Environmental engineering and sustainability for smart agriculture: The application of UAV-based remote sensing to detect biodiversity in oil palm plantations

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Abstract. The United Nations strongly support the progress towards sustainable agriculture, food security, sustainable management of life on land in a simultaneous approach. Oil production, though on increasing demand, is causing severe loss of biodiversity in tropical areas, Indonesia being the country with the most environmental damage due to this crop. Geographical Information Systems (GIS) and Unmanned Aerial Vehicles (UAVs) for base-remote sensing are promising tools to help with environmental conservation in oil palm plantations and to improve production efficiency and quality of crops. While different UAVs exist in the market, multi-rotor UAVs have already been used for oil palm plantation monitoring. There are more than 100 different Vegetation Indices (VIs); the Normalized Difference Vegetation Index (NDVI) is often used in smart agriculture. Still, there is a huge need for algorithms that assess floristic diversity. To maintain some elements of the Indonesian biodiversity within oil palm plantations, experimentation with algorithms were carried out. The imagery shows great potential for future research.

Keywords: UAV; remote sensing; vegetation indices; biodiversity; oil palm plantations.

1. Introduction

The United Nations agreement in 2015 aim to generate progress towards sustainable agriculture, food security, climate action, and sustainable management life on land in a simultaneous approach (UN General Assembly, 2015) For that reason, the development of drone-based technologies for oil palm plantations is part of the efforts to make the industry more environmentally sustainable. During the last ten years, the scientific community has given increasing attention to oil palm expansion and its negative consequences for ecosystems (Dislich et al., 2017). The majority of taxonomic groups including fungi, plants, bees, beetles, ants, amphibians, birds, and mammals, show decreased richness and overall abundance in plantations (Foster et al., 2011). Palm oil has become the most consumed vegetable oil in the world, and the global demand for this fat is expected to increase (FAO, 2016). Besides, palm oil has the highest production among other oil crops, such as soybean, rapeseed and sunflower (Chong et al., 2017). The oil palm (Elaeis guineensis) is a palm species planted extensively in South-East Asia, especially in Indonesia, Malaysia, and Thailand (Petrenko, Paltseva and Searle, 2016; Chong et al., 2017). In 2017 the global oil palm production rose to 66,855 million tonnes, and Indonesia alone produced 34 Mt (Iskandar et al., 2017). Presently, Indonesia is the world’s largest and most rapidly growing producer (FAO, 2017). Indonesia intends to realize and maintain a 7% annual GDP growth
rate, and become one of the world’s tenth largest economies by 2025 (Anderson et al., 2015). Thought the future demand for edible oil is estimated to amount to around 240,000 Mt in 2050, requiring an additional 12 million ha of palms, if average yields continue to rise as in the past years (Corley, 2009). Moreover, the production of palm oil is highly cost- and area-effective compared to other oil crops, this trend is projected to continue in Southeast Asia and other tropical regions (Fitzherbert et al., 2008). To promote better oil palm management practices is necessary to monitoring oil palm plantations. However, it can be time-consuming and expensive (Chong et al., 2017). In the attempt to use time wisely, we should consider updated measurement techniques, instruments, tools, and technologies to describe vegetation in an area at different scales (Grebner et. al. 2012). Unmanned Aerial Vehicles (UAVs) have emerged as important and useful platforms for acquiring remotely sensed data of vegetation, offering the ability to collect imagery with high spatial and temporal resolution (Heaphy et al., 2017). The development of a biodiverse and properly functioning oil palm landscape is a vital conservation priority of the modern era. The objectives of this project research are to review the UAV technology applications within and oil palm plantations and to present an approach to measure plant diversity by detecting background vegetation. Furthermore, this research could be useful to improve the ecosystem services in oil palm plantations. Considering the role of oil palm for the local economy, food security and environmental conservation, a sustainable management is required (Camara et al., 2018).

2. Smart agriculture
2.1. Precision Agriculture
Diverse definitions for Precision Agriculture (PA) exist and many people have different ideas of what PA should encompass. Precision farming or precision agriculture is a farming or agro-industry management concept based on observing and responding to intra-field variations (Whelan and James, 2010). Smart agriculture can promote variable management practices autonomously within the agricultural fields, according to the site conditions (Norton and Swinton, 2018). It relies on technologies like Global Positioning System (GPS) and remote sensing imagery. This technology is capable to (1) optimize production efficiency; (2) optimize quality; (3) improve environmental site conditions and (4) minimize risk (Whelan and James, 2010).

3. Remote sensing
Remote sensing has become an essential tool in fields such as ecology, agriculture, forestry, geography as image capture from the air provides information about the earth’s surface (Coops and Tooke, 2017). Remote sensing is a valuable method to monitor the status and progress of oil palm development, to assist in decision-making for an efficient plantation management and to investigate the effects of oil palm plantations on the environment (Zolkos, Goetz, and Dubayah, 2013; Chong et al., 2017). Thus, remote sensing devices detect a portion of the electromagnetic radiation (table 1), examples are gamma rays, x-rays, ultraviolet, visible light, infrared light, microwaves and radio waves; differences exist concerning their wavelengths (Padua et al., 2017). The sensors used in remote sensing can be categorized as either active or passive (Coops and Tooke, 2017).

According to Shamshiri et al., 2018, remote sensing operations in oil palm plantations can involve several activities, for example 1) Set up and operate a multi-rotor UAV remote sensing system for oil palm plantations; 2) To produce 2D and 3D visual maps of the fields under study; 3) To produce vegetation indices (VI) and Geographical Information System (GIS) maps for health and growth assessment and 4) to record diverse dendrometrics such as canopy size, crown diameters, palms distance and calculate yield per palm and yield per ha (Shamshiri et al., 2018). Despite the increasing importance of new survey tools such as unmanned aerial vehicles (UAVs) and processing software, the implications of how their spatial deployment may interact with species detection have not yet been assessed (Baxter and Hamilton, 2018).

| Table 1. Electromagnetic spectrum of remote sensing. |
|-----------------------------------------------|
| Wavelength (nanometers) | Ultra Visible | NIR | Water absorption | SWIR | LWIR | MWIR | 1mm | 1m |
|------------------------|---------------|-----|-----------------|------|------|------|-----|-----|}
| Ultra Visible          | 400–750       |     |                 |      |      |      |     |     |
3.1. Sensors and vegetation indices

The essential component for carrying out remote-sensing activities is the imaging or sensing payload, which defines the capabilities and the usability of the UAV (Siebert and Teizer 2014; Padua et al., 2017). From low-cost commercial digital single lens reflex cameras to expensive equipment, such as LiDAR sensors, that are specially designed for drones, various options are available (Heaphy et al., 2017; Klemas 2015). The most common sensors (Figure 1) used for forestry and agriculture are, 1) Red-Green-Blue (RGB); 2) Near Infra-Red (NIR); 3) Multispectral; and 4) light detection and ranging (LiDAR). Examples of the imagery that each sensor generates are shown in Figure 2.

![Figure 1. The Most common cameras in the market. RGB: (a) GoPro (b) Canon G9X (c) Panasonic DMC (d) Sony Alpha 7; Near-infrared NIR: (a) Canon S110 (b) Panasonic Lumix 7 and (c) Fujifilm X-M1; Multispectral sensors: (a) Parrot Sequoia; (b) multiSPEC 4C; (c) Tetracam ADC; and (d) MicaSense RedEdge; LiDAR: (a) the Routescene lidar Pod; (b) the Yellowscan Mapper; and (c) the Velodyne PUCK (Padua et al., 2017).](image)

![Figure 2. Example of sensor imagery: a) RGB (Goodbody et al., 2017); b) Near-infrared (geovantage.com); c) Multispectral: (skylab.global); d) LiDAR: (flight-evolved.com).](image)

The Red, Green and Blue (RGB) imagery is often used to generate Digital Terrain Models in agriculture and forestry, this sensor is used for tasks where no special spectrum is required, for example; forest canopy gaps inspection (Getzin, Wiegand, and Schöning, 2012). The Near Infra-Red sensors, are used to detect plant health and plant identification (Torresan et al., 2017). The LiDAR sensors can penetrate the tree cover, being able to generate accurate measurements of biomass and understory plants, but this type of sensor is more expensive and requires specialized software for imagery analysis (Padua et al., 2017). According to Shamshiri et al., 2018, Multispectral sensors can be used to 1) analyse oil palm stress factors, soil types, the need of fertilizers, or insecticides; 2) identify and differentiate plant species or recognize other plants such as weeds; 3) monitor soil and chemical conditions that are, in each case, able to be identified by their unique spectral signature and 4) graphically illustrate vegetation indices such as the Normalized Difference Vegetation Index (NDVI). A Vegetation Index (VI) refers to the ratio of reflectance values at different wavelengths and is commonly used to understand plant photosynthetic activity and structural variations of plants (Huete et al., 2000; Putra and Soni, 2018). Many VIs have been developed and tested for estimation of biophysical parameters of vegetation (Onyia, Balzter, and Berrio, 2018). Information about plant health, water content, environmental stress are often described as vegetation indices (VIs); there are more than 100 existing VIs, which are grouped into seven
categories (Xue, and Su, 2017). For example, the category of Broadband Greenness is used to describe the vigor and health of green vegetation (Ozdemir, and Sumer, 2013). Figure 3 shows the most common VIs belonging to the Broadband Greenness category.

One of the important tasks of remote sensing operations is identification of native an exotic plant species by using the vegetation indices (Shouse, Liang and Fei, 2013); results can propose a better and more adequate plant management within plantations. The determination of vegetation composition by remote sensing is based on the principle, e.g. that every tree species has its own spectral signature (Lisein et al., 2015). However, spectral reflectance patterns from plants are very similar even across different species, making differentiation between invasive and native species a very challenging task using remote sensing (Shouse, Liang, and Fei, 2013).

For the identification and quantification of plant species, UAV high spatial resolution (at centimeter level) is therefore very useful as spectral differences among species can be detected (Ivosevic, Han, and Kwon, 2017). Just a few studies specifically focused on the identification of background vegetation using remote sensing (Lass et al., 2005, Asner et al., 2008; Ustin and Santos, 2010 and Waldchen et al., 2018). Given the technological advances in remote sensing and the increasing demand for automated identification of plants among crop systems, this area of research can generate strong contributions to sustainable land management.

3.2. Unmanned Aerial Vehicles (UAVs)

The potential of UAV in the oil palm industry is enormous as it provides monitoring efficiency, high resolution imagery and it is especially useful for tropical countries where clouds are a serious obstacle for satellite image acquisition (Chong et al., 2017). There are two main types of small UAVs: fixed-wing and multi-rotor (Figure 4). Each type has its own advantages depending on the environment and required task (Padula et al., 2017). Advantages of drones are cost-effectiveness for small projects, very high resolution, positional accuracy; while disadvantages are: sensitivity to bad weather and subject to governmental regulations (Padua et al., 2017).

The fixed-wing drone can travel several kilometers from the launch point, being suitable for mapping with applications in land surveying, agriculture, and forestry. This type of UAV can achieve image resolution up to centimetre level. For take-off is possible by hand or small launch ramp, the flight time is usually up to 1 h, and the payload capacity is small (Lisein et al., 2014). The multi-rotor drone relies on a set of propellers arranged around its core. Multi-rotor drones have an image resolution at millimeter level. They have vertical take-off and their flight time usually is low (approximately 30 min). The payload capacity depends on the number of rotors (Padua et al., 2017). Because of the low-cost and high efficiency, multi-rotor UAV has been used extensively for forestry, spatial ecology, and agriculture surveys, for example; Rokhmana, 2015; Yilmaz et al., 2017 and Goodbody et al., 2017.
4. Oil palm plantations

4.1. Plantation development of oil palm
Most of the world’s species diversity is concentrated in the humid tropical forest, the ideal habitat for oil palm production (Hoffmann et al., 2010). The expansion of oil palm is, therefore, most likely to directly impact tropical biodiversity (Chong et al., 2017). Oil palm plantations without a proper sustainable management plan can affect severely biodiversity and promote land degradation (Schrier-Uijl et al., 2013). According to Dislich et al., (2017) after the productive time of oil palm plantations, in many cases is more feasible to establish a new plantation. The establishment of an oil palm plantation requires to clearing the land, either mechanically or with fire, remove lianas, epiphytes, shrubs and other plants. Between 2007 and 2010, 350,000 ha of oil palm plantations were established annually (Obidzinski et al., 2012). Nowadays, Indonesia is the world’s largest and most rapidly growing producer of palm oil (FAO, 2017). About 10% of Indonesia’s palm oil production comes from government plantations, 40% from smallholders, and 50% of the plantations are private (IPOC, 2006). Oil palms are now grown throughout 43 countries (18.1 million ha), with Indonesia (7.1 million ha) and Malaysia (4.6 million ha) together accounting for about 85% of global crude palm oil production FAO (2017). Indonesia’s biodiversity has been severely damaged by the oil palm plantations (Curran et al., 2004; Mantel et al., 2006). However, according to Foster et al., 2011 and Anderson et al., 2015, investigations related to biodiversity in oil palm plantations are very scarce. Approximately 1100 about oil palms were published; only 4 percent of these focused on biodiversity and conservation, and more than half of those manuscripts have been focused on policy and meta-analysis, rather than the provision of field-based data (Foster et al., 2011).

4.2. Oil palm structure
Oil palm plantations have a simpler structure than forests: the upper canopy is dominated by only one species with a uniform tree age structure, lower canopy, sparse undergrowth, less stable microclimate, and greater human disturbance (Figure 5) (Danielsen et al., 2009; Foster et al., 2011). The understorey of oil palm plantations is hotter, drier, and receives more light than the forest understorey (Drescher et al., 2016). As a result, the high levels of disturbance and propagate pressure, oil palm plantations contain weedier and more unusual, successional plants species than forests (Foster et al., 2011). Oil palm starts to yield fruit 3 – 4 years after planting; Bunches ripen 5 – 6 months after pollination. Seeds normally require temperatures about 35 Celsius to germinate (Duke, 1983). Besides, oil palm requires fertile and well-drained soils (Danielsen et al., 2009). A planting density of 130–140 palms per ha is usually practiced but it varies according to the planting conditions and the type of oil palm breeds (Corley and Tinker 2008). The ability of oil palm plantations to provide habitat depends on plantation age and management intensity (Teuscher et al., 2015).
Figure 5. Vegetation structure of oil palms, ground vegetation and leaf litter in plantations. Young plantations are 8 years since planting, old plantations are 22 years since planting. Statistical significance between old and young plantations indicated by *** for \( p < 0.01 \), ** for \( p < 0.05 \), and * for \( p < 0.10 \) (Luskin and Potts 2011).

4.3. Oil palm biodiversity understory

Because of the oil palm’s light requirements, plantation development generally requires that all other vegetation is removed (Danielsen et al., 2009). However, many oil palm understory vegetation can still grow and play an important role in conserving some elements of the Indonesian biodiversity (Koh and Wilcove 2008). Basri et al., 1995 reports that companies which adopt integrated pest management approach without pesticides, favor the establishment of beneficial plants to attract the insect predators and parasitoids of oil palm pests such as the wasp Dolichogenidea metesae. According to Teuscher et al., 2016 a total of 92 plant species were found in oil palm plantations in Indonesia. Of the 92 plant morphospecies, 64 could be identified of which 25 were alien species. The three most frequent species (Figure 6) were Clidemia hirta (Melastomataceae), Asystasia gangetica (Acanthaceae) and Paspalum conjugatum (Poaceae), which are non-native species.

Figure 6. a) Clidemia hirta (keyserver.lucidcentral.org); b) Asystasia gangetica (butterflycircle.blogspot.com); c) Paspalum conjugatum (singapore.biodiversity.online).

The conservation of forest species requires the preservation of large reserves of intact forest, but we must not lose sight of the importance of conserving biodiversity and ecosystem processes within the oil palm habitat itself (Foster et al., 2011). Besides, ecosystem functioning and the provision of ecosystem services within oil palm landscapes are potentially influenced by the relationship between understory vegetation and arthropods, e.g. biocontrol, pollination, decomposition and soil fertility (Foster et al., 2011).
5. Experiments and Results

5.1. Experiment Data
One goal of the project that is to be introduced is to determine the number and distribution of different species from the aerial imagery taken from a drone. As previously mentioned above, there are various different kinds of algorithms and parameters that can be used for this purpose. Moreover, the height where the image is taken could influence the algorithms and the finding. Taking image above the canopy could help finding the number of the palm trees but not to find the underlying plants. Therefore, the drone should also take image from lower height.

Some algorithms can work for both kind of images regardless of the height were those images are taken. In order to test and validate the usefulness of the algorithms, some images were taken from the surrounding plantation in the university Rhine-Waal green house in Kleve, Germany. Figure 7 to 9 show examples of the images.

In the first phase, two algorithms have been evaluated namely, colour separation algorithm and pixel conversion algorithm. These algorithms are typically used to extract certain features before applying more complex ones, such machine learning approaches. Both algorithms are implemented in MATLAB using image processing toolbox. The images are stored in the RGB format where each pixel stores 24 bits value with 8 bits for each channel.

5.2. Colour Separation Algorithm
The colour separation algorithm is used for separating and analysing the image on each different colour channel. The algorithm converts the image into three different greyscale images using three different colour channels. The intensity of the grayscale images depends on the applied colour channel. This algorithm is quite fast and helpful in separating objects which have different colour properties, e.g. separating tomatoes from their leaves. The images were scaled into the desired size before applying this algorithm.

The grayscale images can be easily evaluated, as the darker the image the lesser the amount of the colour in the corresponding channel and vice versa. Figure 7 and Figure 8 shows two images with corresponding grayscale images after applying the colour separation algorithm. A scale ranging from 0 to 255 shows the transition from black to white respectively as reference.

![Figure 7](image1.png)

**Figure 7.** a) Original RGB image of onion plants and a hose pipe. b) Red channel separated. c) Blue channel separated. d) Green channel separated. e) Scale for comparison.

![Figure 8](image2.png)

**Figure 8.** a) Original RGB image of dead grass with some green plants. b) Red channel separated. c) Blue channel separated. d) Green channel separated. e) Scale for comparison.
The grayscale images from each channel can be processed further on to find certain plants or objects. Applying simple threshold value on a channel can immediately remove the background image and leaving the object of interest in the foreground for further process. Two different channels can be subtracted from one to another for finding certain colour scheme of the objects. Other operation can also be applied in order to find different objects.

5.3. **Pixel Conversion Algorithm**

The pixel conversion algorithm is a further development of the colour separation algorithm. This algorithm can be used to differentiate whether the target object presents in a particular image or not. Depending on the main colour channel of the sought object, the original image and the three greyscale images can be compared in order to discover some region which might contain hidden object with the same features which difficult to distinguish on the original image with all colour displayed.

An example of the application of this algorithm is to determine the occurrence of certain species on the image. In the example in Figure 7, the red channel greyscale image from the colour separation algorithm is used to distinguish between grass and leaves with other species or objects. The pixel which denotes the species can be retained on the image resulting an annotated greyscale image. The result of this process is shown in Figure 9, where the grass and leaves are still visible in their original colour while other objects or species in greyscale. This algorithm might be too trivial for further processing with computer but it provides great advantages for human operator. This is needed in the later process where machine learning will be used for further processing the images, where human expert can work on the annotated images and mark the species in the training data set.

6. **Conclusion and Outlook**

According to Chong et al., 2017, some relevant applications of remote sensing in oil palm plantations are land cover classification, change detection, tree counting, age estimation, pest and disease detection and yield estimation. The type of sensor should be considered, because technical limitations may affect data analysis. The UAVs available in the market can be grouped into fixed-wing and multi-rotor. For small projects, multi-rotor UAVs are cost-effective while also obtaining high resolution data. The vegetation indexes are an essential part of smart agriculture in terms of identifying plant spots that may be related to the proper function of ecosystem services among the fields. As oil palm expansion among the tropics tends to keep on increasing, studies are needed to understand how species diversity varies in different oil palm contexts (Meijaard and Sheil, 2013).

In planted areas, biodiversity management considers the diversity and structural complexity of vegetation and promotes diversity by increasing the height and coverage and by letting plants that cover the ground thrive (Koh et al., 2009). A successful and efficient conduct of planting operations requires a good layout design where remote sensing could contribute to providing the necessary information prior to and during the planting process. The investigation of Teuscher et al., 2016, reveals possibilities of integrating botanical information from ground plants into an algorithm. Plant diversity must be conserved within the remainder of the landscape to provide potential support to a variety of other
ecosystem functions such as pollination, biological control, litter and dung decomposition, maintenance of water quality and environmental awareness (Foster et al., 2011).

The results obtained using two simple algorithms show great potential for finding the amount and distribution of species on the image automatically. In this preliminary experiment, the algorithms can create annotated image with the target species in focus which allow human expert to count the species objectively and then label the image with the corresponding value. This step is the first step for creating training data set for machine learning which will be applied on the aerial imagery taken form the UAV. In addition to the machine learning algorithm, further object classification and recognition algorithms will be investigated further. Evaluation of various different algorithms will also be conducted to evaluate the performance of those algorithms. The performance metrics will later on be used to justify whether there is one powerful algorithm which can perform the task alone or various different kind of algorithms are needed to come with reasonable results. With the help of this kind of algorithms, a method shall be developed to determine the biodiversity of palm oil plantations. Indicators can then be derived from this in order to improve the management of the plantations.

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