



Alfalfa yield estimation using the combination of Sentinel-2 and meteorological data

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ABSTRACT

Context: Alfalfa (*Medicago sativa* L.) is one of the world's most important forages for livestock feeding. Timely yield estimates could provide information to guide management decisions to improve production. Since alfalfa crops typically undergo multiple harvests in a year and demonstrate rapid regrowth, satellite remote sensing techniques present a promising solution for alfalfa monitoring.

Objective: To generate alfalfa yield estimation models at three phenological stages (early vegetative, late vegetative, and budding stages) using vegetation indices (VIs) derived from satellite Sentinel-2 images and their combination with meteorological data.

Methods: We analyzed fields located in Navarre (northern Spain) over two consecutive seasons (2020 and 2021). To generate the yield estimation models, we applied a conventional multilinear regression and two machine learning algorithms (Least Absolute Shrinkage and Selection Operator - LASSO and Random Forest - RF).

Results: Regardless of the statistical approach, the three phenological stages were not optimal when either VIs or meteorological data were used singularly as the predictor. However, the combination of VIs and meteorological data significantly improved the yield estimations, and in the case of LASSO model reached percentages of variance explained (R^2) and normalized root mean square error (nRMSE) of $R^2 = 0.61$, nRMSE = 0.16 at the budding stage, but RF reached a $R^2 = 0.44$, nRMSE = 0.22 at the late vegetative stage, and $R^2 = 0.36$, nRMSE = 0.24 at the early vegetative stage. The most suitable variables identified were the minimum temperature, accumulated precipitation, the renormalized difference vegetation index (RDVI) and the normalized difference water index (NDWI). The RF model achieved more accurate yield estimations in early and late vegetative stages, but LASSO at bud stage.

Conclusion: These models could be used for alfalfa yield estimations at the three phenological stages prior to harvest. The results provide an approach to remotely monitor alfalfa fields and can guide effective management strategies from the early development stages.

1. Introduction

Alfalfa (*Medicago sativa* L.) is one of the most important perennial legumes cultivated worldwide, covering an area of 30 – 35 million hectares (Del Pozo et al., 2023). It is traditionally used for cattle feeding, providing high-quality forage whose content includes easily digestible fiber, crude protein, amino acids and minerals, all of which affect livestock profitability (Chen and Zhang, 2023; Feng et al., 2022). Moreover,

interest in alfalfa crops has increased due to their environmental benefits, such as high rates of carbon (C) sequestration resulting from deep roots, minimal need for nitrogen (N) fertilizer inputs due to the ability for symbiotic atmospheric N fixation, and wide adaptability to different environments (Anthony et al., 2023; Chandel et al., 2021a,b; Hrbáčková et al., 2020). Among its agronomic characteristics, this crop is commonly harvested several times per year and exhibits an ability for rapid regrowth. Because the timing of harvesting after regrowth

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determines yield and forage quality, constant monitoring of regrowth is crucial to optimize the economic performance of the crop (Chen and Zhang, 2023; Garriga et al., 2020; Shi et al., 2017).

Alfalfa currently plays an important role in forage production in Mediterranean environments and holds considerable potential for extending crop cultivation in this climate (Del Pozo et al., 2023; Raes et al., 2023). However, agriculture in the Mediterranean region is greatly threatened by climate change because increasing drought occurrences are expected, associated with a decrease in precipitation and an increase in temperature (Lionello et al., 2014). In fact, climate change could lead to a decrease in alfalfa yield of between 11 % and 33 %, particularly in warm and arid climates (Pourshirazi et al., 2022). Crop yield requires of maximum attention among agricultural researchers and policymakers due to its relevance to ensure food security and farmers revenue (Farmonov et al., 2023; Segarra et al., 2022). Early prediction of crop yields is therefore becoming increasingly important, particular under changing climate conditions, and should facilitate in-field management strategies prior to harvest, by identified of variables for a reliable yield estimations and thus ensuring agricultural, environmental and social sustainability (Farmonov et al., 2023; Noland et al., 2018).

Several methodologies have been reported for *in situ* estimations of alfalfa yield. The traditional method of counting stems, measuring their height, and monitoring their morphological development (Lyons et al., 2016) is tedious and impractical across large areas (Kayad et al., 2016). As an alternative, measuring canopy reflectance through remote sensing technologies has emerged as a non-destructive, rapid and direct method of assessing crops at the field scale (Araus et al., 2021; Araus and Cairns, 2014; Azadbakht et al., 2022; Chandel et al., 2021a,b). Among these, satellite-based technologies coupled with different optical sensors can be used to collect information throughout the crop cycle at large scale (Farmonov et al., 2023). For instance, Sentinel-2A and 2B (launched in 2015 and 2017, respectively, by the European Space Agency), support the monitoring of vegetation at different growth stages due to the spatial, spectral, and temporal resolution of its images (Araus et al., 2021; Farmonov et al., 2023; Segarra et al., 2020a). Satellite-based predictions usually take into account specific spectral bands to formulate vegetation indices (VIs) associated with ground cover or crop health (Araus et al., 2021; Noland et al., 2018). Several studies have used the satellite imagery to estimate the alfalfa yield (Azadbakht et al., 2022; Celis et al., 2024; Chen and Zhang, 2023; Echeverría et al., 2021; Kayad et al., 2016; Moot et al., 2022; Yadav and Geli, 2021). Li et al. (2023) used Sentinel-2 data to estimate alfalfa yields, finding that images obtained during the first harvest provided greater accuracies than those obtained in further harvests. Likewise, Celis et al. (2024) considered potential VIs related to canopy structure and water content derived from Sentinel-2, indicating that VIs were important for estimating crop performance and vegetation health.

Although yield estimation from VIs may generate acceptable results during certain stages of growth (Celis et al., 2024; Li et al., 2023), such indices may not be sufficiently robust at high leaf area (LAI) because values of VIs tend to reach a plateau (Azadbakht et al., 2022). The wide accepted explanation for this effect, commonly named saturation, is that leaf coverage approaches 100 % in dense vegetation around mid-vegetative phases, while biomass continues to grow until the crops reach critical point at which begin to senesce (Thenkabail et al., 2000). As a consequence, numerous authors have indicated that the estimation accuracy might benefit from combining satellite imagery and environmental data (Celis et al., 2024; Farmonov et al., 2023; Moot et al., 2022; Noland et al., 2018; Yadav and Geli, 2021). For instance, case studies reported by Noland et al. (2018), Smeal et al. (1991) and Yadav and Geli (2021) revealed that variables such as temperature and precipitation were determinant in improving predictive models in alfalfa. This underscores the need to include further analysis to better understand which climate variables have significant effects on yield and thus influence the model's performance (Noland et al., 2018).

Once all the information is collected and preprocessed, features are

then extracted by applying several algorithms (Kamir et al., 2020; Perich et al., 2023). Given their simplicity, simple and multiple linear regressions have been widely utilized in remote sensing studies, although these have not been generalized because they are specific to the crop cultivars or crop growth stages being considered (Kamir et al., 2020). Instead, advanced alternative methods in the field of machine learning have been tested recently to estimate crop yield in alfalfa (Azadbakht et al., 2022; Chen and Zhang, 2023; Li et al., 2023). One of the most popular machine learning methods used in predicting crop yields is the random forest (RF) method (Sharma et al., 2021). For example, Li et al. (2023) reported that RF showed promising results for estimating yield in alfalfa when Sentinel-2 data were used. In addition, Azadbakht et al. (2022) reported that compared to linear regressions, the RF model captures multivariate and non-linear relationships among predictors, which significantly improves yield estimations.

Unlike other regions, there has been little focus in the Mediterranean region on combining remote sensing approaches with environmental data and advances in machine learning algorithms for agricultural monitoring. Therefore, this article presents a novel approach to using advanced crop monitoring tools for alfalfa yield estimation in a Mediterranean environment. The main aim was to model and predict the alfalfa yield based on data collected at three different phenological stages: early vegetative (early-veg), late vegetative (late-veg) and budding (bud), using environmental data and Sentinel-2 time-series data from alfalfa fields located in the south of Navarre (northern Spain), a region subjected to an arid Mediterranean continental climate. To achieve this, we evaluated one conventional statistical analysis and two machine learning algorithms that used (i) only VIs as predictors, (ii) only meteorological data and (iii) and these data combined (VIs + meteorological) for each stage of development. This study was organized around the following three research questions:

- 1) What is the importance of phenology in estimating alfalfa yield?
- 2) Which Sentinel-2-derived VIs best contribute to estimation of alfalfa yield before each harvest?
- 3) Do meteorological data contribute towards improving alfalfa yield prediction?

2. Materials and methods

2.1. Study area and field data

The study was conducted in the Community of Navarre in northern Spain, with the fields situated in the southwest part of the region (Fig. 1). This area has a Mediterranean climate, with low and irregular annual precipitation amounts that average between 500 and 600 mm. The mean annual temperature varies between 13.5 °C and 14.4 °C (Agencia Estatal de Meteorología de Navarra, 2024).

A total of 64 commercial fields of alfalfa (cv. Aragon, dormancy = 7–8), located in nine different municipalities (Beire, Caparroso, Falces, Marcilla, Milagro, Murillo el Cuende, Olite, Peralta and Villafranca) of the agricultural zone of Ribera Alta established by Government of Navarre (Fig. 1) were analyzed during two consecutive years (2020 and 2021). The size of the fields was between 1 ha and 29 ha, although the average size was 4.71 ha, and the total area analyzed covered 284 ha. Depending on the field, three irrigation methods were used (central pivot, sprinkler, and surface) (detailed information in supplementary table 1 - Table S1). Crop management was carried out according to organic agriculture regulations for both campaigns by the technical personnel of the NAFOSA feed company located in Peralta municipality at the south of Navarre. The harvests for the entire fields were conducted by the technical staff using a combine harvest machine and then, the biomass yield standardized at 12 % moisture was reported in kg ha⁻¹.

For the purpose of this study, the five harvests per year (normally performed in this region), and three phenological stages (early-vegetative, late-vegetative and bud) for each harvest were included. Due to

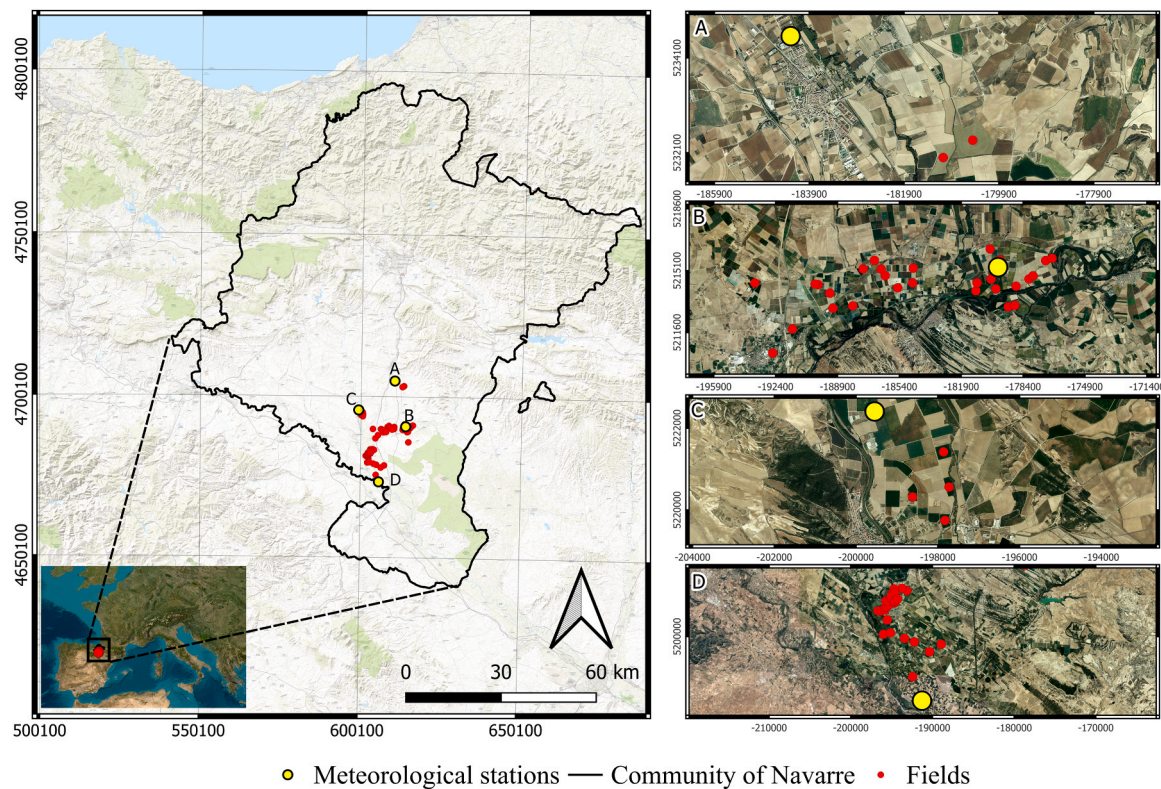


Fig. 1. Geographical location of the study sites in the community of Navarre, Spain. The left panel shows the location of Navarre within Europe, and the location of the fields is shown enlarged in the right panel. For improving visualization of fields under study, four zones were shown (A, B, C, D). The yellow points indicate the locations of the meteorological stations where the data were recorded.

limiting weather conditions for acquiring satellite data (described below) and considering that some alfalfa fields did not reach the bud stage before harvest, the total number of samples analyzed were 532 for early-veg, 526 for late-vegetative and 272 for bud stage, respectively.

2.2. Meteorological data and growing degree days (GDD)

The meteorological data considered in this study included daily average (Tmean), maximum (Tmax), and minimum (Tmin) temperatures (°C) and accumulated precipitation (Prec, mm). Potential evapotranspiration (ETP) and water balance (WB = Prec / ETP) were also considered variables. The ETP is derived from the Penman-Monteith equation as described in [FAO \(1998\)](#). All datasets were obtained from four open-access government meteorological stations representative of the fields being studied ([Fig. 1](#)) (<http://meteo.navarra.es/estaciones/mapadeestaciones.cfm>) and the INTIA website (<https://www.intiasa.es/web/es/regadios/agroclimatologia>). Using the center of the total analyzed fields as a reference point, the maximum distance to the meteorological station was found to be 15 km. [Fig. 2](#) shows a summary of the meteorological data recorded at the four weather stations in both years, 2020 and 2021. These variables were averaged during the growing period among harvests and then the data were interpolated with the inverse distance weighted (IDW) method to obtain data for each field. Considering that the fields showed asynchronous phenological stages due to different harvest dates, all meteorological data were determined independently for each field according to the phenological stage of interest.

In addition, the temperature data was used to calculate GDD as reported by [Charles \(1959\)](#), considering a base temperature of 3.5°C, 7.5°C and 10°C for spring, early summer and the remaining growing season, respectively, according to [Noland et al. \(2018\)](#) and [Sharratt et al. \(1989\)](#). GDD was calculated independently for each field and used to identify three phenological stages: early-veg, late-veg and bud ([Fig. S1](#))

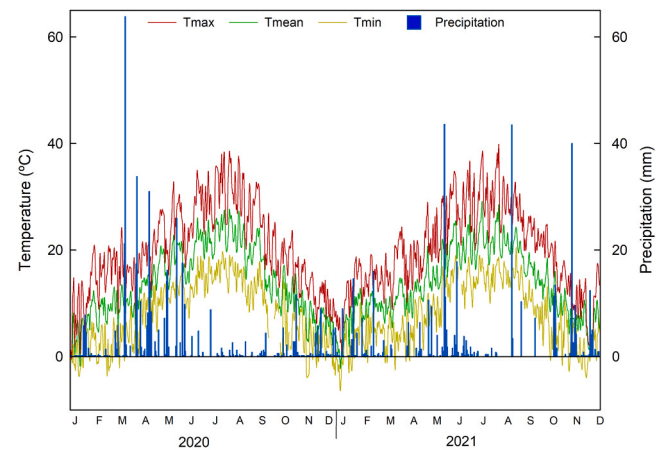


Fig. 2. Daily temperatures (Tmax, Tmean and Tmin) and precipitation data for the years analyzed, covering the two alfalfa growing seasons.

Table 1
Relationship between phenological stage and GDD in alfalfa plants.

Stage number	Stage name	Stage definition	GDD
0	Early vegetative	Stem length is less than 15 cm	173
1	Mid vegetative	Stem length is 16–30 cm	267
2	Late vegetative	Stem length is greater than 31 cm	375
3	Early budding	One to two nodes with buds	491
4	Late budding	Three or more buds	510
5	Early bloom	One node with one open flower	582

Source: Modified from [Ben-Younes \(1992\)](#) and [Reagan \(2018\)](#).

(Ben-Younes, 1992; Reagan, 2018) (Table 1). The GDD were used to select the closest date to the three phenological stages of interest and then to download a valid satellite image.

2.3. Sentinel-2 image download and analysis

Sentinel-2 A+B constellation consists of two identical satellites operating simultaneously, each equipped with a multispectral optical instrument that capture light reflected from the Earth and has important uses in agriculture monitoring (Segarra et al., 2020a). The Sentinel-2 has 13 spectral bands: three for atmospheric correction (B1, B9 and, B10; spatial resolution = 60 m), four visible and near infrared (NIR) bands (B2, B3, B4 and, B8; spatial resolution = 10 m), and six red-edge, NIR and short-wave infrared (SWIR) bands (B5, B6, B7, B8A, B11 and, B12: spatial resolution = 20 m) (Celis et al., 2024). The multispectral bands time series were downloaded from the Copernicus Open Access Hub (<https://dataspace.copernicus.eu/>) for the dates closest to the phenological stage of interest (regarding GDD calculations) for each field (Table S2). Sentinel-2 data was downloaded as orthorectified atmospherically corrected surface reflectance, namely bottom-of-reflectance level-2A product. The data downloaded corresponds to a tile that includes the total fields analyzed and without cloud cover over the plots. When cloud cover exceeded 40 % for most fields, the images were discarded. Sentinel-2 constellation images was used because they offer higher spatial resolution between 10 and 60 m (depending on the spectral band) and more frequent revisit time (repeat cycle of 5 days) than other satellites (i.e. Landsat-8) and thus provide improved capabilities to monitor and capture rapid changes in vegetation (Misra et al., 2020; Segarra et al., 2020a).

Subsequently, all image processing was undertaken with QGIS v.3.18.3 (QGIS, 2022). First, a unique image for each date was generated by combining tiles located in Navarre using the mosaic function. Second, the region of interest was defined in polygons of the 64 fields under study, obtained from the Spanish geographical information system of agriculture parcels (SIGPAC) (<https://sigpac.tracasa.es/navegar/>). Third, the polygons were 10-m buffered with *buffer* tool in QGIS to reduce edge effects.

From the Sentinel-2 bands, ten spectral reflectance VIs were considered in this study (Table 2). The application of different VIs instead of the raw reflectance value for each band is because the indices, which are formulated using relationship between two or more spectral bands, enhance the vegetation signal while minimizing soil background effects (Araus et al., 2021). In addition, temporal integrations of VIs represent specific aspects of crop growth dynamics that make it easier interpretations, communication to stakeholders and therefore, broader applicability compared to using raw reflectance values (Karthikeyan et al., 2020; Perich et al., 2023).

The criteria for selecting the VIs were based on (i) the ability of highlight the green component of the crop as potential indicators for biomass prediction (Pranga et al., 2021), (ii) the general applicability in vegetation monitoring and quantifying the growth dynamics and, (iii) evaluate indices previously reported for forages, including alfalfa crops, such as Normalized Difference Vegetation Index (NDVI), Modified Simple ratio (MSR), Normalized Difference Water Index (NDWI), or Optimized Soil Adjusted Vegetation Index (OSAVI) (Chandel et al., 2021a,b; Chen and Zhang, 2023; Feng et al., 2020; Li et al., 2023; Zhou et al., 2021) but also, analyze others reported as high sensitive to change according to the phenological stages, such those related to chlorophyll content (Gitelson et al., 2003). The NDVI is the most commonly used VI, although limitations related to saturation at high biomass levels have been reported (Thenkabail et al., 2000). Since NDVI it is also susceptible to changes in soil background (Huete, 1988), indices like OSAVI (Baret et al., 1993), Soil Adjusted Vegetation Index (SAVI) (Huete, 1988) and, Renormalized Difference Vegetation Index (RDVI) (Roujean and Breon, 1995) were added. Other relevant index that overcoming the limitation of NDVI is the Enhanced Vegetation Index (EVI) offering a vegetation

Table 2
Spectral vegetation indices (VIs) considered in this study as input variables.

Index name	S-2 Formula	Measures	References
Chlorophyll index green	$CI\ Green = \frac{B7}{B3} - 1$	Chlorophyll content	Gitelson et al., (2003)
Chlorophyll index red edge	$CI\ Red = \frac{B7}{B5} - 1$	Chlorophyll content	Gitelson et al., (2003)
Enhanced vegetation index	$EVI = 2.5 * \frac{B9 - B5}{(B9 + 6B5 - 7.5B1) + 1}$	Biomass	Huete et al. (1997)
Modified simple ratio	$MSR = \frac{B8 - 1}{\sqrt{\frac{B8}{B4} + 1}}$	Biomass	Chen, (1996)
Normalized difference vegetation index	$NDVI = \frac{B8 - B4}{B8 + B4}$	Biomass	Rouse et al., (1974)
Normalized difference water index	$NDWI = \frac{B8 - B11}{B8 + B11}$	Water content	McFeeters, (1996)
Optimized soil adjusted vegetation index	$OSAVI = 1.16 * \frac{B8 - B4}{B8 + B4 + 0.16}$	Vegetation cover	Baret et al., (1993)
Renormalized difference vegetation index	$RDVI = \frac{B8 - B4}{\sqrt{B8 + B4}}$	Biomass	Roujean and Breon, (1995)
Simple ratio	$SR = \frac{B8}{B4}$	Biomass, lignin and starch	Buschmann and Nagel, (1993)
Soil adjusted vegetation index	$SAVI = 1.5 * \frac{B8 - B4}{B8 + B4 + 0.5}$	Vegetation cover	Huete, (1988)

greenness measure and reducing atmospheric influence (Huete et al., 1997). Finally, the Simple Ratio (SR) index could distinguish green vegetation from other objects (Pranga et al., 2021). VIs were calculated through a simple mathematical relationship among the spectral bands with the *raster calculator* tool for each phenological stage and field. Each calculated index was incorporated into the parcels layer and, mean and median values were extracted using the *zonal statistics* tool.

2.4. Statistical analysis and model building for alfalfa yield estimation

2.4.1. Statistical analysis

The total dataset used in this study as input variables consists of meteorological parameters (Tmean, Tmin, Tmax, Prec, ETP, water balance) and the ten VIs (see Table 2) extracted from Sentinel-2 images at each of the three phenological stages studied (early-veg, late-veg and bud). Two different statistical summaries of each VI -mean and median- were calculated for each phenological stage, field, and harvest. Principal component analysis (PCA) was carried out to assess the variables in a reduced bi-dimensional tool using R Studio 4.2.0 (R Core Team, 2024). Pearson's correlations between input variables and the alfalfa biomass yield were calculated using the *cor.test* function in R Studio software.

2.4.2. Estimation of alfalfa yield using MLR and machine learning algorithms

The following analyses were performed using R Studio software. Pre-processing steps of dataset normalization and scaling were performed before running algorithms using the *scale* function. In the modelling framework, the alfalfa yield was set as the target variable. At each run, the total fields were separated randomly into a training group (80 % ≈51 fields) and a testing group (20 % ≈13 fields). To analyze the contribution of the different sets of predictors (VIs, meteorological data, and their combination) to estimate alfalfa yield, first the models were

generated using only the VIs as predictors, then only meteorological data and, finally the combination of VIs and meteorological data were used.

To find the best estimation of alfalfa yield, three algorithms were applied at each phenological stage. Two machine learning algorithms were compared: Least Absolute Shrinkage and Selection Operator (LASSO) and Random Forest (RF) with multiple linear regression (MLR). The algorithms were selected based on the differences in mathematical approaches. Given simplicity and potential wider applicability among farmers, the conventional MLR was used as a basic and simple mathematical approach (Guo et al., 2021; Yue et al., 2018). For its part, LASSO regression is an effective model for eliminating non-informative feature from a group with highly correlated variables and is applicable to small data sets (Araus et al., 2021) and also, it has been tested for yield estimation of crops (Cai et al., 2019; Peng et al., 2020). RF is an ensemble-based robust model, ability to deal with complex relationship and taking advantage of much of information provided; although its interpretability is limited (Araus et al., 2021; Boulesteix et al., 2012). Additionally, RF is one of the most widely used models for alfalfa crops (Azadbakht et al., 2022; Chen and Zhang, 2023; Feng et al., 2020; Li et al., 2023). Other models based on deep learning methods, while potentially could yield better estimations, were not included in this study because these require enormous amounts of data to train and may encounter issues such as reduced interpretability. Additionally, these models usually demand more robust hardware, resources and time, making them less accessible (Taye, 2023; Wang et al., 2022).

a. Multiple linear regression (MLR)

Stepwise MLR analysis was performed using the *lm* function. The selection of the best predictors was performed with the Akaike Information Criterion (AIC) method. The normality of residuals was examined via the *Shapiro-Wilk* test, the multicollinearity level was measured by calculating the variance inflator factor (VIF), and lower collinearity was considered when VIF was lower than ten, using the library *car* and *vif* function.

b. Least absolute shrinkage and selection operator (LASSO)

To generate models with LASSO regression, the *caret* and *ipflasso* libraries were used. The LASSO method applies regularization techniques that penalize any coefficient of linear model tending to zero to avoid overfitting, and identifies the significant predictors to be used in the model (Pannu and Billor, 2017). Ten cross-validation was used to optimize the parameters, and important variables were identified through the coefficient values extracted.

c. Random Forest (RF)

The RF model was created using the *ranger* library. It is an efficient ensemble machine learning algorithm (Breiman, 2001), and is a robust model against outliers issues and prevents overfitting. It is composed of multiple trees, where each tree has an estimated output and the final estimated value is the average of all trees (Chen and Zhang, 2023). The cross-validation method was used for model tuning to find the optimal values for the number of trees, the number of variables to be randomly divided, and the node size. The importance of variables was extracted from the final model obtained.

For the MLR and machine learning algorithms, the goodness of fit of the generated models was evaluated using the adjusted coefficient of determination (R^2) as an indicator of the explained alfalfa yield variance. The root mean square error (RMSE) and the normalized RMSE (nRMSE) relative to the mean were estimated to evaluate the accuracy of the model and these were calculated as follows:

$$RMSE = \sqrt{\frac{\sum_{i=1}^n Y_i - \hat{Y}_i}{n}}$$

$$nRMSE = \frac{RMSE}{\bar{y}}$$

where Y_i and $\hat{Y}_i$ are the measured and the predicted trait, respectively, n is the total number of samples in the test set, and $\bar{y}$ is the mean of the measured trait in the test set. Finally, to provide an external validation of the model, the best yield estimation model was compared to the Navarre regional government's official statistics of biomass yield averaged in the zone under study (Ribera Alta) (https://nastat.navarra.es/es/tablas_powerbi/-/tag/produccion-anual-cultivos).

3. Results

3.1. Year and the effect of the number of harvests on alfalfa yield

The descriptive statistics of the biomass yield values observed in both years are presented in Table 3. Year was observed not to affect yield, although the ordinal number of harvests performed per year had a significant effect. In general, the fifth harvest of the year, usually undertaken during autumn, showed the lowest yield relative to the previous four harvests (Supplementary Fig. S2). For each harvest, a coefficient of variation (CV) between 0.19 and 0.40 were observed across the harvests considered in the study. The first harvest of 2021 showed the highest range with 3.817 kg ha⁻¹ and the lowest was observed for the fourth harvest in 2021 with 2.465 kg ha⁻¹. (Table 3).

3.2. Relationship among alfalfa yield, VIs and meteorological variables

A PCA was carried out to assess the relationship between all studied VIs in a bi-dimensional platform that included the three phenological stages analyzed (Fig. 3A). The early-veg stage was clearly separated from the late-veg and bud stages by two principal components that explained 91.5 % of the variability, with most of indices positioned towards the late-veg and bud directions. In addition, a summary of the correlation analysis between alfalfa yield, meteorological data and the VIs (mean and median values) at the three phenological stages is shown in Fig. 3B and 3C. Overall, for most of the variables analyzed, the correlations were higher in the late-veg and bud stages than in early-veg. Regarding the meteorological data, temperature was negatively correlated with alfalfa yield, while water-related variables (e.g. accumulated precipitation during the growing season) showed positive correlations. For the mean and median values of the VIs, the correlations varied according to the phenological stage. At early-veg, the NDVI and RDVI had the highest correlations with yield ($r \approx 0.13$, $p < 0.05$), while at the late-veg and bud stages, the NDWI and RDVI showed the highest correlation ($r_{(late-veg)} \approx 0.28$, $p < 0.01$; $r_{(bud)} \approx 0.43$, $p < 0.01$).

3.3. Alfalfa yield estimation

The results observed for the alfalfa yield estimation models at the early-veg ($n = 532$), late-veg ($n = 526$) and bud ($n = 272$) phenological stages varied according to the set of predictors and the algorithms used. Nevertheless, there was a decreasing amount of data from the early-veg to bud stages because the fields were harvested at different dates and some of them did not reach the desirable GDD for the study. In general, for all the models applied, R^2 and the accuracy in both training and test sets increased progressively from the early-veg to the bud stages (Table 4). Additionally, no strong differences in the prediction statistics for the training and test set data were observed for most of the models used in this study. One conventional model (MLR) and two machine learning algorithms (LASSO and RF) were applied to evaluate the contribution of VIs, meteorological variables, and their combination to explain alfalfa yield (Table 4).

3.3.1. VI-based estimations

At the three phenological stages studied, the MSR, NDWI and RDVI resulted in the most accurate predictors of yield relative to other indices (Table S4) when the LASSO regression model was applied. This model

Table 3
Alfalfa yield (kg ha⁻¹) obtained from the five harvests in both years.

Year	N° Harvest	n ^a	Mean (kg ha ⁻¹)	Min (kg ha ⁻¹)	Max (kg ha ⁻¹)	SD	CV
2020	1	45	2949.6 ± 128.8	921.40	4208.51	863.89	0.29
	2	51	3063.8 ± 99.74	1740.32	4957.50	712.27	0.23
	3	50	2624.7 ± 90.34	1369.53	4629.32	638.77	0.24
	4	50	2593.8 ± 82.74	1426.03	4440.80	585.09	0.23
	5	52	1779.1 ± 81.38	427.11	3397.50	586.87	0.33
2021	1	59	2311.2 ± 119.7	449.04	4265.91	919.66	0.40
	2	62	2949.3 ± 92.01	1294.20	4944.30	724.50	0.25
	3	64	2886.7 ± 74.16	1016.53	4091.40	593.26	0.21
	4	62	2726.5 ± 67.43	1263.29	3728.65	530.96	0.19
	5	64	1996.6 ± 70.37	603.35	3306.36	562.97	0.28
ANOVA							
Year			0.814				
Harvest			< 0.001				

^a n, number of fields available for each harvest; means; Min, minimum; Max, maximum; SD, standard deviation and CV, coefficient of variation for alfalfa yield. Level of significance for the ANOVA: *p* values < 0.05 were considered significantly different according to the Tukey HSD test.

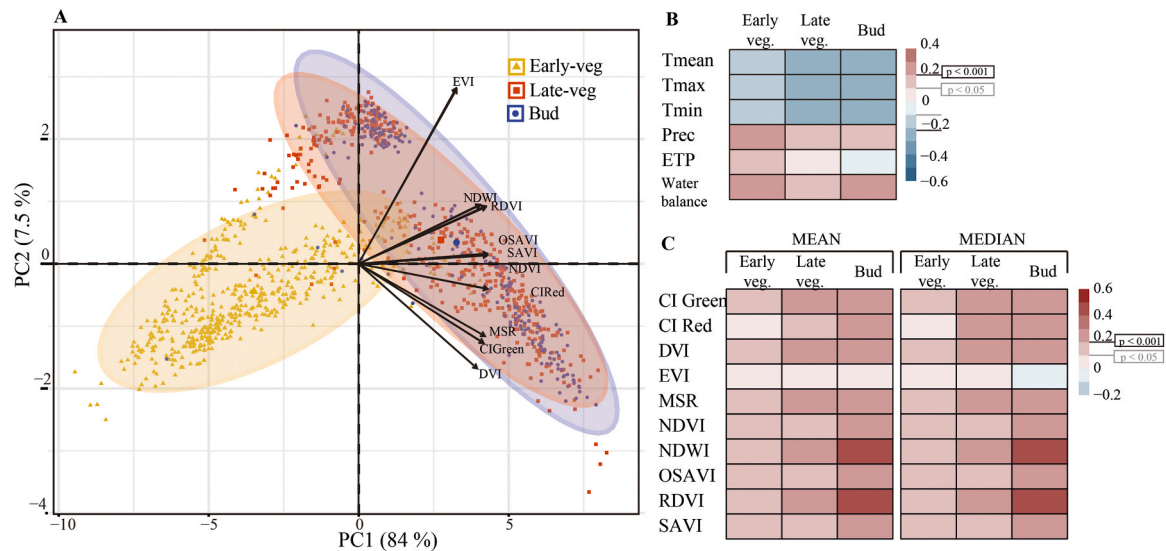


Fig. 3. A Principal component analysis (PCA) of the VIs at the three phenological stages assessed. **B** Heatmap showing the Pearson correlation coefficients between alfalfa yield and meteorological parameters. **C** Heatmap showing the Pearson correlation coefficients between alfalfa yield and VI variables at three phenological stages. The color scale is shown together with the corresponding threshold of significance.

Table 4
Estimation statistics for alfalfa yield using one conventional MLR model and two machine learning algorithms (LASSO and RF) using only Sentinel-2-derived VIs, only meteorological data, and their combination as predictors. Adjusted coefficients of determination (*R*²), root mean square errors (RMSE) in kg ha⁻¹ and normalized RMSE (nRMSE) are given for training and test sets in each model applied.

Model		Early-veg			Late-veg			Bud		
		VIs	Meteo ^a . variables	VIs + Meteo.	VIs	Meteo. variables	VIs + Meteo.	VIs	Meteo. variables	VIs + Meteo.
MLR	<i>R</i> ² _{Train}	0.02*	0.06	0.07**	0.09**	0.07	0.13**	0.34*	0.10	0.45*
	RMSE _{Train}	777	760	754	748	754	729	567	663	515
	<i>R</i> ² _{Test}	0.05	0.07	0.10	0.10	0.13	0.16	0.28	0.18	0.48
	RMSE _{Test}	752	745	729	707	696	686	594	596	474
	nRMSE _{Test}	0.29	0.29	0.28	0.27	0.27	0.26	0.22	0.22	0.17
LASSO	<i>R</i> ² _{Train}	0.07**	0.12	0.16*	0.16*	0.11	0.26*	0.43*	0.18	0.60*
	RMSE _{Train}	767	741	727	727	749	683	546	651	443
	<i>R</i> ² _{Test}	0.09	0.13	0.21	0.13	0.15	0.26	0.32	0.16	<u>0.61</u>
	RMSE _{Test}	731	716	686	698	688	643	611	605	430
	nRMSE _{Test}	0.29	0.28	0.27	0.27	0.26	0.25	<u>0.23</u>	<u>0.22</u>	0.16
RF	<i>R</i> ² _{Train}	0.04*	0.24	0.26**	0.17*	0.34	0.44**	0.28*	0.28	0.41**
	RMSE _{Train}	787	693	678	722	645	591	604	611	545
	<i>R</i> ² _{Test}	0.03	0.33	<u>0.36</u>	0.12	0.35	<u>0.44</u>	0.24	0.38	0.46
	RMSE _{Test}	764	636	618	702	607	560	575	520	486
	nRMSE _{Test}	0.30	0.25	0.24	0.27	0.24	0.22	0.21	0.19	0.18

^a Meteo: Meteorological variables *MEAN values of indices used as predictors; **MEDIAN values of indices used as predictors. The best estimation was underlined.

showed the best estimate for explaining the variability of the alfalfa yield in the test sets. The use of the LASSO model led to R^2 values of 0.09 (nRMSE = 0.285), 0.13 (nRMSE = 0.267) and 0.32 (nRMSE = 0.225) for the early-veg, late-veg and bud stages, respectively (Table 4). VI-based estimations of alfalfa yield resulted in similar accuracies for the three phenological stages analyzed, although slight improvements were observed in the yield estimation models for the late-veg and bud stages.

3.3.2. Meteorological-based estimations

The use of only meteorological variables as predictors in the models improved the estimations relative to VI-based estimations for the three phenological stages analyzed (Table 4). Regarding the relevant predictors, the Tmin, Tmean, accumulated precipitation and water balance were the most important variables selected in the models. Additionally, the RF model led to the best estimate and most accurate results relative to the MLR and LASSO models for explaining the yield variability. The RF resulted in R^2 values of 0.33 (nRMSE = 0.25), 0.35 (nRMSE = 0.23) and 0.38 (nRMSE = 0.19) in the test sets of the early-veg, late-veg and bud stages, respectively.

3.3.3. Combining VIs and meteorological data for alfalfa yield estimation

The combination of VIs and meteorological data used as predictors improved the alfalfa yield estimations and accuracies for the three

phenological stages compared to those obtained when VIs or meteorological variables were used alone (Table 4, Fig. 4). Considering the difference of variation in yield for the best estimations at each phenological stage, the data combination explained 33 %, 31 % and 29 % more variation in yield than the single VI-based estimations for the early-vegetative, late-vegetative and bud stages, respectively. Compared to meteorological-based estimations, the data combination explained 3 %, 8 % and 23 % more variation in yield for each phenological stage, respectively. In addition, the models that best explained the yield variation were the RF when applied to early-veg and late-veg, and LASSO when applied to the bud stage.

The results obtained varied depending on the model considered. For instance, when the conventional MLR model was applied to the early-veg data, it was able to explain up to 10 % of yield variability using Prec., RDVI and CI Red as explanatory variables. For late-veg, 16 % of yield variability was explained using Tmin, NDWI and RDVI, and at the bud stage, 48 % of yield was explained using water balance, NDVI, NDWI and RDVI.

In comparison to MLR, better results were achieved when the analysis was performed with the LASSO model. This model generated R^2 values up to 21 %, 26 % and 61 % of yield variability in the test sets at the early-veg, late-veg and bud stages, respectively, and it was able to explain 11 %, 10 % and 13 % more variation in yield for each

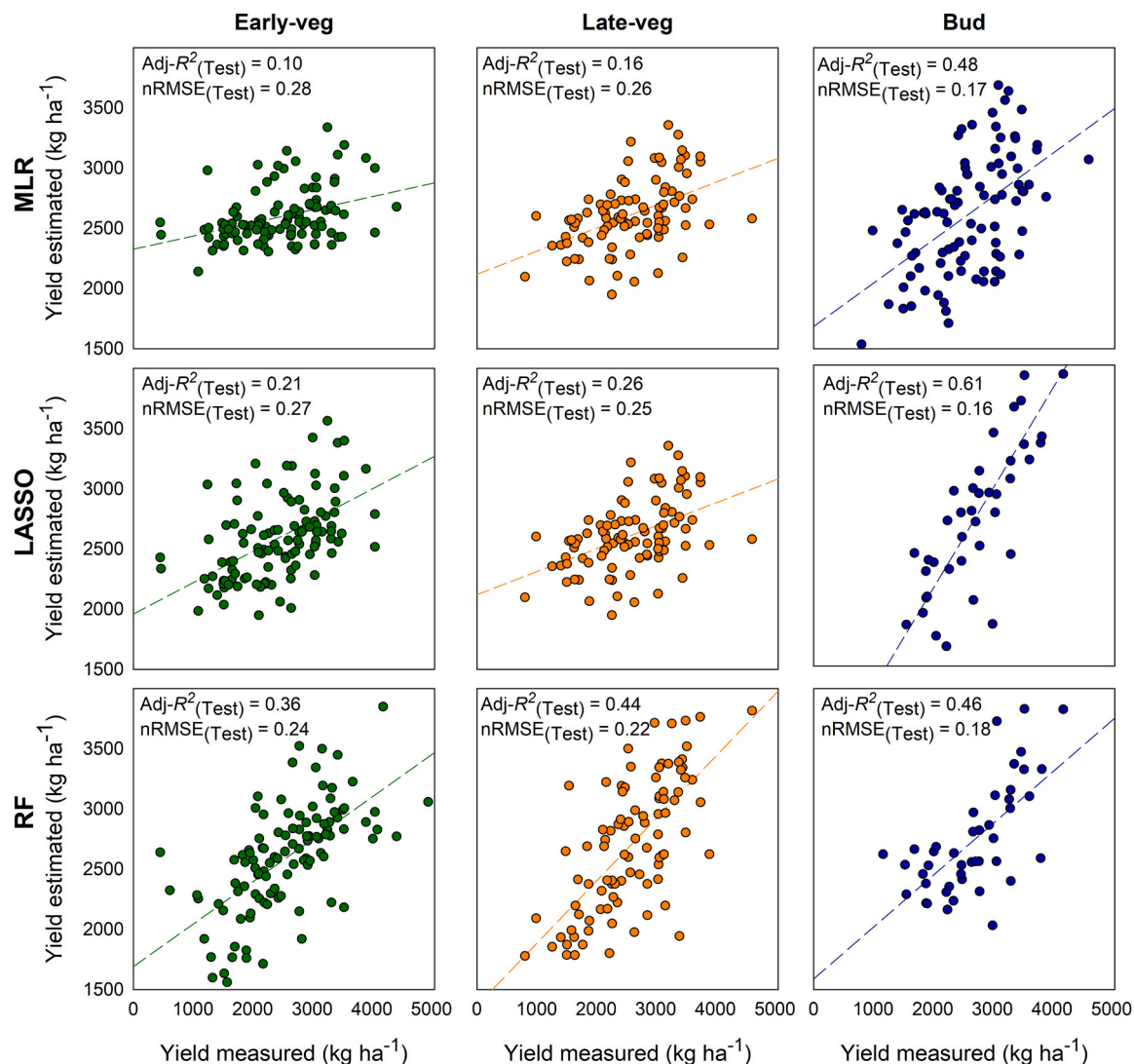


Fig. 4. Measured against the estimated values for alfalfa yield using MLR, LASSO and RF models in the test set. All the models were generated using a combination of VIs and meteorological data as predictors. In each graph, the R^2 and nRMSE of the test set are shown.

phenological stage when compared to MLR. In regard to the explanatory variables given by LASSO regression, some were similar to the variables obtained with MLR, although the variable importance varied (Table S4). At early-veg and late-veg the most important explanatory variables were the Tmean, CI Green and MSR, and at the bud stage these were the water balance, MSR and NDWI.

In the final model analyzed (RF), the yield variability explained was higher than the other models only at early-veg and late-veg stages. RF was able to explain 36 % of yield variability for early-veg and 44 % for late-veg, but at the bud stage the percentage of yield variability was lower ($R^2 = 46$ %) than the value obtained with the LASSO model ($R^2 = 61$ %) (Table 4). In comparison to the LASSO model, RF improved the estimation by 15 % for early-veg and 18 % for late-veg. The most important explanatory variables given by RF for early-veg were the water-balance, precipitation, ETP, and NDWI and for the late-veg and the bud stages they were the Tmin, RDVI and NDWI (Table S5).

Finally, the official biomass yield data for the zone of Navarre under study (Ribera Alta), provided by the Government of Navarre, reported an average of 2537.6 kg ha⁻¹ per harvest for the entire zone. The best estimation in this study resulted in 2706.6 ± 725.15 kg ha⁻¹, representing 7 % overestimation compared to the official data, which showed a difference of 169 kg ha⁻¹.

4. Discussion

Regarding the first research question (What is the importance of phenology in estimating alfalfa yield?), Sentinel-2 data were analyzed due to their high revisit frequency, which is especially useful to detect the numerous harvests and short periods of regrowth of alfalfa crops throughout the year (French et al., 2023). This advantage has allowed us to evaluate three phenological stages in alfalfa, from early to late stages of plant development. Nevertheless, the time series of optical satellites has an inherent challenge given by the presence of clouds, particularly during the winter months, leading to reduced data availability, mainly from October to March, in the region of study. Despite this, since alfalfa exhibits reduced growth during this period of time due to dormancy (Hoppen et al., 2022) and harvests events typically do not occur during these months, several satellite data can be selected to monitor its phenology. There are several strategies to remove the effect of clouds, such as interpolation of missing values (Kamir et al., 2020) or the incorporation of Sentinel-1 Synthetic Aperture Radar (SAR) data (Ahamed et al., 2011), which were not included in this study. In this sense, fusion with the optical Sentinel-2 data could be a promising approach to monitor phenological stages precisely as described by Chen and Zhang (2023).

According to Porter et al. (2014), spectral values and therefore VIs vary with phenological stage. It is due to the morphological feature changes as plants mature, causing change in spectral response. Consequently, yield estimations found in this study were dependent on phenological growth stage. The results suggested that the most suitable phenological stage for estimating alfalfa yield is the bud stage ($R^2 = 0.61$, RMSE = 430 kg ha⁻¹, nRMSE = 0.16). These results were similar compared to previous studies using satellite data in alfalfa crops. For example, Yu et al. (2024) examined the potential of yield estimation through using satellite radar data at different harvest events, finding that the best performing model obtained $R^2 = 0.67$ (RMSE = 680 kg ha⁻¹). Similarly, Kayad et al. (2016) utilized satellite optical data from Landsat-8 obtaining that the highest R^2 was 0.56 (no RMSE was provided). One of the best results in estimating alfalfa yield described in literature, reported an $R^2 = 0.92$ (RMSE = 1100 kg ha⁻¹) (Azadbakht et al., 2022), although the authors explore the use of satellite imagery from two platforms (i.e. Landsat-8 and PROBA-V). However, previous studies performed on alfalfa at different harvests have found similar values compared to the current study, the most of these did not consider yield estimations by phenological stage as showed in this work.

According to our results focused on phenology, the estimations improved progressively from the early-veg to bud stages. This could be attributed (at least in part) to the increased soil background influences at early stages, with reflection from the soil surface creating noise that altered the models' fit. In addition, during the early stages of crop development, the data acquired from most pixels may include mixtures of vegetation, likely due to the presence of weeds. This can affect the signature of the crops during those phenological stages and reduce the accuracy of the estimations (Bolton and Friedl, 2013; Ji et al., 2021). In contrast, at advanced phenological stages there is a reduced soil influence (Segarra et al., 2020b) and sensors can capture more information from the aboveground biomass of the crop (Al-Gaadi et al., 2016). However, at high-density of vegetation could occur a saturation effect of indices, such as NDVI (Thenkabail et al., 2000) and therefore, exploring the use of other indices that minimize this effect and maintain high sensitivity to fully developed canopies corresponding to advanced phenological stages is relevant to obtain reliable estimations at these phenological stages (Ji et al., 2021). Despite the rather poor estimations obtained for the early-veg stage in this study, yield estimation during these stages is desirable so corrective management can be implemented in the field prior to harvest.

The ability to evaluate vegetation changes through satellite images is based on the calculation of VIs using reflectance captured at different wavebands; specifically for Sentinel-2, 13 bands of the spectrum are analyzed from the visible to the shortwave infrared (Araus et al., 2021; Segarra et al., 2020a). Combining two or more spectral bands (VI calculations) is often used to improve the detection of vegetation properties (Araus et al., 2021; Misra et al., 2020). In this study, we calculated ten different VIs (Table 2) to answer the second research question (Which Sentinel-2-derived VIs best contribute to estimation of alfalfa yield before each harvest?).

We observed in the three phenological stages that the MSR, NDWI and RDVI showed the highest correlations with yield (Fig. 3), and these were the most suitable indices for yield estimations. This selection could be due to the NIR (840 nm) and red (668 nm) waveband-derived indices (e.g. MSR) being more sensitive to biomass and chlorophyll content without experience saturation, also the non-linearity of MSR index increase its sensitivity to vigor variations unlike other linear indices (e.g. NDVI), and they might present greater variation than indices calculated from blue bands like the EVI (Chandel et al., 2021a,b). Our results are in line with previous reports where models generated with EVI as the predictor did not provide a significant fit to alfalfa yield (Chandel et al., 2021a,b). In addition to the MSR, the index related to water content (NDWI) was also selected as a potential predictor in this study. Considering that water status is a major component of plant production (Champagne et al., 2003; Chandel et al., 2021a,b), the inclusion of this index improved the yield estimation accuracy as mentioned by Chandel et al. (2021) in alfalfa crops. Finally, the selection of the RDVI could be due to its association with biomass and vegetation cover and also because it is highly sensitive to canopy properties, even under low vegetation cover because its capacity to minimize background reflectance effects while maintaining sensitivity to fully developed canopies (Roujean and Breon, 1995).

Nevertheless, the use of VIs as predictor variables to estimate alfalfa yield resulted in relatively low R^2 and accuracies at the three phenological stages studied. The highest R^2 values obtained were 0.09 (nRMSE = 0.29), 0.13 (nRMSE = 0.27) and 0.32 (nRMSE = 0.23) for the early-veg, late-veg and bud stages, respectively (Table 4). This is consistent with other VI-based models for estimating alfalfa yield reported by Kayad et al. (2016). The results have demonstrated that VI-based models could explain just under 30 % of yield variation, but these might not be enough for application in real time. To overcome this limitation, some authors have argued that estimation accuracy could be improved by combining satellite imagery with environmental data (Celis et al., 2024; Farmonov et al., 2023; Moot et al., 2022; Noland et al., 2018; Yadav and Geli, 2021).

Considering the assumption mentioned before and providing an answer to the third research question (Do meteorological data contribute to improve alfalfa yield prediction?), we have generated models using meteorological variables alone, VIs alone, and the combination of all data (Table 4). According to [Yadav and Geli \(2021\)](#) and [Noland et al. \(2018\)](#), the temperature has a significant role in alfalfa yield prediction, as also reported in our results. However, contrary to our findings, [Yadav and Geli \(2021\)](#) reported that alfalfa yield estimations can be performed using only climate variables, with greatest relevance for Tmax, vapor-pressure deficit and annual precipitation, obtaining an $R^2 = 0.99$ (RMSE = 0.46 ton ha⁻¹). However, for their analysis, the authors integrated data from a long time series (1920–2019) which could contribute to the improvement of estimations. In contrast, our findings suggest that while the yield variabilities explained by the environmental data models ($R^2 = 0.33$, $R^2 = 0.35$ and $R^2 = 0.38$ for early-veg, late-veg and bud, respectively with nRMSE < 0.25) were more accurate than those obtained with VI-data models, the yield variabilities were best explained when VIs and meteorological data were combined.

In this regard, when data were combined, the most suitable VIs selected were similar to those chosen for VI-based models: NDWI and RDVI. Nevertheless, the CI Red index was also included as a relevant yield predictor for early-veg, in particular. In concordance with our results, recent studies in alfalfa have reported the potential of the NDWI and RDVI to be used as important predictors of yield when combined with other indices associated with plant water content or soil covered by vertical projection of vegetation, such as the global vegetation moisture index or soil adjusted vegetation index ([Chandel et al., 2021a,b](#); [Echeverría et al., 2021](#); [Kayad et al., 2016](#); [Li et al., 2023](#); [Payero et al., 2004](#)).

According to our results, the yield estimation showed significant improvements when meteorological data were included. The highest percentage of yield variation explained was found for the bud stage, reaching up to 61 % with high accuracy (nRMSE = 16 %), followed by late-veg ($R^2 = 0.44$, nRMSE = 0.22) and early-veg ($R^2 = 0.36$, nRMSE = 0.24) (Table 4, Fig. 4). Moreover, to our knowledge, few studies have focused on the yield estimation during the vegetative phenological period. For instance, [Kayad et al. \(2016\)](#) obtained lower R^2 values (around 20 %) than ours (36 % - 44 %) during vegetative stages for the majority of the harvests analyzed. Developing prediction models at these phenological stages will be of high value to alfalfa farmers for use in real-time situations.

In the other hand, one conventional MLR and the two machine learning algorithms, LASSO and RF were applied. The implementation of machine learning algorithms in remote sensing applications has increased recently in forage crops like alfalfa ([Tedesco et al., 2022](#)). The comparison of MLR and machine learning techniques carried out in this study showed that RF yielded the highest R^2 values for early-veg and late-veg with the lowest nRMSE (0.24 and 0.22, respectively). However, during the bud stage, the LASSO model performed the best with nRMSE of 0.16 (Table 4). A key study comparing different algorithms methods for estimating alfalfa yield is carried out by [Li et al. \(2023\)](#). In their analysis, MLR, RF, support vector machine (SVM) and artificial neural network were tested together. The findings indicated that RF and SVM achieved the best performance and comparable accuracies, although RF model had the advantage of being approximately three times faster than SVM modelling ([Pranga et al., 2021](#)). Other studies have also incorporated different algorithms to estimate alfalfa yield ([Azadbakht et al., 2022](#); [Feng et al., 2020](#); [Yu et al., 2024](#)). Overall, RF model has been highlighted and selected in most cases given its ability to capture multivariate and non-linear relationships among predictors, with the advantage of being a robust model against outliers and overfitting issues ([Azadbakht et al., 2022](#); [Chen and Zhang, 2023](#)).

The use of satellite imagery and specific meteorological data per field enables to estimate alfalfa yield, regardless of the frequency of harvesting during the year, although with moderate accuracy and

performance during the early-veg stage. The analysis focused on different locations of alfalfa fields allows us to overcome limitations imposed by low numbers of experimental sites and controlled conditions that approximate real field conditions. Other studies have highlighted this issue when using satellite imagery and climatic variables to extrapolate experimental data into regional level ([Celis et al., 2024](#); [Li et al., 2023](#); [Yadav and Geli, 2021](#)). In terms of model analysis, future studies might focus on investigating yield predictions using new data captured during more consecutive campaigns in other years and locations in order to improve model accuracy. The methods used in this study for model performance assessment measure accuracy but, modelling with multi-year data across different fields and independent samples should be considered to generate models with high transferability potential ([Wenger and Olden, 2012](#)); as well as additional features related to soil conditions could also be tested as potential drivers to estimate alfalfa yield. Additionally, advanced techniques of machine learning algorithms could be implemented, such as deep neural networks, to enable processing of large datasets, which would also increase the capacity to estimate crop yield more accurately.

5. Conclusion

Estimation of biomass yield in alfalfa crops is crucial in forage management. This study investigated the potential of using Sentinel-2 imagery, meteorological data and their fusion to estimate yield in alfalfa. The most effective alfalfa yield estimation with Sentinel-2 and environmental data is obtained at the bud stage, followed by the late-veg and early-veg stages. In that respect, the main VIs selected as important variables for most phenological stages were the RDVI and NDWI, and the most important meteorological variables were Tmin and accumulated precipitation. In addition, the modelling framework approach found that RF outperformed other algorithms (MLR and LASSO) during the early and vegetative stages, but LASSO was the best model during the bud stage. While the robustness of the models generated needs to be improved using additional locations, years, etc., the results could provide a novel approach to remotely monitor alfalfa fields at a fine-scale resolution of 10 m from early developmental stages. In this regard, the modeling could be improved by obtaining within-field yield variability and increasing the yield data points by combining geolocated harvester data with remotely sensed data, as has been implemented for other crops ([Hunt et al., 2019](#); [Segarra et al., 2022](#)).

CRedit authorship contribution statement

Jose L. Araus: Writing – review & editing, Methodology, Conceptualization. **Santesteban Luis G.:** Writing – review & editing. **Vatter Thomas:** Software. **Joel Segarra:** Writing – review & editing, Writing – original draft, Methodology. **Gámez Angie L.:** Writing – review & editing, Writing – original draft, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Aranjuelo Iker:** Writing – review & editing, Writing – original draft, Supervision, Project administration, Methodology, Conceptualization.

Declaration of Competing Interest

The authors declare that they have no known financial conflicts or personal relationships that could have influenced the research presented in this manuscript. The work was conducted independently, with no external pressures from any organization, institution, or commercial entity. All authors are committed to maintaining transparency and objectivity in the research process, and no parties had any undue influence on the study's design, data analysis, interpretation of results, or conclusions.

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Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at [doi:10.1016/j.fcr.2025.109857](https://doi.org/10.1016/j.fcr.2025.109857).

Data availability

Data will be made available on request.

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