Camera-Based Vegetation Index from Unmanned Aerial Vehicles

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ABSTRACT

Agriculture assumes a vital role in human life because it provides food, feed for livestock, and bioenergy. The agricultural sector is expected to meet the needs of secure and nutritious food for the community at all times to boost productivity. Providing nutrition, water and light precisely and measuredly is an important effort in plant cultivation to produce quality. This effort can be materialized by implementing smart farming involving devices and information technology. Vast field surveillance or monitoring is made easy with the advent of unmanned aerial vehicle (UAV). Detection of plant condition can be achieved by obtaining Vegetation Index (VI) through camera imaging in UAVs which are more economic compared to multispectral or hyperspectral cameras. This study aims to obtain VI that is accurate but still economical, so that it can be utilized even by small-scale agriculture. The work that will be done is to conduct repair experiments at several stages of image processing to produce a new, more accurate VI. The research stages started from experiments on previous research, to finding new research opportunities in VI. Furthermore, the experiment was carried out with the addition of white balance value parameters and other UAV sensor parameters at the Pre-Processing stage to improve its quality. The hypothesis of adding white balance parameters should prove to be more accurate in correcting shooting in various light conditions. Next, try to modify the feature extraction algorithm using Color Extraction Edge Detection. Followed by modifying it using Back Propagation Neural Network to increase accuracy at the image processing stage. After synthesizing some of these experiments, a new formula or model VI using the camera on the UAV is expected to be produced. This research will contribute to the modification of methods or algorithms at the image processing stage to produce a corrected image in producing a new VI that is more accurate using a camera on a more economical UAV.

CCS CONCEPTS

• **Applied computing**; • **Computers in other domains**; • **Agriculture**;

KEYWORDS

Image Processing, Precission Agriculture, Vegetation Index, Unmanned Aerial Vehicle

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1 INTRODUCTION

To achieve agricultural productivity, Indonesian government is vigorously integrating information and communication technology (ICT) infrastructure by utilizing global technology (Big Data, IoT, AI and other technologies). Technology packages for the agricultural sector are available, but not all of them can be adopted by farmers due to, among others, limited capital, skills, and uneven dissemination activities. Therefore, economic and accessible implementation of agricultural technology is needed for farmers [28].

In maximizing agricultural production, adequate provision of water, fertilizer and pesticide in accordance with the type of plant must be ensured. This effort is known as precision agriculture (PA). The implementation of PA leveraging various technologies, including image processing techniques to optimize the process of agricultural cultivation and help minimize waste and increase productivity is known as smart farming (SF) [19, 20, 25].

The monitoring of the adequacy of plant needs in SF can be achieved through remote sensing (RS) [46]. RS in general employs a range of sensors such as optical sensors (multispectral and hyperspectral), LIDAR, or SAR, where the imaging geometry and content are very distinct. Each RS image pixel corresponds to a spatial coordinate, which facilitates the fusion of pixel information with other data sources. RS data produces geodetic measurements that require sensor reliability and data quality [47].

Fulfillment of plant needs can be tracked from their photosynthetic capacity. Photosynthetic capacity is monitored using Vegetation Index (VI) through mathematical equations which transform some sensitive images of plants. In the history of VI [26, 46], Pearson and Miller (1972) pioneered two indices in the form of ratio: RVI and VIN, for estimation and monitoring of vegetative cover [1]. Rouse et al. furthered the study by introducing the concept of NDVI using MSS data from US NASA's ERTS, (which was changed to Landsat-1) which is widely used to identify and assess the impact of disasters such as drought, fire, flood, frost, or other human-caused disturbance. NDVI is used to measure the photosynthetic capacity of plants. It can also help with monitoring carbon sequestration, water cycle and regulation, and soil fertility [26, 33].

One challenge faced in SF is the implementation of appropriate and economical technology that are easy to operate by farmers [28, 30]. This particular challenge has garnered interest of the researchers to devise the best solution. The commonly used VI in image processing and RS is NDVI. The hyper spectral cameras that are commonly used to produce NDVI values are quite expensive. The solution is to develop vegetation indices using RGB cameras which are much more economical but still accurate [7]. Some commercial digital RGB cameras that are designed to resemble weather stations are capable of capturing interval images of crop phenology automatically [34]. Several ongoing RS research focus on use of UAV, image processing and VI, to get accurate results while staying economical [5, 6, 12, 45].

2 RELEVANT STUDIES

In this section, SF implementation, image processing methods, stress plant detection, UAV utilization and VI in previous studies are reviewed.

2.1 Smart Farming

As the population increases from year to year, the challenges of food production in the 21st century are an increasingly relevant theme. Human dependence on biodiversity will continue to increase, because it is estimated that by 2050 the world will have a population of between 9.4 and 10.1 billion people [18].

Various available digital technology and data applications have an impact on the digitalization in agriculture and are regarded as the fourth agricultural revolution. Potential for improving agricultural economic performance will be within reach with SF which in turn will result in agricultural sustainability. SF can improve PA and connect it to agricultural management system [17]. One challenge in SF is improving the accuracy of plant model simulations that predict the state of plants, irrigation management and harvest dynamically [44].

The latest technology to improve agricultural practices are constantly utilized in SF, while striving to keep the adoption cost low [22]. The agricultural mechanism process at an affordable cost is carried out by applying agricultural equipment leases. This has the potential to boost affordable SF utilization for farmers. Several companies are pushing web-based services to provide online services as well as ready-to-use SF hardware for farmers. The services provided are quite diverse, such as the joint use of aerial and satellite imagery platforms, to applications with Artificial Intelligence (AI) techniques for Decision Support System (DSS) applications, blockchain exploitation, and the use of UAVs in agriculture [21].

2.2 Image Processing

On the one hand, human resources are Critical in the identification strategy and classification of manual plant diseases. However, on the other hand, various errors can arise due to human contributions. Alternatively, Machine Learning (ML) and automatic image processing are the potential solution. The systematic stages of image processing are image segmentation, feature extraction, feature selection and classification to diagnose plant diseases [36].

Image processing and analysis involve reconstructing geometric models based on georeferenced images and apply photogrammetric identification techniques based on image collection through the available image processing software. Algorithms in image processing software will access image properties (camera specifications, geo-reference, resolution, and other information) via EXIF data to produce a point-cloud model that can remove unnecessary or distracting background images [32].

2.3 Remote Sensing (RS)

The high demand for geospatial information makes RS the key technology in PA [10, 24]. Farmers and decision makers alike has many interests in detecting plant stress responses (due to environmental and water adequacy), in addition to information on soil properties, nutrients, biomass, and plant diseases [9, 14, 16, 31]. RS is preferred in PA since it provides processing speed, cost savings, plant preservation and spatiotemporal data of various characteristics (physiological, biochemical and structural plants) at different scales (land, air, and satellite) [11].

Already, RS using UAV has been widely implemented to obtain information from farmland. Prior to the advent UAV, RS using satellites has been proven effective in monitoring status of plant growth and predicting crop yield [8]. Another study conveyed the potential advantages of the Hyperspectral Thermal infrared (TIR) RS compared to the optical RS in the detection of water-induced plant stress [11].

2.4 Unmanned Aerial Vehicle

UAVs being able to fly or hover low have become preferred solution compared to other aerial platform due to their high-resolution results [34]. The flight time of UAVs is limited by their battery capacity, though a simultaneous use of multiple UAVs has been developed to overcome this [5, 40, 43]. Other limitations include long processing time and complex processing of large amounts of image data when done manually, thus necessitating complimentary software [40].

UAV-based multispectral system can be developed to calculate VI and accurately distinguish between healthy and sick plants [15]. Compared to traditional RS, VI based on visible light image acquisition from UAV is better in terms of speed and image resolution [45]. Information on physical properties of soil, water, and vegetation features in the terrestrial environment can be generated from the spectral composition of the radiation flux originating from the earth's surface. This spectral information is converted into a form that can be readily interpreted using models and RS techniques [1].

Land fluctuation, climate change and flight method will affect UAVs when collecting RS images, causing geometric distortion. Earth's rotation, atmospheric disturbances and changes in clouds have minimal effect on the visible RS image [41]. Software can be utilized to perform correction on geometric multispectral mosaic image, one of which is ENVI [45].

3 PROBLEMS AND DISCUSSION

The results of the review of scientific papers on image processing to detect plants from various perspectives are discussed in this section. One of the points of view used in this discussion captures the use of an RGB camera from a UAV which is more cost-effective than a multispectral or hyperspectral camera [7]. RGB camera records spectrum information in visible light observable by human eyes [37].

Table 1: First Generation Indices

Years	Index	Author	Years	Index	Author	Years	Index	Author
1972	RVI	Pearson & Miller	1977	MSBI	Misra et.al.	1981	GSVB	Badhwar
1972	VIN	Pearson & Miller	1977	MGVI	Misra et.al.	1983	ASBI	Jackson et.al.
1974	TVI	Rouse at.al.	1977	MYVI	Misra et.al.	1983	AGVI	Jackson et.al.
1976	GVI	Kauth & Thomas	1977	MNSI	Misra et.al.	1984	TVI	Perry & Lautenschlager
1976	SBI	Kauth & Thomas	1977	PVI	Richardson et.al.	1986	DVI	Clevers
1976	YVI	Kauth & Thomas	1978	AVI	Ashburn	1991	NDGI	Chamard et.al.
1976	NSI	Richardson et.al.	1979	GRABS	Hay et.al.	1991	RI	Escadafal & Huete
1977	SBL	Richardson et.al.	1981	MTVI	Yazdani et.al.	1993	NDI	McNain & Protz
1977	DVI	Misra et.al.						

3.1 Vegetation Index

Vegetation analysis and detection of changes in vegetation pattern and structure are the key to plant assessment and monitoring. Plants with healthy green leaves have unique electromagnetic spectrum. During photosynthesis process, chlorophyll absorbs energy intensely. In visible light electromagnetic spectrum, the peak absorption is at the red zone, while the green zone is reflected by chlorophyll, resulting in distinct green appearance on most leaves. At the same time, NIR spectrum areas are highly representative of the internal structure of the leaf. The strong contrast, especially between the energy reflected in the red and NIR areas of the electromagnetic spectrum, is a focus on developing a quantitative index of vegetation conditions using RS imagery [15, 37, 45].

3.2 Extracting Vegetation Information

RS technology with visible light for arid and semi-arid regions with low vegetative cover is more cost effective, manageable and has higher spatial resolution, as well as provides easily extractable information. Most commercial UAVs are equipped with visible light camera, requiring NIR band without calculating NDVI and other vegetation indices. Therefore, a large number of high-res visible light UAVs cannot be applied for vegetation RS. Taking this into account, experts have developed various visible light Vis using characteristic of the spectral reflection in visible band. One of them selects visible light VI to extract vegetative information [45].

3.3 State of the Art of Vegetation Index

One of preliminary efforts in VI is NASA's program called "Monitoring the Vernal Advancement and Rétrogradation of Natural Vegetation" [1]. It was initiated to identify the relationship between radiometric responses and vegetative cover, by launching a satellite in 1972. The first generation in the field of soil measurement or satellite imaging exploitation used Landsat-MSS [33]. Other more profound programs include LACIE [2]. The use of red channel and NIR on satellite sensors is the start of research for vegetation studies. The intensity of a very complex phenomenon can be broken down into known parameters which can be determined by indices. The implementation of indices in the combination between channels is known as VI [1].

To meet vegetation requirements in a vast area, encompassing excessive image pixels, the concept of VI has been well adapted. In RS image interpretation methods, VI is very useful in detecting land use change (multitemporal data), evaluating vegetative cover density, crop discrimination and crop prediction [2]. VI calculates between the reflections of two bands which makes it possible to eliminate the interference from the influencing factors [3, 13].

The chronology of VI research applied into RS is presented in Table 1 and Table 2. The resulting indices are related to specific research fields of the researchers. Several VIs have shown excellent correlation with different factors, including the productivity of cropland or forest areas and their biomass content [2, 27]. Disagreement between researchers arise primarily due to advantages and disadvantages of each VI and experimental conditions and their fields.

Linear combination or DN was the first phase of VI development (Table 1). While knowledge on physical phenomena that account for interactions between electromagnetic radiation, atmosphere, vegetation cover and soil background was the second phase of VI development (Table 2). Studies show that second-generation VIs are less sensitive to atmospheric effects and soil brightness compared to first-generation indices. The VIs generated from the simulation based on the radiation transfer equation are, under ideal conditions, more accurate. The same sensitivity to vegetation cover under normal conditions using satellite or aerial imagery for a particular application can be determined through experimental research [1].

Each study shows different results, thus in general VI does not have a standard universal value. VI is strongly influenced by atmospheric conditions, sensor calibration, sensor display conditions, solar illumination geometry, soil moisture, color and brightness. A study on VI will be more complex in a heterogenous environment since each environment has distinct characteristics [1].

Various methods of reflectance to eliminate disturbances from external factors (calibration of sensors, atmosphere, display and illumination geometry) on the same radiation on each channel have been proposed to be integrated by several researchers. The purpose of this integration is to fulfill the application of a fairly specific RS (harvest, vegetation management, vegetation detection in inundated areas, and others [1].

3.4 VI Development

VI represents a filtering combination or process of several sets of spectral data to make a single value of each point in an image, usually generated by mathematical model [23]. The most widely-used and well-known VI is NDVI. NDVI makes use of spectral data from the Landsat to monitor agriculture and forestry globally [7].

Table 2: Second Generation Indices

Years	Index	Researcher	Years	Index	Researcher
1974	NDVI	Rouse et.al.	1992	ARVI	Kaufman & Tanre
1980	PVI	Jackson et.al.	1992	GEMI	Pinty & Verstraete
1988	SAVI	Huete	1994	TSARVI	Bannari et.al.
1989	TSAVI	Baret et.al.	1994	MSAVI	Qi et.al.
1991	TSAVI	Baret & Guyot	1994	AVI	Plumer et.al.

Apart from NDVI, there are others VI developed from different purposes. An example of an NDVI variant to treat cases where most of the soil is not covered in vegetation is a SAVI [15]. VI which uses a new method and uses an RGB camera and an NIR camera has also been carried out in a previous study for monitoring rice growth [35].

The relative vegetation abundance (RA) algorithm is also used to determine VI and is used widely in RS studies. RA is used to monitor green fractional vegetation cover (f_c), which is an important phenotypic factor in agriculture, forestry, and ecology. Over the past three decades, the number of studies using the RA algorithm has constantly risen. The most used source of data for estimating fc is Landsat and MODIS series, and high-res satellite data from other aerial sensors are also commonly used [42].

3.4.1 Visible NDVI (vNDVI). vNDVI is developed with red, green and blue bands that are used as a function using an RGB camera. This study used Genetic Algorithm (GA) to estimate the NDVI vegetation value from an uncalibrated RGB camera mounted on UAV. Even though with just an RGB camera, vNDVI is very accurate in estimating NDVI values with an overall mean error percentage of 6.89%, providing a low-cost alternative to RS and plant phenotypes [7].

3.4.2 Normalized Green-Red Difference Index (NGRDI). NGRDI is developed to estimate the biomass of green algae growing on a raft based on UAV and satellite imagery. Research results show that the NGRDI algorithm exhibits high accuracy in monitoring and predicting green algae biomass using UAV imagery [21]. Identification of green algae is carried out using several VIs including NGRDI, NGBDI, GLI and EXG, and accuracy evaluation is carried out based on collected survey data [42].

Vegetation and non-vegetation pixels in high-res visible light images are easily distinguishable based on visual identification and VI accuracy evaluation using NGRVI. NGRVI vegetation information provides vegetation information extracted accurately using optimal threshold obtained from iterative methods. Based on the visual interpretation features that are easily distinguishable between vegetation and non-vegetation pixels in high-res visible light RS images, we can evaluate the accuracy of vegetation information extraction based on NGRVI [45].

3.5 Vegetation Index Comparison

VI based on RGB imagery is widely implemented for various types of plants. The comparison of the accuracy of the NGRDI, EXG, EXG-EXR, and GLI color indices, which were used to extract vegetation information, has an average vegetation identification accuracy of more than 91%. EXG-EXR indices seem to be the ideal choice if only the visible band is available [4].

Other comparisons are made for VI from digital cameras, namely, VARI in the form of normal daytime RGB images and $NRBI_{NIR}$ based on NIR nighttime images. It is in the result that NRBINIR has spatial heterogeneity when point source of light (center) is used, in contrast to daytime RGB images. Additional experiments using a forklift shows that ISO sensitivity and a cDNNIR have a significant effect on NRBINIR's sensitivity to camera-to-object distance. The result affirms that NRBINIR is more sensitive to all agronomy data for the whole season, including the preliminary reproduction stage. VARI has a very high correlation with the LAI [34].

Different measurements can be taken with images taken from different cameras, light conditions and flight altitude. Experiments based on ExG concludes that light conditions and flight altitude have little to no effect on reproductivity. Different cameras produce different degrees of ExG for genotype, while flight altitude and light conditions are found to be inconsequential for genotype comparison [39].

In pine tree research, there are significant differences in spectral characteristics between sick and healthy pine tree, especially in red light band. This phenomenon shows the possibility that sick plants can use three bands Red, Green and Blue only. After comparing 12 types of VI based on RGB, it is found that VI VEG after VI RGI is the optimal vegetation index [46].

3.6 RGB-based Vegetation Index in UAV

Economic commercial RGB cameras mounted on UAVs are able to predict sugar cane harvest, displaying potentials to be used in practice. The spatial variability of plant height (PH) and sugarcane stem density can be mapped by UAV-based RGB images. The ExG index obtained from the RGB image shows a good correlation. The results of this study indicate that images from consumer class cameras mounted on UAVs have the potential to be used in the future by farmers to predict crop yields [38].

4 METHODOLOGY PROPOSAL

A number of new studies compare image processing methods for agricultural purposes, in particular detecting stress in various crops [36]. Other studies develop VIs using various parameters [4, 46]. There are still unexplored opportunities and potential in research and development of VI based on camera images from UAVs [38].

The research stages will be carried out in the following stages:

- Look for new research opportunities on vegetation indices using cameras on UAVs. At this stage an experiment will be carried out in accordance with previous research in making

a camera-based vegetation index on the UAV and trying to find opportunities for improvement.
- Conducting experiments on the hypothesis that the addition of white balance parameters by modifiying the automatic white balance algorithm and other parameters of the UAV sensor in the pre-processing stage to improve its quality.
- Modifying the Feature Extraction Algorithm using Color Extraction Edge Detection, it was known in previous studies that this algorithm produced the best value.
- Modifying the classification algorithm using Back Propagation Neural Networks to improve accuracy at the image processing stage.
- After all the stages have been carried out, the final research is to produce a new formula or new model for the vegetation index using a camera on the UAV which is accurate and can be carried out in various light conditions.

5 CONCLUSION

Through the proposed methods mentioned in the previous section, it is expected that the accuracy of VIs based on RGB camera images will improve, while staying economical. Methods used in previous studies may be used as a reference to develop and produce more effective and more efficient methods in determining VIs. Numerous methods and parameter derived from VIs based on RGB cameras on UAV have been developed. Continued research and development of several white balance parameters as well as parameters from other UAV sensors will be a novelty in determining VI RGB-based cameras to UAVs.

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