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Unmanned aerial vehicle (UAV) technical applications, standard workflow, and future developments in maize production – water stress detection, weed mapping, nutritional status monitoring and yield prediction

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As a consequence of rapid ongoing technological developments and increasing integration into agricultural mechanization and agricultural intelligence, UAVs are gradually starting to play an increasingly important role in field crop management and monitoring. This review introduces and covers the development in four major applications of UAVs in maize production: (i) water stress detection, (ii) weed mapping, (iii) nutrient status monitoring and (iv) yield prediction. In addition, this review summarizes UAV data management methods, explains how expert systems work in UAV systems, and provides standardized workflow data for farmers in maize production. In addition, the strengths, weaknesses, opportunities, and threats of UAV use in maize production are analyzed. Based on more than eighty publications and our own research, the discussion and conclusions point out key issues in UAV usage in maize cropping and research gaps that need to be filled, along with a number of recommendations for the development of UAVs in maize production in the future.

Keywords
Unmanned aerial vehicles (UAVs), maize, field management, data management, expert systems

Unmanned aerial vehicles (UAVs) can be fitted with specific functional sensors (multispectral, hyperspectral, and thermal, etc.) suitable for agricultural purposes to enable image acquisition and data collection while flying across crop fields at a low altitude. In addition to remote sensing, UAVs can also be used for other agricultural activities such as field surveillance, plant counting, weed mapping, yield prediction, irrigation management, plant disease detection, plant health monitoring, and crop spraying (Tsouros et al. 2019a). Crop spraying is an important application of UAVs. UAVs equipped with tanks fly to the sites where weeds grow, and spray variable rates of herbicides based on weed maps instead of uniform blanket application (Castaldi et al. 2017, Yang et al. 2018). However, due to the potential environmental hazards of pesticide drift, aerial spraying is forbidden in European countries (Directive 2009/128/EC). It is only allowed if there are no viable alternatives but reduced impacts on human and the environment as compared with ground-based pesticide application should be proved (Reger et al. 2018). Nevertheless, as the progress of technology (e.g. smart drones, high-performance UAVs, and longer flight durations, etc.) and changes of legal boundaries, UAV-based crop spraying applications will be an important aspect in the future.

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Most studies have shown that low agricultural water use efficiency (Fang et al. 2010), excessive nitrogen application (Cui et al. 2008), and pesticide overuse (Brauns et al., 2018) are the main problems of maize production all over the world. Given the constraints imposed by these problems, more sustainable maize production needs to find innovative ways of solving them. Since UAVs have so many benefits in agricultural production, it is natural to use them in maize cropping. Moreover, maize has significant size and leaf area make it the most promising crop to work with UAV technologies because large size and leaf area are easy for UAVs to execute remote sensing and spraying. Some new applications of this system have been used in maize cropping, for example, water stress detection (Shi et al. 2019), yield prediction (Maresma et al. 2016), weed mapping (Castaldi et al. 2017), and height estimation (Wang et al. 2019). Table 1 shows the differences between traditional ground level precision maize production and UAV-based maize production in field management. Traditional ground level precision maize production relies on tractor-mounted sensors, field deployed sensors, or portable test devices for field monitoring. However, the movement of tractors on the field could cause soil compaction and crop damage. On the contrary, UAV-based maize production uses UAVs fitted with sensors to fly across crop fields at a low altitude and this avoids the problems in ground level precision maize production. UAVs can cover more areas in a short time and can provide more comprehensive field information than ground level precision technologies. Furthermore, UAV-based site-specific aerial spraying is more flexible and more faster than tractor-based variable-rate spraying.

Table 1: Differences between traditional ground level precision maize production and UAV-based maize production in field management

	Ground level precision maize production	UAV-based maize production	References
Water stress detection	Tractors, handheld infrared thermometer, portable air temperature meter	UAV multispectral sensors	Zhang et al. (2019b)
Yield prediction	Yield monitors and yield maps	UAV multispectral sensors	Jeffries et al. (2020), Vergara-Díaz et al. (2016)
Weed mapping	Tractors, spectrometers, fluorescence sensors	UAV multispectral sensors	Castaldi et al. (2017)
Nutrient status monitoring	Tractors, handheld chlorophyll leaf clip sensors	UAV multispectral and hyperspectral sensors	Gabriel et al. (2017)
Crop spraying	Tractor-based variable-rate spraying	UAV-based site-specific spraying	Castaldi et al. (2017)

However, the review of recent UAV technology progress in maize production is very limited. Up to now, UAVs do not have a standardized workflow in maize production, and this can cause confusion when farmers are trying to use UAV systems because a high level of expertise is needed at different field management stages to choose the suitable strategies and to process data (Orakwe and Okoye 2016, Tsouros et al. 2019b, Zhang and Kovacs 2012). This increases the difficulty of UAV use and reduces labor productivity because not all farmers possess this kind of professional knowledge. Therefore, a well-structured standardized workflow is urgently needed to guide farmers and to improve system efficiency in UAV-based maize production.

This review compiles the recent UAV studies in maize production in a systematic approach, summarizes the data acquisition and processing methods, designs a standard workflow for maize production, and offers a clear guide for maize producers. The aims of this paper are (i) to review scientific literature about the current use and development of UAV technologies in maize production; (ii) to explain how UAV technologies can solve problems in maize production; (iii) to design a standard UAV workflow for farmers in maize production; and (iv) to provide estimations for the future development of UAVs in maize production.

1. Uses of UAVs in maize production field management

Based on sixty-two studies published over the last 10 years on the use of UAVs in maize production, UAV research can be classified as the following types (Figure 1): water stress detection (10%), nutrient status monitoring (18%), weed mapping (19%), yield prediction (27%), height estimation (13%), plant distance estimation (3%), maize lodging estimation (3%), maize number counting (3%), and others (3%). This review focuses solely on the introduction of UAVs in water stress detection, nutrient status monitoring, weed mapping, and yield prediction, which are considered to be the dominant factors that impact production costs.

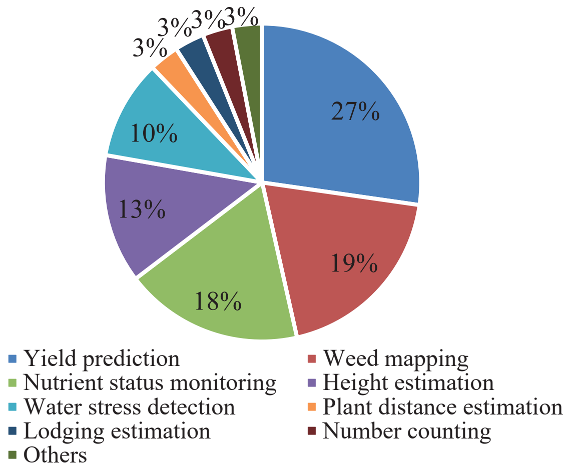

Figure 1: Proportions of UAV application types in maize production (Based on 62 studies published over the last 10 years)

1.1 Maize water stress detection

Accurate crop water stress detection is needed in a comprehensive irrigation management to achieve maximum water use efficiency and thus reduce costs. In recent years, two methods have been predominantly applied to detect water stress in plant: on-site measurement of soil water content and plant-based physiological indicators measurement (Ihuoma and Madramootoo 2017). However, these conventional methods are time-consuming, costly, and failed to depict the crop water status of the entire field (Zhang et al. 2019b, 2019a). Due to the benefits of being easy to operate, flexible, and non-invasive coupled with high-resolution images, UAVs have been increasingly used as an alternative production practice in crop water stress monitoring (Park et al. 2017, Poblete et al. 2018, Zhang et al. 2019b). Under different water availability conditions, crop leaves reflect different light spectrums and show different canopy temperatures and UAV sensors are able to differentiate water stress plants from water sufficient plants (Sylvester 2018).

The research on UAV-based maize water status monitoring is very limited. Zhang et al. (2019b) established crop water stress index regression models to map maize water status at the reproductive and maturation stages based on nine vegetation indices (e.g. normalized difference vegetation index, soil-adjusted vegetation index, etc.) extracted from UAV multispectral images. Comparing the maize water stress estimation results derived from regression models with ground-based data, the R^2 value could reach 0.81. It proves the feasibility of UAV-based maize water status monitoring. However, this research does not demonstrate to what extent these maize water stress estimation regression models can be used under varying conditions (e.g. other maize cultivars, other locations, etc.). Furthermore, most of the UAV-based maize water stress detection studies only concentrate on single critical growth stage instead of the whole growth period of maize and the prediction models can only be used under certain circumstances.

Based on the literature available so far, a general standardized procedure of UAV-based maize water stress detection is summarized as: (i) using UAVs equipped with sensors to collect data from maize fields, (ii) measuring field level maize ground-truth data, (iii) modelling and calibrating the UAV data with ground level maize truth data, and (iv) generating maize water status maps that indicate the exact amount of water which should be site-specifically irrigated in different plots or even spots instead of widely applied.

1.2 Maize weed mapping

Weeds are estimated to cause approximately 30% to 60% of potential yield losses in maize production worldwide (Castaldi et al. 2017, Chikoye et al. 2005, Oerke 2006, Safdar et al. 2015, Usman et al. 2001). Some farmers carry out uniform blanket herbicide spraying for weed control instead of site-specific spraying and this causes the excessive use of synthetic chemical herbicides on the fields (Castaldi et al. 2017, Pelosi et al. 2015). Herbicides have significantly reduced weed infestation in fields, but the excessive use of herbicides has led to environmental and ecological problems such as groundwater pollution, soil contamination, and biodiversity loss (Castaldi et al. 2017, Pelosi et al. 2015, Peña et al. 2013). Consequently, site-specific and efficient weed management is a measure of major importance when it comes to reducing the frequency and amount of herbicide usage in maize production (Burgos-Artizzu et al. 2011).

UAVs equipped with image sensors fly at low altitudes and are capable of distinguishing weed patches from crops in a less expensive way (Prince Czarnecki et al. 2017). Next, UAVs equipped with tanks filled with liquid herbicide fly to the field to spray precise amounts of herbicide based on observed weed site, weed density, and weed spatial distribution (Pelosi et al. 2015, Peña et al., 2013). UAV-based weed mapping and spraying help to reduce the amount of herbicides applied to fields and reduce environmental pollution (Castaldi et al. 2017, Pelosi et al. 2015).

The accuracy of UAV maize weed mapping ranges from 61% to 98% in seven studies and the accuracy is evaluated by comparing the weeds estimated from UAV images with actual on-ground weed counting (Table 2). Castaldi et al. (2017) observed herbicide savings of between 14% and 39.2% in UAV-based weed map patch spraying (spraying herbicides only on the site where weeds grow) in maize fields compared to conventional blanket application (evenly spraying herbicides on the entire field). Due to weed heterogeneity within the field, the saved amount of herbicide was different. Compared with uniform blanket application, site-specific patch spraying did not identify any significant differences in maize and weed biomass (Castaldi et al. 2017, Pelosi et al. 2015). This means that patch spraying does not compromise maize yield and has the same weed control effects as blanket application. UAV weed mapping is a possible option to support precision herbicide patch spraying in maize fields without any economic yield loss. Mink et al. (2018) found that UAV weed mapping reduced herbicide use by 90% in post-emergence maize weed treatments. They developed a canopy height model combined with vegetation indices and crop geographic coordinates in the field to distinguish weeds from maize by their height at maize three leaf stage. It demonstrated 96% accuracy in maize weed mapping (Mink et al. 2018).

Table 2: UAVs used in maize weed mapping

Sensors	Weed mapping methods	UAV remote indices	Accuracy	References
Visible light (RGB)[1)], NIR[2)]	Support vector machine algorithm (SVM)	NDVI[3)]	82%	Pelosi et al. (2015)
Visible light (RGB), NIR, multispectral	Support vector machine algorithm (SVM)	NDVI	61%	Castaldi et al. (2017)
Multispectral	Object-based image analysis	NDVI	95%	Peña-Barragán and Kelly (2012)
Multispectral	Object-based image analysis	NDVI	86%	Peña et al. (2013)
Visible light (RGB), multispectral	Object-based image analysis	NDVI, ExG[4)]	98%	Peña et al. (2014)
Visible light (RGB), multispectral	Canopy height model, weed height model	NDVI, ExR[5)], ExG	96%	Mink et al. (2018)
Hyperspectral	Support vector machine (SVM), machine learning (ML)	Cnorm[6)] and GRDB7)	64%	Casa et al. (2019)

[1)] RGB: red, green and blue; [2)] NIR: near infrared; [3)] NDVI, normalized difference vegetation index; [4)] ExG, excess green index; [5)] ExR, excess red index; [6)] Cnorm, (700 – 515) / (700 + 515); 7) GRBD, band depth 540 – 690.

However, the main obstacle to UAV weed mapping is finding effective algorithms to identify pixels which depict weeds in the digital images and remove unrelated background (Burgos-Artizzu et al. 2011). Because some weeds are similar in appearance (e.g. shape, color, etc.) to crops in the early stages of development, it is difficult to discriminate weeds from crops (Burgos-Artizzu et al. 2011, Peña-Barragán and Kelly 2012). The accuracy of discrimination affects the outcomes of weed mapping and site-specific treatment (Hamuda et al. 2016).

1.3 Maize nutritional status monitoring

At different development stages, maize has varying nutrient demands (Rhezali and Lahlali 2017). In order to ensure sufficient nutrient supply, it is crucial to monitor the site-specific nutrient needs at different critical stages of maize growth. With the assistance of UAVs, maize real-time nutrient status in each plot can be detected by sensors. Comprehensive nutritional status monitoring maps extracted from UAV images could be valuable tools in variable rates of fertilizer application.

Most of the UAV nutrient monitoring studies in maize concentrated on maize nitrogen status assessment (Cilia et al. 2014, Corti et al. 2018, Gabriel et al. 2017, Krienke et al. 2017, Quemada et al. 2014, Rhezali and Lahlali 2017) because nitrogen nutrient indices are the best indicators to assess maize nutritional status (Gabriel et al. 2017) (Table 3). Cilia et al. (2014) highlighted the potential of using UAVs to obtain maize nitrogen status maps of the entire field, because the estimated nitrogen content derived from UAV images showed good correlation with field level maize nitrogen measurements (R^2=0.70) (Cilia et al. 2014). Quemada et al. (2014) also confirmed the reliability of UAVs in nitrogen status assessment at maize flowering stage because the UAV image derived index (TCARI/OSAVI) was negatively correlated with maize nitrogen balance index (R = -0.84).

Although these studies showed the feasibility of UAV-based maize nitrogen status monitoring, the prediction accuracy can be affected by canopy structure, pigment concentration, leaf water content, and other nutrient deficiencies except nitrogen (Gabriel et al. 2017). To minimize the impact of these interfering factors, further research should use more UAV remote indices as independent variables in maize nitrogen status estimation models. Using more remote indices to predict maize nitrogen status has been proved to be more stable and more reliable than using single one because a single index is easily affected by the factors mentioned above (Cilia et al. 2014, Gabriel et al. 2017, Quemada et al. 2014).

Table 3: UAVs used in maize nitrogen status monitoring

Sensors	UAV remote indices	Prediction models	Phenology stage of maize	References
Multispectral	BNDVI[1)], GNDVI[2)], GC[3)]	Linear regression, least square regression	V6+V9	Corti et al. (2018)
Hyperspectral	MCARI/MTVI2[4)], NNI[5)]	Ordinary least squares regression	Pre-flowering stem elongation	Cilia et al. (2014)
Hyperspectral	TCARI[6)]/OSAVI[7)]	Polynomial regression	Flowering	Gabriel et al. (2017)
Hyperspectral, thermal	TCARI/OSAVI	Linear regression	Flowering	Quemada et al. (2014)

1) BNDVI: Blue Normalized Difference Vegetation Index; 2) GNDVI: Green Normalized Difference Vegetation Index; 3) GC: Ground Cover;
4) MCARI/MTVI2: Modified Chlorophyll Absorption Ratio Index/Modified Triangular Vegetation Index 2; 5) NNI: nitrogen nutrition index;
6) TCARI: Transformed Chlorophyll absorption in reflectance index; 7) OSAVI: Optimized soil-adjusted vegetation index.

Based on the four references presented in Table 3, the basic workflow of UAVs in maize nitrogen monitoring is summarized as (i) UAV sensors capture images above maize fields, then derive vegetation indices which characterize the nitrogen status of maize; (ii) determine maize nitrogen concentration using ground level destructive measurements in some representative plots; (iii) by means of a series of regression analyses, selecting the best index or combined indices to predict maize nitrogen status which leads to the results that strongly correlate with ground level maize nitrogen measurements.

1.4 Maize yield prediction

Maize yield prediction prior to harvest is very important for farmers to enable them to take decisions about the input of water, fertilizers, pesticides, labor, transportation, space for storage as well as for predicting market constellation and developing optimal economic strategies (Geipel et al. 2014). In most cases, some farmers estimate the yield based on their experience, yield maps, or partly field sampling (Ping and Dobermann 2005). These methods are over-reliance on experience and the results cannot convey accurate information about fields and proved to be labor-intensive and time-consuming (Li et al. 2016, Wahab et al. 2018). Compared to these methods, the UAV-based system reduces labor and there by improve economic performance (Tsouros et al. 2019a), saves time (Tsouros et al. 2019a), and expands the area of field investigation (Barbedo 2019). The yield is inferred through its correlation with UAV data in mathematical modeling, then a maize yield prediction model can be given to decision makers (Herrmann and Bdolach 2019).

Vegetation indices (e.g. WDRVI, BNDVI, NDVI, ExG) derived from UAV images are considered to be effective variables in different forecast models for yield prediction (Table 4) (Geipel et al. 2014, Herrmann and Bdolach 2019, Vergara-Díaz et al. 2016, Wu et al. 2019, Zhang et al. 2020). During vegetative growth stages, different prediction models were developed to predict maize yield, such as linear regressions (Zhang et al. 2020, Zhu et al. 2019), random forest regressions (Han et al. 2019, Li et al. 2016), partial least squares regressions (Herrmann and Bdolach 2019, Wu et al. 2019), etc. The R2 ranges from 0.37 to 0.94 because the goodness of fit of the models is affected by many variables (e.g. maize growth stages, sensor sensitivity, weather conditions, locations, etc.) (Zhang et al. 2020).

Table 4: UAVs used in maize yield prediction

Sensors	UAV remote indices	Image/ data processing software tools	Prediction models	R2	Phenology stages of maize	References
Multispectral	Wide dynamic range vegetation index (WDRVI)	JMP Pro 12 statistical package	Linear and quadratic regression	0.92	V12	Maresma et al. (2016)
Visible light (RGB)[1)]	Excess green (ExG) color feature	Curve Fitting Toolbox of Matlab	Linear regression	0.37	R2, R3, R6	Zhang et al. (2020)
Multispectral, Hyperspectral	Structure of motion (SfM) mean point height	Smart3DCapture software	Random forest regression	0.78	R3, R4	Li et al. (2016)
Multispectral	Normalized difference vegetation index (NDVI)	ENVI software	Exponential regression	0.72	R2-R3	Vergara-Díaz et al. (2016)
Multispectral	LiDAR point clouds	Python 2.7, and R × 64 3.5.3	Linear regression	0.85	Jointing period of summer maize	Zhu et al. (2019)
Visible light (RGB), multispectral, hyperspectral	Vegetation indices (VIs)	Matlab 7.6, PLS-toolbox	Partial least squares regression	0.73	R2	Herrmann and Bdolach (2019)
Multispectral	Blue and near infrared wavelength bands (BNDVI)	Agisoft PhotoScan professional software	Partial least squares regression	0.4-0.69	Entire growing season	Wu et al. (2019)
Multispectral	BIOVP: a volume metric used to estimate crop biomass within a plot	Pix4D software	Random forest regression	0.94	V12, VT	Han et al. (2019)

[1)] RGB: red, green and blue; R2 is the coefficient of determination of the maize yield prediction model

However, in case of using only UAV derived vegetation indices in maize yield prediction models is not sufficient to get convincing results (Geipel et al. 2014). Maize height, canopy cover, and other structural information extracted from UAV remote sensing can be considered as independent variables in yield prediction models simultaneously with UAV derived vegetation indices to improve yield prediction accuracy (Geipel et al. 2014, Han et al. 2019, Zhu et al. 2019). Some studies have shown the correlation of maize yield with maize height before mid-season stage (Katsvairo et al. 2003, Yin et al. 2011a, 2011b).

2. Standard workflow of UAVs in maize production

Recently, the most widespread commercial application of UAVs in maize production on the market has followed this standard workflow: UAV-based field data collection → Farm Management Information Systems → UAV field operation management (DJI 2020, PrecisionHawk 2020, XAG, 2020).

2.1 UAV-based field data collection

UAVs fitted with multispectral sensors fly across the entire field at a low altitude to collect images and data from crops. The sensors then transmit the collected information to locally installed software such as Agisoft PhotoScan and this a common and valid option for most UAV users (Kaimaris et al. 2017, Radoglou-Grammatikis et al. 2020). Apart from processing the data on local personal computers or workstations, some UAV companies provide cloud services which can also assist in data processing (DJI 2020, PrecisionHawk 2020, XAG, 2020). UAVs could be operated by farmers themselves or farmers could source professional licensed operators nearby from an UAV commercial service platform to operate the UAVs for them (Zhang et al. 2020).

2.2 Farm Management Information Systems (FMIS)

FMIS are databases designed to manage, implement, and record farm operations systematically (Burlacu et al. 2014, Pedersen and Lind 2017, Sørensen et al. 2010, Zhai et al. 2020). In UAV-based maize production, FMIS are integrated systems with different functional components to assist farmers in real time decision making (DJI 2020, PrecisionHawk 2020, XAG 2020): automated data processing, expert systems, user-controlled interfaces, and farm recordkeeping systems, etc. (Sørensen et al. 2011, 2010). The inputted farm data in FMIS are analyzed automatically by expert systems (Boursianis et al. 2020, Kenneth and Chinecherem 2018). Expert systems are powerful tools based on human expert analytical experience, agronomic data from previous years, and computer simulated human expert reasoning process, etc. to predict crop nutritional status, generate prescription maps, design customized expert reports, and give suggestions on fertilization, irrigation, and plant protection, etc. (DJI 2020, Prasad and Babu 2006, Rani et al. 2011). Other artificial intelligence methods can also involve in UAV data processing, such as artificial neural networks for predicting crop nutritional status (Jha et al. 2019), random forest for modelling maize above-ground biomass (Han et al. 2019), fuzzy logic for forecasting crop water requirements (Talaviya et al. 2020), etc. User-controlled interfaces allow farmers to control and to access processing and analysis functions (Murakami et al. 2007). All field work executed in a plot is recorded in farm recordkeeping systems (Saiz-Rubio and Rovira-Más 2020). The data generated in a current year production cycle in the FMIS are used to assess performed field work and will be stored on local personal computers, laptops, or cloud-based storage systems as baseline information for next season production (XAG 2020). All storage options are valid; farmers can choose appropriate data storage paths depending on their needs (DJI 2020).

2.3 UAV field operation management

Farmers can manage and supervise UAVs in the performance of their field tasks through a smart remote controller (PrecisionHawk 2020). Mission planning software designs automated missions for UAVs so that they can carry out field tasks automatically without manual operation (Srivastava et al. 2020). Farmers send instructions from smart remote controllers to manipulate UAVs to execute the requested movements (e.g. take-off, speeding, spraying, and landing, etc.) (DJI 2020). After receiving the radio signals sent from remote controllers, UAVs move automatically along designated routes to execute remote sensing or spraying. During the mission, UAVs share the real-time location with smart remote controllers (XAG 2020). If the UAVs were out of the designated tracks, farmers can adjust the flight paths by sending instructions from smart remote controllers.

3. Strengths, weaknesses, opportunities, and threats (SWOT) analysis of UAVs in maize production

Based on the literature available so far, a SWOT table can be elaborated, depicting the major strengths, weaknesses, opportunities, and threats of UAV use in maize production (Table 5).

Table 5: SWOT analysis of UAVs used in maize production

Strengths	**Weaknesses**
Minimize labor input	Data processing
Increase productivity	Data interpretation
Reduce resource wastage	Weather reliant
Accurate real-time field monitoring	High investments for small-scale farmers
Fewer working hours	Special education and training
Opportunities	**Threats**
Yield prediction	UAV crash
Nutrient status monitoring	UAV maintenance
Irrigation management	Unstable UAV performance
Identify weeds and diseases	Short flight time of each mission
Generate prescription maps	Unclear data ownership regulations

The strengths of UAVs in maize production are the reduction of labor input, higher productivity and thus higher economic performance, reduced resource wastage, accurate real-time field monitoring, and fewer working hours. Complicated data processing and data interpretation are the weaknesses that restrict the development of UAVs. A weakness of UAV operation is that it is weather dependent. Windy and rainy weather conditions are not ideal for UAVs and flights should be suspended under these circumstances (Tsouros et al. 2019a). Depending on platforms and sensors, the price of UAVs can be different. In 2018, the average price of a domestic brand crop spraying UAV was $14815 in China (Yang et al. 2018). A basic GPS guidance system in precision agriculture costs $800 to $1500 in the US in 2017 (Andrews 2017). The investments of UAVs are quite high especially for small size farmers because their production scale is small and the benefit, they could get from UAV technologies is limited (Yang et al. 2018). Farmers need special education and training, and this is another weakness of UAV adoption in maize production because not all farmers are willing to acquire new knowledge (Michels et al. 2019, Tamirat et al. 2018).

The UAV system offers opportunities for maize yield prediction, maize nutrient status monitoring, maize irrigation management, identification of maize weeds and diseases, and generation of prescription maps. But it also comes with some threats. Farmers need to run the risk of their UAV crashing; this happens sometimes (Barbedo 2019). UAV maintenance is an essential expense if an UAV were to be out of action. Unstable UAV performance also bothers farmers from time to time. The UAV flight time in each mission ranges from 8 to 60 minutes at full load (Candiago et al. 2015, Norasma et al.

2019, Tsouros et al. 2019a). Short flight time of each mission is another threat which affects UAV application because farmers need to refill application materials or to recharge energy frequently after each flight (Yang et al. 2018). This reduces the working efficiency. Longer flight time of each mission could be desirable for farmers. Fixed wing UAVs have long flight time, high speeds, high load capacity, stable performance and can cover large areas in a single mission, but they need wide space for take-off and landing (Boon et al. 2017).Comparing with fixed wing UAVs, multi-copter UAVs have slower speeds, shorter flight time, less payloads, but they are more flexible and more manoeuvrable because they can take off and land off vertically in constrained areas (Tsouros et al. 2019a). Therefore, fixed wing UAVs are best for large scale field investigation or spraying; instead multi-copter UAVs are good for small areas precise mapping or site-specific spraying. Finally, data ownership regulations have to be clarified in standard regulations to avoid conflicts of interest.

4. Discussion

Compared with traditional ground level precision maize production, UAVs offer an innovative way in irrigation management, nutrient status monitoring, weed mapping, and yield prediction. With the support of UAV precision technologies and FMIS, farmers can improve their work efficiency, reduce labor, and lower resource wastage. UAVs provide farmers greater access to real-time information on maize fields in a few hours and carry out comprehensive digital field monitoring and intelligent management. Farmers are released from the burden of complex data processing and intricate agricultural task planning, and all the agricultural activities are managed, planned, and recorded by the FMIS. This is the most significant merit of UAV-based agricultural production systems.

However, there are some severe limitations when using UAVs in maize production. UAV data management and UAV operations are very complicated. Without special training and education, farmers will not be able to handle it properly. The high purchase cost restricts UAV development in small scale farmers because their production scale is small and the benefit, they could get from UAV technologies is limited (Yang et al. 2018). Unstable performance bothers farmers from time to time when they are using UAVs (Sinha et al. 2016). Furthermore, UAV-based field management is not a general practice in maize production currently and it is not clear if they can replace the traditional ground level precision agriculture technologies in the future. Unclear data ownership regulations may cause conflicts of interest between farmers and data management platforms (Saiz-Rubio and Rovira-Más 2020, Wiseman et al. 2019). All these factors added together could increase the difficulty of UAV use in maize production and reduce work efficiency.

5. Conclusions and recommendations

This article contributes to the use, research, and development of UAVs in maize production, and leads to better understanding of the role of UAVs in maize production. The application of UAV technologies can solve some, but not all, problems in maize production. The advantages and potential of UAVs should not be overestimated. Compared to traditional ground level precision agriculture technologies, most of the UAV systems are still in the preliminary development and experimental stages. Moreover, the conclusions of UAV-based studies are only drawn from limited researches on specific field and maize variety conditions. The applicability of these conclusions in different circumstances needs to be verified. The large-scale commercial use of UAVs in maize production still has a long way to go. Up to now, most of the studies have focused on the technical level of UAV use, and not on the economic, social, ecological aspects or impact of UAVs in maize production systems. Future research is needed in these areas: education and training, impact assessment, technology assessment, economic evaluation, ecological evaluation, sustainable scheme, proper data ownership regulations.

Overall, there are some recommendations regarding UAV use in maize production in the future:

(i) Development of cost-effective UAVs, to make them more commercially acceptable to small-scale farmers;
(ii) Improvement of UAV performance, increases in the working time and load capacity of UAVs in a single flight, and reduction of UAV crashes; UAV unsupervised operation also needs to be improved because most countries only allow UAVs to be operated under supervision and this makes operation costly;
(iii) Improvement of UAV spraying accuracy and avoid drifting, to promote the adjustment of aerial spraying legal regulations;
(iv) Construction of user-friendly and high efficiency data management platforms to accelerate the ability of data transmission, processing, and interpretation;
(v) Offer of special training and education to farmers who have purchased UAVs, ensuring they get sufficient technical guidance and support services;
(vi) Clearer legal and regulatory frameworks to govern data management, which includes data collection, sharing, using, control, and accessibility;
(vii) Enhancement of network connections between UAV data management platform members and promotion of data sharing and benefit sharing among them;
(viii) Building of UAV system-based field management demonstration sites or farms and provision of consultancy and extension services to farmers.

References

Andrews, J. (2017): Six budget GPS guidance system options for farmers. https://www.fwi.co.uk/machinery/6-budget-gps-guidance-system-options-for-farmers, accessed on 5 June 2020

Barbedo, J. G. A. (2019): A Review on the Use of Unmanned Aerial Vehicles and Imaging Sensors for Monitoring and Assessing Plant Stresses. Drones 3, 40. https://doi.org/10.3390/drones3020040

Boon, M. A.; Drijfhout, A. P.; Tesfamichael, S. (2017): Comparison of a fixed-wing and multi-rotor uav for environmental mapping applications: a case study. Int. Arch. Photogram. Remote Sens. Spatial Inf. Sci. XLII-2/W6, 47–54. https://doi.org/10.5194/isprs-archives-XLII-2-W6-47-2017

Boursianis, A. D.; Papadopoulou, M. S.; Diamantoulakis, P.; Liopa-Tsakalidi, A.; Barouchas, P.; Salahas, G.; Karagiannidis, G.; Wan, S.; Goudos, S. K. (2020): Internet of Things (IoT) and Agricultural Unmanned Aerial Vehicles (UAVs) in smart farming: A comprehensive review. Internet of Things 100187. https://doi.org/10.1016/j.iot.2020.100187

Brauns, B.; Jakobsen, R.; Song, X.; Bjerg, P. L. (2018): Pesticide use in the wheat-maize double cropping systems of the North China Plain: Assessment, field study, and implications. Science of The Total Environment 616–617, pp. 1307–1316. https://doi.org/10.1016/j.scitotenv.2017.10.187

Burgos-Artizzu, X. P.; Ribeiro, A.; Guijarro, M.; Pajares, G. (2011): Real-time image processing for crop/weed discrimination in maize fields. Computers and Electronics in Agriculture 75, pp. 337–346. https://doi.org/10.1016/j.compag.2010.12.011

Burlacu, G.; Costa, R.; Sarraipa, J.; Jardim-Golcalves, R.; Popescu, D. (2014): A Conceptual Model of Farm Management Information System for Decision Support, in: Camarinha-Matos, L.M., Barrento, N. S.; Mendonça, R. (Eds.), Technological Innovation for Collective Awareness Systems, IFIP Advances in Information and Communication Technology. Springer Berlin Heidelberg, Berlin, Heidelberg, pp. 47–54. https://doi.org/10.1007/978-3-642-54734-8_6

Candiago, S.; Remondino, F.; De Giglio, M.; Dubbini, M.; Gattelli, M. (2015): Evaluating Multispectral Images and Vegetation Indices for Precision Farming Applications from UAV Images. Remote Sensing 7, pp. 4026–4047. https://doi.org/10.3390/rs70404026

Casa, R.; Pascucci, S.; Pignatti, S.; Palombo, A.; Nanni, U.; Harfouche, A.; Laura, L.; Di Rocco, M.; Fantozzi, P. (2019): UAV-based hyperspectral imaging for weed discrimination in maize. Precision agriculture 19. https://doi.org/10.3920/978-90-8686-888-9_45

Castaldi, F.; Pelosi, F.; Pascucci, S.; Casa, R. (2017): Assessing the potential of images from unmanned aerial vehicles (UAV) to support herbicide patch spraying in maize. Precision Agric 18, pp. 76–94. https://doi.org/10.1007/s11119-016-9468-3

Chikoye, D.; Udensi, U. E.; Fontem Lum, A. (2005): Evaluation of a new formulation of atrazine and metolachlor mixture for weed control in maize in Nigeria. Crop Protection 24, pp. 1016–1020. https://doi.org/10.1016/j.cropro.2005.02.011

Cilia, C.; Panigada, C.; Rossini, M.; Meroni, M.; Busetto, L.; Amaducci, S.; Boschetti, M.; Picchi, V.; Colombo, R. (2014): Nitrogen Status Assessment for Variable Rate Fertilization in Maize through Hyperspectral Imagery. Remote Sensing 6, pp. 6549–6565. https://doi.org/10.3390/rs6076549

Corti, M.; Cavalli, D.; Cabassi, G.; Vigoni, A.; Degano, L.; Gallina, P. M. (2018): Application of a low-cost camera on a UAV to estimate maize nitrogen-related variables. Precision Agriculture pp. 675–696. https://doi.org/10.1007/s11119-018-9609-y

Cui, Z.; Chen, X.; Miao, Y.; Zhang, F.; Sun, Q.; Schroder, J.; Zhang, H.; Li, J.; Shi, L.; Xu, J.; Ye, Y.; Liu, C.; Yang, Z.; Zhang, Q.; Huang, S.; Bao, D. (2008): On-Farm Evaluation of the Improved Soil N–based Nitrogen Management for Summer Maize in North China Plain. Agronomy Journal 100, p. 517. https://doi.org/10.2134/agronj2007.0194

Directive (2009): Directive 2009/128/EC on the sustainable use of pesticides, 2009. 16. October 2018. https://www.europarl.europa.eu/RegData/etudes/STUD/2018/627113/EPRS_STU(2018)627113_EN.pdf, accessed on 5 June 2020

DJI (2020): Comprehensive Solution and Intelligent Operation. [WWW Document]. AGRAS T16. https://www.dji.com/t16?site=brandsite&from=nav, accessed on 5 June 2020

Fang, Q. X.; Ma, L.; Green, T. R.; Yu, Q.; Wang, T. D.; Ahuja, L. R. (2010): Water resources and water use efficiency in the North China Plain: Current status and agronomic management options. Agricultural Water Management 97, pp. 1102–1116. https://doi.org/10.1016/j.agwat.2010.01.008

Gabriel, J. L.; Zarco-Tejada, P. J.; López-Herrera, P. J.; Pérez-Martín, E.; Alonso-Ayuso, M.; Quemada, M. (2017): . Airborne and ground level sensors for monitoring nitrogen status in a maize crop. Biosystems Engineering 160, pp. 124–133. https://doi.org/10.1016/j.biosystemseng.2017.06.003

Geipel, J.; Link, J.; Claupein, W. (2014): Combined Spectral and Spatial Modeling of Corn Yield Based on Aerial Images and Crop Surface Models Acquired with an Unmanned Aircraft System. Remote Sensing 6, pp. 10335–10355. https://doi.org/10.3390/rs61110335

Hamuda, E.; Glavin, M.; Jones, E. (2016): A survey of image processing techniques for plant extraction and segmentation in the field. Computers and Electronics in Agriculture 125, pp. 184–199. https://doi.org/10.1016/j.compag.2016.04.024

Han, L.; Yang, G.; Dai, H.; Bo, X.; Yang, H. (2019): Modeling maize above-ground biomass based on machine learning approaches using UAV remote-sensing data. Plant Methods 15, 10 (2019). https://doi.org/10.1186/s13007-019-0394-z

Herrmann, I.; Bdolach, E. (2019): Assessment of maize yield and phenology by drone-mounted superspectral camera. Precision Agriculture 21, pp. 51–76. https://doi.org/10.1007/s11119-019-09659-5

Ihuoma, S. O.; Madramootoo, C. A. (2017): Recent advances in crop water stress detection. Computers and Electronics in Agriculture 141, pp. 267–275. https://doi.org/10.1016/j.compag.2017.07.026

Jeffries, G. R.; Griffin, T. S.; Fleisher, D. H.; Naumova, E. N.; Koch, M.; Wardlow, B. D. (2020): Mapping sub-field maize yields in Nebraska, USA by combining remote sensing imagery, crop simulation models, and machine learning. Precision Agric 21, pp. 678–694. https://doi.org/10.1007/s11119-019-09689-z

Jha, K.; Doshi, A.; Patel, P.; Shah, M. (2019): A comprehensive review on automation in agriculture using artificial intelligence. Artificial Intelligence in Agriculture 2, pp. 1–12. https://doi.org/10.1016/j.aiia.2019.05.004

Kaimaris, D.; Patias, P.; Sifnaiou, M. (2017): UAV and the comparison of image processing software. International Journal of Intelligent Unmanned Systems, ISSN: 2049-6427

Katsvairo, T. W.; Cox, W. J.; Van Es, H. M. (2003): Spatial Growth and Nitrogen Uptake Variability of Corn at Two Nitrogen Levels. Agron. J. 95, pp. 1000–1011. https://doi.org/10.2134/agronj2003.1000

Kenneth, C.; Chinecherem, O. (2018): A Review of Expert Systems in Agriculture. International Journal of Computer Science and Information Security (IJCSIS) 16(4), pp. 126-129

Krienke, B.; Ferguson, R. B.; Schlemmer, M.; Holland, K.; Marx, D.; Eskridge, K. (2017): Using an unmanned aerial vehicle to evaluate nitrogen variability and height effect with an active crop canopy sensor. Precision Agric 18, pp. 900–915. https://doi.org/10.1007/s11119-017-9534-5

Li, W.; Niu, Z.; Chen, H.; Li, D.; Wu, M.; Zhao, W. (2016): Remote estimation of canopy height and aboveground biomass of maize using high-resolution stereo images from a low-cost unmanned aerial vehicle system. Ecological Indicators 67, pp. 637–648. https://doi.org/10.1016/j.ecolind.2016.03.036

Maresma, Á.; Ariza, M.; Martínez, E.; Lloveras, J.; Martínez-Casasnovas, J. (2016):. Analysis of Vegetation Indices to Determine Nitrogen Application and Yield Prediction in Maize (Zea mays L.) from a Standard UAV Service. Remote Sensing 8, 973. https://doi.org/10.3390/rs8120973

Michels, M.; Fecke, W.; Feil, J.; Musshoff, O.; Pigisch, J.; Krone, S. (2019): Smartphone adoption and use in agriculture empirical evidence from Germany. Precision Agriculture. https://doi.org/10.1007/s11119-019-09675-5

Mink, R.; Dutta, A.; Peteinatos, G.; Sökefeld, M.; Engels, J.; Hahn, M.; Gerhards, R. (2018):. Multi-Temporal Site-Specific Weed Control of Cirsium arvense (L.) Scop. and Rumex crispus L. in Maize and Sugar Beet Using Unmanned Aerial Vehicle Based Mapping. Agriculture 8, p. 65. https://doi.org/10.3390/agriculture8050065

Murakami, E.; Saraiva, A. M.; Ribeiro, L. C. M.; Cugnasca, C. E.; Hirakawa, A. R.; Correa, P. L. P. (2007): An infrastructure for the development of distributed service-oriented information systems for precision agriculture. Computers and Electronics in Agriculture 58, pp. 37–48. https://doi.org/10.1016/j.compag.2006.12.010

Norasma, C.Y.N., Fadzilah, M.A., Roslin, N.A., Zanariah, Z.W.N., Tarmidi, Z., Candra, F.S., 2019. Unmanned Aerial Vehicle Applications In Agriculture. IOP Conf. Ser.: Mater. Sci. Eng. p. 506, 012063. https://doi.org/10.1088/1757-899X/506/1/012063

Oerke, E.-C. (2006): Crop losses to pests 13. Journal of Agricultural Science (2006), 144, pp. 31–43. https://doi.org/10.1017/S0021859605005708

Orakwe, L. C.; Okoye, N. M. (2016): Advanced Decision Support and Data Acquisition Systems for Field Irrigation Management: A Review. International Journal of Advanced Engineering and Management Research, Vol.1 Issue 1, pp. 78-93

Park, S.; Ryu, D.; Fuentes, S.; Chung, H.; Hernández-Montes, E.; O'Connell, M. (2017): Adaptive Estimation of Crop Water Stress in Nectarine and Peach Orchards Using High-Resolution Imagery from an Unmanned Aerial Vehicle (UAV). Remote Sensing 9, p. 828. https://doi.org/10.3390/rs9080828

Pedersen, S. M.; Lind, K. M. (2017): Precision Agriculture: Technology and Economic Perspectives, Progress in Precision Agriculture. Springer International Publishing. https://doi.org/10.1007/978-3-319-68715-5

Pelosi, F.; Castaldi, F.; Casa, R. (2015): Operational unmanned aerial vehicle assisted post-emergence herbicide patch spraying in maize: a field study. In: Stafford, J.V. (Ed.), Precision Agriculture '15. Wageningen Academic Publishers, The Netherlands, pp. 159–166. https://doi.org/10.3920/978-90-8686-814-8_19

Peña, J. M.; Torres-Sánchez, J.; de Castro, A. I.; Kelly, M.; López-Granados, F. (2013): Weed Mapping in Early-Season Maize Fields Using Object-Based Analysis of Unmanned Aerial Vehicle (UAV) Images. PLOS ONE 8, e77151. https://doi.org/10.1371/journal.pone.0077151

Peña, J. M.; Torres-Sánchez, J.; de Castro, A. I.; Serrano-Pérez, A.; López-Granados, F. (2014): Comparing visible and color-infrared UAV imagery for early-season weed mapping the case of maize as a wide row crop. RHEA-2014. Second International Conference on Robotics and associated High-technologies and Equipment for Agriculture and forestry: new trends in mobile robotics, perception and actuation for agriculture and forestry, pp. 319-327. http://hdl.handle.net/10261/160279

Peña-Barragán, J. M.; Kelly, M. (2012): Object-based Approach for Crop Row Characterization in UAV Images for Site-specific Weed Management. Proceedings of the 4th GEOBIA, May 7-9, 2012 - Rio de Janeiro - Brazil. p. 426

Ping, J. L.; Dobermann, A. (2005): Processing of Yield Map Data. Precision Agric 6, pp. 193–212. https://doi.org/10.1007/s11119-005-1035-2

Poblete, T.; Ortega-Farías, S.; Ryu, D. (2018): Automatic Coregistration Algorithm to Remove Canopy Shaded Pixels in UAV-Borne Thermal Images to Improve the Estimation of Crop Water Stress Index of a Drip-Irrigated Cabernet Sauvignon Vineyard. Sensors 18, p. 397. https://doi.org/10.3390/s18020397

Prasad, G. N. R.; Babu, D. A. V. (2006): A Study on Various Expert Systems in Agriculture. Georgian Electronic Scientific Journal: Computer Science and Telecommunications 4(11), pp. 81-86

PrecisionHawk (2020): Deploy a Turnkey Drone Mapping and Analytics Solution for Agriculture. For Agriculture-count crops, quantify plant health and maximize yield. https://www.precisionhawk.com/agriculture, accessed on 30 November 2020

Prince Czarnecki, J. M.; Samiappan, S.; Wasson, L.; McCurdy, J. D.; Reynolds, D. B.; Williams, W. P.; Moorhead, R. J. (2017): Applications of Unmanned Aerial Vehicles in Weed Science. Advances in Animal Biosciences 8, pp. 807–811. https://doi.org/10.1017/S2040470017001339

Quemada, M.; Gabriel, J.; Zarco-Tejada, P. (2014): Airborne Hyperspectral Images and Ground-Level Optical Sensors as Assessment Tools for Maize Nitrogen Fertilization. Remote Sensing 6, pp. 2940–2962. https://doi.org/10.3390/rs6042940

Radoglou-Grammatikis, P.; Sarigiannidis, P.; Lagkas, T.; Moscholios, I. (2020): A compilation of UAV applications for precision agriculture. Computer Networks 172, 107148. https://doi.org/10.1016/j.comnet.2020.107148

Rani, P. M. N.; Rajesh, T.; Saravanan, R. (2011): Expert Systems in Agriculture: A Review 14. Journal of Computer Science and Applications 3(1), pp. 59-71

Reger, M.; Bauerdick, J.; Bernhardt, H. (2018): Drones in Agriculture: Current and future legal status in Germany, the EU, the USA and Japan. Landtechnik 73(3), pp. 62–80. https://doi.org/10.15150/LT.2018.3183

Rhezali, A.; Lahlali, R. (2017): Nitrogen (N) Mineral Nutrition and Imaging Sensors for Determining N Status and Requirements of Maize. J. Imaging 3, 51. https://doi.org/10.3390/jimaging3040051

Safdar, M. E.; Tanveer, A.; Khaliq, A.; Riaz, M. A. (2015): Yield losses in maize (Zea mays) infested with parthenium weed (Parthenium hysterophorus L.). Crop Protection 70, pp. 77–82. https://doi.org/10.1016/j.cropro.2015.01.010

Saiz-Rubio, V.; Rovira-Más, F. (2020): From Smart Farming towards Agriculture 5.0: A Review on Crop Data Management. Agronomy 10, 207. https://doi.org/10.3390/agronomy10020207

Shi, X.; Han, W.; Zhao, T.; Tang, J. (2019): Decision Support System for Variable Rate Irrigation Based on UAV Multispectral Remote Sensing. Sensors 19, 2880. https://doi.org/10.3390/s19132880

Sinha, J. P.; Kushwaha, H. L.; Kushwaha, D.; Singh, N.; Purushottam, M. (2016): Prospect of Unmanned Aerial Vehicle (UAV) Technology for Agricultural Production Management. International Conference on Emerging Technologies in Agricultural and Food Engineering 27 – 30th December 2016, Agricultural and Food Engineering Department, IIT Kharagpur

Sørensen, C. G.; Fountas, S.; Nash, E.; Pesonen, L.; Bochtis, D.; Pedersen, S. M.; Basso, B.; Blackmore, S. B. (2010): Conceptual model of a future farm management information system. Computers and Electronics in Agriculture 72, pp. 37–47. https://doi.org/10.1016/j.compag.2010.02.003

Sørensen, C. G.; Pesonen, L.; Bochtis, D. D.; Vougioukas, S. G.; Suomi, P. (2011): Functional requirements for a future farm management information system. Computers and Electronics in Agriculture 76, pp. 266–276. https://doi.org/10.1016/j.compag.2011.02.005

Srivastava, K.; Pandey, P. C.; Sharma, J. K. (2020): An Approach for Route Optimization in Applications of Precision Agriculture Using UAVs. Drones 4, 58. https://doi.org/10.3390/drones4030058

Sylvester, G. (2018): E-agriculture in action: drones for agriculture. Food and Agriculture Organization of the United Nations, International Telecommunication Union, 2018. ISBN 978-92-5-130246-0s. http://www.fao.org/3/I8494EN/i8494en.pdf, accessed on 5 June 2020

Talaviya, T.; Shah, D.; Patel, N.; Yagnik, H.; Shah, M. (2020): Implementation of artificial intelligence in agriculture for optimisation of irrigation and application of pesticides and herbicides. Artificial Intelligence in Agriculture 4, pp. 58–73. https://doi.org/10.1016/j.aiia.2020.04.002

Tamirat, T. W.; Pedersen, S. M.; Lind, K. M. (2018): Farm and operator characteristics affecting adoption of precision agriculture in Denmark and Germany. Acta Agriculturae Scandinavica, Section B — Soil & Plant Science 68, pp. 349–357. https://doi.org/10.1080/09064710.2017.1402949

Tsouros, D. C.; Bibi, S.; Sarigiannidis, P. G. (2019a): A Review on UAV-Based Applications for Precision Agriculture. Information 10, 349. https://doi.org/10.3390/info10110349

Tsouros, D. C.; Triantafyllou, A.; Bibi, S.; Sarigannidis, P. G. (2019b): Data Acquisition and Analysis Methods in UAV- based Applications for Precision Agriculture. In: 2019 15th International Conference on Distributed Computing in Sensor Systems (DCOSS). Presented at the 2019 15th International Conference on Distributed Computing in Sensor Systems (DCOSS), IEEE, Santorini Island, Greece, pp. 377–384. https://doi.org/10.1109/DCOSS.2019.00080

Usman, A.; Elemo, K. A.; Bala, A.; Umar, A. (2001): Effect of weed interference and nitrogen on yields of a maize/rice intercrop. International Journal of Pest Management 47, pp. 241–246. https://doi.org/10.1080/09670870110044625

Vergara-Díaz, O.; Zaman-Allah, M. A.; Masuka, B.; Hornero, A.; Zarco-Tejada, P.; Prasanna, B. M.; Cairns, J. E.; Araus, J. L. (2016):. A Novel Remote Sensing Approach for Prediction of Maize Yield Under Different Conditions of Nitrogen Fertilization. Front. Plant Sci. 7. https://doi.org/10.3389/fpls.2016.00666

Wahab, I.; Hall, O.; Jirström, M. (2018): Remote Sensing of Yields: Application of UAV Imagery-Derived NDVI for Estimating Maize Vigor and Yields in Complex Farming Systems in Sub-Saharan Africa. Drones 2, 28. https://doi.org/10.3390/drones2030028

Wang, X.; Zhang, R.; Song, W.; Han, L.; Liu, X.; Sun, X.; Luo, M.; Chen, K.; Zhang, Y.; Yang, H.; Yang, G.; Zhao, Y.; Zhao, J. (2019): Dynamic plant height QTL revealed in maize through remote sensing phenotyping using a high-throughput unmanned aerial vehicle (UAV). Sci Rep 9, 3458. https://doi.org/10.1038/s41598-019-39448-z

Wiseman, L.; Sanderson, J.; Zhang, A.; Jakku, E. (2019): Farmers and their data: An examination of farmers' reluctance to share their data through the lens of the laws impacting smart farming. NJAS - Wageningen Journal of Life Sciences 90–91, 100301. https://doi.org/10.1016/j.njas.2019.04.007

Wu, G.; Miller, N. D.; de Leon, N.; Kaeppler, S. M., Spalding, E. P. (2019): Predicting Zea mays Flowering Time, Yield, and Kernel Dimensions by Analyzing Aerial Images. Front. Plant Sci. 10, 1251. https://doi.org/10.3389/fpls.2019.01251

XAG, 2020. XSAS intelligent agriculture systems [WWW Document]. XSAS intelligent agriculture systems. URL https://www.xa.com/xsas, accessed on 5 June 2020

Yang, S.; Yang, X.; Mo, J. (2018): The application of unmanned aircraft systems to plant protection in China. Precision Agric 19, pp. 278–292. https://doi.org/10.1007/s11119-017-9516-7

Yin, X.; Jaja, N.; McClure, M. A. M.; Hayes, R. (2011a): Comparison of Models in Assessing Relationship of Corn Yield with Plant Height Measured during Early- to Mid-Season. JAS 3, p. 14. https://doi.org/10.5539/jas.v3n3p14

Yin, X.; McClure, M. A.; Jaja, N.; Tyler, D. D.; Hayes, R. M. (2011b): In-Season Prediction of Corn Yield Using Plant Height under Major Production Systems. Agron. J. 103, pp. 923–929. https://doi.org/10.2134/agronj2010.0450

Zhai, Z.; Martínez, J. F.; Beltran, V.; Martínez, N. L. (2020): Decision support systems for agriculture 4.0: Survey and challenges. Computers and Electronics in Agriculture 170, 105256. https://doi.org/10.1016/j.compag.2020.105256

Zhang, C.; Kovacs, J. M. (2012): The application of small unmanned aerial systems for precision agriculture: a review. Precision Agric 13, pp. 693–712. https://doi.org/10.1007/s11119-012-9274-5

Zhang, L.; Niu, Y.; Zhang, H.; Han, W.; Li, G.; Tang, J.; Peng, X. (2019a): Maize Canopy Temperature Extracted from UAV Thermal and RGB Imagery and Its Application in Water Stress Monitoring. Front. Plant Sci. 10, 1270. https://doi.org/10.3389/fpls.2019.01270

Zhang, L.; Zhang, H.; Niu, Y.;Han, W. (2019b): Mapping Maize Water Stress Based on UAV Multispectral Remote Sensing. Remote Sensing 11, 605. https://doi.org/10.3390/rs11060605

Zhang, M.; Zhou, J.; Sudduth, K. A.; Kitchen, N. R. (2020): Estimation of maize yield and effects of variable-rate nitrogen application using UAV-based RGB imagery. Biosystems Engineering 189, pp. 24–35. https://doi.org/10.1016/j.biosystemseng.2019.11.001

Zhu, W.; Sun, Z.; Peng, J.; Huang, Y.; Li, J.; Zhang, J.; Yang, B.; Liao, X. (2019): Estimating Maize Above-Ground Biomass Using 3D Point Clouds of Multi-Source Unmanned Aerial Vehicle Data at Multi-Spatial Scales. Remote Sensing 11, p. 2678. https://doi.org/10.3390/rs11222678

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Declaration of interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Xiuhao Quan: conceptualization, methodology, formal analysis, investigation, writing-original draft, visualization, writing – review& editing.

Reiner Doluschitz: conceptualization, validation, resources, writing-review & editing, supervision.

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