An RGB sensor-based aerial robotic platform for sustainable precision agriculture

Ayodeji Opeyemi Abioye (corresponding author)
Lecturer & Researcher
Robotics, Control, and Autonomous Systems, Department of Electrical and Electronics Engineering, Modibbo Adama University of Technology, Yola.
abioye.ayodeji@mautech.edu.ng

Nathan David
Senior Lecturer
Department of Electronics Engineering, University of Nigeria, Nsukka.
nathan.david@unn.edu.ng

Abstract

The communication between aerial and ground is beginning to have enormous benefits in Agriculture by modernising the ways in which farmers work. The application of Unmanned Aerial Vehicles (UAVs) is therefore becoming widely accepted as it is beginning to have a huge impact on food sustainability and security. The aim of this paper is to present an on-going research on the use of aerial robotic systems for practising sustainable precision agriculture by small and medium scale maize, rice, and sugar cane plantation farmers in the West African savannah. The objective is to design and develop practical UAV-based solutions that would enable the adoption of the precision agriculture farming technique by these farmers. The proposed method involved the development of a 450 mm quad-rotor UAV platform with RGB sensor for capturing high-resolution RGB image data, to be analysed using a combination of computer vision, machine learning, and photogrammetric techniques, to extract useful information for appropriate application of the precision agriculture techniques. From the image data analysis, farmers would be able to monitor crop health, pest invasion, detect weed, crop diseases, monitor farm irrigation requirement, crop growth, and estimate crop yield. The overall intention is to develop sustainable methods in farming that would increase the crop yield, minimise the use of chemicals while optimising both production and profit based on real time information.

1 Introduction

Over the last five decades, there has been a growing shift from traditional agricultural practices to precision agriculture. This is due to the evolution of satellite and manned aircraft technologies to support the more efficient technique of precision agriculture. However, the downside of this is the fact that satellite and manned aircraft technologies are too expensive and therefore unaffordable to many small and medium scale, commercial and subsistence farmers. Within the last decade, there has been increasing shift towards the adoption of unmanned aerial vehicles (UAVs) in precision agriculture due to its lower cost and greater usage flexibility over the satellite and manned aircraft alternatives. But the problem is that the UAV often requires more expensive sensors such as the multi-spectral, ultra-spectral, and thermal infra-red sensors which may be large in size for the UAV payload cavity and too heavy for the UAV to carry in flight for long periods of time. These often results in the development of bigger and more expensive UAVs which may still be outside the available budget of small and medium scale farmers.

Therefore, in other to address this problem, we are proposing using a regular RGB sensor camera that is small in size, light weight, and has the capability of capturing high-resolution 4K images, combined with machine learning algorithm to synthesis some of the data normally collected for precision agriculture. In this research, a small 450 mm quad-rotor UAV platform, with RGB camera sensor installed, was developed and used to capture RGB images over an hectare of rice farmland, with the aim of developing standardised RGB vegetation map indices for common agricultural crops grown in the West African savannah; in order to support precision agricultural practices in this region, as well as the development of autonomous robotic solutions to support sustainable agricultural operation.

2 Literature review

2.1 Precision Agriculture

In precision or data-driven agriculture, high-resolution data are used to maximize agricultural output, while minimizing agricultural input. According to Bongiovanni and Lowenberg-Deboer (2004), precision agriculture is the application of "the right input, at the right place, at the right time with the right amount" through an integration of remote sensing, geographical information system (GIS), and global position system (GPS) technology with an effective agricultural management system (Norasma et al., 2019). In precision or data-driven agriculture, farmers are able to optimise the supply of water and application of fertilizer and pesticides, while maximizing agricultural productivity, quality, and yield.

Initial remote sensing efforts for precision agriculture involved the placement of remote sensors (thermal, multi-spectral, and hyper-spectral sensors) on towers over the crop field, where their fixed positions were the main limitation for data collection (Norasma et al., 2019). Other efforts included the use of manned aircraft flying over agricultural farmlands, capturing image data, for further processing. Satellite imaging is also being used in crop monitoring for very large agricultural farmlands, where the main limitations were its prohibitive cost, low image resolution, and its low sampling frequency (Norasma et al., 2019; Shamshiri et al., 2018). UAVs allow plant observation below cloud cover that prevents larger high-altitude aircraft and satellites from performing the same mission. They can be deployed quickly and repeatedly, and are less costly than piloted aircraft. They are flexible in terms of flying height and timing of missions, and can obtain very high-resolution imagery (Shamshiri et al., 2018). UAVs can be flown below clouds and in light rain (Berni et al., 2009). UAVs can carry multi-spectral sensors for soil and crop analysis (Van Der Wal et al., 2013). Advantages of the UAV includes low altitude flight, flying in cloudy and drizzly weather conditions, less economical expense, real-time capability and the ability for fast data acquisition, can fly below the clouds, imagery is available 'on-demand', images are geo-referenced, enabling direct links with GIS packages, and low maintenance (Norasma et al., 2019).

2.2 UAV applications in Precision Agriculture

UAV applications in precision or data-driven agriculture include weed detection and management, crop growth monitoring and yield estimation, crop health monitoring and disease detection, irrigation management, and pest monitoring and control.

Weed detection and management Weeds are undesirable plants growing among planted crops competing for available resources such as water, space, soil, sunlight, nutrient, etc. causing losses to crop yields and poor growth. In conventional farming, the predominant weed management technique is to spray the same amounts of herbicides over the entire farmland, including weed-free areas. The overuse of herbicides can result in environmental pollution, the evolution of herbicide-resistant weeds, and increased cost of weed management (Tsouros et al., 2019). To address this problem, images gathered by the UAV can be used to determine the weed distribution across the farmland, precisely showing where chemicals should be applied the most, the least, and where not needed.

Crop growth monitoring and yield estimation Regular collection of information and visualization of crops using UAVs, provides increased opportunities to monitor crop growth and record the variability observed in several parameters of the field such as biomass, chlorophyll, and nitrogen levels, which can be used to determine were additional fertilizers application may be required (Tsouros et al., 2019). RGB images captured by the UAV can be used in the creation of three-dimensional maps of crops and farmland showing crop height, and column and row distances between plants.

Crop health monitoring and diseases detection By scanning the farmland using UAVs carrying RGB, NIR, hyper-spectral, and multi-spectral sensors, it is possible to identify temporal and spatial reflectance variations before they can be detected by naked eyes and associate these changes with crop healths for an early response (Shamshiri et al., 2018), as shown in Figure 1. Diseases in crops can cause significant economic loss due to the reduced yield and the reduction of quality. UAVs can be used to monitor crops constantly to detect and contain the diseases in time and in order to avoid spreading to other healthy crops. UAVs can also be used to precisely target-spraying only the infected areas (Tsouros et al., 2019).

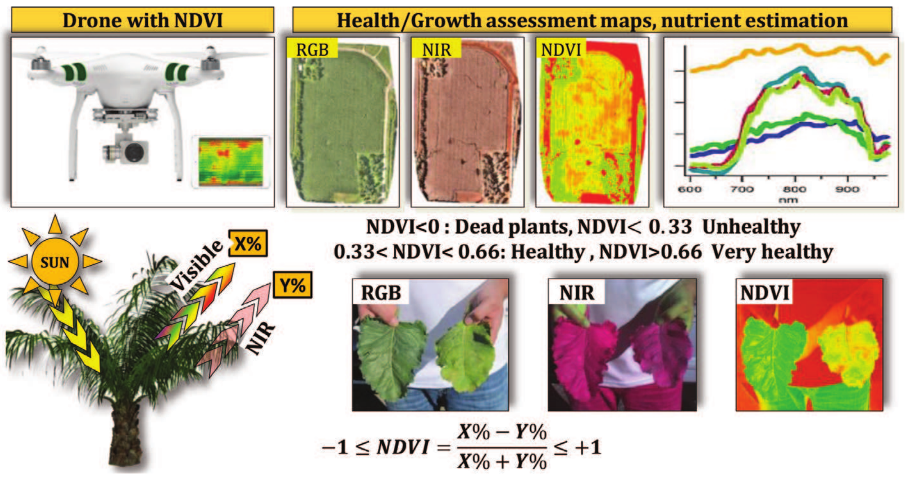


Figure 1: UAV sample NDVI mapping for health assessment and disease detection (Shamshiri et al., 2018).

Irrigation management It is estimated that 70% of the water consumed worldwide is used for the irrigation of crops (Chartzoulakis and Bertaki, 2015). UAVs can be used in precision irrigation to identify crop sections lacking sufficient water, thereby improving the efficiency of water use, by ensuring effective water application to the right place, at the right time, and in the right quantity. This would help the farmer save time and water resources, increased crop productivity, and quality (Tsouros et al., 2019).

Pest monitoring and control Pests on farmland affect crop growth resulting in poor yield. UAVs can be used in both monitoring and control of pest. A UAV equipped with a high resolution RGB sensor combined with a thermal sensor can be used to accurately identify areas of the farmland with pest infestation. UAVs can also be used in the control of pests by equipping them with pesticide carrying and spraying mechanism. With the aid of altitude and attitude sensors, UAVs can target-specific plant areas where pest are localised. This would increase the efficiency of pesticide application while reducing groundwater and soil pollution by spray chemical. Shamshiri et al. (2018) estimates that UAV spraying is five times faster than conventional tractor and machinery equipment.

3 Methodology

This research work is divided into three phases. The first phase involves routinely capturing RGB image data to study the RGB properties of maize, rice, and sugar cane plantation in the West African savannah. The second phase is to analyse and apply computer vision and machine learning techniques to the RGB images in order to extract useful data for precision agriculture. The third phase is the design and development of a pesticide and herbicide spraying UAV capable of carrying 10 kg payload with a 45 - 60 minutes flight time, as an integrated autonomous robotic solution to aid farming operation by precisely responding to crop needs.

3.1 UAV platform

The UAV platform developed for the first phase of this research was the Aiden Aide UAV, a small 450 mm span quadcopter with a Pixhawk flight controller, GPS for guided flight mode, a 2.4 GHz Turnigy TGY 9ch Tx / Rx radio controller, and a 915 MHz telemetry radio for telemetry data and way-point navigation. An SJCAM was installed onboard the UAV for capturing RGB images. The UAV weighs about 1.5 kg and has a 25 minutes battery flight time.

3.2 Mission planning

The QGroundControl station, shown in Figure 3, was used for mission planning. Two flight operations were performed during each weekly capture operation. First a manual flight and second a way-point navigation flight pre-programmed into the QGroundControl station as shown in Figure 3. The way-point navigation flight enables reliable repeatability of the weekly capture operation.

3.3 UAV aerial footage capture operation

The Aiden Aide UAV was routinely flown over an hectare of rice farm, capturing aerial footages, as part of the research into optimising, improving, and making future farming operations more sustainable, developing standardised RGB vegetation index, and automating tedious farming operations.

(a) Aiden Aide UAV test flight.

(b) Aiden Aide UAV GPS-ready.

Figure 2: Developed Aiden Aide UAV platform for phase one operation.

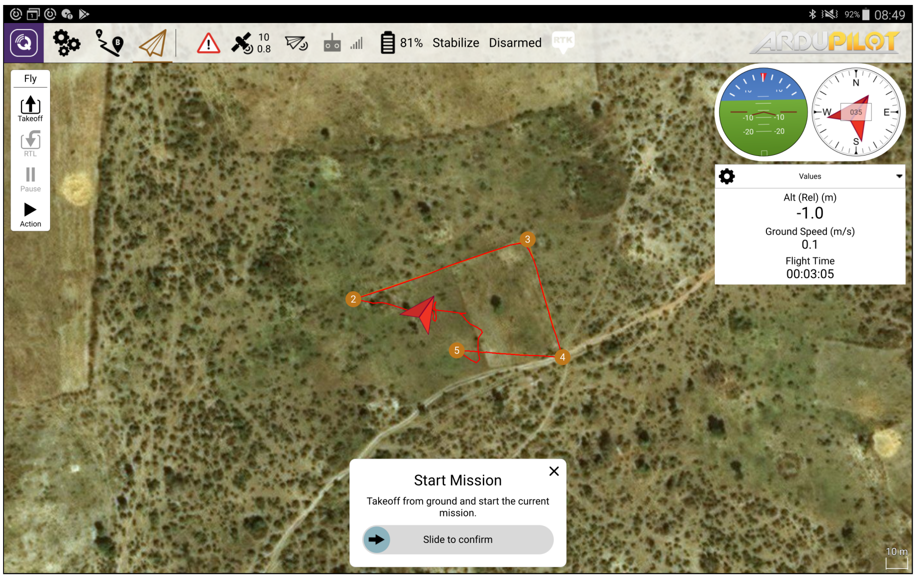


Figure 3: QGroundControl station mission planner way-point navigation screenshot - Week 5.

4 Results and Discussion

In this section, the result of the first seven weeks of the current rice farming season in North-Eastern Nigeria (mid-June to mid-October 2020), are presented, analysed, and discussed.

4.1 Result - Captured RGB images

Figure 4 shows the RGB camera aerial footage image capture for the first seven Weeks, except Week 2 aerial footage image, which was not captured. Also, due to mission planner failure, Week 4 and Week 6 aerial footage were captured via manual RC joystick control flight only.

From the RGB images in Figure 4, an increase in green vegetation cover due to planted group could be gradually observed. The five white patches in Figure 4c and the three white patches in Figure 4d are residual water collected after the previous rainfall (2-3 days). The more retentive the soil is to water the better the rice yield. Therefore, as the rain becomes more frequent over subsequent weeks, more water patches like these would be expected to appear all over the rice farm.

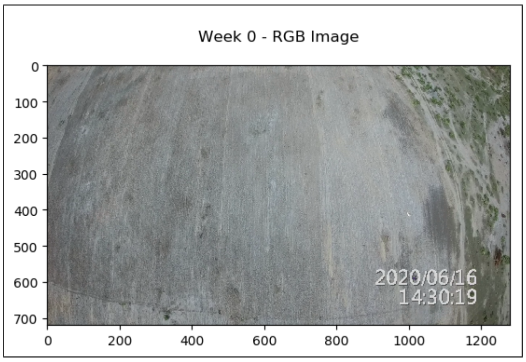
4.2 Preliminary image analysis

4.2.1 RGB image decomposition

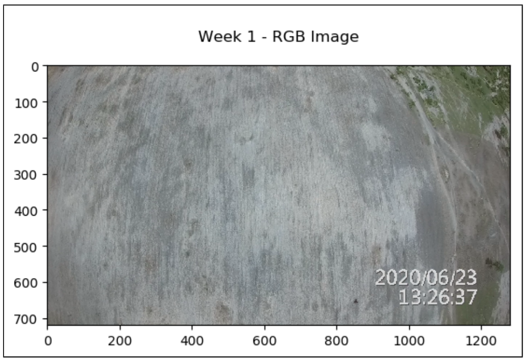
In order to extract information stored on different spectrum of the RGB sensor, the RGB image was decomposed into its constituent components of Red, Green, and Blue (using OpenCV), as shown in Figure 5. The components were compared to each other, in order to determine patterns of interests that could be useful in developing a standard RGB-based vegetation index map for rice farms in the West African savannah. The difference between these image components were not very visible. Therefore, the histogram of the RGB image components were computed and studied as presented in the following section.

4.2.2 RGB histogram analysis

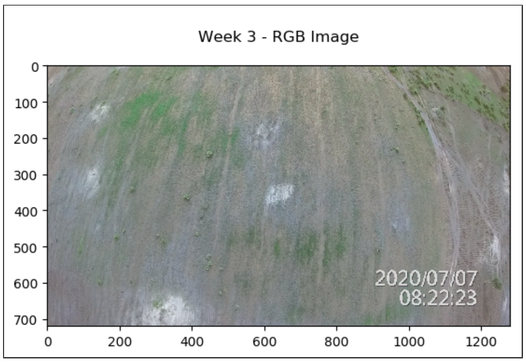
In order to calculate the histogram of the Red, Green, and Blue image components, OpenCV's *calcHist* function was used. Python's Matplotlib *pyplot* library function was used to plot the histogram. Figure 6 shows the histogram of each of the RGB images given in Figure 4. From these histograms, it can be observed that the Green component was becoming more dominant than the Red and Blue components, as the weeks progressed from Week 0 to Week 6. Therefore, the Green component was explored further in the following section.



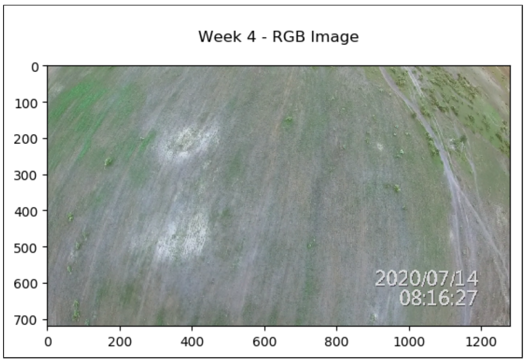
(a) Week 0 RGB Image.



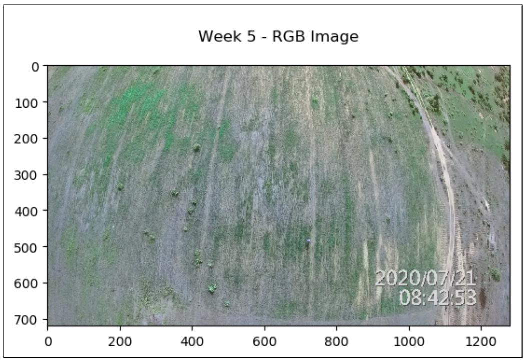
(b) Week 1 RGB Image.



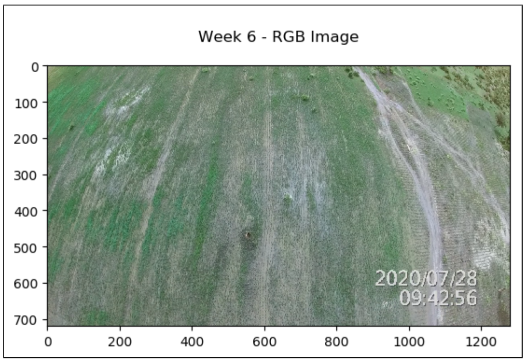
(c) Week 3 RGB Image.



(d) Week 4 RGB Image.



(e) Week 5 RGB Image.



(f) Week 6 RGB Image.

Figure 4: Six Weeks RGB Images.

4.2.3 Green difference

Since the Green component was becoming the most significant and dominant image component, an image analysis was performed to estimate and visual how significant this change was. A bitwise 'AND' operation was perform on the Red and Blue components using the OpenCV *cv2.bitwise_and(img1,img2)* function. The resulting image was used to generate an image mask, after image thresholding using *cv2.THRESH_BINARY_INV* and *cv2.THRESH_OTSU*. The image mask was combined with the Green image component using the OpenCV bitwise 'AND'

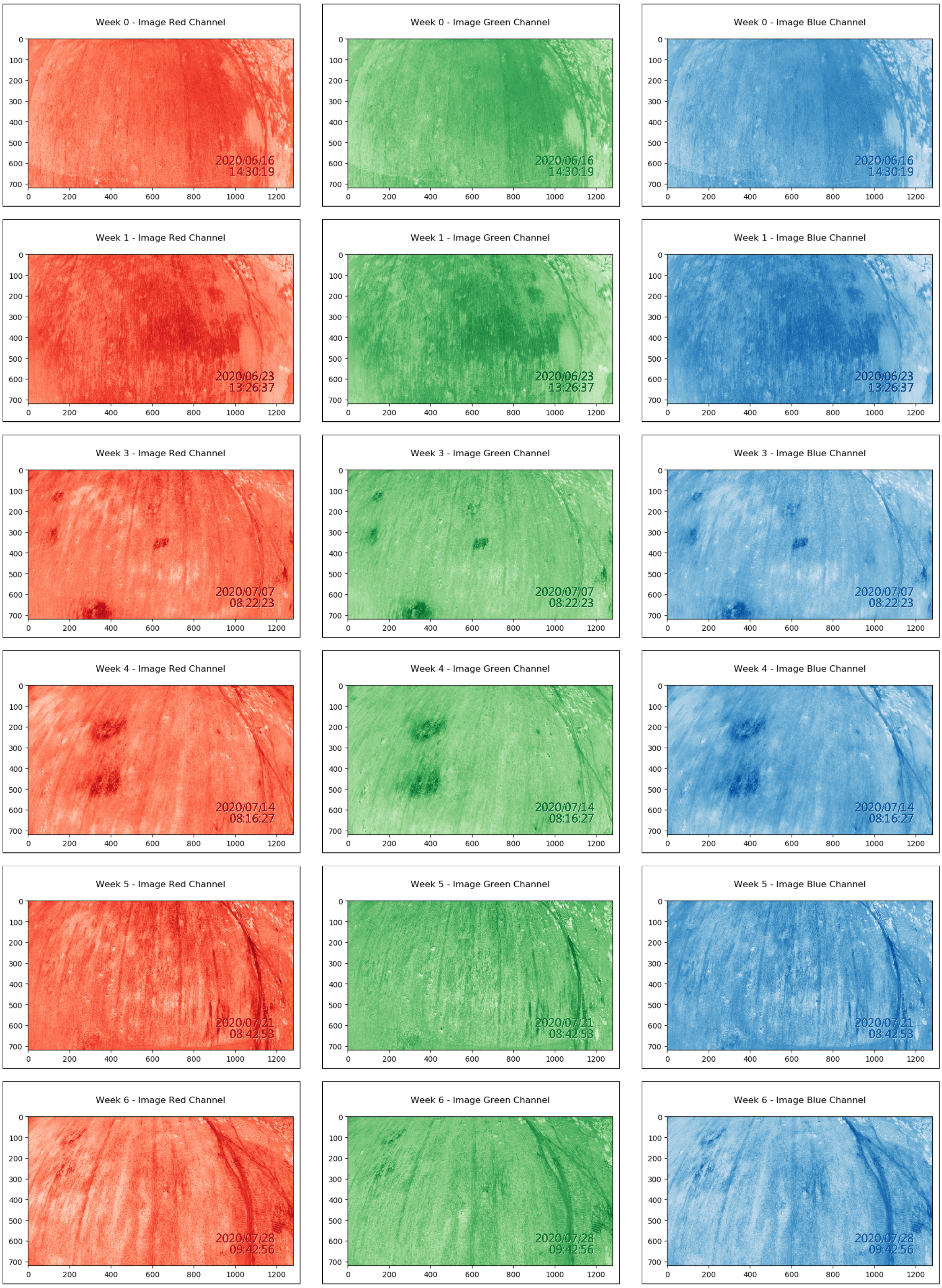
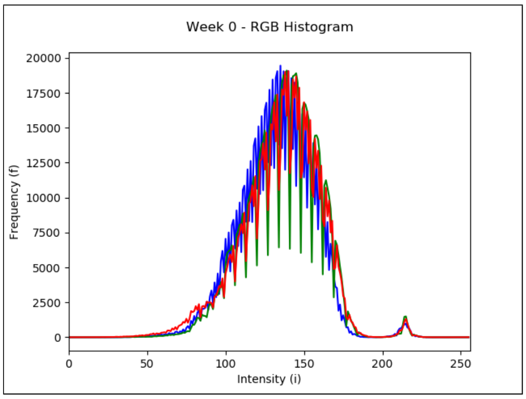
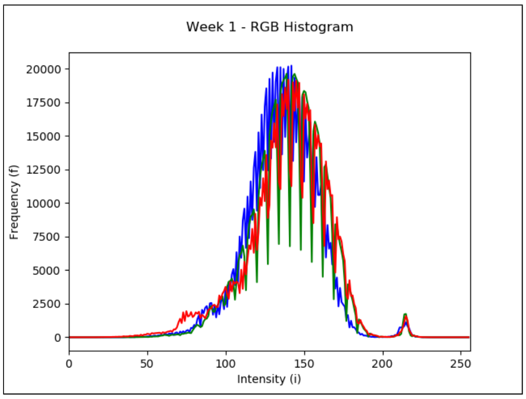


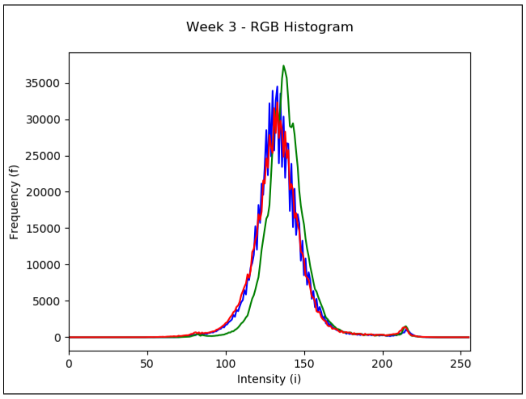
Figure 5: Week 0 - 6 Red, Green, and Blue image components.



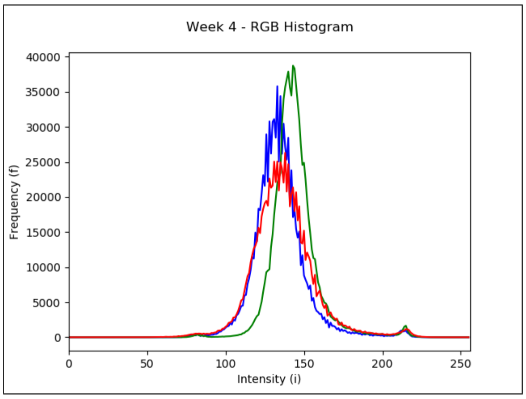
(a) Week 0 RGB Histogram.



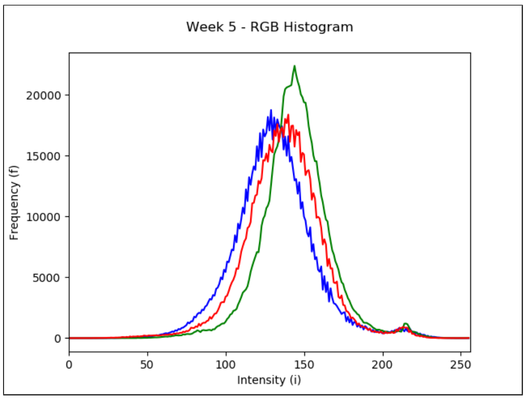
(b) Week 1 RGB Histogram.



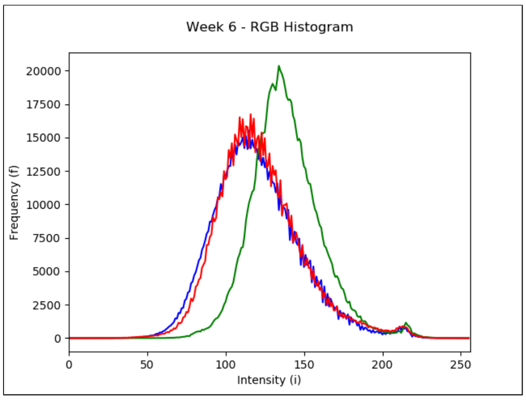
(c) Week 3 RGB Histogram.



(d) Week 4 RGB Histogram.



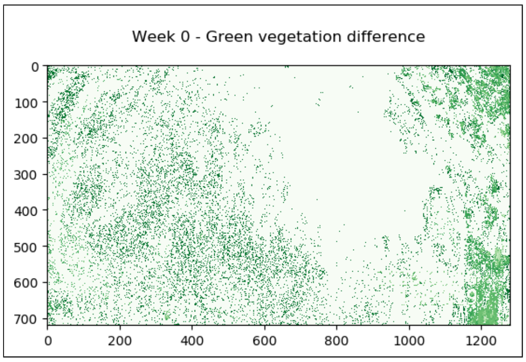
(e) Week 5 RGB Histogram.



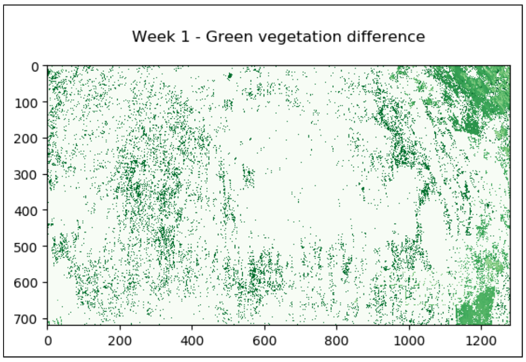
(f) Week 6 RGB Histogram.

Figure 6: Six Weeks RGB Image Histogram.

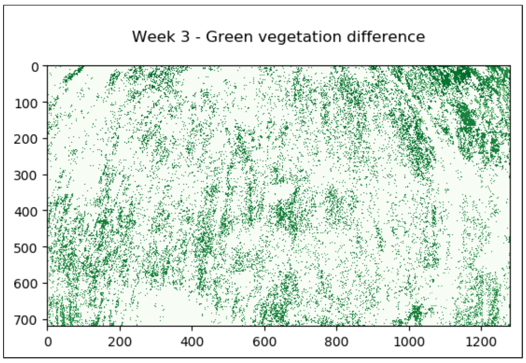
operation to give the Green difference images shown in Figure 7. From the resulting images, the distribution of the green vegetation was clearly visible.



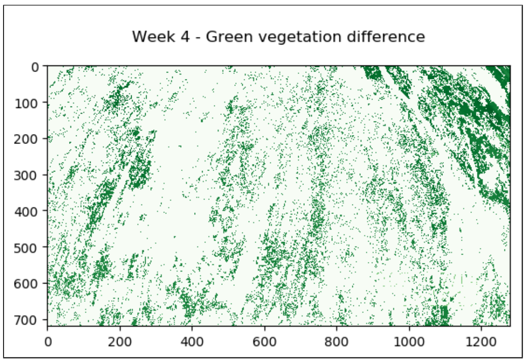
(a) Week 0 Green vegetation cover.



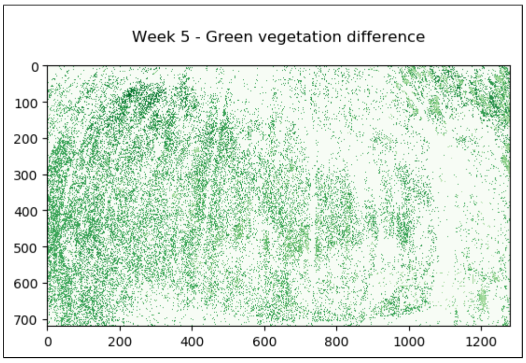
(b) Week 1 Green vegetation cover.



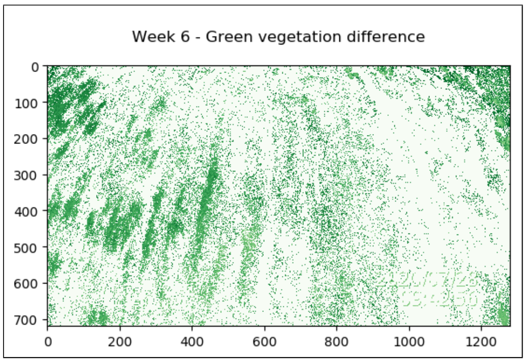
(c) Week 3 Green vegetation cover.



(d) Week 4 Green vegetation cover.



(e) Week 5 Green vegetation cover.



(f) Week 6 Green vegetation cover.

Figure 7: Six Weeks green vegetation cover.

4.3 Discussion

From the result and image analysis performed, the increasing green vegetation cover was clearly visible in the green difference images. However, it is unclear whether the green vegetation cover are signs of a healthy crop or weed infestation. A popular method of determining this difference is with the aid of multi-spectral and ultra-spectral sensors because each crop has a unique spectral signature that can be used to identify them. In order to develop an RGB sensor alternative to the popular alternative, advance image analysis involving machine learning would need to be applied to determine unique RGB spectral signatures of the rice crop.

The green difference images could be used to monitor crop growth and for early crop yield estimation. An standardised index could be developed to correlate crop age in weeks against expected green vegetation difference index benchmark, assuming the results remains consistent throughout the farming season and across subsequent farming seasons.

5 Conclusion

5.1 Summary

As part of the need to develop sustainable methods in farming that would increase crop yield, minimise the use of chemicals while optimising both production and profit based on real time information, we propose the integration of RGB sensor-based aerial robotic platform into the farming operation. In this research, a small 450 mm quad-rotor UAV platform was developed and used to capture RGB sensor images of an hectare of rice farmland. These images were captured weekly for the first seven weeks of the current farming season. The results were presented, analysed, discussed. From the histogram of the decomposed RGB image components, the Green components was observed to be increasing in dominance over the Red and Blue components from week to week. A green difference analysis was used to extract the green vegetation cover, which could be used for crop growth monitoring and early yield estimation. The green difference was also proposed to be used as part of the standardised RGB vegetation index for rice crops in the West African savannah.

5.2 Limitations

The lack of installed beacons on farmland to mark farm boundary affects flyover repeatability adjustment for distance, direction, and altitude. Also, the limits the accurate re-orientation of captured images for comparing images across successive weeks using artificial neural network or deep learning.

Although RGB sensors are low cost, light weight, small sized, have low energy requirement, can acquire high resolution images, and are easy to use, compared to the other types of imaging sensors, their captured image quality can be affected by weather and prevailing lighting conditions. They are inadequate for analysing several vegetation parameters that require spectral information in the non-visible spectrum, and are therefore commonly used in tandem with the other types of imaging sensors (Tsouros et al., 2019).

5.3 Further works

The UAV RGB sensor captured images would be used in the 3D reconstruction of the agricultural farmland using photogrammetric techniques to combine overlapping scene images. This technique would be used in extracting three-dimensional digital surface terrain models and orthophotos. Digital Elevation Models (DEMs) of the crops and orthomosaics can be created and used to extract specific information about the 3D characteristics of the crops such as crop height, density, canopy, etc. as described in (Tsouros et al., 2019).

Machine learning techniques such as artificial neural network and deep learning, would be applied to extract useful information from the RGB sensor data captured by the UAV, to distinguish crops from weeds in greed difference vegetation. Other parameters of interest includes: estimating crop growth rate, yield estimation, disease detection, and conducting plant census.

In order to further improve on the RGB sensor technique being developed for analysing vegetation parameters, specific spectral information not available in the visible spectrum, could be determined by combining the RGB sensor with multi-spectral, ultra-spectral, and thermal infra-red sensors.

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