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Reviewing Vegetation Indices for Mobile Application: Potentials and Challenges

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ABSTRACT

Vegetation are quantitative metrics that are used to assess the density of vegetation as well as its health and vitality. Vegetation indices are important in precision agriculture and monitoring environmental conditions. For years, vegetation indices have been derived from remote sensing or aerial imaging data, with focus on large plantation estate and green coverage. Recently, there is a growing interest in using mobile phone for measuring vegetation indices at a more affordable cost. The spectral range for vegetation indices extends from 400 nm to 900 nm, which places it in the VIS and NIR spectral categories, respectively. The CMOS sensor that is typically found in mobile phone cameras has the capacity to capture NIR images. This paper aims to give a background in understanding vegetation indices available and weighing the suitability of using these indices for mobile applications. The potential of using these indices has been establish when the studies indicate several works have successfully used mobile phone camera to capture vegetation indices formulation, but still additional features is needed to ensure the standardisation and consistency of image calibration.

1. Introduction

Vegetation indices are quantitative measurements used to assess the density, health, and vitality of vegetation. The principle underlying these indices is that fact that plants have their own unique spectral fingerprints, which means the plants uniquely reflect and absorb light at different wavelengths. Researchers can learn a lot about the properties of plants by looking at the reflectance or radiance numbers at different wavelengths across the electromagnetic spectrum.

Vegetation indices are important in monitoring environmental conditions and in precision agriculture. Using vegetation indices, environmental issues such as soil erosion, land degradation, deforestation, and habitat loss can also be monitored [1,2]. By analysing vegetation patterns, scientists can learn more about how human activities such as land use and climate change affect

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ecosystems. In precision agriculture, vegetation indices provide data regarding plant health, growth, and yield [3,4]. This allows farmers to detect stress, nutrient deficiency, and disease outbreaks. Consequently, this will result in swift solutions such as optimizing irrigation, fertilization, and insect management practices, leading to an increase in crop yield and resource efficiency.

For years, vegetation indices have been derived from remote sensing or aerial imaging data, with focus on large plantation estate and green coverage. However, recently, there is growing interest in ground sensor, digital camera and mobile phone for measuring vegetation indices at a more affordable cost [5-9]. As an example, by having a mobile phone camera equipped with vegetation indices, farmers are able to analyse the status of their fields, detect regions of stress, and make educated decisions regarding irrigation, fertilisation, or insect management. In urban environments, where green spaces are important for air quality and overall well-being, mobile phone cameras with vegetation indices can help citizens and city planners monitor the health of urban vegetation. Thus, this paper aims to give a background in understanding vegetation indices available and weighing the suitability of using these indices for mobile applications.

This paper starts with an introductory section that provides an overview of vegetation indices and the sensors employed to acquire the variables utilised in their computation. Subsequently, a systematic review conducted with the purpose of examining vegetation indices and application of digital and mobile phone cameras (sensors). This review includes a discussion of the potentials and challenges associated with the utilisation of vegetation indices for mobile application. In conclusion, this paper will finish with some recommendations for further research.

1.1 Research Background
1.1.1 The principles of vegetation indices

Vegetation indices are made by adding up the reflectance values of spectral bands that are linked to qualities of plants. The choice of these bands highly depends on the property of the plant being studied and the skills of the sensor being used to get the data. For example, the most used vegetation index, Normalized Difference Vegetation Index (NDVI), uses the red and near-infrared (NIR) spectrum bands to measure how green the plants are and how much photosynthesis is going on. Figure 1 depicts in detail the spectrum of spectral bands for vegetation indices and the information they convey.

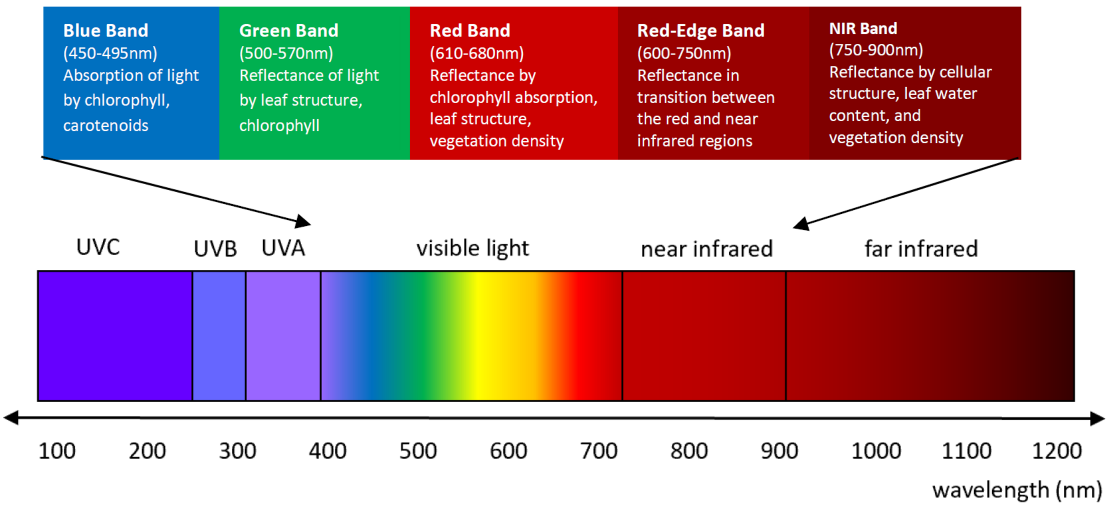

Fig. 1. The range spectral bands in vegetation indices with related absorbance and reflectance by vegetation

The visible light spectrum (VIS) extends from 400 to 680 nm, which includes the blue, green, and red colours. This indicates that the colour of a plant is determined by the hue of light that reflects into our eyes. We see a plant as green, because the leaves reflect green bands, and absorbs most of the blue band and red bands. What our eyes fail to see is that plant also reflect near infrared (NIR) band too during photosynthesis. The higher or more NIR reflected indicates the healthier a plant is. Vegetation indices compose pictures that show how much plants are photosynthesizing.

Vegetation indices are based on three principles: reflection differences, normalization and ratioing, and correlation with ground measurements. Reflectance differences provide information about vegetation presence and condition, while sensitivity to properties helps assess health and vigour. Normalization and ratioing minimize external factors and establish correlations with ground measurements, enabling estimation of vegetation conditions over large areas.

Overall, the idea behind vegetation indices is to use spectral information to measure and track the traits of plants. By figuring out what information is important from remote sensing data, these indices can be used in many ways in agriculture, forestry, ecology, and tracking the environment. After understanding the spectrum, we look most used vegetation indices, with formula and common application, as shown in Table 1.

Table 1
Vegetation Indices with formula and application respectively [10-12]

Vegetation Index	Formula	Applications
Normalized Difference Vegetation Index (NDVI)	NDVI = (NIR - Red) / (NIR + Red)	Crop monitoring, vegetation health, land cover mapping
Enhanced Vegetation Index (EVI)	EVI = 2.5 * ((NIR - Red) / (NIR + 6 * Red - 7.5 * Blue + 1))	Vegetation health monitoring, biomass estimation, land surface phenology
Soil-Adjusted Vegetation Index (SAVI)	SAVI = ((NIR - Red) / (NIR + Red + L)) * (1 + L)	Vegetation health monitoring in areas with varying soil cover, vegetation stress
Green Normalized Difference Vegetation Index (GNDVI)	GNDVI = (NIR - Green) / (NIR + Green)	Assessing vegetation health, quantifying green vegetation cover, crop monitoring
Difference Vegetation Index (DVI)	DVI = NIR - Red	Vegetation vigour assessment, drought monitoring, crop yield estimation
Normalized green–red difference index	NGRDI = (G−R)/(G+R)	Crop monitoring, vegetation health, land cover mapping
Leaf Area Index (LAI) CT=CanopyTransmittance	LAI = (K * CT) / (1 - CT)	Crop growth monitoring, forest structure analysis, ecosystem modelling
Chlorophyll Index (CI)	CI = (R750 - R705) / (R750 + R705)	estimating chlorophyll content in vegetation, assessing plant health, detecting stress
Crop Water Stress Index (CWSI)	CWSI = (Tc - To) / (Ts - To)	Irrigation scheduling, drought monitoring, precision agriculture

Despite the potential advantages of EVI, GNDVI, and SAVI over NDVI, NDVI has an extended history of use in remote sensing and precision agriculture [11]. The NDVI performance based on ground-truth data have been well-documented and studied over the years. However, with the increased focus on alternative vegetation indices produced from multispectral sensors could potentially contribute to a global understanding of the application of remote-sensing data to the evaluation of crop health. In recent years, RGB sensors have become increasingly popular in scientific study, with a special emphasis being placed on the development of low-cost solutions for farmers. In contrast to NDVI, the most common RGB vegetation index, NGRDI, was applied primarily using photos captured by unmanned aerial vehicles (UAV)s.

1.1.2 Sensors

Sensors are needed to capture the absorbance and reflection of light at specific wavelength. The useful range for vegetation indices is between 400 nm up till 900 nm. Therefore, most sensors used must have the capacity to capture visible and NIR light. The most prominent sensors used in commercial or large farming are, hyperspectral and multispectral. Accessing satellite data usually involves navigating data providers, obtaining permissions, and managing data storage and processing resources. Aerial sensors require coordination of flight operations and specialized training for data collection. Processing satellite and aerial imagery often requires advanced remote sensing techniques and software. Table 2, summarized the major types of sensors used for vegetation indices.

Table 2
Major types of sensors used for Vegetation Indices [4,11,12]

Sensors	Spectral Range	What is Measured	Limitation
Hyperspectral	VIS-NIR reflectance (380-2500 nm)	Continuous or discrete spectra for each pixel in spectral range	Cost Heavy payload Extraction information process
Multispectral	VIS-NIR reflectance (380-1000 nm)	Few bands for each pixel in spectral range	Limited to few spectral bands
Digital Camera	VIS reflectance (380-700 nm) *900 nm without IR filter	Gray scale or colour images	Limited visual spectral bands and properties
Thermal	Infrared emission (7-14 μn)	Pixelated temperature	High resolution camera Heavy payload
LiDAR	Specific VIS-NIR bands (e.g., 1064 nm)	Physical measurement (distance, reflectivity)	Cost Heavy payload Sensitive to small variation in path length

Looking for a more affordable solution, several researchers altered digital camera with CMOS (Complementary Metal-Oxide-Semiconductor) sensors [6-9,13]. CMOS sensors used in mobile phones typically capture images in the visible light spectrum, ranging from approximately 400 to 700 nm [14,15]. They are not specifically designed for capturing narrow spectral bands like multispectral or hyperspectral sensors. However, some mobile phones with modified camera systems or additional filters may have extended spectral capabilities, capturing near-infrared (NIR) wavelengths around 700 to 900 nm.

CMOS sensors, but some articles prefer RGB sensors, are usually found in low-cost consumer drones and cameras. These sensors, which can be used to visually monitor crop health and detect any clear abnormalities, such as pests or illnesses, are commonly found in low-cost consumer drones and camaras. However, they have a limited ability to quantify the more subtle alterations in plant reflectance that are indicative of changes in vegetation health and productivity. These differences can be a good indicator of how well vegetation is doing. In the field of precision agriculture, RGB sensors can provide a quick visual evaluation of crop health, although multispectral sensors are typically more suited for the computation of the vegetation index as well as a more in-depth investigation of the vegetation's health and production. In addition, RGB sensors can provide a quick visual assessment of crop health.

1.2 The Research Gap

The search for existing reviews using the terms "vegetation indices", "mobile application", and "systematic review" returns no results. Altering the search terms from "mobile application" to "digital camera" and using only the word "review" brought back 12 articles that may be considered potentially relevant. After conducting more research, we looked at a total of eight review publications that indicated the usage of adapted digital cameras or on-shelf cameras to measure vegetation indices [3,4,11,12,17-19]. Thus, this paper aims to investigates the gaps by reviewing vegetation indices for mobile application.

2. Methodology

2.1 Systematic Review Process

We adopted a systematic review process to provide a more comprehensive and less biased picture of the vegetation index application in the computer science field and point to key challenges moving forward. We searched Google Scholar and IEEE Xplore database on June, 2023 basing on different keyword pairs as listed in Table 3. Each database was searched with all allowable search parameters that did not result in a full-text search; that is, we searched the title alone with Google Scholar and title/abstract/author keywords in IEEE Xplore. The duration for this review ends in year 2023, June.

Table 3
Keywords pairing between two fields

Vegetation Indices	Computer Science/Application
Vegetation Index (VI)	Artificial Intelligence
Normalized Difference Vegetation Index (NDVI)	Machine learning
Difference Vegetation Index (DVI)	Deep learning
Enhanced Vegetation Index (EVI)	Image Processing
Soil-Adjusted Vegetation Index (SAVI)	Image classification
Green Normalized Difference Vegetation Index (GNDVI)	Feature extraction
	Regression analysis
	RGB images
	NIR images

The broad spectrum of pair keywords used for the initial search yielded a total of 6,417 articles. This was to establish the relation between the field of computer science and vegetation indices, in which the increasing numbers of publication started around the 2010s. This is the period when advancements in machine learning, deep learning, and computer vision gained traction, allowing researchers to leverage these technologies for the analysis of remote sensing data, including vegetation indices. By examining the second filter for duplicates, out-of-range dates, and articles outside the scope, these articles are eliminated, leaving 576 articles in the second stratum.

These articles are further refined by examining research that employs digital cameras or mobile phone cameras for data collection, which is the main focus of this paper. The shortlisted paper does not examine articles that utilize available datasets or database. Figure 2 provides a summary of the article selection process that resulted in the final 29 articles.

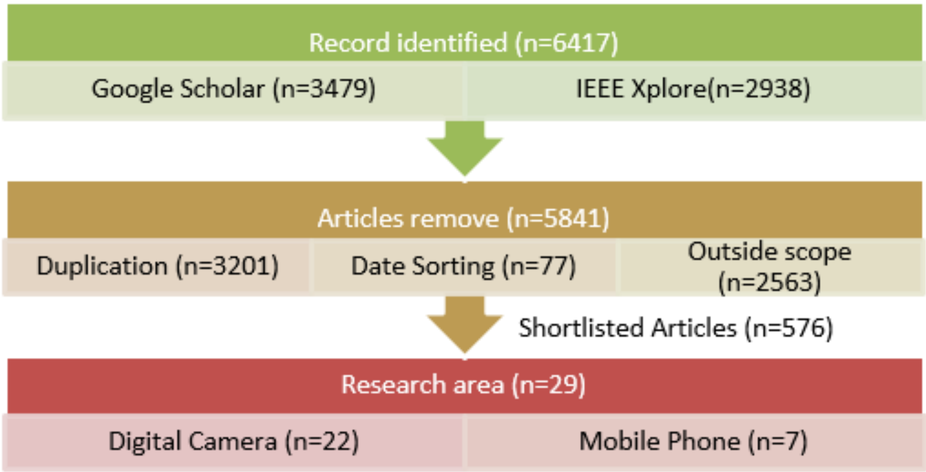

Fig. 2. The summation articles selected during filtering processes

The completed articles were reported in Table 4. Thirteen articles report the use of LAI as their vegetation indices, whereas nine articles record the use of NDVI. However, only seven out of 29 articles documented using a mobile phone as the medium for data collection. LAI, LSAI, NDVI, NGRDI and CWSI are the vegetation indices that have been derived from Table 4 for further comprehension.

Table 4
Summary of Selected Article for Reviewing

	Articles/Year	**Vegetation Indices**	**Sensors**
1	A Method Based on Digital Image Analysis for Estimating Crop Canopy Parameters [20]	LAI	Digital Camera - Olympus C740 Ultra Zoom
2	A new method of leaf area index measurement based on the digital images [22]	LAI	Digital Camera
3	Estimation of paddy rice leaf area index using digital photography [29]	LAI	Digital camera
4	Recent advancements in optical field leaf area index, foliage heterogeneity, and foliage angular distribution measurements [36]	LAI	Digital Camera
5	Estimating leaf area index of sugarcane based on multi-temporal digital images [27]	LAI	Digital camera
6	Digital camera-based measurement of crop cover for wheat yield prediction [26]	LAI	Digital camera
7	Intercomparison of instruments for measuring leaf area index over rice [32]	LAI	Digital Camera
8	Estimation of Forest Leaf Area Index Using Height and Canopy Cover Information Extracted from Unmanned Aerial Vehicle Stereo Imagery [28]	LAI	Digital camera UAV
9	Comparison RGB Digital Camera with Active Canopy Sensor Based on UAV for Rice Nitrogen Status Monitoring [23]	LAI	Digital camera UAV
10	Determining the Leaf Area Index and Percentage of Area Covered by Coffee Crops Using UAV RGB Images [25]	LAI	Conventional camera UAV
11	Mapping Two Competing Grassland Species from a Low-Altitude Helium Balloon [34]	LAI	UAV-digital camera
12	The Research of Leaf Area Index Analyzer based on Embedded Platform [37]	LAI	Fish-eyes camera LAI2000
13	Feasibility of using mobile phone to estimate forest Leaf Area Index: a case study in Yunnan Pine [38]	LAI	Mobile phone Camera

14	A novel methodology for using digital cameras to calculate spectral parameters [15]	NDVI	Digital Camera - Albeit
15	Commercial Off-the-Shelf Digital Cameras on Unmanned Aerial Vehicles for Multitemporal Monitoring of Vegetation Reflectance and NDVI [6]	NDVI	Commercial COTS-Camera RGB and thermal sensors UAV
16	Cost-Effective Multispectral Imaging System for Precision Agriculture [7]	NDVI	Digital action camera Drone
17	Low-cost multispectral imaging system for crop monitoring [5]	NDVI	Multispectral and RGB Camera, drone
18	Modification of Pocket Camera as A Sensor for UAV-Based Plant Health Detection System [8]	NDVI	Cannon Digital Camera, UAV
19	NDVI image extraction of an agricultural land using an autonomous quadcopter with a filter-modified camera [13]	NDVI	Rasberri Pi Zero, drone
20	Vegetation indices-based segmentation for automatic classification of brown spot and blast diseases of rice [39]	NDVI, EVI, GVI and SAVI	Digital Camera
21	Detection of Bacterial Leaf Blight Disease Using RGB-Based Vegetation Indices and Fuzzy Logic [24]	NGRDI	RGB camera UAV
22	Open-Source Software for Crop Physiological Assessments Using High Resolution RGB Images [35]	NGRDI	Digital Camera
23	Feasibility of using smart phones to estimate chlorophyll content in corn plants [9]	NGRDI, GDR	Mobile Phone Camera
24	A mobile thermal-RGB imaging tool for mapping crop water stress of grapevines [21]	CWSI	Miniature thermal sensors RGB Camera
25	Applying RGB- and Thermal-Based Vegetation Indices from UAVs for High-Throughput Field Phenotyping of Drought Tolerance in Forage Grasses [40]	Water stress, CWSI	Camera RGB and Thermal UAV
26	Estimation of Triangular Greenness Index for Unknown Peak Wavelength Sensitivity of CMOS-acquired Crop Images [30]	TGI	CMOS sensor
27	Remote Sensing with Simulated Unmanned Aircraft Imagery for Precision Agriculture Applications [17]	TGI	UAV - Digital Camera
28	Implications of Very Deep Super-Resolution (VDSR) on RGB imagery for grain yield assessment in wheat [31]	VR	RGB camera
29	Leaf spot area index: A non-destructive mangrove leaf spot estimation technique [33]	LSAI	Digital Camera and Mobile Phone

2.2 Vegetation Indices Extraction
2.2.1 Leaf area index (LAI)

Remotely-sensed LAI is vital to describe the vegetation canopy and assess plant growth condition and healthy status. LAI direct methods including destructive sampling, falling object method, and point the oblique manner are accurate but time-consuming and hazardous to vegetation. Indirect methods for obtaining LAI uses optical principle, and a standard equipment of plant canopy analyser such as LAI-2200C, have smooth operation and no vegetation damage. Data collection for indirect methods include the usage of digital camera attach to drone or UAV [23,25,26,28,36].

Low-cost adaptation for LAI using mobile phone camera is reported in several articles [32,33,38]. The developed fisheye camera method (DHP) has been extensively implemented together with plant canopy analyser. Figure 3 depicts the LAI-Mobile instrument, which utilises a fisheyes lens clipped onto a mobile phone [38]. Prior to capturing the canopy hemispheric image, the mobile phone is affixed to a selfie stick. The image pre-processing and LAI extraction from the image are conducted using CAN–EYE V6.1 software (http://www6.paca.inra.fr/can-eye/Download). Image optimization through image correction and super resolution will help improve the LAI measurement [33].

Fig. 3. LAI-Mobile instrument: (a) mobile phone equipped with spherical lens; (b) mobile phone fixed with selfie stick; (c) an example fisheye image acquired by LAI-Mobile [38]

2.2.2 Leaf spot area index (LSAI)

LSAI as the name indicates, focuses to smaller area as compared to LAI. The health of a tree can be estimate through the study of spot area to the leaf area. As the Eq. (1) indicate

$$LSAI = \frac{SA_{cm^2}}{LA_{cm^2}} \tag{1}$$

where SA_{cm^2} is the total area of the leaf spots and LA_{cm^2} denotes the total area of the leaf. The ratio nature of the LSAI makes it leaf-size independent. The data acquisition using a mobile phone for LSAI is improved through the use of black self-stick board [33]. A 2-centimeter-by-2-centimeter white square is inserted on the board for image rectification and calibration purposes. The corner point of the white square is used to transform the image into a front-parallel view in order to eradicate the projective transformation caused by the camera's orientation. Since the calibration square's area is known (in this case, 4 cm2), the leaf and leaf spot areas can be estimated relative to the calibration square and measured in centimetres.

Fig. 4. A black self-stick board to enhanced foreground-background variation. [33]

2.2.3 Normalized difference vegetation index (NDVI)

NDVI remains the most popular vegetation indices despite other indices for precision agriculture such as EVI, SAVI or GNDI, regardless the types of sensors used [11]. The RGB sensors had increased popularity in scientific studies in the past few years, primarily with the focus of developing low-cost solutions available to farmers. In order to compute NDVI in Eq. (2), the value of NIR is needed. In order to compute NDVI, the NIR value is required. As shown in Eq. (3), the NIR constant can be derived from the visible spectrum without any additional sensors [39]. A digital camera with no NIR-blocking filter will have the potential to produce a better sensitivity balance between visible and NIR.

$$NDVI = \frac{NIR-RED}{NIR+RED} \tag{2}$$

$$NIR = 1.8474519 \times (RED - 0.1936929) \times (GREEN + 0.12401134) \times BLUE \tag{3}$$

2.2.4 Normalised green-red difference index (NGRDI)

Chl is the most important pigment of plants since it plays a crucial role in photosynthesis. Therefore, estimation of Chl contents carries information on plant growth and health. The normalised green-red difference index (NGRDI) is a well-known vegetation index for RGB sensors that is primarily implemented using UAV images. By replacing near-infrared with green reflectance, NGRDI provides a similar level of sensitivity to variations in chlorophyll content in plants as NDVI. As shown in Eq. (4) NGRDI does not require NIR; the green and red spectra are sufficient for computation.

$$NGRDI = \frac{GREEN-RED}{GREEN+RED} \tag{4}$$

In order to improve the ability of digital cameras to estimate chlorophyll content, mobile phone cameras were used to acquire chlorophyll data using spectral absorption photometry (SAP) approach [9]. The SAP method gets light passing through a leaf, giving varieties illumination condition. The settings of camera, including sensor light sensitivity (ISO) and exposure time, were set in auto mode and the camera selected them based on light conditions. Light-aided spectral absorption photometry (LASAP) offers constant illumination value through an LED light source. Figure 5 depicts the instrument for SAP and LASAP.

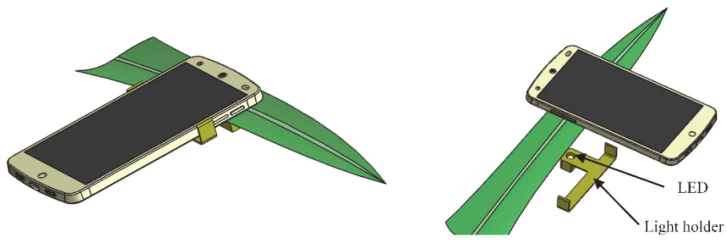

Fig. 5. SAP instrument: without background light (left) and with light source (right) [9]

2.2.5 Crop water stress index (CWSI)

CWSI is an indirect indicator of crop water demand, typically used for irrigation scheduling. CWSI uses differences between the canopy surface temperature (T_c) and air temperatures (T_a) that increases with the diminishing crop capacity to fulfil the evaporative demand. The CWSI can be derived the following equation,

$$CWSI = \frac{(T_c-T_a)-(T_c-T_a)_{LL}}{(T_c-T_a)_{UL}-(T_c-T_a)_{LL}} \tag{5}$$

where $(T_c - T_a)$is the difference between the canopy and air temperature also referred to as 'stress degree day'. $(T_c - T_a)_{LL}$ is the lower baseline limit corresponding to the full transpiring canopy and $(T_c - T_a)_{UL}$is the upper baseline limit that corresponds to the canopy under the highest water stress. Mobile phone enabled thermal infrared imaging sensors to provide flexibility to growers to have real-time visualization of Tc and understand the water stress. Figure 6 depicts the CWSI instrument with thermal sensor attached to tablet. The thermal and RGB image gives the relevant baseline equations that could be developed with the site-specific data to extract the upper and lower limits of water stress.

Fig. 6. CWSI instrument: thermal sensor attached to tablet proving thermal image [21]

2.3 Summary

In summary, the utilisation of the camera feature on a mobile phone indicates the necessitates of using an extra device or technique, as indicated in Table 5. This additional feature is to ensure the standardisation and consistency of image calibration, therefore yielding a suitable result for vegetation indices formulation.

Table 5
The summarization of [4,11,12]

Vegetation Indices	What is Measured	What is indicated	Techniques Applied
Leaf area index (LAI) [38]	canopy hemispheric image	plant growth condition and healthy status	1. fisheyes lens clipped onto a mobile phone 2. the mobile phone is affixed to a selfie stick
Leaf spot area index (LSAI) [33]	spot area to the leaf area	health of a tree	Use a black self-stick board with a 2cmby 2cm white square is for image rectification and calibration purposes
Normalized difference vegetation index (NDVI) [9]	The NIR value reflected by the leaf	plant health	1. Use a digital camera with no embedded NIR-blocking filter 2. Different wave bands lens clipped onto a mobile phone
Normalised green-red difference index (NGRDI) [9]	Chl contents	plant growth and health	1. replace near-infrared with green reflectance in formula 2. have an addon accessories to hole the leaf and add lighting while taking the picture
Crop water stress index (CWSI) [21]	canopy surface temperature and air temperatures	crop water demand	1. Mobile phone enabled thermal infrared imaging 2. thermal sensor attached to tablet proving thermal image

3. Potentials and Challenges
3.1 The Potentials

The use of mobile phones to determine the vegetation indices is gaining popularity and has the potential to be of great assistance. Even in remote areas, mobile phones are becoming common, providing the potential as a cheaper solution and general tool for acquiring vegetation data. As a result, vegetation index estimations can be more widely applied. Users do not require expensive multi-spectral camera, drone or speciality agriculture application because they already own mobile phone.

The portability and compactness of a mobile phone makes the farmers to easily carry it into the field and can be used it to collect real-time data and analyse crops on the spot. This makes it easy for farmers to make decisions and check on the health of plants right away. And with built in sensors such as GPS and an accelerometer, additional metadata provide additional information that can be crucial to plant health analysis.

Mobile phones make it possible for people to take part in citizen science projects and crowdsourcing, where they can help watch vegetation by capturing and sharing data. This information can tell us a lot about the patterns and changes in vegetation on a bigger scale.

Even though mobile phones have a lot of potentials for vegetation indices, there are some things to keep in mind. Mobile phone cameras might not have the same image quality or spectral range as remote sensing sensors, which could affect how accurate and precise vegetation index data are. Also, mobile application for vegetation indices requires to be calibrated and validated to make sure that the data are reliable and consistent.

3.2 The Challenges

Mobile phone cameras may not be as good as remote sensing devices in terms of image quality, spectral resolution, and dynamic range. Machine vision can improve picture quality, fix sensor limitations, and make vegetation index calculations more accurate.

The different specification of mobile phones makes it difficult for vegetation indices to be consistent and comparable across devices and applications. Thus, it is important to set up standardised protocols and suitable calibration techniques. For example, the used of black-stick board to calibrate standard size in getting the LSAI [33].

The scattering and absorption of spectrum can change the accuracy of the estimation of vegetation indices. Getting rid of these effects and making vegetation indices more accurate can be done by having a controlled environment or making correction algorithms. For example, the used of LED in LASAP to control the lighting variables for NGRDI [9].

The calculation and processing of vegetation indices can be very consuming, especially dealing with high resolution images to be runnable real-time on mobile phone. Cloud-based options can also be used to let remote servers handle data processing and storage. Thus, the mobile phone serves to acquires data, and providing the output and feedback after cloud processing.

4. Conclusions

The spectrum range for vegetation indices are between 400nm to 900nm, which falls under the VIS and NIR spectral, which is possible to capture using mobile phone camera. The mobile phone camera uses CMOS sensors, in which without the NIR filter, has the capability to captures NIR images. This paper completed the review on seven articles that use mobile phone as the acquiring tools and to calculate the vegetation indices. The LAI, LSAI, NDVI, NGRDI and CWSI had shown promising results.

Mobile phones are increasingly being used to determine vegetation indices, making them more accessible and user-friendly for farmers. These devices allow for quick and intuitive estimations of vegetation indices, enabling early response to plant stress or changes. Mobile phones also enable participation in citizen science projects and crowdsourcing, allowing for monitoring vegetation patterns and shifting. However, there are challenges to consider when using mobile phones for vegetation indices. Camera quality and spectral resolution may be lower than those found in remote sensing devices, affecting the accuracy and precision of vegetation index data. Researchers can develop algorithms for image processing to improve picture quality and compensate for sensor limitations.

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