

# Using remote sensing and machine learning to identify biodiversity offsets

**Dr. Pablo Pérez Chaves**

*Director / Finnish Overseas Consultants*

*Finland*

pablo.perez@finnoc.fi

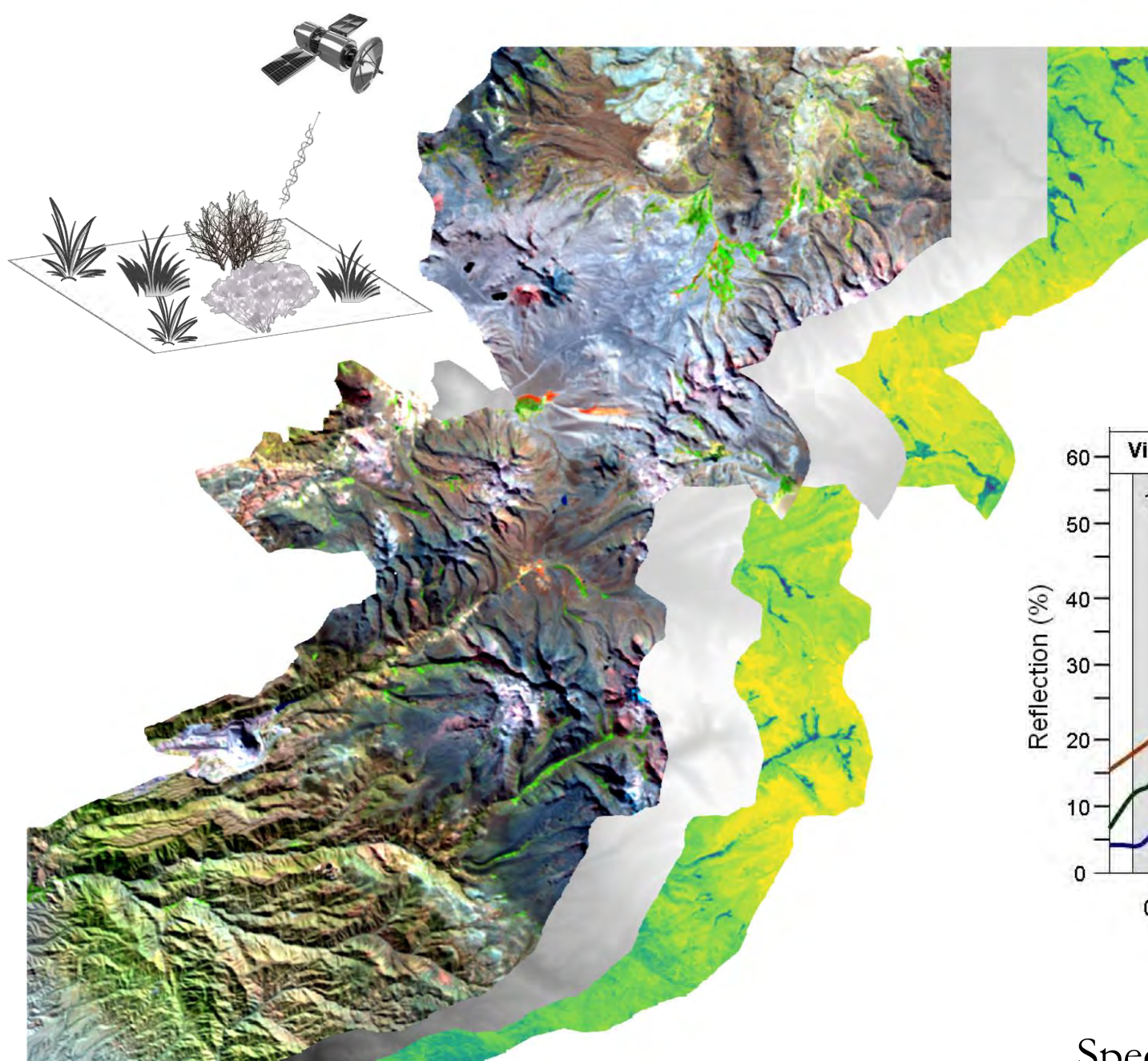
[www.finnoc.fi](http://www.finnoc.fi)



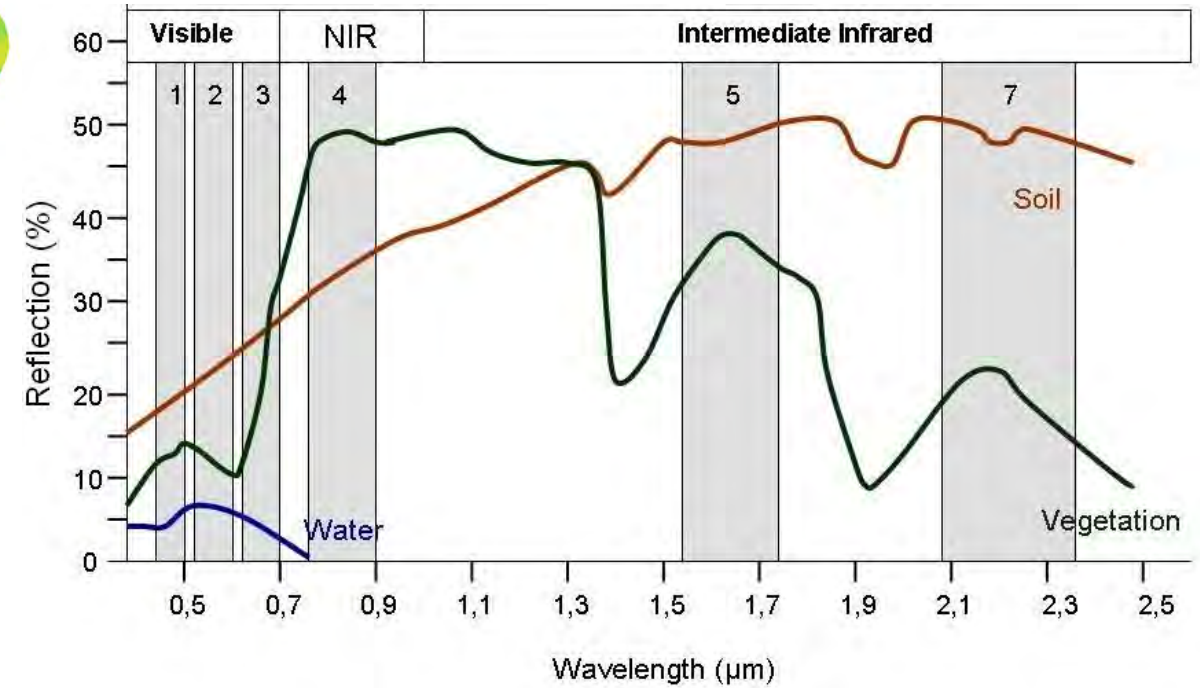
# Content

- Usefulness of remote sensing in mapping biodiversity
- How to improve biodiversity impact assessments?: A proposed framework
- Practicalities of the framework in EIAs

# Usefulness of remote sensing in mapping biodiversity



Different objects, such as vegetation, rivers, soils or even different plant species reflect the sun's radiation in a different way. These spectral values are ecologically informative layers and hence, are very useful for biodiversity studies at local scales. Satellite imagery cover large extensions, can be freely available and provide continuous spectral information.

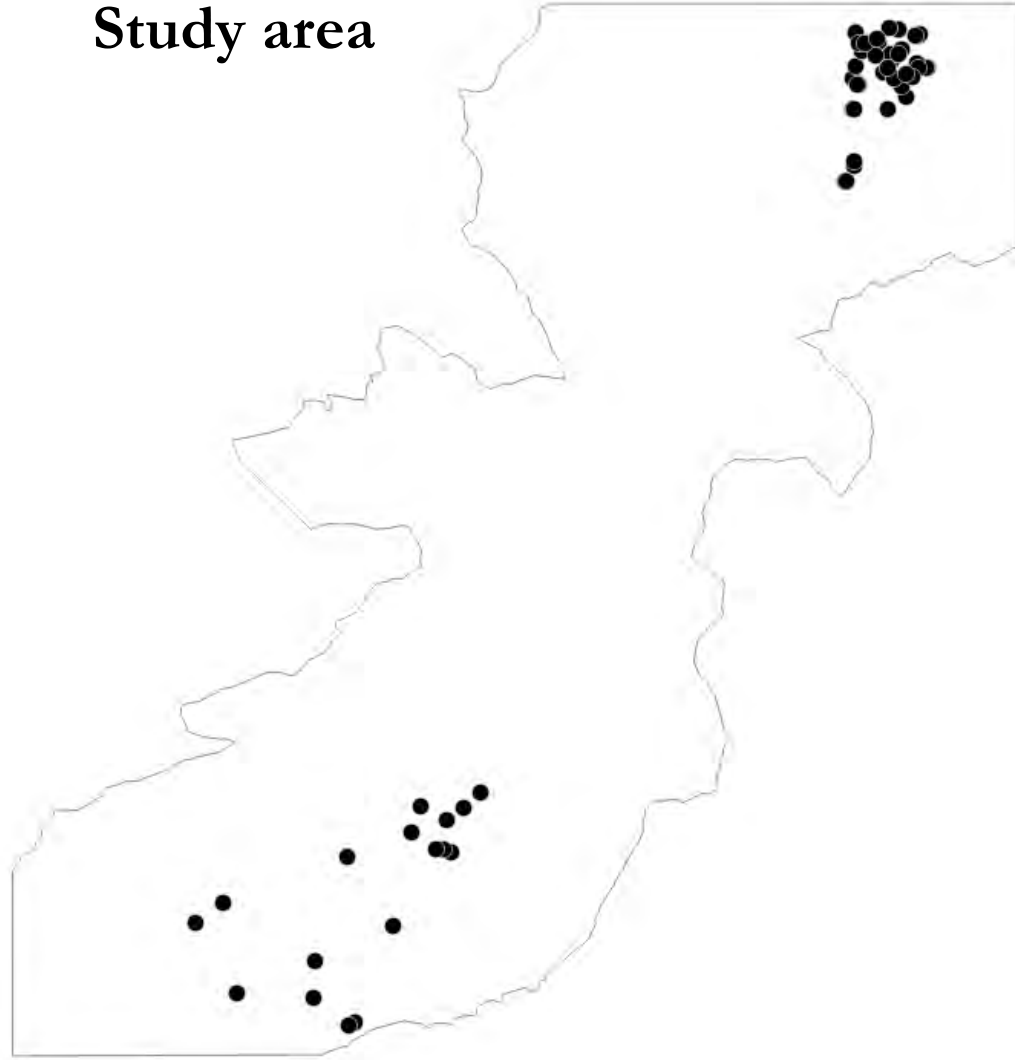


Spectral signatures of surfaces

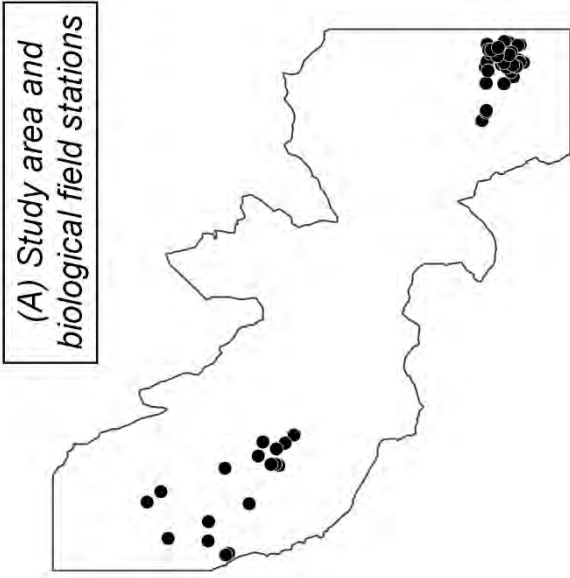
How to improve biodiversity impact  
assessment?: A proposed framework

# Baseline studies

Study area

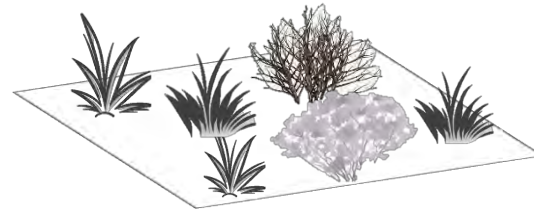


Sampling units (~60 50-m transects) from field-data were used to characterize the vegetation cover (%) of shrubs and herbaceous plants in the study area

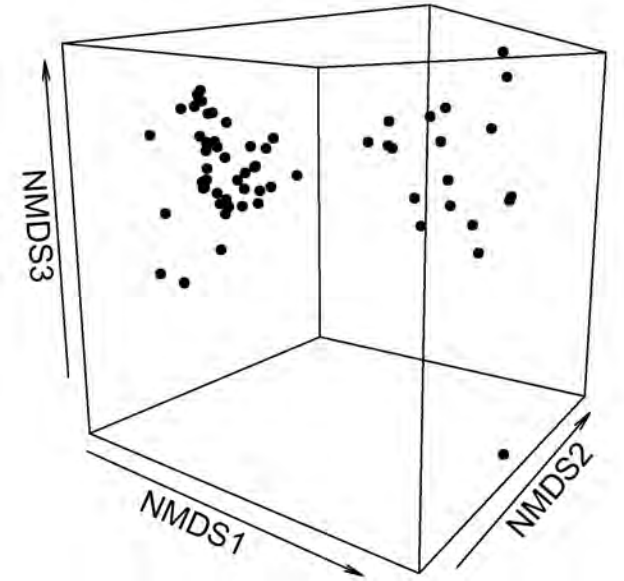


Community matrix

Species / Plot	Species A	Species B	Species C	Species D	Species E	...	Species "n"
Plot 1	0	1	1	1	1	...	1
Plot 2	0	0	0	0	1	...	0
Plot 3	1	1	1	1	0	...	0
Plot 4	0	1	0	0	0	...	1
...	...	...	...	...	...	...	...
Plot "m"	1	1	0	0	0	...	1

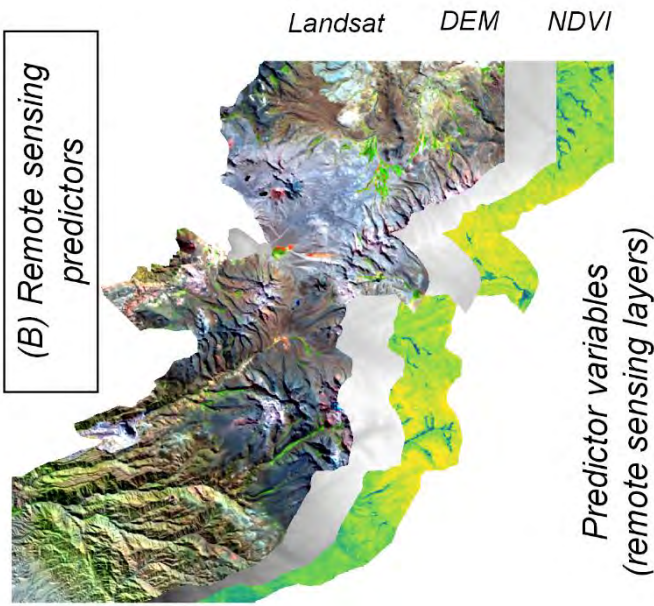
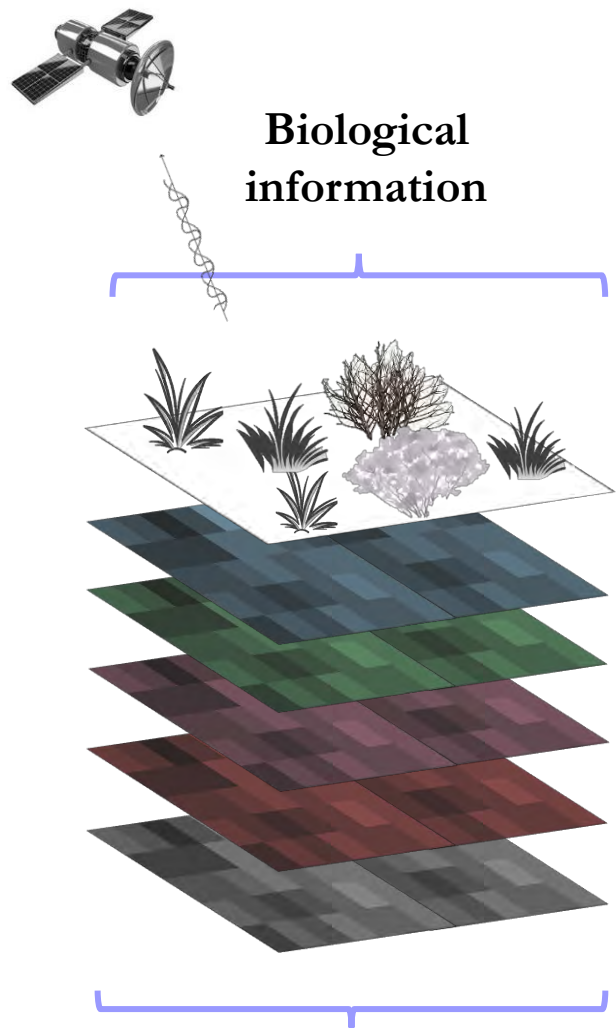
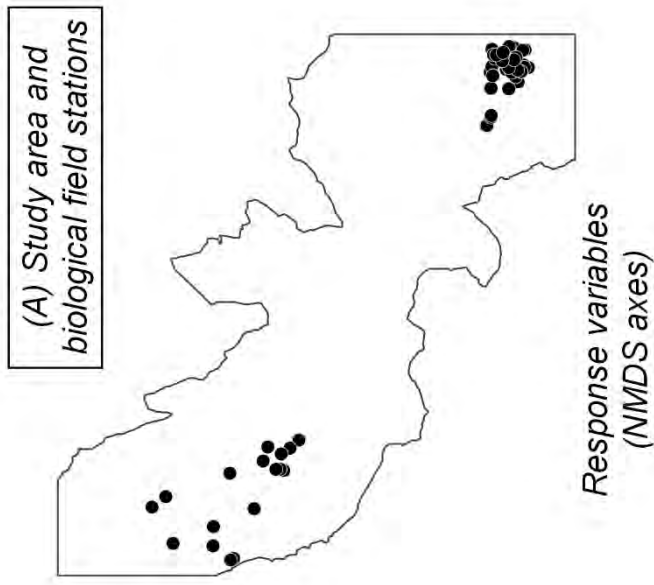


If two dots (representing the sampling plots) are closer to each other it means they share more species in common, or that they are floristically more similar.



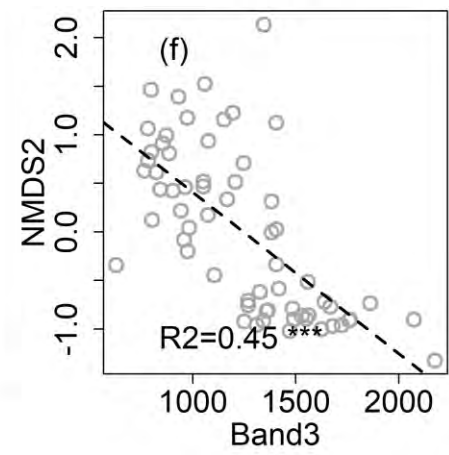
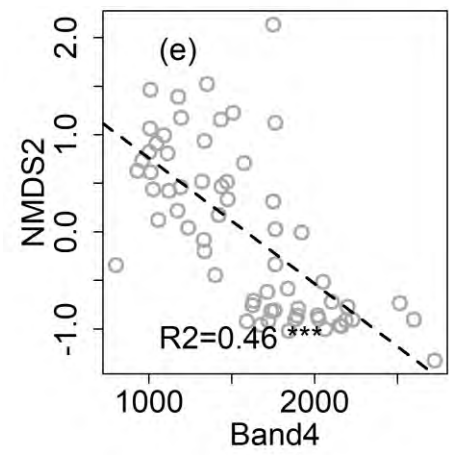
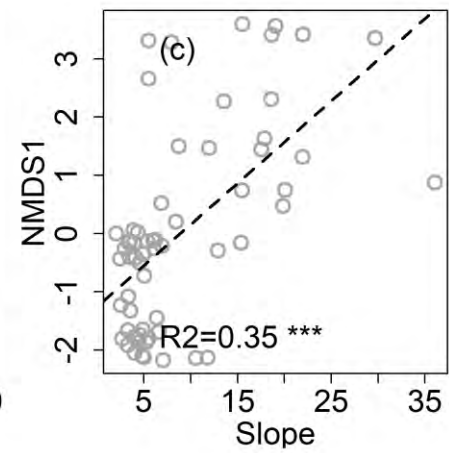
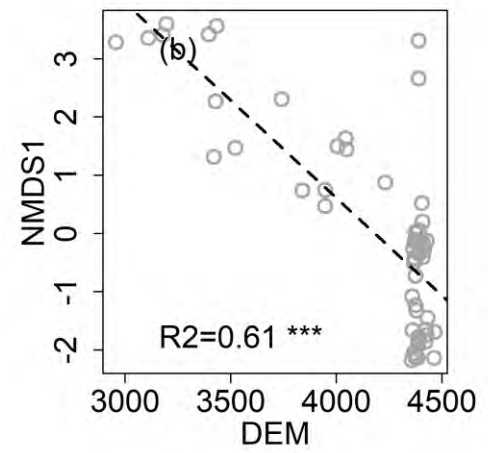
Each of this axes are indicators or metrics of the species composition

**Floristic ordination (NMDS)**

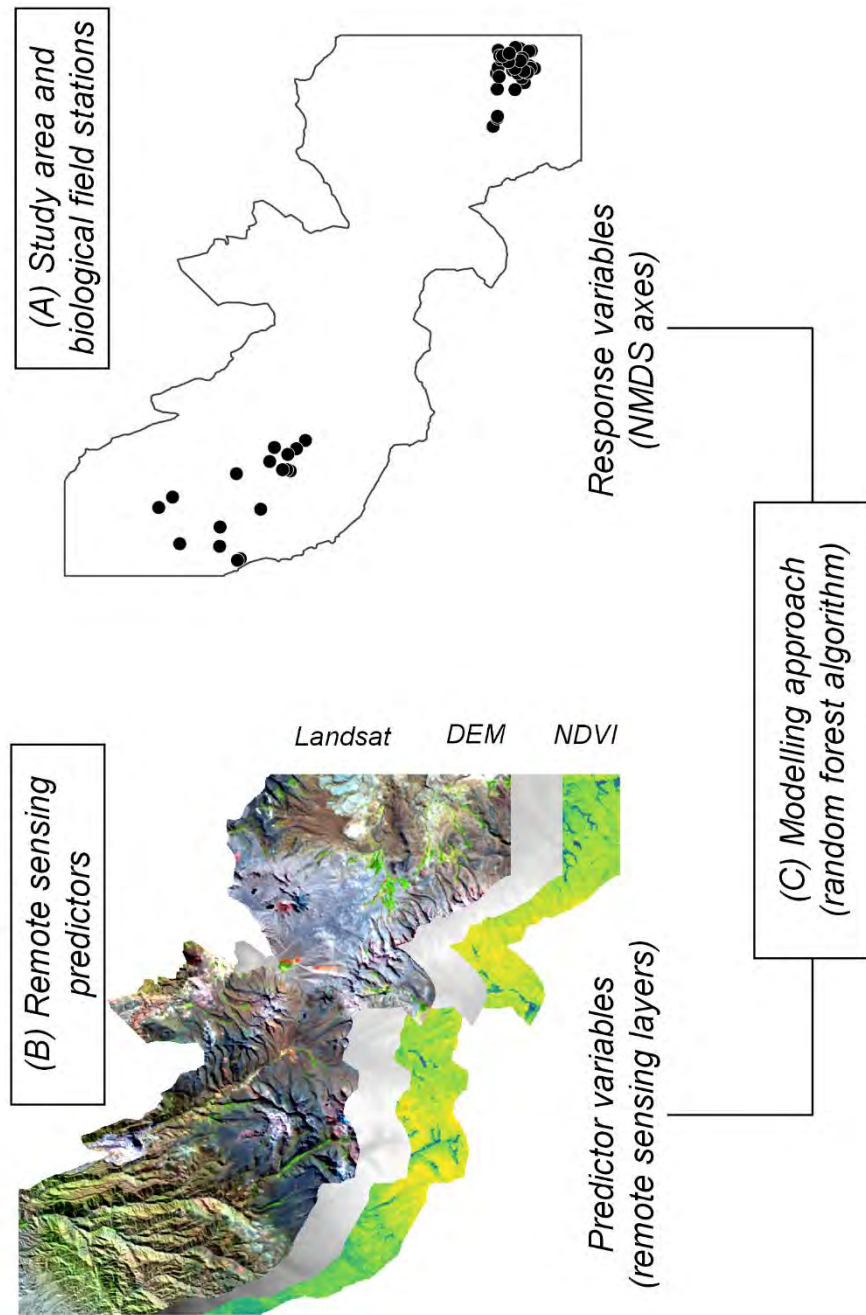


“band1“, “band2“, “band3“, “band4“, “band5“, “band6“, “band7“, “ndvi“, “dem“, “slope“

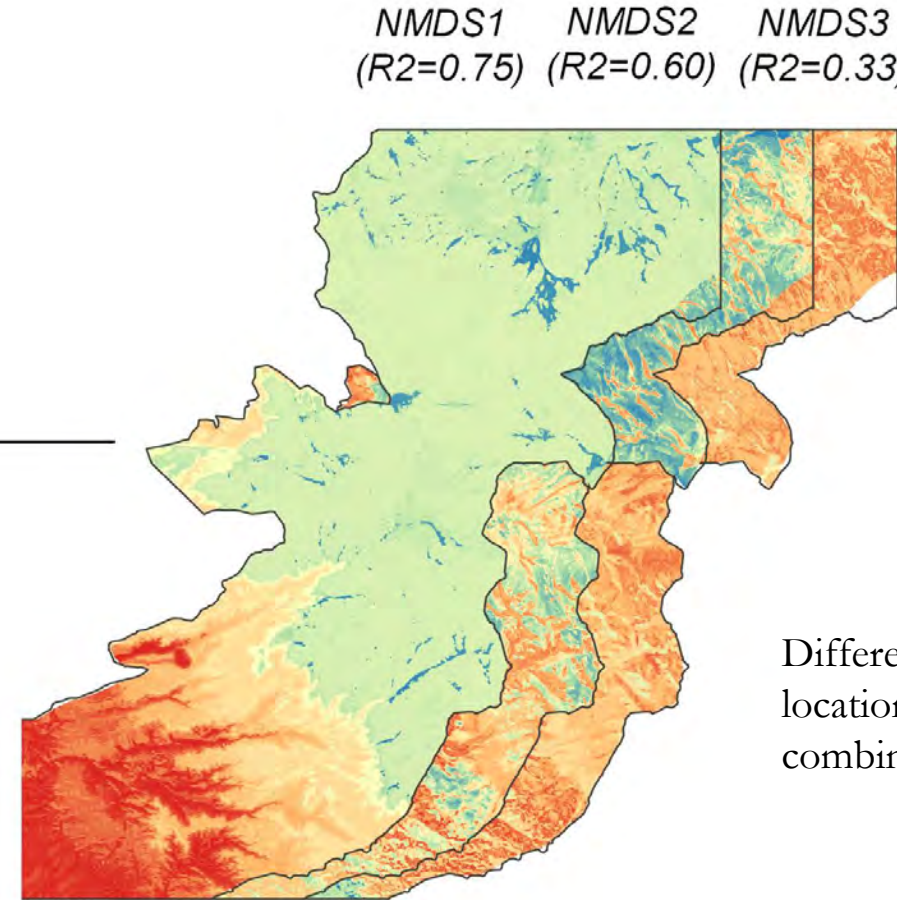
Just through simple linear regressions, remote sensing predictors explain a great percentage of the species composition





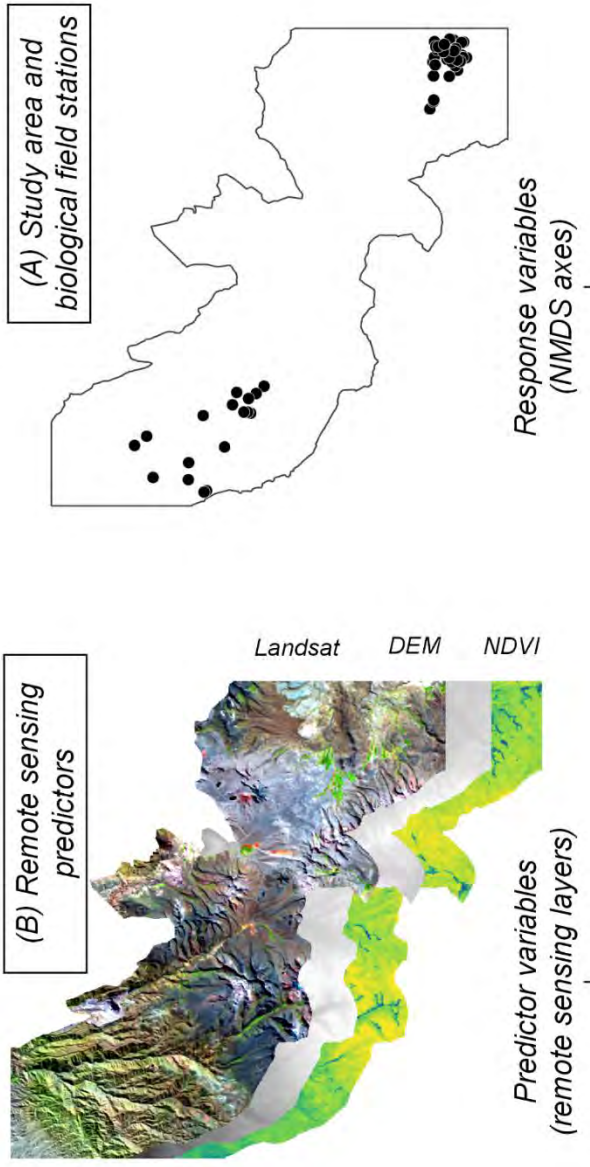


Using machine learning techniques (random forest regression) it is possible to spatially predict the species composition patterns (“biodiversity patterns”)

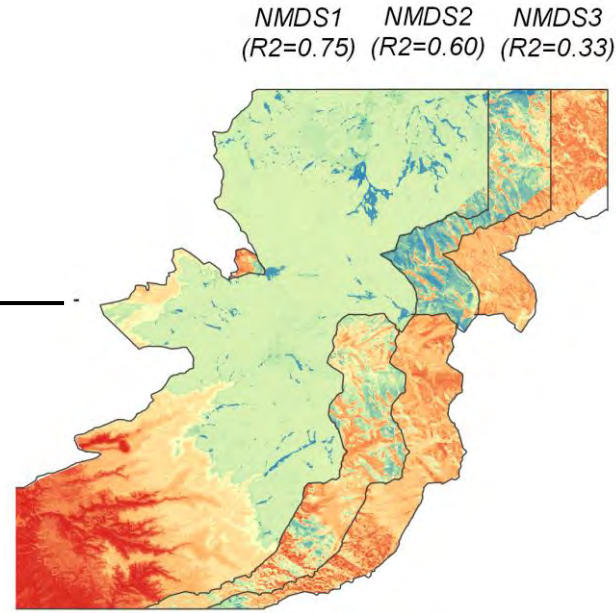


Different colours show locations that have different combination of species

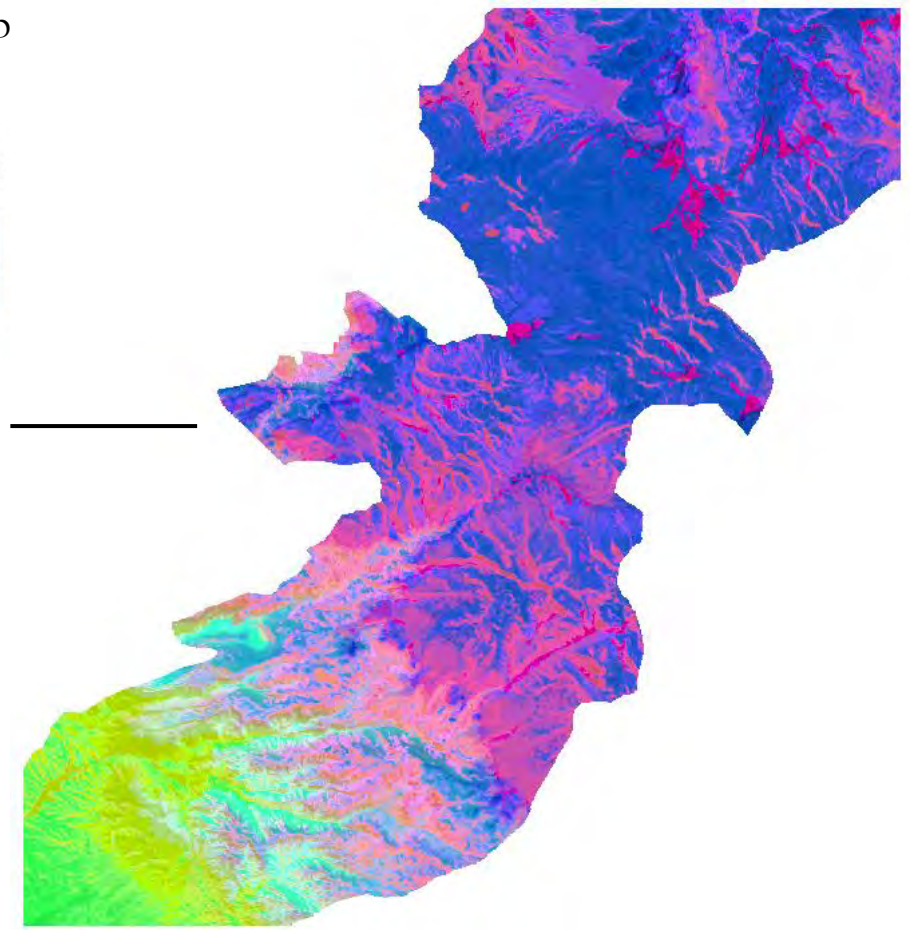
(C1) Maps of biodiversity patterns



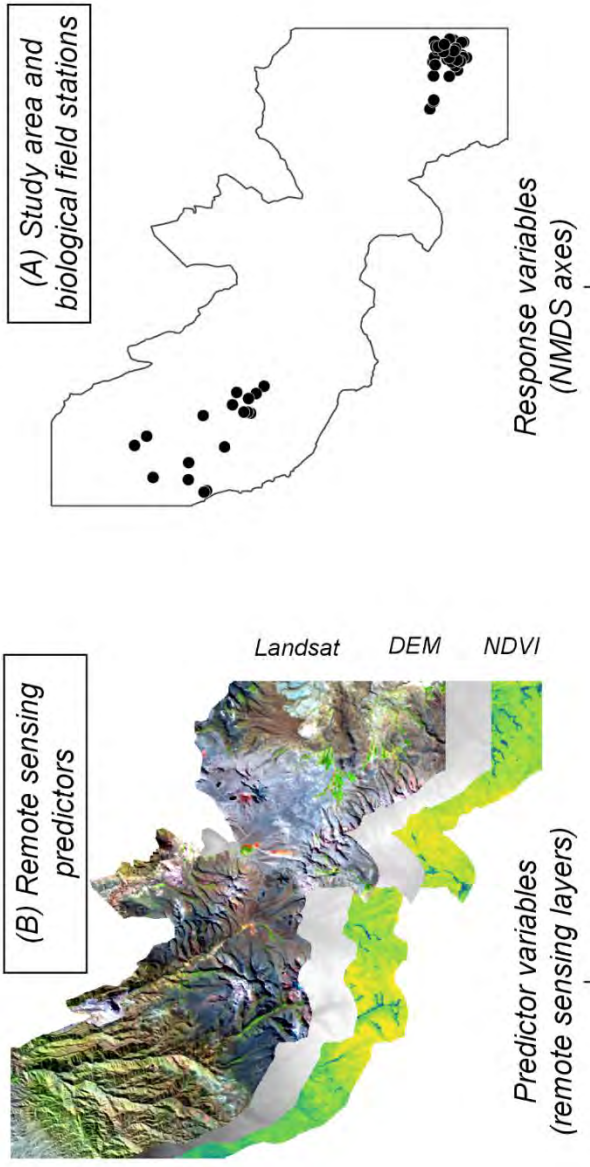
By combining these three maps (representing the species composition axes) in one RGB (red-gree-blue) colour composite, we can visualize better the species composition in a single map



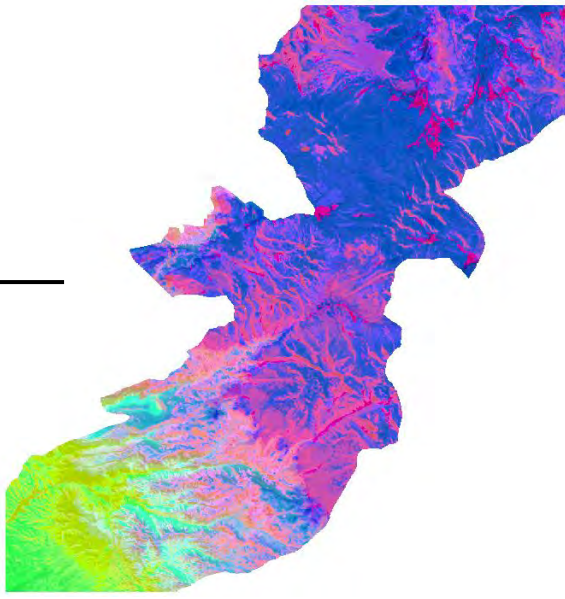
Each colour represents an area that has a unique or “singular” combination of species



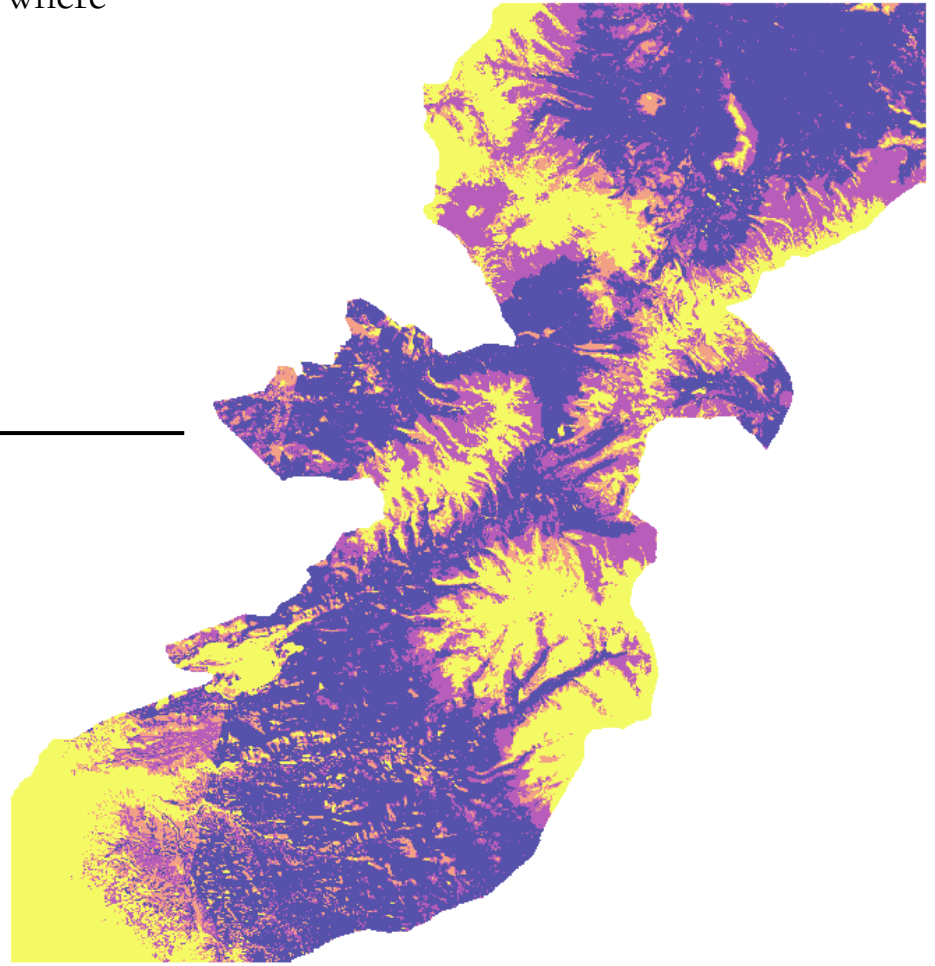
(C2) Beta-diversity / Singularity map



Since we are dealing with spatial predictions and machine learning, we should avoid extrapolation and overprediction. Therefore, we suggest the AOA approach to identify locations where we can actually trust the predictions



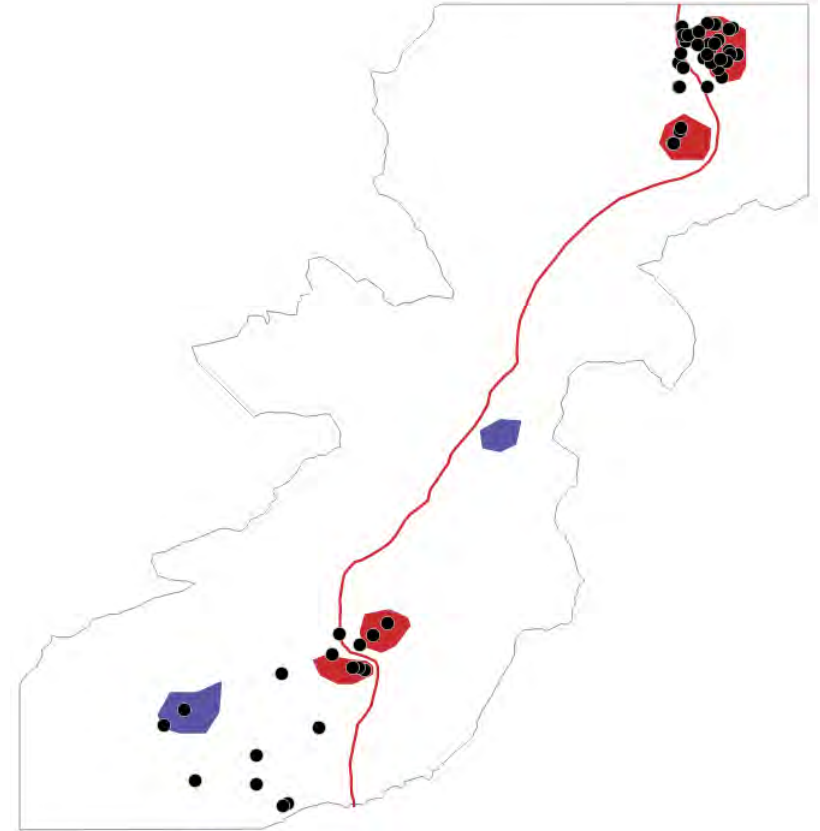
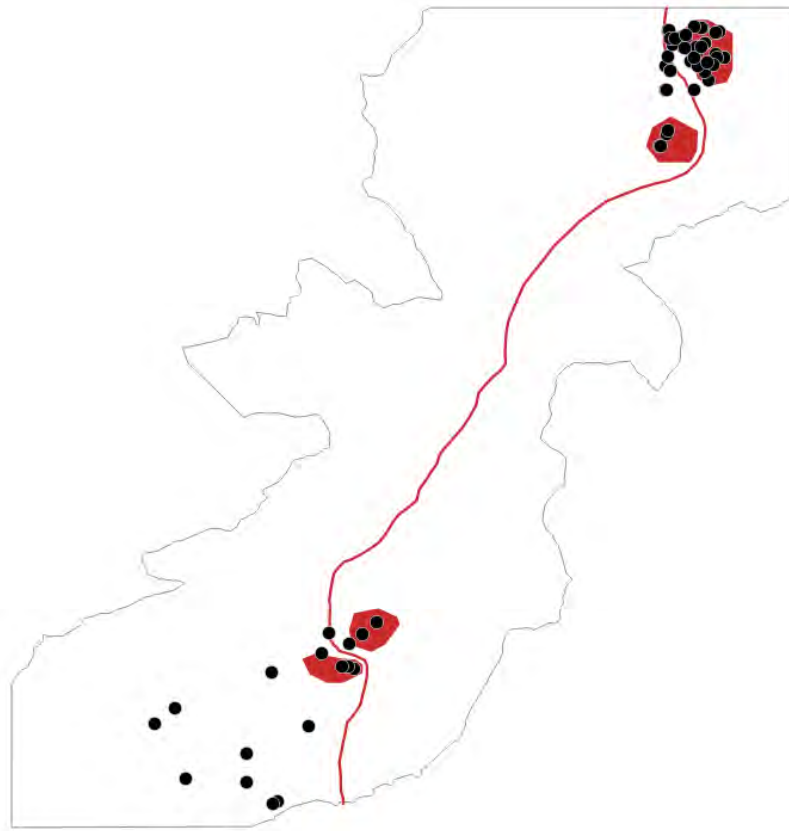
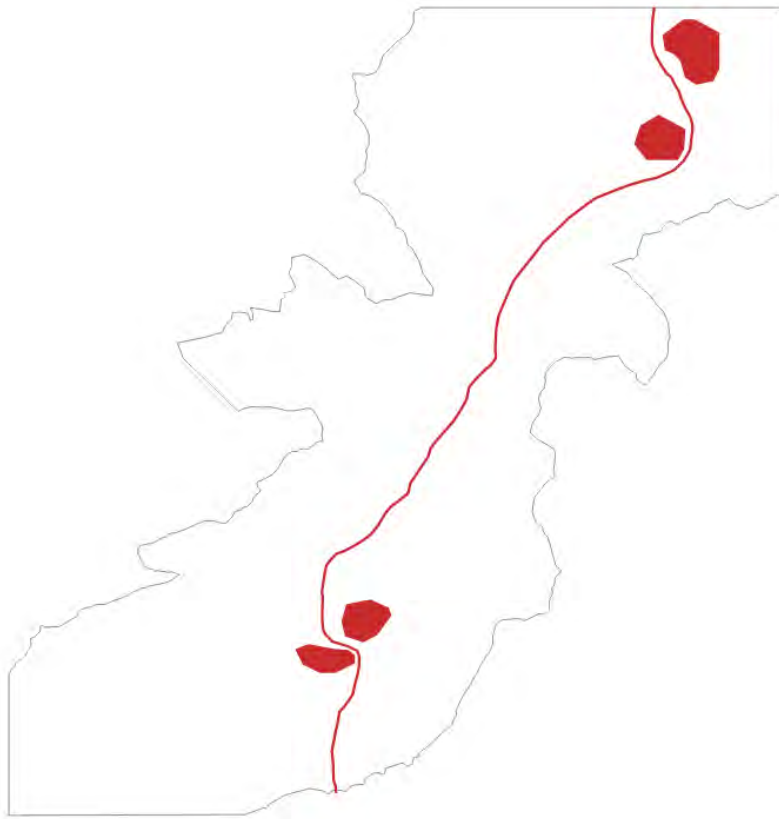
Purple colours show areas where the predictions are reliable, and yellow colours, locations where predictions should be interpreted with caution.



(C3) Area of Applicability (AOA) / Uncertainty map

Practicality

# Impact Assessment

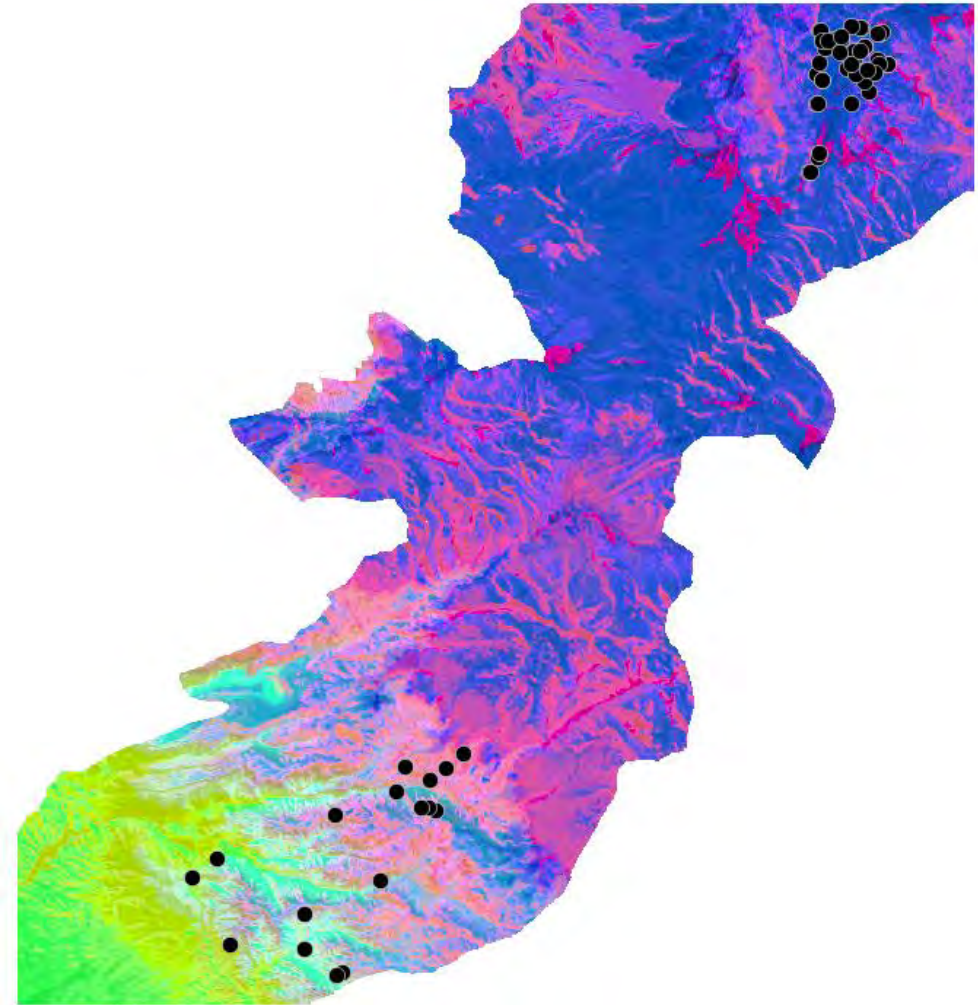


- Planned infrastructure
- New infrastructure
- Transects

Projects are not static, on the contrary there will always be changes in the alignment of components or new infrastructure.

# Practicality

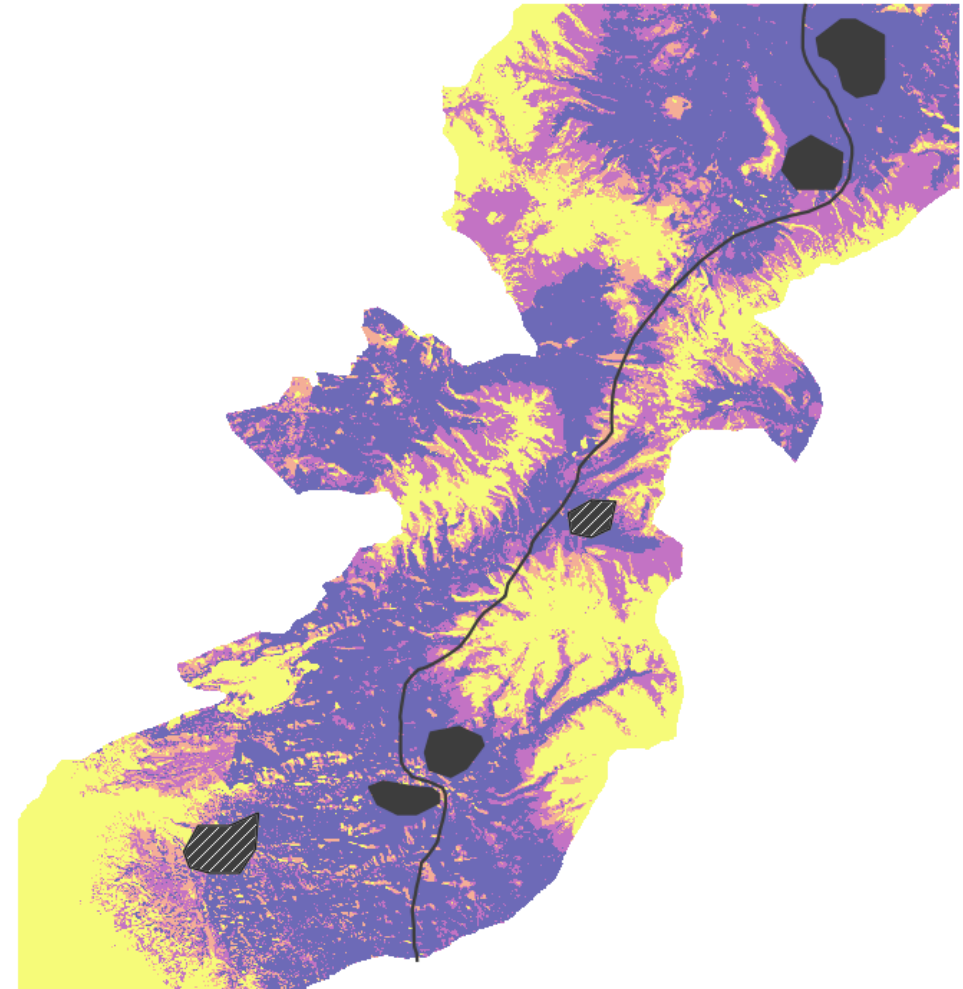
- Available biological information it is often scattered and only cover focalized locations. By combining field-data with freely available remote sensing predictors, it is possible to map biodiversity patterns in areas where field-data is yet missing.
- We should still account for uncertainty in the spatial predictions.



*Beta-diversity / Singularity map*

# Practicality

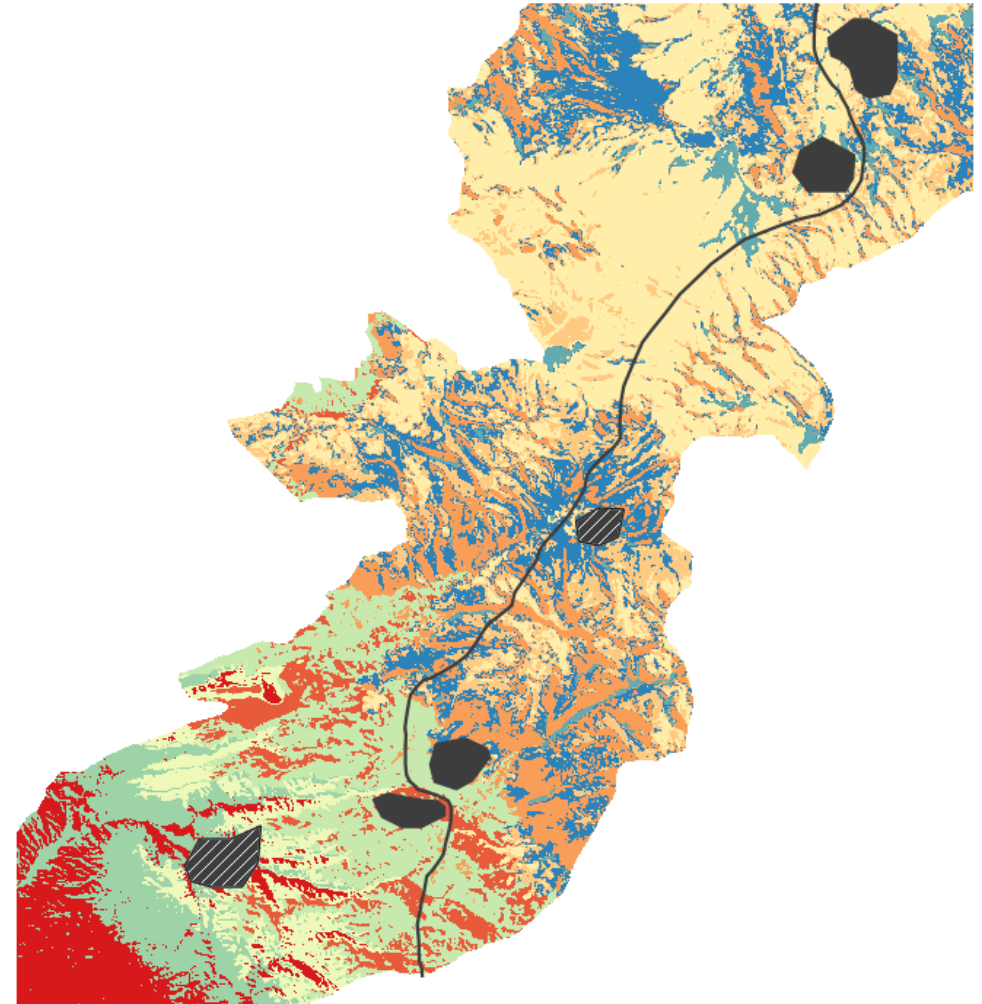
- Through the area of applicability (AOA) method / uncertainty maps it is possible to know if changes in the project alignment or design will require more field work.
- It is also possible to determine areas that require higher sampling effort for complementing the EIA baseline studies.



*Area of Applicability (AOA) /  
Uncertainty map*

# Practicality

- Having maps of biodiversity patterns throughout a project's study area allow:
  - (i) avoiding species communities with key species / endangered species.
  - (ii) properly quantifying a project footprint's impact on biodiversity
  - (iii) identifying suitable areas for “like-for-like” compensation schemes.



*K-means classification (10 classes)  
Beta-diversity / Singularity map*



# Let's continue the conversation!

Post questions and comments in the IAIA23 app.



**Dr. Pablo Pérez Chaves**

*Director / Finnish Overseas Consultants (FinnOC)*

*Finland*

pablo.perez@finnoc.fi

*www.finnoc.fi*

# References

**Chaves, P.P.**, Echeverri, N.R., Ruokolainen, K., Kalliola, R., Doninck, J.V., Rivero, E.G., Zuquim, G., & Tuomisto, H. 2021. Using forestry inventories and satellite imagery to assess floristic variation in bamboo-dominated forests in Peruvian Amazonia. *Journal of Vegetation Science* 32: e12938.

**Chaves, P.P.**, Ruokolainen, K., & Tuomisto, H. 2018. Using remote sensing to model tree species distribution in Peruvian lowland Amazonia. *Biotropica* 50: 758–767.

**Chaves, P.P.**, Ruokolainen, K., Van doninck, J., & Tuomisto, H. 2022. Impact of spatial configuration of training data on the performance of Amazonian tree species distribution models. *Forest Ecology and Management* 504: 119838.

**Chaves, P.P.**, Zuquim, G., Ruokolainen, K., Van doninck, J., Kalliola, R., Gómez Rivero, E., & Tuomisto, H. 2020. Mapping Floristic Patterns of Trees in Peruvian Amazonia Using Remote Sensing and Machine Learning. *Remote Sensing* 12: 1523.

Zuquim, G., Tuomisto, H., **Chaves, P.P.**, Emilio, T., Moulatlet, G.M., Ruokolainen, K., Van doninck, J., & Balslev, H. 2021. Revealing floristic variation and map uncertainties for different plant groups in western Amazonia. *Journal of Vegetation Science* 32: e13081.

Meyer, H., & Pebesma, E. 2021. Predicting into unknown space? Estimating the area of applicability of spatial prediction models. *Methods in Ecology and Evolution* 12: 1620–1633.

Meyer, H., Reudenbach, C., Hengl, T., Katurji, M., & Nauss, T. 2018. Improving performance of spatio-temporal machine learning models using forward feature selection and target-oriented validation. *Environmental Modelling & Software* 101: 1–9.

Rocchini, D., Luque, S., Pettorelli, N., Bastin, L., Doktor, D., Faedi, N., Feilhauer, H., Féret, J.-B., Foody, G.M., Gavish, Y., Godinho, S., Kunin, W.E., Lausch, A., Leitão, P.J., Marcantonio, M., Neteler, M., Ricotta, C., Schmidlein, S., Vihervaara, P., Wegmann, M., & Nagendra, H. 2018. Measuring  $\beta$ -diversity by remote sensing: A challenge for biodiversity monitoring. *Methods in Ecology and Evolution* 9: 1787–1798.