

Long-term legacy of sowing legume-rich mixtures in Mediterranean wooded grasslands

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# Agriculture, Ecosystems and Environment

## Long-term legacy of sowing legume-rich mixtures in Mediterranean wooded grasslands

--Manuscript Draft--

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| <b>Manuscript Region of Origin:</b> | SPAIN   |
| <b>Abstract:</b>                    | <p>The oversowing of legume-rich mixtures is a management practice gaining importance in Mediterranean silvopastoral farms due to enhanced forage production, quality, and ecosystem service provision. However, the oversowing of legume species can be expensive in silvopastoral farms due to the high cost of legume seeds and seeding operations and low persistence under inadequate management. The study aimed to assess the long-term impacts of legume-rich mixtures oversowing on pasture production of Mediterranean wooded grasslands with a remote sensing approach. The study was conducted on six Dehesa farms in Western Spain, where legume mixtures had been sown in different years from 2002 to 2015 in part of the farms. The effects of legume species oversowing were assessed by analyzing the variation across years of a set of derived vegetation indices in sown and unsown areas of each farm. Among all considered vegetation indices, the Simple Ratio (SR) and the Normalized Difference Vegetation Index (NDVI) showed the highest capacity in estimating grassland yield (Pearson's <math>r = 0.58</math> and <math>0.52</math>, <math>P &lt; 0.01</math>, respectively) and N content (<math>r = 0.52</math> and <math>0.48</math>, <math>P &lt; 0.05</math>, respectively). All normalized vegetation indices increased after the sowing and remained significantly higher than before sowing (<math>P &lt; 0.001</math>) for the whole monitoring period. Furthermore, the sowing also positively affected the temporal stability of each vegetation index, being interannual variability significantly higher (<math>P &lt; 0.01</math>) before the sowing than after. The study confirmed the hypothesis that the oversowing of legume-rich mixtures in Mediterranean wooded grasslands effectively improves intra- and interannual biomass production and stability. Remote sensing using Landsat images proved to be an effective tool to assess the impacts of grassland management practices in the long term in silvopastoral systems.</p> |
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## Supplementary Material

### Long-term legacy of sowing legume-rich mixtures in Mediterranean wooded grasslands

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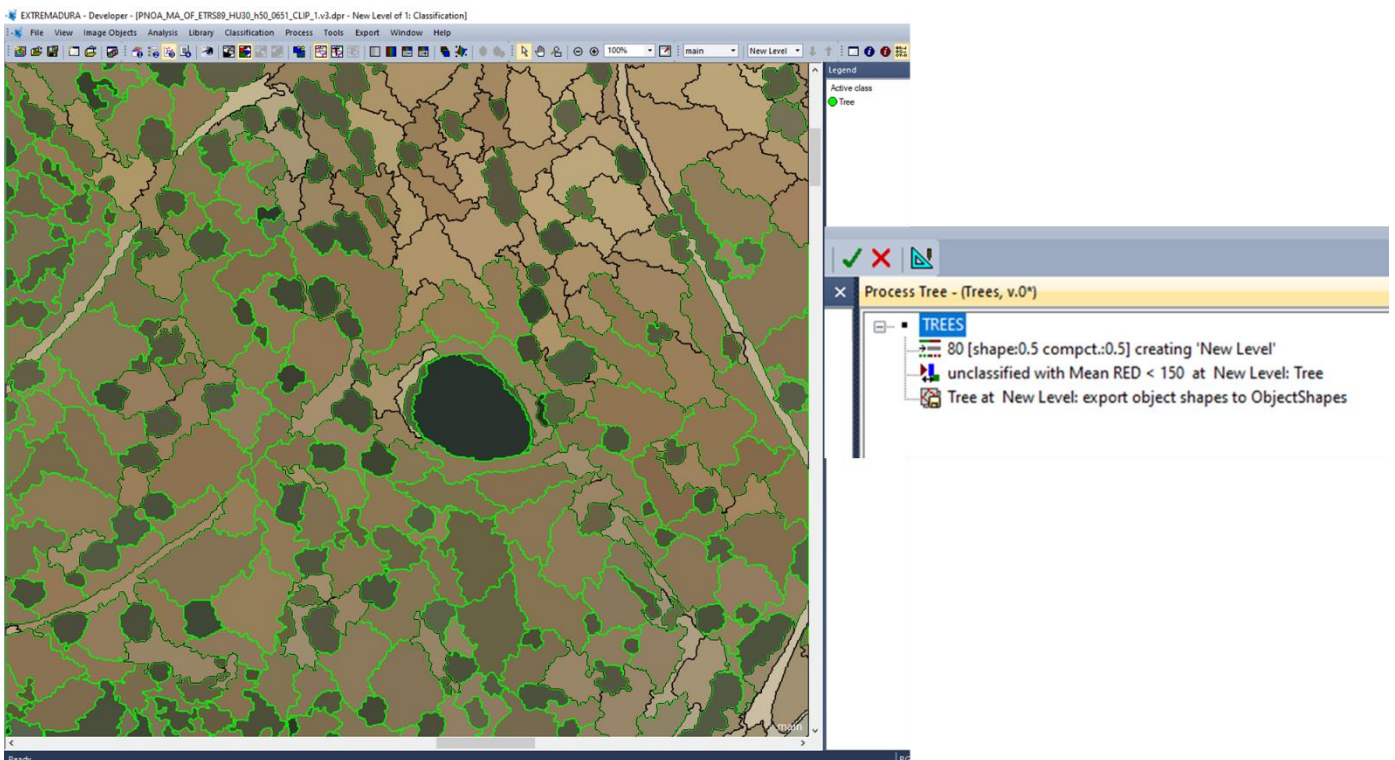
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## High-resolution orthophotos processing with eCognition®.

Orthophotos from PNOA (<http://centrodedescargas.cnig.es/CentroDescargas/index.jsp#>) were processed at the field level with the eCognition® software (ver 9.0.1, Trimble Inc., Sunnyvale, California, USA). Before creating the final open pasture layer in a GIS environment, shapefiles identifying trees (as in this example) and small buildings were generated through algorithms based on shape and reflectance at the red and blue bands. The list of used algorithms, parameters, and their values is reported in Table 1S. An example of object identification output is reported in Fig. 1S.

**Table 1S. Algorithms, parameters, and their values as set in the eCognition process tree to identify trees, small buildings, and streets**

| Algorithm                    | Parameter  | Objects |                             |
|------------------------------|--|---------|-----------------------------|
|                              |  | Trees   | Small buildings and streets |
| Multiresolution segmentation | Scale parameter  | 80      | 15                          |
|                              | Shape  | 0.5     | 0.7                         |
|                              | Compactness  | 0.5     | 0.5                         |
| Assign class                 | Threshold condition<br>(Feature: Layer,<br>Mean value) | RED<150 | BLUE>135                    |



**Fig. 1S. Output of a process-tree-based object classification performed with the eCognition software.**

**Table 2S. Tree-covered and open pasture area (%), available pixels for the remote sensing analysis (%), and area covered by the available pixels (m<sup>2</sup>) in the field study.**

| <b>Farm</b> | <b>Field</b> | <b>Tree cover (%)</b> | <b>Open pasture (%)</b> | <b>Available pixels (%)</b> | <b>Area covered by available pixels (m<sup>2</sup>)</b> |
|-------------|--------------|-----------------------|-------------------------|-----------------------------|---|
| Farm1       | 2010         | 0.29                  | 0.71                    | 0.44                        | 418569  |
|             | 2011         | 0.21                  | 0.79                    | 0.70                        | 391708  |
|             | 2012         | 0.29                  | 0.71                    | 0.45                        | 233977  |
|             | 2013         | 0.22                  | 0.78                    | 0.72                        | 667038  |
|             | 2014         | 0.25                  | 0.75                    | 0.49                        | 89792   |
|             | Control      | 0.21                  | 0.79                    | 0.62                        | 623031  |
| Farm2       | 2002         | 0.35                  | 0.65                    | 0.21                        | 30539   |
|             | 2005         | 0.29                  | 0.71                    | 0.39                        | 136617  |
|             | 2011         | 0.41                  | 0.59                    | 0.15                        | 67256   |
|             | Control      | 0.37                  | 0.63                    | 0.17                        | 29639   |
| Farm3       | 2005         | 0.44                  | 0.56                    | 0.10                        | 18374   |
|             | 2011         | 0.30                  | 0.70                    | 0.36                        | 34879   |
|             | 2014         | 0.37                  | 0.63                    | 0.15                        | 19953   |
|             | Control      | 0.45                  | 0.55                    | 0.20                        | 32077   |
| Farm4       | 2002         | 0.33                  | 0.67                    | 0.44                        | 394200  |
|             | 2007         | 0.75                  | .25                     | 0.33                        | 217800  |
|             | 2012         | 0.31                  | 0.69                    | 0.28                        | 39600   |
|             | 2014         | 0.20                  | 0.80                    | 0.43                        | 90900   |
|             | Control      | 0.20                  | 0.80                    | 0.61                        | 207900  |
| Farm5       | 2003         | 0.23                  | 0.77                    | 0.57                        | 149722  |
|             | 2011         | 0.09                  | 0.91                    | 0.83                        | 583737  |
|             | 2015         | 0.21                  | 0.79                    | 0.44                        | 43039   |
|             | Control      | 0.19                  | 0.81                    | 0.60                        | 148110  |
| Farm6       | 2002         | 0.56                  | 0.44                    | 0.03                        | 7012  |
|             | 2003         | 0.61                  | 0.39                    | 0.02                        | 2861  |
|             | 2014         | 0.31                  | 0.69                    | 0.27                        | 28719   |
|             | 2015         | 0.51                  | 0.49                    | 0.06                        | 24287   |
|             | Control      | 0.40                  | 0.60                    | 0.22                        | 27376   |

## Effect of legume-rich-mixtures oversowing on biomass production and Nitrogen canopy content over the ages.

A previous study conducted by Hernández-Esteban et al. (2018) in the same study site reported a significant increase in pasture biomass production and quality in fields oversown with legume-rich mixtures compared to unsown. Data already reported in that study were reworked according to the methodological scheme of the present research by performing a normalization of biomass production ( $\text{Mg ha}^{-1}$  of DM) and N pasture content ( $\text{g m}^{-2}$  of N) measured in 2016 in oversown fields with respect to control fields for each  $j$ th field of the  $i$ th farm as follows:

$$nrValue_{i,j,k} = \frac{Vsown_{i,j} - Vcontrol_i}{Vcontrol_i}$$

Exponential regression models were fitted to test the effect of age on normalized biomass production and N pasture content. No significant effects of age were observed for both variable. Results are reported in Fig 2S.

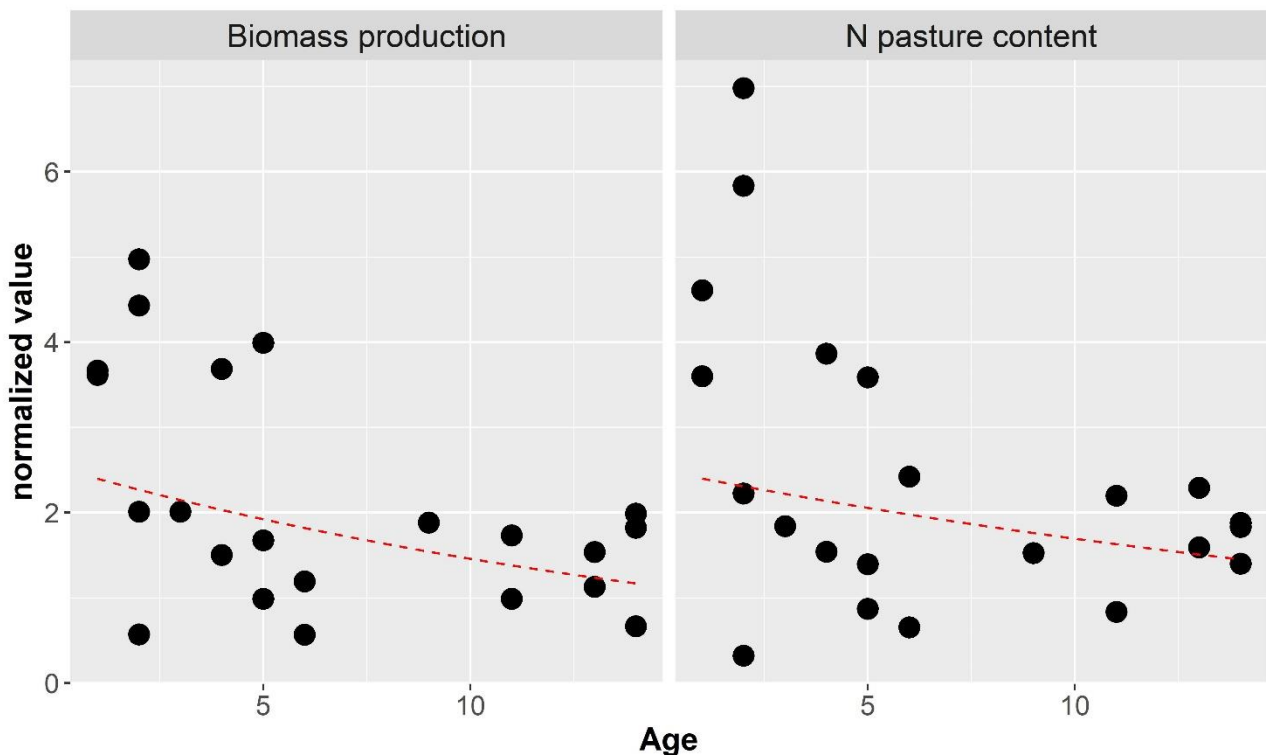
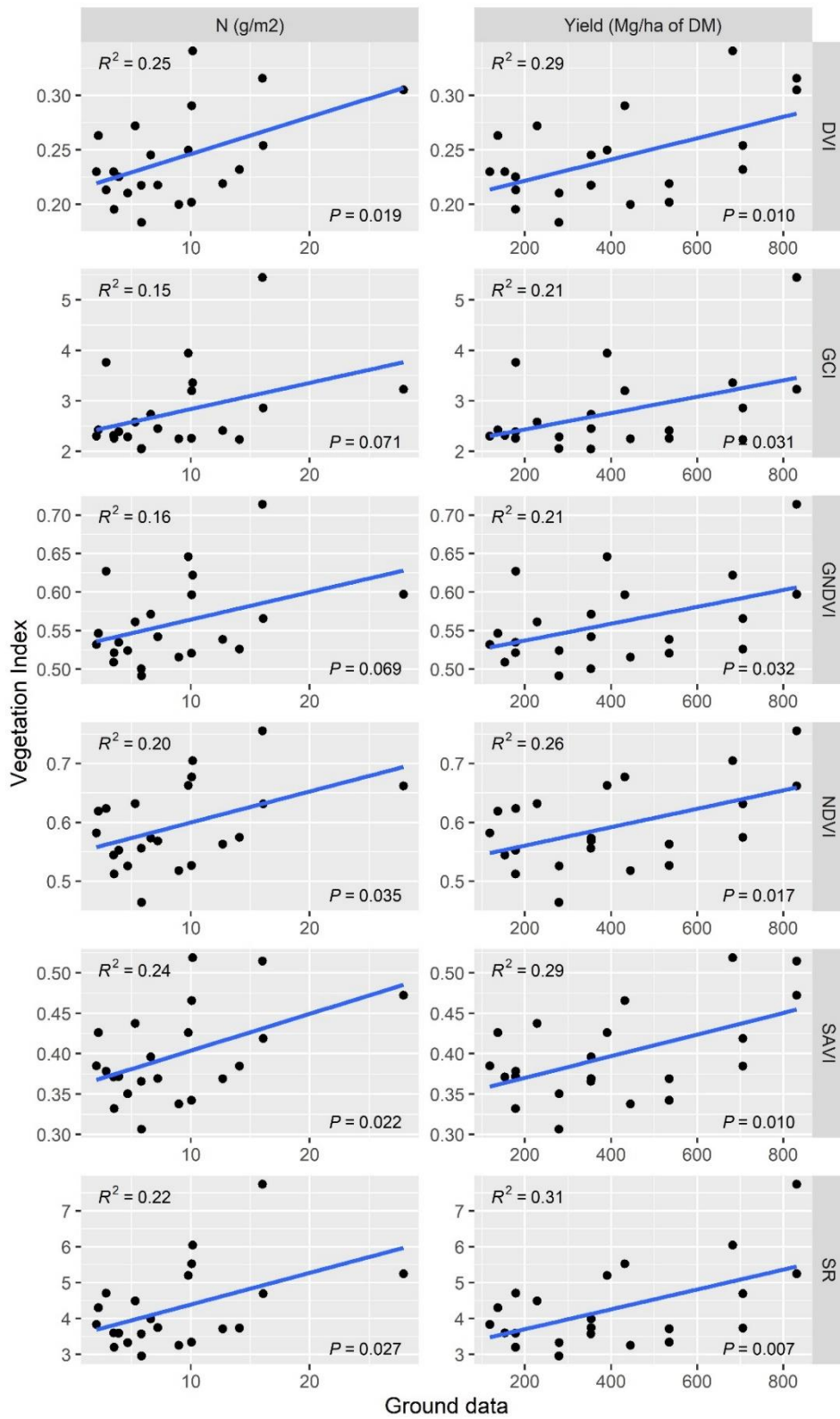


Fig. 2S. Relationships between the normalized biomass production, normalized N pasture content, and the age of sown pastures. The red lines represent the fitted exponential model.



**Fig. 3S. Relationships between Vegetation Indices and N pasture content (g m<sup>-2</sup> of N) and biomass production (Mg ha<sup>-1</sup> of DM) observed in the study fields in 2016.**

### **Declaration of interests**

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

1 **Long-term legacy of sowing legume-rich mixtures in Mediterranean wooded grasslands**

2

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11

12 **Abstract**

13 The oversowing of legume-rich mixtures is a management practice gaining importance in  
14 Mediterranean silvopastoral farms due to enhanced forage production, quality, and ecosystem  
15 service provision. However, the oversowing of legume species can be expensive in silvopastoral  
16 farms due to the high cost of legume seeds and seeding operations and low persistence under  
17 inadequate management. The study aimed to assess the long-term impacts of legume-rich mixtures  
18 oversowing on pasture production of Mediterranean wooded grasslands with a remote sensing  
19 approach. The study was conducted on six Dehesa farms in Western Spain, where legume mixtures  
20 had been sown in different years from 2002 to 2015 in part of the farms. The effects of legume  
21 species oversowing were assessed by analyzing the variation across years of a set of derived  
22 vegetation indices in sown and unsown areas of each farm. Among all considered vegetation  
23 indices, the Simple Ratio (SR) and the Normalized Difference Vegetation Index (NDVI) showed  
24 the highest capacity in estimating grassland yield (Pearson's  $r = 0.58$  and  $0.52$ ,  $P < 0.01$ , respectively)  
25 and N content ( $r = 0.52$  and  $0.48$ ,  $P < 0.05$ , respectively). All normalized vegetation indices increased  
26 after the sowing and remained significantly higher than before sowing ( $P < 0.001$ ) for the whole  
27 monitoring period. Furthermore, the sowing also positively affected the temporal stability of each  
28 vegetation index, being interannual variability significantly higher ( $P < 0.01$ ) before the sowing than  
29 after. The study confirmed the hypothesis that the oversowing of legume-rich mixtures in  
30 Mediterranean wooded grasslands effectively improves intra- and interannual biomass production  
31 and stability. Remote sensing using Landsat images proved to be an effective tool to assess the  
32 impacts of grassland management practices in the long term in silvopastoral systems.

33 **Keywords.** Legume oversowing; agroforestry systems; remote sensing; temporal stability;  
34 vegetation indices; Landsat; sustainable intensification

35 **1. Introduction**

36 Grassland ecosystems cover about 25% of the Earth's surface and 70% of the total agricultural  
37 terrestrial area (Conant, 2010). About 17M km<sup>2</sup> of grasslands worldwide are identified as  
38 silvopastoral systems (Zomer et al., 2009). Grasslands are the most important sources of food  
39 worldwide as they support livestock activities, such as beef and milk production, which offer  
40 livelihoods for about 1 billion people among the poorest countries and one-third of the global  
41 protein intake (Steinfeld et al., 2006). Wooded grasslands provide a wide range of ecosystem  
42 services (Torralba et al., 2016), such as fodder production (Porqueddu et al., 2016; Seddaiu et al.,  
43 2018), biodiversity conservation (Bagella et al., 2020), C sequestration (Mosquera-Losada et al.,  
44 2011; Pulina et al., 2022), and water and nutrient cycles regulation (Lozano-Parra et al., 2018; Nair  
45 et al., 2019), among others.

46 The increasing demand for high-quality animal products complies with the need for sustainable and  
47 resource-efficient pasture-based farming systems such as silvopastoral farms (Moreno et al., 2018).  
48 However, these grazing systems are threatened by low profitability (Palomo-Campesino et al.,  
49 2018), which is partly associated with abandonment and intensification trends. Abandonment trends  
50 can lead to undergrazing, which, combined with climate change, contributes to land degradation and  
51 the loss of palatable vegetation (Mahyou et al., 2016). On the other hand, intensification through  
52 overgrazing can hamper tree regeneration processes compromising the long-term preservation of  
53 silvopastoral systems (Rossetti and Bagella, 2014) and soil and herbaceous cover degradation  
54 (Kairis et al., 2015). For these reasons, the sustainability of these agroecosystems requires  
55 management practices and tools to reverse the abandonment and degradation in marginal areas.

56 Pasture improvement by sowing legume-rich mixtures in extensively managed grasslands is gaining  
57 importance due to enhanced forage production and quality (Nichols et al., 2012; Teixeira et al.,  
58 2015; Sanna et al., 2018; Edwards et al., 2019). Legume oversowing can expand the forage growing  
59 season (Mason et al., 2019) and improve soil functions by strengthening fertility and N and C

60 cycling (Bondaruk et al., 2020). Legumes sowing can modify soil microbial community  
61 composition playing a crucial role in their persistence (Collins et al., 2017). This mechanism can  
62 trigger the increase of microbial biomass in the soil, enhancing the overall soil functional diversity  
63 and N fixation and C sequestration (Moreno et al., 2021). However, the oversowing of legume  
64 species can be expensive due to the high cost of legume seeds and seed mixtures (Schaub et al.,  
65 2021) and low persistence under grazing mismanagement (Muir et al., 2011; Hayes et al., 2019).  
66 Nevertheless, legume-based forage systems can represent a solution facing the rising costs for  
67 inputs (e.g. fertilizers) whenever proper management can ensure their persistence. For this reason,  
68 the sustainability of such practices is highly related to the persistence over years of the most  
69 important species introduced with the sowing.

70 Assessing the long-term persistence of legume sown fields requires monitoring large spatial and  
71 temporal scales. There is great interest and numerous attempts to use satellite imagery (e.g.  
72 Landsat) for monitoring grassland productivity and quality (Wachendorf et al., 2018; Reinermann et  
73 al., 2020). Remote sensing data offer a cost-effective solution to monitoring phenology,  
74 productivity, and quality of grasslands over relatively large areas and long time scales. However,  
75 finding an appropriate spatial and temporal scale to detect changes remains a significant challenge  
76 in most circumstances and pasturelands (Liu et al., 2016; Berra et al., 2019).

77 Understanding the impacts of both abiotic and biotic drivers of primary production of the  
78 herbaceous component in wooded grasslands represents a challenge because of the presence of  
79 trees. In fact, in the case of such agroforestry systems, the intimate mixing of plant strata with very  
80 different phenological patterns is complex, making it challenging to discern the contribution of each  
81 stratum to the overall phenological phases detected with satellite imagery. Different approaches  
82 aiming to exclude and isolate the effect of trees emerge from the literature. For instance, based on  
83 the differences between Normalized Difference Vegetation Index (NDVI) dynamics, the spectral  
84 signal from trees can be isolated from those attributable to grassland layers (Lu et al., 2003; Gómez-

85 Giráldez et al., 2019). In wooded grasslands where tree vegetation is dominated by evergreen  
86 mature-scattered trees, such as Spanish Dehesas, tree pixels can be isolated based on the assumption  
87 that they keep a constant value throughout the year (González-Dugo et al., 2021). The availability  
88 of higher-spatial-resolution images (e.g. those from the Sentinel2 satellite) allows for adopting more  
89 detailed techniques, such as using a GPS device to reference the trees and exclude pixels including  
90 them (Fernandez-Habas et al., 2021) or applying classification techniques of the landscape such as  
91 the Object-based image analysis (OBIA) integrated with LiDAR (Light Detection and Ranging)  
92 data (Helleesen and Matikainen, 2013). However, its relatively small temporal availability, as  
93 compared to Landsat, hinders the assessment of long-term effects.

94 A previous study conducted by Hernández-Esteban et al. (2018) reported a significant increase in  
95 pasture yield and quality in fields sown with legume-rich mixtures compared to unsown. However,  
96 it is still uncertain if these improvements are sustained in the long term or if it is a transient effect.  
97 This study hypothesized that the oversowing of legume-rich mixtures could improve pasture  
98 productivity and stability in the long term and that remote sensing could represent a tool to assess  
99 the effectiveness of this practice in Mediterranean wooded grasslands. The aims of the study were:  
100 (i) to assess to what extent pasture production and quality (N content) can be monitored by means  
101 remotely sensed vegetation indices in Mediterranean wooded grasslands; (ii) to evaluate the long-  
102 term effects of legume oversowing on the temporal trends of these indices, and on (iii) their  
103 temporal variability as an indicator of the stability of the forage availability and quality.

104

## 105 **2. Materials and Methods**

### 106 *2.1. Study Site*

107 The study was conducted on six Dehesa farms located in central-western Spain, in the Extremadura  
108 community (39°57'/39°46' N – 6°28'/5°56' O). The climate is Mediterranean pluviseasonal

109 continental (Rivas-Martínez et al., 2011), characterized by hot, dry summer and cold, rainy winter.  
110 The average annual temperature in the farms ranges from 16.0 °C to 17.5 °C, while the average  
111 annual rainfall ranges from 500 mm to 700 mm (Hernández-Esteban et al., 2019). The Dehesa  
112 vegetation within the farms is composed of scattered trees, primarily evergreen oaks such as  
113 *Quercus suber* L. and *Q. ilex* L., sparse shrubs species, and herbaceous annual self-seeding species  
114 that form the grassland system. Grasslands are managed through continuous grazing of cattle, pigs,  
115 sheep, and some wild cervids.

116 In each farm, different legumes-rich mixtures (*Trifolium subterraneum* L. subsp *brachycalycinum*  
117 and *yanninicum*, *Ornithopus sativus* L., *T. incarnatum* L., *T. michelianum* Savi var *balansae*, *T.*  
118 *resupinatum* L., *T. vesiculosum* Savi, and *T. glanduliferum* Boiss) have been sown over the years  
119 (from 2002 to 2015) in multiple large areas within each farm, aiming to improve the overall  
120 grassland productivity and forage quality. As a result, each farm comprises a chronosequence of  
121 several legume-sown fields, remaining the rest of the farm as unsown areas. These large unsown  
122 areas were considered as control. Details of the size and number of sown areas in each farm are  
123 reported in Table 1. The age of sowing, location, and limits of each sown field was gathered by  
124 interviewing farmers. Further details on sowing and overall grassland management are reported by  
125 Hernández-Esteban et al. (2018) and Hernández-Esteban et al. (2019).

## 126 2.2. Ground data collection

127 Pasture production and quality were characterized by measuring the annual grassland yield (kg m<sup>-2</sup>  
128 of dry matter, DM), biomass nitrogen content in spring or peak of content (kg m<sup>-2</sup> of N), and plant  
129 functional group (relative abundance of grasses, legumes, and forbs) composition.

130 Grassland yield was measured in 2016. Six exclusion cages (1 m x 1 m) were placed per field,  
131 allowing estimating the biomass production under grazing during the growing season. The  
132 exclusion cages were placed within the sown fields and in areas where sowing was never performed  
133 before, identified as control unsown fields. At the end of the growing season (end of spring),

134 biomass was cut at ground level inside each cage within a 50 cm x 50 cm square quadrat. Biomass  
135 was then oven-dried until it reached constant weight to determine the DM content. The N content  
136 on plant biomass was measured using the Dumas Method in a DUMATHERM Gerhardt analyzer.

137 Plant inventory was carried out through the Point Transect method (Southwood and Henderson,  
138 2009), recording plant species every 100 cm in eight random 25 m transects within each field (200  
139 individuals per field). The relative abundance of the three main functional groups (grasses, legumes,  
140 and forbs) was then calculated. Detail on biomass, plant inventory, and N measurements are  
141 reported in Hernández-Esteban et al. (2018).

### 142 *2.3. Remote sensing method to assess the long-term impacts of legume-rich mixtures oversowing*

143 Freely available high-resolution orthophotos (PNOA,  
144 <http://centrodedescargas.cnig.es/CentroDescargas/index.jsp#>) were used to distinguish between  
145 trees, built-up areas (i.e., streets, houses or rural buildings), and small water ponds from pasture  
146 areas in sown and control fields. The images were processed at the field level with the eCognition<sup>®</sup>  
147 software (ver 9.0.1, Trimble Inc., Sunnyvale, California, USA). A tree-decision-based algorithm  
148 was set up to identify trees and built-up areas, resulting in vectorial shapefiles delineating trees and  
149 other elements from pasture. An example of object classification is reported in Supplementary  
150 Material (Fig. 1S). The few water ponds were identified and mapped using the QGIS software (ver.  
151 3.6.0-Noosa, QGIS Development Team, <https://qgis.org/it/site/>). Pasture layers were derived as the  
152 difference between the borders of each field and the identified objects (trees, streets, buildings,  
153 water ponds).

154 Multispectral images from Landsat satellites (<https://www.usgs.gov/landsat-missions>) were  
155 acquired among those available and free from clouds in the study areas. For each farm, images were  
156 acquired from four years before the first sown to four years after the last sown, in the time window  
157 from March 20<sup>th</sup> to May 31<sup>st</sup>, corresponding to spring. In the study areas, the maximum pasture  
158 biomass growing rates and the highest forage availability can be observed in this period.

159 A total of 125 images were obtained from 1998 to 2019. All images were downloaded and then pre-  
160 processed to perform the DOS1 (Dark Object Subtraction) method for atmospheric correction and  
161 get the TOA (Top Of Atmosphere) reflectance values using the QGIS Semi-Automatic  
162 Classification Plugin (Congedo, 2020). The characteristics of satellites, sensors, and spectral bands  
163 used for the study are reported in Table 2.

164 Spectral reflectance at the green, red, and NIR bands was extracted from images using the raster  
165 package (Hijmans, 2020) within the R (version 4.0.5) environment (R Core Team, 2021). The  
166 extraction was performed by using the shapefiles of the pasture layer previously built as extracting  
167 layers. Moreover, the percentage of the total pixel area (30 m x 30 m) covered by the pasture layer  
168 was calculated to exclude pixels with less than 70% (about 630 m<sup>2</sup>) of pasture coverage.

169 A set of Vegetation Indices (VI) in the range of the selected bands (SR, GCI, DVI, NDVI, GNDVI,  
170 SAVI) was calculated from the extracted reflectance values. Details on indices, formulas and their  
171 description are reported in Table 3.

172 A flowchart of the remote sensing methodology adopted in this study is provided in Figure 1.

#### 173 *2.4. Assessment of the long-term impacts of legume-rich mixtures oversowing*

174 To assess to what extent remotely sensed vegetation indices (VIs) could be used to monitor pasture  
175 yield and quality, a correlation analysis was performed between VIs and the observed data for yield  
176 (g m<sup>-2</sup> of DM), N pasture content (g m<sup>-2</sup> of N), grasses (%), legumes (%), and forbs. The  
177 significance of Pearson's correlation index (r) was tested by performing a two-tails Student's t-test.  
178 Furthermore, the root-mean-square error (RMSE) of the linear regression between VIs and ground  
179 data was calculated. Previous to these analyses, both ground data and VIs were averaged at the field  
180 level.

181 To assess the long-term effects of legume sowing and to minimize any influence of the interannual  
182 variability of remotely sensed images and the effect of the different satellite sensors, VI values of

183 sown fields were normalized with respect to the control fields (nrVI) for each  $j$ th field of the  $i$ th  
184 farm at each  $k$ th sensing date as follows:

$$185 \quad nrVI_{i,j,k} = \frac{VI_{sown_{i,j,k}} - VI_{control_{i,k}}}{VI_{control_{i,k}}}$$

186 where the  $VI_{sown}$  and the  $VI_{control}$  were the VIs values in the sown and control areas averaged at  
187 the field level, respectively. Furthermore, to assess if this effect was dependent on the time since  
188 sowing, we calculated the temporal distance (years) between the VI sensing and the year when the  
189 sowing was carried out in that field. This variable was called age. A positive age indicates years  
190 after sowing, and a negative age indicates years before the sowing, being zero in the year of  
191 sowing. The temporal stability of the remotely-sensed data was calculated by analyzing the temporal  
192 dynamics of the standard deviation of nrVIs (sdVI) across ages, adopting a mobile time windows  
193 approach to calculate moving standard deviation. For each nrVI, the standard deviation at the  $j$ th  
194 field and the  $k$ th age (sdVI) was calculated within a window of three years ( $m=3$ ) as follows:

$$195 \quad sdVI_{j,k} = \sqrt{\frac{1}{m} \sum_{i=k-m+2}^{k+2} (nrVI_{i,j} - \overline{nrVI_j})^2}$$

196 where  $nrVI_{i,j}$  is the nrVI value at the  $i$ th age, and  $\overline{nrVI_j}$  is the average value within the window.

197 The effect of sowing was assessed by fitting a linear mixed-effect model (lme), with both nrVI and  
198 sdVI as response variables and period (before sowing vs. after sowing) and age (years to/from  
199 sowing) as predictors, assigning the field as a random factor. If the effect of the age on nrVIs was  
200 not significant, highlighting the absence of any significant trend, a one-tail Student's t-test was  
201 performed to compare before and after sowing periods in order to test differences between the  
202 average nrVI and nrVI = 0. If the effect of age on sdVIs was significant, linear or 2<sup>nd</sup>-degree  
203 polynomial regressions were fitted to test for temporal trends in each period (i.e., before and after  
204 the sowing).

205 Data analysis and statistical computations were performed using the RStudio application of R  
206 software (version 4.0.5) (R Core Team, 2021). The significance of statistical computations was  
207 evaluated at  $P < 0.05$  unless otherwise stated.

208

### 209 **3. Results**

#### 210 *3.1. Pasture pixels' availability in the wooded grasslands*

211 The mean, maximum, minimum, and standard deviation of each VI in control and sown areas both  
212 before and after the sowing are reported in Table 4.

213 As expected, a negative exponential relationship ( $R^2=0.77$ , data provided in Supplementary  
214 Material, Table 2S) was found between the field tree cover and the number of treeless pixels  
215 available for the analysis (i.e., pasture areas). The adopted method in selecting useful pixels allowed  
216 us to explore, on average, 37% of the total field area, ranging from values lower than 5% in the  
217 high-covered fields (tree cover  $> 50\%$ ) to a useful surface higher than 60% in the low-covered  
218 fields (tree cover  $< 20\%$ ).

#### 219 *3.2. Relationships between ground and remote sensing data*

220 The mean and the standard deviation of grassland yield ( $\text{Mg ha}^{-1}$ ), the relative abundance (%) of  
221 grasses, legumes, and forbs, and the N pasture content ( $\text{g m}^{-2}$  of N) are reported in Table 5. All the  
222 VI had a significant positive correlation ( $P < 0.05$ ) with the observed grassland yield ( $\text{Mg ha}^{-1}$  of  
223 DM) in 2016. The highest correlation indices were observed between yield and SR ( $r=0.56$ ; RMSE  
224 =  $1.95 \text{ Mg ha}^{-1}$ ) and NDVI ( $r=0.54$ ; RMSE =  $2.03 \text{ Mg ha}^{-1}$ ). The N content ( $\text{g m}^{-2}$  of N) had a  
225 significant positive correlation with all indices except for GCI and GNDVI (both  $r=0.39$ ,  $P=0.07$ ).  
226 No significant correlations between the relative abundance of the considered functional groups and  
227 the VI were observed. Results are in detail reported in Table 6.

228 Further information about the pasture biomass production and N pasture content over ages and the  
229 linear regressions between each VI and ground data showing significant correlations are reported in  
230 the Supplementary Material (Fig. 2S, Fig. 3S)

### 231 *3.3. Effect of sowing legume-rich pastures on vegetation indices*

232 The period significantly ( $P < 0.001$ ) affected each nrVI, which were significantly higher after sowing  
233 than before. The dynamics of each nrVI are reported in Figure 2. The age within the period did not  
234 affect the nrVIs, highlighting the absence of significant trends before and after sowing periods.

235 The mean values of nrVIs were significantly different from 0 (sown VI > control VI) after the  
236 sowing, while no significant differences were observed before ( $P < 0.001$ ).

### 237 *3.4. Stability of NDVI across years*

238 Each sdVI was affected by period ( $P < 0.01$ ) and age within the period ( $P < 0.001$ ). The average sdVI  
239 was always higher before the sowing than after, regardless of the VI used. Furthermore, significant  
240 increasing trends of sdVI were observed before the sowing, while no trend was observed after  
241 sowing (Figure 3).

242

## 243 **4. Discussion**

### 244 *4.1. The challenge of assessing wooded pastures by satellite images*

245 In this study, identifying and limiting pasture areas allowed reaching an adequate level of  
246 completeness of information about the pasture contribution to primary productivity. However, the  
247 lower availability of pixels under high-covered fields implies a loss of spatial information from  
248 multispectral data. Nevertheless, the information from the treeless pixels can be more accurate than  
249 those deriving from the raw dataset in wooded grassland (Franklin, 1991). The higher spatial  
250 accuracy can result in higher precision in estimating primary production (Seaquist et al., 2003;

251 Duncanson et al., 2020). Furthermore, the integrated approach adopted in this study allowed  
252 distinguishing trees from pasture without analyzing spectral differences during drier periods, as  
253 proposed by Gómez-Giráldez et al. (2019), minimizing the amount of data to manage in performing  
254 the long-term analysis. On the other hand, the adopted methodology required integrating different  
255 types of images – the high-resolution RGB orthophotos with the Landsat long-term series –  
256 resulting in a two-step workflow that requires access to different databases. Despite this could  
257 hamper the automatic deployment of a decision-support system, the automatic separation performed  
258 with eCognition, even if challenging, guarantees a high accuracy (Gomes et al., 2018; Arenas-  
259 Corraliza et al., 2020; Pearse et al., 2020).

260 The observed significant correlations between VIs and ground data on grassland biomass  
261 production confirmed a large body of literature reporting the effectiveness of these indices derived  
262 from the green-red-NIR regions in predicting forage availability (Muñoz et al., 2010; Maselli et al.,  
263 2013; Gómez-Giráldez et al., 2019; Rezende et al., 2020). The VIs proved their reliability in  
264 describing the overall biomass patterns, even if their performances can be limited due to the  
265 saturation issues, as observed by Ullah et al. (2012) using NDVI and SAVI. Although it is  
266 recognized the ability of NDVI and SR to estimate foliar N content and chlorophyll in grassland  
267 ecosystems (e.g., Gamon et al., 1995), the lower effectiveness of VIs in predicting the N content  
268 was expected. The chlorophyll concentration, its distribution, and other chemical constituents are  
269 functions of the spectral reflectance at the leaf level (e.g., Sims and Gamon, 2002), while spectral  
270 reflectance is a function of leaf area index and other biophysical properties, such as overall  
271 vegetation cover, at the pasture canopy level. Factors affecting vegetation reflectance can vary  
272 according to the scale (Zarco-Tejada et al., 2003). For this reason, VIs that can adequately predict  
273 nitrogen content at the leaf scale might underperform at the pasture canopy level, limiting their  
274 effectiveness in predicting nitrogen patterns. Another limitation could be represented by the  
275 influence of weather fluctuation on relationships between VIs and ground data, i.e., under drought  
276 conditions (Wagle et al., 2014; Zhao et al., 2018). Even if only the relationships derived from only

277 one year of ground data, a large literature supports the effectiveness of used VIs in predicting  
278 biomass patterns in Dehesa agroecosystems (e.g., Serrano et al., 2018; Gómez-Giráldez et al., 2019;  
279 Serrano et al., 2021), and a large range of conditions in terms of productivity and nitrogen pasture  
280 content was explored. Furthermore, the study was oriented to describing the relative patterns of  
281 oversown vs. unsown areas without the purpose of predicting the actual biomass production or  
282 nitrogen.

#### 283 *4.2. The effectiveness and persistence of sown legume-rich pastures*

284 The observed VIs dynamics confirmed the hypothesis that legume oversowing could enhance the  
285 spring forage availability of wooded grasslands. The results confirmed what was already observed  
286 in the same study fields in the experiments conducted by Hernández-Esteban et al. (2018), aiming  
287 to assess, among others, the effect of legume oversowing on forage availability. The increased  
288 forage availability after sowing can be attributable to the enhancement of N<sub>2</sub>-fixing-species in plant  
289 communities (Bondaruk et al., 2020), as well as to the synergy that can occur between legume and  
290 no-fixing-species which may promote grasses growth and biomass production (Nyfeler et al., 2009).  
291 This can induce, at the same time, a potential loss of species richness, as observed by Jaurena et al.  
292 (2016). Nevertheless, this undesirable side effect was not observed within the study side, according  
293 to what was reported by Hernández-Esteban et al. (2019).

294 The positive effect of legume oversowing on forage productivity associated with the enhanced N  
295 availability is also reflected in the long-term persistence of higher values of each VI after the  
296 sowing. Although the remote-sensed dataset did not allow to fully confirm the findings of  
297 Hernández-Esteban et al. (2018), which observed an increasing pattern of soil N content, the  
298 absence of any progressive decrease of VIs after sowing can be considered as an indicator of an  
299 improved soil N cycling (Gómez-Rey et al., 2012; Teixeira et al., 2015) thanks to a triggered  
300 activity of *Rhizobium* bacteria (Moreno et al., 2021). In addition, legume oversowing may have had  
301 a robust positive effect also on the other native plant species composing the floristic communities of

302 grassland, especially grasses, which have benefited from enhanced N availability over time and  
303 which maximized their N use efficiency under these specific conditions induced by oversowing  
304 (Suter et al., 2015; Cong et al., 2017). Furthermore, the oversown legume-rich mixtures were  
305 composed of hard-seeded species that directly affected the grassland seed bank. The long-lasting  
306 dormancy that can be induced through this biological mechanism represents an adaptation strategy  
307 facing interannual weather variability, guaranteeing the persistence over time of legume species  
308 (Beuselinck et al., 1994; Teixeira et al., 2015; Hayes et al., 2019).

#### 309 *4.3. The effect of legume oversowing on temporal variability*

310 The evidence emerging from the remotely sensed dataset confirmed the hypothesis that the legume  
311 oversowing could smooth the interannual variability of forage production. The increasing temporal  
312 variability that was observed before sowing could be related to an overall degradation of grassland  
313 without proper agronomic management leading to the restoration of soil fertility and pasture quality.  
314 This interpretation can explain the choice to improve those fields through an oversowing with  
315 legume-rich mixtures. All the factors leading to an increased and more persistent biomass  
316 productivity (improvement of C and N cycling, increased N availability through N fixation,  
317 dormancy mechanism associated with the hardseedness) are expected to play a crucial role in  
318 reducing the temporal fluctuations, which are mainly associated with environmental and weather  
319 variability (Gea-Izquierdo et al., 2009). The decrease in temporal variability of biomass production  
320 can be attributed to the increase in species richness (Caldeira et al., 2005), which can enhance the  
321 stability of biomass availability through the compensatory effect induced by the reduction of  
322 synchrony (defined as the extent to which species population density covary positively over time)  
323 between species (Valencia et al., 2020). However, this mechanism can only partially explain what  
324 was previously found in the same study site by Hernández-Esteban et al. (2019), which observed an  
325 increase of species richness only for legumes and a decrease of forbs richness under drought  
326 conditions in the ages soon after sowing. These findings highlight that in these agroecosystems,

327 biomass temporal variability after sowing is mainly driven by the enhanced fertility (i.e., C cycling)  
328 and nutrient (i.e., nitrogen) availability induced by oversowing, which in turn could also improve  
329 the efficiency in using yield-limiting factors such as nitrogen itself and water (El- Madany et al.,  
330 2021).

331

## 332 **5. Conclusions**

333 This study confirmed the hypothesis that the oversowing of legume-rich mixtures in Mediterranean  
334 wooded grasslands could effectively improve intra- and interannual biomass production of the  
335 herbaceous vegetation component. The long-term dynamics of the derived vegetation indices  
336 highlighted the positive role of legume oversowing in guaranteeing higher forage availability  
337 compared to unsown areas. Furthermore, legume enrichment proved to be an effective solution to  
338 reduce the temporal fluctuations of forage provision mainly due to the interannual variability of  
339 factors driving biomass production, i.e., water availability and meteorological conditions.

340 Remote sensing through Landsat images analysis resulted in a suitable tool to assess the impact of  
341 grassland management in the long term under the specific environmental conditions characterized  
342 by the presence of the trees. Furthermore, combining different image analysis tools allowed  
343 reaching an adequate level of information about the grassland contribution to the primary  
344 productivity during spring in wooded grasslands, even if the availability of valuable pixels is  
345 affected by the tree cover. Further insights may concern the study of the effect of weather patterns  
346 on the relationships between vegetation indices and field data to explore the broadest range of  
347 conditions and strengthen the predictive capacity of remote sensing.

348 The results of this study highlight that the combination of new software resources and big-data  
349 analytics for predictive modeling can provide cost-effective, integrated farm-level decision support  
350 tools for sustainable grassland management.

351

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365

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607 Table 1. Farms, soil classification (Soil Survey Staff, 2014), year of sowing, and sown species within the  
608 study area

| Site code | Farm         | Coordinates and elevation    | Soil                            | Year of sowing | Size of the sown field (ha) | Tree cover (%) | Mixture species   |
|-----------|--------------|------------------------------|---------------------------------|----------------|-----------------------------|----------------|---|
| Farm1     | Atoquedo     | 39.77 N; 5.92 W<br>371 m asl | <i>Eutric Cambisol</i>          | 2010           | 83.34                       | 0.29           | <i>Trifolium subterraneum</i> ; <i>T. subterraneum</i> ssp <i>yannanicum</i> ; <i>T. subterraneum</i> ssp.  |
|           |              |                              |                                 | 2012           | 45.42                       | 0.29           | <i>brachycalycinum</i> ; <i>T. incarnatum</i> ;   |
|           |              |                              |                                 | 2013           | 81.48                       | 0.22           | <i>T. vesiculosum</i> ; <i>T. resupinatum</i> ;   |
|           |              |                              |                                 | 2014           | 14.49                       | 0.25           | <i>T. michelianum</i> ; <i>T. glanudliferum</i> ; <i>Ornithopus sativus</i> ; <i>Lupinus luteus</i>   |
|           |              |                              |                                 | Control        | 80.37                       | 0.21           |   |
| Farm2     | La Caña      | 39.29 N; 6.13 W<br>265 m asl | <i>Eutric Cambisol</i>          | 2002           | 11.56                       | 0.35           | <i>Trifolium subterraneum</i> ; <i>T. subterraneum</i> ssp <i>yannanicum</i> ; <i>T. subterraneum</i> ssp.  |
|           |              |                              |                                 | 2005           | 30.62                       | 0.29           | <i>brachycalycinum</i> ; <i>T. incarnatum</i> ;   |
|           |              |                              |                                 | 2011           | 40.12                       | 0.41           | <i>T. vesiculosum</i> ; <i>T. resupinatum</i> ;   |
|           |              |                              |                                 | Control        | 14.03                       | 0.37           | <i>T. michelianum</i> ; <i>T. glanudliferum</i> ; <i>Ornithopus sativus</i> ; <i>Lupinus luteus</i>   |
| Farm3     | La Ciervina  | 39.71 N; 6.13 W<br>373 m asl | <i>Eutric Cambisol</i>          | 2005           | 14.89                       | 0.44           | <i>Trifolium subterraneum</i> ; <i>T. subterraneum</i> ssp <i>yannanicum</i> ; <i>T. subterraneum</i> ssp.  |
|           |              |                              |                                 | 2011           | 7.34                        | 0.30           | <i>brachycalycinum</i> ; <i>T. incarnatum</i> ;   |
|           |              |                              |                                 | 2014           | 10.00                       | 0.37           | <i>T. vesiculosum</i> ; <i>T. resupinatum</i> ;   |
|           |              |                              |                                 | Control        | 12.76                       | 0.45           | <i>T. michelianum</i> ; <i>T. glanudliferum</i> ; <i>Ornithopus sativus</i> ; <i>Lupinus luteus</i>   |
| Farm4     | Las Casillas | 39.50 N, 6.48 W<br>433 m asl | <i>Dystric Cambisol</i>         | 2002           | 75.21                       | 0.33           | <i>Trifolium subterraneum</i> ; <i>T. subterraneum</i> ssp <i>yannanicum</i> ; <i>T. subterraneum</i> ssp.  |
|           |              |                              |                                 | 2007           | 24.44                       | 0.75           | <i>brachycalycinum</i> ; <i>T. incarnatum</i> ;   |
|           |              |                              |                                 | 2012           | 11.58                       | 0.31           | <i>T. vesiculosum</i> ; <i>T. resupinatum</i> ;   |
|           |              |                              |                                 | 2014           | 24.96                       | 0.20           | <i>T. michelianum</i> ; <i>T. glanudliferum</i> ; <i>Ornithopus sativus</i> ; <i>Lupinus luteus</i>   |
|           |              |                              |                                 | Control        | 29.34                       | 0.20           |   |
| Farm5     | La Villa     | 39.85 N; 6.48 W<br>404 m asl | <i>Chromic Cambisol-Luvisol</i> | 2003           | 22.54                       | 0.23           | <i>Trifolium subterraneum</i> ; <i>T. subterraneum</i> ssp <i>yannanicum</i> ; <i>T. subterraneum</i> ssp.  |
|           |              |                              |                                 | 2010           | 64.01                       | 0.09           | <i>brachycalycinum</i> ; <i>T. incarnatum</i> ;   |
|           |              |                              |                                 | 2015           | 7.30                        | 0.21           | <i>T. vesiculosum</i> ; <i>T. resupinatum</i> ;   |
|           |              |                              |                                 | Control        | 20.97                       | 0.19           | <i>T. michelianum</i> ; <i>T. glanudliferum</i> ; <i>Ornithopus sativus</i> ; <i>Lupinus luteus</i> ; <i>Lolium multiflorum</i> (2015); <i>Cynodon dactylon</i> (2003-2010) |
| Farm6     | Valdelacasa  | 39.96 N; 5.95 W<br>288 m asl | <i>Dystric Cambisol</i>         | 2002           | 22.40                       | 0.56           | <i>Trifolium subterraneum</i> ; <i>T. subterraneum</i> ssp <i>yannanicum</i> ; <i>T. subterraneum</i> ssp.  |
|           |              |                              |                                 | 2003           | 13.65                       | 0.61           | <i>brachycalycinum</i> ; <i>T. incarnatum</i> ;   |
|           |              |                              |                                 | 2014           | 8.14                        | 0.31           | <i>T. vesiculosum</i> ; <i>T. resupinatum</i> ;   |
|           |              |                              |                                 | 2015           | 34.09                       | 0.51           | <i>T. michelianum</i> ; <i>T. glanudliferum</i> ; <i>Ornithopus sativus</i> ; <i>Lupinus luteus</i>   |
|           |              |                              |                                 | Control        | 9.73                        | 0.40           |   |

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611 **Table 2. List of satellites and sensors, interval between scenes detection, and characteristics of spectral**  
612 **bands used in the study**

| <b>Satellite</b>               | <b>Repeat interval</b> | <b>Bands</b>           | <b>Wavelengths<br/>(<math>\mu\text{m}</math>)</b> | <b>Spatial<br/>resolution (m)</b> |
|--------------------------------|------------------------|------------------------|---|-----------------------------------|
| Landsat 4-5 TM; Landsat 7 ETM+ | 16 days                | Band 2 – green         | 0.52-0.60   | 30                                |
|                                |                        | Band 3 – red           | 0.63-0.69   | 30                                |
|                                |                        | Band 4 – near-infrared | 0.77-0.90   | 30                                |
| Landsat 8 OLI                  | 16 days                | Band 3 – green         | 0.53 - 0.59                                       | 30                                |
|                                |                        | Band 4 – red           | 0.64 - 0.67                                       | 30                                |
|                                |                        | Band 5 – near-infrared | 0.85 - 0.88                                       | 30                                |

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617 **Table 3. Vegetation indices derived from Landsat green, red, and near-infrared bands used in the**  
 618 **study.**

| Vegetation Index                                     | Equation   | Description  | Reference                 |
|--|--|--|---------------------------|
| Simple Ratio (SR)                                    | $SR = \frac{\rho_{nir}}{\rho_{red}}$   | The SR allows distinguishing green leaves from other objects in the scene or stressed from no-stressed vegetation. When SR value is close to 1, the object has similar reflectance in red and NIR bands (e.g. soil). Green objects may have an SR value much higher than 1.  | Pearson and Miller (1972) |
| Green Chlorophyll Index (GCI)                        | $GCI = \frac{\rho_{nir}}{\rho_{green}} - 1$                                      | The GCI is a chlorophyll content proxy index based on NIR and green reflectance. In general, the chlorophyll content is directly related to vegetation. It allows distinguishing high-biomass hotspots better than NDVI.   | Gitelson et al. (2005)    |
| Difference Vegetation Index (DVI)                    | $DVI = \rho_{nir} - \rho_{red}$  | The DVI can distinguish soil from vegetation in a scene, being sensitive to the amount of photosynthetically active vegetation in the plant canopy.  | Tucker (1979)             |
| Normalized Difference Vegetation Index (NDVI)        | $NDVI = \frac{\rho_{nir} - \rho_{red}}{\rho_{nir} + \rho_{red}}$                 | The NDVI is a dimensionless index, that describes the difference between visible and near-infrared reflectance of vegetation cover,. It ranges from -1 to 1. A densely green-leafed area tends toward values close to 1, while water and built-up areas tend to zero or negative values, the latter likely indicating water. |                           |
| Green Normalized Difference Vegetation Index (GNDVI) | $GNDVI = \frac{\rho_{nir} - \rho_{green}}{\rho_{nir} + \rho_{green}}$            | The GNDVI is a photosynthetic activity proxy index commonly used to determine water and nitrogen uptake into the plant canopy. Compared to the NDVI index, it is more sensitive to chlorophyll concentration, considering the green instead of the red reflectance.  | Gitelson et al. (1996)    |
| Soil-Adjusted Vegetation Index (SAVI)                | $SAVI = \frac{\rho_{nir} - \rho_{red}}{\rho_{nir} + \rho_{red} + 0.5} (1 + 0.5)$ | The SAVI is an index derived from NDVI that minimizes soil brightness influences using a correction factor. A correction factor of 0.5, which is used in arid regions where vegetative cover is low, is adopted in this study  | Huete (1988)              |

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622 **Table 4. Mean value, standard deviation, and range of variation of the Vegetation Indices in control**  
 623 **zones and sown fields before and after the sowing**

| <b>Zone</b> | <b>Period</b> | <b>Index</b> | <b>mean</b> | <b>sd</b> | <b>max</b> | <b>min</b> |
|-------------|---------------|--------------|-------------|-----------|------------|------------|
| Control     |               | DVI          | 0.18        | 0.05      | 0.32       | 0.08       |
|             |               | GCI          | 2.16        | 1.06      | 5.48       | 0.86       |
|             |               | GNDVI        | 0.49        | 0.11      | 0.72       | 0.30       |
|             |               | NDVI         | 0.48        | 0.11      | 0.76       | 0.25       |
|             |               | SAVI         | 0.31        | 0.08      | 0.52       | 0.15       |
|             |               | SR           | 3.11        | 1.08      | 7.27       | 1.67       |
| Sown        | Before        | DVI          | 0.17        | 0.05      | 0.41       | 0.08       |
|             |               | GCI          | 1.90        | 1.17      | 9.22       | 0.66       |
|             |               | GNDVI        | 0.45        | 0.11      | 0.82       | 0.25       |
|             |               | NDVI         | 0.45        | 0.12      | 0.84       | 0.18       |
|             |               | SAVI         | 0.29        | 0.08      | 0.62       | 0.13       |
|             |               | SR           | 2.95        | 1.37      | 12.17      | 1.45       |
|             | After         | DVI          | 0.21        | 0.06      | 0.41       | 0.09       |
|             |               | GCI          | 2.75        | 1.35      | 7.95       | 0.70       |
|             |               | GNDVI        | 0.55        | 0.12      | 0.80       | 0.26       |
|             |               | NDVI         | 0.55        | 0.13      | 0.84       | 0.25       |
|             |               | SAVI         | 0.35        | 0.09      | 0.60       | 0.16       |
|             |               | SR           | 3.90        | 1.69      | 11.80      | 1.69       |

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627 **Table 5. Grassland biomass production (Mg ha<sup>-1</sup> of DM ± standard deviation), relative abundance of**  
 628 **legumes, forbs, and grasses (%), and Nitrogen pasture content (g m<sup>-2</sup> of N) observed in 2016 in the**  
 629 **field study.**

| Farm  | Year of sown | Grassland yield (Mg ha <sup>-1</sup> of DM) | Legumes (%) | Forbs (%) | Grasses (%) | N pasture content (g m <sup>-2</sup> of N) |
|-------|--------------|---|-------------|-----------|-------------|--|
| Farm1 | 2010         | 2.79±2.17                                   | 50.0        | 29.8      | 20.2        | 5.8  |
|       | 2011         | 3.54±2.79                                   | 28.8        | 29.8      | 41.3        | 6.6  |
|       | 2012         | 4.45±2.41                                   | 45.2        | 15.4      | 39.4        | 9.0  |
|       | 2013         | 5.35±3.55                                   | 41.3        | 25.0      | 33.7        | 10.0                                       |
|       | 2014         | 2.79±2.00                                   | 34.6        | 33.7      | 31.7        | 4.7  |
|       | Control      | 1.78±0.57                                   | 15.2        | 45.1      | 39.7        | 3.5  |
| Farm2 | 2002         | 2.28±1.40                                   | 31.3        | 32.9      | 35.8        | 5.3  |
|       | 2005         | 3.74±2.07                                   | 39.4        | 20.2      | 40.4        | 7.1  |
|       | 2011         | 6.82±1.44                                   | 35.6        | 21.2      | 43.3        | 10.1                                       |
|       | Control      | 1.37±0.58                                   | 19.2        | 37.8      | 43.0        | 2.2  |
| Farm3 | 2005         | 3.54±1.90                                   | 51.0        | 37.5      | 12.5        | 7.2  |
|       | 2011         | 4.76±1.90                                   | 36.5        | 41.3      | 28.8        | 9.4  |
|       | 2014         | 5.35±2.11                                   | 67.3        | 26.9      | 11.5        | 12.7                                       |
|       | Control      | 1.78±0.50                                   | 54.4        | 28.6      | 20.2        | 3.9  |
| Farm4 | 2002         | 3.53±1.98                                   | 26.9        | 26.9      | 46.2        | 5.8  |
|       | 2007         | 3.41±2.29                                   | 26.9        | 25.0      | 48.1        | 5.2  |
|       | 2012         | 5.54±1.55                                   | 39.4        | 29.8      | 30.8        | 10.0                                       |
|       | 2014         | 7.06±1.75                                   | 49.0        | 28.8      | 22.1        | 14.1                                       |
|       | Control      | 1.18±0.50                                   | 34.8        | 27.8      | 37.4        | 2.1  |
| Farm5 | 2003         | 3.79±2.34                                   | 25.0        | 48.1      | 26.9        | 9.4  |
|       | 2010         | 3.91±1.53                                   | 44.2        | 40.4      | 15.4        | 9.8  |
|       | 2015         | 8.31±2.13                                   | 26.9        | 33.7      | 39.4        | 16.0                                       |
|       | Control      | 1.78±0.74                                   | 24.1        | 43.3      | 32.7        | 2.9  |
| Farm6 | 2002         | 4.32±1.75                                   | 36.5        | 42.3      | 25.0        | 10.1                                       |
|       | 2003         | 3.88±2.44                                   | 27.9        | 27.9      | 35.6        | 9.1  |
|       | 2014         | 8.31±1.75                                   | 90.4        | 27.9      | 14.4        | 27.9                                       |
|       | 2015         | 7.06±2.26                                   | 76.9        | 7.7       | 16.3        | 16.1                                       |
|       | Control      | 1.53±0.42                                   | 44.6        | 40.5      | 24.5        | 3.5  |

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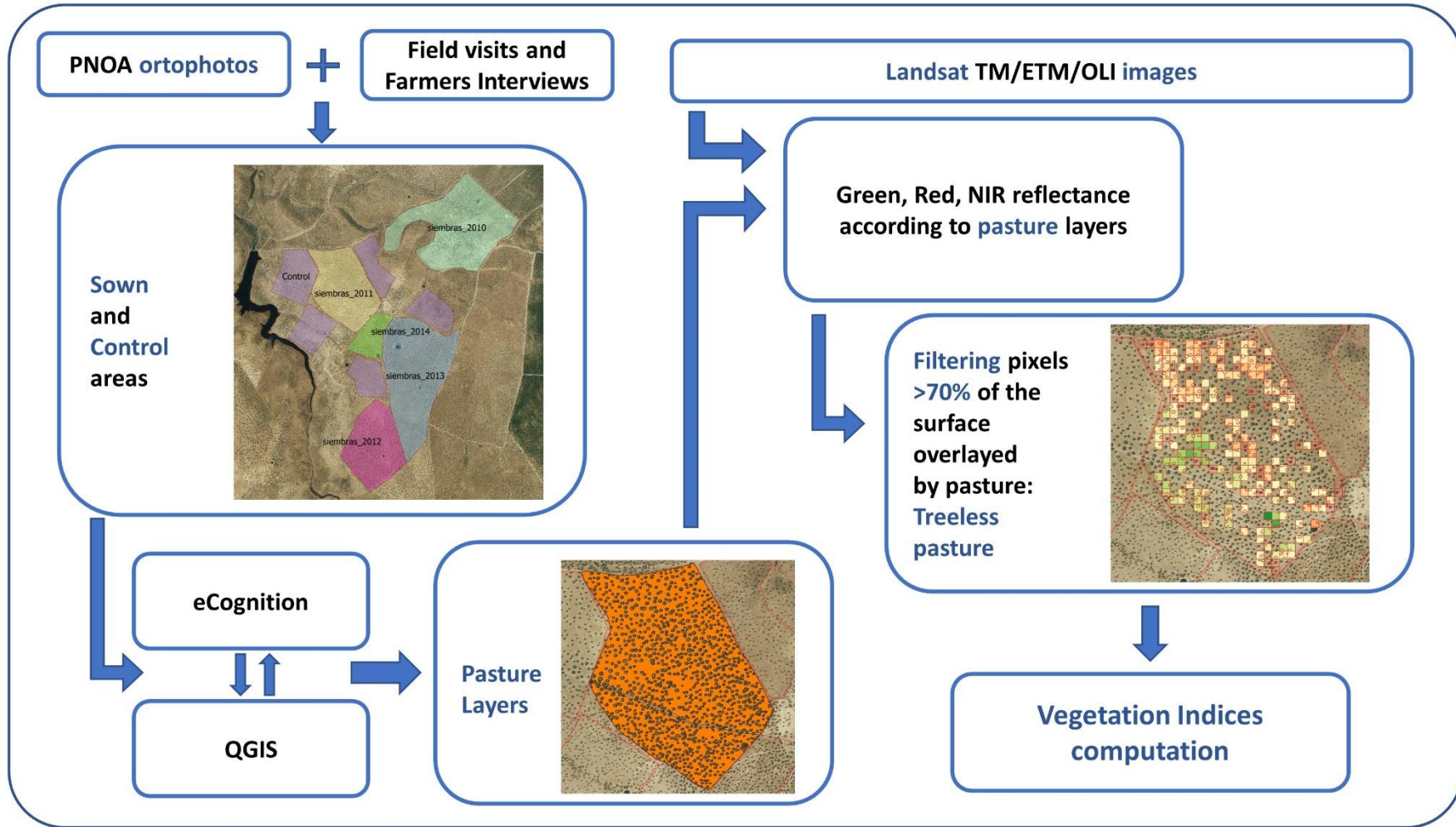
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635 **Table 6. Pearson's correlation index (r), p-value of the correlation analysis, and root mean square**  
 636 **error (RMSE) of the relationships between the Vegetation Indices derived from multispectral Landsat**  
 637 **remote sensed data and the field ground data (Yield, pasture N, grasses, legumes, and forbs) collected**  
 638 **in 2016 in the study fields.**

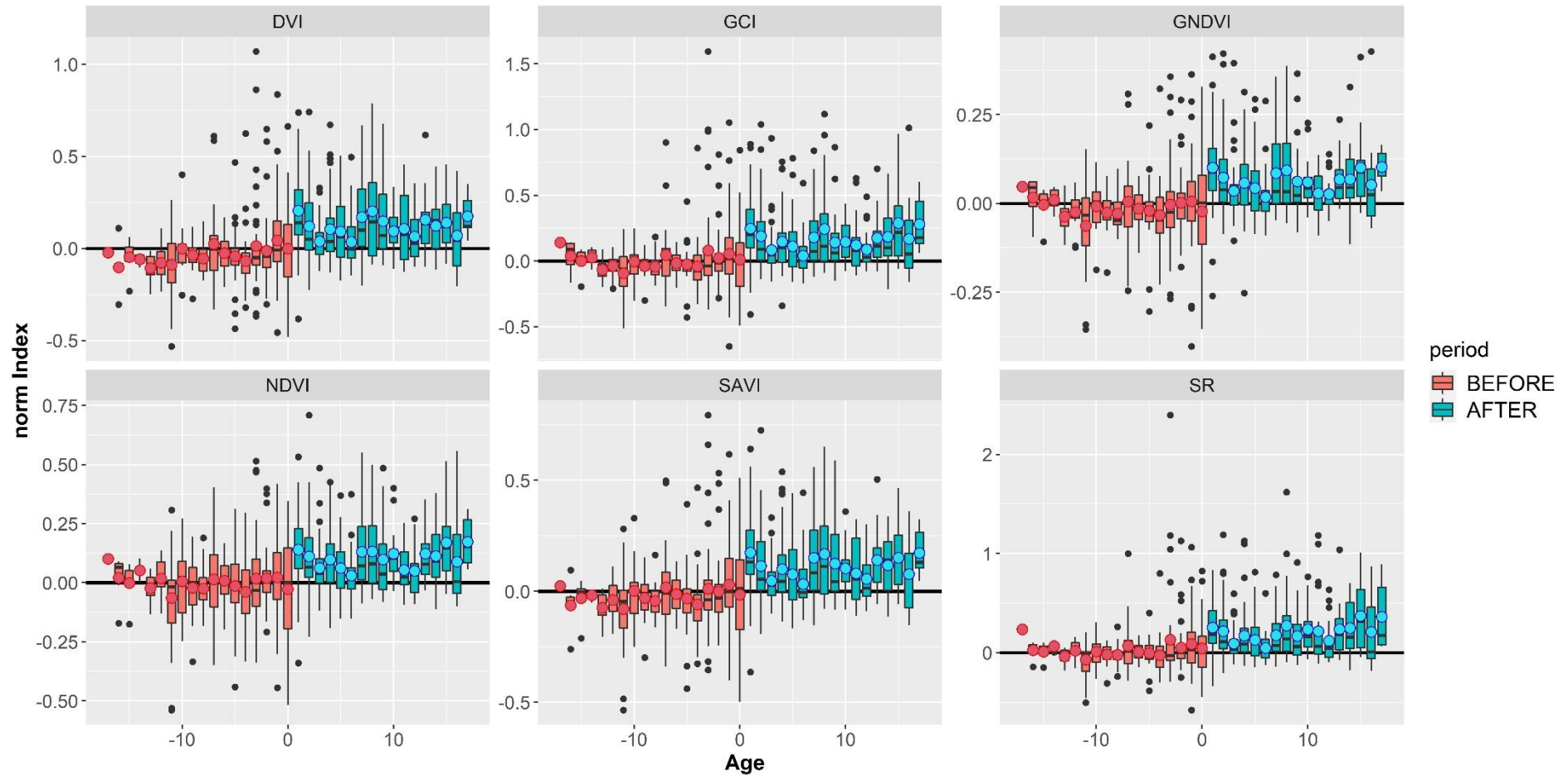
| Ground data                  |         | Vegetation Indices |       |       |       |       |       |
|------------------------------|---------|--------------------|-------|-------|-------|-------|-------|
|                              |         | DVI                | GCI   | GNDVI | NDVI  | SAVI  | SR    |
| Yield (Mg ha <sup>-1</sup> ) | r       | 0.54               | 0.46  | 0.46  | 0.50  | 0.54  | 0.56  |
|                              | p-value | 0.010              | 0.031 | 0.032 | 0.017 | 0.010 | 0.007 |
|                              | RMSE    | 1.98               | 2.08  | 2.09  | 2.03  | 1.98  | 1.95  |
| N (g m <sup>-2</sup> )       | r       | 0.50               | 0.39  | 0.39  | 0.45  | 0.48  | 0.47  |
|                              | p-value | 0.019              | 0.072 | 0.069 | 0.035 | 0.022 | 0.027 |
|                              | RMSE    | 5.41               | 5.73  | 5.72  | 5.55  | 5.44  | 5.49  |
| Grasses (%)                  | r       | 0.11               | -0.05 | -0.05 | 0.05  | 0.10  | 0.05  |
|                              | p-value | 0.581              | 0.794 | 0.817 | 0.807 | 0.63  | 0.797 |
|                              | RMSE    | 11.00              | 11.05 | 11.05 | 11.05 | 11.02 | 11.05 |
| Legumes (%)                  | r       | 0.08               | -0.08 | -0.08 | -0.03 | 0.03  | -0.04 |
|                              | p-value | 0.696              | 0.685 | 0.703 | 0.894 | 0.87  | 0.853 |
|                              | RMSE    | 17.17              | 17.17 | 17.17 | 17.22 | 17.21 | 17.21 |
| Forbes (%)                   | r       | -0.11              | 0.25  | 0.23  | 0.051 | -0.05 | 0.07  |
|                              | p-value | 0.588              | 0.206 | 0.240 | 0.795 | 0.800 | 0.723 |
|                              | RMSE    | 9.37               | 9.14  | 9.17  | 9.41  | 9.41  | 9.40  |

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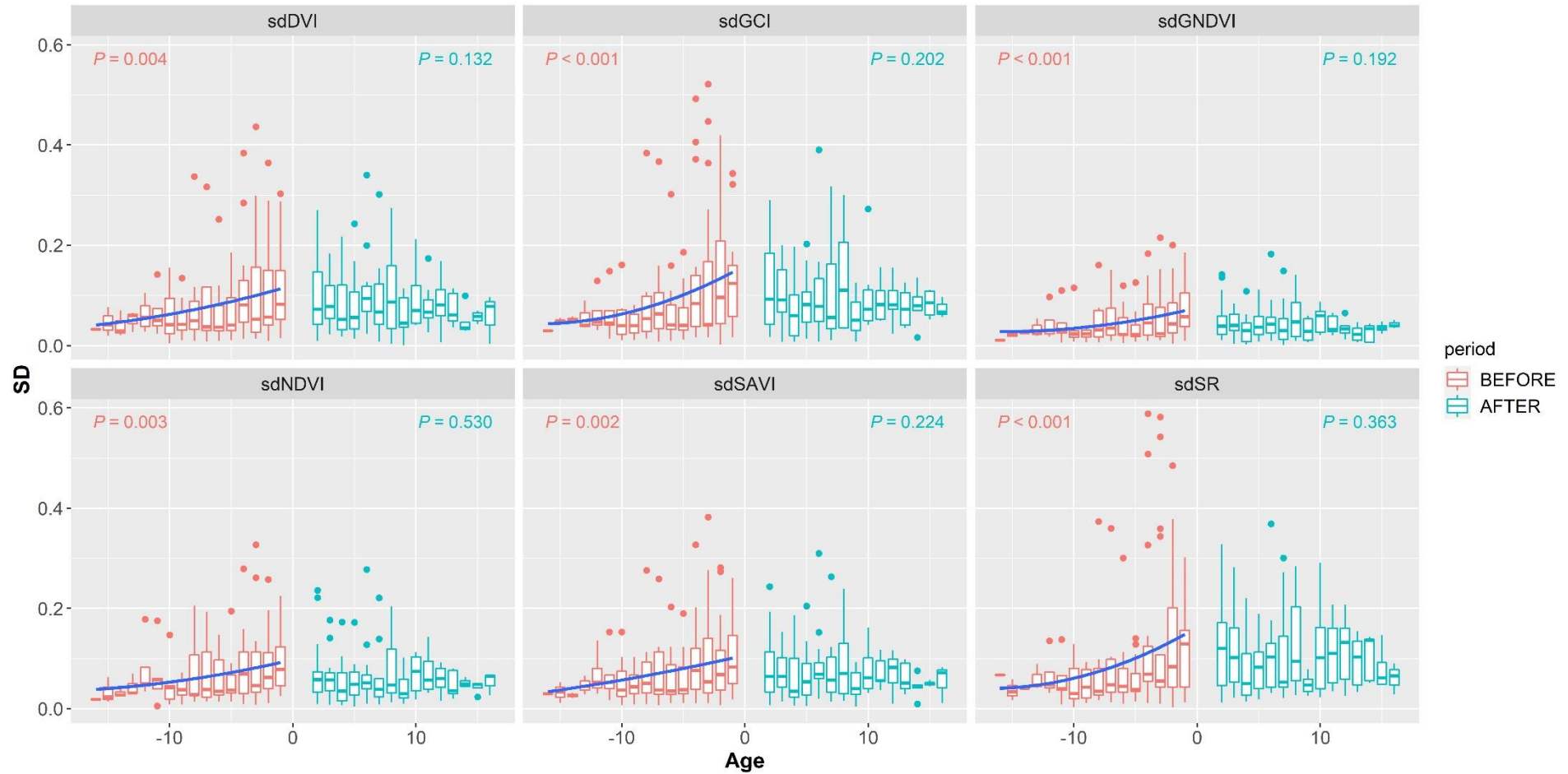
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648 **Figure 2. Temporal dynamics of normalized Vegetation Indices before (red) and after (blue) the sowing. The horizontal line at 0 represents the control.**  
649 **The line within the box represents the median value; the box edges represent the interquartile range, the whiskers represent the 95% confidence**  
650 **interval, black dots outside the boxes represent the outliers, and coloured dots represent the average value.**

651



654 **Figure 3. Dynamics of an indicator of temporal stability before (red boxes) and after (blue boxes) the sowing, based on the three-year standard deviation**  
 655 **of each normalized Vegetation Indices. The line within the box represents the median value, the box edges represent the interquartile range, the**  
 656 **whiskers represent the 95% confidence interval, and the dots outside the boxes represent the outliers. The significance of the fitted linear model before**  
 657 **(red, left) and after (blue, right) is reported at the top of each plot. The 2<sup>nd</sup> order regression model is then represented with a blue line when significant.**