Estimation of failures in soybean crops from aerial images obtained by RPA

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Abstract

The dissemination of Remotely Piloted Aircraft (RPA) in the agricultural sector made it possible to map crop failures and disease incidence. This work aims to estimate crop failures. For that purpose, we conducted three experiments with a soybean crop at the IFSULDEMINAS school farm - Inconfidentes Campus, by carrying out an aerial survey with an RPA, which generated an orthophoto of the area of interest. To quantify the failures existing in the experiments, we carried out a supervised classification to distinguish the soybean plants of the exposed soil. After the classification, the kappa index was calculated to verify whether the classification was satisfactory. With this, it was possible to calculate the percentage of failures obtained in each plot of the experiment. Finally, we analyzed the variance to verify if the percentage of failures of each plot had significant differences between them. We observed that in two experiments, there was a statistical difference in the number of failures, and in one experiment there was no difference.

Keywords: Crop failures. Aerophotogrammetry. Supervised classification.

Introduction

Currently, Remotely Piloted Aircraft (RPA) has been adopted in photogrammetry/remote sensing studies, as it has proved to be a low-cost way of obtaining high spatial and spectral resolution data compared to human-crewed aircraft or orbital satellites. Another advantage of collecting data with RPA platforms is their excellent temporal resolution, as they can be obtained at any time, including being repeated more than once on the same day, unlike images obtained from orbital satellites (CHAVES; LA SCALEA, 2015).

In Brazil, the RPAs have been increasingly used in farming, especially in geotechnology. This sector has been using RPAs with high spatial and temporal resolution images that can accurately map crop failures and incidence of diseases and compare the plant distribution patterns in the images, among other applications (CATANI, 2018).

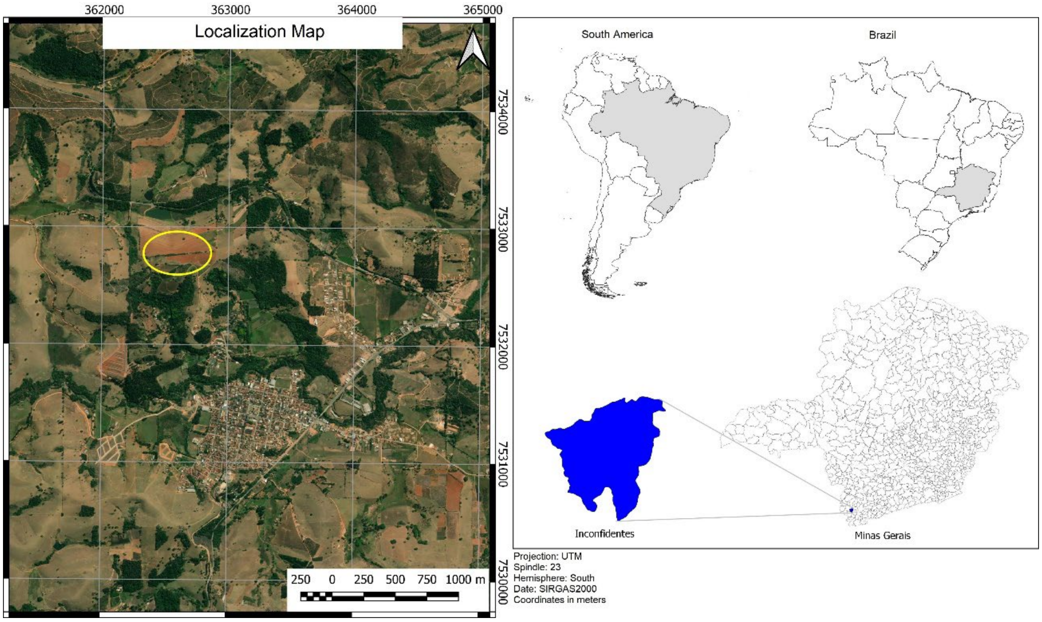
Identifying crop failures helps the rural producers determine the number of existing plants and consequently estimate the production. The quantity of plants per hectare is an important component of productivity. Furthermore, the high spatial resolution makes it possible to identify diseases and invasive plants that contribute to those failures. This work was developed to quantify failures present in three experiments in soybean cultivation.

Material and methods

Study area

We selected an area containing the soybean crop from the IFSULDEMINAS school farm, Inconfidentes/MG Campus, with its central location at coordinates 22º 18' 21" S and 46º 20' 3" W (FIGURA 1).

Figure 1 - Study Area Location Map



Source: Prepared by the authors (2021).

Base Experimentation

We analyzed three experiments with soybean: VCU1 – Precocity, VCU2 – Precocity, and VCU2 – Productivity.

The VCU1 – Precocity experiment contained 12 commercial varieties F3:6 PREC 10, F3:6 PREC 15, F3:6 PREC 9, F3:6 PREC 13, F3:6 PREC 17, F3:6 PREC 14, F3:6 PREC 8, F3:6 PREC 95R51, F3:6 PREC M 5947 IPRO, F3:6 PREC M 6410 OPRO, F3:6 PREC TMG 7067 IPRO, F3:6 PREC BMX Desafio RR.

The VCU2 – Precocity experiment contained 16 commercial varieties S0:3 Prec 1, S0:3 Prec 2, S0:3 Prec 4, S0:3 Prec 5, S0:3 Prec 6, F3:5 Prec 27, F3:5 Prec 28, F3:5 Prec 31, F3:5 Prec 33, F3:5 Prec 45, Test ANTA 82, Test 95R51, Test M6410, Test NS 7300, Test M5917, Test M5947.

The VCU2 - Productivity experiment contained 16 commercial varieties S0: 3 PROD 1, S0: 3 PROD 2, S0: 3 PROD 3, S0: 3 PROD 5, S0: 3 PROD 10, F3: 5 PROD 73, F3: 5 PROD 85, F3: 5 PROD 97, F3: 5 PROD 98, F3: 5 PROD 139, Test CZ 48B 32 IPRO, Test P98Y30, Test P98Y12, Test P98Y11, Test TMG2185, Test M8210.

The experimental design used was randomized blocks (RBD) with three replications, consisting of four rows of five meters in length and spacing of 0.50 meters between rows.

Aerial survey

We planned the aerial survey with the following flight parameters: height of 60 m, a longitudinal cover of 85%, a lateral cover of 75%, and a speed of 15 m/s. The aircraft used was the Phantom 4 Pro V2 drone provided by the Land Surveying and Cartography Sector of IFSULDEMINAS – Inconfidentes Campus.

Besides the flight parameters, we also defined four control points intended to provide external guidance. According to Coelho and Brito (2009), the primary objective of external orientation is to obtain the position and attitude of the camera at the time of the capture. Using the spatial resection through the collinearity equations (equations 1 and 2), it is possible to define the six elements of the external orientation of a photograph (X_0, Y_0, Z_0, k, φ, ω) from at least three non-collinear control points.

$$x' = -c\frac{m11(X-Xo)+m12(Y-Yo)+m13(Z-Zo)}{m31(X-Xo)+m32(Y-Yo)+m33(Z-Zo)} \quad (01)$$

$$y' = -c\frac{m21(X-Xo)+m22(Y-Yo)+m23(Z-Zo)}{m31(X-Xo)+m32(Y-Yo)+m33(Z-Zo)} \quad (02)$$

In which:
c: camera constant – focal length (image space);
X , Y , Z: coordinates of points in object space;
X_0,Y_0, Z_0: coordinates of the perspective center in object space;
Mij: elements of the rotation matrix (k, φ, ω)
x', y': coordinates of the points in the image space;

Then, we positioned four control points (TABELA 1- points 1 to 4) in the study area and two checkpoints (TABELA 1- points 5 and 6). Control points were placed at the ends of the terrain. Checkpoints were positioned between the control points. The control and checkpoints (TABELA 1) are in the UTM projection system in the time zone 23 and the southern hemisphere, using SIRGAS2000 as a reference system.

After the aerial survey, we used Agisoft Photoscan Version 1.42 for the orthophoto. The control points were used to process the images (TABLE 1). Then, the homologous points present in the photographs were aligned and triangulated, generating the digital surface model and, later, the orthophoto of the study area.

Supervised classification

Subsequently, the supervised classification was carried out in the QGIS 3.10.0 software using the minimum distance method, making it possible to identify crop failures.

For the learning of the supervised algorithm, 20 samples were collected for classification, and 12 samples were taken to check the classes of interest. We selected two classes, one of them for the identification of the soybean crop and the other for the failures. The failures correspond to the exposed soil since the plants were in the final growth stage; so, we could not visualize the soil between the planting rows, as shown in Figure 2.

To validate the classification performed, we generated the confusion matrix and, using equations 3 and 4, we calculated the Kappa index and global accuracy. The coefficients calculated by the Kappa index are qualified based on the table developed by Landis and Koch in 1977 (MOREIRA, 2001) (TABELA 2).

$$K = \frac{N\sum_{i=1}^{r} x_{ii} - \sum_{i=1}^{r}(x_{i+} * x_{+i})}{N^2 - \sum_{i=1}^{r}(x_{i+} * x_{+i})} \quad (3)$$

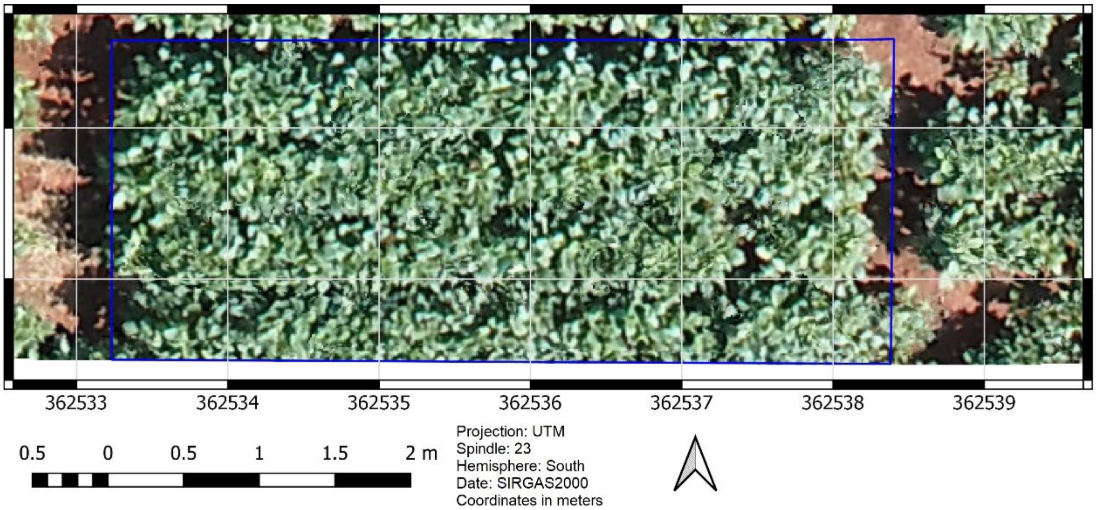
in which:
K = Kappa coefficient;
N = Number of observations (sample points);
r = Number of rows in the error matrix;
X_{ii} = Observations in row i and column i;
X_{i+} = Marginal total of row i;
X_{+i} = Marginal total of column i.

TABLE 1 – Control and Checkpoints

Point	West (m)	North (m)	Geometric altitude (m)	Standard deviation E (m)	Standard deviation N (m)	Standard deviation h (m)
1	362615.326	7532686.034	938.651	0.003	0.004	0.007
2	362528.377	7532687.702	938,621	0.004	0.004	0.006
3	362594.085	7532761.747	929.264	0.003	0.003	0.008
4	362503.832	7532751.198	930.503	0.002	0.006	0.011
5	362583.128	7532686.661	938.645	0.004	0.004	0.009
6	362564.280	7532756.762	929.477	0.003	0.004	0.006

Source: Prepared by the authors (2021).

Figure 2 – Verification of vegetation cover



Source: Prepared by the authors (2021).

$$EG = \frac{A}{N} * 100 \tag{4}$$

in which:
EG = Global accuracy;
A = Overall hit (Sample points with hit);
N = Number of sampling points.

Table 2 – Kappa index adapted from Moreira (2001)

Kappa Index Variation	Concordance
Less than 0.20	Poor, Bad
Between 0.21 and 0.40	Weak, Reasonable
Between 0.41 and 0.60	Moderate, Good
Between 0.61 and 0.80	Very Good
Between 0.81 and 1.00	Excellent

Source: Prepared by the authors (2021).

Failure identification

At the end of the classification, we divided the classified image. An image was created for each plot of the three experiments (VCU1 – Precocity, VCU2 – Precocity, and VCU2 – Productivity).

We then developed an algorithm using the Octave software, version 6.3.0, which scanned the images of the plots of each experiment, identifying the number of pixels classified as soy, and the number of pixels classified as a failure. This identification allows us to generate the percentage of failures present in each plot.

Analysis of Variance (ANOVA)

After the quantification of failures in each plot for each experiment, we performed an analysis of variance (ANOVA), comparing the means by the Scott-Knott test (1974) at 5 % probability, using SISVAR 4.3 software (FERREIRA, 2011).

Results and discussion

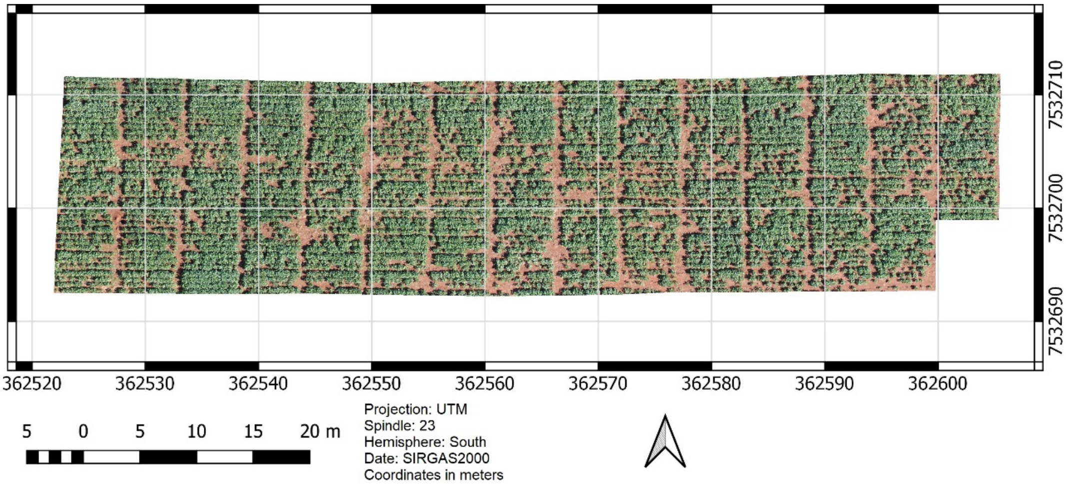
Aerial survey

An orthophoto with a spatial resolution of 1.15 cm was generated at the end of the aerial survey (FIGURE 3).

In this way, it was possible to perform the supervised classification by the proposed method. With the classification completed, we verified, for the entire study area, that the class with soybean (FIGURE 4– Green Color) is in 74.84 % of the area, and the other 25.16 % have failures (FIGURE 4 - Red Color).

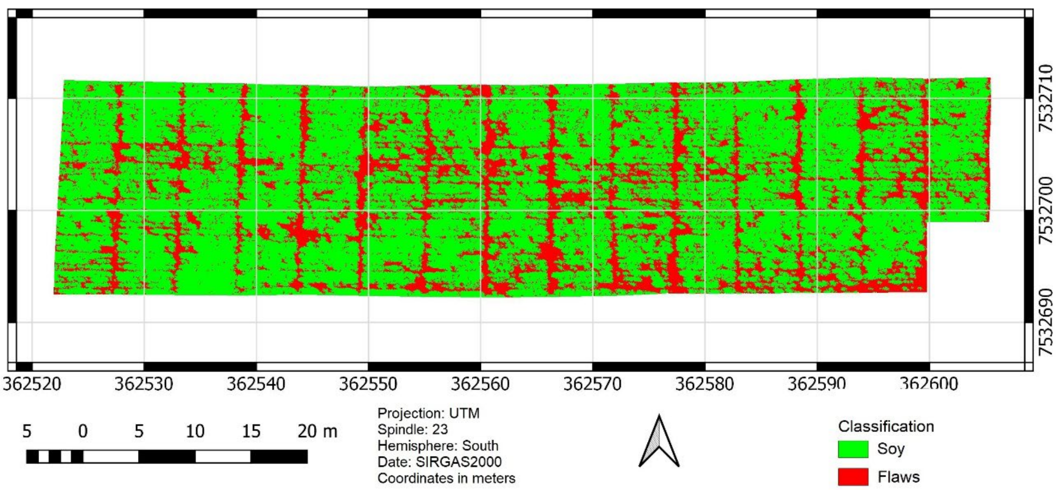
However, seeking to consolidate the results and validate the orthophoto classification, we

Figure 3 – Study area



Source: Prepared by the authors (2021).

Figure 4 – Classified Study Area (Green: Soy; Red: Failures)



Source: Prepared by the authors (2021).

generated the confusion matrix (TABELA 3) and, consequently, the kappa index and the global coefficient.

The kappa index resulting from the classification was 0.9777. According to Moreira (2001), Kappa values between 0.8 and 1.0 are considered excellent. The global coefficient that indicates the classification accuracy was 98.92%, which was also coherent and satisfactory, and the closer to 100%, the better the global coefficient.

Table 3 – Confusion Matrix (Values in pixels)

	Soybean Probing	Soil Probing	Total
Soybeans	90.487	87	90.574
Soil	1.618	65.015	66.633
Total	92.105	65.102	157.207

Source: Prepared by the authors (2021).

Failure identification

After performing the classification and validation of the classification, the classified orthophoto was subdivided into three blocks (FIGURA 5), the red color represents the VCU1 experiment – Precocity, the magenta color represents the VCU2 experiment – Precocity, and the blue color represents the VCU2 experiment – Productivity, so the percentage of failures was counted for each of the plots of each experiment.

Analysis of Variance (ANAVA)

When evaluating the percentage of failures for the VCU1 - Precocity experiment, we found significant differences (TABELA 4). There was a variation of 24.18 % in failures. The varieties F3:6 PREC 95R51, F3:6 PREC M 6410 OPRO, F3:6 PREC 10, F3:6 PREC 13, F3:6 PREC BMX Desafio PR, F3:6 PREC TMG 7067 IPRO, F3:6 PREC 8, F3:6 PREC 15, F3:6 PREC 17 and F3:6 PREC 9 had the lowest percentage of failures. Varieties F3:6 PREC M 5947 IPRO and F3:6 PREC 14 had the highest percentage of failures.

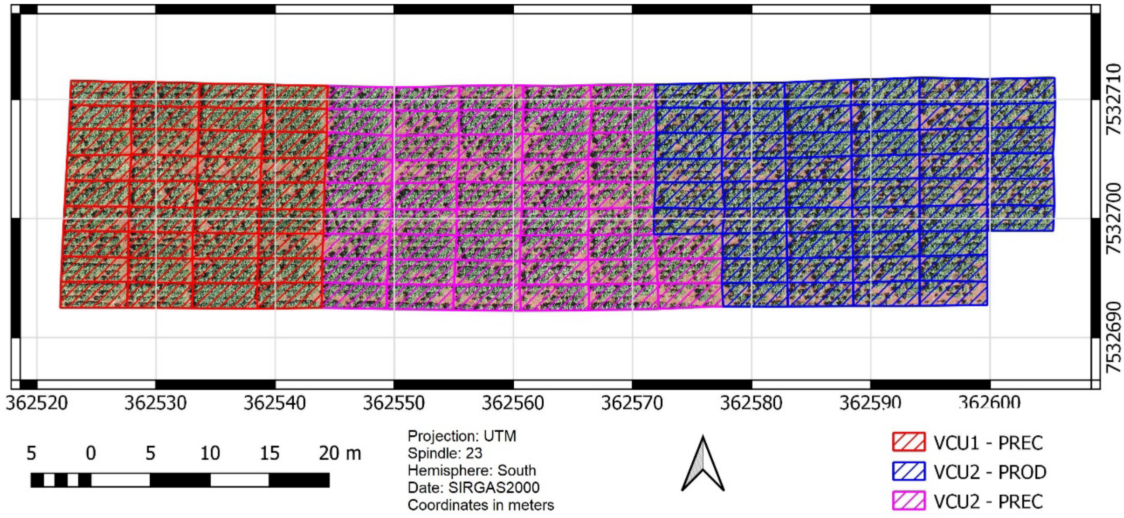
When evaluating the percentage of failures for the VCU1 - Precocity experiment, we found significant differences (TABELA 5). There was a variation of 27.19%. The varieties S0:3 Prec 2, F3:5 Prec 33, F3:5 Prec 27, F3:5 Prec 45, and S0:3 Prec 4 showed a lower percentage of failures, and varieties Test M6410, F3:5 Prec 31, Test M5917, Test 95R51, Test ANTA 82, S0:3 Prec 1, F3:5 Prec 28, Test M5947, Test NS 7300, S0:3 Prec 6 and S0:3 Prec 5 had a higher percentage of failures.

When evaluating the percentage of failures for the VCU2 – Productivity experiment, no significant differences were found between them (TABELA 6). There was a variation of 26.08 %.

Conclusion

Experiment VCU1 – Precocity had the lowest means of failures when compared to the other experiments, having a percentage of failures of 19.66 %, while experiment VCU2 – Productivity had an intermediate percentage of 26.05 %, and experiment VCU2 – Precocity had a percentage of 28.25 %, being the largest of the three experiments. However, the VCU2 – Productivity experiment was the only one that did not present significant differences between the plots.

Figure 5 – Study Area Division (Red: VCU1 – PREC; Magenta: VCU2 – PREC; Blue: VCU2 – PROD).



Source: Prepared by the authors (2021).

Table 4 – Means of the percentage of failures for the VCU1 experiment – Precocity

Treatments	Means	Test results
F3:6 PREC 95R51	14.07 %	A
F3:6 PREC M 6410 OPRO	14.12 %	A
F3:6 PREC 10	14.70 %	A
F3:6 PREC 13	15.40 %	A
F3:6 PREC BMX Desafio RR	15.44 %	A
F3:6 PREC TMG 7067 IPRO	16.09 %	A
F3:6 PREC 8	16.62 %	A
F3:6 PREC 15	19.95 %	A
F3:6 PREC 17	20.63 %	A
F3:6 PREC 9	22.58 %	A
F3:6 PREC M 5947 IPRO	31.64 %	B
F3:6 PREC 14	34.65 %	B
General Mean	19.66 %	
CV (%)	30.20	

*Means followed by the same letters in the columns do not differ from each other at the 5 % probability level by the Scott-Knott test (1974).

Source: Prepared by the authors (2021).

Table 5 – Means of the percentage of failures for the VCU2 experiment – Precocity

Treatments	Means	Test results
S0:3 Prec 2	15.71 %	A
F3:5 Prec 33	15.95%	A
F3:5 Prec 27	19.62%	A
F3:5 Prec 45	20.37 %	A
S0:3 Prec 4	21.04 %	A
Test M6410	26.44 %	B
F3:5 Prec 31	27.19 %	B
Test M5917	28.13 %	B
Test 95R51	28.80%	B
Test ANTA 82	29.41 %	B
S0:3 Prec 1	29.81%	B
F3:5 Prec 28	32.94%	B
Test M5947	36.11%	B
Test NS 7300	38.29%	B
S0:3 Prec 6	39.21%	B
S0:3 Prec 5	42.90%	B
General Means:	28.25%	
CV (%) =	28.53	

*Means followed by the same letters in the columns do not differ from each other at the 5% probability level by the Scott-Knott test (1974).

Source: Prepared by the authors (2021).

Table 6 – Means of the percentage of failures for the VCU2 experiment – Productivity

Treatments	Means	Test results
Test P98Y30	15.16%	A
Test TMG2185	20.07%	A
Test P98Y11	20.68%	A
Test P98Y12	20.94%	A
F3: 5 PROD 139	21.46%	A
F3: 5 PROD 85	21.55%	A
F3: 5 PROD 73	21.85%	A
Test CZ 48B 32 IPRO	22.99%	A
S0: 3 PROD 1	25.53%	A
Test M8210	25.80%	A
S0: 3 PROD 2	27.66%	A
F3: 5 PROD 97	28.63%	A
S0: 3 PROD 10	29.12%	A
F3: 5 PROD 98	33.90%	A
S0: 3 PROD 3	40.25%	A
S0: 3 PROD 5	41.24%	A
General Means:	26.05%	
CV (%) =	36.33	

*Means followed by the same letters in the columns do not differ from each other at the 5 % probability level by the Scott-Knott test (1974).

Source: Prepared by the authors (2021).

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