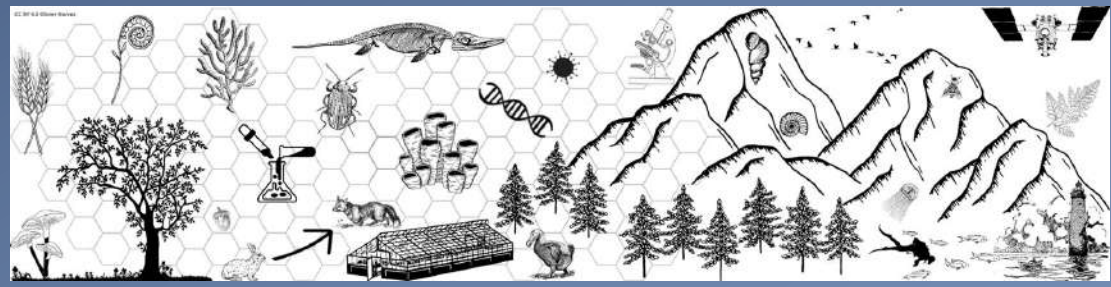
Biodiversity and AI

27 Janvier 2026

Cas d’usage en Biodiversité



Yvan Le Bras
MNHN / PNDB-Data Terra / UAR DoHNÉE
French BON
France

Biodiversity and AI: French context

Major topics

Images and AI	Traits, phenotypes, visual perception, evolution, … Species or individual recognition, counts, 3D, …
Sounds and AI	
Texts and AI	
Genomes and AI	
Remote sensing and AI	
Predictive AI	Scenarios, species distribution, past/future, …

Major topics

Habitat monitoring

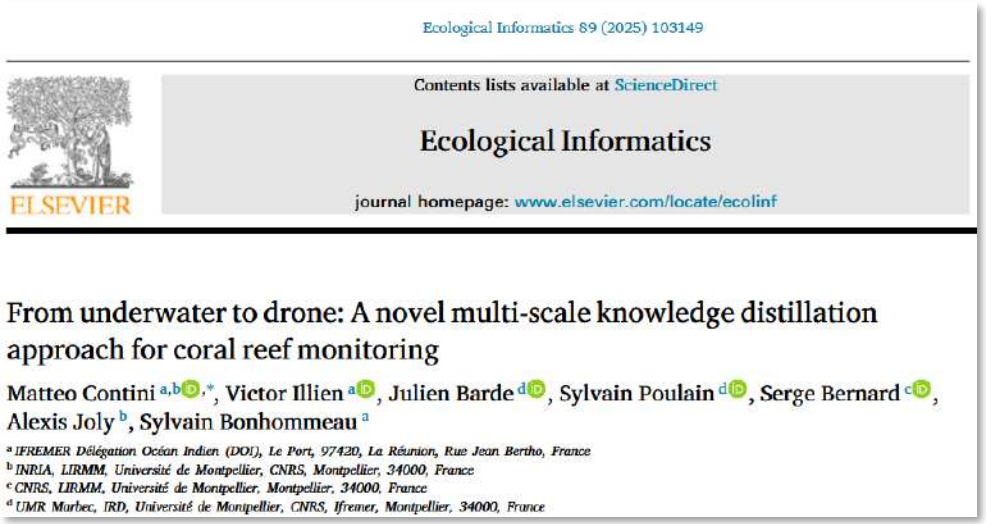
« A transformer-based deep-learning model is trained on underwater images to detect the presence of 31 classes covering various coral morphotypes, associated fauna, and habitats »

« the multiscale methodology successfully extends fine-scale classification to larger reef areas, achieving a high degree of accuracy in predicting coral morphotypes and associated habitats »

Images and AI

Traits, phenotypes, visual perception, evolution, …

Species or individual recognition, counts, 3D, …



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Contents lists available at ScienceDirect

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journal homepage: www.elsevier.com/locate/ecolinf

From underwater to drone: A novel multi-scale knowledge distillation approach for coral reef monitoring

Matteo Contini [a,b,*], Victor Illien [a], Julien Barde [d], Sylvain Poulain [d], Serge Bernard [c], Alexis Joly [b], Sylvain Bonhommeau [a]

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[b] INRIA, LIRMM, Université de Montpellier, CNRS, Montpellier, 34000, France
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[d] UMR Marbec, IRD, Université de Montpellier, CNRS, Ifremer, Montpellier, 34000, France

https://doi.org/10.1016/j.ecoinf.2025.103149

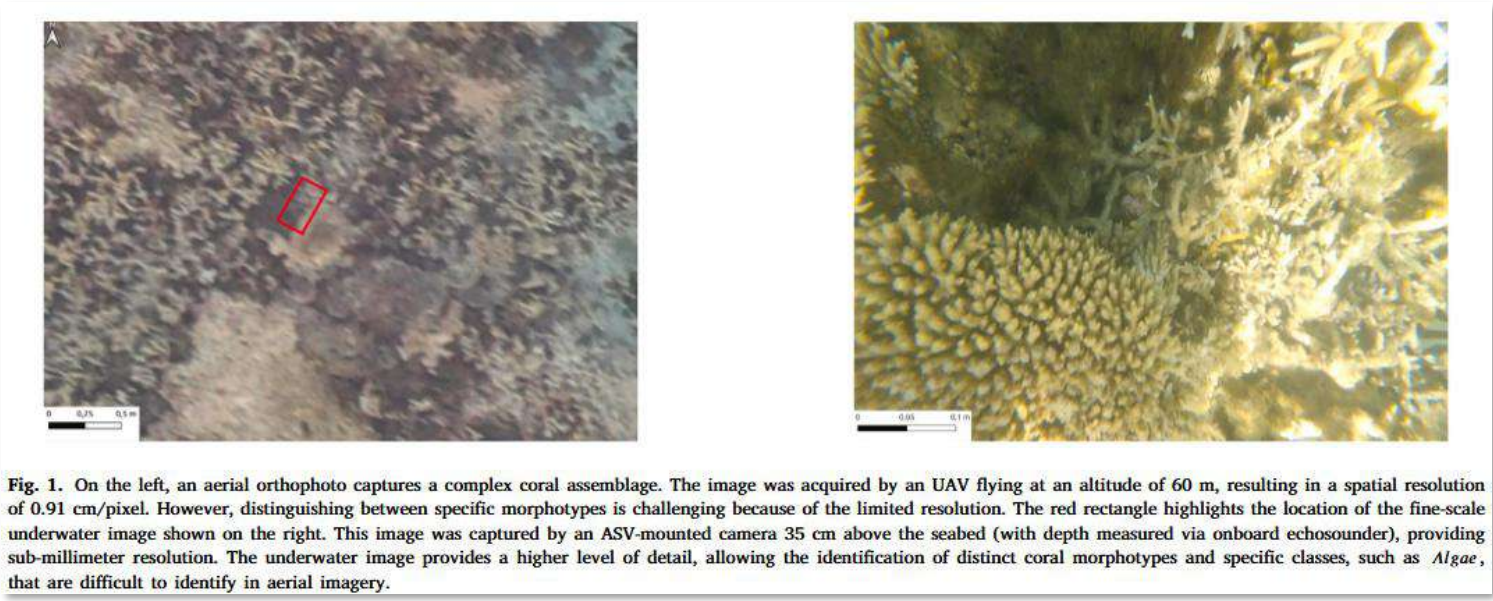


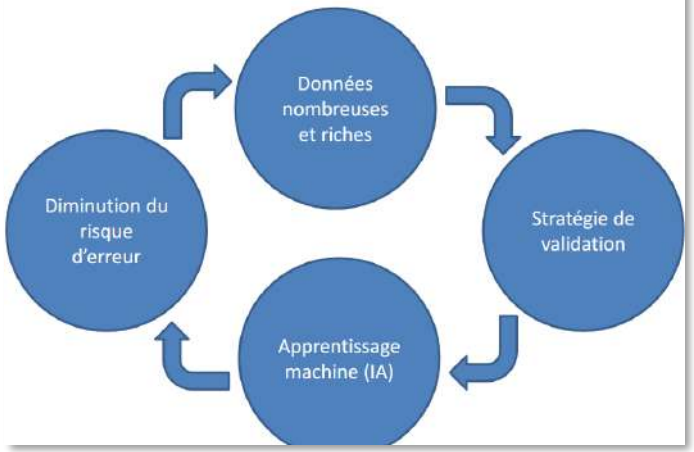
Fig. 1. On the left, an aerial orthophoto captures a complex coral assemblage. The image was acquired by an UAV flying at an altitude of 60 m, resulting in a spatial resolution of 0.91 cm/pixel. However, distinguishing between specific morphotypes is challenging because of the limited resolution. The red rectangle highlights the location of the fine-scale underwater image shown on the right. This image was captured by an ASV-mounted camera 35 cm above the seabed (with depth measured via onboard echosounder), providing sub-millimeter resolution. The underwater image provides a higher level of detail, allowing the identification of distinct coral morphotypes and specific classes, such as *Algae*, that are difficult to identify in aerial imagery.

Major topics

Citizen science and acoustics: Vigie Chiro

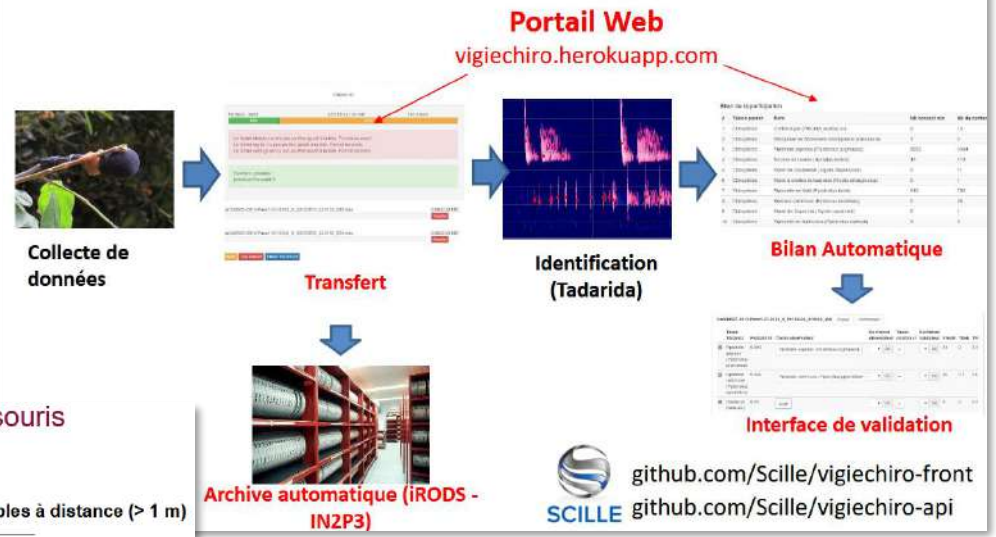
Ecoacoustique + sciences participatives

=> beaucoup d'opportunités !



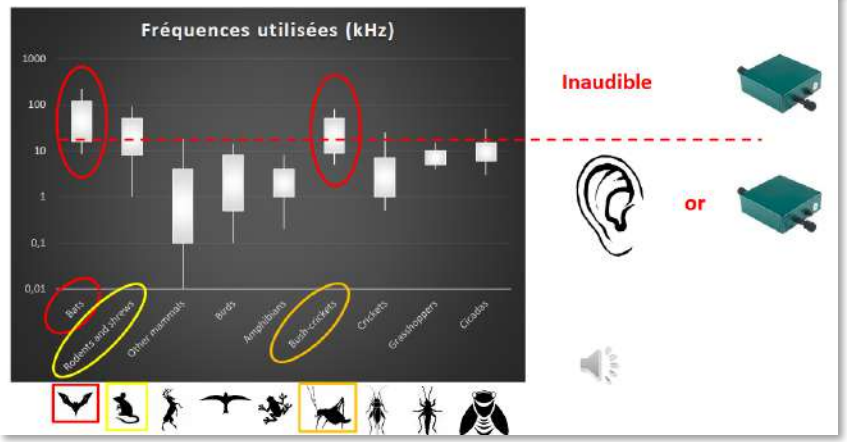
Sounds and AI

- Fonctionnement de Vigie-Chiro / Tadarida



Pas seulement les chauves-souris

Principaux groupes vocalisants et détectables à distance (> 1 m)

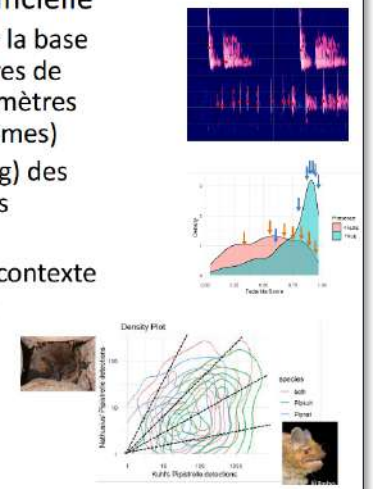


Tadarida : une boite à outil logicielle avec plusieurs couches d'intelligence artificielle

1) Identification automatique des cris sur la base d'un apprentissage automatique par arbres de décisions (random forest) et de 150 paramètres acoustiques (fréquences, amplitude, rythmes)

2) Regroupement automatique (clustering) des cris en séquences de cris, aggregation des résultats

3) Correction des erreurs en fonction du contexte et des autres enregistrements sur la nuit complète (classification contextuelle)



=> Besoin de beaucoup de données d'apprentissage !

=> Validations participatives !

Major topics

Extracting Plant Species Names from textual data

A Transformer-based Nlp Pipeline for Enhanced Extraction of Botanical Information Using Camembert on French Literature

Ayoub Nainia[1], Régine Vignes-Lebbe[1], Eric Chenin[2], Maya Sahraoui[13], Hajar Mousannif[4], and Jihad Zahir[24]

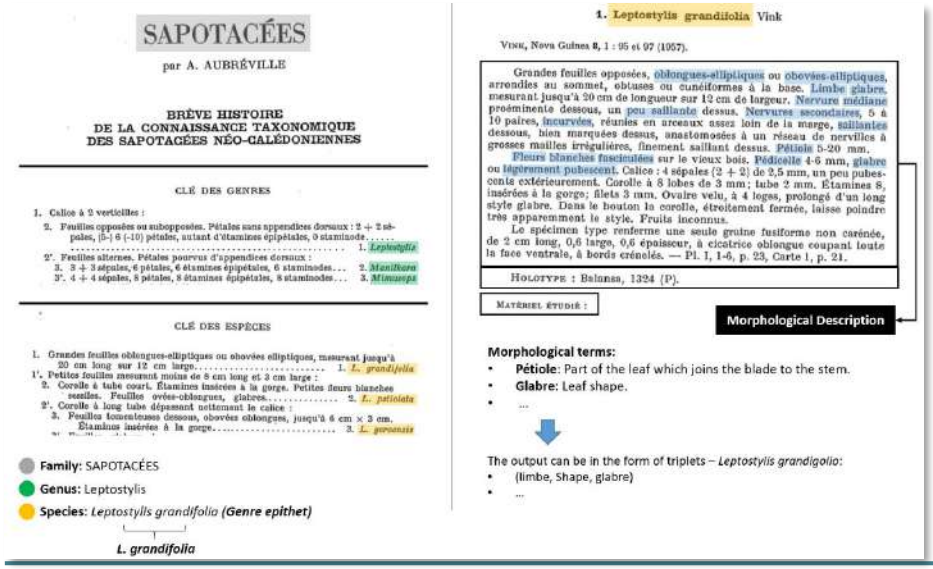
https://doi.org/10.5121/csit.2024.140605

1. **Genus epithet**: The species designation consists of the genus name, capitalized at the beginning, followed by a lowercase epithet
2. **G. epithet**: Alternatively, the species name may present with the initial letter of the genus in uppercase, followed by the epithet in lowercase.
3. **Genus epi-thet or G. epi-thet**: In the OCR-processed version of the floras, the epithet may break at the end of a line, introducing a third form that necessitates consideration.

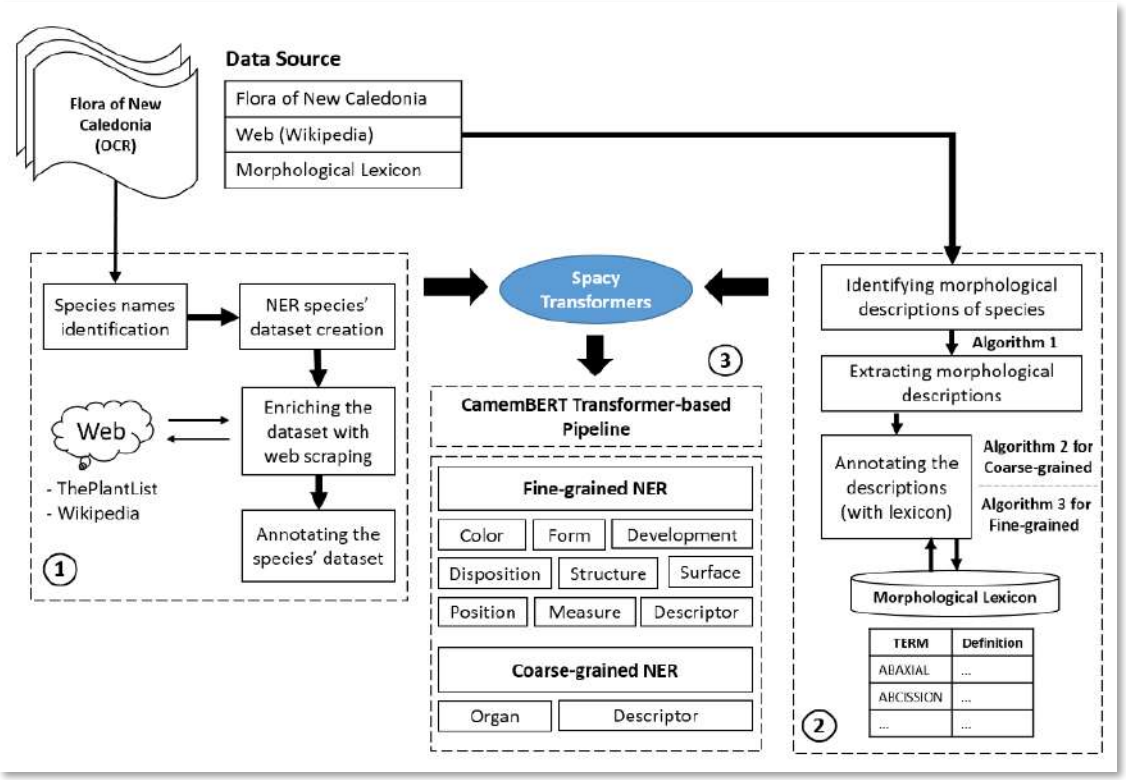
Table 1. Dataset Summary

Data	Flora of New Caledonia	Botanical Lexicon
Size	25 documents	3530 entries
Data Type	Ocerized Text	Text (Dataframe)
Data Source	National Museum of Natural History	Compiled from various glossaries online

Texts and AI

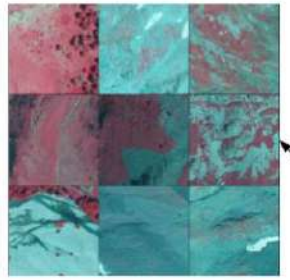


Plant species names and their descriptive morphological terms from flora of New Caledonia.

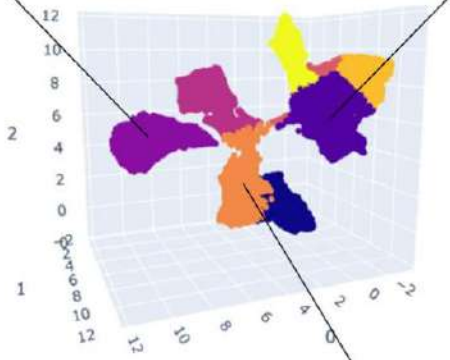


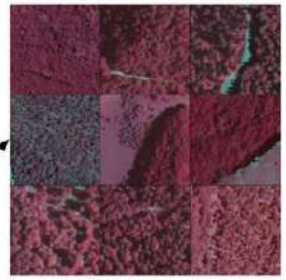
Major topics

From aerial photographs for vegetation surveys to RS

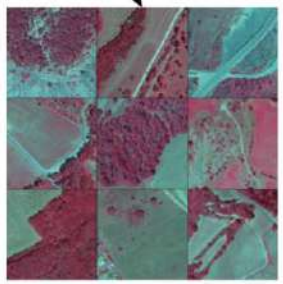


(a) Example images belonging to cluster 1

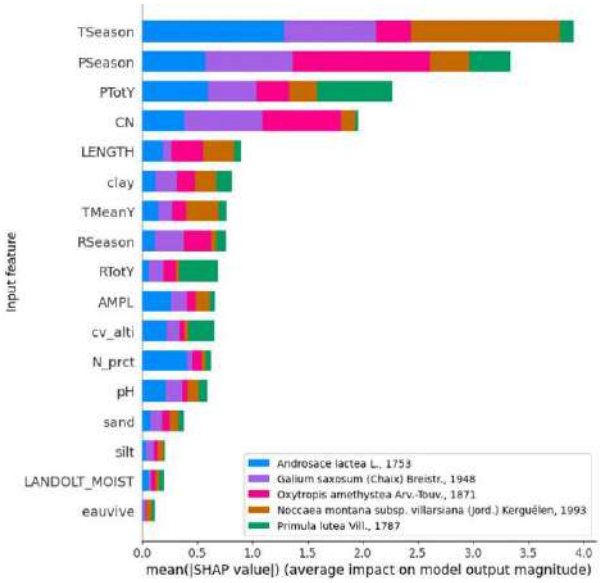




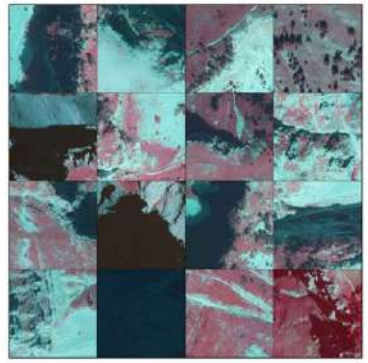
(b) Example images belonging to cluster 2



(c) Example images belonging to cluster 3



(a) Feature importance for an example cluster



(b) Example images

Remote sensing and AI

BRITISH ECOLOGICAL SOCIETY Methods in Ecology and Evolution

RESEARCH ARTICLE | Open Access

Introduction to deep learning methods for multi-species predictions

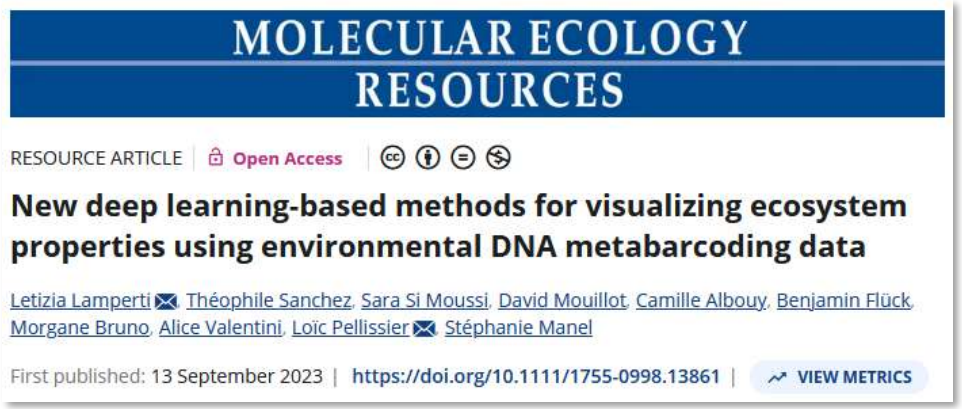
Yuqing Hu, Sara Si-Moussi, Wilfried Thuiller

First published: 28 November 2024 | https://doi.org/10.1111/2041-210X.14466 | VIEW METRICS

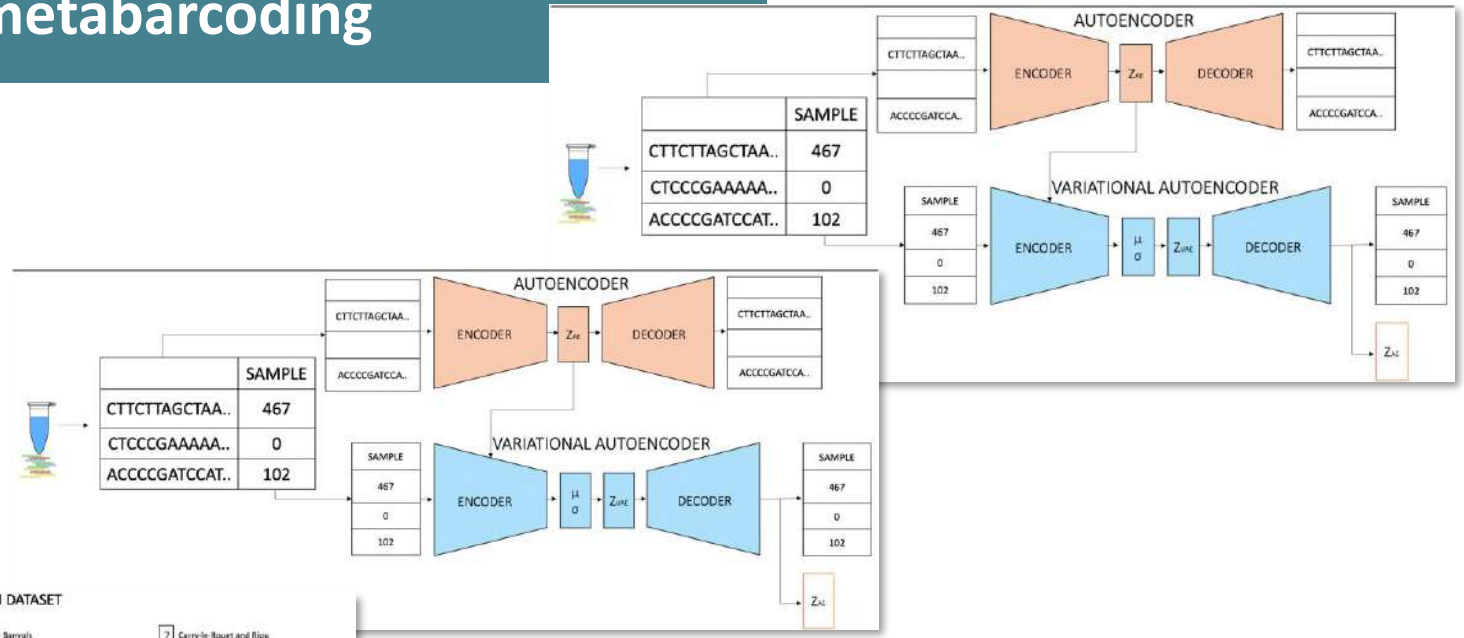
https://doi.org/10.1111/2041-210X.14466

Major topics

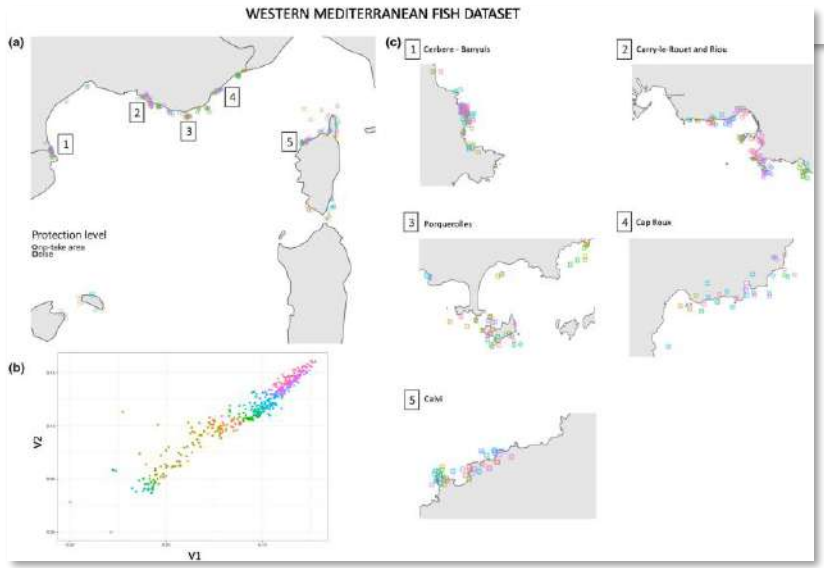
Biodiversity indicators from eDNA metabarcoding

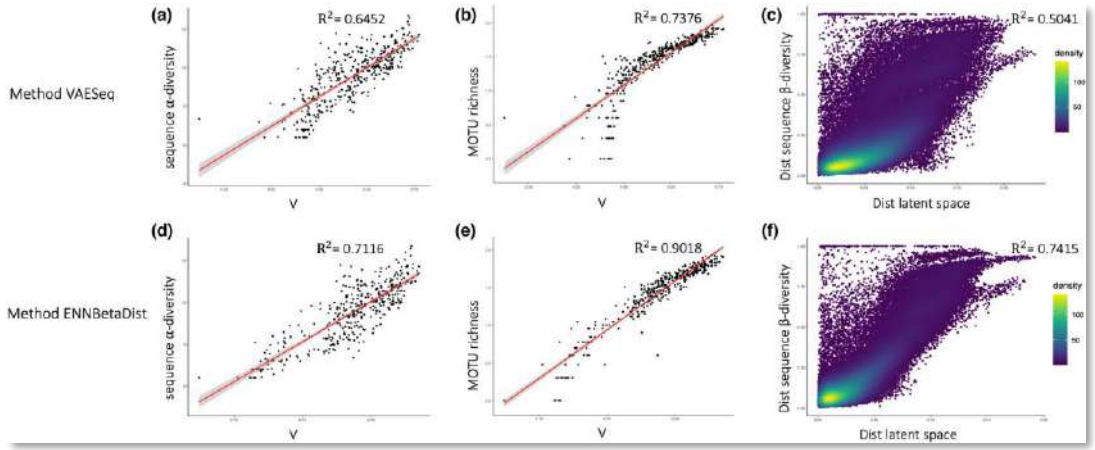


https://doi.org/10.1111/1755-0998.13861



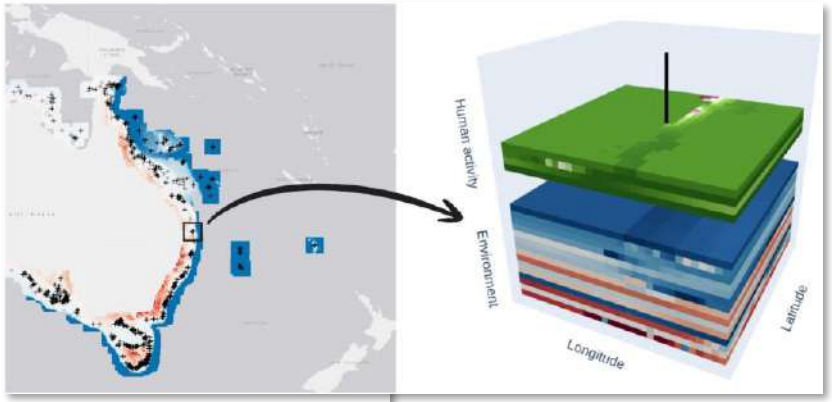
Genomes and AI





Major topics

Occurences prediction



Occurrence data (Reef Life Survey)

Socio-Environmental variables

Variable	Source	Res.	Time Res.	Unit
FSLEs (strength)	CNES [7]	0.04°	daily	$days^{-1}$
FSLEs (orientation)	CNES [7]	0.04°	daily	*degrees*
Bathymetry	GEBCO [8]	0.0042°		m
Chlorophyll	Copernicus [9]	4km	daily	$mg.m^{-3}$
SST	Copernicus [10]	0.05°	daily	*kelvin*
Salinity	Copernicus [11]	0.083°°	weekly	*P.S.U.*
pH	Copernicus [12]	0.25°	monthly	
Surface Current (u)	Copernicus [13]	0.25°	daily	$m.s^{-1}$
Surface Current (v)	Copernicus [13]	0.25°	daily	$m.s^{-1}$
Wind (u)	Copernicus [14]	0.125°	hourly	$m.s^{-1}$
Wind (v)	Copernicus [14]	0.125°	hourly	$m.s^{-1}$
Wave Height	Copernicus [15]	0.2°	daily	m
Oxygen	Copernicus [16]	0.25°	daily	$mmol.m^{-3}$
Mixed layer thickness	Copernicus [11]	0.083°	daily	m
Nitrate	Copernicus [16]	0.25°	daily	$mmol.m^{-3}$
Protection level	Australian Marine Parks	0.01°		$m.s^{-1}$
Distance to port	Global Fishing Watch	0.01°		km
Population density (log)	Gridded Population of the World	0.0083°	5 years	km^{-2}
Human gravity	[17]	0.01°		$mmol.m^{-3}$
Degree heating Week	NOAA	0.05°	daily	

bioRxiv
THE PREPRINT SERVER FOR BIOLOGY

New Results

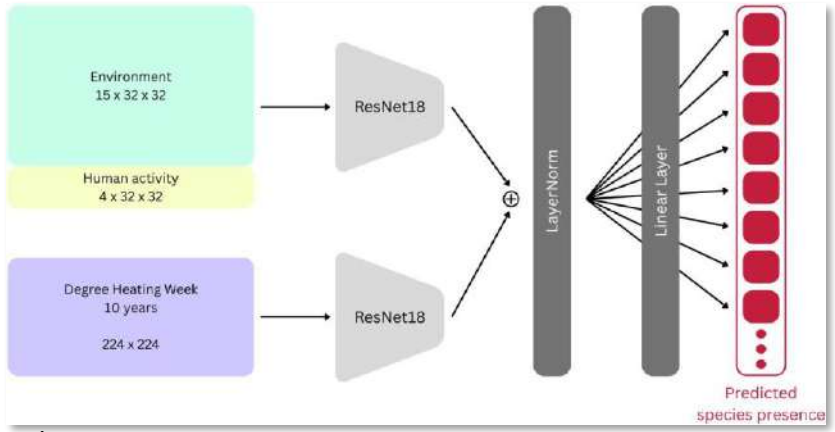
A multi-modal ResNet model to predict coastal fish occurrences using a seascape approach

Gaétan Morand, David Mouillot

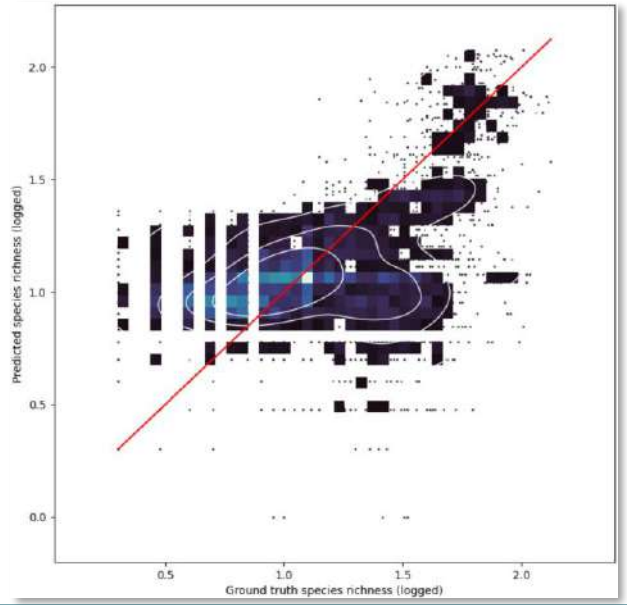
doi: https://doi.org/10.1101/2025.10.29.682812

https://doi.org/10.1101/2025.10.29.682812

Model architecture and training



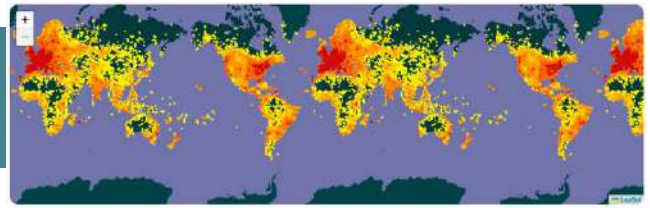
Species richness



Predictive AI Scenarios, species distribution, past/future, …

Success stories

Pl@ntnet: “Le Shazam des plantes”



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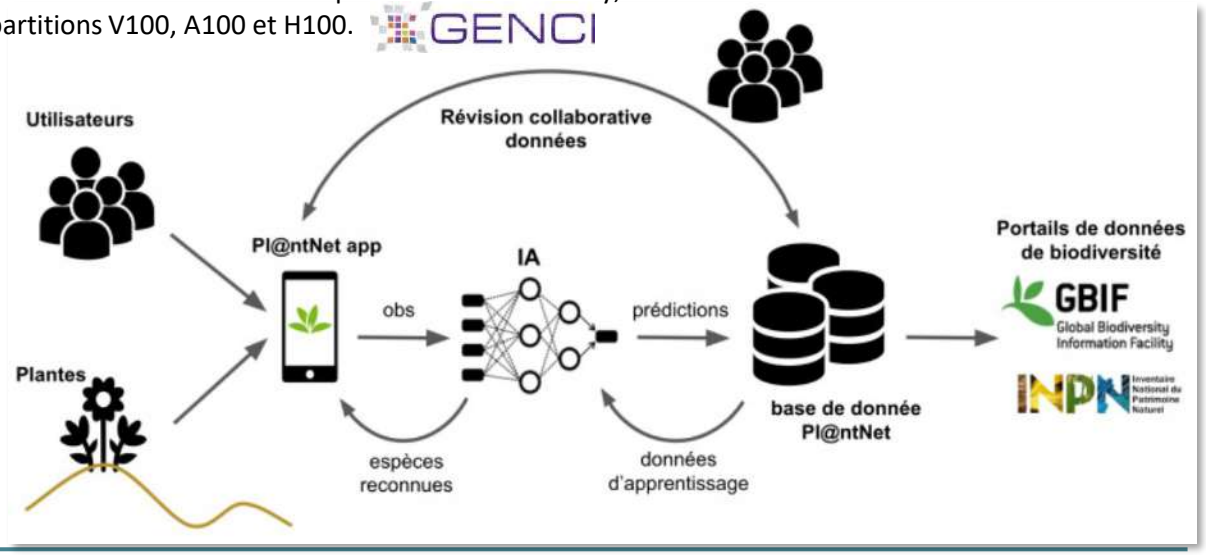
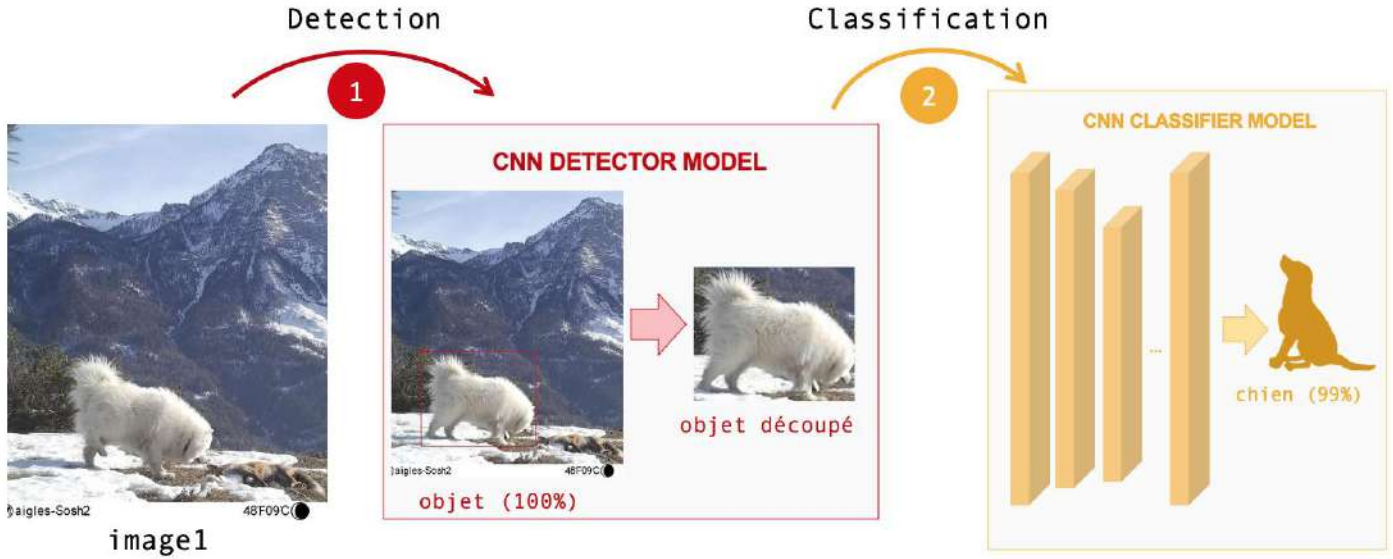
Ce projet a bénéficié des ressources informatiques et de stockage de GENCI à l'IDRIS grâce à la subvention 2024- A0171011389 sur le supercalculateur Jean Zay, partitions V100, A100 et H100. GENCI



Interactive plant identification based on social image data Alexis Joly, Hervé Goëau, Pierre Bonnet, Vera Bakić, Julien Barbe, Souheil Selmi, Itheri Yahiaoui, Jennifer Carré, Elise Mouysset, Jean-François Molino, Nozha Boujemaa, Daniel Barthélémy *Ecological Informatics*, 2014, 23, pp.22-34. ⟨10.1016/j.ecoinf.2013.07.006⟩

Success stories

DeepFaune



A l'heure actuelle, le modèle utilise **37 classes**. Chaque image ou vidéo qui lui est soumise, prise de jour comme de nuit, est prédite comme contenant:

- rien: classe 'vide'
- une présence humaine: classes 'humain', 'véhicule'
- un ongulé sauvage: classes 'bison, 'bouquetin', 'cerf', 'chevreuil', 'chamois/isard', 'daim', 'éland', 'mouflon', 'renne', 'sanglier'
- un autre grand mammifère: classes 'glouton', 'loup', 'lynx', 'ours'
- un petit mammifère: classes 'blaireau', 'castor', 'écureuil', 'genette', 'hérisson', 'lagomorphe', 'loutre', 'marmotte', 'mustélidé', 'ragondin', 'raton laveur', 'renard'
- un animal domestique: classes 'chien', 'chat', 'chèvre', 'équidé', 'mouton', 'vache'
- un animal autre, de la classe 'oiseau' ou de la classe 'micromammifère'

Rigoudy, N., Dussert G., the DeepFaune consortium, Spataro, B., Miele, V. & Chamaillé-Jammes, S. (2023) *The DeepFaune initiative: a collaborative effort towards the automatic identification of the European fauna in camera-trap images.* European Journal of Wildlife Research

Dussert, G., Chamaillé-Jammes, S. Dray, S. & Miele, V. (2024) *Being confident in confidence scores: calibration in deep learning models for camera trap image sequences.* Remote Sensing in Ecology and Conservation

Dussert, G., Dray, S., Chamaillé-Jammes, S. & Miele, V. (2025) *Paying Attention to Other Animal Detections Improves Camera Trap Classification Models.* biorxiv