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TOPICAL REVIEW

# From Satellite to UAV-Based Remote Sensing: A Review on Precision Agriculture

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**ABSTRACT** The applications of remote sensing technologies to precision agriculture were reviewed. The different uses of conventional satellites and unmanned aerial vehicles (UAVs) for data collection were also examined. The ways in which the collected data have been used in terms of precision agriculture are laid out in further detail. Modern UAVs provide a range of advantages over conventional satellites in data collection and analysis. In addition, precision agriculture itself is a wide topic; and practitioners, researchers, and policy planners need to account for a complex value chain with diverse stakeholders. Thus, in order to further the discussion in a meaningful manner, the later sections of this article provide additional analysis on topics deemed crucial for the development of precision agriculture: a discussion on key technological limitations for scaling, a corresponding list of suggestions for the development of solutions, and a brief overview on the current social-economical landscape of the agriculture industry.

**INDEX TERMS** Aerial mapping, agriculture 2.0, precision agriculture, remote sensing, unmanned aerial vehicles.

## I. INTRODUCTION

Precision agriculture (PA) is a data-driven and methodical approach towards agricultural activities such as farming. The International Society of Precision Agriculture defined the field in 2019: Precision Agriculture is a management strategy that gathers, processes and analyzes temporal, spatial and individual data and combines it with other information to support management decisions according to estimated variability for improved resource use efficiency, productivity, quality, profitability and sustainability of agricultural production. The aim of PA is to maximize the net yield of current efforts in the agricultural activities by either minimizing the resources required per unit output, resource efficiency or by maximizing the yield per unit input, yield efficiency.

According to a recent report by the United Nations (UN), there are some worrying trends in terms of the current world total agricultural output against the growth and shifting dietary consumption of the population [1]. Increasing the total output of consumable agricultural products with current techniques and measures could result in the exacerbation of the climate conditions due to the sheer inefficiency of said means. This in turn would further negatively affect the resulting crop yield as crop yield is highly dependent on the climate itself. Thus, it would require a mass paradigm shift in the way people farm and the rethinking of how it plays its part in the society of today, and the ever growing cities of tomorrow.

For foods that are consumed regularly and in large quantities, agricultural efficiency is of utmost importance. Even tough, modern development of data analysis and AI solutions has given us new tools to tackle food insecurity issues [2], securing growing population food availability

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issues globally is far to be solved. Take one of the many staple foods around the world for example: rice. Paddy fields are known to be difficult to manage due to the many different precise requirements at the different stages of the paddy's growth. Even a slight deviation in the water levels could result in a devastating blow the final yield, and thus it takes intense care and clever engineering to manage a paddy field [3]. According to studies done by [4] and [5], up to 18 million metric tons of rice are lost globally (4% in overall rice production) due to mismanagement of water provision. This amount totaled up to a total of 3.6 billion USD lost around the globe every year. Other factors such as the pH level of the soil too plays a big role in the final yield and the resulting consumable rice itself, which has been a matter of concern and subject of study as of late [6]. In addition, a research done in India has reported that up to 37% of the overall losses in seed yield of paddy are caused by uncontrolled weed growth [7], among a host of other challenges. Therefore, it could be seen that there are huge gaps of enablement through technology that could be explored in this domain for the betterment of society, and remote sensing is a key component due to the sheer scale and coverage required in agriculture, e.g., like water usage and lost preventive systems [8], industry scale autonomous vehicles [9] and IoT-based solutions with humanitarian thoughts [10] and so on.

Modern remote sensing related PA activities utilizes either satellite or UAVs to provide a bird's eye view of a plantation, necessitated by the sheer scale of site; though the latter is increasing in popularity as of late. Equipped with an assortment of specialized cameras and algorithms, the data collected enables the user to generate a plethora of useful insights on a large area effectively; e.g. vegetation indices analysis, hydrological mapping, stress gauging, disease mapping, weed monitoring and so on. For instance, a recent study in 2016 has devised a solution to perform weed detection [11]. Specifically, the authors leveraged on hyper-spectral remote sensing methods in which the differences in reflected wavelength enables the mapping of weed density in a given area. This is only a single example among a range of other ways by which remote sensing can be applied to PA that could help make a significant difference to agriculture as known currently - discussed in more detail in the following sections.

In particular, this study aims to provide an overview of the current state of remote sensing in the context of PA with reasonable depth in each of the sections being reviewed; specifically, the work focuses on the utilization of conventional satellite and more recently, UAVs for said task. Section II focuses on data collection with satellites and UAVs, followed by the different ways those data could be used in the context of PA in Section III. In addition, rather than just providing an account of the different approaches and instruments being developed throughout the years, this study endeavors to provide further insights on the different aspects of the subject matter with an end goal of mass public adoption of remote sensing for PA. Thus, Section IV presents a discussion on a few noteworthy limitations of such system in democratizing precision agriculture at scale, with a series of corresponding recommendations for future work to address them. Finally, Section V attempts to shed light on some of the social and economical roadblocks towards adoption by providing a brief yet insightful discussion on the current landscape of the agricultural industry and farming community, the actual impact of modern technology in agricultural context, the relationship between the two, and some recommendations on ways for improvements. The paper makes a significant contribution by offering an in-depth analysis of critical technological limitations in scaling precision agriculture, presenting practical solutions, and providing insights into the current socio-economic landscape of the agricultural industry.

## II. DATA COLLECTION

In the past, aerial imagery from satellite data have been used throughout the growing seasons to monitor crop health, but the use of such technology has been severely limited by low revisit rates and coarse spatial resolutions [12], [13]. Said challenges in satellite imaging for precision agriculture have limited the potential of its uses since the 1990s. Specifically, a report by Mausel et al. in [14] has clearly indicated that the low resolution of the imaging data from satellite sources would impact the accuracy of precision agriculture activities; Moran et al. in [13] outright questioned the feasibility of using said mean for remote agriculture due to the long time period between image acquisition and delivery to its user. Thus, new ways of obtaining aerial images has to be explored in order to improve the overall viability of precision agriculture in general.

In light of this, recent developments in UAVs have prompted the development of the low altitude sensing systems (LARS), a schema of acquiring images of the Earth's surface at low altitude using UAVs. A study in [15] shows a 200 times improvement to the resolution of aerial images taken by a UAV when compared to the satellite imaging. However, using UAVs for remote sensing has its own shortcomings. Most of the UAVs have low airborne endurance, typically less than 30 minutes [16], which effectively limits the operational area of such a device in a mission. On top of that, with UAVs gaining increasing popularity in the civilian market, new regulations enforced by regional government has limited their activities, especially the large-scale UAVs, effectively hamstringing adoption rate and pace of innovation [17]. However, the advantages of deploying UAVs for remote sensing of crops greatly surpass its downsides, with potential to significantly increase the agricultural efficiency per capita across the board. In the climate of current agricultural projections and possible acute shortages in the near future, such an edge could not be ignored.

The aforementioned data collection methods of satellite imaging and UAV imaging is discussed with detail in the following subsections.

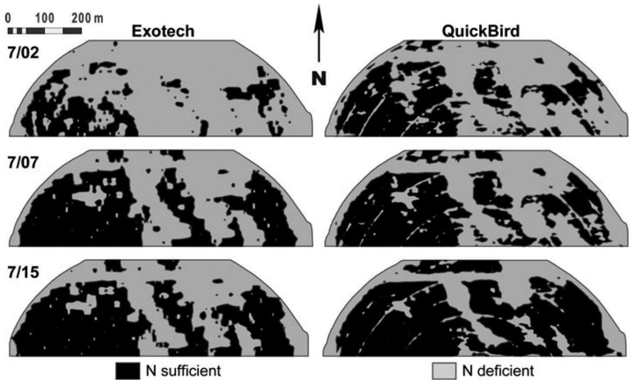



**FIGURE 1.** Comparison of Nitrogen sufficiency between Exotech ground-based data to the Quickbird Satellite data. The former has pronounced jagged edges due to the lower resolution of the readings [18].

### A. SATELLITE-BASED REMOTE SENSING

Remote sensing for precision agriculture started off first and foremost utilizing satellite-based sensors. Purpose-built satellite units such as the Quickbird satellite were launched with on board multi-spectral imaging sensors, with precision of up to 6.5 meters per pixel (mpp). The remote sensing conducted by [18] studied the Normalized Difference Vegetation Index (NDVI) of crops to calculate nitrogen content sufficiency. Comparisons of satellite data with ground probes demonstrated that satellite data provides a finer output, with an accuracy of up to 81%, as shown in Fig. 1. However, the measurements utilized were normalized to a reference area. Similar methods have been utilized by [19] to determine nitrogen content in winter wheat, as well as to determine nitrogen along with phosphorous, potassium, and organic matter content in the same crop. Nitrogen content and chlorophyll concentration in cereals in India have also been observed using multi-spectral imaging from satellite data [20].

A more unconventional usage of multi-spectral satellite imagery has been conducted by [21] to gauge crop and land cover in order to reduce soil erosion in olive orchards, and they were able to do so with an overall accuracy of 90%. Alternatively, [22] utilized a multitude of available satellites to compute leaf carbon and spectral reflectance for sugar and beet agricultural management. The study showed that such methodology produced error of less than 20%. They subsequently manage to increase the resolution of the data to 3 mpp, courtesy of the convolution of multiple satellite sensors. Remote sensing satellites have also been used to perform vegetation heaviness measurement in the case of [23].

Due to the coarse resolution of satellite imagery, various methods of analysis were levied in order to extract useful information from them; i.e., computer vision classifier and statistical decision tree techniques. For example, an accuracy of up to 84% was obtained for the task of shrub detection through said means [24]. In addition, satellite data were also used to measure the soil organic carbon (SOC) utilizing hyperspectral sensors [25]. The same researcher, in another work documented in [26], uses hyperspectral sensors from the satellite to distinguish wild oat and grass on a wheat field. The results from the hyperspectral sensors were able to closely match results generated using on-the-ground near vis-NIR spectroscopy. Satellite-based remote sensing can also be utilized for crop yield prediction through prediction of in-field spatial variability. This is in general done by combining information such as NDVI, the farmer's average paddock yield, as well as other on the ground sensor measurements. [27] demonstrated that such techniques can produce results of up to 80%, while [28] demonstrated very similar results using the same techniques. A brief summary of researches on satellite imagery for precision agriculture is tabulated in Table 1.

However, for remote sensing to be more effective in precision agriculture, more images of much higher detail would be required. Moreover, satellite-based remote sensing is expensive and sparse in availability, as in the case of the Quickbird satellite which many studies rely on. As of the time of writing, the Quickbird satellite has been decommissioned, thus many of the methods of precision agriculture derived from it need to be adapted to different satellite-based sensors, should they be further implemented. These aspects are the driving forces behind the push for utilizing lower-to-ground remote sensing methods which serves as a motivator for UAV-based remote sensing.

### B. UAV-BASED REMOTE SENSING

Before the introduction of small-scale UAVs, a known method of lower-to-ground remote sensing is to utilize manned aircraft equipped with multi-spectral or electro-optics (EO) sensors. Examples are crop pest management using a Cessna U206 to monitor pest population [30] or to monitor wheat crop stress as early as 1998 [31]. These techniques provide much better resolution data as compared to satellite-based remote sensing, but are very involved in setup such that data gathering quickly becomes very expensive and time consuming.

The direct solution for lower-to-ground sensing technologies that can be operated at a much lower cost are the UAVs, commonly coined under the umbrella term - drones. In fact, there have been many such examples where UAVs have been used for remote sensing in the past 2 decades, ranging from fixed-wing aircraft, to blimps, and to multi-rotor aircraft. Such forms of remote sensing usually incorporate similar technologies that were once deployed on satellites, such as multi-spectral cameras and EO cameras.

Classically, many drone-based remote sensing in early stage involves usage of small-scale air vehicles that are remotely piloted from a ground station. One example includes the use of an EO camera on a fixed-wing UAV to map the growth of squarose knapweed [32], and then assess weed invasions [33] using aerial-based GPS imaging [34]. Other

**TABLE 1.** Summary of precision agriculture through satellite imagery.

| Year | Satellite | Data Location | Type of Crops | Type of Analysis | Ref. |
|---|---|---|---|---|---|
| 2004 | IKONOS | USA | Grain | Spatial variability | [28] |
| 2005 | QuickBird | USA | Arid land | Image classification | [23] |
| 2005 | QuickBird | USA | Sugar beet | Nitrogen concentration | [22] |
| 2007 | QuickBird | China | Winter wheat | Nitrogen concentration | [19] |
| 2008 | EO-1 | India | Cereal | Plant biochemical index (PBI) | [20] |
| 2008 | QuickBird | Spain | Olive orchards | Image classification | [21] |
| 2008 | EO-1 | Australia | Soil | Carbon prediction | [25] |
| 2009 | QuickBird | Spain | Mediterranean crops | Object detection | [24] |
| 2009 | QuickBird | China | Winter wheet | Variation in soil properties | [29] |
| 2009 | Landsat 5 | Australia | Cereal | Spatial yield variability | [27] |
| 2010 | QuickBird | Spain | Wheat | Image classification | [26] |
| 2010 | QuickBird | USA | Corn field | Nitrogen concentration | [18] |

fixed-wing UAV applications also include range and resource monitoring for rangeland applications [35]. In the United States, Edge 540T fixed-wing UAVs have been equipped with EO cameras to monitor biomass and nitrogen status of corn, alfafa and soybean crops [36], [37]. In Japan, one unconventional form of remotely piloted UAV involves the use of both EO cameras and multi-spectral imaging sensors on a blimp in order to assess Leaf Area Index (LAI) and biomass volume of crops [38]. For smaller field areas such as rice fields in Thailand, remotely piloted helicopters (also called single-rotor UAVs) such as the X-Cell Fury 91 have also been equipped with EO cameras to estimate the yield and biomass of rice crops [39]. The utilization of small-scale remote controlled helicopter removes the necessity for a landing strip in order to takeoff and land. In addition, it has also afforded the aircraft the capability to hover at a fixed location persistently, which is very helpful for monitoring purposes, albeit at the expense of energy efficiency.

As a preliminary idea, remotely-piloted aircraft serve as a good proof of concept for low altitude remote sensing applications. However, the need for trained pilots as well as constant monitoring of the UAV while in operation prevented UAV-based remote sensing from being scalable. This is because not all crop owners are willing to put in the hours required to become competent with piloting, nor is hiring a pilot on an hourly basis necessarily cost and time effective. However, due to recent massive development in UAV autopilot technologies, automating these flights in manner with minimal human intervention has become increasingly common [40], [41]. Moreover, with image processing techniques getting more reliable and thus increasingly adopted, post processing of sensor data can often be done automatically such that the system front end can be easily configured to serve only the relevant digested insights to the user. All information processing can be done at a back end unit or within a dedicated offsite server.

Early development of autonomous UAVs are mostly of the fixed-wing variant. One of the first available UAV for crop monitoring was the Vector-P UAV (Fig. 11(a)). It was designed to have multiple downwards looking cameras, and equipped with the capability to acquire NIR and multi-spectral images [42]. The system showed the potential of monitoring crop utilizing UAV at a very early stage, where it was used to evaluate the LAI of winter wheat through digital photography with orthomosaic-ed tiles [37], [43]. Similar implementation of UAV assisted monitoring was further improved by giving the systems the ability of geo-referencing each image-based on the instance GPS location by Mark and Hardin [44], improving the capability of remote sensing with UAVs. Over time, increasingly advance systems were developed by various researchers, such as utilizing digital compasses and attitude sensors along with either a stereo-vision camera or laser range finder, and the integration of various data streams to enable the collection of accurate three-dimensional geographic information [45], [46], [47], [48]. The MLB Bat 3 UAV (Fig. 11(b)), designed by the United States Department of Defence Space Test Program, is an aircraft developed as an autonomous drone intended for rangeland mapping and monitoring [49], [50]. The primary form of sensing is through vision processing and image classification by utilizing an EO camera [51], [52]. Such an autonomous system has been successful in providing large scale coverage for monitoring and mapping of terrains without user intervention or the need to handle raw sensor data directly.

Other autonomous fixed-wing remote sensing applications used hobby-grade aircrafts as well, such as the ANACONDA fixed-wing (Fig. 11(c)) to perform sensing in tandem with an industrial GEMS 35 multi-spectral camera [53]. The device was used to identify the typical crop indicators, namely the LAI and fractional vegetation cover in order to predict crop yield of sorghum produce [54]. More examples of hobby-grade aircraft being applied to autonomous remote sensing includes a self-constructed fixed-wing plane built in Spain equipped with miniature hyperspectral and thermal cameras built by Headwall Photonics to assess fluorescence, temperature, as well as narrow-band reflectance of crops for water stress gauging of citrus orchards [55]. Although most application uses multi-spectral cameras, it is not a prerequisite for remote sensing as there have been applications with monochrome and infrared cameras on hobby grade aircraft. More specifically, the X8-Skywalker (Fig. 11(d)) was used to assess crop stress through NDVI sensing from a 50 minute flight and over 480 orthomosaic stitched images [56].

One interesting aircraft developed for remote sensing in the United States is the Pathfinder-Plus (Fig. 11(e)). The Pathfinder-Plus is an autonomous, solar powered vehicle with theoretically unlimited flight time. It was equipped with two very high spatial resolution cameras: a Hasselblad 555ELD camera body with a Kodak Professional DCS Pro Back Lens for RGB imaging, as well as a DuncanTech MS3100 for multi-spectral and narrow-band imaging. The aircraft has been utilized to monitor drip irrigation issues by gauging the water stress, as well as mapping crop ripeness and weed proliferation in the Kauai Coffee Plantation [57], [58]. The idea of such systems is to create a remote sensing platform that could operate on a 24/7 basis and at a much lower altitude as compared to satellite imagery. Another such attempt has been made in France, where a L'Avion Jaune autonomous glider (Fig. 11(f)) was equipped with a pair of DSLR cameras with spectral filters to capture multi-spectral information. The study was used to measure the LAI, NDVI, nitrogen uptake, as well as Green-NDVI (GNDVI) of small plot wheat crops in France [59].

Asides from remote sensing, autonomous fixed-wing aircraft also opens up the avenue for the automation of other laborious agricultural activity such as crop dusting. For example, an automated pesticide spraying was performed in Brazil through wireless sensor networks used to detect wind direction and intensity and provide information feedback to an overhead UAV system with a chemical spraying device. This information is then used to allow the UAV to make flight adjustments to the routes that can reduce the waste of pesticides and fertilizers [60]. The potential of UAVs have also been extensively studied and favoured to be the means for future precision agriculture advancement by independent researchers in Ukraine [61].

The same autonomous pesticide spraying idea was successfully developed and implemented with rotorcraft UAVs in Japan, where in 2001, up to 1,565 unmanned Yamaha RMAX helicopters (Fig. 12(e)) were sold for the use of agriculture spraying across rice fields [62], [63], and mapping of crop area through GPS assisted mosaic-ed images [64]. Another example of agriculture assistance drone is the DJI Agras MG-1 (Fig. 12(f)), with the capacity to deliver pesticide to an area of 4000–6000 $m^2$ within 10 minutes, along with a 10 kg payload [65].

Besides autonomous fixed-wing UAVs, rotorcraft UAVs (both single- and multi-rotor) have also been widely developed in the past. In the documented works by [66] and [67], the researchers have modified a commercially available RC helicopter, Benzin Acrobatic (Fig. 12(a)), to be equipped with an MCA-6 six-band multi-spectral camera used for thermal and multi-spectral sensing of wheat water stress through thermal imaging and NDVI measurements. In Spain, the MD4-1000 UAV from Microdrones (Fig. 12(b)) equipped with a similar MCA-6 multi-spectral camera from Tetracam Inc. was used for mapping weeds in sunflower crop through accurate orthomosaic-ed multi-spectral UAV images [68], [69].

Drones from the renowned drones manufacturer, DJI, have also played a big part in the past few years. One of their flagship product, the Phantom 2 (Fig. 12(c)) has been used to equip with a Go Pro 3+ EO camera for monitoring rice stress levels in Germany [70]. In addition, another multi-rotor product of DJI, the Matrice 100 (Fig. 12(d)) equipped with a DJI Zenmuse X3 RGB camera and a Parrot Sequoia multi-spectral sensor have also been used in wheat plots segmentation for better crop cycle nitrogen management [71].

More studies have been done to assess the utility of UAV-based imagery on phenotyping crops. A study in Brazil by [72] evaluates an algorithm that incorporates canopy height model (CHM) into the fourth band of the RGB imagery by comparing the accuracy of identifying the canopies of orange trees. The study used both multi-rotor and fixed-wing UAV: DJI Phantom 3 mounted with PowerShot S100 RGB digital camera and senseFly eBee with senseFly Duet T camera. Another study by [73] used a HP-X4-E1200 with a Sony Alpha 6000 camera to map the LAI and height of maize canopy via oblique imagery.

Asides from phenotyping crops, drones are also used to detect weeds in order to determing the proper amount and distribution of pesticides. A study in Pakistan by [74] uses a DJI Phantom 4 with an RGB sensor TCS34725 and a NIR sensor 230218 applied object-based image analysis (OBIA) algorithm to detect weed patches between and within wheat crop rows. Another study by [75] that took place in France proposed a method for weed detection using convolutional neural networks (CNNs), and utilised a DJI Phantom 3 Pro drone mounted with a 36-megapixel RGB camera on bean and spinach fields.

A few comparison studies were done to assess the reliability of satellite-based imagery against UAV-based imagery. One of the studies took place in Senegal by [76] compare the aboveground biomass (AGB) of mangroves estimated by UAV imagery against three different estimates obtained by: Sentinel-1 imagery, Sentinel-2 imagery, and a combination of both Sentinel-1 and Sentinel-2 imagery. A Parrot Bebop 2 mounted with an RGB camera, operated autonomously using Pix4dCapture in circular missions, is used to obtain images to estimate AGB. The ground truth data for AGB was obtained via field measurements of 100 different trees and compared with the estimates. The study concludes that the combination of both Sentinel-1 and Sentinel-2 imagery yields the best estimate.

Another case study in Germany by [77] compared Sentinel-2 satellite and UAV imagery by obtaining three pairs of multi-spectral imagery on two different crop fields of wheat and barley on similar dates. The HP-X4-E1200 multi-rotor UAV by HEXAPILOTS is equipped with a MicaSense RedEdge-M multi-spectral camera and an RGB camera (Fig. 2), and the reference data is obtained by measuring 20 sample points of each field, each spanning 2 m of diameter in a circular area and located at least 2 m away from the tractor lane. Various agronomic parameters such as plant leaf nitrogen and LAI are calculated and compared. Sentinel-2 imagery was able to recognize the same large-scale patterns obtained by UAV imagery, although smaller patterns are influenced by features such as tramlines due to them being unable to be accurately georeferenced by the satellite. The paper concludes with a suggestion of integrating both Sentinel-2 and UAV imagery for improved results.

UAV-based remote sensing is also used on monitoring soil salinity. A study in the Netherlands by [78] attempted to measure the soil salinity in order to evaluate salt stress in quinoa crops. The study used three multi-rotor UAVs each mounted with a different payload. Two Altura AT8 mounted with a Rikola hyperspectral camera and a WIRIS thermal camera respectively, and a Riegl Ricopter mounted with a Riegl VUX-SYS LiDAR scanner. Another study that took place in China evaluated the effect of spring irrigation on soil salinity [79], in which a Matrice 600 six-rotor UAV mounted with a Micro-MCA multispectral sensor is used to obtain imagery of sunflower, corn, and wheat fields before and after spring irrigation.

A brief summary of researches on UAV imagery for precision agriculture is tabulated in Table 2.

## III. APPLICATIONS OF REMOTE SENSING DATA

Many precision agriculture research nowadays is geared towards the implementation and development of new sensors and instruments, for example, hyper-spectral imaging systems in [85] and EO camera in [57]. The aim is to be able to obtain crop, soil, and microbial properties of a specific area in quasi real time, where the most advanced area of PA is variable rate technology (VRT), effectively sensors that are capable of detecting field variability over time. Operational success of VRT requires that accurate maps of crop areas regarding crop, soil, and other microbial factors can be developed consistently over time.

### A. CROP HEALTH MONITORING

Crop health monitoring is crucial for food security, sustainability, and economic stability. It allows early detection of issues such as presence of diseases and pests, and enables crop yield to be optimized, reducing resource use and promoting environmental responsibility. It's essential for safeguarding food supplies, ecosystems, and economies. Generally, monitoring of vegetation is done via mapping of various vegetation indices via the use of either RGB, NIR, or multi-spectral cameras. This is done through converting the reflectance of several spectrums of light into a single number value, a comprehensive list of various indices can be viewed in [93]. Generally, the indices are divided into three categories, namely for

1) vegetation structure, which covers cover foliage, sheer biomass, LAI, and absorbed photosynthetically active radiation (PAR);
2) biochemistry, which include water consumption, pigment composition, protein content, and other plant structural materials; and
3) plant physiology/stress, which measures the state of xanthophylls, change in chlorophyll content, or water stress.

The primary and most common index used to gauge crop health is the NDVI. This index simply allows the measurement of the denseness of a vegetation canopy, and can be calculated by simply using a NIR camera and an RGB EO camera [94].

More sophisticated configurations include the use of LiDAR and GPS information to generate a point cloud that accurately represents the area of study. Hyperspectral and LiDAR information is put through HyperSpecIII and SpectralView, which combines GPS data to georeference the camera position, and then form an orthorectified hyperspectral image, which is then mosaic-ed to create a point cloud of the area [95]. The end result is a map such as that shown in Fig. 3 where the exact height and position of each tree can also be extracted.

Furthermore, Deep Learning can be implemented to monitor crop health. Techniques such as Convolutional Neural Network (CNN) are implemented with UAV-based multi-spectral imagery in [96] to identify citrus trees. The results of this study show high overall accuracy of 96.24% (precision of 94.59% and recall of 97.94%), being the first instance of CNN application on citrus trees using UAV-based multi-spectral imagery.

### B. WEED CONTROL

Weed control is essential for optimizing crop growth and yield. It minimizes competition for resources, enhances nutrient uptake, and reduces yield losses. Precise weed management also conserves resources, lowers costs, and promotes sustainable farming practices [98]. A study done in the Philippines by [99] utilized orthomosaic images stitched together from a single RGB camera and georeferenced via GPS data. From the RGB bands of the aerial images, 7 different vegetation indices were then generated using ENVI 5.1 software. A support-vector machine (SVM) was then utilized to classify plants into crop species and weeds. In this study, a comparison to classifying accuracy of the weeds in the oil palm plantation was done between the application of SVM and artificial neural network (ANN) was done. The SVM proved to be superior to ANN in their

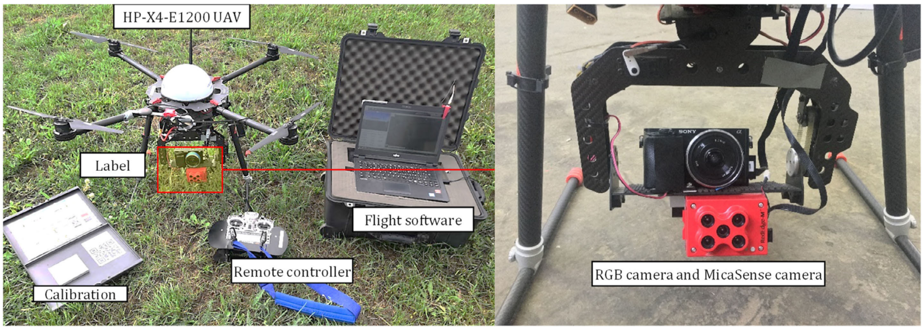



**FIGURE 2.** UAV setup used for comparing Sentinel-2 and UAV multi-spectral imageries [77].

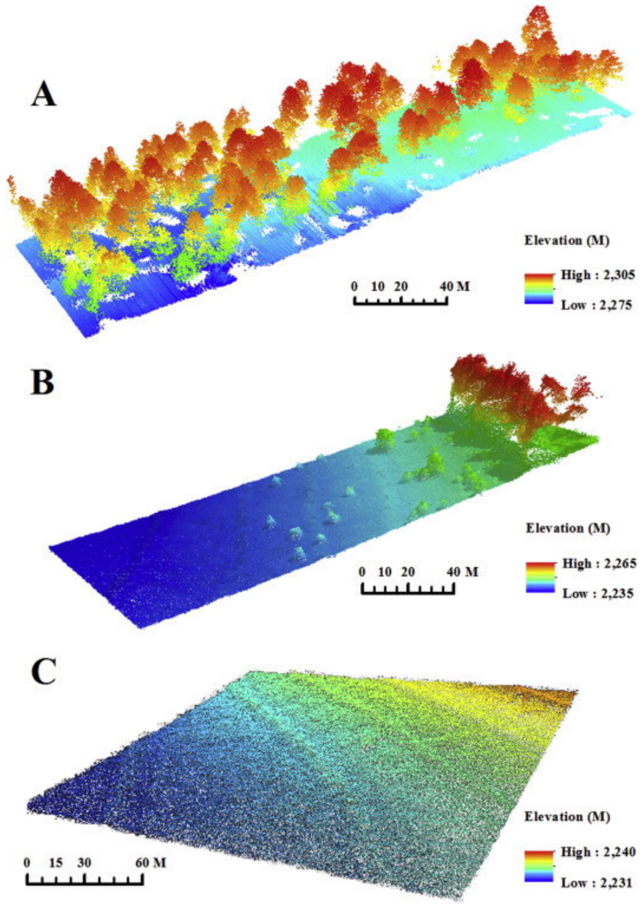



**FIGURE 3.** Orthorectified images turned to NDVI color based point cloud showing the height and position of each tree [97].

study. It is then proposed that the accuracy of the study can be further improved by utilizing gray level co-occurrence matrices, which allows the camera to gauge the texture of the crop area.

In another study conducted by a group of researchers from Brazil [100], a UAV spraying control system supported by onboard image processing was developed in real time which uses normalized difference vegetation index (NDVI) algorithm. It has greatly improved CPU usage and memory consumption compared to conventional methods, increasing the effectiveness of weed control.

A study conducted using satellite-based remote sensing applied multi-spectral imagery to compare the accuracies of supervised and unsupervised segmentation approaches in building extraction [101]. This study has found that both approaches yield similar accuracies, which proves that weed detection can be applied with more automation through the latter approach.

For UAV-based multi-spectral imagery used for weed control, [102] implemented semi-automated extraction of tree crowns to monitor the vegetation vigor of heterogenous citrus and olive orchards in Italy. The results of this study showed high accuracy with an F-score of 0.85 to 0.91 for olive and bergamot respectively. This enables areas with low vegetation vigors which may be caused by weed growth to be detected and handled appropriately.

### C. INFECTIOUS DISEASE EPIDEMIOLOGY AND MAPPING

Infectious disease epidemiology and mapping is crucial for monitoring and controlling diseases that can destroy crops and livestock. By tracking disease spread and its patterns, farmers can implement targeted interventions, optimize resource allocation, and safeguard food production, ensuring sustainable and efficient agriculture. An interesting study was done by a group of researchers on the impact of changes in land usage on infectious disease epidemiology by using information - footages and other miscellaneous data - captured with a UAV [103]. The essence revolves around the usage of UAV and processing of the captured information to study land usage, local population changes, forestry characteristics and so on, which is key to epidemiological studies of diseases. The following highlights the rationalization behind the idea from a epidemiological point of view.

One of the main manner by which epidemiologists in detecting, tracking and modelling diseases is by studying the environment itself [104]. They have relied on variously sourced spatial and environmental data for this express purpose; the data would ideally need to have maximal coverage and detail. The most readily available mean of collecting these data are through cumbersome means such

**TABLE 2.** Summary of precision agriculture through UAV imagery.

| Year | Type of UAV | UAV Model | Mode of Operation | Deployed Location | Payload | References |
|---|---|---|---|---|---|---|
| 2000 | Blimp | NIAES | Remote pilot | Japan | EO camera, multi-spectral sensor | [38] |
| 2000 | Fixed-wing | Hobbyist RC Plane | Remote pilot | USA | EO camera | [35] |
| 2002-2004 | Fixed-wing | Pathfinder-Plus | Autonomous | USA | EO camera | [57], [58] |
| 2003-2005 | Fixed-wing | Edge 540T | Remote pilot | USA | EO camera | [36], [80] |
| 2004-2007 | Single-rotor | Copter 1B | Autonomous | Switzerland | EO camera | [81], [82] |
| 2006-2010 | Fixed-wing | Vector-P UAV | Autonomous | USA | multi-spectral sensor, NIR camera | [37], [42], [43] |
| 2007-2010 | Fixed-wing | SIG RASCAL-110 | Remote pilot | USA | EO camera | [33], [34] |
| 2007-2011 | Fixed-wing | MLB Bat 3 UAV | Autonomous | USA | EO camera | [49]–[52] |
| 2008 | Glider | L'Avion Jaune | Remote pilot | France | multi-spectral sensor | [59] |
| 2008 | Single-rotor | Mini UAV of weControl AG | Autonomous | Switzerland | EO camera, NIR camera | [15] |
| 2008 | Multi-rotor | Microdrones MD4-200 | Autonomous | Switzerland | Multi-spectral sensor | [15] |
| 2009 | Kite | KAG | Remote pilot | USA | Multi-spectral sensor | [83] |
| 2009 | Single-rotor | Benzin Acrobatic | Autonomous | Spain | Multi-spectral sensor, thermal sensor | [66], [67] |
| 2010 | Single-rotor | X-Cell Fury 91 | Remote pilot | Thailand | Multi-spectral sensor | [39] |
| 2011 | Single-rotor | Modified RC Helicopter | Autonomous | USA | Multi-spectral sensor | [84] |
| 2012 | Multi-rotor | VIPtero | Autonomous | Italy | Multi-spectral sensor | [85] |
| 2015 | Fixed-wing | AeroDrone PAM-20 | Autonomous | Ukraine | Sprayer | [61] |
| 2016-2017 | Multi-rotor | MD4-1000 | Autonomous | Spain | Multi-spectral sensor | [68], [69] |
| 2016 | Multi-rotor | Self-assembled | Autonomous | USA | Multi-spectral sensor, NIR camera | [86] |
| 2016 | Multi-rotor | Vulcan Hexacopter | Autonomous | Greece | Multi-spectral sensor, thermal sensor | [87] |
| 2016-2017 | Single-rotor | Yamaha RMax | Autonomous | South Korea, Japan | EO camera, sprayer | [63], [64] |
| 2016 | Multi-rotor | DJI Phantom 2 | Autonomous | Germany | EO camera, action camera | [70] |
| 2016 | Multi-rotor | HiSystem's MK Okto XL | Autonomous | China | Multi-spectral sensor | [88] |
| 2017-2018 | Fixed-wing | Anaconda | Autonomous | USA | EO camera, multi-spectral sensor | [53], [54] |
| 2017 | Multi-rotor | 3D Iris | Autonomous | Australia | EO camera | [89] |
| 2017 | Fixed-wing | X8-Skywalker | Autonomous | Peru | Monochrome camera, NIR camera | [56] |
| 2017 | Multi-rotor | Quadrotor by ENROUTE | Autonomous | Japan | EO camera | [90] |
| 2018 | Multi-rotor | Parrot Sequoia | Autonomous | Italy | Multi-spectral sensor | [91] |
| 2018 | Multi-rotor | DJI Matrice 100 | Autonomous | Brazil | EO camera, multi-spectral sensor | [71] |
| 2018 | Multi-rotor | DJI Phantom 3 Pro | Remote pilot | France | RGB camera | [75] |
| 2019 | Multi-rotor | Parrot Bebop 2 | Autonomous | Senegal | RGB camera | [76] |
| 2019 | Multi-rotor | DroneHEXA | Autonomous | Spain | Multi-spectral sensor | [92] |
| 2019 | Multi-rotor | DJI Phantom 4 | Remote pilot | Pakistan | RGB sensor, NIR sensor | [74] |

**TABLE 2.** *(Continued.)* **Summary of precision agriculture through UAV imagery.**

| | | | | | | |
|---|---|---|---|---|---|---|
| 2019 | Multi-rotor | Altura AT8, Riegl Ricopter | Remote pilot | Netherlands | Hyperspectral camera, thermal camera, LiDAR scanner | [78] |
| 2021 | Multi-rotor | Matrice 600 | Autonomous | China | Multi-spectral sensor | [79] |
| 2022 | Multi-rotor | HP-X4-E1200 | Autonomous | Germany | RGB camera | [73] |
| 2022 | Multi-rotor | HP-X4-E1200 | Autonomous | Germany | RGB camera, multi-spectral sensor | [77] |
| 2022 | Multi-rotor, fixed-wing | DJI Phantom 3, SenseFly eBee | Remote pilot | Brazil | RGB camera | [72] |

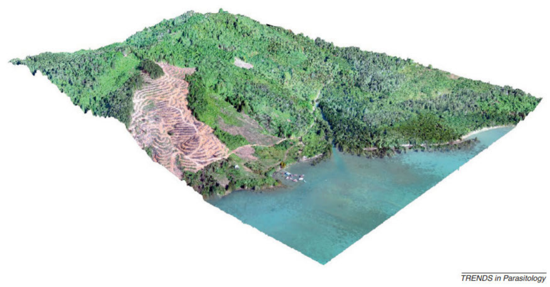



**FIGURE 4. 3D model of the study site in Sabah, Malaysia used for disease vector mapping and epidemiology [103].**

as satellite base imaging and aerial surveys by plane. These methods are irregular - a single satellite provides limited coverage of the earth at long interval and its performance is subjected to local weather condition - costly per iteration and does not provide support on demand. Thus, the issue of cost and scale stands in the way of faster and and more accurate epidemiological studies; a bottleneck. Thus, the advent of cheap and highly scalable UAVs would provide a mean to significantly overcome the aforementioned shortcomings.

Fig. 4 and Fig. 5 are some of the desired and useful results that are generated from the models in the study that would be used for disease vector mapping and epidemiological studies. From these figures, it shows the potential of UAVs to collect detailed spatial information in real-time at relatively low cost, which can provide spatially and temporally accurate data critical to understanding the linkages between disease transmission and environmental factors. Further detailed discussion on similar related technologies in the context of biomedical and epidemiological discussion could be found in [105] and [106]. The first article discusses new or improved technologies being applied or likely to be applied in the future to worldwide research on plant virus epidemiology, while the second article focuses on the landscape ecology and epidemiology of malaria associated with rubber plantations in Thailand.

### D. SPECTRAL IMAGING

Spectral imaging in precision agriculture is vital for assessing crop health and optimizing resource management. It provides detailed information about plant characteristics, allowing farmers to detect nutrient deficiencies, diseases, and stress early. This data-driven approach enhances crop yield, minimizes inputs, and supports sustainable and efficient agricultural practices. There are primarily two different types of spectral imaging beyond the visible light (VL) and NIR spectrums. These are the multi-spectral and hyperspectral imaging techniques. Multi-spectral refers to imaging for 5 to 12 bands of measurement of the energy of spectrums outside of the VL and NIR ranges. Hyperspectral imaging refers to imaging of hundreds to several thousand channels of bandwidth over the same range of spectrums [107], [108]. In general, hyperspectral imaging has better performance in profiling endmembers due to the almost continuous spectra of imaging. However, this increase in performance also increases data processing complexity as data from hundreds to thousands of narrow bands of information can be difficult to handle in real time. This causes hyperspectral processing to currently only be handled in a post flight manner.

Two types of sensors are predominantly used for multi/hyperspectral imaging: charge-coupled device (CCD) and a complementary metal-oxide-semiconductor (CMOS) sensor. CMOS sensors are faster at acquiring and measuring spectrum energy levels, but is more prone to noise and dark currents which can cause blemishes in image. Data imaging techniques are primarily split into three categories, which include point scanning, line scanning, and plan scanning techniques, which are depicted in Fig. 6 [109], [110], [111].

The usage of hyperspectral sensors on UAV systems are not trivial. However, the processes and methods of usage of the sensors are similar, regardless of UAV system type or sensor type. Discounting UAV system operations prior to flight, the sensors themselves need to be calibrated for incoming light, by managing the lens aperture to suit the incoming light levels. The use of navigation grade GPS is also not suitable for hyperspectral georeferencing and scanning on a UAV [112]. Hence, the use of ground control points (GCPs) are necessary to facilitate accurate georeferencing for post-processing steps. However, late developments of ultra-wide-band (UWB) positioning and inertial-based navigation systems enable more precise mapping, hence are able to

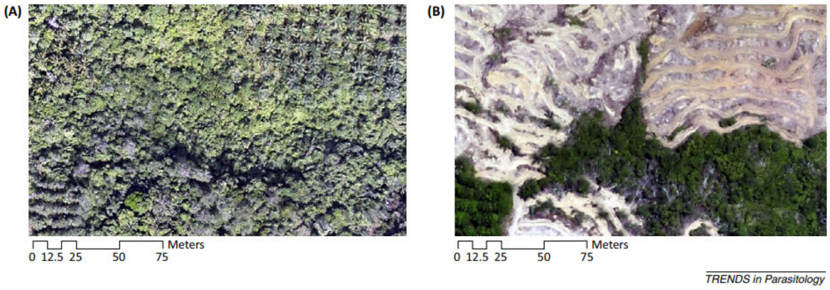



**FIGURE 5.** Mapping changes to land cover at the study site in Sabah, Malaysia: (A) Study site in February 2014; (B) Same study site in May 2014 after the start of clearing to create a rubber plantation [103].

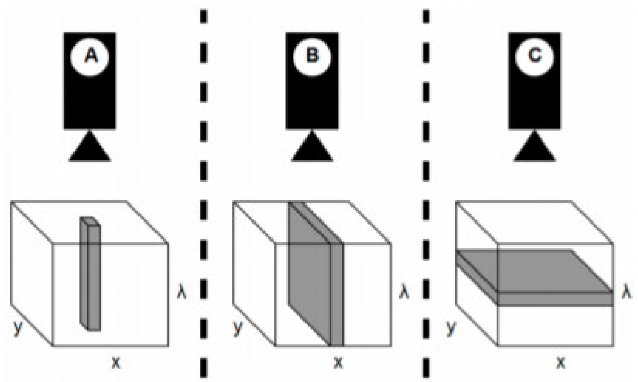



**FIGURE 6.** Various scanning modes: (A) Point scanning; (B) Line scanning; (C) Plane scanning [113].

minimize the number of required GCPs. The GCPs are usually white references on the ground.

## IV. LIMITATIONS OF REMOTE SENSING IN PRECISION AGRICULTURE

The following subsections provides a discussion on the limitations and challenges facing the creation of commercially viable and massively scalable remote sensing technologies for PA, as distilled from the preceding reviews. Despite being an actively research field, the literature is fragmentary and newly developed tools or applications in academia seldom translate down the market value chain in any meaningful manner. In addition, current researchers looking to adopt deep learning methodologies to PA studies may find it hard to do so simply due to the scarcity of labelled datasets in the domain; it is non-trivial in complexity and cost to create such datasets, but nonetheless crucial. Thus, the following seeks to provides an impetus to the topic by reviewing some of the aforementioned challenges, and proposes corresponding directions for future research to overcome them in order to further the discussion.

### A. TEMPORAL MAPPING METHODS

Most methods employed in the aforementioned applications where certain sense of intelligence is required such as classification of crop type, object detection to detect presence of weed, and image segmentation in the case of land cover analysis, revolves around the usage of traditional Machine Learning and manual Feature Extraction methods. It has been shown that Deep Learning approaches outperforms the former in terms of robustness and accuracy, and thus has been widely adopted as of late [89], [114], [115].

However, the specific model that was most widely used is of the convolutional neural network (CNN) variant while other viable models have been underutilized; CNN is the current de facto model used for vision applications. One such promising alternative model that has been scarcely applied is the recurrent neural network (RNN), which has seen later adoption as compared to the more obvious CNN. RNN is capable of not only spatial information comprehension - as in CNN - it is capable of comprehending the temporal characteristics of the data. Succinctly, it is capable of understanding or analysing an object as it persist as across different time-frames, yielding a richer set of latent representation of the observations.

In a comprehensive survey paper which studies the application of Deep Learning methods on agriculture applications, only a few attempts have been made to utilize RNN [114]. An example of such a study is illustrated in Fig. 7 to 9 [116]. Though the study was done using satellite images, the core principle and methodologies are similarly applicable to drone-based footage and applications.

For applications on drone footages, spatial-temporal approaches may prove to be non-trivially more robust and provides better result than simple spatial analysis as with typical CNN models. This rationalization is founded upon the fact that drone flies at a lower altitude than satellites and hence the fields and plains captured would not be as well defined - nor entirely encapsulated in a single frame with obvious divisive edges - as seen in the figures above. For example, in land cover and usage analysis, the demarcation between land types would not be as immediately obvious as seen in the above figures when the footages are taken at a much lower altitude, and hence spatial data alone may not be sufficient. However, if the model is capable of understanding the changes - or constancy - across different progressive frames and their inter-correlational relationship, it could be more robust in its classification. The same rationalization

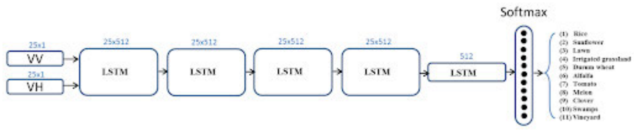



**FIGURE 7.** An RNN Deep Learning model with Long-Short Term Memory cells (LSTM) used for crop type classification [116].

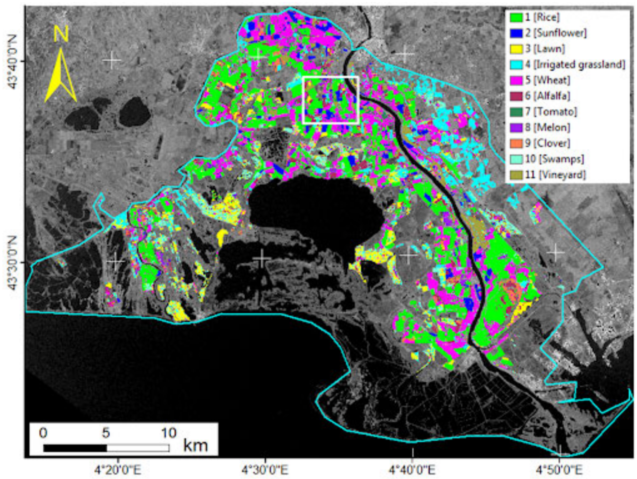



**FIGURE 8.** Resulting output of the RNN classifier [116].

could be applied to health monitoring for plants; NVDI measurements are dependent on the angle of camera to the plant during capture, and on external factors such as ambient lighting conditions and ambient occlusions, and hence a single frame may not be sufficiently representative of the actual condition due to these undesired augmentations. However, when the same subject could be analyzed from multiple perspective and successive readings, a more robust classification result should be attainable; since the external augmentation sources could be more reliably identified by having more sample of the same subject from a different spatial-temporal perspective and eventually be filtered.

### B. LACK OF DATABASE

In precision agriculture, machine learning employs data from sensors, satellites, and historical records. It preprocesses, extracts features, and employs various algorithms like regression, classification, and clustering to predict crop yields, detect diseases, and optimize resource allocation. Models are trained, validated, and integrated into real-time monitoring systems. The training of such models require sufficient database to provide raw material.

The majority of machine learning implementations used are comprised of supervised learning methods - which requires a large set of labelled data - and thus the availability of labelled data is currently a bottleneck in the research and implementation of machine learning-based remote sensing applications.

The datasets currently available are highly specific, localized and sparse. The former means that for most settings - geographic locations and conditions - and plant types, there are no dataset readily available for training. Thus, an effort to create, clean and label a dedicated dataset specifically for a particular area - e.g. Malaysian rain forest - would be a topic worthy of further research and development. The data would necessarily need to include details such as the local vegetations with a range of geographical information that encapsulates the maximum possible variance of real world scenarios, along with a sufficient sample size. Note that the dataset created for different purposes or tasks would need a corresponding label type, such as plant species for species classification, data on healthy-unhealthy plants for plant-health analysis, labelled land types for land usage segmentation and so on. For illustration purposes, some examples of prominent work on dataset creation on other topics could be found in [117], [118], and [119].

Given that the database is sufficiently available, precision agriculture can be further improved by optimizing machine learning techniques. For example, a study conducted in 2021 utilises UAV multispectral imagery of citrus orchard and an onion crop to compare and assess different classification methods [120].

### C. COORDINATED LARGE-SCALE OPERATIONS

Other important areas of research for the application of UAV to agricultural activities one should take note of would be scalability and multi-agent coordinations [121]. In particular, the bottleneck lies in the limited flight time and coverage capability of individual UAV, which leads to difficulty in scaling, with estimated 1.5 $km^2$ for multi-rotor UAV, and 5 $km^2$ for fixed-wing UAV [106]. This is further complicated by cumbersome and inefficient processes of post data processing, as most are not done in real-time and thus any defects in the raw data itself would necessitate another scheduled flight anew. To truly proliferate the usage of UAV for wide scale precision farming in real world applications, it would necessarily need to be affordable, easy to use and highly scalable.

To remedy aforementioned problems, multiple approaches were proposed to overcome these limitations, one of which is to model the problem as a multi-objective optimization task with multiple drone units working in tandem [121], [122], [123].

Succinctly, the problem could be broken down into 3 core challenges.

1) How does one derive a control scheme that is robust, scalable and intelligent in a highly complex setting with each agent capable of functioning interdependently?
2) How does one enable detailed data collection and communication between all drone units, miscellaneous ground peripherals if any, and the respective ground stations so that the full richness of data types could be effectively collected in real-time at scale?
3) How does one relay and mediate the transfer of the high volume of information and data generated from the above in a secure, transparent, and reliable manner?

A variety of solutions of different nature and complexity could be proposed to solve the aforementioned issues,

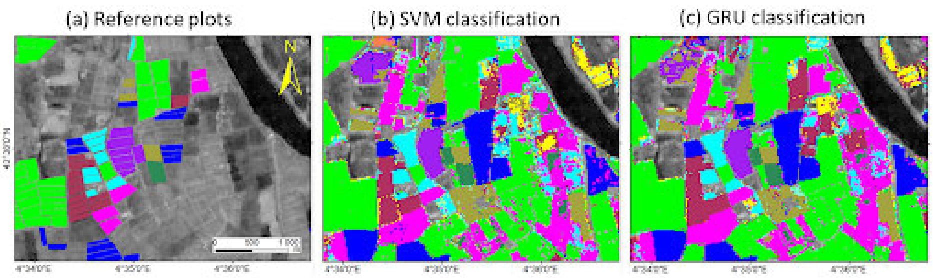



**FIGURE 9. Comparison of the outputs (b) and (c) from different models with respect to the input (a). It could be seen that (c) provides a more consistent and accurate output in comparison [116].**

but a few recent technological breakthroughs warrants special attention. The following corresponds directly to the challenges raised above.

1) Reinforcement Learning. Recent advancement in Reinforcement Learning in creating non-explicitly defined agents has been significant [124]. The problem of deriving a complex scheme of behaviour in an environment where modelling - defining explicit rules and describing the task - would be prohibitive, Reinforcement Learning thrives. The agent may be able to learn of a sufficiently optimal control scheme just by interacting with the environment repeatedly until convergence to a sufficient optima. Scenarios such as changes in weather conditions, flight path, individual drone failures could theoretically be learned in a similar in this approach. Though problems in difficulty of preparing the test environment and guarantee of convergence would need to be addressed in advance and would itself warrant extensive further research.
2) Internet-of-Things (IoT). As the farm of tomorrow gets more and more automated and integrated in the efforts toward highly efficient agriculture - e.g. precision farming - holds a promising future [125]. The interests in digitizing the common farm have been picking up too, such as the recent work by Microsoft Corporation with the introduction of their end-to-end IoT platform for precision agriculture. There are already a few key innovation that were explored in [126] for general farming and also for the application of UAV in farming. Specifically, the utilization of a high resolution wind map from IoT connected sensors scattered through the farm enabling an algorithm to take advantage of the wind condition, while planning for drone flight path. Th said algorithm managed to improve a single drone's area coverage by 30% with the wind map aided flight path planning. One could conceivably extend the usage of IoT for multi-agent drones in the same agricultural setting. Other examples of how IoT could be utilized in precision farming would be, though not limited to, the enabling of direct communications between the individual drone units for peer-to-peer coordination, and the deployment of a sensor network across the farm which could provide real-time update of the individual drone's location in addition to the usual GPS-based approach.
3) Blockchain. One crucial consideration in designing large-scale collaborative systems is the means of information transfer and hence communication - the way which data are communicated between units. Though traditional means of communications and their protocols may suffice for small scale applications, they are woefully unprepared for applications where near real-time information from thousands of sensors and many units of UAVs would need to be channeled with minimal error in a secure manner. This is especially of importance where coordination and communication is required between multiple drone units from multiple farms facilitated by multiple parties or other similar complex settings. Blockchain is made specifically for circumstances such as this, especially variants such as IOTA which is designed specifically for IoT use cases - it gets more efficient and faster as the number of users increases [127].

It should be noted that each of the above could entirely be a research topic in and of itself in terms of their individual functionalities and how they complement one another to form an entirely new paradigm for future applications that embodies similar characteristics. (2) and (3) could be neglected if communications between agents are not crucial; e.g. decentralized drone swarms, where the units are not communicating but could still function in a coordinated manner through other means [128].

## V. SOCIAL AND ECONOMIC IMPLICATIONS FOR ADOPTION OF REMOTE SENSING IN AGRICULTURE

In addition to reviewing the technology and their advancements, attention must also be paid to the follow up of their applications, a non-trivial undertaking due to the sheer scale and complexity of the agriculture industry. In this Section, a high-level overview summarizing the current agricultural industry is given, followed by a brief exposition of the UAV market in precision agriculture and how it is affecting the landscape of the industry.

According to a study by the Food and Agriculture Organization (FAO) of the UN, the global agriculture trade is worth a total of 1.6 trillion USD, tripling its value in a mere 15 years [129]. Agriculture itself in its entirety makes up a total of 10% of the world's gross domestic production (GDP), or 70 trillion USD with more than a third of the world's land dedicated to the activity [130]. The significant increase is attributed to the enriched world population, with a large population being raised from poverty and low-income status rapidly in emerging nations such as China and the trend of growth is projected to continue - an indication of the rising agriculture demand and consumption globally [131]. Meanwhile, the commercialization of UAV is projecting a similar trend of upward growth with an estimated servable market size of 127 billion USD across industries, and 32.4 billion USD in agriculture alone [132]. Thus, it could be seen that there is a large serviceable potential and market demand for UAV and its accompanying suite of technological solutions as highlighted in the preceding sections in precision agriculture. However, the road to adoption and actually fulfilling the demand may prove to be an arduous one.

One of the immediate challenge is the adoption of precision agriculture technology by farmers. Even for some of the more advanced farms cultivating popular crops in large-scale operations, the penetration rate of precision agricultural technologies is still surprisingly low. For example, in the United States soybean and corn farms that utilizes simple tech such as yield mapping sits only at 50%, and those that utilizes GPS positioning systems are less than 26%, with more intricate and advance tech having a lesser adoption rate still [133], [134]. Upon further analysis, the main obstacles constituting the challenge of adoption are threefold; a lack of capital, the lack of tech-readiness of the farming populace, and the lack of cross-platform support of precision farming solutions.

According to a study by The World Bank, it is found that approximately 65% of agricultural labourers live below the poverty line or below 3.10 USD per day [135]. This automatically excludes a sizeable portion of farmers from adopting better technology such as UAV for precision agriculture in their own farm due to the disproportionately large gap of the cost of a single agriculturally equipped UAV and their income. As for small farm owners in first world countries that could conceivably afford such a device, they too face cost issues as the service and operational cost for such devices are high to begin with. Not only that, it is found in [133] that the previously adopted precision agriculture technologies such as older yield mapping systems, GPS systems and variable-rate systems have little impact on the final net return, with approximately 2.5% increase with yield mapping, 2% with GPS guidance systems and 1.1% with variable-rate systems. Thus, the incentives to invest a significant amount of time to set up, and upfront capital to invest in these technologies may be hard to justify for most farmers, especially smaller scale farm owners.

On another hand, one of the prerequisites of adopting advance precision farming technologies is the availability of fundamental digital infrastructures such as internet access. Though the amount of people being brought online through the more readily available mobile internet - an approximately 43% of the global population as of 2018 - more than half of the population still have no access to this modern basic necessity [136]. This fundamental blockade in turn prevents the affected populace from developing the critical basic tech knowledge needed for adoption in the first place. In fact, according to the McKinsey's Industry Digitization Index, the agricultural sector is the slowest in terms of digitization due to the aforementioned problem. Fig. 10 is adopted from a report published by The World Bank which shows a very strong correlation of these factors with digitization efforts [137]. The problem is further exacerbated by the proprietary nature of existing agritech solutions which makes cross-platform interactions between different solutions from different providers to address more complex tasks not possible without advance technical skills or am outright not viable - a non-trivial issue as each piece of solution has a high capital requirement - acting as additional deterrence to adoption [138].

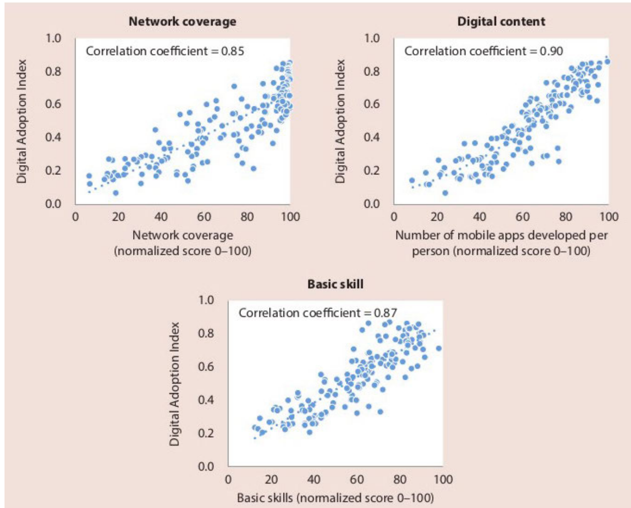
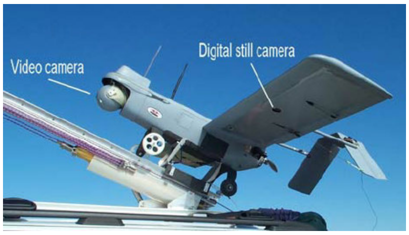



**FIGURE 10. Correlation of adoption prerequisites with the rate of digital adoption [137].**

Beyond the above-mentioned issues, there are also the challenge of the public's perception on UAV in general, which may pose resistance towards wide scale adoption, ethical usage and possible misuse especially with mobile intelligent systems such as an AI-powered UAV fleet, data privacy and cybersecurity issues as with all modern digital systems, the lack of a solid legislative framework around its usage, and the absence of flexible financing along the entire value chain to kick-start an industry wide adoption amongst many others [139], [140], [141], [142], [143]. The specifics of these matters are outside the scope of this paper but they could serve very well as the basis for future studies.

The challenges listed above are highly complex and by no means solvable in a short time, but the following are some recommendations that could serve as a starting point for future endeavors. Work towards a solution would most definitely

(a) Vector-P [43].




(b) MLB Bat 3 UAV [150].

(c) ANACONDA fixed-wing [151].

(d) X8-Skywalker [152].

(e) Pathfinder [153].

(f) L'Avion Jaune [154].

**FIGURE 11.** Examples of autonomous fixed-wing UAV utilized for remote sensing.

(a) Benzin acrobatic.

(b) MD4-1000 [155].

(c) DJI Phantom 2 [156].

(d) DJI Matrice 100 [157].

(e) Yamaha RMAX [158].

(f) DJI Agras MG-1 [159].

**FIGURE 12.** Examples of autonomous rotorcraft UAV utilized for remote sensing.

require a two-prong, top-down and bottom-up approach as the problems are both institutionally-systemic, and individual-specific. To address the former, regional governments could push harder towards encouraging adoption by providing tariff exceptions, tax reliefs, testing sandbox environments or similar benefits to offset the initial capital commitment required to transition to high-tech agriculture and drive higher risk innovations. In addition, they should also work with agricultural specific ministries, public labour institutions and private entities in finalizing on a comprehensive legislative framework on the specifics of high-tech agricultural practices to provide policy certainty, e.g., on the usage of UAV in agriculture at a large scale and individual level.

The solution providers and adopters as of now are highly fragmented and limited in actual application, a common trait at the early stage of an industrial revolution [143]. Though agritech is garnering increasing attention, the sector still lacks the resource impetus required to kick-start an organic, industry-wide revolution - resource in term of public and private capital, human resources, infrastructures and so on. Thus, heavy financing would be needed to drive further innovation and technopreneurship to get things started. One suggestion as put forth is to drive initial growth with government capital investment at the early stage, and then later pulls in private capital once the initial results are shown to be promising [144].

On the other end of the spectrum with bottom-up approaches, attention and effort will need to be put into the education of farmers in utilizing modern technologies, as a large portion of the farming population are either underserved and lacking in education, or are tech-avoidant due to the age gap - 56% of the farming workforce in Europe are over the age of 55, and only 39% of farms uses smartphones or tablets [145]. As such, work that upskills individuals at the grass-root level must not be overlooked either. Upskilling programs that equips older farmers with the necessary skills to transition, and in training new generation of farm owners would be crucial towards building the farm of the future.

To support the promotion of UAV-based remote sensing, a set of process recommendations can be made for government policies, technical services, training, security, data services, and after-sales insurance. First, government policies can be developed to encourage the adoption of UAV remote sensing in agriculture, while services from the industries and universities can provide technical support for the selection and use of UAVs and sensors. Then, training can be provided to farmers to ensure they have the necessary skills to operate the UAVs and to interpret the data collected. Here, security measures must be put in place to protect the privacy of farmers and their data. Data services can be established to help farmers manage and analyze the data collected, and after-sales insurance can be offered to protect farmers from financial losses due to equipment failure or other issues.

## VI. CONCLUSION

Precision agriculture is a data-driven approach aimed at maximizing agricultural efficiency. Concerns arise from the growing gap between global agricultural output and shifting dietary needs, which conventional farming practices may exacerbate. For example, paddy fields face challenges such as soil pH issues, water mismanagement, and weed growth. This leads to substantial losses which compromise agricultural efficiency. Satellite-based and UAV-based remote sensing offers promising solutions by providing comprehensive insights regarding the crops, such as enabling weed detection using hyperspectral imagery. This study explores the state of remote sensing in PA by detailing aspects such as data collection, applications, limitations, and socio-economic implications; aiming to promote widespread adoption and addressing critical technological and societal challenges in modern agriculture.

While satellite-based methods has its uses in monitoring crop health, its limitations reduce its effectiveness in the field. This motivates the recent advancement of using unmanned aerial vehicles (UAVs) for low altitude sensing systems (LARS) to provide higher-resolution imagery compared to satellites. However, remote sensing via UAVs also have their limitations compared to that of satellites, including short flight durations and regulatory constraints. Despite these challenges, the advantages of remote sensing via UAVs are substantial, having potential for enhancing agricultural efficiency in the face of global challenges like food scarcity and climate variability.

Contemporary research on precision agriculture focuses on advancing sensor technologies like hyper-spectral imaging systems and electro-optic cameras to provide real-time data, particularly for Variable Rate Technology (VRT) applications which monitors field variability over time. VRT's effectiveness depends on reliable generation of accurate maps depicting crop conditions, soil features, and microbial factors. This study delves into the applications of remote sensing in precision agriculture, encompassing Crop Health Monitoring, Weed Control, and Infectious Disease Epidemiology and Mapping.

The development of successful and scalable remote sensing technologies for PA faces challenges. The literature in this field is fragmented. Researchers interested in applying deep learning to PA struggle with the scarcity and lack of variety in readily-available datasets. These issues significantly increase the cost of implementing deep learning in PA. Addressing these issues is crucial for advancing PA technology. Future research should focus on overcoming these challenges to facilitate progress in the field, and learn from cross industry studies, related to trust-based win-win gain sharing models [146], to find proper balance between the costs, implementation resources needed for proper RDI process and revenue sharing to allow faster growth of needed solutions and data sets for further studies.

The global agriculture industry is witnessing substantial growth due to increasing population and demand. The UAV market in precision agriculture holds significant promise. However, adoption faces challenges, including limited capital among farmers, inadequate technology literacy, and a lack of digital infrastructure. To address these issues, an approach is recommended: governments can offer incentives, tariff exceptions, and legislative frameworks to encourage adoption. Heavy financing, initially from the government, can drive innovation. Additionally, education programmes to educate farmers in PA technology can be implemented, university-industry collaboration could be used to reduce development costs [147] and community-based environment data collection models [148], with proper data quality measures validation solutions [149], could be used among farmers to enhance the value of collected and shared for themselves and their peers. To promote UAV-based remote sensing, measures such as: government policies, technical support, training, security measures, data services, and after-sales insurance should be established.

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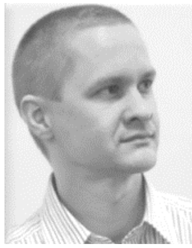

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