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Review Article

How Can Aerial Imagery and Vegetation Indices Algorithms Be Used for Monitoring Crops Through Geotagged System? A Review

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Abstract: As the world population grows, it is crucial that food production is linearly proportional to the growing demands for food across the globe. The agriculture sector has many opportunities as well as challenges in the upcoming years. Many innovations have been achieved in the previous years, and more technologies are being researched annually. To automise agriculture, unmanned aerial vehicles (UAVs) are extensively being studied to be applied in agriculture. This technology is being explored by integrating it with other sciences as well, such as vegetation indices. Vegetation indices allow extensive analysis to be done on the images taken through the UAV. Currently, many studies are done to monitor crops using information obtained from vegetation indices derived from aerial imagery. The crops that are monitored are also geotagged so that precise information can be extracted. This paper will be assessing the usage of aerial imagery, vegetation indices as well as geotagging to monitor crops.

Keywords: Aerial Imagery; Vegetation indices; Geotagging; Unmanned Aerial Vehicle (UAV)

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1. Introduction

Conventionally, site-based surveys and sampling, as well as lab-based analysis, have been utilised for crop monitoring. However, these methods are labour-intensive, time-consuming, and damaging to the crops, making them unsuitable for large-scale applications (Maimaitijiang *et al*., 2017). Unlike manual on-site monitoring tracking, remote sensing allows non-invasive, fast, and efficient crop monitoring. This is made possible thanks to significant advances in unmanned aerial vehicles (UAVs), different sensors, geo-referencing systems, and image processing algorithms (Gogoi *et al*., 2018). Remote sensing using UAVs, unlike satellite sensing, allows images of higher spatial and temporal resolution to be taken at a low cost, with less interference from atmospheric conditions (Cuaran & Leon, 2021). The ability to generate photos in a short amount of time and process them quickly enables regular and detailed monitoring of environmental changes even when satellite images are not available (Longhitano, 2010). Geo-tagged images and labels, as well as any device with precise location annotation, not only able to demarcate recognised geographic terms but also indicate new areas of interest based on the data (Rattenbury *et al*., 2007). In addition, geotagging enables the spatial indexing of content. As a result, it is a procedure that increases the production of geographical databases, geo-referenced Web resources, and geo-referenced multimedia content by using known geographic locations. Furthermore, UAVs can carry different sensors, such as a high spectrometer, multi-spectrometer, and radar (Fu *et al*., 2021). A computerised camera that communicates with an independent Global Positioning System (GPS) receiver (e.g., via a Bluetooth® connection) may also be used in conjunction with a sophisticated camera or Personal Digital Assistant (PDA) with a GPS receiving sensor to allow geotagging . The photographs taken can then be synced with a GPS tracking gadget (Chandan *et al.*, 2021). Besides, many of the multispectral UAV cameras provide high spatial resolution spectral information in the Red, Red Edge, and Near Infrared (NIR) bands for vegetation applications. Most indices (vegetation indices, VIs) have been designed to monitor, analyse, and map temporal and geographical fluctuations of vegetation in both field and tree crops based on the combination of these three bands (Yao *et al*., 2019). The use of numerous indices in the interpretation of multispectral drone data plays a very crucial role in precision agriculture. As a result, research investigations concentrating on the classification and differentiation of these indices are vital to importing critical information (Singh *et al*., 2021). Some studies have shown that vegetation indices derived from RGB cameras can produce results that are comparable to or better than those obtained from multispectral photos (Gracia-Romero *et al*., 2017). VIs are algorithms used to extract information from the spectral signature of vegetation (Janse, 2019). Differences and changes in plant green leaves and canopy spectral properties are used to understand vegetation information from remotely sensed photos (Xue & Su, 2017). Variables such as vegetation biochemical properties, physical properties, environmental influences, soil background properties, moisture content, and others have a substantial impact on the spectral signature of vegetation (Janse, 2019). The most common validation approaches are explicit or implicit associations between VIs derived and vegetation variables of interest examined on site, such as vegetation cover, Leaf Area Index (LAI), biomass, growth, and vigour evaluation. (Xue & Su, 2017). There are several applications in which these vegetation indices are used. Some of the applications are listed below (Payero *et al*., (2004), Thenkabail *et al*., (2000))

- Plants pigment estimation
- Soil nutrient analysis
- Crop growth management
- Nutrients Management
- Pesticides management
- Selection of growth traits
- Crop yield estimation
- Use of remote sensing for crop modelling

2. Usage of Aerial Imagery for Crop Monitoring

Agricultural robots, including UAVs, are at the forefront of the smart agriculture revolution (Muchiri & Kimathi, 2016). UAVs are not only cheaper than most other agricultural machinery, but they are also easier to use (Kim *et al.*, 2019). UAVs (or drones) have grown in popularity and use, with prices dropping and more user-friendly software being available (Klouček *et al*., 2019). UAVs are useful because of (a) their spatial resolution, which allows for local-scale analysis at the level of individual trees (Komárek *et al*., 2018) and (b) their temporal resolution, which allows for rapid deployment (Müllerová *et al*., 2017). However, agricultural UAVs, on the other hand, have several technical limits, including battery efficiency, flying time, communication distance, and payload (Bueren *et al*., 2015).

Remote sensing with Unmanned Aircraft Systems (UASs) provides the advantage of ultra-high resolution capability, temporal flexibility, and cost-effective data collecting as compared to satellite surveillance (Zhang & Kovacs, 2012). These UAVs are mounted with RGB, multispectral as well as hyperspectral cameras to effectively monitor crops in large plantations (Martins *et al*., 2021), aimed to develop a new VI specifically to monitor coffee ripeness. Four flights were conducted using the following quadcopters throughout the coffee ripening period to acquire spectral information on the crop canopy. The Micasense RedEdge

MX (MicaSense, Seattle, WA, USA) multispectral camera was mounted on the DJI Matrice 100 (DJI Innovations, Shenzhen, China). The bands that are registered are 475 nm ±20 nm (Blue), 560 nm ±20 nm (Green), 668 nm ±10 nm (Red), 840 nm ±40 nm (NIR), and 717 nm ±10 nm (RedEdge). Next, DJI Phantom 4 Pro was equipped with an RGB camera which captures the bands 450 nm ±16 nm (Blue), 560 nm ±16 nm (Green), and 650 nm ±16 nm (Red). Agisoft™ Metashape software, version 1.5.3 (Agisoft LLC, St. Petersburg, Russia) was used to process the captured images into georeferenced orthomosaics. The studies showed that the spectra of unripe and mature fruits may be easily distinguished in the laboratory when the fraction of unripe fruits decreases. However, using aerial imaging, it can be difficult to tell them apart, especially when there are extensive crop canopies that cause spectral confusion. Due to its cheaper cost compared to the RedEdge MX, the RGB camera can be a viable alternative for monitoring coffee ripeness, especially on small farms.

A study by Zhang *et al*., (2019) evaluated the use of UAV-based airborne imaging on replicated turfgrass field trials for Bermuda grass (*Cynodon* spp.) and zoysiagrass (*Zoysia* spp.) using two cameras which are GoPro Hero 4 (GoPro, Inc. San Mateo, CA, United States) visual camera which acquires 7-megapixel images in true colour (Red, R; Green, G, and Blue, B, bands) as well as Parrot Sequoia (MicaSense, Seattle, WA, United States) multispectral camera that measures at four narrow spectral bands (green: 530–570 nm; red: 640–680 nm; red edge: 730–740 nm; NIR: 770–810 nm) installed individually on two similar quadcopters which is the Solo quadcopter (3D Robotics, Berkeley, CA, United States). Pix4Dmapper Pro 4.2.27 (Pix4D SA, Lausanne, Switzerland) software was used to create the orthomosaic. The findings of Zhang *et al*., (2019) revealed that by utilising a UAV platform, it is possible to develop a common model to forecast ground Normalised Difference Vegetation Index (NDVI) for both Bermuda grass and zoysiagrass, as well as possibly other species, without compromising considerable precision. However, before building a generic model to improve data collection effectiveness, some challenges must be solved, and the current model's constraints must be considered. Several UAV-based systems and sensors must be evaluated for a similar goal to see if the model is platform or sensor-dependent. In addition, Zhang *et al*., (2019) also stated that more studies using improved thermal and hyperspectral sensors during drought stress, as well as for disease diagnosis, should be conducted to compare their utility to more widely available UAV-based photography platforms.

3. Application of Vegetation Indices Algorithm in Crop Monitoring

VIs have been employed in agriculture to classify land cover and identify crop types. Although the original bands' spectral information is mostly used for crop classification, VIs can provide additional information for more extensive studies (Arvor *et al*., 2011). VIs have been frequently employed for crop monitoring studies, in addition to crop mapping and identification, because they can serve as simple and powerful markers of crop maturity, stress, and biophysical properties, all of which are influenced by environmental conditions and management approaches (Gouveia *et al*., 2017). Using spectral measurement, many researchers have established VIs for calculating vegetation cover and biochemical characteristics quantitatively and qualitatively (Janse, 2019).

Field variables including plant density, canopy volume, and, most importantly, crop production had a direct impact on the VIs performance. These factors make crop monitoring to be a challenging task. Moreover, the VIs is also affected by variation of ripeness classes. This is due to temporal fruit colour change which caused the removal of chlorophyll as well as the presence of anthocyanins which alters the crop canopy spectral reflectance. For instance, coffee plants have a high nutritional demand from the fruit filling through ripening, especially for NPK, which leads to an increase in nutrient translocation from the leaves to the fruits (Laviola *et al*., 2019; Martins *et al*., 2021). This can cause nutritional deficiencies, as well as variations in leaf reflectance in the visible (400–700 nm) and near-infrared (700–1100 nm) wavelengths (Ayala & Beyl, 2015), which can be detected more easily with VIs that are more sensitive to chlorophyll pigments (Lin *et al*., 2019). These characteristics combined to provide these VIs, particularly the Coffee Ripeness Index (CRI), a stronger capacity to distinguish plants with unripe fruits from those with mature fruits because of its higher sensitivity to changes in the red wavelength.

A study by Zhang *et al*. (2019) showed that Visible Atmospherically Resistant Index (VARI) and NDVI data collected from high-resolution UAV photography provide precise predictions of ground measurements like the percentage of green cover and NDVI. In the investigation, VARI was an excellent predictor of ground percentage of green cover, indicating that if the ground percentage of green cover is the focus, a more economical digital camera should be used for data gathering. For weed pressure identification (Torres-Sánchez *et al*., 2013), disease incidence detection (Mahlein, 2016; Brodbeck *et al*., 2017), and drought stress detection (Mahlein, 2016; Brodbeck *et al*., 2017), multi-spectral cameras may yield more details.

Sotille *et al*. (2020) evaluated the ability of the NDVI from UAVs, Sentinel-2, and Landsat 8 to identify vegetation patches in the ice-free environment of Hope Bay, Antarctic Peninsula. Using a threshold range of NDVI for vegetation likely in Hope Bay developed according to statistical characteristics, vegetation was recognised for algae, mosses, and lichens for several platforms, such as UAV, Sentinel-2, and Landsat 8, for algae, mosses, and lichens. The NDVI statistical parameters provide thresholds that allow for normalisation and classification of pixels with dense vegetation covering in the "nearly certain" class, which is typified by the highest values. The same is true for regions classified as "likely" or "extremely probable" because they have sparse or non-vibrant vegetation. By combining vegetation type details with NDVI categorisation, a trend has been found for Hope Bay communities, with areas with a prevalence of algae and mosses primarily assigned to the higher probability classes "very probable" and "almost certain," and areas with a prevalence of lichens primarily assigned to the lower class "probable”. The categorisation’s findings indicate that there is a strong link between uniting classes and vegetation types.

Flowering pixel counts generated from the threshold Normalised Difference Yellowness Index (NDYI) map were able to approximate genuine flower volumes throughout the course of five experimental site years. In general, integrating blooming progress to estimate yield requires more information than just a single photograph to ensure consistent accuracy. Although the prediction of output values are not particularly way up, findings showed that the area under the flowering progress curve (AUFPC) has the potential to forecast output, particularly for crops that produce colourful flowers (e.g., canola and cotton) under a variety of environmental conditions (Zhang *et al*., 2021).

Yuhao *et al.,* (2020) aimed to employ aerial images and an object-based image analysis technique to construct rice field maps and to apply soil plant analysis technologies to confirm VIs in rice field maps. The author stated that findings revealed that Normalised Difference Red Edge Index (NDRE) has the strongest association, followed by Optimised Soil Adjusted Vegetation Index (OSAVI) and Soil Adjusted Vegetation Index (SAVI). The NDVI has the lowest correlation. In evaluating the level of chlorophyll content in paddy, NDRE was one of the best markers. However, in the future, more stations for soil plant analysis development (SPAD) data collection should be added to provide good variable maps and precise geographic distribution.

4. Implementation of Geotagging in Aerial Imagery

The activity of assigning geographic coordinates to media depending on the place of a mobile device is known as geotagging. Images, movies, websites, text messages, and QR codes can all use geotags to provide time stamps or other contextual information. Bauer *et al*. (2019) developed software that combines computer vision and machine learning algorithms to monitor lettuce. The user will need to provide the field's GPS coordinates, which can be found in the metadata or on Google Maps. The algorithm would then return the harvest region's GPS coordinates. Growers and farmers can use new analysis functions to map lettuce size distribution throughout the field, allowing them to identify linked GPS tagged produce areas and conduct precision agricultural practices to improve actual yield and crop marketability before harvest. Sotille *et al*. (2020) used eMotion 2 software to provide position information (geotags) to photographs taken during flight logs for the monitoring of vegetated areas in the ice-free region of Hope Bay, Antarctic peninsula. Sottini *et al*. (2019) used landscape ecology criteria and Geographically Weighted Regression modelling, we combined the cumulative viewshed derived from geotagged photo information openly accessible on Flickr with raster data on geomorphology, historical locations, and global ecosystems. Scientists, administrators, and public planners can utilise this data to develop programs, strategies, and regulations to improve the visual quality of the agricultural landscape. The models utilised in this study verified the significance of agricultural cultivations for landscape value and enabled a regional assessment of agricultural externalities consistency, which has apparent consequences for territorial governance and rural development decisions. It facilitates the detection of regions of interest where agricultural ecosystem land use planning and management strategies should take non-material landscape advantages into account. Farmers were located using a Geographic Information System and geo-tagged using a mix of public and private sources (GIS). Using digital maps as a platform, governments, investors, sectors, regulatory bodies, and farmers will be able to connect. (Singh *et al*., 2021).

5. Conclusions

In a nutshell, it is evident that the usage of UAVs, VIs as well as geotagging play important roles in facilitating the crop monitoring processes. Into agriculture 4.0, many researchers tend to incline towards machine learning algorithms to automate the monitoring process as well as to make it more efficient. Moreover, these tools or technologies will improve farmers' lives as it improves yield, and saves time as well as energy.

It is hoped that more farms, as well as plantations, will adopt these methodologies so that any gaps in this research will be identified. The applicability of these studies in the real world can also be assessed in terms of limitations as well as the opportunities that are present to further enhance these technologies for the betterment of the agricultural sector.

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