BIOPHYSICAL CHARACTERIZATION AND ASSESSMENT OF MAJOR AGRICULTURAL CROPS BASED ON THEIR SPECTRAL REFLECTANCE IN BUTUAN CITY, AGUSAN DEL NORTE, PHILIPPINES

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ABSTRACT

This study demonstrates the significance of spectral reflectance in characterizing the biophysical condition of major crops in Butuan City, Agusan del Norte, Philippines. Spectral reflectance can be related to biophysical indicators of plant health. In this study, bananas, coconuts, corn, and mangos were considered, as they are major crops in Butuan City, according to the Bureau of Agricultural Statistics of the Department of Agriculture-Caraga. Reflectance spectra were measured just above the crop's canopy using an Ocean Optics USB4000 VIS-NIR. Five (5) sampling sites were visited assessed for each crop, with 100 samples measured. The setup was comprised of the sensor and associated fiber optics, that were positioned just above the canopy. A ladder and pole were used for tall trees such as coconuts and mangos. A spectrometer was connected to a laptop computer that performed the scanning procedure, displayed plots of the observed reflectance, and stored the reflectance data. The spectral measurements were performed in five modes (one on top of the canopy and four on the side of the canopy at 45o of separation) for bananas, coconuts, and mangos, while only three modes (one on top of the canopy and two on the side) were used for corn. Each mode involved 20 scans, the average of which represents the spectral reflectance of the sample at that particular site. For each 20-scan sequence, the average value represents the spectral reflectance of the sample at that sampling site. Each crop's average spectral reflectance curves were plotted using MS Excel 2013 to visually represent its biophysical characteristics. Based on the results, bananas, corn, and mangos had lower reflectance values in the visible region and a high reflectance value in the near-infrared region ranging from 40-70%, indication that they were heathy. However, coconuts were unhealthy indicated by their low reflectance values (10-25%) in the near-infrared region. The results were validated using field survey and yield data.

Keywords: Spectral reflectance, biophysical characterization, major agricultural crops, Visible Region (V.R.), and Near-Infrared Region (NIR)

1. INTRODUCTION

Agriculture continues to be a major source of gross domestic product, total employment, and livelihood of the rural sector. It is also the primary source of livelihood for the country, and poor households suffer most from food insecurity. Mindanao holds high prospects for agricultural development in the country. It is considered the country's food basket, supplying the country’s food requirements of about 40 percent and contributing more than 30 percent to the national food trade. However, food security is a big challenge in the country due to the adverse effects of climate change on agriculture and the food demand of the country’s increasing population.

Remote sensing plays a vital role in agriculture by providing timely spectral reflectance information that can be linked to biophysical indicators of plant health [1]. Quantitative techniques can be applied to spectral data, whether acquired from close-range or by aircraft or satellite-based sensors, to estimate crop status or condition [2]. Modern agricultural crop production relies on close monitoring of the crop status. This makes it possible to manage resources effectively for economical and environmentally responsible agricultural practices. The most commonly used monitoring technologies are based on point sampling of the crop's biophysical characteristics.

The reflectance of healthy green vegetation increases dramatically in the NIR, where from about 700–1300 nm, a plant leaf typically reflects 40–50% of the energy incident, and water content controls reflectance in the mid-infrared [3]. Healthy vegetation beyond 1300 nm typically absorbs or reflects incident energy, with reflectance peaks at about 1600 and 2200 nm. Absorptions occur because of water absorption around 1400 and 1900 nm, with the exact position of water absorption bands varying [4], [5].

Several studies showed that remote sensing techniques had been shown to be timely, non-destructive, and provide spatial estimates for monitoring vegetation conditions [2], [6]–[11]. Hence, this study was conducted to characterize and assess the biophysical condition of the major crops in Butuan City, Agusan del Norte, Philippines, from its spectral reflectance for crop management from the farmer level and appropriate action from the agricultural sector-related agencies.

2. LITERATURE REVIEW

Application of Remote Sensing in Crop Monitoring and Assessment

Remote sensing plays a vital role in agriculture by providing timely spectral reflectance information that can be linked to biophysical indicators of plant health. The condition of the crop, from seedlings to the status and trend of their growth, can be monitored by remote sensing. It is also helpful in obtaining data on crop productivity. There is a growing need to explicitly connect the two methodologies for mapping and monitoring vegetation conditions across a range of scales.

Modern agricultural crop production depends on close monitoring of the crop status. Remote sensing methods are increasingly being used to monitor a range of remotely detectable vegetation properties. This makes it possible to manage resources effectively for economical and environmentally responsible agricultural practices. The most commonly used monitoring technologies are based on point sampling of the crop's biophysical characteristics. [12].

At a large scale, gathering data on crop status early in the crop's growth is even more crucial than gathering precise production data after harvest. Recently, there has been growing demand to explicitly integrate the two approaches for mapping and monitoring vegetation conditions across a range of scales as remote sensing methods are used more frequently for monitoring various remotely detectable vegetation properties in developing technologies. Regional crop growth projections based on filed reports are often expensive, subject to significant mistakes, and unable to give spatially detailed, real-time forecasts or assessments of crop conditions.

Aircraft or Satellite-based Sensors

Since the 1970s, satellite remote sensing has emerged as one of the critical techniques for local, regional, and worldwide crop monitoring [13]. Satellite systems provide temporally and spatially continuous data covering most of the globe using relatively few instruments. Along with developing remote sensing applications, satellite data has become the uppermost source for monitoring large-scale crop conditions. USDA of the U.S. and FAO developed their crop monitoring systems based on remote sensing.

The availability of free medium- to high-resolution satellite data has opened up new possibilities for creating timely, all-weather satellite-driven crop monitoring capabilities at high geographical and temporal resolutions. The processing and information extraction capabilities of satellite data, combined with meteorological, soil, and elevation data, have been substantially improved by cloud computing platforms like Amazon, Google Earth Engine (GEE), and Microsoft A.I. for Earth [14]. However, satellite metrics do not accurately capture factors that affect agricultural yield and do not interpret crop growth quantitatively.

Although satellite data and processing capacities are no longer constrained, various institutes and agencies have used satellite-derived crop monitoring approaches to inform policymakers about crop production and food security problems. However, these approaches still do not provide near-real-time, reliable, and quantitative crop information [15].

Site-based Sensors

Compositional, structural, and functional qualities have long been evaluated using site-based approaches as indicators of vegetation status, and these methods are still commonly employed today [12]. It can provide near real-time and relatively low-cost information [16]. Measures of vegetation function are typically limited to observations of tree health and stress, including canopy health and the presence of plant parasites. For continuous sampling and narrow wave selection, spectral reflectance is a good and practical measure that can accurately reflect some physiological traits of crops [17]. The precise measurement of leaf spectral reflectance within the range of 350-1300 nm depends on the interaction between light and crops and its impact on the spectral properties of green leaves. To get the crop leaf spectral data, handheld or near-ground spectral sensors are often employed.

High-resolution hyperspectral digital multispectral sensors, spectrometers, and a variety of other ground optical sensors have been introduced to collect reflectance data at various regions of the spectrum to estimate crop productivity [18]. Field spectroscopy, a type of ground-based remote sensing, provides a large number of spectral bands recorded over the electromagnetic spectrum ranging from 350 to 2500 nm [4], [17], [19].

3. METHODOLOGY

Study Area

This study focused on characterizing the biophysical properties of major agricultural resources in Butuan City, such as coconut, banana, mango, and corn. The city has 816.62 km² total land area, of which 48.64% is an agriculture area, 32.82% is forestland, 7.48% is grass/shrub/pasture land, and 11.06% is built-up areas [11]. It simply shows that the city's primary utilization of the total area is devoted to agriculture. The study area and municipal boundaries are shown in Figure 1.

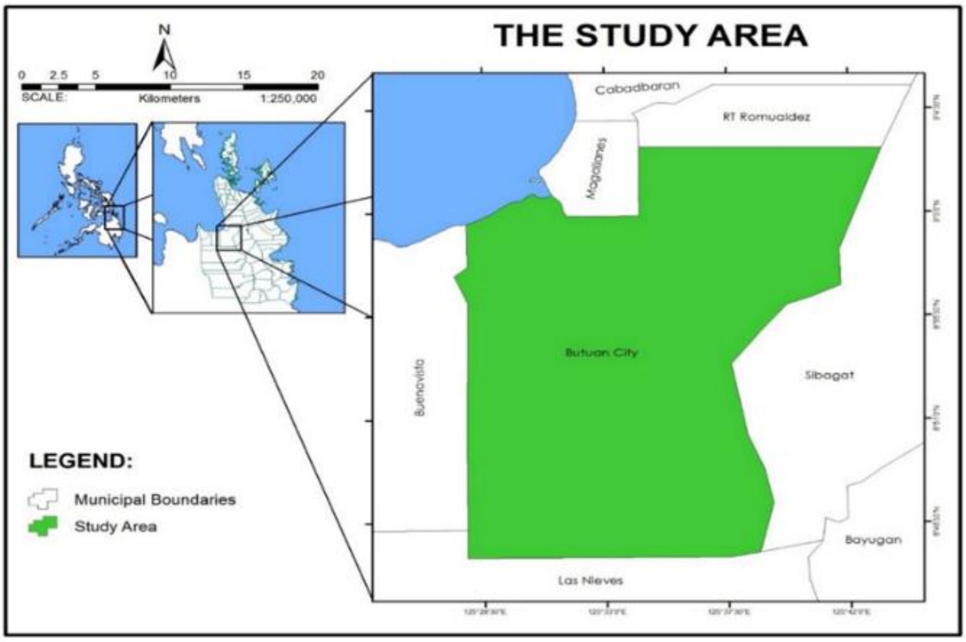

Figure 1 The Study Area

The conduct of this study involved (i) identification of the plantation areas of banana, coconut, corn, and mango, (ii) in-situ spectral measurements, and (iii) data processing for biophysical characterization of the major crops in Butuan City.

Identification of Plantation Areas of Banana, Coconut, Corn, and Mango

The plantation areas were identified based on the result shown in

Figure 2, an object-based image classification of the high-value crops using LiDAR data and color aerial imagery (orthophoto) of Butuan City with a high overall accuracy of 94.36%, Kappa Index Agreement (KIA) nearest to 93% [8]. This study was under the Phil-LiDAR 2 Project of Caraga State University, funded by DOST-PCIEERRD. Based on the result, the agricultural resources in Butuan City were mango, coconut, rice, corn, fallow, oil palm, and banana. Bananas, coconut, corn, and mango were among the top major agricultural resources in the city, contributing 0.5%, 13.67%, 0.02%, and 2.00%, respectively, to the total classified features in area distribution.

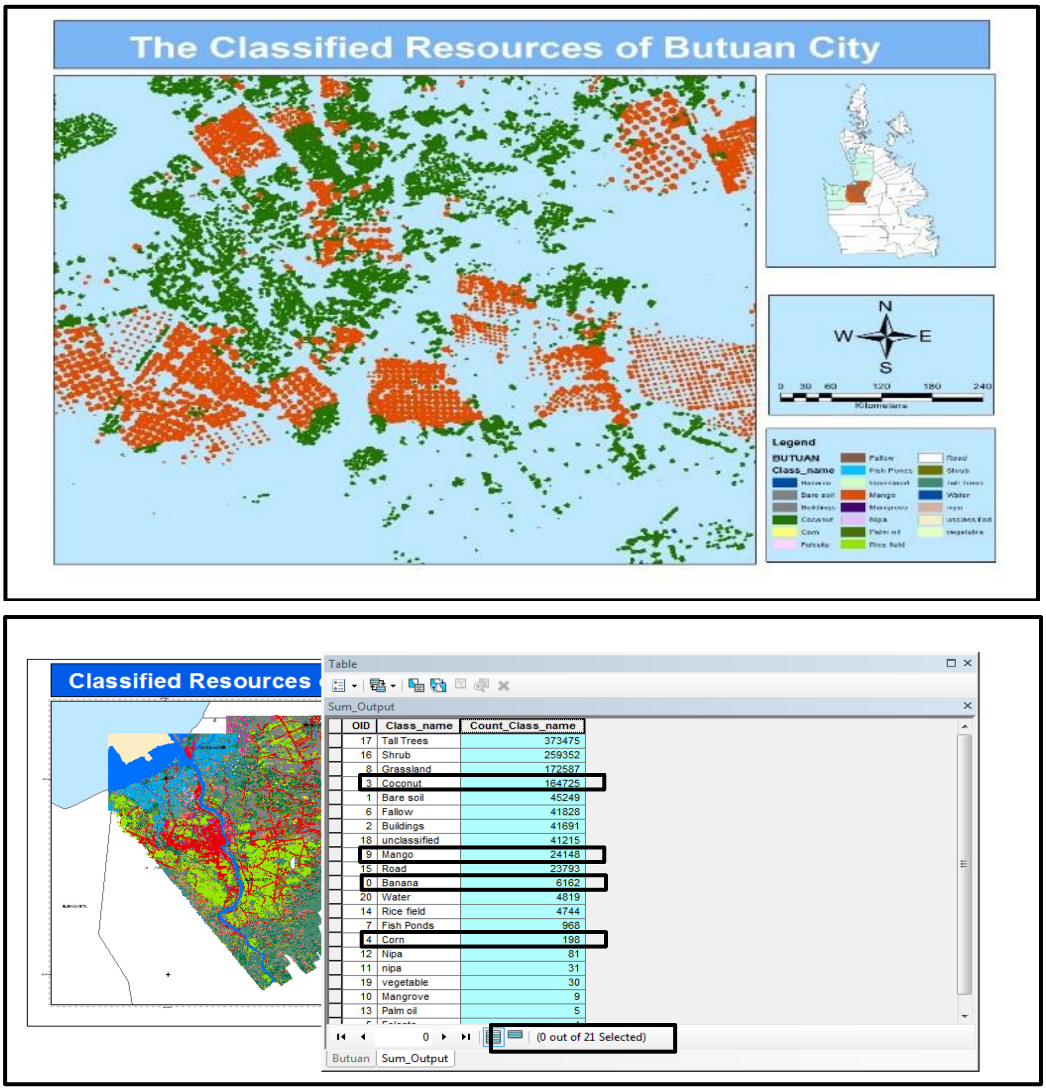

Figure 2 The Classified Resources in Butuan City and Its Areal Distribution

In-situ spectral measurement of Banana, Coconut, Corn, and Mango

Measurement of spectral characteristics for banana, coconut, corn, and mango was necessary to determine each crop's unique spectral signatures and establish a unique relationship between the sampled crop from the other high-value crops. For seasonal crops like corn, spectral reflectances of complete stages (vegetative, reproductive, and senescence stages) were measured.

The spectral reflectance curve of each crop was gathered on-site using Ocean Optics USB4000 VIS-NIR spectrometer. This plug-and-play instrument performs automated absorption and transmission across a wavelength range extending from visible to near I.R. wavelengths. The spectrometer was connected to a laptop computer that performed the scanning procedure, displayed the plot of the observed reflectance, and stored the reflectance data. For tall trees like mango and coconut, the sensor is mounted in an improvised pole, attached to fiber optics, and positioned just above the canopy. The sample setup of spectral measurements for corn and mango is shown in Figure 3.

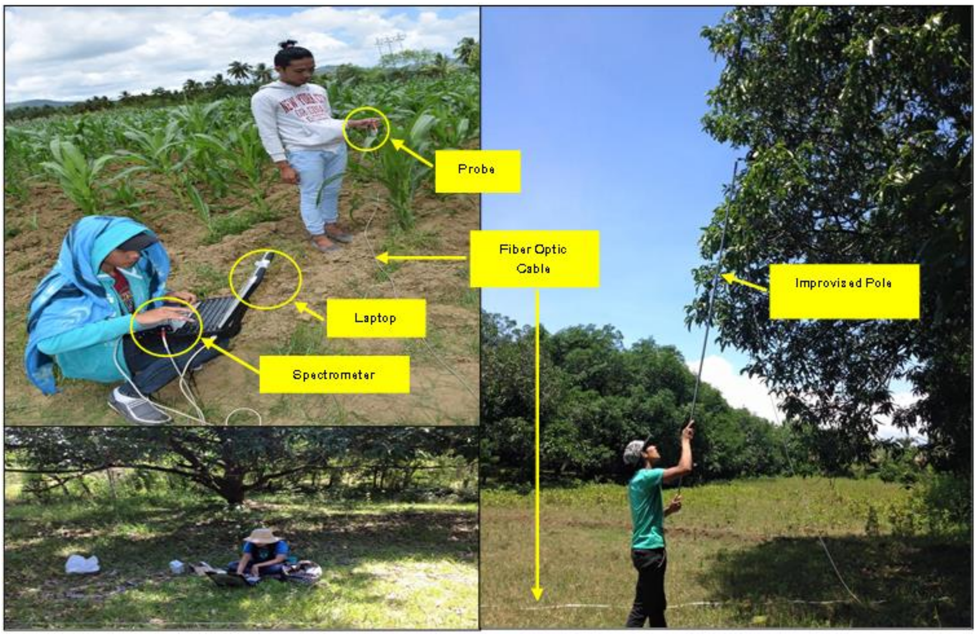

Figure 3 Actual Setup for Spectral Measurement of Corn and Mango

The measurements were taken on a clear sunny day between 9 AM to 2 PM intervals. Each sample taken had three trials, with 30 scans and measured within 2 minutes. Each trial has one dark reference and two light references (before and after crop measurement). These references also have 30 scans and were taken within 2 minutes, excluding the dark reference. For banana, coconut, and mango, the spectral measurement was performed in five modes (one on top of the canopy and four on the side of the canopy at 45 degrees separation) while only three modes (one on top of the canopy and two on the side) for corn. For each mode, it took 20 scans, the average of which represents the spectral reflectance of the sample at that sampling site.

All gathered data were converted to Microsoft Excel format, and the reflectance was calculated using the equation below.

$$R = \frac{L_{canopy}}{L_{panel}}\ x\ 100\% \qquad (1)$$

where R is the canopy reflectance, Lcanopy is the measured radiance above the canopy (average), and Lpanel is the radiance measured for the calibration panel.

Data Processing for Biophysical Characterization

The measured spectral reflectance was processed using Microsoft Excel. Spectral Data were compiled in one spreadsheet file to compute the average reflectance and graphically assess the spectral patterns of each crop. The spectral reflectance curve was then analyzed and interpreted the biophysical condition of the major agricultural crops.

4. RESULTS AND DISCUSSION

From the classified map, sampling sites were determined for field measurements. For bananas, field measurements were conducted in Brgy. Santo Niño, Lumbocan, Banza, and Cabcabon, while cornfield measurements were conducted in Brgy. Ampayon, Sumilihon, Taguibo and Cabcabon. In addition, field measurements for coconut and mango were conducted in Brgy. Bancasi, Pinamanculan and Sumilihon. The selection of sampling points was based on the area and yield production report from the Department of Agriculture-Caraga [20]. Figure 4 and Figure 5 show the sampling points of the major crops for spectral measurements.

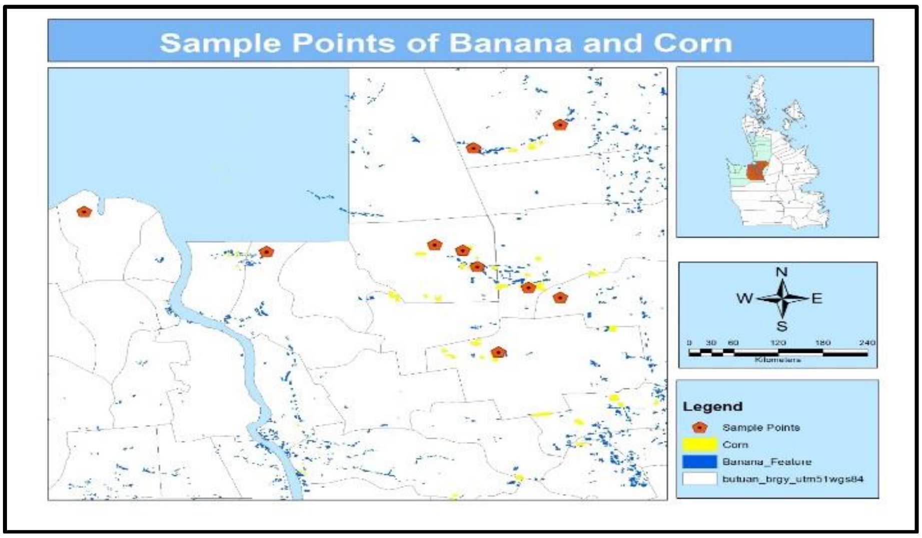

Figure 4 Sampling Points of Banana and Corn

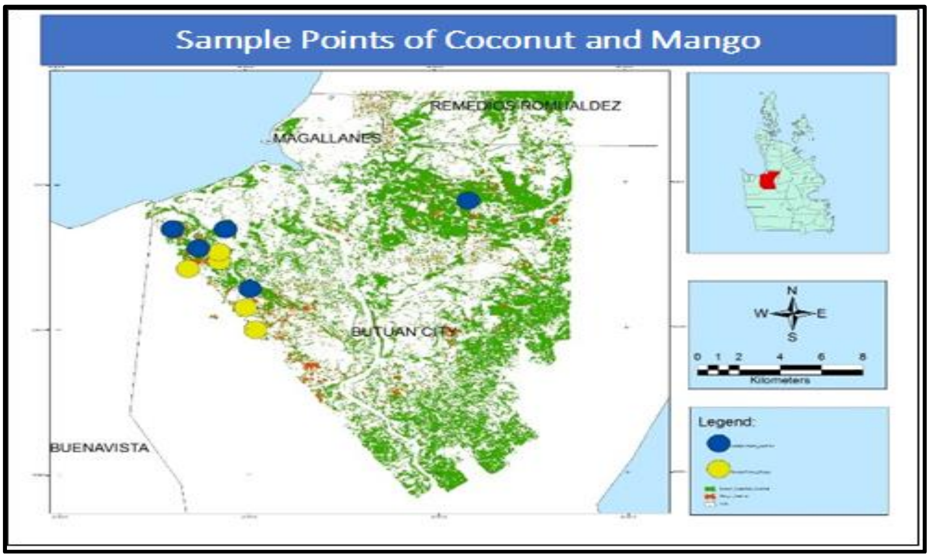

Figure 5 Sampling Points of Coconut and Mango

The physical characteristics of the banana, coconut, corn, and mango were determined based on their spectral reflectance measured during in-situ field measurement using a spectrometer. Its spectral reflectance can be detected in the three EMS regions as Visible Region (400-700 nm), Near Infrared Region (700-1350 nm), and Mid Infrared Region (1350-2500 nm). Visible Region has low reflectance, high absorption, and minimum transmittance. In contrast, NIR has reflectance and transmittance with very low absorption, and in MIR, both reflectance and transmittance decrease from medium to low [11].

In the spectral measurement, wavelength and reflectance values were measured, and the summary of the values for bananas is presented in Figure 6. Based on the results, the banana had a high reflectance value in the Near Infrared Region, with Sample 2 having the lowest reflectance value with a range of 30-50% at 700-800 nm wavelengths, while Sample 5 had the highest reflectance value of 40-75% between 700-800 nm wavelengths. It was observed during the fieldwork measurement that Sample 2 had experienced drying of leaves resulting in a lower reflectance value. Sample 2 was in the upland area where soil moisture was low.

The reflectance of healthy green vegetation increases dramatically in the NIR, where from about 700–1300 nm, a plant leaf typically reflects 40–50% of the energy incident, and water content controls reflectance in the mid-infrared. Healthy vegetation beyond 1300 nm normally absorbs or reflects incident energy, with reflectance peaks at about 1600 and 2200 nm. Absorptions occur because of water absorption around 1400 and 1900 nm, with the exact position of water absorption bands varying. With this, all samples were considered healthy vegetation, which adhered to the study of [3].

The same measurement was also conducted on coconut trees in the identified sampling sites. Spectral reflectance was measured in five samples using a spectrometer, and the result is shown in Figure 7. The result indicates that samples 1, 2, 3, and 5 reflectance values at the Near Infrared Region range of about 10-25% only, while the highest reflectance value was observed in Sample 4, ranging from 10-50% at 700-900 nm wavelengths. This implies that these samples were not in a healthy condition. It was noted during the fieldwork that these samples were experiencing drying and dying leaves.

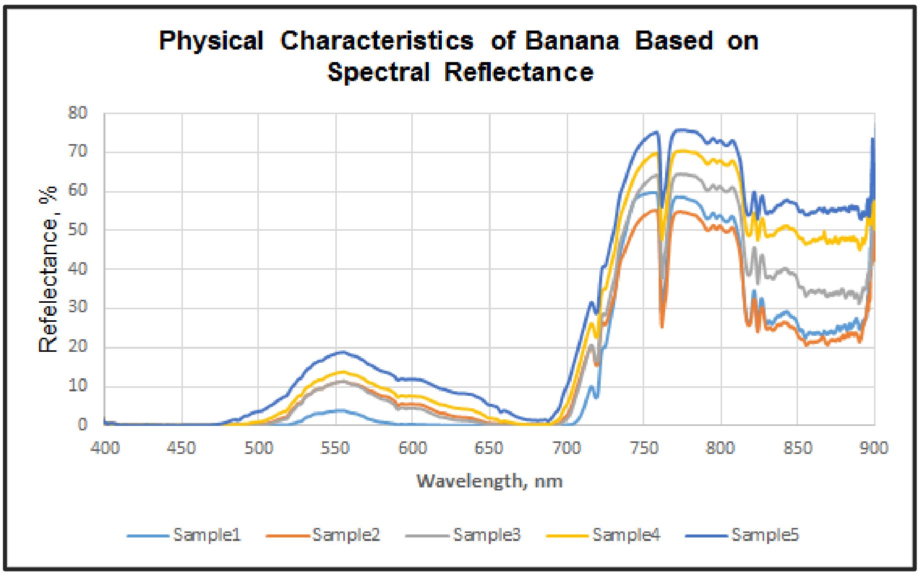

Figure 6 Spectral Reflectance of Banana

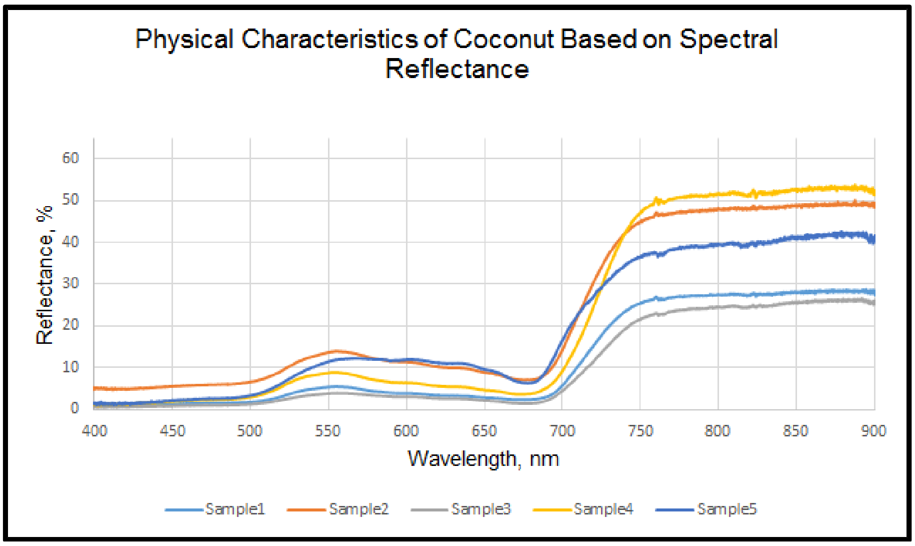

Figure 7 Spectral Reflectance of Coconut

Also, the spectral measurements of corn were measured at three stages (vegetative, reproductive, and senescence) since it is a seasonal crop, and the result is shown in Figure 8. Based on the result, there was an observed distinct difference in the spectral signature of each stage. It was observed that the vegetative and reproductive stage had low reflectance values at the Visible Region from 400-700 nm wavelengths, which means that at this stage, the crops had high chlorophyll and water absorption value used for photosynthesis [11]. The results indicated that the crops were considered healthy based on their reflectance characteristics and behavior.

On the other hand, there was an observed high reflectance value at the visible Region at the senescence stage, which indicates lower water absorption. Hence, the crops experienced low moisture content, and the result agreed with the condition of the crops at the senescence stage.

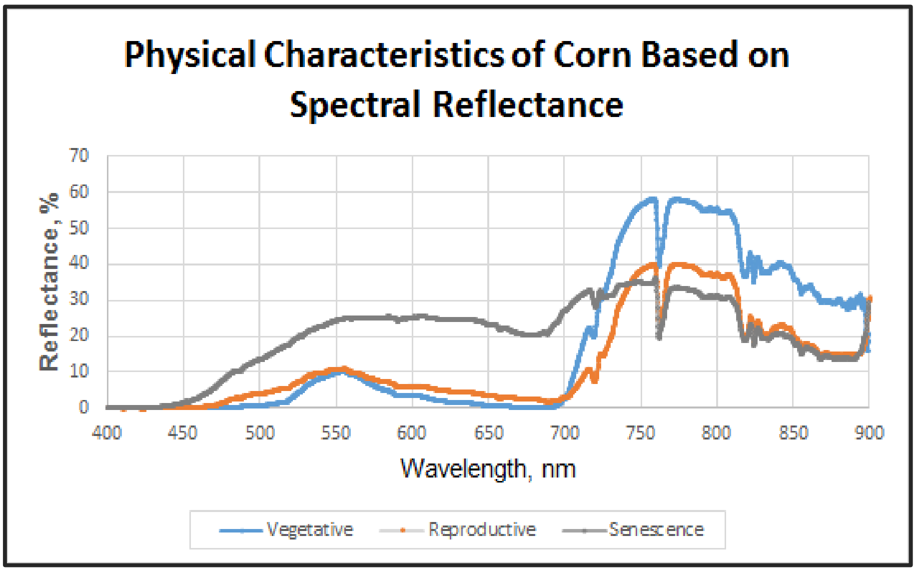

Figure 8 Spectral Reflectance of the Different Stages of Corn

Lastly, the spectral signatures of mango were measured, and the result is shown in Figure 9. Based on the results, all five (5) samples had a lower reflectance value at the Visible Region of about 10-20% and a high reflectance value at the Near Infrared Region at 700 – 900 nm wavelength of about 40-70%. Hence, the mango crops during this period are considered healthy vegetation.

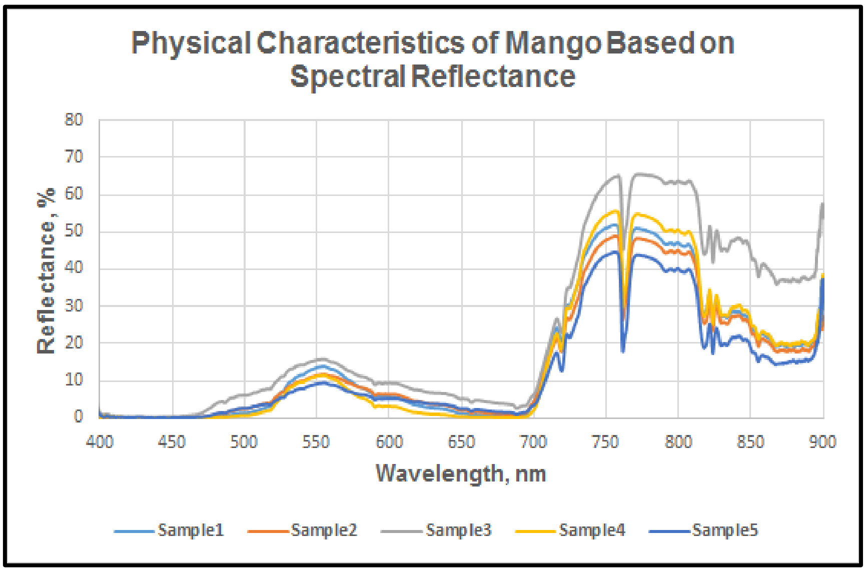

Figure 9 Spectral Reflectance of Mango

5. CONCLUSION

This study, therefore, demonstrates the acceptable and straightforward technique in characterizing the biophysical condition of the major agricultural crops in Butuan City based on the on-site spectral measurements. The findings of this concluded that remote sensing techniques could lead to accurate crop monitoring by collecting and processing in-situ spectral data.

Moreover, using spectral reflectance data has an enormous potential application in the agricultural sector, such as inventory and mapping of high-value crops. Based on the result of this study, banana, corn, and mango crops were considered healthy because they had a lower reflectance value in the Visible Region and a high reflectance value in the Near-Infrared Region. In contrast, coconut crops were in unhealthy condition since the reflectance value in Near-Infrared Region was about 10-25% low.

Hence, the biophysical characterization of major crops based on their spectral reflectance is a great approach to monitor the biophysical condition of the crops. But, based on the result of this study and observation during the in-situ spectral measurement activity, there is a need for appropriate monitoring and management of the farmer's practices from the agricultural-related sectors since most of the farmers were practicing multi crops farming system. Production might be affected due to the conflict of the nutrient requirement of crops. The researchers also suggested future studies to explore the relationship of spectral reflectance to crop yield. A study for economic analysis is also highly recommended for optimizing the research output.

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