Remote monitoring of pasture and animals in extensive farming is functional to genetic improvement

Daniele Pietrucci (1), Marco Milanesi (1), Chiara Evangelista (2), Raffaello Spina (2), Bruno Ronchi (4), Nicola Lacetera (2), Riccardo Primi (2), Giovanni Chillemi (1)

(1) Dipartimento per la Innovazione nei sistemi Biologici, Agroalimentari e Forestali (DIBAF), Tuscia University, Viterbo, Italy, Viterbo, Italy

(2) Dipartimento di Scienze Agrarie e Forestali (DAFNE), Tuscia University, Viterbo, Italy, Viterbo, Italy

daniele.pietrucci@unitus.it

Introduction

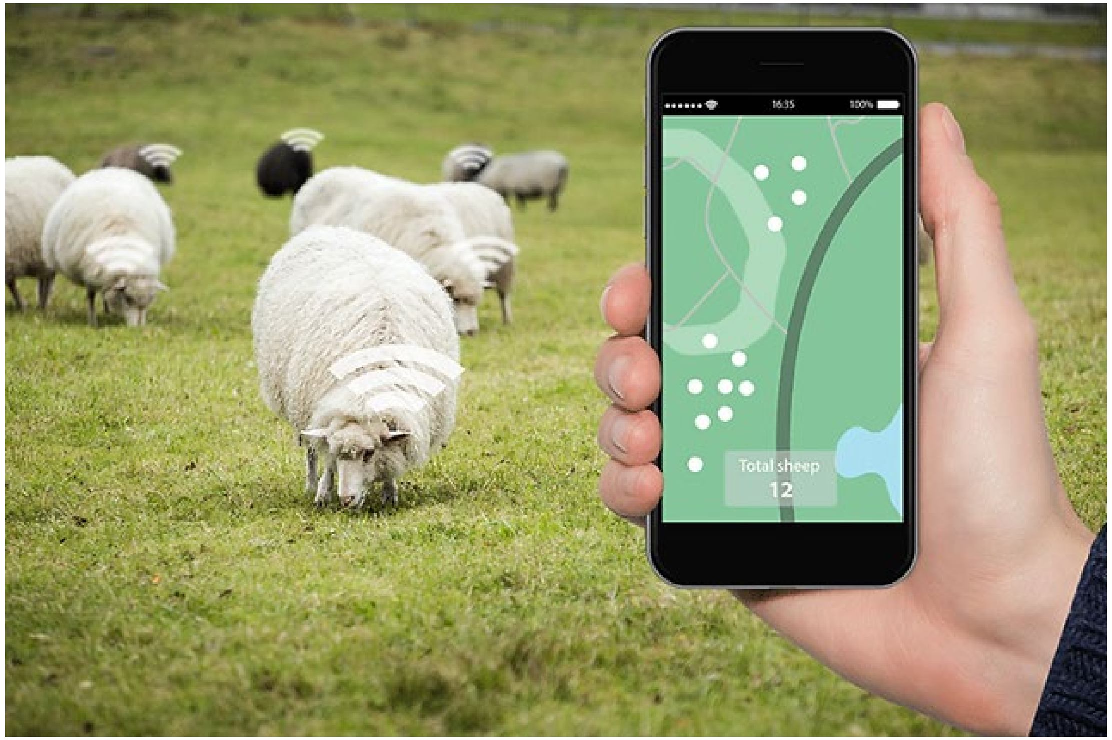
- 🌱 **Grassland-based agriculture** is the main fodder source for ruminants, crucial for meeting global animal-based food demand and sustainable food production (***Stumpf et al., 2020***).

- 🏠 **Grass-fed products** are also commercially valuable due to higher antioxidants and vitamins (***Joubran et al., 2020***; ***Prache et al., 2020***)

- 🐄 The reduction of grazing activities in Europe is due to the **depopulation of mountain areas**, leading to natural **regrowth of tree species in the fields** (***Pallotta et al., 2022***).

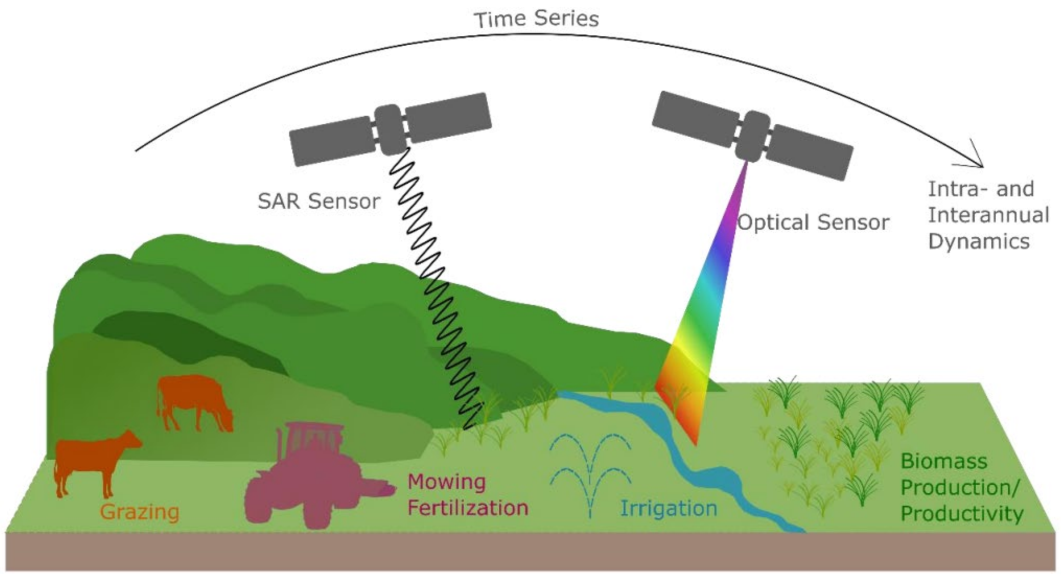
Introduction

- A **Decision Support System** using **Internet of Things technology** is essential for informing farmers about the available biomass, in terms of both quantity and quality, ensuring optimal pasture management



Introduction

- Existing methods for pasture quality analysis are generally **laboratory-based and require labor-intensive preprocessing steps**, which can take several days to complete and are often environmentally harmful due to the use of chemicals and energy-intensive processes
- **Remote sensing** encompasses all techniques that collect data from a distance greater than two meters above ground level, including satellites



Reinermann et al., 2020

50% NIR

8% RED

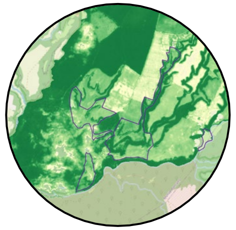
40% NIR

30% RED

Our research question

- The main goal of the project is to develop a **Decision Support System** (**DSS**) that enables farmers to make short-term decisions, directing livestock to pasture areas with higher feed quantity and quality

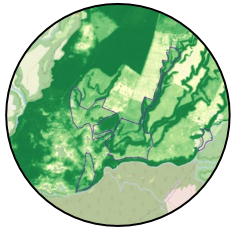
Lab data

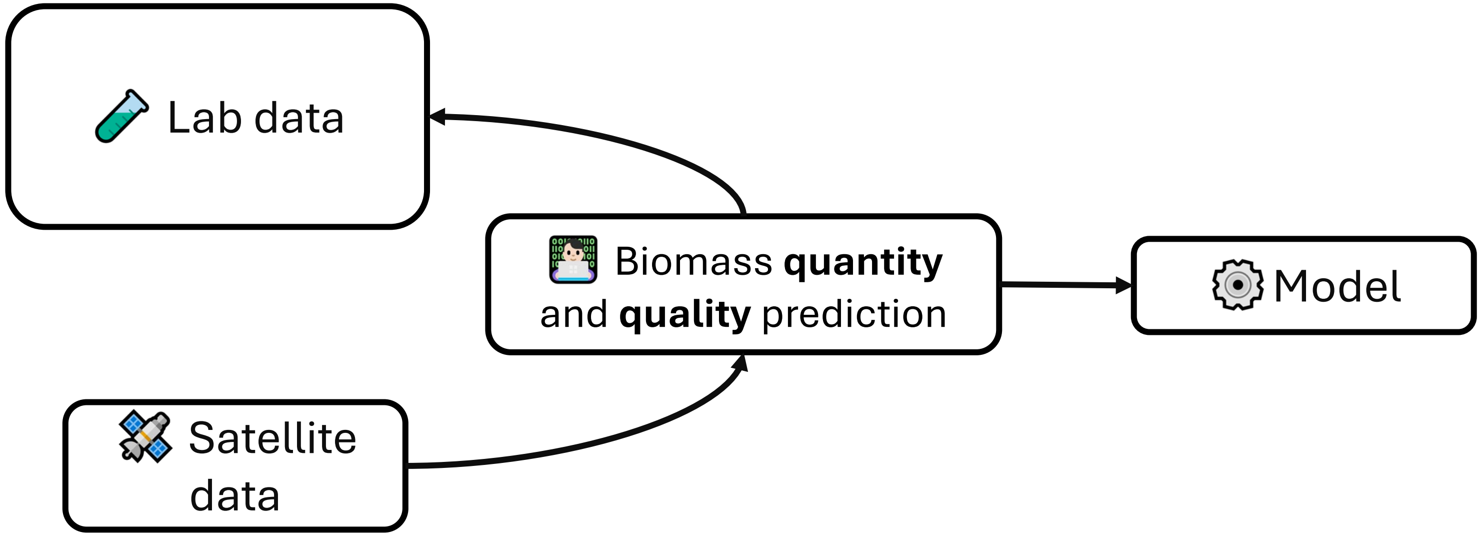


Satellite data

Our research question

- The main goal of the project is to develop a **Decision Support System** (**DSS**) that enables farmers to make short-term decisions, directing livestock to pasture areas with higher feed quantity and quality
- By integrating lab data on biomass with satellite imagery, the **tool will predict biomass availability**





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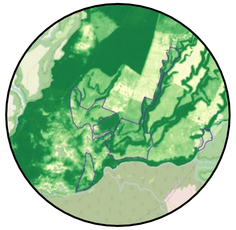
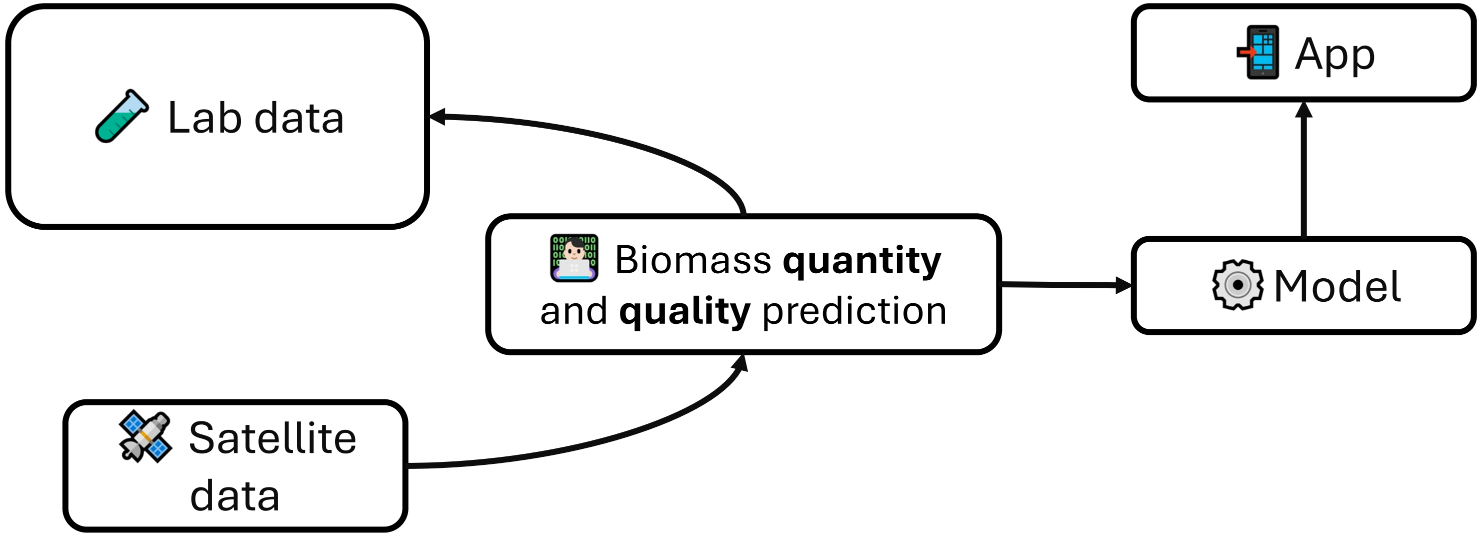
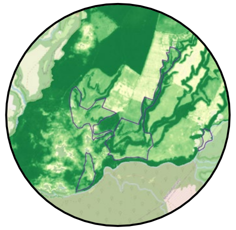
- By integrating lab data on biomass with satellite imagery, the **tool will predict biomass availability**
- This **DSS** could be offered as a mobile application for farmers

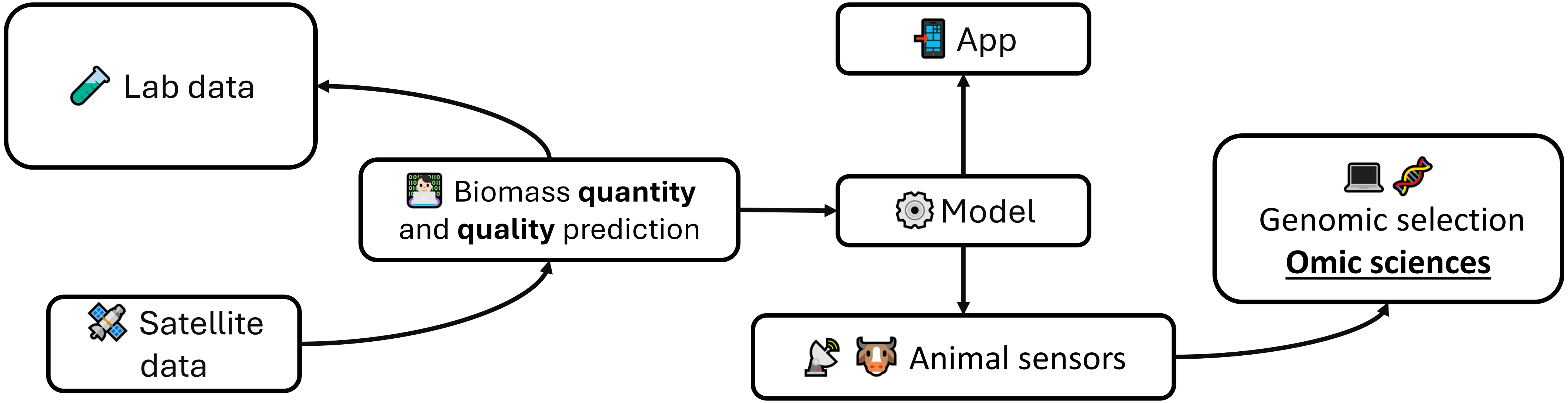




Our research question

- The main goal of the project is to develop a **Decision Support System** (**DSS**) that enables farmers to make short-term decisions, directing livestock to pasture areas with higher feed quantity and quality
- By integrating lab data on biomass with satellite imagery, the **tool will predict biomass availability**
- This **DSS** could be offered as a mobile application for farmers
- Additionally, combining this information with other data sources (e.g., animal sensors, video) can refine **genetic breeding programs** by identifying and characterizing animals that respond differently to environmental challenges using 'omics' technologies.





Our research question

- The model was initially developed for the **EU Sebastien Project** Service
- The model will be enhanced and applied in the **Agritech project**, within the FLAGSHIP solution between **tasks 5.1.2 and 5.2.3**.

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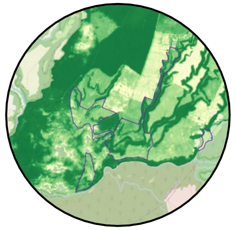
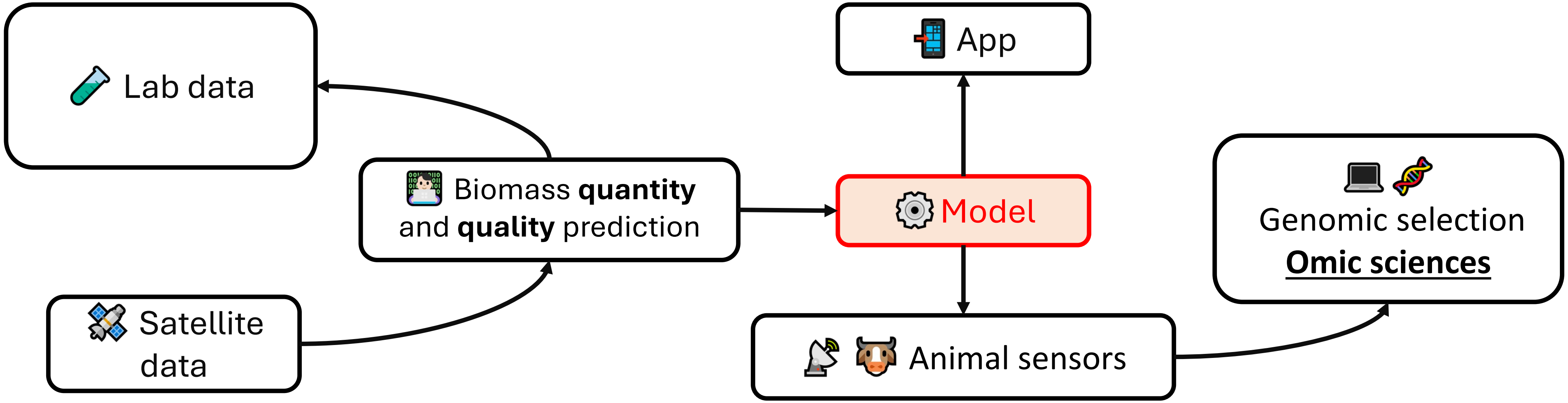
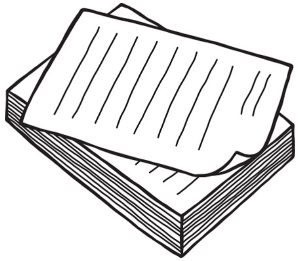




Methods
Data collection



- Data were collected from June 2023 to May 2024 at three farms in northern Lazio (Italy)
- 🧪 the pasture samples were analyzed through laboratory analyses

- **Farm A**: 124 samples
- **Farm B**: 116 samples
- **Farm C**: 27 samples

Sampling:

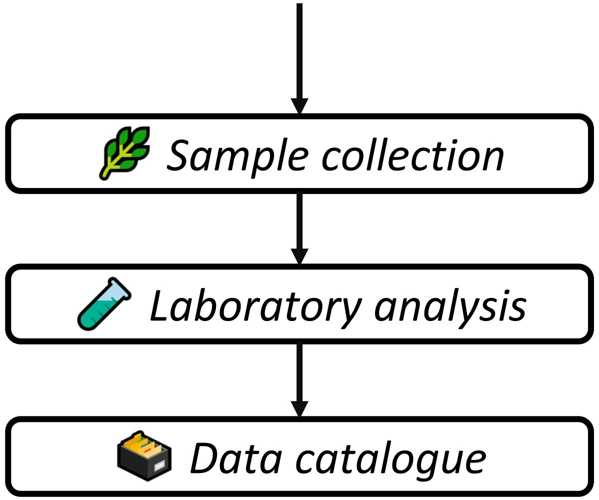
- 🏠 on three different fields…
- 🍀 …with different floreal characteristics;
- 📍 in different areas for each farm;
- 📅 in different seasons of the year;

Methods
Data collection

- Laboratory analyses

For each sample:

- Latitude and Longitude (WGS84)
- Date (YYYY-MM-DD)
- Fresh grass (kgDM*ha^{-1})
- Dry matter (kg*ha^{-1})
- Ashes (%)
- Crude Proteins (%)
- Lipids (%)
- aNDFom (%)
- ADF (%)
- ADL (%)
- FIBER (%)



Sampling:

- 9 samples for each farm for each date
- Area of 5 m^2
- NDVI for 3 comparable sampling areas

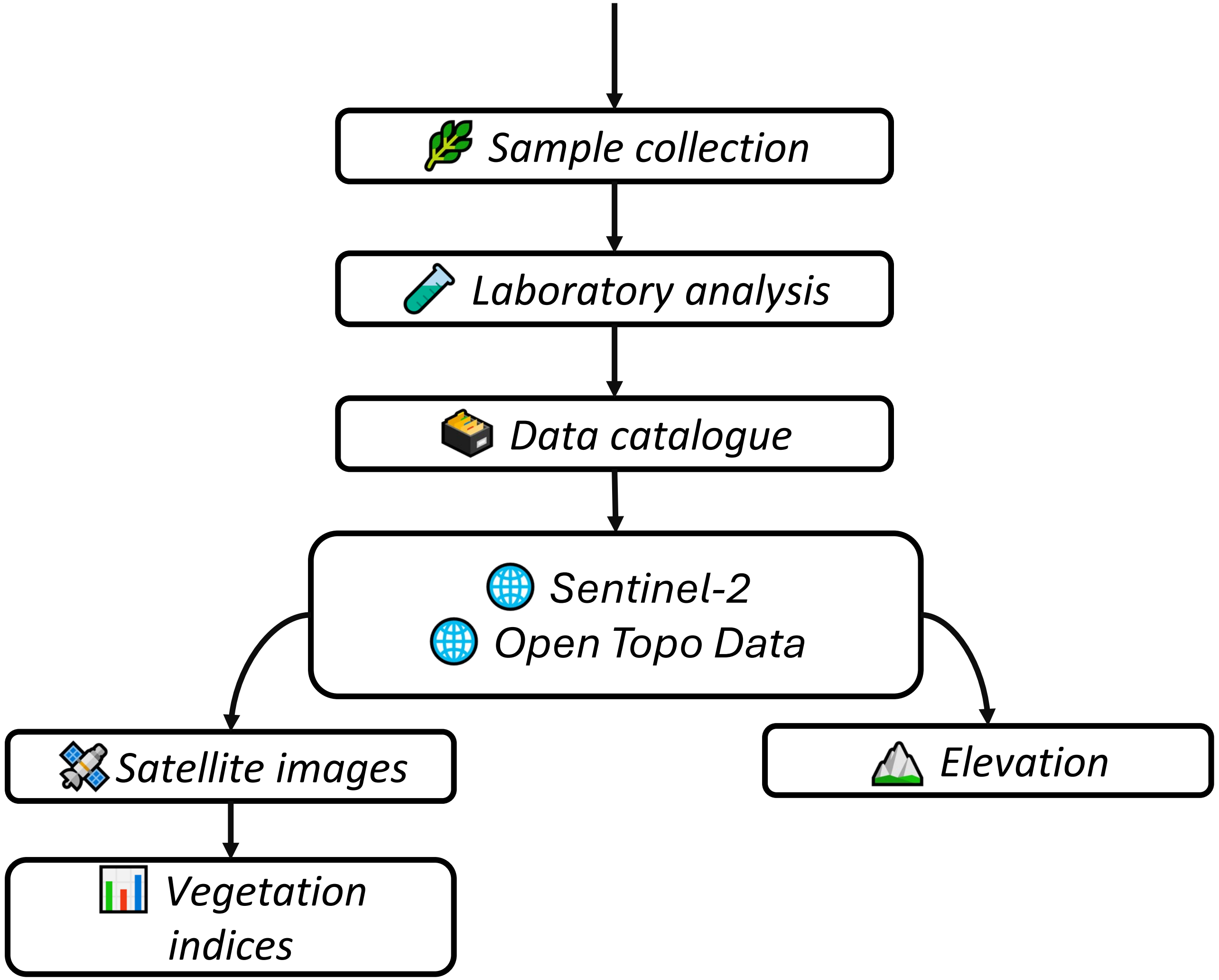
Methods Pipeline

- 🧪 Laboratory analyses
- 🖥 Computational approach

These information:

- 🗺 Latitude and Longitude (WGS84)
- 📅 Date (YYYY-MM-DD)

Where used to retrieve **elevation** and **vegetation indices** for each sampling point



Methods
Our pipeline

Features

- Seasons
  - winter, spring, summer, autumn
- Sentinel-2 spectral bands
  - B02, B03, B04, B08, B08, B08A, B12
- Vegetation indices
  - NDVI, NDWI, GCI, ARVI
- Elevation data (meters)

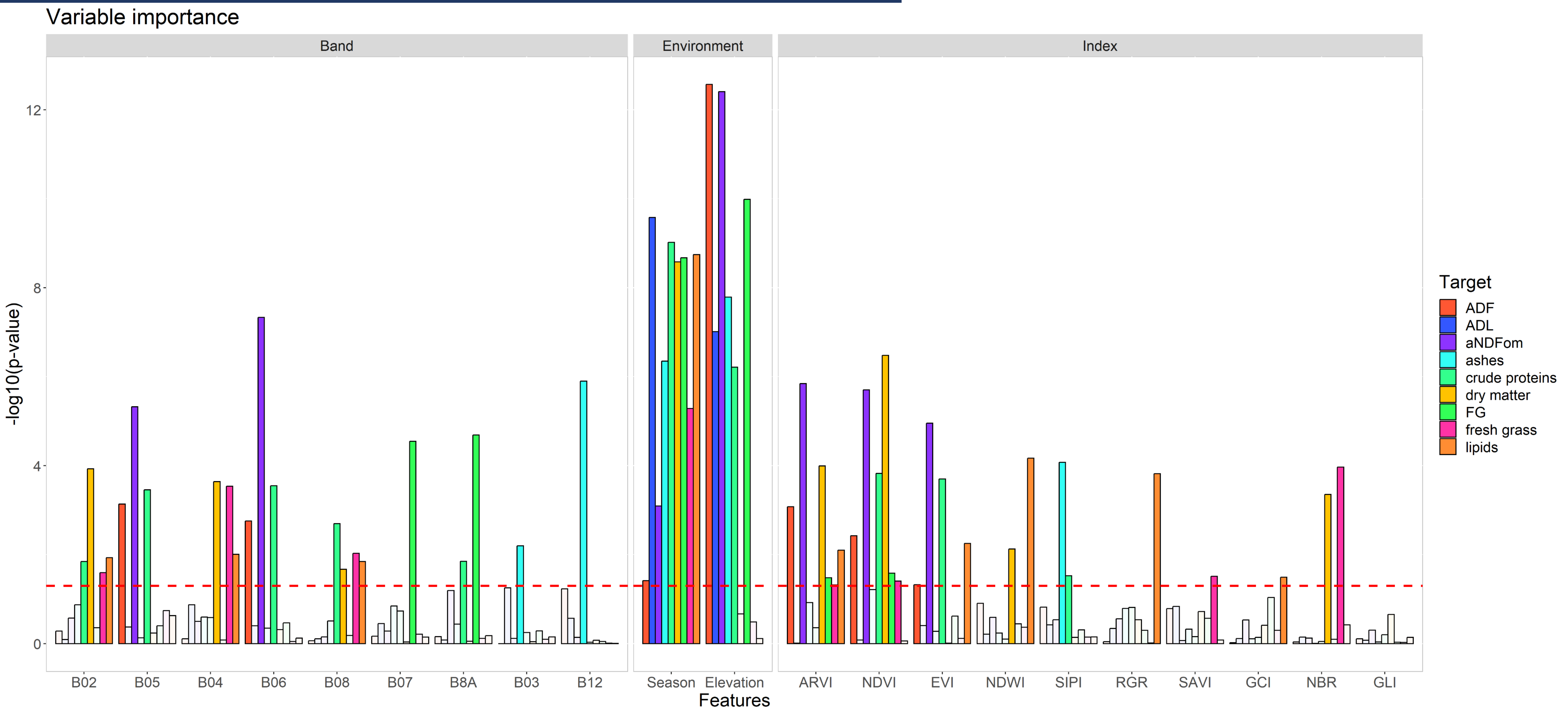
Used to **predict**

Targets

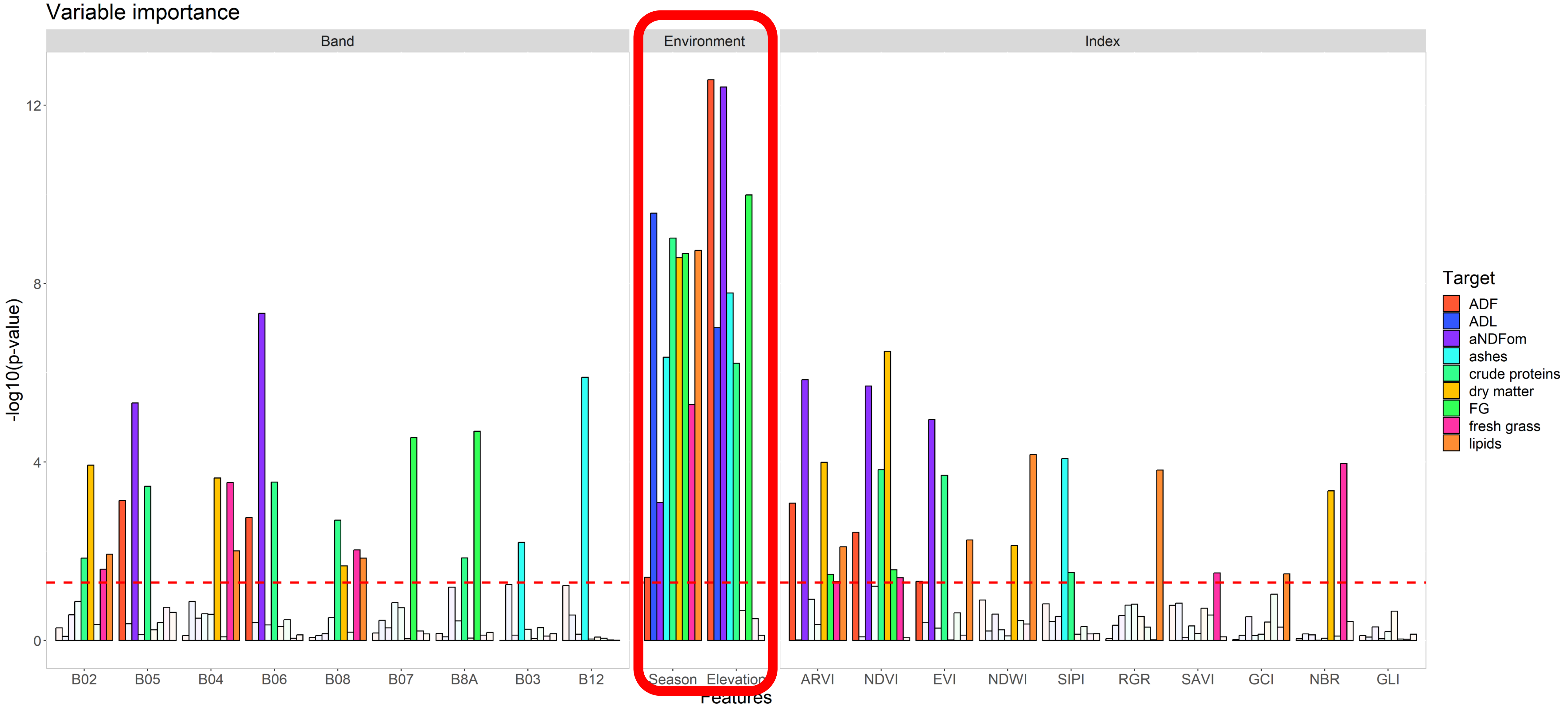
- Fresh grass ($kgDM*ha^{-1}$)
- Dry matter ($kg*ha^{-1}$)
- Ashes (%)
- Raw Proteins (%)
- Lipids (%)
- NDF (%)
- ADF (%)
- ADL (%)
- FG (%)

Methods
Our pipeline

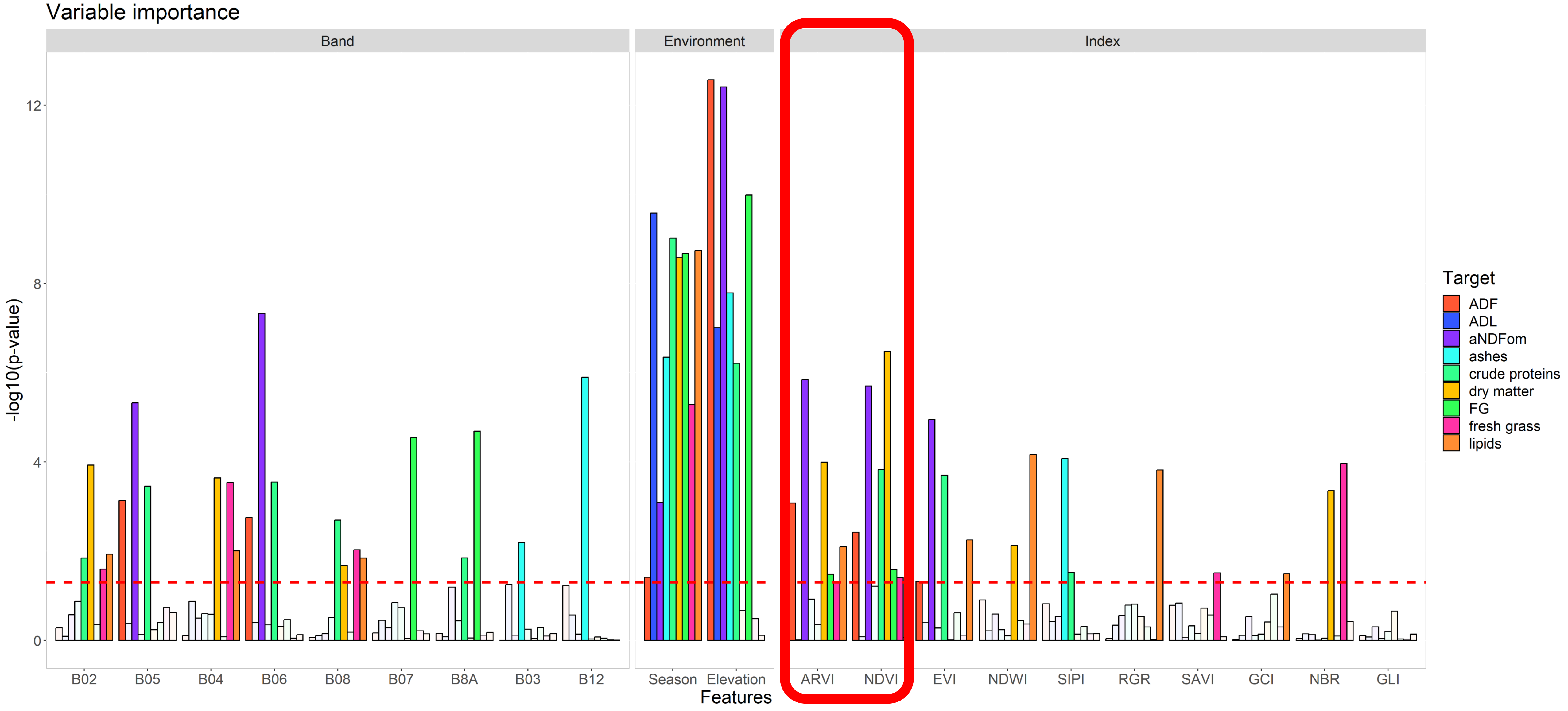
1. Removal of outlier data
2. Evaluate the importance of all variables to subset the most important ones
3. Perform Linear Regression Analysis
4. Evaluate the model



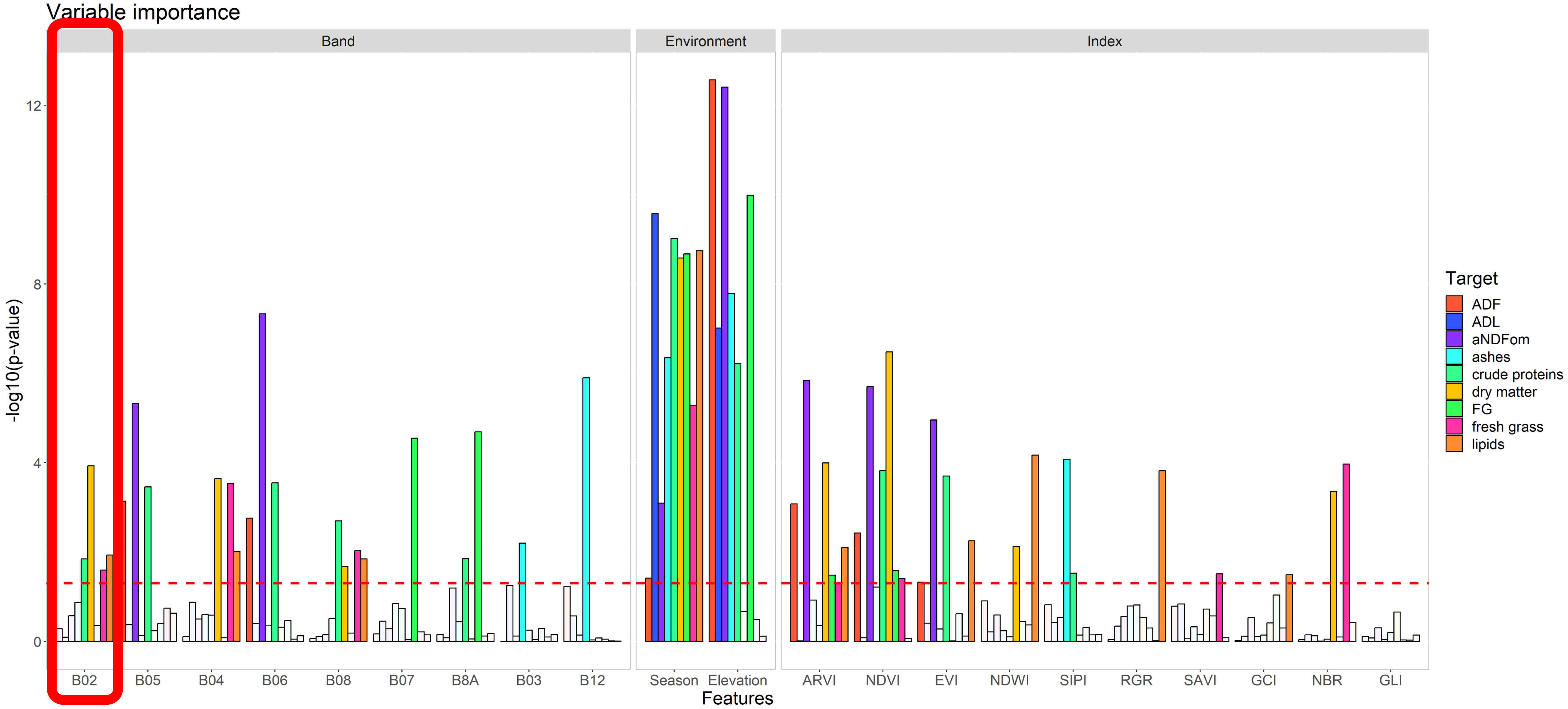
The importance of the features in the prediction was compared across all targets



Among all variables, **the season and elevation proved to be the most important**. Season appears in all variables, while elevation is important for all variables except dry matter and fresh matter



Among the indices, **ARVI** and **NDVI** are present in the models for 6 out of 9 variables.



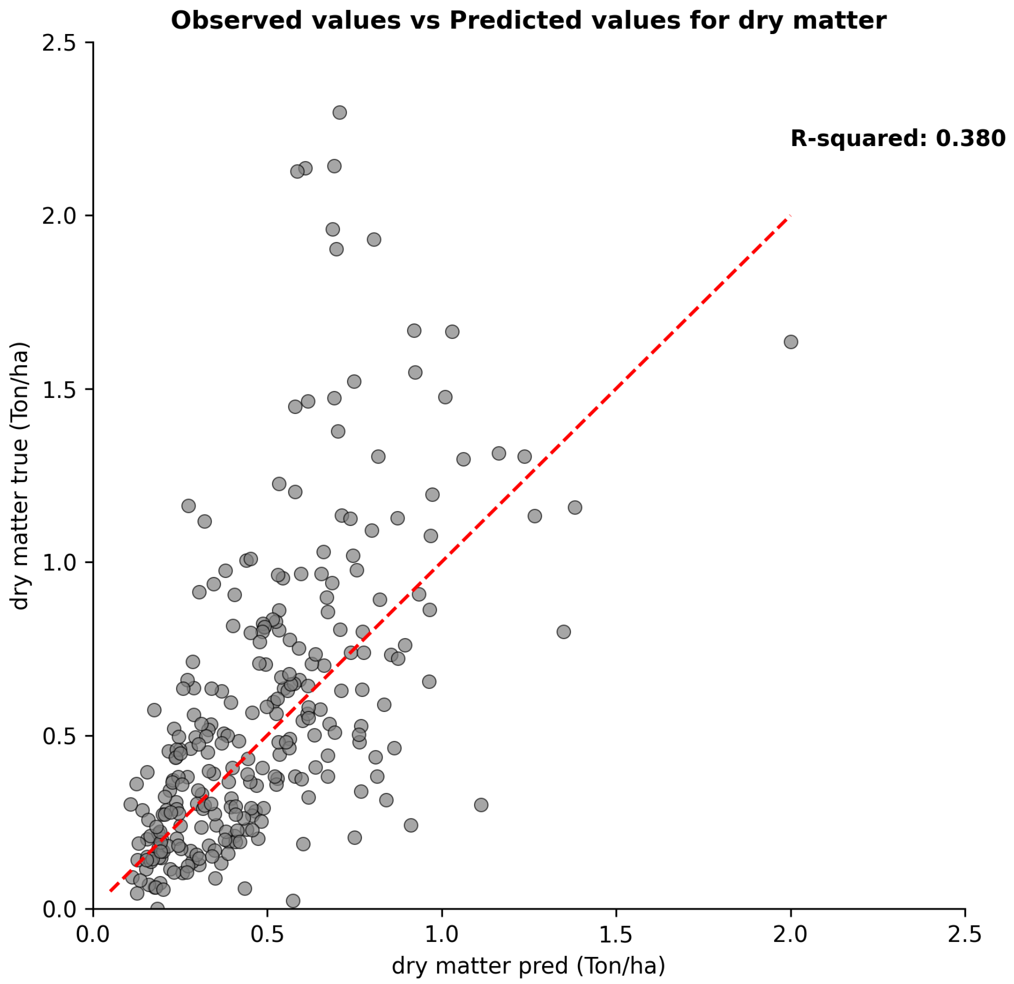
Among the bands, the most relevant one turned out to be **B02** (4 variables)

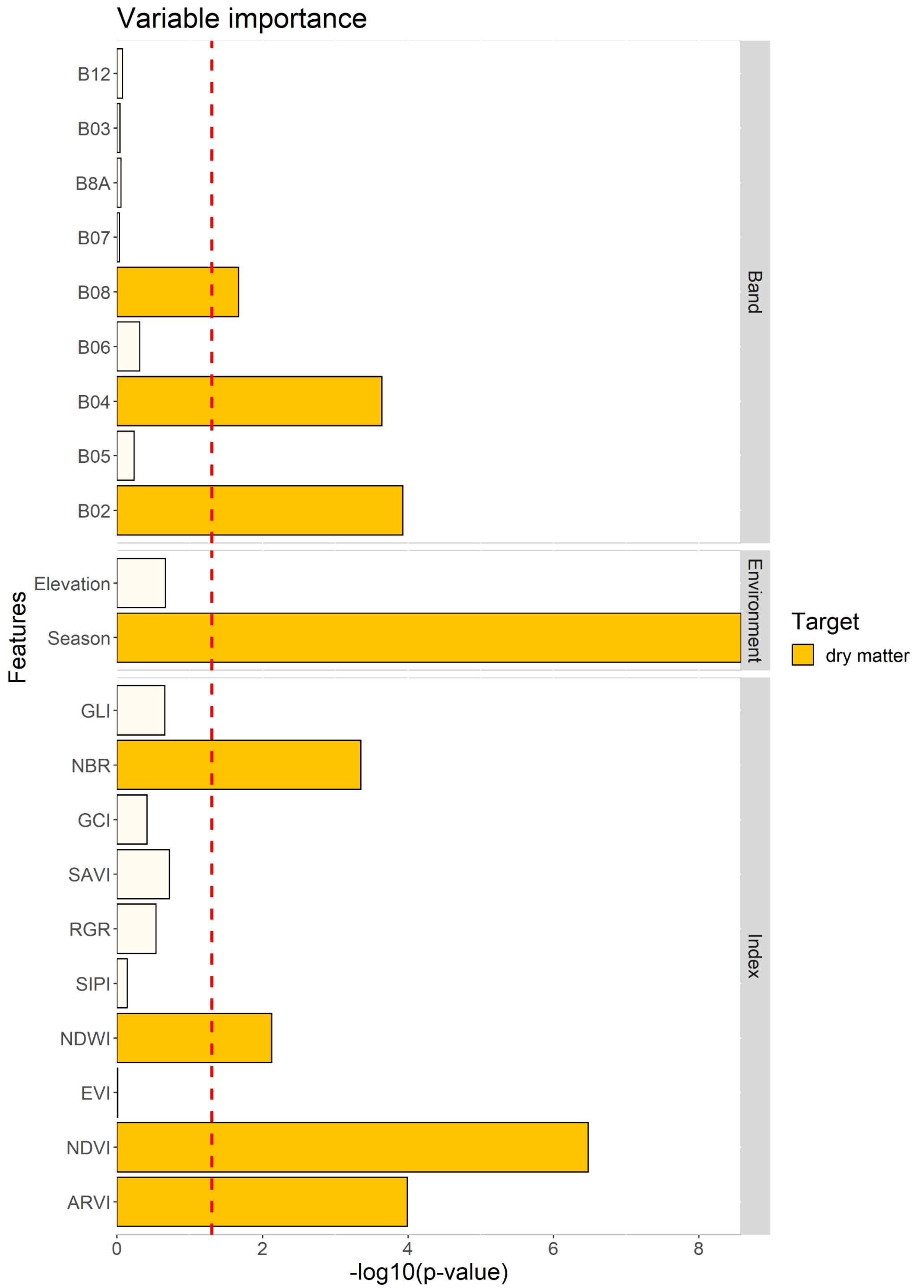
Results

- The pipeline results show the following R^2 and MAE (Mean Absolute Error) values for the target variables. <u>In all cases, the real model outperforms a naive random model</u>

Target	«real» MAE	«naive» MAE	R^2
🌿 Fresh grass	0.86	1.21	0.32
🧈 Dry matter	0.24	0.33	0.38
☁ Ashes	2.08	2.58	0.33
Crude Proteins	4.46	6.74	0.51
Lipids	0.40	0.54	0.40
🐄 aNDFom	7.95	10.74	0.44
🐄 ADF	6.25	7.96	0.35
🐄 ADL	2.41	2.81	0.29
🐄 FIBER	5.30	7.07	0.46

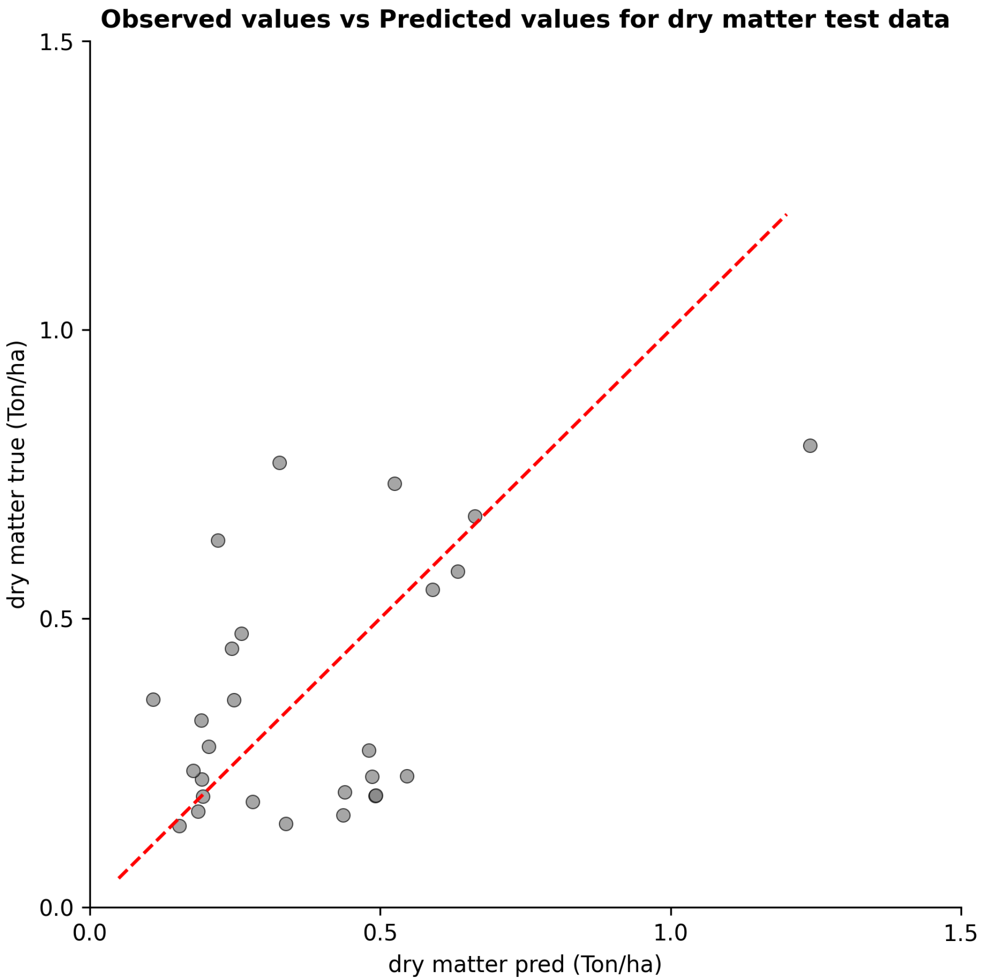
Results

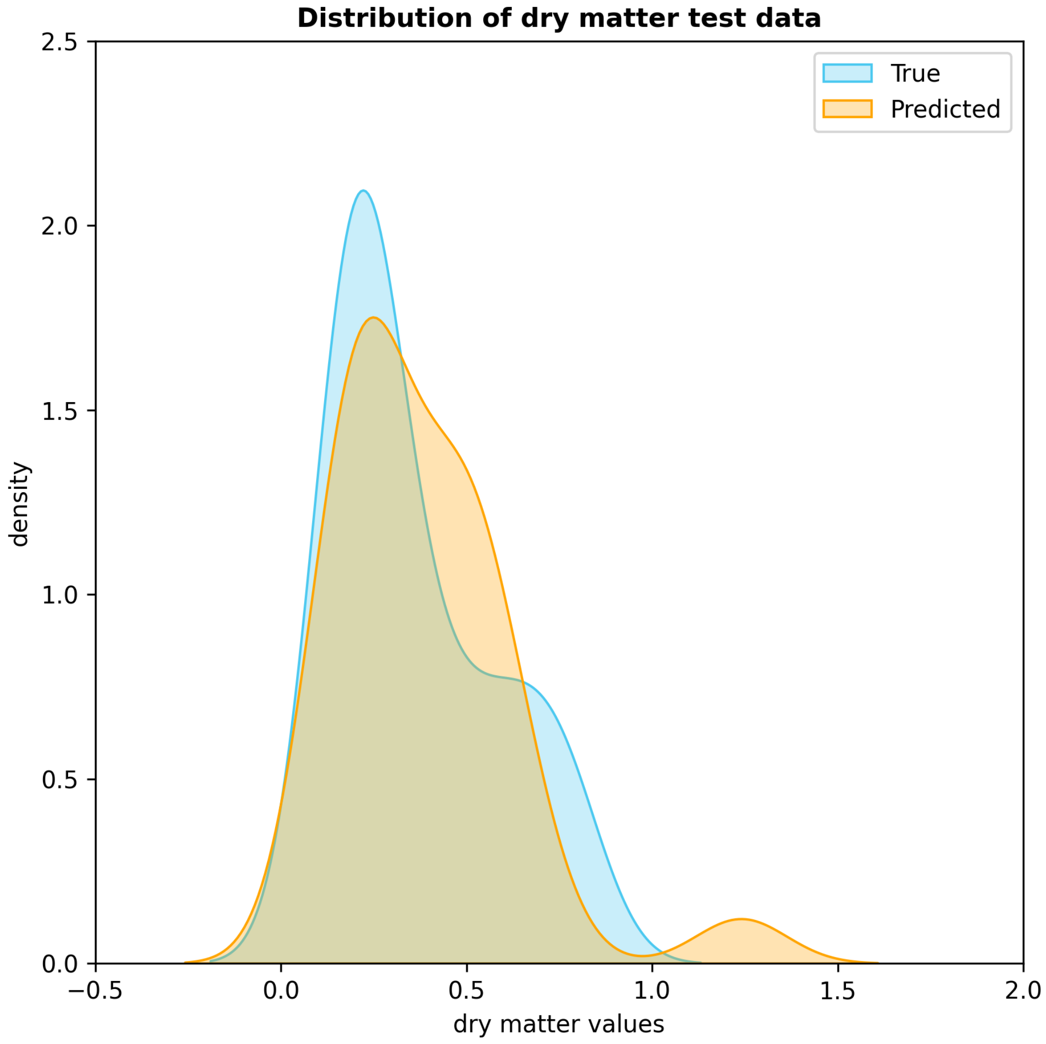

Observed values vs Predicted values for dry matter
R-squared: 0.380
dry matter true (Ton/ha)
dry matter pred (Ton/ha)
0.0
0.5
1.0
1.5
2.0
2.5


Variable importance
Features
Band
B12
B03
B8A
B07
B08
B06
B04
B05
B02
Environment
Elevation
Season
Index
GLI
NBR
GCI
SAVI
RGR
SIPI
NDWI
EVI
NDVI
ARVI
-log10(p-value)
0
2
4
6
8
Target
dry matter

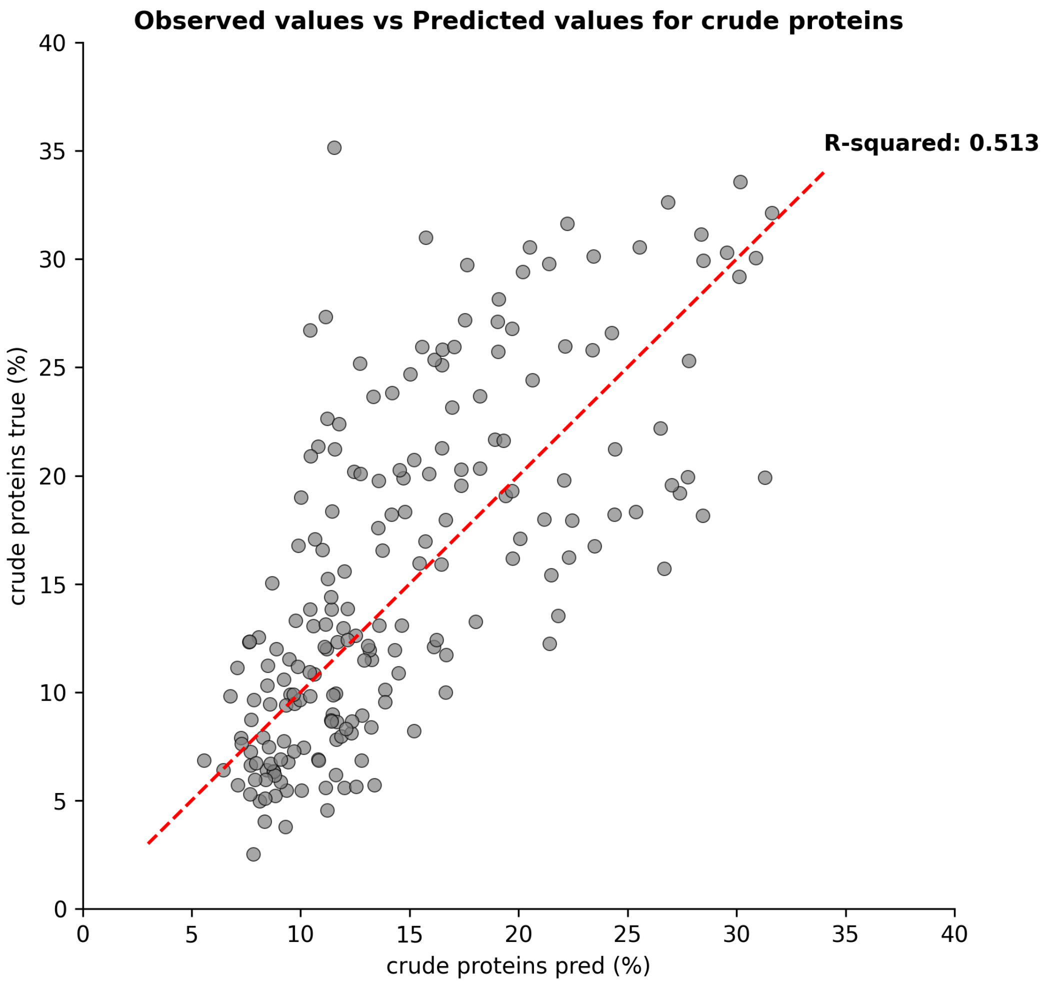
Results

Real dry matter	0.36±0.21
Predicted dry matter	0.38±0.23

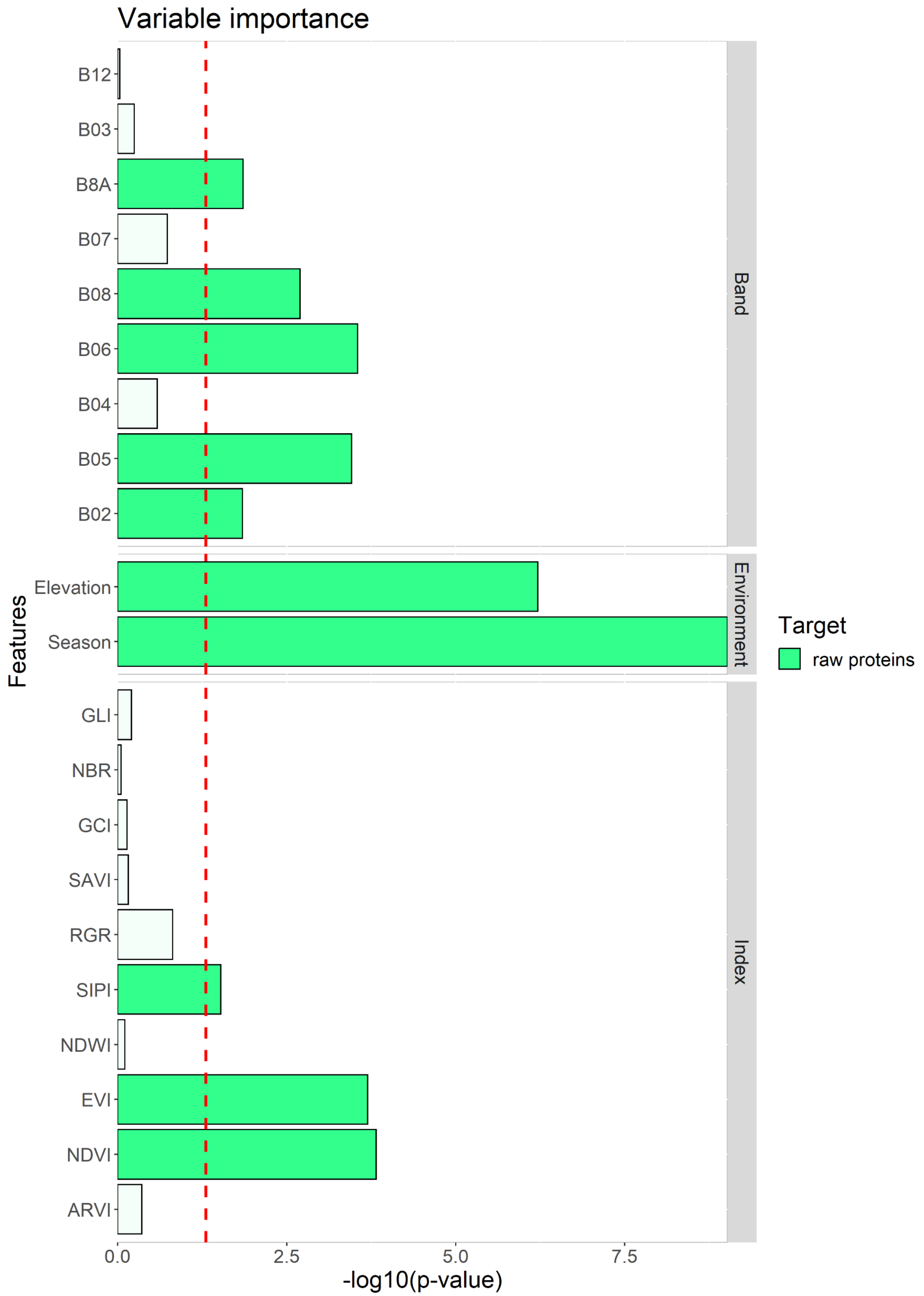




Results



Observed values vs Predicted values for crude proteins
R-squared: 0.513
crude proteins true (%)
crude proteins pred (%)
0
5
10
15
20
25
30
35
40



Variable importance
Features
B12
B03
B8A
B07
B08
B06
B04
B05
B02
Elevation
Season
GLI
NBR
GCI
SAVI
RGR
SIPI
NDWI
EVI
NDVI
ARVI
Band
Environment
Index
Target
raw proteins
0.0
2.5
5.0
7.5
-log10(p-value)

Results

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- dds.sebastien-project.eu

A

Fresh grass	446.27 ton
Dry matter	46.96 ton

B

Fresh grass	79.55 ton
Dry matter	6.95 ton

Discussion

- This is the first effort to develop statistical methodologies and models for the analysis of different soil types from **multiple farms**, with **annual data collection** and a wide variety of crop types

- Given the integration of different types of data, the accuracy level (R^2) is lower than that reported in the literature (**Akari et al., 2019**). However, **this study demonstrates that it is possible to create a generalized system for data analysis**, whose accuracy can improve with the collection of new data (**Ara et al., 2019**)

- The model also accounts for the effect of the season, a known factor in determining pasture characteristics (**Ara et al., 2019**)

Next steps

- The next steps in the model's development include:

- 🌿 collecting a larger number of samples to improve the model's accuracy
- ⚙️ applying artificial intelligence methods and multitarget prediction techniques
- 📲 add the prediction of biomass quality parameters to the application
- 🧬 Combining this information with other sensors to study the animals' phenotype, identifying those that consume more or less pasture and under specific conditions. These studies can serve as a basis for characterizing the animals through omics sciences

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Spoke 5: Sustainable productivity and mitigation of environmental impact in livestock systems

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THE CONSORTIUM

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Coordinator: Fondazione Centro Euro-Mediterraneo sui Cambiamenti Climatici (CMCC)

Topic: Public Open Data (POD) – Type of action: CEF-TC-2020-2

Duration: 30 months - Starting date: Jan 2022

Total budget: € 1.338.553,18

Total CEF Contribution: € 1.003.914,89

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Agreement No: INEA/CEF/ICT/A2020/2373580
Action No: 2020-IT-IA-0234

Supplementary data

Take-home message

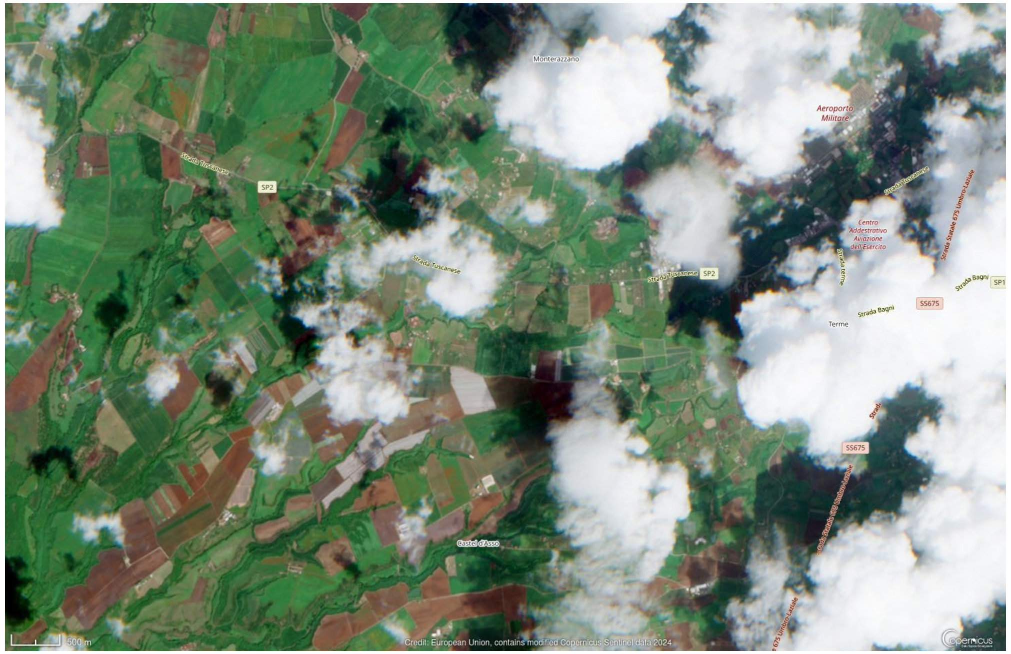
An **automated model** for the analysis of pasture quality and quantity data was created, based on **remote sensing**

The model is based on the analysis of **annual field data**, integrating information from **different farms**.

The most important features were identified, highlighting the effect of the **season**, the **vegetation indices**, and the **bands**

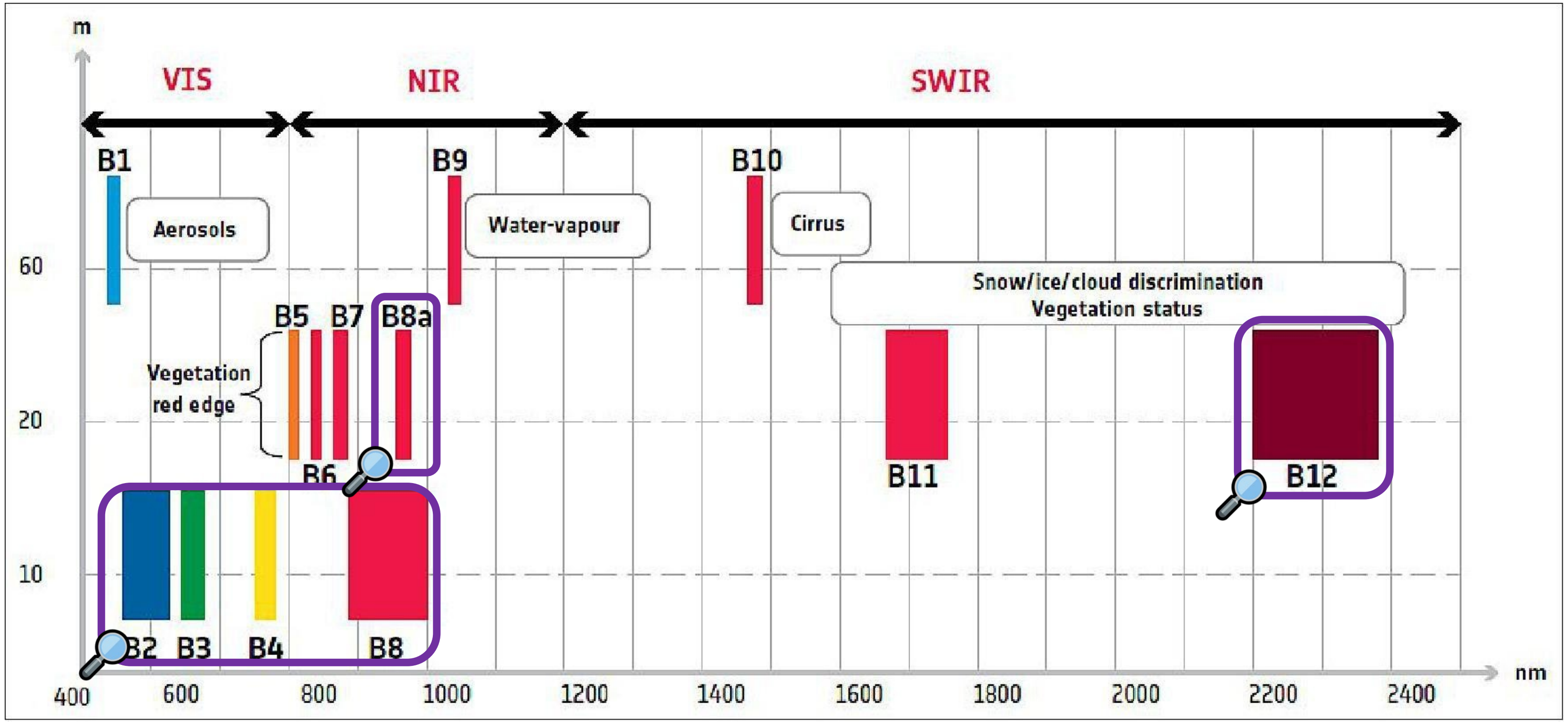
Methods
Filtering data

- Outlier values for biomass quantity and quality, with values three times higher than the standard deviation
- Data for which it was not possible to calculate bands and indices with Sentinel-2 due to cloud cover (>30%) (***Askari et al., 2019***)



Methods
Vegetation indices 🍃📊

- Vegetation indices delineate subtle changes in **spectral signatures** caused by variations in **plant health** and **density** that cannot be distinguished by the human eye



Methods
Bands🍃 📊

Band	Resolution (m(px)	Range (nm)	Used to
B01 (areosol)	60	443±20	Identify aereosol
B02 (blue)	10	490±60	Soil and vegetation identification
B03 (green)	10	560±35	Water (muddy vs clear), Oil in water and vegetation
B04 (red)	10	665±35	Dead foliage, vegetation type
B05 (red edge)	20	705±15	Classify vegetation
B06	20	740±15	Classify vegetation
B07	20	783±20	Classify vegetation
B08	10	842±115	Classify vegetation
B08A	20	865±20	Classify vegetation
B09	60	945±20	Water vapour
B10	60	1375±30	Cloud Detection
B11	60	1610±90	Moisture content and soil vegetation
B12	20	2190±180	Moisture content and soil vegetation

Methods
Vegetation indices 🍃 📊

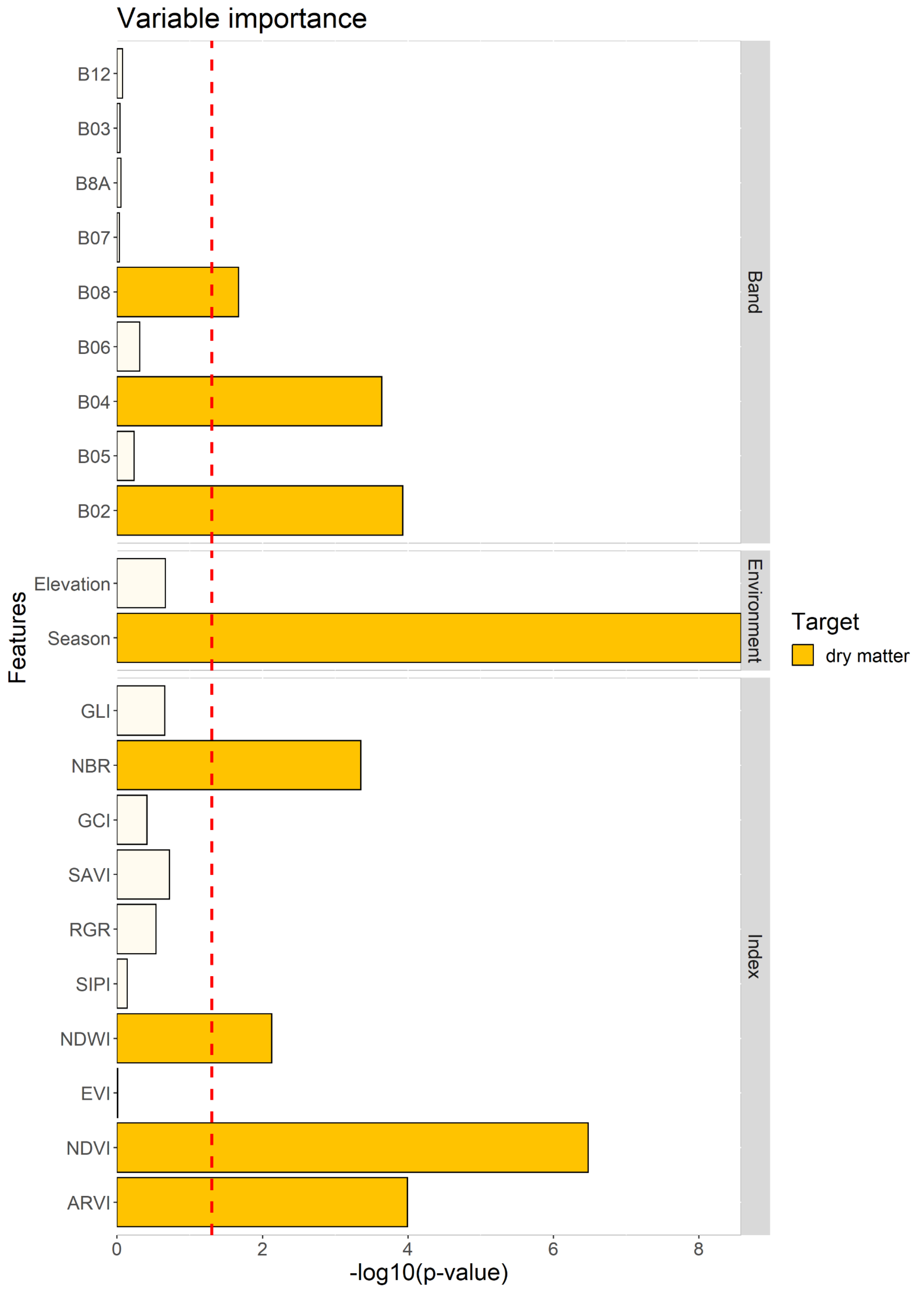
- Normalized Difference Vegetation Index (**NDVI**) $NDVI = (B08 - B04)/(B08 + B04)$
- Normalized Difference Water Index (**NDWI**) $NDWI = (B03 - B08)/(B03 + B08)$
- Green Chlorophyll Vegetation Index (**GCI**) $GCI = (B08)/(B03) - 1$
- Atmospherically Resistant Vegetation Index (**ARVI**) $ARVI = \frac{[B08A - B04 - 0.069(B04 - B02)]}{[B08A + B04 - 0.069(B04 - B02)]}$
- Green Leaf Index (**GLI**) $GLI = \frac{[2*B03 - B04 - B02]}{[2*B03 + B04 + B02]}$
- Simple Ratio Red/NIR Ratio Vegetation-Index (**RGR**) $RGR = B04/B03$
- Soil Adjusted Vegetation Index (**SAVI**) $SAVI = \frac{(B08 - B04)(1 + 0.725)}{(B08 + B04 + 0.725)}$
- Enhanced Vegetation Index (**EVI**) $EVI = \frac{2.5(B08 - B04)}{[B08 + 6*B04 - 7.5*B02] + 1}$
- Structure Insensitive Pigment Index (**SIPI**) $SIPI = (B08 - B02)/(B08 - B04)$
- Normalized Burn Ratio (**NBR**) $NBR = (B08 - B12)/(B08 + B12)$

Methods
Vegetation indices 🍃 📊

Index	Sentinel-2 bands	Range	Function
NDVI	B04, B08	[-1, +1]	Proxy for greeness, crop growth and vegetation cover (**Farias**). Negative values correspond to water, values close to 0 correspond to rocks, snow and sand. Positive values correspond to grassland (0.2-0.4) and forests (close to 1) (**Sentinel-2**)
NDWI	B03, B08	[-1, +1]	Takes into account water content in vegetation, green healthy vegetation has values between 0.02 and 0.6 (**Pignarolo**)
GCI	B03, B04	[-1, +1]	Estimation of canopy chlorophyll content (**Wu**)
ARVI	B02, B04, B08	[-1, +1]	Used to estimate the Aeresol content. The range for an ARVI is -1 to 1 where green vegetation generally falls between values of 0.20 to 0.80. (**Sentinel-2**). Aimed to reduced the atmospheric effect (**Karnieli**)
GLI	B02, B03, B04	[-1, +1]	Used to estimate the Chlorophyll content (**Wu**)
SAVI	B04, B08	[-1, +1]	Used to reduce the soil effect (**Piragnolo**, **Karnieli**)
SRR/NIR	B03, B04	[0, +Inf)	Estimates the amount of green vegetation. Values close to infinity indicating a high amount of vegetation.
EVI	B04, B08	[-1, +1]	Highly sensitive to the dense canopy of dense forests, as well as resistant to the effects of dark soils, the atmosphere and residual clouds (**Villanueva**)
SIPI	B02, B04, B08	[0, 2]	Characterizes the photosynthetic activity and pigment concentration in vegetation. It is less influenced by variations in canopy structure, and it provides a more direct measure of vegetation productivity and biomass (**Vahidi**). SIPI values range from 0 to 2, where healthy green vegetation ranges from 0.8 to 1.8 (**Sentinel**)
NBR	B08, B12	[-1, +1]	Used to identify burned areas, range between -1 and +1 (**Alcaras**)

Results

- The **NDVI** index showed strong correlations with DM in soybeans (***Rodigheri et al., 2020***) and corn (***Janousek et al., 2023***).
- The **ARVI** in demonstrated high correlations with NDVI, suggesting their potential as alternatives for biomass-related studies (***Aliyu et al., 2022***)
- Also the **NDWI** index was previously identified as a good predictor for biomass (***Serrano et al., 2019***)
- The **B02 (Blue)**, **B04 (red)** and **B08 (NIR)** bands were also evaluated as good predictors for dry pasture biomass (***Fernandes et al., 2020***)



Results

- The **NDVI**, **EVI**, and **SIPI** indices have previously been identified as predictors of nitrogen content in plants (***Fernandes et al., 2024***; ***Pandey et al., 2022***).

- Wavelengths within the **B02 (blue)** and **B05 (Red Edge 1)** bands have recently been proposed as predictors of nitrogen content in pastures and predicting crude proteins (***Zhao et al., 2018; Askari et al., 2022***)

- We also reported the role of **Season** and **Elevation** in predicting the protein content