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Optimizing Herbicide Use in Fodder Crops with Low-Cost Remote Sensing and Variable Rate Technology

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Abstract: The current Common Agriculture Policy (CAP) foresees a reduction of 50% in the use of herbicides by 2030. This study investigates the potential of integrating remote sensing with a low-cost RGB sensor and variable-rate technology (VRT) to optimize herbicide application in a ryegrass (*Lolium multiflorum* Lam.) fodder crop. The trial was conducted on three 7.5-hectare plots, comparing a variable-rate application (VRA) of herbicide guided by a prescription map generated from segmented digital images, with a fixed-rate application (FRA) and a control (no herbicide applied). The weed population and crop biomass were assessed to evaluate the efficiency of the proposed method. Results revealed that the VRA method reduced herbicide usage by 30% (0.22 l ha^{-1}) compared to the FRA method, while maintaining comparable crop production. These findings demonstrate that smart weed management techniques can contribute to the CAP's sustainability goals by reducing chemical inputs and promoting efficient crop production. Future research will focus on improving weed recognition accuracy and expanding this methodology to other cropping systems.

Keywords: mediterranean climate; low-cost sensor; spatial analysis; machine learning; RGB

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1. Introduction

In May 2020, the European Commission announced two pesticide reduction targets as part of the Farm to Fork Strategy: a 50% reduction in the use and risk of chemical pesticides and a 50% reduction in the use of more hazardous pesticides. In Portugal, in the period from 2000–2020, despite the sale of plant protection products per used agricultural area having decreased by 38%, the total consumption of these products was 9706 tons, of which

25% was herbicides used for weed control [1]. In Mediterranean regions, weed control in rainfed fodder crops under no-till farming is usually necessary before sowing crops and after crop emergence [2].

Sustainable agriculture is essential for future food security. The current reliance on chemical inputs like plant protection products (PPPs) and fertilizers contributes to pollution, biodiversity loss, climate change, and resource depletion, posing risks to the environment and human health. Balancing effective farming with reduced hazardous inputs requires adopting innovative technologies and efficient agricultural practices [3]. It is important to adopt new management approaches and instruments such as remote sensing and VRA technologies capable of reducing the amount of herbicide used with the environmental and operation cost–benefit analysis without affecting agricultural yield [4,5]. Unlike satellite approaches that often require complex algorithms based on large datasets, proximal remote sensing approaches aim to provide users with cheap, simple, and open-source technologies to design their own decision support tools [6]. Many remote sensors have been used so far to monitor plants over time to manage crop protection [7]. Commercially available systems, e.g., WeedSeeker (Ntech Industries Inc., Ukiah, CA, USA), distinguish green plant material from the soil and other background elements and spray only where plant material is present in pre-emergence weed control. Post-emergence control often benefits from artificial intelligence methods, as they can effectively distinguish between the green plant material of different species and the background [8,9].

Weeds do not appear homogeneously in the plot, so it may be appropriate to eliminate them according to their presence in each specific point of the plot. The risk assessment examines the potential damage caused by pests, including weeds, and determines the need for direct control using economic thresholds or development models. Although the focus is mainly on other enemies, weeds are also considered [10]. Leveraging precision agriculture technologies and data-driven insights helps monitor and control pest and weed infestations more efficiently, ultimately enhancing crop production [11].

Machine learning and deep learning methods can analyze high-dimensional data with unknown statistical characteristics for precision crop protection by learning the model structure directly from training data [12–14] and have proven to be very efficient in locating weeds in crops for site-specific weed management [15] based on shape descriptors with supervised or unsupervised learning methods. To know and quantify their presence at each of these points with a high level of certainty, the collection of close images can be a crucial technique due to its high level of resolution [16]. Adequate instruments and time are needed to filter and process data into information. The classification of the images must be evaluated and validated to assess the quality of detection of the different constituents of the image. An example of these validation methods is the kappa coefficient [17], whose objective is to provide a basis for comparing classified and reference data and verifying whether they agree. Table 1 shows Cohen's kappa coefficient matrix.

Table 1. Cohen's kappa coefficient matrix [17].

		Reference Data			
		1	**2**	**3**	**Total**
Classified data	1	a	b	c	D
	2	d	e	f	E
	3	g	h	i	F
	Total	A	B	C	T

Here, the value of A corresponds to the sum of a, d, and g; the value of D corresponds to the sum of a, b and c; T corresponds to the sum of the rows which must be equal to the sum of the columns of the matrix; the value of k1 is calculated by applying Equation (1); and the value of k2 is obtained by applying Equation (2) [17].

$$\mathrm{k1} = \frac{(a+e+i)}{T}, \tag{1}$$

$$\mathrm{k2} = \left(\frac{A}{T} \times \frac{D}{T}\right) + \left(\frac{B}{T} \times \frac{E}{T}\right) + \left(\frac{C}{T} \times \frac{F}{T}\right), \tag{2}$$

The value of kappa is determined as shown in Equation (3) [17].

$$\mathrm{kappa} = \frac{k1 - k2}{1 - k2}, \tag{3}$$

The precision of each reference value is determined according to Equations (4)–(6) [17].

$$\mathrm{Precision}\ 1 = \frac{a}{A}, \tag{4}$$

Reference value 2:

$$\mathrm{Precision}\ 2 = \frac{e}{B}, \tag{5}$$

Reference value 3:

$$\mathrm{Precision}\ 3 = \frac{i}{C} \tag{6}$$

Thus, it is necessary to find methodologies to know the variation in the number of weeds in the plot in a faster and more expeditious way, ensuring that the herbicide application is performed only in the areas where it is necessary, with the detail that the crop requires, and in a manner compatible with application sprayers. Although the advances in variable-rate control systems allow for individual opening and closing of the sprayer nozzles to be controlled in a very short time [18], the most common sprayers can still only provide metric-level accuracy due to their boom sections, it not being necessary to create prescription maps with centimeter or even sub-centimeter detail.

These methodologies of weed control may benefit farmers by increasing grower profits and reducing the amount of herbicide released into the environment. Therefore, the objective of this trial was twofold: (1) to propose a methodology for mapping weeds through digital imagery in a sufficiently rapid, low cost, and autonomous manner for the farmer; and (2) to evaluate the efficiency of variable-rate herbicide application on a fodder crop.

2. Materials and Methods

The field surveyed, covering three plots of 7.5 ha each, is located in southern Portugal at Herdade da Comenda, Elvas, geographic coordinates 38°53′39″ N, 7°03′03″ W. The predominant soil of the field is, according to the Food and Agriculture Organization (FAO) classification, a Luvisol matching to Pag and Sr Mediterranean soil types [19], and climate, according to Köppen–Geiger classification, is Csa [20].

2.1. Sowing Operation and Crop Management

Sowing rate of 43 kg ha^{-1} of a winter ryegrass (*Lolium multiflorum* Lam.) under no-till farming took place in mid-October after irrigation, weed control of a fixed rate of a glyphosate-based herbicide with 3.00 l ha^{-1}, and a basal dressing of 150 kg ha^{-1} NPK 7-21-21 fertilizer. During tillering stage—Moment 1 (M1)—the field was sampled at one point per hectare, approximately. Considering the similar soil conditions of the total area under study and the most commonly used techniques of crop management, crop biomass was evaluated under three different grass weed controls: no herbicide application (Plot I), VRA of 0.5 to 0.75 l ha^{-1} of post-emergence control of broad-leaved weeds using Florasulam (Plot II), and fixed rate application of 0.75 l ha^{-1} of the same herbicide (Plot III). Figure 1 shows the delimitation areas of the three plots under study and sampling points.

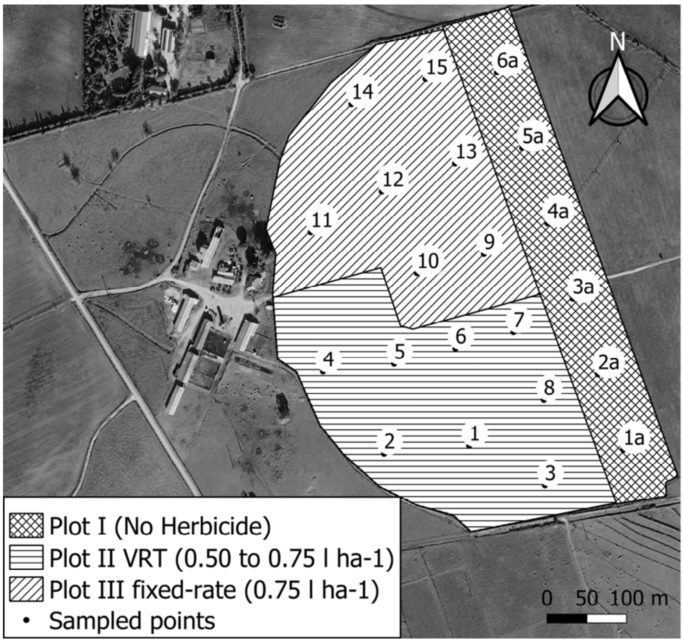


Figure 1. Delimitation of the areas under study and sampling points in Plots I, II, and III.

Herbicide rate was defined considering grass weed growth stage and total percentage of plants per sampling area based on a segmented image. A three-point mounted sprayer, Amazone UF, with a 12 m spray bar width and a New Holland T5 120 tractor, both ISOBUS compatible, applied the prescription map recorded in a shape file folder.

Twenty-five days after the herbicide application—Moment 2 (M2)—condition of grass weeds and yield of fresh matter (FM) and dry matter (DM) of the fodder crop were determined. The collected samples, with one sample made up of three sub-samples, were weighed to determine the FM production per hectare, and subsamples in small paper bags were kept at 65 °C until they reached constant weight to determine forage moisture content and DM content, according to the Kjeldahl method [21].

2.2. Image Segmentation and Classification

The percentage of plants per sampling area were determined by manual counting followed by a segmented image of the crop and grass weeds in each georeferenced point, obtained manually at 0.80 m height from the soil by an RGB sensor in a Xiaomi Redmi 8 (Xiaomi Co, Beijing, China) smartphone camera with 12 MP. Figure 2 shows the overall workflow of the image segmentation procedure.

Image segmentation was performed using QGIS software version 3.28.4 [22]. From each image, Red (R), Green (G), and Blue (B) bands were extracted to determine Excess Green Index (ExG) (Equation (7)), and then the GRASS GIS module r.neighbors was used to calculate maps using the spatial neighborhood [23].

$$\text{ExG Index} = 2 \times G - R - B, \tag{7}$$

GRASS r.neighbors operation sum makes each cell category value a function of the category values assigned to the cells around it, and stores new cell values in an output raster map layer. For spatial neighborhood operations, the diameter of the circular area was set to 9 pixels. In two steps, the value of this index was determined for the classification of the image into 3 zones: (i) soil, (ii) crop, and (iii) weeds. First, soil was distinguished from the vegetation by the application of a filter of 0 or 1 for ExG Index values below and above 50, respectively; secondly, weeds and crops were distinguished from values below and above 120, respectively (Figure 3).

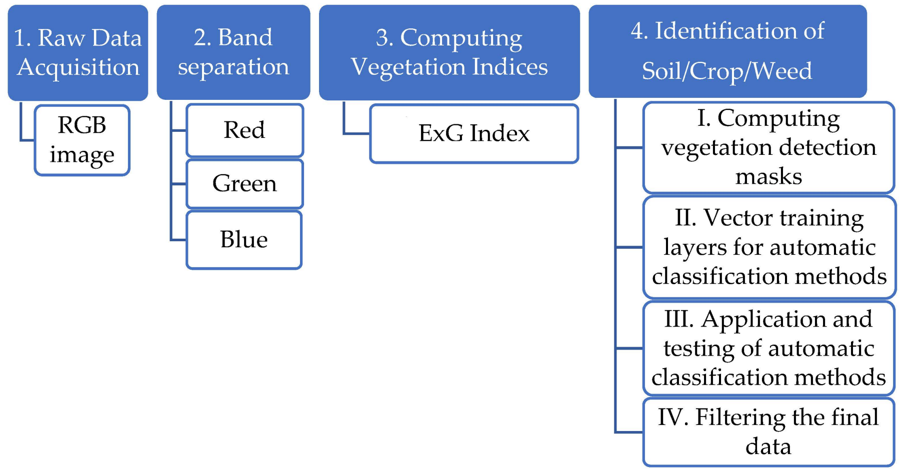
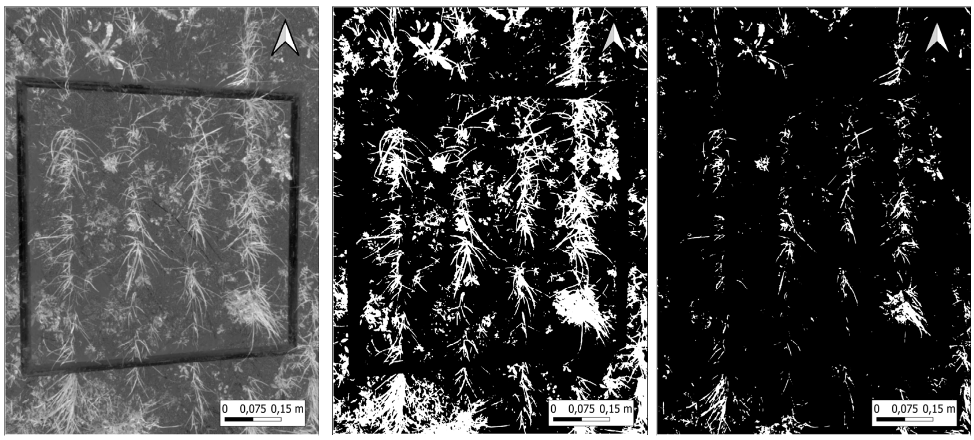


Figure 2. The overall workflow of the image segmentation procedure.



(**a**) (**b**) (**c**)

Figure 3. Image processing steps: (**a**) ExG index, (**b**) ExG50 filter, (**c**) ExG120 filter.

2.3. Data Analysis

A statistical and inferential analysis was carried out to begin analyzing the general data (Appendix A, Table A1), including the coefficient of variation, standard deviation, and interquartile analysis, in RStudio©v.2023.4.3.2 with the R©psych Package v. 2.4.3 CRAN Repository [24,25]. The data were then grouped by plot, moment of sampling, herbicide doses applied, and the dependent variables (the parameters % of crop plants, % of weed plants, and crop productivity in t ha^{-1}).

The Shapiro–Wilk test was conducted on each dependent variable to assess normality. Variables that did not follow a normal distribution were evaluated using the Kruskal–Wallis test, while those with a normal distribution were analyzed using ANOVA. Post hoc analyses after the Kruskal–Wallis test employed Dunn's test, implemented in RStudio©v.2023.4.3.2 using the R©dunn.test Package v.1.3.6 from the CRAN Repository [24,26]. For post hoc analyses following ANOVA, Tukey's HSD test was applied. Lastly, a correlation matrix was utilized to identify relationships between the dependent variables.

3. Results

3.1. RGB Imagery Classification

Figure 4a shows the result of the classified image and Figure 4b the respective validation with 150 points randomly generated by the software.

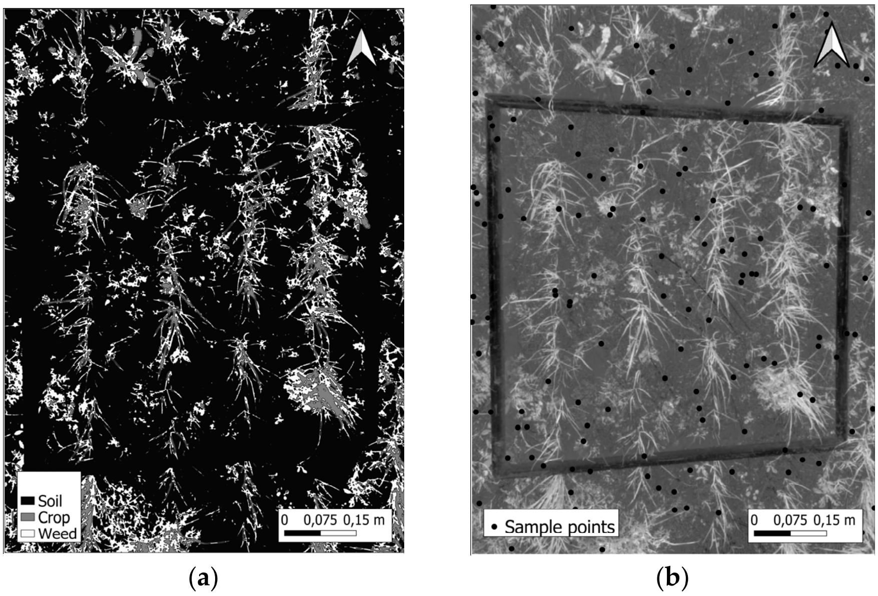


Figure 4. (**a**) Classified image and (**b**) respective validation.

Table 2 presents the results of the validation of the kappa coefficient, and the estimated precision for the identification of soil, crops, and weeds in the 150 points randomly generated.

Table 2. The validation of the kappa coefficient (left), and the estimated precision for the identification of soil, crops, and weeds (right).

***N* = 150**		**Precision (%)**		
k1	0.78	Estimation	Soil	99
k2	0.58		Crop	20
k3	0.48		Weed	45

For kappa validation, coefficient matrices were generated for each image, "crossing" the estimation made by the image classification method with the actual data of the RGB image using the sample observation. The final kappa coefficient calculated for the image classification method was calculated with a precision of 78% (k1), and assumes the value of 0.48 (k), framing the classification in the category of moderate performance [17]. According to the kappa coefficient, the classification can distinguish soil from the image with an accuracy of 99%, and weeds with an accuracy of 45%.

Figure 5 represents the spatial distribution of broadleaf weeds before the herbicide application, the prescription cartography per plot, and the percentage of broadleaf weeds in the plant population after the herbicide treatment.

Considering the multiplication of the total area of Plots II and III by the applied amounts of herbicide, an average reduction of 0.22 l ha^{-1} was achieved using the VRA in Plot II. These results mean a 30% reduction in the amount of herbicide used in the fixed dose parcel.

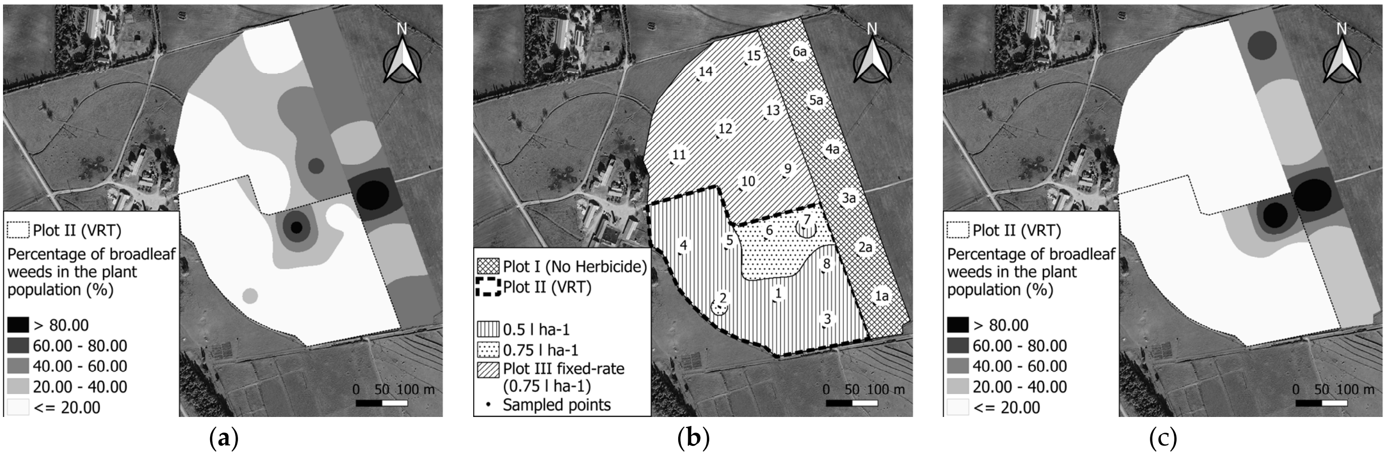


Figure 5. Spatial distribution of (**a**) broadleaf weeds before herbicide application, (**b**) prescription cartography per plot, and (**c**) final distribution of weeds after treatment.

3.2. Variations of % of Crop and Weed Plants and Productivity

The total database has 42 sample points, 21 of which are from moment M1 and 21 from moment M2. Therefore, the productivity (t ha^{-1}) was calculated for moment M2, when the crop was harvested. Outliers were removed before conducting the statistical analysis, and the processed data are presented in Table 3.

Table 3. Descriptive and inferential statistics for the parameters % crop and % weed plants, and crop productivity per sample point (t DM ha^{-1}).

	% Crop	% Weed	Productivity
Min	5.13	0.00	0.06
Max	100.00	85.10	1.93
Median	79.33	8.50	0.93
Mean ± sd	75.10 ± 94.87	17.10 ± 85.10	0.89 ± 1.86
SE mean	3.43	3.50	0.10
CI mean	6.97	7.00	0.20
sd	20.59	20.70	0.59
CV	0.27	1.20	0.67

Min—minimum; Max—maximum; sd—standard deviation; SE—squared error; CI—confidence interval; CV—coefficient of variation.

The data for the dependent variables do not follow a normal distribution, so the Kruskal–Wallis test was used as a non-parametric alternative to assess the influence of the plot, the moment, and the dose applied. These results are presented in Table 4.

Table 4. Results of the Shapiro–Wilk and normality tests for dependent variables.

Dependent Variable	Shapiro–Wilk Test	Normality Test	Plot	Moment	Dose Applied
% crop	0.002	Kruskal-Wallis	0.070 *	0.040 *	0.040 *
% weed	0.000	Kruskal-Wallis	0.005 **	0.020 *	0.003 **
Productivity	0.02	Kruskal-Wallis	0.000 ***	-	0.000 ***

Significance codes: 0 "***"; 0.001 "**"; 0.01 "*".

The results of the Kruskal–Wallis test indicate that there is a very significant difference between the plots and the doses applied when it comes to productivity. These two groups also showed high significance for % weed. For % crop, both groups showed lower significance, as did the moment for % weed. Despite these differences, all groups showed significance for all variables.

For the plot and dose applied groups, which presented some significance for all of the variables' parameters, post hoc analysis was carried out to identify which groups differed from one another. Dunn's test was used for multiple comparisons. The results are presented in Table 5.

Table 5. Dunn's test results for the plot and dose applied groups which presented significance in the Kruskal–Wallis test.

Parameter	Group	Approach	Adjusted p-Value	Significance [1]
% crop	Plot	Plot I vs. Plot II	0.095	
		Plot I vs. Plot III	0.041	
		Plot II vs. Plot III	1.000	
	Dose applied	0 vs. 0.50	0.019	*
		0 vs. 0.75	0.118	
		0.50 vs. 0.75	0.418	
% weed	Plot	Plot I vs. Plot II	0.003	*
		Plot I vs. Plot III	0.005	*
		Plot II vs. Plot III	1	
	Dose applied	0 vs. 0.50	0.001	*
		0 vs. 0.75	0.008	*
		0.50 vs. 0.75	0.49	
Productivity	Plot	Plot I vs. Plot II	0.008	*
		Plot I vs. Plot III	0.000	*
		Plot II vs. Plot III	0.079	
	Dose applied	0 vs. 0.50	0.007	*
		0 vs. 0.75	0.000	*
		0.50 vs. 0.75	0.463	

[1] Significance code: Adjusted p-value ≤ 0.01 "*".

The % crop parameter only presents a difference between the group without herbicide and with 0.50 l ha^{-1}. For this dependent variable, all of the other approaches showed no significance.

For % weed, there was a difference between the 0 dose and the other two doses, but there was no difference between the 0.50 and 0.75 l ha^{-1} doses. There were also differences between the No-Herbicide plot and the others, with no difference between VRA and fixed-rate application. The productivity parameter follows the same trend as % weed.

The boxplots in Figure 6 show the differences explained by Dunn's test. The median % weed drops from around 30 % in the No-Herbicide plot to around 5 % in the VRA and fixed-rate plots. The differences found in relation to the doses applied are very similar. As for yields, the median of the No-Herbicide plot (<0.2 t ha^{-1}) is clearly lower than the yields of the VRA and fixed-rate plots. As with the doses applied, where the herbicide application was zero, yields were very low compared to the sites where either of the two doses studied were applied.

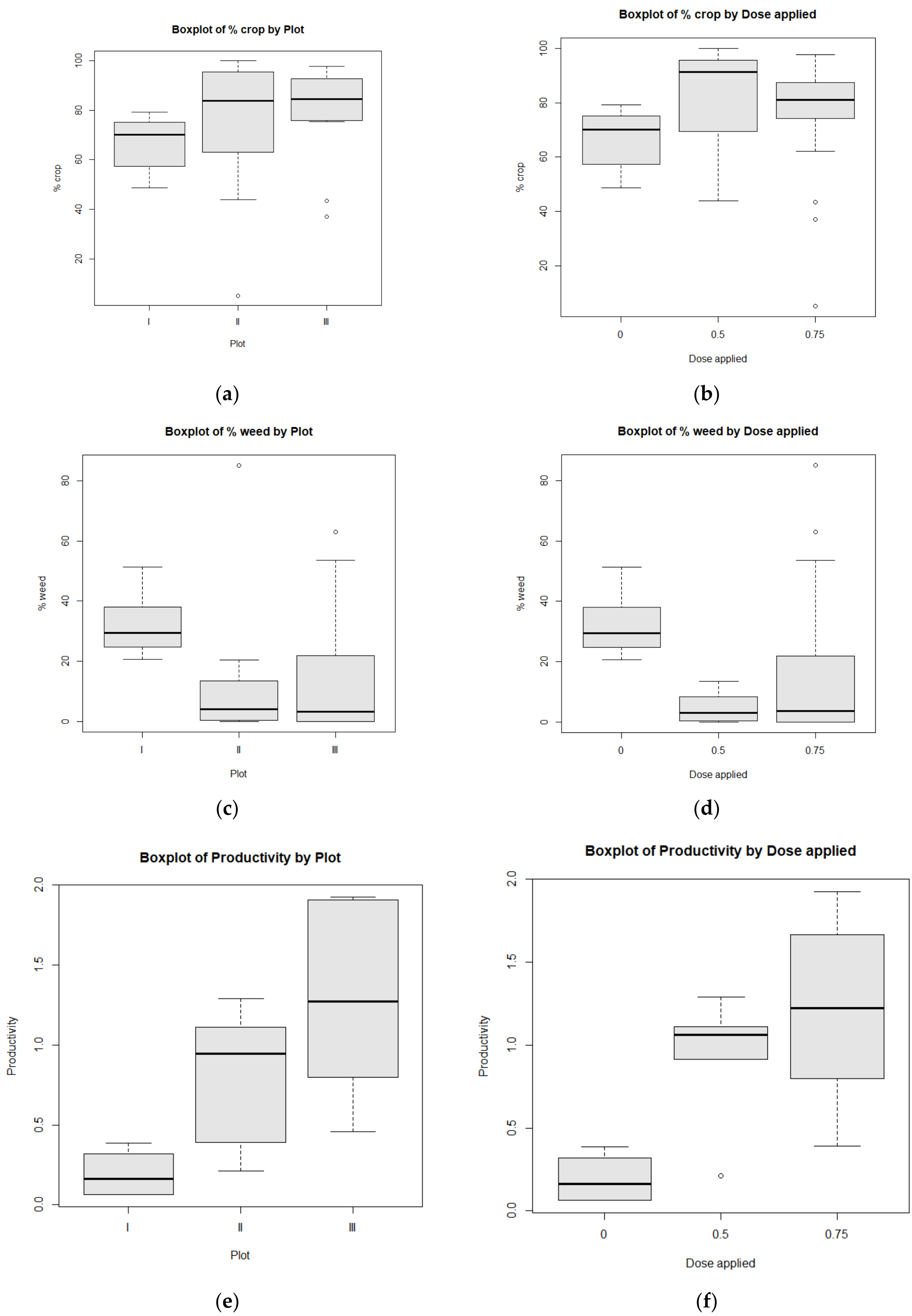
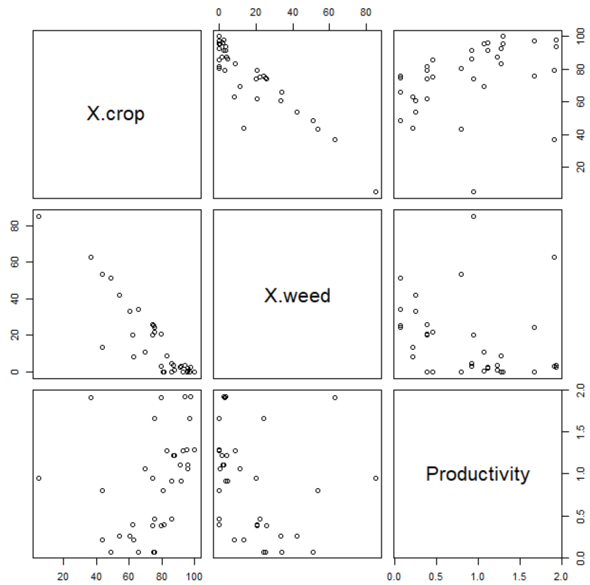


Figure 6. (**a**) Boxplot of % crop by plot, (**b**) Boxplot of % crop by dose applied, (**c**) Boxplot of % weed by plot, (**d**) Boxplot of % weed by dose applied, (**e**) Boxplot of productivity by plot, and (**f**) Boxplot of productivity by dose applied.

3.3. Relationships Between Crop Parameters

To understand the relationship between the study's dependent variables, a correlation matrix was created. The results of the correlation matrix are presented in Figure 7.



	% crop	% weed	Productivity
%crop	1.00	−0.90	0.35
%weed	−0.90	1.00	−0.26
Productivity	0.35	−0.26	1.00

(**a**) (**b**)

Figure 7. Bivariate analysis of dependent variables under study: (**a**) b-plots; (**b**) correlation matrix.

The % crop plants parameter presents a very strong negative correlation (−0.90) with the % weed plants parameter. However, the DM productivity (t ha^{-1}) does not show good correlations with the % crop plants and % weed plants parameters.

4. Discussion

4.1. RGB Imagery Classification

In this study, a proximal and low-cost sensor combined with an enhanced open-source software image tool highlighted the opportunity to digitally determine the percentage of weeds in a fodder crop and compute a VRA of a herbicide. Compared to other studies using different classification methods, our kappa value of 78% is similar to those with 77% using object-based algorithms [27] or 73% using the Random Forest (RF) model [28]. Regarding the accuracy of weed identification, our method reaches 45%, less than Islam et al.'s [29], which reached values of 96% and 94%, for the RF and Support Vector Machine models, and 63% for the K-Nearest Neighbors model. Although having a lower value, our proposal using the RGB sensor of a smartphone as a low-cost sensor computed an image for later classification in Geographic Information System (GIS) software, allowing moderate distinction of the soil, weeds, and crops, even considering its earlier growth stage. This method provides a friendly and light computational solution for farmers to find out the quantities of weeds in a plot, making it possible to know their location in space, as well as facilitating the adjustment of the doses of herbicide in the zoning areas to the needs of each specific point.

4.2. Impact of VRA of Herbicide on % of Crop Plants, Weed Plants, and Final DM Productivity (t ha^{-1})

As expected, the non-application of herbicide (Plot I) results in the continued presence of a large percentage of weeds. The percentage of weeds clearly decreases in Plots II and III with the application of herbicide, and there is also an increase in crop production and homogeneity of the crop shown by the reduction of the value of the CV. Both of these plots demonstrate the benefits of herbicide in crop production. Despite a lower production than Plot III, the results of Plot II with was an average reduction of 0.22 l ha^{-1} demonstrate that a clear reduction in the weed population was achieved, even in the areas with a lower percentage of herbicide (0.50 l ha^{-1}). This finding corresponds to a reduction in the total herbicide applied and certainly contributes to a greater economic and environmental impact than the injudicious weed control in a fixed-rate application system. A similar contribution was made by Gundy and Dille [30], who have implemented variable-rate herbicide applications based on soil physical properties in grain sorghum.

4.3. Practical Insights and Future Trends

There are clear differences in the presence of weeds at the sampling points in relation to the weed control management used and whether herbicide was applied.

Although there is no direct relationship between % weed and productivity, as with the presence of weeds in the different management approaches, the DM productivity of the forage also responded to the application of the herbicide.

While VRT may incur higher initial costs due to the need for digital imagery, data storage, and analysis infrastructure, it is designed to optimize herbicide use over time, potentially leading to long-term cost savings and huge environmental benefits. These facts are highlighted by Masi et al. [31], regarding various types of variable-rate technologies.

Regarding the concern about weed recognition accuracy and the potential risk of herbicide application failures, we acknowledge that this is an important limitation of the proposed methodology. While the reported recognition accuracy of the proposed method is lower than those of the RF and KNN methods, this methodology prioritizes rapid and low-cost processing, which could be advantageous for real-time field applications. However, we agree that improving recognition accuracy is crucial in minimizing the risk of untreated weed patches. These problems associated with the increasing weed resistance highlighted by Hulme [32] require the close attention of many countries, especially those which are already on a trajectory for future weed resistance increases but have limited capability to address this problem.

The specific threshold values we used (e.g., 50 and 120 for the ExG Index) were calibrated for the Xiaomi Redmi 8 camera used in this study. If a different camera were used, these parameters might indeed require recalibration. To minimize the need for recalibration, future work could investigate the use of standardized color calibration techniques or normalization algorithms to reduce variability between cameras. By standardizing the input images regardless of the camera used, the same parameters could potentially be applied across devices, reducing the need for extensive software adjustments.

In future research, it would be very interesting to investigate the difference between applying or not applying herbicide, in terms of the response of weeds to this management approach, productivity, environmental and economic benefits, and how much this management approach would reduce the use of these plant protection products. Future studies should explore strategies to enhance weed recognition accuracy while maintaining cost-effectiveness.

5. Conclusions

This work demonstrates the effectiveness of a low-cost sensor in enabling smart spraying technology for weed control in fodder crops. The research hypothesis, which proposed that a low-cost and relatively simple digital imagery method could map weeds and enable variable-rate herbicide application, was confirmed. The results showed a significant reduction in herbicide use (30%) compared to the fixed-rate method, thereby contributing to both economic benefits for farmers and environmental sustainability goals.

Although the method requires some technical knowledge in the use of GIS software and operator supervision, it does not rely on costly sensors or continuous sampling, making it a practical and accessible solution for farmers with existing mechanized equipment. By defining homogeneous zones for targeted herbicide application, the proposed method aligns with the goals of the Common Agricultural Policy (CAP) 2030, particularly those related to reducing chemical inputs and promoting sustainable farming practices.

However, further research is needed to address certain limitations, such as the lower weed identification accuracy compared to more sophisticated methods (e.g., RF and SVM), and to explore strategies for improving recognition rates without increasing costs. Additionally, future studies should investigate the long-term impact of variable rate herbicide application on crop yield and profitability across different crops and farming systems.

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Abbreviations

The following abbreviations are used in this manuscript:

CAP	Common Agriculture Policy
VRT	Variable-rate technology
VRA	Variable-rate application
M1	Moment 1
M2	Moment 2

FM	Fresh matter
DM	Dry vatter
R	Red
G	Green
B	Blue
ExG	Excess Green
CV	Coefficient of Variation
RF	Random Forest
GIS	Geographic Information System

Appendix A

Table A1. Percentage of weed plants per sample point, at each sample moment, on different plots.

	Plot	I (No Herbicide)						II (VRA)									III (Fixed-Rate)					
	Sample Point	**1a**	**2a**	**3a**	**4a**	**5a**	**6a**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**
Ryegrass	M1	54.0	79.3	7.4	74.6	48.7	42.0	86.1	62.1	43.9	91.2	95.3	5.1	76.7	69.4	37.1	87.4	97.6	75.3	43.5	75.7	83.3
	M2	60.7	74.2	3.4	75.7	65.9	28.2	91.5	81.5	63.1	95.8	100.0	74.1	2.7	95.5	79.3	87.1	93.8	85.6	80.6	96.9	92.6
Weed	M1	42.1	20.7	92.6	25.4	51.3	55.4	4.6	20.4	13.5	2.6	0.0	85.1	16.1	11.1	62.9	1.1	2.4	22.0	53.6	24.3	8.8
	M2	33.3	25.8	96.6	24.3	34.1	62.4	3.4	0.0	8.3	2.1	0.0	20.3	97.3	0.3	3.1	3.8	3.6	0.0	0.0	0.0	0.0

VRA—Variable-rate application; M1—Moment 1; M2—Moment 2.

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