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Review Article

How can aerial imagery and vegetation indices algorithms monitor the geotagged crop?

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ABSTRACT

There is very little to no literature on the use of geotagging to monitor crops from aerial photos, even though many technologies have been created to do so. Current crop monitoring methods, relying on field data and lab analysis, are inefficient due to high labor, time, and potential harm, limiting their broad use. With the use of vegetation indices (VI) and geotagging, this paper highlights the benefits of crop-specific monitoring with unmanned aerial vehicles (UAV). This study systematically searched the original articles published from the 1st of January 2016 to the 7th of October 2021 in the databases of Scopus, ScienceDirect, Commonwealth Agricultural Bureaux (CAB) Direct, and Web of Science (WoS) using Boolean string: "aerial imagery" AND "vegetation index" OR "vegetation indices" AND "crop". Out of the papers identified, 28 eligible studies did meet our inclusion criteria and were evaluated. This review thoroughly discusses the advantages of aerial imagery, vegetation indices, and geotagging tools in the context of crop monitoring. It was found that geotagged crop monitoring using UAV empowers farmers with data-driven insights using vegetation indices, enabling them to make informed decisions before acting, transforming agriculture towards a digital future. This study offers valuable insights for researchers and industry players, helping them identify effective and context-specific crop monitoring strategies for diverse plantations, crops, and budgets. Moreover, by utilizing the advanced computational capabilities of artificial intelligence (AI), we can analyze a wide range of vegetation indices to gain a comprehensive understanding of crop health and conduct accurate predictions.

1. Introduction

Food security is turning into a significant global concern because of a few anthropogenic factors which negatively impacts the agricultural sector, the major source of agri-food production globally. For example, rapid population expansion, urbanisation, industrialization, farmland scarcity, decreasing fresh water, and environmental degradation (Abbasi et al., 2022). Global food security is in jeopardy due to population expansion and climate change. Therefore, in order to control the effects of climate change and meet the growing demand for food, a parallel increase in sustainable food production is needed (Mutengwa et al., 2023). Innovative and effective solutions are required to address the predicted supply–demand imbalance. Thus, evaluating crop monitoring practices is a crucial task. For crop monitoring, ground data collection as well as lab-based analysis, are being practiced. These methods are time-consuming, labour-intensive, damaging, and unsuitable for use on a broad scale Maimaitijiang et al. (2017) which leads to inefficiency. In addition, when we additionally need to determine the

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global positioning system (GPS) location of trees for governance purposes and to periodically check on their state over time, the challenge becomes considerably more challenging and tiresome (Ammar et al., 2021).Despite the fact that precision farming and agriculture first emerged in the 1980s (Mulla, 2013), a lot of geographic information systems (GIS), remote sensing (RS), and unmanned aerial vehicle (UAV) were only employed early in the new millennium(Che Omar et al., 2019). Remote sensing with UAV provides the advantage of ultra-high resolution capability, temporal flexibility, and cost-effective data collecting as compared to satellite monitoring (Zhang and Kovacs, 2012). Fusion of images collected from a UAV integrated with multiple sensors has become popular in recent years because data fusion improves plant trait estimation by combining advantages of rich spectral, spatial, structural, and thermal information contained in diverse sensor systems (Maimaitijiang et al., 2020). Vegetation indices (VI) can be extracted from aerial photography to assist farmers in monitoring crop stress situations (Radoglou-Grammatikis et al., 2020). VI have been frequently employed for crop monitoring studies, in addition to crop mapping and identification, because they can serve as simple and powerful indicators of crop maturity, stress, and biophysical properties, all of which are influenced by environmental conditions and management approaches (Gouveia et al., 2017). Adding geographic data to different media in the form of metadata, or geotagging, is the process of adding coordinates such as latitude and longitude. Other metadata that may be included include bearing, altitude, distance, and place names (Buladaco and Ubay, 2020). By storing and presenting geographically referenced data to geotag the crop, GIS can create a spatial database (Mohidem, 2021). These spatial databases can be useful to monitor individual trees to distinguish between healthy and unhealthy trees for better monitoring activities. Although various technologies have been developed to monitor crops there's little to no literature on the usage of geotagging to monitor crop from aerial images. This review emphasizes on the advantages of crop specific monitoring using UAV through the aid of VI and geotagging.

2. Materials and methods

2.1. Search strategy

This systematic review has adhered to the Preferred Reporting Items for Systematic Reviews recommendations (PRISMA) (Moher et al., 2009). The method also referred to the Pickering and Byrne (Pickering and Byrne, 2014) systematic quantitative literature review method. Initially, a systematic search of the peer-reviewed articles was conducted using the electronic databases: Scopus, ScienceDirect, Commonwealth Agricultural Bureaux (CAB) Direct, and ISI Web of Science (WoS) (Fig. 1). All searches for the investigated topic were conducted on the 7th of October 2021, using the following semantic keywords: "aerial imagery" AND "vegetation index" OR "vegetation indices" AND "geotag*" OR "geotag*" OR "tag*" AND "crop" based on the titles and/or abstracts and/or keywords. This study used several search term combinations based on the criteria or limitations of each database (Table 1). No geographical restrictions were applied for the identification process. Time boundaries for published articles are filtered from the 1st of January 2019 to the 31st of December 2021 to encompass only the geotagged crop's most recent aerial imagery and vegetation indices algorithm. The themes identified in the search engine were saved in Mendeley version 1.19.2 (Mendeley Ltd, London, UK). The papers were screened using guidelines (Koricheva and Gurevitch, 2014) based on the following two categories: (i) not published in English and (ii) non-original research. Only original articles and conference papers were selected for eligibility.

2.2. Selection criteria

The full text of the original articles that meet those two categories were reviewed in detail based on acceptance or rejection criteria, such as paper appropriateness to review objectives. In addition, articles unrelated to aerial imagery, vegetation indices, and geotagging application of crop monitoring were excluded. Finally, 28 articles were included in the systematic review, whereby their decisions were subsequently used for data extraction and synthesis processes.

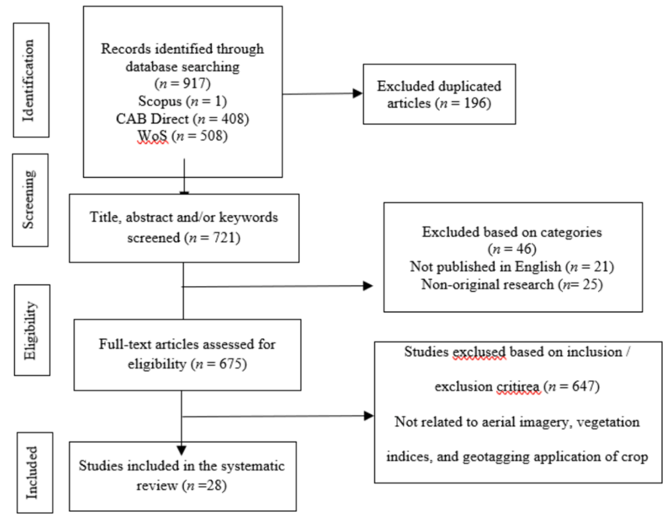

Fig. 1. Flow diagram for the study selection.

Table 1
The search strategies.

Database	Search terms
Scopus	(TITLE-ABS-KEY ("aerial imagery") AND TITLE-ABS-KEY ("vegetation index") OR TITLE-ABS-KEY ("vegetation indices") AND TITLE-ABS-KEY ("geo-tag*") OR TITLE-ABS-KEY ("geotag*") OR TITLE-ABS-KEY ("tag*") AND TITLE-ABS-KEY ("crop"))
CAB Direct	(ab:("aerial imagery") AND ab:("vegetation index") OR ab:("vegetation indices") AND ab:("geotag*") OR ab:("geo-tag*") OR ab:("tag*") AND ab:("crop")
WoS	(((((AB=("aerial imagery")) AND AB=("vegetation index")) OR AB=("vegetation indices")) AND AB=("geotag*")) OR AB=("geo-tag*")) OR AB=("tag*") AND AB=("crop")

2.3. Data extraction

The author independently extracted data from all included studies while co-authors cross-checked the findings. Common themes were discovered and collated, and the co-authors considered and conform any discrepancies. Details about the research in the articles were derived, including (i) type of aerial imagery, (ii) type of vegetation indices algorithm, (iii) type of geotagging tools, and (v) their practical application in crop monitoring. Data were extracted into a standardised Microsoft Excel 2018 spreadsheet (Microsoft Corporation, Redmond, WA, USA).

2.4. Data synthesis

A summary of the extracted information from the included studies were tabulated. The results were compared narratively, and the (i) advantages for each aerial imagery type, (ii) advantages for each vegetation indices algorithm, (iii) for each geotagging tool, (iv) benefit to agricultural industries and (v) future research was explored. Then, the gap from earlier studies was addressed.

3. Results

3.1. Selection of eligible articles

The search approach from electronic databases found 917 potentially relevant studies, of which 196 duplicated studies were eliminated. After the initial inspection of the title, abstract and/or keywords, additional eligibility checks were done on the 721 articles. Then, out of 675 pieces that excluded those that were not published in English and non-original research, a total of 28 full-text articles that finally met the inclusion criteria of the current systematic review were selected in the filtering. Below, the authors show a brief synthesis of the general results obtained after conducting the first level of the analysis (relevance and adequacy). Initially, the authors analysed scientific publications in terms of papers' number of journals and researcher countries.

The publications that were reported in journals and proceedings are visualized in the doughnut chart (Fig. 2. The Remote Sensing Journal (MDPI) was found to be the most popular journal contributing to 18 % of the publications filtered; then, there are Horticulture Journal (MDPI) and Computers and Electronics in Agriculture (Elsevier) which, each of them accounting for 7 %.

Based on the top three authors' countries, the pie chart (Fig. 3) shows how both USA and China contributed to 21 %. As a step back for India, i. e. 11 % are the countries that consist of many researchers who have published their studies regarding our reviewed topics. Following these are scientists from Pakistan, Italy, Canada, Italy, France, Malaysia, Denmark, Japan, Argentina, Portugal, Spanish, Brazil, and Korea, each contributing to 4 % of the entire country.

3.2. Application of aerial imagery and vegetation indices for monitoring geotagged crop

3.2.1. Utilization of aerial imagery in crop monitoring

UAV are categorized according to its body type, such as fixed wing, multirotor or vertical take-off and landing (VTOL). Fixed wing UAV need a runway to take off, alternatively they can be catapulted or tossed by hand. Moreover, such UAV require a runway to land safely, be trapped in a net, or deployed with a landing parachute (Alghamdi et al., 2021). On the other hand, multi-rotor UAV can operate on a broader range of conditions than fixed-wing drones due to their VTOL capability, as they do not require additional room to take off and land. The only setback of multirotor is its short flight endurance and range. Due to its ability to combine the most significant features of both fixed-wing and rotary-wing, hybrid VTOL UAVs offer an excellent solution to this issue

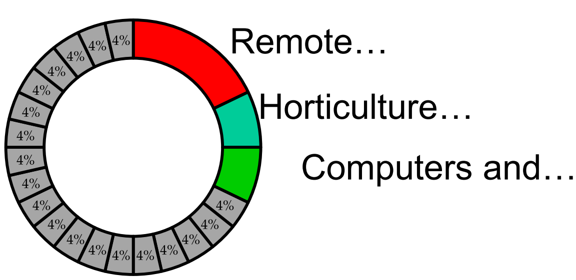

Fig. 2. Scientific articles published by researchers from different journals (by the 18th of June 2021). Other publications, whereby each of 4 % out of the total publications includes the Journal of the Indian Society of Remote Sensing, Structural Health Monitoring, Journal of Forensic Sciences, HortTechnology, Journal of Applied Research on Medicinal and Aromatic Plants, Journal of Animal and Plant Sciences, New Medit, International Journal of Remote Sensing, Frontiers in Plant Science, IEEE Sensors Journal, Aestimum, Plant Disease, Pertanika Journal of Science and Technology, Sensors, International Journal of Applied Earth Observation and Geoinformation, IEEE Geoscience and Remote Sensing Letters, River Research and Applications, Agronomy, Applied Geography, ad Frontiers in Plant Science.

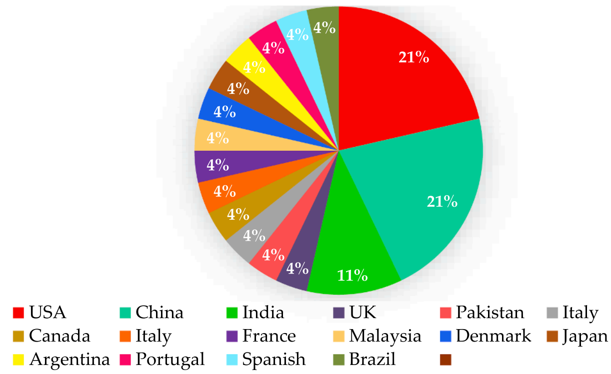

Fig. 3. Scientific articles published by researchers from different countries (by 21 April 2021).

(Gu et al., 2017).

3.2.2. Vegetation indices algorithm in crop monitoring application

Satellite or aerial imaging can extract target's spectral reflectance with different types of sensors. The red, green, and blue bands of the electromagnetic spectrum are the only ones that the red green and blue (RGB) sensors can collect data from. In contrast, the multispectral sensors collect near-infrared, short wave or red-edge bands (Furukawa et al., 2021). Additionally, hyperspectral sensors enable an analysis of a wide range of continuous wavelengths across the electromagnetic spectrum, whereas thermal sensors detect temperatures using an infrared camera. Furthermore, light detection and ranging (LIDAR) images collects data in the near-infrared wavelength. The VI and their respective formulas are presented in Table 2.

3.2.3. Implementation of geotagging tools for monitoring crops

Latitude and longitude are used as geographic identifiers in the process of geotagging. Users can use geotagging to access a range of location-specific data from a device. While geo-mapping shows the location of a given photograph's subject matter on top of a map or satellite picture, it is also a visual representation of the geographic position of geotagged assets. Table 3 shows the geotagging software used and its purpose.

3.3. Advantages of different platforms and approaches in crop monitoring

3.3.1. Advantages of aerial imagery

The most recent RGB and multispectral sensors on UAV have made it possible to gather imagery with better spatial and temporal resolution at lower costs as well as detailed information on crop spectral patterns (Martins et al., 2021). The artefact, according to Hatton et al. (2019), is particularly noticeable in pictures taken by low-altitude aircraft, such UAV, using sensors with wide-angle lenses. The fine spatial resolution separates picture pixels containing shadow and non-shadow areas, allowing plants in various areas of an image to be viewed from different angles and displaying varied degrees of sun or shade depending on the view angle. The reduced data collecting period may also contribute to increased accuracy when using aerial systems, according to Hatton et al. (2019) analysis. UAV flights collected data for the same area far more quickly than ground-based systems which is an average flight time of about 11 min compared to an average of four hours. Fixed-wing platforms are often more appropriate when covering relatively large areas, up to hundreds of hectares in size, according to Hatton et al. (2019). The pilot may fly the "Sky Arrow" light aircraft using a small portion of the gasoline needed to power a typical farm vehicle because it has the lowest weight class (Very Light Aircraft, VLA) of any industrial aircraft. The normalized difference vegetation index (NDVI) sensor can gather enough ultra-scale crop imagery to cover four or five fields in a single

Table 2
Reviewed studies that used vegetation indices for crop monitoring.

Research paper	Vegetation index	Equation
Martins et al. (2021)	Coffee Ripeness Index (CRI)	$CRI = \left(\frac{R_{Red}}{R_{target}}\right)100$
Martins et al. (2021)	Green-red Ratio Ripeness Index (GRRI)	$GRRI = \frac{G}{R}$
Martins et al. (2021)	Modified Chlorophyll Absorption in Reflectance Index 1 (MCARI1)	$MCARI1 = 1.2[2.5(R_{NIR} - R_{red}) - 1.3(R_{NIR} - R_{Green})]$
Martins et al. (2021); Zhang et al. (2019); Sotille et al. (2020); Pádua et al. (2019); Bayle et al. (2019); Sankaran et al. (2019); Yuhao et al. (2020); Towers and Poblete-echeverría (2021); Nallaperuma and Asaeda (2020); Zhao et al. (2019); Alexander (2020); Chang et al. (2020) and Bai et al. (2019)	Normalized Difference Vegetation Index (NDVI)	$NDVI = \frac{(R_{NIR} - R_{Red})}{(R_{NIR} + R_{Red})}$
Martins et al. (2021); and Yuhao et al. (2020)	Normalized Difference RedEdge Index (NDRE)	$NDRE = \frac{(R_{NIR} - R_{Red})}{(R_{NIR} + R_{RedEdge})}$
Martins et al. (2021); and Zhang et al. (2019)	Green Normalized Difference Vegetation Index (GNDVI)	$GNDVI = \frac{(N - G)}{(N + G)}$
Zhang et al. (2019)	Normalized Difference Red Edge Index (NDRI)	$\frac{R_{NIR} - R_{RedEdge}}{R_{NIR} + R_{RedEdge}}$
Zhang et al. (2019)	Normalized difference index (NDI)	$\frac{(g - r)}{(g + r)}$
Zhang et al. (2019)	Excessive green index (ExG)	$2g - r - b$
Zhang et al. (2019)	Excessive red (ExR)	$1.4r - g$
Zhang et al. (2019)	Excessive green index minus excess red index (ExGR)	$3g - 2.4r - b$
Zhang et al. (2019)	Visible atmospherically resistant index (VARI)	$\frac{(g - r)}{(g + r - b)}$
Zhang et al. (2019)	Green leaf index (GLI)	$\frac{(2g - b - r)}{(2g + b + r)}$
Hatton et al. (2019); Sankaran et al. (2019)	Green normalized difference vegetation index (GNDVI)	$\frac{R_{NIR} - R_{Green}}{R_{NIR} + R_{Green}}$

Table 2 (*continued*)

Research paper	Vegetation index	Equation
Hatton et al. (2019)	Blue normalized difference vegetation index (BNDVI)	$\frac{R_{NIR} - R_{Blue}}{R_{NIR} + R_{Blue}}$
Bayle et al. (2019)	Normalized Anthocyanin Reflectance Index (NARI)	$\frac{\left(\frac{1}{R_{Green}} - \frac{1}{R_{RedEdge}}\right)}{\left(\frac{1}{R_{Green}} + \frac{1}{R_{RedEdge}}\right)}$
Zhang et al. (2021)	Normalized Difference Snow Index (NDSI)	$\frac{(R_{Green} - R_{Swir})}{(R_{Green} + R_{Swir})}$
Sankaran et al. (2019); Yuhao et al. (2020); and Bai et al. (2019)	Soil Adjusted Vegetation Index (SAVI)	$\frac{R_{NIR} - R_{Red}}{(R_{NIR} + R_{Red} + L)}*(1 + L)$
Yuhao et al. (2020)	Optimized Soil Adjusted Vegetation Index (OSAVI)	$\frac{R_{NIR} - R_{Red}}{(R_{NIR} + R_{Red} + L)}*(1 + 1)$
Stilwell et al, (2019)	red edge position (REP) vegetation index	$REP = \frac{-(b_1 - b_2)}{(a_1 - a_2)}$

Table 3
Reviewed studies on geotagging software used and its purpose.

Research paper	Geotagged software	Purpose of geotagging application
Mohite et al. (2020)	RuPS	To geotag the crop growth stage images and boundary of Cotton, Soybean and other crops (Red Gram, Orange, Chilly, Okra, Mango).
Raj et al. (2021)	ERDAS Imagine	To geotag non-vegetated urban and other regions, as well as various vegetation components and density classes.
Sotille et al. (2020)	eMotion 2	To geotag the image of maritime Antarctic vegetation
Zhang et al., 2019	GPS	To geotag the multispectral images during flight at turfgrass field
Sottini et al. (2019)	Flickr Application Programming Interface	To geotag photo metadata with raster data on crop
Singh et al. (2021)	GIS	To geotag medicinal plant cultivator based on region's agro-ecological conditions

trip (Bauer et al., 2019). Researchers were able to measure the spatial organisation of mite movement and viral propagation around a primary mite-virus source because to the high resolution of the airborne sensors (Stilwell et al., 2019). Only a few sites might have biophysical parameters established, but aerial imagery can deliver continuous data with a 1 m resolution throughout a terrain (Stilwell et al., 2019).

Spatial interpolation, which relies on the idea that entities close to one another are more likely to be correlated, is made possible by this imaging and its relationship to the ground-based biophysical data (Stilwell et al., 2019). The entire trifecta of data (satellites, aircraft, and drones), following Rocke et al. (2021), are non-invasive, which means they will not harm vegetation or soils. Additionally, processing and verifying drone data offers a perspective that walk-over ground observation cannot. Compared to orbital sensors, which have their core wavelength in the larger chlorophyll absorption zone (650–675 nm), the UAV red band is notably more shifted to the green region, resulting in a slightly higher reflectance for vegetation (Sotille et al., 2020). Data fusion can efficiently manipulate the corresponding nature of image capturing geotagging (ICGT) module which is application flexible. For autonomous inspection, it can be mounted on a UAV or unmanned ground vehicle (UGV), or it can be mounted on a stationary platform for data collection (Zhao et al., 2019). According to Sankaran et al. (2019) research of simulated satellite images made by UAV, image resolutions more than or equals to 1 m per pixel could be effective for delivering first-class data for precise evaluations of biomass and seed yield performance. This was supported by Yuhao et al. (2020) claimed that biomass and seed yield performance could be evaluated using high-quality data obtained from images with resolutions up to 1 m per pixel. A poorer-quality image may be appropriate for crops with varied plot sizes (Sankaran et al., 2019). Pádua et al. (2019) found that the UAV imagery could help better understand the vineyard's multi-temporal dynamics.

3.3.2. Advantages of different types of vegetation indices algorithms

According to Martins et al. (2021) a VI that considers the quantity of red in the field can produce a more accurate valuation measuring the freshness of the fruit, which is beneficial for harvest planning. Coffee Ripeness Index (CRI), due to its better sensitivity to changes in the red wavelength, presents improved ability of distinguishing plants with unripe fruits than those with ripe fruits. Visible atmospherically resistant index (VARI) and NDVI data collected from high-resolution UAV photography provide precise estimates of ground measurements like the density of green cover and NDVI (Zhang et al., 2019). To assess plant stress, Hatton et al. (2019) stated that pigment index (PI) evaluates reflectance from blue, green, and near-infrared (NIR) regions acquired using a customised broadband camera. When aerial imagery was obtained when sudden death syndrome (SDS) leaf symptoms were present and before plant senescence, the outcomes showed that PI could better characterise SDS than blue normalised vegetation index (BNDVI) and green normalised vegetation index (GNDVI). PI serves as an indicator for both plant stress and photosynthetic activity regarding maturation. Lower PI values indicate that photosynthesis in plant cells decreases until maturity is reached. The leaf area index and biomass have a high association with NDVI, hence it was selected for yield-related field phenotyping (Bauer et al., 2019). Red Edge Position (REP) indices derived from airborne hyper-spectral sensor data were shown to be useful in assessing wheat streak mosaic virus (WSMV) spread (Stilwell et al., 2019). Furthermore, mites per tiller, the percentage of tillers infected with mites, and the percentages of infected with the virus reduced with rising REP values. Relative chlorophyll values and leaf area index (LAI) progressed with REP values. Terrain or digital elevation modelling may be pushed to its limits when analyzing a feature of 20 or 30 cm. However, when combined with vegetative indices, it could prove the presence of a potential burial even when field examinations and orthomosaic are unsuccessful (Rocke et al., 2021). NDVI was used to classify and identify Antarctic vegetation cover in Hope Bay based on the statistical analysis (Sotille et al., 2020). Besides that, LiDAR data and aerial photography can be used to detect building based on vegetation-mask generated utilizing the NDVI amount of the image-based connected filter (Zhao et al., 2019). In terms of producing shrub cover maps, the normalized anthocyanin reflectance index (NARI) based model outperformed the model based on NDVI, with an area under the curve (AUC) of 0.92 compared to 0.58 (Bayle et al., 2019). According to Bai et al. (2019), NDVI performed better than Soil-adjusted vegetation index for LAI estimation. When thermal imaging is unavailable or of low resolution, spectral indices employing the infrared bands could be used as a proxy for land surface temperature (LST) or sharpening thermal bands (Alexander, 2020). Over five years at five distinct trial sites, the threshold of the normalised yellow difference index (NDYI) map's flowering pixel digit was able to match the number of actual flowers (Zhang et al., 2021). The NDVI time series was an essential data source to identify blooming in general, and the flowering times estimated by our technique accurately predicted the actual flowering periods. The maxima of the differential yellowness index (DYI) time series and the valley of the NDVI time series were combined to form the enhanced area yellowness index (EAYI) during flowering times. The EAYI is a more accurate measure of canola flower density and may be a reliable indicator of short-term changes in yield. Since the stream water level was the best predictor of NDVI, the pixel value peak of NDVI bands was used to assess the dynamics of the vegetation in the riparian area (Nallaperuma and Asaeda, 2020).The perpendicular vegetation index (PVI) and NDVI indices that provided better measures of aboveground biomass and yield (especially percent ground cover) can be utilised to estimate the other plot studies for each waterbody (Olanrewaju et al., 2019). Extracting multiple vegetation indicators from the narrow-band multispectral camera (with 5–12 bands) may improve the potential for phenotyping (Sankaran et al., 2019). It is important to know how these VI are assessed as well as it's mechanism. Table 4 shows the type of images used, software used as well as the accuracy assessment method and values.

3.3.3. Advantages of different types geotagging tools

The geotagging of farmers on digital maps, along with information about species, production output, and pricing, can open up a channel for large purchases from farmers, just like it has in other industrialised nations An application called geotagging makes use of GIS software to calculate how many farmers are cultivating a specific medicinal plant in a specific area. The geotagged application was linked with an agro-climatic district of Punjab to correlate the plant's climate that helps farmers to monitor their crops (Singh et al., 2021).The number of images uploaded, which will be geotagged, was positively connected with other visitor monitoring techniques, and it could be utilised to offer details on the movements, itinerary, and distribution of visitors (Sottini et al., 2019). Sottini et al. (2019) stated that the random forest model supported the significance of agricultural productions in relation to the value of obtaining a spatial as well as the landscape evaluation of the externalities' consistency produced through agriculture, offering obvious benefits appropriate for the territory government's decisions and rural development. The Rups application enabled the verification of the growth stage and was also useful for validating the estimated and actual sowing time window (Mohite et al., 2020). The geotagged images enabled ground-truthing of satellite images such as non-vegetated urban and other places, as well as a variety of areas with various vegetation components and density classes through ERDAS Imagine (Raj et al., 2021). As for Sotille et al. (2020) and (Zhang et al., 2019), the images are geotagged during flight by the UAV itself which is referred to as telemetry log. The telemetry log contains this data, which is helpful when processing images.

4. Benefit to the agricultural industry

Martins et al., (2021) created a novelty the literature of remote sensing studies on coffee fruit ripening assessment, that is an important element in determining beverage quality. Zhang et al., (2019) stated that UAV has a significant potential to gather more complete data for turfgrass breeders during early part of the season of shortlisting as well as in extensive trials. Hatton et al., (2019) stated that on a spatial resolution, PI has the potential to assist both breeders and farmers identify high SDS-infected soybean with increased certainty. AirSurf-L can assist with large-scale field phenotyping and yield-related trait analytics for growers and producers of fresh vegetables. By improving actual lettuce yield and offering accurate crop quality measurement (for example, lettuce size), two crucial factors in agricultural production, commercialization, and logistics management, it directly supports lettuce production (Bauer et al., 2019). Wheat farmers might assess and forecast the potential zone of impact for mite origin fields (e.g., volunteer weed) using the risk metrics produced from these distance estimates (Stilwell et al., 2019). For large-scale canola breeding operations, the results produced by Zhang et al. (2021) demonstrated a more accurate yield estimation trend. Yuhao et al. (2020) claimed that by offering farmers a broad map to adjust their agricultural input, such as boosting input to strained areas while reducing input to healthy parts, as required, farmers may simply track crop growth and paddy condition in real-time using a

Table 4
Reviewed VI's and its corresponding type of image and software used, accuracy assessment and values.

Vegetation Index	Type of images	Software	Accuracy Assessment	Accuracy factors/method	Author
Coffee Ripeness Index	RGB Multispectral image from MicaSense RedEdge MX	Agisoft™ MetaShape SoftwareQGIS	R^2:0.70	Correlation between CRI and unripe fruits	(Martins et al., 2021)
VARI & NDVI	RGB and Multispectral from Parrot Sequoia	Pix4Dmapper Pro 4.2.27 ArcGIS	R^2 Ground percent green cover & NDVI NDVI – 0.88VARI – 0.89	Correlation analysis between ground based VI and UAV based VI.	(J. Zhang et al., 2019)
Pigment index	UAV mount with Sony alpha 5100 camera to detect Blue(B), Green(G) and NIR	Agisoft PhotoscanArcGIS 10.3	−0.79 (spearman's rho)	Correlation between PI and SDS score	(Hatton et al., 2019)
NDVI	Very light aircrafts, with NDVI sensors	python GUI package, Tkinter	R^2 Small regions:0.978 Large regions: 0.98Mixed: 0.9997	Correlation between NDVI from aerial imagery based automatic lettuce counting and manual counting.	(Bauer et al., 2019)
Red Edge Position	Airborne –AISA Eagle hyperspectral sensor	ENVI	R^2: 0.82	Correlation between ground-based chlorophyll measured using SPAD meter and REP obtained from aerial imagery	(Bauer et al., 2019)
NDVI	Sentinel 2 Landsat 8 UAV image	Pix 4D	UAV detected maximum value of NDVI.(0.23)	Classification of vegetation density according to different classes using NDVI maps.	(Sotille et al., 2020)
NARI	Sentinel 2	–	Area under Curve (AUC): 0.96	Receiver operating characteristic (ROC) curves obtained from NARI time series to distinguish between shrublands and grasslands using different models.Then compute AUC using Mann-Whitney to find most significant.	(Bayle et al., 2019)
NDVI	Landsat 8		LAI Estimation: $R^2 = 0.79$	Correlation between NDVI and measured LAI.	(Bai et al., 2019)
NDYI	Multispectral image from MicaSense RedEdge MX andMODIS data from Terra and Aqua	Pix4DmapperAnd ArcGIS	$R^2 = 0.42$	Correlation between flowering pixel numbers from threshold NDYI map and actual flower numbers	(T. Zhang et al., 2021)
EAYI	Sentinel 2Landsat 8 Gaofen-2 Image		$R^2 = 0.31–0.70$	correlations between the EAYIand canola coverage	(Zang et al., 2020)
NDRE	Multispectral from Parrot Sequoia	Agisoft Photoscan software andeCognition software	$R^2 = 0.974$	correlation between remotely sensed NDVI and SPADchlorophyll readings and nutrient content	(Yuhao et al., 2020)
NDVI	Pleiades-1A (0.5 m), SPOT 6 (1.5 m), Planet Scope (3.0 m), and Rapid Eye (level 3A, 5.0 m).A three-band modified multispectral camera of 16 megapixel (8-bit)Mounted on an octacopter	QGIS	r = −0.67–0.91 r = 0.51–0.73	Correlation between NDVI and biomass. NDVI and seed yield	(Sankaran et al., 2019)
NDVI	A 12 band Multiple Camera Array (MCA) Tetracam system from a manned aircraft	ENVI	$R^2 = 0.84$	Correlation between %ground cover and NDVI	(Olanrewaju et al., 2019)

vegetation index map. Before conducting laborious yield experiments, breeders can use the prediction models from this study as screening instruments to assess a variety of genotypes quickly (Olanrewaju et al., 2019). Farmers or winemakers can use vigour maps to gain valuable insights about the state of their vineyards, allowing them to take prompt action to address problem areas or monitor treatment response (Pádua et al., 2019). Punjab potentiated mapping demonstrates the region's organic biophysical ability by calculating the number of farmers cultivating a given medicinal plant in a particular agro-ecological region (Singh et al., 2021). The geographically weighted regression model (GWR) from the Flickr geotagged image metadata, confirmed the significance of agricultural cultivations for the value of the landscape and made it possible to assess the consistency of the externalities produced by agriculture spatially. This evaluation was advantageous for decisions regarding territorial government and rural development (Sottini et al., 2019).

5. Future research

Future studies, according to Martins et al. (2021), should utilize machine learning (ML) algorithms to predict fruit maturity and beverage quality using the CRI and other indicators (e.g., solar radiation, degrees Brix, canopy, temperature). More research utilising numerous UAV platforms and sensors on separate turfgrass species in various locations and with varying weather conditions is necessary before developing a comprehensive model for predicting ground measurement for turfgrass (Zhang et al., 2019). According to Hatton et al. (2019), SDS should be evaluated early on in subsequent studies to determine whether it may be identified using broadband multispectral imaging before evident symptoms manifest. Improving the platform's capability to integrate other vegetation indices obtained by multi- and hyper-spectrum imaging sensors is crucial because AirSurf-L has only been evaluated using NDVI imagery (Bauer et al., 2019). Efforts to track virus presence on a larger extent might make it possible to verify these virus distribution forecasting in naturally occurring epidemic scenarios (Stilwell et al., 2019). To show a relationship between anthocyanin level in leaves and NARI utilising ground measurement of leaf spectroscopy and accounting for local temperature conditions, topographic factors, and species contributions to canopy-level reflectance, more research is necessary (Bayle et al., 2019). To increase simulation validity in high-yield and low-yield jujube garden, it is important to examine the effects of tree age and form on CO^2 assimilation parameters and the use of remote sensing data to optimise these parameters (Bai et al., 2019). To increase the accuracy of yield estimation, future studies should study and assess a multivariate model including a variety of vegetative indices related to new yield components and extra reflectance information from the pod stage (Zhang et al., 2021). Future research should focus on sensors with a narrower spectral band gap (hyperspectral), particularly in the red edge region and, more precisely, in the red edge's blue shift, which offers the ability to monitor agricultural crops. Due to the size of the data, machine learning techniques can soon be used to interpret multispectral imagery taken by UAVs using programming languages like Python and other related web-based programmes. The study's findings can then be communicated in real-time to automation and robotics to facilitate quick decision-making (Yuhao et al., 2020). Sankaran et al. (2019) mentioned that various platforms, such as low orbiting satellites (LOS)-based multispectral imaging and UAV-based multispectral and thermal imaging, could be used to integrate ML algorithms.

6. Discussion

The latest advancements in drone technology, with its improved spatial and temporal resolution sensors, are revolutionizing crop monitoring. These advancements enable us to gather detailed information on crop spectral patterns at lower costs, allowing for faster data collection and improved accuracy in assessments. UAV offer several advantages, including faster data collection compared to ground-based systems, efficient coverage of large areas, and non-invasive monitoring that complements ground observations. This technology also provides valuable insights into vineyard dynamics and allows for precise biomass and yield estimations. Researchers found that UAV imagery with 1 m per pixel resolution is ideal for accurate estimations, while lower-resolution images may still be sufficient for larger plot sizes. Overall, UAV-based crop monitoring offers significant benefits for improving agricultural practices and food security.

VI offer powerful tools in remote sensing for estimating various biophysical parameters of vegetation. This review explored their applications and limitations across various studies. Red-based VI like CRI and VARI aided in fruit ripeness assessment and green cover density estimation. PI evaluated plant stress and photosynthetic activity. NDVI's strong correlation with leaf area index and biomass made it valuable for yield-related phenotyping. REP indices effectively assessed wheat streak mosaic virus spread. Combining NDVI with digital elevation models revealed potential burials. NDVI successfully classified Antarctic vegetation cover, while NARI outperformed it in generating shrub cover maps. NDVI outperformed (SAVI)Sfor leaf area index estimation. Spectral indices using infrared bands served as proxies for land surface temperature when thermal data was unavailable or of low resolution. NDYI accurately estimated flowering times and flower density in canola, while EAYI provided a more precise measure of canola flower density. Peak NDVI values effectively assessed the dynamics of vegetation in the riparian area. PVI and NDVI offered accurate estimates of aboveground biomass, yield, and percent ground cover. Extracting multiple VI from narrow-band multispectral cameras improved phenotyping potential. However, VI are sensitive to atmospheric conditions and sensor characteristics, and choosing the most suitable VI depends on the specific application and study area. Combining multiple VI may be necessary for more robust results. These valuable tools hold significant potential for various applications, but understanding their limitations and choosing the appropriate VI is crucial for accurate and reliable results.

Geotagging farmers on digital maps offers significant potential for improving agricultural practices and market access. This technology allows for the collection and analysis of valuable data, including species cultivated, production output, pricing, and even crop growth stages. This information can be used to facilitate large-scale purchases from farmers, connect them to relevant markets, and optimize agricultural production based on local climate and conditions. The reviewed studies have demonstrated the effectiveness of geotagging in various agricultural contexts. One of the key advantages of geotagging is its ability to ground-truth satellite images. This ground-truthing information is crucial for improving the accuracy and reliability of satellite-based agricultural monitoring systems. The integration of geotagging with other technologies, such as UAV, further enhances its capabilities. This data streamlines image processing workflows and provides valuable insights into crop health and productivity. Overall, geotagging emerges as a powerful tool for revolutionizing agricultural practices and ensuring food security. By harnessing the combined power of geospatial data, advanced technologies, and farmer-centric approaches, we can create a more sustainable and equitable agricultural landscape.

The monitoring technologies reviewed offer valuable tools for improving agricultural practices and optimizing decision-making. These technologies benefit coffee fruit ripening assessment, turfgrass breeding, soybean disease detection, fresh vegetable production, pest management, canola yield prediction, and vineyard management. Additionally, it enables mapping medicinal plant cultivation and assessing agricultural landscape externalities, contributing to informed planning and resource allocation.

Future research in the reviewed papers on crop monitoring holds significant potential for advancements. The proposed research directions encompass utilizing machine learning for fruit maturity and quality prediction, exploring diverse platforms and species for turfgrass breeding, investigating early disease detection, integrating additional vegetation indices, validating virus spread predictions, establishing the relationship between anthocyanin level and NARI, optimizing CO^2 assimilation through remote sensing, developing multivariate models for yield estimation, exploring hyperspectral sensors, integrating machine learning and automation, and leveraging various platforms with machine learning algorithms. These research avenues hold promise for improving crop monitoring, optimizing resources, enhancing food security, and contributing to a more sustainable agricultural future.

7. Conclusion

This comprehensive review provides a systematic analysis of the benefits of crop monitoring through geotagging methods using aerial photos and vegetation indices. It delves into the positive impact of these technologies on the agricultural industry and explores potential future research directions to further strengthen the existing body of knowledge. This paper primarily focuses on peer-reviewed publications released from January 1, 2016, to October 7, 2021. This study holds immense value for researchers, offering insights into existing gaps and opportunities within the realm of crop monitoring. Additionally, it empowers key industry stakeholders to identify effective crop monitoring strategies tailored to specific plantation or orchard sizes, crop types, and allocated budgets. The utilization of UAV empowers farmers to make informed decisions prior to undertaking agricultural activities. By integrating VI and geotagging with UAV, farmers can revolutionize their operations towards a more digitally driven approach to agriculture. Furthermore, prospective studies focusing on hyperspectral sensors with narrower gaps hold promise in elucidating enhanced vegetation indices tailored to specific crops. The continuous evolution of artificial intelligence opens avenues for its application or integration into existing platforms, promising more reliable results. Leveraging the computational advantages of AI, a plethora of vegetation indices can be harnessed to comprehensively understand crop health or engage in predictive analysis. This synthesis of cutting-edge technologies propels agriculture into an era of heightened precision and efficiency.

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CRediT authorship contribution statement

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Declaration of competing interest

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

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