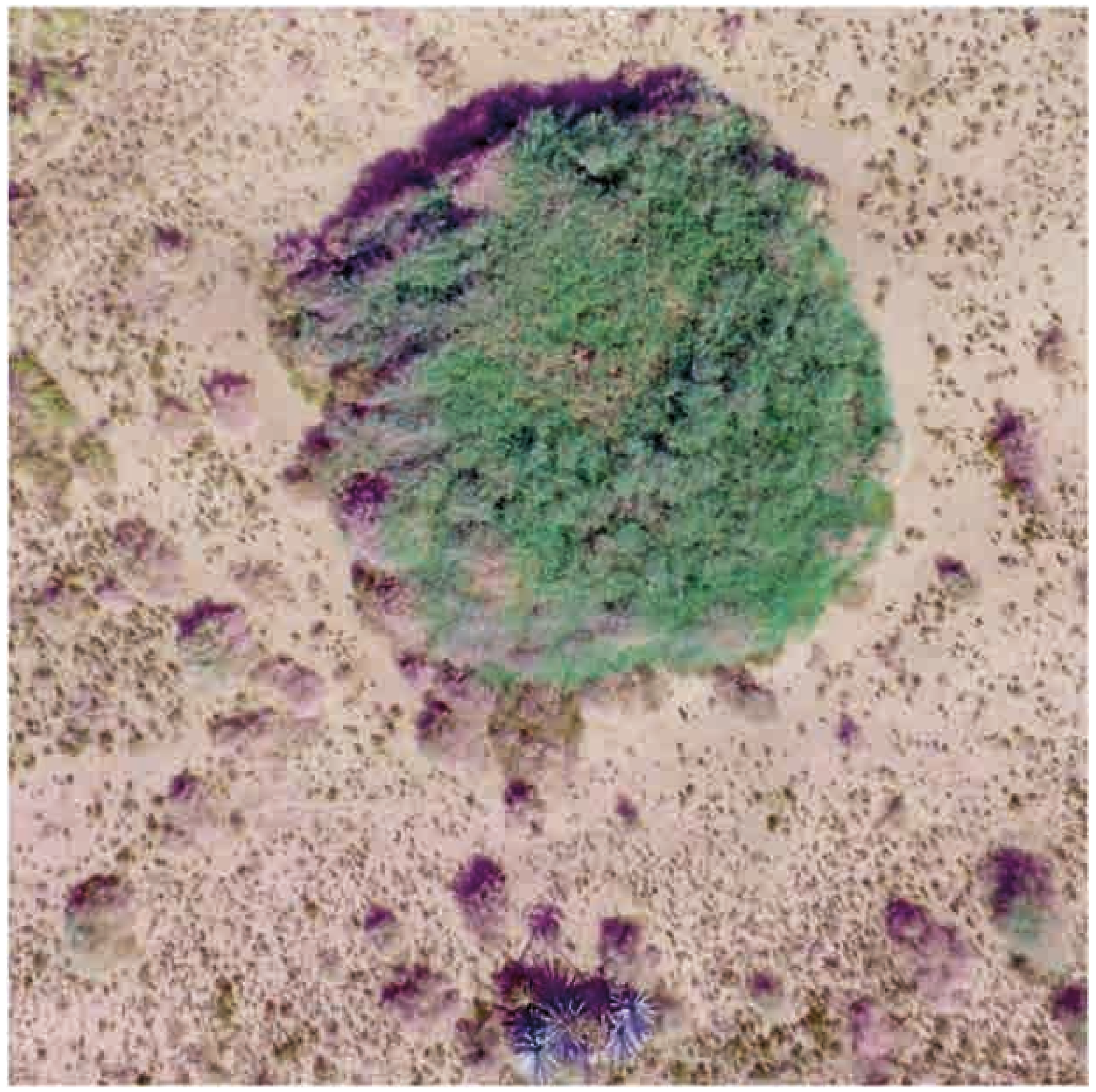
Characterization of vegetation spatial patterns



Population dynamics, ecosystem functioning and landscape degradation processes

Guirado et al. 2018. Ecohydrology. *Guirado et al. 2017. Remote Sensing*

Very High Resolution image datasets

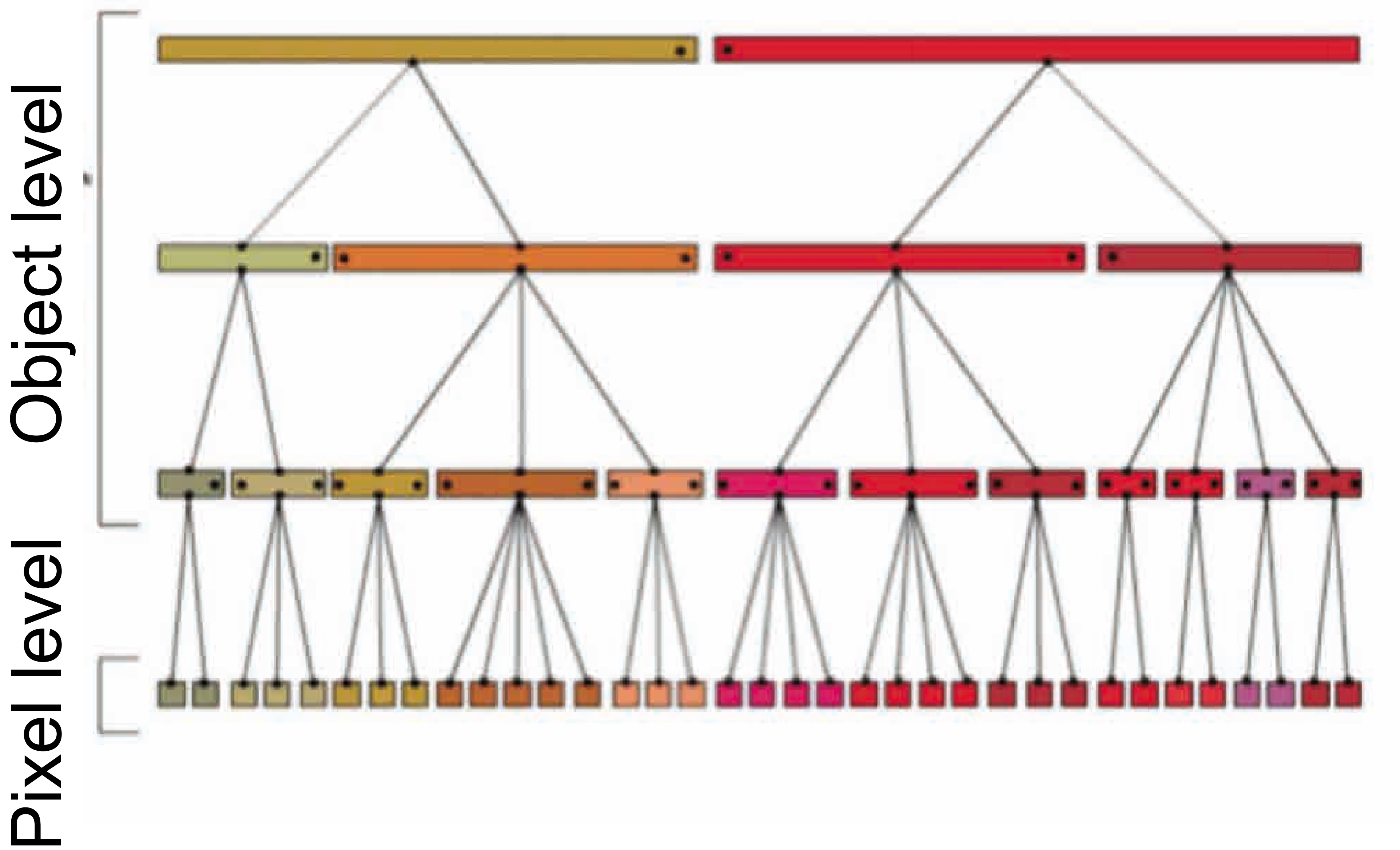
Google Earth	Airborne	UAV
		
0.5 m / pixel	0.1 m / pixel	0.03 m / pixel
Free	Very high cost	High cost

New technologies for precise shrub mapping

OBIA

Object-based image analysis (OBIA).

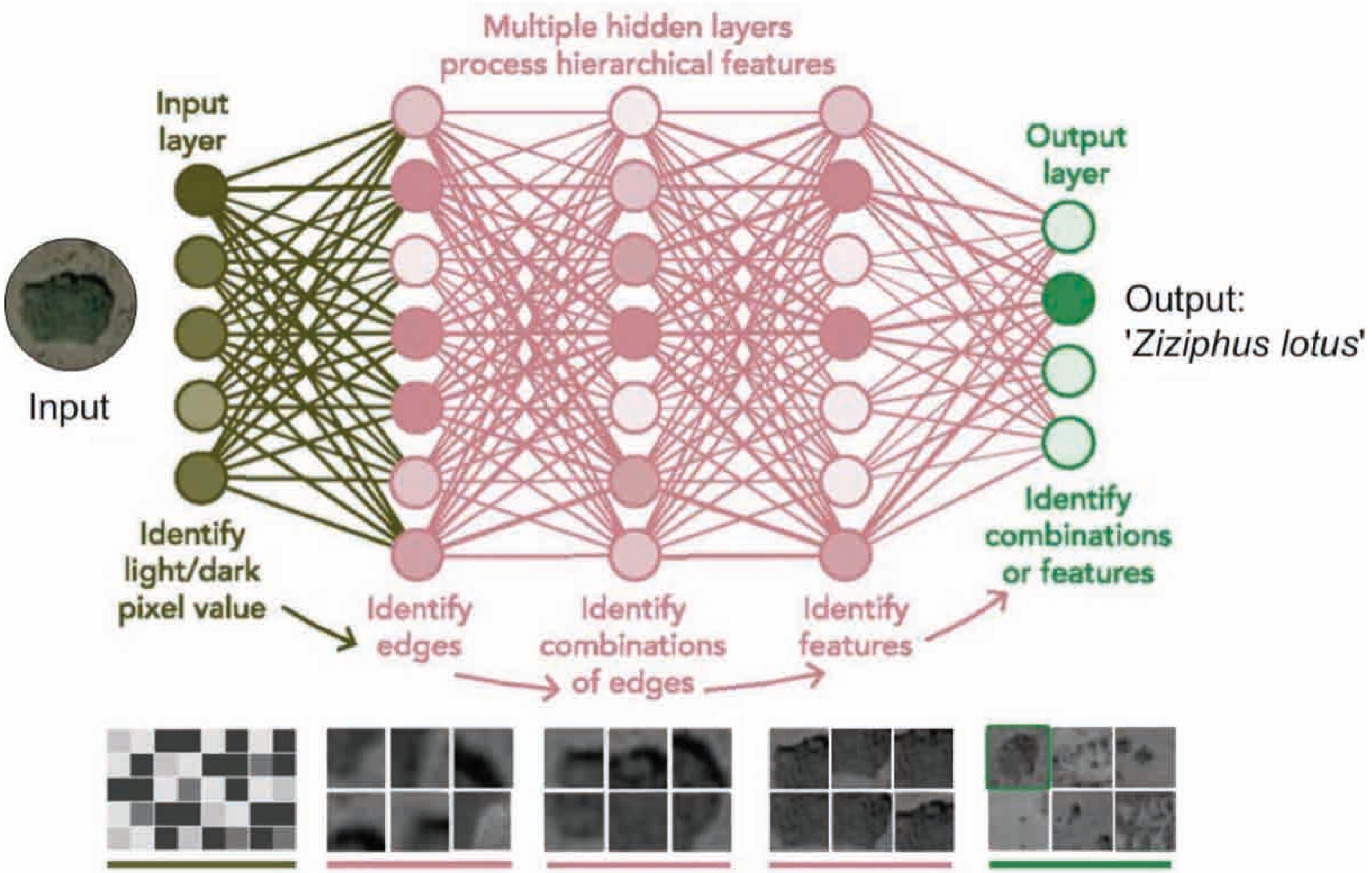
A geographical method that groups pixels into objects with similar characteristics (scale, shape, color)



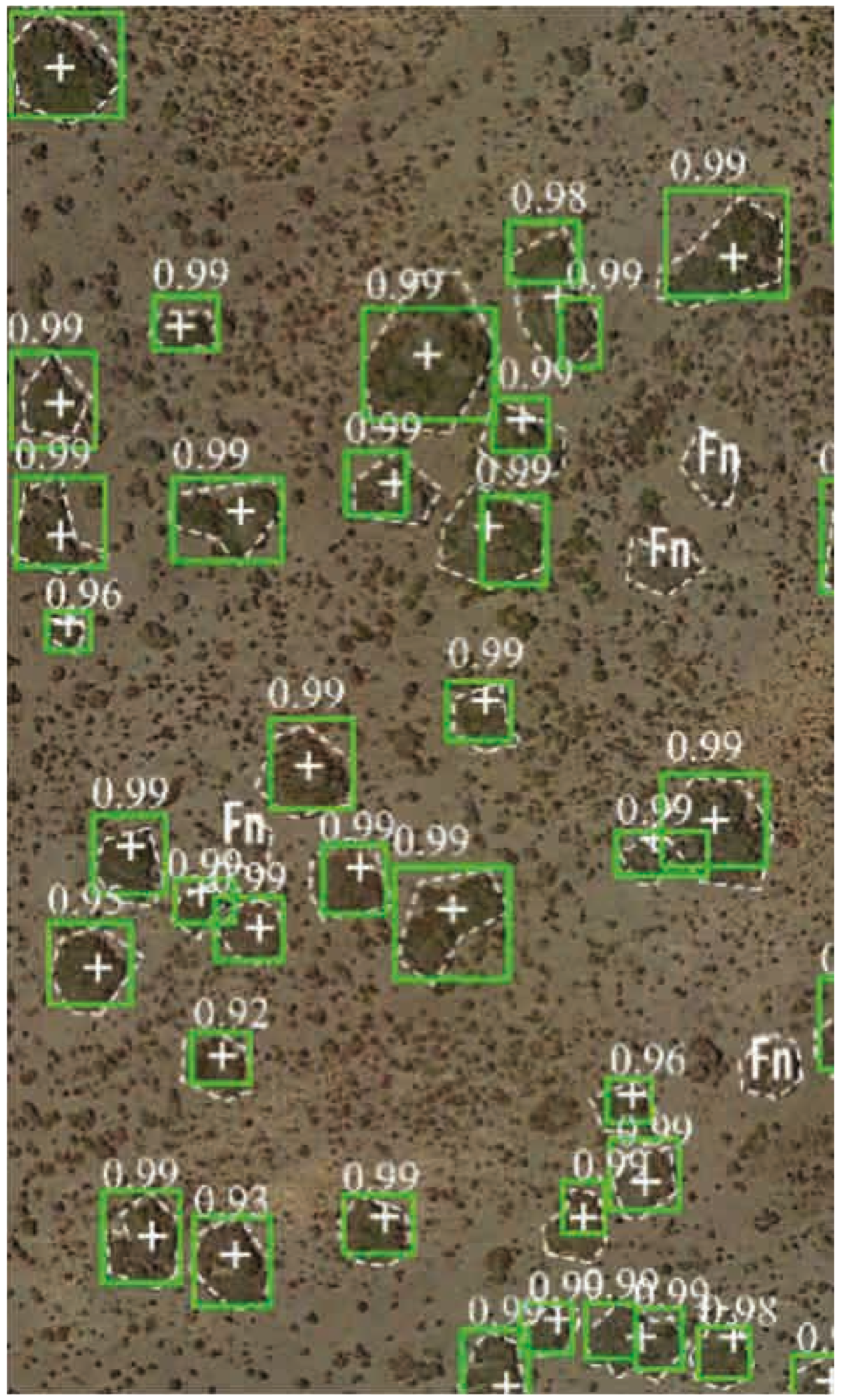
Artificial Intelligence for precise shrub mapping

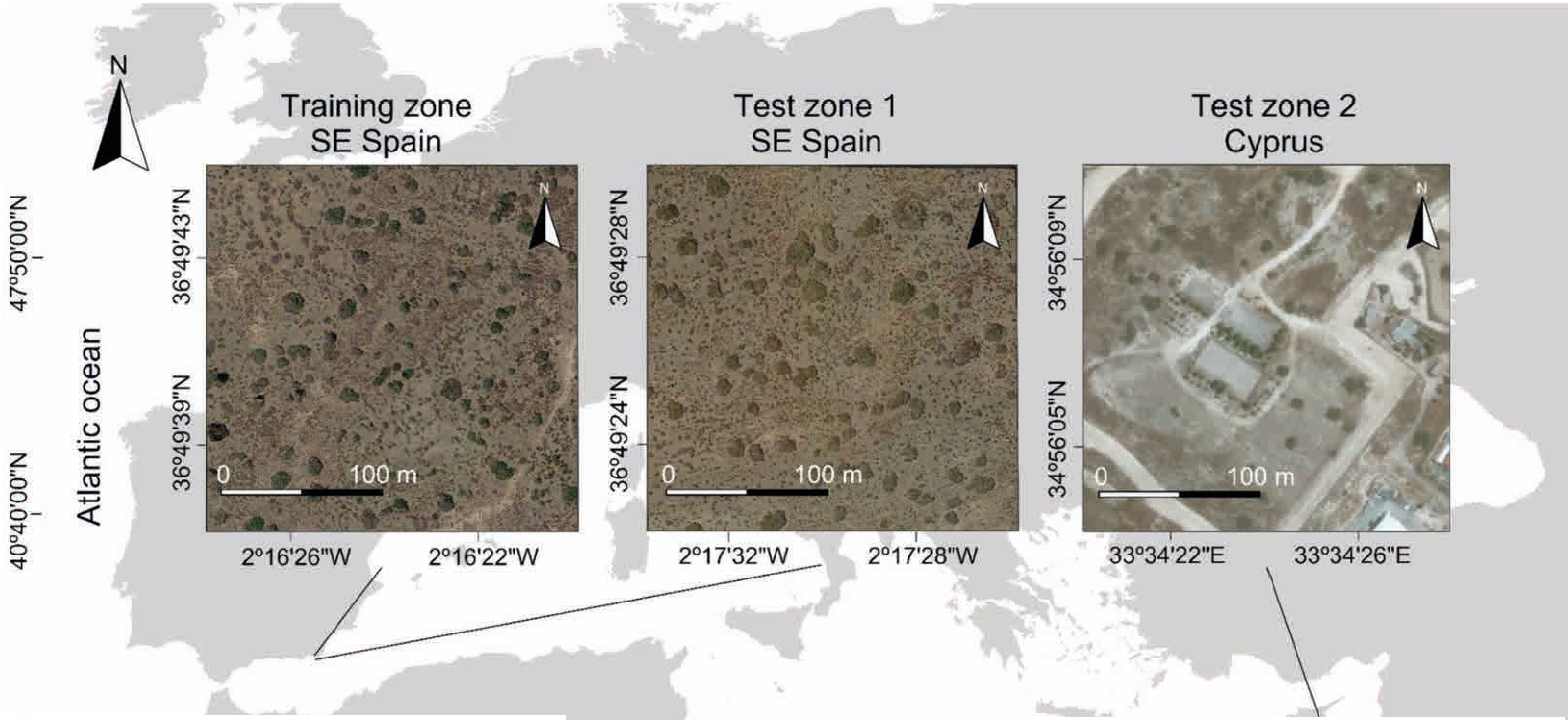
CNN Convolutional Neural Networks (Deep-learning).

Computer vision method with multilayer networks, with input image, hidden layers and classified output.

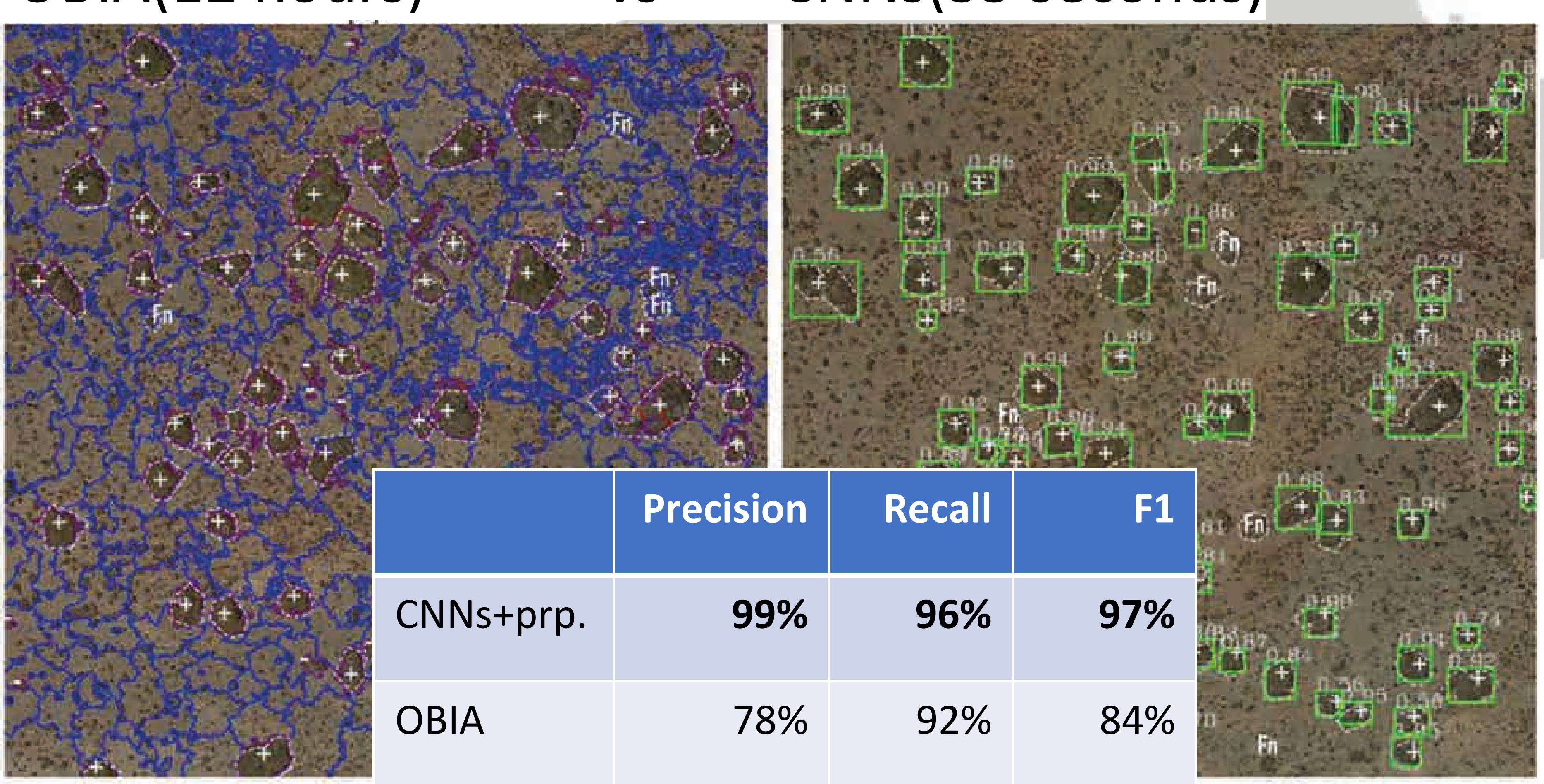


modificado de PNAS



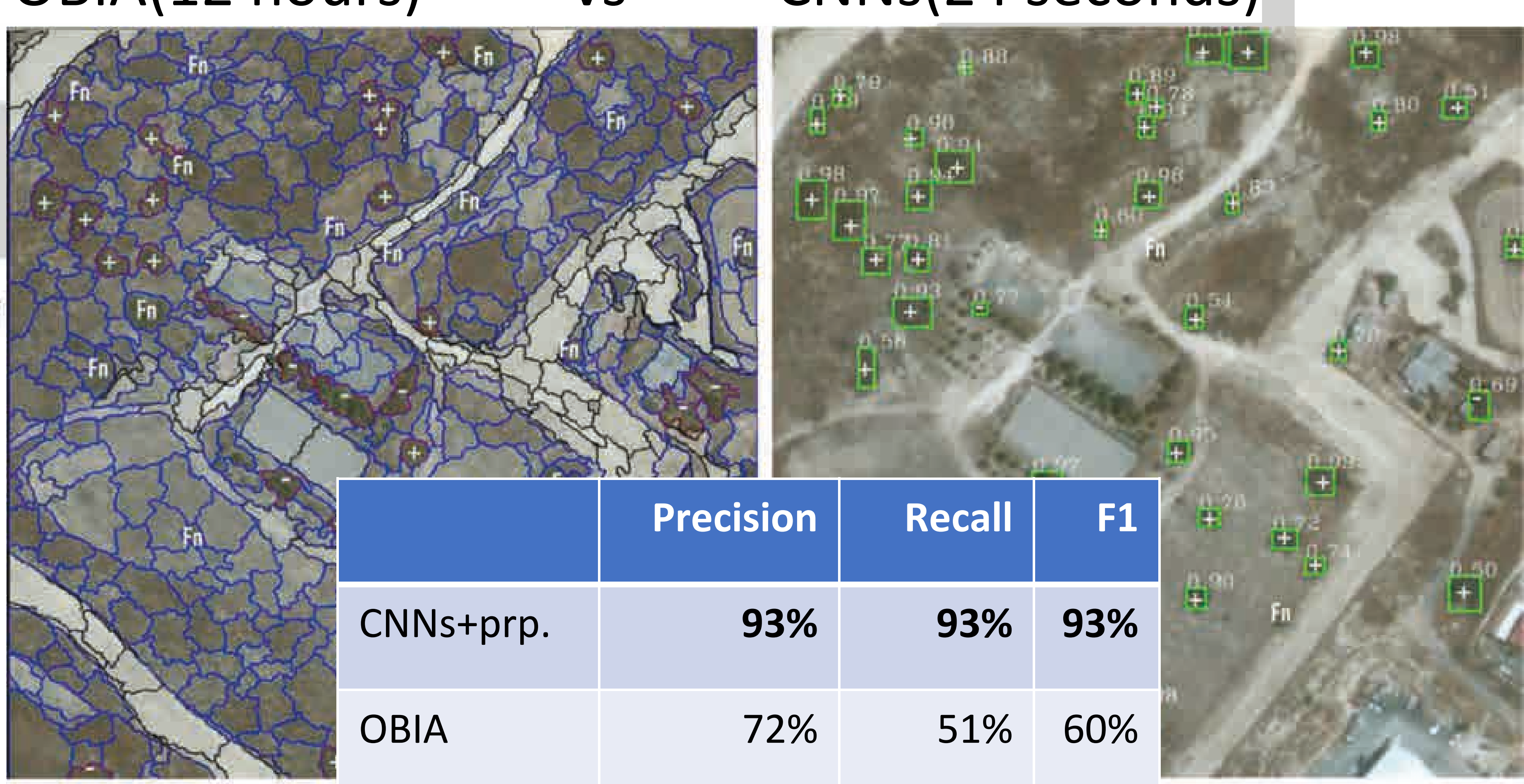


OBIA(12 hours) vs CNNs(35 seconds)



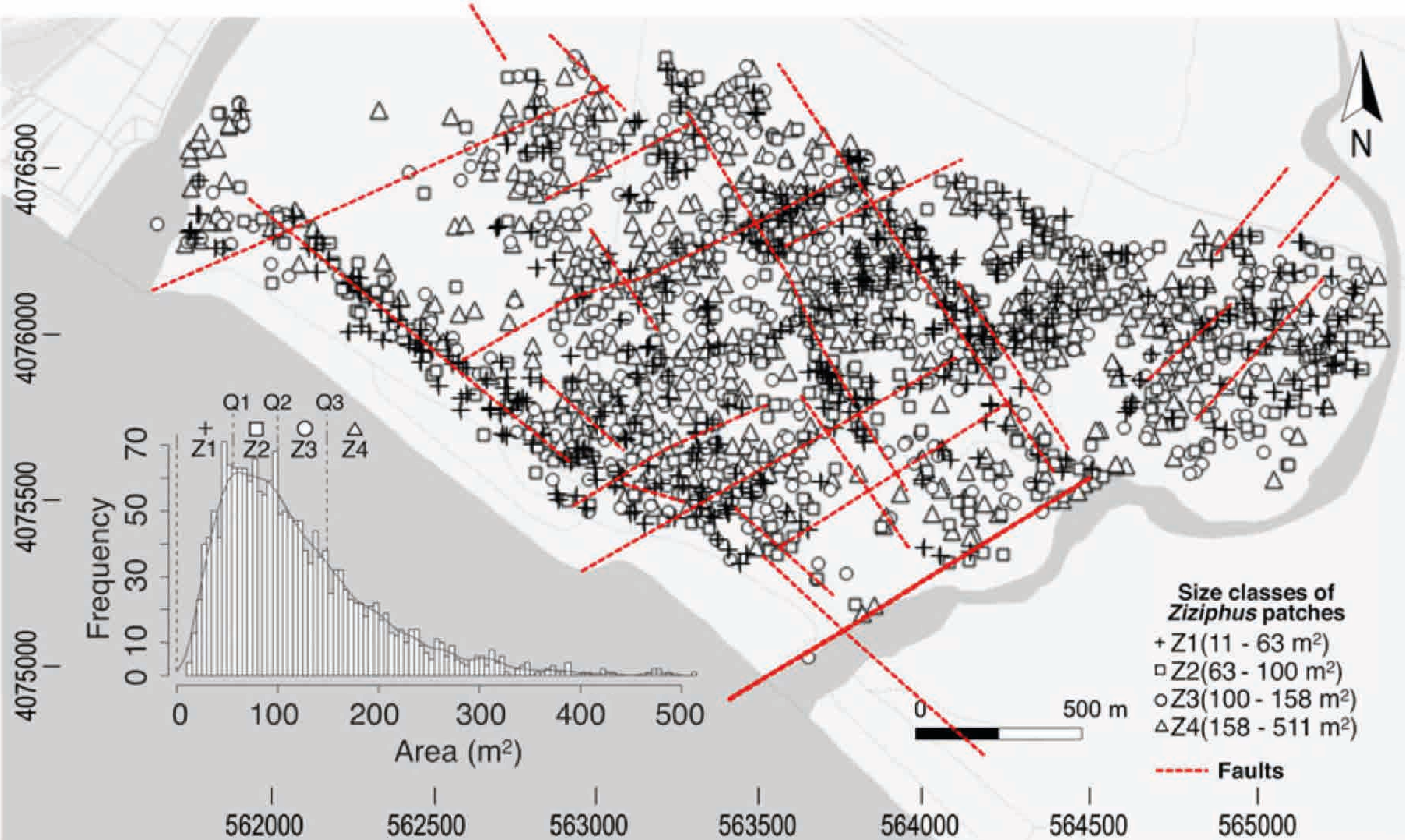
	Precision	Recall	F1
CNNs+prp.	**99%**	**96%**	**97%**
OBIA	78%	92%	84%

OBIA(12 hours) vs CNNs(24 seconds)

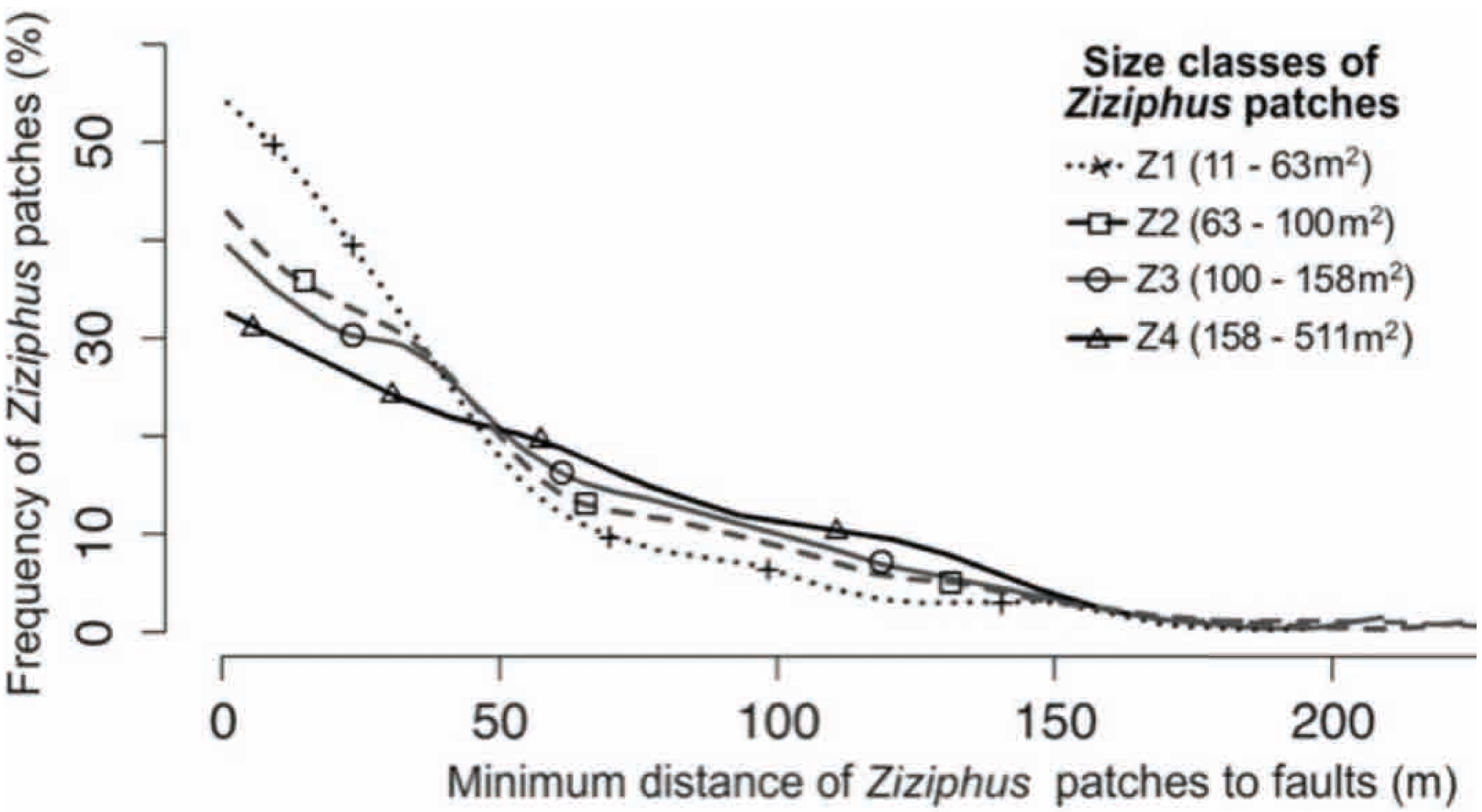


	Precision	Recall	F1
CNNs+prp.	**93%**	**93%**	**93%**
OBIA	72%	51%	60%

Inferring Groundwater Dependent Ecosystems from precision maps



Shrubs are close to bedrock fractures!



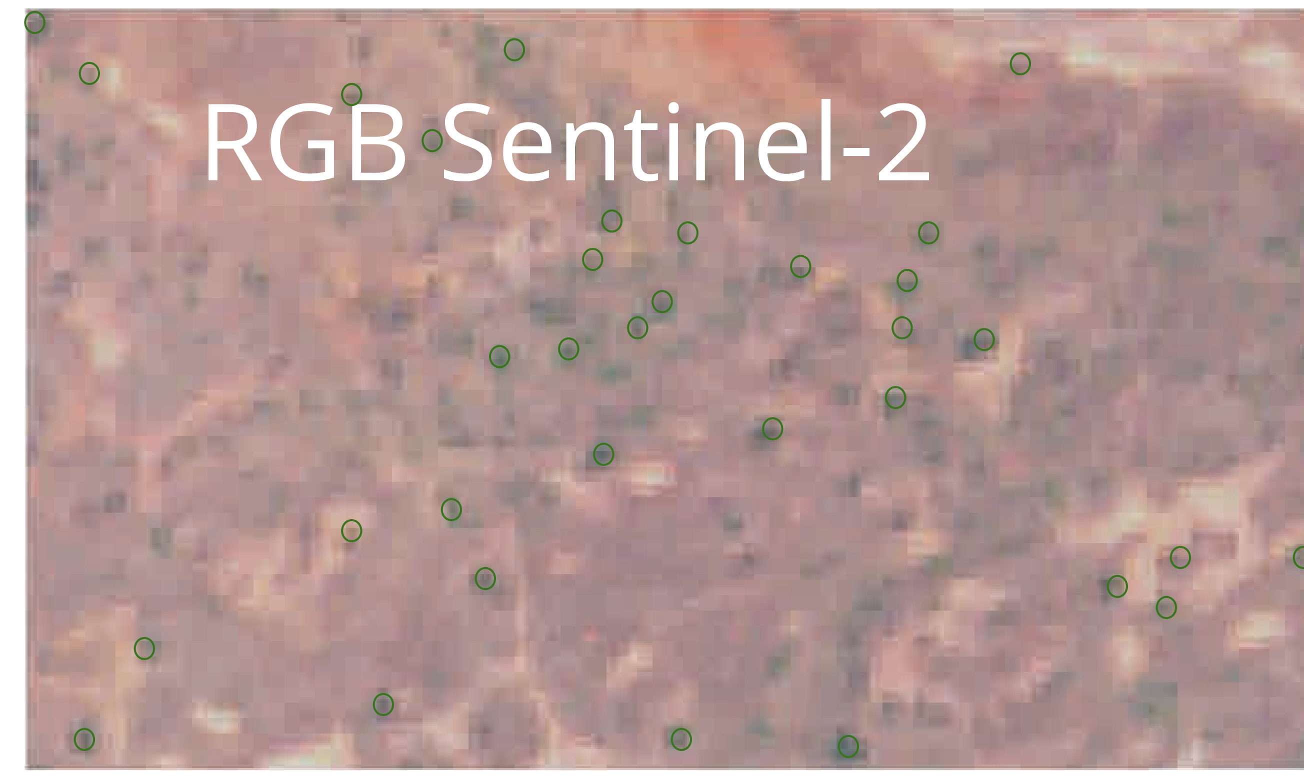
Distance of *Ziziphus* patches to fracture zones (m)	Z1	Z2	Z3	Z4	All
Observed median AMD	33.0	39.0	42.5	50.0	41.1
Observed average AMD	43.1	50.8	52.9	61.7	52.1
Observed *SD* of AMD	1.8	2.1	1.9	2.2	2.0
Random average AMD	116.7	130.6	157.0	136.4	135.2
Random *SD* of AMD	6.4	7.5	8.6	7.3	7.5

AMD to faults comparisons	Observed difference in AMD (m)	Critical difference in AMD (m)	Significant difference of AMD
Z1-Z2	58.2	92.9	False
Z1–Z3	71.1	91.1	False
Z1–Z4	183.7	92.2	True
Z2–Z3	12.9	92.2	False
Z2–Z4	125.4	93.3	True
Z3–Z4	112.5	91.5	True

Sentinel NDVI to infer groundwater dependence

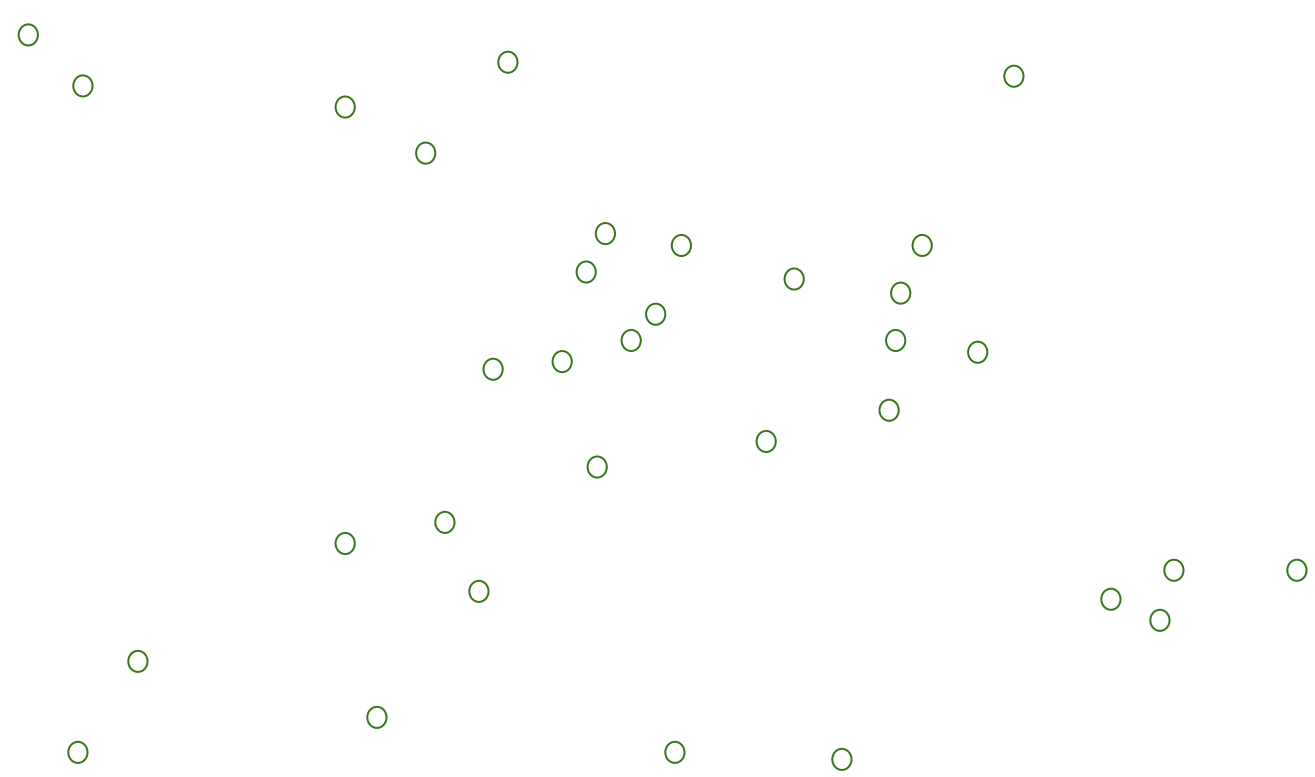
RGB images
(Red, Green, Blue)

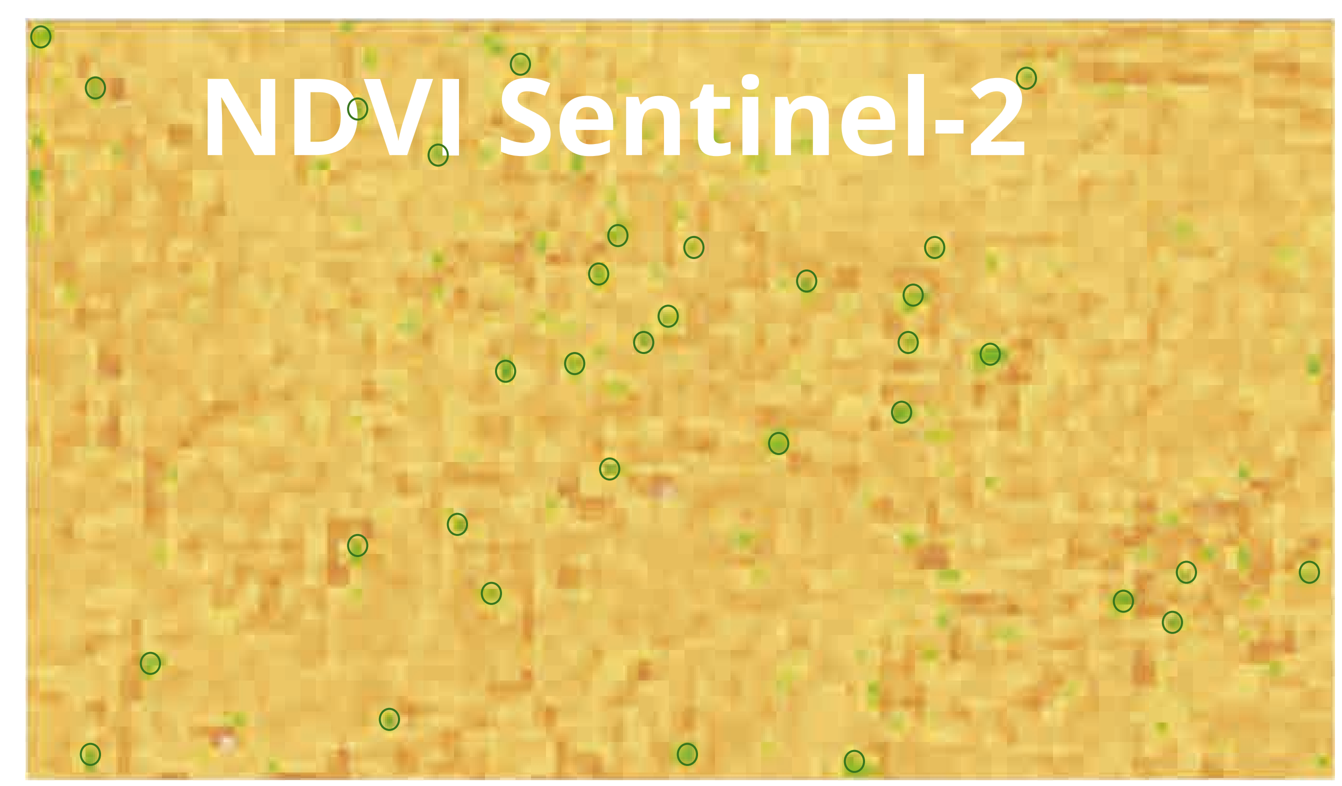
Google Earth 0.5 m / pixel



Sentinel-2 10 m / pixel

Normalized
difference
vegetation index
(NDVI)





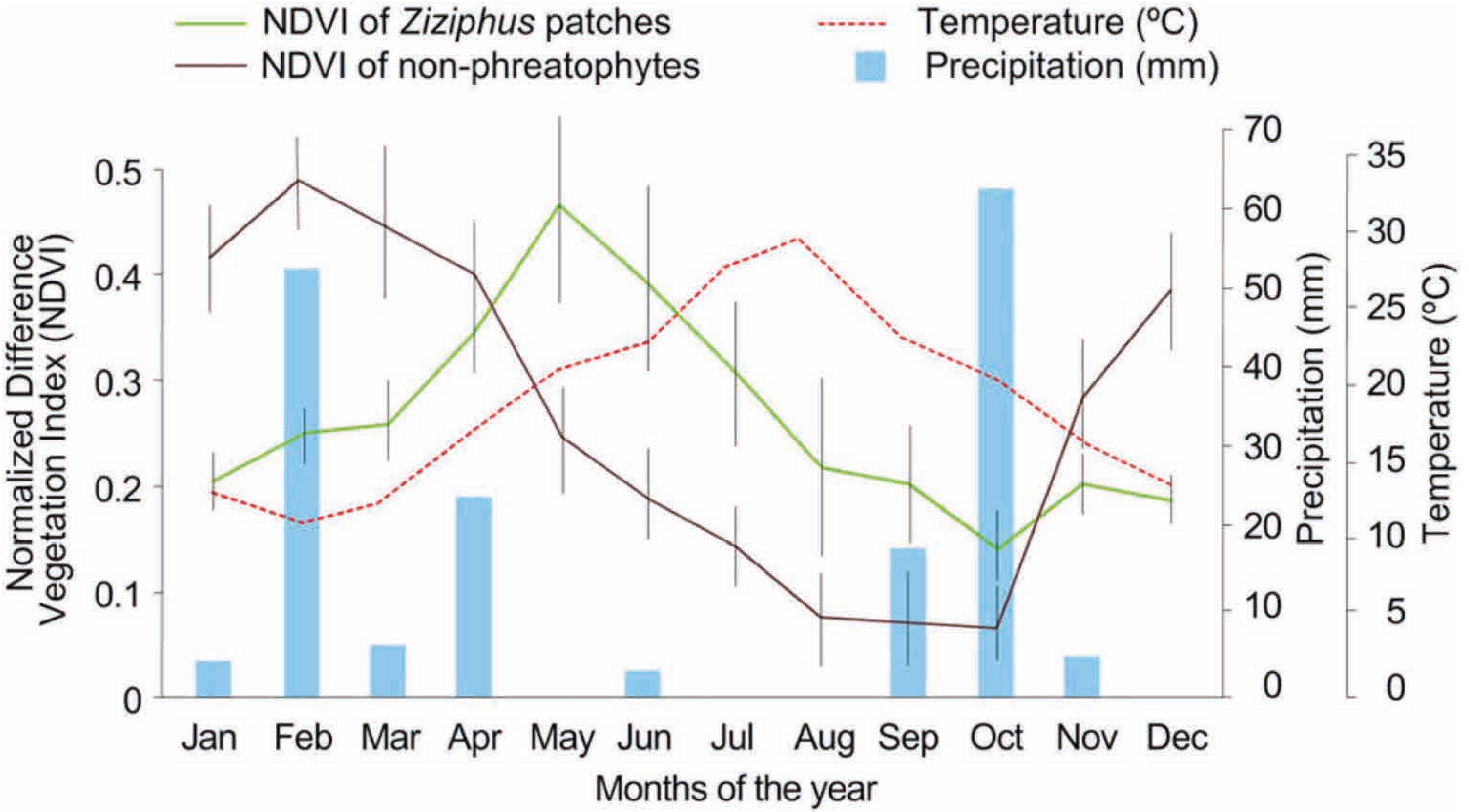
Sentinel-2 10 m / pixel

42 pixels per class

Source: NASA, ESA, Google

Validating Groundwater Dependent Ecosystems from Sentinel-2 NDVI

Temperature, precipitation and NDVI of *Z. lotus* (average 2015-2016)



Conclusions and Policy implications

- CNNs perform well to identify corals, detect whales and map shrubs in VHR imagery.
- Sentinel NDVI 10m pixels allowed to demonstrate groundwater dependence of *Ziziphus lotus* shrubs
- Habitat 5220* must be urgently assessed, registered and protected under the Water Framework Directive as a groundwater dependent ecosystem.

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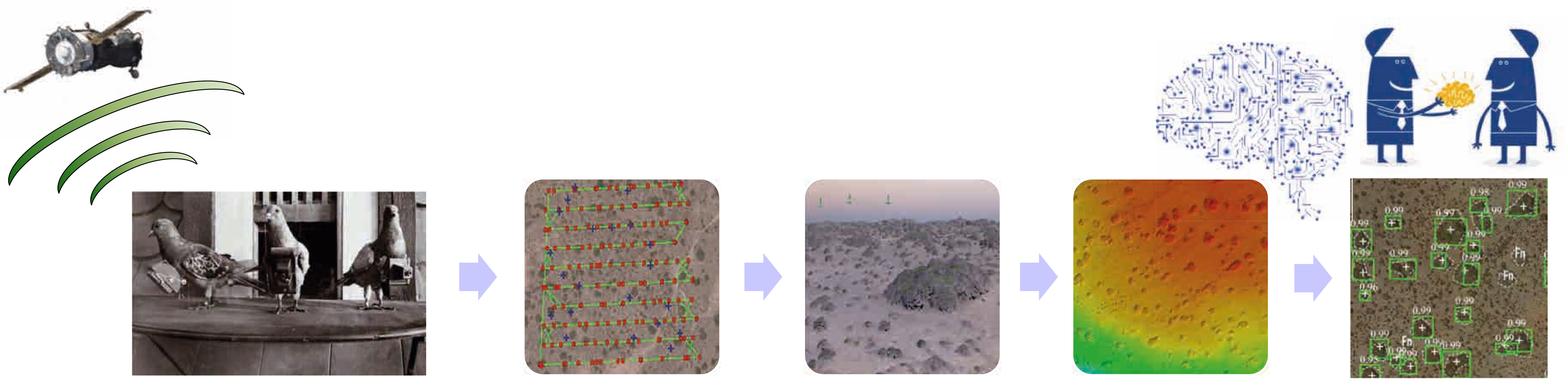
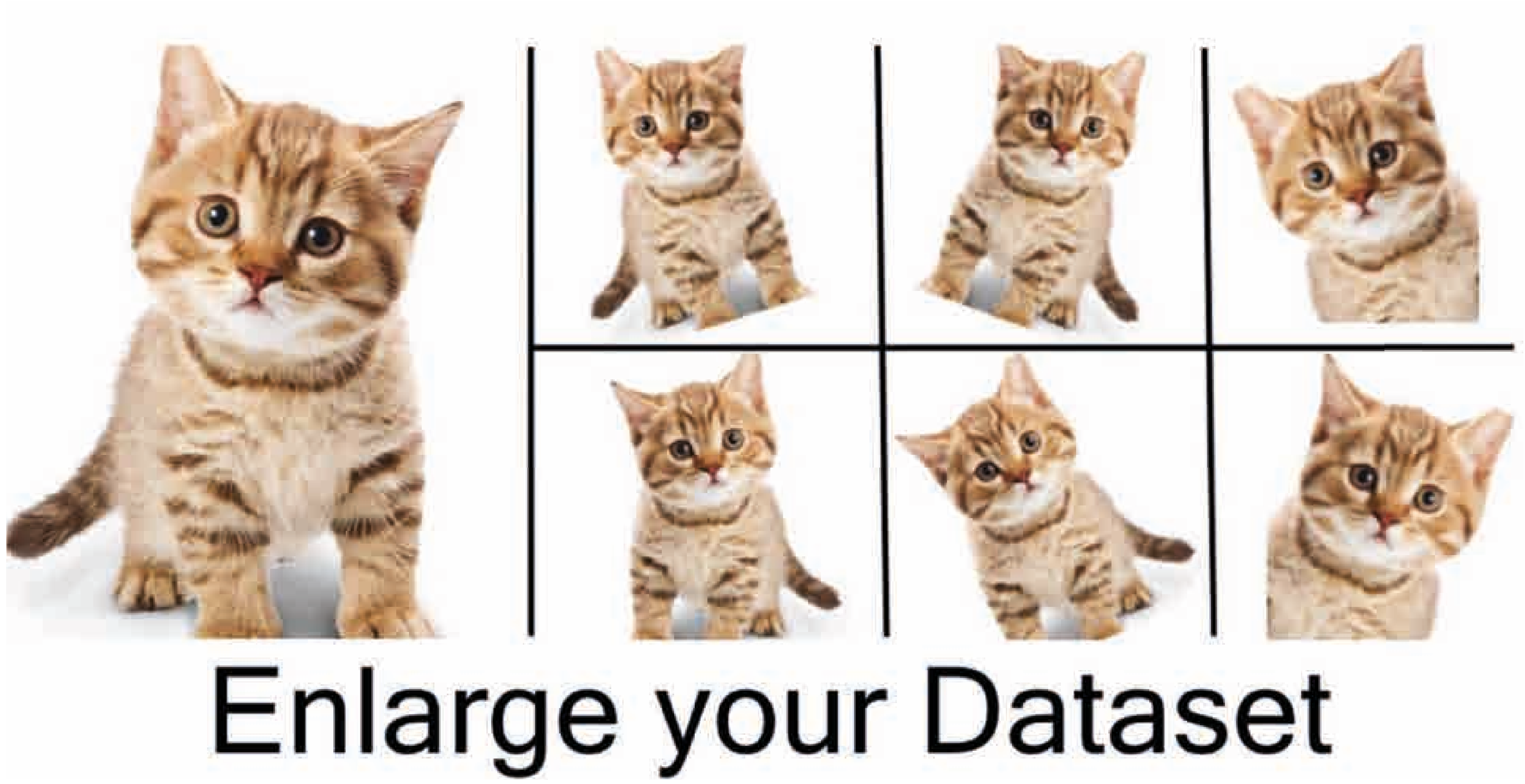
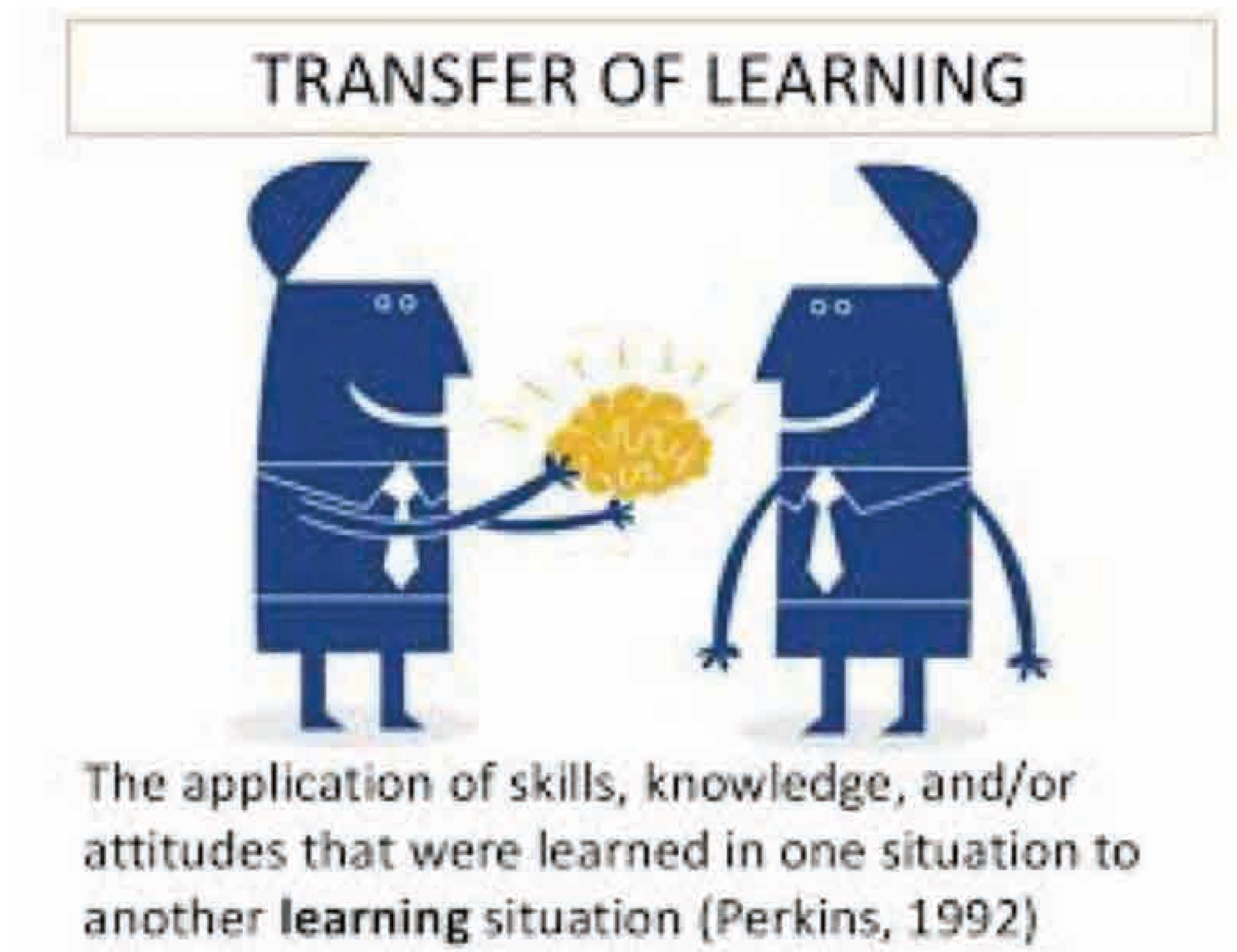


LifeWatch ERIC Scientific Community Meeting
Rome – Italy – May 27-29 2019

Data augmentation

Transfer learning





Different types of DL tasks: