

**SÃO PAULO STATE UNIVERSITY
JABOTICABAL CAMPUS**

**SMARTPHONE IMAGE-BASED METHODS FOR QUICK,
NON-INVASIVE ASSESSMENTS IN AGRICULTURE**

Vinicius dos Santos Carreira

Mechanization in Precision Agriculture Technologist

2022

**SÃO PAULO STATE UNIVERSITY
JABOTICABAL CAMPUS**

**SMARTPHONE IMAGE-BASED METHODS FOR QUICK,
NON-INVASIVE ASSESSMENTS IN AGRICULTURE**

Vinicius dos Santos Carreira
Advisor: Prof. Dr. Rouverson Pereira da Silva

Dissertation submitted to the College of
Agricultural and Veterinary Sciences -
UNESP, Jaboticabal Campus, as part of the
requirements for obtaining the title of MSc. in
Agronomy (Plant Production).

2022

C314s Carreira, Vinicius dos Santos
Smartphone image-based methods for quick, non-invasive
assessments in agriculture / Vinicius dos Santos Carreira. --
Jaboticabal, 2022
63 p. : il., tabs., fotos

Dissertação (mestrado) - Universidade Estadual Paulista
(Unesp), Faculdade de Ciências Agrárias e Veterinárias,
Jaboticabal
Orientador: Rouverson da Silva Pereira

1. Processamento de imagem. 2. Engenharia agrícola. 3.
Sistemas digitais. I. Título.

Sistema de geração automática de fichas catalográficas da Unesp. Biblioteca da
Faculdade de Ciências Agrárias e Veterinárias, Jaboticabal. Dados fornecidos pelo
autor(a).

Essa ficha não pode ser modificada.



UNIVERSIDADE ESTADUAL PAULISTA

Câmpus de Jaboticabal



CERTIFICADO DE APROVAÇÃO

DISCENTE: VINICIUS DOS SANTOS CARREIRA

**TÍTULO DA DISSERTAÇÃO: SMARTPHONE IMAGE-BASED METHODS FOR QUICK,
NON-INVASIVE ASSESSMENTS IN AGRICULTURE**

AUTOR: VINICIUS DOS SANTOS CARREIRA

ORIENTADOR: ROUVERSON PEREIRA DA SILVA

Aprovado como parte das exigências para obtenção do Título de Mestre em AGRONOMIA
(PRODUÇÃO VEGETAL), pela Comissão Examinadora:

Prof. Dr. ROUVERSON PEREIRA DA SILVA (Participação Virtual)

Departamento de Engenharia e Ciências Exatas DECEX / FCAV UNESP Jaboticabal

Prof. Dr. GUSTAVO DI CHIACCHIO FAULIN (Participação Virtual)

Fatec Shunji Nishimura / Pompeia/SP

Professor Doutor MARIO LUIZ TRONCO (Participação Virtual)

Departamento de Engenharia Mecânica / Universidade de São Paulo/São Carlos

Jaboticabal, 26 de julho de 2022.

AUTHOR'S CURRICULUM INFORMATION

VINICIUS DOS SANTOS CARREIRA was born to Valdemir Donizetti Carreira and Maria Isabel dos Santos Carreira, on April 19th, 2000, in Cândido Mota, São Paulo, Brazil. He graduated from university in Mechanization in Precision Agriculture Technology at FATEC (São Paulo Technological College) “Shunji Nishimura” in 2020. During the degree he worked for two years at the Research & Development Center, Jacto Agrícola. In 2021/1 he started his master's degree in Agronomy (Plant Production) and focused on accessible techniques using image processing for digital farming.

“You see, gentlemen, reason is an excellent thing, there’s no disputing that, but reason is nothing but reason and satisfies only the rational side of man’s nature, while will is a manifestation of the whole life, that is, of the whole human life including reason and all the impulses. And although our life, in this manifestation of it, is often worthless, yet it is life and not simply extracting square roots.”

Fyodor Dostoyevsky

ACKNOWLEDGEMENTS

Firstly, I would like to thank God for giving me life and St. Mary for her intercession.

Many of my professional and even personal decisions were made after insightful conversations with my advisor, PhD. Rouverson Pereira da Silva. I would like to thank for his timely scientific and human contributions.

The steps before the master's degree were crucial to expand my experience. I would like to thank all people from my undergraduate degree at FATEC "Shunji Nishimura", especially the GECOM group (Mechanized Harvesting Study Group) and professor MSc. Edson Massao Tanaka. I would also like to thank all collaborators from Jacto Agrícola, where I worked for two years in the Research & Development Center.

I would like to thank my family, especially my parents Valdemir Donizetti Carreira and Maria Isabel dos Santos Carreira, and my brother Alexandre dos Santos Carreira. Over the years I have seen their unshakable strength, even through so many negative events. Their faith and doctrine inspire me every day and I couldn't be more grateful for anything in the world.

Finally, I would like to thank my few but so special friends from the high school and college, including the LAMMA group (Laboratory of Agricultural Machinery and Mechanization) and RSRG group (Rouverson Silva Research Group).

SUMMARY

CHAPTER 1 – GENERAL INTRODUCTION.....	1
1.1 Introduction	1
1.2 Literature review.....	1
1.2.1 Agricultural assessments and available technologies.....	1
1.3.2 Image processing.....	4
References.....	7
CHAPTER 2 – ASSESSING INTRA-ROW SPACING USING IMAGE PROCESSING: A PROMISING DIGITAL TOOL FOR SMALLHOLDER FARMERS	10
Abstract.....	10
1. Introduction	10
2. Materials and Methods.....	13
2.1. Experiment location	13
2.2. Data Collection	13
2.3. Image Processing	14
2.4. Pre-Processing	15
2.5. Region of Interest (ROI).....	15
2.6. Local maxima (Peaks)	16
2.7. Analysis	16
3. Results	17
3.1. Overall aspects and performance	17
3.2. Metrics for analyzing planting performance	19
4. Discussion	20
5. Conclusion	21
References	22
CHAPTER 3 – SMARTPHONE IMAGE-BASED FRAMEWORK FOR QUICK, NON- INVASIVE MEASUREMENT OF SPRAY NOZZLES CHARACTERISTICS.....	29
Abstract.....	29
1. Introduction	29
2. Materials and methods.....	32
2.1. Nozzle characteristics	32
2.2. Spray angle distribution pattern measurement using a patternator.....	32
2.3. Spray image acquisition.....	32
2.4. Image pre-processing	33

2.5. Spray angle detection	33
2.6. Spray distribution shape	34
2.7. Solid stream jet	36
2.8. Comparison and analysis.....	36
3. Results	37
3.1. Spray angle.....	38
3.2. Spray distribution pattern	39
3.3. Solid stream jets detection.....	41
3.4. Field validation.....	42
4. Discussion.....	43
5. Conclusions	45
References.....	46
CHAPTER 4 – FINAL CONSIDERATIONS	52

SMARTPHONE IMAGE-BASED METHODS FOR QUICK, NON-INVASIVE ASSESSMENTS IN AGRICULTURE

ABSTRACT — Image processing timely contributes for agricultural purposes. Its outstanding benefit of extracting information from the field can replace time-consuming, labor-intensive methods. However, most times innovative methods use high-complexity systems and expensive equipment. Low-income regions are not able to finance such costs. Therefore, we concentrate efforts to develop smartphone image-based methods for agricultural measurements using a mobile device. Smartphone are widespread technology known as flexible, affordable systems. To prove our hypothesis that low-complexity approaches can be useful, we analyzed two agricultural operations. In Chapter 2, we describe how two image-based methods (Region of Interest and Local Maxima) can detect maize plants and estimate their uniformity with overall results of RMSE of 3.98 cm and R^2 of 0.90. In Chapter 3, we created a smartphone image-based framework to measure macro spray characteristics, including spray angle, distribution shape and solid stream jets. Using image enhancement and morphological operations, our framework accurately resembles traditional methods and can be useful for quick screening of spray nozzles. Therefore, we prove that smartphone use can go beyond ordinary activities and help to spread digital assessments in agriculture.

Keywords: Image processing; digital agriculture; affordable technology

CHAPTER 1 – GENERAL INTRODUCTION

1.1 Introduction

Agricultural digitalization is inevitable; when it is synchronized with global demand, it can replace manual intervention, improve production processes and reduce environmental impacts. Moreover, researchers and companies have consistently been developing new technologies supported to address the increasing demand for food. However, it is unclear if the food chain problem is related to not merely production but also accessibility. While big farms can afford high-tech products and hire highly skilled people, smallholder farmers and manufacturers still rely on more traditional and inefficient labor-intensive methods. To address these issues, an emerging method is image processing. This method is used to manipulate image properties to extract data (e.g., color spectrum, object size and position). Images are acquired using devices with different complexity levels, ranging from mobile phones to high-speed cameras. The mobile phone is now a widespread technology; therefore, it can be useful for low-cost image-based methods.

Therefore, our efforts were focused on developing smartphone image-based methods for agricultural assessments. In Chapter 1, we present a brief literature review on the concept of digital image and existing image processing methods using mobile devices for agricultural purposes. Thereafter, each chapter corresponds to a specific agricultural assessment method. In Chapter 2, we describe a digital tool based on mobile images and morphological operations, which was developed to assess planting performance. In Chapter 3, we describe a framework for quick, non-invasive screening of poor spray nozzles on indoor and outdoor measurements using mobile images and morphological operations. Finally, in Chapter 4 we present a perspective based on the previously discussed concepts.

1.2 Literature review

1.2.1 Agricultural assessments and available technologies

Timely indoor and outdoor measurements can help in analyzing product quality more effectively. These results can lead to improvements in engineering and help farmers in accurate decisions-making. Indoor measurements are typically used for in-depth investigations under controlled conditions for testing each possible variable.

Outdoor measurements focus on practical investigations and yield fewer specific results due changes into environmental conditions. For example, assessments of spraying systems are initially performed under laboratory conditions to measure flow rate, distribution shape and droplet size (BUTTS et al., 2019b; GRIESANG et al., 2022; MASSOLA et al., 2018). The models of spray nozzles that meet these requirements are then commercialized. On-farm, the nozzles should be periodically assessed to monitor the spray quality (i.e., flow rate and distribution). However, agricultural assessments face several challenges since many well-known methods rely on manual, labor-intensive investigations. With computer-based systems being predominantly used in several fields in the wake of the digital revolution, researchers have concentrated their efforts on developing technological solutions, using their knowledge of computer science (TIAN et al., 2020). Consequently, digital approaches now exist for various agricultural assessments, as we described below.

Tilling operations directly affect soil microrelief and the interactions between soil and water (ZHAO et al., 2018). Recently developed systems accurately performed soil roughness modelling, thus providing timely insights into less invasive tilling. MARTINEZ-AGIRRE; ÁLVAREZ-MOZOS; GIMÉNEZ (2016) used an aluminium structure embedded with a laser scanner to obtain the soil profile. This profilometer had a vertical accuracy of 1.25 mm and a measurement interval of 5 mm. The authors conducted tests under five completely different tillage conditions to accurately discriminate soil roughness classes created by tillage operations. However, it was unable to represent 3-D terrain, which limited the effectiveness of the soil analysis. More complex tools than laser scanners, 3-D systems have also been used for such applications. MARINELLO et al., (2015) used a low-cost sensor know as 'Microsoft Kinect' for dynamic characterization of soil microrelief. They generated 3-D models under different tillage systems and accurately discriminated soil conditions.

After plant emergence, a stand count helps farmers in taking yield estimation and planting errors into account in the decision-making process (AMPATZIDIS; PARTEL, 2019). The most widely used technology for planting assessments is the unnamed aerial vehicles (UAV). UAVs serve as platforms for remote sensing purposes and its outstanding capability of monitoring fields with high efficiency has made them common for several crops (DELAVARPOUR et al., 2021). Convolutional neural

networks (CNNs) associated with high-resolution imagery that has been proven to be key in counting spinach plants; yet they can fail to differentiate plants among weeds and double spacing elements (VALENTE et al., 2020). A similar approach using deep learning was applied to estimate plant emergence uniformity, which considered density, spacing and days after emergence (VONG et al., 2022). These results outperformed those of previous studies and could accurately discriminate treatments in different planting depths, a typical condition that constraints plant emergence. An alternative system for such analysis is light detection and ranging (LiDAR) sensors. A ground vehicle embedded with such a sensor can traverse crop row while scanning the bottom of each plant and measuring plant location and spacing (SHI et al., 2015).

Although emergence plays an important role in crop yield, plants face several other challenges during the growth stage. A high incidence of diseases and pests reduce crop vitality. Therefore, regular monitoring is required to eliminate or control the invading organisms. Instead of manual, labor-intensive sampling, farmers can now use image-based systems to detect and classify the severity of diseases (NGUGI; ABELWAHAB; ABO-ZAHHAD, 2021). As discussed previously, CNNs have been used for such image-based systems. It deep learning technique was trained to classify wheat blast severity disease under controlled conditions. Images were captured over several days to follow the disease progression. The authors accurately classified three levels of blast severity, thus opening pathways for the use of image-based systems for breeding programs. However, further research is required to validate such techniques under field conditions (FERNÁNDEZ-CAMPOS et al., 2021). Soybean was also benefit from the use of CNNs (KARLEKAR; SEAL, 2020). Authors used a public database that contained images divided into 14 sub-categories occupying 486 GB. Because images had complex backgrounds, the authors used component size-based segmentation to crop the leaf area before training a CNN with six convolutional layers and a 70-30% proportion of training and testing data. This method achieved an accuracy of 98.14% and outperformed the previous studies.

Spraying systems control plant diseases by delivering agrochemicals to the target surface. Overall, spray nozzles have complex engineering and break the liquid sheet into droplets. Moreover, environmental conditions and the composition of agrochemicals dramatically affects the dynamics of these droplets (WANG et al.,

2022). Because droplets are mostly uncountable to the human eye, computer-based systems have been developed to analyze spray quality. Non-laser-based laboratory equipment usually has a high-speed camera to capture spray images at microscopic scale. A light source illuminates the droplets against a contrasting black background. Then, their size and velocity were measured using image processing algorithms (SIJS et al., 2021). Smartphone applications can also provide timely field measurements. Simple segmentation techniques were used to count and measure spray droplets after reaching water sensitive papers (FERGUSON et al., 2016).

The result of every decision-making is then visualized during harvesting. Agricultural assessments in this stage depend on crop morphological and growth characteristics. By way of example, citrus plants strongly benefit from technological assessments because automated fruits counting helps to estimate ripening and yield, replacing manual, labour-intensive methods. If methods are low-complexity, basic image processing operations can accurately detect fruits. ZHANG et al., (2022) first transformed the color space into a more suitable scale and then used a circular Hough Transformation algorithm to detect rounded shapes i.e., fruits. Regardless of the tree density, the authors reported a precision of 91.69% and a processing time of 1.10 seconds. Otherwise, if methods demand a high-complexity or if the fruits shape are not perfectly rounded, object detection techniques may be more suitable. MIRHAJI et al., (2021) used You Only Look Once (YOLO) models to detect fruits after annotating several images for training. Different illumination conditions were assessed and data augmentation was considered. The YOLO v4 model produced a mean error of -8.55% and was selected as the best approach for counting fruits and estimating yield.

1.3.2 Image processing

Overall, an image may be defined as a two-dimensional function given by $f(x,y)$, where x and y are spatial coordinates. The digital representation of these points is the result of sampling and quantization, which discretize spatial coordinates and their intensities, respectively. Image dimensions or number of pixels are represented by width $\times$ height (Figure1). A pixel is the basic unit of digital images and represents color information. Therefore, the greater the number of pixels, the higher the spatial resolution. For example, an image with a resolution of 1280 $\times$ 720 consists of 921,600 pixels. If images are monochromatic using a grayscale of 8-bits, the pixel values range

from 0 (black) to 255 (white). However, if images are colored, it is necessary to use a system for representing their colors (e.g., RGB, HSV, CMYK, Lab etc.). The popular RGB color system consists of three elements or color intensities: red, green and blue, respectively (Figure 2).

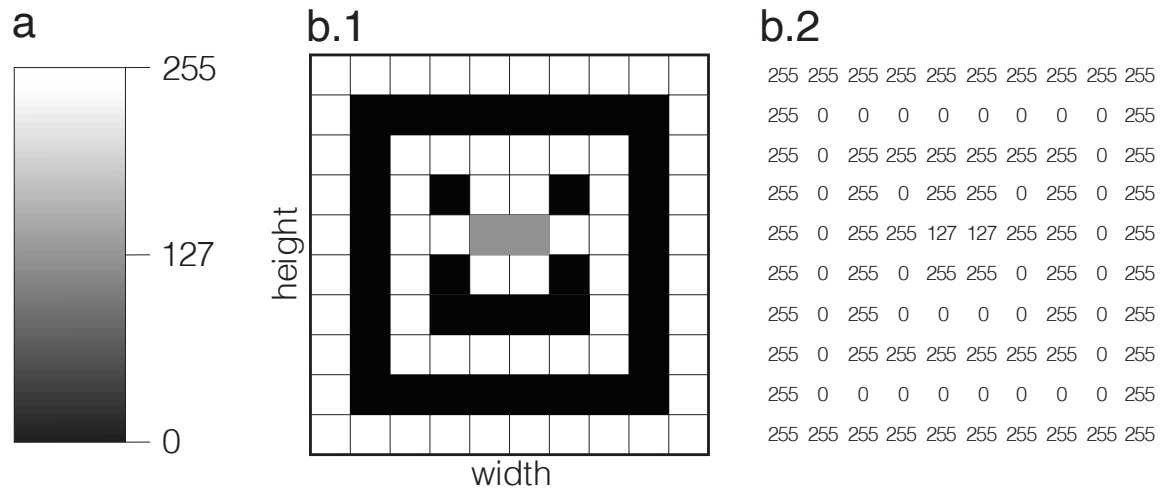


Figure 1. a. monochromatic scale; b.1 grayscale image and b.2 matrix values.

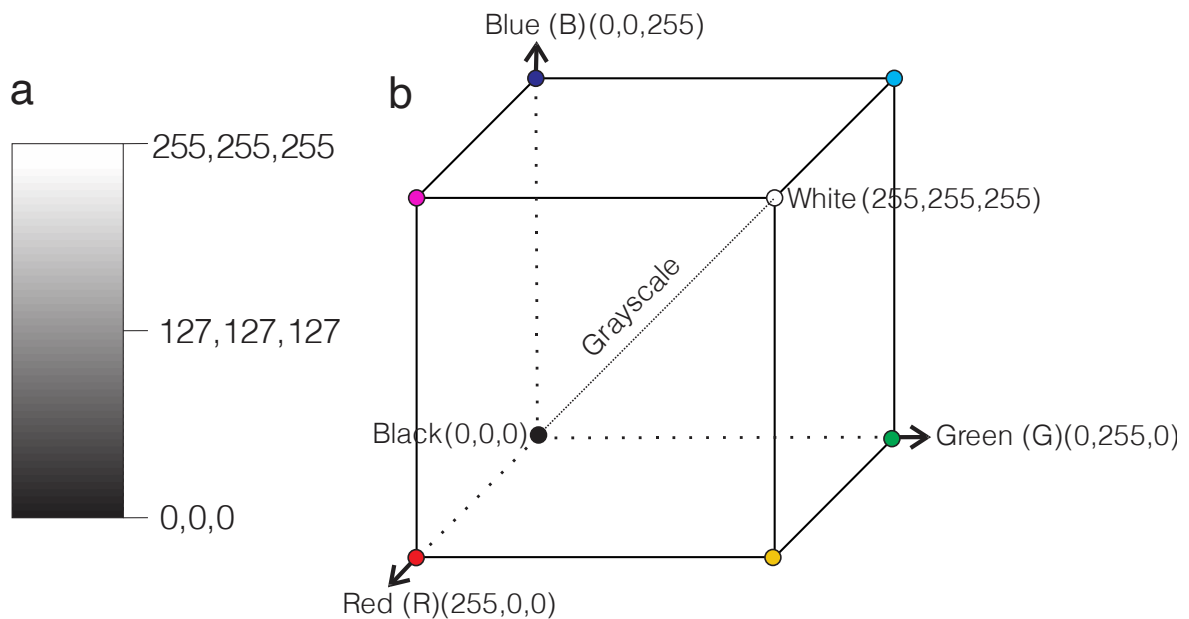


Figure 2. RGB color system; a. grayscale values and b. RGB color cube.

Digital images are key structures for remotely monitoring the real universe. The applications of image processing techniques range from skin cancer detection (ZHANG et al., 2020) to astronomical observations (FARRENS et al., 2020; JANSSEN et al., 2021). Therefore, its complexity also varies. Image processing range from simple adjustments (e.g., brightness, saturation and contrast) to complex models for object

detection. Here, we describe some popular techniques used for agricultural purposes. Image enhancement ideally improves image quality to modify the information and can be classified into point operations and spatial operations (JAIN, 1989; NIXON; AGUADO, 2020). Point operations modify the pixel value independently of shape or coordinates, exclusively replacing each pixel value with a new one. These basic operations produce significant visual differences without high computational demand. Some common techniques are contrast stretching, grayscale reversal and histogram modelling. Otherwise, spatial operations involve manipulations using a pixel's neighborhood. Usually, a square template or filter with an odd size is placed at the region of interest to produce new pixel values (NIXON; AGUADO, 2020). Some common techniques are interpolation and spatial filtering e.g., mean and median filters.

1. *Contrast stretching* stretches the pixel value histogram to the minimum and maximum possible intensity values e.g., 0-255 for 8-bit images. If the minimum value is 75, it will be stretched to a minimum value of 0.
2. *Grayscale inversion* inverts the range of values so that 0 represents white and 255 represents black.
3. *Histogram equalization* is another contrast-enhancement method. It differs from contrast stretching because it modifies all the pixel intensity values using a probability density function to produce a flatter histogram.
4. *Mean and median filtering* are sliding-window techniques used to smoothen images by reducing the degree of variation in the pixel neighborhood. Overall, the central value of in the window is replaced by the mean or median of all surrounding pixels, depending on the kernel size.

The word 'morphology' refers to the study of forms and shapes in many fields. Likewise, mathematical morphology was introduced in the last century for describing the features of digital images (BATCHELOR; WALTZ, 2012) . Although commonly listed as a low-complexity technique, morphological operations can have diverse applications, including image cleaning, path detection, text finding and object detection (GATOS, 2014). The fundamentals of mathematical morphology can be defined using set theory notation and its operations, such as union ($\cup$), intersection ($\cap$) and

complement. The operation occurs using a structuring element i.e., small-sized template or mask to interact with a certain image using neighborhood operations. An output image is then generated indicating where its interactions were successful. The interaction follows a *Hit-and-Miss* function. If the pixels in the structuring element match all the corresponding image pixels, it is known as 'fit' (Figure 3). Some of the most basic morphology operations in binary images are erosion, dilatation, opening, closing, filling and skeletonization.

1. *Erosion* removes white pixels (Boolean 1, object) to black pixels (Boolean 0, background). It can split two objects in an image, thin out shapes and strip away extrusions. The structuring element must 'fits' pixels neighbourhood in the image.
2. *Dilatation* expands shapes by adding white pixels at the boundaries. It can join two objects, resize shapes and repair breaks.
3. *Skeletonization* detects the object's core after consecutives erosions, reducing the shape to its essential information.
4. *Filling* fills the interior regions in an object.

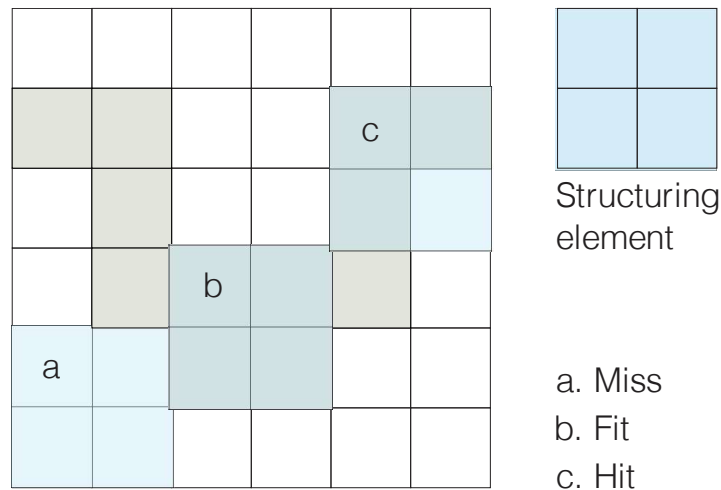


Figure 3. Hit-or-miss function using a structuring element, a. 'miss' when no pixels matches, b. 'fit' when all pixels matches and c. 'hit' when not all pixels matches.

References

AMPATZIDIS, Y.; PARTEL, V. UAV-Based High Throughput Phenotyping in Citrus Utilizing Multispectral Imaging and Artificial Intelligence. **Remote Sensing**, v. 11, n. 4, p. 410, jan. 2019.

BATCHELOR, B. G.; WALTZ, F. M. Morphological Image Processing. In: BATCHELOR, B. G. (Ed.). . **Machine Vision Handbook**. London: Springer London, 2012. p. 801–870.

BUTTS, T. R. et al. Droplet size and nozzle tip pressure from a pulse-width modulation sprayer. **Biosystems Engineering**, v. 178, p. 52–69, fev. 2019.

DELAVARPOUR, N. et al. A Technical Study on UAV Characteristics for Precision Agriculture Applications and Associated Practical Challenges. **Remote Sensing**, v. 13, n. 6, p. 1204, jan. 2021.

FARRENS, S. et al. PySAP: Python Sparse Data Analysis Package for multidisciplinary image processing. **Astronomy and Computing**, v. 32, p. 100402, 1 jul. 2020.

FERGUSON, J. C. et al. Assessing a novel smartphone application – SnapCard, compared to five imaging systems to quantify droplet deposition on artificial collectors. **Computers and Electronics in Agriculture**, v. 128, p. 193–198, 1 out. 2016.

FERNÁNDEZ-CAMPOS, M. et al. Wheat Spike Blast Image Classification Using Deep Convolutional Neural Networks. **Frontiers in Plant Science**, v. 12, 2021.

GATOS, B. G. Imaging Techniques in Document Analysis Processes. In: DOERMANN, D.; TOMBRE, K. (Eds.). . **Handbook of Document Image Processing and Recognition**. London: Springer London, 2014. p. 73–131.

GRIESANG, F. et al. Effect of working pressure and spacing of nozzles on the quality of spraying distribution. **Crop Protection**, v. 151, p. 105818, 1 jan. 2022.

JAIN, A. K. **Fundamentals of Digital Image Processing**. [s.l.] Prentice Hall, 1989.

JANSSEN, M. et al. Event Horizon Telescope observations of the jet launching and collimation in Centaurus A. **Nature Astronomy**, v. 5, n. 10, p. 1017–1028, out. 2021.

KARLEKAR, A.; SEAL, A. SoyNet: Soybean leaf diseases classification. **Computers and Electronics in Agriculture**, v. 172, p. 105342, 1 maio 2020.

MARINELLO, F. et al. Application of the Kinect sensor for dynamic soil surface characterization. **Precision Agriculture**, v. 16, n. 6, p. 601–612, 1 dez. 2015.

MARTINEZ-AGIRRE, A.; ÁLVAREZ-MOZOS, J.; GIMÉNEZ, R. Evaluation of surface roughness parameters in agricultural soils with different tillage conditions using a laser profile meter. **Soil and Tillage Research**, v. 161, p. 19–30, 1 ago. 2016.

MASSOLA, M. P. et al. Spray volume distribution pattern and droplet size spectrum from ceramic nozzles. **Revista Brasileira de Engenharia Agrícola e Ambiental**, v. 22, p. 804–809, nov. 2018.

MIRHAJI, H. et al. Fruit detection and load estimation of an orange orchard using the YOLO models through simple approaches in different imaging and illumination conditions. **Computers and Electronics in Agriculture**, v. 191, p. 106533, 1 dez. 2021.

NGUGI, L. C.; ABELWAHAB, M.; ABO-ZAHHAD, M. Recent advances in image processing techniques for automated leaf pest and disease recognition – A review. **Information Processing in Agriculture**, v. 8, n. 1, p. 27–51, 1 mar. 2021.

NIXON, M. S.; AGUADO, A. S. 3 - Image processing. In: NIXON, M. S.; AGUADO, A. S. (Eds.). **Feature Extraction and Image Processing for Computer Vision (Fourth Edition)**. [s.l.] Academic Press, 2020. p. 83–139.

SHI, Y. et al. Improvement of a ground-LiDAR-based corn plant population and spacing measurement system. **Computers and Electronics in Agriculture, Precision Agriculture**. v. 112, p. 92–101, 1 mar. 2015.

SIJS, R. et al. Drop size measurement techniques for sprays: Comparison of image analysis, phase Doppler particle analysis, and laser diffraction. **AIP Advances**, v. 11, n. 1, p. 015315, 1 jan. 2021.

TIAN, H. et al. Computer vision technology in agricultural automation —A review. **Information Processing in Agriculture**, v. 7, n. 1, p. 1–19, 1 mar. 2020.

VALENTE, J. et al. Automated crop plant counting from very high-resolution aerial imagery. **Precision Agriculture**, v. 21, n. 6, p. 1366–1384, 1 dez. 2020.

VONG, C. N. et al. Corn emergence uniformity estimation and mapping using UAV imagery and deep learning. **Computers and Electronics in Agriculture**, v. 198, p. 107008, 1 jul. 2022.

WANG, S. et al. Effects of Adjuvants on Spraying Characteristics and Control Efficacy in Unmanned Aerial Application. **Agriculture**, v. 12, n. 2, p. 138, fev. 2022.

ZHANG, N. et al. Skin cancer diagnosis based on optimized convolutional neural network. **Artificial Intelligence in Medicine**, v. 102, p. 101756, 1 jan. 2020.

ZHANG, X. et al. Yield estimation of citrus fruit using rapid image processing in natural background. **Smart Agricultural Technology**, v. 2, p. 100027, 1 dez. 2022.

ZHAO, L. et al. Effect of soil surface roughness on infiltration water, ponding and runoff on tilled soils under rainfall simulation experiments. **Soil and Tillage Research**, v. 179, p. 47–53, 1 jun. 2018.

CHAPTER 2 – ASSESSING INTRA-ROW SPACING USING IMAGE PROCESSING: A PROMISING DIGITAL TOOL FOR SMALLHOLDER FARMERS¹

Abstract: Assessing planting to ensure well-distributed plants is important to achieve high yields. Digital farming has been helpful in these field assessments. However, these techniques are at most times not available for smallholder farmers or low-income regions. Thus, to contribute such producers, we developed two methods to assess intra-row spacing in commercial fields using mobile photos and simple image processing. We assessed a maize field after mechanized planting in 7 and 12 days after planting (DAP) and in two farming systems (conventional and no-till) to acquire images at height of one meter and perpendicular to the ground. In the first method, we used morphological operations based on the HSV scale and the center of mass to extract the region of interest (ROI), corresponding to the maize plant. In the second method we used local maxima equations (Peaks) to find prominence values corresponding to the maize plant and extract their coordinates. No-till images were deleted due to excessive weeds. Thus, before acquiring the images, it is necessary to remove these elements. The methods achieved an overall RMSE of 3.48 cm (<5.63 cm) and R^2 of 0.90 (>0.71). Precision and recall were higher than 0.88. There was no difference between actual and estimated CV values, except in conventional tillage in 7 DAP using ROI due to leaves overlapping. The method Peaks was more accurate to detect multiple spacing but miss spacing was correctly detected in both methods. However, the larger the leaves, the worse the detection. Thus, our proposed methods were satisfactory and are promising for assessing planting in a remote and accessible way.

Keywords: computer vision, machine assessment, spatial arrangement.

1. Introduction

Well-distributed seeds support plant development by reducing nutrient competition against weeds (KARAYEL et al., 2006). Moreover, it can adjust the population density and contribute to yield gains (ZHANG et al., 2014). For every 10 percentage points added in the coefficient of variation of intra-row spacing, about 1.22 Mg ha⁻¹ of maize grain would not be yielded in some fields (HÖRBE et al., 2016). Thus, the spacing between plants should be as equidistant as possible, with high uniformity. Another assessment refers to machine performance. Seed or emerged plant distribution in any crop can demonstrate the machine efficiency to deposit seeds along the crop row (BADUA et al., 2021). However, seeds are below-ground and invisible to

¹ Article published by [Agronomy](#), JCR 3.417 (Qualis CAPES A1)

the machine operator, and no real-time resources are available for on-field measurements, only for laboratory conditions (LEI et al., 2021; XIA et al., 2011). Seed spacing can be assessed by digging and counting, but plant spacing is available only after emergence. If, however, the intra-row has much miss-spacing, it may indicate low-vigour seeds or a poorly adjusted machine. Multiple spacing or multiple plants together also indicates poor adjustment. The farmer should adjust the machine for the next area or season based on these results.

The traditional assessment of plant distribution consists of measurements using tape measure or any standard tool. However, it can be time-consume, labor-intensive since most methods are based on manual techniques suggested decades ago when few technologies were available (S. D. KACHMAN; J. A. SMITH, 1995). Several digital tools have been developed to replace it. By way of example, computer vision and remote sensing have become key tools (TIAN et al., 2020). The development of these versatile tools is encouraged due to massive data flow in agriculture. Such systems support decision-making and automate routine tasks (SPARROW; HOWARD, 2020). Despite a digital revolution in agriculture, few tools exist to assess intra-row spacing in commercial fields. An often alternative from the regular literature for assessing intra-row spacing is the use of ultrasonic sensors, 3D scanners or LiDAR embedded in mobile structures to detect objects (NAKARMI; TANG, 2012; SHI et al., 2013, 2015). The method by (NAKARMI; TANG, 2012) relied on a system that collects TOF (Time-of-flight) images in crop inter-row to find the stem of each plant and measure the spacing. It produced a R^2 up to 0.95 and RMSE up to 0.017 cm. Few researchers have assessed the intra-row spacing using exclusively imaging techniques. A ground vehicle with an embedded camera was used to acquire images. Then, the maize plants were detected using Naïve Bayes, and following post-processing, the intra-row spacing was be measured (L. TANG; L. F. TIAN, 2008). In a similar study, (BRILHADOR; SERRARENS; LOPES, 2015) used morphological operations and vegetation index (generated by RGB colours) to detect maize plants. They found precision results ranging from 59% (with straw and mature plants) to 89% for plant stems. For intra-row spacing, error up to 1 cm was described; however, no further analysis was performed with these data. Studies also quantified plant population density. (LIU et al., 2017) used a mobile structure to take images of a wheat crop. They manually determined for each

image the coordinates of each existing plant. It produced a relative error up to 12% in relation to actual population density. A successfully emerging method is remote sensing using an unnamed aerial vehicle (UAV) embedded with RGB or multispectral cameras. Machine learning models can detect plants in these high-resolution images that provide useful and versatile data to analyze plantation arrangement (HOSSEINY; RASTIVEIS; HOMAYOUNI, 2020; OSCO et al., 2021)

However, high-complexity methods and expensive equipment do not necessarily help farmers, especially the small ones. Digital agriculture is described in some countries as a well-known benefit system, but few farmers can support these investments (ANITEI; VERES; PISLA, 2021). In contrast, new techniques such as digital maps, remote sensing, and auto-guidance are mostly available and benefit big farms that support high financial costs (DEICHMANN; GOYAL; MISHRA, 2016). Digital agriculture should consider the socio-economic context of developing countries. Despite the difficult access, the use of mobile phones has spread quickly in low-income regions as some sub-Saharan countries, in contrast to the internet or more recent equipment (DEICHMANN; GOYAL; MISHRA, 2016). New technologies are not sustainable without a positive social impact. The well-known justification of producing more food due to population growth is questionable since the main problem of food security is the access and inequality (NALLY, 2016; ROSE et al., 2021), which may also involve the use and availability of technologies. The regular literature focuses on plant detection or counting. Thus, indispensable reasons are ignored: planting machine performance and intra-row spatial arrangement. Analysis as miss spacing, multiple spacing, and the coefficient of variation are extremely useful (S. D. KACHMAN; J. A. SMITH, 1995). In addition, these metrics demand an in-depth investigation considering different tillage systems. Moreover, it is not clear how and if these techniques will serve as a basis for future digital tools, especially to the smallholders and low-income regions. Therefore, based on the need to contribute to the planting assessment with alternative, remote and accessible methods, we developed two image processing methods to assess intra-row plant spacing using mobile images.

2. Materials and Methods

2.1. Experiment location

We conducted our study in a commercial field localized in the municipality of Cândido Mota, in the state of São Paulo, Brazil. The maize crop was planted using two farming systems: conventional tillage and no-till. The farmer adopted a population density of 70.000 plants ha⁻¹ and 3.5 seed m⁻¹ in an inter-row spacing of 50 cm.

2.2. Data Collection

To capture early crop growth dynamics, data was collected in two periods: 7 and 12 days after planting (DAP). We assessed a crop row in both tillage systems to count each plant and measure the intra-row spacing across five meters. To facilitate image acquisition, we recorded a video using a mobile camera with resolutions of 13 MP, 1080 P, and 30 FPS (Figure 1b). To ensure an adequate pixel spatial resolution and minimal distortions (LIU et al., 2017), a height of one meter and a perpendicular angle (90°) were considered as the reference. We used a level indicator from the mobile device to maintain its stability and a standardized object beside the crop row. To avoid differences over day lighting, we recorded every video at the same hour: about 04:00 pm in clear sky. No-till rows were recorded twice: with an original aspect and after cleaning excessive organic material, weeds or plants remain from the harvesting, which may affect the image processing (HAMUDA et al., 2017). We partitioned the dataset (Figure 1a) into conventional (Conv_), no-till (Notill_), and no-till after cleaning (Notill_mod). The images were extracted from each video (Figure 1c). We selected images based on perpendicularity, blurring, and motion.

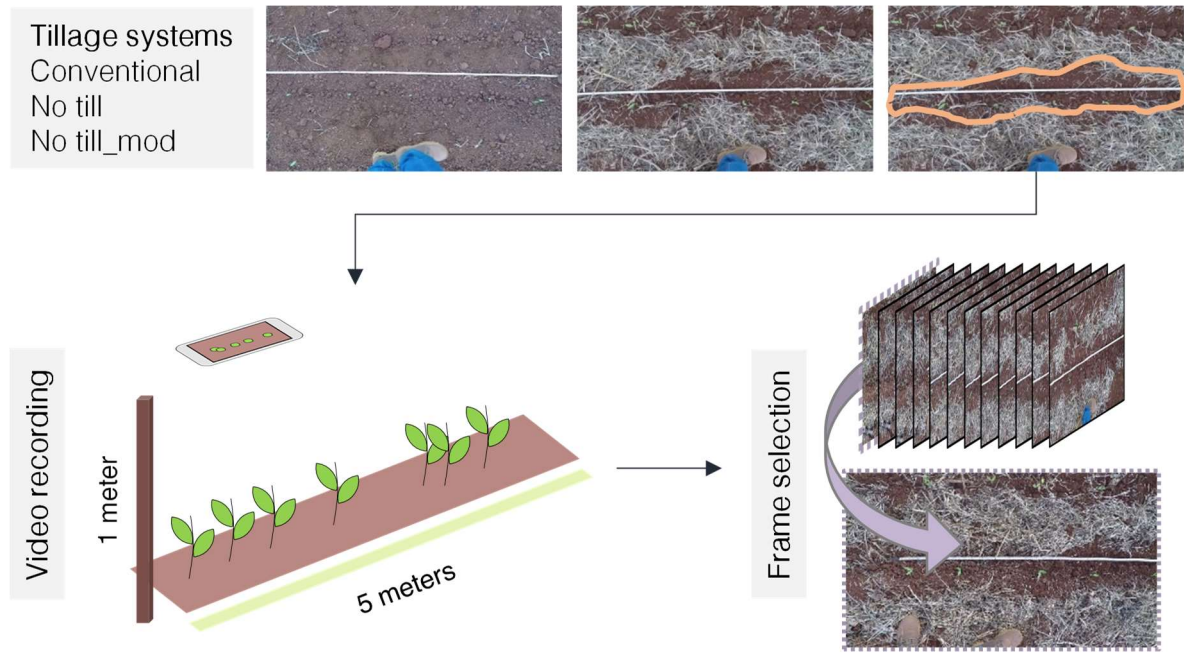


Figure 1. (a) Tillage systems used to create our dataset; (b) video recording method and (c) manual frame selection.

2.3. Image Processing

We processed the images using the OpenCV (BRADSKI; Kaehler, 2008) and scikit-image (VAN DER WALT et al., 2014) libraries in a pipeline developed in Python (code available upon request). Our main goal was to extract features (green objects) and measure the spacing between them in a semi-automatic way. We used two methods: in the first, we detected the region of interest (ROI) and created bounding boxes; in the second, we used a grayscale histogram to detect local maxima values that correspond to maize plants (Figure 2).

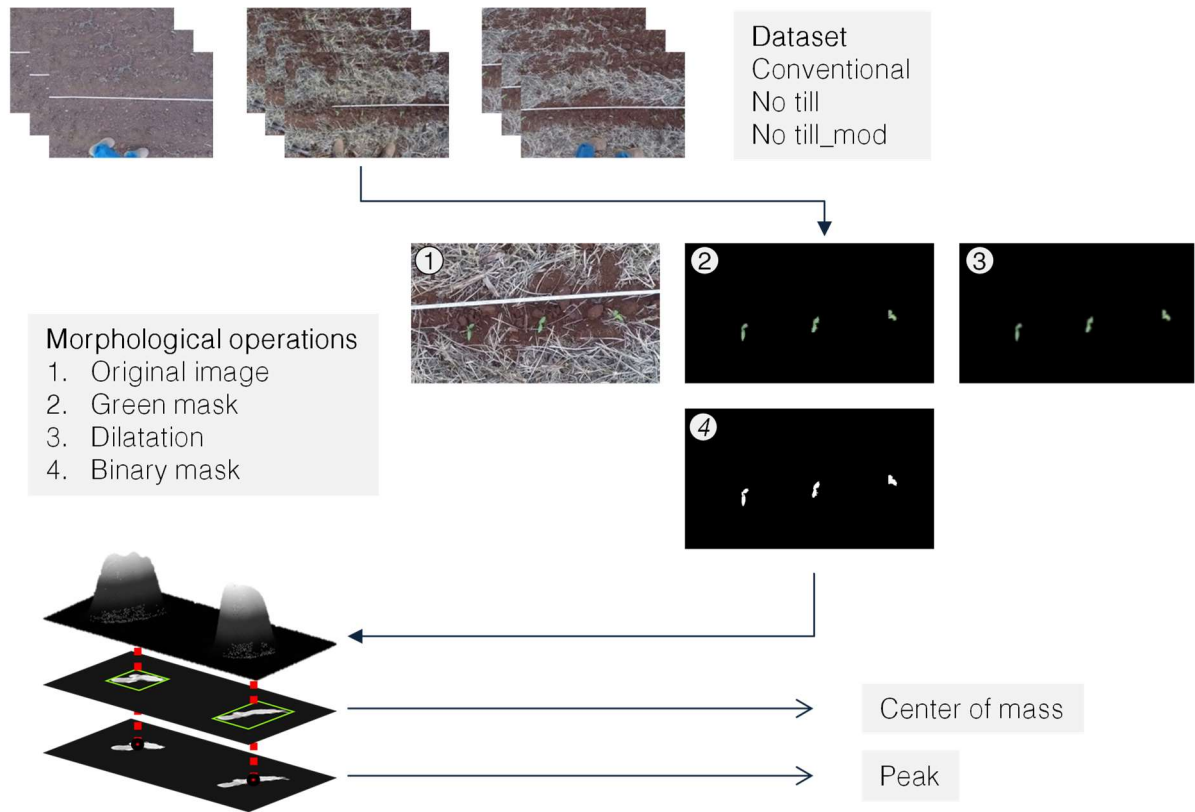


Figure 2. Dataset and morphological operations using Python libraries.

2.4. Pre-Processing

To standardize the input image, each one was cropped to remove parallel rows and a Gaussian filter was used in 3×3 sizes to reduce pixel noises. The next step was to determine the spectrum corresponding to the green in a HSV scale and highlight only green objects. At the same time, we applied a slight dilatation to smooth the noise around the plant and emphasize the ROI mainly due to leaf twisting or points of dim illumination.

2.5. Region of Interest (ROI)

In the first method, we created boxes around the binary objects (maize plants) using the boundingRect function. The coordinates of these bounding boxes were extracted and we calculated the center of mass (Figure 2) using the 'moments calculus', which considers pixels' distribution in a given area to determine the center (TEH; CHIN, 1988), as described in Equation (1):

where M_{00} is the moment zero and x and y are the pixel values in each bounding box. The following replacements were made at the positions to calculate the first moment on each axis (x, y) (Equation 2):

$$M_{10} = \sum_x \sum_y xl(x, y); \quad M_{01} = \sum_x \sum_y yl(x, y) \quad (2)$$

Then, the coordinates can be calculated using Equation 3:

$$xc = \frac{M_{10}}{M_{00}}; yc = \frac{M_{01}}{M_{00}} \quad (3)$$

2.6. Local maxima (Peaks)

In the second method, our approach was based on finding pixel gray-scale values corresponding to the plant. A peak is a prominent value in comparison to neighbouring pixels. A similar method was used to count crop rows and plants, extracting peaks values from a confidence map (OSCO et al., 2021). In this way, we used the mask with plants and the “peaks_local_max” function from the library scikit-image. The general concept was that a function $f(x)$ has a local max at c if there is an open interval in I containing c so that $f(x) \leq f(c)$ for all values of x in I . We determined 50 pixels between peaks to avoid multiple peaks in very short distances.

2.7. Analysis

We analyzed both proposed methods using Precision and Recall metrics (Equations 4 and 5) (26):

$$Precision = \frac{Tp}{Tp + Fp} \quad (4)$$

$$Recall = \frac{Tp}{Tp + Fn} \quad (5)$$

where Tp is the number of detected plants; Fp is the number of misdetections; and Fn is the number of failed detections. The distance between centroids was calculated using the Euclidean distance (Equation 6). We converted the number of pixels to the metric system using the standardized object besides the crop row. The coefficient of

determination (R^2) and Root Mean Square Error (RMSE) were used to evaluate the intra-row spacing accuracy.

$$d = \sqrt{(x_1 - x_2)^2 + (y_1 - y_2)^2} \quad (6)$$

3. Results

In this section we described the overall aspects and performance (Section 3.1.) and the specific assessment for planting performance (Section 3.2.).

3.1. Overall aspects and performance

In both methods, precision and recall were above 0.88 Recall was lower in 12 DAP and using the ROI method, as the closest intra-row spacing supports the leaves overlapping and merges the two bounding boxes (Figure 3a). It problem occurs mostly as the plant grows, since its vegetative structure will grow with more and larger leaves. It did not occur in the Peaks methods. However, the detection can also be compromised if this spacing is very close since it will not be possible to distinguish the prominence value. The overall R^2 was 0.90, but for 12 DAP_Notill_mod_ROI was 0.71. The RMSE was also highest in 12 DAP, with 5.63 cm (Table 1). The coordinate point was not exactly in the plant center due to larger leaves, increasing the bounding boxes size and changing the center of mass (Figure 3a).

The centroids were different between the two methods. Although these deviations are minimal, the greater the bounding box in ROI, the less probable the centroid in the same coordinate as the Peaks (Figure 4).

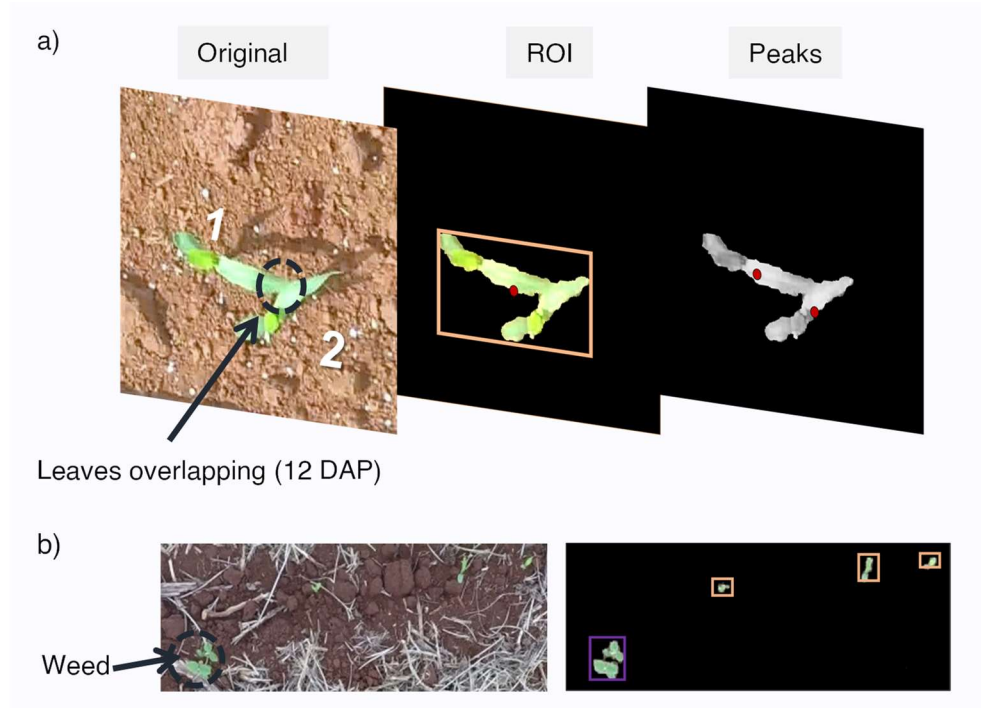


Figure 3. Example of (a) leaves overlapping and (b) intra-row weeds.

Table 1. Detection and accuracy results.

	Methods	Precision	Recall	R^2	RMSE, cm
7 DAP	Conv_ROI	1.00	0.91	0.90	2.84
	Conv_Peaks	1.00	1.00	0.92	2.55
	Notill_mod_ROI	1.00	1.00	0.90	1.86
	Notill_mod_Peaks	1.00	1.00	0.98	1.75
12 DAP	Conv_ROI	1.00	0.88	0.98	5.63
	Conv_Peaks	1.00	0.93	0.98	5.05
	Notill_mod_ROI	1.00	0.91	0.71	4.70
	Notill_mod_Peaks	1.00	0.91	0.81	3.50

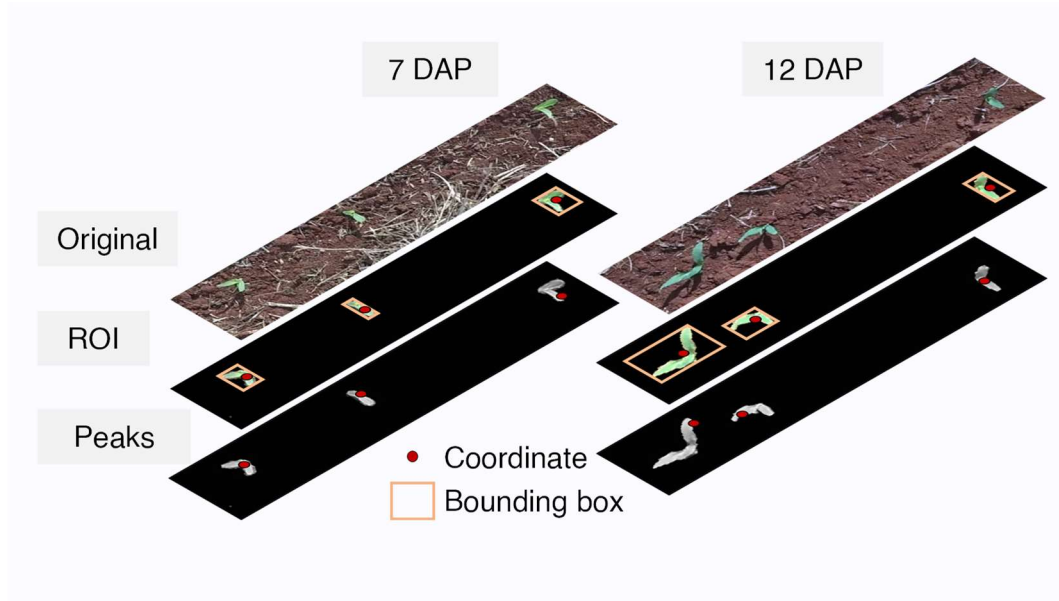


Figure 4. Overall aspects from both methods (No till_mod).

3.2. Metrics for analyzing planting performance

There is no significant difference between the CV ($p > 0.05$), except in Conv_ROI 7 DAP, due to multiple spacing misdetection (Table 2). Very short spacing between two plants contributes to the leaves overlapping in the ROI method, in contrast to the Peaks method. Both methods were accurate to detect miss spacing.

Table 2. Descriptive statistics, specific planting metrics and CV.

	Methods	As, cm	Std, cm	Multiple	Miss	CV
7 DAP	Conv_field	40	13	1	0	0.33
	Conv_ROI	42	6	0	0	0.14*
	Conv_Peaks	38	12	1	0	0.31 ^{ns}
	Notill_mod_field	34	9	0	0	0.28
	Notill_mod_ROI	34	8	0	0	0.24 ^{ns}
	Notill_mod_Peaks	34	8	0	0	0.24 ^{ns}
12 DAP	Conv_field	31	18	4	2	0.58
	Conv_ROI	27	17	1	2	0.65 ^{ns}
	Conv_Peaks	27	16	3	2	0.60 ^{ns}
	Notill_mod_field	36	9	1	0	0.26

Notill_mod_ROI	35	8	1	0	0.27 ^{ns}
Notill_mod_Peaks36		8	1	0	0.24 ^{ns}

^{ns} not significant ($p > 0.05$); * significant ($p < 0.05$). Note: As, average spacing; Std, standard deviation; CV, coefficient of variation of intra-row spacing; Multiple, very short spacing and Miss, very long spacing.

4. Discussion

Our research consisted of creating a remote method to replace intra-row manual assessment using an easy-to-access tool. Such an approach facilitates on-field assessment and can support smallholder farmers to assess their crops effortlessly. The great novelty of this research study, therefore, resides in solving such a task in a unified way using images acquired by a simple mobile phone. In addition, we can perform this task without the need of high-performance hardware, allowing producers or decision-makers who live in low-income regions to use them as well.

Weeds are a major problem in plant detection because they mostly have the same architecture and color as the crop. In our approach, it was enough to eliminate one dataset (Notill_). (L. TANG; L. F. TIAN, 2008) proposed a method that excluded these objects using their physical dimensions; however, it is not always appropriate since weeds vary in size. Thus, before acquiring the images, it is necessary to prepare the sample area. It does not mean that the straw (key component in no-till systems) must be removed. We only need to remove the weeds, as well as other common residues in agricultural areas such as stones and excesses of green organic matter. Therefore, our methods satisfied two distinct farming systems: conventional and no-till. It is beneficial because most works listed in the review used only conventional tillage soils, which is not representative for some regions. Conventional tillage is easy to analyze by image processing as there is no straw around the plant. In addition, distances were accurately measured since there was a standard tool with a known size. If we know the object's actual size and the pixel size, no geographical system is necessary, only simple ratio equations. However, to ensure the consistency of these measurements, a high-resolution image is required (JIN et al., 2017), in addition to keeping the distance and angle as perpendicular as possible. Strong variations in these parameters can compromise the results obtained by the image. Our method did not use any structure equipment to fix the camera; we used only an object as a height reference and a level

indicator of the mobile phone itself. Slight variations are expected as the person walked alongside the crop row which is not totally flat. Thus, it is necessary to remove blurred images before processing. This is a downside of accessible techniques.

The assessment of intra-row spacing can assist in decision-making for future crop implementation by understanding the origin of poor plant uniformity. Previous studies had satisfactory results detecting plant stems and measuring intra-row spacing. Using a 3D sensor, (NAKARMI; TANG, 2012) achieved an overall RMSE of 0.017 cm, outperforming the imaging techniques; our methods achieved 3.48 cm; and a comparable method from (L. TANG; L. F. TIAN, 2008) achieved an accuracy of 1.70 cm. The R^2 values were similar and greater than 0.90, while (BRILHADOR; SERRARENS; LOPES, 2015) achieved 0.96. However, the cost-effectiveness of our easy-to-access system outweighs these results. For our proposal, we were not able to exactly find the plant center. We obtained small lateral deviations, especially for the ROI method, where the leaves have heterogeneous distribution inside the bounding box. The sensitivity is greater using the Peaks method since it considers the local maxima value; however, color variations across the leaves can also affect it. Even so, our results demonstrated high values of R^2 , precision, and recall. There is no difference in CV (except for Conv_ ROI 7 DAP). Miss spacing originated from very long distances between plants and they were also successfully detected. In contrast, multiple spacing is more complex. In the ROI, if the leaves between plants overlap, multiple plants become one. A manual intervention on the image can be done to break the overlapping; however, it would compromise the automation even more. The only action to assist the ROI method is to acquire images soon after emergence before the leaves grow. Image resolution should be as high as possible to detect the green object without much soil noise. In the Peaks method, due to the analysis by value prominence, there is a greater efficiency to detect multiple spacing. However, the recommendations for ROI are valid to avoid more deviations.

5. Conclusion

Our approach clearly demonstrated the applicability and accessibility of imaging techniques to assess planting distribution and intra-row arrangement. Required low computational resources and obtained satisfactory results. It is possible to use in either conventional or no-till systems. For planting assessment metrics, multiple spacing was

difficult to detect since the closest distance between plants can induce their detection as a single object. The Peaks method achieved a better performance since it uses the value prominence. However, it is also recommended to avoid larger leaves (many days after planting) since they can overlap. For miss spacing, both methods were efficient, and for the coefficient of variation, only one condition obtained a significant difference. These methods can be used in any crop after mechanized planting, such as maize, soybean, beans, and cotton. However, crops with irregular or scattered spacing are not recommended due to leaves overlapping. These approaches can encourage different avenues for future assessment considering accessibility. Mobile phones are common tools in many countries, including developed or developing; therefore, we need to use more of them in this way. Among the possibilities, we can consider a mobile application based on our considerations or even the use from advisors, which must only take photos on-field and process it using the script, following our guidelines. The development of a totally automatic thresholding is also highly encouraged.

References

- AMPATZIDIS, Y.; PARTEL, V. UAV-Based High Throughput Phenotyping in Citrus Utilizing Multispectral Imaging and Artificial Intelligence. **Remote Sensing**, v. 11, n. 4, p. 410, jan. 2019.
- ANITEI, M.; VERES, C.; PISLA, A. Research on Challenges and Prospects of Digital Agriculture. **Proceedings**, v. 63, n. 1, p. 67, 2021.
- ASGARIAN, A. et al. Experiments and modeling of the breakup mechanisms of an attenuating liquid sheet. **International Journal of Multiphase Flow**, v. 130, p. 103347, 1 set. 2020.
- AZIZI, A. et al. Estimation of Soil Surface Roughness Using Stereo Vision Approach. **Sensors**, v. 21, n. 13, p. 4386, jan. 2021.
- BADUA, S. A. et al. Ground speed and planter downforce influence on corn seed spacing and depth. **Precision Agriculture**, 2 jan. 2021.
- BATCHELOR, B. G.; WALTZ, F. M. Morphological Image Processing. In: BATCHELOR, B. G. (Ed.). **Machine Vision Handbook**. London: Springer London, 2012. p. 801–870.
- BERMUDEZ, F.; PINHEIRO, J. B. Selection to high productivity and stink bugs resistance by multivariate data analyses in soybean. **Bragantia**, v. 79, n. 2, p. 250–259, 2020.
- BRILHADOR, A.; SERRARENS, D. A.; LOPES, F. M. **A Computer Vision Approach for Automatic Measurement of the Inter-plant Spacing**. (A. Pardo, J.

Kittler, Eds.)Progress in Pattern Recognition, Image Analysis, Computer Vision, and Applications. **Anais...**: Lecture Notes in Computer Science.Cham: Springer International Publishing, 2015.

BUTTS, T. R. et al. Evaluation of spray pattern uniformity using three unique analyses as impacted by nozzle, pressure, and pulse-width modulation duty cycle. **Pest Management Science**, v. 75, n. 7, p. 1875–1886, 2019a.

BUTTS, T. R. et al. Droplet size and nozzle tip pressure from a pulse-width modulation sprayer. **Biosystems Engineering**, v. 178, p. 52–69, fev. 2019b.

CARVALHO, F. K. et al. Viscosity, surface tension and droplet size of sprays of different formulations of insecticides and fungicides. **Crop Protection**, v. 101, p. 19–23, 1 nov. 2017.

ÇETIN, N.; SAĞLAM, C.; DEMIR, B. Determination of spray angle and flow uniformity of spray nozzles with image processing operations. **Journal of Animal and Plant Sciences**, v. 29, n. 6, p. 1603–1615, 2019.

CHENG, P. et al. On the prediction of spray angle of liquid-liquid pintle injectors. **Acta Astronautica**, The Fifth International Conference on Tethers in Space. v. 138, p. 145–151, 1 set. 2017.

D. LUCK, J. et al. Development and Evaluation of an Automated Spray Patternator Using Digital Liquid Level Sensors. **Applied Engineering in Agriculture**, v. 32, n. 1, p. 47–52, 2016.

DAFSARI, R. A.; VASHAHI, F.; LEE, J. EFFECT OF SWIRL CHAMBER LENGTH ON THE ATOMIZATION CHARACTERISTICS OF A PRESSURE-SWIRL NOZZLE. **Atomization and Sprays**, v. 27, n. 10, 2017.

DE MOURA ARAÚJO, G. et al. Sugarcane Harvesting Quality by Digital Image Processing. **Sugar Tech**, v. 23, n. 1, p. 209–218, 1 fev. 2021.

DEICHMANN, U.; GOYAL, A.; MISHRA, D. Will digital technologies transform agriculture in developing countries? **Agricultural Economics**, v. 47, n. S1, p. 21–33, 2016.

DELAVARPOUR, N. et al. A Technical Study on UAV Characteristics for Precision Agriculture Applications and Associated Practical Challenges. **Remote Sensing**, v. 13, n. 6, p. 1204, jan. 2021.

FARRENS, S. et al. PySAP: Python Sparse Data Analysis Package for multidisciplinary image processing. **Astronomy and Computing**, v. 32, p. 100402, 1 jul. 2020.

FERGUSON, J. C. et al. Assessing a novel smartphone application – SnapCard, compared to five imaging systems to quantify droplet deposition on artificial collectors. **Computers and Electronics in Agriculture**, v. 128, p. 193–198, 1 out. 2016.

FERNÁNDEZ-CAMPOS, M. et al. Wheat Spike Blast Image Classification Using Deep Convolutional Neural Networks. **Frontiers in Plant Science**, v. 12, 2021.

FUNG, M. C. et al. CFD Modeling of Spray Atomization for a Nasal Spray Device. **Aerosol Science and Technology**, v. 46, n. 11, p. 1219–1226, 1 nov. 2012.

GATOS, B. G. Imaging Techniques in Document Analysis Processes. In: DOERMANN, D.; TOMBRE, K. (Eds.). . **Handbook of Document Image Processing and Recognition**. London: Springer London, 2014. p. 73–131.

GRIESANG, F. et al. Effect of working pressure and spacing of nozzles on the quality of spraying distribution. **Crop Protection**, v. 151, p. 105818, 1 jan. 2022.

HAMUDA, E. et al. Automatic crop detection under field conditions using the HSV colour space and morphological operations. **Computers and Electronics in Agriculture**, v. 133, p. 97–107, 1 fev. 2017.

HÖRBE, T. A. N. et al. Optimization of Within-Row Plant Spacing Increases Nutritional Status and Corn Yield: A Comparative Study. **Agronomy Journal**, v. 108, n. 5, p. 1962–1971, 2016.

HOSSEINY, B.; RASTIVEIS, H.; HOMAYOUNI, S. An Automated Framework for Plant Detection Based on Deep Simulated Learning from Drone Imagery. **Remote Sensing**, v. 12, n. 21, p. 3521, jan. 2020.

JAIN, A. K. **Fundamentals of Digital Image Processing**. [s.l.] Prentice Hall, 1989.

JANSSEN, M. et al. Event Horizon Telescope observations of the jet launching and collimation in Centaurus A. **Nature Astronomy**, v. 5, n. 10, p. 1017–1028, out. 2021.

JEDELSKY, J. et al. Air–liquid interactions in a pressure-swirl spray. **International Journal of Heat and Mass Transfer**, v. 121, p. 788–804, 1 jun. 2018.

JEKEL, C. F. et al. Similarity measures for identifying material parameters from hysteresis loops using inverse analysis. **International Journal of Material Forming**, v. 12, n. 3, p. 355–378, 1 maio 2019.

JEON, J. et al. Experimental Study on Spray Characteristics of Gas-Centered Swirl Coaxial Injectors. **Journal of Fluids Engineering**, v. 133, n. 12, 23 dez. 2011.

JIN, X. et al. Estimates of plant density of wheat crops at emergence from very low altitude UAV imagery. **Remote Sensing of Environment**, v. 198, p. 105–114, set. 2017.

KARAYEL, D. et al. Laboratory measurement of seed drill seed spacing and velocity of fall of seeds using high-speed camera system. **Computers and Electronics in Agriculture**, v. 50, n. 2, p. 89–96, 1 fev. 2006.

KARLEKAR, A.; SEAL, A. SoyNet: Soybean leaf diseases classification. **Computers and Electronics in Agriculture**, v. 172, p. 105342, 1 maio 2020.

KOOIJ, S. et al. What Determines the Drop Size in Sprays? **Physical Review X**, v. 8, n. 3, p. 031019, 20 jul. 2018.

L. TANG; L. F. TIAN. Plant Identification in Mosaicked Crop Row Images for Automatic Emerged Corn Plant Spacing Measurement. **Transactions of the ASABE**, v. 51, n. 6, p. 2181–2191, 2008.

LEI, X. et al. Seed motion characteristics and seeding performance of a centralised seed metering system for rapeseed investigated by DEM simulation and bench testing. **Biosystems Engineering**, v. 203, p. 22–33, mar. 2021.

LI, H. et al. Video and image classification using atomisation spray image patterns and deep learning. **Biosystems Engineering**, v. 200, p. 13–22, 1 dez. 2020.

LIU, S. et al. A method to estimate plant density and plant spacing heterogeneity: application to wheat crops. **Plant Methods**, v. 13, n. 1, p. 38, dez. 2017.

MAHAJAN, S.; DAS, A.; SARDANA, H. K. Image acquisition techniques for assessment of legume quality. **Trends in Food Science & Technology**, v. 42, n. 2, p. 116–133, 1 abr. 2015.

MARANGONI, A.; DA COSTA FERREIRA, M. Influence of working pressure and spray nozzle on the distribution of spray liquid in manual backpack sprayers. **Arquivos do Instituto Biológico**, v. 86, 2 dez. 2019.

MARCAL, A. R. S.; CUNHA, M. Development of an image-based system to assess agricultural fertilizer spreader pattern. **Computers and Electronics in Agriculture**, v. 162, p. 380–388, 1 jul. 2019.

MARINELLO, F. et al. Application of the Kinect sensor for dynamic soil surface characterization. **Precision Agriculture**, v. 16, n. 6, p. 601–612, 1 dez. 2015.

MARTINEZ-AGIRRE, A.; ÁLVAREZ-MOZOS, J.; GIMÉNEZ, R. Evaluation of surface roughness parameters in agricultural soils with different tillage conditions using a laser profile meter. **Soil and Tillage Research**, v. 161, p. 19–30, 1 ago. 2016.

MASSOLA, M. P. et al. Spray volume distribution pattern and droplet size spectrum from ceramic nozzles. **Revista Brasileira de Engenharia Agrícola e Ambiental**, v. 22, p. 804–809, nov. 2018.

MIRHAJI, H. et al. Fruit detection and load estimation of an orange orchard using the YOLO models through simple approaches in different imaging and illumination conditions. **Computers and Electronics in Agriculture**, v. 191, p. 106533, 1 dez. 2021.

NAKARMI, A. D.; TANG, L. Automatic inter-plant spacing sensing at early growth stages using a 3D vision sensor. **Computers and Electronics in Agriculture**, v. 82, p. 23–31, 1 mar. 2012.

- NALLY, D. Against Food Security: On Forms of Care and Fields of Violence. **Global Society**, v. 30, n. 4, p. 558–582, 1 out. 2016.
- NGUGI, L. C.; ABELWAHAB, M.; ABO-ZAHHAD, M. Recent advances in image processing techniques for automated leaf pest and disease recognition – A review. **Information Processing in Agriculture**, v. 8, n. 1, p. 27–51, 1 mar. 2021.
- NIXON, M. S.; AGUADO, A. S. 3 - Image processing. In: NIXON, M. S.; AGUADO, A. S. (Eds.). **Feature Extraction and Image Processing for Computer Vision (Fourth Edition)**. [s.l.] Academic Press, 2020. p. 83–139.
- OSCO, L. P. et al. A CNN approach to simultaneously count plants and detect plantation-rows from UAV imagery. **ISPRS Journal of Photogrammetry and Remote Sensing**, v. 174, p. 1–17, 1 abr. 2021.
- PRINCEN, J.; ILLINGWORTH, J.; KITTLER, J. A formal definition of the Hough transform: Properties and relationships. **Journal of Mathematical Imaging and Vision**, v. 1, n. 2, p. 153–168, 1 jul. 1992.
- ROSE, D. C. et al. Agriculture 4.0: Making it work for people, production, and the planet. **Land Use Policy**, v. 100, p. 104933, 1 jan. 2021.
- S. D. KACHMAN; J. A. SMITH. Alternative Measures of Accuracy in Plant Spacing for Planters Using Single Seed Metering. **Transactions of the ASAE**, v. 38, n. 2, p. 379–387, 1995.
- SARKAR, S.; KARMIN, S.; KRUGER, G. R. **Spray characterization by optical image analysis**. . In: ASTM SPECIAL TECHNICAL PUBLICATION. 2016. Disponível em: <<https://www.scopus.com/inward/record.uri?eid=2-s2.0-85033714213&doi=10.1520%2fSTP159520160036&partnerID=40&md5=49dc6365fd544730260955807554ab87>>
- SCHULZ, F. et al. A measuring system for monitoring multi-nozzle spraying tools. v. 32, n. 5, p. 055902, mar. 2021.
- SHI, Y. et al. Automatic corn plant location and spacing measurement using laser line-scan technique. **Precision Agriculture**, v. 14, n. 5, p. 478–494, 1 out. 2013.
- SHI, Y. et al. Improvement of a ground-LiDAR-based corn plant population and spacing measurement system. **Computers and Electronics in Agriculture**, Precision Agriculture. v. 112, p. 92–101, 1 mar. 2015.
- SIJS, R. et al. Drop size measurement techniques for sprays: Comparison of image analysis, phase Doppler particle analysis, and laser diffraction. **AIP Advances**, v. 11, n. 1, p. 015315, 1 jan. 2021.
- SPARROW, R.; HOWARD, M. Robots in agriculture: prospects, impacts, ethics, and policy. **Precision Agriculture**, 23 out. 2020.

- TEH, C.-H.; CHIN, R. T. **On image analysis by the methods of moments**. Proceedings CVPR '88: The Computer Society Conference on Computer Vision and Pattern Recognition. **Anais...** In: PROCEEDINGS CVPR '88: THE COMPUTER SOCIETY CONFERENCE ON COMPUTER VISION AND PATTERN RECOGNITION. Ann Arbor, MI, USA: IEEE Comput. Soc. Press, 1988. Disponível em: <<http://ieeexplore.ieee.org/document/196290/>>. Acesso em: 2 abr. 2021
- TIAN, H. et al. Computer vision technology in agricultural automation —A review. **Information Processing in Agriculture**, v. 7, n. 1, p. 1–19, 1 mar. 2020.
- VALENTE, J. et al. Automated crop plant counting from very high-resolution aerial imagery. **Precision Agriculture**, v. 21, n. 6, p. 1366–1384, 1 dez. 2020.
- VAN DER WALT, S. et al. scikit-image: image processing in Python. **PeerJ**, v. 2, p. e453, 19 jun. 2014.
- VONG, C. N. et al. Corn emergence uniformity estimation and mapping using UAV imagery and deep learning. **Computers and Electronics in Agriculture**, v. 198, p. 107008, 1 jul. 2022.
- WANG, S. et al. Effects of Adjuvants on Spraying Characteristics and Control Efficacy in Unmanned Aerial Application. **Agriculture**, v. 12, n. 2, p. 138, fev. 2022.
- XIA, L. et al. **Performance Monitoring System for Precision Planter Based on MSP430-CT171**. (D. Li, Y. Liu, Y. Chen, Eds.) Computer and Computing Technologies in Agriculture IV. **Anais...**: IFIP Advances in Information and Communication Technology. Berlin, Heidelberg: Springer, 2011.
- ZHANG, N. et al. Skin cancer diagnosis based on optimized convolutional neural network. **Artificial Intelligence in Medicine**, v. 102, p. 101756, 1 jan. 2020.
- ZHANG, Q. et al. Maize yield and quality in response to plant density and application of a novel plant growth regulator. **Field Crops Research**, v. 164, p. 82–89, 1 ago. 2014.
- ZHANG, X. et al. Yield estimation of citrus fruit using rapid image processing in natural background. **Smart Agricultural Technology**, v. 2, p. 100027, 1 dez. 2022.
- ZHAO, L. et al. Effect of soil surface roughness on infiltration water, ponding and runoff on tilled soils under rainfall simulation experiments. **Soil and Tillage Research**, v. 179, p. 47–53, 1 jun. 2018.
- ZHOU, Q. et al. Prediction of Spray Angle from Flat Fan Nozzles. **Journal of Agricultural Engineering Research**, v. 64, n. 2, p. 139–148, 1 jun. 1996.
- ZHOU, Z. et al. Numerical simulations of water spray on flame deflector during the four-engine rocket launching. **Advances in Space Research**, v. 65, n. 4, p. 1296–1305, 15 fev. 2020.

ZHU, H.; SALYANI, M.; FOX, R. D. A portable scanning system for evaluation of spray deposit distribution. **Computers and Electronics in Agriculture**, v. 76, n. 1, p. 38–43, 1 mar. 2011.

CHAPTER 3 – SMARTPHONE IMAGE-BASED FRAMEWORK FOR QUICK, NON-INVASIVE MEASUREMENT OF SPRAY NOZZLES CHARACTERISTICS²

Abstract: Agricultural spray nozzles are small yet key components for delivering agrochemicals to the target surface. Their complexity demands specific assessment to guarantee the spray quality. The usual equipment measures it accurately; however, it can be time-consuming and invasive. An alternative for rapid, non-invasive measuring methods in agriculture is image processing. Therefore, our goal was to develop an innovative smartphone image-based framework to analyze spray characteristics and detect poor spray nozzles under indoor or outdoor environments. We used flat fan and hollow cone nozzles, with three sizes and three working pressures. A mobile phone with 12 MP was used to acquire spray images. The images were automatically stored and processed using a cloud computing platform. Spray angle was measured by finding edges in binary images and using Hough transform function. Single spray distribution shape was characterized by extracting the pixel gray-scale value profile across a horizontal line in three regions of the image. Finally, solid stream jets were detected using a function to calculate gray-scale peaks. The actual spray characteristics were measured using an automatic horizontal patternator with 120 glasses (25 mm grooves). As results, image-based spray angle MAPE and MAE were 4.45° and 4.40%, respectively, leading to an underestimation in most cases. Specific regions of the image accurately resembled the measured spray distribution shape, except for hollow cone nozzles when working at low pressures. Moreover, solid stream jets were correctly detected at three different flow rates. Our framework was validated for both indoor (laboratory) and outdoor (field) conditions and had comparable results. Therefore, our insights absolutely contribute for rapid, non-invasive measurement of spray nozzles through a digital approach and open pathways towards more affordable and flexible methods for agricultural assessments.

Keywords: Agricultural spraying; cloud computing; digital system.

1. Introduction

Breaking a liquid sheet into droplets in a controlled way is not easy (KOOIJ et al., 2018). However, it is necessary for many processes including food, automotive and pharmaceutical industries. Spraying systems are used in a wide range of applications and with different complexities, from nasal-spray (FUNG et al., 2012) to rocket launching (ZHOU et al., 2020). At the farm level, pesticide applications mostly use hydraulic nozzles to deliver the agrochemical to the target surface. The spray generation process starts when the liquid leaves the nozzle orifice as a liquid sheet and disruptive aerodynamics forces transform it into unstable ligaments, forming the

² Article published by [Smart Agricultural Technology](#)

primary breakup. In the secondary breakup, this liquid is again disrupted, producing droplets (ASGARIAN et al., 2020; BERMUDEZ; PINHEIRO, 2020). It depends on physical liquid properties such as surface tension and viscosity, which can change dramatically when agrochemicals are added to water (CARVALHO et al., 2017).

Thousands of dollars of agrochemicals pass through this small yet complex component. A poor spray nozzle can compromise the entire agricultural operation even when using expensive pesticides and modern machines. Therefore, spray nozzles must be assessed constantly following the ISO 5682-1 (2017) and ISO 5682-2 (2017). Such standards prescribe several indoor (laboratory) or outdoor (sprayer) measurements. A test using a single nozzle is appropriate to analyze the spray distribution shape, angle and symmetry. The spray shape is important to differentiate nozzle designs. In a cartesian plane, flat fan and full cone nozzles have an unimodal shape, whereas hollow cone nozzles have a bimodal shape (Marangoni and Ferreira, 2019). Conversely, tests with multiple nozzles simulate the spray boom and its liquid distribution. Spray booms with low uniformity result in underdosing and overdosing during the spraying operation (BUTTS et al., 2019a).

However, measuring manually these spray characteristics is time-consuming, invasive and human intervention can cause errors (Luck et al., 2016; Schulz et al., 2021). This is also an issue for other applications in agriculture. Therefore, several techniques imported from computer science have been adapted to improve agricultural assessments in recent years, such as image processing, sensors and robots (Azizi et al., 2021; Araújo et al., 2021; Mahajan et al., 2015; Marcal and Cunha, 2019). Conventional image processing techniques can range from basic operations (changes in brightness, contrast and color) to morphological operations (NIXON; AGUADO, 2020). The main purpose is to extract information from the region of interest (Minov et al., 2015a). As an example, segmentation subdivides the image into regions by determining a threshold and excluding or including specific pixels. The subsequent step is the feature extraction based on color, geometry, position or any other characteristic (HAMUDA et al., 2017).

For spray applications, image processing was mostly used to analyze droplet size and velocity. Usually, a powerful light source illuminates a screen and highlights the droplets (shown as dark spots) (Minov et al., 2015b). The images are acquired by high-

speed cameras and the software performs a threshold to detect the in-focus droplets (SARKAR; KARMIN; KRUGER, 2016; SIJS et al., 2021). Under field conditions, water sensitive papers may be a cheaper alternative. When a droplet hits the collector, small blue spots are formed and features are extracted to measure the coverage area and droplet impact size (FERGUSON et al., 2016; ZHU; SALYANI; FOX, 2011). Moreover, other spray characteristics were also analyzed by image processing systems, such as liquid sheet breakup (JEDELSKY et al., 2018; JEON et al., 2011). The spray angle was assessed by finding spray edges in contrast to the background (ÇETIN; SAĞLAM; DEMİR, 2019; CHENG et al., 2017). The spray distribution was also studied using manual extraction of pixel profiles (ÇETIN; SAĞLAM; DEMİR, 2019). However, there is no consistent guideline and comparison between measured and estimated. Authors described the needed for broader studies with more accurate and automatic methods. Furthermore, these studies were mostly developed under strict environmental conditions and cannot be exported to the field.

A usual horizontal patternator accurately measures spray characteristics but is large and hard to move around. Moreover, spray characteristics measurements can be time-consuming depending on nozzle size since a representative volume of liquid must be collected. Alternatively, portable patternators are easy to move around and can be useful for outdoor measurements but are still material, invasive and time-consuming methods. Both can be easily built for manual testing. However, they become expensive depending on the level of embedded technology (e.g., automatic measurement). A digital and versatile method would be more interesting for both indoor and outdoor measurements, especially for rapid screening of poor spray nozzles. An emerging method in agricultural assessments is smartphone-based systems. It would constitute a rapid, portable and digital approach. Smartphones are multi-tasking technologies much more portable than portable patternators and used worldwide, even in low-income regions. Therefore, our objective was to develop a smartphone image-based framework in a cloud computing platform for rapid, non-invasive measurement of spray characteristics. Our specific objectives were summarized in 1) measure spray characteristics (distribution shape, angle and solid stream jets) using a totally digital and remote method; 2) use the framework to detect poor spray nozzles that do not

meet the quality criteria and 3) validate the framework for indoor and outdoor measurements.

2. Materials and methods

2.1. Nozzle characteristics

Two types of spray nozzles (Jacto, Brazil) were used: flat fan ADI and hollow cone JCI. Flat fan pre-orifice ADI nozzles had a nominal spray angle of 110°. Three nozzle sizes (ISO 01, 03 and 04), were tested at three working pressures of 200, 350 and 500 kPa, corresponding with a droplet size spectrum ranging from fine to medium (110-01), medium to coarse (110-03) and coarse to very coarse (110-04), respectively, according to ISO 25358 (2018). Hollow cone JCI nozzles had a nominal angle of 80°. Three nozzle sizes (ISO 0075, 02, and 03) were tested at three pressures of 400, 1000 and 2000 kPa, corresponding with a droplet size spectrum ranging from very fine (80-0075), very fine (80-02) and very fine to fine (80-03), respectively, according to ISO 25358 (2018). It was important to include a range of spray angles and droplet size spectra as it can affect image analysis.

2.2. Spray angle distribution pattern measurement using a patternator

An automated horizontal patternator with 120 collection glasses (25 mm grooves) and 3000 mm of total width (AAMS Salvarani, Belgium) was used to measure the spray liquid distribution according to ISO 5682-1 (2017), using a single hydraulic nozzle at a spray nominal height of 500 mm. Tests were completed when at least one glass reached approximately 300 mL. After each spray, a device with ultrasonic sensors traveled above the glasses and measured the liquid volume with a minimum value of 10 mL. Spray angle was calculated using basic trigonometric functions based on spray height and filled glasses. The patternator error (± 25 mm) was assumed for this calculus. These laboratory tests were performed under climate-controlled conditions to avoid sudden changes in air and water temperature and relative humidity, as specified by the standards cited before.

2.3. Spray image acquisition

A system was created to capture spray images. A regular small flow rate bench with an open front of 400 mm x 400 mm was used and the nozzle was positioned at the upper center portion. A LED light was positioned above and in front of the spray

using a tripod. The camera was at the same height and 1000 mm away from the nozzle (Figure 1). A mobile phone iPhone 7 with 12 Mp (4608 x 2592 px) and 4.00 mm focal length was used to take images corresponding with a spatial resolution of approximately 0.05 cm x 0.05 cm. At least two photos were taken for each spray test. The images were automatically processed using the cloud computing platform Google Colaboratory and a report summarizing the results was generated and stored. As the entire script was run using the smartphone, no local computer was used.

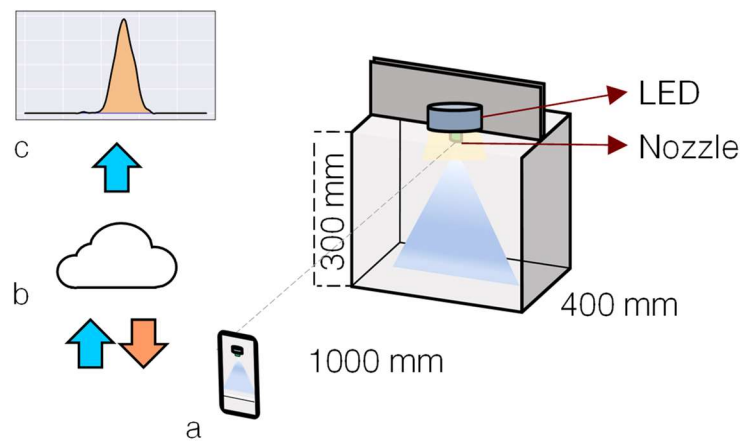


Figure 1. Indoor experimental setup: a) image acquisition; b) processing using cloud computing and c) results report.

2.4. Image pre-processing

The images were processed with Python programming language, using the libraries OpenCV (Bradski & Kaehler, 2008) and scikit-image (VAN DER WALT et al., 2014). A median filter was used to decrease image noise and then the images were converted into gray-scale values.

2.5. Spray angle detection

A threshold was used to separate background from the spray region. It was difficult to establish a fixed value of thresholding due to the spray dynamics (LI et al., 2020). Therefore, several automatic thresholding methods were tested using the scikit-image library. The 'thresholding_mean' function was selected. The 'Canny edge' function was used to detect spray edges in the binary image and the Hough transform function was used to draw straight lines on them. The Hough transform is a feature extraction technique, which calculates the number of points that satisfy a parametric constraint (NIXON; AGUADO, 2020; PRINCEN; ILLINGWORTH; KITTLER, 1992). Therefore, in

a binary image the spray edge points can be 'connected', forming a straight line. Each line detected has its own properties and an angle in relation to the image axis (Figure 2).

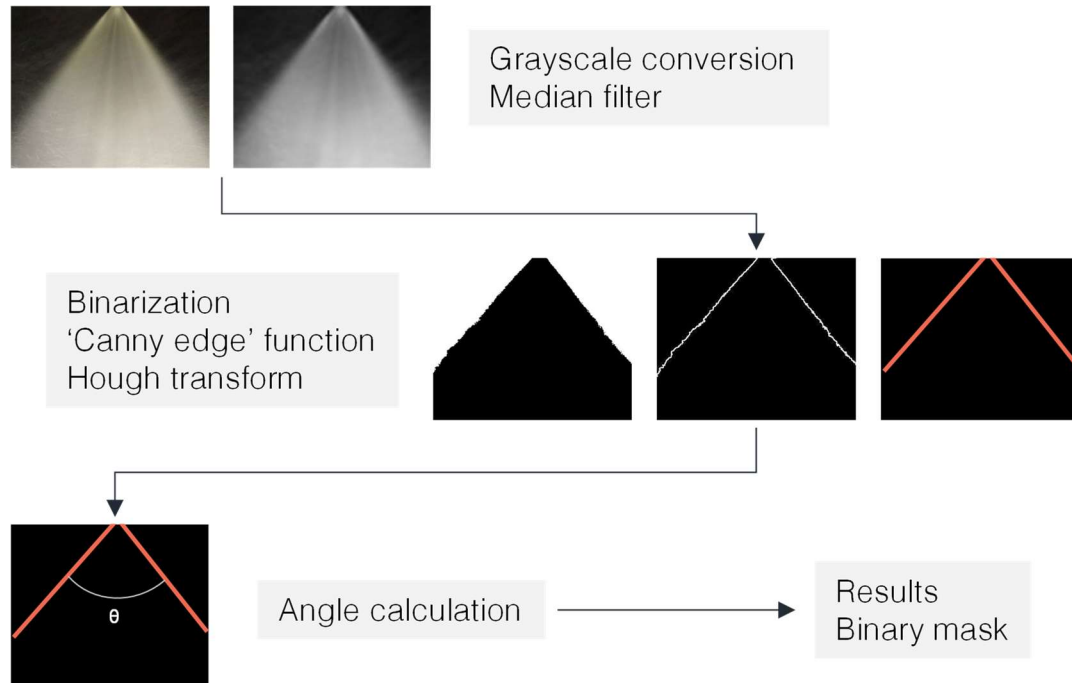


Figure 2. Step-by-step of morphological operations to detect and calculate spray angle.

2.6. Spray distribution shape

Theoretically, flat fan nozzles concentrate the liquid in the center, whereas hollow cone nozzles distribute the liquid in the cone perimeter. If images have gray-scale values, an alternative to characterize the spray distribution shape is to plot a profile of gray-scale values across an image horizontal segment, ranging from 0 (black) to 255 (white). Liquid concentration is probably proportional to the pixel gray-scale value.

However, there is no guideline for establishing which region in the spray fan is best suited to determine the spray distribution shape. For example, it is impossible to extract the pixel profile at distances too far from the nozzle in most cases because the spray breaks up into a fog, as well as have ricocheting droplets. Therefore, three regions of the image were sampled in the measurable spray region (Figure 3). Each sample was 10 px high (y axis) to average pixels and avoid noise. The 'upper' region was 200-210 px (30 mm) away from the nozzle output, far enough to avoid any possible noise by

the 'reflecting pool' in the initial liquid sheet, which is formed due to pixel saturation. The 'middle' region was 300-310 px (90 mm) away from the nozzle output and in the center of the measurable spray. The 'lower' region was 600-610 px (180 mm) away from the nozzle output, which is the maximum distance in the measurable spray. A manual thresholding was used to avoid the background. Therefore, the sample width only overlapped with the spray region.

The distances from the nozzles were different between the measured and estimated pattern. For the patternator, 300 mm is the minimum recommended height and 500 mm is the nominal test height for both nozzles. However, the maximum height using image processing method was 180 mm. Under our hypothesis, one of the sampled regions in the image-based method can be extrapolated to the patternator results and, therefore, be used to characterize their spray distribution shape (unimodal/bimodal) for rapid screening.

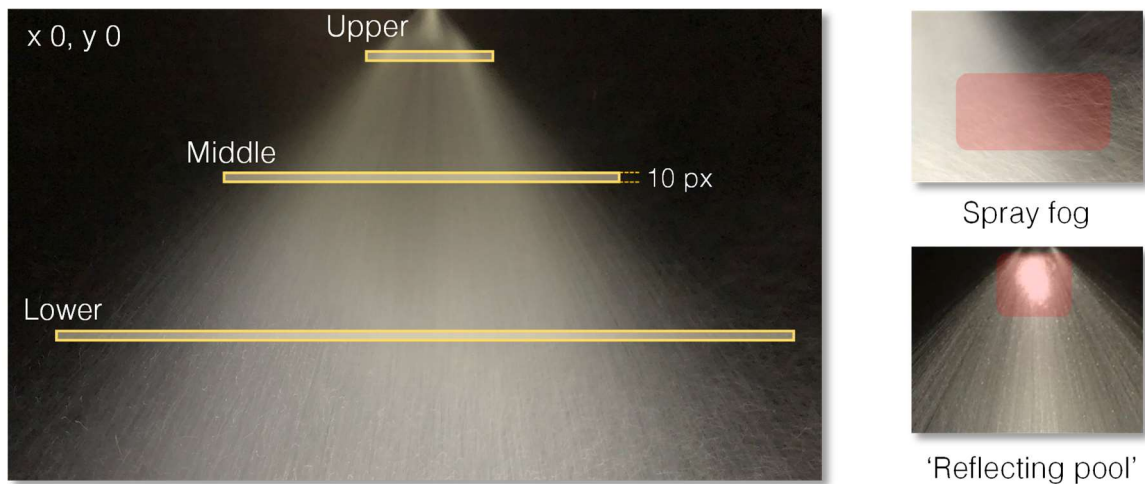


Figure 3. Example of sampled regions: ‘upper’, ‘middle’ and ‘lower’, respectively. Spray fog, ricocheting droplets and ‘reflecting pool’ were some problems during the image processing.

2.7. Solid stream jet

A hollow cone nozzle JCI 80-02 was used working at 400, 1000 and 2000 kPa, representing three completely different flow rates. The nozzle was producing solid stream jets due to manufacturing problems. The measured solid stream jets were counted visually by a specialist. For the smartphone image-based method, pixel samples too close to the nozzle are not representative for considering a solid stream jet (Section 4.), while distances too far apart can be influenced due to spray fog. Considering it, a gray-scale sample at the ‘middle’ region was extracted (300-310 px, 90 mm). Prominent gray-scale local peaks can correspond to solid stream jets, as it is formed due to liquid concentration. Therefore, each prominent peak was detected using a function from the ‘SciPy’ library and a conditional was implemented: when testing flat fan nozzles (unimodal), only 1 prominent peak was acceptable. For hollow cone nozzles (bimodal), only 2 prominent peaks were acceptable. Each peak thereafter was counted as a potential solid stream jet. Graphs were generated to show the peaks location in the spray.

2.8. Comparison and analysis

Estimated angle was compared to the measured spray angle using relative error, MAPE and MAE metrics. The x-axis and y-axis from patternator and image-based distributions were normalized to values ranging from 0 to 1. It was not possible just

overlap the two data even with both axes normalized, as image-based data proportion was completely different. Therefore, a spreadsheet with 120 rows was created to compare the two data. Image-based data dimensionality was reduced by sampling the number of pixels equals the number of filled glasses. This sampling consisted in selected the x-axis pixel (image) with the same or closest normalized value as the x-axis filled glasses (patternator). Thus, both x-axes had the same proportionality. For example, x-axis pixel n° 150 (value of 0.29) to the x-axis filled glass n° 10 (value of 0.29), and so on. Each pixel corresponded to a filled glass (Supplementary data).

The two distribution patterns were compared using the Python library 'similaritymeasures' (JEKEL et al., 2019) which offers possibilities to calculate the difference between two curves. The 'Area method' (AM) calculates the area between two curves. Quadrilateral polygons are constructed by taking consecutives pair points from each curve and these areas are summed. The 'Curve Length' method (CL) takes two corresponding points from two curves to calculate the residual sum of squares and quantify the difference between them (JEKEL et al., 2019). However, the main approach was to characterize single spray distribution shape: unimodal or bimodal. The measured and estimated solid stream jets were compared by counting the number of jets.

3. Results

The methods proposed in this research used morphological operations and cloud computing. Therefore, they are applicable with any current smartphone connected to the internet. Considering all steps, it took approximately 50 seconds to perform the measurement. Although the framework uses a Python script, no high expertise is required. One must just capture the image; open the script and then click 'run script'. Instantly, all the results are showed and sent to a report document stored in the cloud. As a comparison, average time consumed by patternator was 6.39 minutes. It ranged 3.28 to 12.67 minutes and strongly depends on the combination flow rate, pressure and minimum volume of liquid. Moreover, patternator spray boom height and depth adjust, glasses measurement and system resetting consumed times were not considered, but would certainly add more time.

3.1. Spray angle

Spray angle must be <10% of deviation from the nominal angle according to the ISO 5682 (2017). For the flat fan ADI 110 nozzles, tolerance limits ranged from 99 to 121°. However, ADI 110-01 measured spray angles were outside tolerance limits and up to 23% of deviation, as shown in Table 1. Overall, the larger the nozzle size, the bigger the angle. Moreover, when pressure is increased, the spray angle also increases. For the hollow cone JCI 80 nozzles, tolerance limits ranged from 72 to 88°. Unlike before, no clear relation between nozzle size and spray angle was found, but spray angle increases when pressure increases, except for the JCI 80-03 nozzle. The flat fan nozzles ranged from 86.80° to 121.00° (34.20° of interval). Probably due to smaller angles, the hollow cone nozzles were more stable, ranging from 70.00° to 85.10° (15.10° of interval).

The measured region using image processing was near the nozzle, where spray properties are constant. Our hypothesis was that because of gravity, image-based spray angle would always be bigger than the measured. However, in both tests most smartphone image-based results underestimated the spray angle, with relative error ranging from -6.9% to 5.3%. For flat fan ADI nozzles, MAE and MAPE were 5.3° and 4.1%, respectively, with a maximum relative error of -6.7%. For hollow cone JCI nozzles, the MAE and MAPE were 3.6° and 4.7%, respectively, with a maximum relative error of -6.9% (Table 1). Hough transforms detected multiple random straight lines when the image had significant noises, mainly after liquid sheet initial breakup. Therefore, images were cropped to keep only the first 200 px (30 mm), near the nozzle. Even so, the most important result was that poor spray angle nozzles (completely outside tolerance limits even considering patternator error) were detected using image processing (i.e., ADI 110-01).

Table 1. Image-based and measured results for spray angle.

Image processing (°)					Horizontal patternator (°)			Relative error (%)		
Nozzle	kPa	ISO nozzle size								
		01	03	04	01	03	04	01	03	04
ADI	200	85.5	111.6	116.6	86.8±2.9	106.9±2.0	118.3±1.5	-1.5	4.4	-1.4
	350	88.5	108.6	114.6	92.7±2.7	114.3±1.7	121.0±1.4	-4.5	-5.0	5.3
	500	95.5	106.6	116.6	99.0±2.3	114.3±1.7	121.0±1.4	-3.6	-6.7	-3.6

		0075	02	03	0075	02	03	0075	02	03
	400	73.4	75.4	77.4	70.0±3.7	72.0±4.6	80.7±3.2	4.6	4.7	-4.2
JCI	1000	81.4	77.4	80.7	77.3±3.4	80.7±3.2	79.0±3.4	5.1	-4.2	-6.2
	2000	77.3	79.4	76.4	82.4±3.1	85.1±3.0	79.0±3.4	-2.4	-6.9	-3.4

3.2. Spray distribution pattern

The sample region was selected as the one that best resembles the measured spray distribution shape and with the lowest values of AM and CL (Table 2 and 3). Flat fan ADI nozzles had unimodal shapes and the three regions accurately resembled it. The lowest values of AM were observed for 'lower' region, whereas 'upper' had similar results and 'middle' had the worse values. However, the area by itself is not enough as the unimodal shape can be completely different from the patternator data. Hence, the 'upper' region had the better results considering both AM and CL values. The lowest difference between measured and estimated was obtained with the nozzle 110-01, because the spray angle is smaller and, therefore, the area is also smaller. It shows that results should not be compared between nozzle sizes or pressures as they produce different spray coverage. However, measured data is more symmetric and suffers the gravity effect producing longer tails (Figure 4).

Table 2. Metrics used to compare flat fan spray shape from image and patternator.

		110-01			110-03			110-04		
kPa	Regions	AM	CL	Type	AM	CL	Type	AM	CL	Type
200	Upper	3.45	0.42	Unimodal	6.97	0.70	Unimodal	9.09	0.88	Unimodal
	Middle	2.21	2.39	Unimodal	12.13	1.50	Unimodal	13.72	2.17	Unimodal
	Lower	3.81	2.33	Unimodal	7.82	2.37	Unimodal	11.77	3.81	Unimodal
350	Upper	3.18	1.64	Unimodal	7.26	0.83	Unimodal	9.70	1.45	Unimodal
	Middle	4.45	2.16	Unimodal	11.83	1.78	Unimodal	12.31	2.98	Unimodal
	Lower	3.02	1.80	Unimodal	6.85	3.48	Unimodal	9.38	4.05	Unimodal
500	Upper	4.16	0.32	Unimodal	10.06	2.74	Unimodal	11.64	1.37	Unimodal
	Middle	7.18	2.21	Unimodal	14.42	2.91	Unimodal	13.81	2.77	Unimodal
	Lower	2.01	1.22	Unimodal	9.65	3.29	Unimodal	12.56	2.92	Unimodal

AM: Area method; CL: Curve length error; Type: Spray distribution.

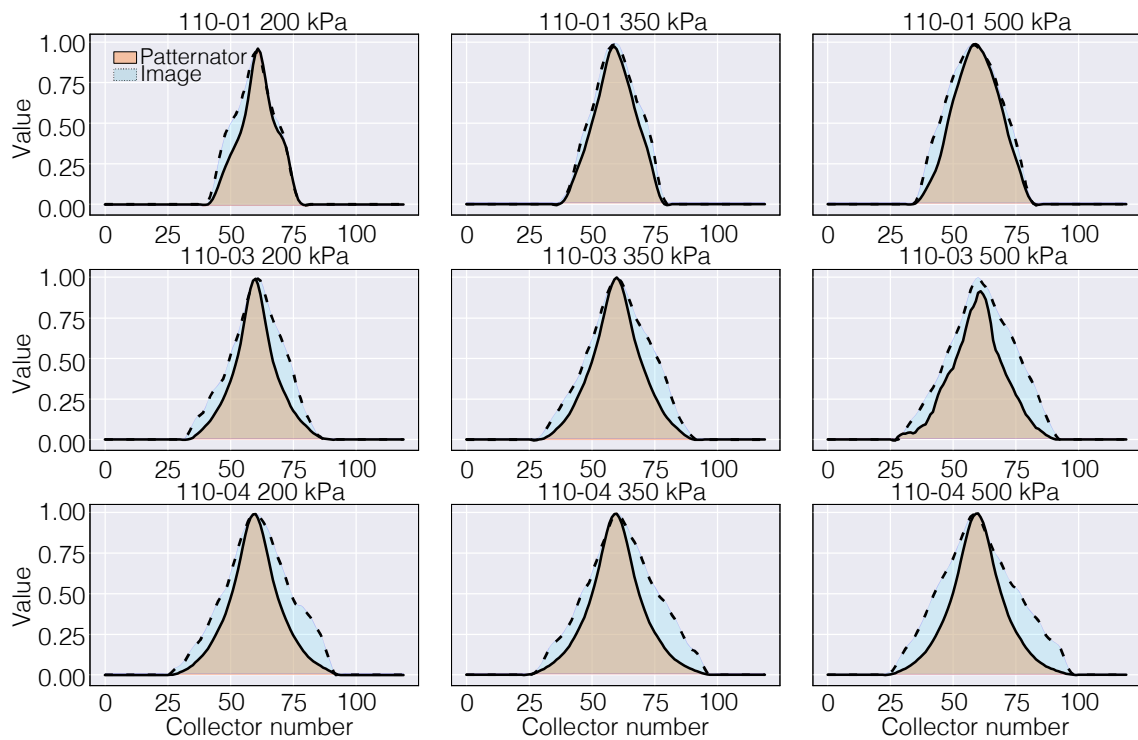


Figure 4. Spray distribution shape for each flat fan ADI nozzle and pressure. These charts represent the ‘upper’ pixel profile, considered as the best region of the image to analyze flat fan nozzles.

The spray from 80-0075 and 80-02 had no comparable distribution results for ‘upper’ and ‘middle’ regions when working at 400 kPa, because the samples showed bimodal distributions, while the measured data was unimodal. Although ‘lower’ region resulted in unimodal shape, it needs to be analyzed careful. This region produced unimodal shape for all nozzles and pressures, probably because the spray breaks up into a fog losing the pixel profile (Section 4.). The ‘middle’ region produced the lowest results for almost all tests and, therefore, it was selected as the best region. Moreover, the error does not increase depending on the nozzle size, since all nozzles have a similar spray coverage. Different from before, measured and estimated data had more similarity and did not show a significant asymmetry or shape distortion (Figure 7).

Table 2. Metrics used to compare hollow cone spray shape from image and patternator.

kPa	Regions	80-0075			80-02			80-03		
		AM	CL	Type	AM	CL	Type	AM	CL	Type
400	Upper	10.15	4.00	Bimodal	8.10	3.20	Bimodal	5.45	2.55	Bimodal

	Middle	9.54	2.82	Bimodal	7.81	2.01	Bimodal	4.12	2.09	Bimodal
	Lower	6.3	0.42	Unimodal	7.36	0.45	Unimodal	3.85	1.23	Unimodal
	Upper	6.46	4.74	Bimodal	4.60	2.41	Bimodal	1.47	2.91	Bimodal
1000	Middle	3.13	0.89	Bimodal	1.03	2.45	Bimodal	2.19	2.92	Bimodal
	Lower	3.59	0.47	Unimodal	3.99	3.54	Unimodal	4.66	4.26	Unimodal
	Upper	6.90	4.58	Bimodal	3.89	2.45	Bimodal	3.03	2.44	Bimodal
2000	Middle	4.58	0.73	Bimodal	3.23	2.37	Bimodal	2.91	3.03	Bimodal
	Lower	4.81	0.92	Unimodal	5.51	3.63	Unimodal	5.37	3.96	Unimodal

AM: Area method; CL: Curve length; Type: Spray distribution.

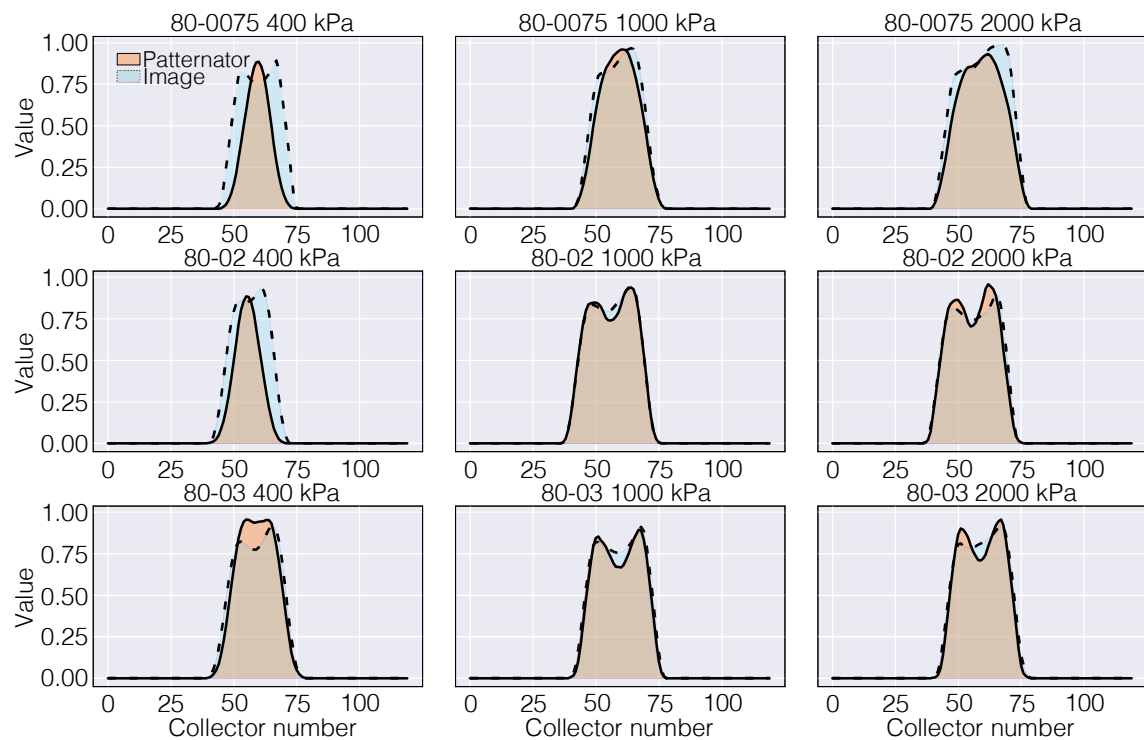


Figure 5. Spray distribution for each hollow cone JCI nozzle and pressure. These charts represent only the ‘middle’ pixel profile, considered as the best region of the image to analyze hollow cone nozzles.

3.3. Solid stream jets detection

The results were the number of peaks and the comparison between visual and image-based detection. At 400 kPa, the nozzle produced one solid stream jet. It corresponded to a peak in the center of the gray-scale distribution. For the other two pressures, the nozzle produced two peaks and the image-based detected it accurately (Figure 6). Is important to note that side peaks are normal jets produces by the hollow cone nozzle (Section 4.).

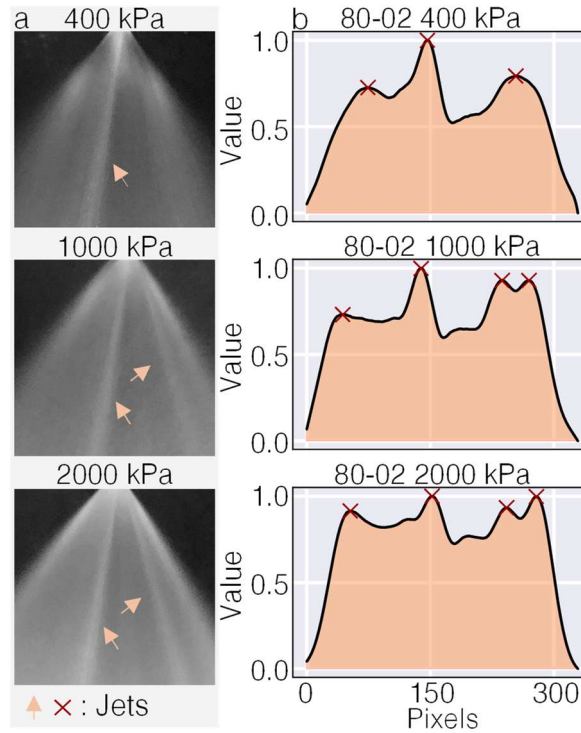


Figure 7. Solid stream jets detection a) original spray and b) gray-scale distribution graph and peaks.

3.4. Field validation

The framework was tested on-field condition at 4:00 pm using a sprayer. Two hollow cones JCI 80-02 were used, with or without solid stream jets. A black background 1000 x 1000 m was placed behind the spray boom. Just the two nozzles tested were spraying while the others of the spray boom were disabled. The nozzle size was taken as a reference to adjust the pixel sample 'middle' region (90 mm away from the nozzle). As soon as indoor measurements, the images were captured, sent to the cloud storage and then processed (Supplementary video). The results showed a strong similarity between on-field and patternator and the method accurately characterize the bimodal shape from hollow cones for all pressures (Figure 7a). The solid stream jets were correctly detected from the JCI 80-02 damaged, excepted for one misdetection at low pressure (400 kPa) (Figure 7b). Spray angle results were comparable to the indoor measurements, with 2, -4 and -8% of relative error at pressures of 400, 1000 and 2000 kPa, respectively (MAE = 3.78° and MAPE = 4.67%).

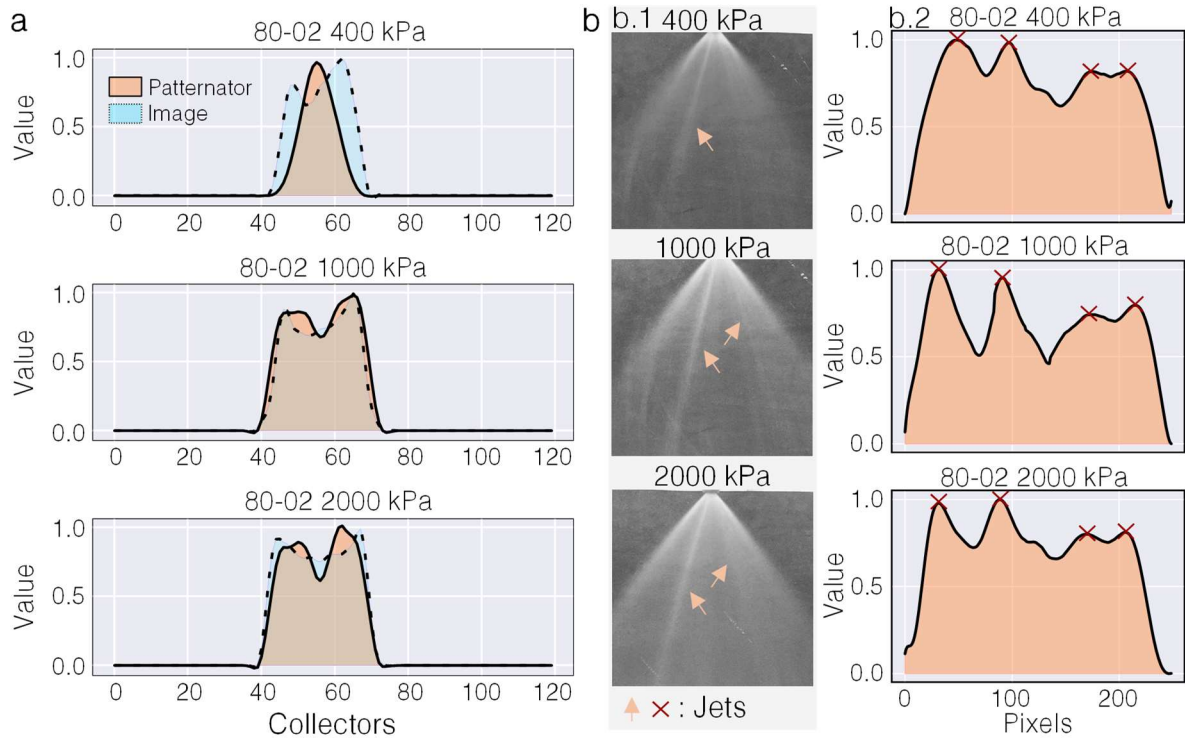


Figure 8. Tests on-field, a) comparison between JCI 80-02 spray shape using the proposed framework and the patternator; b) solid stream jets detection, which b.1 gray-scale images and b.2 image peaks detection.

4. Discussion

No other research has integrated so many aspects to measure spray characteristics using a digital tool. We proposed straightforward methods for rapid, non-invasive measurement of agricultural hydraulic nozzles using an innovative framework. Moreover, we validated our framework for indoor and outdoor measurements. The method is not fully non-destructive because still need to spray liquid for a few seconds. However, none of the methods required high computational resources, as the script was developed using cloud computing, a key environment for increasing processing capacity remotely. For low complexity scripts, Google Colaboratory cloud platform is free of cost and use an open-source programming language. The framework is also far quicker than the indoor horizontal patternator, which consumed an average of 6.39 minutes per spray nozzle. In addition, no data training or advanced computational knowledge was required and a complete guideline is available in each script line. Therefore, a prominent social result is the inclusion and

accessibility, as smartphone use has spread quickly even in low-income regions. Smartphone is portable and multi-tasking technology, allowing data acquisition and processing at the same time.

The morphological operations successfully detected spray angles. The MAPE was lower than 5%. However, most image-based spray angles were lower than the measured angles, in contrast to the hypothesis, which angle would be lower due to the gravity (ZHOU et al., 1996). Threshold was automatic and probably discarded some minor parts of the spray, decreasing the angle. The image resolution and illumination technique also contributed to these noises. Moreover, when the spray binary image had winding edges, the function Hough Transform detected several 'random' lines. Thus, it is recommended to measure the spray angle near the nozzle output, where spray properties are constant. Even so, poor spray angles that have results completely outside the tolerance limits ($>10\%$) were detected. It is clearly useful for our objective of rapid detection of poor spray nozzles.

Spray distribution is useful to characterize nozzle types. An unexpected distribution comes from new nozzles with geometric problems, originating from engineering projects or manufacturing. Flat fan nozzles always resulted in unimodal shapes, regardless of the sampled region. However, in the image, the spray breaks when it reaches the 'lower' region, forming a fog and losing much of the pixel profile pattern. Usually, hollow cones have noticeable differences in comparison to the flat fan distribution. However, when these nozzles were working at low pressures (400 kPa) the distributions were quite similar. The hollow cone nozzles are projected to work in high pressure systems and can be unstable at low pressures. At low pressures, the nozzles 80-0075 and 80-02 had unimodal distributions, but the image-based method resulted in a bimodal distribution shape. A similar situation occurs when the spray height is higher and the hollow cone distribution pattern tends to be more uniform (MASSOLA et al., 2018). Curiously, the hollow cone spray always has a bimodal shape in the 'upper' region, even if the nozzle produces a unimodal shape. Two prominent lines and a hollow center will always be in the nozzle output when viewed in a 2D plane, produced by the swirl chamber (DAFSARI; VASHAHI; LEE, 2017). The 'lower' region is again not recommended due to spray fog. Hence, it is recommended to use 'upper' region for flat fan nozzles and 'middle' region for hollow cone nozzles. The

reason of the difference is diverse, but is probably originated from the liquid sheet dynamic and droplet size.

An important result was to detect solid stream jets, essentially to screen poor spray nozzles. This problem occurs due to nozzle wear, obstruction or during manufacturing. Furthermore, the irregular aesthetic is not good commercially. Although it is easily visible, we proposed a method less subjective for rapid screening. The method accurately detected solid stream jets regardless of its prominence, as the function uses the pixel neighborhood to calculate gray-scale peaks. Curiously, the method detected a solid stream jet more at 400 kPa in outdoor measurement that was not counted by the specialist. However, a peak was counted at 1000 kPa in the same coordinate. Therefore, although it was considered a misdetection, this peak corresponded a potential solid stream jet and was not a random noise.

Overall, outdoor and indoor image-based results were comparable. Both accurately characterize spray shape, angle and solid stream jets. However, illumination conditions constrain outdoor measurements as is not possible to control it. Our recommendation is to use image-based systems at hours with less radiance to avoid saturation (early morning or late afternoon) or park the sprayer next to a shade.

5. Conclusions

Our study clearly demonstrates the possibility of using digital tools for rapid, non-invasive measurement of agricultural hydraulic spray nozzles. An innovative framework was developed based exclusively on smartphone, morphological operations and cloud computing. The portability of smartphones and versatile of cloud platforms constitutes an efficient system, which images are captured and instantly processed. Our results are comparable to regular tests and were validate for indoor and outdoor measurements. The framework can be adapted and used in line production to detect poor quality nozzles and screen production batches during manufacturing. On-field, the consultants can use the framework to assess the farmer sprayer condition. Future studies can be made following our guidelines to analyze the spray boom distribution and its uniformity to support farmers decision-making.

References

- AMPATZIDIS, Y.; PARTEL, V. UAV-Based High Throughput Phenotyping in Citrus Utilizing Multispectral Imaging and Artificial Intelligence. **Remote Sensing**, v. 11, n. 4, p. 410, jan. 2019.
- ANITEI, M.; VERES, C.; PISLA, A. Research on Challenges and Prospects of Digital Agriculture. **Proceedings**, v. 63, n. 1, p. 67, 2021.
- ASGARIAN, A. et al. Experiments and modeling of the breakup mechanisms of an attenuating liquid sheet. **International Journal of Multiphase Flow**, v. 130, p. 103347, 1 set. 2020.
- AZIZI, A. et al. Estimation of Soil Surface Roughness Using Stereo Vision Approach. **Sensors**, v. 21, n. 13, p. 4386, jan. 2021.
- BADUA, S. A. et al. Ground speed and planter downforce influence on corn seed spacing and depth. **Precision Agriculture**, 2 jan. 2021.
- BATCHELOR, B. G.; WALTZ, F. M. Morphological Image Processing. In: BATCHELOR, B. G. (Ed.). **Machine Vision Handbook**. London: Springer London, 2012. p. 801–870.
- BERMUDEZ, F.; PINHEIRO, J. B. Selection to high productivity and stink bugs resistance by multivariate data analyses in soybean. **Bragantia**, v. 79, n. 2, p. 250–259, 2020.
- BRILHADOR, A.; SERRARENS, D. A.; LOPES, F. M. **A Computer Vision Approach for Automatic Measurement of the Inter-plant Spacing**. (A. Pardo, J. Kittler, Eds.) *Progress in Pattern Recognition, Image Analysis, Computer Vision, and Applications*. **Anais...**: Lecture Notes in Computer Science. Cham: Springer International Publishing, 2015.
- BUTTS, T. R. et al. Evaluation of spray pattern uniformity using three unique analyses as impacted by nozzle, pressure, and pulse-width modulation duty cycle. **Pest Management Science**, v. 75, n. 7, p. 1875–1886, 2019a.
- BUTTS, T. R. et al. Droplet size and nozzle tip pressure from a pulse-width modulation sprayer. **Biosystems Engineering**, v. 178, p. 52–69, fev. 2019b.
- CARVALHO, F. K. et al. Viscosity, surface tension and droplet size of sprays of different formulations of insecticides and fungicides. **Crop Protection**, v. 101, p. 19–23, 1 nov. 2017.
- ÇETIN, N.; SAĞLAM, C.; DEMIR, B. Determination of spray angle and flow uniformity of spray nozzles with image processing operations. **Journal of Animal and Plant Sciences**, v. 29, n. 6, p. 1603–1615, 2019.

CHENG, P. et al. On the prediction of spray angle of liquid-liquid pintle injectors. **Acta Astronautica**, The Fifth International Conference on Tethers in Space. v. 138, p. 145–151, 1 set. 2017.

D. LUCK, J. et al. Development and Evaluation of an Automated Spray Patternator Using Digital Liquid Level Sensors. **Applied Engineering in Agriculture**, v. 32, n. 1, p. 47–52, 2016.

DAFSARI, R. A.; VASHAHI, F.; LEE, J. EFFECT OF SWIRL CHAMBER LENGTH ON THE ATOMIZATION CHARACTERISTICS OF A PRESSURE-SWIRL NOZZLE. **Atomization and Sprays**, v. 27, n. 10, 2017.

DE MOURA ARAÚJO, G. et al. Sugarcane Harvesting Quality by Digital Image Processing. **Sugar Tech**, v. 23, n. 1, p. 209–218, 1 fev. 2021.

DEICHMANN, U.; GOYAL, A.; MISHRA, D. Will digital technologies transform agriculture in developing countries? **Agricultural Economics**, v. 47, n. S1, p. 21–33, 2016.

DELAVARPOUR, N. et al. A Technical Study on UAV Characteristics for Precision Agriculture Applications and Associated Practical Challenges. **Remote Sensing**, v. 13, n. 6, p. 1204, jan. 2021.

FARRENS, S. et al. PySAP: Python Sparse Data Analysis Package for multidisciplinary image processing. **Astronomy and Computing**, v. 32, p. 100402, 1 jul. 2020.

FERGUSON, J. C. et al. Assessing a novel smartphone application – SnapCard, compared to five imaging systems to quantify droplet deposition on artificial collectors. **Computers and Electronics in Agriculture**, v. 128, p. 193–198, 1 out. 2016.

FERNÁNDEZ-CAMPOS, M. et al. Wheat Spike Blast Image Classification Using Deep Convolutional Neural Networks. **Frontiers in Plant Science**, v. 12, 2021.

FUNG, M. C. et al. CFD Modeling of Spray Atomization for a Nasal Spray Device. **Aerosol Science and Technology**, v. 46, n. 11, p. 1219–1226, 1 nov. 2012.

GATOS, B. G. Imaging Techniques in Document Analysis Processes. In: DOERMANN, D.; TOMBRE, K. (Eds.). . **Handbook of Document Image Processing and Recognition**. London: Springer London, 2014. p. 73–131.

GRIESANG, F. et al. Effect of working pressure and spacing of nozzles on the quality of spraying distribution. **Crop Protection**, v. 151, p. 105818, 1 jan. 2022.

HAMUDA, E. et al. Automatic crop detection under field conditions using the HSV colour space and morphological operations. **Computers and Electronics in Agriculture**, v. 133, p. 97–107, 1 fev. 2017.

- HÖRBE, T. A. N. et al. Optimization of Within-Row Plant Spacing Increases Nutritional Status and Corn Yield: A Comparative Study. **Agronomy Journal**, v. 108, n. 5, p. 1962–1971, 2016.
- HOSSEINY, B.; RASTIVEIS, H.; HOMAYOUNI, S. An Automated Framework for Plant Detection Based on Deep Simulated Learning from Drone Imagery. **Remote Sensing**, v. 12, n. 21, p. 3521, jan. 2020.
- JAIN, A. K. **Fundamentals of Digital Image Processing**. [s.l.] Prentice Hall, 1989.
- JANSSEN, M. et al. Event Horizon Telescope observations of the jet launching and collimation in Centaurus A. **Nature Astronomy**, v. 5, n. 10, p. 1017–1028, out. 2021.
- JEDELSKY, J. et al. Air–liquid interactions in a pressure-swirl spray. **International Journal of Heat and Mass Transfer**, v. 121, p. 788–804, 1 jun. 2018.
- JEKEL, C. F. et al. Similarity measures for identifying material parameters from hysteresis loops using inverse analysis. **International Journal of Material Forming**, v. 12, n. 3, p. 355–378, 1 maio 2019.
- JEON, J. et al. Experimental Study on Spray Characteristics of Gas-Centered Swirl Coaxial Injectors. **Journal of Fluids Engineering**, v. 133, n. 12, 23 dez. 2011.
- JIN, X. et al. Estimates of plant density of wheat crops at emergence from very low altitude UAV imagery. **Remote Sensing of Environment**, v. 198, p. 105–114, set. 2017.
- KARAYEL, D. et al. Laboratory measurement of seed drill seed spacing and velocity of fall of seeds using high-speed camera system. **Computers and Electronics in Agriculture**, v. 50, n. 2, p. 89–96, 1 fev. 2006.
- KARLEKAR, A.; SEAL, A. SoyNet: Soybean leaf diseases classification. **Computers and Electronics in Agriculture**, v. 172, p. 105342, 1 maio 2020.
- KOOIJ, S. et al. What Determines the Drop Size in Sprays? **Physical Review X**, v. 8, n. 3, p. 031019, 20 jul. 2018.
- L. TANG; L. F. TIAN. Plant Identification in Mosaicked Crop Row Images for Automatic Emerged Corn Plant Spacing Measurement. **Transactions of the ASABE**, v. 51, n. 6, p. 2181–2191, 2008.
- LEI, X. et al. Seed motion characteristics and seeding performance of a centralised seed metering system for rapeseed investigated by DEM simulation and bench testing. **Biosystems Engineering**, v. 203, p. 22–33, mar. 2021.
- LI, H. et al. Video and image classification using atomisation spray image patterns and deep learning. **Biosystems Engineering**, v. 200, p. 13–22, 1 dez. 2020.
- LIU, S. et al. A method to estimate plant density and plant spacing heterogeneity: application to wheat crops. **Plant Methods**, v. 13, n. 1, p. 38, dez. 2017.

- MAHAJAN, S.; DAS, A.; SARDANA, H. K. Image acquisition techniques for assessment of legume quality. **Trends in Food Science & Technology**, v. 42, n. 2, p. 116–133, 1 abr. 2015.
- MARANGONI, A.; DA COSTA FERREIRA, M. Influence of working pressure and spray nozzle on the distribution of spray liquid in manual backpack sprayers. **Arquivos do Instituto Biológico**, v. 86, 2 dez. 2019.
- MARCAL, A. R. S.; CUNHA, M. Development of an image-based system to assess agricultural fertilizer spreader pattern. **Computers and Electronics in Agriculture**, v. 162, p. 380–388, 1 jul. 2019.
- MARINELLO, F. et al. Application of the Kinect sensor for dynamic soil surface characterization. **Precision Agriculture**, v. 16, n. 6, p. 601–612, 1 dez. 2015.
- MARTINEZ-AGIRRE, A.; ÁLVAREZ-MOZOS, J.; GIMÉNEZ, R. Evaluation of surface roughness parameters in agricultural soils with different tillage conditions using a laser profile meter. **Soil and Tillage Research**, v. 161, p. 19–30, 1 ago. 2016.
- MASSOLA, M. P. et al. Spray volume distribution pattern and droplet size spectrum from ceramic nozzles. **Revista Brasileira de Engenharia Agrícola e Ambiental**, v. 22, p. 804–809, nov. 2018.
- MIRHAJI, H. et al. Fruit detection and load estimation of an orange orchard using the YOLO models through simple approaches in different imaging and illumination conditions. **Computers and Electronics in Agriculture**, v. 191, p. 106533, 1 dez. 2021.
- NAKARMI, A. D.; TANG, L. Automatic inter-plant spacing sensing at early growth stages using a 3D vision sensor. **Computers and Electronics in Agriculture**, v. 82, p. 23–31, 1 mar. 2012.
- NALLY, D. Against Food Security: On Forms of Care and Fields of Violence. **Global Society**, v. 30, n. 4, p. 558–582, 1 out. 2016.
- NGUGI, L. C.; ABELWAHAB, M.; ABO-ZAHHAD, M. Recent advances in image processing techniques for automated leaf pest and disease recognition – A review. **Information Processing in Agriculture**, v. 8, n. 1, p. 27–51, 1 mar. 2021.
- NIXON, M. S.; AGUADO, A. S. 3 - Image processing. In: NIXON, M. S.; AGUADO, A. S. (Eds.). **Feature Extraction and Image Processing for Computer Vision (Fourth Edition)**. [s.l.] Academic Press, 2020. p. 83–139.
- OSCO, L. P. et al. A CNN approach to simultaneously count plants and detect plantation-rows from UAV imagery. **ISPRS Journal of Photogrammetry and Remote Sensing**, v. 174, p. 1–17, 1 abr. 2021.
- PRINCEN, J.; ILLINGWORTH, J.; KITTLER, J. A formal definition of the Hough transform: Properties and relationships. **Journal of Mathematical Imaging and Vision**, v. 1, n. 2, p. 153–168, 1 jul. 1992.

ROSE, D. C. et al. Agriculture 4.0: Making it work for people, production, and the planet. **Land Use Policy**, v. 100, p. 104933, 1 jan. 2021.

S. D. KACHMAN; J. A. SMITH. Alternative Measures of Accuracy in Plant Spacing for Planters Using Single Seed Metering. **Transactions of the ASAE**, v. 38, n. 2, p. 379–387, 1995.

SARKAR, S.; KARMIN, S.; KRUGER, G. R. **Spray characterization by optical image analysis**. . In: ASTM SPECIAL TECHNICAL PUBLICATION. 2016. Disponível em: <<https://www.scopus.com/inward/record.uri?eid=2-s2.0-85033714213&doi=10.1520%2fSTP159520160036&partnerID=40&md5=49dc6365fd544730260955807554ab87>>

SCHULZ, F. et al. A measuring system for monitoring multi-nozzle spraying tools. v. 32, n. 5, p. 055902, mar. 2021.

SHI, Y. et al. Automatic corn plant location and spacing measurement using laser line-scan technique. **Precision Agriculture**, v. 14, n. 5, p. 478–494, 1 out. 2013.

SHI, Y. et al. Improvement of a ground-LiDAR-based corn plant population and spacing measurement system. **Computers and Electronics in Agriculture**, Precision Agriculture. v. 112, p. 92–101, 1 mar. 2015.

SIJS, R. et al. Drop size measurement techniques for sprays: Comparison of image analysis, phase Doppler particle analysis, and laser diffraction. **AIP Advances**, v. 11, n. 1, p. 015315, 1 jan. 2021.

SPARROW, R.; HOWARD, M. Robots in agriculture: prospects, impacts, ethics, and policy. **Precision Agriculture**, 23 out. 2020.

TEH, C.-H.; CHIN, R. T. **On image analysis by the methods of moments**. Proceedings CVPR '88: The Computer Society Conference on Computer Vision and Pattern Recognition. **Anais...** In: PROCEEDINGS CVPR '88: THE COMPUTER SOCIETY CONFERENCE ON COMPUTER VISION AND PATTERN RECOGNITION. Ann Arbor, MI, USA: IEEE Comput. Soc. Press, 1988. Disponível em: <<http://ieeexplore.ieee.org/document/196290/>>. Acesso em: 2 abr. 2021

TIAN, H. et al. Computer vision technology in agricultural automation —A review. **Information Processing in Agriculture**, v. 7, n. 1, p. 1–19, 1 mar. 2020.

VALENTE, J. et al. Automated crop plant counting from very high-resolution aerial imagery. **Precision Agriculture**, v. 21, n. 6, p. 1366–1384, 1 dez. 2020.

VAN DER WALT, S. et al. scikit-image: image processing in Python. **PeerJ**, v. 2, p. e453, 19 jun. 2014.

VONG, C. N. et al. Corn emergence uniformity estimation and mapping using UAV imagery and deep learning. **Computers and Electronics in Agriculture**, v. 198, p. 107008, 1 jul. 2022.

WANG, S. et al. Effects of Adjuvants on Spraying Characteristics and Control Efficacy in Unmanned Aerial Application. **Agriculture**, v. 12, n. 2, p. 138, fev. 2022.

XIA, L. et al. **Performance Monitoring System for Precision Planter Based on MSP430-CT171**. (D. Li, Y. Liu, Y. Chen, Eds.) Computer and Computing Technologies in Agriculture IV. **Anais...**: IFIP Advances in Information and Communication Technology. Berlin, Heidelberg: Springer, 2011.

ZHANG, N. et al. Skin cancer diagnosis based on optimized convolutional neural network. **Artificial Intelligence in Medicine**, v. 102, p. 101756, 1 jan. 2020.

ZHANG, Q. et al. Maize yield and quality in response to plant density and application of a novel plant growth regulator. **Field Crops Research**, v. 164, p. 82–89, 1 ago. 2014.

ZHANG, X. et al. Yield estimation of citrus fruit using rapid image processing in natural background. **Smart Agricultural Technology**, v. 2, p. 100027, 1 dez. 2022.

ZHAO, L. et al. Effect of soil surface roughness on infiltration water, ponding and runoff on tilled soils under rainfall simulation experiments. **Soil and Tillage Research**, v. 179, p. 47–53, 1 jun. 2018.

ZHOU, Q. et al. Prediction of Spray Angle from Flat Fan Nozzles. **Journal of Agricultural Engineering Research**, v. 64, n. 2, p. 139–148, 1 jun. 1996.

ZHOU, Z. et al. Numerical simulations of water spray on flame deflector during the four-engine rocket launching. **Advances in Space Research**, v. 65, n. 4, p. 1296–1305, 15 fev. 2020.

ZHU, H.; SALYANI, M.; FOX, R. D. A portable scanning system for evaluation of spray deposit distribution. **Computers and Electronics in Agriculture**, v. 76, n. 1, p. 38–43, 1 mar. 2011.

CHAPTER 4 – FINAL CONSIDERATIONS

High-complexity approach became trend in digital systems for agricultural purposes. The urge for developing innovative and robust methods timely contributes for solving complex problems. With the emerging of powerful hardware components and cloud systems, computing resource is no longer a problem for developing such methods in most cases. However, this reality is not suitable in many regions. Its use for minor problems cannot be appealing precisely because of the lack of proportionality. Because of financial costs of high-tech systems, low-income producers continue to use traditional methods. Moreover, some products are not only inaccessible but also inflexible. If we really are concerned about sustainable technology, our mind must go beyond development to better understand the application and its consequences. Specifically, in this work we followed the Sustainable Development Goals 9 'Industry, Innovation and Infrastructure' and 10 'Reduced Inequalities'.

We think that because its widespread use, smartphone is key for bringing digital tools for low-income regions. Smartphones are user-friendly, flexible and multitask technologies. When synchronized with cloud computing, it becomes a powerful system able to work in many fields. Otherwise, some methods are unhandy and requires more than one equipment to acquire and process data. Our hypothesis of developing image-based methods has proven true when compared to traditional methods. Planting assessments can now be performed using simple smartphones, although images should be taken at early stages of plant growth to avoid leaves overlapping. A plus from our methods besides low-cost is the flexibility, as the user can adjust the color system to detect only plants and does not depend on data training. However, the methods lack mosaicking and can be hard to use without a mobile application. In the same way, spray nozzles macro characteristics can now be assessed under indoor and outdoor conditions. Our guidelines and insights are timely in this segment. However, our methods did not characterize correctly spray distribution from hollow cones working at low pressures. We also did not test using extremely coarse droplets, which can change image characteristics.

Overall, our insights can be useful not only for planting or spraying purposes, but also for other assessments that requires characterization of elements in digital

images. Futures works should further automate our framework and make it available in smartphone applications with user-friendly interfaces. Moreover, several other agricultural operations can benefit of quick, non-invasive measurements and should be studied.