Leibniz Centre for Agricultural Landscape Research (ZALF)

Mapping in-season biomass nitrogen in diversified cropping systems: a machine learning approach

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Introduction: the challenge

- Large-scale conventional farming leads to soil degradation and nutrient imbalances[1,2].
- Diversified cropping systems, like patch cropping, can enhance ecosystem services and optimize resource use[3,4].
- However, managing nitrogen (N) is challenging in these systems due to soil heterogeneity and crop-specific needs[5].

Photo: Pixabay

The possibilities: Remote Sensing and Machine Learning

- Remote sensing: non-destructive tools[6]
- Vegetation indices (NDVI, NDRE) combined with soil, climate, and topographic variables: robust predictive models to estimate chlorophyll content and canopy nitrogen[7].
- Machine learning: Random Forest (RF) and Extreme Gradient Boosting (XGBoost) are effective for this task as they can capture non-linear relationships[8,9].
- However, most existing remote-sensing and machine learning (ML) studies focus on **single crops** rather than multiple crop types or diversified cropping systems[10,11].

Photo: Pixabay

Research Objectives

- The study addresses the challenge of monitoring crop N status in spatially diversified agricultural systems.
- The goal is to develop machine learning models that can predict crop-specific above-ground biomass and nitrogen uptake.

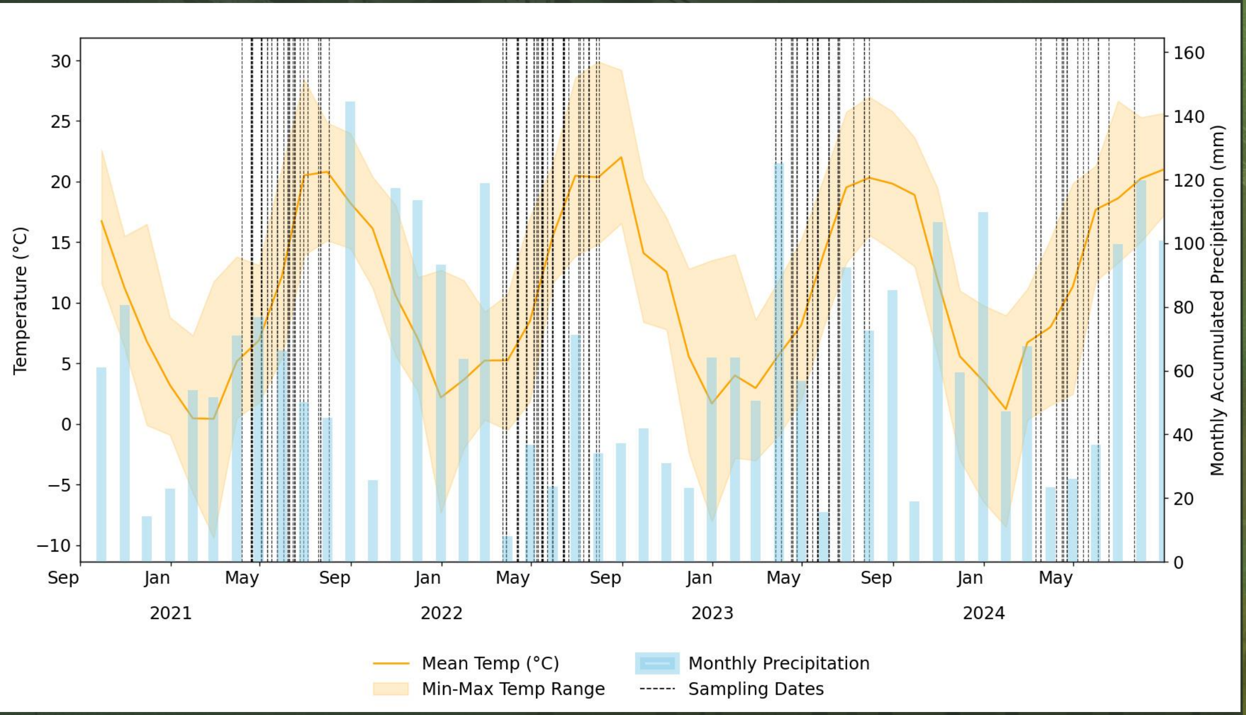
Photo: marqs / Photocase

Central research question

Can multi-source data and ML models reliably estimate in-season crop nitrogen dynamics across co-occurring crop species in a spatially diversified field under heterogenous site conditions?

Study Area & Experimental Setup

- Site: located in Tempelberg, Brandenburg, Germany, as part of the patchCROP landscape experiment
- Soil: Heterogeneous due to glacial sediments
- Elevation: 58.5 to 86.5 m.
- Climate: Continental
- Experimental set-up: established in 2020, consists of 30 patches (72x72 m) and reference fields



Weather conditions during the study period from September 2020 to August 2024, obtained from two weather stations installed at patchCROP. Gray lines indicate the sampling dates.

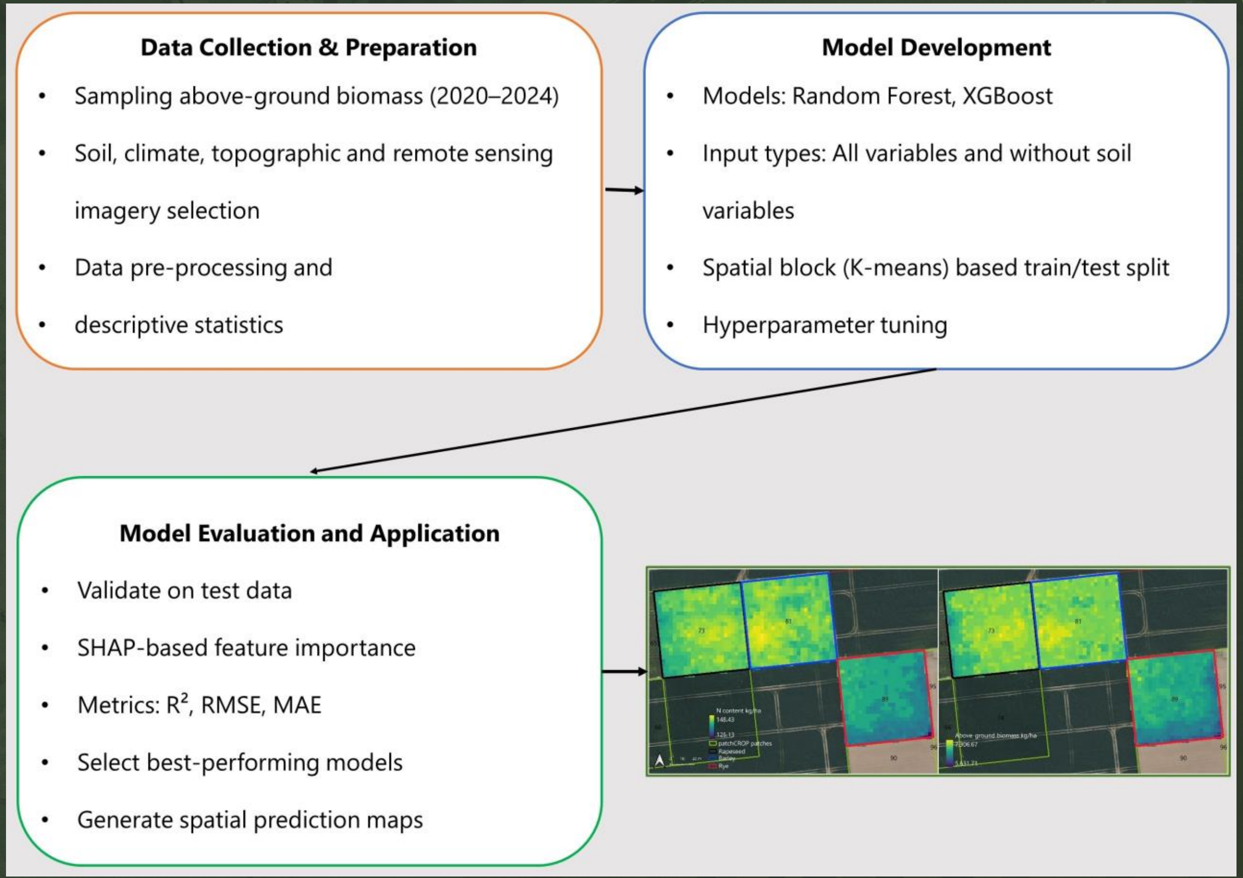
Data Collection

- Six crops (barley, rye, wheat, rapeseed, maize, and sunflower) from 20-2021 to 2024
- **Ground-truth data:** Above-ground biomass, n=563 observations
- **Remote Sensing Data:** PlanetScope (3x3 m resolution) and Sentinel-2
- **Other variables:** climate data (precipitation, PAR), soil variables (Soil moisture and texture), and topographic variables (elevation, slope)

Study location of patchCROP with patches in field 04-00 and adjacent reference fields. (a) biomass transect sampling in the patches (here, two patches are shown with a detailed zoom), (b) biomass sampling locations in the reference fields. Image: Google satellite map, accessed through HCMGIS plugin within QGIS version 3.40.4-Bratislava.

Model Development & Evaluation

- Two machine learning models: **Random Forest (RF)** and Extreme **Gradient Boosting (XGBoost)**.
- Models trained with and without soil variables
- A spatial block split (K-means clustering) to separate training and testing data.
- Model performance evaluation: R^2, RMSE, MAE.



Schematic workflow of data acquisition, data processing, model building, validation, and application.

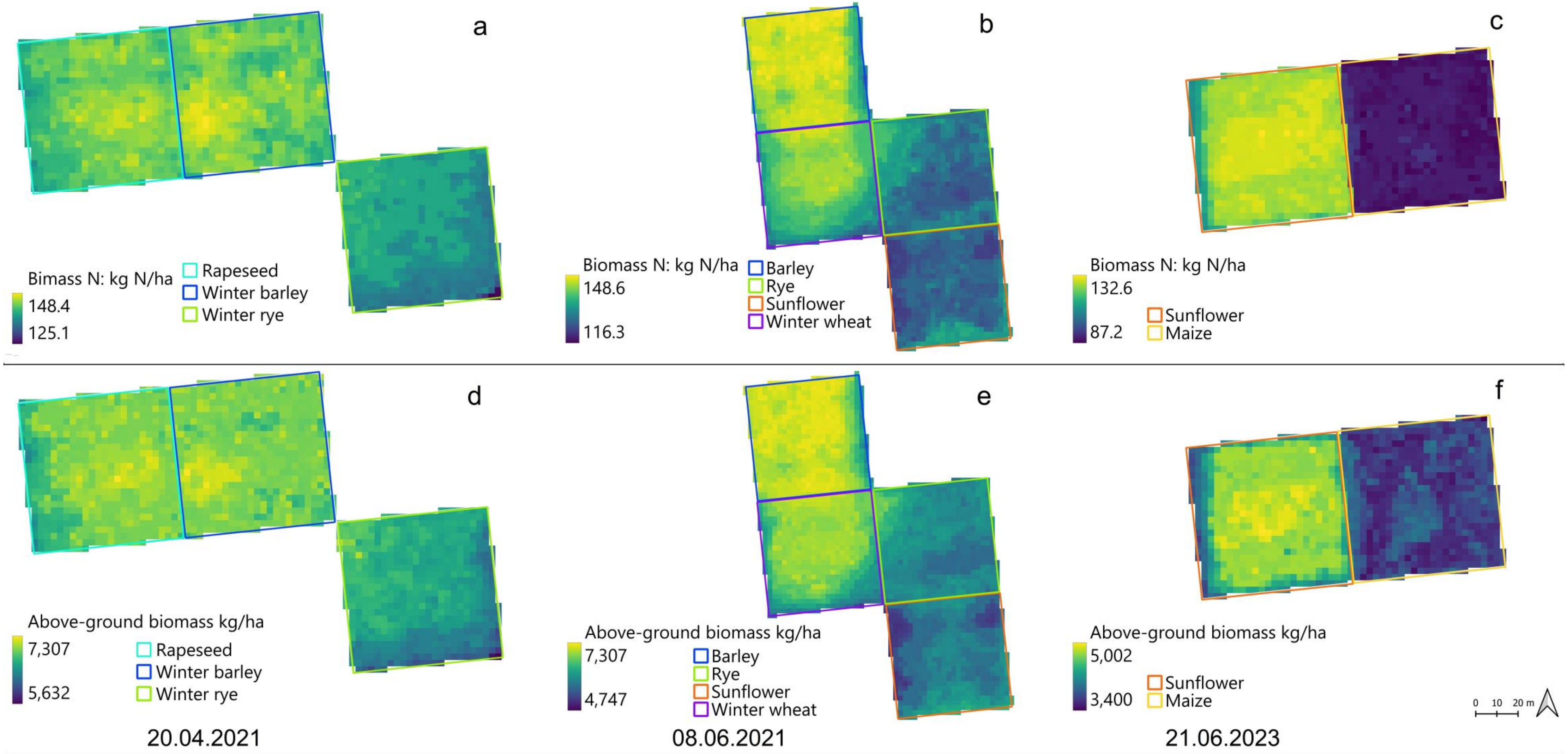
Key Results: Model Performance

- **Random Forest (RF)** models consistently outperformed XGBoost.
- **Biomass:** RF model achieved an **R^2 = 0.75**
- **Nitrogen Uptake:** RF model achieved an **R^2 = 0.65**
- The inclusion of soil variables did not improve model performance

Model ID	Target	Soil Data	R^2	RMSE	MAE
RF-1	Bio_N kg N/ha	Yes	0.61	35.9	26.8
RF-2	Bio_N kg N/ha	No	0.65	34.1	24.1
RF-3	Bio_Dm kg/ha	Yes	0.70	2310.8	1610.6
RF-4	Bio_Dm kg/ha	No	0.75	2078.6	1332.4
XGB-1	Bio_N kg N/ha	Yes	0.60	36.5	26.4
XGB-2	Bio_N kg N/ha	No	0.54	39.0	26.5
XGB-3	Bio_Dm kg/ha	Yes	0.71	2247.1	1573.2
XGB-4	Bio_Dm kg/ha	No	0.63	2558.06	1747.7

nitrogen uptake (Bio_N in kg N /ha) and above-ground biomass (Bio_DM in kg/ha), with and without the inclusion of soil variables.

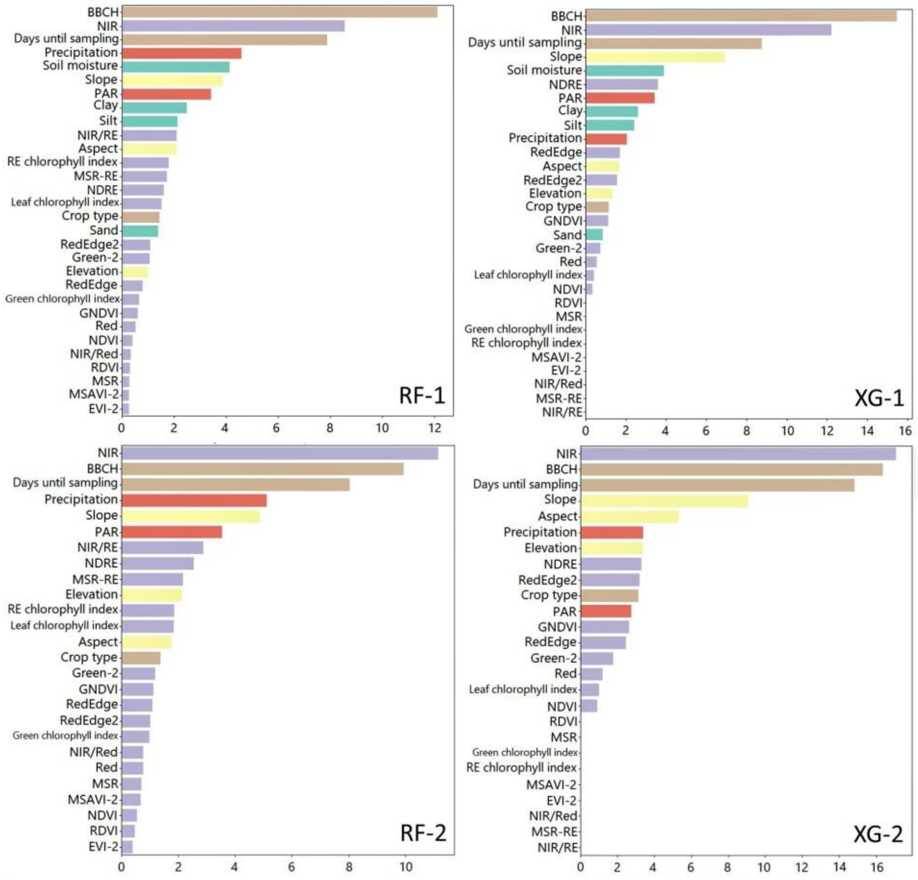
Key Results: Model Performance

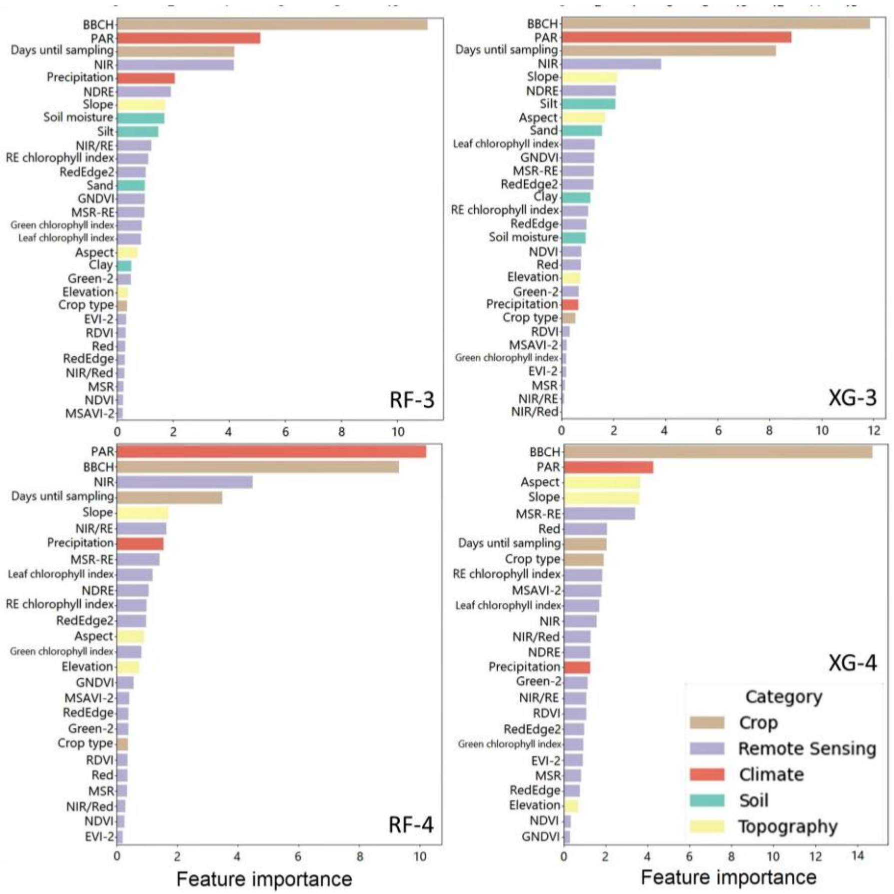


Maps of biomass N uptake in kg N/ha (a, b, c; top panel) and above-ground biomass in kg/ha (d, e, f bottom panel) across multiple crop types (Rapeseed, Barley, Rye, Wheat, Sunflower, and Maize) at three different time points predicted from the RF-2 and RF-4 models.

Key Results: Feature Importance

- Most important variables for predicting **biomass** and **nitrogen uptake** were **BBCH**, followed by **near-infrared (NIR)** reflectance, **accumulated photosynthetically active radiation (PAR),** and **precipitation→h**ighlights the critical role of **crop phenology** in predicting biomass and N





Discussion

- The importance of remote sensing indices and climate data demonstrates their potential for monitoring nitrogen dynamics in diversified cropping systems.
- However, the models showed a systematic bias, overestimating crops with low biomass (e.g., sunflower and maize) and underestimating high-biomass crops (e.g., barley and wheat).
- The low importance of soil texture could be due to the sandy soil conditions and data being limited to the topsoil.

Conclusions

- ✓ Highlighted the potential of using high-resolution satellite data combined with machine learning for multi-crop N monitoring in diversified cropping systems.

- ✓ Provided a foundation for monitoring crop health in new field arrangements and can potentially be integrated with crop models and fertilization strategies in the future.

Thank you for your attention.

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