Cabbage plant (*Brassica oleracea* var. *capitata* L.) quantification cultivated under different soil covers using aerial photographs

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ABSTRACT

Objective: Evaluate the efficiency of cabbage plants (*Brassica olaraceae* var. *capitata* L.) quantification cultivated under different types of mulching, using aerial images captured by RPAS (Remotely Piloted Aircraft System).

Design/methodology/approach: The cabbage plantation used for the study was established under a completely randomized block design with different types of mulch as treatments: black plastic, white plastic, straw, and bare soil. Manual plant counts and automated estimates were performed using two agricultural artificial intelligence platforms (Platforms A and B). The relationship was evaluated using linear regression correlation (R^2), and the following indicators were subsequently used: estimation accuracy (Ps), estimation error percentage (Es), mean absolute error (MAE), and root mean square error (RMSE).

Results: Platform A showed a correlation coefficient range of R^2=0.41 to 0.91. Platform B obtained R^2 values ranging from 0.77 to 0.88. Platform A exhibited the highest estimation accuracy (Ps) with 98.3% and an estimation error (Es) of −1.7% for straw mulch, with a mean absolute error (MAE) of 2.0% and a root mean square error (RMSE) of 1 for bare soil. Both platforms showed underestimations in the number of detected plants, ranging from −6.7% to −1.7%.

Limitations on study/implications: The use of RPAS was limited by atmospheric conditions such as wind and rain.

Findings/conclusions: The effectiveness of counting cabbage plants using RPAS was validated.

Keywords: Precision agriculture, Remotely Piloted Aircraft System (RPAS), drone, Unmanned Aerial Vehicle (UAV).

INTRODUCTION

Cabbage (*Brassica oleracea* L. var. *capitata*) is a cruciferous plant that is consumed worldwide, it is one of the main vegetables in the human diet and is prescribed by nutrition specialists as a source of nutrients and fiber, with potentially positive effects (Galanty *et al.*, 2024). Also, cabbage crop can be achieved either by direct seeding (placing the seed on the soil) or by transplanting (placing previously produced seedlings). Regardless of the strategy the producer uses to grow cabbage, various factors could interfere with adequate plant density, the most common being the presence of pests and diseases (Ngosong *et al.*, 2021; Isaq *et al.*, 2023). It is also known that in warm climate regions, the establishment of appropriate plant density is affected by high temperatures, with the consequent need for plant replacement with live ones (replanting) (Adilov *et al.*, 2021; Osmani *et al.*, 2023). Therefore, locating and counting live plants in the plot is necessary to plan the replanting strategy. One of the current alternatives available for the producers is using aerial photographs and artificial intelligence algorithms for Precision Agriculture (PA) (Maurya *et al.*, 2024).

PA focuses on the efficient use of resources applied to agricultural crops at various stages throughout the management of the agricultural production cycle (Chin *et al.*, 2023; Sangeetha *et al.*, 2024 and Mehedi *et al.*, 2024). Among the technologies used to achieve PA, the use of remote sensors through aerial photographs stands out for detecting, counting, and monitoring cultivated plants (Sangeetha *et al.*, 2024 and Mehedi *et al.*, 2024).

The information on the distribution and location of plants within a plot, as well as the timely determination of the quantity of existing elements, allows the decision-making for crop management (Thakur and Srinivasan, 2024). Therefore, the objective of the present research was to evaluate the effectiveness of the quantification of cabbage plants (*Brassica oleracea* L. var. *capitata*) grown under different soil covers using aerial photographs taken by RPAS (Remotely Piloted Aircraft System).

MATERIALS AND METHODS

Description of the area of study

This study was conducted at the experimental station of the Instituto de Ciencias Agricolas de la Universidad Autonoma de Baja California (ICA-UABC), located at the coordinates 32.407319° north latitude and −115.198853° west longitude. The soil in the experimental plot is of the salic Vertisol type, subtype sodic saline Regosol, belonging to the physiographic subprovince of the San Sebastián Vizcaino Desert (VRs-zwca+RGsoszw/2) (INEGI, 2007 and 2021b). The climate of the region is described as very dry and hot with summer rains, with temperatures ranging from 13 °C to 33.5 °C (BW(h')hw(x')) (INEGI, 2020 and 2021a).

Experimental design and description of treatments

A plot with a cabbage crop was established with a completely randomized block design with three replicates. The cabbage crop was established with four treatments, which were: black plastic mulch, white plastic mulch, straw mulch, and bare soil. Each treatment consisted of two crop beds. The crop beds were oriented north-south, with a length of 6.0 m, separated by 1.8 m, with a height of 0.2 m. Each bed had a pressurized irrigation system with a double drippers watering line. Commercial drip tape with an average water discharge of 1.0 L ha^{-1} per dripper was used. Each dripper was spaced at 0.2 m.

Crop establishment

The crop material was cabbage (*Brassica oleracea* L. var. *capitata*) of the Supreme Vantage® variety [Sakata Seed America, Inc. USA]. The seeds were germinated in commercial polystyrene trays with 338 cavities. 45 days after germination, the transplant was performed on September 27, 2023. The crop design had a triangular staggered distribution, with 0.4 m spacing between plants and 0.5 m between rows (Escobosa *et al.*, 2024).

Agronomic management

The land preparation tasks consisted of one pass with a harrow and the formation of the planting beds. Subsequently, trenches were made where the pipes for the irrigation system were installed. The detailing of the planting beds, as well as the installation of covers and the irrigation system, was done manually. During the soil preparation tasks, Paraquat (dimethyl-4,4-bipyridylium dichloride-1; DRAGOCSON® Dragón, Mexico) was applied to control Bermuda grass (*Cynodon dactylon*). Broadleaf weed control was performed manually and mechanically. Irrigation management consisted of weekly applications. The pests that appeared were thrips (*Thrips tabaci*) and Bagrada bug (*Bagrada hilaris*). These were controlled through weekly applications of systemic insecticide (thiamethoxam, chlorantraniliprole; Durivo®, Syngenta Group, Mexico).

Fertilization was applied weekly through the irrigation system. The fertilization dose per hectare consisted of 330, 100, 150, 40, and 15 kg ha^{-1} of nitrogen (N), phosphorus (P), potassium (K), calcium (Ca), and magnesium (Mg), respectively (Escobosa *et al.*, 2024). The fertilizer sources were urea [$CO_2(NH_2)_2$], phosphoric acid (H_3PO_4), potassium sulfate (K_2SO_4), calcium nitrate [$Ca(NO_3)_2$], and magnesium sulfate ($MgSO_4$).

Acquisition of aerial images and processing

The images were obtained on October 24, 2023, 27 days after the transplant (DAT). A DJI® Phantom 4 RTK multispectral RPAS was used (DJI, 2019b). The flight path was designed in the native application for the iOS system, DJI Ground Station Pro (DJI GS Pro) (DJI, 2019a). The flight parameters used were perpendicular flight of the course, stationary image capture, forward speed of 1 m s^{-1}, flight altitude of 38.5 m, 80% front and side overlap, and a gimbal angle of $-84.1°$. The images were georeferenced using five ground control points positioned with a GNSS RTK differential GPS, South Galaxy G7 (Prado *et al.*, 2020; SOUTH, 2024).

The obtained aerial images were used to generate the orthomosaic composed of multispectral bands. These images underwent radiometric correction using PIX4DFields software (Pix4D, 2024), used under an academic license with (key: 61b1b106). The obtained bands in the composite orthomosaic were: blue (B: 450±16 nm), green (G: 560±16 nm), red (R: 650±16 nm), red edge (RE: 730±16 nm), and near-infrared (NIR: 840±26 nm) (DJI, 2019c). The orthomosaic was analyzed using the open-source Geographic Information System (GIS) software QGIS v.3.22.10 (Qgis, 2023).

The first count was performed manually, visually identifying the cabbage plants present in the image (García *et al.*, 2020). For the count, the agricultural-type orthomosaic composition was used, requiring the combination of the red (R), near-infrared (NIR), and blue (B) bands. This image was overlapped with 40% transparency over the Modified Soil Adjusted Vegetation Index (MSAVI2) (Equation 1). This index minimized the effect of bare soil, which allowed the visual differentiation of vegetation (Suman *et al.*, 2024).

Finally, a point shapefile was created and used in edit mode to mark each visible plant with a vertix.

$$MSAVI2 = \left(\frac{1}{2}\right) \times \left(2(NIR+1) - \sqrt{(2 \times NIR + 1)^2 - 8 \times \left(NIR - Rojo^2\right)}\right) \quad \text{(Equation 1)}$$

Automated quantification and identification of plants were performed using two online platforms focusing on artificial intelligence for precision agriculture. The platforms used were Agremo (Platform A) (Agremo, 2024b) and Solvi (Platform B) (Solvi, 2024c). In Platform A, the estimation procedure involved: uploading the orthomosaic, specifying the type of crop to be analyzed, providing the planting density used, and finally running the quantification tool (Agremo, 2024a). For Platform B, the procedure for quantification involved: uploading the multispectral orthomosaic. Subsequently, a training sample representing the treatments used was selected. The sample consisted of a rectangular section containing 22% of the plants from the experiment. Each present plant was marked within the training area (Figure 1). Finally, the quantification instruction was executed (Kitano *et al.*, 2019; Solvi, 2024a).

Once the quantification tools were executed on both platforms, the results were exported. Platform A provided the result in Portable Network Graphics (PNG) format. This file was georeferenced and vectorized within the initial project where the manual quantification had been done (Qgis, 2024a). Platform B allowed the export of the identified objects in shape format (shp). This format is compatible with major GIS software. Subsequently, a polygon was created in shape format (shp), which delimited each crop bed. This vector file was the input to use the point counting tool within a polygon (Qgis, 2024b). This way, the number of detected plants was obtained for each platform and each planting bed.

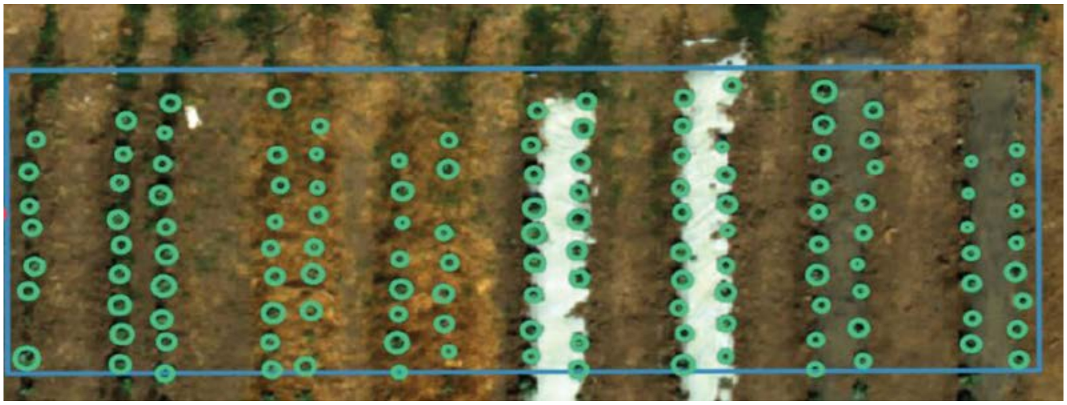

Figure 1. Training surface of Platform B.

Data Statistical Analysis

The statistical analysis was performed by comparing estimates from both platforms. For this purpose, the correlation method (R^2) was used through linear regression in Minitab v18 software (Minitab, 2021). Subsequently, the estimates were evaluated using the following indicators: estimation accuracy (Ps) (Equation 2); percentage error in estimation (Es) (Equation 3); mean absolute error (MAE) (Equation 4); and root mean square error (RMSE) (Equation 5) (Kitano *et al.*, 2019; García *et al.*, 2020 and Li *et al.*, 2023). The equations used are presented below.

$$Ps = (Estimated\ plants) / (Plants\ counted) \quad \text{(Equation 2)}$$

$$Es = (Estimated\ plants - Plants\ counted) / (Plants\ counted) \quad \text{(Equation 3)}$$

$$MAE = 1 / N \sum_{i=1}^{N} \left| Es_i \right| \quad \text{(Equation 4)}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}\left(\left(Estimated\ plants - Plants\ counted\right)^2\right)}{N}} \quad \text{(Equation 5)}$$

RESULTS AND DISCUSSION

Manual quantification identified 567 cabbage plants. Figure 2 shows the spatial distribution. The plants were transplanted on a surface of 200 m^2, which corresponded to a planting density of 2.8 plants m^{-2}. Table 1 indicated the number of plants counted manually and the estimation made by both platforms, as well as their presence in each type of mulching.

The estimates made by both platforms correlated positively with the manual counts (Figure 3). The correlation coefficients were in ranges above R^2=0.77. Except for the estimate made by platform A in black plastic mulching (R^2=0.41) (Figure 3A). Additionally, platform A presented the highest correlation coefficient with an R^2=0.91 (Figure 3G) in bare soil. Therefore, platform A had the widest range of correlation coefficient variability. Like platform A, platform B had its minimum R^2=0.77 (Figure 3B) in black plastic mulching; and the maximum correlation value (R^2=0.88) (Figure 3H) in bare soil. According to Aziz *et al.*, (2023), correlation is affected by the presence of false positives, mainly corresponding to the presence of shadows, weeds and rocks.

The reliability indicators obtained during the experiment (Table 2) show that platform A achieved the highest estimation accuracy (Ps) in straw mulching with 98.3%. Platform B achieved its highest accuracy in treatments with black plastic mulching and straw mulching, both with (Ps=96.8%). Both estimation platforms achieved their lowest accuracy in white plastic mulching (Platform A Ps=97%; Platform B Ps=87%). According to Li *et al.*, (2024), the high reflectance provided by white plastic covers reduces accuracy in plant identification, as their reflectance values are lower than those of white surfaces.

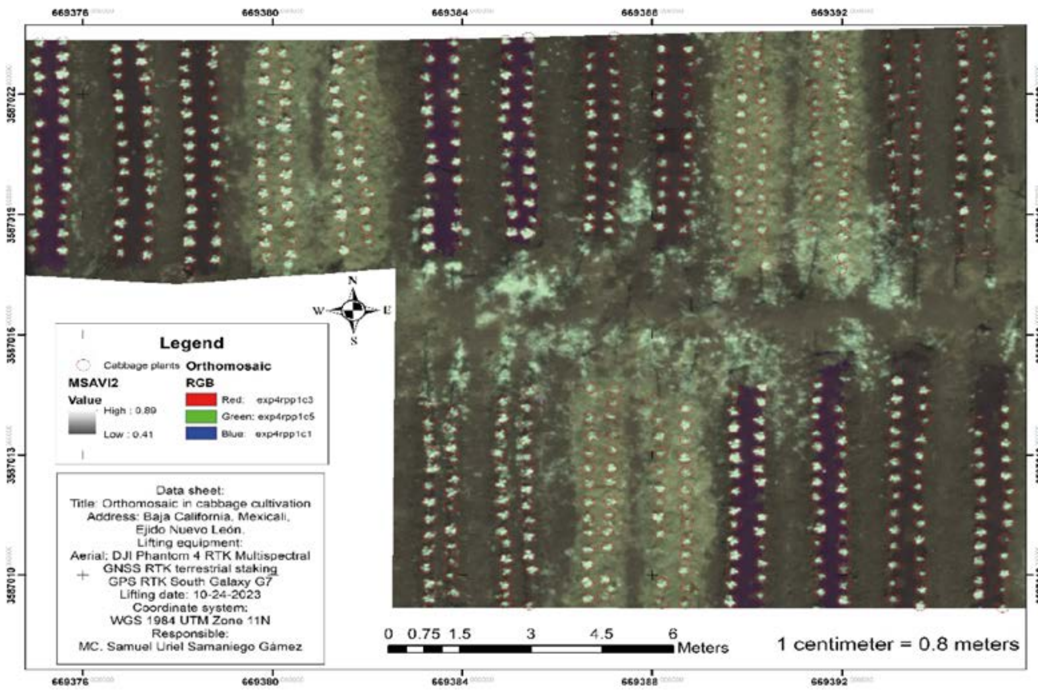

Figure 2. Spatial distribution of cabbage plants identified manually different types of mulching.

Table 1. Plants counted and detected in the mulch treatments.

Mulch treatment	Manual counting	Plants counted by:	
		Platform A	Platform B
Black plastic	163	159	158
White plastic	136	132	154
Straw	162	159	157
Bare soil	106	104	99
Total	567	554	568

Table 2. Reliability indicators obtained in the experiment.

Platform	Mulch treatment	Ps (%)	Es (%)	MAE (%)	RMSE
A	Black plastic	97.6	−2.4	2.4	1.291
	White plastic	97.0	−3.0	3.0	1.095
	Straw	98.3	−1.7	3.1	1.080
	Bare soil	98.0	−2.0	2.0	1.000
B	Black plastic	96.8	−3.2	3.2	1.472
	White plastic	87.0	13.0	13.0	4.099
	Straw	96.8	−3.2	4.5	1.354
	Bare soil	93.3	−6.7	6.7	1.936

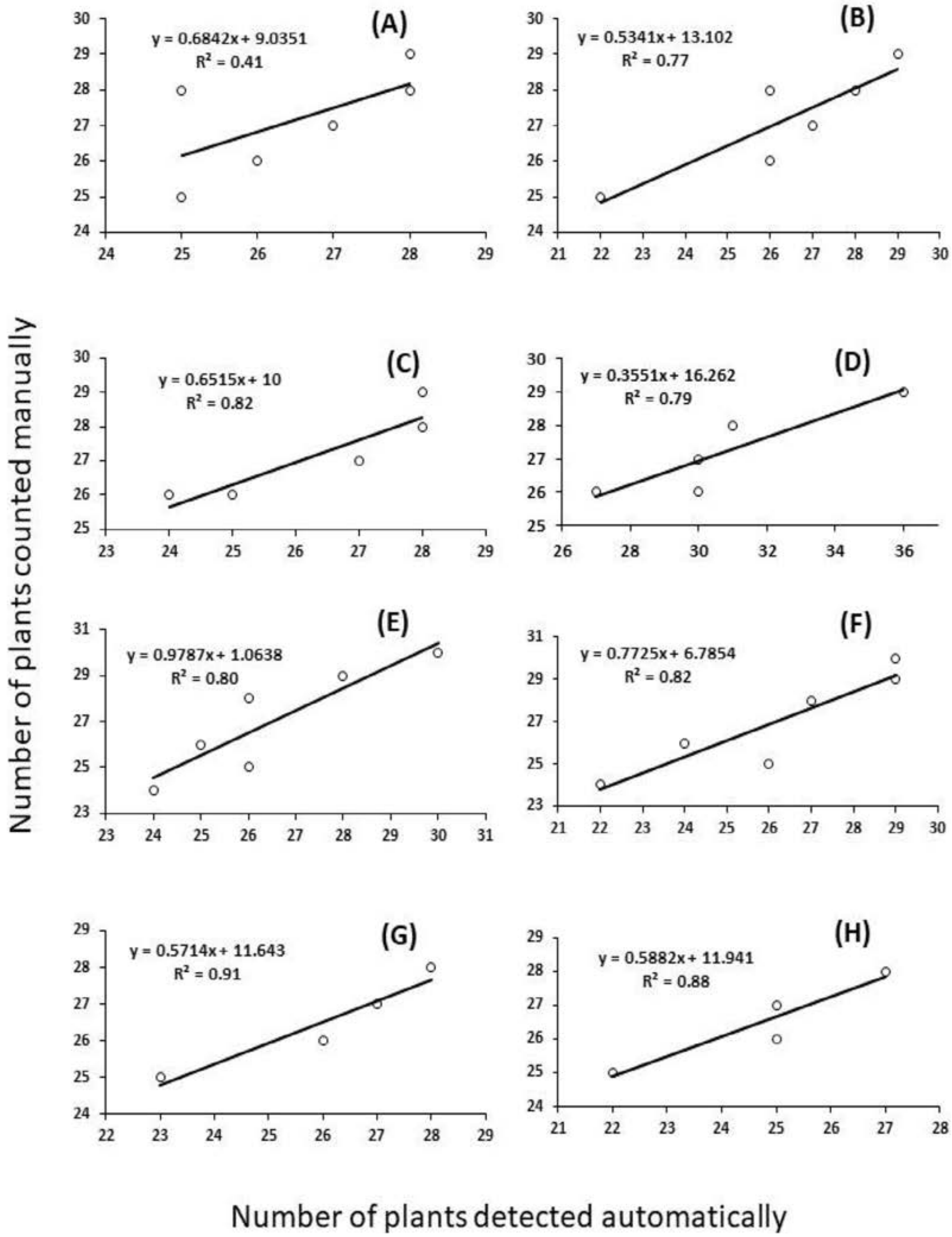

Figure 3. Linear regression for both estimation platforms: platform A in black mulching (A); platform B in black mulching (B); platform A in white mulching (C); platform B in white mulching (D); platform A in straw mulching (E); platform B in straw mulching (F); platform A in bare soil (G); platform B in bare soil (H).

The accuracy values in plant number estimation match those reported by other authors (Neupane *et al.*, 2019; García *et al.*, 2020 and Prado *et al.*, 2020).

Both platforms showed underestimations in the number of cabbage plants detected. The range of underestimation (Es) was from −1.7% to −6.7%. Platform B was the only one that showed overestimation (Es=13.0%) in white plastic mulching. This overestimation affected the total value of the mean absolute error indicator for platform B (MAE=3.2 to 13%). The RMSE ranged from 1 to 4.09. According to Du *et al.* (2024), the detection of elements in plastic covers is affected by sample sizes, the presence of shadows, and surrounding vegetation; increasing the number of repetitions, with different sample sizes, will result in greater estimation accuracy.

CONCLUSIONS

The counting and location of plants has been carried out in different studies. These will focus on the development of tools for quantification, and on the reliability of different cameras and flight parameters (Paz, and Medrano, 2016; Chu *et al.*, 2019; Jiang *et al.*, 2019; Koh *et al.*, 2019; Jang *et al.*, 2020; Shirzadifar *et al.*, 2020; Valente *et al.*, 2020 and Villareal *et al.*, 2020). In the current research, aerial photographs taken by RPAS proved to be a reliable resource for quantifying transplanted cabbage plants under different soil covers.

The two AI platforms used for plant detection and quantification showed varying degrees of reliability, with platform A exhibiting the lowest degree of error in estimations.

The cover soil material or the absence of mulching, influenced in the reliability of the plant quantification, where the white plastic cover showed lower degrees of reliability for the estimation of plants.

The results obtained from RPAS images and processed by AI platforms should be verified by humans; this is because the estimations made are still not entirely accurate.

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"Conceptualization, S.G.S.U. y N.R.; methodology, S.G.; software, S.G.S.U.; validation, Y.J., N.R., P.A.; formal analysis, V.G.R.E.; research, V.G.R.E.; resources, N.R.; data curation, P.A.; writing—original draft preparation, S.G.S.U.; writing—review and editing, N.R.; visualization, V.G.R.E.; supervision, N.R.; project management, S.G.B.Y.

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