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A review on high through-put field phenotyping by Unmanned Aerial Vehicles based Remote sensing (UAV-Rs) technologies in precision agriculture

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Abstract
Remote sensing in agriculture is a frontier area that leverages advanced technologies to revolutionize farming practices. By harnessing the power of sensors mounted on satellites, drones, and aircraft, remote sensing enables the collection and analysis of data about crops and land from a distance. Crop phenotype refers to a comprehensive set of physiological and biochemical characteristics that are influenced by the genetic information and environmental factors. Phenotyping plays a prominent role in predicting the genotypic and phenotypic expression patterns in relation to yield improvement. Conventional approaches for acquiring phenotypic data in field is labour intensive and time-consuming process. Therefore, the emergence of Unmanned Aerial Vehicle based remote sensing platforms (UAV-Rs) equipped with diverse sensors has recently revolutionized the high-throughput phenotyping. Sensor based crop phenotyping involves in rapid and nondestructive collection of large-scale plant phenotypic data through UAV-Rs technologies. This review examines how the strategic use of imaging spectroscopy of UAV-Rs facilitates the compliance monitoring of crop phenotype, in the assessment of crop geometric and quantitative traits, in the estimation of vegetation indices and in the biotic and abiotic stresses responses through different spectroscopy imaging technologies such as RGV, multispectral, hyperspectral, thermal, LIDAR and RADAR.

Keywords: Unmanned aerial vehicle, remote sensing, crop phenotyping, spectroscopy imaging, crop geometric traits

Introduction
In 21st century, the challenge in crop research lies in accurate forecasting of crop performance amidst the dynamic backdrop of climate change. The extremities of climate change and global warming necessitates the development of high yielding stress tolerant varieties. The advances in next generation DNA sequencing have significantly enhanced genotyping efficiency, the progress in characterizing plant traits has been comparatively slower over the past three decades. Consequently, limitations in phenotyping capabilities restrict our capacity to unravel the genetic quantum of plant traits, particularly those associated with complex physiological and biophysical status traits. The use of remote sensing tools in high-throughput field-phenotyping has emerged as a rapid, cost effective and non-destructive method for plant screening (White *et al.*, 2012) [60].
Remote sensing is the discipline of both art and science that acquires information about objects without direct physical contact using various techniques and technologies. The beginning of remote sensing in agriculture is involved in large area inventories and regional crop mapping. The present day contribution of Remote sensing in agriculture involves in pest management, irrigation scheduling, crop growth monitoring, nutrient management, stress detection, Invasive species detection and in natural resource management and in its applications. The traits that influence the performance index of a crop includes the crop phenology, crop canopy, greenness index of canopy, leaf inclination, canopy temperature depression, plant density and leaf nitrogen content which can be measured through remote sensing by measuring radiance and extracting the former (Weiss *et al.*, 2019) [59].
Remote sensing systems employed in precision agriculture can be categorized based on the platform on which the sensors are mounted and also based on the type of sensors utilized. These platforms include satellites, aerial vehicles such as drones and aircraft (Unmanned aerial vehicles), and ground-based installations (Unmanned ground vehicles) [Fig.01].

Since the1970s satellite-based products have played a significant role in precision Agriculture whereas in more recent times, aerial platforms, including aircraft and unmanned aerial vehicles (UAVs), have gained popularity and are being increasingly utilized in Precision Agriculture. The UAV based remote sensing (UAV-Rs) can attain the plot level resolution by measuring several hundreds of plots in one mission through high resolution thermal and multispectral imaginary captured at an altitude ranging from 30 – 100 m (Tattaris *et al.*, 2016) [54]. Ground-based platforms and devices are the tractor mounted sensors and the hand-held instruments which includes infrared thermometers, sped meter and an NDVI through spectral radiometer. These measures canopy temperature depression, chlorophyll content index and vegetation behavior respectively. The calculation of NDVI involves using wavelengths in the near infrared (NIR) and visible (VIS) regions of the electromagnetic spectrum. NDVI can measure the chlorophyll content and describe the photosynthetic capacity of the plant. It can estimate crop biomass at different phenophases of crop along with the nitrogen deficiency and crop senescence rate (Raun *et al.*, 2001 and Babar *et al.*, 2006) [46, 2]. Canopy temperature serves as a direct measure of the plants transpiration rate and is closely associated with stomatal conductance and plant water status, exhibiting a robust correlation with plant performance under stress conditions (Berliner *et al.*, 1984) [4].

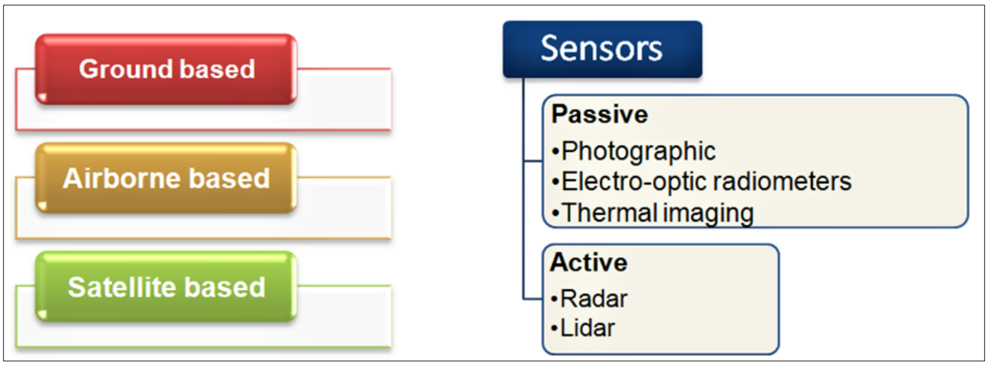
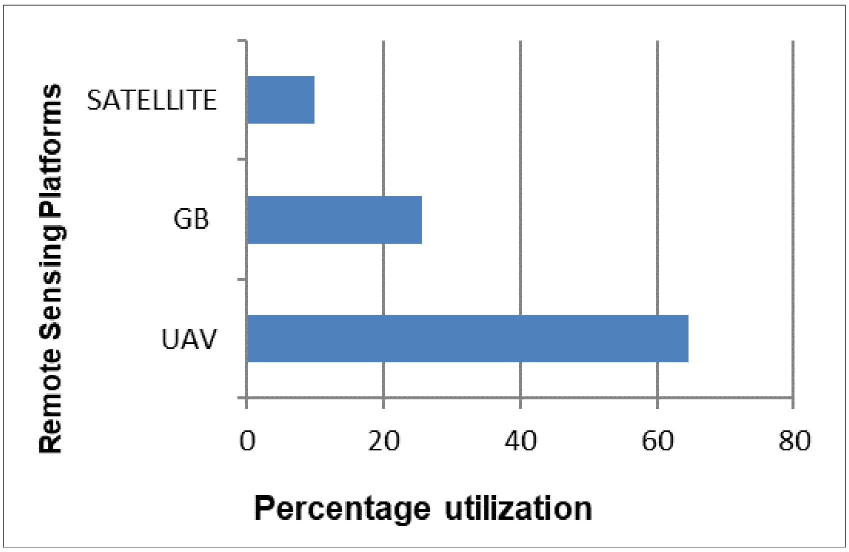
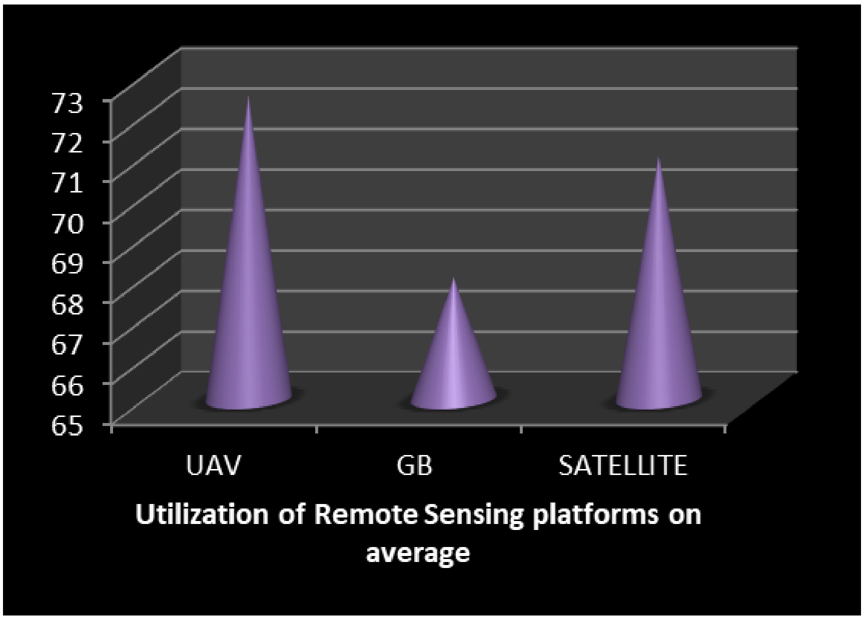


Fig 1: The picture represents the types of remote sensing and fundamental sensor systems used in remote sensing

Ground based systems are also known as proximal remote sensing as they are situated in close proximity to the targeted surface, whether it is land surface or plant (Sishodia *et al.*, 2020) [52]. On the other hand, sensors can be classified into passive and active (Fig. 01). Each of these different platforms and sensors serves specific purposes and provides valuable information for monitoring and managing crops. The role of Satellite based imaging technologies in agriculture is extremely useful, whereas the major limitations of using satellite sensors includes high cost, less spatial resolution for observing desirable traits and cloudy weather conditions (Issei *et al.*, 2010, Sankaran *et al.*, 2015 and Gevaert *et al.*, 2015) [24, 49, 15]. The large-scale field condition monitoring with the sensors having high spatial and spectral resolutions can be performed by UAV-Rs. UAV-Rs are flexible and low-altitude affordable tools of remote sensing for field monitoring and precision agriculture (Hunt *et al.*, 2005, Liebisch *et al.*, 2015 and Candiago *et al.*, 2015) [23, 31, 8] Hence, this review is to evaluate the feasibility of Unmanned Aerial Vehicles of Remote sensing (UAV-Rs) in high through-put phenotyping and to provide an overview of current techniques of UAV-Rs. Extraction of plant phenotypic data includes two approaches one is traditional and the other is through remote sensing. Traditional method involves direct measurement of phenotypic data such as plant height, biomass, leaf area index, chlorophyll and carotenoid content, protein, soil moisture content by standard procedures at field in a destructive and time-consuming manner. It is an outdated approach of phenotyping that doesn't provide a through phenotypic data extraction of plant with no parallelism between genotype and phenotype (Rahaman *et al.*, 2015) [45].





(UAV- Unmanned Aerial Vehicle, GB- Ground Based)

On the other hand sensor based field phenotyping of crop using Unmanned Aerial Vehicle of remote sensing technology have the ability in productive study of the phenotypic characters of large areas in non-destructive manner with convenient flexibility in operating and providing demand access to data with high level of spectral and spatial resolution (Yang *et al.*, 2017) [63]. The correlation between manual approach and UAV-Rs based estimates showed correlation of R^2 >0.8 (Han *et al.*, 2018) [21]. Images captured by sensors play a prominent role in monitoring crop geometric and agronomic traits (Feng *et al.*, 2021) [12]. Various sensors equipped on UAVs are described as follows. The use of UAV-Rs imaging technology in precision agriculture has been in use since 2010 (Schirrmann *et al.*, 2016) [50].

Various sensors mounted on UAV-Rs

Commercial UAV-Rs currently utilize a range of sensors, including digital cameras or visible imaging cameras (RGB), multispectral cameras, infrared thermal imagers, hyperspectral cameras, LIDAR (Light Dectection and Ranging), synthetic aperture radar (SAR) and 3D-cameras. These sensor choices are influenced by factors such as cost, low power consumption, small size and light weight design, payload capacity, and technological advancements as highlighted in studies by (Sankaran *et al.*, 2015) [49].

Visible light imaging or RGB UAV-Rs

RGB cameras are widely utilized among the image processing applications It involves in the detection of visual symptoms of plants, such as diseases that causes the alteration of color composition in leaves and the presence of insects and pathogensi on the foliage. Color plays a significant role in the detection of disease as it implies in the analysis of intensity of disease. The single pixel of an RGB image is represented by three colours such as Red, Green, and Blue. It has 8 bit monochrome standard consisting of 24 bist/pixel representing 8 bist for each color (Padmavathi *et al.*, 2016) [43].

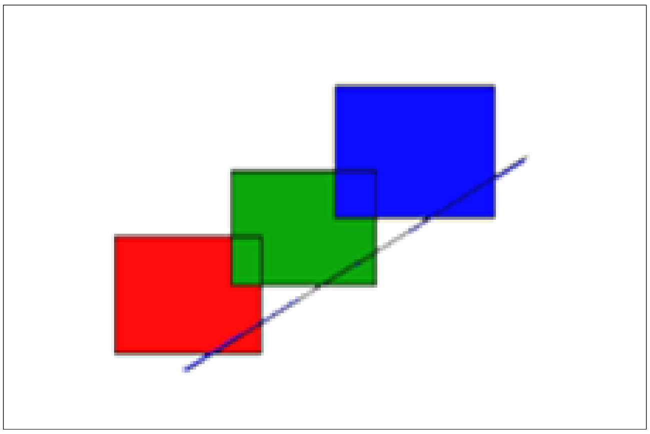


Fig 2: RGB Pixel Representation

The captured photographic images has to be converted in to another form, by image pre-processing techniques to minimize the noises and interferences for getting noiseless and enhanced image of interest. (Fig. 02). It involves multiple collection of techniques such as Image filtering, Image segmentation (Color mapping, Clustering), Edge detection (Fig. 03). These techniques removes the noise in original image and improves the quality and visual appearance of image making it better for image analysis Visible or RGB imaging is widely regarded as a highly effective imaging technique for plant stress-related studies. This approach provides valuable insights by analyzing crop canopy coverage and the colour of the surface canopy (Lee *et al.*, 2013) [29]. (Bendig *et al.*, 2015) [3] estimated the biomass (R^2 = 0.9) of maize at early stages by using RGB vegetation indices through combined linear regression models.

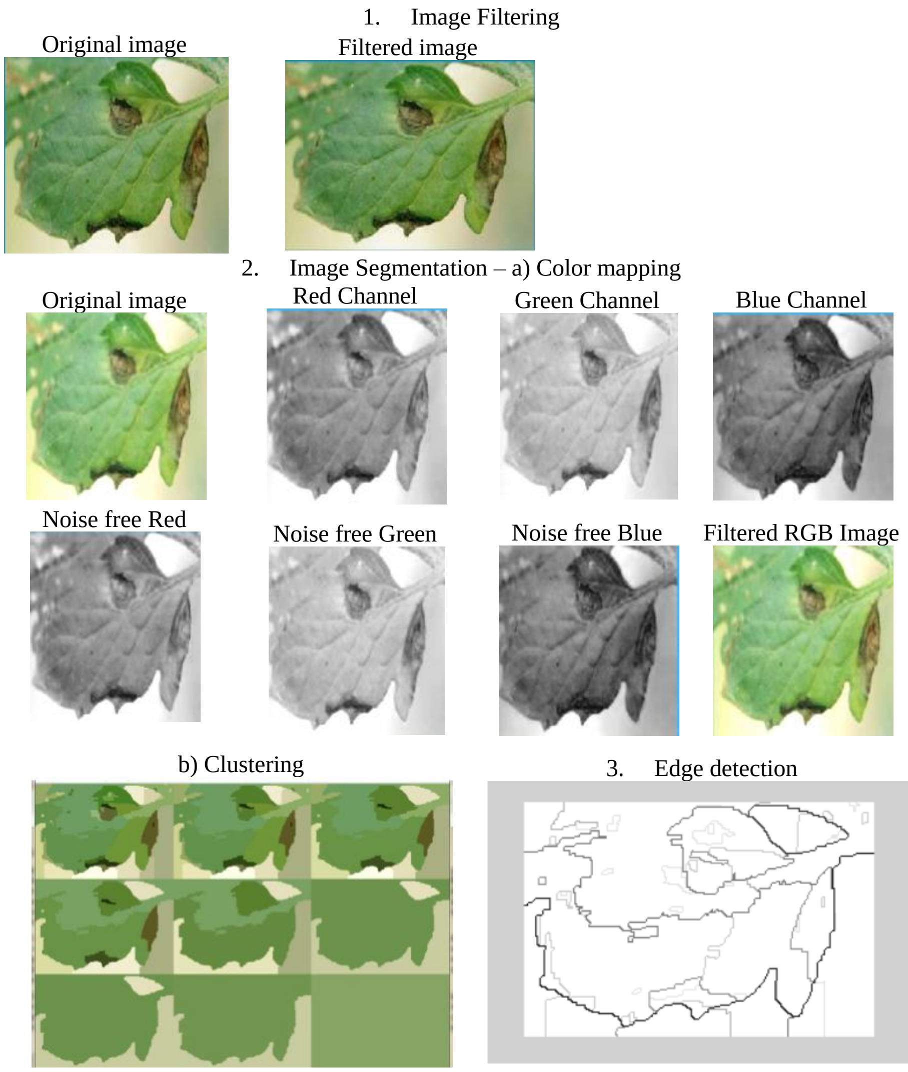


Fig 3: The picture represents RGB Image Pre-processing of original image to processed image (Padmavathi *et al.*, 2016) [43]

Through, hyperspectral imaging, the reflectance spectroscopy can me analyzed from each spatial element of the image. Hyperspectral images are more advantageous when compared with multispectral images due to higher band formation, better spatial resolution and in accurate capturing of spectral characteristics of crops. The future trajectory of crop phenotping research employing UAV-Rs lies in the adoption of hyperspectral imaging technology. However, additional research is needed to explore the applicability of physical inversion models based on hyperspectral remote sensing, comprehend the intricate mechanisms of mixed spectral decomposition models for various field components such as crops, soil, etc. and develop improved methods for element extraction. Hyperspectral imaging in recent years has become a widely used approach for acquiring crop traits, including crop water content, leaf nitrogen concentration, chlorophyll content, LAI (Leaf Area Index), and various other physical and chemical parameters and in the prediction of crop yield (Yang *et al.*, 2017) [63].

Thermal imaging

Thermal imaging relies on alterations in plant respiration and evapotranspiration, induced by diseases, which subsequently result in significant changes in thermal emissions (Nicholas 2004) [41]. Imaging the crop canopy can detect the modifications in radiative properties of plant canopy resulted due to the pathogen. The radiometric expressions of crop pathological studies can be categorized in to two types such as due to modifications of plant-water status and senescence symptoms occurred in plant due to pathogen. The change in plant water relationship due to pathogen attack results in the reduction of leaf stomatal conductance, decreasing the transpiration, altering the evapotranspiration correlated with an increase in plant surface temperature. This increased surface temperature can be attained by measuring the radiative energy emitted by leaf surface in the thermal infrared spectral in the range between 8-14 µm (Nicholas 2004) [41]. Some of the leaf modifications of pathogen related indicates lower height and density of plants, change in leaf angle, leaf curling, premature abscission of lower leaves (Nicolas, 2004 and Nilsson, 1995) [41, 42]. Stomatal conductance is an important traits that assist drought avoidance contributing to drought tolerance. Plant can minimize water loss during drought by regulating transpiration through stomatal conductance (Upadhyaya *et al.*, 2012) [55]. By using infra-thermo camera plant canopy differences (Fig. 04) can be quantified and are shown to be in strongly correlation with transpiration status in potatoes, rice, wheat and sugar beet (Fukuoka, 2005) [14]. The thermal digitized image of the plant canopy can be obtained in a short time of within one minute. UAV-Rs equipped with infrared thermal imagers offer a fast and non-destructive method to obtain crop canopy temperature with in short time with thermal sensitivity exceeding 80 mK. Therefore enabling the effective identification of temperature differences within crop canopy under different environmental conditions.

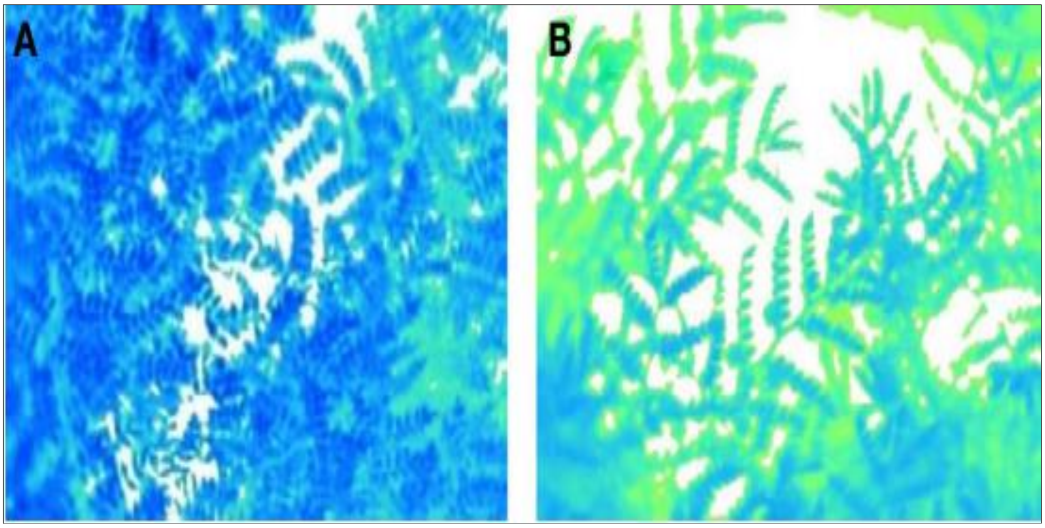


Fig 4: Canopy imagery of Chickpea captured by Infra-Thermal camera indicating A. Cooler canopy and B. Warmer Canopy (Upadhyay *et al.*, 2012) [55]

LIDAR and SAR

Light Detection and Ranging (LIDAR) is an active sensor that emits its own energy source for illumination, distinguishing it from other sensors. Its ability to operate at night time significantly enhances its utility. This technique has also found application in pant high-throughput phenotyping research (Andujar *et al.*, 2019) [1]. By utilizing LIDAR, it becomes possible to obtain the three-dimensional structure of the canopy. Plant canopy height and above-ground biomass can be estimated based on the data collected by this sensor (Wang *et al.*, 2017) [58]. Synthetic Aperture Radar technology is an active micro-sensor which is of two types *i.e.*, focused and non-focused. It has the capability to acquire high resolution radar images comparable to optical images even in adverse weather conditions with low visibility. It can operate continuously enabling round the clock monitoring. SAR is used for various applications in crop phenotyping such as crop identification, monitoring crop acreage, estimation of key crop traits and yield prediction. It offers robust technical support for remote sensing-based large-scale crop growth monitoring.

The traditional methods used to obtain remote sensing images of Earth's surface by satellites often fell short in providing sufficient spatial and temporal resolutions (Nebiker *et al.*,2008) [39]. In moderm times these challenges can be effectively addressed throught the utilization of low-cost and flexible unmanned platforms, such as UAV-Rs. These platforms can provide practical solution to achieve improved spatial and temporal resolutions for remote imaging applications (Nex *et al.*, 2014 and Colomina *et al.*, 2014) [40, 10]. On the other hand, the quality of the acquired images can be affected by various factors such as wind speed, flight altitude and speed, sensor performance, aircraft vibration and image correction methods. Therefore, it is essential to explore strategies that ensure high-quality image acquisition. Efficient processing of large-scale remote sensing data obtained from UAV-Rs continues to be a challenge, and in developing the robust and fast algorithms tailored to specific sensors used.

Applications of UAV-Rs based Crop phenotyping

The utilization of unmanned aerial vehicle based remote sensing imaging has rapidly gained traction as an advancing technology in recent years, finding widespread application in crop monitoring. This technology offers numerous advantages such as high efficiency, more spatial and temporal resolution and low cost (Holman *et al.*, 2016) [22]. Since, 2010, high-throughput phenotyping by UAV-Rs has been introduced to precision agriculture (Sankaran *et al.*, 2015) [49] in a range of applications like crop geometric traits (Yang *et al.*, 2017) [63], Bio-physical traits and vegetation indices, plant growth monitoring, Weed management, Nutrient deficiency, Abiotic and Biotic stresses (Yuan *et al.*, 2016) [65] and crop yield prediction (Zhou *et al.*, 2017) [71].

Plant density and lodging assessment

Crop emergence and plant density are the important physiological traits in the estimation of crop yield. The conventional method for obtaining plant density is based on labour intensive and time-consuming visual counting on ground. In order to overcome this challenge, UAV-Rs image-based methods are developed for high resolution crop segmentation. Feng *et al.*, 2023 [13] developed UAV-Rs multispectral image-based cotton seedling stand count estimation using different algorithms such as YOLOv5, YOLOv7 and Center Net. Jin *et al.*, 2017 [25] utilized high resolution RGB imagery to estimate the plant density of wheat at the emergence stage. Chu *et al.*, 2017 [9] estimated Lodging severity of maize crop by using UAV-Rs based on height percentile against preset threshold through models of multiple grid lines.

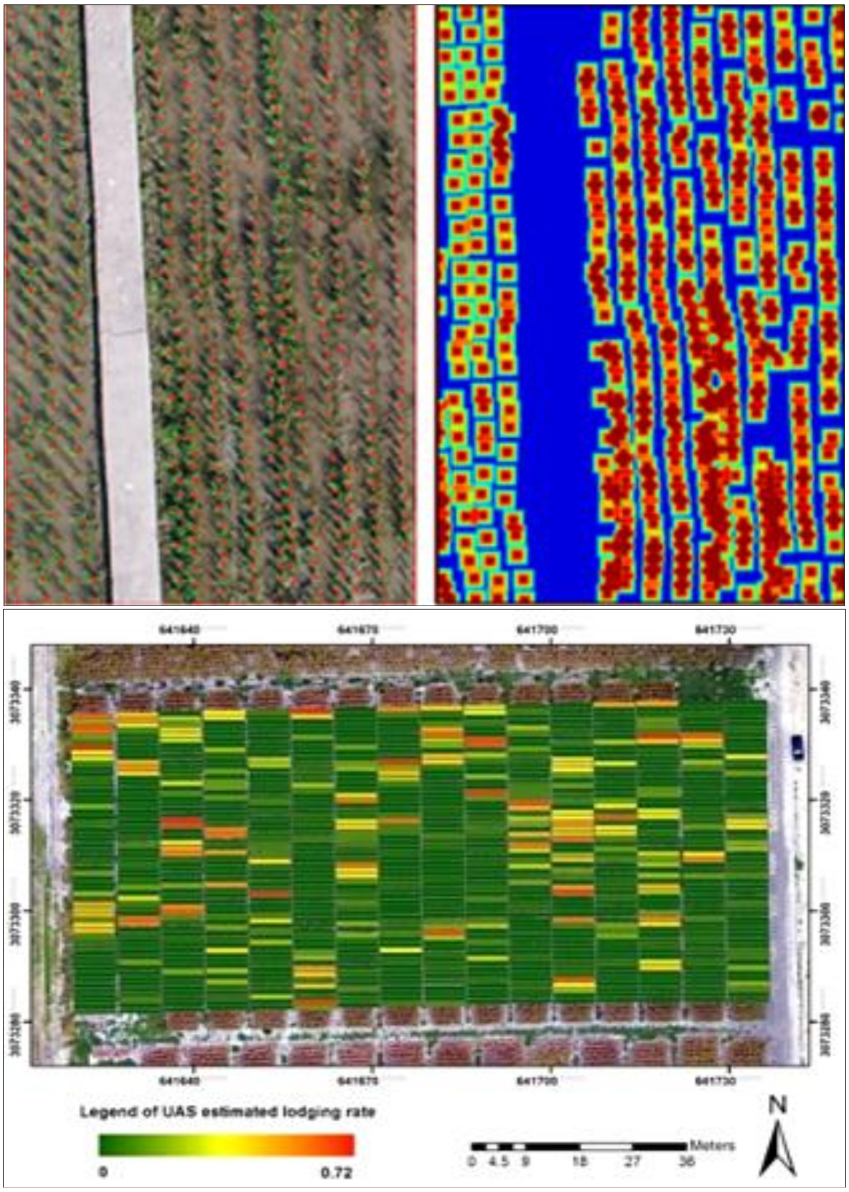


Fig 5: Example of Rice plant seedling count annotated manually (Left) and by UAV-Rs based RGB Imagery (Wu *et al*., 2019) [62] and estimation of lodging in maize by Chu *et al*., 2017 [9].

A machine vision-based method is developed by Lu *et al.,* 2016[33] for automated estimation of wheat plant density. The potential of UAV-Rs imaging systems in capturing high-resolution RGB images for the detection and estimation of crop stand counts in various crops has been demonstrated in corn (Vong *et al.,* 2021) [57], Wheat (Schirrmann *et al.,* 2016) [50], Cotton, Potato (Li *et al.,* 2019) [30], Rapeseed (Zhao *et al.,* 2018) [69], Sorghum (Ghosal *et al.,* 2018) [16] and Rice (Wu *et al.,* 2019) [62] [Fig. 05]. In barley, distinct phenological events are detected by UAV-Rs based RGB imagery by Burkart *et al.,* 2018 [6].

Detection of Crop Geometric and Quantitative traits

By using the image analysis acquired by UAV-Rs, crop geometric traits can be rapidly obtained which includes as following.

a) Plant height

Plant height is the important parameter that is affected by the availability of water and impacts lodging, radiation interception of the plant. To extract the plant height from RGB images includes Digital Surface Model (DSM), Digital Terrain Model (DTM), Crop Surface Model (CSM)(Holman *et al.,* 2016, Guerra *et al*., 2016, Pena *et al.,* 2018) [22, 19, 44]. It can be extracted from digital images through Photogrammetric point clouds (Khanna *et al.,* 2015, Malambo *et al.,* 2018) [28, 34].

b) Ground canopy cover (GCC)

GCC is associated with photosynthesis and area subjected to transpiration capacity of plant (Mullan *et al.,* 2010) [38]. The data extracted at the pixel-level from high-resolution images acquired by UAVs yielded superior results in estimating Ground Canopy Cover (Sankaran *et al.,* 2015) [49]. By using UAV-Rs based RGB imaging chu *et al*. 2016 analyzed cotton plant height and demonstrated the potential of RGB imagery in estimating canopy cover by an empirical model which showed a strong correlation (R^2 = 0.99) with the observed canopy cover.

c) Biomass

Plant Biomass is one of the critical trait for yield prediction. It can be ascertained by plant dry weight, plant height, leaf area index and above ground canopy (Feng *et al.,* 2021) [12] UAV-

Rs based RGB imagery is used to obtain biomass by the application of 3D data (Kachamba *et al.*, 2016) [27]. Highly accurate above ground biomass of rice crop is estimated by combining normalized difference vegetation indices obtained through multispectral imagery and multivariate regression model (R^2 =0.78) (Zheng *et al.*, 2019) [70]. The above ground biomass of winter wheat is estimated by spectral information through hyperspectral images (Yue *et al.*, 2018) [64]. The accuracy of the biomass is increased when estimated with spectral indices combined with plant height.

Leaf area index (LAI)

LAI is the major functional trait that is related to energy intercepted, net primary production, nutrient use efficiency, water use efficiency and carbon balance of the plant. Mathews and Jensen 2013 estimated LAI of vineyard through RGB images. LAI can be quantified by remote sensing through statistical, optical and radiation transmission models based on spectral reflectance and vegetation indices obtained through hyperspectral imagery. (Lu *et al.*, 2016) [33].

d) Yield

Yield can be quantified by combining physiological parameters such as chlorophyll content, biomass, LAI and Vegetation indices. Wang *et al.*, 2017 [58] developed yield estimation model by using UAV based hyperspectral imaging and signified the correlation (R^2 =0.78) between NDVI at the booting stage with the yield. The linear regression analysis of crop height and vegetation indices of multispectral are used to estimate yield by Maresma *et al.*, 2016 [35].

Table 1: Some of the widely used vegetation indices by UAV-Rs platform (R = Reflectance)

Vegetation Indices	Formula	Associated traits	References
Normalized Difference Vegetation Index	$\mathrm{NDVI} = \frac{\mathrm{NIR} - \mathrm{RED}}{\mathrm{NIR} + \mathrm{RED}}$	LAI, Yield, Biomass, Canopy senescence	Lopes *et al.*,2012 [32]
Green Normalized Difference Vegetation Index	$\mathrm{GNDVI} = \frac{\mathrm{NIR} - \mathrm{GREEN}}{\mathrm{NIR} + \mathrm{GREEN}}$	LAI, Nitrogen content, Protein content, Water content, Chlorophyll content	Yang *et al.*, 2017 [63]
Difference Vegetation Index	$\mathrm{DVI} = \mathrm{NIR} - \mathrm{RED}$	Nitrogen, Chlorophyll	Jordan 1969 [26]
Green Red Vegetation Index	$\mathrm{GRVI} = \frac{\mathrm{GREEN} - \mathrm{RED}}{\mathrm{GREEN} + \mathrm{RED}}$	Phenological indicator	Motohka *et al.*, 2010 [37]
Enhanced Vegetation Index	$\mathrm{EVI} = \frac{2.5(\mathrm{NIR} - \mathrm{RED})}{(\mathrm{NIR} + 6\mathrm{RED} - 7.5\mathrm{BLUE} + 1)}$	Biomass related traits with eliminated background soil inteferences	Gurung *et al.*, 2009 [20]
Chlorophyll Index	$\mathrm{CI} = \frac{\mathrm{NIR}}{\mathrm{GREEN}} - 1$	Nitogen estimation of plant	Daughtry *et al.*, 2000 [11]
Chlorophyll Index at red edge	$\mathrm{CIRI} = (\mathrm{R}800 - \mathrm{R}705) - 1$	Chlorophyll	Zang *et al.*, 2018 [68]
Optimized Soil Adjusted Vegetation Index	$\mathrm{OSAVI} = \frac{1.16(\mathrm{R}\,800 - \mathrm{R}\,670)}{(\mathrm{R}\,900 + \mathrm{R}\,670 + 0.16)}$	Accurate crop growth monitoring with eliminated interference of aerosols	Yang *et al.*, 2017 [63]
Photochemical Reflectance Index	$\mathrm{PRI} = \frac{(\mathrm{R}\,750 - \mathrm{R}\,670)}{(\mathrm{R}900 + \mathrm{R}\,670 + 0.16)}$	Water status, chlorophyll content, Nitogen estimation	Suarez *et al.*, 2009 [53]
Plant Senescence Reflectance Index	$\mathrm{PSRI} = \frac{(\mathrm{R}\,690 - \mathrm{R}\,500)}{\mathrm{R}550}$	Leaf and Fruit senescence, Chlorophyll and Nitrogen	Zang *et al.*, 2018: Yu *et at.*, 2018 [68, 64]
Effective Leaf Area Index	$\mathrm{ELAI} = -0.441 + 0.285\frac{\mathrm{NIR}}{\mathrm{RED}}$	Yield estimation	Wojtowicz *et al.*, 2005 [61]
Vegetation Drought Index	$\mathrm{VDI} = \frac{(\mathrm{R}970 - \mathrm{R}900)}{(\mathrm{R}970 - \mathrm{R}900)}$	Water stress	Suarez *et al.*, 2009 [53]
Heavy metal stress sensitive index	$\mathrm{HMSSI} = \frac{\mathrm{CIRE}}{\mathrm{PSRI}}$	Detection of Heavy metals	Zang *et al.*, 2018 [68]
Anthocyanin Reflectance Index	$\mathrm{ARI} = \frac{\mathrm{R}550 - 1}{\mathrm{R}700 - 1}$	Detection of Anthocyanin and Cadmium Stress	Zea *et al.*, 2022 [67]

Spectral Vegetation indices and physiological traits

Spectral Vegetation indices are the key traits for estimating Plant Canopy cover associated traits such as Active photosynthetic tissue, above ground biomass, Leaf area Index, Nitrogen content, Plant nutrients status, and yield prediction. An index is obtained by doing a sum/ difference/ ratio of reflectance at different wavelengths. The photosynthetically active tissue typically show absorption in visible region with the reflectance in infrared region. A large number of spectral vegetation indices (Table 1) can be easily derived by multispectral and hyperspectral images through different statistical empirical models and the key crop traits such as LAI, Crop canopy cover, Biomass, Yield prediction, Plant water status, Chlorophyll and Nitrogen content can be estimated the physiological parameters are the key traits in discerning crop growth changes in response to environment and in estimating yield of the crop. The important traits that are dissected through UAV-Rs includes Chlorophyll content and canopy temperature. Chlorophyll content can be estimated by vegetation indices based on linear regression model. Uto *et al.*, 2013 [56] estimated the highly accurate rice chlorophyll denities using hyperspectral imaging in the range of 340nm to 763 nm. The leaf carotenoid content, net photosynthesis and the correlation between chlorophyll fluorescence and net photosynthesis in vineyard is demonstrated by high resolution hyperspectral imaging (Zarco-Tejada *et al.*, 2013) [66]. Crop canopy temperature is one of the major physiological trait in identifying drought and thermo tolerant varieties. It determines s the transpiration rate, stomatal conductance and leaf water potential during water stress conditions (Zang *et al.*, 2018) [68].

The water stress of cotton crop is assessed using UAV-Rs thermal imagery at 0.01-m resolution (Bian *et al.*, 2019) [5]. Upadhyaya *et al.*, 2012 [55]. Quantified plant canopy temperature differences in chickpea by using an infra-thermo camera. Sagan *et al.*, 2019 [48]. evaluated the potential of thermal camers in detecting vegetation stress.

Abiotic and Biotic stress related traits

In the scenario of the climate change, Plant in its life cycle faces several abiotic and biotic stress conditions. Abiotic stress includes drought or water deficit, heat, salinity, chilling and freezing injury and heavy metal stress. Drought is the most significant factor constraining yield. Therefore, it is essential to comprehend and identify drought stress in crops to enhance water use efficiency. Instead of monitoring plant physiological traits resulted in response to drought by traditional techniques, by scrutinizing the leaf metabolite concentrations through leaf reflectance spectroscopy properties of plants that undergone stress, one can estimate the drought stress. Burnett *et al.*, 2021 [7] for the first time uncovered the use of hyperspectral data in detecting stress induced abscisic acid phytohormone and proline. Through spectroscopy, the drought stress can be detected even before the visual appearance of drought stress in plants. Therefore, representing a powerful technology in reducing yield limitations. Gibson-Poole *et al.*, 2017 [17] evaluated the occurence of potato blackleg bacterial disease by using RGB imagery technology. The potassium deficiency and susceptibility of green peach aphid is quantified by multispectral images in canola (Severtson *et al.*, 2016) [51]. In addition to this detection of disease stress can be monitored commonly by multispectral, hyperspectral and infrared imaging technology.

Future aspects

The studies mentioned above have demonstrated the effectiveness of UAV-based remote sensing for high through-put plant phenotyping. However, there are several challenges that need to be addressed to translate this to real world applications. To strengthen UAV-based remote sensing for plant phenotyping, future studies should focus on introducing low-cost and high-performance UAVs with stable flight capabilities and high-performance phenotyping sensors. Sensor based analysis of crop phenotyping can enhance accuracy. Establishing multi-parameter prediction models for crop yield and improving data analysis methods will aid in extracting more traits supporting precision crop management. To deepen our understanding, further research should delve in to the connection between genotype, phenotype, and environment, exploring gene-phenotype relationships through quantitative trait locus and genome-wide association studies. By fostering collaboration among researchers, institutes and countries, the field of UAV-based remote sensing for plant phenotyping can advance collectively, leading to significant progress in precision agriculture and sustainable crop management.

Conclusion

In conclusion, unmanned aerial vehicle remote sensing (UAV-Rs) has emerged as a powerful tool for high-throughput plant phenotyping, offering various advantages such as high efficiency, low cost, and adaptability to complex field environments. Different sensors, including RGB, multi-spectral, hyperspectral, infrared thermal imaging, LIDAR, and fluorescence sensors, have been used to gather plant phenotypic information, enabling the analysis of traits like plant height, LAI, biomass, yield, weed detection, and physiological parameters. While UAV-Rs shows great promise, challenges remain in reducing influencing factors and optimizing UAV flight parameters for improved efficiency. Nevertheless, with advancements in UAV capabilities, sensor technology, data processing methods, and regulatory policies, UAV-Rs is poised for broader and more impactful applications in field-based crop phenotyping.

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