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Using information from images for plantation monitoring: A review of solutions for smallholders

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Technologically empowering farmers/smallholders notably accelerates the knowledge transfer to monitor plantations in developing countries. Advanced, cost-effective technologies can rapidly increase the effectiveness of using expenses, labor, and time. There is no limit to using digital cameras for non-destructive measurements, such as nutrient monitoring, pests and diseases, yield monitoring, and other information related to individual plant conditions in the plantation area. This paper elaborates the fundamental concepts and best practices for future research on how to use image information from a single digital camera in decision support systems as a solution to monitoring plantations such as coffee, cocoa, and tree crops. This paper reviews the recent and potential research on plantation monitoring using a digital camera and other suitable integrated sensors. Moreover, we propose a protocol for use as a possible solution for smallholders to cope with the limitation in network/internet access infrastructure. Following this protocol, an integrated system for monitoring the farm activities of smallholders can be established.

Contents

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1. Introduction

Nowadays, optical sensors, such as hyperspectral and consumer-grade cameras, are being rapidly developed to obtain optimum image quality. Hyperspectral cameras offer a large number of image datasets, which can be further divided into useful narrower wavelengths; however, the price is not affordable for smallholders. As an alternative, consumer-grade cameras have emerged as a solution to provide adequate information on monitoring farm activities. A digital camera captures detailed information, which offers potential uses related to biophysical properties, such as monitoring nutrients, phenology, pests, and diseases; yield; and other activities in plantation areas. Many studies [1–5] have focused on the band properties for assessing plant health through vegetation indices (VIs) instead of incorporating visual or other types of sensor information.

Unmanned aerial vehicles (UAVs) have commonly been used for agricultural monitoring recently, and their use has been on the rise. Pádua et al. [6] indicated the pros and cons of the existing remote sensing technologies and the use of UAVs, as well as terrestrial surveying instruments, which are highly accurate. Although UAVs are used for multipurpose agricultural monitoring, their maintenance cost is low, especially for smallholders with smaller plantation areas, plantations with dense shade trees, and a hilly plantation terrain [7]. For farmers/smallholders who still require UAVs for agricultural monitoring, a previous study [8] demonstrated the use of low-cost UAVs integrated with a wireless sensor network system.

In general, the use of ground-based remote sensing is more appropriate for these plantation conditions and more suitable for smallholders. In plantations with very dense shade trees, it may be difficult to collect information related to biophysical properties through aerial remote sensing. Spectral information received by sensors varies to a large extent. Color band properties obtained from red, green, and blue (RGB) data may not adequately assess the biophysical properties of interesting vegetation objects. Combining RGB and near-infrared (NIR) bands with high spatial and temporal resolutions of cameras can provide continuous monitoring of plant canopy phenology during the growing season [9].

Besides the sensors, processing images and sensor information need information technology (IT) knowledge to develop a farm management system. Farmers' economic and behavioral aspects also need to be taken into account before recommending an appropriate solution for complex real-world agricultural production [10]. Also, information provided in the header of each image, such as time of capture and coordinate, can be used for plantation monitoring and developing a decision support system (DSS). Moreover, optical sensors, like consumer-grade cameras, are useful for measuring the height of plants and the diameter of trees, which are related to factors such as carbon footprint, yield estimation, and canopy cover. Besides the sensors, the process of converting images into information to develop a DSS is the most important step.

In several developing countries, most farmers/smallholders do not know how to use the Internet for farm management and lack the scientific knowledge to ensure the sustainability of their farm. Furthermore, the network connection is not sufficiently stable to implement the internet-based DSS monitoring, for example, when uploading images for non-destructive plant analysis. In Indonesia, most farmers/smallholders located in rural areas apply traditional farming methods. With these limitations, the socio-technology gap may still exist in the future until the required infrastructure is improved.

This paper makes the following contributions: (1) provides scientific information that can be potentially used/embedded in RGB information for specific purposes on a time-series basis; (2) offers a potential solution for farmers/smallholders regarding the use of a sensor (digital camera), a protocol for processing images, and a DSS; (3) critically reviews recent papers related to plant monitoring using a camera; and (4) investigates the potential of monitoring and decision-making.

2. Image properties and additional useful information

To date, consumer-grade digital cameras comprise of three major RGB bands and the full spectrum can range from 200 to 1,200 nm. The RGB ratio in each spectrum/corresponding wavelength and color is also different. A particular wavelength can be obtained using specific external or internal filters. Unlike a spectrometer, satellites, and multispectral cameras, only broadband VIs can be achieved using consumer-grade cameras. Nevertheless, most previous studies have claimed that the information obtained using consumer-grade cameras is comparable to that obtained from scientific equipment and other alternative devices, such as spectrometer and hyperspectral cameras.

Common VIs are obtained by combining one or more available bands. Some studies [11–13] have used more than one camera to capture visible and NIR bands. Broadband VIs can also be used to assess several agricultural parameters, such as chlorophyll, nitrogen, biomass, pest and disease recognition, and yield. Broadband VIs are proposed in some studies [7,14–17], which are recommended to be used at the appropriate times and weather conditions.

Several studies [7,18,19] have shown that incorporating additional information with RGB values can improve the accuracy of measurement compared to using RGB values only, while assessing the greenness of vegetation. Using additional information (Table 1) from the images acquired, self-calibration is obtained without any further calibration process. The use of a single band may be useful for vegetation monitoring, as in the study conducted by Sakamoto et al. [20]. They also incorporated additional image information, such as F-Stop, exposure time, and ISO as exposure value components.

Also, F-stop information in the image header is useful for object recognition (i.e., estimating plant height, fruit size, and other information related to physical properties). Mrovlje and Vran [30] showed that F-stops are highly correlated with the distance between the camera and the object, and it can be potentially used as a parameter of measurement. A change in the focal length at a constant imaging distance yields a different image scale and viewing angle [25]. Some studies [31,32] used a linear discriminant analysis classifier for object recognition. The combination of these parameters needs to be tested in the context of close-range digital photogrammetry to obtain complex information on the object (i.e., yield size and the sum of yield kernel).

The other information is the "date taken," which does not seem to be crucial but is important in terms of time series, historical data, and the recognition of the captured time information. During image processing, the "date taken" is given more emphasis than the processing time. It cannot be affected by the processing time because image processing can be conducted at any time after performing measurements.

Besides additional information recorded in the image header, several sensors, such as the degree of freedom (DOF), irradiance, and positioning sensors, can be integrated with the image header information. Such information can be recorded separately, but the key parameter to integrate all this information needs to be decided (i.e., the "date taken" information of all sensors). Commercially available sensors are already built into the UAVs and are useful for defining the orientation and positioning of the calibration. Recent studies have shown that one or more sensors are used for agricultural monitoring via ground-based/terrestrial remote sensing. Luhmann [25] showed high accuracy of a single camera concerning a local reference body that appeared in the same image (using a DOF sensor as a reference) in estimating object size properties.

Regarding uncertain natural light, irradiance sensors are required to calibrate the camera values. The main challenges of using a consumer-grade camera are unfavorable weather conditions and different capturing times, due to which the measurement values may highly deviate despite being captured on the same day under different conditions. Some devices such as Parrot Sequoia® and Sentera® are also embedded with an irradiance sensor wherein the camera values can be corrected. These devices are not affordable for the farmers/smallholders in developing countries. Sakamoto et al. [33] proposed the method of calibrating the digital number value of a camera with incoming light intensity using the irradiance sensor. For applying a low-cost system, an additional sensor, such as an irradiance sensor, may not be required.

3. System framework

This framework focuses on on-the-go plantation monitoring and skips the use of an unstable and weak internet network in rural areas. The system framework is a critical tool in acquiring information from the sensors (and from supporting government agencies) and disseminating to the farmers/

Table 1 – Image properties in JPEG format.

No.	Parameter	Purpose	Reference
Image properties (optical sensor/camera)			
1	RGB information	1. Assessing color of object information 2. Indices 3. Object recognition/signature	[7,14,21]
2	Date taken	1. Identifying data and time of the captured object 2. Time-series information	This study
3	Dimensions (width & height)	Recognizing the sum pixel of object/ background in the images	This study
4	Camera model	Recognizing from which camera the object is taken	This study
5	F-Stop	1. Plant/fruit size, plant height, and diameter 2. Determining exposure value	[22–26] [20]
6	Exposure time	Determining exposure value	[20]
7	ISO speed	Determining exposure value	[20]
Additional & optional information (obtained from another sensor) could be embedded with image information			
8	Degree of freedom (DOF)	Recognizing the camera motion	[27]
9	Irradiance sensors	Adjusting the color information obtained from the main camera	[28]
10	Positioning sensors	Assessing the location of the captured object	[28]
11	Other camera information (zenith position)	1. Assessing light intensity using EV as the reference for the main camera 2. Gap fraction	[29]

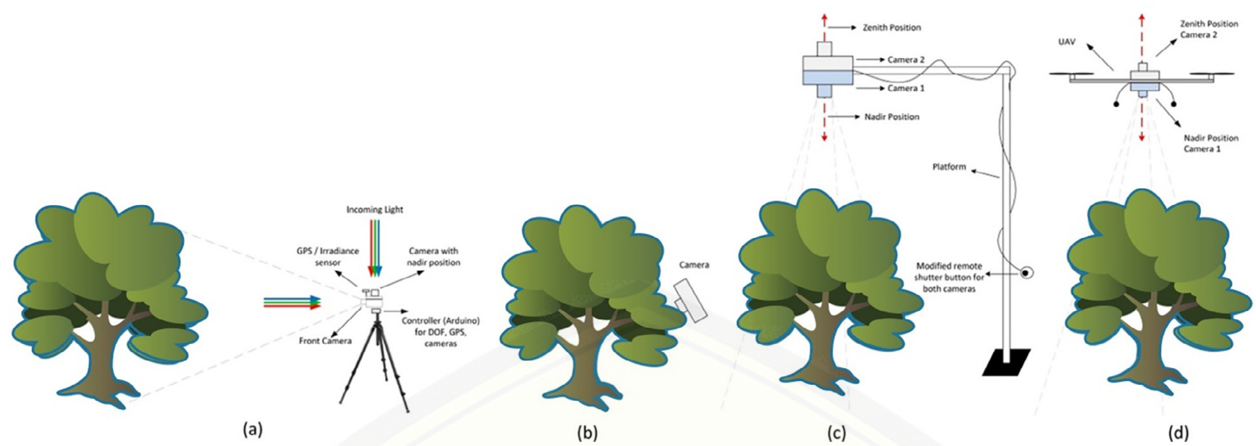

Fig. 1 – Several methods for assessing information using proposed sensors: (a) terrestrial; (b) direct-leaf; (c) above-canopy (pole); and (d) above-canopy (UAV).

smallholders efficiently with an aim to support their decision-making. The components and framework required are reviewed in this section.

A camera is the primary sensor for capturing valuable information on plant/plantation conditions over a period (e.g., minute by minute, or hour by hour). Besides cameras, additional information obtained from sensors, such as elongation sensors [34], DOF sensors [27], irradiance sensors [35], and positioning sensors [8], can be integrated with a controller board, such as Arduino, like an embedded system [36]. Also, a custom shutter button for cameras can be integrated with Arduino along with other sensors to obtain information simultaneously and store it in particular data storage facilities, such as a secure digital (SD) card or a wireless network (wherever applicable).

Several single-plant capturing methods were offered in recent studies, namely direct-leaf measurements with [7,13,37] or without artificial light [38,39], above-canopy

Table 2 – Pros and cons of existing plantation measurement methods using optical sensors.

Measurement Methods	Pros	Cons	Remarks
Direct-leaf	• Highest resolution • Feasibility of capturing several images per plant • Possible application at any time using an artificial light source (day and night application) • Easy recognition of leaf underside with IR band	• More focus on leaf greenness • Daytime application using sunlight as the light source	• Ground-based RS • A camera is required • The video format is used for machine vision
Above-canopy (pole)	• Very high resolution • Feasibility of capturing whole plant canopy • Feasibility of estimating plant height using an image and scale-pole reference	• Daytime application • Measurement interference due to background	• Ground-based RS • A camera is required • DOF and irradiance can be implemented • The video format is used for machine vision
Above-canopy (UAV)	• Very high resolution • Fine flexibility Useful for plantation mapping and plantation boundary recognition	• Accuracy depends on the density of shade trees condition • High cost of equipment and maintenance • A short period of power consumption	• Aerial RS • A camera is required • Position, DOF, and irradiance sensors can be implemented • The video format is used for machine vision
Terrestrial	• Multipurpose measurements involving plant height, tree diameter, leave angle, and width of the canopy • Measurement of gap fraction • Identifying shade tree condition (using Azimuth camera position) useful for 3D object reconstruction	• The background can affect the measurement • Daytime application • Need for the standard measurement position	• Ground-based RS • A camera is required • DOF and irradiance sensors may be required • The video format is used for machine vision

measurements from a pole, and measurements with UAVs (Fig. 1). Each method has its advantages and disadvantages, which are presented in Table 2.

In Indonesia, poor internet connectivity prevails in remote areas. Therefore, image processing and analysis cannot be conducted in a cloud application. Fig. 2 shows two DSS models that adopt various technologies and are applicable in various network infrastructure conditions. Technologies such as web services, mobile ad-hoc network (MANET) and routing [40,41], quick response (QR) [42], machine vision (MV) [43], augmented reality (AR) [44], artificial intelligence (AI) [45], web/mobile GIS [46], and remote sensing (RS) [47] can be used simultaneously or in a series called hybrid application systems. Hybrid application systems are needed to accommodate the analysis of collected data, which can be done using a desktop application on the farmer's side and implementing the government policy through internet application. Fig. 2a shows a DSS model for farmers/smallholders where the network infrastructure is available (even with a poor connection) in the plantation. Fig. 2b shows the potential use of MANET technology that links information exchange between farmers and the government/experts when the network infrastructure is not available in the plantation. In general, information exchange can be performed using any web service. According to Nugroho et al. [48], a control mechanism incorporated with web services is suitable for low and unstable internet connections, especially in rural areas. Using these services, the government agencies play an important role in updating the information on the farmer's side using a calibration model, such as a DSS, and in simultaneously collecting data from the farmers related to what the farmers update in their desktop/mobile applications.

Smallholders, agricultural extension officers, and the government have leading roles as DSS enablers. Smallholders are responsible for surveying and retrieving images of plant-condition data according to the recommended schedule, as well as processing data with applications provided by the agencies in the form of desktop or mobile applications. Besides, farmers can obtain recommendations in the form of web/mobile maps, AR, or other DSSs based on data obtained from survey fields and other information provided by the agencies/experts.

The agencies/experts play a role in developing both desktop and mobile applications (such as MANET, QR, MV, AR, AI, web/mobile GIS, and RS). Also, they update the models, weather information, and any related information on the farmers' application, which aims to support decision-making and provide recommendations.

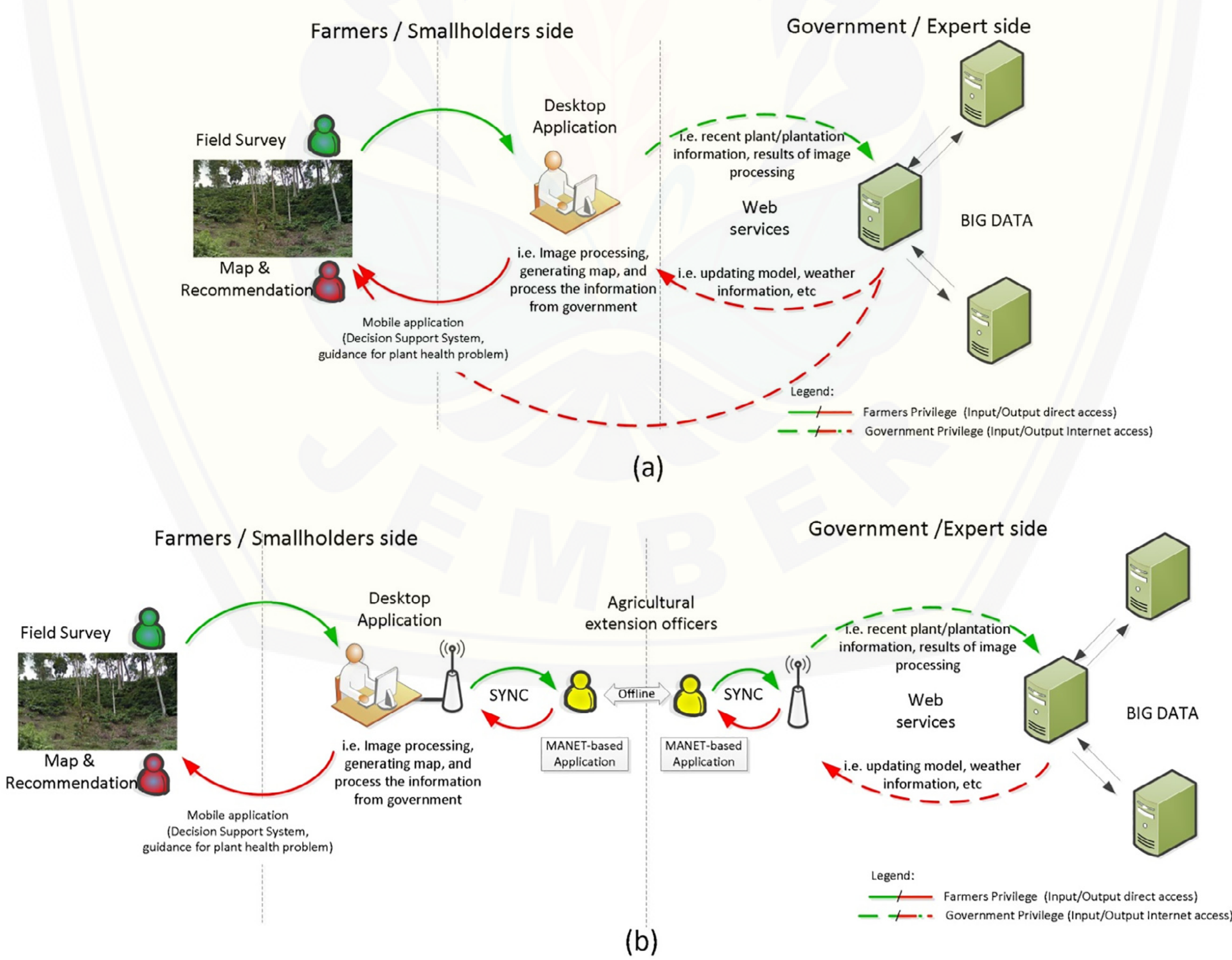

Fig. 2 – Model of a decision support system for farmers/smallholders: (a) network infrastructure is available; (b) network infrastructure is not available.

Agricultural extension officers are assigned to mediate farmers and the government, supported by MANET-based applications in carrying out this role. MANET-based applications can be used to solve the problem of lack of network infrastructure. By utilizing the MANET-based application, agricultural extension officers who visit farmers or the government can synchronize the data obtained from the survey automatically.

4. Utilization of positioning sensors in a plantation

The use of ground-based GPS tracking may face difficulties for plantation mapping, due to varying vegetation densities in agroforestry areas. The uses of aerial vehicles for boundary mapping are recommended to overcome these difficulties. Although farm boundary and plantation mapping are required, these are the most crucial steps, and therefore, should be conducted first (i.e., in the land clearing process) before conducting other farm activities. An assisted GPS (A-GPS)-enabled mobile phone can be used to position sensors in the plantation, but these sensors are proven to be less accurate than commercial autonomous GPS (i.e., Garmin). According to Zandbergen [49] and Zandbergen and Barbeau [50], the median error of A-GPS is ~ 8 m. This error may increase due to the density of shade trees and the availability of cellular services. However, this problem can be solved by several options: first, the public agencies provide aerial mapping and draw the plantation boundaries. Second, the government or an expert provides the mobile application that has editable recorded positioning data obtained from the field survey for field boundary correction.

With this boundary identification, the coordinate of each plant in the plantation area can be identified to determine the uniformity of distance between primary plants and the total number of secondary plants (i.e., shade trees). The coordinate of each plant will be used for future plant management related to the plant position. This technique can be an alternative method for smaller plantations with or without shade trees where acquiring information from an aerial vehicle may be difficult. Obtaining such information is even more difficult in the case of plantation areas with intercropping as the corresponding plant may be hidden by other plant canopies. Fig. 3 shows different plantation conditions with different planting patterns and conditions of shade trees.

The abovementioned issue is not evident in mapping the plantation area of cereal crops, such as wheat, paddy, and corn, because UAVs can sufficiently generate the plantation map of these crops for providing the crop information as the plantation is mostly situated in open fields with no shade trees. In the plantation area, however, the use of UAVs may help only in mapping. Nonetheless, it faces difficulties in matching the exact position coordinates while performing ground-based checks to recognize and identify a particular plant, due to different canopy widths, plant heights, and densities of shade tree day-by-day.

5. Implementation of the framework

Sustainability of agricultural and forestry commodities can be obtained by establishing cooperation and collaboration between farmers/smallholders and the government. Through this system, the public agencies contribute directly and carry out actions to support farmers. The inputs from farmers/smallholders are required to support the interaction between the government and farmers. However, mobile applications are useful for transferring information from governments and/or farmers' desktop applications based on the survey data related to particular farm activities.

The QR generator and reader applications are required in plant identification and its recorded data history. The outputs of these field surveys are maps and recommendation related to each field activity. Unlike cereal crops, the maps of perennial crops are relatively homogenous, especially in terms of plant coordinates/pattern. Therefore, positioning sensors are not required in every farm activity. The use of QR technology is promising in offering high accuracy and consistency in recording and minimizing human error in plantation management [51]. Different nutrient needs, yield, pests and disease occurrence, and other plant health indicators in each plant are the main reasons for improving plantation management systems.

The main key to plantation management is identifying the plantation area. By figuring out the boundary of the planta-

Fig. 3 – Various plantation conditions (coffee, cocoa, and rubber trees).

tion area, farmers/smallholders can recognize the total number of primary plants, nutrients, shade trees, and secondary plants that need to be planted and applied to obtain the maximum yield. Many farmers/smallholders in rural areas do not know the exact plantation area that they cultivate. Therefore, the total yield of smallholders is not optimum, compared to the availability of their plantation area [52]. The protocol of plantation mapping using a QR code as a plant identifier is presented in Fig. 4.

The major inputs from the farmers are the information extracted from the images of the field survey. To support the protocol presented in Table 3, a detailed process to analyze the images for particular agricultural monitoring purposes should be conducted in farmers' desktop applications. Some detailed processes of particular agricultural monitoring, such as counting yield kernels in coffee branches and counting mango fruit, were discussed by Zandbergen [49] and Zandbergen and Barbeau [50], respectively. The protocol of image processing for handling the images obtained from the field survey is shown in Table 3.

Qian et al. [42] and Tarjan et al. [53] optimized the use of QR technology for continuously tracing the agro-food chain between different process chains. The results showed that the continuous traceability between different process chains can be implemented using extended breadth, deepened depth, and improved precision. Therefore, QR can be utilized for on-farm application [54]. The QR system can be used to easily recognize the captured images of a QR code and link them to a particular position of an individual plant in the plantation. The QR code is also used continuously for plant identification and recorded during the measurement and as time series to primarily recognize individual plant health. However, the plantation condition, including the illumination, varies to a large extent. Thus, according to Liu et al. [55], using the QR code is also feasible across various illuminations. A printed QR code of a particular size used for labeling trees or plants can also be used as a reference for an alternative method for recognizing the bole diameter, plant height, and plant measurement identity (Fig. 5). The QR technology can be adopted in precision agriculture for tracing and monitoring each plant's health in the plantation without worrying about ways in which the plant information can be recorded over a period of time.

Web/mobile GIS is a potential technology that can be implemented to these integrated systems. This technology is mostly applied to support efficient, accurate, and rapid decision-making in agricultural monitoring [46,56,57]. With this application at the end level for implementing DSSs, farmers/smallholders can easily recognize the historical data of each plant and determine the activities that need to be conducted next, by scanning the QR code of the plant using their mobile devices.

6. Challenges and prospects

The challenge is how to integrate various methods proposed by some studies [43,47,59–61] for plantation monitoring using a consumer-grade camera and corresponding sensors as a

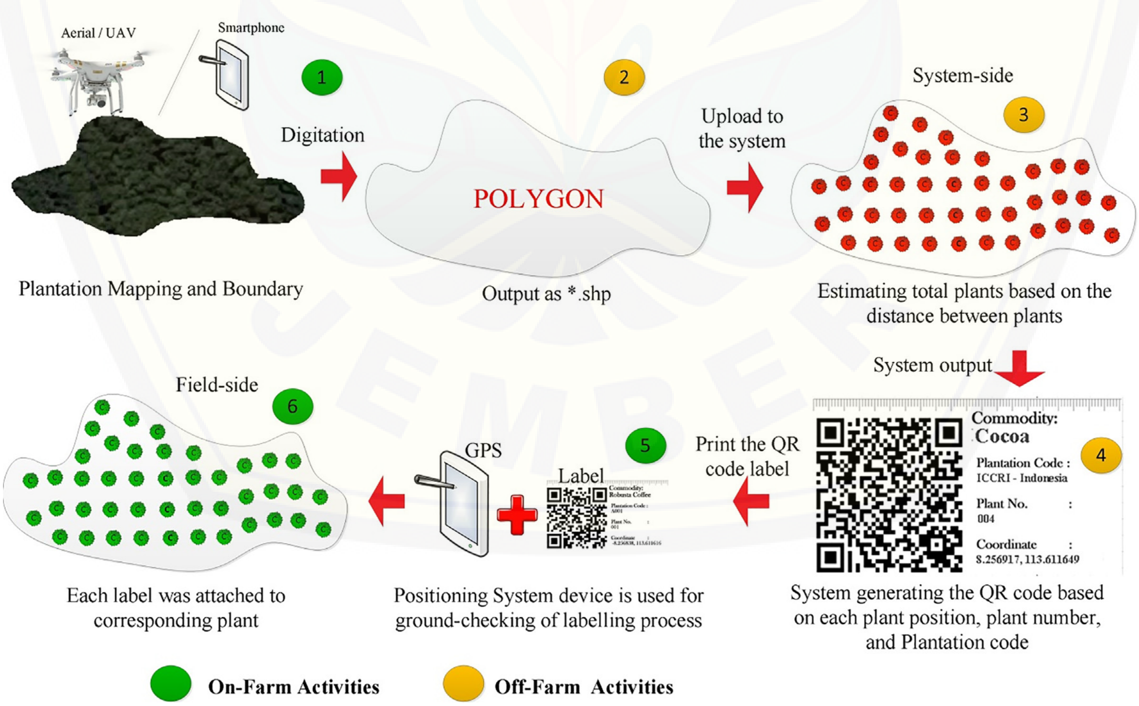

Fig. 4 – Protocol of plantation mapping using a QR code as plant identifier: (1) mapping the area to be used for plantation is considered once, except extensive or narrowed plantation areas; (2) the map generated by a UAV/mobile-based tracking or a Google map can be used for digitation (output as *.shp); (3) system application for processing all inputs from field surveys, including the plantation boundary for other plantation management purposes; (4) one of the outputs is the QR code, which corresponds to plant position, number, and any information related to plant properties; (5) GPS is used for ground-based checks in the labeling process; and (6) the results are labeled plants for future management.

Table 3 – Learning-based protocol to process image information.

Process protocol	Remark
Input: • Upload/copy pictures from SD card of the camera to a particular folder in the computer (PC) • Upload/copy the reference data related to additional information of the sensors (if applicable)	Pattern of capturing the object should be in sequence. The object can be a single leaf for direct-leaf measurement or the canopy cover of each plant for above-canopy measurement. For example, the sequence order in capturing three different leaves per plant in terms of assessing leaf greenness: 1. Capture the QR of the 1st plant → image1.jpg 2. Capture the 1st leaf of the 1st plant → image2.jpg 3. Capture the 2nd leaf of the 1st plant → image3.jpg 4. Capture the 3rd leaf of the 1st plant → image4.jpg 5. Capture the QR of the 2nd plant → image5.jpg 6. Capture the 1st leaf of the 2nd plant → image6.jpg 7. Capture the 2nd leaf of the 2nd plant → image7.jpg 8. Capture the 3rd leaf of the 2nd plant → image8.jpgMachine learning is required for the QR identification of each image and other analytical purposes
Step 1. Scan all images in a particular folder to extract the header of image information and recognize the QR code to identify each plant information	**Output:** 1. Date and time taken 2. Plant position information 3. Other image-header information 4. (i.e., image1.jpg and image5.jpg are recognized as QR codes containing plant information)
Step 2. Extract RGB information of selected images corresponding to each QR	1. In addition to scanning the printed QR code, nowadays QR code information can be easily extracted from the captured file/image. 2. All images related to the recorded plant are sequenced after capturing the QR code file until the upcoming QR files are located.
Step 3. Embed the image information and additional information from the sensors properly in the database	"File name" of image and "date taken" can be used as references to recognize additional information of the sensors
Step 4. Process the recorded data according to the available information	1. Calibration models with particular information (i.e., climate data) provided by the government are required 2. Internet connection is required. Information is received through web services
Step 5. Generate map and DSS	This information is required by the government for monitoring and observationThe DSS can be an augmented reality (AR) or virtual reality (VR), which is used for monitoring and field observation [44]. Previous field measurement information can be displayed with this technology when making observations.

Fig. 5 – QR code as a plant label reference to estimate (a) coffee fruit properties; (b) cocoa fruit properties; (c) plant height identification.

complex and integrated sensing system. Support from the government in providing and implementing technologies is required. The challenges and prospects of some agricultural monitoring in plantations are explained below.

6.1. Nutrient monitoring

Previous studies [18,62,63] have explored the nitrogen content at the plant level by analyzing the greenness information of plant leaves. Although the sum of nitrogen uptake is commonly linear with the uptake of other nutrients, information related to the need of other nutrients, such as phosphorus (P) and potassium (K), is limited. A deeper exploration and a combination of some parameters may be useful for estimating other nutrient needs. According to the Indonesian Coffee and Cocoa Research Institute [64], besides nitrogen (N), other macronutrients such as P and K are highly correlated with tree diameter, plant height, and branch length.

6.2. Pest and disease monitoring

Another prospect lies in exploring the potential use of optical sensors to assess the information related to pest and disease monitoring [65]. Several types of pests and diseases were identified successfully using consumer-grade cameras, which can help to identify hundreds of pests and diseases present in a particular plant. Pests can be monitored easily by identifying the pest carriers such as worms and insects. Conversely, diseases can be recognized by identifying the presence of symptoms in plants.

6.3. Yield monitoring

Ramos et al. [24] developed a close-range machine vision system to count and identify harvestable and non-harvestable fruits in coffee plants. Although this system provides acceptable results, more detailed exploration of such methods is required by incorporating additional parameters. For future research, incorporating image property components, such as F-stops and other information from sensors like DOF, can increase the measurement distance.

Plant height and diameter are usually considered for identifying yield. Studies conducted by Jiang et al. [66] and Hämmerle and Höfle [67] can be adopted to estimate plant height in the plantation area. These parameters are used to estimate the quality and quantity of wood in industries and latex/rubber production. Most farmers/smallholders perform measurements manually and record measurement data improperly. A specialized tool of a specific brand, such as Forestry Pro by Nikon®, is still expensive for smallholders in developing countries. The use of cameras may be feasible in providing low-cost devices for smallholders.

7. Concluding remarks

In this paper, a critical review on using image information for plantation monitoring in terms of a DSS has been conducted. This study aimed at delving further into research on plantation monitoring and the implementation of technologies to enable effortless plantation activities by smallholders. A digital camera potentially offers information regarding plantation management. These sets of information include nutrient management, pest and disease management, yield monitoring, and other activities in the plantation. The review highlights the future research potential related to the use of image information for plantation management, especially in areas with high-density trees, agroforestry, and narrow plantation areas. This paper draws the following conclusions and recommendations:

1. The public agencies and experts could play active roles in improving the basic infrastructure, especially in processing the images/video information to support the decision-making of smallholders.
2. Possible issues worth further research include handling image/video information through MANET, QR, MV, AR, AI, web/mobile GIS, RS, data processing, and scheduling by both farmers and the experts, and cloud computing. To implement big data in the field of agriculture [58], especially in developing countries, there is no need to wait for the even spread of network and sensor infrastructure. One of the recommended solutions is to use image information obtained from consumer-grade cameras, including both mobile cameras and regular cameras. If a remote area has no infrastructure, the data could be taken periodically by agricultural extension officers utilizing applications based on MANET [40,41]. The data can be analyzed in the cloud server based on the proposed system framework, and then, the analyzed data are sent back to the farmers by the extension officials using MANET-based applications.

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Conflict of interest

The authors declare that there is no conflict of interest.

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