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Systematic Literature Review: Application of Unmanned Aerial Vehicle in Agriculture

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Abstract

In recent years, the application of Unmanned Aerial Vehicle (UAV) or drone technology in agriculture has gained popularity. However, in Bhutan, its application is far beyond reach. This systematic literature review synthesizes research on UAV applications in agriculture following PRISMA 2020 guidelines. From an initial 300 records (sourced from Google Scholar, Sci-Hub, and printed literature), 138 peer-reviewed studies met the inclusion criteria and were catalogued in Zotero. Findings are organized into five primary domains, which include crop monitoring and management, agrochemical spraying, crop damage assessment, surveying and mapping, and phenotyping, each encompassing specific secondary themes. Compared with satellites, manned aircraft, and ground systems, UAVs provide higher spatial and temporal resolution, operational flexibility, and cost-effectiveness, leveraging RGB, multispectral, hyperspectral, LiDAR, and thermal sensors. Empirical evidence demonstrates UAV utility for soil nutrient estimation, early pest and disease detection using vegetation indices (e.g., NDVI), precision spraying, rapid damage assessments, high-accuracy mapping, and enhanced phenotyping and yield estimation when combined with machine learning. Notable limitations include short flight time, regulatory constraints, weather sensitivity, and challenges in scaling plot-level results regionally. A key research gap identified is the absence of standardized, scalable methodologies and multi-location validation to translate plot-level UAV findings into reliable regional monitoring systems.

Keywords: *Remote sensing; UAVs; UAS, Agriculture; Application*

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1 Introduction

Advanced farming techniques, such as precision agriculture and smart farming, now serve as the foundation for sustainable agricultural practices (Budiharto et al., 2019; Tsouros et al., 2019). They utilize state-of-the-art communication and remote sensing systems, integrated with AI-powered data analysis and decision-making strategies (Istiak et al., 2023; Prakash et al., 2022; Tsouros et al., 2019). Over recent years, significant technological advancements in Unmanned Aerial Vehicle (UAV) have led to their widespread adoption and application in precision farming (Istiak et al., 2023).

Unmanned Aerial Vehicles (UAVs), commonly referred to as drones, are operated remotely and equipped with advanced tools such as multispectral cameras, sensors, and communication systems integrated with intelligent decision-making capabilities (Ampatzidis et al., 2020). They are designed to handle tasks like data collection, analysis, and execution (Eskandari et al., 2020; Rejeb et al., 2022). Compared to satellites and piloted aircraft, UAVs offer a more technologically advanced, cost-effective, efficient, and real-time solution for performing actions (Islam et al., 2021; Tsouros et al., 2019).

The growing adoption of UAVs in precision agriculture is driven by several advantages over traditional remote sensing methods. Tsouros et al. (2019) reported that satellite imagery often falls short due to its low spatial resolution and infrequent capture intervals, making it unreliable for consistent agricultural monitoring. Moreover, delays between image acquisition and availability further limit its utility, while environmental factors like cloud cover frequently obstruct data collection. Similarly, the use of manned aircraft (MA) is limited by high operational costs, making it unfeasible for frequent flights to obtain multiple crop images (Tsouros et al., 2019). In addition, UAVs are highly significant as they can operate more effectively than ground-based (GB) systems since they can survey extensive areas in a short time, without causing any damage (Guan et al., 2019; Rejeb et al., 2022). The commonly used sensors for UAVs are Visible light sensors (RGB), Multispectral sensors, Hyperspectral sensors, Light detection and ranging sensors (LiDAR), and Thermal sensors (Tsouros et al., 2019).

Bhutan recognizes the vast potential of utilizing Unmanned Aerial Vehicles to transform its agricultural sector and meet the nation's growing food demand. By 2023, the agriculture and livestock sectors are expected to provide sustenance for an estimated 837, 288 people, requiring significant production growth across key commodities compared to 2021 production (Ministry of Agriculture and Livestock [MoAL], 2023). Cereals production must rise to 289, 748 metric tons, reflecting an approximately 78% increase from 162, 931 metric tons. Similarly, the combined output of vegetables, fruits, roots, tubers, mustard, and spices is projected to reach 140,160 metric tons, reflecting a 13% increase from 124, 116 metric tons.

To meet these demands, Bhutan will need to significantly enhance agricultural and livestock production while ensuring farmers' incomes are sufficient to maintain food affordability (MoAL, 2023). However, achieving this ambitious goal is challenged with several obstacles in particular with an increasing amount of arable land left fallow, farm-labor shortage caused by increasing number of migrations to other service sectors, and persistent human-wildlife conflicts (National Statistical Bureau [NSB], 2023).

One significant way to address these challenges and enhance production is to adopt modern farming technologies, such as UAVs and other evolving smart and precision farming innovations. Strategic integration of these advanced tools will not only address the immediate challenges but also support long-term agricultural sustainability and productivity. Thus, this study aims to explore different applications of UAVs in the agriculture sector and guide the policy makers while framing the guidelines and developing policy related to drone usage and application in Bhutan.

2 Materials and Method

2.1 Gathering of Literature

This article was developed through a systematic literature review of studies conducted by various authors across different regions of the world. The review process adopted PRISMA 2020 guidelines (Page et al., 2020), encompassing three primary stages: identification of relevant journal articles, screening of collected literature, and inclusion of eligible studies (Figure 1).

Identification Phase: Relevant literature was sourced from Google Scholar, Sci-Hub, and printed academic books. A total of 300 articles were initially identified using keywords such as remote sensing, UAS, UAV, drone, agriculture, vegetative index, Agrisoft, and Pix4D.

Before screening, 66 articles were excluded: 50 due to duplication, 5 for being unrelated to agriculture, and 11 for lacking proper authorship.

Screening Phase: The remaining 234 articles underwent rigorous screening. Of these, 100 were excluded based on predefined eligibility criteria: 67 for low methodological quality, 13 for restricted access (non-open access), and 16 for insufficient information content. These exclusions primarily involved non-peer-reviewed publications, inaccessible full texts, and studies published more than 15 years before 2025. However, the excluded articles were revisited to retrieve any potentially overlooked information. As a result, 4 of the 100 excluded articles were reinstated for inclusion.

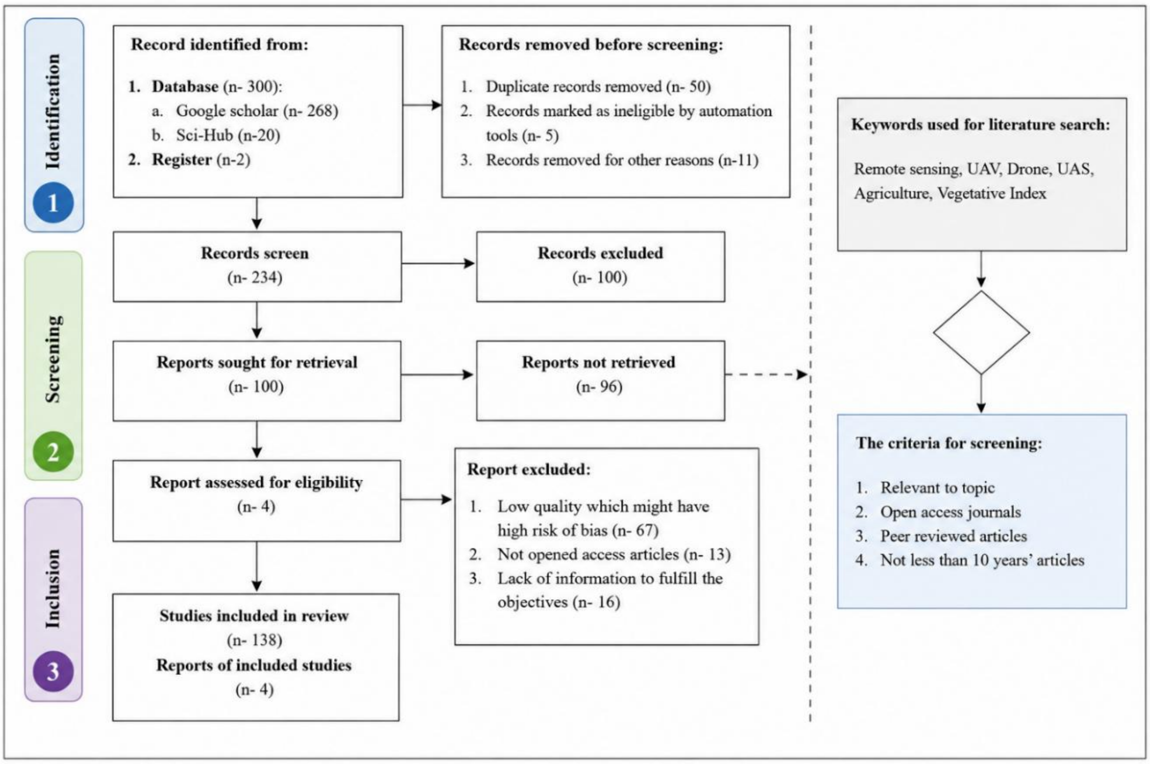

Figure 1. Process of PRISMA 2020 for systematic review

Source: Adapted from Page MJ, McKenzie JE, Bossuyt PM, Boutron I, Hoffmann TC, Mulrow CD. *The PRISMA 2020 statement: an updated guideline for reporting systematic reviews.*

Inclusion Phase: A total of 138 articles were ultimately selected for inclusion in this systematic review (Figure 1). These articles were deemed highly relevant to the study's objective, which focuses exclusively on drone applications in agricultural crop farming, excluding livestock-related research. Particular emphasis was placed on the methodological approaches and identified research gaps within the selected studies to ensure comprehensive data extraction. All included articles were catalogued using the open-access reference management software Zotero, facilitating accurate in-text citation and bibliographic referencing.

2.2 Conceptual Framework

Based on existing literature, the application of drones in agriculture is structured within a conceptual framework comprising two hierarchical levels: primary and secondary thematic areas (Figure 2). The primary thematic areas represent the core categories of drone utilization, each encompassing specific secondary thematic areas that reflect distinct use cases. Five primary thematic domains were identified: (i) crop monitoring and management, (ii) agrochemical spraying, (iii) crop damage assessment, (iv) surveying and mapping, and (v) phenotyping characterization. Each domain is further subdivided into concise secondary themes, as illustrated in Figure 2. The results and discussion section of this study are organized according to these thematic classifications to effectively address the research objectives.

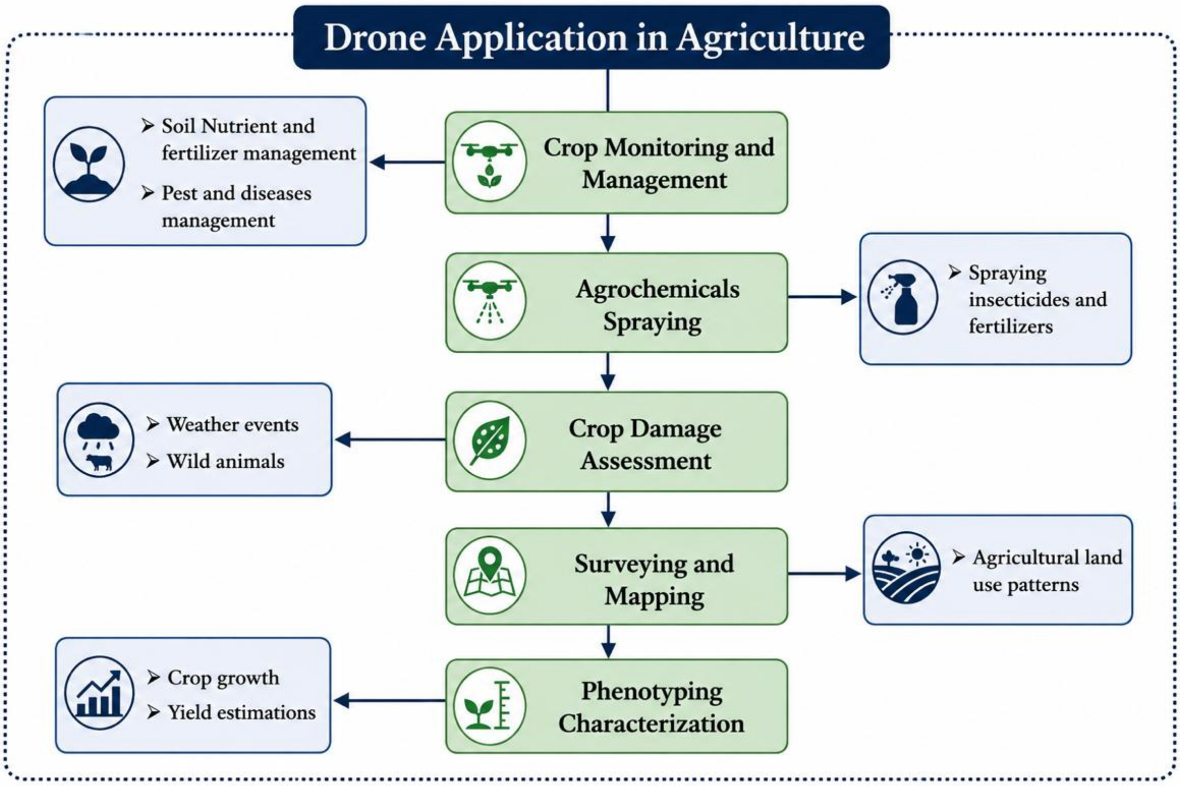

Figure 2. Conceptual framework for drone application in agriculture

3 Results and Discussion

3.1 Crop Monitoring and Management

Monitoring and managing crop health is crucial, as soil health, pests, and diseases can lead to substantial economic losses by decreasing yield and quality (Tsouros et al., 2019). This section will cover UAV use in Soil nutrient and fertilizer management, and Pest and Disease management

3.1.1 Estimating Soil Nutrient and Fertilizer Management

Two important markers of soil fertility and health are soil organic matter (SOM) and soil total nitrogen (STN). STN is necessary for plant growth, while SOM improves soil structure, water-holding ability, and nutrient retention. Farmers can increase crop yields and optimize nutrient management techniques by precisely predicting these characteristics (Yang et al., 2021).

Yang et al. (2021) conducted a study in Northeast China using a DJI M600 Pro UAV, equipped with a Resonon Pika L hyperspectral camera for the collection of samples on SOM and STN. They applied the particle swarm optimization (PSO) technique to refine the input weights and bias parameters of the extreme learning machine (ELM) model, enhancing its capability to predict soil organic matter (SOM) and soil total nitrogen (STN) with greater precision. The optimized PSO–ELM framework, developed using the selected preference bands, demonstrated superior predictive performance, achieving R^2 of 0.73 and RPD of 1.91 for SOM, and R^2 of 0.63 with an RPD of 1.53 for STN- when compared to the support vector machine (SVM), partial least squares regression (PLSR), and conventional ELM models which commonly used root mean square error (RMSE), and mean absolute error (MAR). The findings offer valuable insights for advancing soil nutrient monitoring through imaging spectrometry in precision agriculture.

3.1.2 Pest and Disease Management

Drones play a crucial role in detecting crop stress caused by pests and diseases. By capturing high-resolution aerial images over large areas in a short time, UAVs enable efficient monitoring of pest and disease outbreaks at various crop growth stages. These images provide valuable data for early detection and management of such outbreaks.

One key application of UAV imagery is the extraction of vegetation indices, such as the Normalized Difference Vegetation Index (NDVI) (Candiago et al., 2015). NDVI is calculated using the ratio of near-infrared (NIR) light to visible red light (Candiago et al., 2015). In comparison to healthy plants, stressed or unhealthy plants reflect more visible light and less NIR light (Peñuelas and Filella, 1998). The use of UAVs enhances precision agriculture practices, enabling targeted spraying of pesticides and accurate monitoring of the intervention's effectiveness over time (Tsouros et al., 2019). This targeted approach not only optimizes resource usage but also minimizes environmental impact. Table 1 provides an overview of the types of UAVs used for pest detection across different crops. Based on rotor configuration, unmanned aerial vehicles (UAVs) are classified and designated differently. For example, Zhang et al. (2019) employed a quadrotor drone equipped with RGB and multispectral sensors (RGB+M), comprising three visible and three multispectral bands, to assess fall armyworm infestation in wheat. The imagery was used to evaluate outbreak severity and to generate spatial maps that supported precision pesticide application as reported by growers.

Table 1. Different types of UAVs are used for Pest detection in different crops

Platform details	Type	Spectral resolution	Sensor details	No. of spectral bands	Field observation	Plant name	Arthropod common name	Reference
md4-1000, Microdrones	four rotors	RGB	α ILCE-5100L with an E 20 mm F2.8 lens, Sony	3	Visual inspection of images	Grape	Cotton jassid	Del-CampoSanchez et al. 2019
Aeryon Scout, Aeryon Labs Inc	four rotors	RGB + M	Photo3S, Aeryon Labs Inc. + ADCLite, Tetracam Inc	3 + 3	Outbreak reported by grower	Wheat	Fall armyworm	Zhang et al. 2014
Spreading Wings S800, SZ DJI Technology Co.	Six rotors	M	Mini-MCA6, Tetracam Inc.	6	Damage assessments	Potato	Colorado potato beetle	Hunt and Rondon 2017, Hunt et al. 2017

Note: *RGB- Red, Green, Blue; M- Multispectral*

3.2 Spraying of Agrochemicals

One significant application of drones in agriculture is the spraying of agrochemicals, such as pesticides and fertilizers, across farmland (Hunt et al., 2010; Neupane & Baysal-Gurel, 2021; Prakash et al., 2022). UAVs equipped with specialized sprayers disperse fluids through nozzles in the form of fine droplets under controlled pressure (Baysal-Gurel, 2021). This pressure is generated by a spray motor, ensuring effective and uniform application (Velusamy et al., 2022). As shown in Table 3.2, the 3CD-15 and WSZ-0610 drones differ in performance due to variations in their technical configurations. The 3CD-15 drone is equipped with four spray nozzles and operates at a maximum speed of 6 m/s with a spray rate of 0.54 L/min, carrying up to 15 L of chemicals and achieving a maximum flight time of 20 minutes (Table

2). In contrast, the WSZ-0610 drone has two spray nozzles, a lower maximum speed of 4 m/s, and a spray rate of 0.72 L/min while carrying 10 L of chemicals for a similar flight duration (Table 2). Owing to its higher payload capacity and operational speed, the 3CD-15 drone is more suitable for large-scale farm operations than the WSZ-0610 model.

Table 2. Drones used in spraying pesticides in recent times

Types of drones	Volume of pesticides (L)	Max. Flight time full load (min)	Max. speed (m/s)	Discharge rate (L/min)	No. of nozzles
DJI Agrus MG-1S	10	10	12	0.379	4
3WQF120-12	12	30	5	0.8	2
3CD-15	15	20	6	0.54	4
WSZ-0610	10	20	4	0.72	2
HY-B-15L	15	15	4.5	0.38	5

Source: Adapted from Borikar et al. (2022)

Compared to traditional methods like speed sprayers or wide-area sprayers, UAVs offer superior efficiency and reduced pesticide usage. The quantity of pesticides applied per hectare has a direct correlation with environmental pollution and worker health risks (Chin et al., 2023; Geipel et al., 2014; MoAL, 2023; Tetila et al., 2020). By minimizing pesticide consumption, UAVs help address these challenges. For instance, they can achieve large-scale decontamination, covering up to 50 hectares per day, while requiring only about 10 minutes to spray 0.5 hectares of farmland (Kim et al., 2019). Thus, this precision and efficiency make UAVs a highly effective solution for modern, sustainable agriculture (Table 3). Chen et al. (2020) employed drones for the control of rice planthoppers and reported a control success rate of 90.8%. This high level of effectiveness demonstrates the practical applicability of drone-based pest management in real-world agricultural settings.

Table 3. Effectiveness of managing agricultural pests using drones

Crop	Chemicals	Pest	Unit	Control efficiency	References
Rice	Treatment 1, 3, 5	Rice planthoppers	%	90.8	(Chen *et al.*, 2020)
Wheat	Deltamethrin	Sunn pest	%	96	(Sheikhigarjan *et al.*, 2024)
Sugarcane	Chlorfenapyr, chlorantraniliprole, and lufenuron.	Fall armyworm	%	94.94	(Song *et al.*, 2020)

3.3 Crop Damage Assessment

Accurate crop damage assessment is essential for determining actual losses caused by extreme weather events or wild animal activity. This process is particularly important to assess the causes and to enable appropriate intervention. Moreover, for insurance companies, it ensures timely and fair compensation for losses (Cao et al., 2020; Rejeb et al., 2022; Su et al., 2018). Traditional methods of damage assessment are often time-consuming and labour-intensive (Su et al., 2018). In contrast, UAVs enable rapid and precise crop damage assessments, significantly reducing the time required to evaluate losses (Baluja et al., 2012; Candiago et al., 2015; Cen et al., 2019; Geipel et al., 2014; Istiak et al., 2023; Tsouros et al., 2019).

3.3.1 Weather Events

Drones equipped with thermal cameras and multispectral sensors are highly effective in detecting the impacts of extreme weather conditions, such as temperature extremes (frost, heat) and precipitation anomalies like flooding or drought (Geipel et al., 2014; Negash et al., 2019; Tsouros et al., 2019). For instance, thermal sensors can identify temperature anomalies, enabling the pinpointing of frost-affected areas, while NDVI values are instrumental in detecting crops under drought stress (Hunt et al., 2010; Tsouros et al., 2019). The practical applications of vegetation indices for crop assessment under various weather events are as follows. These are based on a study by Budiharto et al. (2019), Islam et al. (2021) and Tsouros et al. (2019).

- **Drought**: Use NDVI, NDWI, and SAVI to monitor stressed areas and prioritize irrigation (Budiharto et al., 2019).
- **Floods**: Apply NDWI to locate waterlogged areas and NDVI to track crop recovery (Costa et al., 2020).
- **Hailstorms**: Employ NDVI and EVI to identify broken or damaged canopies (Tsouros et al., 2019).
- **Frost or Heat Stress**: Monitor CI and GNDVI for signs of chlorophyll loss or degradation (Kim et al., 2019; Meinen & Robinson, 2021).

3.3.2 Wild Animals

Drones equipped with high-resolution RGB, multispectral, thermal, LiDAR, or hyperspectral sensors and cameras play a critical role in assessing crop damage caused by wild animals

(Robinson, 2021). These advanced imaging tools enable early detection, detailed analysis, and precise monitoring of crop conditions, helping farmers take timely action.

- **RGB Cameras**: They capture high-definition images of the crops in natural colour. It can be used to visually assess physical damage from animal activity (e.g., grazing, trampling) (del Cerro et al., 2021; Mogili & Deepak, 2018).
- **Multispectral Cameras**: They capture data in multiple colour bands of the electromagnetic spectrum, typically including visible light, near-infrared (NIR), and sometimes red-edge and shortwave infrared (SWIR), which will help in identifying areas where animals have caused harm, based on differences in vegetation health (Hunt et al., 2010).
- **Thermal cameras:** They measure temperature differences across the field, capturing heat signatures. It identifies areas with potential water stress or compacted soil from animal activity, which can affect temperature regulation of plants (Cen et al., 2019; Tetila et al., 2020)
- **LiDAR (Light Detection and Ranging):** It uses laser pulses to create highly detailed 3D maps of the crop field. It can help assess ground-level disturbances caused by animal movement, such as tracks or grazing marks (Negash et al., 2019).
- **Hyperspectral Sensors:** They capture a wide range of wavelengths, from visible to infrared, allowing for more detailed analysis of plant health. It helps to detect stress in plants due to grazing or trampling, allowing for early intervention (Neupane & Baysal-Gurel, 2021).

By utilizing these sensors, drones provide comprehensive insights into crop health and damage, ensuring efficient monitoring and timely responses to minimize losses caused by wild animals (Table 4). Dobosz et al. (2023) evaluated the use of drones equipped with various sensors for assessing crop damage. To ensure accuracy and replicability, areas of crop damage smaller than 3 m² were excluded from the field study. Among the three drones tested, the highest assessment performance was achieved by the drone using a DSM-based filter with a threshold value of 0.4, yielding a performance of 118.4%. This drone demonstrates potential for rapid crop damage assessment following natural disasters in the country.

Table 4. Evaluation accuracy of various methods in crop damage assessment

Method	Estimated crop damage area (% of the reference area)	Remarks

NDVI based- filter value threshold- 0.12	224.4 (39.2)	Area below 3m^2 is omitted
DSM- based- filter value threshold- 0.4	678.7 (118.4)	
CART based- DSM filter value threshold- 0.73	309.2 (54)	

Note: numbers in parenthesis are in percentage *Source: Adapted from (Dobosz et al., 2023)*

3.4 Surveying and Mapping

Surveying and mapping are other areas where UAVs are widely used. Under this section, the application of UAVs in agricultural land use is explained in detail.

Drones play important roles, and it has multiple advantages in various types of industries, particularly surveying and mapping, in today's rapidly changing technological landscape (Espinoza et al., 2017; Meinen & Robinson, 2021; Rejeb et al., 2022). It offers high-resolution, cost-effective, and efficient spatial data collection for land use planning and resource management (Rejeb et al., 2022). They enable participatory mapping, fostering community involvement in identifying traditional land resources, land rights, and boundaries (International Fund for Agricultural Development [IFAD], 2009). Traditionally, surveyors had to rely on ground-based methods, which were both time-consuming and expensive (Tech Collective, 2024).

National Land Commission [NLC], 2025) categorized Bhutan's land into four micro land use zones: *1) Kamzhing:* A land with or without bench terraced which can be used for the production of crops, establishment of orchards, plantations and pasture development, *2) Protected Chhuzhing:* An irrigated and bench terraced land used for cultivation of paddy, *3) Regulated Chhuzhing:* An irrigated and bench terraced agricultural land that are outside of *Protected Chhuzhing*, which can be used for paddy production as well as for other crops, and *4) Agricultural Leased Land:* This term refers to leased state land for commercial agriculture and cattle production, with the right to use but not ownership.

Compared to conventional satellite and ground-based methods, drones overcome limitations like cloud cover, high costs, and time inefficiencies (Mogili & Deepak, 2018; Tsouros et al., 2019). The accuracy rate of UAVs in land use applications is given in Table 5. Thus, it supports precision agriculture, enhancing productivity, tenure security, and informed decision-making for sustainable agricultural practices at local and regional levels (Kachamba *et al*., 2016).

Table 5. Accuracy rate of UAVs in the Agriculture Land Use study

Image composite	Overall accuracy (%)
RBG	74
RBG+NIR	80
RBG+NIR+DSM	88

Source: Adapted from (Chen et al., 2020)

3.5 Phenotyping Characterization of Crops

One key application of drones in agriculture is crop phenotyping and characterization. Amongst many applications, the emphasis is given to crop yield estimation and crop growth assessment.

3.5.1 Crop Yield Estimation

Accurate crop yield and quality assessments are critical for decision-makers at national and regional levels to enable timely decisions (Tao et al., 2020). Such data is essential for crop insurance, delivery estimates, harvest planning, quality optimization, storage requirements, and financial management (Horie *et al.*, 1992). A reliable crop yield prediction model empowers farmers to make informed decisions on different farming methods for maximizing profit.

One effective approach for achieving precision in yield estimation is the application of remote sensing (RS) technologies, which include ground-based, satellite-based, and UAV (Unmanned Aerial Vehicle)-based platforms. Among these, UAVs offer significant advantages over the other two in terms of data quality, cost-effectiveness, and operational flexibility (Gago et al., 2015; Ju & Son, 2018; K.c. et al., 2021; Tao et al., 2020). For example, ground-based platforms are labour-intensive, time-consuming, and risk damaging crops during data collection, while satellite platforms often face challenges such as mixed pixels, long observation intervals, and low spatial and temporal resolution (Tao et al., 2020).

In contrast, UAV imagery, particularly when integrated with machine learning (ML) techniques, can enhance assessment precision and reduce or even eliminate the need for terrestrial surveys. The accuracy of crop yield and quality estimation improves as the crop progresses through its growth stages, highlighting the importance of timely sensing (Ballester et al., 2017). The precision rates for wheat yield estimation at various plant growth stages are provided in Table 6, and common vegetative indices used for different plants are provided in Table 7. Across all wheat growth stages, the most effective assessment method is combining spectral indices methods with a drone equipped with hyperspectral sensors. This method has achieved R^2 values of 0.4 at the jointing stage, 0.65 at the flagging stage, and 0.75 at the flowering stage, respectively, when compared with manual measurements and traditional spectral indices (Tao et al., 2020).

Table 6. Winter wheat yield estimation in different growth stages by using partial least squares regression (PLSR)

Growth Stage	Information	R^2	RMSE (Kg/Ha)	NRMSE (%)
Jointing	SIs	0.35	1415.6	26.8
	SIs+H	0.37	1364.4	25.8
	SIs+H_{CSM}	0.4	1287.3	24.4
Flagging	SIs	0.57	1155.7	21.9
	SIs+H	0.62	1102.2	20.9
	SIs+H_{CSM}	0.65	1069.6	20.3
Flowering	SIs	0.7	989.4	18.8
	SIs+H	0.74	891.9	16.9
	SIs+H_{CSM}	0.75	875.3	16.5

Note: *SI- Spectral Indices, H- Ground measured plant height, H_{CSM}- UAV-based hyperspectral images, RSME- Root-Mean-Square error, NRMSE- Normalized Root-Mean-Square Error*

Source: Adapted from (Tao et al., 2020)

Table 7. Vegetative Indices (Spectral Indices) used for different crop growing stages

SN	Vegetation Index	Formulation	Scale of Application	Estimated parameter	References
1	Normalized Difference Vegetation Index	NDVI = (NIR -R)/ (NIR + R)	Crown	Biomass, vegetation density	(John Wilson Rouse *et al.*, 1974)
2	Red edge difference vegetation index (REDVI)	REDVI = NIR -RE	Crown	Vegetation coverage	(Cao *et al.*, 2013)
3	Normalized Difference Red-Edge	NDRE = (NIR - RE)/(NIR + RE)	Leaves	Biomass	(Barnes *et al.*, 2000)
4	Red edge chlorophyll index (CIRE)	CIRE = (NIR/RE) - 1	Leaves	Chlorophyll	(Anatoly A Gitelson *et al.*, 2005)

Note: *Vegetation indices (G = green, R = red, RE = red edge, NIR = near infrared)*

3.5.2 Crop Growth Assessment

The assessment of crop growth is a crucial aspect of agriculture, as it directly influences productivity in designated land areas. Traditionally, researchers relied on ground-level observations to identify, select, and cultivate crops with favourable genetic and physical traits. However, collecting extensive, high-quality phenotypic data in open-field conditions remains a significant challenge due to its labour-intensive and time-consuming nature (Holman et al., 2016).

In recent years, UAS have emerged as an important tool for crop growth assessment. For example, Nebiker et al. (2008) demonstrated an early milestone by integrating UAVs with cost-effective multispectral cameras for remote sensing to assess the health of grapevine crops. Similarly, Hunt et al. (2010) utilized multispectral UAV imagery for crop monitoring, identifying a strong correlation between the leaf area index and the green Normalized Difference Vegetation Index (green NDVI).

Ampatzidis & Partel (2019) advanced this approach by developing a method that combines UAVs, multispectral imaging technology, and deep learning-based convolutional neural networks to analyze phenotypic traits in citrus plants. Their method achieved remarkable results, with a precision of 99.9% and a recall of 99.7% for identifying and counting 4,916 citrus trees in an orchard. Additionally, they estimated canopy sizes with 85.5% accuracy and identified, mapped, and counted tree gaps with 100% precision and 94.6% recall (Table 8).

Table 8. Comparison of manual and UAV technologies in measuring the plant growth and gaps

UAV based remote sensing technique	Number of detections	Ground truth	Precision (%)	Recall (%)	F-Score (%)
Plant growth	4904	4916	99.9	99.7	98.8
Plant gap	106	112	100	94.6	97.3

Source: Adapted from Ampatzidis & Partel (2019)

Likewise, Holman et al. (2016) introduced and evaluated an approach to quickly estimate crop height and growth rate using multi-temporal, ultra-high spatial resolution (1 cm/pixel), 3D digital surface models of crop field trials. These models were generated through Structure from Motion (SfM) photogrammetry, utilizing aerial imagery captured during multiple flights

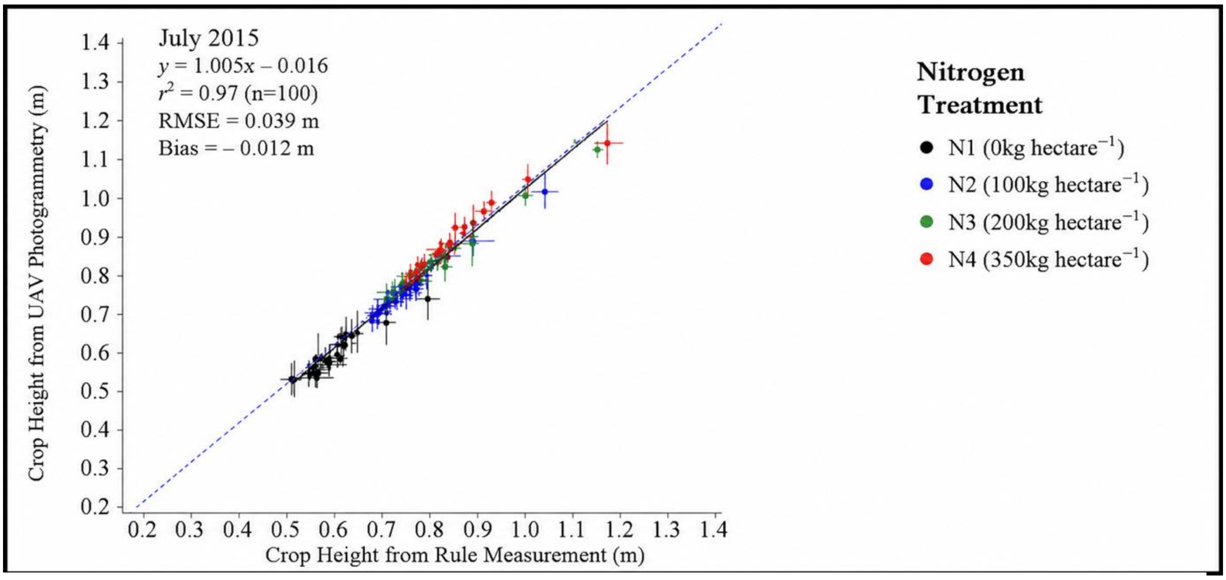

Figure 3. Comparison between manual vs UAVs for crop growth assessment. *Source: Adapted from Holman et al. (2016)*

of an Unmanned Aerial Vehicle (UAV) equipped with an RGB camera. The result showed that the UAV-generated surface model with the highest precision and the Terrestrial laser scanner (TLS) both demonstrated a Root Mean Squared Error (RMSE) of 0.03 meters when compared to the traditional manual 2-meter rule approach, indicating the high applicability of UAVs in measuring the crop height (Figure 3). The model demonstrates an accuracy rate of 97% (r^2 =0.97) at a 0.05 significance level which proves its application in crop height measurement.

The most used software for data collection and processing in UAV applications for agriculture is PIX4D and Agisoft. Figure 4 illustrates the data acquisition and analysis workflow for agricultural drone applications using Agisoft PhotoScan or Cyclone 8.1 (Holman et al., 2016). This workflow applies to field data collected with UAVs as well as LiDAR systems. After importing the data, a critical step is to assess data quality and align the data based on geo-coordinates to generate a Digital Surface Model (DSM). Using the DSM, prescriptions for various agricultural applications are prepared according to the type of intervention and subsequently assigned to the drone for implementation in the selected fields and crops. To evaluate the effectiveness of UAV-based applications, statistical analyses are conducted using different models to compare the precision and performance of drones equipped with various sensors.

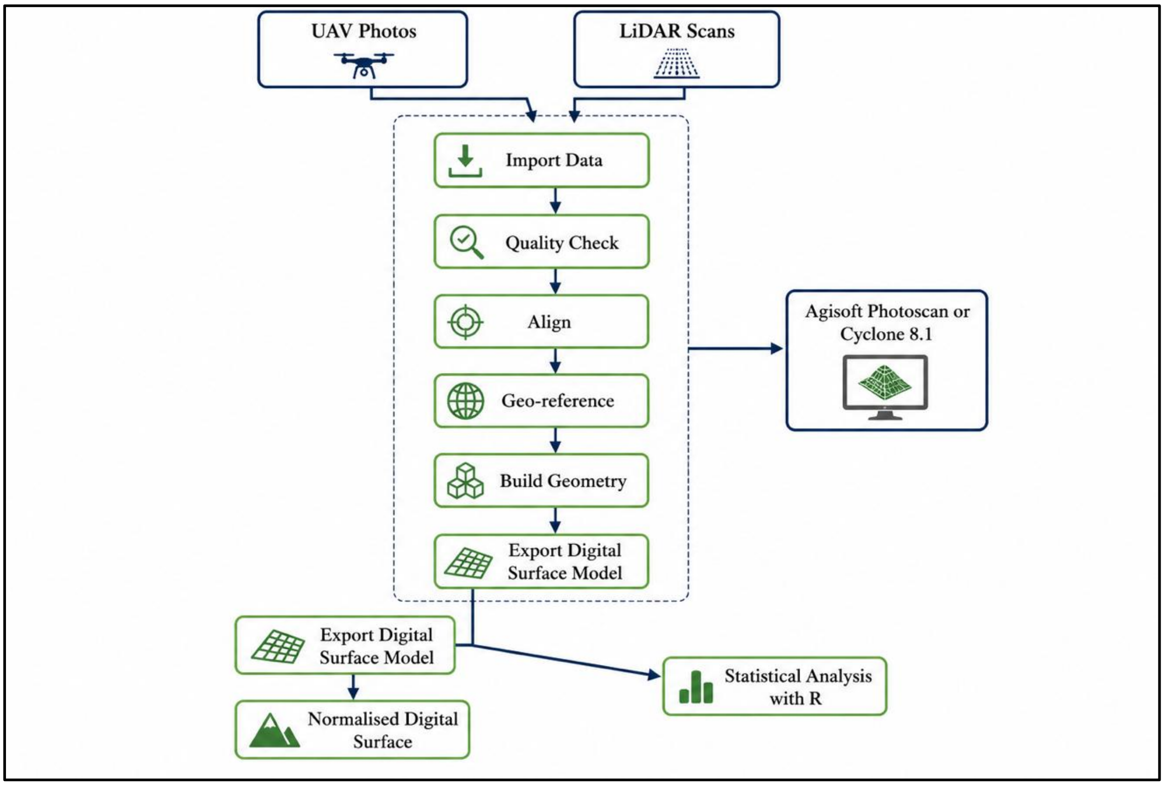

Figure 4. Workflow for data collection and processing. *Source: Adapted from Holman et al., (2016)*

3.6 Limitations of UAVs in Agriculture

- The sustainable flight time of UAVs is relatively short, and in long-distance flight missions, batteries need to be replaced midway to complete flight operations (Eskandari et al., 2020).
- UAVs are predominantly utilizing for estimating crop yields at the field-plot level; however, extending these estimates to regional scales presents greater challenges. While plot-level yield data can serve as a basis for regional yield calculations, such extrapolation may introduce considerable bias due to substantial variations in growing conditions across different plots (Kim et al., 2019).
- There will be local flight restrictions, which will prevent the UAV from performing normal flight operations (Bah et al., 2018; Rejeb et al., 2022).
- It is highly affected by weather factors, especially during rainy and stormy days when data collection cannot be achieved. It will result in missing plant growth data (Holman et al., 2016; Tetila et al., 2020).

4 Conclusion

This review demonstrated that UAVs had matured into versatile tools for crop farming, offering superior spatial-temporal resolution, cost-effectiveness, and operational flexibility compared with satellite, manned aircraft, and ground-based approaches. The peer reveiewed articles used in this study showed that UAVs were effective for soil nutrient and fertilizer management, early pest and disease detection through vegetation indices, targeted agrochemical spraying, rapid crop damage assessment, detailed surveying and mapping, and high-throughput phenotyping and yield estimation, especially when combined with machine learning and hyperspectral or multispectral sensors. However, persistent limitations must be addressed before widespread adoption: limited battery life and flight time, weather sensitivity leading to missed observations, and risks of bias when scaling plot-level findings to regional estimates. To realize UAVs' potential, coordinated efforts are needed to standardize methodologies, validate models across environments, strengthen regulatory frameworks, and invest in training and infrastructure. For countries facing food security and land use challenges, such as Bhutan, integrating UAV technology into national agricultural programs can support targeted interventions, improve resource efficiency, and inform policy. Future research should prioritize scalable approaches and operational trials that bridge experimental results and practical implementation. Addressing these gaps will accelerate adoption and maximize agricultural benefits from UAV technologies.

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6 Authors' contribution statement

Thinley Gyeltshen, Kinzang Thinley, and Pema Yangdon- Study conception and design, analysis of research based on thematic areas, and drafting of manuscript. Domang, Tenzin Rabgay, Dr. Tshering Penjor, Sherab Lhamo, and Nangsel Tshomo- Information gathering and formulation of conceptual framework.

7 References

Ampatzidis, Y., & Partel, V. (2019). UAV-based high throughput phenotyping in citrus utilizing multispectral imaging and artificial intelligence. *Remote Sensing, 11*(4), 410. https://doi.org/10.3390/rs11040410

Ampatzidis, Y., Partel, V., & Costa, L. (2020). Agroview: Cloud-based application to process, analyze and visualize UAV-collected data for precision agriculture applications utilizing artificial intelligence. *Computers and Electronics in Agriculture, 174*, 105457. https://doi.org/10.1016/j.compag.2020.105457

Bah, M. D., Hafiane, A., & Canals, R. (2018). Deep learning with unsupervised data labeling for weed detection in line crops in UAV images. *Remote Sensing, 10*(11), 1690. https://doi.org/10.3390/rs10111690

Baluja, J., Diago, M. P., Balda, P., Zorer, R., Meggio, F., Morales, F., & Tardaguila, J. (2012). Assessment of vineyard water status variability by thermal and multispectral imagery using an unmanned aerial vehicle (UAV). *Irrigation Science, 30*(6), 511–522. https://doi.org/10.1007/s00271-012-0382-9

Budiharto, W., Chowanda, A., Gunawan, A. A. S., Irwansyah, E., & Suroso, J. S. (2019). A review and progress of research on autonomous drone in agriculture, delivering items and geographical information systems (GIS). In *2019 2nd World Symposium on Communication Engineering (WSCE)* (pp. 205–209). IEEE. https://doi.org/10.1109/WSCE49000.2019.9041004

Candiago, S., Remondino, F., De Giglio, M., Dubbini, M., & Gattelli, M. (2015). Evaluating multispectral images and vegetation indices for precision farming applications from UAV images. *Remote Sensing, 7*(4), 4026–4047. https://doi.org/10.3390/rs70404026

Cao, Y., Li, G. L., Luo, Y. K., Pan, Q., & Zhang, S. Y. (2020). Monitoring of sugar beet growth indicators using wide-dynamic-range vegetation index (WDRVI) derived from UAV multispectral images. *Computers and Electronics in Agriculture, 171*, 105331. https://doi.org/10.1016/j.compag.2020.105331

Cen, H., Wan, L., Zhu, J., Li, Y., Li, X., Zhu, Y., Weng, H., Wu, W., Yin, W., Xu, C., Bao, Y., Feng, L., Shou, J., & He, Y. (2019). Dynamic monitoring of biomass of rice under different nitrogen treatments using a lightweight UAV with dual image-frame snapshot cameras. *Plant Methods, 15*(1), 32. https://doi.org/10.1186/s13007-019-0418-8

Chen, P.-C., Chiang, Y.-C., & Weng, P.-Y. (2020). Imaging using unmanned aerial vehicles for agriculture land use classification. *Agriculture, 10*(9), 416. https://doi.org/10.3390/agriculture10090416

Chin, R., Catal, C., & Kassahun, A. (2023). Plant disease detection using drones in precision agriculture. *Precision Agriculture, 24*(5), 1663–1682. https://doi.org/10.1007/s11119-023-10014-y

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

Dobosz, B., Gozdowski, D., Koronczok, J., Žukovskis, J., & Wójcik-Gront, E. (2023). Evaluation of maize crop damage using UAV-based RGB and multispectral imagery. *Agriculture, 13*(8), 1627. https://doi.org/10.3390/agriculture13081627

Eskandari, R., Mahdianpari, M., Mohammadimanesh, F., Salehi, B., Brisco, B., & Homayouni, S. (2020). Meta-analysis of unmanned aerial vehicle (UAV) imagery for agro-environmental monitoring using machine learning and statistical models. *Remote Sensing, 12*(21), 3511. https://doi.org/10.3390/rs12213511

Espinoza, C. Z., Khot, L. R., Sankaran, S., & Jacoby, P. W. (2017). High-resolution multispectral and thermal remote sensing-based water stress assessment in subsurface irrigated grapevines. *Remote Sensing, 9*(9), 961. https://doi.org/10.3390/rs9090961

Gago, J., Douthe, C., Coopman, R. E., Gallego, P. P., Ribas-Carbo, M., Flexas, J., Escalona, J., & Medrano, H. (2015). UAVs challenge to assess water stress for sustainable agriculture. *Agricultural Water Management, 153*, 9–19. https://doi.org/10.1016/j.agwat.2015.01.020

Geipel, J., Link, J., & Claupein, W. (2014). Combined spectral and spatial modeling of corn yield based on aerial images and crop surface models acquired with an unmanned aircraft system. *Remote Sensing, 6*(11), 10335–10355. https://doi.org/10.3390/rs61110335

Guan, S., Fukami, K., Matsunaka, H., Okami, M., Tanaka, R., Nakano, H., Sakai, T., Nakano, K., Ohdan, H., & Takahashi, K. (2019). Assessing correlation of high-resolution NDVI with fertilizer application level and yield of rice and wheat crops using small UAVs. *Remote Sensing, 11*(2), 112. https://doi.org/10.3390/rs11020112

Holman, F. H., Riche, A. B., Michalski, A., Castle, M., Wooster, M. J., & Hawkesford, M. J. (2016). High throughput field phenotyping of wheat plant height and growth rate in field plot trials using UAV-based remote sensing. *Remote Sensing, 8*(12), 1031. https://doi.org/10.3390/rs8121031

Horie, T., Yajima, M., & Nakagawa, H. (1992). Yield forecasting. *Agricultural Systems, 40*(1), 211–236. https://doi.org/10.1016/0308-521X(92)90022-G

Hunt, E. R., Hively, W. D., Fujikawa, S. J., Linden, D. S., Daughtry, C. S. T., & McCarty, G. W. (2010). Acquisition of NIR-green-blue digital photographs from unmanned aircraft for crop monitoring. *Remote Sensing, 2*(1), 290–305. https://doi.org/10.3390/rs2010290

International Fund for Agricultural Development. (2009). *Traditional land resources, land rights, and boundaries*.

Islam, N., Rashid, M. M., Pasandideh, F., Ray, B., Moore, S., & Kadel, R. (2021). A review of applications and communication technologies for Internet of Things (IoT) and unmanned aerial vehicle (UAV)-based sustainable smart farming. *Sustainability, 13*(4), 1821. https://doi.org/10.3390/su13041821

Istiak, M. A., Syeed, M. M. M., Hossain, M. S., Uddin, M. F., Hasan, M., Khan, R. H., & Azad, N. S. (2023). Adoption of unmanned aerial vehicle (UAV) imagery in agricultural management: A systematic literature review. *Ecological Informatics, 78*, 102305. https://doi.org/10.1016/j.ecoinf.2023.102305

Ju, C., & Son, H. I. (2018). Multiple UAV systems for agricultural applications: Control, implementation, and evaluation. *Electronics, 7*(9), 162. https://doi.org/10.3390/electronics7090162

Kachamba, D. J., Ørka, H. O., Gobakken, T., Eid, T., & Mwase, W. (2016). Biomass estimation using 3D data from unmanned aerial vehicle imagery in a tropical woodland. *Remote Sensing, 8*(11), 968. https://doi.org/10.3390/rs8110968

K.C., S., Ninsawat, S., & Som-ard, J. (2021). Integration of RGB-based vegetation index, crop surface model and object-based image analysis approach for sugarcane yield estimation using unmanned aerial vehicle. *Computers and Electronics in Agriculture, 180*, 105903. https://doi.org/10.1016/j.compag.2020.105903

Kim, J., Kim, S., Ju, C., & Son, H. I. (2019). Unmanned aerial vehicles in agriculture: A review of perspective of platform, control, and applications. *IEEE Access, 7*, 105100–105115. https://doi.org/10.1109/ACCESS.2019.2932119

Meinen, B. U., & Robinson, D. T. (2021). Agricultural erosion modelling: Evaluating USLE and WEPP field-scale erosion estimates using UAV time-series data. *Environmental Modelling & Software, 137*, 104962. https://doi.org/10.1016/j.envsoft.2021.104962

Ministry of Agriculture and Livestock. (2023). *Food and nutrition security policy of Bhutan*. Royal Government of Bhutan. https://www.moal.gov.bt/policy/

Mogili, U. R., & Deepak, B. B. V. L. (2018). Review on application of drone systems in precision agriculture. *Procedia Computer Science, 133*, 502–509. https://doi.org/10.1016/j.procs.2018.07.063

National Statistics Bureau. (2023). *Integrated agriculture and livestock census report*. Royal Government of Bhutan.

Nebiker, S., Annen, A., Scherrer, M., & Oesch, D. (2008). *A light-weight multispectral sensor for micro UAV: Opportunities for very high resolution airborne remote sensing*. https://www.semanticscholar.org/paper/A-Light-weight-Multispectral-Sensor-for-Micro-UAV-Nebiker-Annen/955a70058c6fa1b1a3fbfa17c5aef6818068e024

Negash, L., Kim, H.-Y., & Choi, H.-L. (2019). Emerging UAV applications in agriculture. In *2019 7th International Conference on Robot Intelligence Technology and Applications (RiTA)* (pp. 254–257). IEEE. https://doi.org/10.1109/RITAPP.2019.8932853

Neupane, K., & Baysal-Gurel, F. (2021). Automatic identification and monitoring of plant diseases using unmanned aerial vehicles: A review. *Remote Sensing, 13*(19), 3841. https://doi.org/10.3390/rs13193841

Page, M. J., McKenzie, J. E., Bossuyt, P. M., Boutron, I., Hoffmann, T., Mulrow, C. D., Shamseer, L., & Moher, D. (2020). Mapping of reporting guidance for systematic reviews and meta-analyses generated a comprehensive item bank for future reporting guidelines. *Journal of Clinical Epidemiology, 118*, 60–68. https://doi.org/10.1016/j.jclinepi.2019.11.010

Peñuelas, J., & Filella, I. (1998). Visible and near-infrared reflectance techniques for diagnosing plant physiological status. *Trends in Plant Science, 3*(4), 151–156. https://doi.org/10.1016/S1360-1385(98)01213-8

Prakash, S., Kumar, M., Jat, D., Jyoti, B., Subeesh, A., Agrawal, K. N., Tiwari, P. S., Mehta, C. R., Singh, P. L., & Singh, K. (2022). *Applications of drones in agriculture: Status and scope*. Indian Council of Agricultural Research. http://krishi.icar.gov.in/jspui/handle/123456789/80715

Rejeb, A., Abdollahi, A., Rejeb, K., & Treiblmaier, H. (2022). Drones in agriculture: A review and bibliometric analysis. *Computers and Electronics in Agriculture, 198*, 107017. https://doi.org/10.1016/j.compag.2022.107017

Su, J., Coombes, M., Liu, C., Guo, L., & Chen, W.-H. (2018). Wheat drought assessment by remote sensing imagery using unmanned aerial vehicle. In *2018 37th Chinese Control Conference (CCC)* (pp. 10340–10344). IEEE. https://doi.org/10.23919/ChiCC.2018.8484005

Tao, H., Feng, H., Xu, L., Miao, M., Yang, G., Yang, X., & Fan, L. (2020). Estimation of the yield and plant height of winter wheat using UAV-based hyperspectral images. *Sensors, 20*(4), 1231. https://doi.org/10.3390/s20041231

Tetila, E. C., Machado, B. B., Astolfi, G., Belete, N. A. de S., Amorim, W. P., Roel, A. R., & Pistori, H. (2020). Detection and classification of soybean pests using deep learning with UAV images. *Computers and Electronics in Agriculture, 179*, 105836. https://doi.org/10.1016/j.compag.2020.105836

Tsouros, D. C., Bibi, S., & Sarigiannidis, P. G. (2019). A review on UAV-based applications for precision agriculture. *Information, 10*(11), 349. https://doi.org/10.3390/info10110349

Velusamy, P., Rajendran, S., Mahendran, R. K., Naseer, S., Shafiq, M., & Choi, J.-G. (2022). Unmanned aerial vehicles (UAV) in precision agriculture: Applications and challenges. *Energies, 15*(1), 217. https://doi.org/10.3390/en15010217

Wood, S. A., Robinson, P. W., Costa, D. P., & Beltran, R. S. (2021). Accuracy and precision of citizen scientist animal counts from drone imagery. *PLOS ONE, 16*(2), e0244040. https://doi.org/10.1371/journal.pone.0244040

Yang, X., Bao, N., Li, W., Liu, S., Fu, Y., & Mao, Y. (2021). Soil nutrient estimation and mapping in farmland based on UAV imaging spectrometry. *Sensors, 21*(11), 3919. https://doi.org/10.3390/s21113919

Zhang, H., Wang, G., Lei, Z., & Hwang, J.-N. (2019). Eye in the sky: Drone-based object tracking and 3D localization. In *Proceedings of the 27th ACM International Conference on Multimedia (MM '19)* (pp. 899–907). Association for Computing Machinery. https://doi.org/10.1145/3343031.3350933