Revista Ciência Agronômica, v. 51, Special Agriculture 4.0, e20207748, 2020
Centro de Ciências Agrárias - Universidade Federal do Ceará, Fortaleza, CE
www.ccarevista.ufc.br

Artigo Científico
ISSN 1806-6690

UAV applications in Agriculture 4.0

Aplicações de UAVs na Agricultura 4.0

Lucas Rios do Amaral[1]*, Cristiano Zerbato[2], Rodrigo Greggio de Freitas[3], Marcelo Rodrigues Barbosa Júnior[4] and Isabela Ordine Pires da Silva Simões[5]

ABSTRACT - Unmanned Aerial Vehicles (UAVs) have potentially significant application in agriculture and, with the emergence of the digital farming era and Agriculture 4.0, this platform has become increasingly important. UAV imagery may improve or even replace routine data surveys, as well as optimize phytosanitary product application. High-spatial resolution imagery makes UAVs attractive for several applications where traditional satellite sensing is still unsuitable. With the significant recent development of data science techniques, UAVs have a prominent position in assisting farmers for more efficient decision-making and automating agricultural processes. Thus, this work addresses the main agricultural applications of UAVs into five major topics: topographic survey, physiological assessments, biophysical assessments, monitoring of biological targets, and spraying of phytosanitary products and application of bio inputs.

Key words: Drones. RPA. Digital Agriculture. Precision Agriculture. Remote Sensing.

RESUMO - As potencialidades de uso de UAVs na agricultura são enormes e, com a entrada na era da digitalização das lavouras e da Agricultura 4.0, essa plataforma tem ganhado cada vez mais importância. Levantamento rotineiros de dados em campo podem ser melhorados ou mesmo substituídos por imagens obtidas via UAVs e as aplicações de produtos fitossanitários podem ser otimizados. A altíssima resolução espacial das imagens torna os UAVs atrativos para diversas aplicações que o tradicional sensoriamento via satélite ainda não atendem. Ainda, com o enorme desenvolvimento recente das técnicas e aplicações de ciência dos dados, os UAVs têm posição de destaque para auxiliar o agricultor na tomada de decisão mais eficiente e na viabilização da automação de processos agrícolas. Assim, neste trabalho abordaremos as principais aplicações dos UAVs na agricultura, dividindo o texto em cinco grandes tópicos: Levantamento topográfico, Avaliações fisiológicas, Avaliações biofísicas, Monitoramento de alvos biológicos, e Pulverização de produtos fitossanitários e aplicação de bioinsumos.

Palavras-chave: Drones. ARP. Agricultura Digital. Agricultura de Precisão. Sensoriamento Remoto.

DOI: 10.5935/1806-6690.20200091
Editores do artigo: Professor Daniel Albiero - daniel.albiero@gmail.com e Professor Alek Sandro Dutra - alekdutra@ufc.br

* Author for correspondence
[1]Professor Doutor, Faculdade de Engenharia Agrícola, Universidade Estadual de Campinas/UNICAMP, Campinas-SP, Brasil, lucas.amaral@feagri.unicamp.br (ORCID ID 0000-0001-8071-4449)
[2]Professor Doutor, Departamento de Engenharia Rural, Escola de Ciências Agrárias e Veterinárias, Universidade Estadual Paulista/UNESP, Jaboticabal-SP, Brasil, cristiano.zerbato@unesp.br (ORCID ID 0000-0002-4534-5454)
[3]Mestrando do Programa de Pós-Graduação em Engenharia Agrícola, Faculdade de Engenharia Agrícola, Universidade Estadual de Campinas/UNICAMP, Campinas-SP, Brasil, r228594@dac.unicamp.br (ORCID ID 0000-0002-9787-2678)
[4]Mestrando do Programa de Pós-Graduação em Produção Vegetal, Escola de Ciências Agrárias e Veterinárias, Universidade Estadual Paulista/UNESP, Jaboticabal-SP, Brasil, marcelo.junior@unesp.br (ORCID ID 0000-0002-7207-2156)
[5]Doutoranda do Programa de Pós-Graduação em Engenharia Agrícola, Faculdade de Engenharia Agrícola, Universidade Estadual de Campinas/UNICAMP, Campinas-SP, Brasil, i117271@dac.unicamp.br (ORCID ID 0000-0002-8350-8242)

INTRODUCTION

To feed the world population estimated to reach nearly 10 billion people by 2050, the world agricultural productivity must increase between 14 and 28%, according to the United Nations Food and Agriculture Organization (FAO, 2018), posing a challenge for agriculture. To assist in this endeavor, technology has been increasingly used in the field, outlining the terms Precision Agriculture (PA), Digital Agriculture (DA), and Agriculture 4.0 (Agri 4.0). Although DA and Agri 4.0 still have no clear and unanimous definition, the International Society for Precision Agriculture (ISPA) current definition of PA is quite comprehensive. This suggests that soon these terms will have no differentiation, being simply understood as an efficient and sustainable way of practicing agriculture: “Precision Agriculture is a management strategy that gathers, processes and analyzes temporal, spatial, and individual data and combines it with other information to support management decisions according to estimated variability for improved resource use efficiency, productivity, quality, profitability and sustainability of agricultural production.” Such approach leads to an intense “agricultural digitalization” by various types of data collected from multiple sources, such as soil, plant, climate, relief and several other factors, making data science and information technology application mandatory in agriculture to support proper decision making.

Among the diverse data sources for a more sustainable and technological agriculture (generalized in this text as Agri 4.0), we may stress the different remote sensing (RS) technologies. Remote sensing is the act of acquiring information about a target without being in contact with it. In the case of agriculture, sensors and cameras coupled to different platforms can be used to monitor or map an area by RS. Such platforms are divided into orbital (satellites), aerial (planes and Unmanned Aerial Vehicles - UAVs), and terrestrial (including those carried or pulled by agricultural machinery). *Orbital platforms have evolved significantly in recent years, continuously providing products with several agriculture applications while improving the quality of spatial, spectral, and temporal resolutions. Similarly, RS using terrestrial platforms has evolved significantly in terms of sensors and applications. UAVs are up-and-coming tools for use in agriculture, mainly due to their diverse applications (TSOUROS *et al*., 2019; YANG *et al*., 2017), being one of the Agri 4.0 techniques that have developed the most in recent years. This is explained by the fact that, depending on the desired application, acquiring data by UAVs (usually images) has several advantages over other platforms, such as its flexibility. For example, users can choose the UAV-Sensor set that best fits their needs and define the flight plan according to specific situations and desired image quality, ensuring data quality for the most diverse applications. An obstacle to the use of this technology is the high computational requirements for data processing, especially for large areas and/or high-resolution images. However, these complications tend to decrease with the development of big data and the Internet of Things (IoT).

To define the best UAV-Sensor set, one must understand the intended application for the equipment. Different characteristics must be considered in selecting an UAV, especially regarding their performance (coverage area per time unit), autonomy (flight time without interruption for refueling or recharging), and load capacity (sensor or payload that must be transported). The coupled sensor must be defined based on the RS survey objective and primarily on the spectral band at which the sensor works. Sensors that work with the visible spectrum are limitedly applicable to what the human eye is capable of differentiating. On the other hand, multispectral sensors, which also comprise the infrared spectrum, provide greater sensitivity to changes in vegetation vigor, plant canopy, and soil moisture. Hyperspectral sensors have narrower bands and in greater quantity, increasing target recognition potential based on their spectral behavior, besides enabling better predictive results with the use of machine-learning algorithms. Thermal sensors have great potential for tracing stresses, such as water deficit and pests attack, despite several factors interfering with their measurements. Thus, choosing the sensor with the appropriate characteristics for the desired purpose is essential to acquire useful and efficient information for Agri 4.0 decision-making.

Considering that, this work is a literature review on studies addressing UAVs main agricultural applications and their peculiarities. This paper is divided into five general UAVs agricultural applications: topographic survey, physiological assessments, biophysical assessments, monitoring of biological targets, and spraying of phytosanitary products and application of bio inputs.

TOPOGRAPHIC SURVEY

Topographic data is widely used as strong supporting information in several research fields and civil applications, such as environmental management and landscape planning (PIJL *et al*., 2020). Advances in photogrammetry techniques, often used to assist topographical surveys, were driven by remote sensing technology; for example, detailed three-dimensional reconstructions of landscapes are used to calculate erosion volume (MEINEN; ROBINSON, 2020a).

The modernization of remote sensing techniques for topography makes data increasingly accessible and accurate. The main output of such approach is the Digital Elevation Model (DEM), which represents continuous elevations over a topographic surface defined in two ways: the model that contains aboveground information such as vegetation cover, known as Digital Surface Model (DSM); and the model containing purely ground information (i.e., soil surface modeling), known as Digital Terrain Model (DTM). The height difference between DTM and a DSM may generate a third model, such as the canopy height model (CHM - PIJL *et al*., 2020).

DEMs based on UAV imagery were previously applied only in urban areas but are now useful for agricultural applications. An example of this is the “motion structure” technique, used to generate a 3D point cloud from a combination of overlapped 2D images, widely used to trace and quantify erosion on agricultural fields (CÂNDIDO *et al*., 2020; GIANNETTI *et al*., 2020; MEINEN; ROBINSON, 2020a). Regarding plant measurements, Millan *et al.* (2020) showed that 3D digital reconstruction of plant canopies enables the detection of abrupt changes in their inclination angle, which may be related to canopy damage. Such crop biophysical assessment will be addressed later in this text.

Acquired images need to be georeferenced for an accurate photogrammetry approach based on the aerial mapping. However, georeferencing precision and accuracy vary according to the type of Global Navigation Satellite System (GNSS) embedded in the UAV. The most common and affordable UAVs contain a GNSS only for navigation purposes - precise on a metric scale but insufficient for high-precision surveying (centimeter or even millimeter), - as most topographic applications. The ground control points (GCPs) approach provides high-precision mapping, as observed by Meinen and Robinson (2020b) when mapping erosion in an agricultural landscape. Despite their efficiency, other studies consider GCPs as a disadvantage of UAV technology, deeming its field acquisition as time-consuming and laborious, while no quantity and distribution standard guarantees maximum accuracy (REN *et al*., 2020). Considering this, some popular positioning techniques are used to improve GNSS, such as the real-time kinematic correction (RTK) and the post-processed kinematic correction (PPK). While RTK is applied simultaneously during the flight, PPK corrects positioning during post processing, back at the office. Studies show RTK and PPK positioning systems to provide higher quality positioning for UAVs than GCPs for a correct georeferencing (TOMAŠTÍK *et al*., 2019; WOO *et al*., 2018). However, even with the use of RTK or PPK, more in-depth research are require to obtain maximum positioning accuracy, ensuring sub-centimeter-level accuracy in the obtained DEMs. Yet, Forlani *et al*. (2018) argue that GCPs are necessary despite RTK-enabled UAVs, possibly due to the stability of the camera calibration parameters.

PHYSIOLOGICAL ASSESSMENTS

Spatial and temporal information about crop vigor and development, especially during the growing season, can optimize site-specific management, improving inputs efficiency (e.g., applying nutrients and phytosanitary products - NÄSI *et al*., 2018; MODICA *et al*., 2020). Data on these characteristics may be acquired using UAV-embedded sensors. The sensors can easily capture pants reflectance behavior and, through data analysis, guide decision-making. In some cases, plants may show easily identifiable behavior, such as withering, yellowing, reduced growth, etc., enabling inspection by visible spectrum and field campaigns. However, some behaviors can only be identified using sensors capable of capturing specific reflectance signals, acquired by multi-spectral or hyperspectral sensors. Below, we describe some applications of these types of sensors in detecting water stress and quantifying plants vigor and nutritional status.

Water stress

The flexibility enabled by UVAs in comparison to manually obtained data - such as by the use of infrared thermometers, which impairs plant properties mapping due to the limited amount of data (CRUSIOL *et al*., 2020), - fostered the conduction of several studies to assess crops water stress. Thus, the successful application of UAV technology is an attractive alternative for irrigation management based on the use of thermal imaging to measure crop canopy temperature (KING *et al*., 2021). Likewise, the daily monitoring of plant water status, estimated by shortwave-infrared bands (KANDYLAKIS *et al*., 2020), enables measuring plant physiological responses to water stress (IHUOMA; MADRAMOOTOO, 2019). Studies show the increasing use of thermal cameras coupled to UAVs, especially to measure canopy leaves withering (ZHOU *et al*., 2020). Besides measuring crop canopy, this technique is also applicable for estimating water demand based on soil surface temperature observation (HEINEMANN *et al*., 2020). Multi-spectral sensor imaging can also assist in identifying plant genotypes susceptible and tolerant to water stress, as plants spectral behavior is a well-established detector of changes in canopy structure and growth (SHENDRYK *et al*., 2020). Maimaitijiang *et al*.

(2020) integrated thermal images with multispectral sensors data to forecast soybean crops and obtained better results when compared with the use of a single sensor.

Vigor and nutrition of the plants

The classic approach for remote sensing, including UAV imagery, involves using multispectral sensors and calculating different vegetation indices related to plant physiological status, such as plant pigment concentration, vigor, aboveground biomass, stress (BUCHAILLOT *et al*., 2019; GARCÍA-MARTÍNEZ *et al*., 2020). Spectral data is most commonly used by combining individual bands, usually including the infrared (IR) band due to its sensitivity to vigor vegetation variation, constituting vegetation indices (VIs). More than one hundred VIs have been recently developed to investigate vegetation biophysical and chemical properties (XUE; SU, 2017).

The analysis of plant nutritional status by UAV remote sensing allow us to highlight some relevant information, especially regarding the management of nitrogen fertilization, considered the most demanded nutrient for plant growth, development, and quality (LIU *et al*., 2017). Quantifying the variability in terms of nitrogen status and plant growth during the growing season can determine whether variable-rate applied fertilizer is worth being implemented in the field (ARGENTO *et al*., 2020). This topic has been recently addressed by Yang *et al*. (2020) on wheat, Thompson and Puntel (2020) on maize, Zheng *et al*. (2020) on rice, and Grüner *et al*. (2020) on legume-grass mixtures.

VIs present variable sensitivities to variations in the plant canopy and their efficiency in measuring plant vigor relies on some plant properties, such as leaf area index, leaf chlorophyll content, and crop phenological stage (OLSON *et al*., 2019). Among the VIs, the normalized difference vegetation index (NDVI) is traditionally the most widespread (HASSAN *et al*., 2019) for providing good agronomic inferences for most grain crops during the early growth stages. However, NDVI often loses sensitivity during the most advanced growth stages due to the high leaf area index and relative canopy homogeneity (SULIK; LONG, 2016; YUE *et al*., 2019). In this case, the main problem is at the red band, as its reflectance reaches a very low level in situations with high canopy cover (FU *et al*., 2014), losing the ability to differentiate crop vigor, which is known as “saturation.” Thus, the red-edge band has been preferred in detriment of the red band, resulting in the normalized difference red-edge (NDRE) index.

In contrast to the saturation effect problem, low canopy cover in the early growth stages may cause problems related to mixed-pixels, i.e., the same pixel contains reflectance information from both plant and soil. To improve the performance of VI-based quantifications and target classification, approaches based on computer vision have been tested. Ballasteros *et al*. (2020) found that computer vision techniques should be applied to UAV multispectral images to extract useful information for eliminating noise sources, such as the soil effect.

Given the higher cost incurred by multispectral sensors with bands in the infrared, several UAV users tend to opt for RGB cameras, so that several vegetation indices have been proposed for this sensor (GARCÍA-MARTÍNEZ *et al*., 2020; DU; NOGUCHI, 2017; SCHIRRMANN *et al*., 2016). The triangular greenness index (TGI), for example, was developed to be sensitive to leaf chlorophyll content, applicable to nitrogen management (HUNT *et al*., 2012). Some users have modified RGB cameras to use more traditional VIs, such as NDVI, by removing the blue band and including the near infrared band. However, such procedure is limited for two reasons: 1) the absence of the blue band prevents images from being generated in true color composition, possibly compromising visual photointerpretation; 2) the reflectance measured by the modified infrared band present some calibration issues (NIJLAND *et al*., 2014; ZHANG *et al*., 2020). According to Nijland *et al*. (2014), cameras with such modification should be avoided, recommending the original RGB cameras for reliable detection and monitoring of plant stress, growth, and phenology. Vergara-Diaz *et al*. (2015) presented a RGB image-based approach to predict grain yield, quantify nutrient deficiencies, and measure the impacts of yellow rust based on vegetation indices using two methods: green area (GA) and greener area (GAA); both quantify the number of green pixels in the image, but the second does so by excluding yellowish-green tones. The authors found both methods to show robust and reliable results, comparable to predictions made using NDVI and agronomic quantifications in the field.

BIOPHYSICAL ASSESSMENTS

Information on the variability of the crop biophysical attributes, such as growth stage, biomass accumulation, and general crop conditions, are highly useful for farmers to monitor their crops development and plan further management, such as determining the timing of inputs application and the harvest beginning. Although UAV have many applications in Agri 4.0, estimating biomass, nutrient demand, and productivity is undoubtedly among the most popular uses (HASSLER; BAYSAL-GUREL, 2019). Accordingly, point clouds and 3D modeling have been used in agriculture mainly to estimate aboveground biomass (AGB), model tree structure and crop canopies, and detect weed (HASSLER; BAYSAL-GUREL, 2019). 3D vegetation height models proved to be a reasonable estimate of the height of cereal crops (BROCKS, 2018; WATANABE *et al*., 2017) and orchards (DÍAZ-VARELA *et al*., 2015; DILLEN *et al*., 2016); combining vegetation height estimates with one or more VIs from multispectral data provided reasonable AGB estimates (BENDIG *et al*., 2015; YUE *et al*., 2017). To this end, different sensors and image processing techniques can be used for 3D modeling.

Depth sensors are within the set of sensors that can be embedded in UAV for agricultural applications, generating point clouds and 3D models. Among these sensors, two technologies stand out: the Light Detection and Ranging (LiDAR) technology, often called laser scanning, and RGB-D cameras. RGB-D cameras are a relatively inexpensive and effective way to generate depth data, capturing an extra value in each RGB pixel – which indicates the distance from the sensor to that point in the image (CHÉNÉ *et al*., 2012; SHANI; VIT, 2018; WANG; LI, 2014). For that, an active sensor is used to measure the distance between the sensor and the target on the ground, estimating the time delay from signal emission (target reflectance) until its detection by the sensor itself (SARBOLANDI *et al*., 2015). The KINECT 2.0 (Microsoft Corporation, Redmond, WA, USA), the Xbox One video game console technology, is probably the best-known sensor for this purpose.

A simpler alternative than the two aforementioned technologies is the processing of high-resolution images associated with the 'Structure from Motion' (SfM) algorithms to generate dense point clouds and 3D models. The key to this method is the ability to calculate camera position, orientation, and geometry from a set of overlapped images that capture the scene complete three-dimensional structure from a wide range of positions or, as the name suggests, images derived from sensor motion (JAMES *et al*., 2014). Several authors agree that a negative aspect of this technology is the demand for images with high overlap degree and wide distribution of GCPs to obtain reliable 3D models. However, higher spatial resolution images improve models accuracy (HOLMAN *et al*., 2016) and RGB cameras are sufficient for such application, incurring low acquisition costs.

The literature contains several studies approaching plant height estimation using LiDAR sensors (JIMENEZ-BERNI, 2018), RGB-D sensors (CHÉNÉ *et al*., 2012; SHANI; VIT, 2018; WANG; LI, 2014), and RGB sensors with image processing by SfM algorithm (HASSAN *et al*., 2019a; HASSLER; BAYSAL-GUREL, 2019; HOLMAN *et al*., 2016; HU *et al*., 2018; MADEC *et al*., 2017; BROCKS, 2018; WATANABE *et al*., 2017; DÍAZ-VARELA *et al*., 2015; DILLEN *et al*., 2016). Plant height is an important variable to assess the general condition of crops and assist in productivity estimates (LAZCANO; DOMÍNGUEZ, 2011), as well as in providing a good approximation for biomass estimation (BENDIG *et al*., 2014; OTA *et al*., 2015; TILLY *et al*., 2015). Stem height seems to be sensitive to stresses caused to the crop and is also an input variable for models used for assessing water stress (BLONQUIST *et al*., 2009) and crop susceptibility to damping off (BERRY *et al*., 2003). Considering that, such estimates may provide meaningful canopy structure inferences, especially attractive for field phenotyping (MADEC *et al*., 2017). Individual plant height or canopy height can be obtained by extracting the highest points detected in the dense point cloud.

Some authors highlight the inability to isolate plants singular details in models generated from data obtained by UAV due to their movement during image acquisition, probably due to wind (WILLKOMM *et al*., 2016). Such movement may cause changes in plant structure, which may explain height underestimation by models (MADEC *et al*., 2017). Hassan *et al*. (2019a) reported SfM to underestimate plant height in relation to estimates obtained by LiDAR sensor embedded in terrestrial vehicle, attributing such finding to UAV images coarser spatial resolution and SfM limited ability to penetrate plant canopy when compared to LiDAR point cloud. Canopy structure and density were also found to influence final estimates (GEIPEL *et al*., 2014).

An important point about the 3D modeling using UAVs is that plant height and canopy volume measurement depends on the appropriate digital terrain model (DTM) acquisition, used to assess soil surface profile (the point cloud lowest limit). The most common methods used to assess DTM are: 1) interpolation and adjustment of the terrain surface using GCPs and traditional topographic surveying techniques (Method 1 - WEISS; BARET, 2017); 2) pixel segmentation of the digital surface model (DSM) collected during crop development, discriminating vegetation from soil pixels (Method 2 - GEIPEL *et al*., 2014); and 3) DTM obtained by pre-planting or post-harvesting flights (BENDIG *et al*., 2013; HOLMAN *et al*., 2016; WU *et al*., 2017), when there is no above-ground vegetation (Method 3). Alternatively, DTM can also be obtained by interpolating position records acquired during any agricultural operation as long as the vehicle is equipped with high-accuracy GNSS (Method 4). Madec *et al*. (2017) compared plant height estimates based on the DTM provided by interpolated position records during planting and those provided by DSM pixels segmentation (Method 2), obtaining similar performance between the methods. Holman *et al*. (2016) compared plant height estimates obtained by Method 2 and Method 3, with DTM obtained by post-harvest terrain point cloud, and found better estimates for Method 2. This result might be explained by the fact that whenever DEM construction contains bias, this bias will be present in both DTM and DSM, canceling its influence. However, when DTM and DSM data are collected at different times, such as post-harvesting, several issues may influence the result, such as variations in flight characteristics, images collection and processing, as well as changes in the soil surface itself, altering such bias and influencing DSM calculation.

Field measurements of aboveground biomass (AGB) are particularly problematic to acquire due to the laborious and destructive methods required to assess it. Nondestructive methods to estimate AGB have been extensively investigated using 2D images and VIs (HASSAN *et al*., 2019b; HASSLER; BAYSAL-GUREL, 2019; MARINO; ALVINO, 2019; VILJANEN; HONKAVAARA, 2018), but few studies are investigating the use of 3D methods for this purpose. Walter *et al*. (2018) found good AGB estimates in wheat plots using RGB camera embedded in UAV to measure canopy volume and height. Other studies estimated grass biomass using 3D models and found good correlations with actual values (CHANG *et al*., 2017; GRÜNER *et al*., 2019). Good AGB estimates were also obtained by combining 3D vegetation height estimates with VIs from multispectral data (BENDIG *et al*., 2015; YUE *et al*., 2017).

Temporal crop monitoring is also an interesting application. Several 3D point clouds generated during harvest may enable modeling plant growth or abrupt changes in their development, called 4D point clouds (HASSAN *et al*., 2019a; HASSLER; BAYSAL-GUREL, 2019; HOLMAN *et al*., 2016).

Another exciting agricultural application of UAVs is the fast and efficient counting of plants, fruits, and others. Rahnemoonfar and Sheppard (2017) employed a UAV-based fruit counting method in a citrus crop. They used VI to segment treetops from images background and then implemented a counting method based on canopies mean green area. She *et al*. (2014) studied a similar proposal to quantify Christmas trees, where the algorithm sought to locate and count the maximum reflectance locations within the moving split windows of trees conical tops. Years later, these researchers published another paper addressing measuring issues in areas densely covered by plants and describing a method for accurate counting in these environments based on the Support Vector Machine algorithm (SHE *et al*., 2018). Chen *et al*. (2017) also demonstrated that computer vision and deep learning algorithms could count apples and oranges using UAV-acquired images.

MONITORING OF BIOLOGICAL TARGETS

Identifying agents that depreciate agricultural production – such as weeds, insect pests, and phytopathogenic agents (plant diseases) - is a routine and mandatory task to promote proper phytosanitary treatment and ensure crop productivity. The methods for on-site identification of these agents are usually manual and require sampling efforts to make a field assessment representative. Given UAV operational performance and high spatial resolution, its use for performing such diagnosis seeks to automate and ensure greater representativeness of the evaluations, remediating satellite monitoring deficiencies. Making this application viable via UAV-embedded sensors pose some challenges regarding the identification of characteristics that directly or indirectly differentiate the targets, their proper classification, and the promotion of automated learning by computational means.

Good quality imagery allows proper characterizations of scenes and targets. Thus, the high spatial resolution images of UAV potentially increases investigation accuracy, as the phenomenon to be identified can be captured by pure pixels (YE *et al*., 2020). This process enables target individualization and contributes to proper target identification, as shown by López-Granados *et al*. (2016) with *Sorghum halepense* plants, individually identified with pixels of 0.01 to 0.04 m. However, these authors stress that quality orthomosaics with high spatial resolution require many images, resulting in longer flights and post-imaging processing with high computational cost.

The spectral quality of the embedded sensors also influences identification results. Castaldi *et al*. (2017) observed that narrow bands of multispectral sensors were more relevant than spatial resolution to identify weeds and produce herbicide prescription maps. Helminthsporiosis severity in wheat was classified by identifying symptom characteristics in RGB images with a spatial resolution of 0.034 m (HUANG *et al*., 2019), but specific wavelengths of a hyperspectral sensor were used to identifying two tomato diseases and quantifying the severity of symptoms (ABDULRIDHA *et al*., 2019). Thermal bands, which have a coarser spatial resolution, are less frequently used. However, integrating their spectral information to other spectral bands may improve diseases and pests identification, even in the early stages, given the sensitivity to plants physiological changes (MESSINA; MODICA, 2020).

For choosing a sensor, one must consider not only the efficiency in recording target behavior, but also differences in operational imaging performance. For example, multispectral sensors must fly at lower altitudes to obtain the same spatial resolution of an RGB sensor, requiring more time or number of UAV flights, higher financial cost, and longer image processing time (LÓPEZ-GRANADOS *et al*., 2016). No consensus has been reached regarding the best choice among the different sensors and their potential for specific applications, as many different target and environmental factors may influence the final result. Thus, the importance of the images spatial and spectral properties varies according with targets characteristics and mapping purposes.

After ensuring the quality of images, the focus is on extracting characterization attributes, such as color, shape, texture, and statistics for the target or symptoms produced in the plant (BAH *et al*., 2018; ZHANG *et al*., 2018; SIEBRING *et al*., 2019). However, the agricultural environment is challenging due to the complexity of its elements patterns and dynamics. Spectral and phenological patterns may be similar when weeds and crops pertain to the same family (LÓPEZ-GRANADOS *et al*., 2016); in this context, considering weeds and crop positioning may assist in the identification. Positioning analysis and spatial relation among pixels enables identifying crop rows and, consequently, weed arrangements (BAH *et al*., 2018). Gao *et al*. (2018) used spatialized information on crop row and interrow space to improve weed classification as crop and weeds have similar colors and shapes in the initial stages.

For phytopathology, identifying the precise agent (e.g., fungus species) is challenging because similar symptoms can be common to several pathogens (HUANG *et al*., 2019). Specific VIs can infer some symptoms based on morphological and physiological changes that alter spectral response (XUE; SU, 2017). Abdulridha *et al*. (2019) evaluated relations that allowed the identification of early-stage citrus canker symptoms in trees and fruits using data from hyperspectral images.

Dynamic targets, such as agricultural pests, are yet more challenging due to difficulties with angle of view and focal length, even when photographing static fruit fly targets (*Drosophila suzukii*) trapped in adhesive traps (ROOSJEN *et al*., 2020). Xiao *et al*. (2018) analyzed static images of insects in public digital libraries, clearing a path for future diagnosis of pests using UAVs. However, field conditions are still very restrictive for the direct identification of pests using UAVs, so that indirect target-spectral response relations are more commonly used, as occurred with the near-infrared (NIR) response of soybean plants attacked by *Aphis glycines* (ALVES *et al*., 2019). Considering that such response may be easily confused with any other kind of stress affecting the plants and classification attributes selected in the images may vary with the algorithm and predictive model used, the selection for a given crop may not be applicable for others crops nor for changes in the calendar year, due to the introduction of new elements in the scene (BAH *et al*., 2018). These circumstances may drastically reduce the capacity of predictive models built under different conditions. Also, this biological targets identification strategy requires the supervision of experts with reasonable computational skills and knowledge about calibrating machine-learning algorithms, which is unlikely for alleged end-users, such as farmers (HUNTER *et al*., 2020).

Although various classifier algorithms such as support vector machine (SVM) and random forest (RF) have been applied with relative success (CASTALDI *et al*., 2017; CAO *et al*., 2018), deep learning (DL) techniques have shown more exciting results for complex classification (WIESNER-HANKS *et al*., 2019; ROOSJEN *et al*., 2020) such as agricultural issues. One of DL advantages is its automatic hierarchical extraction of attributes (LIAKOS *et al*., 2018), solving one of the significant bottlenecks of machine learning techniques, which is the requirement of experts for supervising this procedure (BAH *et al*., 2018). DL techniques greater learning capacity is conditioned by the database that must be sufficiently large and characterize the problem (KAMILARIS; PRENAFETA-BOLDÚ, 2018), which may also pose a challenge to the use of this algorithm. Even so, this seems to be quite feasible for digital images and data from various sensors that have been used in Agri 4.0.

Considering the above, despite the difficulties for field collection of images due to the influence of soil, lighting, and the shading or occlusion of elements of interest (HAMUDA *et al*., 2016), the major bottlenecks in identifying biological targets using UAVs are not encountered in the platform itself, but in the processing of collected information, especially in the models and attributes used. However, the advances in artificial intelligence, especially regarding DL, whose agricultural applications are still relatively recent, rise great expectations.

SPRAYING OF PHYTOSANITARY PRODUCTS AND BIO INPUTS DISPENSING

The increased amount of field information allows a high-precision identification of site-specific inputs demands. In this sense, besides assisting in data collection (as presented so far), UAV spraying systems have the potential to satisfy these spraying and inputs application demands - as traditional input application systems, whether manual, aerial or using a tractor, sometimes fail in meeting the peculiarities of the crop production system. A historical and growing scientific-technical development of spraying with UAVs has been recorded in Asia, especially China, South Korea, and Japan, fostered by local characteristics such as small-scale production units, in sloping areas, and with manpower shortage (YANG *et al*., 2018). In the USA, UAVs fully serve specific applications in viticultural areas (GILES; BILLING, 2015). Spraying UAVs have recently become an alternative for situations where traditional sprayers are unfeasible. Vertical take-off, ability to maneuver in tight spaces, autonomous operation, quick access to points of interest, and null damage to the crops by wheels are some of spraying UAVs advantages compared to agricultural machinery. However, further scientific knowledge on UAVs spraying and industry standards for this equipment are made necessary (HE *et al*., 2017). In this sense, we observed at least three directions for the technical and scientific development of this operation: a) development of spraying UAVs; b) research to establish ideal conditions for operation; and c) development of supplementary systems to increase process efficacy.

Development of spraying UAVs

Vertical take-off UAVs with one or multiple engines are often employed in spraying activity. Although most of them are powered by electricity, larger machines with higher load capacity mainly use combustion engines, while some hybrid formats are already available (LAN; CHEN, 2018). When operations require a high volume of spraying solution per unit of area, the load capacity and spraying flow rate applied by a UAV constitute a limiting factor for its general application in replacing traditional spraying machinery. The tank capacity of spraying UAVs usually holds 5.0 to 20.0 liters, but some models hold up to 30.0 liters (HE *et al*., 2017). There is no technological limitation for the development of UAVs with greater capacities; this merely occurs due to a deliberation of manufacturers and developers considering stringent regional laws, such as documents Part 107 and Part 137 of the American Federal Aviation Agency (FAA, 2020). Such documents restrict UAV operation according to load capacity and make training mandatory for UAV operators who might handle chemical and biological products. Thus, research has been developed to decrease the recommended pesticide flow rates, in order to make UAV spraying suitable. Japan, the birthplace of UAV spraying, has developed flow rates of up to 1.0 l/ha, characterized as of ultra-low volume compared with original applications of up to 30.0 l/ha (HE *et al*., 2017).

Across many countries, local adaptations of the spraying UAVs operation have experimentally enabled the use of this equipment in various crops, such as rice (LI *et al*., 2019), corn (ZHENG *et al*., 2017), soybeans (ZHANG *et al*., 2019), wheat (WANG *et al*., 2019), cotton (YAO *et al*., 2018), sugarcane (ZHANG *et al*., 2020), citrus (PAN *et al*., 2017) and grapes (GILES; BILLING, 2015). However, this method’s applicability in the most diverse crops leads to questions about the operational performance of such equipment. Considering only flight time, Wang *et al*. (2019) achieved a performance of 4.1 ha/h applying insecticide on wheat, while Giles and Billing (2015) obtained a similar performance (4.5 ha/h) testing UAV application on a vineyard. However, Wang *et al*. (2017) report that flight time corresponds to only 30% of the total time spent to complete a spraying operation; the other 70% time is used for pre-flight checklists, batteries exchange, inputs reservoir supply, and other similar activities. Nevertheless, Yang *et al*. (2018) mention several evaluations in which UAVs were superior to other spraying devices, similar to what Martinez-Guanter *et al*. (2020) observed compared to a tractor sprayer in operations with olive and citrus.

The efficiency of UAV treatments seems to be relatively consistent with the other spraying methods (XIAO *et al*., 2020; WANG *et al*., 2019), even though intermediate parameters for the quality of spraying (that is, deposition uniformity) may be below other application modes (WANG *et al*., 2019). Results such as those by Lou *et al*. (2018) show 26% better control for aphids and 6% better for mites in favor of the terrestrial sprayer in cotton crop; however, adjustments of spraying parameters have stimulated research seeking efficiency improvement for UAVs.

Ideal conditions for spraying

Efficient spraying requires correct choice and regulation of the spraying system, according to environmental conditions and characteristics of the targets. Mistaken decisions when selecting a spraying nozzle may lead to differences of up to 30% in treatment effectiveness, as Chen *et al*. (2020) observed in their study of nozzles unsuitable for grasshopper control in different vegetative stages of rice. Correct choices in this matter determine the best coverage of the target and the consequent increase in the efficiency of phytosanitary treatment and reduction of drift problems. The most frequently-tested nozzles are 110 degrees with a flow rate of 0.1 to 0.2 gallons (CHEN *et al*., 2020). However, there are several suitable specifications for spraying, especially concerning the characteristics of the target. Nozzles generating larger droplets, with a volume median diameter (VMD) above 160 microns, have better droplet deposition, better penetration, and less drift for spraying insecticides on rice (CHEN *et al*., 2020). Moreover, adequate flow rate, flight speed and height are critical parameters for defining the best spraying conditions.

The speed of a UAV modifies its engine rotation, changing the airstream field formed towards the vegetation that is necessary for droplet deposition, causing variation in airflow and consequent alteration in droplet deposition. This occurs because the weight variation changes the battery discharge curve and, consequently, the engine operation (MARTINEZ-GUANTER *et al*., 2020). The stronger the air vortex, the greater the deposition on the flight path; while weaker vortices provide deposition both on the path and laterally. For very weak vortices, the deposition is subject to the direction and force of the wind (GUO *et al*., 2019). Zheng *et al*. (2017) report adequate distribution results with speeds of up to 6.0 m/s.

The vortex's influence is also directly related to flight height, which can modify the deposition density and penetration (ZHANG *et al*., 2020), achieving up to 40% variations in droplet distribution (GUO *et al*., 2019). Proper flight height, as well as speed and direction of flight, were especially important for application in crops such as citrus (TANG *et al*., 2018), olives trees (MARTINEZ-GUANTER *et al*., 2020), and peach trees (MENG *et al*., 2020), whose morphological structures and canopy density had a relevant impact on the spraying quality. The best spraying distribution and coverage result was achieved with 1.4 m above the canopy in the citrus crop (HOU *et al*., 2019), while for defoliant applications on cotton, it was with 1.5 m and speeds of 2.5–3.8 m/s, depending on the UAV used (LIAO *et al*., 2019). Zhang *et al*. (2020) defined a height of 3.0 meters, a volume of 15.0 l/ha, and a speed of 4.0 m/s as optimal reference parameters for spraying sugarcane, due to the need of reaching the lowest leaves. These parameters clarify the multifactorial influence required to achieve application quality and the need for a more significant number of tests under different conditions.

Supplementary systems to increase UAV spraying efficiency

At least two research lines aim to develop optimization systems for spraying with UAVs: 1) one focuses on real-time spraying control, considering variations in environmental conditions; 2) the other seeks to define spraying criteria based on characteristics of the target, using varied strategies to increase performance.

Real-time sensing systems are an essential step in enabling more specific and optimized interventions with UAVs. Issues in this area are still challenging because they require both hardware and software with high computational cost, directly related to the energy consumption of the batteries and load capacity. One strategy for increased spraying efficiency and reduced environmental risks, mainly represented by drift, is by developing systems to adapt flight parameters in real-time (HE *et al*., 2017); for example, by using a network of wireless sensors in the field, sending positional information of wind speed and direction, in order to correct parameters of the UAV (FAIÇAL *et al*., 2017). With a greater degree of sophistication, a neural network fed with information on ambient temperature, relative air humidity, wind speed, and UAV settings (such as flight speed and altitude, number of rotors and spray nozzles, and a prescribed volume of application), was developed to control in real-time the volume and size of spray droplets, in order to improve the quality of deposition of the phytosanitary product (WEN *et al*., 2019). For real-time interventions, which require the operator's command, flight speed is an essential component for command communication between the control base and the UAV, to the point of ensuring accuracy in spraying (HE *et al*., 2017). According to UAV flight conditions, Lian *et al.* (2019) overcame this challenge by developing a quick-response system for adjustment of the spraying flow rate.

As for the definition of spraying criteria according to characteristics of the target, the application support systems aim to increase the automation and accuracy of the activity, defining areas of application and non-application in high definition images (GAO *et al*., 2019). One of the significant challenges for image classification is its implementation in real-time during the flight. Alternatively, previously acquired imagery or sensing data can be used to streamline real-time processing. In this sense, Wang *et al*. (2019) developed a system that autonomously defined the application and non-application areas in rice cultivation using previously surveyed characteristics of the fields (e.g., color and texture parameters) to feed a support vector machine (SVM) classifier. The real-time image processing also imposes previously mentioned challenges, such as response time, embedded hardware, energy consumption, among others.

In short, there was remarkable development in UAV spraying in the last five years. The diversity of agricultural UAV application is a challenge to the constant development and adaptation of these spraying systems, requiring further investigation that might make the activity agronomically functional and efficient while also being safe for people and the environment. The definition of optimal parameters for flight, automation systems, and real-time decision support will contribute to this objective. Research initiatives such as that of Ivić *et al*. (2019) share these goals; some contributions were the development of swarm control systems for spraying UAVs to fully automate the operation, thus increasing application accuracy, and improving performance. As a result of these advances, other applications for dispersion of different types of inputs using UAVs will be studied more frequently, such as the distribution of seeds (LI *et al*., 2016), fertilizers, and bio inputs. The latter is already commercially implemented and has been validated by Teske *et al*. (2019), in order to distribute natural enemies using UAVs in the field and to spread these populations.

CONCLUSIONS

1. UAV applications in agriculture have evolved substantially in recent years with the prospect of replacing activities of low human performance, such as crop monitoring sampling. Another contribution is improving the efficiency of agricultural operations, such as the site-specific application of phytosanitary products. However, most research efforts have been developed within the scope of Agri 4.0, that is, data-focused research, which would enable autonomous decision-making or with a minimum dependency of a human expert. In this sense, data science applications are growing exponentially in agriculture through machine learning, big data, and the Internet of Things. We have already ensured subcentimetric image accuracy through the sensor's high resolution and high-frequency data acquisition. This is due to the flexibility of obtaining these data, enabling a wide range of agricultural applications. To this end, computer vision techniques are proposed to replace the visual assessment of human-field technicians and experts, with the remarkable difference that the entire field could be investigated with very high resolution through image analysis without sampling approaches, providing quality information for the farmer's decision-making. In an optimal scenario, not even the farmer's decision-making would be required, as the AI itself would identify unbalanced parts of the field and their causes, selecting the most effective control methods and activating the proper autonomous-machinery responsible for such interventions;
2. Implementing such a project requires much development regarding data transmission capacity as well as cloud storage and processing. Currently, data communication in the field still lacks the efficiency necessary for such an approach. The 5G system is promising in this regard. However, several questions still require clarification, such as the actual data transfer rates over long distances and the costs for implementing such a dedicated structure in the rural environment. Similarly, machine learning techniques still require significant effort to obtain a robust database in order to recognize patterns under different situations in the agricultural environment, such as plants with different colors and shapes caused by different types of stress, like climate and pathogenic attack. Therefore, the application of such techniques in the agricultural field faces much more challenges than the same approach in the industrial environment, in which there is environmental control over most factors that interfere with automated predictions. The fact is that agricultural automation requires AI learning about the most varied and representative situations in the fields, requiring extensive and robust databases to apply Agri 4.0 comprehensively. Thus, UAVs, as a high-resolution data acquisition platform, are a reality. In contrast, the knowledge that these data can provide for Agri 4.0 applications is still difficult to fully understand and quantify.

REFERENCES

ABDULRIDHA, J. *et al*. Detection of target spot and bacterial spot diseases in tomato using UAV-based and benchtop-based hyperspectral imaging techniques. **Precision Agriculture**, v. 21, p. 955-978, 2020. https://doi.org/10.1007/s11119-019-09703-4.

ABDULRIDHA, J.; BATUMAN, O.; AMPATZIDIS, Y. UAV-based remote sensing technique to detect citrus canker disease utilizing hyperspectral imaging and machine learning. **Remote Sensing**, v. 11, 2019. https://doi.org/10.3390/rs11111373.

ALVES, T.M. *et al*. Optimizing band selection for spectral detection of Aphis glycines Matsumura in soybean. **Pest Management Science**, v. 75, p. 942-949, 2019. https://doi.org/10.1002/ps.5198.

ARGENTO, F. *et al*. Site-specific nitrogen management in winter wheat supported by low-altitude remote sensing and soil data. **Precision Agriculture**, 2020. https://doi.org/10.1007/s11119-020-09733-3.

BAH, M.D; HAFIANE, A.; CANALS, R. Deep learning with unsupervised data labeling for weed detection in line crops in UAV images. **Remote Sensing**, v. 10, 2018. https://doi.org/10.3390/rs10111690.

BENDIG, J.; BOLTEN, A.; BARETH. G. UAV-based Imaging for Multi-Temporal, very high Resolution Crop Surface Models to monitor Crop. **Photogrammetrie - Fernerkundung - Geoinformation**, p. 551-562, 2013. https://doi.org/10.1127/1432-8364/2013/0200.

BENDIG, J. *et al*. Estimating biomass of barley using crop surface models (CSMs) derived from UAV-based RGB imaging. **Remote Sensing**, v. 6, p. 10395-10412, 2014. https://doi.org/10.3390/rs61110395.

BENDIG, J. *et al*. Combining UAV-based plant height from crop surface models, visible, and near infrared vegetation indices for biomass monitoring in barley. **International Journal of Applied Earth Observation and Geoinformation,** v. 39, p. 79-87, 2015. https://doi.org/10.1016/j.jag.2015.02.012.

BERRY, P.M. *et al*. A calibrated model of wheat lodging compared with field measurements. **Agricultural and Forest Meteorology**, v. 119, p. 167-180, 2003. https://doi.org/10.1016/S0168-1923(03)00139-4.

BLONQUIST, J.M.; NORMAN, J.M.; BUGBEE, B. Agricultural and Forest Meteorology Automated measurement of canopy stomatal conductance based on infrared temperature. **Agricultural and Forest Meteorology**, v. 149, p. 1931-1945, 2009. https://doi.org/10.1016/j.agrformet.2009.06.021.

BROCKS, S. Estimating Barley Biomass with Crop Surface Models from Oblique RGB Imagery. **Remote Sensing**, v. 10, 2018. https://doi.org/10.3390/rs10020268.

BUCHAILLOT, M.L. *et al*. Evaluating maize genotype performance under low nitrogen conditions using RGB UAV phenotyping techniques. **Sensors**, v. 19, 2019. https://doi.org/10.3390/s19081815.

CÂNDIDO, B.M. *et al*. High-resolution monitoring of diffuse (sheet or interrill) erosion using structure-from-motion. **Geoderma,** v. 375, p. 114477, 2020. https://doi.org/10.1016/j.geoderma.2020.114477.

CAO, F. *et al*. Fast detection of sclerotinia sclerotiorum on oilseed rape leaves using low-altitude remote sensing technology. **Sensors,** v. 18, 2018. https://doi.org/10.3390/s18124464.

CASTALDI, F. *et al*. Assessing the potential of images from unmanned aerial vehicles (UAV) to support herbicide patch spraying in maize. **Precision Agriculture**, v. 18, p. 76-94, 2017. https://doi.org/10.1007/s11119-016-9468-3.

CHANG, A. *et al*. Crop height monitoring with digital imagery from Unmanned Aerial System (UAS). **Computers and Electronics in Agriculture**, v. 141, p. 232-237, 2017. https://doi.org/10.1016/j.compag.2017.07.008.

CHEN, P. *et al*. Droplet deposition and control of planthoppers of different nozzles in two-stage rice with a quadrotor unmanned aerial vehicle. **Agronomy**, v. 10, 2020. https://doi.org/10.3390/agronomy10020303.

CHEN, S. *et al*. Effect of droplet size parameters on droplet deposition and drift of aerial spraying by using plant protection UAV. **Agronomy**, v. 10, 2020. https://doi.org/10.3390/agronomy10020195.

CHEN, S.W. *et al*. Counting Apples and Oranges with Deep Learning: A Data-Driven Approach. **IEEE Robotics and Automation Letter**, v. 2, p. 781-788, 2017. https://doi.org/10.1109/LRA.2017.2651944.

CHÉNÉ, Y. *et al*. On the use of depth camera for 3D phenotyping of entire plants. **Computers and Electronics in Agriculture**, v. 82, p. 122-127, 2012. https://doi.org/10.1016/j.compag.2011.12.007.

COSTA, L.; NUNES, L.; AMPATZIDIS, Y. A new visible band index (vNDVI) for estimating NDVI values on RGB images utilizing genetic algorithms. **Computers and Electronics in Agriculture**, v. 172, p. 105334, 2020. https://doi.org/10.1016/j.compag.2020.105334.

CRUSIOL, L.G.T. *et al*. UAV-based thermal imaging in the assessment of water status of soybean plants. **International Journal of Remote Sensing**, v. 41, p. 3243-3265, 2020. https://doi.org/10.1080/01431161.2019.1673914.

DÍAZ-VARELA, R.A. *et al*. High-Resolution Airborne UAV Imagery to Assess Olive Tree Crown Parameters Using 3D Photo Reconstruction: Application in Breeding Trials. **Remote Sensing**, v. 7, 2015. https://doi.org/10.3390/rs70404213.

DILLEN, M. *et al*. Biomass and Bioenergy Productivity , stand dynamics and the selection effect in a mixed willow clone short rotation coppice plantation. **Biomass and Bioenergy**, v. 87, p. 46-54, 2016. https://doi.org/10.1016/j.biombioe.2016.02.013.

DU, M., NOGUCHI, N. Monitoring of Wheat Growth Status and Mapping of Wheat Yield ' s within-Field Spatial Variations Using Color Images Acquired from UAV-camera System. **Remote Sensing**, v. 9, 2017. https://doi.org/10.3390/rs9030289.

FAIÇAL, B.S. *et al*. An adaptive approach for UAV-based pesticide spraying in dynamic environments. **Computers and Electronics in Agriculture**, v. 138, p. 210-223, 2017. https://doi.org/10.1016/j.compag.2017.04.011.

FAO. Global report on food crises, 2018.

FORLANI, G. *et al*. Quality assessment of DSMs produced from UAV flights geo-referenced with on-board RTK positioning. **Remote Sensing**, v. 10, 2018. https://doi.org/10.3390/rs10020311.

FU, Y. *et al*. Winter wheat biomass estimation based on spectral indices, band depth analysis and partial least squares regression using hyperspectral measurements. **Computers and Electronics in Agriculture**, v. 100, p. 51-59, 2014. https://doi.org/10.1016/j.compag.2013.10.010.

GAO, J. *et al*. Fusion of pixel and object-based features for weed mapping using unmanned aerial vehicle imagery. **International Journal of Applied Earth Observation and Geoinformation**, v. 67, p. 43-53, 2018. https://doi.org/10.1016/j.jag.2017.12.012.

GAO, P. *et al*. Article development of a recognition system for spraying areas from unmanned aerial vehicles using a machine learning approach. **Sensors**, v. 19, 2019. https://doi.org/10.3390/s19020313.

GARCÍA-MARTÍNEZ, H. *et al*. Corn Grain Yield Estimation from Vegetation Indices, Canopy Cover, Plant Density, and a Neural Network Using Multispectral and RGB Images Acquired with Unmanned Aerial Vehicles. **Agriculture**, v. 10, p. 277, 2020. https://doi.org/10.3390/agriculture10070277.

GEIPEL, J.,; LINK, J.; CLAUPEIN, W. Combined spectral and spatial modeling of corn yield based on aerial images and crop surface models acquired with an unmanned aircraft system. **Remote Sensing**, v. 6, p. 10335-10355, 2014. https://doi.org/10.3390/rs61110335.

GIANNETTI, F. *et al*. Assessment of UAV photogrammetric DTM-independent variables for modelling and mapping forest structural indices in mixed temperate forests. **Ecological Indicators**, v. 117, p. 106513, 2020. https://doi.org/10.1016/j.ecolind.2020.106513.

GILES, D.K.; BILLING, R.C. Deployment and performance of a uav for crop spraying. **Chemical Engineering Transactions**, v. 44, p. 307-312, 2015. https://doi.org/10.3303/CET1544052.

GRÜNER, E.; ASTOR, T.; WACHENDORF, M. Biomass Prediction of Heterogeneous Temperate Grasslands Using an SfM Approach Based on UAV Imaging. **Agronomy**, v. 9, 2019. https://doi.org/10.3390/agronomy9020054.

GRÜNER, E.; WACHENDORF, M.; ASTOR, T. The potential of UAV-borne spectral and textural information for predicting aboveground biomass and N fixation in legume-grass mixtures. **PLoS One**, v. 15, p. 1-21, 2020. https://doi.org/10.1371/journal.pone.0234703.

GUO, S. *et al*. Distribution characteristics on droplet deposition of wind field vortex formed by multi-rotor UAV. **PLoS One,** v. 14, 2019. https://doi.org/10.1371/journal.pone.0220024.

HAMUDA, E.; GLAVIN, M.; JONES, E. A survey of image processing techniques for plant extraction and segmentation in the field. **Computers and Electronics in Agriculture**, v. 125, p. 184-199, 2016. https://doi.org/10.1016/j.compag.2016.04.024.

HASSAN, M.A. *et al*. Accuracy assessment of plant height using an unmanned aerial vehicle for quantitative genomic analysis in bread wheat. **Plant Methods**, v. 15, p. 1-12, 2019a. https://doi.org/10.1186/s13007-019-0419-7.

HASSAN, M.A. *et al*. A rapid monitoring of NDVI across the wheat growth cycle for grain yield prediction using a multi-spectral UAV platform. **Plant Science**, v. 282, p. 95-103, 2019b. https://doi.org/10.1016/j.plantsci.2018.10.022.

HASSLER, S.C.; BAYSAL-GUREL, F. Unmanned aircraft system (UAS) technology and applications in agriculture. **Agronomy**, v. 9, 2019. https://doi.org/10.3390/agronomy9100618.

HE, X.K.; BONDS, J.; HERBST, A., Langenakens, J. Recent development of unmanned aerial vehicle for plant protection in East Asia. **International Journal of Agricultural and Biological Engineering**, v. 10, p. 18-30, 2017. https://doi.org/10.3965/j.ijabe.20171003.3248.

HEINEMANN, S. *et al*. Land surface temperature retrieval for agricultural areas using a novel UAV platform equipped with a thermal infrared and multi-spectral sensor. **Remote Sensing**, v. 12, 2020. https://doi.org/10.3390/rs12071075.

HOLMAN, F.H. *et al*. High throughput field phenotyping of wheat plant height and growth rate in field plot trials using UAV based remote sensing. **Remote Sensing**, v. 8, 2016. https://doi.org/10.3390/rs8121031.

HOU, C. *et al*. Optimization of control parameters of droplet density in citrus trees using UAVs and the Taguchi method. **International Journal of Agricultural and Biological Engineering**, v.12, p. 1-9, 2019. https://doi.org/10.25165/j.ijabe.20191204.4139.

HU, P. *et al*. Estimation of plant height using a high throughput phenotyping platform based on unmanned aerial vehicle and self-calibration: Example for sorghum breeding. **European Journal of Agronomy**, v. 95, p. 24-32, 2018. https://doi.org/10.1016/j.eja.2018.02.004.

HUANG, H. *et al*. Detection of helminthosporium leaf blotch disease based on UAV imagery. **Applied Sciences**, v. 9, p. 1-14, 2019. https://doi.org/10.3390/app9030558.

HUNT, E.R. *et al.* A visible band index for remote sensing leaf chlorophyll content at the Canopy scale. **International Journal of Applied Earth Observation and Geoinformation**, v. 21, p. 103-112, 2012. https://doi.org/10.1016/j.jag.2012.07.020.

HUNTER, J.E. *et al*. Coverage and drift potential associated with nozzle and speed selection for herbicide applications using an unmanned aerial sprayer. **Weed Technology**, v. 34, p. 235-240, 2020. https://doi.org/10.1017/wet.2019.101.

IHUOMA, S.O.; MADRAMOOTOO, C.A. Crop reflectance indices for mapping water stress in greenhouse grown bell pepper. **Agricultural Water Management**, v. 219, p. 49-58, 2019. https://doi.org/10.1016/j.agwat.2019.04.001.

IVIĆ, S.; ANDREJČUK, A.; DRUŽETA, S. Autonomous control for multi-agent non-uniform spraying. **Applied Soft Computing**, v. 80, p. 742-760, 2019. https://doi.org/10.1016/j.asoc.2019.05.001.

JAMES, M.R.; ROBSON, S. Mitigating systematic error in topographic models derived from UAV and ground-based image networks. **Earth Surface Processes and Landforms**, v. 39, p. 1413-1420, 2014. https://doi.org/10.1002/esp.3609.

JIMENEZ-BERNI, J.A. High Throughput Determination of Plant Height, Ground Cover, and Aboveground Biomass in Wheat with LiDAR. **Frontiers in Plant Science**, v. 9, p. 1-18, 2018. https://doi.org/10.3389/fpls.2018.00237.

KAMILARIS, A.; PRENAFETA-BOLDÚ, F.X. Deep learning in agriculture: A survey. **Computers and Electronics in Agriculture**, v. 147, p. 70-90, 2018. https://doi.org/10.1016/j.compag.2018.02.016.

KANDYLAKIS, Z. *et al*. Water Stress Estimation in Vineyards from Aerial SWIR and multi-spectral UAV data. **Remote Sensing**, v. 12, 2020. https://doi.org/10.3390/RS12152499.

KING, B.A. *et al*. Thermal Crop Water Stress Index Base Line Temperatures for Sugarbeet in Arid Western U.S. **Agricultural of Water Management**, v. 243, p. 106459, 2021. https://doi.org/10.1016/j.agwat.2020.106459.

LAN, Y.; CHEN, S. Current status and trends of plant protection UAV and its spraying technology in China. **International Journal of Precision Agricultural Aviation**, v. 1, p. 1-9, 2018. https://doi.org/10.33440/j.ijpaa.20180101.0002.

LAZCANO, C.; DOMÍNGUEZ, J. The use of vermicompost in sustainable agriculture: impact on plant growth. **Soil Nutrients**, p. 1-23, 2011.

LI, J. *et al*. Vertical distribution and vortex structure of rotor wind field under the influence of rice canopy. **Computers and Electronics in Agriculture**, v. 159, p. 140-146, 2019. https://doi.org/10.1016/j.compag.2019.02.027.

LI, J.Y. *et al*. Design and test of operation parameters for rice air broadcasting by unmanned aerial vehicle. **International Journal of Agricultural and Biological Engineering**, v. 9, p. 24-32, 2016. https://doi.org/10.3965/j.ijabe.20160905.2248.

LIAKOS, K.G. *et al*. Machine learning in agriculture: A review. **Sensors**, v. 18, p. 1-30, 2018. https://doi.org/10.3390/s18082674.

LIAN, Q. *et al*. Design of precision variable-rate spray system for unmanned aerial vehicle using automatic control method. **International Journal of Agricultural and Biological Engineering**, v. 12, p. 29-35, 2019. https://doi.org/10.25165/j.ijabe.20191202.4701.

LIAO, J. *et al*. Optimization of variables for maximizing efficacy and efficiency in aerial spray application to cotton using UASs. **International Journal of Agricultural and Biological Engineering**, v. 12, p. 10-17, 2019. https://doi.org/10.25165/j.ijabe.20191202.4288.

LIU, H.; ZHU, H.; WANG, P. Quantitative modelling for leaf nitrogen content of winter wheat using UAV-based hyperspectral data. **International Journal of Remote Sensing**, v. 38, p. 2117-2134, 2017. https://doi.org/10.1080/01431161.2016.1253899.

LÓPEZ-GRANADOS, F. *et al*. Object-based early monitoring of a grass weed in a grass crop using high resolution UAV imagery. **Agronomy for Sustainable Development**, v. 36, 2016. https://doi.org/10.1007/s13593-016-0405-7.

LOU, Z. *et al*. Effect of unmanned aerial vehicle flight height on droplet distribution, drift and control of cotton aphids and spider mites. **Agronomy,** v. 8, 2018. https://doi.org/10.3390/agronomy8090187.

MADEC, S. *et al*. High-throughput phenotyping of plant height: Comparing unmanned aerial vehicles and ground lidar estimates. **Frontiers in Plant Science**, v. 8, p. 1-14, 2017. https://doi.org/10.3389/fpls.2017.02002.

MAIMAITIJIANG, M. *et al*. Soybean yield prediction from UAV using multimodal data fusion and deep learning. **Remote Sensing of Environment**, v. 237, p. 111599, 2020. https://doi.org/10.1016/j.rse.2019.111599.

MARINO, S.; ALVINO, A. Detection of Spatial and Temporal Variability of Vegetation Indices. **Agronomy**, v. 9, 2019. https://doi.org/10.3390/agronomy9050226.

MARTINEZ-GUANTER, J. *et al*. Spray and economics assessment of a UAV-based ultra-low-volume application in olive and citrus orchards. **Precision Agriculture**, v. 21, p. 226-243, 2020. https://doi.org/10.1007/s11119-019-09665-7.

MEINEN, B.U.; ROBINSON, D.T. Where did the soil go? Quantifying one year of soil erosion on a steep tile-drained agricultural field. **Science of The Total Environment**, v. 729, p. 138320, 2020a. https://doi.org/10.1016/j.scitotenv.2020.138320.

MEINEN, B.U.; ROBINSON, D.T. Mapping erosion and deposition in an agricultural landscape: Optimization of UAV image acquisition schemes for SfM-MVS. **Remote Sensing of Environment**, v. 239, p. 111666. 2020b. https://doi.org/10.1016/j.rse.2020.111666.

MENG, Y. *et al*. Experimental evaluation of UAV spraying for peach trees of different shapes: Effects of operational parameters on droplet distribution. **Computers and Electronics in Agriculture**, v. 170, p. 1-12. 2020. https://doi.org/10.1016/j.compag.2020.105282.

MILLAN, V.E.G.; RANKINE, C.; SANCHEZ-AZOFEIFA, G.A. Crop loss evaluation using digital surface models from unmanned aerial vehicles data. **Remote Sensing**, v. 12. 2020. https://doi.org/10.3390/rs12060981.

MODICA, G. *et al*. Monitoring the vegetation vigor in heterogeneous citrus and olive orchards. A multiscale object-based approach to extract trees' crowns from UAV multi-spectral imagery. **Computers and Electronics in Agriculture**, v. 175, p. 105500. 2020. https://doi.org/10.1016/j.compag.2020.105500.

NÄSI, R. *et al*. Estimating biomass and nitrogen amount of barley and grass using UAV and aircraft based spectral and photogrammetric 3D features. **Remote Sensing**, v. 10, p. 1-32. 2018. https://doi.org/10.3390/rs10071082.

NIJLAND, W. *et al*. Monitoring plant condition and phenology using infrared sensitive consumer grade digital cameras. **Agricultural and Forest Meteorology**, v. 184, p. 98-106. 2014. https://doi.org/10.1016/j.agrformet.2013.09.007.

OLSON, D. *et al*. Relationship of drone-based vegetation indices with corn and sugarbeet yields. **Agronomy Journal**, v. 111, p. 2545-2557. 2019. https://doi.org/10.2134/agronj2019.04.0260.

OTA, T. *et al*. Aboveground Biomass Estimation Using Structure from Motion Approach with Aerial Photographs in a Seasonal Tropical Forest. **Forests**, v. 6, p. 3882-3898. 2015. https://doi.org/10.3390/f6113882.

PAN, Z. *et al*. Droplet distribution and control against citrus Leafminer with Uav spraying. **International Journal of Robotics and Automation**, v. 32, p. 299-307. 2017. https://doi.org/10.2316/Journal.206.2017.3.206-4980.

PIJL, A. *et al*. TERRA: Terrain Extraction from elevation Rasters through Repetitive Anisotropic filtering. **International Journal of Applied Earth Observation and Geoinformation**, v. 84, p. 101977. 2020. https://doi.org/10.1016/j.jag.2019.101977.

RAHNEMOONFAR, M.; SHEPPARD, C. Deep Count: Fruit Counting Based on Deep Simulated Learning. **Sensors**, v. 17, p. 1-12. 2017. https://doi.org/10.3390/s17040905.

REN, H. *et al*. An improved ground control point configuration for digital surface model construction in a coal waste dump using an unmanned aerial vehicle system. **Remote Sensing**, v. 12. 2020. https://doi.org/10.3390/rs12101623.

ROOSJEN, P.P.J. *et al*. Deep learning for automated detection of Drosophila suzukii: potential for UAV-based monitoring. **Pest**

Management Science, v. 76, p. 2994-3002. 2020. https://doi.org/10.1002/ps.5845.

SARBOLANDI, H.; LEFLOCH, D.; KOLB, A. Kinect range sensing: Structured-light versus Time-of-Flight Kinect. **Computer Vision and Image Understanding**, v. 139, p. 1-20, 2015. https://doi.org/10.1016/j.cviu.2015.05.006.

SCHIRRMANN, M. *et al*. Monitoring Agronomic Parameters of Winter Wheat Crops with Low-Cost UAV Imagery. **Remote Sensing**, v. 8, 2016. https://doi.org/10.3390/rs8090706.

SHANI, G.; VIT, A. Comparing RGB-D Sensors for Close Range Outdoor. **Sensors**, v. 18, 2018. https://doi.org/10.3390/s18124413.

SHE, Y. *et al*. Applications of small UAV systems for tree and nursery inventory management. **In Proceeding of the 12th International Conference on Precision Agriculture (ICPA)**, Sacramento, CA, USA, 20-23 July 2014.

SHE, Y. *et al*. Applications of High-Resolution Imaging for Open Field Container Nursery Counting. **Remote Sensing**, v. 10, 2018. https://doi.org/10.3390/rs10122018.

SHENDRYK, Y. *et al*. Fine-scale prediction of biomass and leaf nitrogen content in sugarcane using UAV LiDAR and multi-spectral imaging. **International Journal of Applied Earth Observation and Geoinformation**, v. 92, p. 102177. 2020. https://doi.org/10.1016/j.jag.2020.102177.

SIEBRING, J. *et al*. Object-based image analysis applied to low altitude aerial imagery for potato plant trait retrieval and pathogen detection. **Sensors**, v. 19, 2019. https://doi.org/10.3390/s19245477.

SULIK, J.J.; LONG, D.S. Spectral considerations for modeling yield of canola. Remote **Sensing of Environment**, v. 184, p. 161-174. 2016. https://doi.org/10.1016/j.rse.2016.06.016.

TANG, Y. *et al*. Effects of operation height and tree shape on droplet deposition in citrus trees using an unmanned aerial vehicle. **Computers and Electronics in Agriculture**, v. 148, p. 1-7, 2018. https://doi.org/10.1016/j.compag.2018.02.026.

TESKE, A.L. *et al*. Optimised dispensing of predatory mites by multirotor UAVs in wind: A distribution pattern modelling approach for precision pest management. **Biosystems Engineering**.,v. 187, p. 226-238, 2019. https://doi.org/10.1016/j.biosystemseng.2019.09.009.

THOMPSON, L.J.; PUNTEL, L.A. Transforming unmanned aerial vehicle (UAV) and multi-spectral sensor into a practical decision support system for precision nitrogen management in corn. **Remote Sensing**, v. 12, 2020. https://doi.org/10.3390/rs12101597.

TILLY, N.; AASEN, H.; BARETH, G. Fusion of Plant Height and Vegetation Indices for the Estimation of Barley Biomass. **Remote Sensing**, v. 7, p. 11449-11480, 2015. https://doi.org/10.3390/rs70911449.

TOMAŠTÍK, J. *et al*. UAV RTK/PPK method-An optimal solution for mapping inaccessible forested areas? **Remote Sensing**, v. 11, 2019. https://doi.org/10.3390/RS11060721.

TSOUROS, D.C. *et al*. A review on UAV-based applications for precision agriculture. **Information**, v. 10, 2019. https://doi.org/10.3390/info10110349.

VERGARA-DIAZ, O. *et al*. Grain yield losses in yellow-rusted durum wheat estimated using digital and conventional parameters under field conditions. **The Crop Journal**, v. 3, p. 200-210, 2015. https://doi.org/10.1016/j.cj.2015.03.003.

VILJANEN, N.; HONKAVAARA, E. A Novel Machine Learning Method for Estimating Biomass of Grass Swards Using a Photogrammetric Canopy Height Model, Images and Vegetation Indices Captured by a Drone. **Agriculture,** v. 8, 2018. https://doi.org/10.3390/agriculture8050070.

WALTER, J. *et al*. Photogrammetry for the estimation of wheat biomass and harvest index. **Field Crops Research**, v. 216, p. 165-174, 2018. https://doi.org/10.1016/j.fcr.2017.11.024.

WANG, G. *et al*. Comparison of spray deposition, control efficacy on wheat aphids and working efficiency in the wheat field of the unmanned aerial vehicle with boom sprayer and two conventional knapsack sprayers. **Applied Sciences**, v. 9, p. 1-17, 2019. https://doi.org/10.3390/app9020218.

WANG, L. *et al*. Vision-based adaptive variable rate spraying approach for unmanned aerial vehicles. **International Journal of Agricultural and Biological Engineering**, v. 12, p. 18-26, 2019. https://doi.org/10.25165/j.ijabe.20191203.4358.

WANG, S.L. *et al*. Performances evaluation of four typical unmanned aerial vehicles used for pesticide application in China. **International Journal of Agricultural and Biological Engineering**, v. 10, p. 22-31, 2017. https://doi.org/10.25165/j.ijabe.20171004.3219.

WANG, W., LI, C. Size estimation of sweet onions using consumer-grade RGB-depth sensor. **Journal of Food Engineering**, v. 142, p. 153-162, 2014. https://doi.org/10.1016/j.jfoodeng.2014.06.019.

WATANABE, K. *et al*. High-throughput phenotyping of sorghum plant height using an unmanned aerial vehicle and its application to genomic prediction modeling. **Frontiers in Plant Science**, v. 8, p. 1-11, 2017. https://doi.org/10.3389/fpls.2017.00421.

WEISS, M.; BARET, F. Using 3D Point Clouds Derived from UAV RGB Imagery to Describe Vineyard 3D Macro-Structure. **Remote Sensing**, v. 9, p. 111, 2017. https://doi.org/10.3390/rs9020111.

WEN, S. *et al*. Design of plant protection uav variable spray system based on neural networks. **Sensors,** v. 19, 2019. https://doi.org/10.3390/s19051112.

WIESNER-HANKS, T. *et al*. Millimeter-Level Plant Disease Detection From Aerial Photographs via Deep Learning and Crowdsourced Data. **Frontiers in Plant Science**, v. 10, p. 1-11, 2019. https://doi.org/10.3389/fpls.2019.01550.

WILLKOMM, M.; BOLTEN, A.; BARETH, G. Non-destructive monitoring of rice by hyperspectral in-field spectrometry and UAV-based remote sensing: Case study of field-grown rice in

North Rhine-Westphalia, Germany. **The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences**, 2016–July, p. 1071-1077, 2016. https://doi.org/10.5194/isprsarchives-XLI-B1-1071-2016.

WOO, H. *et al*. Evaluating ortho-photo production potentials based on UAV real-time geo-referencing points. **Spatial Information Research**, v. 26, p. 639-646, 2018. https://doi.org/10.1007/s41324-018-0208-9.

WU, M. *et al*. Evaluation of orthomosics and digital surface models derived from aerial imagery for crop type mapping. **Remote Sensing**, v. 9, p. 1-14, 2017. https://doi.org/10.3390/rs9030239.

XIAO, D.Q. *et al*. Classification and recognition scheme for vegetable pests based on the BOF-SVM model. **International Journal of Agricultural and Biological Engineering**, v. 11, p. 190-196, 2018. https://doi.org/10.25165/j.ijabe.20181103.3477.

XIAO, Q. *et al*. Comparison of droplet deposition control efficacy on phytophthora capsica and aphids in the processing pepper field of the unmanned aerial vehicle and knapsack sprayer. **Agronomy**, v. 10, 2020. https://doi.org/10.3390/agronomy10020215.

XUE, J.; SU, B., 2017. Significant remote sensing vegetation indices: A review of developments and applications. **Journal of Sensors**, 2017. https://doi.org/10.1155/2017/1353691.

YANG, G. *et al*. Unmanned Aerial Vehicle Remote Sensing for Field-Based Crop Phenotyping: Current Status and Perspectives. **Frontiers in Plant Science**, v. 8, 2017. https://doi.org/10.3389/fpls.2017.01111.

YANG, M. *et al* Assessment of Water and Nitrogen Use Efficiencies Through UAV-Based Multispectral Phenotyping in Winter Wheat. **Frontiers in Plant Science**, v. 11, p. 1-16, 2020. https://doi.org/10.3389/fpls.2020.00927.

YANG, S.; YANG, X.; MO, J. The application of unmanned aircraft systems to plant protection in China. **Precis. Agric.,** v. 19, p. 278-292, 2018 https://doi.org/10.1007/s11119-017-9516-7.

YAO, W. *et al*. Effect of UAV prewetting application during the flowering period of cotton on pesticide droplet deposition. **Frontiers of Agricultural Science and Engineering**, v. 5, p. 455-461, 2018. https://doi.org/10.15302/J-FASE-2018232.

YE, H. *et al*. Identification of banana fusarium wilt using supervised classification algorithms with UAV-based multi-spectral imagery. **International Journal of Agricultural and Biological Engineering**, v. 13, p. 136-142, 2020. https://doi.org/10.25165/j.ijabe.20201303.5524.

YUE, J. *et al*. Estimation of Winter Wheat Above-Ground Biomass Using Unmanned Aerial Vehicle-Based Snapshot Hyperspectral Sensor and Crop Height Improved Models. **Remote Sensing**, v. 9, 2017. https://doi.org/10.3390/rs9070708.

YUE, J. *et al*. Estimate of winter-wheat aboveground biomass based on UAV ultrahigh-ground-resolution image textures and vegetation indices. **ISPRS Journal of Photogrammetry and Remote Sensing**, v. 150, p. 226-244, 2019. https://doi.org/10.1016/j.isprsjprs.2019.02.022.

ZHANG, D. *et al*. Detection of rice sheath blight using an unmanned aerial system with high-resolution color and multi-spectral imaging. **PLoS One**, v. 13, p. 1-15, 2018. https://doi.org/10.1371/journal.pone.0187470.

ZHANG, K.F. *et al*. Experimental study of single-rotor UAV on droplet deposition distribution in soybean field. **Applied Ecology and Environmental Research**, v. 17, p. 13833-13844, 2019. https://doi.org/10.15666/aeer/1706_1383313844.

ZHANG, N. *et al*. Monitoring daily variation of leaf layer photosynthesis in rice using UAV-based multi-spectral imagery and a light response curve model. **Agricultural and Forest Meteorology**, v. 291, 2020. https://doi.org/10.1016/j.agrformet.2020.108098.

ZHANG, X.Q. *et al*. Effects of Spray Parameters of Drone on the Droplet Deposition in Sugarcane Canopy. **Sugar Tech**, v. 22, p. 583-588, 2020. https://doi.org/10.1007/s12355-019-00792-z.

ZHENG, H. *et al*. Enhancing the nitrogen signals of rice canopies across critical growth stages through the integration of textural and spectral information from unmanned aerial vehicle (UAV) multi-spectral imagery. **Remote Sensing**, v. 12, 2020. https://doi.org/10.3390/rs12060957.

ZHENG, Y.J. *et al*. Modelling operation parameters of UAV on spray effects at different growth stages of corns. **International Journal of Agricultural and Biological Engineering**, v. 10, p. 57-66, 2017. https://doi.org/10.3965/j.ijabe.20171003.2578.

ZHOU, J. *et al*. Classification of soybean leaf wilting due to drought stress using UAV-based imagery. **Computers and Electronics in Agriculture**, v. 175, p. 105576, 2020. https://doi.org/10.1016/j.compag.2020.105576.