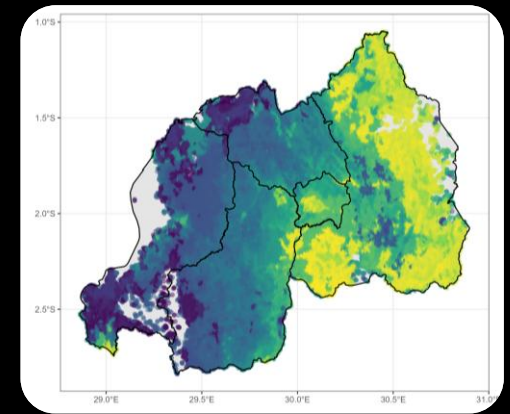
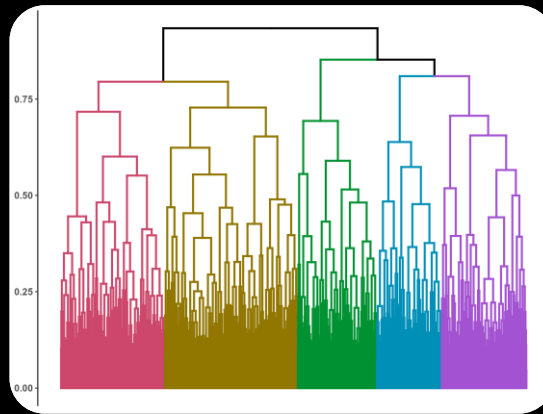
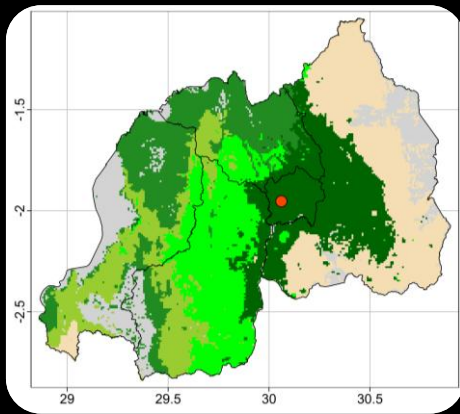


Practical Training on Data-Driven Systems Agronomy

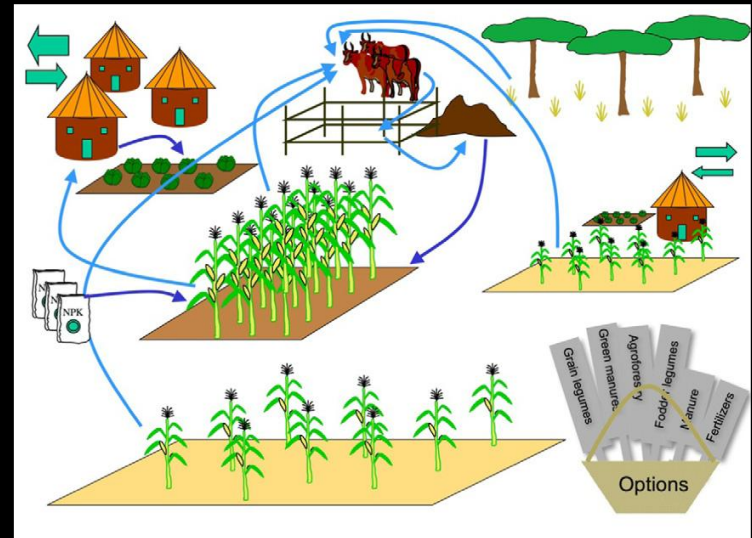


Frédéric Baudron

UM6P, 26 May 2025

Systems agronomy

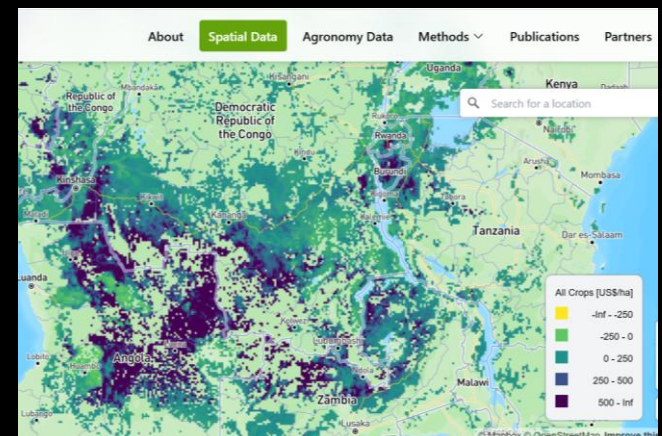
- A methodological approach which seeks to understand cropping, farm household, and farming systems and their interactions, and design a broad basket of options for diverse farming conditions and diverse contexts (*Giller et al., 2011*)
- Which options for what context?
 - Where? For whom? What?



(*Giller et al. 2011*)

Agronomy-at-scale

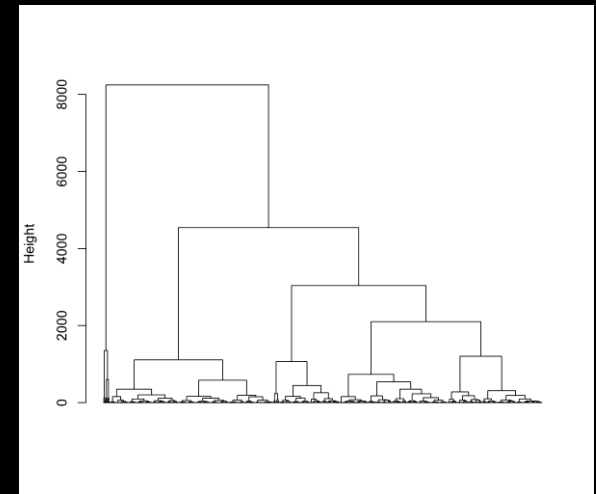
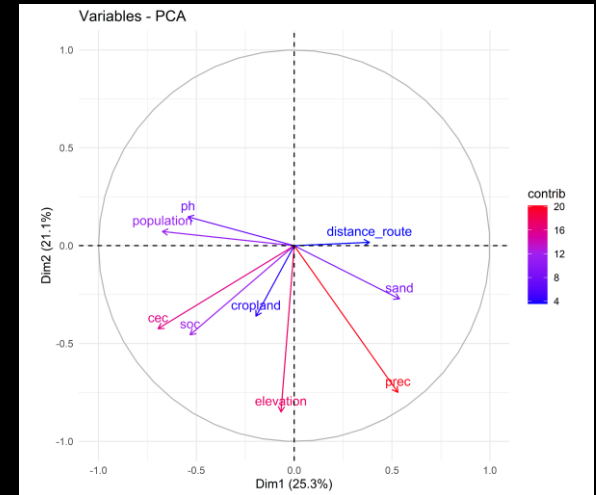
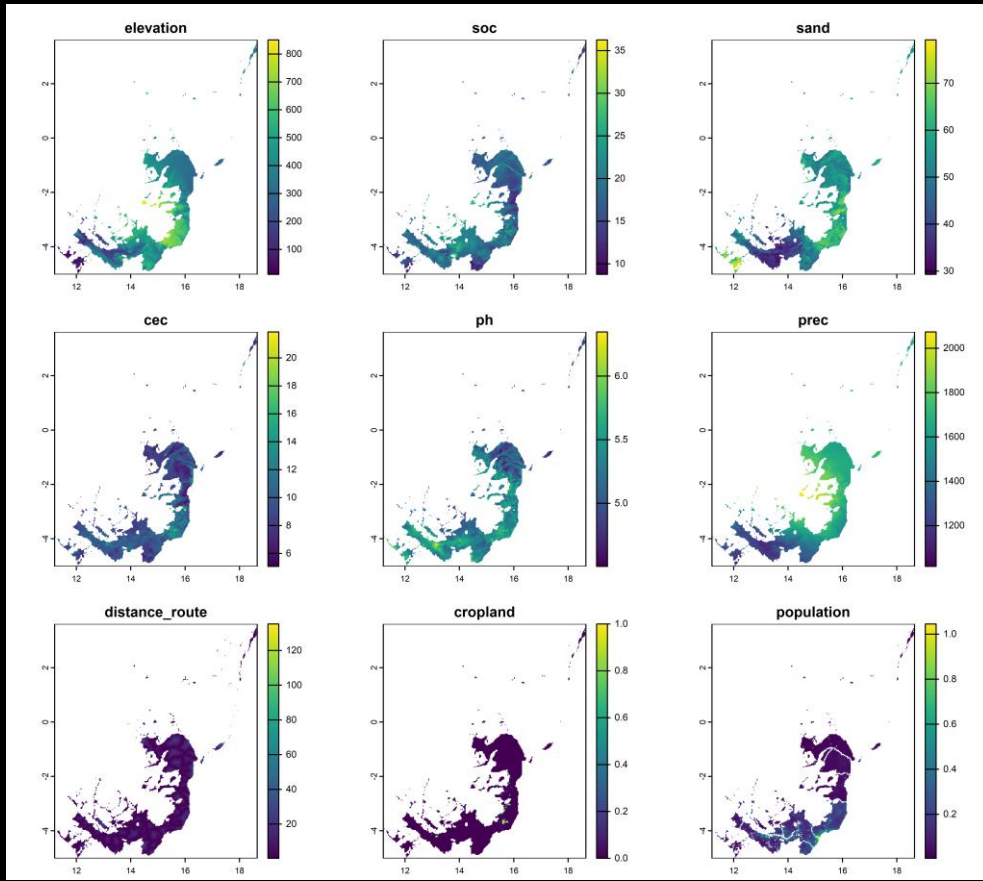
- The use of digital data, geo-spatial tools, analytics, workflows, and interfaces to develop, validate, and disseminate agronomy solutions at scale (*Vanlauwe et al. 2020*)
 - Answering the questions of where? for whom? and what? in a data-driven manner and at scale



WHERE? Recommendation domains

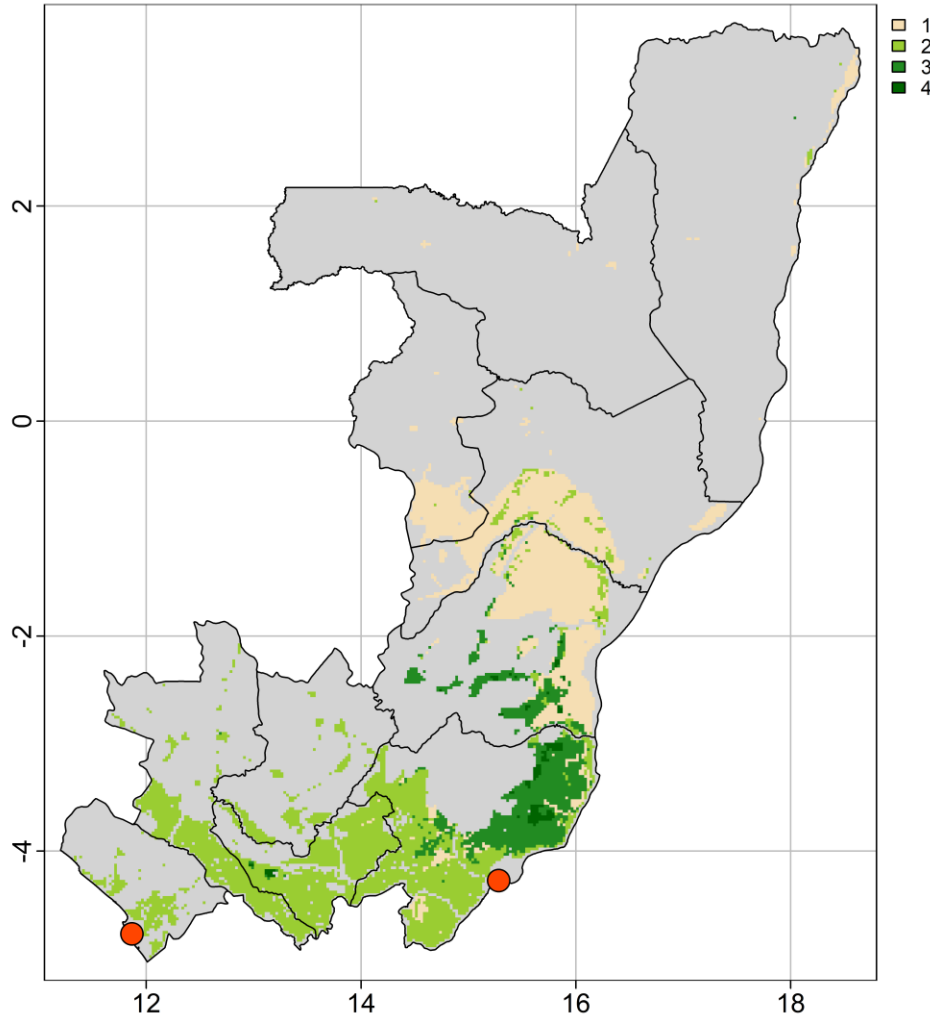
- Recommendation domains: sections of landscapes sharing similar biophysical and socioeconomic characteristics, where specific interventions (*e.g., technologies, policies, investments*) are likely to be effective (*Muthoni et al., 2017; Notenbaert et al., 2013*)
- Top-down approach: deductive method of clustering using (increasingly available) gridded geospatial layers
- Bottom-up approach: using geospatial models trained with adoption or performance georeferenced data

Clustering (PCA + HCA)

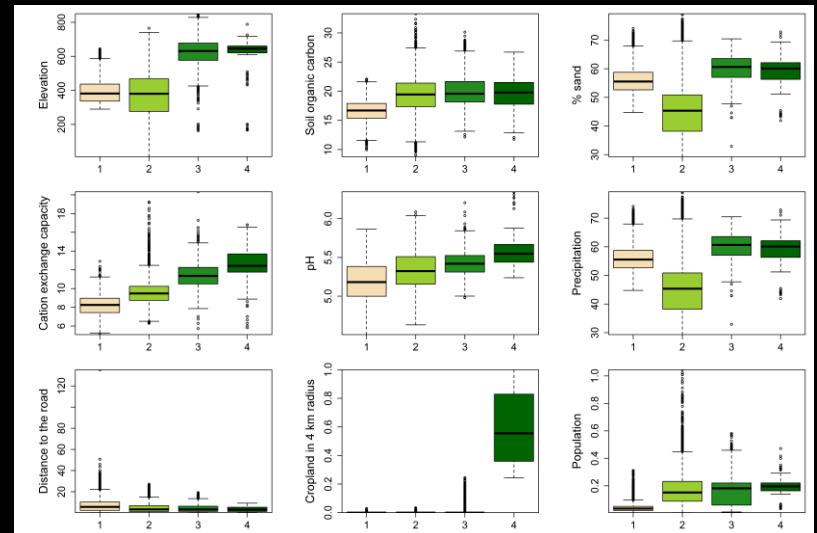
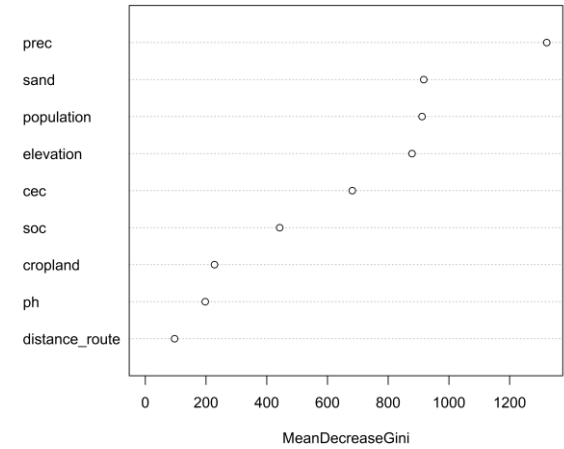


Clustering (PCA + HCA)

Domains

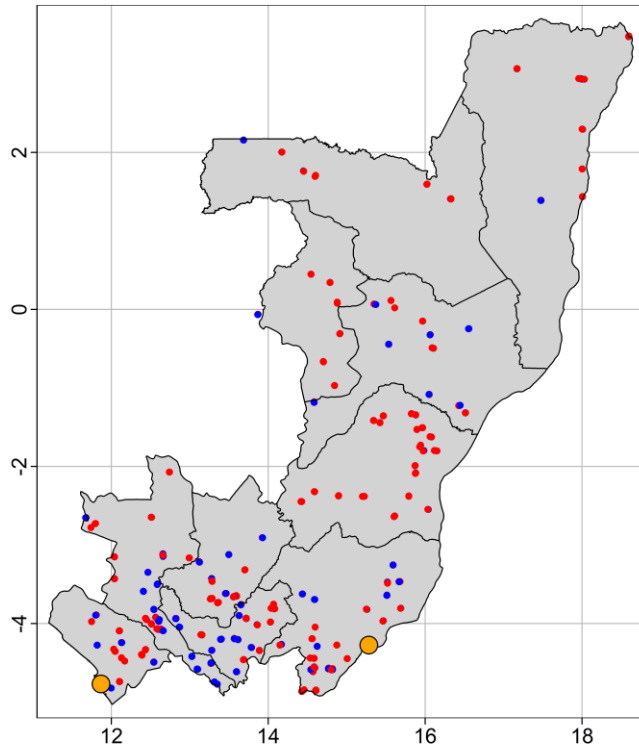


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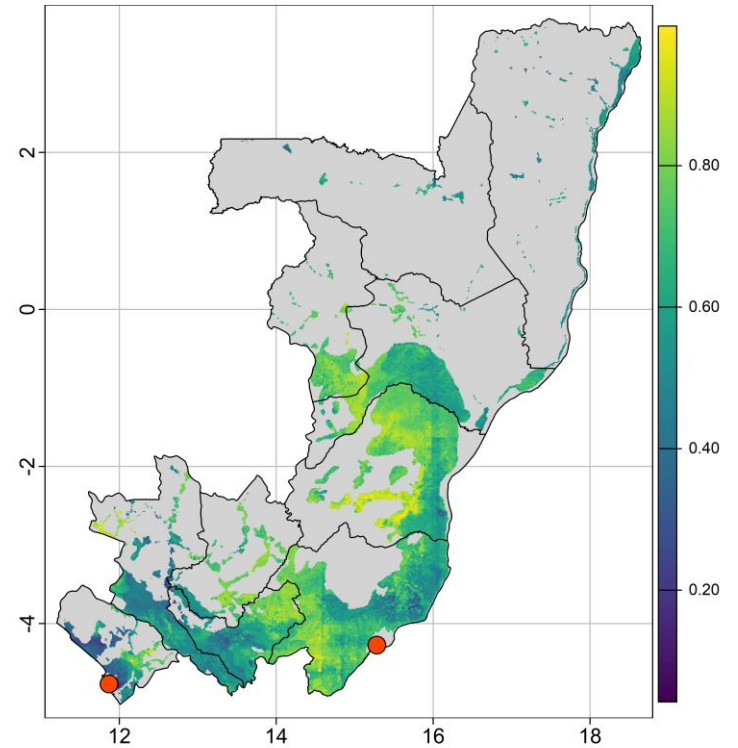


Bottom-up approach

Presence/absence de safoutiers



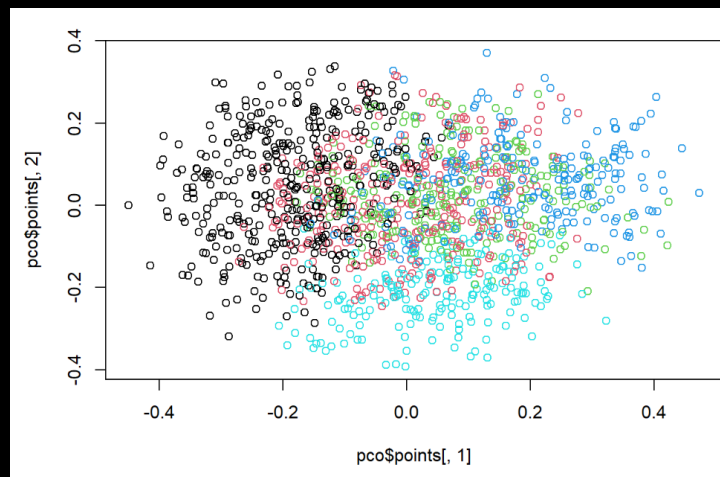
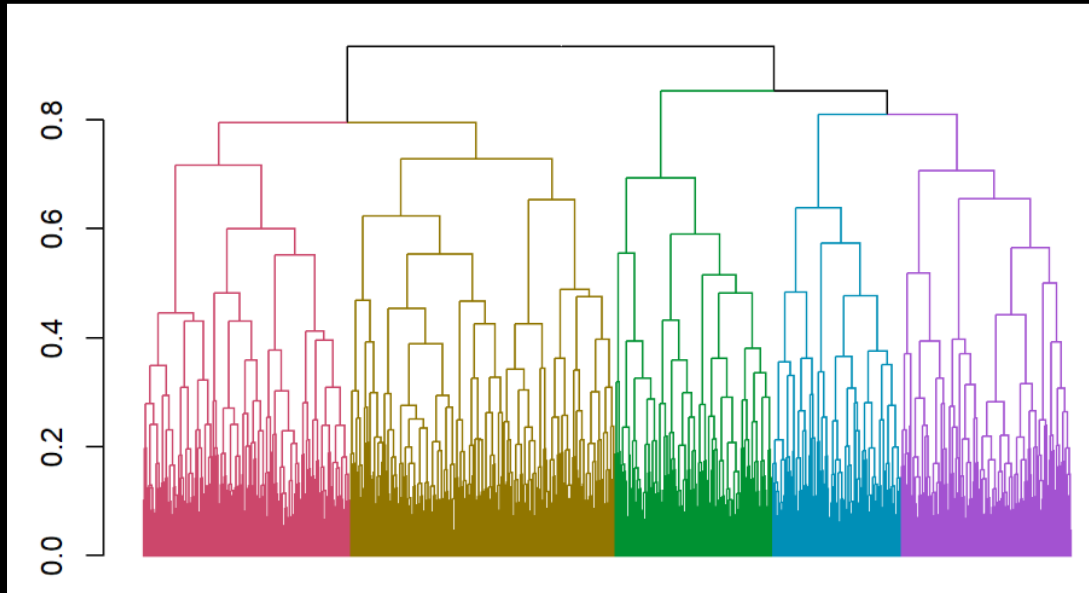
Probabilité d'occurrence du safou



FOR WHOM? Farm typologies

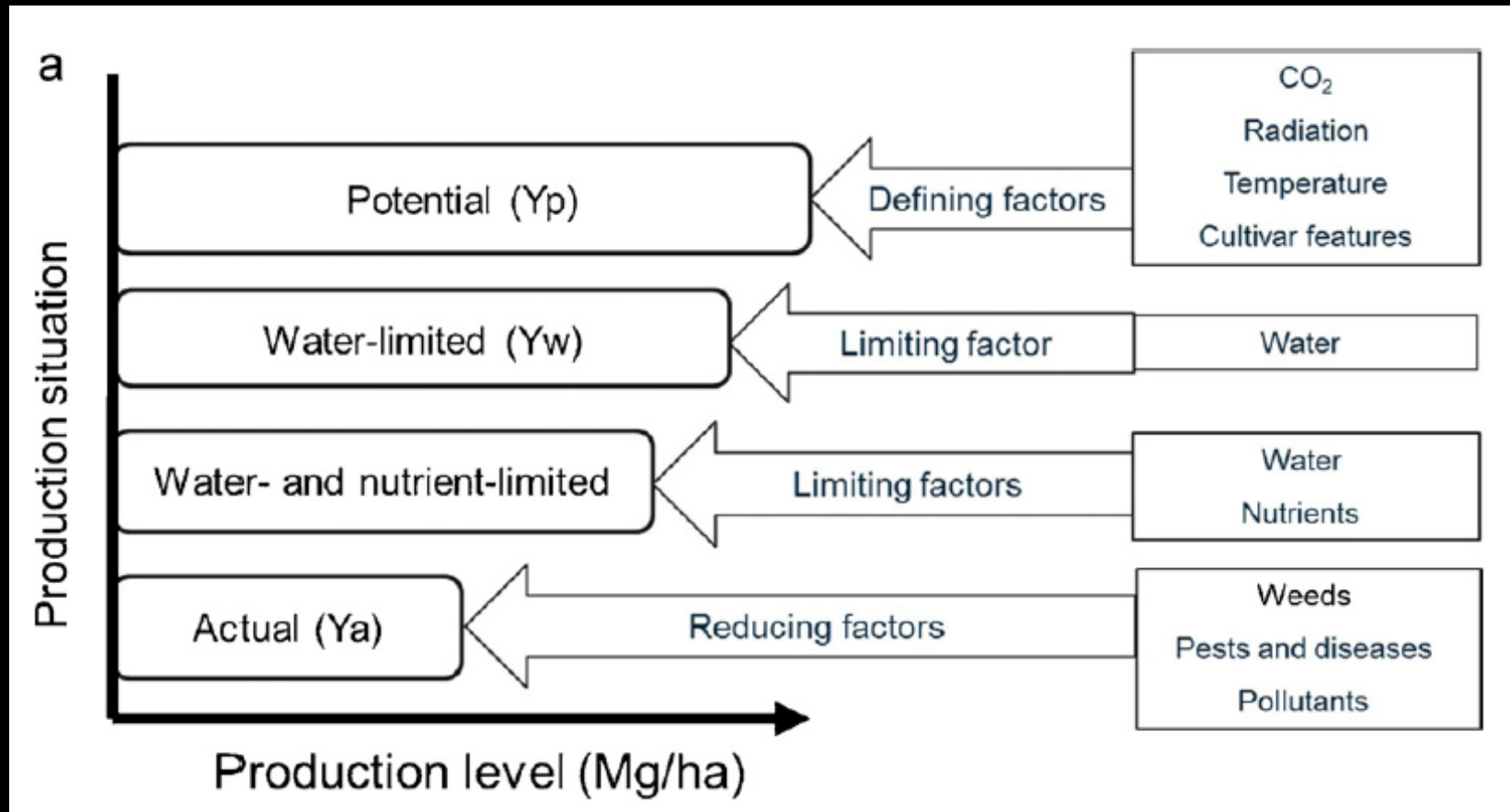
- Farm typologies: characterizing the diversity of farming systems and their distribution in heterogeneous communities, as a basis for prioritizing interventions (*Hammond et al., 2020*)
- Quantitative statistical typologies, without a priori selection of discriminant variables (*Tittonell et al., 2010*)
- Qualitative expert-based typologies involving farmers and other knowledgeable stakeholders, based on a specific research hypothesis (*Kebede, 2009*)

Clustering (nMDS + HCA) and interpretation



- **Type 1:** migrants, with low income, renting land, mainly in savanna biome.
- **Type 2:** land owners with low income (vulnerable).
- **Type 3:** Land owners with high income, diverse farms, perennial crops, stable cultivated area.
- **Type 4:** Land owners with high income, diverse farms, perennial crops, expanding.
- **Type 5:** pluriactivity, mainly subsistence farming, high income from natural resources, mainly in forest and mosaic biomes.

WHAT? Yield gap analysis

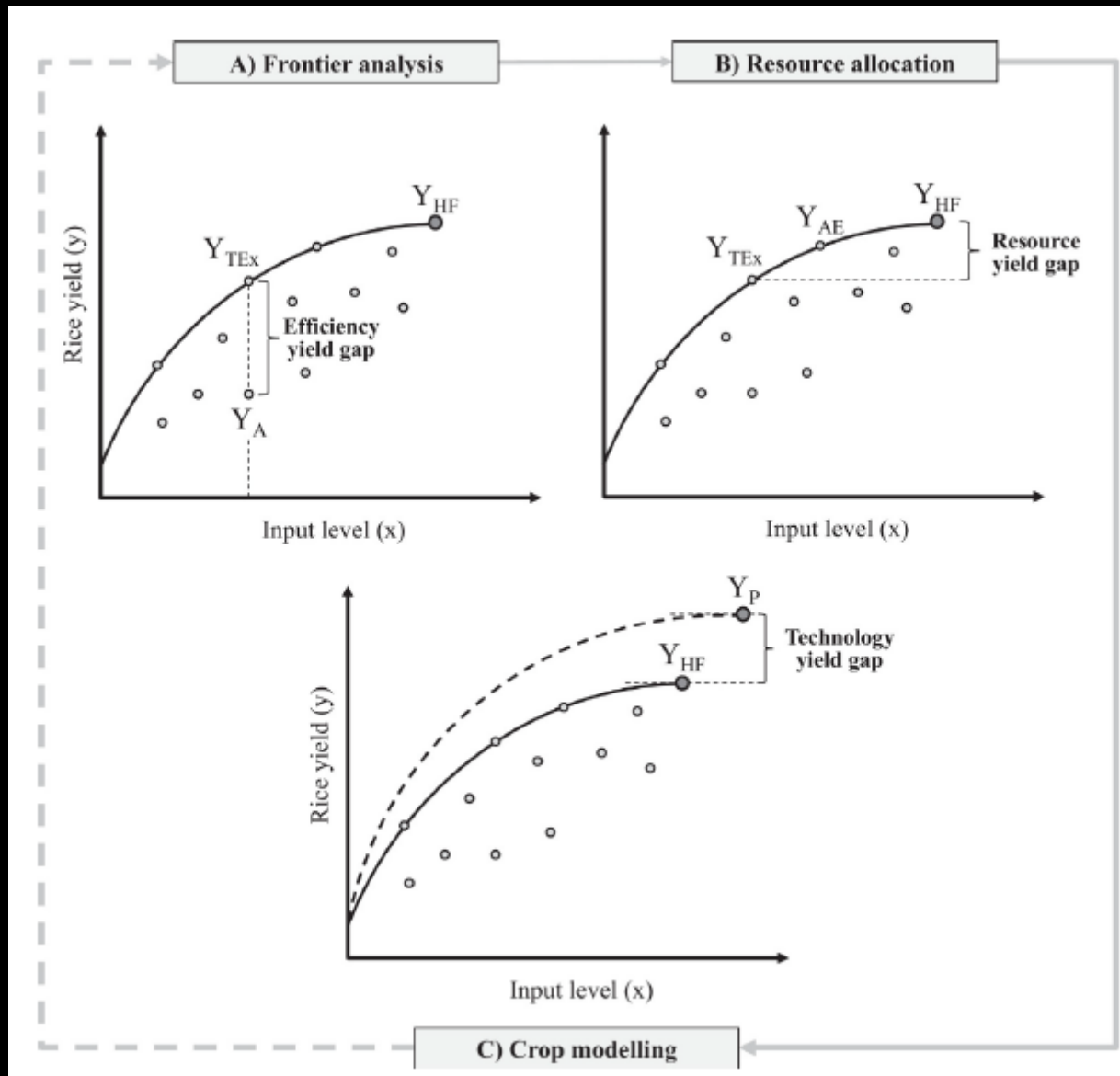


(van Ittersum et al. 2013)

WHAT? Yield gap analysis

- Frontier analysis to decompose yield gaps (efficiency, resource and technology yield gap) and understand the relative importance of biophysical and crop management factors explaining these gaps (*Silva et al., 2017*)
- Machine learning using random forest and post hoc calculation of SHapley Additive exPlanations (SHAP) values, reflecting the contribution of each variable to the yield in each field (*Nayak et al., 2024*). Spatial predictions using different scenarios.

Stochastic frontier analysis



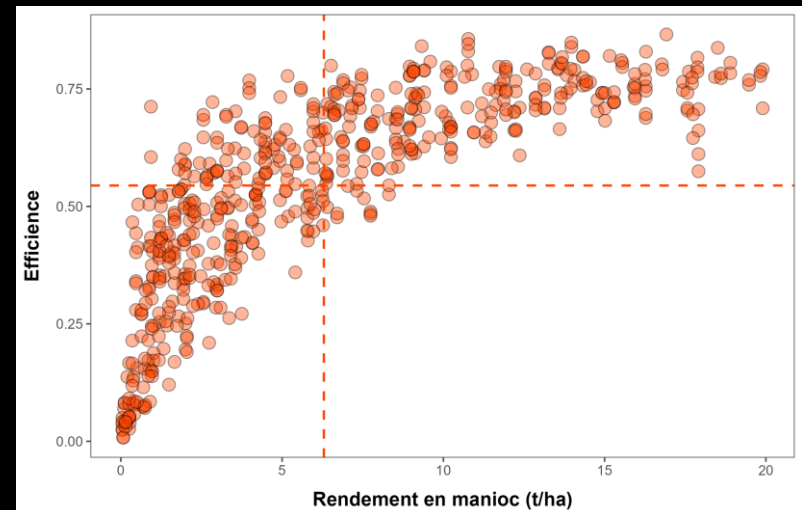
(Silva et al. 2017)

Results

Tableau 1 – effets des différents facteurs biophysiques et de gestion de la culture sur le rendement en manioc. Le model a été construit avec la fonction `sfa()` to package R `frontier`. Les facteurs en gras sont ceux ayant un effet significatif à P-value < 0.1.

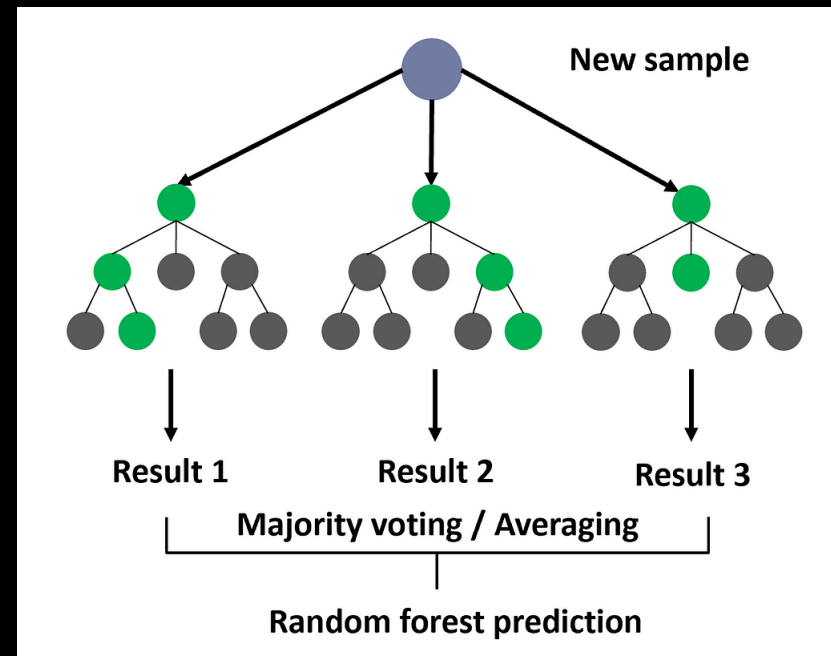
| | Coefficient | Erreur std | z value | Pr(> z) |
|---|-------------|------------|---------|----------|
| <i>Frontière de production</i> | | | | |
| Intercept | 0.310 | 0.171 | 1.807 | 0.07 |
| Sarclage: 2 sarclages | 0.478 | 0.124 | 3.860 | < 0.01 |
| Sarclage: 3 sarclages | 0.508 | 0.139 | 3.653 | < 0.01 |
| Sarclage: 4 et + sarclages | 0.251 | 0.161 | 1.557 | 0.12 |
| Sarclage: pas de sarclage | 0.213 | 0.165 | 1.297 | 0.19 |
| Végétation précédente: forêt dense | 0.029 | 0.142 | 0.201 | 0.84 |
| Végétation précédente: savane arbustive | 0.186 | 0.100 | 1.856 | 0.06 |
| Végétation précédente: savane herbacée | -0.268 | 0.140 | -1.907 | 0.06 |
| Durée de jachère: 1-2 ans | -0.302 | 0.213 | -1.419 | 0.16 |
| Durée de jachère: 3-5 ans | -0.114 | 0.115 | -0.998 | 0.32 |
| Durée de jachère: 6-11 ans | 0.110 | 0.114 | 0.962 | 0.34 |
| Durée de jachère: Pas de jachère/végétation naturelle | -0.355 | 0.128 | -2.774 | 0.01 |
| Utilisation du tracteur | 0.579 | 0.202 | 2.869 | < 0.01 |
| Association tubercules | 0.072 | 0.095 | 0.757 | 0.45 |
| Association céréales | -0.074 | 0.092 | -0.804 | 0.42 |
| Association légumineuses | 0.012 | 0.093 | 0.128 | 0.90 |
| Association légumes | -0.012 | 0.083 | -0.145 | 0.88 |
| Association banane plantain | -0.068 | 0.091 | -0.746 | 0.46 |
| Association arbres (non-fruitiers) | 0.233 | 0.090 | 2.604 | < 0.01 |
| Domaine: mosaïque | -0.348 | 0.116 | -2.994 | < 0.01 |
| Domaine: savane | -0.477 | 0.170 | -2.807 | < 0.01 |
| Altitude (log) | 0.889 | 0.142 | 6.279 | < 0.01 |
| Carbone organique du sol (log) | 0.655 | 0.257 | 2.551 | 0.01 |
| Sable (log) | 0.141 | 0.368 | 0.384 | 0.70 |
| pH (log) | -2.738 | 1.394 | -1.965 | 0.05 |
| Température moyenne (log) | 8.249 | 1.707 | 4.832 | < 0.01 |
| Précipitation | -3.657 | 0.567 | -6.448 | < 0.01 |
| <i>Effets d'inefficience</i> | | | | |
| Intercept | -97.578 | 303.843 | -0.321 | 0.75 |
| Surface cultivée (log) | 3.406 | 9.819 | 0.347 | 0.73 |
| Propriété | 15.710 | 47.735 | 0.329 | 0.74 |
| <i>Evaluation du modèle</i> | | | | |
| $\sigma^2 = \sigma_v^2 + \sigma_u^2$ | 73.021 | 219.220 | 0.333 | 0.74 |
| $\gamma = \sigma_u^2 / \sigma^2$ | 0.995 | 0.014 | 72.585 | < 0.01 |

- Mean YLD = 6295 kg/ha
- HFY = 16864 kg/ha
- Efficiency = 54.4 %
- Mean tech. eff. YLD = 10439 kg/ha
- Mean eff. YG = 3970 kg/ha
- Mean res. YG = 7083 kg/ha

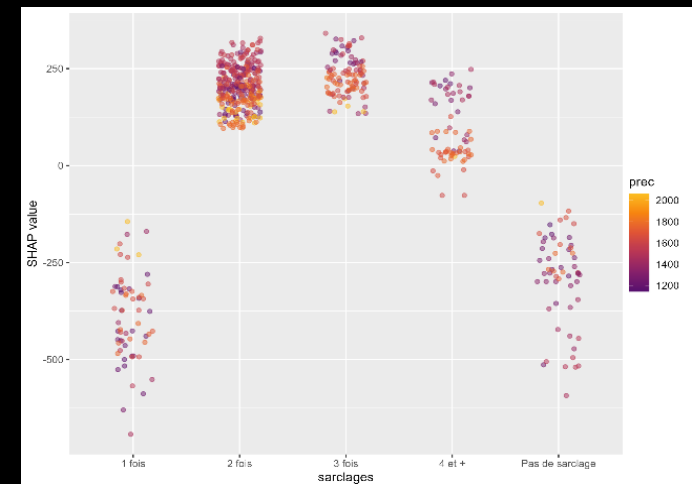
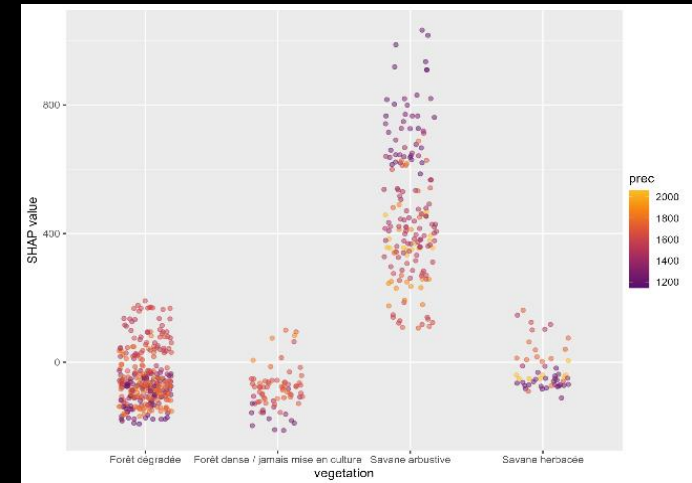
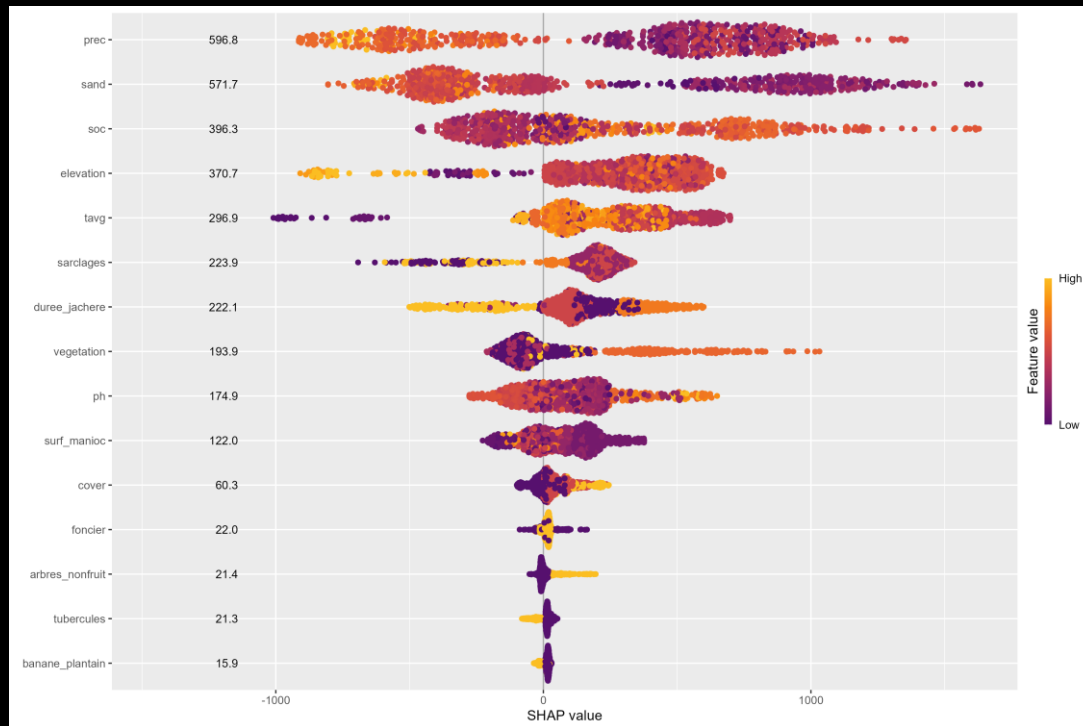


Random forests

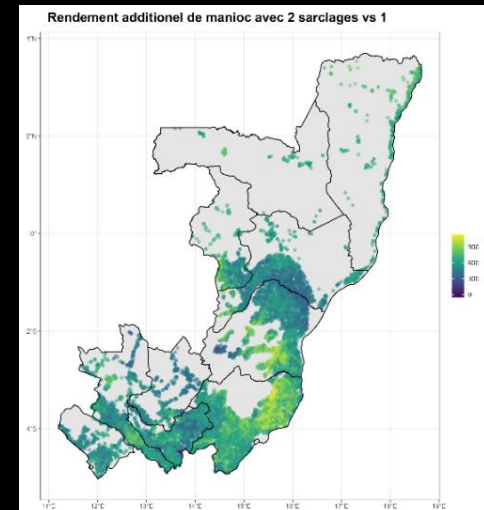
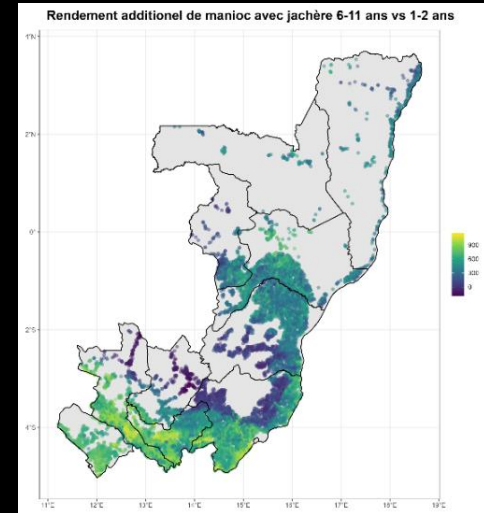
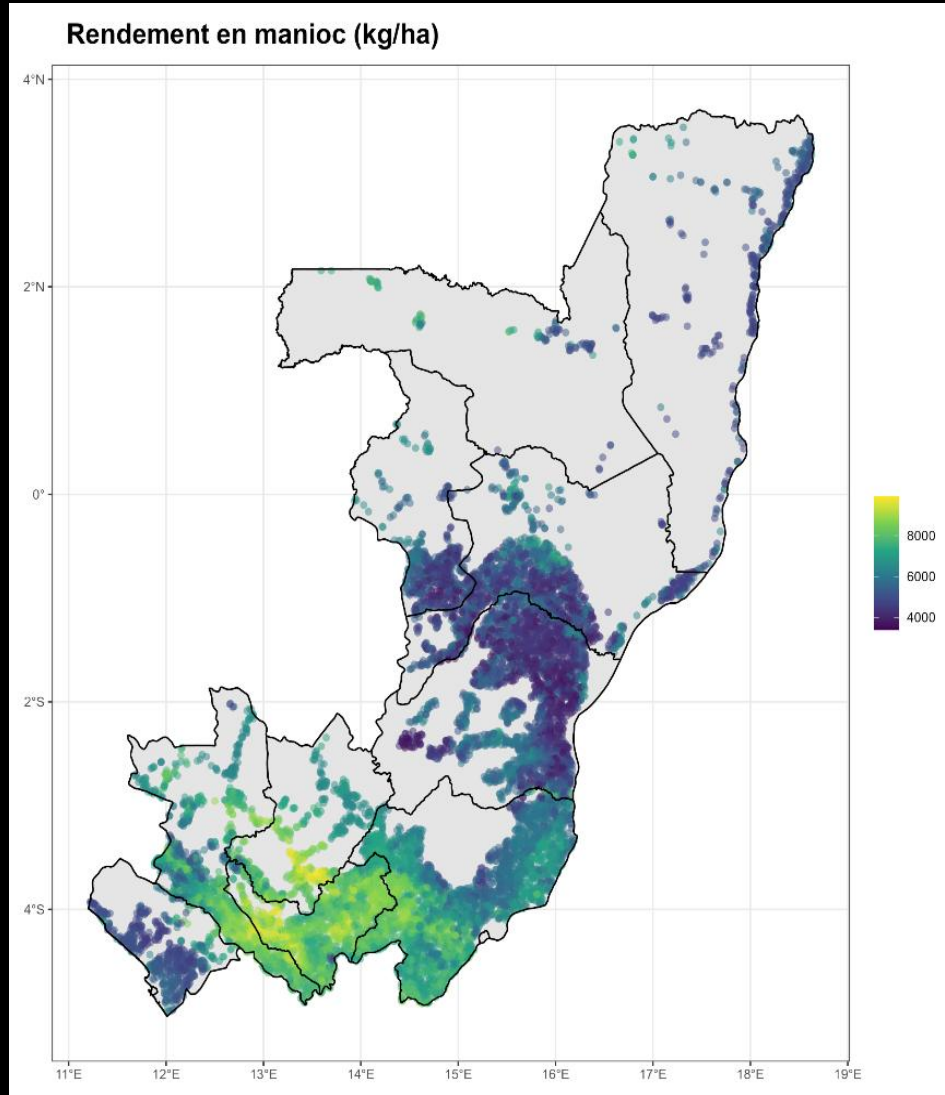
1. Creation of n tree bootstrap samples
2. Construction of one tree per sample using m try explanatory variables selected randomly
3. Calculation of OOB error
(*mean square error or % of observation misclassified*)
4. Aggregation of predictions
(*means or majority voting*)
5. Calculation of mean OOB



SHAP values from RF



Spatial predictions from RF





**Thank you for
your interest!**

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