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REVIEW ARTICLE

Enhancing agronomical attribute detection through RPAS-based image analysis - A review

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Abstract

The integration of Remotely Piloted Aircraft Systems (RPAS) into agronomical research has revolutionized the collection and analysis of spatial and temporal crop data. RPAS, equipped with high-resolution multispectral, thermal and visible cameras, provide a cost-effective and flexible alternative to traditional laboratory and manual methods. This review synthesizes recent advancements in RPAS-based image analysis for agronomic applications, with a focus on crop monitoring, weed detection, biomass estimation and yield prediction. A critical evaluation of the published information reveals that most studies utilize low-altitude flights with commercial drones integrated with sensors capable of capturing data with high spatial resolution. Image processing techniques, such as vegetation indices, machine learning algorithms and object-based image analysis, are commonly employed to extract biophysical and biochemical parameters. The review of the literature demonstrates a strong correlation between RPAS-derived metrics and ground-based measurements, validating their utility in precision agriculture. However, variability in sensor calibration, flight parameters and environmental conditions presents challenges to reproducibility and scalability. Overall, RPAS-based image analysis offers a promising avenue for enhancing data-driven decision-making in agriculture, contributing to more sustainable and efficient farming practices in the future.

Keywords:agronomic crops; biomass; plant phenology; plant pigments; weed detection

Introduction

The number of agricultural workers in India has been steadily declining and is projected to fall to 25.7 % by 2050, leading to a critical shortage of farm labour (1). These shortages in Indian agriculture are a growing concern, affecting productivity, cropping patterns and economic viability and are driven by a combination of socioeconomic factors and government policies. Addressing these challenges requires a multifaceted approach, including increased mechanization, policy adjustments and innovative farming practices, to ensure sustainable agricultural productivity. In this context, drones equipped with remote sensing technology play a critical role in resource management, disease detection and environmental conservation, making them indispensable tools in farming. Low-cost remote sensing, particularly using drones, has emerged as a viable alternative to satellite-based methods. The standard abbreviations used for drones are Unmanned Aircraft Systems, Unmanned Aerial Vehicle, RPAS and Dynamic Remotely Operated Navigation Equipment and Directional Remotely Operated Navigation Equipment. A variety of RPASs have been developed because of advancements in fabrication, navigation, remote control and battery storage technologies. These drones are useful in situations where human access is challenging, dangerous, or impossible. In recent years, flying robots have gained popularity owing to their wide range of applications, including military surveillance, planetary exploration and search-and-rescue. According to a previous study, agronomic crops comprise approximately 70 % of global crop production (2).

The current manual methods, such as measuring stick (plant height) (3), densiometer (canopy cover) (4), SPAD and laboratory methods (chlorophyll content and plant nitrogen content) (5,6), weed indices (weed discrimination) and special harvesting techniques (Leaf Area Index (LAI), biomass and yield), are labour-intensive and complex in nature. Therefore, the use of reflectance spectroscopy for the prediction and classification of the above-mentioned traits in agronomic crops could be an effective strategy for optimizing growing conditions. This could contribute significantly to advances in agronomic research and global crop production. Plants change their reflectance pattern under undesirable conditions (7,8). These changes in reflectance were utilized by researchers to make these assessments easier by combining RPAS-based sensors. This technique, known as spectral imaging, combines traditional imaging and spectroscopy. Unlike traditional imaging, which captures images in three primary colours (red, green and blue), spectral imaging collects data in several narrow, contiguous spectral bands. This allows for a detailed analysis of the spectral properties of objects, providing both spatial and spectral information (9–11). Other techniques, such as imaging and spectroscopy, provide structural/visual and spectral information, respectively. Detailed information on these three techniques is provided by Tan, Chen (12). The core principle of spectral imaging is to collect and analyse the spectral signatures of objects, which are unique patterns of light absorption, reflection and emission at different wavelengths. This is achieved using sensors that can capture images at various spectral bands, including ultraviolet, visible, Near-Infrared (NIR), thermal infrared and mid-infrared regions. This comprehensive spectral data enables the identification and classification of materials based on their spectral signatures (10). The collected data are then processed using chemometric techniques and machine learning algorithms to extract meaningful information about the object's composition and condition (9,13,14). These modern technologies are transforming agriculture by enhancing its precision, efficiency and sustainability. By leveraging RGB, multispectral and hyperspectral imaging, RPAS can detect crop health issues, monitor growth patterns and assess environmental impacts with unprecedented accuracy. The integration of artificial intelligence and internet of things technologies further enhances the potential of RPAS to provide real-time data for informed decision-making.

This review explores the current state of research on agronomical crops by synthesizing the existing literature on various plant attribute detection using RPAS-based imagery, not soil-related attributes.

Applications of Spectral Vegetation Indices (SVI) in agriculture

SVI serve as powerful tools for farmers, researchers and policymakers as well as enabling data-driven decision-making, improve crop health and productivity by conserving resources (15). With advancements in satellite and RPAS technologies, these indices have become increasingly accessible, thus revolutionizing modern farming practices (16). These indices utilize spectral reflectance across multiple wavelengths to monitor soil moisture, nutrient levels, water stress, pests and diseases and yield potential with high accuracy (17). By integrating drones with geographic mapping, machine learning and AI, modern farming is shifting toward sustainable and resource-efficient practices. Beyond agriculture, SVI have broad applications in forestry, environmental monitoring and land-use planning, further enhancing their significance in ecosystem management and conservation. Different agricultural indices cater to various aspects of crop monitoring. SVI, such as NDVI (Normalized Difference Vegetation Index), EVI (Enhanced Vegetation Index) and SAVI (Soil-Adjusted Vegetation Index), assess plant vigour, biomass (18) and canopy structure (19). Water indices, including the NDWI (Normalized Difference Water Index) and LSWI (Leaf Surface Water Index), assist in detecting drought stress and optimizing irrigation (20). Nutrient indices such as CCCI (Canopy Chlorophyll Content Index) and NDRE (Normalized Difference Red Edge Index) help assess plant nutrient status and guide precision fertilizer application (21). Similarly, other indices used in agriculture, such as stress detection indices, soil-adjusted indices and productivity-related indices, are explored in Appendices 1, highlighting their applications in various agronomical studies.

Deriving morphological attributes from spectral imagery

The morphological attributes of crops and vegetation play a crucial role in assessing plant health, growth dynamics and overall agricultural productivity. An image captured through multiple sensors provides detailed spatial and spectral information about plant canopies. With advancements in remote sensing and imaging technologies, spectral imagery has emerged as a powerful tool for the accurate and efficient extraction of morphological characteristics. Table 1, summarizes the previous studies related to morphological attribute detection. Further the table highlight different sensor types, method used to derive different attributes and precision.

Plant height

In agronomical or crop production studies, plant height is used to select the best crop management strategy in terms of yield and environmental sustainability. Plant height represents a balance between maximizing light capture and distributing resources for structural growth and yield. It serves as an important indicator of traits such as relative yield (28), senescence (35) and biomass accumulation (3). RPAS-based approaches for plant height measurement allow for rapid and large-scale data collection. Structure from Motion (SfM) algorithms are commonly used to reconstruct 3D scenes by overlapping 2D images (36) and matching features present in multiple images, including camera positions and orientations. This process enables the extraction of morphological and structural attributes, such as plant height, from 3D reconstructions (SfM dense point clouds), orthomosaics and Digital Surface Models (DSMs), also known as Digital Elevation Models (DEM). Orthomosaics provide distortion-corrected images of fields, allowing for the identification of areas of interest (37). Whereas DSMs offer 2D representations using colour scales to depict height elements (38), providing a pseudo-colour presentation of the field. SfM point clouds, which often provide superior precision, can be used directly to obtain plant height measurements. However, point clouds are large, difficult to handle and computationally expensive because they include millions of data points and their size can grow exponentially with increased imaging quality and overlap. DSM datasets, on the other hand, are substantially smaller and require less processing power and storage space. Therefore, DSMs are a more effective way to extract plant height, although they are usually less accurate than point clouds. Plots are defined on the orthomosaic, 3D reconstructions are created and altitude data are extracted from the DSM rather than the point cloud in the majority of plant height estimation techniques (4).

RPAS based plant height extraction methods mentioned in previous studies. Digital Terrain Model (DTM) method identifies ground pixels and interpolates missing values to create a DTM, which is then subtracted from the DSM to obtain accurate plant height measurements (3,27,28), making it particularly useful in fields with bare-ground areas. The difference-based method determines plant height by subtracting a pre-crop DSM (captured before plant emergence) from a flight DSM taken when the canopy is fully developed (24,25). A computationally efficient alternative is the exposed alley subtraction method, which estimates the ground height by identifying ground points in plot alleys and subtracting them from the plot height values. When no visible ground is available, the self-calibration method estimates the ground level by integrating RPAS data with a small number of manually measured

Table 1. Summary of previous studies related to morphological attributes

Crop	Attribute	Type of sensors	Indices	Method	RPAS software	Precision	Reference
Soybean	PH VF	RGB, MSI and thermal	RGB - R, G, B, Color intensity (INT), Kawashima index (IKAW), Principal compound analysis index (IPCA) MSI - G, R, RE, NIR, NDVI, GNDVI, NDRE Thermal - Tc	DSM - DEM SVM classifier	Pix4Dmapper	PH - 0.78 (R^2) VF – 99.59 % (OA)	(22)
Sorghum	PH LAI	LiDAR and RGB	-	Original point height – ground elevation (DEM) RFR models	Pix4Dmapper LiDARMill	PH (R^2) - 0.975 (LiDAR) 0.873 (RGB) LAI (R^2) - 0.950 (LiDAR) 0.939 (RGB)	(23)
Soybean	PH CC LAI	RGB and Satellite imagery	RECI, NDVI, GNDVI, NDRE, RVI, EVI, EVI2, OSAVI, MCARI, TCARI, MCARI/OSAVI, TCARI/OSAVI, WDRVI, SIPI, VARI, TVI_{Trans}	DSM-DEM	Pix4Dmapper	PH - 0.898 (R^2) LAI - 0.927 (R^2)	(18)
Rice	PH	RGB and MSI	NDVI, VF and SPAD values	multiple linear regression (MLR)	Agisoft Metashape	0.838 (R^2)	(14)
Maize	PH	RGB		crop surface DSM - bare soil DSM	Agisoft Photoscan	0.9 (R^2)	(24)
Soybean	PSA Vigor estimation PH	RGB	- green chromatic coordinates -	binary classification, SVM algorithm - crop surface DSM - bare soil DSM	Agisof PhotoScan	PSA - 0.82 (R^2)	(25)
Maize (M) soybean (S)	PH	LiDAR	-	CHM LiDAR variables (LVs) laser interception index (LII), canopy relief ratio (CRR)	TerraScan	CHM (R^2) – 0.649 (M), 0.408 (S), 0.821 (M&S) LVs (R^2) – 0.822 (M), 0.448 (S), 0.966 (M&S)	(26)
Lentils	VAGR CVGR	RGB and MSI	GNDVI, BNDVI, NGRDI -	Maximum Likelihood (ML) DSM and DTM	Pix4D software	-	(19)
Maize	PH	MSI	-	DSM - DTM	-	-	(27)
Maize	PH	RGB	-	DSM - DTM	Pix4d Mapper	0.024 (SE)	(3)
Cover crops	PH	RGB and MSI	-	DSM - DTM	Agisoft Metashape	0.94 (R^2)	(28)
Maize	LAI	MSI	Normalized Difference Texture Index (NDTI), Difference Texture Index (DTI) and Ratio Texture Index (RTI), NDVI, NDRE, MTCI, DVI, RVI, CT_{RE}, EVI, OSAVI	SVM	Pix4D mapper	0.813 (R^2) and 0.297 (RMSE)	(29)
Winter barley	PH	SVC	-	Cloud-to-Cloud Distance Calculation	Agisoft Metashape	24.9-35.6 mm (AE)	(30)
Cauliflower	RGR	RGB	-	multi-modal monitoring approach	VIA software	8.3122 (RE)	(31)
Winter wheat	PH CC LAI	HSI	NDVI, RVI, EVI, EVI2, GI, MSAVI, OSAVI, WDRVI, TVI_{Trans}, DVI1, DVI2, DVI3, MTVI1, MTVI2, SAVI, LAIDI, PSND, RDVI, SLAIDI, SPVI, DCNI, NDRE, NDII, NDWI	PLSR, RF	UF HiperGator-RV, POSPac UAV, Spectral View software	Varies	(32)
Maize	LAI	MSI	NDVI, MSAVI2, GWDRVI, GLI, RECI, MSR, EVI1, EVI2, NLI, MDD, DVI, GRVI, OSAVI, NRI, MNDI, NDRE, RESAVI, GNDVI, RVI	stacking ensemble learning model with deep forest (DF), deep neural network (DNN), SVR and linear regression (LR)	Pix4Dmapper	Varies	(33)
Winter wheat	LAI	RGB and MSI	NDVI, NDRE, OSAVI, MCARI, TCARI, GNDVI, RGBVI, GLI	convolutional neural networks (CNN), multi-source feature fusion network	Pix4d Mapper	0.8745 (R^2) and 0.5461 (RMSE)	(34)

PH – Plant Height; RGB – RGB imagery; MSI – Multispectral Imagery; HSI– Hyper Spectral Imagery; CC – Canopy Cover; LAI – Leaf Area Index; SVC – Stereo Vision Camera; VAGR – Vegetation Area Growth Rate; CVGR – Crop Volume Growth Rate; VF – Vegetation Fraction; sUAS – small UAS; thermal – Thermal imagery; PSA – Plant Spatial Abundance canopy heights. Beyond ground height estimation, the accuracy of plant height extraction using RPAS images also depends on selecting the correct pixels representing plant tops. In addition to filtering out erroneous pixels, optimizing the SfM metrics significantly enhances DSM-based plant height measurements (4).

In recent years, various algorithms have been employed to extract plant height from RPAS imagery, thereby enhancing the efficiency and accuracy of crop phenotyping. Machine learning algorithms, such as Support Vector Machines (SVM), Random Forests (RF) and Decision Trees (DT), have been applied to RPAS-derived data to estimate plant height and yield, demonstrating their effectiveness in agricultural studies. Comparing RPAS-based measurements of plant height to terrestrial measurements, it is frequently found that the former tends to underestimate the results. The main causes of this underestimation are the incorporation of ground pixels in point clouds and the failure to record sparse pixels connected to structures such as canopy apexes. Another reason is inaccurate location data that ultimately affect the quality and accuracy of DSM. However, there have also been reports of overestimation, which is frequently caused by the influence of nearby plots that are higher (39). Taking pictures with at least 85 % overlap over regions with uniformly spaced Ground Control Points (GCPs) is a recommended technique for accurate plant height extraction. The accuracy was increased by employing a high-precision GPS and positioning the GCPs in the same spots on several flights. With developments in RPAS technology, notably Real-Time Kinematic (RTK) GPS, the necessity for GCP placement can be considerably reduced or even eliminated (12).

Canopy cover

Canopy cover is an important measure of plant development that regulates light interception, weed control, biomass buildup and total yield potential (4). RPAS imagery is widely used to monitor canopy cover changes in crop fields using various classification methods. One common approach involves categorizing orthomosaic pixels as vegetative or non-vegetative (40). Several classification techniques have proven effective, with thresholding of colour parameters being the most commonly used (19,28). This method relies on factors such as hue and saturation values, the green vegetation index, lightness, green-magenta and blue-yellow color space, ExG and the NGRDI index (4). However, owing to variations in soil colour and lighting conditions across different time points, normalizing or calibrating image colour parameters before analysis is essential to ensure accuracy. In addition, shadows and other vegetation types must be considered to improve classification reliability. Beyond thresholding, advanced classification techniques such as K-means clustering, Gaussian mixture models, SVMs and Fully Convolutional Networks (FCNs) can achieve high accuracies. Among these, K-means clustering and FCNs are particularly advantageous because of their ability to process large datasets quickly and efficiently (41). Because this approach does not improve weed pixel categorization, reliable canopy cover predictions require weed suppression or eradication. Classification methods, such as the SVM algorithm and Maximum Likelihood (ML) classifier, can be used to identify colour changes among orthomosaics to increase accuracy. These techniques have been effective in accurately identifying crops such as watermelon, soybeans, sorghum (9), maize, weeds and soil (42). Additionally, assessing productivity in large production fields with mixed varieties would greatly benefit from sophisticated classification techniques that can differentiate between multiple varieties of a single crop (4).

LAF

Another essential canopy attribute measurable via RPAS-derived orthomosaics is the LAI. Its function in photosynthesis, transpiration and nutrient cycling makes it a crucial biophysical characteristic of interest. It is defined as the one-sided leaf area per unit ground surface area. To achieve desired canopy characteristics, common methods link SVI, extracted colours and image variables. The structural complexity of the canopy has also been quantified in order to determine the LAI. These measurements, which include the geographical distribution of leaves in three dimensions, show the crop canopy's variability and spatial patterns (43). A substantial, high correlation was found between manual LAI measures in maize and a linear regression model that was developed by applying stepwise selection on the complexity metrics. The standard deviation of point height and the rumple index were chosen by the majority of models as two important predictors for LAI. The use of colour calibration standards was lessened by this technique (4,43). LAI was estimated by establishing an empirical relationship between NDVI values and ground-measured LAI using regression models developed through prior calibration experiments. Alternatively, models that convert vegetation indices to LAI have been utilized. LAI values were calculated for each pixel and the average LAI for the plot was determined by taking the mean over the area of interest (23). Ensemble learning algorithms can serve as substitutes for individual machine learning algorithms in developing LAI prediction models (33). The strong correlation between LAI and biomass accumulation and yield highlights its importance in crop monitoring.

Canopy roughness

In agriculture, canopy roughness is a measure of the variability or unevenness in the height and structure of a plant canopy. It is important because it affects variables like wind flow, light distribution and microclimate conditions within the canopy. Precise measurement of canopy roughness is necessary for applications such as biomass estimation, crop health monitoring and modelling of energy exchanges between the land surface and atmosphere. Herrero-Huerta, Bucksch introduced canopy roughness as a novel trait for crop phenotyping, quantifying surface irregularities using high-resolution 3D point clouds derived from imagery captured by RPAS (44). Canopy roughness is computed for each pre-processed plot through a two-step process. First, point roughness is determined by calculating the Euclidean distance between each point and the best-fitting plane formed by neighbouring points within a user-defined radius (0.10 m). Second, plot-level canopy roughness is derived by computing the interquartile range and median of the roughness values from all points within the plot.

Deriving biochemical attributes from spectral imagery

Crop biochemical characteristics are crucial markers of plant health since they are involved in important ecological functions such as respiration, transpiration, photosynthesis and responses to stress. Given their direct impact on foliar photosynthetic rate and primary production, leaf chlorophyll and nitrogen (N) content distinguish out among them. Despite their significance, it has been difficult to directly extract biochemical information from RGB visuals using SVI. Research shows that though multispectral and hyperspectral imaging yield better results, pigment estimate accuracy is still inconsistent. Experts are increasingly using hyperspectral photography in conjunction with Artificial Intelligence (AI) tools (viz., SVM, RF) to enhance crop modelling and pigment profiling.

Biochemical analysis depends on selecting the most responsive wavelengths for different plant traits (45,46). Studies indicate that using specific wavelengths provides greater precision in differentiating C_3 and C_4 crop metabolisms compared to broader spectral bands such as blue, green, red or NIR. This section focuses on the precise extraction of leaf pigments, N content and water status of plants from RPAS-derived imagery for accurate crop management. Table 2, summarizes the previous studies related to biochemical attributes in agronomic crops.

Plant pigments

Plant pigments include chlorophylls, carotenoids, anthocyanins and flavonoids, each playing distinct roles in plant health and development. Detecting these pigments is essential for understanding plant physiology, health and stress responses. Recent studies have utilized various spectral bands and SVI such as NDRE to estimate chlorophyll a and chlorophyll b. While correlations have ranged from low to moderate, incorporating LAI significantly improved accuracy in maize. However, these findings appear to be crop-specific, as studies on soybean have shown only moderate correlations (22). To further enhance accuracy, researchers suggest integrating additional biophysical traits such as texture analysis while eliminating background pixels. The variation in leaf chlorophyll content and lighting conditions during data acquisition remains a challenge, emphasizing the need for higher spectral resolution sensors. Notably, thermal radiation has been explored as a complementary method, as leaf chlorophyll content influences crop canopy temperature (22). These findings highlight the limitations of current assessments and the necessity for more advanced sensor technologies (22,59). The advanced method like wavelength-specific approaches have proven effective in distinguishing crops like maize, sugarcane, coffee and wheat, offering enhanced pigment profiling (60). The Hyperspectral Vegetation Index (HVI) is emerging as a powerful tool for assessing pigment levels such as chlorophyll a, b, carotenoids, anthocyanins and flavonoids. Utilizing reflectance hyper spectroscopy, HVI enables more precise remote and proximal sensing of biochemical and morphological traits, offering a non-invasive, highly accurate approach for crop health monitoring. By focusing on narrow-band spectral indices, HVI could enable improved classification of different crop varieties within the same environment, making it a promising alternative for High-Throughput Pigment phenotyping (HTP) (46). The integration of hyperspectral sensors with AI-driven approaches has significantly improved pigment classification in crops. High-resolution spectral equipment enables rapid and precise data collection, while machine learning (61), deep learning (62) and data mining facilitate more accurate, HTP analysis. Despite the progress in spectral imaging and AI-driven pigment analysis, current models still require refinement to improve the estimation of biochemical compounds such as anthocyanins and flavonoids (46,63,64). Hence, improvement in advanced sensor technologies, AI-driven predictive modelling and spectral data optimization will be crucial for enhancing plant pigment analysis.

Leaf nitrogen

N is a crucial nutrient, significantly influencing photosynthesis and overall yield, despite constituting only 2–4 % of the crop's dry matter (65). Effective N management is key to improve fertilizer use efficiency and reducing input costs, which requires aligning N application with the crop's specific demands. Optical sensing technologies, particularly those that measure reflectance related to chlorophyll content, offer a rapid and non-destructive way to assess crop N status. Chlorophyll content, a strong indicator of N availability, has been widely used to estimate crop N status. Advances in multispectral and hyperspectral sensing have enabled more precise monitoring of canopy N content over time, providing a better understanding of how N availability affects maize health (6). The visible spectrum, where chlorophyll strongly absorbs radiation in the red and blue bands, contrasts with the NIR region, which reflects the structural features of leaf mesophyll (56). This discrepancy allows for the use of indices like NDVI, often sensitivity to canopy structure and soil background, as well as saturation effects when LAI is high (66). Later, NGRDI used, which accounts for variations in pigment concentration and canopy structure. However, even these indices can experience saturation effects at higher LAI levels, making them less effective in differentiating crop development stages (56). To overcome these challenges, more advanced indices have been proposed. For instance, the NDI, which relies on blue-green reflectance, is less impacted by canopy structure and provides a more accurate reflection of N variations, particularly in rice crops. Similarly, the DCNI was developed to improve N estimation in wheat and maize by minimizing the effects of canopy structure. RPAS-derived indices, such as the NDRE, have proven particularly useful for detecting reduced chlorophyll levels and canopy cover under N deficient conditions. However, the accuracy of these results depends on the precision of GCPs obtained through RTK (50). Furthermore, combined chlorophyll indices such as MCARI/MTVI2 and TCARI/OSAVI have proven more effective at estimating both chlorophyll a and b content (Cab) and nitrogen content (% Na) by reducing structural and soil influences, with MCARI/MTVI2 showing strong correlation to Cab (R^2 = 0.69) and % Na (R^2=0.59) without being affected by LAI (67). Additionally, dynamic spectral index approaches, such as two-band combinations, are becoming increasingly popular. These methods can generate potential indices, helping to identify the most accurate canopy N content predictors for different crops and environments (68). For instance, in cotton and maize crops, these dynamic indices have proven effective in determining optimal N concentrations. One more commonly used tool is nitrogen nutrient index, which is based on the critical N concentration the minimum N level required for optimal growth. RPAS-based active sensors, such as the RapidSCAN CS-45, have also been used to develop spectral models for monitoring growth indicators like LAI, leaf dry matter and N accumulation in winter wheat (21). Additionally, hyperspectral remote sensing has shown great promise in estimating canopy N content (6). Despite these advantages, SVI often struggle with generalization due to variations in environmental conditions, crop varieties and growth stages, which can introduce uncertainties in the canopy N content spectral estimation models (69,70). Overall, advancements in optical sensing, particularly through RPAS and hyperspectral technologies, offer promising solutions for precision N management in crops, though ongoing refinement is necessary to ensure their applicability across different crops, growth stages and environmental conditions.

Water status detection

Water-related spectral reflectance indices are essential tools widely used in agricultural and ecological applications, such as assessing surface water bodies, estimating vegetation water status, evaluating soil water content and monitoring wetlands like paddy rice fields. These indices are primarily derived from the visible, NIR and Shortwave Infrared (SWIR) bands, as they effectively capture

Table 2. Summary of previous studies related to biochemical attributes

Crop	Attribute	Type of sensors	Indices	Method	RPAS software	Precision	Reference
Soybean	chll content N concentration	RGB, MSI and thermal	RGB = R, G, B, INT, IKAW, IPCA MSI = G, R, RE, NIR, NDVI, GNDVI, NDRE Tc	PLSR, RFR, ELR, SVM based classifier	Pix4Dmapper	Varies	(22)
Soybean	chll content N concentration	RGB, MSI and thermal	R, G, B, INT, IKAW, IPCA G, R, RE, NIR, NDVI, GNDVI, NDRE Tc	PLSR, SVR, ELR	Pix4Dmappersoft ware	Varies	(22)
Soybean	plant water status	Thermal imaging	Normalized Relative Canopy Temperature (NRCT)	/	Thermo-Vision Joe-C	0.93 (R^2)	(47)
Soybean	Leaf N concentration	RGB and Satellite imagery (Worldview-2/3)	C (coast), B, Y (Yellow), G, R, RE, NIR1, NIR2, RECI, NDVI, GNDVI, NDRE, RVI, EVI, EVI2, OSAVI, MCARI, TCARI, MCARI/OSAVI, TCARI/OSAVI, WDRVI, SIPI, VARI, TVI_{Trans}	PLSR, RFR, SVR, ELR	Pix4Dmapper	0.591 (R^2)	(18)
Winter wheat	LNA PNA NNI	RapidSCAN CS-45 sensor	NDVI, NDRE, RESAVI, DVI, SAVI, RERVI, PVI, REDVI, RVI, REWDRVI, VIopt1, TVI_{Trans}, OSAVI, RRE, RERDVI, CIRE, CCCI	/	/	Varies	(21)
Corn	PNC PNU NNI	Crop Circle Phenom sensor	NDVI, NDRE, CCC, LAI, RVI, CCCI, fPAR, Tc and Tair temperature	simple regression (SR), eXtreme Gradient Boosting (XGB) models	-	Varies	(48)
Maize	crop coefficient (Kc) values	MSI	NDVI, SAVI, EVI, TCARI, GNDVI, VARI	RFR, MLR	-	RFR - 0.65 (R^2) MLR - <0.4 (R^2)	(49)
Soybeans	leaf N content water status	MSI	G, R, RE, NIR, CI_R, CVI, EVI, EVI2, ExGR, GCI, GLI, GNDVI, GRVI, MExG, MNGRD, NDRE, NDREI, NDVI, NG, NGRD, OSAVI, PSND, RDVI, RECI, GDPR, RVI, SAVI, SCCI, TCARI, TCARI-OSAVI, TACRIRE, TACRI-OSAVI.RE, GIT, WDRVI, WDVI	ML method	Pix4D Mapper	Varies	(5)
Maize	N deficiency stress	MSI	NDRE	-	Pix4Dmapper	0.9097 (R^2)	(50)
Winter wheat	soil water stress level	MSI	soil water stress indices (SWSIs) - NDVI, GNDVI, EVI, EVI2, SAVI, OSAVI, GOSAVI, MCARI, MSR, SIPI, NDRE, GRVI, RVI, ExG, CIRE, DVI, MTCI, MTCI2, NDVIRE, NLI, PPR, RDVI, NRI, TCARI, TVI_{Tri}	Stacking Ensemble Learning Model	Pix4DMapper	0.79 (R^2)	(51)
maize	water status	MSI	GCI, MExG, MNGRD, NDRE, NDREI, NDVI, NGRD, PSND, RECI, RGD, RVI, SAVI, TCARI, TCARI/OSAVI, TCARRE, WDRVI WDRVI – Grain Yield MNGRD – RWC NDVI – Stomatal conductance	ML classification	OpenDroneMap	0.985 (R^2) 0.8559 (R^2) 0.8967 (R^2)	(52)
Soybean	Soil Moisture Content	MSI and Thermal-Infrared	texture features, texture indices and thermal-infrared vegetation indices MTVI, SAVI, OSAVI, MSAVI, DVI, GNDVI, GCVI, NLI, RVI, RDVI, MSR, NDRE, TVI_{Tri}, NDVI, EVI	XGB, RF, Genetic Algorithm-optimized Backpropagation Neural Network (GA-BP)	Yusense Map	0.78	(53)
cotton	water stress Classification	RGB imagery	ExGI, NDVI, structure features	CNN, RF classifier	Agisoft Metashape	91 %	(54)
Maize	Soil Moisture	MSI	NDVI, RVI, GNDVI, OSAVI, TVI_{Trans}, MSAVI	RF, Particle Swarm Optimization-SVM (PSO-SVM)	DJIModify	Varies	(55)
Maize	nutrient status	RGB, visible-infrared region (OCN) records reflected light in the Orange (O) 615 nm, Cyan (C) 490 nm and near infrared (N) 808 nm wavelengths	NGRVI, NDVI-ON	-	Agisoft PhotoScan	-	(56)
otton	leaf water potential	RBG	NGRDI, ExG, NGBDI, VDVI	Sparrow Search Algorithm (SSA)-Extreme Learning Machine (ELM) model	OpenCV	0.85 (R^2)	(57)
Maize	Leaf water content	MSI	ExG, NDVI, NDWI, NDRE, GVI, SAVI, EVI, GNDVI, OSAVI, TVI_{Tri}, NDCI	MLR, ridge regression (RR), RFR, particle swarm optimization (PSO)	ENVI 5.6 ArcGIS 10.8	MLR - 0.80 (R^2) RR - 0.81 (R^2) RFR - 0.88 (R^2) PSO - 0.89 (R^2)	(58)

Chll - Chlorophyll; LNA - Leaf N Accumulation; LNC - Leaf N Concentration; PNA - Plant N Accumulation; NNI - Nitrogen Nutrition Index; thermal - Thermal imagery; MSI - Multispectral Imagery; sUAV - small UAV the spectral reflectance characteristics of water and vegetation (20). While thermal and microwave bands are also valuable for large-scale drought monitoring and soil moisture assessment, especially with coarse resolution (71,72). They are not as useful for field and sub-field agricultural applications that require finer spatial resolution. Although various responses in water, vegetation and soil are visible in the NIR and SWIR bands, the blue band is rarely utilized in water-related studies due to its high susceptibility to atmospheric contamination and its similar response to surface water and vegetation (20). Infrared thermography has been utilized for many years to assess canopy temperature, which is closely linked to the water status of plants. This connection arises because, during drought, stomata close, reducing transpiration rates and consequently decreasing heat dissipation. As a result, canopy temperatures become higher than those of the air and plants that have sufficient water (47). The relationship between leaf water content and crop moisture conditions is crucial, as water is vital for photosynthesis, nutrient uptake and overall plant metabolism (73). When plants experience different levels of moisture, their tissue structure, physiological and ecological signs and shape change leads to slow growth, wilting and leaf chlorosis, while excessive water can cause root diseases and hypoxia, negatively impacting plant health (74). These changes affect how they reflect light (75). This makes it possible to use remote sensing technology to check plant moisture levels. With multispectral imagery, monitoring crop moisture content has become more feasible, enabling efficient and timely irrigation management. Studies have explored RPAS-based multispectral images to estimate the water status of crops (58). The integration of thermal-infrared remote sensing with multispectral data enhances the accuracy of estimating crop water status, such as leaf water content, canopy transpiration and soil moisture content (53). This fusion of data allows for a more comprehensive understanding of how crops respond to moisture stress, providing valuable insights into field-scale crop management. RPAS technology has shown considerable promise in enhancing soil moisture monitoring, offering advantages like high spatial resolution, mobility and timeliness, overcoming the limitations of traditional in-situ measurements and satellite data (55). Moreover, combining RPAS-based multispectral sensing with advanced algorithms, such as the Random Forest Regression (RFR) algorithm, has the potential to improve precision irrigation and optimize water use distribution on the field scale (49,76).

Deriving biomass and yield attributes from spectral imagery

Biomass serves as a vital metric for assessing crop growth and health; however, traditional measurement techniques often require destructive sampling, which can be both expensive and labour-intensive (32). Predicting biomass at the early stages is crucial for enhancing decisions related to yield estimation and crop management (77). Table 3 summarizes the previous studies related to biomass and yield attributes in agronomic crops. Recent advances in sensors and machine learning have significantly improved these capabilities. Bareth, Hütt utilized RPAS plant height to estimate biomass (85). These structural crop traits have shown strong potential as reliable indicators of biomass and nitrogen uptake. Urquizo, Ccopi highlighted the importance of agronomic variables, including seedling growth and individual plant height, in guiding critical management decisions such as irrigation and fertilization (88). Hu, Fan focused on the upper, middle and lower canopy layers to develop biomass-prediction models (89). Among these upper canopy model provided better prediction accuracy, especially during mid-to late growth stages, compared to whole-plant models (R^2= 0.24-0.34), hierarchical RPAS-based approaches achieve better accuracy (R^2= 0.53-0.70). Zhai, Li predicted the biomass by integrating spectral, structural and textural information (82). Textural features were derived using a gray-level co-occurrence matrix algorithm. The prediction accuracy decreases with increasing flight height (82). The vegetation cover fraction (83) and canopy cover (84) were used along with plant height and SVIs to predict biomass. This is because SVIs alone provide a poor accuracy. Hyperspectral images, along with different learning models, were used for winter canola biomass estimation (86). The binary prediction model utilizing time-series multispectral phenotyping imagery, achieving over 93 % accuracy in classifying soybean maturity, with successful validation in an independent breeding trial. Convolutional Neural Networks (CNNs) have been effectively used for agricultural monitoring tasks, including flower detection, fruit counting and yield estimation. However, they require large labelled datasets that are often difficult to obtain. Kumar, Desai introduced a semi-automatic image annotation method to facilitate the creation of labelled datasets for maize (79). Additionally, integrating remote sensing data into crop growth models, particularly through data assimilation techniques such as the Ensemble Kalman Filter (EnKF), has proven effective. Guo, Hao found that incorporating LAI into the WOFOST model significantly improved maize yield predictions, further enhanced by integrating RPAS-based crop traits (87). Integration of methods like RPAS images with GCPs, statistical and machine learning models enhances the accuracy. Further refinement of methods used for prediction of biomass and yield will support sustainable farming.

Weed discrimination from spectral imagery

Weed mapping using RPAS have enabled the generation of site-specific weed treatment maps, significantly reducing herbicide use by targeting infestations more precisely. Table 4, summarizes the previous studies related to weed discrimination in agronomic crops. While early methods primarily classified vegetation outside crop rows as weeds (99), recent approaches integrate spectral analysis and machine learning to detect weeds both within and between rows (100). A key innovation in these methods is the shift toward object-based image analysis. Which segments high-resolution RPAS imagery into meaningful objects, incorporating spatial and contextual data for more accurate classification (92). Although hyperspectral imaging provides detailed spectral information, its high cost and processing demands limit its practical use, whereas low-cost RPAS with RGB or NIR sensors offer efficient and accessible alternatives. RGB imagery, in particular, has proven effective in weed detection when combined with advanced classification techniques (99). Detecting late-season perennial weeds is especially valuable. As these infestations tend to recur in the same locations over multiple seasons, aiding in the creation of management zones for future precision interventions (91). However, distinguishing small weeds from crops during early growth stages remains challenging due to visual similarities. To overcome this, Lin, Zhang developed a fine feature aggregation module based on the ConvNeXt framework (95). Which enhances feature extraction and improves segmentation accuracy for small and early-stage weeds. These advancements highlight the growing potential of RPAS-based technologies in supporting precise, cost-effective weed management strategies.

Table 3. Summary of previous studies related to biomass and yield attributes

Crop	Attribute	Type of sensors	Indices	Method	RPAS software	Precision	Reference
Maize	Yield estimation	RGB	-	scale-invariant feature transform (SIFT) algorithm	Agisoft Photoscan Professional	Varies r2=0.83 – 0.92	(24)
Winter wheat	Yield estimation	MSI	NDVI, EVI, DVI, SAVI	MLK analysis	Pix4Dmapper	R2 = 0.807	(78)
Maize	Tassel detection	RGB and MSI	-	k- means clustering	Agisoft Photoscan	0.97438	(79)
Oat	AGB	MSI	NDVI, GNDVI, TVI_{Tri}, RTVI, NGRDI, VARI, ExGR	PLS, SVM, Artificial neural network (ANN), RF, K-Mean Clustering Algorithm	Pix4Dmapper	Varies	(80)
Maize	Yield estimation (Hill)	RGB and MSI	NDVI (Sentinel), GRVI	Linear R, MLR	-	Varies	(27)
Wheat	Yield estimation	thermal and RGB	NDVI (Green-Seeker)	Elastic Net (ELNET), SVM, Gaussian Process Regression (GPR), Generalized Linear Model (GLM), Spike, Slab Regression (SpikeSlab), Multivariate Adaptive Regression Spline (MARS), PLS, RF, K-Nearest Neighbours (KNN), Stepwise Linear Regression (SLR), XGB, Cubist.	-	Varies	(77)
Oat	AGB	MSI	NDVI, GNDVI, NDRE, SAVI, OSAVI, DVI, RVI, NDI, GLI, ExGR	PLSR, SVR, RFR	Pix4D Mapper	Varies	(81)
Wheat	AGB	RGB	ExG, ExB, GLI, VARI, ExGR, RGBVI, MGRVI, NGRDI, GRRI, NDI	Random Forest Regression (RFR), Gradient Boosting Regression Trees (GBRT), Ridge Regression (RR), Least Absolute Shrinkage, Selection Operator (Lasso), SVR	Pix4D Mappersoftware	R2 = 0.845 to 0.852	(82)
Cover crops (Black oat, Rye, Hairy vetch, Egyptian clover, White mustard)	AGB	MSI	NDVI, OSAVI, GNDVI, CI_G, NDREI, CIRE, TVI_{Tri}	Species-specific and global (including all species) regression models, stepwise multiple regression	Pix4Dmapper	Varies	(83)
soybean	Fresh Biomass	MSI	TGI, CIVE, ExG, ExR, ExGR, NGRDI, GLI, VARI, G, R, B, DVI, GARI, GCI, GDVI, GNDVI, GOSAVI, GRVI, GSAVI, IPVI, MNLI, MSAVI, MSR, NLI, NDVI, OSAVI, RDVI, SAVI, SR, TDVI, NDRE	RF, PLSR algorithm	Agisoft PhotoScan	Varies	(84)
Winter wheat	Fresh and dry Biomass	RGB	-	Structure from Motion and Multiview Stereopsis (SfM/MVS) analysis, LR	Agisoft Metashape	Varies	(85)
Winter canola	AGB	HSI	NDVI, MNDVI, SRVI1, SRVI2, ARVI, SAVI, OSAVI, EVI, PRI, RDVI, VOGREI, mrNDVI, TCARI, CI, MTCI, NDRE, DCNI, WDRVI, MSR, MSAVI, NDI	Ada boost, XGB, RF, GBRT, SVR, GPR Gaussian Process Regression	Cubert Utils Touch	Varies	(86)
Alfalfa	AGB	RGB and MSI	ExG, NDVI	Statistical modelling algorithm	Pix4Dmapper	Varies	(66)
Maize	Yield estimation	RGB	GCC, RCC, BCC, Gray, RGRI, GLI, VARI, MRBVI, NGBDI, GBDI, IKAW, NGRDI, MGRVI, RGBVI, CIVE	World Food Studies (WOFOST) model, Ensemble Kalman Filter (EnKF), Extended Fourier Amplitude Sensitivity Test (EFAST), SUBPLEX optimization algorithm	Agisoft Metashape	Varies	(87)
Forage oat	AGB	MSI	DVI, NDVI, GNDVI, NDRE, ENDVI, RDVI, EVI, VDVI, WDRDVI, TVI_{Trans}, SAVI, OSAVI, CVI, MSAVI, MCARI, TCARI, NPCI, GCI, RECI, SIPI, ARI	LR, RFs, SVMs, NNs	Pix4Dmapper	RF – 0.52 (R^2) SVM – 0.50 (R^2)	(88)
Cotton	AGB	RGB and MSI	NDVI, NNIR, RVI, DVI, WDRVI, GRVI, GNDVI, BNDVI, GDVI, EVI, SIPI2, SAVI, OSAVI, GOSAVI, CI_G, RESR, ARVI, TVI_{Tri}, GRDVI, MSR, GMSR	Hierarchical (H) and whole plant (W) model, RF, LR, SVM	Pix4D mapper	H – 0.53-0.70 (R^2)	(89)
Rice	Mature Biomass estimation	RGB	R, G, B, VARI, GRVI, MGRVI, RVI, DVI, NDVI	SVR	Pix4DMapperYusense Map	0.78 (R^2)	(90)
Sorghum	AGB	MSI	-	RF, SVM, K-NN	Agisoft MetaShape	RF – 0.80 (R^2) SVM – 0.64 (R^2) K-NN – 0.50 (R^2)	(8)

RGB - RGB imagery; MSI - Multispectral Imagery; HSI - Hyper Spectral Imagery; Thermal - Thermal imagery; AGB - Above Ground Biomass; RUE - Radiation Use Efficiency

Table 4. Summary of previous studies related to weed discrimination

Crop	Attribute	Type of sensors	Indices	Method	RPAS software	Precision	Reference
Oat	weed mapping	RGB	NGRDI, GLI, VARI, CI, RI, BI	Auto matic object-based, Automatic pixel-based, Manual object-based, Manual pixel-based RF, K-means algorithm	Agisoft PhotoScan software	Vary	(91)
Sunflower Cotton	Broad Leaved and Grass Weeds	RGB	Red normalized, Green normalized, Blue normalized, R/B, R/G, NRGDI, NPCI, VARI, WI, ExB, ExG, ExR, ExGR, CIVE, VEG	Multiresolution Segmentation Algorithm (MRSA) Automatic Object-oriented Image Analysis (OBIA), Multilayer Perceptron (MLP) neural network	Agisoft PhotoScan Professional eCognition Developer 9 software	83.64 % and 78.16 %	(92)
Sorghum	Weed segmentation	Motion blur UAV images	-	DeepLabv3+, 4 variants of Fully Convolutional Networks, UNet	-	89 % (F1 score)	(93)
Chicory Lincoln beet	Weed detection	RGB	-	YouOnlyLookOnceversion7 (YOLOv7)	Roboflow's online tools, Python	Varies 50 – 75 %	(94)
Sugar beets	segmentation of weed and crop	UAV images with semantic annotations	-	fine-grained feature-guided UNet, Contextual Feature Fusion (CFF) module	-	92.37 %	(95)
Maize Tomato	Weed classification	RGB	-	CNNs models - VGG16, Resnet152, Inception- Resnet-v2	Agisoft PhotoScan software	Varies 36 – 99 %	(96)
Maize and Tomato	Weed classification	RGB	-	Vision transformer Swin-T model	-	Varies 60 – 99 %	(97)
Sugarcane	Weed detection	MSI with RBG channels	-	feature-based Deep Neural Network	Drone Deploy Pix4D	90.5 %	(98)
Maize	weed-induced yield loss	RGB and MSI	-	SVM (used crop-weed leaf cover ratios)	Agisoft Metashape	R2 = 0.17 to 0.97	(42)
Potato	Weed segmentation	RGB	-	YOLOv8, Mask R-CNN models	Agisoft Metashape	R2= 0.902 0.920	(37)

RGB – RGB imagery; MSI – Multispectral Imagery; HSI – Hyper Spectral Imagery; UAV – Unmanned Arial Vehicle

Conclusion

Image analysis using RPAS has become a significant asset in agronomy, providing high-resolution, timely and cost-efficient data collection. Nevertheless, variations in data collection protocols, sensor calibration and analytical techniques hinder its widespread adoption and the ability to compare studies. The precision varied depending on the sensor fusion, SVIs, algorithms employed and the methodology used. Therefore, future studies should aim to create standardized workflows, integrate multi-sensor data and utilize advanced machine learning and AI models to enhance accuracy and automation. Combining RPAS data with ground truth and satellite observations can further improve temporal coverage and analytical depth. Moreover, real-time processing and cloud-based platforms could enable immediate decision-making in precision agriculture. With ongoing technological progress and interdisciplinary collaboration, RPAS has the potential to become a fundamental element in sustainable, data-driven agronomic management.

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Authors' contributions

VV conceptualized the study and prepared the original draft. MV and RKP administered the project, supervised the work and provided resources for manuscript preparation. SN, BD and RR contributed to validation and manuscript review and editing. PMV, KM and GS were responsible for visualization. All authors read and approved the final manuscript.

Compliance with ethical standards

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