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Effects of Silicon Application on Yield, Spectral Index, and Fall Armyworm (*Spodoptera frugiperda*) Infestation on Maize (*Zea mays*) Crop

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Abstract: This paper presents the implementation of statistical and remote sensing techniques to analyze the spectral response, grain yield, and infestation of fall armyworm (*Spodoptera frugiperda*) in corn (*Zea mays*) based on the application of edaphic and foliar treatments with silicon, comparing the results with those reported in the literature where it has been demonstrated that the incorporation of this nutrient in different crops improves the activity of the enzyme nitrate reductase and dry matter weight gain. The results show that the foliar application of silicon tends to increase grain production in the crop, while the soil treatment does not improve yield. Similarly, foliar silicon application improves the Normalized Difference Vegetation Index, which improves plant health and could be correlated with higher grain yield of the crop. An inverse correlation was detected between the use of foliar silicon and the Normalized Difference Water Index and a direct relationship in the case of direct field application. As for the analysis of the data to verify the influence of the use of silicon on fall armyworm infestation, no statistically significant evidence was found that would lead to the conclusion that the application of this element, whether in soil or foliar form, could lead to a decrease in crop infestation.

Keywords: crop production; plant performance; normalized difference vegetation index (NDVI); precision agriculture; pest control; unmanned aerial vehicle (UAV)

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1. Introduction

Silicon (Si), considered by researchers as a beneficial but non-essential element in plant metabolism [1], ranks as the second most important and abundant element in the earth's crust [2–4]. There have been various conjectures regarding its importance in phosphorus and magnesium metabolism in plants [1] and its potential role in sulfur metabolism, which enhances biomass production in grasses by improving cell wall integrity and, consequently, nitrogen absorption [5]. However, the results have shown ambiguities and inconsistencies regarding pest resistance, yield, and production per area [6,7].

Authors such as Graham [8] and Menzies et al. [9] have studied the benefits of Si in plants and concluded that it strengthened the physical leaf barriers against biotic factors and increased the photosynthetic area. In Colombia, [10] analyzed the average rice yield (*Oryza sativa* L.) by incorporating 20 and 40 kg/ha of Si in addition to the traditional fertilizer doses. They obtained higher yields with the 40 kg/ha dose (8558 kg/ha), which was 19% higher than the average of all treatments. Years later, [11], using laboratory methods such as hydrofluoric acid etching and safranin–phenol staining commonly used in Gram staining, quantified the amount of Si in various tissues of the rice plant (a grass species related to maize). They found significant amounts of Si in the leaf epidermis, along the cell walls in the parenchyma, and in the root tissues. The researchers in [12] discovered that incorporating Si in mono-silicic acid before sowing at a dose of 100 mg kg^{-1} in forage oats cultivation (*Avena sativa* L.) resulted in increased dry matter production due to plant height and stem diameter. They also concluded that the best time for Si application was in an edaphic form before sowing, as it positively affected soil dynamics and the elements required by the plant in the initial phenological stages.

According to [13], the initial phenological stages were subdivided into vegetative emergence approximately 7–10 after planting, vegetative one-first leaf, vegetative two-second leaf, vegetative third leaf, and vegetative n leaf where n represents the last leaf before vegetative tasseling. After that, the six subdivisions of the reproductive stage were R1 silking, R2 blister, R3 milk, R4 dough, R5 dent, and R6 physiological maturity.

For maize crops (*Zea mays*), [2] determined that the incorporation of Si did not improve soil chemical attributes such as pH, hydrogen (H^+) + aluminum (Al^{+3}), or total aluminum content. However, it did lead to an increase in chlorophyll index values.

Regarding the analysis of vegetative indices taking into account the use of fertilizers, [14] evaluated different nitrogen doses at planting and various phenological stages of maize using the Normalized Difference Vegetation Index (NDVI) obtained from ground-based passive remote sensors (GreenSeeker sensors). They found a linear relationship between the nitrogen dose and NDVI and concluded that this index was a reliable tool for analyzing the effect of nitrogen doses on maize plants. Furthermore, [15] demonstrated that incorporating Si into nitrogen fertilization in maize improved the activity of the enzyme nitrate reductase, dry matter weight gain, and the accumulation of nitrogen and Si in the leaves. However, there was no significant increase in proline, an amino acid that performs osmotic adjustment in the presence of Si.

Field spectroradiometers have also been the focus of research to obtain reflectance values and estimate maize grain yield. The researchers in [16] successfully predicted maize yields at different phenological stages using a field spectroradiometer. They found that the flowering stage (VT) was the best time to predict maize yields. They also determined that the wavelength corresponding to the red edge provided sufficient information to predict maize yields, concluding that the remaining wavelengths and their combinations did not improve the predictions.

This study implemented remote sensing techniques to contribute to management in traditional or technified agriculture. Some aspects addressed included vegetative development and production estimations, losses caused by biotic and abiotic factors, and using reflectance data from satellite or high-resolution inputs. These aspects could be detected through image processing using algorithms and various vegetation indices [17]. Currently, remote sensing methods utilizing reflectance values offer advantages and limitations. High-resolution multispectral images can detect changes in crop leaf area and correlate them with plant nutrient or moisture content. However, this capability is limited in early growth stages and in quantifying plants' nutritional, chemical, or moisture content [18]. Under this theory, yield variability and estimation could be the most critical data to farmers or agronomists interested in improving crop management decisions like those for corn, and it is possible to detect and estimate yield production with remote sensing [19].

The objective of this study was to analyze the spectral response, grain yield, and insidiousness of fall armyworm (*Spodoptera frugiperda*) infestation in corn (*Zea mays*) following the application of different treatments of the crop with Si and to compare the results with those reported in the literature.

The following are the paper's contributions: based on the use of silicon edaphic and foliar treatments, statistical and remote sensing approaches were used to examine the spectrum response, grain production, and autumn armyworm (*Spodoptera frugiperda*) infestation in maize (*Zea mays*). We found proof that foliar silicon application tended to increase crop grain production, whereas soil treatment had no positive impact on yield. By applying foliar silicon, it was possible to increase the Normalized Difference Vegetation Index, which boosted plant health and was associated with a crop with higher grain output. We achieved the detection of a direct association in the case of direct field application and discovered an inverse relationship between foliar silicon use and the Normalized Difference Water Index. Finally, this paper shows that no statistically significant data supported the hypothesis that silicon application, whether in soil or foliar form, could reduce fall armyworm infestation of crops.

The structure of this document is as follows: the introduction and literature review that came before this investigation are included in Section 1. A description of the experimental design, necessary mathematical and software tools, and spectral indices utilized in the analysis are all included in Section 2, which is a review of the materials and methods used. Section 3 examines essential issues that should be considered in light of the methodologies used and offers the results. The research results are presented in Section 4, focusing on comparing the gathered data with those given in the scientific literature and emphasizing the study's key findings.

2. Materials and Methods

The methodology used for the execution of this study consisted of several stages, summarized in Figure 1. The first stage involved delimiting and preparing the field for maize sowing. The second stage included strategically placing three treatments in the field and sowing yellow-maize-variety ICA V-305, using rice husk and pine sawdust as substrates to avoid the external Si effect on the treatments. The third stage involved the collection of field data, including grain yield measurements from a sample size of 60 plants, the total count of fall armyworm (*Spodoptera frugiperda*) individuals, and the field data acquisition using a Parrot Sequoia multispectral sensor mounted on an unmanned aerial vehicle (UAV). The sensor had a resolution of 1.2 MP per band, with four bands (green (550 nm BP 40 nm), red (660 nm BP 40 nm), red edge (735 nm BP 10 nm), and near-infrared (790 nm BP 40 nm)).

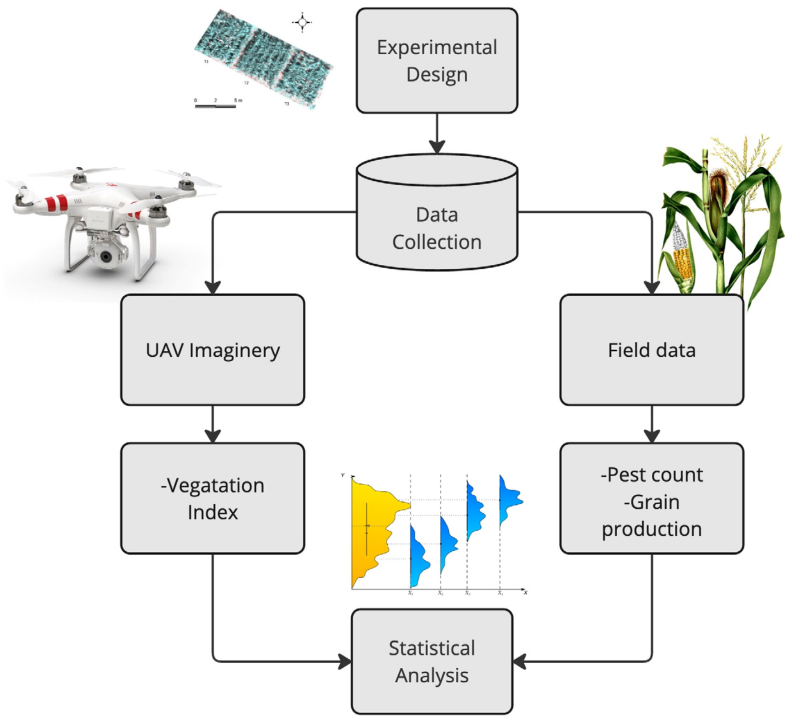


Figure 1. The methodology applied in this study.

Subsequently, a radiometric correction was applied to the orthoimage, converting a digital number (DN) or digital level values to the reflectance values to compare and calculate different vegetation indices. A 16-bit orthoimage was generated with a ground sampling distance (GSD) of 4 cm/px. Finally, the ability of the multispectral sensors carried by a UAV to detect differences in the spectral response of maize plants to foliar and soil applications of Si, as well as the incidence of fall armyworms, was determined. Two vegetation indices, NDVI (Normalized Difference Vegetation Index) and NDWI (Normalized Difference Water Index), were used for analysis.

The study area was in the municipality of Anapoima, in the department of Cundinamarca, Colombia. The experimental crop covered an area of 75 square meters, divided into three equal plots of 25 square meters each, as shown in Figure 2. T1 represents the control treatment, T2 represents the foliar application of Si treatment, and T3 represents the direct soil (edaphic) application of Si treatment.

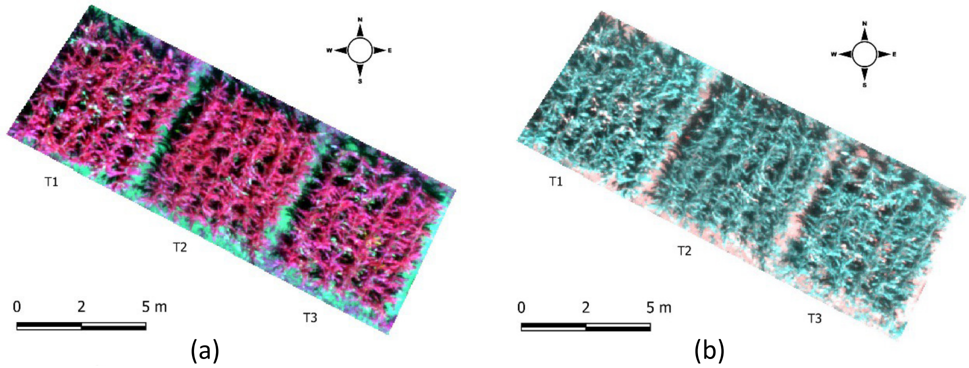


Figure 2. Orthoimage of the study area: (**a**) false color; (**b**) true color. T1 = Control; T2 = Foliar Si; T3 = Edaphic Si.

2.1. Treatments of Si Source Used

The source of Si used was mono-silicic acid (brand: Organigran Silicio 56, empresagro Colombia, S.A., Cali, Colombia, www.empresagro.com, accessed on 3 November 2023), a soluble form that plants absorb. To determine the effect of Si on maize plants and the incidence of fall armyworm (*Spodoptera frugiperda*), the same dosage (15 kg/ha, recommended by the manufacturer) was applied for T2 and T3, divided into three phenological stages of crop development as follows: 25% of the dosage after sowing at V1 stage, another 25% at V6 stage, and the remaining 50% at V10 stage. The foliar application of Si (T2) was performed using a manual spraying pump, directed at each plant separately from other nutrients (N, P, K, Ca, Mg, and Fe). Similarly, the edaphic application of Si (T3) was applied in granular form at the base of the plant. The substrate was characterized as loamy–clayey, with an average pH of 5.3, C 530.2 g/kg, N 5.9 g/kg, P 4.6 g/kg, K 7.7 g/kg, Ca 4.4 g/kg, and Mg 1.3 g/kg [20].

2.2. Method for Pest Quantification and Grain Yield

The variables under study were the incidence of the fall armyworm (*Spodoptera frugiperda*) and grain yield. The incidence of the pest was quantified through total population counts for each treatment, conducted at five different time points (17, 28, 36, 41, and 47 days after planting) when the maize plants were most susceptible to *S. frugiperda* attacks and before the onset of the reproductive phase at 57 days (VT). The second variable, maize grain yield, was obtained by sampling 60 plants per treatment (50% of the total population) at 156 days after planting (R6) and recording the weight in grams for each plant.

2.3. Principal Component Analysis (PCA)—Remote Sensing Method

To determine the bands in the orthoimage that contained the most information while ensuring minimal correlation and preserving the significant aspects [21], a Semi-Automatic Classification Plugin tool was employed. Specifically, the Band Processing feature within the tool was utilized for Principal Component Analysis (PCA) in the open-source Geographic Information System software (QGIS, version 3.26). This analysis generated new bands that exhibited a low correlation in statistical terms and visually resembled a panchromatic image.

2.4. Selection and Calculation of Spectral Indices

The selection and calculation of spectral indices were performed in this study, focusing on those most closely related with grain production and plant moisture in maize. The Normalized Difference Vegetation Index (NDVI), widely used in numerous investigations due to its direct correlation with biomass and photosynthetic activity [22], was determined using data gathered from the electromagnetic spectrum's near-infrared and red regions of light reflectance. The amount of chlorophyll in plants, connected to photosynthesis and vegetation vigor, was quantified with the NDVI. The range of NDVI readings is -1 to 1, with values near 1 indicating healthy, thick vegetation and near -1 indicating a lack of vegetation. Numerous applications of NDVI include crop monitoring, drought assessment, detecting changes in land use, and monitoring the health of ecosystems.

The Normalized Difference Water Index (NDWI) provides quantitative values of leaf moisture content in plants [23]. It is a parameter used to assess the presence and quantity of water in plants and ecosystems. It is calculated using information from the reflectance in the near-infrared and green bands of the electromagnetic spectrum. The NDWI provides a measure of moisture and water availability in vegetation, which can help monitor drought, identify flooded areas, and assess the health of aquatic ecosystems. NDWI values range from -1 to 1, where higher values indicate a more significant presence of water in vegetation. NDWI has been used in various studies and applications, such as water resource management, water body detection, and crop and ecosystem health evaluation. The equations for these indices are presented in Table 1. The indices were calculated using the Raster Calculator tool in the GIS software (QGIS).

Table 1. Indices used in this study with their respective algorithms and authors.

Index	Equation	Reference
NDVI	$\frac{NIR-Red}{(NIR+Red)}$	[24]
NDWI	$\frac{(Green-NIR)}{(Green+NIR)}$	[25]

Note: *NIR* = near-infrared: a band with a wavelength of 790 nm; red: a band with a wavelength of 660 nm; green: a band with a wavelength of 550 nm. Each wavelength has a bandwidth of 40 nm.

2.5. Statistical Design and Analysis of Variance (ANOVA)

The statistical design employed in this study was the Analysis of Variance (ANOVA) in a Randomized Complete Design (RCD). This is because the soil substrate was controlled and homogeneity was guaranteed for the three treatments; an excavation of 10×20 cm was made in the soil, covered with plastic to isolate the substrate from the soil. An Analysis of Variance (ANOVA) is a statistical method used to assess if the means of three or more groups or treatments significantly differ. The ANOVA derives an F statistic, which indicates the statistical significance of these differences by comparing the variability within each group to the variability between the groups. It can be said that there is at least one significant difference between the groups if the F statistic is significant and higher than a predetermined threshold. The ANOVA has been utilized in various areas from scientific research to market studies to evaluate whether observed differences between groups are statistically significant or the result of chance. A simple ANOVA arrangement was used for the pest, spectral, and yield production variables. Once the results of the Analyses of Variance were validated, the assumptions were checked by applying parametric tests such as the F-test for normal data; otherwise, the Kruskal–Wallis test was used, a non-parametric statistical test to see if the medians of three or more independent groups significantly differ from one another. When the data do not conform to the assumptions of normality or equal variances, it is a good substitute for the Analysis of Variance (ANOVA). The test computes a test statistic based on the ranks, compares it to a critical value from the chi-square distribution, and ranks the observations across all groups. If the test statistic is more than the threshold value, the groups have substantial differences. The Kruskal–Wallis test allows for the comparison of group medians without making any assumptions about the distributional qualities of the data. It is frequently used in various domains, especially in studies where the data are ordinal or skewed. A confidence level of 95% or higher (α = 0.05) was established for this study.

3. Results and Discussion

3.1. Incidence of Si on Fall Armyworm (Spodoptera frugiperda) Infestation

The Analysis of Variance (ANOVA) to compare the incidence of fall armyworm in the ICA V-305 corn variety allowed determining if there were significant differences between the treatments and the control with a preestablished significance level of α = 0.05. The results in Table 2 show no significant differences between treatments (p = 0.722). The descriptive graphs in Figure 3a show a slight tendency to a higher incidence of fall armyworm with Si. Figure 3b shows a deviation from normality in the Si foliar treatment.

Table 2. ANOVA for comparison of fall armyworm incidence with the different treatments.

Cases	Sum of Squares	df	Mean Square	F	p	η^2
Treatment	2.301	2	1.150	0.328	0.722	0.008
Residuals	288.005	82	3.512			

Note: Type I Sum of Squares.

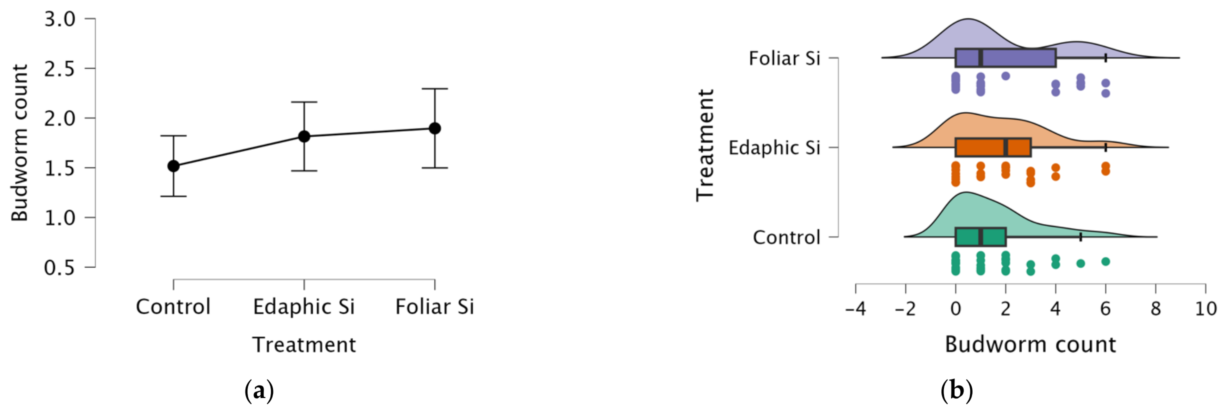


Figure 3. Descriptive plots of contrast between treatments for fall armyworm pest incidence: (**a**) factors with error bars of standard error; (**b**) raincloud plots to support verification of normality and homoscedasticity assumptions.

Considering the exploratory analysis in Figure 3b, the homoscedasticity assumptions (equality of variances) were verified with Levene's test (see Table 3), which was approved (p = 0.088). Figure 4 allowed for verifying the residuals' normality, which showed a significant deviation from normality, so a Kruskal–Wallis (KW) non-parametric test needed to be performed to corroborate the ANOVA results. The KW test reinforced the conclusion that there was no incidence of treatment for the amount of fall armyworm (kw = 0.297, p = 0.862).

Table 3. Levene's test for equality of variances between treatments.

F	df1	df2	p
2.507	2.000	82.000	0.088

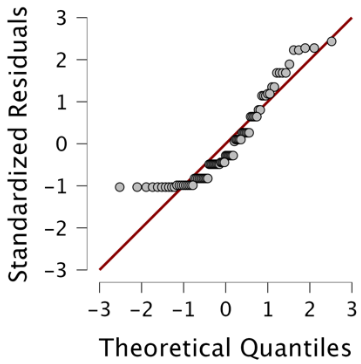


Figure 4. Q–Q plot to verify the normality of the residuals.

3.2. Incidence of Silicon on Grain Yield

Regarding grain yield from the use of foliar and edaphic Si treatments, compared with the control treatment, the ANOVA showed significant differences between treatments with an effect size between 0.06 and 0.14 that could be interpreted as medium (f = 7.481, p < 0.001, η^2 = 0.113). Figure 5a shows that applying foliar Si improved grain yield, while the production with edaphic Si decreased the yield for the substrate significantly used. This fact can be verified in the Post Hoc Comparisons of Table 4. Figure 5b shows the possible normality of the data but gives indications of heteroscedasticity (non-equality of variances), which was tested with a significant Levene's test (f = 3.982, p = 0.021), so it was necessary to use the non-parametric KW test, which was also significant for grain yield (kw = 14.606, p < 0.001).

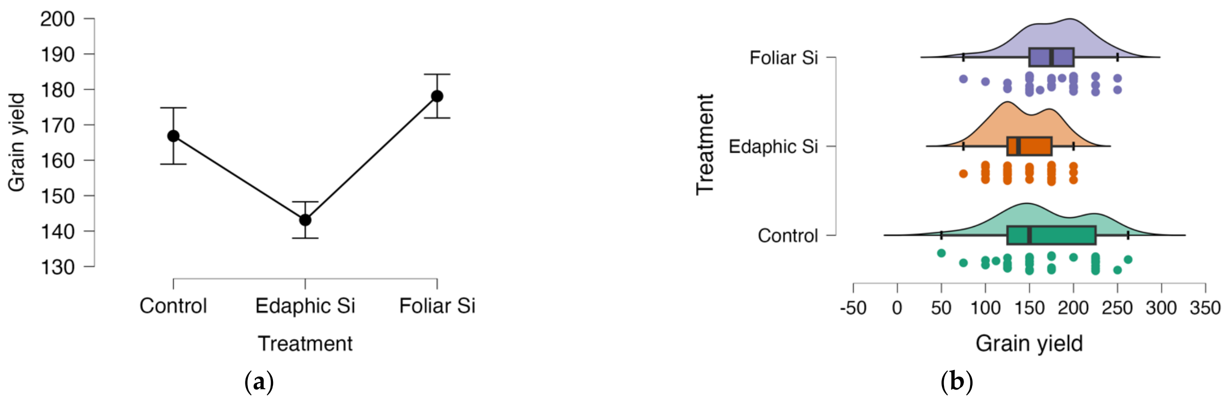


Figure 5. Descriptive plots of contrast between treatments for grain yield: (**a**) factors with error bars of standard error; (**b**) raincloud plots to support verification of normality and homoscedasticity assumptions.

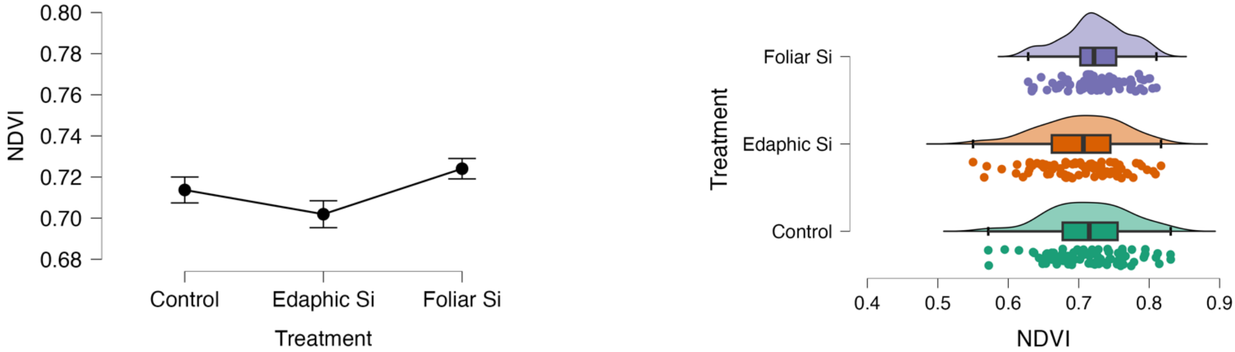
Table 4. Post-hoc test between treatments.

		95% CI for Mean Difference					
		Mean Difference	**Lower**	**Upper**	**SE**	**t**	p_{tukey}
Control	Edaphic Si	23.725	1.810	45.640	9.232	2.570	0.030 *
	Foliar Si	−11.250	−33.165	10.665	9.232	−1.219	0.445
Edaphic Si	Foliar Si	−34.975	−56.890	−13.060	9.232	−3.789	<0.001 ***

Note: p-value and confidence intervals adjusted for comparing a family of three estimates (confidence intervals corrected using the Tukey method). * p < 0.05, *** p < 0.001.

3.3. Analysis of Vegetation Index

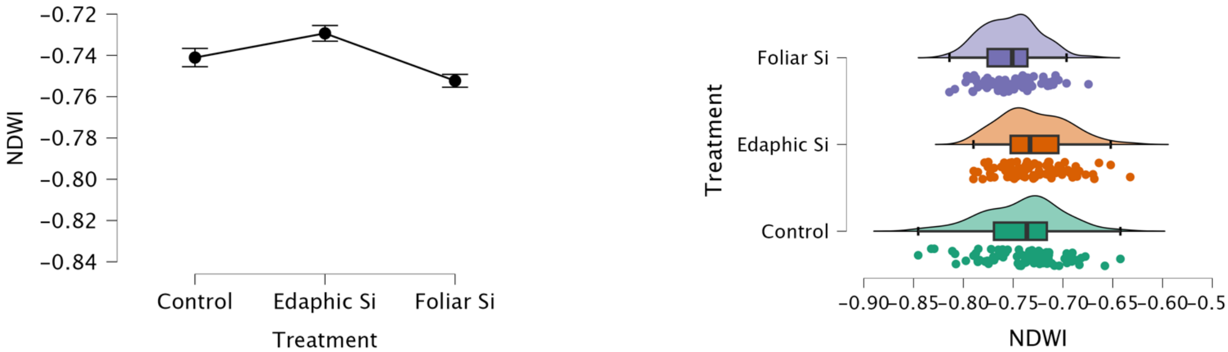
Based on the inputs from the airborne multispectral sensor, the NDVI and NDWI vegetation indices were evaluated to analyze the crops' spectral response after applying the Si treatments. For the case of the NDVI index, significant differences were reported between edaphic and foliar Si. Concerning the control treatment without Si with a small effect size ($f = 2.432$, $p = 0.034$ *, $\eta^2 = 0.028$), it could be interpreted that the variance of the NDVI response variable was not significantly affected by the treatment with Si. The descriptive graphs of the treatments are illustrated in Figure 6, which are consistent in shape with the graphs in Figure 5, obtaining lower values than the control treatment with edaphic Si and higher values with foliar Si. The most significant differences reported by the Post Hoc Comparison statistical analysis were between the treatment with efficacious Si and foliar Si ($t = -2.618$, $p = 0.025$ *).



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

Figure 6. Descriptive plots of contrast between treatments for NDVI index: (**a**) factors with error bars of standard error; (**b**) raincloud plots to support verification of normality and homoscedasticity assumptions.

As for the NDWI index, significant differences were found between the edaphic and foliar Si treatments with a median effect size ($f = 9.043$, $p < 0.001$ ***, $\eta^2 = 0.071$). The median effect size ($0.06 \leq \eta^2 \leq 0.14$) indicated that the variability in the variance of the NDWI index was to some extent associated with the application of the foliar or edaphic Si treatment. Figure 7 illustrates the descriptive plots for comparing the treatments and control with the NDWI index. On the other hand, the Post Hoc Comparisons showed significant differences between efficacious and foliar Si ($t = 4.252$, $p < 0.001$ ***).



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

Figure 7. Descriptive plots of contrast between treatments for NDWI index: (**a**) factors with error bars of standard error; (**b**) raincloud plots to support verification of normality and homoscedasticity assumptions.

Figure 8 shows the graphical output of the results of the vegetation indices used in this study, which provided quantitative data on the physiological state of the corn plant as a function of the silicon treatment. Figure 8 (left side) showed that the lowest NDVI values were found in the edaphic Si treatment and the highest values were found in the foliar Si treatment, which indicated healthier plants and, therefore, higher grain yields (see Figures 5 and 6). On the other hand, the NDVI values in the control treatment were not affected by the Si treatment. Figure 8 (right side) shows NDWI values, which measured the plant's moisture content, where high values corresponded to high plant water content.

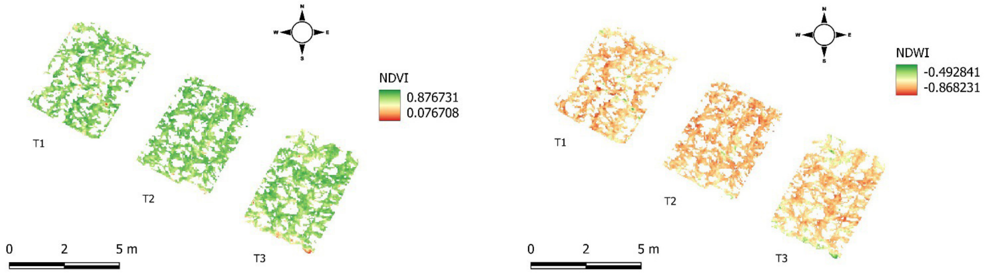


Figure 8. Spectral response of treatments with two vegetation indices.

4. Conclusions

The results of the study indicated that the presence of silicon (Si) in the corn variety ICA V-305, regardless of the application method (foliar, edaphic, or absence of Si), did not have a significant impact on the incidence of fall armyworm infestation, contrary to reports by authors such as Graham [8] and Menzies et al. [9]. The silica-cellulose membrane in the leaf epidermis did not exhibit any discernible effect on the natural resistance of the plant against fall armyworm attacks. The observed incidence of this pest could be attributed to various factors, including the long-standing presence of the corn variety in the market for over 25 years, widespread cultivation by multiple producers in the region, and the inherent genetic susceptibility of the variety to biotic factors such as fall armyworm infestations. These results suggested that appropriate management measures should be implemented to lessen fall armyworms' effects on sensitive maize varieties [26].

The outcomes also showed that, compared with the edaphic silicon treatment, silicon application using the foliar approach significantly increased grain production, consistent with that reported in [10]. These results unequivocally demonstrated the favorable effects of foliar silicon application on numerous plant physiological processes, such as nutrient uptake and production. The beneficial results demonstrated the significance of silicon supplementation as a potential method for increasing crop productivity and optimizing crop growth.

Utilizing remote sensing techniques for monitoring plant responses to silicon application methods enabled the inference of two crucial aspects. Firstly, elevated values of the Normalized Difference Vegetation Index (NDVI) indicated enhanced photosynthetic capacity and the increased uptake of essential soil nutrients, such as nitrogen. Consequently, this was reflected in amplified grain production within corn crops, as demonstrated by previous studies [27–30]. Furthermore, similar outcomes could be attained by employing unmanned aerial vehicles (UAVs) equipped with high-resolution multispectral passive sensors for remote sensing. Secondly, negative deviations in the NDWI (Normalized Difference Water Index) values, which gauge plant moisture content during harvest, offered insights into elevated grain yield within the ICA V-305 corn variety. These informative vegetation indices could be computed by leveraging free GIS software to georeference orthoimages obtained through UAV-based remote sensing, enabling accurate predictions by integrating different vegetation indices.

Ground control points (GCPs) could be used as reference markers to increase horizontal and vertical placement accuracy. These GCPs are recognizable ground features with known coordinates that could be used to achieve precise georeferencing. Furthermore, by utilizing more exact Continuously Operating Reference Stations (CORS), the coordinates of the GCPs could be triangulated and aligned with higher degrees of accuracy, thus improving the overall positional reliability in the remote sensing process.

Limitations of the study included the use of other maize varieties or climatic variations that allowed the reproducibility of the study in other areas; however, in this aspect, the most common maize variety in Colombia was used in addition to a study area with a tradition of maize cultivation. Other aspects such as confounding factors should be analyzed; in this study, the variability of the experimental plots was controlled, the climatic factors being all the plots in the same geographical location, and the influence of the management of other crops, taking into consideration that they were not close to the experimental plots.

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