



Evaluation of the most scalable, accurate and cost trade-offs machine learning framework to estimate the Mediterranean wood-pasture yield

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Abstract

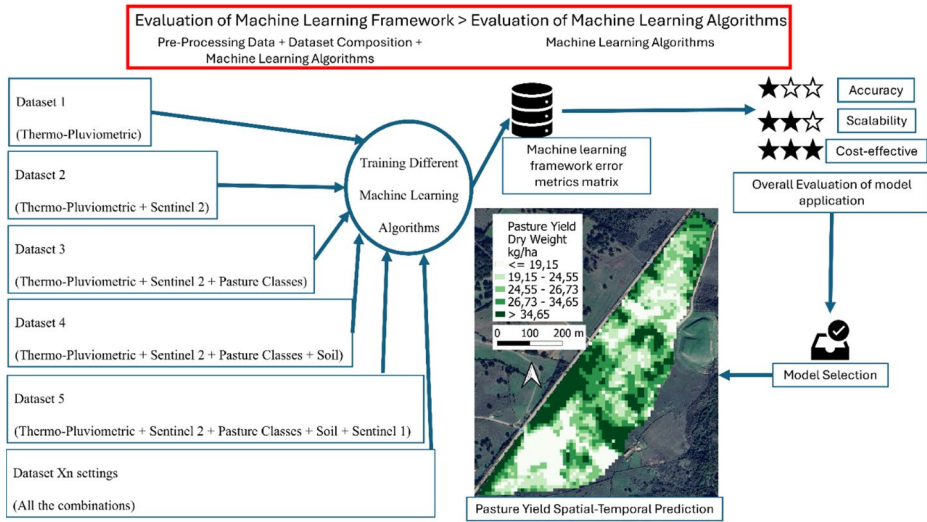
Purpose Sustainable grazing management requires precise knowledge of daily nutritional requirements and the quantity and quality of pasture dry matter. Combining multiple data sources with machine learning models can create accurate predictive systems to optimize feeding, cut expenses, and maintain pasture productivity, helping farms stay economically viable long-term.

Methods This study evaluated 69 machine learning models—combinations of three algorithms and 23 datasets including thermo-pluviometric, pasture classification, Sentinel 1 & 2, and soil data—from a one-year study on two Mediterranean wood-pasture fields located in Sardinia (Italy). The models were compared for accuracy, scalability, and application cost to identify the most effective framework for predicting pasture and grazing conditions.

Results The most accurate framework used the Ensemble Learner (EL) algorithm with thermo-pluviometric, Sentinel-2 and pasture classification data, achieving RMSE 469.92 kg·ha⁻¹ DW, MAE 402.61 kg·ha⁻¹ DW and R² 0.98, but is impractical at large scale because pasture classification inputs require highly qualified staff and time-consuming on-site surveys. A scalable, zero-cost alternative uses EL with thermo-pluviometric and Sentinel-2, with comparable error metrics.

Conclusions Research should focus on the whole Machine Learning workflow, from problem definition and covariate selection to preprocessing and evaluation rather than algorithms alone. Reliable pasture-yield modeling should include at least the thermo-pluviometric and Sentinel-2 multispectral data. Future work will apply models to estimate yield, map management zones, and generate grazing-rotation prescription maps using measured pasture utilization.

Graphical Abstract



Keywords Machine learning · Multi data source · Precision livestock farming · Model scalability · Cost-effective covariates

Introduction

Wood-pastures are important components of the Mediterranean landscape and play a key ecological role, covering roughly 20.3 million hectares in the EU—about 4.7% of its land area—with 15.1 million hectares under grazing (García de Jalón et al., 2018). Nowadays, many grazing systems require supplementary feeding to meet livestock nutritional needs, driven by factors such as climate change (Martins-Noguerol et al., 2023), pasture encroachment by woody vegetation as human presence in pastoral areas declines, and reduced pasture yields. Supplementary feeding increases farm costs and should be applied only when pasture production cannot sustain stocking rates (Tozer et al., 2004). Consequently, from both economic and environmental perspectives, optimizing pasture management to minimize reliance on supplementary feed is essential (Hills et al., 2015).

Efficient and sustainable pasture management requires reliable monitoring of above-ground biomass, a key indicator of grassland sensitivity to climatic variation and human pressures such as overgrazing and land degradation. This need is particularly acute in marginal, drought-prone Mediterranean wood-pastures, where limited precipitation threatens productivity and persistence (Daliakopoulos et al., 2017).

Nowadays, field-based monitoring tools such as pasture probes are used. However, they come with several challenges, including the cost of purchasing equipment, the need for user training, on-site calibration requirements, and the expenses associated with large-scale implementation. In addition, monitoring operations can be time-consuming (Ghajar & Tracy, 2021).

Remote sensing is the most widely used approach for estimating pasture biomass because of its spatial and temporal coverage, cost-effectiveness, accessibility, and capacity to deliver consistent vegetation productivity data (Furnitto et al., 2025). Comparative studies show that proximal (field-based) sensors provide very high-resolution point measurements but lack spatial representativeness and demand intensive fieldwork and repeated campaigns (Gargiulo et al., 2023). For small plots or calibration purposes, proximal sensing is valuable; but for landscape-scale monitoring, UAV and satellite remote sensing are better suited to provide representative, comparable data across large areas (Orsini et al., 2019). Typically, satellite and UAV observations from thermal, multispectral, hyperspectral and SAR sensors are calibrated against georeferenced proximal measurements—such as herbometers and pasture meters—to improve biomass estimates (Adar et al., 2023).

Vegetation indices derived from remote sensing can be confounded by external factors including soil properties, agronomic management, cloud cover and climatic variability (Orsini et al., 2020; Pettorelli et al., 2014). The scattered nature of wood-pastures requires quantifying woody cover and its spatial distribution, since trees, shrubs and mixed grass species complicate classification and can cause vegetation indices to be confused with bare soil or surface water (Clementini et al., 2020). Integrating multiple data sources—such as meteorological records, satellite and UAV imagery, soil data (including physical, chemical and biochemical properties such as microbial composition), and pasture classification maps—can improve aboveground biomass estimates by combining remote observations with field measurements (Sanna et al., 2021).

To assess the yield and quality of pasture yield fields it is also important to measure categorical data such as pasture and floristic classification (Zwick et al., 2024). Those measurements by their nature are difficult to use in a linear regression because they can lead to very low error metrics. To overcome these limitations, merging data that differ in measured variables, units, and spatio-temporal resolution remains a significant challenge, for which Artificial Intelligence can provide valuable support. Artificial-intelligence methods, including machine-learning algorithms, are widely used to integrate heterogeneous datasets and to model nonlinear relationships between predictors and biomass (Chlingaryan et al., 2018; Chollet & Allaire, 2018; Fiorentini et al., 2022). Recent studies demonstrated the potential of machine learning to improve pasture yield estimation: examples include Landsat-8 combined with machine learning (Huang et al., 2024), models that simulate pasture yield across environments to identify limiting factors (Chasen et al., 2025), and Sentinel-2 based predictions of tropical forage quality and composition (Fernandes et al., 2024; Stumpe et al., 2024).

However, spectral reflectance from satellite imagery results from multiple interacting factors—climate, soil, pasture classification, management practices and phenological stage—therefore satellite data alone often cannot fully capture actual biomass or yield (Fiorentini et al., 2024). Therefore, instead of focusing solely on testing machine-learning models, the attention should shift to the entire workflow: starting from precise problem definition and covariate selection, through careful preprocessing of training data, to robust evaluation of predictive performance (Zhang et al., 2022). In other words, both datasets and algorithms must be assessed together, rather than evaluating algorithms in isolation on a single dataset.

In this perspective, model evaluation should extend beyond purely statistical performance metrics to include also considerations on feasibility, scalability, and real-world applicability. Minimizing errors such as RMSE and MAE or maximizing R^2 remains important (Raschka,

2020), but these objectives do not ensure that a model can be effectively deployed at scale. In practice, approaches that are highly optimised under controlled conditions may prove impractical when confronted with heterogeneous environments, limited data availability, or operational constraints. Therefore, we advocate for a more holistic assessment framework in which predictive accuracy is complemented by criteria such as data requirements and data acquisition costs, ease model transferability and implementation (Rainio et al., 2024).

Assessing the relative value of different data types is crucial for developing cost-effective, scalable models for pasture yield estimation that minimize—or eliminate the need for extensive in-situ sampling. Satellite and meteorological data can often be acquired remotely via APIs and web services, whereas pasture classification and soil data typically require labor-intensive field sampling and laboratory analyses. For upscaling models to regional extents, the preferred predictors are therefore those that are readily accessible and have the highest feasible spatial and temporal resolution. Accordingly, this study aims to calibrate and validate multiple machine-learning frameworks—combining different algorithms and multi-source datasets—to identify the most accurate, scalable, timely and cost-effective approach for estimating aboveground biomass and pasture yield across Mediterranean wood-pastures.

Materials and methods

Overview of the experimental site

The study was conducted for one year (from May 2023 to April 2024) in the pasture fields of a cattle farm located in Luogosanto, Sardinia, Italy (40°58'4.19" N, 9° 6'49.27" E, 402 m asl). Two natural pasture fields were selected due to their different hydrological layout: the first field (Field A), with an area of 21.3 ha, was marked by waterlogging after intense rainfall due to the flat to gently sloping landform and to the presence of a shallow and relatively impermeable bedrock, while limited or no waterlogging was observed in the second field (Field B), having an area of 4.3 ha (Fig. 1). The shallow sandy loam soil cover, interrupted by occasional to common rock outcrops, was developed from the monzogranite and monzogranitic granodiorite bedrock and, to a limited extent, from their slope deposits. The overall pasture area of the two fields (25.6 ha) was grazed by 18 beef cows and 10 calves during the study period, with no rotational grazing system or virtual fencing. The pasture classification was determined on all points in spring (23 May 2024) to facilitate the plant classification based on flowering and determine the fraction of the pasture area covered with woody species. As a natural pasture, the area is not subject to formal agronomic management. Grazing is managed informally across the different paddocks, based on the experience of the farmer rather than according to a planned rotational or productivity-driven regime.

Measurements

The aboveground pasture dry biomass was measured using a pasture meter (Grassmaster II Pro, Novel Ways, New Zealand) calibrated by retrieving at least 10 biomass samples inside a quadrat frame (45 × 45 cm) and measuring the relative capacitance value of the grass (c) by the Grassmaster, which was demonstrated to be proportional to the water content of the

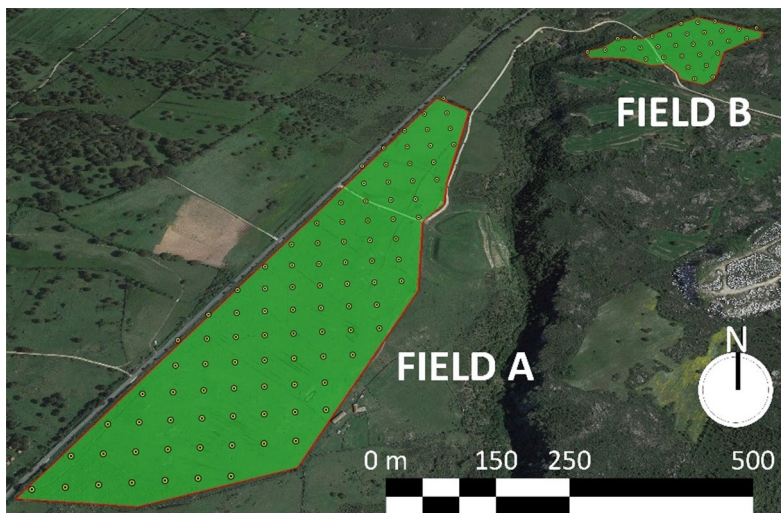


Fig. 1 Experimental pasture fields (Field A and Field B) with the geolocated points (yellow circles) on which the biomass monitoring, pasture classification and soil analysis were conducted

grass (Serrano et al., 2020). The non-pabular species (trees, woody plants or other non-pastured species) were not considered in the biomass measurements to estimate the available forage yield and because the pasture meter detects only herbaceous covers. The pasture meter was used to estimate the dry weight on monthly basis (total of 12 reading sessions from May 2023 to April 2024) on a total of 128 geolocated points distributed on a regular grid of 50×50 m for field A and 30×30 m for field B (Fig. 1).

The biomass at each point was estimated as the average of 15 pasture meter readings collected in a circle within a radius of 5 m around the geolocated points. The dry weight was determined by placing the fresh samples in an oven at 60°C for 72 h and used to calculate the linear regression relating the readings to the dry biomass sample, expressed as a linear equation (Eq. 1).

$$y = a * c + b \quad (1)$$

Where: (i) y was the dry matter of the pasture (kg ha^{-1} DW); (ii) a the gradient; (iii) c the relative capacitance value measured with the pasture probe and (iv) b the intercept.

The coefficient of determination R^2 was used to estimate the accuracy of the regression curve. Two linear regressions were calculated for the calibration of the pasture meter on the dry yield (Y_d) in kg ha^{-1} of fresh or dry weight, respectively. The first regression was measured in spring (15 May 2023) and applied to spring and autumn readings (Eq. 1):

$$Y_d = 0.8274 * c + 2133.9 \quad (R^2 = 0.78) \quad (\text{kg ha}^{-1} \text{ DW}) \quad (2)$$

The second regression was calculated in winter (29 January 2024) and employed for the least productive seasons (winter and summer) (Eq. 3):

$$Y_d = 0.4206 * c + 739.49 \quad (R^2 = 0.74) \quad (\text{kg ha}^{-1} \text{ DW}) \quad (3)$$

Pasture classification

The pasture classification was used to characterize the wood-pasture condition and was carried out on an area of approximately 10×10 m around the geolocated point to assess the presence of woody species, whose percentage cover was visually estimated. According to this, the pasture classification included both whether woody species were observed on the points or not (binary classification) and the eventual percentage of woody cover. The geolocated points were assigned to one of the following classes:

- wood-pasture points, when shrubs or trees were present within the square plot (arbitrarily at least two woody plants). For these points, the percentage of woody cover was also estimated visually;
- pasture points, when no woody species were present;
- pasture points with asphodel, when asphodel (*Asphodelus microcarpus* Salzm. et Viv.) was abundant in the area;
- rocky pasture points, when exposed rock was visible.

Therefore, woody cover was included both as a categorical descriptor of wood-pasture presence and as a continuous covariate based on the visually estimated percentage cover at each sample point within the 10×10 m plots, thus preserving spatial heterogeneity and ensuring consistency with the spatial resolution of Sentinel-1 and Sentinel-2 data. In addition, the average woody cover of the pasture fields was calculated as the average percentage of woody cover of all sample points.

Soil analysis

During Spring 2023 soil samples were collected by auger from the 0–15 cm topsoil layer on each of 128 geolocated points. In some places, near to rock outcrops, actual sampling depth varied between 10 and 15 cm. Samples were taken as composite samples obtained by merging three auger replicates randomly distributed within a few meter distance from the geolocated central point. Samples were oven-dried at 35 °C and 2-mm sieved. Physical and chemical analyses were conducted on the fine earth fraction to determine Sand, Silt, Clay, pH in water and in KCL, Organic Carbon (OC), Total Nitrogen (TN), Carbon to Nitrogen ratio (C/N), available phosphorus (P_A), Exchangeable Calcium (Ca_{ex}), Magnesium (Mg_{ex}), Sodium (Na_{ex}), Potassium (K_{ex}), Exchangeable acidity (Ac_{ex}), Cation exchange capacity (CEC), base saturation (BS), exchangeable sodium percentage (ESP), and few further indices derived from the above properties.

Covariates

The covariates used to train the machine learning models were fifty-seven which are related to different elements of the agroecosystem with different spatial-temporal resolutions. The selected covariates should comprehensively represent all components of the agricultural system, including crop-related factors, soil characteristics and climate parameters (Fiorenzini et al., 2024). The covariates list is: (i) month of the year, (ii) thermo-pluviometric, (iii)

pasture classification, (iv) SAR of the Sentinel-1 satellites, (v) multispectral bands and vegetation indexes of the Sentinel-2 satellites and (vi) soil data.

The scalability of the machine learning models is mainly related to the type and availability of the covariates used for model training. Covariates that rely on in-situ measurements, such as pasture classification and soil data, require field surveys and laboratory analysis that are time-consuming, costly, and site-specific, which limits the possibility of applying the models at larger spatial scales. Conversely, covariates derived from globally available datasets, such as thermo-pluviometric variables and satellite data from Sentinel-1 and Sentinel-2, are freely accessible and consistently available over wide geographic areas. The use of these datasets facilitates the transferability and scalability of the models, although differences in spatial and temporal resolution among data sources may affect the level of detail of the predictions. The list of the dataset groups and covariates used to train the machine learning models are reported in Table 1.

The month of the year refers to the month of the pasture meter measurements. The thermo-pluviometric data are calculated as mean temperature (°C) and sum of precipitation (mm) related to the day of the survey, obtained from the NASA POWER API service (Sparks, 2018). The satellite image of Sentinel 1 and Sentinel 2 satellite constellations that are more closely related to the day of the survey were downloaded with the maximum cloudiness of 30% in the case of Sentinel 2. The multispectral images of Sentinel 2 were used to calculate 19 vegetation indexes which are reported at Table 1, While the C-band of Sentinel-1 was used to calculate the radar backscatter coefficient (σ^0) for the VV and VH polarizations (Table 1).

Machine learning modelling framework

To identify the best machine learning framework for the estimation of the dry matter of wood-pastures, a combination of 3 machine learning algorithms with 23 datasets from 5 data groups were considered. Consequently, a total of 69 different models were evaluated (Table 2).

Three machine learning algorithms were compared, Random Forest (RF) (Svetnik et al., 2003), eXtreme Gradient Boosting, aka XGBoost (XGB) (Chen & Guestrin, 2016) and Ensemble Learner (EL) (Mienye & Sun, 2022). These machine learning algorithms were selected due to their ease of comparison in the scientific literature (Chlingaryan et al., 2018).

RF uses an ensemble-learning method consisting of many decisions or regression trees and (Breiman, 2001; Kim & Lee, 2016) a bagging technique to split the dataset into homogeneous subsets (trees) in parallel. When building each tree, RF randomly samples the training data, and a random subset of features is used to create a predictive model. Final predictions are made by combining (bagging) all trees/models and using the average predicted results. Like RF, XGB uses an ensemble learning method but uses boosting rather than bagging.

The EL is a model trained to determine the weights to be assigned to the individual predictions from the trained RF and XGB models which allow to create a new layer of output mapping that can lead to higher predictive performance than the single learning algorithm (Zhou, 2009). The EL was implemented using a stacking approach. Specifically, predictions from the tuned Random Forest and XGBoost models were combined using the stacks framework in R. The ensemble weights were learned through a regularised linear meta-model fitted on cross-validated (out-of-fold) predictions of the base learners. This procedure prevents

Table 1 Dataset Group, covariates and its unit measure, source and spatial and temporal resolution

Dataset Group	Covariates	Unit Measure	Source	Spatial Resolution	Temporal Resolution
Thermo-Pluviometric	Mean Temperature of the day	°C	NASA POWER	55.56 km ²	Hour
Pasture Classification	Sun Precipitation of the day	mm	NASA POWER	55.56 km ²	Hour
	Binary Classification	Character Variable	In-Situ measurement	50 m ²	Year
	Percentage cover of woody species	%	In-Situ measurement	50 m ²	Year
Sentinel 1	VV; VH	decibels	Google Earth Engine	100 m ²	Each 5 days
Sentinel 2	blue, green, red, nir	nm	Google Earth Engine	100 m ²	Each 5 days
Soil	GARI, GCI, GNDVI, GOSAVI, IPVI, MSAVI2, NDVI, NG, NNIR, NR, OSAVI, RDVI, SR, TDVI, VARI Green	Adimensional	Google Earth Engine	100 m ²	Each 5 days
	VARI, VDV1, Vig, WDRVI	%	In-Situ measurement	50 m ²	Year
	Sand, Silt, Clay,	Adimensional			
	pH H ₂ O, pH KCL,	g kg ⁻¹			
	OC,	g kg ⁻¹			
	TN,	Adimensional			
	C/N,	mg kg ⁻¹			
	P_A,	meq 100 g ⁻¹			
	Ca_ex, Mg_ex, K_ex, Na_ex, Ac_ex, and CEC	%			
	BS	%			
	ESP	Adimensional			
	Mg/K, Ca/Mg, K/Na				

Table 2 Dataset number and its covariate composition

Dataset Group Used
Pasture Classification
Thermo-Pluviometric
Sentinel 1
Sentinel 2
Soil properties
Thermo-Pluviometric & Pasture Classification
Thermo-Pluviometric & Sentinel 1
Thermo-Pluviometric & Sentinel 2
Thermo-Pluviometric & Soil properties
Sentinel 1 & Pasture Classification
Sentinel 1 & Sentinel 2
Sentinel 1 & Soil properties
Sentinel 2 & Pasture Classification
Sentinel 2 & Soil properties
Soil & Pasture Classification
Thermo-Pluviometric & Sentinel & 1 Pasture Classification
Thermo-Pluviometric & Sentinel 2 & Pasture Classification
Thermo-Pluviometric & Soil properties & Pasture Classification
Sentinel 1 & Soil properties & Pasture Classification
Sentinel 2 & Soil properties & Pasture Classification
Sentinel 1 & Sentinel 2 & Pasture Classification
Thermo-Pluviometric & Sentinel 1 & Sentinel 2 & Soil properties
Thermo-Pluviometric & Sentinel 1 & Sentinel 2 & Soil properties & Pasture Classification

information leakage because the meta-learner is trained only on predictions generated from resampled training folds. Overfitting was further controlled through regularization during the blending step and by evaluating candidate weights across multiple resampling iterations. The final ensemble was then constructed by fitting the selected base models on the full training data and combining them using the learned weights.

The entire modelling procedure, pre-processing the data, training, tuning and testing operations were performed in R statistical programming languages, by using the tidymodels R package (Kuhn & Wickham, 2020). The pasture classification was encoded by converting nominal data (e.g. factors-strings) into one or more numeric binary model terms corresponding to the levels of the original data. Before training the models, all the rows that have reported a pasture yield equal to 0 were removed.

To remove highly correlated predictors was used the “step_corr()” R tidymodels function which allows to remove predictors that have high correlation, in this work the correlation threshold was 0.8. The spatial autocorrelation was handled by using the “spatial_block_cv()” R spatialsample function to train and evaluate the machine learning frameworks.

All the machine-learning model hyperparameters were adjusted using a 15-grid search (Raschka, 2020). The machine learning model was evaluated using the main statistical parameters for error evaluation, thus the R^2 , the Mean Absolute Error (MAE) and the Root Square Mean Error (RSME) (Arratia et al., 2025; Rainio et al., 2024; Soman et al., 2022). To identify the most important variables that allow the increase the accuracy of each model, a variable importance was computed by using the vip function of the vip R package (Kuhn & Wickham, 2020).

Results

Descriptive statistics and time series analysis

During the 12-month study period, 1280 observations of dry matter (DM) pasture yield were collected to estimate the annual average yield shown in Fig. 2a. Mean yearly DM yield was $993 \pm 1840 \text{ kg ha}^{-1}$ for Field A and $1371 \pm 2287 \text{ kg ha}^{-1}$ for Field B. The higher productivity of Field B is likely associated with reduced waterlogging, which supported a steeper spring growth response. The dry yield distribution showed slight negative average skewness (-0.22) and kurtosis of 1.37 . The biomass dynamics followed a clear unimodal seasonal pattern, with a single peak in June (maximum 5537 kg ha^{-1} in Field A) due to the increasing average temperature coupled to favourable precipitation (Fig. 2b), followed by summer drought with nearly-zero precipitation and high temperature, that caused the fall of the forage availability and constrained post-peak regrowth. Outside spring, the average yield declined sharply and remained low from July to February (153 and 215 kg ha^{-1} for Fields A and B, respectively), with limited inter-month variability. The absence of biomass in September–October (bare soil condition) reflected a true seasonal growth cessation due to the previous summer drought and the insufficient rainfall in early autumn. This high variability of the forage distribution caused by the climatic conditions during the year was reflected on the standard deviation of the yearly average biomass data, that resulted very high on both fields. The pasture classification data indicated that woody species covered 7.2% of the area.

The two fields (Field A and Field B) have the same USDA soil texture class (sandy loam), very similar organic carbon content (around 2.4%), pH (5.8 to 6.0 on average), and CEC ($23 \text{ meq } 100 \text{ g}^{-1}$) but differ in several other properties (Table 3). The main differences are related to P_A , K_A , K_2O , Ca_ppm , Ca_ex , Na_ex , K_ex , Mg_K and K_Na that are sometimes higher in Field A, and sometimes lower ($+53\%$, -44% , $+37\%$, $+37\%$, $+35\%$, -71% , $+66\%$, -159% respectively).

Fig. 2 Average dry weight pasture yield (Y_d) on Field A and Field B from May 2023 to April 2024 (a). Average monthly temperature and cumulated precipitation (b)

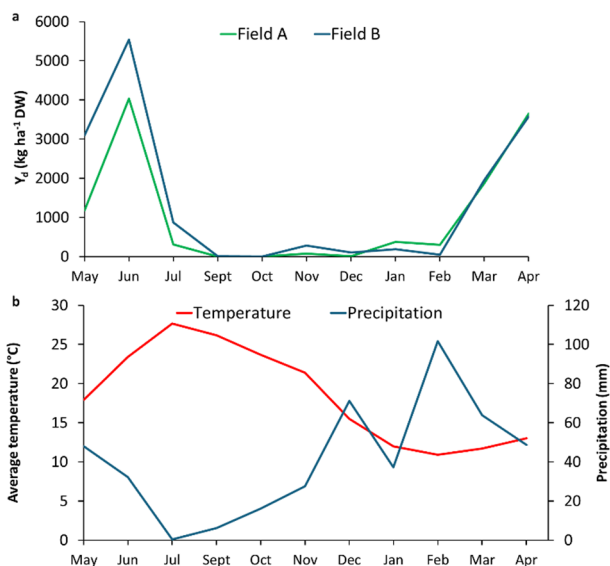


Table 3 Average and standard deviation values of the analysed soil properties in Field A and Field B

Field	Sand	Silt	Clay	pH	pH_KCl	D_pH	CO
A	607.20 (± 143.99)	219.20 (± 49.9)	174.20 (± 103.62)	5.96 (± 0.49)	4.76 (± 0.51)	1.20 (± 0.19)	23.58 (± 7.33)
B	598.90 (± 100.06)	226.70 (± 75.37)	174.80 (± 41.49)	5.83 (± 0.35)	4.41 (± 0.36)	1.42 (± 0.29)	22.44 (± 4.82)
Field	SO	Nt	C_N	P_A	K_A	K ₂ O	Ca_ppm
A	40.70 (± 12.65)	1.70 (± 0.53)	13.88 (± 2.11)	8.55 (± 5.48)	110.00 (± 100.15)	132.00 (± 120.18)	1247.50 (± 762.71)
B	38.74 (± 8.33)	1.41 (± 0.3)	16.12 (± 3.08)	4.04 (± 1.21)	158.1 (± 94.6)	190.35 (± 113.89)	791.90 (± 443.33)
Field	Mg_ppm	Ca_ex	Mg_ex	Na_ex	K_ex	B_Sum	CEC
A	286.41 (± 261.65)	6.23 (± 3.81)	2.38 (± 2.18)	0.89 (± 0.56)	0.28 (± 0.25)	9.79 (± 6.54)	23.01 (± 6.73)
B	209.05 (± 146.22)	3.95 (± 2.21)	1.72 (± 1.2)	0.58 (± 0.12)	0.48 (± 0.29)	6.75 (± 3.25)	23.41 (± 5.1)
Field	BS	Ex_Ac	Mg_K	Ca_Mg	ESP	K_Na	
A	39.69 (± 19.42)	13.21 (± 4.28)	11.46 (± 7.88)	3.48 (± 1.28)	3.83 (± 1.89)	0.34 (± 0.28)	
B	28.61 (± 9.28)	16.29 (± 4.29)	3.87 (± 2.33)	3.12 (± 1.75)	2.58 (± 0.67)	0.88 (± 0.53)	

Machine learning modelling framework

All trained frameworks showed slightly better performance on the training data than on the evaluation data (S1, S2, Tables 4 and 5). The differences in error metrics between training and evaluation for each model were small (average $0.1 R^2$) and not readily significant, indicating no overfitting. We nevertheless applied `spatial_block_cv()`, a spatial block cross-validation method that enforces spatial separation between training and validation folds, which reduced the spatial leakage and helped to ensure that evaluation results reflected true out-of-sample performance.

The best machine learning framework resulted the combination of Thermo-Pluviometric & Sentinel 2 & pasture classification and EL which reached a RMSE, MAE and R^2 of $469.92 \text{ kg ha}^{-1} \text{ DW}$, $402.61 \text{ kg ha}^{-1} \text{ DW}$ and 0.98 respectively (Tables 4 and 5), while the worst-performing framework was Sentinel-2 and XGB, which showed a RMSE +52% higher than the Thermo-Pluviometric & Sentinel-2 & pasture classification and EL. The difference in predictive accuracy between the two frameworks was +512.84 in RMSE, +252.53 in MAE and +0.11 in R^2 . The best machine learning framework that did not require any in-situ measurements was the Thermo-Pluviometric & Sentinel 2 and EL, which predictive accuracy difference compared to the best framework was a RMSE and MAE of $-1.2 \text{ kg ha}^{-1} \text{ DW}$, $-1.68 \text{ kg ha}^{-1} \text{ DW}$ respectively (Tables 4 and 5).

When examining the ten best-performing models, the thermo-pluviometric covariate group is consistently included, underscoring its dominant importance in predictive performance. Sentinel-2 data appeared in 8 of the top 10 models, further highlighting their substantial contribution. Soil variables are included 6 times, pasture classification 5 times, and Sentinel-1 data 4 times. Regarding the top 10 algorithms, the EL method appears 6 times, while RF is selected in 4 models; notably, XGB did not appear among the best-performing approaches.

Figure 3 presents the ten covariates that contribute most to the performance of the most accurate machine learning framework. Thermo-pluviometric variables (temperature and precipitation) exhibited the highest importance score (89), followed by the Sentinel-2 near-infrared (NIR) band (26.4) and the RDVI (9.45). In contrast, survey period, pasture classification, and soil variables contributed substantially less to model performance, with importance scores of 2.32, 0.6, and 0.4, respectively. Figure 4 illustrates the predicted pasture dry weight yield generated by the second-best performing machine learning framework, which consists of ensemble learners trained on thermo-pluviometric and Sentinel-2 data collected over Field A.

Discussions

The annual biomass dynamics followed the typical productivity pattern of Mediterranean natural pastures, which are generally characterised by a pronounced growth peak in spring (March–June), driven by the favourable combination of increasing temperatures and adequate precipitation, followed by a secondary, less pronounced growth phase in late summer (August–October) when rainfall occurs (Pornaro et al., 2018). However, in the present study, pasture productivity was strongly influenced by waterlogging conditions—particularly in Field A, which consistently exhibited lower productivity than Field B. Under these

Table 4 Error metrics related to the sixty-nine-machine learning framework during the evaluation phase, sorted in descending order by the RMSE results

Dataset	Model	RMSE	MAE	R^2
Thermo-Pluviometric & Sentinel 2 & Pasture Classification	EL	469.92	402.61	0.98
Thermo-Pluviometric & Sentinel 2	EL	471.12	404.29	0.98
Thermo-Pluviometric & Sentinel 2	RF	492.96	411.39	0.98
Thermo-Pluviometric & Sentinel 2 & Pasture Classification	RF	505.96	431.17	0.98
Thermo-Pluviometric & Soil properties	EL	514.09	436.36	0.97
Thermo-Pluviometric & Soil properties & Pasture Classification	EL	523.27	435.86	0.97
Thermo-Pluviometric & Sentinel 1 & Sentinel 2 & Soil properties & Pasture Classification	EL	525.87	437.35	0.97
Thermo-Pluviometric & Sentinel 1 & Sentinel 2 & Soil properties	RF	533.80	474.97	0.98
Thermo-Pluviometric & Sentinel 1 & Sentinel 2 & Soil properties & Pasture Classification	RF	536.75	476.24	0.98
Thermo-Pluviometric & Sentinel 1 & Sentinel 2 & Soil properties	EL	539.93	449.25	0.98
Thermo-Pluviometric	RF	546.82	477.45	0.97
Thermo-Pluviometric	XGB	546.84	476.45	0.97
Thermo-Pluviometric	EL	554.90	486.29	0.97
Thermo-Pluviometric & Soil properties	RF	563.68	498.20	0.97
Thermo-Pluviometric & Pasture Classification	EL	574.53	507.08	0.97
Thermo-Pluviometric & Pasture Classification	RF	576.27	513.94	0.97
Thermo-Pluviometric & Soil properties & Pasture Classification	RF	576.32	510.12	0.97
Pasture Classification	EL	598.38	523.36	0.96
Thermo-Pluviometric & Soil properties & Pasture Classification	XGB	599.40	494.83	0.96
Thermo-Pluviometric & Sentinel 2 & Pasture Classification	XGB	602.02	478.22	0.97
Thermo-Pluviometric & Sentinel 1 & Pasture Classification	EL	602.09	534.63	0.97
Thermo-Pluviometric & Pasture Classification	XGB	605.77	531.26	0.96
Thermo-Pluviometric & Sentinel 1	EL	606.48	527.37	0.96
Sentinel 1	EL	606.73	509.40	0.96
Thermo-Pluviometric & Sentinel 1 & Pasture Classification	RF	608.55	542.26	0.96
Thermo-Pluviometric & Sentinel 1 & Sentinel 2 & Soil properties & Pasture Classification	XGB	612.93	473.37	0.96
Soil properties	EL	614.84	517.76	0.97
Sentinel 1 & Pasture Classification	EL	616.94	523.59	0.96
Pasture Classification	XGB	617.85	546.36	0.96
Thermo-Pluviometric & Soil properties	XGB	620.27	509.39	0.95
Thermo-Pluviometric & Sentinel 1	RF	621.13	534.12	0.96
Sentinel 1	RF	625.48	540.98	0.96
Sentinel 1	XGB	626.51	527.08	0.96
Soil properties & Pasture Classification	EL	628.36	530.15	0.96
Sentinel 1 & Pasture Classification	RF	629.47	555.60	0.97
Sentinel 1 & Soil properties & Pasture Classification	EL	629.71	527.95	0.96
Thermo-Pluviometric & Sentinel 1 & Sentinel 2 & Soil properties	XGB	636.40	500.82	0.96
Sentinel 1 & Soil properties	EL	638.99	527.91	0.96
Sentinel 1 & Pasture Classification	XGB	639.44	528.26	0.95
Thermo-Pluviometric & Sentinel 2	XGB	653.02	514.47	0.95
Soil properties	RF	656.94	570.23	0.96
Soil properties & Pasture Classification	RF	670.96	584.81	0.96
Sentinel 1 & Soil properties	XGB	672.79	495.50	0.95

Table 5 Error metrics related to the sixty-nine-machine learning framework during the evaluation phase, sorted in descending order by the RMSE results

Dataset	Model	RMSE	MAE	R^2
Soil properties	XGB	683.82	508.94	0.95
Sentinel 1 & Soil properties & Pasture Classification	RF	687.44	591.26	0.95
Sentinel 1 & Sentinel 2	EL	687.89	464.23	0.94
Thermo-Pluviometric & Sentinel 1	XGB	696.63	599.41	0.95
Sentinel 1 & Soil properties	RF	699.66	602.00	0.95
Thermo-Pluviometric & Sentinel 1 & Pasture Classification	XGB	700.72	610.75	0.95
Sentinel 2 & Pasture Classification	EL	709.07	473.94	0.94
Sentinel 1 & Sentinel 2 & Pasture Classification	EL	718.18	458.44	0.94
Sentinel 1 & Sentinel 2	XGB	727.5	502.09	0.93
Sentinel 1 & Soil properties & Pasture Classification	XGB	739.68	561.95	0.93
Sentinel 2 & Soil properties & Pasture Classification	EL	742.81	523.35	0.94
Sentinel 2 & Pasture Classification	RF	761.83	494.74	0.93
Sentinel 2	EL	764.75	470.29	0.93
Sentinel 2 & Soil properties & Pasture Classification	XGB	766.83	549.72	0.93
Sentinel 1 & Sentinel 2 & Pasture Classification	RF	771.32	488.79	0.93
Soil properties & Pasture Classification	XGB	788.5	641.05	0.91
Sentinel 2	RF	797.09	499.78	0.92
Sentinel 2 & Soil properties	EL	799.11	550.87	0.93
Sentinel 1 & Sentinel 2	RF	801.89	493.6	0.92
Sentinel 2 & Soil properties & Pasture Classification	RF	832.24	579.79	0.93
Sentinel 2 & Soil properties	RF	840.25	575.64	0.93
Sentinel 2 & Soil properties	XGB	876.65	567.02	0.91
Sentinel 2 & Pasture Classification	XGB	924.01	636.05	0.89
Sentinel 1 & Sentinel 2 & Pasture Classification	XGB	928.42	589.23	0.9
Pasture Classification	RF	979.1	803.08	0.95
Sentinel 2	XGB	982.76	655.14	0.87

conditions, the combination of high precipitation and declining temperatures during late autumn and winter inhibited the occurrence of the secondary late-summer growth phase. As a result, biomass availability remained low, with limited variability until the onset of the subsequent spring (Fig. 2). In addition, summer drought caused a sharp decline in yield, with effects persisting into early autumn, when no forage was detected (bare soil) in September and October. The presence of trees and non-pabular woody species typical of Mediterranean scrub further reduced the average forage yield (993–1371 kg ha⁻¹ DM) compared to herbaceous Mediterranean pastures, where yields typically range from 1400 to 1800 kg ha⁻¹ DM (Hakyemez et al., 2008). The high standard deviation of the mean annual yield reflected both the marked spatial heterogeneity within the fields and the inherent seasonal variability in forage availability. Yield variability, both between and within fields, was further exacerbated by unregulated grazing patterns adopted by the breeder.

The combination of thermo-pluviometric variables, Sentinel-2 data, floristic–pasture classification, and the Ensemble Learner algorithm was the most accurate modelling framework (Table 4). This framework achieved the lowest error metrics and the highest coefficient of determination (R^2), indicating that integrating climate, multispectral satellite imagery, and detailed floristic information provides the most robust explanation of spatial and temporal variation in pasture yield (Raschka, 2020). The predictive improvement associated with this

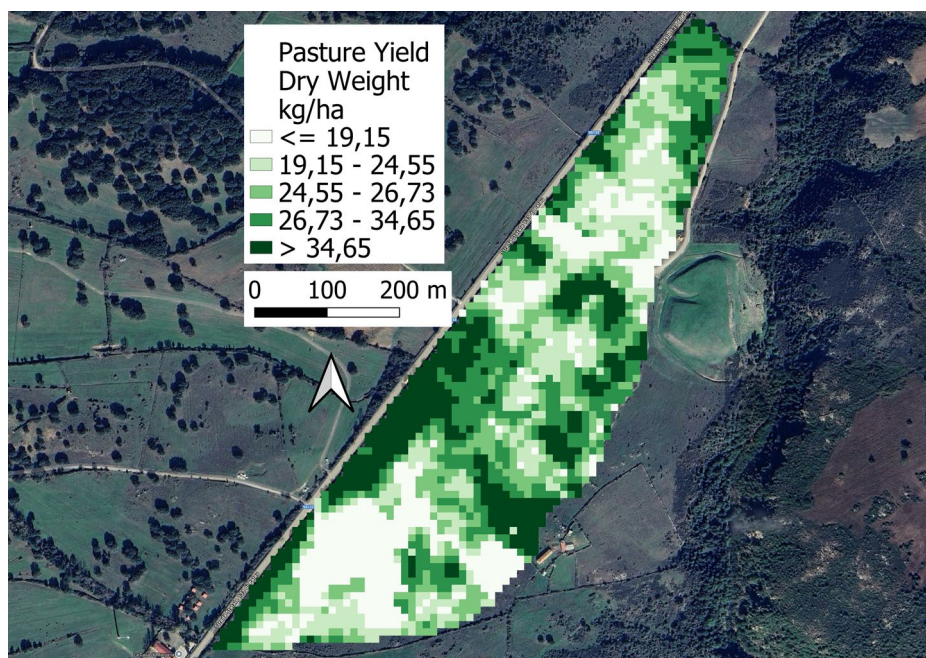
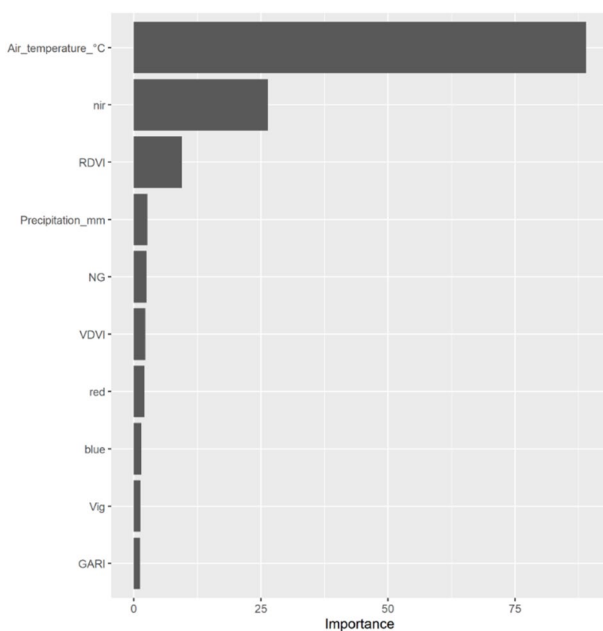


Fig. 3 Pasture yield dry weight prediction of the Ensemble Learners trained with the Thermal-Pluviometric and Sentinel 2 data over Field A

Fig. 4 Variable importance analysis related to the ten most important features of the RF that composes the EL of the best (Thermo-Pluviometric & Sentinel 2 & pasture classification and EL) framework



framework is consistent with established evidence showing that temperature, precipitation and vegetation functional composition (NIR bands and Vegetation Indexes) jointly monitor forage growth dynamics (Chasen et al., 2025; García-Baquero et al., 2020). The error metrics obtained with this framework are fully aligned with the best-performing models reported in recent literature (Chasen et al., 2025; Fernandes et al., 2024; Huang et al., 2024; Stumpe et al., 2024).

The second-best framework—comprising thermo-pluviometric variables and Sentinel-2 data combined with the Ensemble Learner—performed almost identically to the best framework (Arratia et al., 2025; Rainio et al., 2024). The differences in RMSE and MAE between the two are nearly negligible ($1.2 \text{ kg ha}^{-1} \text{ DW}$ and $1.68 \text{ kg ha}^{-1} \text{ DW}$, respectively), and their R^2 values are effectively equivalent (Sardaro et al., 2024). This suggests that the second most accurate framework can be used without significant loss of accuracy compared to the most accurate. Importantly, unlike the best framework, the second-best model relies solely on scalable, low-cost covariates (Ledvinka et al., 2026). This finding indicates that including pasture classification data does not produce a significant increase of the accuracy to justify the additional time, financial costs, and specialised expertise required for field surveys (Defalque et al., 2024). Therefore, when balancing accuracy, scalability, and cost-effectiveness, the second-best framework can be considered the most suitable approach for operational applications.

The high performance of frameworks relying on temperature, precipitation and Sentinel-2 data can be explained by their strong mechanistic relevance and by the free, temporally frequent, and globally available nature of these datasets (Gargiulo et al., 2023). Thermo-pluviometric variables exert first-order control on pasture growth by determining the length of the vegetative season, the rate of photosynthesis and respiration, and the soil water available to plants (Martins-Noguerol et al., 2023). Periods of adequate rainfall promote rapid biomass accumulation, whereas drought or poorly timed rainfall deficits strongly reduce dry-matter production (Liu et al., 2023). Likewise, deviations from optimal temperatures either enhance or constrain annual productivity depending on species traits and moisture availability (Chasen et al., 2025). Because these processes drive most interannual and spatial variability in forage production, models that incorporate climate variables consistently outperform those that do not.

Therefore, to apply these models, climate data must be highly accurate and detailed. In fact, several scientific studies have reported that climate data derived from models such as NASAPOWER and ERA5 contain errors that can be significant (Mutlu, 2025; Tan et al., 2023). Tan et al. (2023) reported that NASAPOWER and ERA5 can capture the overall climatology patterns reasonably but underestimate and overestimate no / tiny and heavy precipitation. Also Mutlu (2025) reported some significant error when a comparison of re-analysis data with in-situ weather stations measurement. Therefore, the use of basic weather stations, with temperature and rainfall data, is essential for accurate estimates.

Regarding satellite datasets, Sentinel-2 proved markedly more informative than Sentinel-1. Even among the ten best frameworks identified, Sentinel-1 (VV and VH) contributed from the seventh position onwards and did not improve predictive accuracy when added to other data sources (Hashemi et al., 2024). Conversely, Sentinel-2 multispectral indices showed consistent, strong relationships with pasture yield, confirming previous studies that highlighted the value of optical vegetation indices for biomass monitoring (Fernandes et al., 2024; Huang et al., 2024; Stumpe et al., 2024).

Soil physical and chemical properties also influence pasture yield by regulating root development, nutrient availability, and water-holding capacity (Darch et al., 2022; Serrano et al., 2013). However, although soil data can help improve yield estimates, their collection is expensive, labour-intensive, and rarely scalable at the regional level.

In this study, the soil characterization and pasture classification data were collected only once for the entire studied period, and so those data were the same for each point and survey dates. This led to little variability of machine learning models, and therefore these variables had a limited contribution to modeling pasture yield in space and time. This result is consistent with other findings showing limited accuracy gains when soil surveys are limited to one survey.

In order to understand whether soil and pasture classification data are important, it is advisable to plan a sampling plan that allows this information to be acquired for each survey date, but this approach certainly requires considerable time, expense and difficult to scale up, which does not allow for the development of a system that can actually be used by farms that need to plan their activities on a weekly basis. Moreover, being natural pasture, animals graze and reduce the variability of the spatial distribution of biomass. This makes it difficult to create a model compared to that of a meadow or grassland where pasture planning and agronomic management are applied. For future work the data can be integrated with floristic composition data, which allows for the calculation of the pastoral value of the pasture and the palatability of the species in the field, which is the basis for planning rotational grazing.

The machine learning algorithms with the best consistent performance were Random Forest and Ensemble Learner models. Their ability to handle nonlinear interactions and mixed data types makes them well suited to integrating climatic and remotely sensed covariates (Gawdiya et al., 2024).

Notably XGB did not appear among the best-performing approaches in this study. This may be explained by its sensitivity to hyperparameter tuning and its tendency to overfit when the signal-to-noise ratio is limited or when predictors are highly correlated, as is often the case with multispectral indices and climate variables. In contrast, Random Forest and Ensemble methods are generally more robust to multicollinearity and require less intensive tuning (Chlingaryan et al., 2018), which likely contributed to their superior and more stable performance across frameworks.

The analysis also demonstrated that models based solely on one data source whether Sentinel-1, Sentinel-2, or non-CSI pasture classification can achieve acceptable performance, but combining at least two sources, particularly Sentinel-2 and climate data, produces substantially more accurate results (Balasubramaniam et al., 2025). This insight is crucial for optimizing data collection strategies and reducing costs: only the most influential variables should be prioritised to improve model accuracy while minimizing unnecessary fieldwork.

Collectively, our findings indicate that integrating thermo-pluviometric covariates with Sentinel-2 multispectral imagery and applying an Ensemble Learner provides the most favourable compromise between predictive accuracy, operational scalability and economic efficiency. This approach achieved robust out-of-sample performance while requiring modest computational resources and readily available remote-sensing inputs, thus facilitating large-scale operational adoption. For reproducibility and to demonstrate the method's scalability in an operational context, model predictions for neighbouring agricultural fields are presented via an interactive web application (see Supplementary Materials): <https://agronomofiorentini.shinyapps.io/ECPA2025/>.

The model can be directly applied to design and fine-tune grazing-rotation strategies, including integration with virtual-fencing technologies. By optimizing the management of available forage biomass, these applications reduce labour demands on the stockperson and enable more efficient planning of supplementary feed inputs (forages and concentrates) during periods of forage scarcity in the field. In practice, coupling near-real-time biomass predictions with rotational grazing—either manual or controlled through virtual fencing—supports the decision-making that improves pasture utilization, animal welfare and farm-level feed-cost efficiency.

Conclusions

The most accurate machine-learning framework for predicting Mediterranean wood-pasture yield combined an ensemble-learning (EL) algorithm with thermo-pluviometric variables, Sentinel-2 multispectral data, and pasture classification data, achieving the lowest error metrics. However, this top-performing framework is not scalable to the regional level because the pasture classification data require field measurements. Collecting, georeferencing, and digitizing these data is time-consuming, costly, and requires specialist expertise.

A more scalable—and effective cost-free—alternative that does not require any in-situ measurements uses Thermo-Pluviometric variables and Sentinel-2 data with the same EL algorithm. Its RMSE and MAE are only slightly higher than the most accurate framework, while R^2 remained unchanged, making it an excellent trade-off between accuracy, scalability, and cost-time saving. As a result, this second model can be adopted without significant losses in precision compared to the most accurate framework.

The analysis also shows substantial variation across model–data combinations: the worst frameworks produced error metrics nearly twice as large as the best. This indicates that both the choice of algorithm and the composition of the input dataset strongly influence predictive performance. On this basis, it is recommended that researchers modeling Mediterranean wood-pasture yield include, at least thermo-pluviometric variables and Sentinel-2 multispectral data (these features consistently appear among the top ten frameworks). Where resources permit, inclusion of soil data and pasture classification can further improve accuracy; Sentinel-1 may be regarded as a secondary, optional source despite being freely available.

Future research will implement the most effective model to map pasture yield, define management zones, and create prescription maps that guide grazing rotation strategies based on observed pasture use by livestock. By improving the management of available forage, these tools can reduce the labour demands on the stockperson and allow for more strategic planning of supplemental feeds (both forages and concentrates) during times of limited pasture availability. In practice, integrating near-real-time biomass estimates with adaptive paddock allocation—whether manually managed or controlled via virtual fencing—enhances decision-making, leading to better pasture utilization, improved animal welfare, and greater efficiency in feed costs at the farm level.

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Data Availability The authors confirm that the data supporting the findings of this study are available from the corresponding author upon reasonable request.

Declarations

Competing interests The authors declare no competing interests.

Ethical and informed consent This article does not contain any studies conducted on human or animal subjects by any of the authors.

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