ISSN 2359-6562 (ONLINE) 2359-6562 (CD-ROM)

CORN PLANTS (*ZEA MAYS)* CAPTURED FROM A REMOTE PYLON IN THE EARLY VEGETATIVE STAGE WERE COUNTED.

CONTAGEM DE PLANTAS DE MILHO (*ZEA MAYS) EM* ESTÁGIO VEGETATIVO INICIAL CAPTURADAS A PARTIR DE UMA RPA

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RESUMO: O Milho (*Zea mays L.)* é uma das culturas mais sensíveis aos padrões de plantio. O método mais comum para a contagem do estande de plantas é através da inspeção visual, atividade que dispende um intenso esforço laboral e demorado, podendo o produtor rural tomar decisões menos lucrativas. O objetivo foi desenvolver um fluxo de trabalho capaz de ser operacionalizado, confiável e rápido para o monitoramento das primeiras fases vegetativas do milho na produção de grãos através de imagens aéreas de alta resolução adquiridas por uma Aeronave Remotamente Pilotada (RPA) em condições de campo, sendo o índice de vegetação utilizado para extração das informações da planta através da fase vegetativa em relação ao solo. Os contornos de cada objeto foram contabilizados pela diferenciação dos objetos através da simulação em mapas topográficos. A diferença na performance contagem em função da resolução espacial foi observado e o melhor fluxo de trabalho foi a de 6,6 mm, com taxas de acerto de 135%, ou seja, com superestimação de 35% superior do que a contabilização real. Para que o fluxo seja implementado de forma correta, as plantas de milho não podem ultrapassar as 3 folhas no momento da coleta das imagens.

Palavras-chave: Aeronave Remotamente Pilotada, Inteligência Artificial, Milho.

COUNTING OF MAIZE PLANTS (ZEA MAYS) IN THE INITIAL VEGETATION STAGE CAPTURED FROM A RPA

ABSTRACT: Corn (Zea mays L.) is one of the crops most sensitive to planting patterns. The most common method for counting the plant stand is through visual inspection, an activity that requires an intense and time-consuming labor effort, and the rural producer may make less profitable decisions. The objective was to develop a workflow capable of being operationalized, reliable and fast for monitoring the first vegetative stages of maize in grain production through high resolution aerial images acquired by a Remotely Piloted Aircraft (RPA) in field conditions, the vegetation index being used to extract plant information through the vegetative phase in relation to the soil. The contours of each object were accounted for by differentiating objects through simulation on topographic maps. The difference in counting performance as a function of spatial resolution was observed and the best workflow was the 6.6 mm, with hit rates of 135%, that is, with an overestimation of 35% higher than the actual counting. For the flow to be implemented correctly, corn plants cannot exceed 3 leaves at the time of image collection.

Keywords: Remotely Piloted Aircraft, Artificial Intelligence, Corn.

1 INTRODUCTION

Studies have demonstrated that corn is highly responsive to various types of agronomic management, including plant population density. Corn has a low capacity to compensate for planting failures within a given spacing, resulting in production losses in a

Recebido em 23/12/2021 e aprovado para publicação em 22/01/2022
DOI: http://dx.doi.org/10.17224/EnergAgric.2022v37n1p64-75

given area at the end of its cycle (SANGOI *et al.* , 2012) . The method used to count the population of emerged plants is visual inspection. This method, in turn, is a laborious, arduous, and time-consuming activity performed by farmers and researchers. Therefore, studies on methods for evaluating the final plant population are necessary. Furthermore, data processing and analysis procedures must be agile enough to allow farmers to make decisions within a reasonable timeframe on the basis of the acquired data, considering the actual need for replanting, for example.

With the advent of remotely piloted aircraft (RPAs), many studies have explored a previously unexplored perspective, one linked to a layer close to the atmosphere called the troposphere. Like GPS (*global positioning system*) technology, RPA also provides benefits to the civilian sector (RODRIGUES *et al.*, 2017) . Remote sensing platforms, through the use of this tool, are among the most recent remote sensing technologies for vegetation areas (SALAMÍ; BARRADO; PASTOR, 2014) and demonstrate high flexibility in use, low operational cost, and high spatial and temporal resolution (HUNT *et al.* , 2010) .

New tools for improving corn cultivation are needed to better understand what affects final corn productivity. One of the parameters used to estimate new areas of study is the number of publications on various platforms available on the internet. Between 2016 and 2019, the number of searches using the keyword RPAs (remotely piloted aircraft systems) increased, as demonstrated by the increase in the number of publications from 14,100 to 23,600, 1,260 to 2,132, and 3,973 to 7,161 on the academic search platform *Google Scholar*, *the Web of Science* database, and *Scopus*, respectively.

Despite the growing number of publications and numerous benefits of new technologies demonstrated by the research and development sector, the adoption of new technologies, such as automated robot systems, is still underutilized by rural producers in Brazil, with an adoption rate of only 6.5%, mainly among grain producers (SOARES FILHO; CUNHA, 2015) . However, efforts are being made to develop and implement low-cost, high-performance operational tools to ensure continuous sustainable development in the agricultural grain production chain.

Zea mays) is among the commodities with the highest global production and is considered one of the most important annual grain crops worldwide, with over 70% of global corn production occurring in the Americas and Asia, represented by the United States, China, Brazil, and Argentina. Even though Brazil is the third largest corn producer, significant efforts are underway to establish Brazil as a major producer on an even larger scale, as exemplified by research projecting production, consumption, and export increases of 20.2%, 19.7%, and 33.4%, respectively, between the crop years 2018/2019 and 2028/2029 (MAPA, 2019) . In the state of São Paulo, the increase follows the same trend, with a productivity growth rate of 3.5% per year from 2009--2018, which is higher than the national projection of 3% during the next decade (MAPA, 2019).

Within the next few decades, therefore, there will be significant increases in production levels, either through increased area occupied by the crop or through increased productivity via resource optimization. With respect to the latter, research shows that corn cultivation has proven highly responsive to various management practices. Different approaches can be used to optimize productivity, including cross-planting (SILVA *et al.* , 2015) . One management method involves the proper and uniform distribution of seeds across the area where the crop will be planted, according to the region and hybrid.

The implementation of remote sensing tools for agricultural monitoring via aerial or satellite imagery is gaining importance because of increased awareness of data-driven decision-making in the field. Successful studies have been conducted by Thorp. et al. (2008) used hyperspectral satellite imagery data to estimate population densities in cornfields. In their study, the best performance was achieved in more advanced phenological stages ($R^2 = 0.79$) when images with spatial resolutions of 6 meters were used. However, the estimation of vegetative phenological stages is significantly limited by the abundance of ground cover relative to vegetation. The use of unmanned aerial vehicles is a tool that could be used to fill this gap.

Therefore, the limitations of remote sensing platforms can be overcome by collecting aerial images via a remotely piloted aircraft, which has been developed as a new way of acquiring aerial images (TORRES-SÁNCHEZ *et al.* , 2014) . Data extraction via the integration of the RPAS with their respective coupled sensors (RGB, multispectral, hyperspectral, and thermal) has been extensively researched to estimate biomass (BENDIG *et al.* , 2015) , leaf area index (BENDIG *et al.* , 2015; MATHEWS; JENSEN, 2013) , plant height, nitrogen (JORGE; BRANDÃO; INAMASU, 2014; PÖLÖNEN *et al.* , 2013) , chlorophyll (CLEVERS; KOOISTRA, 2012) , and temperature (GÓMEZ-CANDÓN *et al.* , 2016) . Crops and weeds are detected through aerial images with submillimeter spatial resolutions. (PEÑA et al., 2013) . Although studies have shown that it is possible to detect differences between new and old leaves of the corn crop (R^2 = 0.89) (GNÄDINGER; SCHMIDHALTER, 2017) , segmentation between economic crops and induced weeds is highly challenging due to similarities in spectral responses.

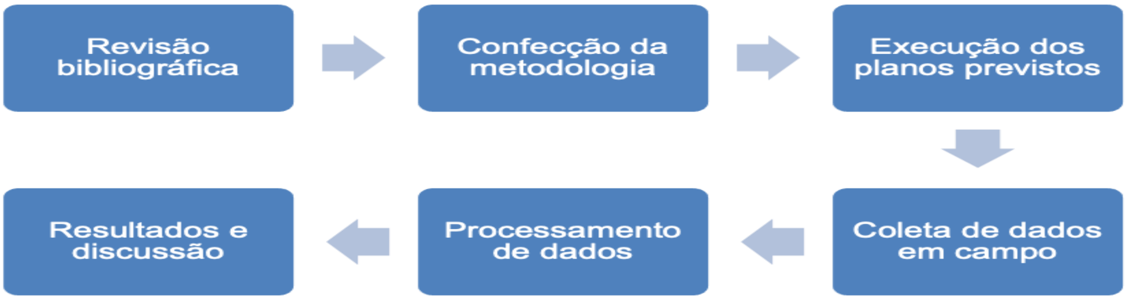
The objective of this study was to contribute to the development of tools for counting corn plants in the early vegetative stage. To this end, the accuracy of the count was evaluated via open-source computer programs at different spatial resolutions through aerial images captured by a small remotely piloted aircraft. In short, a workflow was implemented for extracting metric data from plants via high-spatial-resolution images via the following steps: (i) flight planning, (ii) aerial image collection, (iii) identification of green and nongreen regions, (iv) geometric extraction of green objects, (v) plant counting, and (vi) validation.

2 MATERIALS AND METHODS

In the deductive method, research starts from principles recognized as true, called the major premise, and establishes relationships with a second minor premise. In this way, starting from logical reasoning, one arrives at the truth of what is proposed, the conclusion (LAKATOS; MARCONI, 2003).

The workflow was executed in the following order: literature review, methodology development, execution of the planned steps, field data collection, and data processing via open-source software (Figure 1).

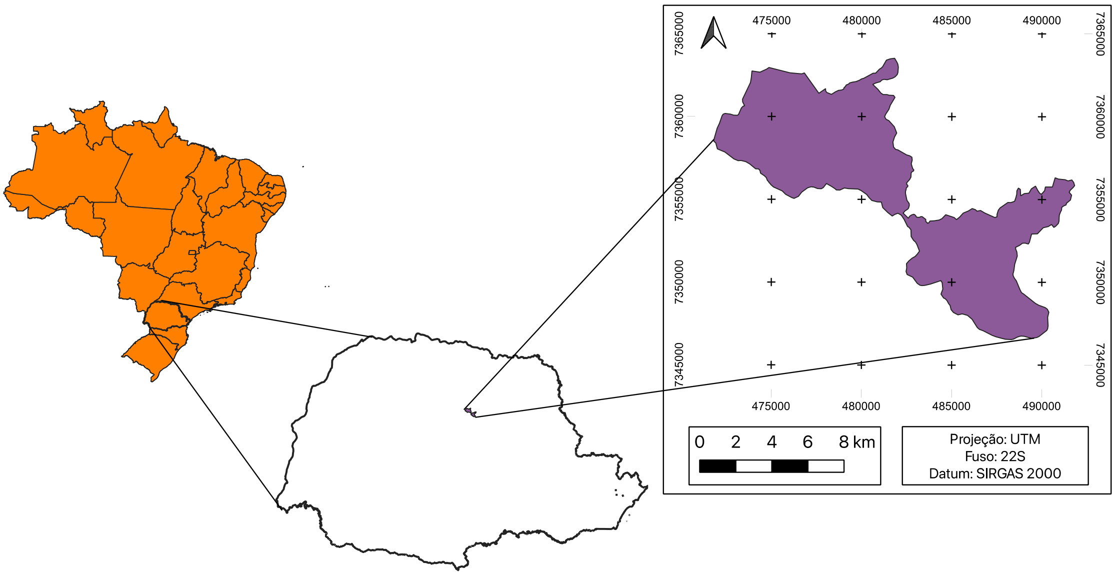
Figure 1. Workflow diagram



2.1 Experimental Area

The study area is located on a rural property in the municipality of Mauá da Serra, state of Paraná (Figure 2), with an area of 80 ha, which, at the time of image collection, was planted with corn (phenological stage V2, 2 true leaves). All crop management, including corn sowing and other cultivation practices, was carried out by the producer during the 2020–2021 summer growing season.

Figure 2. Location map of the municipality of Mauá da Serra, located in the state of Paraná, Brazil.



2.2 PLATFORM, sensor, and field data

Mavic Pro (DJI, Shenzhen, China) was used to capture the digital aerial image data. The data collection system consists of a long-range remote controller (2.4 GHz) and an aerial vehicle with 4 rotors.

The experimental area was randomly sampled in 5 subareas of 0.25 ha (50 × 50 meters) to account for spatial differences within each plot (Figure 03) and to randomize possible weeds and crop residues from previous crops.

Figure 3. Distribution of the 5 areas on the rural property located in Mauá da Serra, Paraná state.

Source: Google Earth (2020).

The aircraft, in turn, has a controller that is connected to satellite navigation systems composed of receivers for these signals, which are mostly from the American *Global Positioning System (GPS) constellation and the Russian Glonass* system, in addition to sensors that measure environmental conditions, enabling autonomous flights with a high degree of stability.

Image collection via the Remotely Piloted Aircraft (RPA) was performed through autonomous flight. First, the remote control was connected to a smartphone to configure all the flight information via a flight planning application. For this purpose, the *Drone Deploy application* (San Francisco, United States) was chosen. Flight plans in autonomous mode allow for standardization of flights, producing parallel lines and enabling total area coverage with the ability to capture standardized images in each area. To simulate different spatial resolutions and flight altitudes, flights were conducted at 10 m above the ground, resulting in average spatial resolutions per pixel of 3.3 mm, with subsequent reductions (by a factor of 0.5) to 6.6 mm and 13.2 mm.

The aerial images were collected at a nadir angle perpendicular to the RPA's flight direction via an RGB (*Red, Green, Blue*) sensor with the following characteristics: 12 megapixel resolution (4000 × 3000 *pixels*), 1/2.3-inch CMOS, 30 frames per second, 5 mm actual focal length, and 6.17 mm sensor width, coupled to a structure called a gimbal allowing movement and stabilization of the sensor during flight on three axes (tilt, roll, and spin).

The use and operation of this technology requires a high degree of safety, from takeoff and flight programming to landing. Therefore, the Remotely Piloted Aircraft (RPA) must offer safe operation to avoid disaster risk, and the operator (remote pilot) must be trained and duly regulated by the responsible agencies (Anatel, ANAC, and DECEA). All procedures followed the recent legislation in force for visual line-of-sight (VLOS) operations within the publication of the Aeronautical Cartographic Institute (ICA-100/40), entitled "Remotely Piloted Aircraft Systems and Access to Brazilian Airspace," from the Brazilian Ministry of Defense, Air Force Command, which is responsible for air traffic.

2.3 Data preprocessing

After the images were collected, they were processed via the open-source program *ImageJ*. The steps performed in this program were as follows: first, only the center of the image was cropped; then, the original 4000 × 3000 pixel image was transformed into 615 ×

600 pixels, with equal height and width proportions; and second, the images were reduced and resized to reduce spatial resolution via the "*scale*" procedure. Both procedures were performed automatically via the program's macro function.

The final preprocessing step (actual counting) was performed via *software* with the R language and environment (*RStudio Team*, 2020) for statistical and graphical computing. The *FIELDimageR package was used.* (MATIAS; CARAZA-HARTER; ENDELMAN, 2020) was used for image preprocessing and finalization in counting the plants in the images. The *fieldCrop function* was used to select the area of interest. To do this, the area of interest was cut by selecting the four corners of the area in the *RStudio window*.

After the area of interest was selected, a mask was created for soil removal. For this purpose, the *fieldMask function* was used to classify the soil pixels on the basis of the *overall hue index* (HUE).

2.4 Plant count

Within the same package, the *FIELDimageR* (MATIAS; CARAZA-HARTER; ENDELMAN, 2020) , the *fieldCount* function was used to perform the automated counting of corn plants. The *EBImage package* (PAU *et al.* , 2010) performs image segmentation to distinguish between the background and plants. First, a binary transformation is applied to the distance field created by *fieldMask*, generating a grayscale image with the minimum distance between the background pixels.

This grayscale image is interpreted as a topographic map, and the transformation is performed in the different "watersheds" to identify the boundaries of these watersheds (SOILLE, 2013) , which are interpreted as different objects, and in the example used, plants.

Data validation was implemented through visual inspection of each plant in the collected image for the purpose of counting the current number of plants in the images.

2.5 Evaluation of classification performance.

The accuracy rate, a percentage indicator of evaluation based on the relationship between the estimated count (Ce) and the actual count (Ca), was calculated via expression 1:

Hit rate = (Ce/Ca) * 10 (1)

3 RESULTS AND DISCUSSION

Image analysis via open-source software (R Studio) was used to count corn plants under commercial field conditions for grain production via the *FIELDimageR plugin.* (MATIAS; CARAZA-HARTER; ENDELMAN, 2020) . The performance evaluation was based on the accuracy rate of plant counting, i.e., counting the estimated number of plants and counting the visual number of plants.

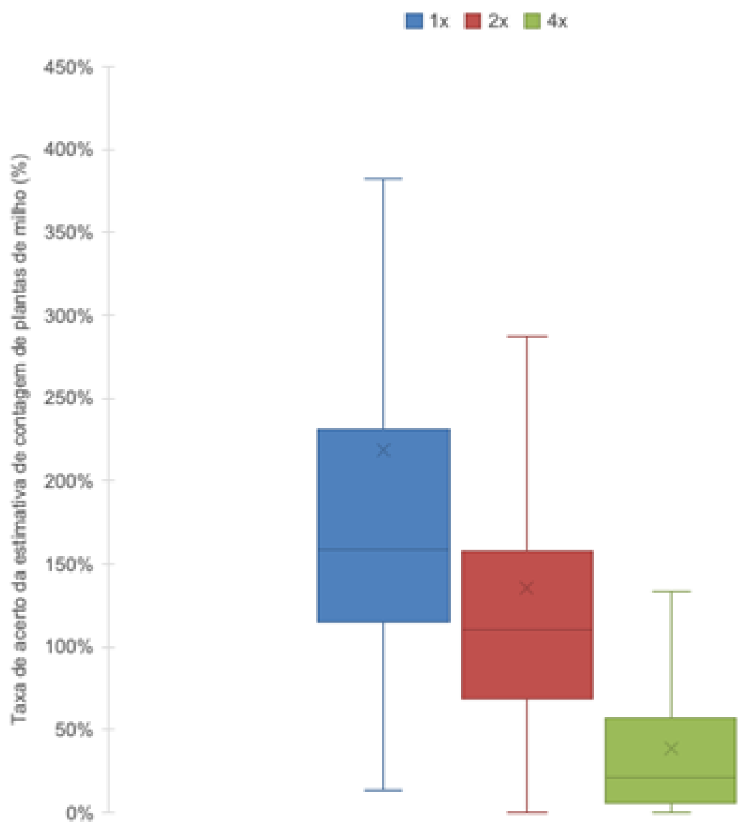
A total of 226 images were captured from the RPA in 5 flight plans. Each flight plan produced an average of 52 images. In the first stage of preprocessing, filtering was performed to observe the image quality. Furthermore, to identify the different flight plans, the flight automation application itself captures an image before the flight plan begins. Therefore, it is necessary to eliminate this image at the beginning of each plan, which accounts for 5 images, resulting in 221 images processed in three processing stages at different spatial resolutions (0.33, 0.66, and 1.32 mm). The average results for each spatial resolution are presented in Table 1.

Table 1. Overall average accuracy rate (%) in the 2x and 4x reduction tests on the original image resolution.

Pixel resolution		
1x	2x	4x
219	135	39

To better understand the data distribution at each spatial resolution, a box plot was created (Figure 4). Through the diagram, it was possible to observe that the data resulting from the processing of the original aerial images, as well as their reduction, had a dispersed distribution with values that exceeded the stipulated maximum limits, which were calculated by summing the third quartile and 1.5 times the interquartile range (disregarded in the graph for better visualization). Eight points were found to be *outliers* in the processing of the original images, and six points in the images were reduced by 2 and 4 times (n=221). Furthermore, more than 75% of the data in the original images were above 100% accuracy, unlike the results of the processing of the images reduced by 4 times, where slightly less than 100% of the data were below 100% accuracy, further evidenced by the difference between the groups through the positions of the medians outside the boxes.

Figure 4. Bar chart of the accuracy rates of corn plant count estimation at different spatial resolutions (original, 2- and 4-fold reductions).

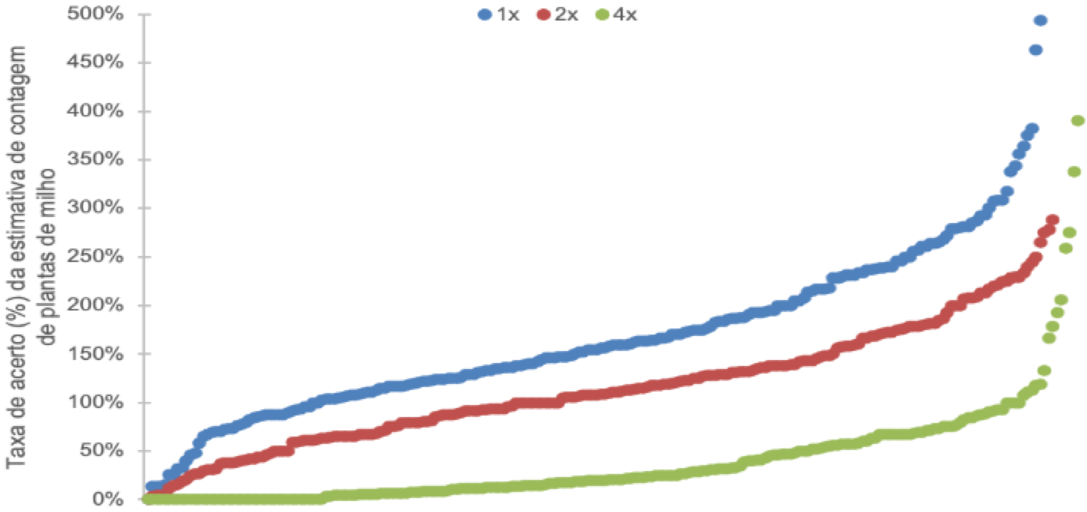


Importantly, resizing the images, decreasing their size, penalizes the binarization process of the Excess Green (ExG) index and, consequently, the ability of this flowchart to determine the correct geometry of the corn plant. Furthermore, resizing the images increases the ground pixel size (GSD), resulting in a larger area to be sampled per pixel unit.

Therefore, detecting the boundaries of green objects relative to the ground becomes critical, especially for the quality of identifying the object contours.

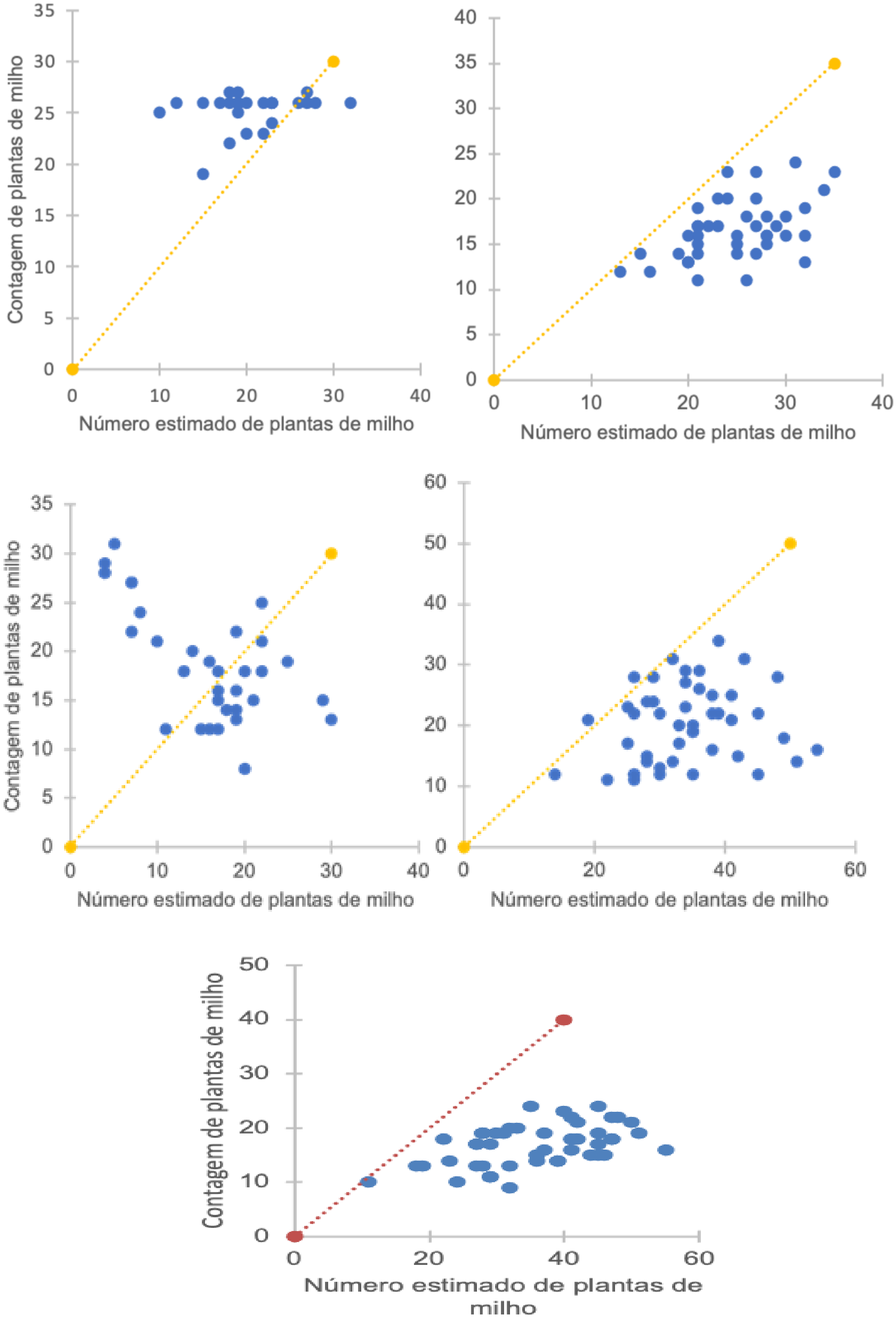
Although the diagram graph summarizes the information, it is not possible to identify the values of each point. Therefore, a scatter plot was created (Figure 11), allowing visualization of the accuracy rate in estimating the count of each point in ascending order. The accuracy rates were proportional among the 3 groups. The accuracy rates followed a proportionality trend. High accuracy rates resulting from the processing of the original image provided high accuracy rates in subsequent processing. However, as seen in the diagram graph, 75% of the data were overestimated; that is, they performed a count above the real number. This can be observed at the beginning of the graph near the axis of the independent variables.

Figure 5. Accuracy rates of corn plant count estimation at different spatial resolutions, which were originally reduced 2- and 4-fold.



Finally, a scatter plot was created to compare the estimated corn plant count values with the current count values on the basis of the count estimates in the original images (Figure 6). This graph shows how far the estimated values are from the current values. This graph also shows the dispersion already observed in the previous figures, providing a better understanding of the characteristics of each area where the images were collected. All areas resulted in high dispersions, but in area 01, the data showed the closest approximation to the current line. In areas 2, 4, and 5, the points below the line indicate that the count estimates in these areas were overestimated, with differences of, on average, 61%, 110%, and 163%, respectively. For area 01, the count obtained through this workflow was underestimated by an average of 18.5%.

Figure 6. Scatter plot of the estimated number of plants and corn plant count.



Current studies depict the use of ground vehicles and satellite imagery to estimate plant conditions in the field. The first technique relies on robots that cover a small area and depend on accessible terrain for traffic. The second data acquisition method, on the other hand, does not achieve resolutions sufficient to reach satisfactory levels for this type of processing and analysis. Satisfactory results have been obtained through the combined use of UAVs and counting corn plants in the early vegetative stage via decision tree classification (VARELA et al., 2018). This workflow proposal utilizes existing technological advancements through *off-the-shelf equipment* capable of moving through the airspace and autonomously capturing images combined with open-source and free software for the identification of corn plants in the early vegetative stage under commercial field conditions for grain production.

Some limitations from this field research can be observed: (i) data collection at more advanced vegetative stages may decrease the accuracy of this flowchart because of overlapping leaves between plants in the rows, leading to an underestimation of the number of plants; (ii) plant density (plants per hectare) was not calculated, as it was not the focus of the article, in addition to the need for high accuracy in the RPA position, values that can be achieved only through the use of receivers from global navigation satellite systems such as RTK (real-time kinematic) or PPK (postprocessed kinematic). (kinematic). One strategy to deliver more information about the area more effectively and with faster models is through data collection by subsampling and spatial analysis. This approach has great potential, but it does not face the high computational costs required for processing or the decrease in image resolution when images undergo image mosaicking.

The main contribution of this article is the development of a procedure for managing operations carried out in early-stage corn cultivation by rural producers. This study is based on a methodology that combines traditional imagery and image processing via open-source software. The result of this workflow enables the digitized counting of corn plants via small UAVs and RGB sensors, contributing to the optimization of data collection in the early stages of corn cultivation.

Future work should address (a) cameras with sensors capable of producing higher resolution; (b) the possible influences of wind on the quality of collected images and on possible differences in counting and classification; and (c) the potential of various soil removal options, which are based on other indices, should be explored.

4 CONCLUSION

A workflow diagram for identifying corn plants under commercial field conditions was generated. The methodology used involved collecting aerial images to detect the geometry of the existing vegetation in the area, followed by processing to identify plant characteristics. The goal of this study was to implement and test the workflow diagram via data collected from a small remotely piloted aircraft on a grain production farm, with the potential for scaling up the use of operations under field conditions. Although the workflow diagram is capable of reproducing the proposed analyses, with an accuracy rate varying between 39% and 219%, a better adjustment in processing is still necessary. The original image with a resolution of 0.66 mm in the identification and counting of corn plants obtained the best accuracy rate (135%), that is, 35% greater than the expected count. Reducing the image magnification by 4x negatively affected the accuracy rate because of two main characteristics: low sensitivity in identifying the green outlines of plants and a decrease in the ability of the topographic model used to identify the geometry of the analyzed object. The results indicate that the ideal phase for collecting images for estimating plant counts is between 2 and 3 leaves.

5 REFERENCES

BENDIG, J.; WILLKOMM, M.; TILLY, N.; GNYP, ML; BENNERTZ, S.; LENZ-WIEDEMANN, VIS; BARETH, G.; MIAO, Y.; CAO, Q. Very high resolution Crop Surface Models (CSM) from UAV-based stereo images for rice growth monitoring in

Northeast China. **gis.Science - Die Zeitschrift fur Geoinformatik** , Minnesota, v. 40, no. 1, p. 1-9, 2015.

CLEVERS, JGPW; KOOISTRA, L. Using hyperspectral remote sensing data for retrieving canopy chlorophyll and nitrogen content the potential of plant–soil feedback view project using hyperspectral remote sensing data for retrieving canopy chlorophyll and nitrogen content. **IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing** , Middelburg, v. 5, no. 2, p. 574-583, 2012.

GNÄDINGER, F.; SCHMIDHALTER, U. Digital counts of maize plants by Unmanned Aerial Vehicles (UAVs). **Remote Sensing** , Freising - Germany, v. 9, no. 6, p. 544, 2017.

GÓMEZ-CANDÓN, D.; VIRLET, N.; LABBÉ, S.; JOLIVOT, A.; REGNARD, JL Field phenotyping of water stress at tree scale by UAV-sensed imagery: new insights for thermal acquisition and calibration. **Precision Agriculture** , Meddeelin, v. 17, no. 6, p. 786-800, 2016.

HUNT, ER; DEAN HIVELY, W.; FUJIKAWA, S.J.; LINDEN, DS; DAUGHTRY, C.S.T.; MCCARTY, GW Acquisition of NIR-green–blue digital photographs from unmanned aircraft for crop monitoring. **Remote Sensing** , Basel, v. 2, no. 1, p. 290-305, 2010.

JORGE, LAC; BRANDÃO, ZN; INAMASU, RY Insights and recommendations of use of UAV platforms in precision agriculture in Brazil. **Remote Sensing for Agriculture, Ecosystems, and Hydrology XVI** , Amstherdam, v. 9239, no. 2004, p. 923911, 2014.

LAKATOS, EM; MARCONI, MA. **Fundamentals of scientific methodology** . 5th ed. São Paulo: Atlas, 2003.

MAPA. **Agribusiness Projections:** Brazil 2018/2019 to 2029/2029. Long-term projections. deadline. Brasília, DF: Ministry of Agriculture, Livestock and Supply, 2019. Available at: http://www.agricultura.gov.br/assuntos/politica-agricola/todas-publicacoes-de-politica-agricola/projecoes-do-agronegocio/projecoes-do-agronegocio-2018-2019-2028-2029/view. Accessed on: May 8, 2021.

MATHEWS, A.J.; JENSEN, JLR Visualizing and quantifying vineyard canopy LAI using an unmanned aerial vehicle (UAV) collected high density structure from motion point cloud. **Remote Sensing** , Basel, v. 5, no. 5, p. 2164-2183, 2013.

MATIAS, FI; CARAZA-HARTER, MV; ENDELMAN, JB FIELDimageR: An R package to analyze orthomosaic images from agricultural field trials. **The Plant Phenome Journal** , Madison, vol. 3, no. 1, p. 1-6, 2020.

PAU, G.; FUCHS, F.; SKLYAR, O.; BOUTROS, M.; HUBER, W. EBImage-an R package for image processing with applications to cellular phenotypes. **Bioinformatics** , Oxford, vol. 26, no. 7, p. 979-981, 2010.

PEÑA, JM; TORRES-SÁNCHEZ, J.; CASTRO, AI; KELLY, M.; LÓPEZ-GRANADOS, F. Weed mapping in early-season maize fields using object-based analysis of unmanned aerial vehicle (UAV) images. **PLoS ONE** , San Francisco, v. 8, n. 10, p. 1-11, 2013.

PÖLÖNEN, I.; SAARI, H.; KAIVOSOJA, J.; HONKAVAARA, E.; PESONEN, L. Hyperspectral imaging based biomass and nitrogen content estimations from lightweight UAV. **Proceedings of SPIE** , Dresden, v. 8887, p. 88870J-1-88870J-9, 2013. Paper presented at the 15th Remote Sensing For Agriculture, Ecosystems, and Hydrology Conference, 2013, Dresden.

RODRIGUES, BT; RODRIGUES, MT; CAMPOS, S.; CAMPOS, M.; TARUMOTO, MB. Possibilities and methods of use of DRONES/UAVs in agriculture. *In* : PUTTI, FF; SILVA, ALC; GABRIEL FILHO, LRA (org.). **Technologies in sustainable agriculture** . Tupã: Friends of Nature Association of Alta Paulista, 2017. p. 249-269.

SALAMÍ, E.; BARRATED, C.; PASTOR, E. UAV flight experiments applied to the remote sensing of vegetated areas. **Remote Sensing** , Basel, v. 6, no. 11, p. 11051-11081, 2014.

SANGOI, L.; SCHMITT, A.; VIEIRA, J.; PICOLI JÚNIOR, GJ; SOUZA, CA; CASA, RT; SCHENATTO, DE; GIORDANI, W.; BONIATTI, CM; MACHADO, GC; HORN, D. Variability in the spatial distribution of plants in the row and grain yield of maize. **Revista Brasileira de Milho e Sorgo** , Belo Horizonte, v. 11, n. 3, p. 268-277, 2012.

SOARES FILHO, R.; CUNHA, JPAR. Precision agriculture: Particularities of its adoption in southwestern Goiás - Brazil. **Agricultural Engineering** , Jaboticabal, v. 35, n. 4, p. 689-698, 2015.

VARELA, S.; DHODDA, P.; HSU, W.; PRASAD, PV; ASSEFA, Y.; PERALTA, N.; GRIFFIN, T.; SHARDA, A.; FERGUSON, A.; CIAMPITTI, I. Early-season stand count determination in corn via integration of imagery from unmanned aerial systems (UAS) and supervised learning techniques. **Remote Sensing,** Basel, v. 10, no. 3, p. 343, 23 Feb. 2018.

SILVA, PRA; TAVARES, LAF; SOUSA, SFG; CORREIA, TPS; RIQUETTI, NB. Profitability in cross-seeding of soybean. **Brazilian Journal of Agricultural and Environmental Engineering** , Campina Grande, v. 19, n. 3, p. 293-297, 2015.

SOILLE, P. **Morphological Image Analysis** : Principles and Applications. 2nd ed. Berlin: Springer-Verlag, 2013. v. 20.

THORP, K.R.; STEWARD, B.L.; KALEITA, AL; BATCHELOR, WD Using aerial hyperspectral remote sensing imagery to estimate corn plant stand density. **Transactions of the ASABE** , St. Joseph, vol. 51, no. 1, p. 311-320, 2008.

TORRES-SÁNCHEZ, J.; PEÑA, JM; ASTRO, AI; LÓPEZ-GRANADOS, F. Multitemporal mapping of the vegetation fraction in early-season wheat fields using images from UAV. **Computers and Electronics in Agriculture** , Amsterdam, v. 103, p. 104-113, 2014.