__Original Research Article__

Applicability of multispectral images to detect soil organic carbon content in land suitability assessment: A case of a sugarcane plantation

Abstract - Soil organic carbon is important for sugarcane production as it plays a significant role in the development of soil aggregates and soil improvement in any agricultural soil, hence increasing soil health. Increasing soil organic matter encourages soil aggregation and slows the rate of organic matter breakdown. Soil aggregates act as nuclei for soil stabilization with time. It improves soil attributes by increasing organic carbon content in the soil and enhances the physical properties of the soil that favor water infiltration and retention. However, traditional methods of SOC determination like laboratory analyses are expensive and time-consuming. The objective of the study was to assess the applicability of multispectral images to determine SOC content in the surface soil. The research adopted two means to determine SOC of sugarcane. Under the first method, the lands were selected according to the sugarcane productivity in the study area, namely: low (35-54 t ha^{-1}), medium (55-79 t ha^{-1}), and high (80-100 t ha^{-1}) productivity. Soil samples were collected up to 15cm depth. Walkley and Black Method was used for SOC determination in the laboratory. Simultaneously, multispectral images of each land were obtained using a drone platform. Multispectral images were then used to calculate Normalized Difference Vegetation Index (NDVI), Bare Soil Index (BSI), and Modified Secondary Soil Adjusted Vegetation Index (MSAVI2). These indices were used to predict SOC. The outcome was compared with SOC obtained from the laboratory analysis results. The results showed that the soil organic carbon (SOC) varied between 2.72 and 3.63% from the mean for the the highest and lowest productivity lands respectively. The results of regression analysis observed a moderate correlation between SOC and the BSI values (0.4828). Weak correlations were observed in MSAVI2 (0.0269) and NDVI (0.0858). Future research should focus on improving these indices for SOC determination with increasing sample quantity.

Keywords - Soil organic carbon, land suitability assessment, multispectral images, sugarcane

1. Introduction

Land is an essential resource for humankind (Schoonover and Crim, 2015). However, its productivity is rapidly declining due to continuous use. Land degradation is caused mainly by anthropogenic activities resulting loss of biodiversity and vegetation cover, soil nutrient imbalance, and depletion of soil organic matter (SOM) and water retention capacity (Mng'ong'o *et al.,* 2021). Soil degradation is considered as a subset of land degradation and it is resulted mainly due to mismanagement of lands.

It is important to launch land use planning practices to protect land resources for future use. This is the ultimate goal of land management. Land evaluation is identified as a basic step of the land use planning process and Land Suitability Assessment (LSA) is one such methods of land evaluation. It helps manage land use while minimizing land degradation (Mugiyo *et al.,* 2021)

Land Suitability Assessment has identified some limiting factors for each particular crop grown. Accordingly, it is expected that a particular land is suitable for a particular crop if it has good soil quality. However, soil quality cannot be directly measured always; instead, indicators are used for explaining it. For example, soil organic carbon (SOC) is one of the most important indicators which is used as an indicator of soil quality assessment (Kheir *et al.,* 2010).

Typically, organic carbon (OC) is a major component of SOM which is recognized as a critical soil health feature (Chen *et al.,* 2000). Therefore, in order to promote crop productivity through soil management, it is necessary to constantly determine SOC content in the soil. SOC content is usually detected under laboratory conditions but it is a time-consuming and costly method (Koparan, 2019). Therefore, it would be vital if a cost-effective and time-saving new technology such as remote sensing applications could be used to detect SOC content.

Traditional SOC determination techniques may be replaced in future by indirect methods that utilize Geographic Information Systems (GIS) and Remote Sensing (RS) (Post *et al.,* 2001). According to Koparan (2019), image acquiring of remote sensing can be done with the help of satellites and Unmanned Arial Vehicle (UAV) systems. In order to determine SOC stock, Bhunia *et al.* (2019) have used both ground verification and data from space-borne satellites in districts in India. Meanwhile, Gomez *et al.* (2008) have used RS data as well as visible and near-infrared reflectance hyper-spectral proximate data to compare the predictions of SOC. Castaldi *et al.* (2018) introduced the method called 'bottom-up' to predict SOC from RS data that do not involve any chemical or physical laboratory examinations.

In light of this, the present study aimed to determine the applicability of multispectral images to detect SOC instead of laboratory testing for the purpose of land suitability assessment in a sugarcane field. The research also desired to find the correlation between the measured SOC and different vegetation indices (Normalizes Difference Vegetation Index, Bare Soil Index, and Modified Soil Adjusted Vegetation Index 2) in such an applicability.

2. Material and methods

2.1 Study Area

Sugarcane lands of Lanka Sugar Company Ltd., Pelwatte, which is located in Monaragala District of the Uva Province in Sri Lanka (6.7230° N and 81.2044° E) (Figure 1) and 175m above sea level, under tropical climate, were used as the study site. Nine (9) lands, each with 1 ha extent, were selected for obtaining soil samples and multi-spectral images. The field is covered with sugarcane cultivation and replanting is carried out, as needed.

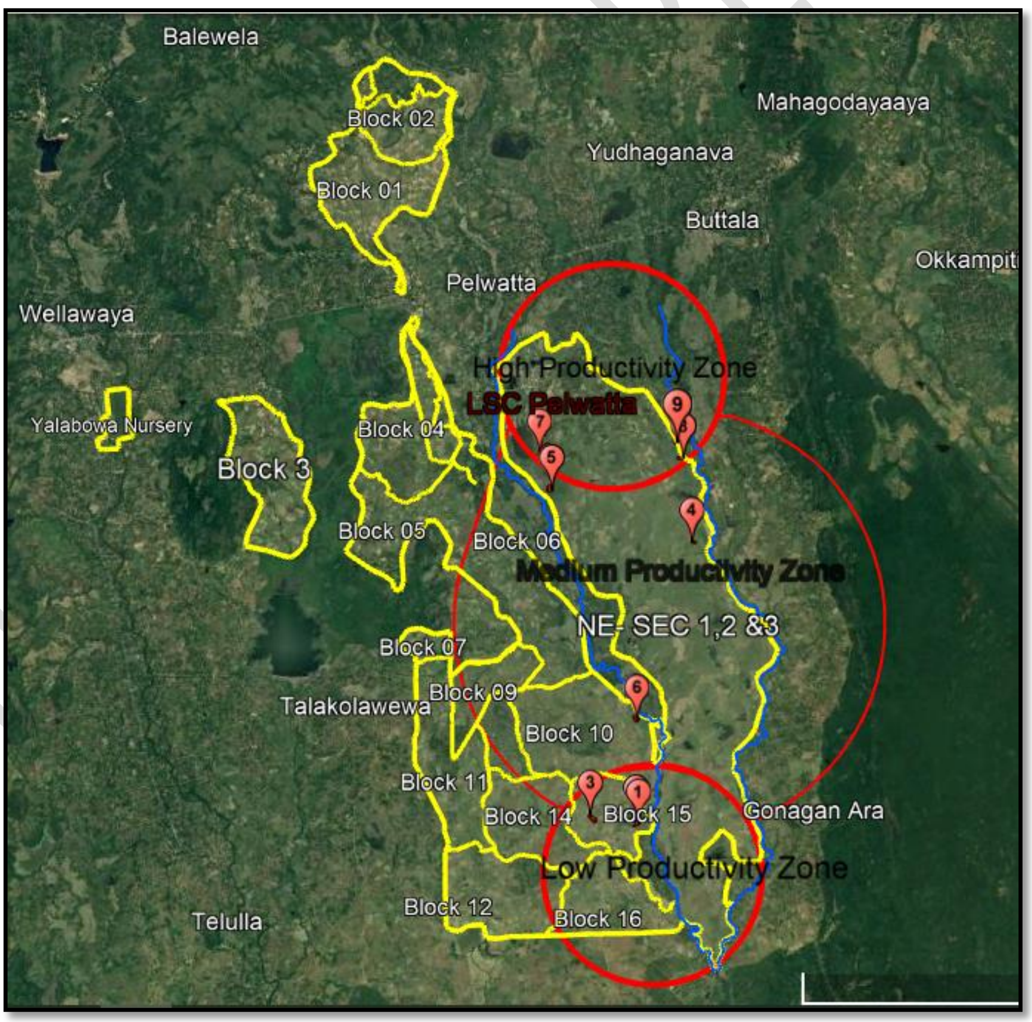

Figure 1: Study area of Lanka Sugar Company Ltd., Pelwatte Unit.

These lands were chosen for the experiment based on the productivity of the sugarcane crop. Accordingly, the lands with a yield of 35-54 t ha^{-1} were considered as lands belonging to the low productivity zone; the yield between 55-79 t ha^{-1} was under the moderate productivity zone; and the yield between 80-100 t ha^{-1} was categorized into the lands belonging to the high productivity zone by considering yield quantity of sugarcane lands. 3 replicates from each productivity category were used. Figure 2 depicts the research methodology related to the present study.

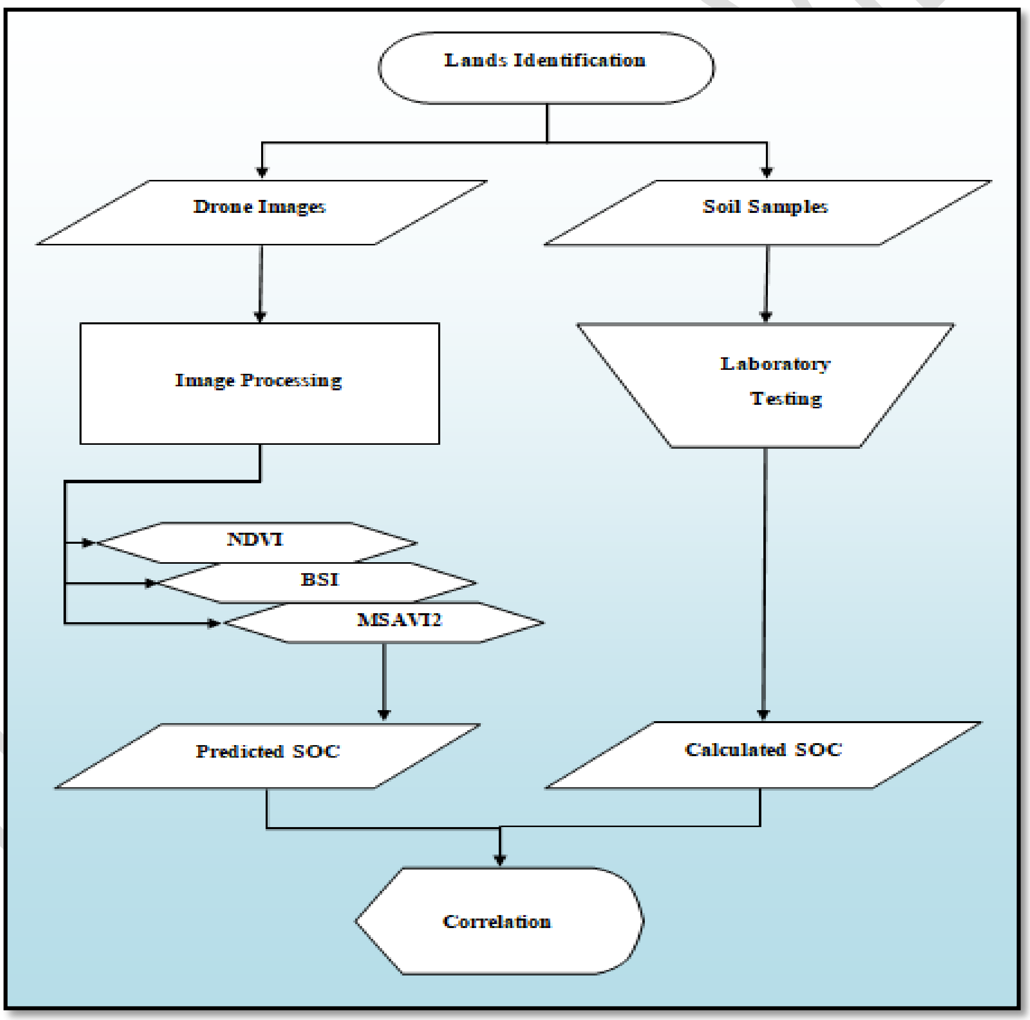

Figure 2: Flow chart of research methodology.

2.2 Soil Sampling and Analysis

Soil samples were collected from each 1 ha land, under three yield productivity classes, 2 to 4 weeks before ploughing using an augur up to a depth of 0-15 cm. Under each category of productivity, three plots were selected and from each plot, 5 representative soil samples were collected. Consequently, 45 soil samples were collected from 9 plots and SOC contents were measured. The obtained soil samples were subjected to laboratory testing to calculate the SOC concentration using Walkley-Black Wet Oxidation Method (World Bank, 2021) according to Eq. (1).

$$\%OC = \left[MFe \times \left(Vblank - Vsample\right) \times 0.003 \times 100 \times f \times mcf\right]/W \quad (1)$$

where;

V_{blank} = volume of titrant in blank, ml

V_{sample} = volume of titrant in sample, ml

M_{Fe} = concentration of standardized FeSO4 or (NH4)2 Fe(SO4)2.6H2O solution,

molarity

f = correction factor, 1.3

W = weight of soil, g

mcf = moisture correction factor, 1

Besides, undisturbed ring samples were taken for bulk density determination. A hand held GPS device was used to get the location information of the each sampling point.

2.3 Spatial Data Collection and Processing

Acquisition of multispectral images was carried out using drone technology parallel with the collection of soil samples. The drone was flown horizontally at an altitude of 25 m and images were taken with a spatial resolution of 3 cm pixels and the ground coordinates were obtained correctly by the RTK GPS receiver. Obtained multispectral images were processed and geo-referenced using Agisoft Metashape Professional 1.7.6 software. Thereafter, multispectral images, which consist of 5 bands, were processed using ERDAS Imagine 2014 software. MATLAB 2009b software was used to perform analytics on resultant images.

2.4 Calculating Indices

Normalized Difference Vegetation Index (NDVI) (Koparan, 2019), Bare Soil Index (BSI) (Bhunia *et al.*, 2019), and Modified Secondary Soil Adjusted Vegetation Index (MSAVI2) (Koparan, 2019) associated with each land plot were calculated using processed images from ERDAS Imagine 2014 and MATLAB 2009b software. Following equations show the parameters associated with the calculation of these indices.

$$NDVI = NIR - Red/NIR + Red \quad (2)$$

$$BSI = [(Red + Green) - (Red + Blue)/(NIR + Green) + (Red + Blue)] \times 100 + 100 \quad (3)$$

$$MSAVI2 = \left[2NIR + 1 - \sqrt{(2NIR + 1)^2 - 8(NIR - Red)}\right]/\ 2 \quad (4)$$

where;

NIR – Near Infrared Radiation

Red – Red Band

Green – Green Band

Blue – Blue Band

2.5 Statistical Analysis

Linear regression analysis method was performed to investigate the correlation between the calculated indices and the SOC determined by the laboratory testing. Accordingly, NDVI, BSI, and MSAVI2 indices and respective SOC of the plots obtained from laboratory analysis were graphed using scatter plots. The correlations between these parameters were determined using MATLAB 2009b software.

3. Results & Discussion

The SOC of 9 plots was obtained by using laboratory analysis method and indices analysis method and the results are presented by dividing plots into three productivity categories of low, medium and high. Furthermore, by using the index analysis method, the relationships between each productivity category and the obtained SOC were found and represented by graphs (Figure 3, Figure 4 and Figure 5).

3.1 Soil Sampling and Analysing

Table 1 shows the mean SOC values of the samples collected from 9 plots according to their three different productivity categories.

Productivity Category	Mean SOC (%)
Low	2.96±0.22
Medium	3.24±0.26
High	3.38±0.22

Table 1: Measured SOC content values of three productivity classes. Each value has been presented as a mean ± standard deviation of them taken from each field plot.

In accordance with the laboratory analysis method, SOC values obtained in the low productivity zone were in the range of 2.7-3.0% whereas SOC values in the medium and high productivity zones were in the range of 3.0-3.5 and 3.2-3.6%, respectively (Table 1). This shows that there was a positive relationship between SOC and productivity and correspondingly, the lower productivity was observed for the lower SOC soils.

3.2 Relationship between Observed SOC and Indices

Table 2 shows the mean NDVI, BSI, and MSAVI2 values obtained for three different productivity classes.

Productivity Category	Mean NDVI	Mean BSI	Mean MSAVI2
Low	-0.0197±0.051	-0.031±0.016	-0.014±0.039

Moderate	-0.004±0.077	0.01±0.010	-0.008±0.060
High	-0.133±0.061	-0.006±0.076	-0.091±0.045

Table 2: Descriptive statistics of indices.

As per the Figure 3, the correlation between NDVI and observed SOC content of each plot was 0.02694. This is relatively a weak relationship and the observed R^2 was 0.0007256 (Table 3). The observed SOC had 0.07% variation with the regression of the mean NDVI of each plot. When comparing with Figure 4 the correlation between BSI and observed SOC content of each plot was 0.4828. This highlights a moderate relationship between the two variables. There was a 23.3% variation with observed SOC and the regression of the Mean BSI of each plot. The correlation value 0.08582 (Figure 5) showed a weak relationship between MSAVI2 and observed SOC content of each plot. The observed R^2 was 0.007365 and also, there was 0.7% variation with observed SOC and the regression of the mean MSAVI2 of each plot.

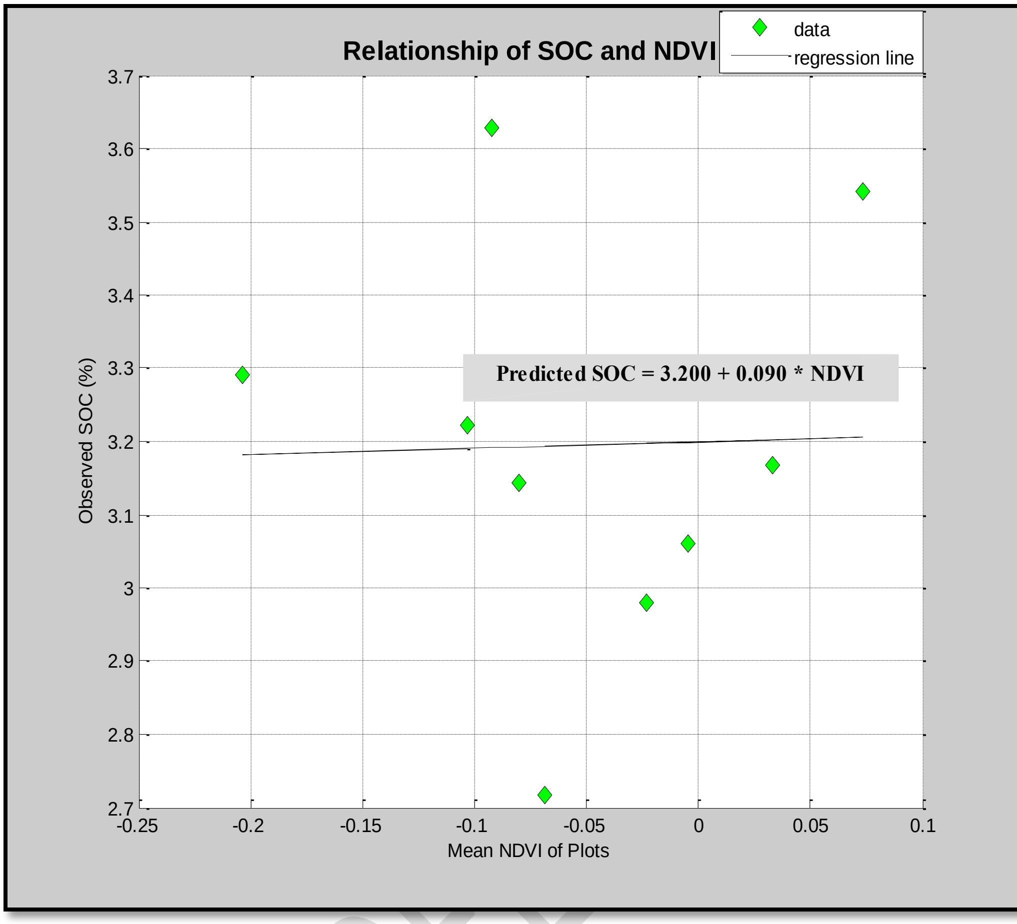

Figure 3: Relationship between measured SOC and mean NDVI.

Regression Line Equations	**Variables**	R^2	**R**
Predicted SOC = 3.200 + 0.090 * NDVI	NDVI	0.0007256	0.02694
Predicted SOC = 3.222 + 3.123 * BSI	BSI	0.2331	0.4828
Predicted SOC = 3.210 + 0.408 * MSAVI2	MSAVI2	0.007365	0.08582

Table 3: Relationship between observed SOC and indices.

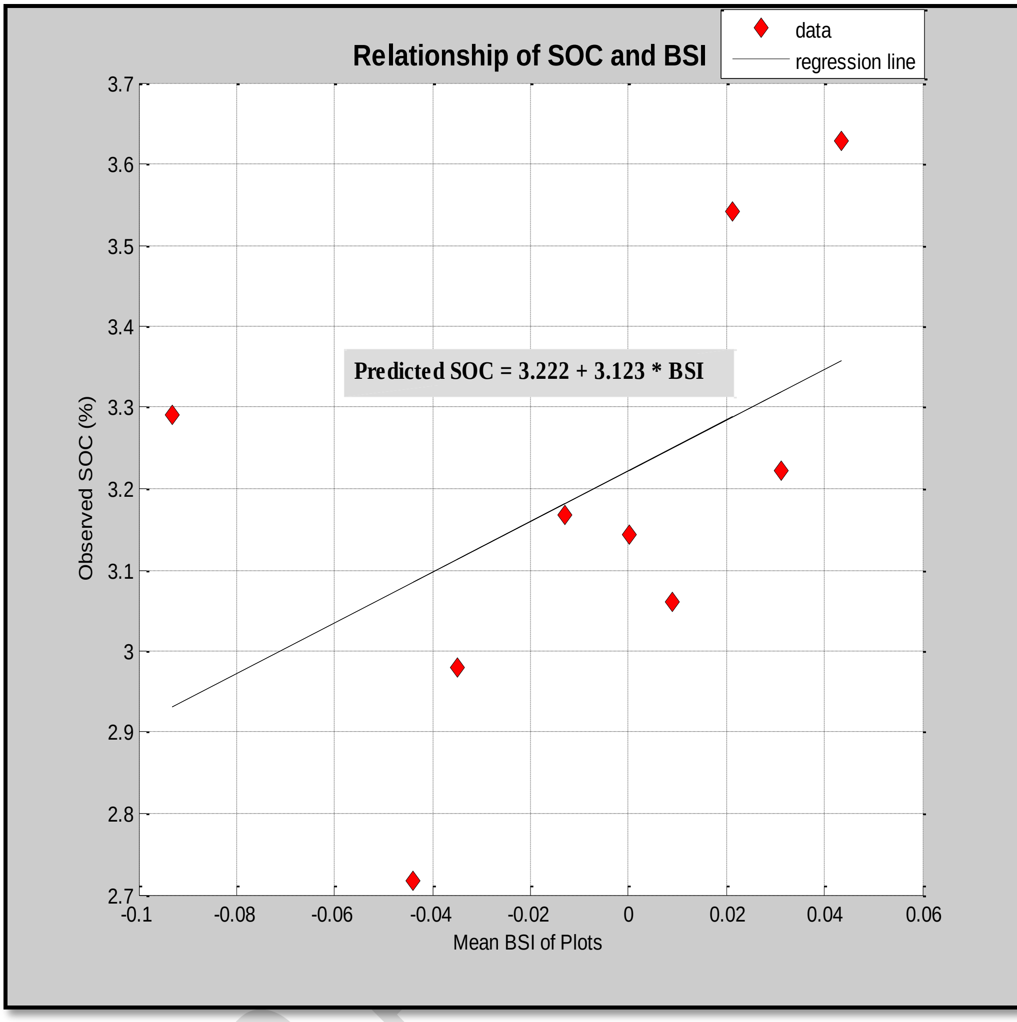

Figure 4: Relationship between measured SOC and mean BSI

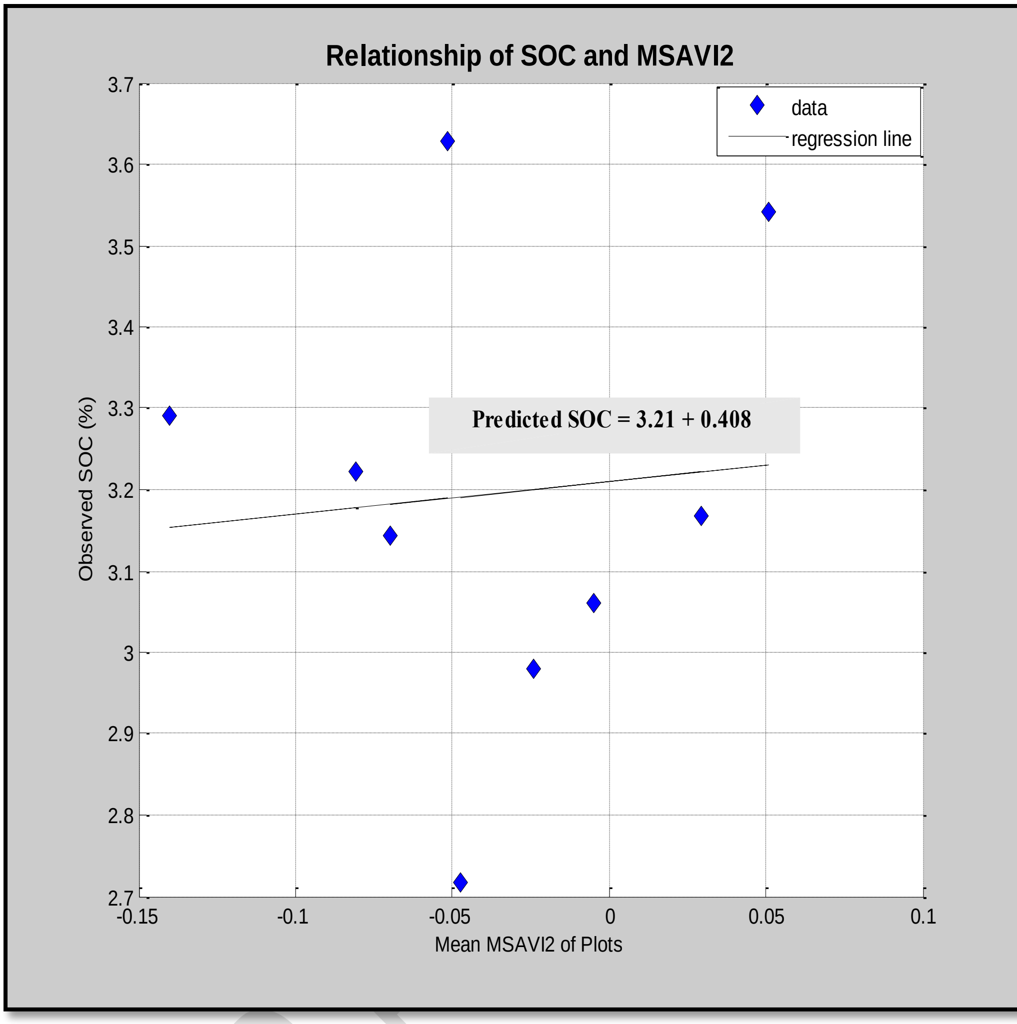

Figure 5: Relationship between measured SOC and mean MSAVI2

Land can be considered as a very essential thing for man. When a land is used for agricultural purposes its soil is the most valuable resource. Therefore, in order to promote productivity in agriculture, it is necessary to assess whether the land is suitable for each crop. There, soil quality can be taken as a major criterion for determination of productivity. SOC is one of the leading indicators of agricultural productivity when it comes to soil quality. Therefore, it is important to detect SOC regularly. In many cases, soil samples are taken from the land and subjected to laboratory testing. But, this is a very expensive and time-consuming task and therefore, present study was conducted to see whether a cost-effective and efficient method like remote sensing could be used for this purpose without destruction. Accordingly, the ability to capture multispectral images using a drone platform and thereby to detect SOC was carried out by indices analysis.

According to the laboratory analysis method, SOC values obtained in the low productivity zone were in the range of 2.7-3.0% whereas SOC values in the medium and high productivity zones were in the range of 3.0-3.5 and 3.2-3.6%, respectively (Table 1). It was clear that there was a positive relationship between SOC and productivity and accordingly, the lower productivity was observed for the lower SOC soils. It is proven that application of fertilizers has significant effect on the level of SOC and thereby on crop productivity (Studdert, 2000). Therefore, changes of SOC in the sugarcane fields is partially supported by application of fertilizers (Table 4). But, retention of SOC in the different productivity lands might be attributed to the unique features of such lands in particular soil moisture content, clay type, parent material etc.

		Plant Crop		
Application	**Urea (Kg/ha)**	**TSP (Kg/ha)**	**MOP (Kg/ha)**	**Time Period**
Basal Dressing	501	100	75	
Top Dressing 01	1100			45 Days After Planting
Top Dressing 02	150		75	90 Days After Planting
		Ratoon Crops		
Top Dressing 01	50	100	75	14 Days After Planting
Top Dressing 02	100			60 Days After Planting
Top Dressing 03	150		75	120 Days After Planting

Table 4: Fertilizer application of Lanka Sugar Company Ltd., Pelwatte Unit.

Corresponding to previous analysis conducted by Sugarcane Research Institute of Sri Lanka in Pelwatte Nucleus Estate, SOC percentage of soils have ranged from 0.2 to 1.0% (Crop Nutrition Division, 2022). These values are lesser than that of the current study. The reason might be they have sampled sols from different locations to what we collected and it supports the variability of

SOC in the lands of Lanka Sugar Company Ltd., Pelwatte. Thus, improving SOC content in all lands at least to the values obtained at the locations of the present study will be essential in terms of improving soil quality. On the other hand, it s linked with the productivity of sugarcane (Bot *et al.,* 2005). Minimizing the activities such as burning, tillage, overgrazing and continuous cropping can be advocated to maintain SOC levels at the desired condition in these lands.

According to Bhunia *et al.* (2019), there is a significant correlation between SOC and NDVI (R = 0.74, P<0.0075,). In contrast, Koparan (2019) shows a weak negative correlation between SOC and NDVI which was obtained from Landsat 8 and Planetscope multispectral imageries: -0.39 and -0.35, respectively. However, in this study, there was a very weak direct relationship between mean NDVI and observed SOC of each category.

When considering the relationship between mean BSI and observed SOC of each productivity category (Figure 4), it has given a medium satisfactory correlation *i.e.* 0.4828. Hence, it can be concluded that there is a moderate direct relationship between mean BSI and observed SOC (P=0.1880). Bhunia *et al.* (2019) show a statistically significant relationship between SOC and BSI (R = -0.72; P<0.0000). Conversely, Koparan (2019) shows a weak negative relationship as -0.44 between SOC and BSI which has been obtained from both Landsat 8 and Planetscope satellite imageries.

It is apparent that the amount of reflected and emitted spectra from soil surface is affected by soil humidity by decreasing reflectance values (Nocita *et al.*, 2013). The present study showed a moderate correlation with SOC concentration of lands where moisture content was near field capacity. Contrasting results are reported in some other studies as well (Kumar *et al.*, 2016).

The relationship between mean MSAVI2 and observed SOC of each yield category soil was quite similar to the relationship between mean NDVI and observed SOC. With regards to Figure

5, the correlation is 0.08582 and the *P* value was 0.8267. Thus, it is apparent that there was a weak correlation between mean MSAVI2 and observed SOC of each productivity category. According to Koparan (2019), the relationship between SOC and MSAVI2 has a moderate negative correlation (R = -0.54, $P<0.0001$) under both Landsat 8 and Planetscope satellite multispectral imageries.

Soil organic carbon is associated with soil color, nutrient-holding capacity, and also helps maintain soil composition (Ismail *et al.*, 2012). Under this context, soil color and image intensity relationships can be established between SOC concentration and satellite imagery data. In the present study, high productivity soils had a dark brown color and the medium and low productivity lands had a reddish brown and light brown color, respectively. This is in agreement with Castaldi *et al.* (2016) and accordingly, soils with dark hues have higher SOC contents when compared to the soils with bright hues in the case of equal moisture and the same parent materials.

BSI regression equation for SOC detection developed in the present study can be used to determine SOC in land with bare soil. The amount of soil samples required to precisely estimate SOC levels for a region will need to be determined in future research work. Further, drone images are least subject to the effects of atmospheric effects. The present findings will enhance and deliver more accurate soil data. In fact, this study will help researchers and farm managers to choose the best management strategies for their work, farm operations, and research. It will also help preserve SOC contents and improve precision agriculture farming systems.

4. Conclusion

SOC content of the sugarcane lands related to the study as assessed by soil samples collection and laboratory test is in the favorable range for sugarcane cultivation. The study found that NDVI and MSAVI2 indices show a weak relationship with the measured SOC in the selected study area and a moderate relationship with BSI. Therefore, further studies should be conducted to determine how different vegetation indices would affect the estimation of SOC.

BSI is suitable for SOC detection by multispectral images of a land. But, this index should be further enhanced in future studies when predicting SOC in sugarcane lands.

It is also desirable to see how effective the contribution of Bright Index (BI) is to identify salt spot areas in multispectral images. Also, it is worthwhile to improve NDVI and MSAVI2 indices and examine their applicability for sugarcane plots.

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