

Capgemini 

la ruche **bee** creative.

AI4EO CHALLENGE

SEEING BEYOND THE VISIBLE

06/07/2023

INTRODUCTION

AI4EO Challenge : Seeing Beyond the Visible



Organizers and partner



Autonomous space solutions company (Poland)



European Space Agency



Precision farming software company (Poland)

Goal

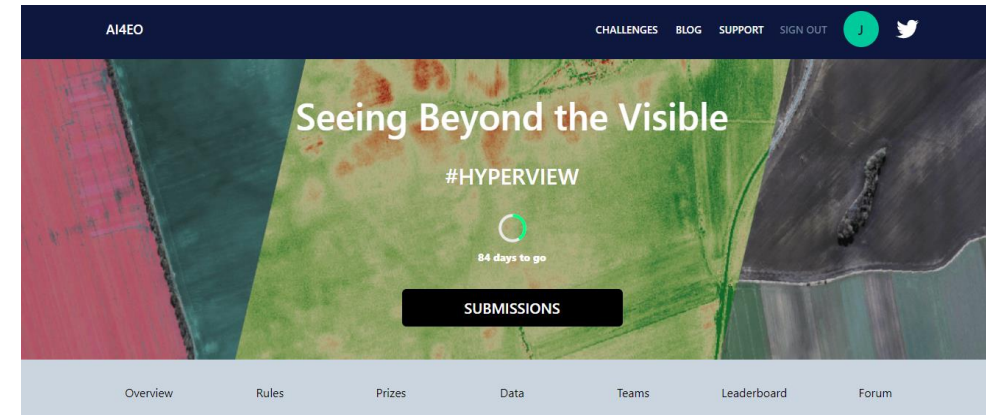
Generate a model for prediction of **soil parameters** from **hyperspectral imaging** data of agricultural areas

Timeline

From the 9th of February to the 1st of July 2022

Prizes

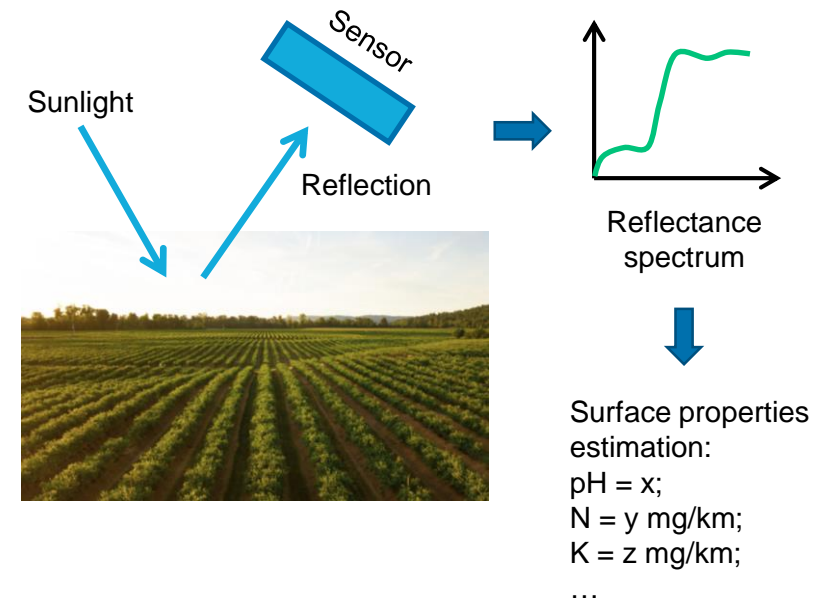
Best predictive model will be deployed on Intuition-1 satellite set to launch in Q1 2023
Top 5 teams invited for joint-paper publication



Soil parameter estimation for sustainable farming



- As the global population is increasing, there is a growing need for more **efficient** methods of **food production**
- **Macro-nutrients** (N, K, P, ...) have a direct impact on agriculture yields, and are commonly supplied in the form of **fertilizers**
- Excessive use of fertilizers has a **detrimental** impact on **biodiversity** and **public health**
- Methods of soil property **estimation** from **reflectance spectra** will help minimize resource input and make farming more sustainable (precision farming)



Resources :

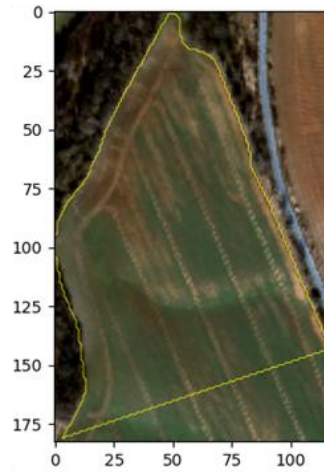
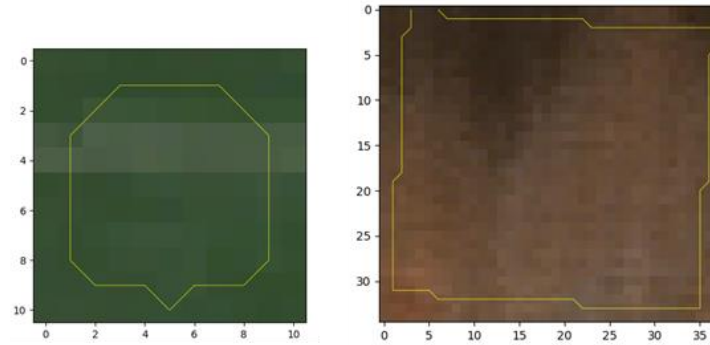
Chabrilat, et al. Imaging Spectroscopy for Soil Mapping and Monitoring. *Surv Geophys* 40, 361–399 (2019). <https://doi.org/10.1007/s10712-019-09524-0>
Burton, et al. 2020, *J. Electrochem. Soc.* <https://doi.org/10.1149/1945-7111/ab6f5d>

DATA SET ACQUISITION

Challenge dataset



Training set
1732 patches
Known soil parameters



RGB representation of patches :

Yellow outline : masks delimiting parcels

Soil Parameters :

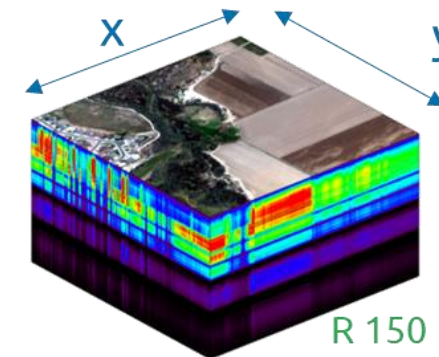
- P2O5** : Phosphorus content of fertilizers
- K** : Potassium
- Mg** : Magnesium
- pH** : measure of soil acidity

Spectral range :

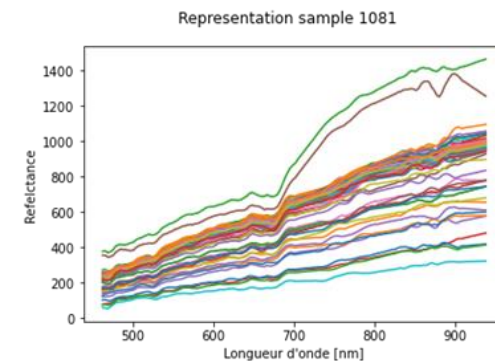
- 150 bands** : 462-942nm, 3.2nm resolution
- Visible range and early Near-Infrared

Spatial resolution :

1px = 4m²

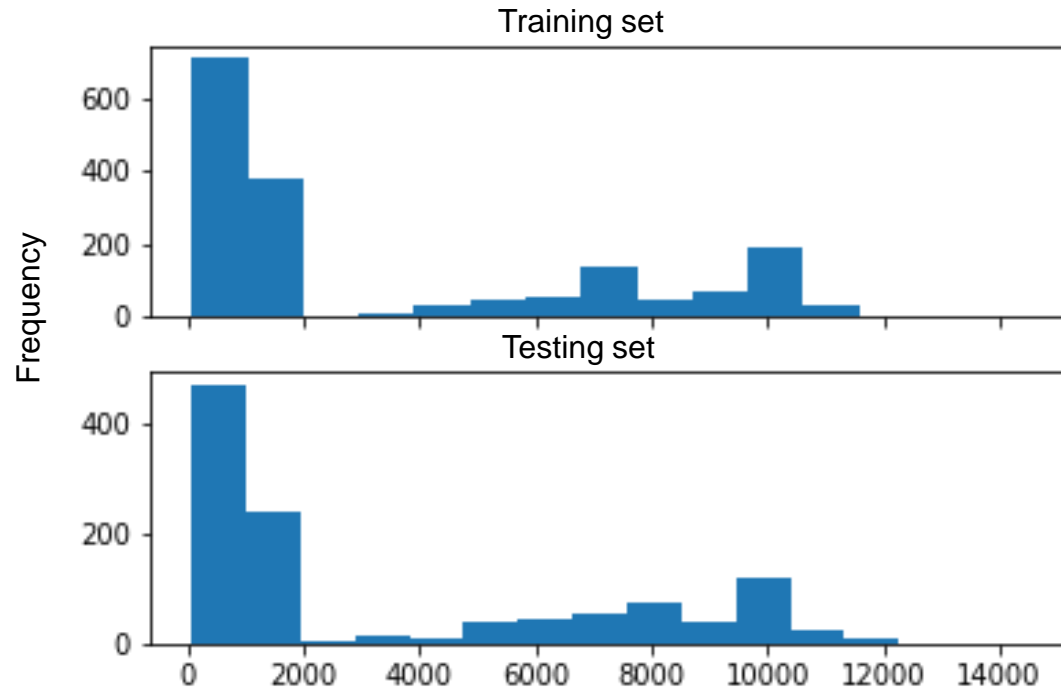


3D

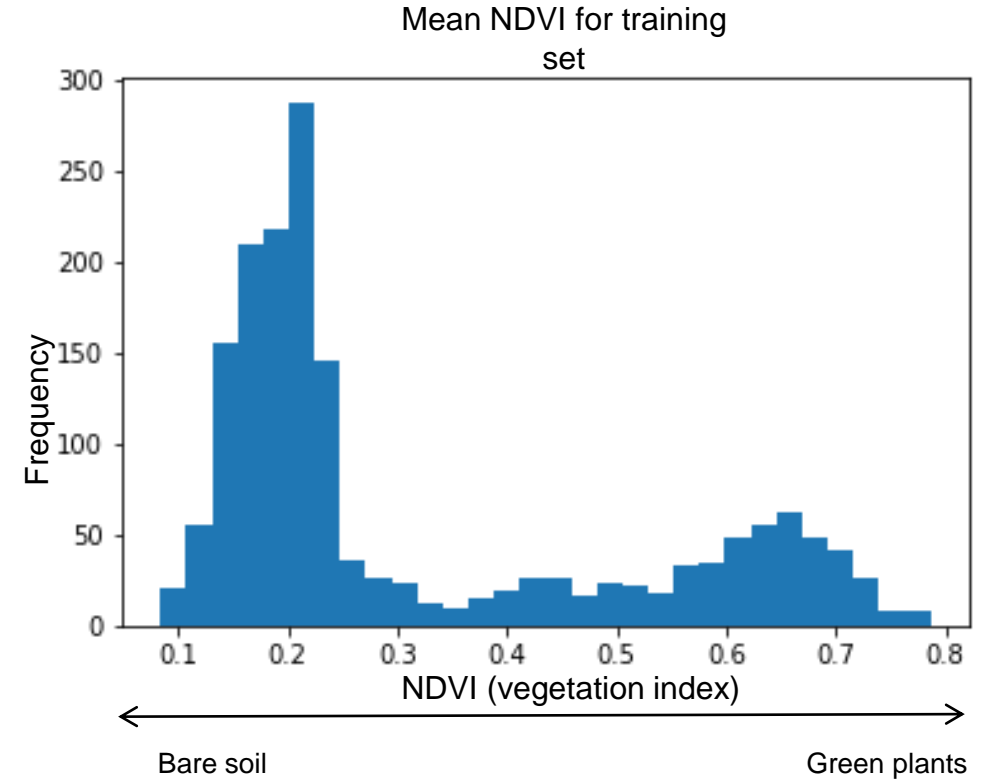


2D

Limited, high dimension and heterogeneous



Répartition des images par taille
(Nb de pixels)

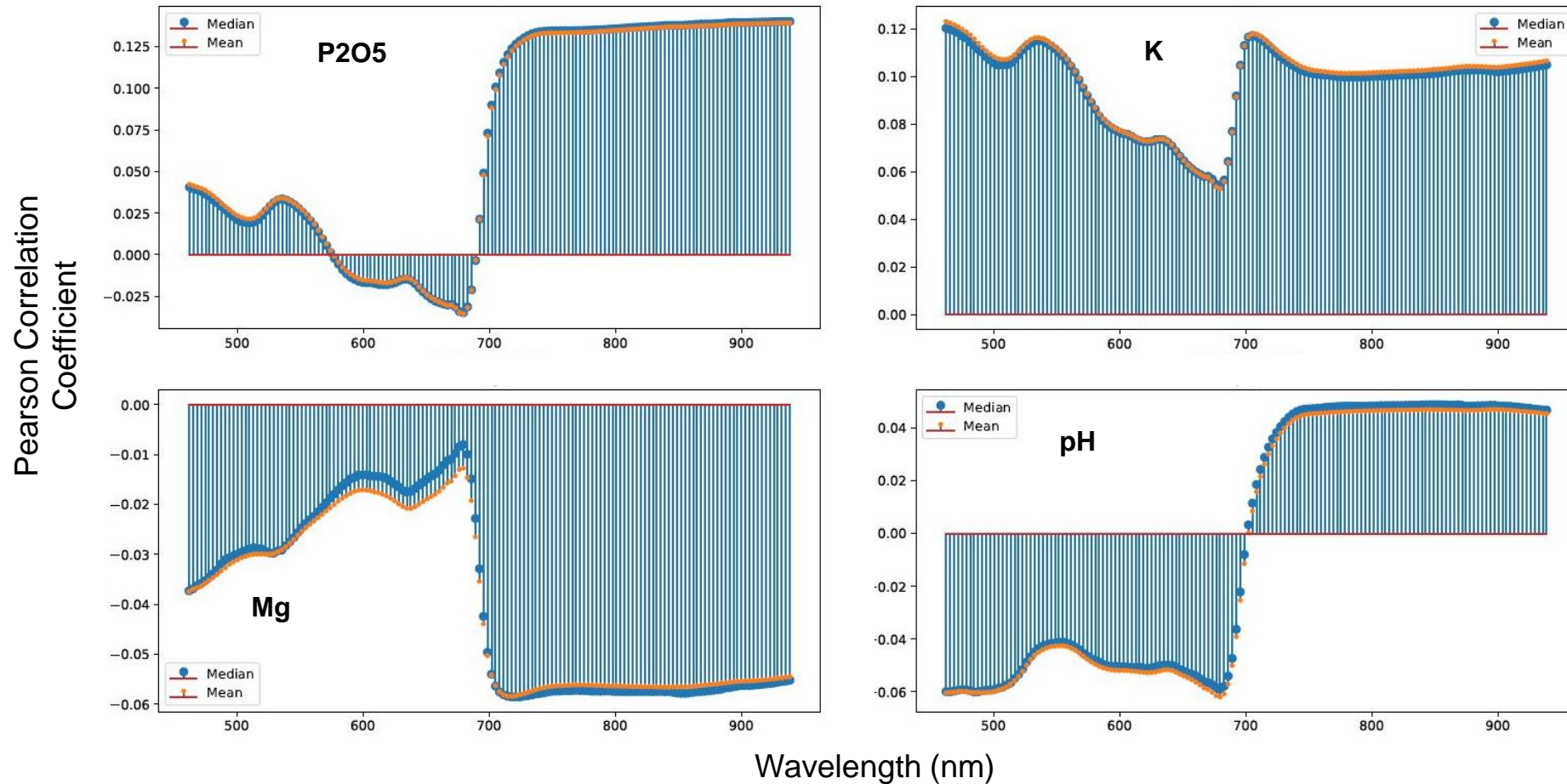


$$\text{NDVI} = \frac{(\rho_{\text{NIR}} - \rho_{\text{Red}})}{(\rho_{\text{NIR}} + \rho_{\text{Red}})}$$

Reflective content is
heterogeneous



Correlation between band reflectance and soil parameters



Very **Weak correlation** (< 0.12) between reflectance per wavelength and soil parameters
Note : Correlation between Vegetation Index and soil parameters also low : ~ 0 R-squared value

How to develop a predictive model for soil parameters from hyperspectral imaging data ?



Challenge scoring of testing set parameters predictions :

$$Score = \sum_{i=1}^4 \left(\frac{MSE_i}{MSE_i^{base}} \right) / 4 \quad \text{with: } MSE_i = \frac{\sum_{j=1}^{|\psi|} (p_j - \hat{p}_j)^2}{|\psi|}$$

Challenge score : Ratio of MSE (mean square error) of predictions over MSE of base solution, averaged over the four parameters

Lower score = Better predictions



How to develop a predictive model for soil parameters from hyperspectral imaging data ?



Challenge scoring of testing set parameters predictions :

$$Score = \sum_{i=1}^4 \left(\frac{MSE_i}{MSE_i^{base}} \right) / 4 \quad \text{with: } MSE_i = \frac{\sum_{j=1}^{|\psi|} (p_j - \hat{p}_j)^2}{|\psi|}$$

Challenge score : Ratio of MSE (mean square error) of predictions over MSE of base solution, averaged over the four parameters

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Main obstacles :

- Low **sample size** (1732 for training set), high **heterogeneity**
- **High dimensionality**
- Those soil nutrients usually do **not** display clear **absorption features**

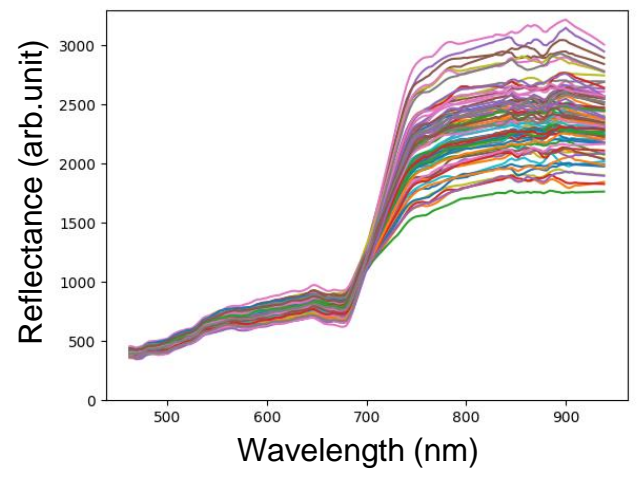


DATA PRE-PROCESSING



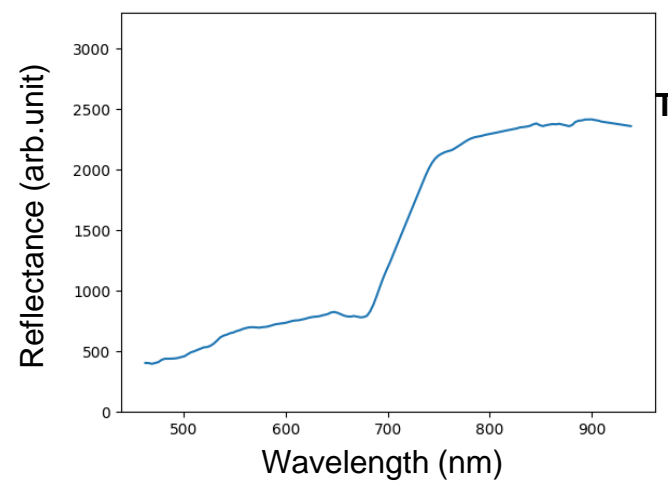
Pre-processing

Raw spectra of all pixels of an image



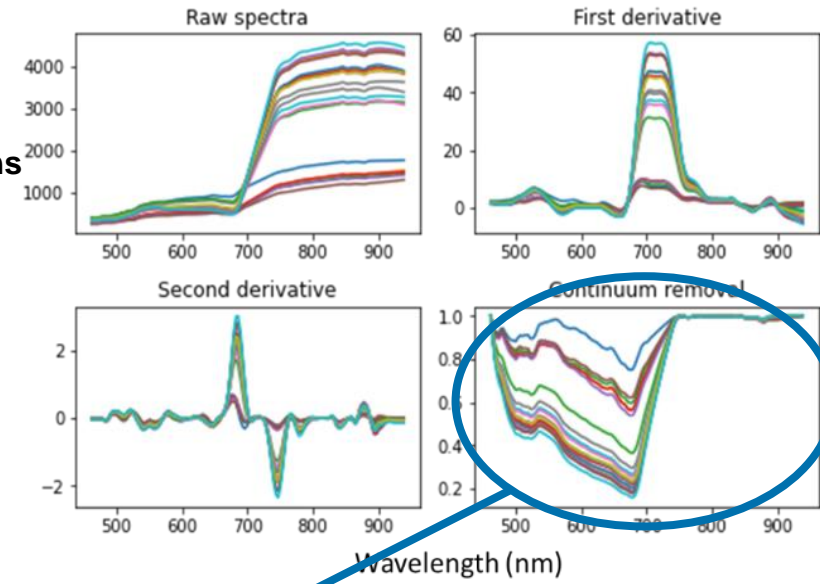
Average spectrum
➔

Average reflectance spectrum of an image



Transformations
➔

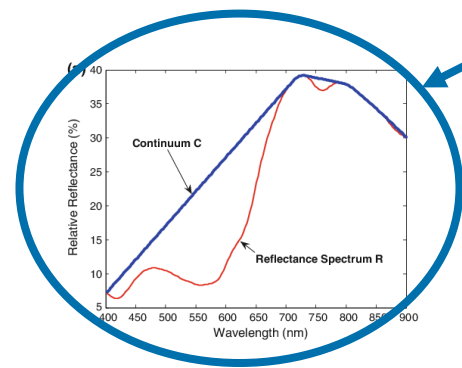
Spectral transformations, sample 1190 to 1209



- An image is represented by a vector of shape $(x, 150)$ where x is the number of pixels

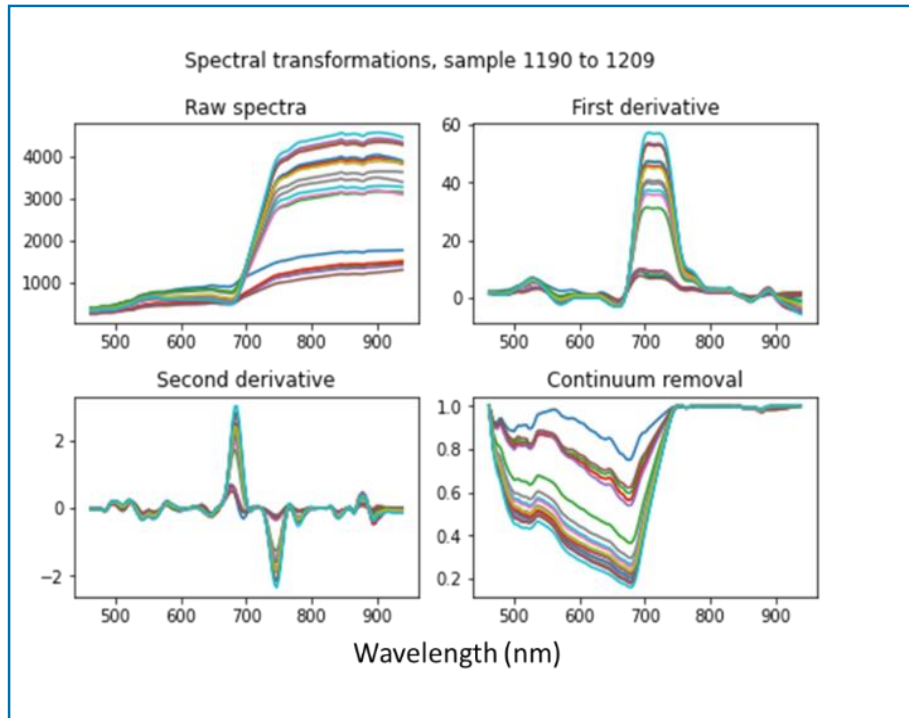
- It is now represented by a $(1, 150)$ vector

Finally it is represented by a $(1, 600)$ vector
(150 dims x 4 transformations)

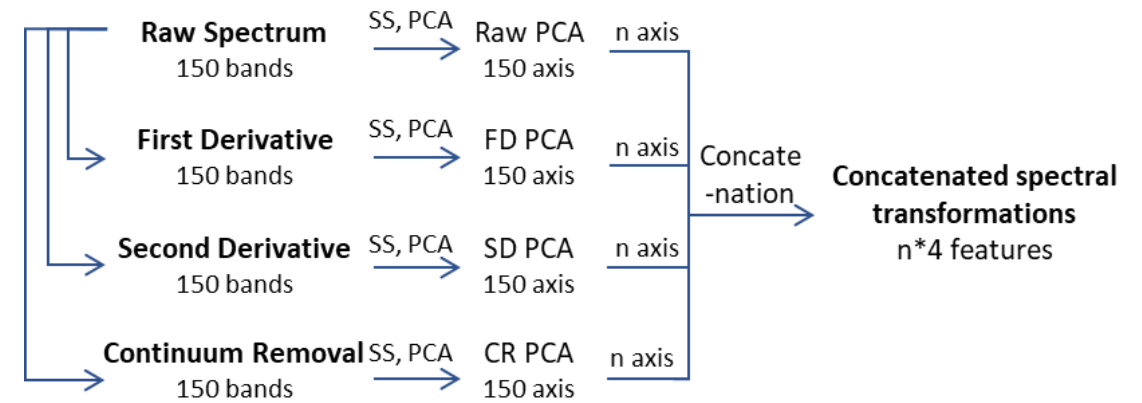




Pre-processing



PCA reduction des dimensions



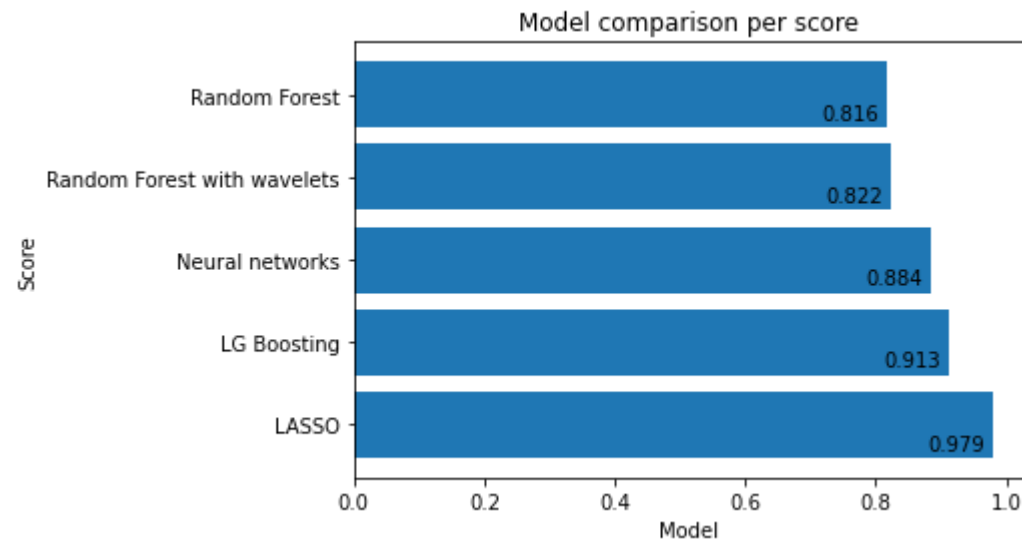
RESULTS

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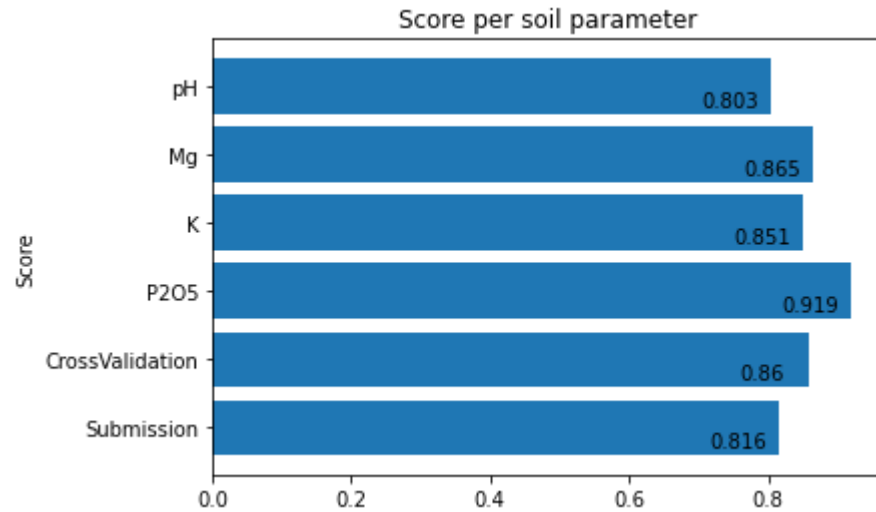


RESULTS

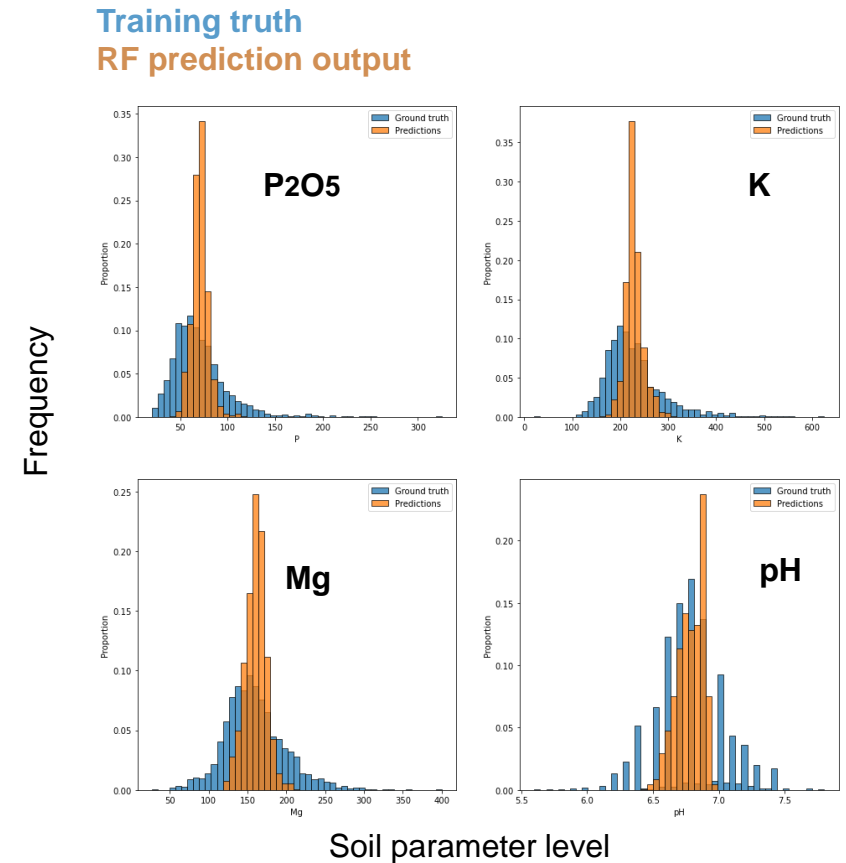
- ✓ Several methods of Machine Learning have been implemented, in order to choose the best prediction model.
- ✓ Using cross validation to choose the best hyperparameters of ML models and analyse the contribution of spectrum transformations and dimension reduction
- ✓ Best submission scores :



Random Forest predictions

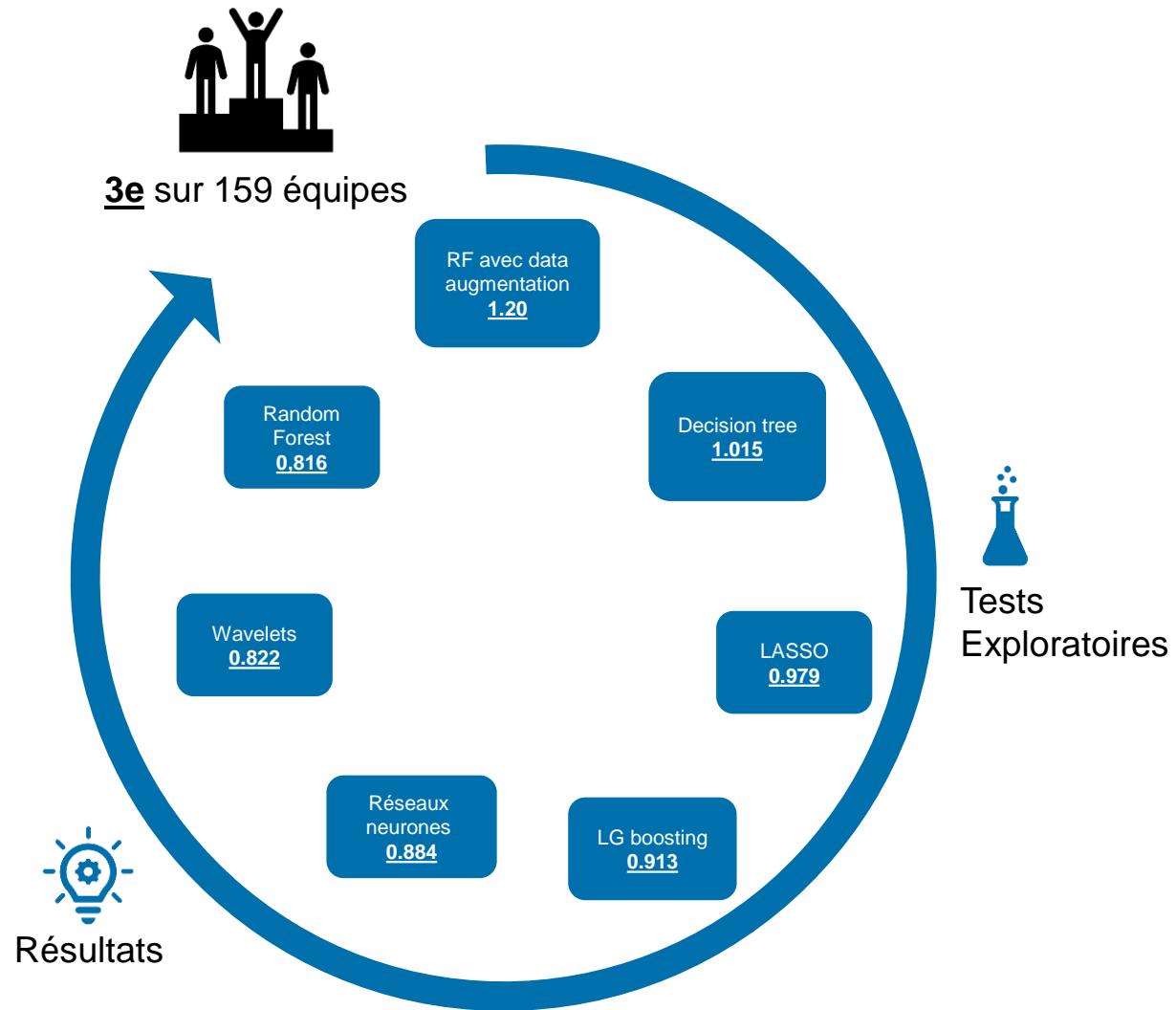


- ✓ **Prediction** distribution centred around parameter mean
- ✓ Model performs better for **pH**, worse for **P2O5**



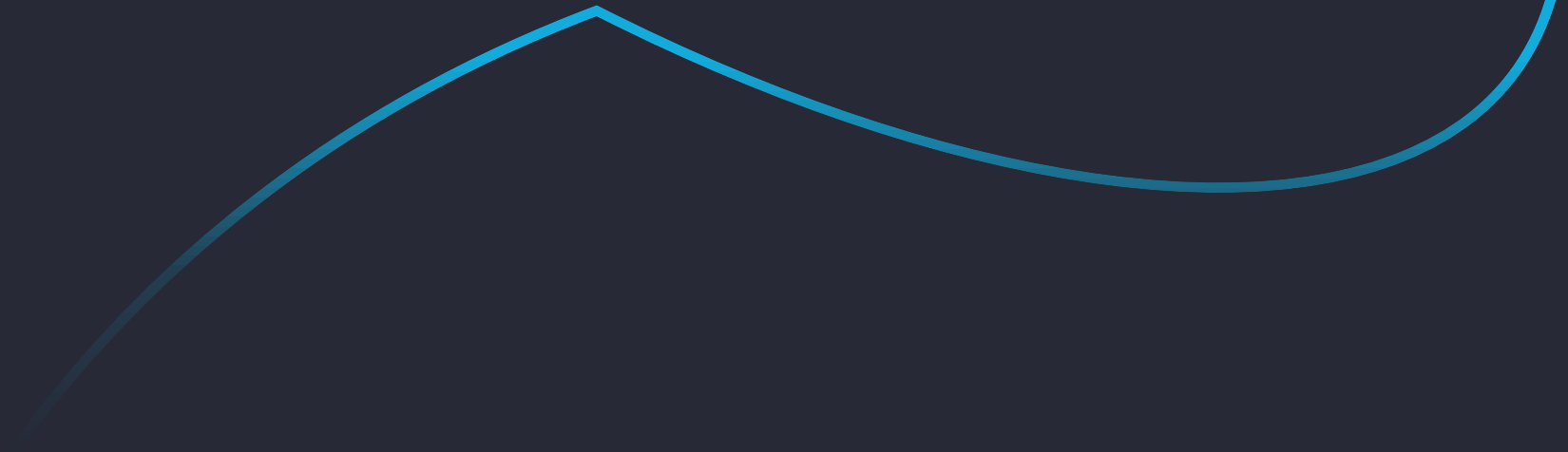
RESULTS

LEGEND	Objectif initial
E	



Model	Date	Score officiel	Cross-validation	P2O5	K	Mg	pH	Pre-processing	Parameters	Comments
RandomForest		0,816	0,860	0,919	0,851	0,865	0,803	Mean of sample > (Transfo : FD/SD/CR) > StandardScaler > PCA > Concatenation of n first PCA axis for each transfo (n*4 feature total)	RF : bootstrap = False, max_features = log2(P) / sqrt(K, Mg, pH), n_estimator = 10000, min_samples_leaf = 2/4	40 pca axis for P (160 total), 35 for K, Mg (140 total), 50 for pH (200 total) 2ème soumission (19/06) : 0,817

CONCLUSION





CONCLUSION

- Ø First step for sustainability agriculture
- Asset to France 2030 program support by Science&IA, C&CA offer
- Prospects : Space Agencies, Env & Agriculture Ministry, Carbon Farming

MERCI DE VOTRE ATTENTION



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