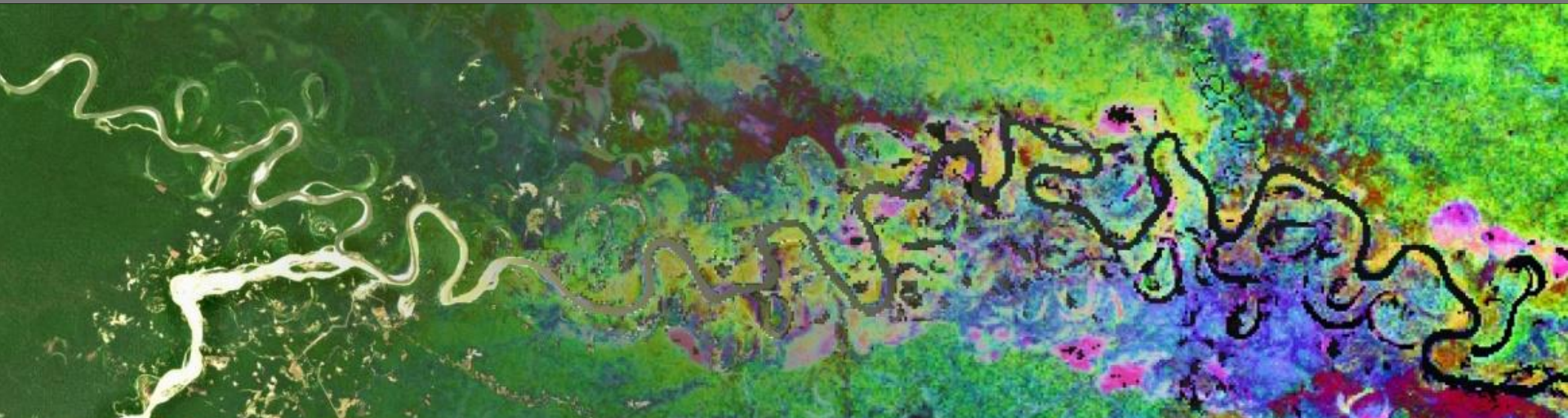


# Observation de la Terre par imagerie optique : de la mesure physique à l'indicateur écologique (part II)

Jean-Baptiste Féret

UMR TETIS, INRAE — [jb.feret@teledetection.fr](mailto:jb.feret@teledetection.fr)



*Apports, intérêts, limites de la télédétection pour mieux connaître la biodiversité*

Atelier du métaprogramme BIOSEFAIR, 14 novembre 2023

- **Introduction**
- **Explore spatial, temporal and spectral dimensions from space**
- **A quick dive into the spectral space**
- **Current missions and forthcoming opportunities**
- **Earth observation and biodiversity : one approach among many**
- **Conclusions and perspectives**

# From remotely sensed information to ecological information

- **What is needed to assess biodiversity metrics from space?**
  - Information related to composition, functions, structure...
  - species occurrence & species / species community distribution
  - Vegetation traits related to phenology, photosynthesis, LMA, nitrogen, water content...
  - ...
- **What do we measure from space ?**
  - Signal reflected, emitted, backscattered from Earth surface
  - ... combining multiple factors intrinsic and extrinsic to surfaces / objects of interest
- **How to translate satellite acquisition into ecologically meaningful information ?**
  - [physical & statistical] models to assess continuous vegetation biophysical properties
  - Classifiers to discriminate among vegetation types or species
  - Methods integrating spatiotemporal information to produce higher level metrics
    - Phenometrics related describing pixelwise seasonality
    - Spatial heterogeneity of spectral information (~ spectral variation hypothesis)
    - ...

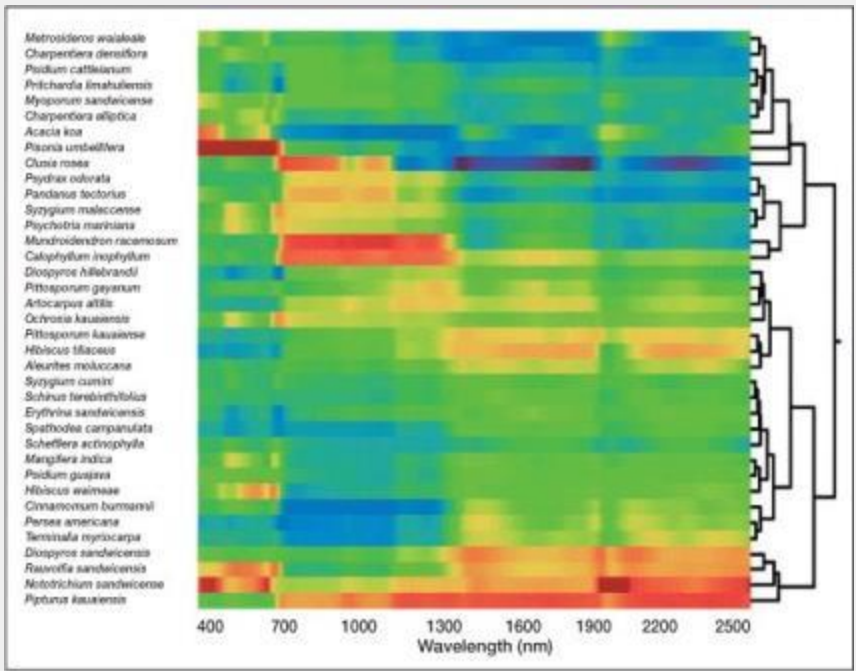
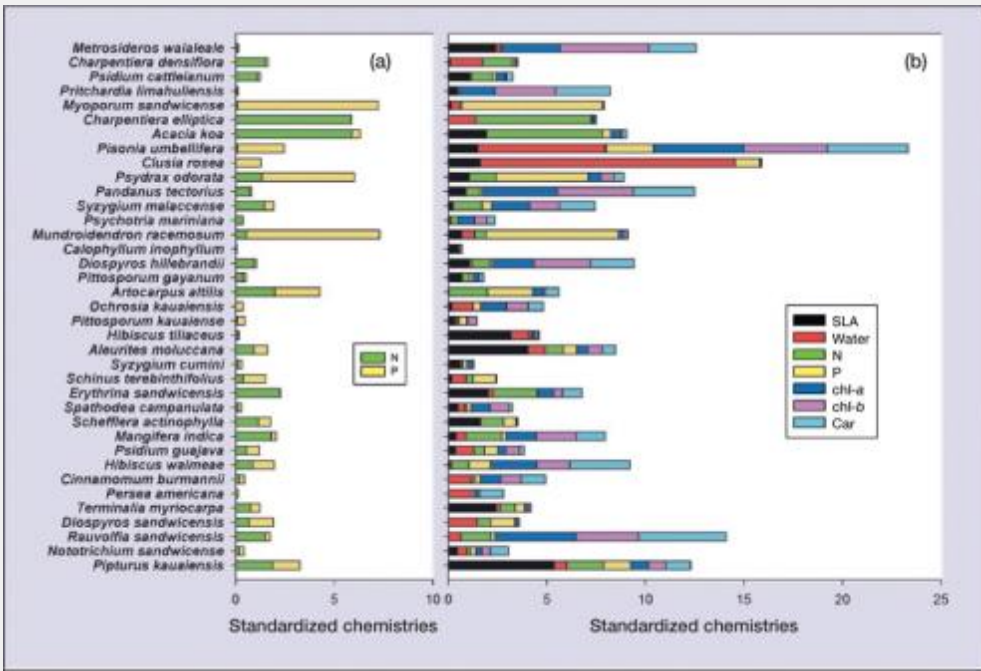
# From remotely sensed information to ecological information

- **How to link reflectance & optical traits to ecological information?**
  - Identify a relationship between spatial heterogeneity in spectral information and environmental / ecological heterogeneity / biodiversity



# From remotely sensed information to ecological information

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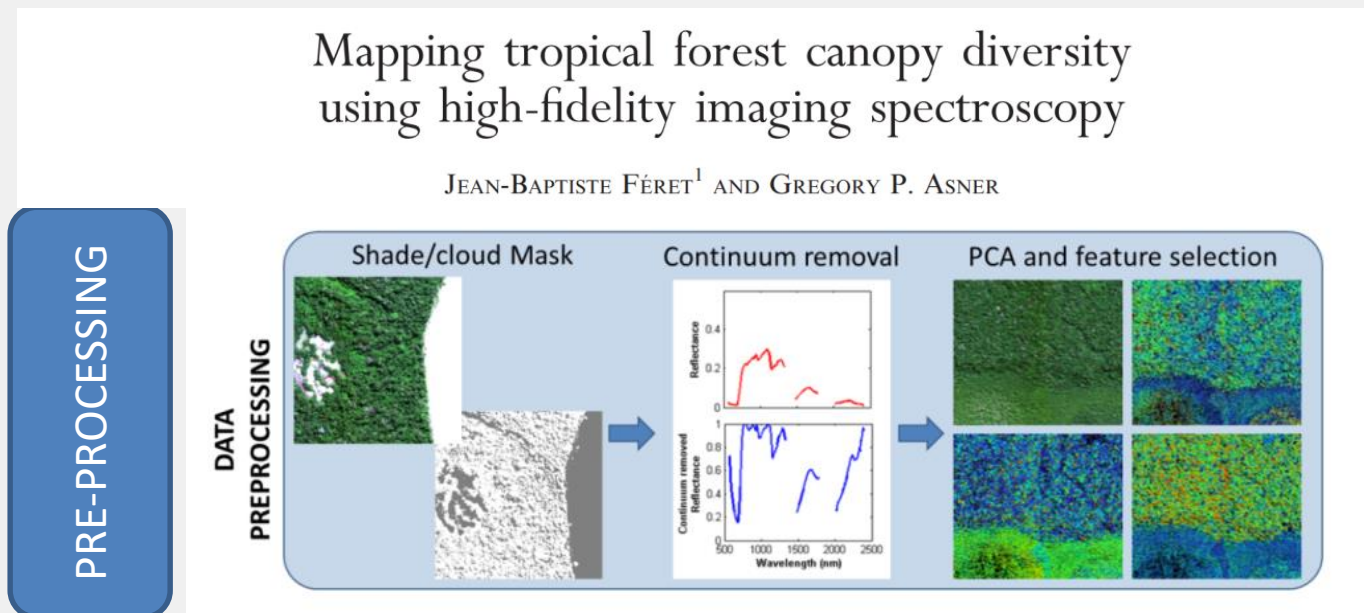
Asner & Martin (2009), *Frontiers in Ecology and the Environment*, 7:269-276.  
 Asner et al. (2009), *Ecological Applications*, 19:236-253.  
<http://spectranomics.stanford.edu/>

# From remotely sensed information to ecological information

- **How to link reflectance & optical traits to ecological information?**
  - Identify a relationship between spatial heterogeneity in spectral information and environmental / ecological heterogeneity / biodiversity
- **Which information should be used to approximate ‘optical traits’?**
  - Transformed reflectance ([Féret & Asner, 2014](#), [Laliberté et al., 2020](#))
  - Spectral indices ([Schneider et al., 2017](#))
  - Biophysical properties ([Hauser et al., 2021](#))
- **How to express spectral variations ?**
  - Univariate / multivariate space
  - Discrete / continuous space
- **Which ground observations should be compared with spectral information ?**
  - Species / taxonomic diversity
  - Functional diversity
  - ...

# From remotely sensed information to ecological information

- Which information should be used to approximate ‘optical traits’ ?
  - Transformed reflectance ([Féret & Asner, 2014](#), [Laliberté et al., 2020](#))
    - No prior assumption on thematic relevance of spectral information
    - Data driven → possibly limiting when studying sites independently
    - Manual or automated feature selection (PCs or bands) may be needed
    - Transformation (PCA / MNF) may help reduce influence of sensor noise & artifacts



Féret & Asner (2014) Mapping tropical forest canopy diversity using high-fidelity imaging spectroscopy.

*Ecological Applications*, 24 – 1289-1296 <https://doi.org/10.1890/13-1824.1>

Laliberté et al. (2020) Partitioning plant spectral diversity into alpha and beta components.

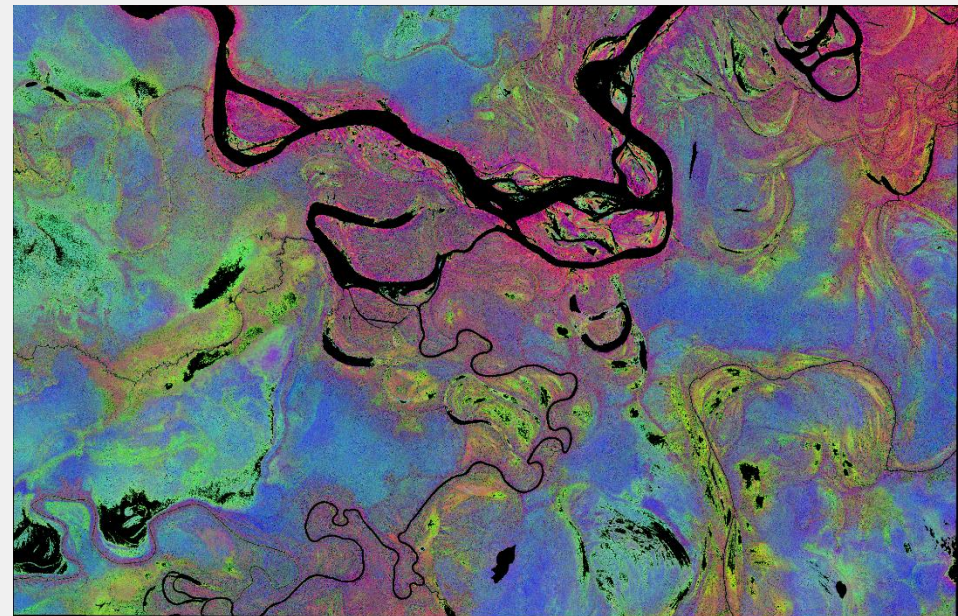
*Ecology Letters*, 23(2) – 370-380 <https://doi.org/10.1111/ele.13429>

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Application on Amazonian forest, Peru:

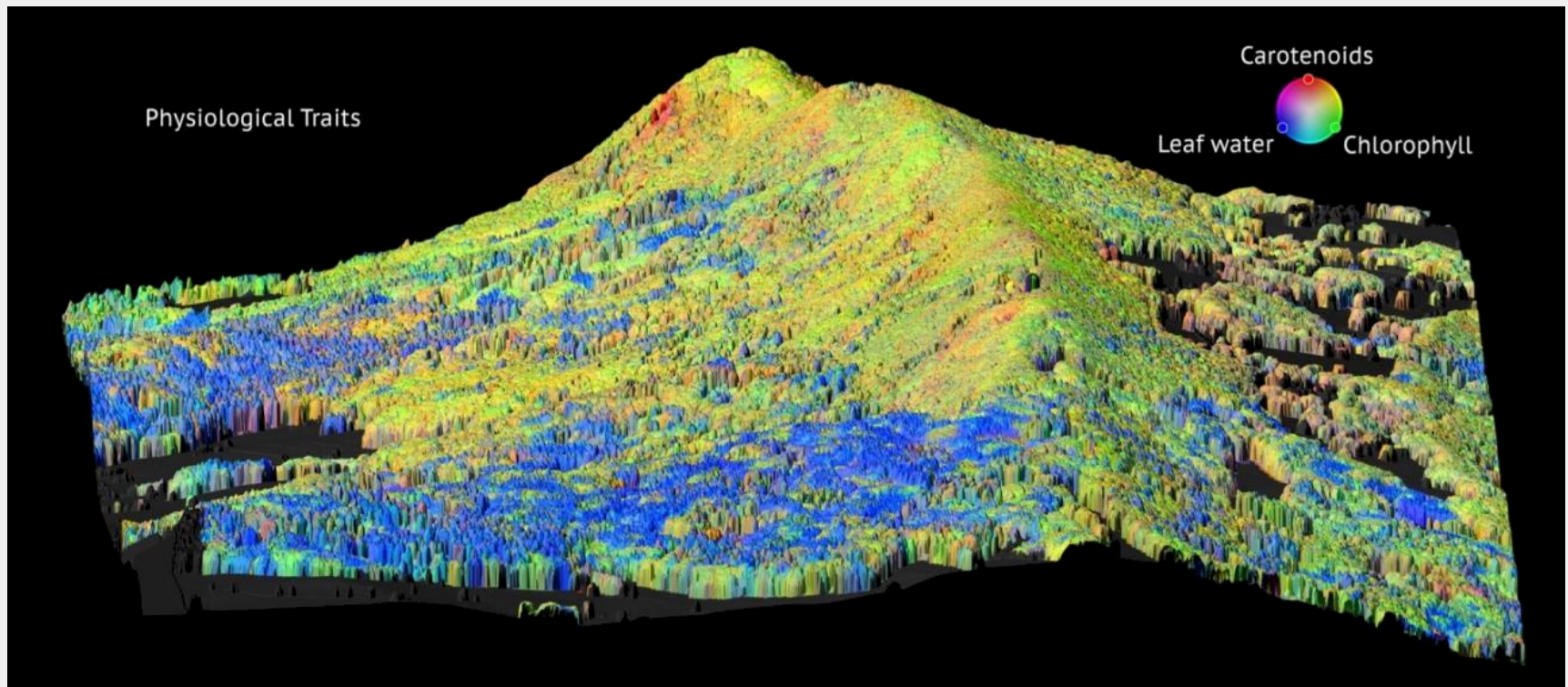
Continuum removal & SPCA performed on S2 image, three components selected for display





# From remotely sensed information to ecological information

- **Which information should be used to approximate ‘optical traits’ ?**
  - Transformed reflectance (Féret & Asner, 2014)
  - Spectral indices ([Schneider et al., 2017](#))
    - Selection of spectral indices based on their correlation with vegetation traits
    - Many SI identified in the literature, possibly strongly correlated
    - Influenced by multiple factors (structure & chemistry), sensitive to sensor noise

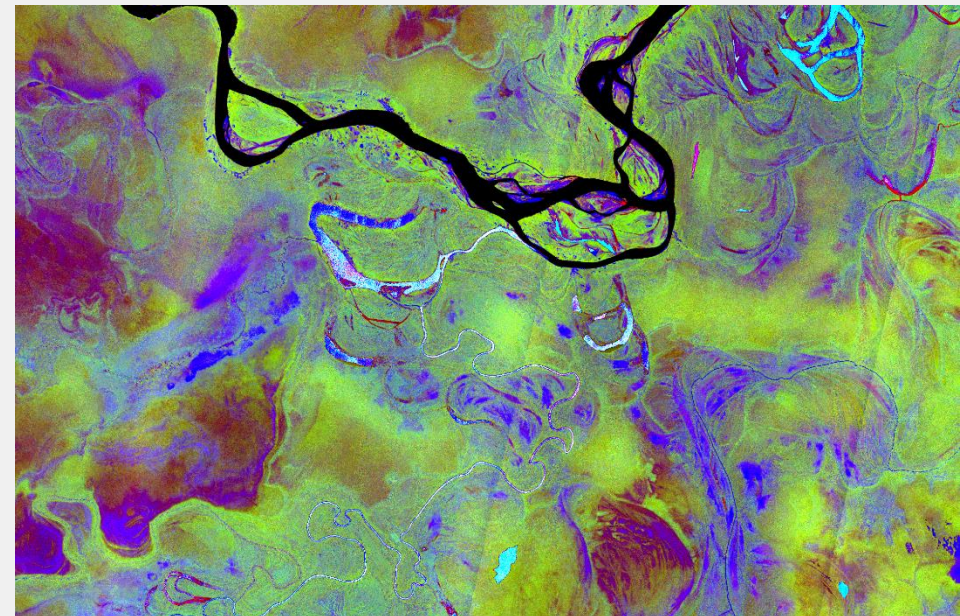


Schneider et al. (2017) Mapping functional diversity from remotely sensed morphological and physiological forest traits. *Nature Communications*, 8 – 1441 <https://doi.org/10.1038/s41467-017-01530-3>

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Application on Amazonian forest, Peru:  
Color composite MCARI, mNDVI<sub>705</sub>, NDWI<sub>1</sub>

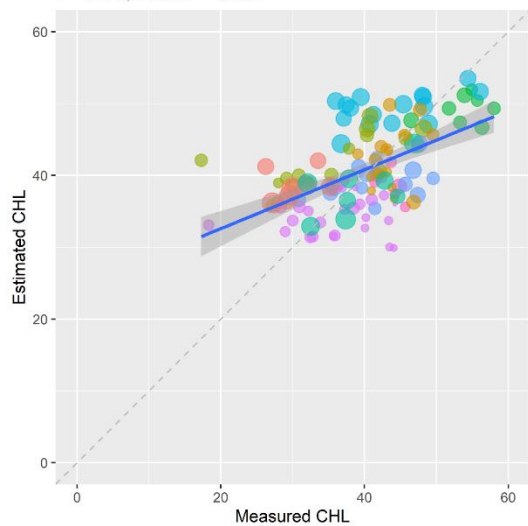


# From remotely sensed information to ecological information

- Which information should be used to approximate 'optical traits' ?
  - Transformed reflectance (Ferret & Asner, 2014)
  - Spectral indices (Schneider et al., 2017)
  - Biophysical properties ([Hauser et al., 2021](#))
    - Estimate vegetation biophysical properties based on spectral information
    - Computationally more intensive than spectral indices
    - Easier interpretation by ecologists/agronomists (leaf chemistry, LAI...)

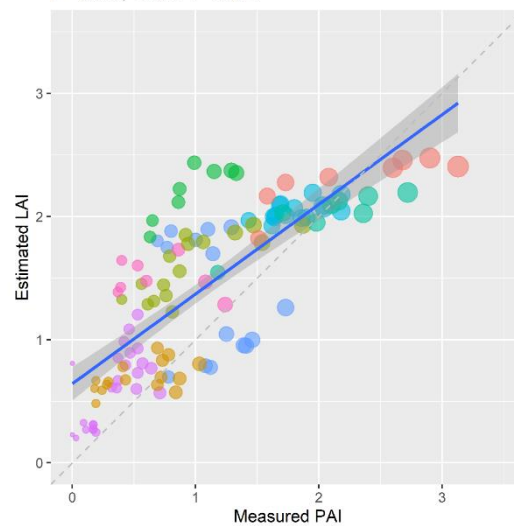
## Leaf chlorophyll content

$r = 0.55$ ,  $RMSE = 6.66$



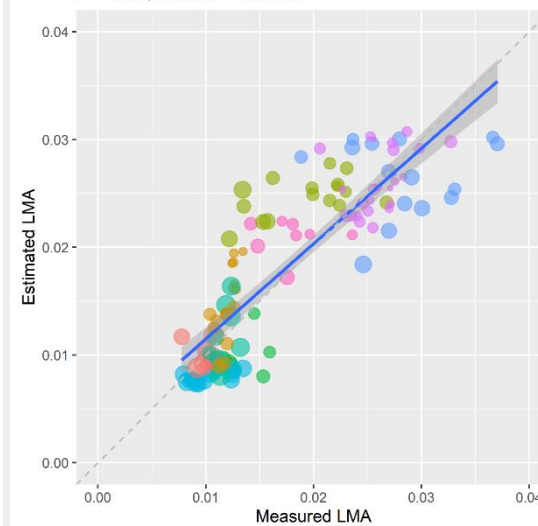
## Leaf Area Index

$r = 0.78$ ,  $RMSE = 0.58$



## Leaf Mass per Area

$r = 0.85$ ,  $RMSE = 0.0042$



LAIMES



Vegetation.type

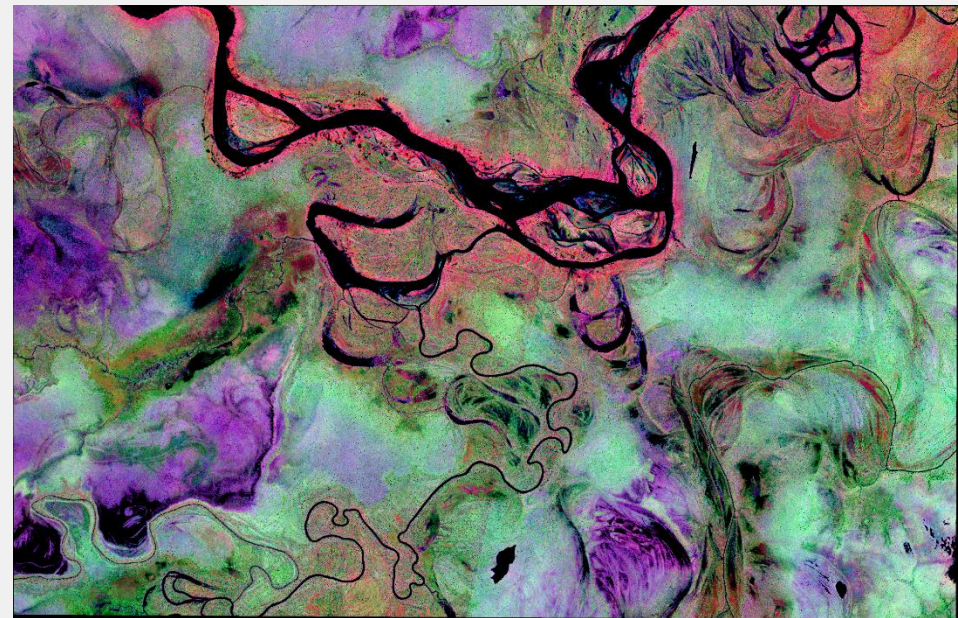
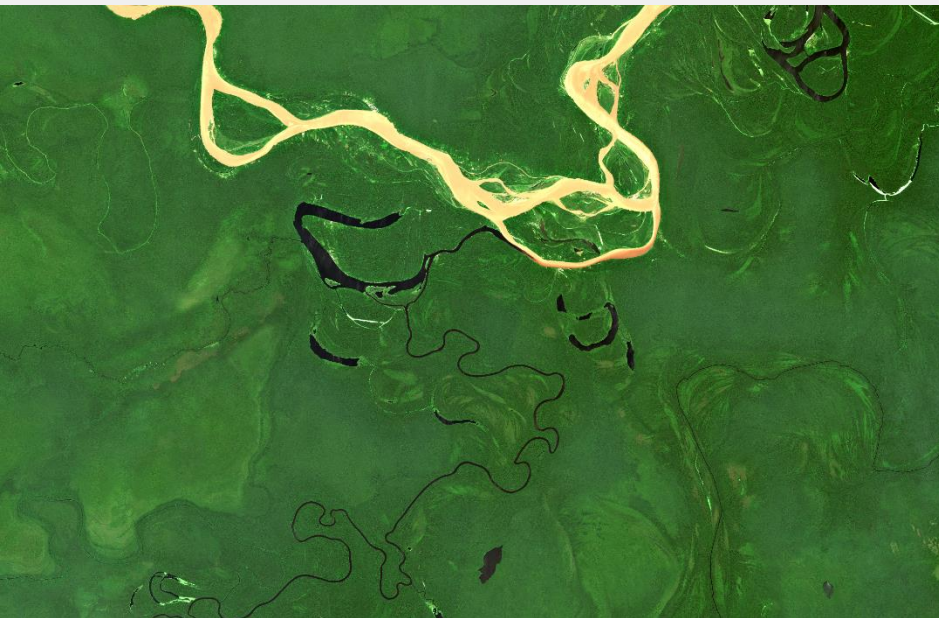


# From remotely sensed information to ecological information

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Application on Amazonian forest, Peru:

Estimation of LAI (red), CHL (green) & EWT (blue) from S2 image and PROSAIL hybrid inversion

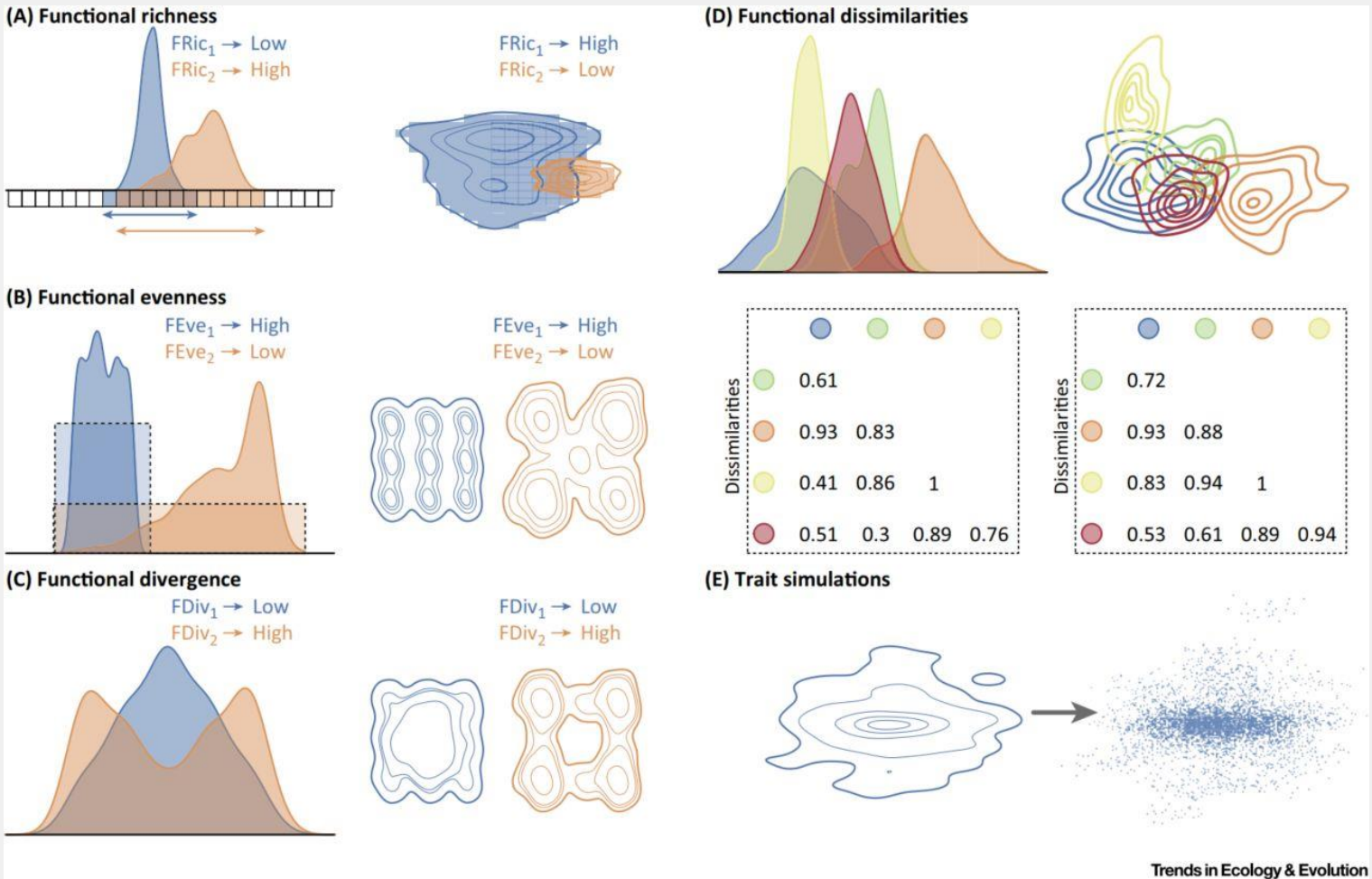


# From remotely sensed information to ecological information

- **How to express spectral variations ? Integrating spectral variations over a spatial extent**
  - Define a spatial extent matching with ecological hypotheses, ground & RS observations
    - Forest ecosystems: surface of inventory plots  $\sim 0.25 - 1$  ha
    - Statistics may need min number of pixels constraining surface unit from RS
    - Regular grid, moving window...
  - Explore feature space (spectral index, biophysical properties, principal components...)
    - Univariate space (potentially limiting for complex ecological processes):
      - Standard deviation, spectral range of feature over spatial extent
    - Multivariate space
      - Mean distance from centroid, mean coefficient of variation, entropy
  - **Discrete / continuous space**
    - Continuous space: trait space / spectral space
    - Discrete space: classification / clustering of trait space / spectral space

# From remotely sensed information to ecological information

- Analyzing continuous feature space to estimate functional metrics from trait distribution
  - Functional richness, evenness, divergence, dissimilarity:
    - [Villéger et al. \(2008\)](#), [Carmona et al. \(2016\)](#)

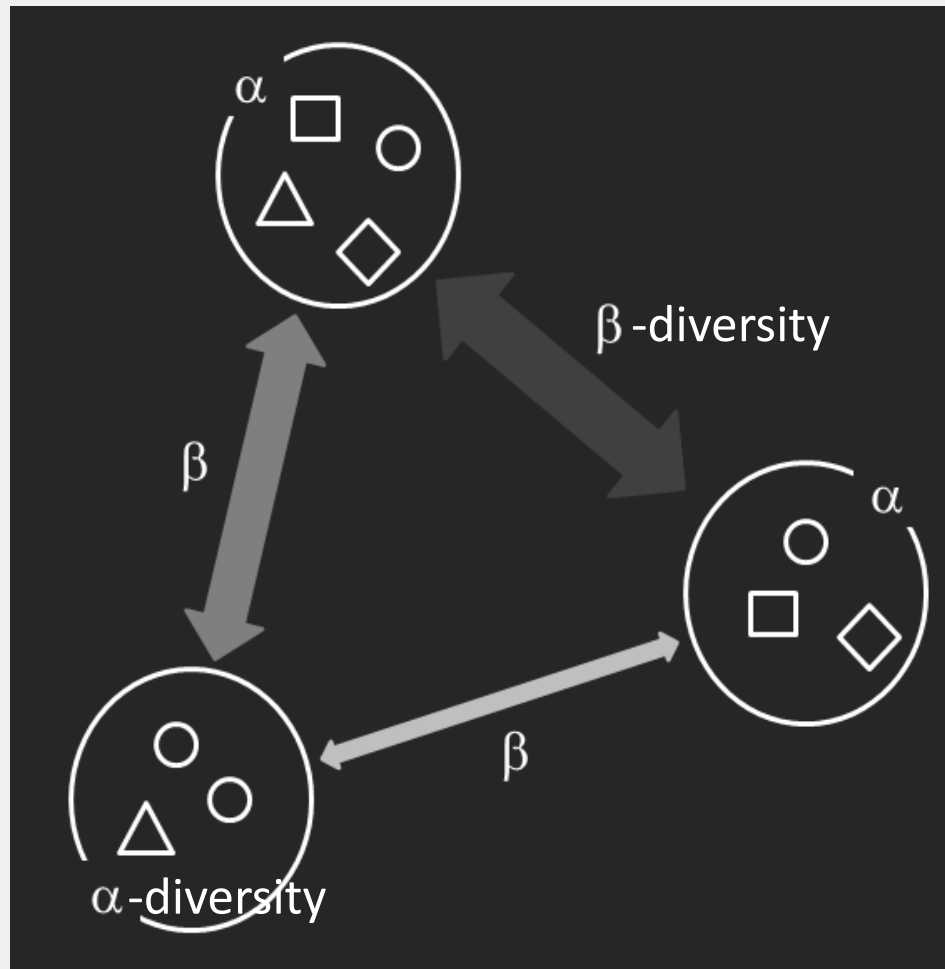


# From remotely sensed information to ecological information

- Analyzing discrete feature space to estimate taxonomic / species inventory metrics
  - Clustering produces 'spectral species', similar to 'optical types' ([Ustin & Gamon, 2010](#))
  - $\alpha$ - and  $\beta$ -diversity metrics based on cluster inventory
  - Analogy between species and spectral species is strongly scale dependent

## usual metrics for $\alpha$ -diversity :

- Richness
- Shannon index
- Simpson index
- Fischer index
- ...



## usual metrics for $\beta$ -diversity :

- Bray Curtis dissimilarity
- Jaccard distance
- ...

# From remotely sensed information to ecological information

Based on a 'naive' approach of the problem:

- 1. Species diversity metrics are computed from plot inventories
  - 2. Tree species can be discriminated based on spectral information
- Use cluster inventories to compute spectral diversity metrics

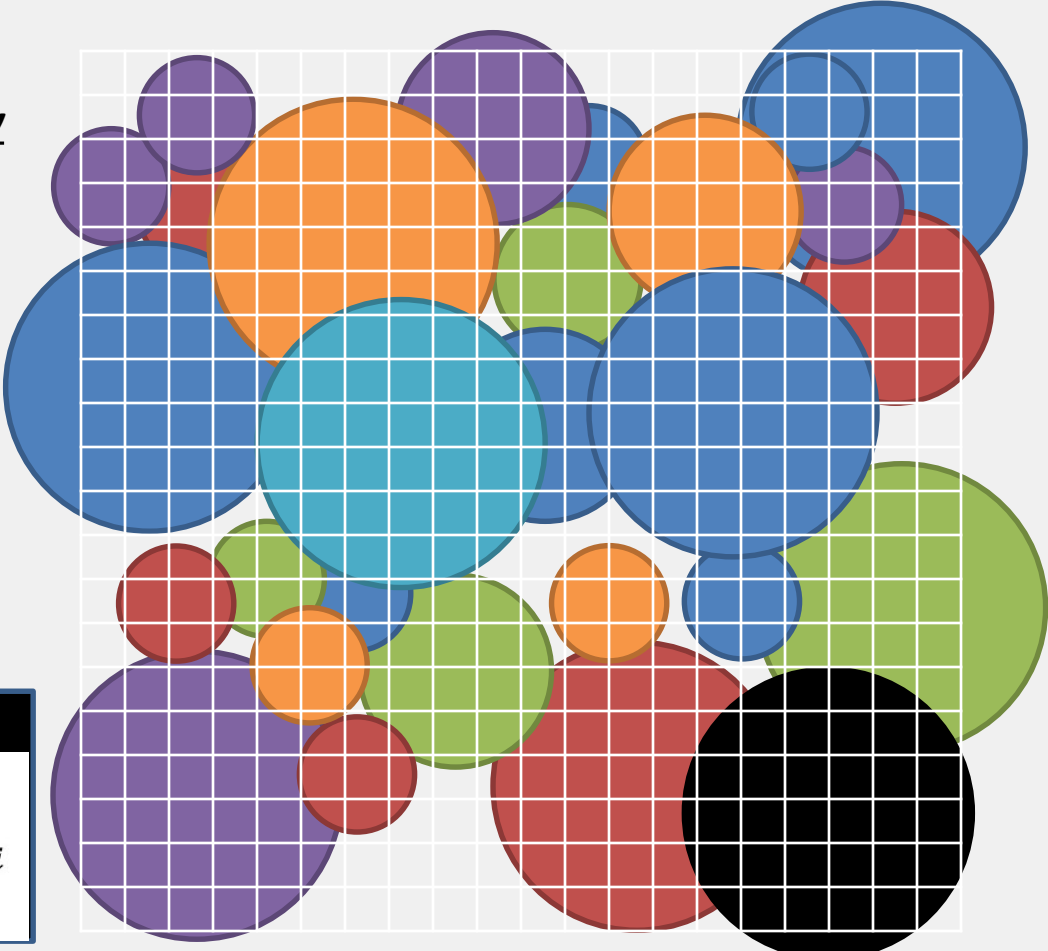
### Species inventory

- $p_1$  sp1
- $p_2$  sp2
- $p_3$  sp3
- $p_4$  sp4
- $p_5$  sp5
- $p_6$  sp6



Shannon index

$$H' = - \sum_{i=1}^s p_i \ln p_i$$



### Cluster inventory

- $p_1$  pixels cluster 1
- $p_2$  pixels cluster 2
- $p_3$  pixels cluster 3
- $p_4$  pixels cluster 4
- $p_5$  pixels cluster 5



Shannon index

$$H' = - \sum_{i=1}^s p_i \ln p_i$$

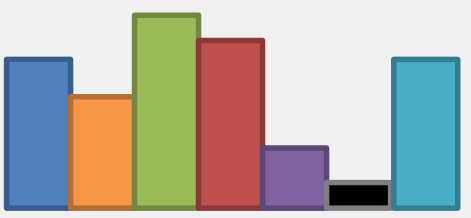


# From remotely sensed information to ecological information

Based on a 'naive' approach of the problem:

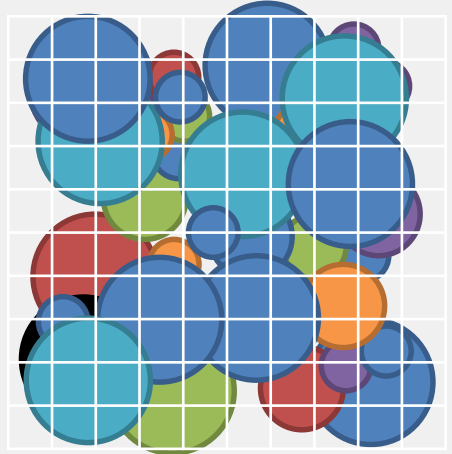
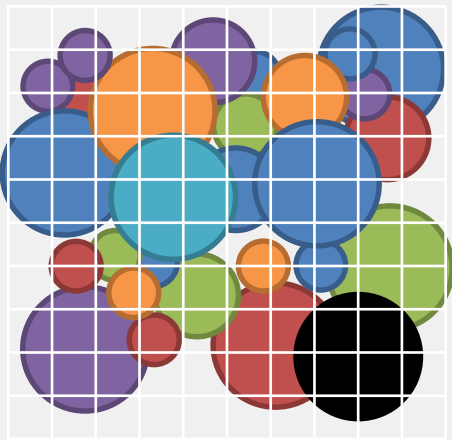
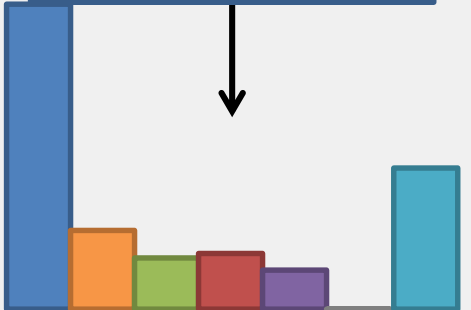
- 1. Species diversity metrics are computed from plot inventories
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## Species distribution

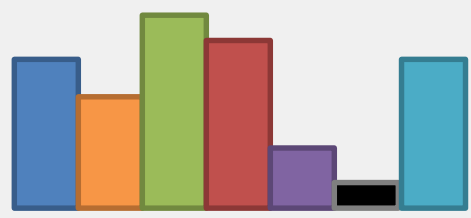


Bray Curtis Dissimilarity

$$BC_d = \frac{\sum |x_i - x_j|}{\sum (x_i + x_j)}$$

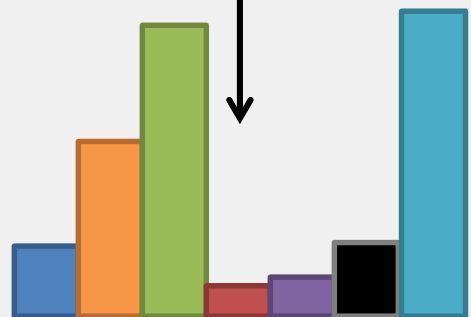


## Cluster distribution

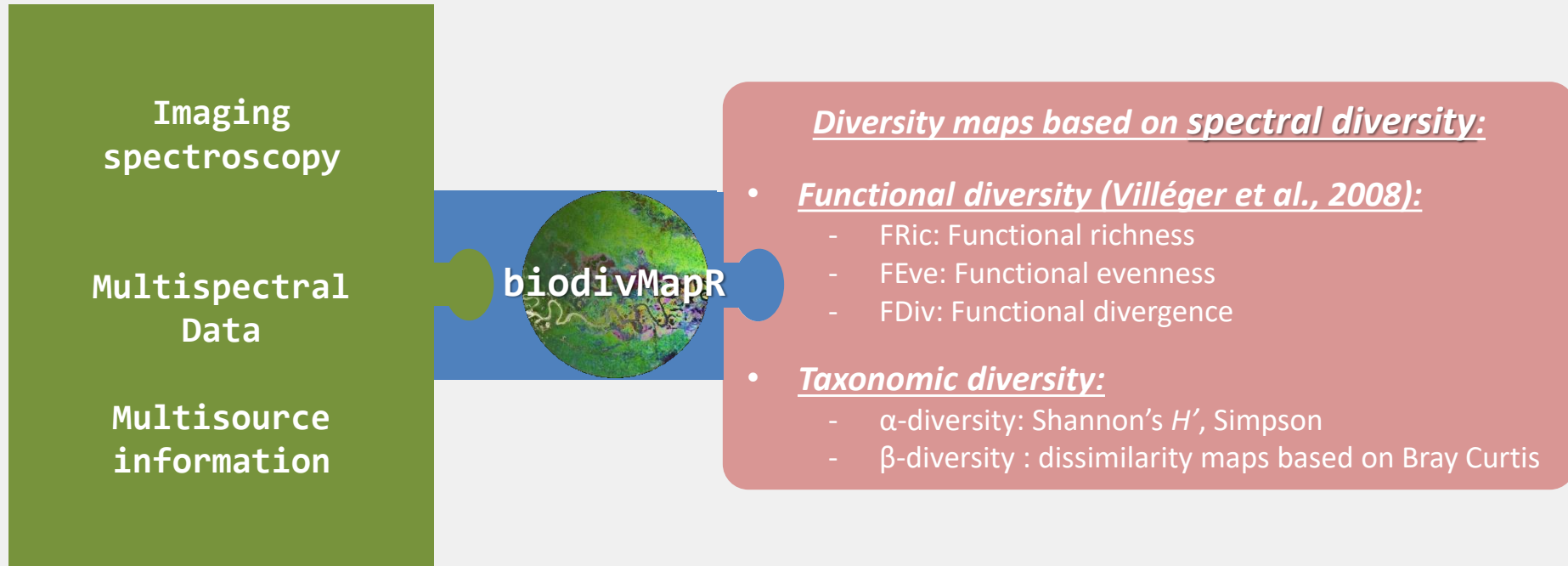


Bray Curtis Dissimilarity

$$BC_d = \frac{\sum |x_i - x_j|}{\sum (x_i + x_j)}$$



# Mapping biodiversity using spectral diversity



## APPLICATION

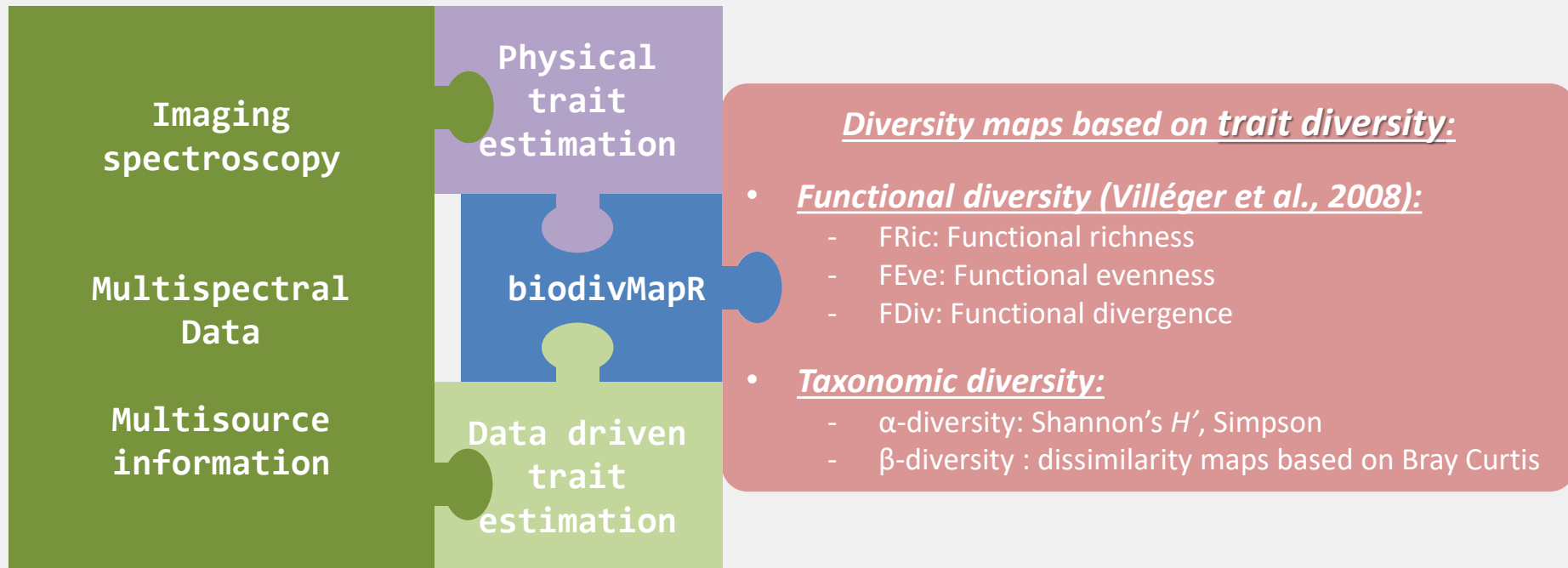
**biodivMapR: An R package for  $\alpha$ - and  $\beta$ -diversity mapping using remotely sensed images**



Jean-Baptiste Féret  | Florian de Boissieu 

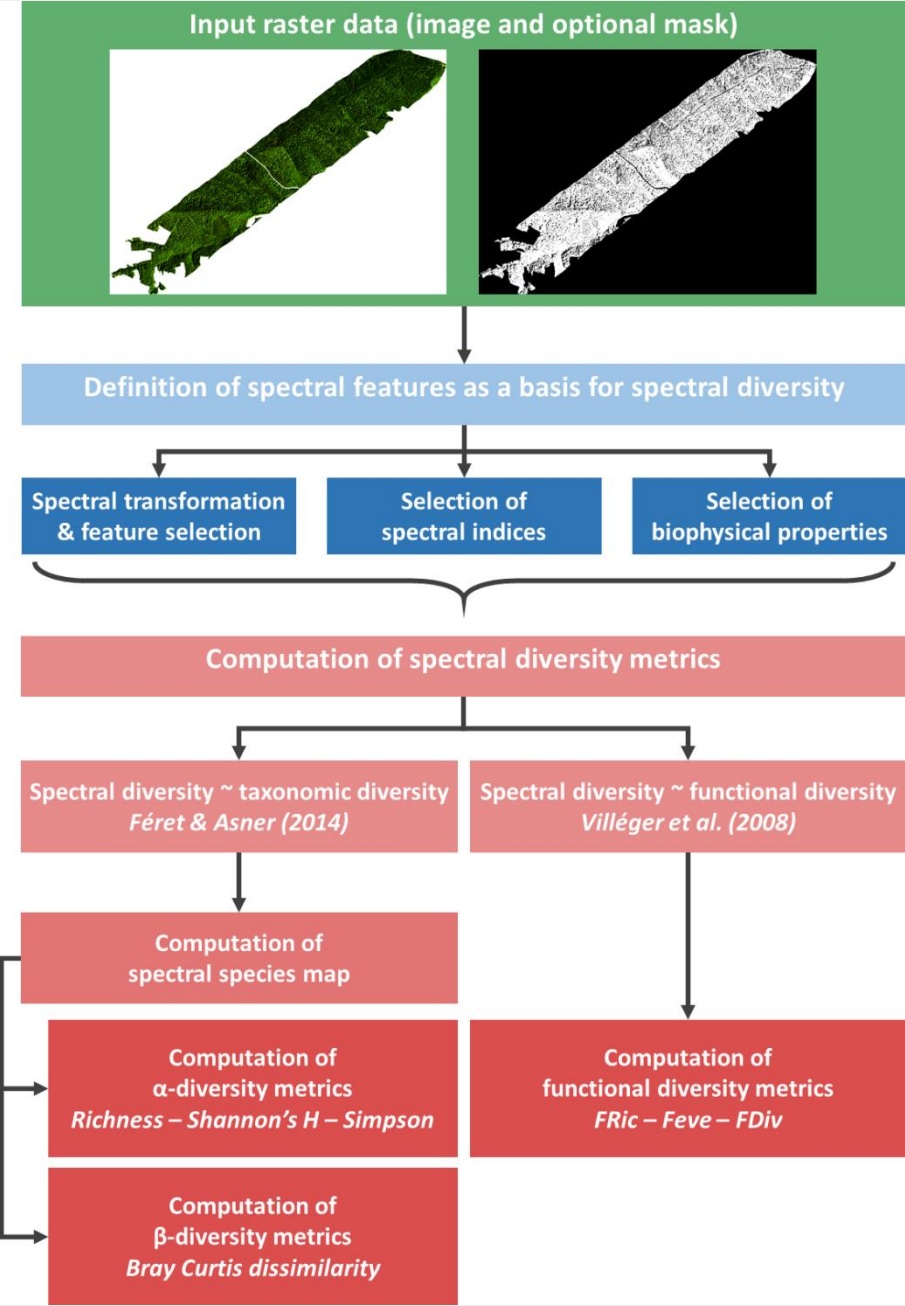
<https://jbferet.github.io/biodivMapR/index.html>

# Mapping biodiversity using vegetation traits estimated from RS



- Spectral diversity / optical trait diversity can be useful indicators of biological diversity
- The link between remotely sensed indicators and diversity metrics collected on the ground is not systematic

# Mapping biodiversity using vegetation traits estimated from RS



# Mapping biodiversity using bioDivMapR on imaging spectroscopy

*Ecological Applications*, 24(6), 2014, pp. 1289–1296  
© 2014 by the Ecological Society of America

ECOLOGICAL  
APPLICATIONS  
ECOLOGICAL SOCIETY OF AMERICA

## Mapping tropical forest canopy diversity using high-fidelity imaging spectroscopy

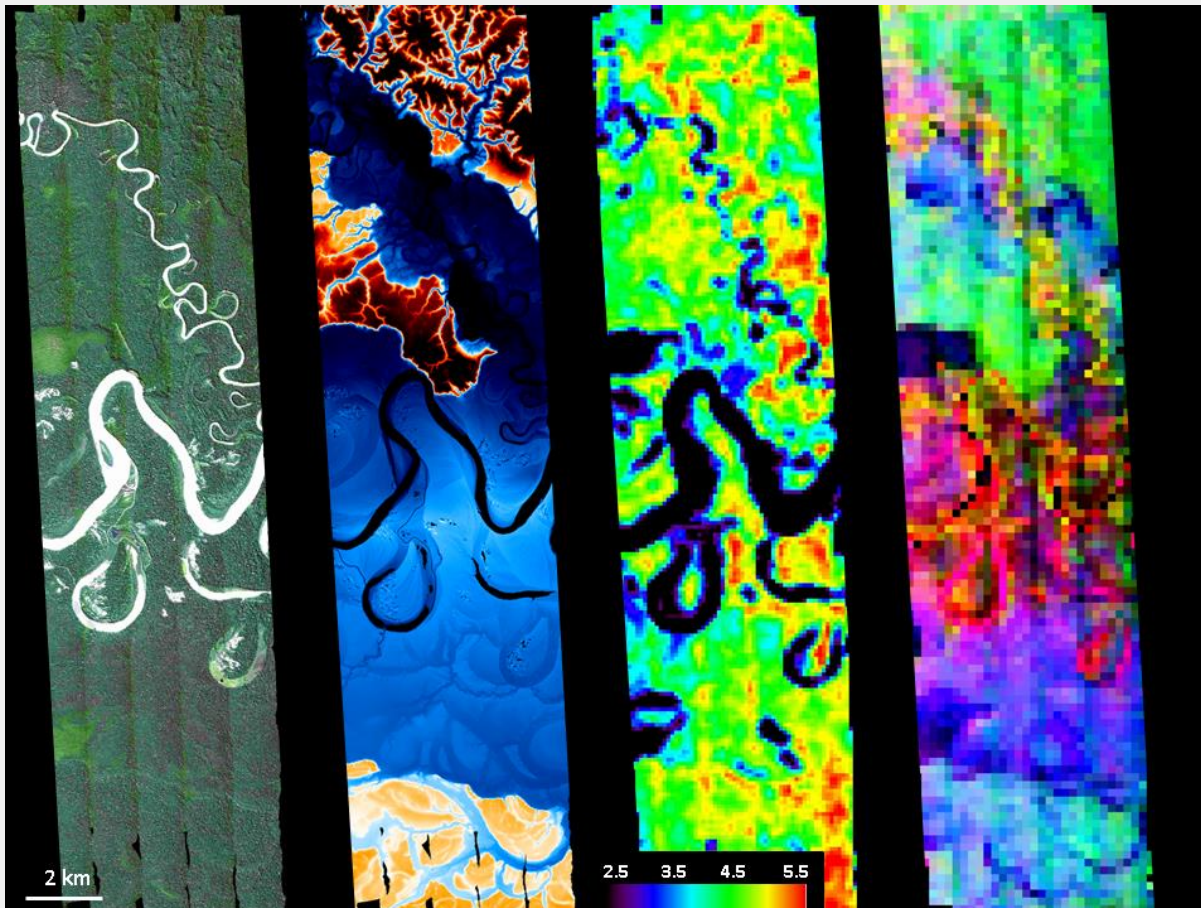
JEAN-BAPTISTE FÉRET<sup>1</sup> AND GREGORY P. ASNER

RGB

DEM

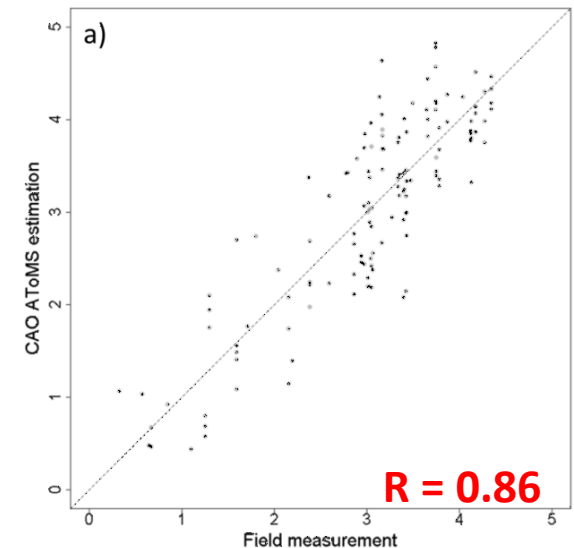
$\alpha$ -diversity

$\beta$ -diversity



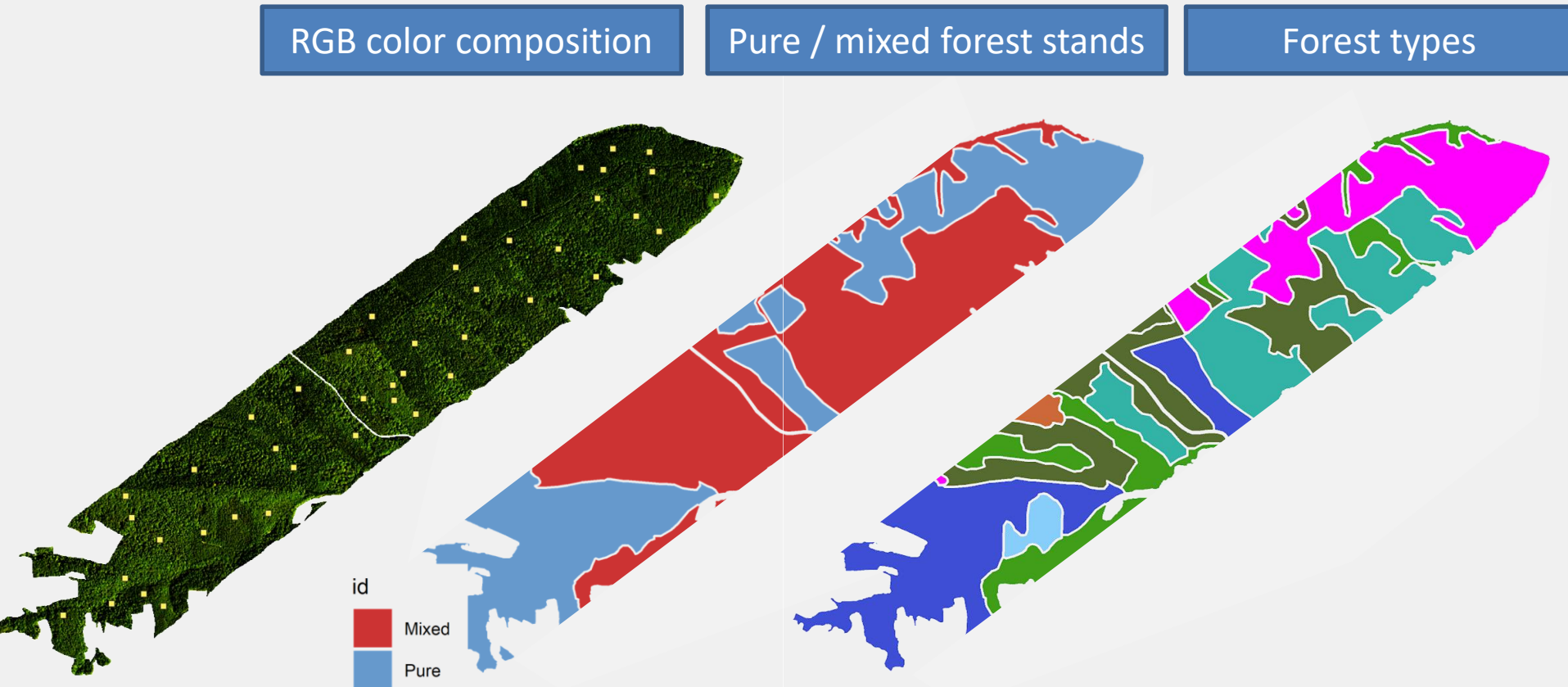
Validation  
(153 plots, 10+ sites)

Shannon's  $H'$



# Mapping biodiversity using `biodivMapR` on imaging spectroscopy

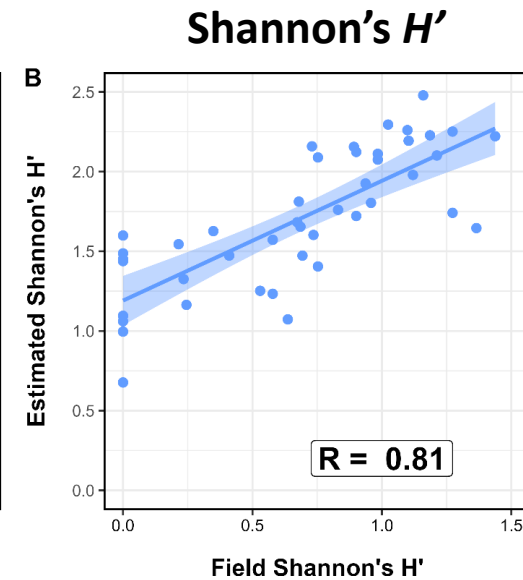
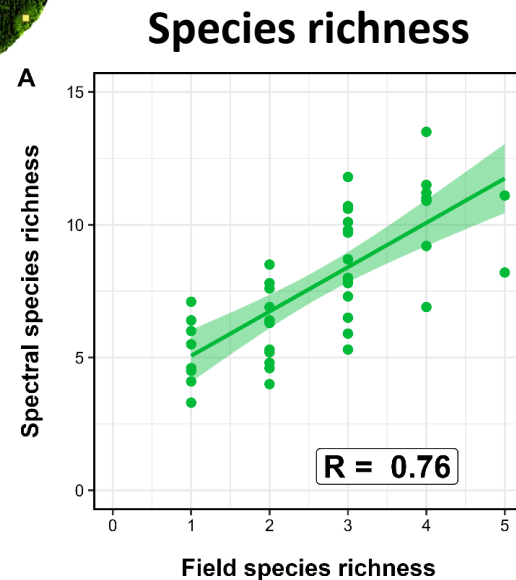
- Temperate forest: Fabas forest (Southwest of France)
- 4m spatial resolution, spectral domain = VSWIR
- **Direct validation:**     **44 field plots inventoried**
- Indirect validation:     BD Forêt (forest types inventoried between 2007 and 2018)



# Mapping biodiversity using `biodivMapR` on imaging spectroscopy

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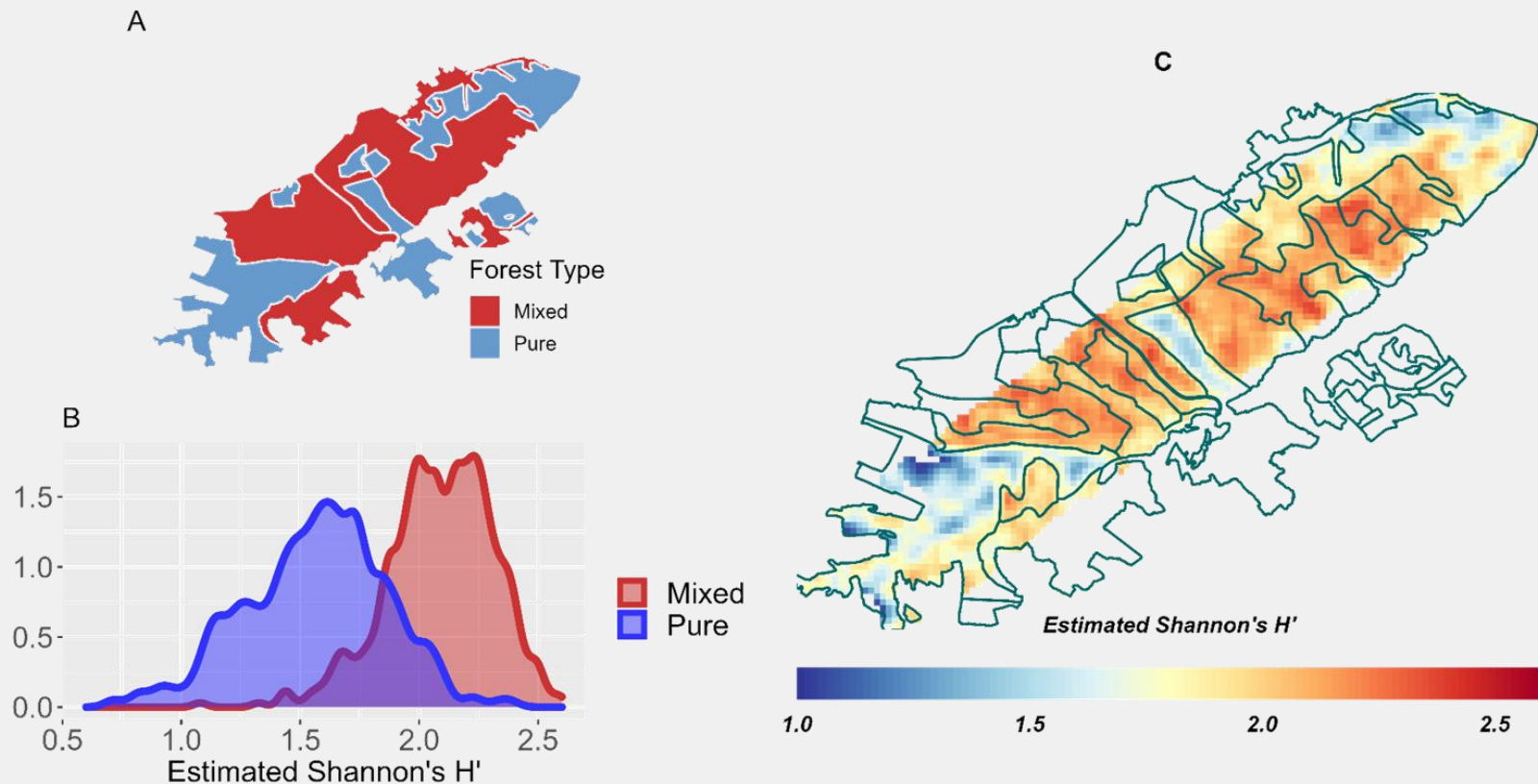
## $\alpha$ -diversity



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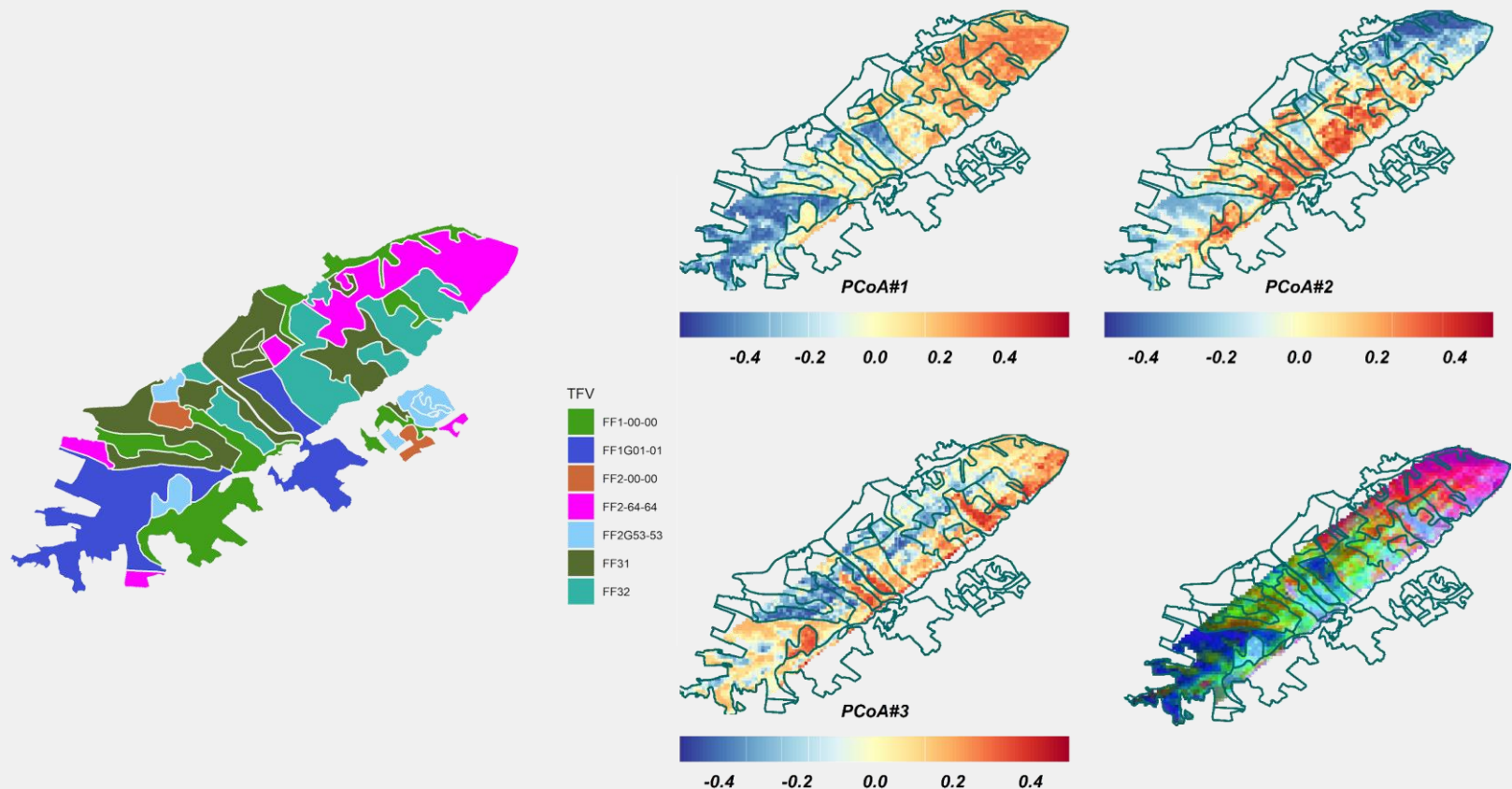




# Mapping biodiversity using `biodivMapR` on imaging spectroscopy

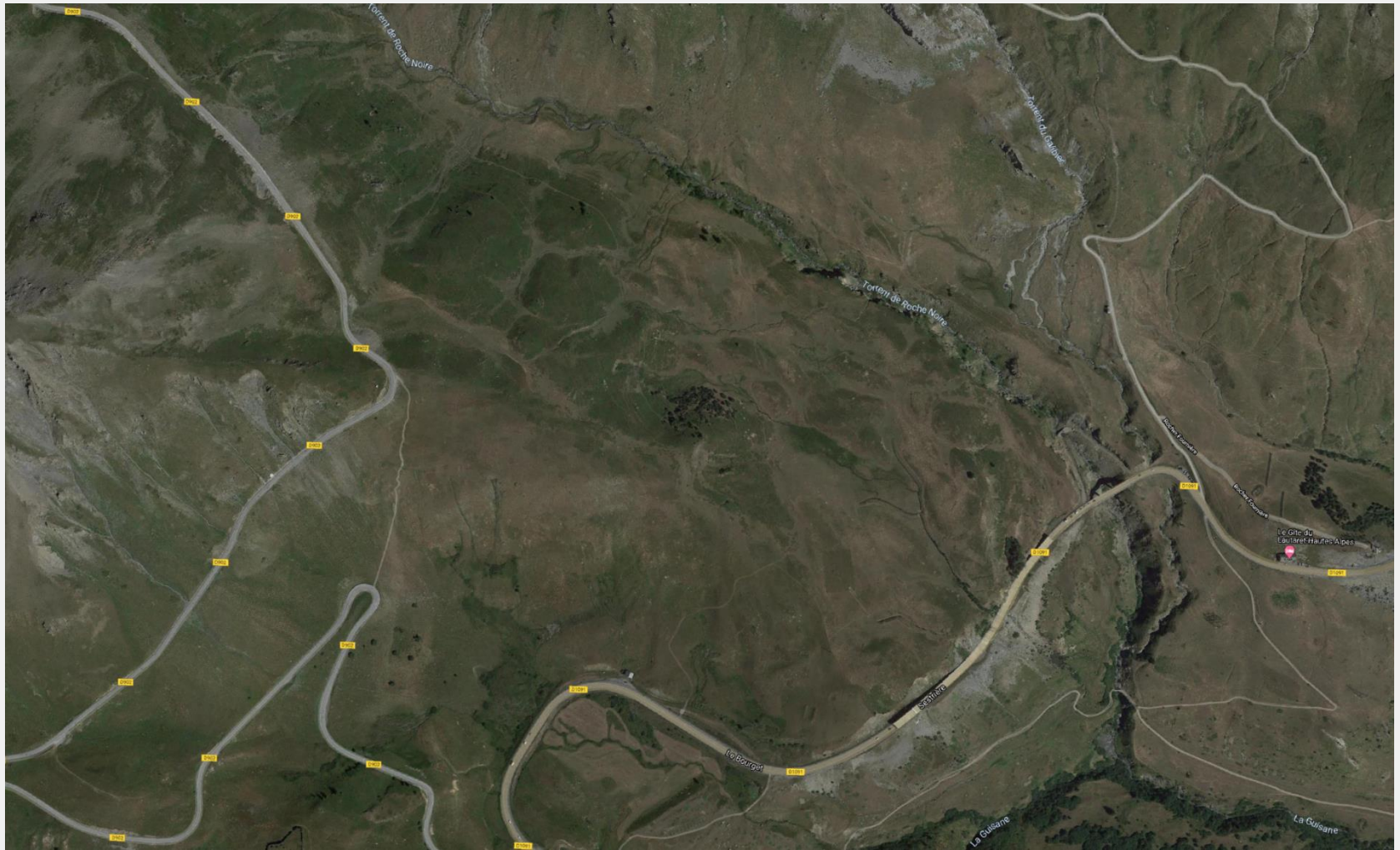
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## $\beta$ -diversity



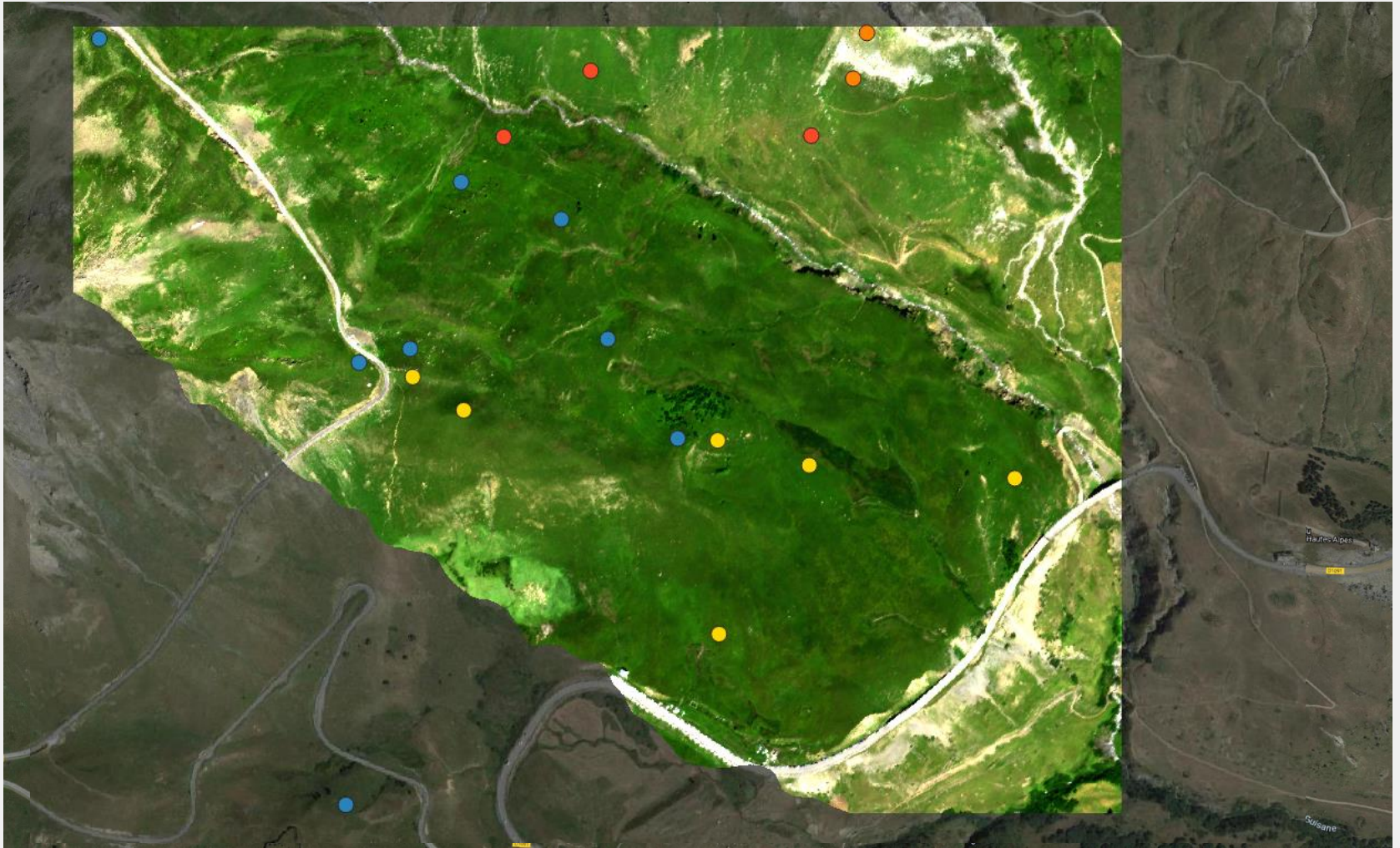
# Mapping biodiversity using `biodivMapR` on imaging spectroscopy

- Subalpine grasslands : Lautaret pass (France, Hautes Alpes)



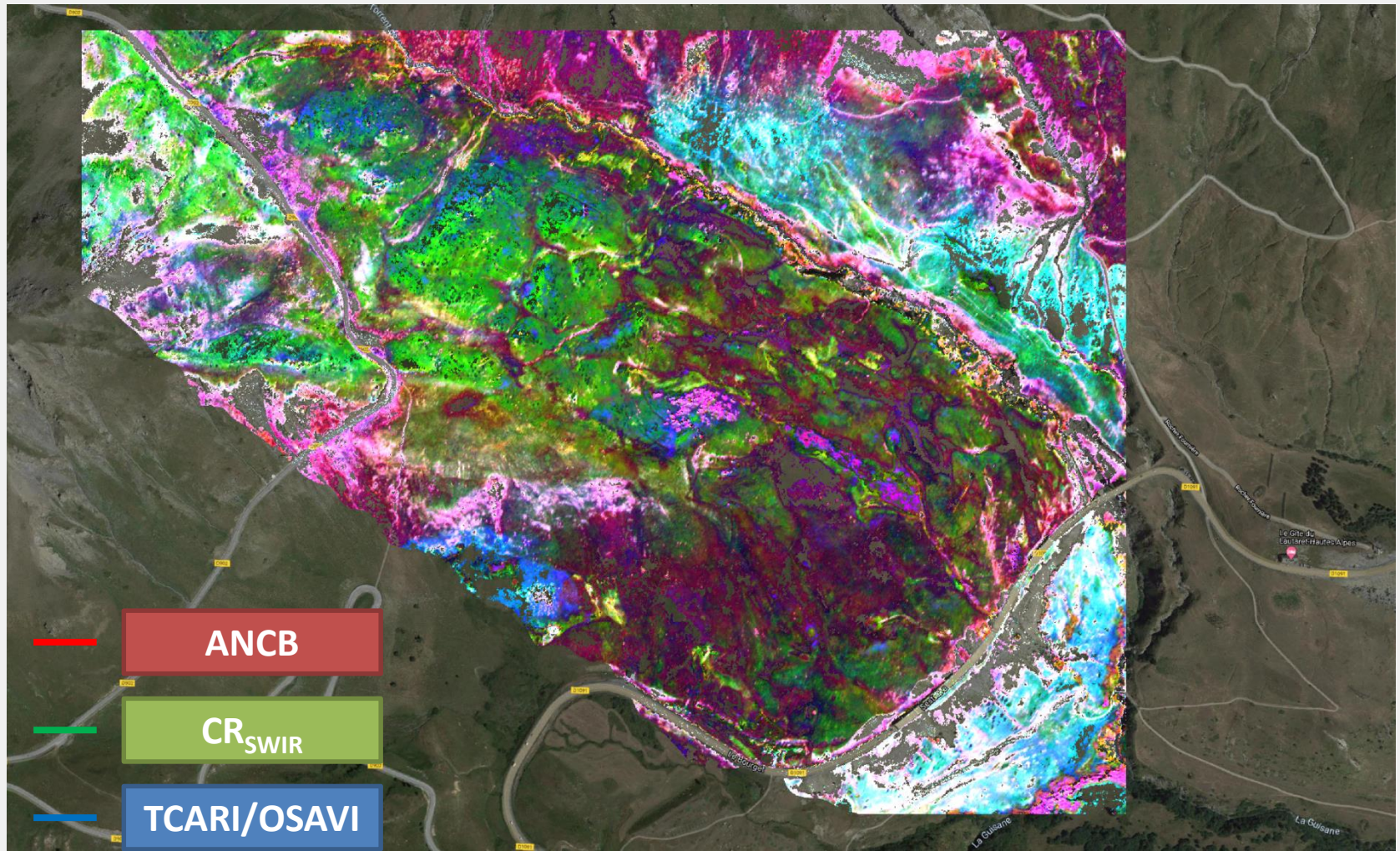
# Mapping biodiversity using `biodivMapR` on imaging spectroscopy

- Subalpine grasslands : Lautaret pass (France, Hautes Alpes)
  - Imaging spectroscopy acquired over the study area



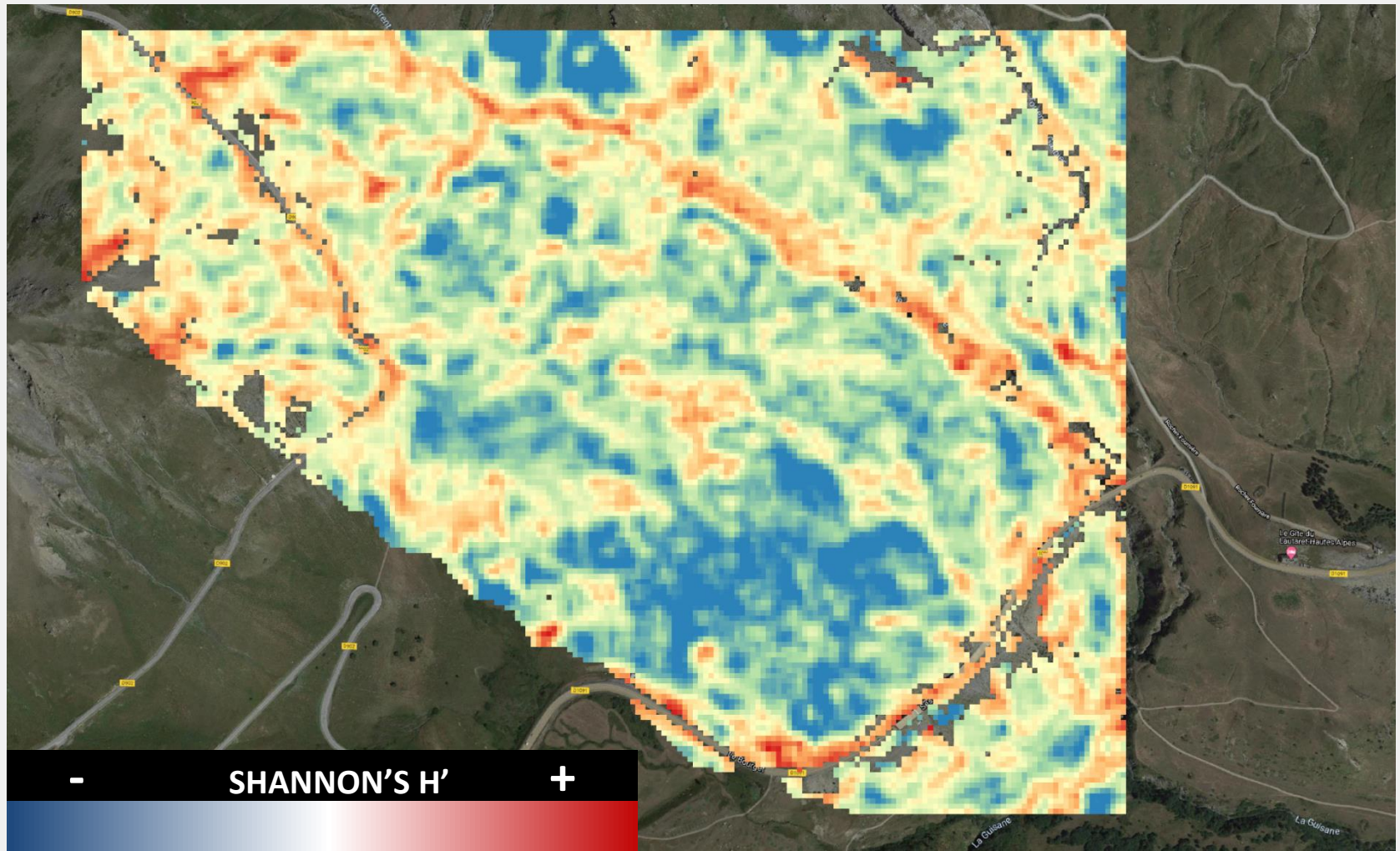
# Mapping biodiversity using `biodivMapR` on imaging spectroscopy

- Subalpine grasslands : Lautaret pass (France, Hautes Alpes)
  - Computation of three spectral indices related to vegetation traits ([Pottier et al., 2014](#))



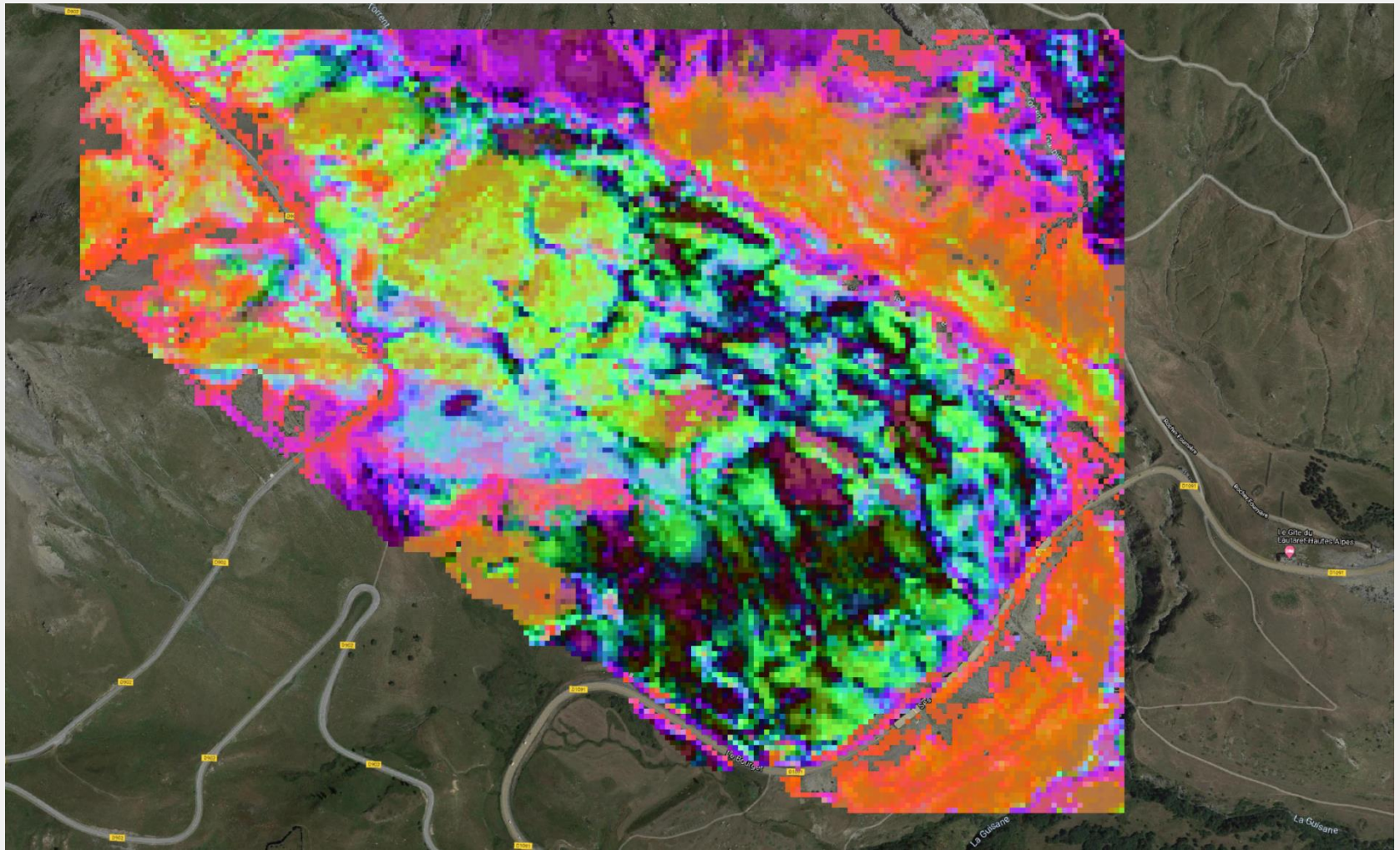
# Mapping biodiversity using *biodivMapR* on imaging spectroscopy

- Subalpine grasslands : Lautaret pass (France, Hautes Alpes)
  - Shannon index estimated with *biodivMapR*
    - High diversity in the neighborhood of mountain path: artifacts due to mix of rocks and vegetation increasing variability



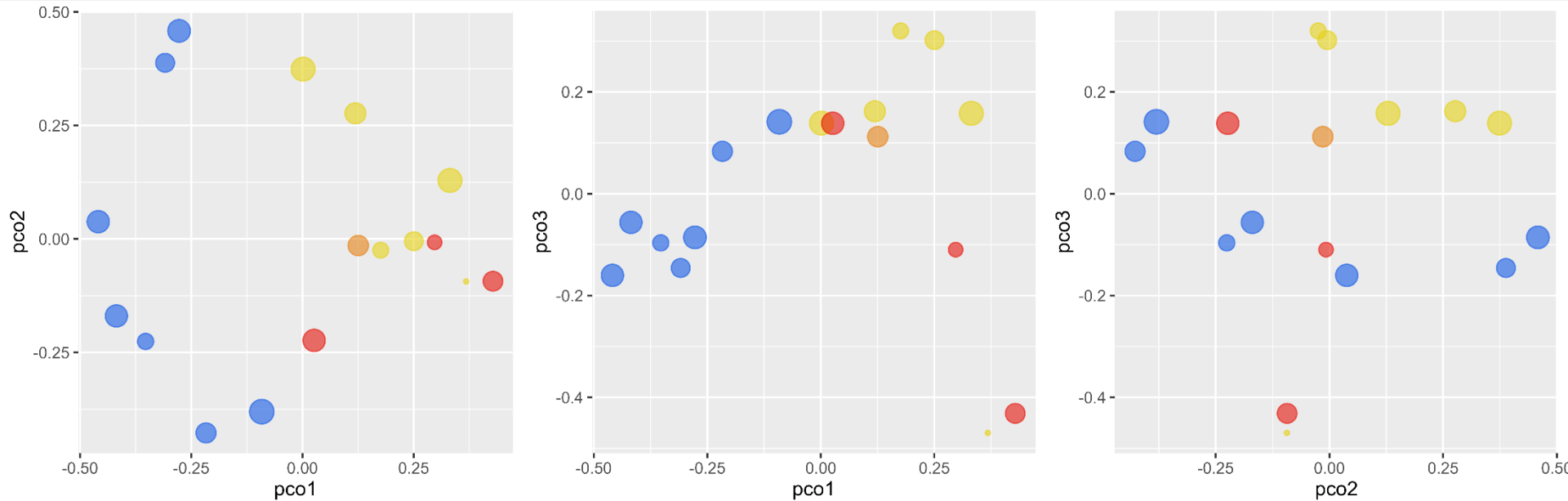
# Mapping biodiversity using *biodivMapR* on imaging spectroscopy

- Subalpine grasslands : Lautaret pass (France, Hautes Alpes)
  - Bray Curtis dissimilarity + PCoA estimated with *biodivMapR*
  - Diversity patterns correspond to main plant communities



# Mapping biodiversity using *biodivMapR* on imaging spectroscopy

- Subalpine grasslands : Lautaret pass (France, Hautes Alpes)
    - Bray Curtis dissimilarity + PCoA estimated with *biodivMapR*
- Diversity patterns correspond to main plant communities



**FG** : open subalpine grasslands dominated by *Festuca violacea*, mostly found on south-facing steep slopes

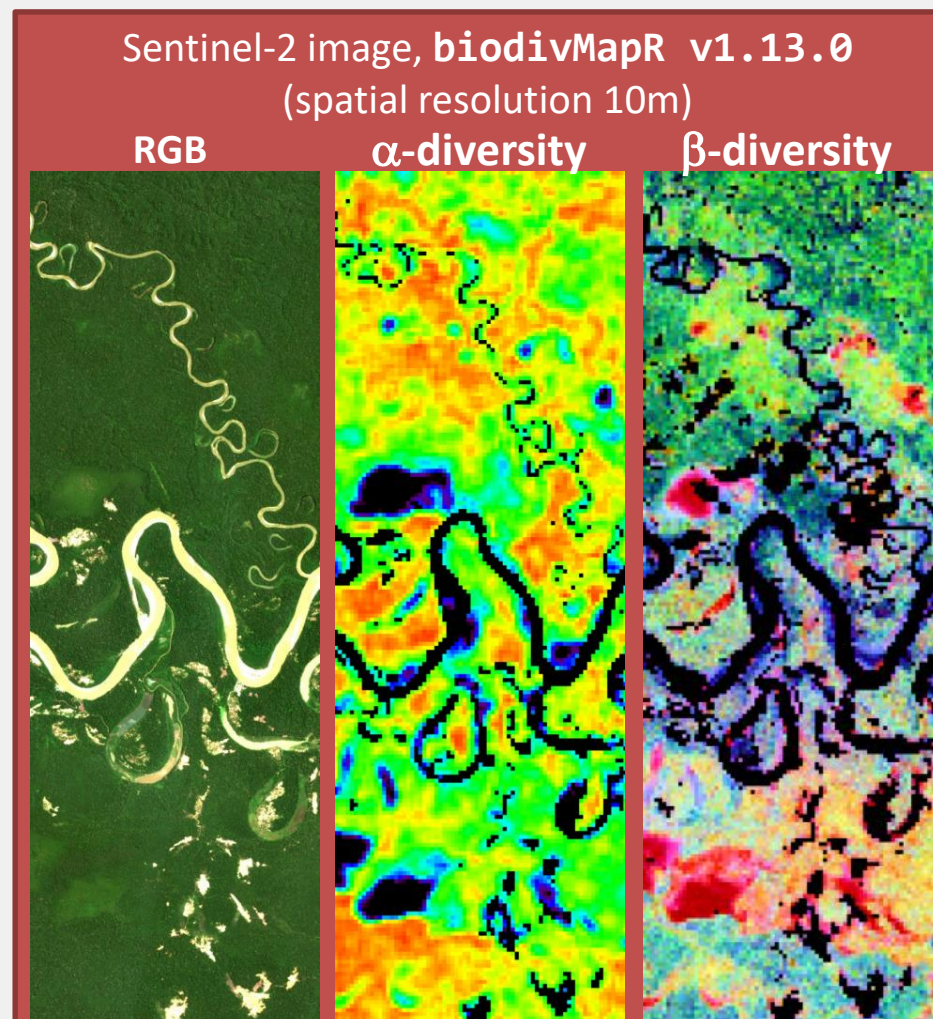
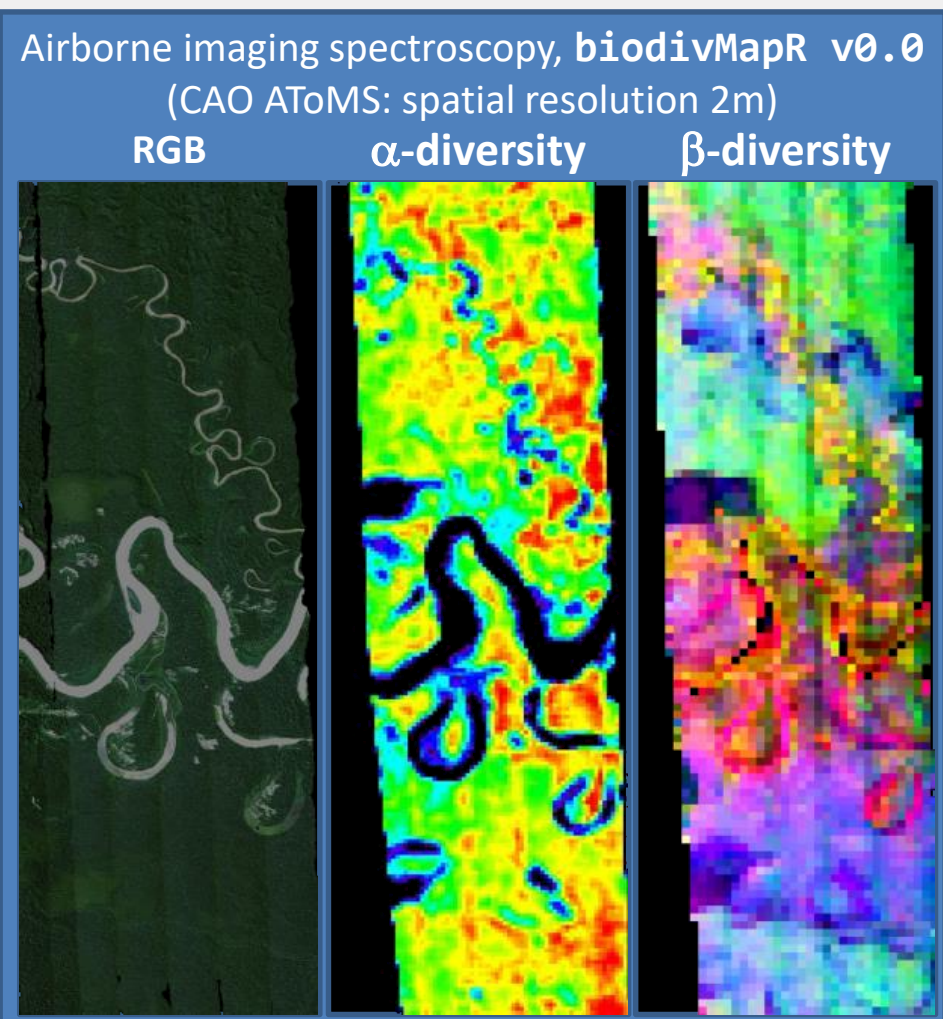
**FP** : tall subalpine grasslands dominated by *Patzkea paniculata* (syn. *Festuca paniculata*), mostly found on south-facing gentle slopes with deep soil

**SC** : sparsely vegetated grasslands dominated by *Sesleria caerulea* on south-facing, debris-covered slopes

**V**: low stature heaths dominated by *Vaccinium uliginosum* and *Vaccinium myrtillus*, mostly found on north-facing slopes

# Mapping biodiversity using `biodivMapR` on Sentinel-2 images

- Comparison between airborne imaging spectroscopy and Sentinel-2 satellite images



Need to perform more quantitative validation :

- On multiple dataset and forest/vegetation types
- With different methods & different diversity metrics



- Comparison between floristic patterns obtained with `biodivMapR` and a supervised approach
  - Chaves et al. (2020) mapped floristic patterns of Peruvian rainforest
  - Supervised method taking advantage of forest inventory data, Landsat satellite data, climate, soil and elevation data
  - 10 floristic classes defined
  - Spatial resolution of the product : 450 m







*remote sensing*



*Article*

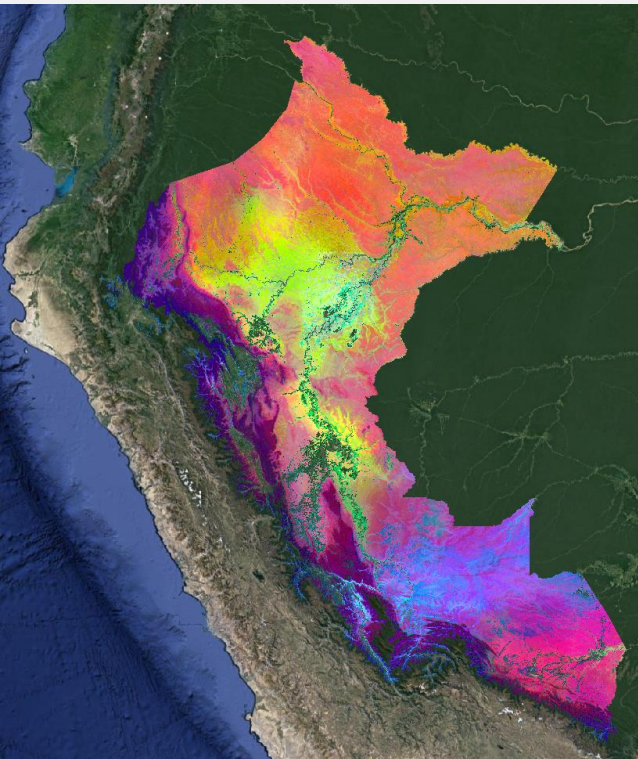
## Mapping Floristic Patterns of Trees in Peruvian Amazonia Using Remote Sensing and Machine Learning

Pablo Pérez Chaves <sup>1,\*</sup> , Gabriela Zuquim <sup>1,2</sup> , Kalle Ruokolainen <sup>1</sup>, Jasper Van doninck <sup>3</sup> , Risto Kalliola <sup>3</sup>, Elvira Gómez Rivero <sup>4</sup> and Hanna Tuomisto <sup>1</sup> 

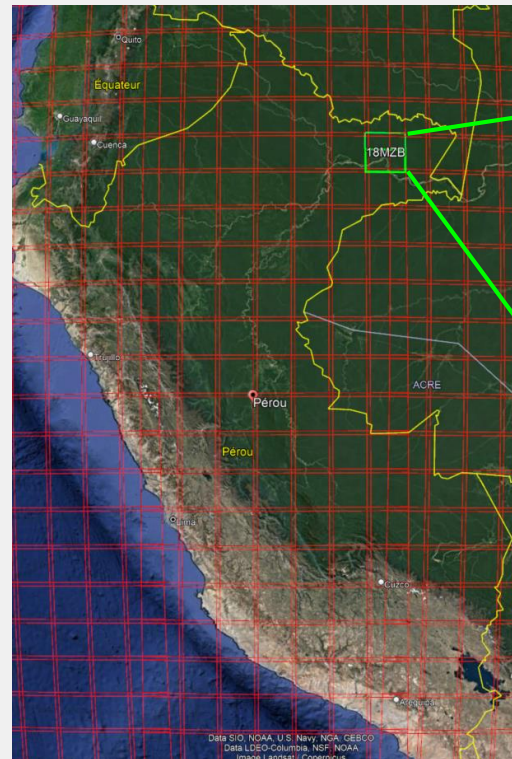
Received: 20 March 2020; Accepted: 9 May 2020; Published: 10 May 2020

# Mapping biodiversity using `biodivMapR` on Sentinel-2 images

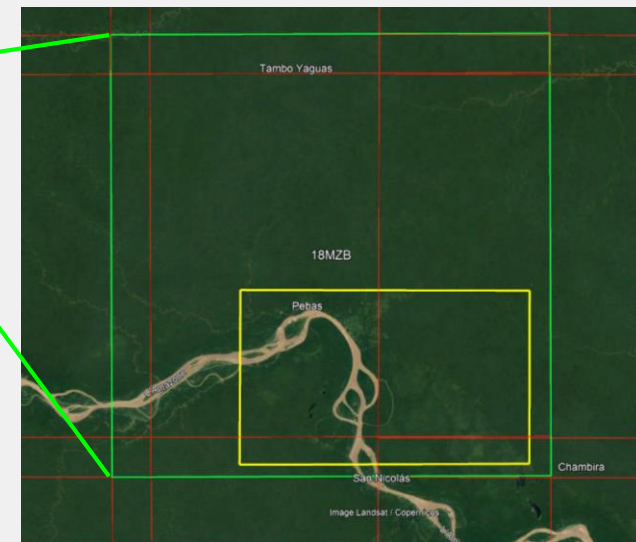
- Download floristic map [Chaves et al. 2020]
- Download Sentinel-2 data corresponding to a limited area
- Apply `biodivMapR` to produce diversity maps



Map of floristic patterns of trees  
in Peruvian Amazonia



Sentinel-2 tiling grid over  
Peru



Extraction of a study area  
(yellow box)

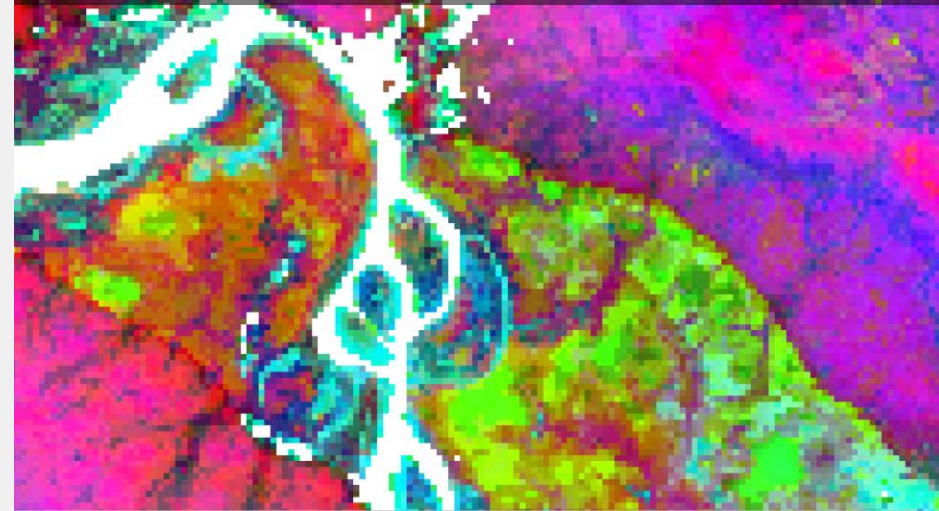
# Mapping biodiversity using `biodivMapR` on Sentinel-2 images

- Sentinel-2 image and corresponding floristic map

RGB visualisation of Sentinel-2 acquisition



Reference data (Chaves et al., 2020)



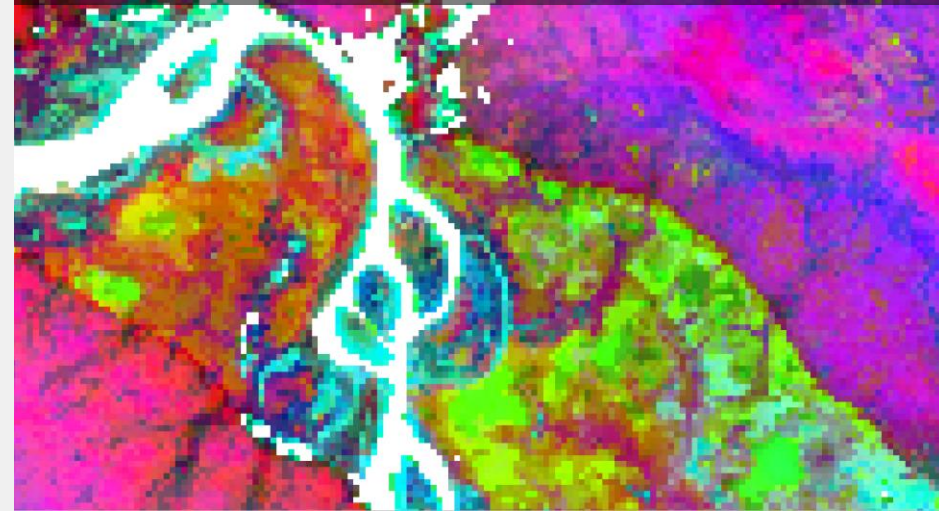
# Mapping biodiversity using `biodivMapR` on Sentinel-2 images

- Sentinel-2 image and corresponding floristic map
- $\alpha$  and  $\beta$  diversity maps (Shannon index) produced with `biodivMapR`

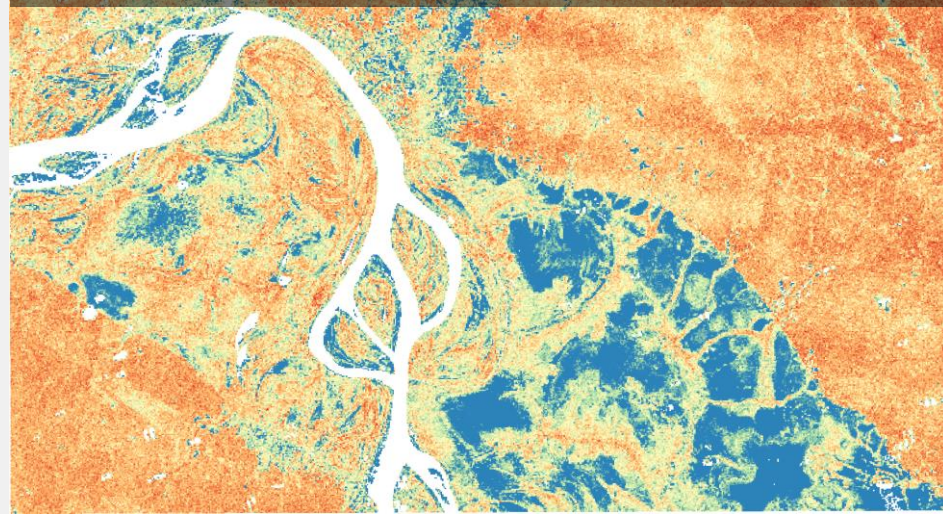
RGB visualisation of Sentinel-2 acquisition



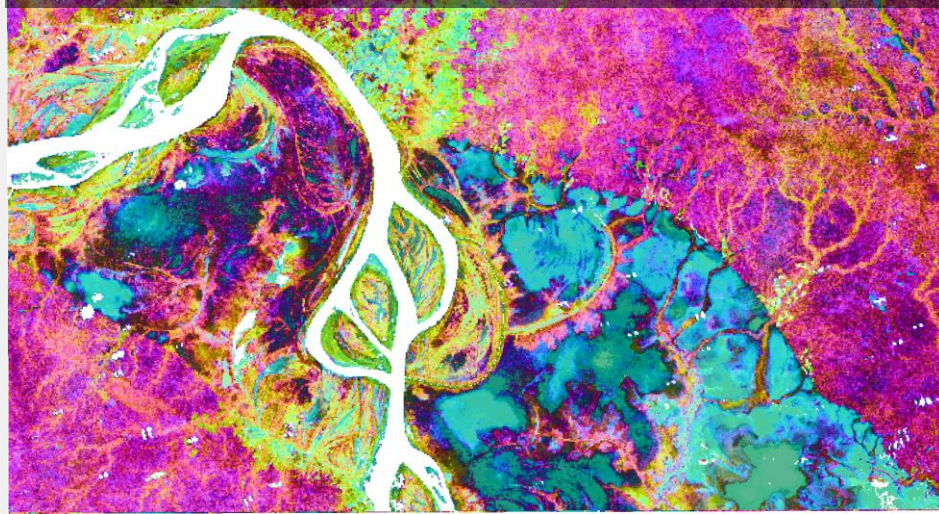
Reference data (Chaves et al., 2020)



Shannon index mapped with `biodivMapR`



$\beta$ -diversity mapped with `biodivMapR`



- **Introduction**
- **Explore spatial, temporal and spectral dimensions from space**
- **A quick dive into the spectral space**
- **Current missions and forthcoming opportunities**
- **Earth observation and biodiversity : one approach among many**
- **Conclusions and perspectives**

# Conclusions & perspectives

- **Increasing amount of Earth observation data from multiple platforms (UAV, plane, satellite)**
- **Optical sensors acquire information related to various vegetation properties, allowing monitoring vegetation status, function, composition, stress through biophysical properties**
- **Multispectral sensors (Sentinel-2, Landsat) currently provide abundant information**
- **New spaceborne sensors (thermal infrared, LiDAR, hyperspectral, radar) open perspectives to assess relevant metrics for vegetation monitoring, biodiversity & ecological applications**
- **Multiple ways to convert RS information into ecologically meaningful information**
  - **Identify data type, sensor or sensor combination providing relevant info**
    - **Trade-off between spectral, spatial, temporal information**
  - **Identify a method and corresponding hypotheses acceptable for situation of interest**
    - **Spectral variation hypothesis, landscape metrics, phenometrics...**
- **Need to increase collaboration between ecologists & RS scientists**

# Thank you !

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