Sugarcane Classification Using Spectral Signature and Object-Based Image Analysis (OBIA) in LiDAR Data Sets

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Abstract

The aim of this study is to classify and identify the different stages of sugarcane by combining the spectral signature and Object-based Image Analysis (OBIA) with Light Detection and Ranging (LiDAR) data sets. Preliminary field spectral measurement is carried out to determine the growth stages of sugarcane. Spectral measurement is done using the Ocean Optics USB4000 VIS NIR a miniature spectrometer pre-configured for general visible and near-IR measurements. It covers a wide wavelength range, from 350 to 1000 nm field spectrometer device, and a 20-meter fiber optic cable and white reference panel. The spectral signatures of sugarcane are evaluated within the spectrum range of 400 to 700 nanometer to fit the spectral range of the RGB bands of the orthoimages. A Normalized Digital Surface Model (nDSM) was created using the LiDAR data. The nDSM was paired with Orthoimages and segmented for feature extraction in OBIA. A rule-set was developed in eCognition software to classify the sugarcane growth stages. A machine learning algorithm called Support Vector Machine (SVM) was used to classify sugarcane growth stages in the image. SVM model was constructed using the nDSM. High overall accuracies are obtained for the growth stages of sugarcane. Establishment stage is 80%, Tillering stage is 92% and Yield Formation/Ripening stage is 83%. With the remotely sensed data like LiDAR and the specific band ratios derived from the spectral signature of sugarcane, proves to be reliable features in classifying the growth stages of sugarcane.

Keywords — *spectral signature, sugarcane growth stages*

I. INTRODUCTION

The Philippines is a country where agriculture is a major industry. The sugar industry in the Philippines has performed well in terms of production making it the ninth largest sugarcane producer in the world as per the latest reports of the United Nations Food and Agricultural Organization, FAO Stats., published in September 2017 and second on the rank among the Association of Southeast Asian Nations (ASEAN) countries in 2015. Geographic Information System (GIS) and Remote Sensing today are widely used for agricultural activities such as monitoring and yield estimation, assessment and the like for precision technology. Sugarcane is the fourth largest crop in the country with about 80% of the products consumed locally. Considering its demand, there is a need to properly check the crop growth and crop yield. Studies shows on how to check the sugarcane crops by remote sensing. Methods in remote sensing have been discovered like OBIA, SVM, Spectral Signatures, GPS and LiDAR data.

Remote sensing is increasingly used in different agricultural applications. Hyper-spectral remote sensing in large continuous narrow wavebands providing significant advancement in understanding the subtle changes in biochemical and biophysical attributes of the crop plants and their different physiological processes, which otherwise are indistinct in multispectral remote sensing[1]. Hyper-spectral remote sensing data can provide a significant spectral measurement capability over the conventional remote sensor systems and hence becomes very useful in identification and modelling of terrestrial ecosystem characteristics[2]. Spectral signatures, which are simply plots of the spectral reflectance of an object as a function of wavelength[3][4], provide important qualitative and quantitative information for image classification. Therefore, spectral signatures are the basis for classifying remotely sensed data [5].

The mapping of sugarcane is significant for yield prediction and crop damage risk assessment. The use of remote sensing in identifying of sugarcane varieties had been applied using multi-spectral remotely sensed data in South Africa[6]and Brazil [7][8]and hyper spectral remotely sensed data in Australia [9], Brazil [8][10] and the USA [11].

Spectral response depends on canopy architecture, environmental condition and light source water content, nitrogen deficiency, LAI (leaf area index). Remotely sensed images were being classified into classes of landscape features using spectral signatures since the spectral signatures of like features have similar shapes. The spectral signature leads to a better separation between physical materials and objects [12].

Object-Based Image Analysis (OBIA), a new approach that makes a possible simulation of visual interpretation through knowledge-modelling. To that end semantic nets were being built based on the usage of attributes such as shape, spectral behaviour, texture, morphology, and context, among others that are used in image analysis[13]. A machine learning algorithm is one of the widely used classifiers[14][15] . Among the machine learning algorithms, Support Vector Machine (SVM) has recently received a lot of attention and the number of works utilizing this technique has increased exponentially. Support Vector Machines have gained popularity because of their ability to generalize well given a limited number of training samples. Only a quarter of the original training samples in an image requires to produce an equally high accuracy in classifying the two crops. SVM's ability to generalize well from a limited amount and/or quality of training data is the most important characteristic [16][17].

With the advances in LiDAR technologies and using OBIA, it provides opportunities for detailed classification of sugarcane growth stages. To aid in classifying sugarcane growth stages, this study therefore demonstrates by using LiDAR data, remote sensing techniques, and object-based image analysis to delineate the growth stages in the study area. This paper explores by applyingthe remote sensing paradigm by determining the unique spectral features by performing spectral measurements and employing remote sensing techniques combining moderate resolution image (Orthoimages), spectral signatures, and LiDAR-derived datasets to classify sugarcane growth stages.

MATERIALS AND METHODS

A. Study Area

The site is in Medellin, Cebu, Philippines where their major crop is sugarcane. The study area for this mapping is Barangay Poblacion (11°08'07.0"N 123°57'43" E), which is one of the villages of Medellin as shown in Figure 1.

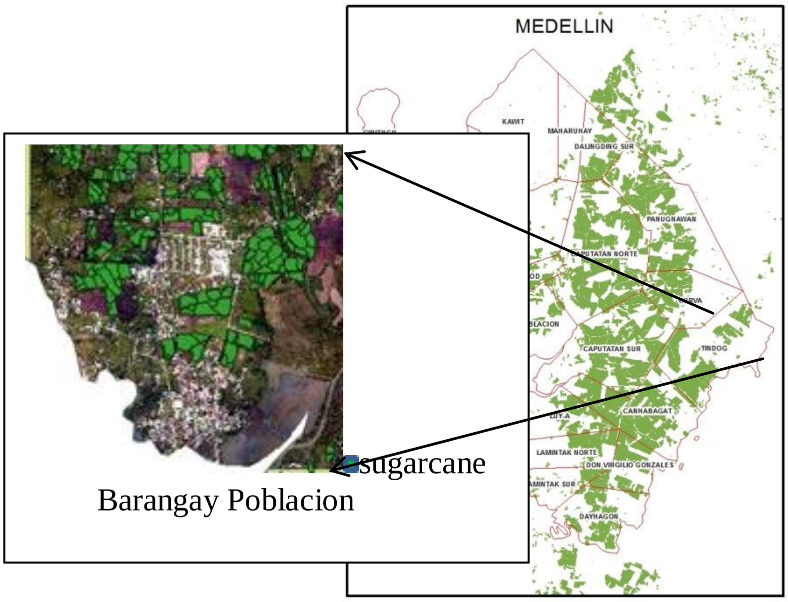


Fig. 1:**Map of study area with sugarcane at Barangay Poblacion, Medellin, Cebu Philippines**

B. Process Workflow

This study used the spectral signature and object-based image analysis for classification of sugarcane growth stages. Shown in Figure 2 is the Process Workflow.

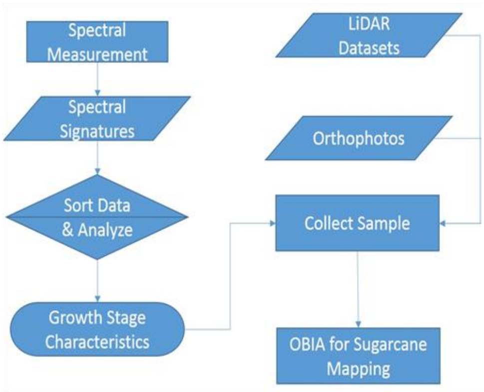


Fig. 2: **Process Workflow**

a). Spectral Measurement

This study used the spectral data to delineate the spectral signatures of the sugarcane growth stages using Object-Based Image Analysis (OBIA). The preliminary measurements were in Medellin, Cebu Philippines. The Portable Toughbook computer with Ocean-view software and field spectrometer device ranges from 300nm to1000nm wavelength, 20-meter fibre optic cable and white reference panel measures thespectral reflectance. Good light source obtained estimable integration time of 2 to5 mms, with 25 degrees' default FOV (field of view) for Ocean Optics USB4000 VIS NIR. Field spectral data gathering has preferable environmental consideration (cloud cover, wind factor, light intensity) to acquire good spectral response of the target (pure material) with its allowable time of gathering of 10:00 AM to 2:00 PM. Each phenological stage has 10 samples with three replications in each sample. The USB4000 VIS NIR device acquires the integration time (dependent to light source), white reference and dark reference. The device requires calibration. The white and dark reference measures to the environment to where the target of interest is out. Favoured integration time will make sure that the electromagnetic signals take in a single full range of spectrum at specified time. During field data acquisition, consistency of target to probe distance is essential because it is a common error that should be minimized. Orientation of the fibre optic probe is at nadir (90 degrees). Analysis of the spectral reflectance determines the unique spectral response characteristics of the sugarcane growth stages.

b). Image Processing and Analysis

In this study, the image combines LiDAR dataset and remotely-sensed orthoimages to classify the growth stages of sugarcane. First, sample collections from the three different growth stages of sugarcane, taking into consideration the insights gained from the spectral characteristics of each growth stages. To find the best features distribution and inspection of the samples in different configurations of the 3D feature-space. The different stages separate using raw colour features by using raw RGB channels. The next step is image segmentation using LiDAR nDSM and orthoimages. In this step, applying feature selection procedure identifies the best features. And finally, developing rule sets in eCognition software version 9.0 classifies the image objects to delineate the growth stages of sugarcane. In this study, it employs a supervised learning algorithm called SVM (Support Vector Machine) to classify sugarcane at various growth stages in orthoimages. Extraction of sample objects per sugarcane growth stages from the segmented images. Thefeatures of these sets of samples are for creating class definitions and classification using SVM algorithm. Another set of samples are then collected per growth stages to tests the accuracy of the samples.

II. RESULTS AND DISCUSSION

A. Sugarcane Spectral Analysis

Looking at the spectral plots in Figure 3 below, observation shows that the spectral signature of the respective sugarcane growth stage is separable at 750 to 850 nanometer (nm) or at the near infrared spectrum. This separability between spectral plots provides insight on how we can discriminate sugarcane from the aerial photographs and satellite images. In this study though, we will be using orthoimages with only three bands representing the RGB spectrum. Evaluation therefore of spectral signatures of sugarcane will be within the spectrum range of 400 to 700 nanometer to fit the spectral range of the RGB bands of the orthoimages.

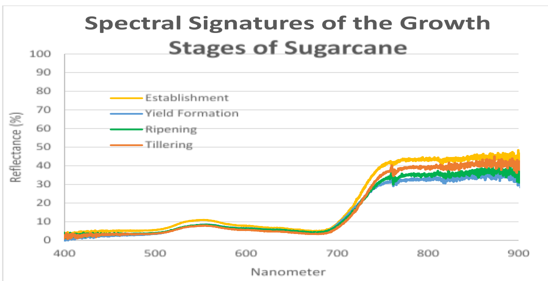


Fig. 3: **Spectral Signatures of the Growth Stages of Sugarcane at the spectrum range of 750 to 850 nm**

In Figure 4 below, observation shows that the sugarcane at Establishment and Tillering stages are highly separable from the other growth stages at 500 to 600 nanometer or at the green spectrum. In the green spectrum, the Yield Formation and Ripening stage spectra are highly correlated. This is also the case at the red spectrum or at the 600 to700 nanometer range in Figure 5. But a closer evaluation at the blue spectrum or at 400 to 500 nanometer rangeshows that these sugarcane stages are separable in Figure 6.

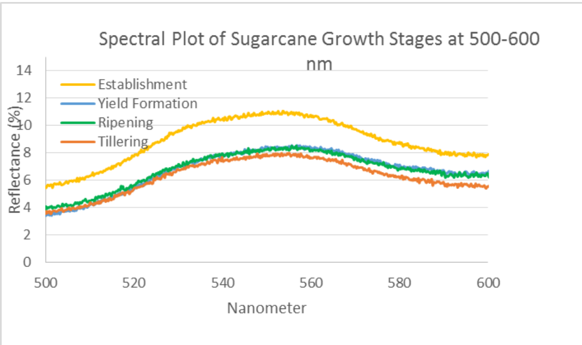


Fig. 4:**Spectral Plot of Sugarcane Growth Stages at 500 to 600 nm**

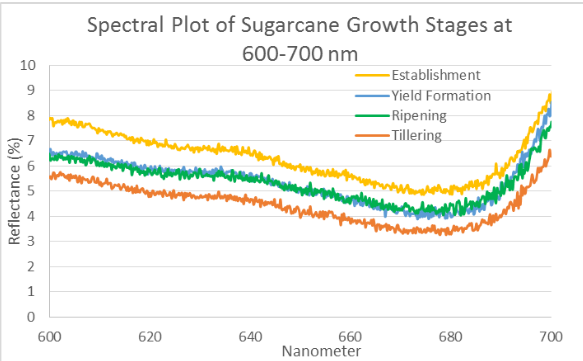


Fig. 5:**Spectral Plot of Sugarcane Growth Stages at 600 to 700 nm.**

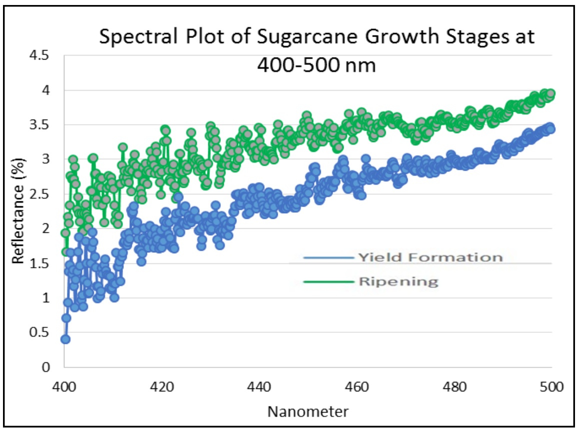


Fig. 6:**Spectral Plot of Sugarcane Growth Stages at 400 to 500 nm.**

C. Image Processing and Classification Results

a). Feature Selection

To find the best features distribution and inspection of the samples in different configurations of the 3D feature-space. The different stages separate using raw colour features by using raw RGB channels. The different stages separate using raw colour features by using raw RGB channels. Shown in Figure 7 are the 3D plots of the samples in the best feature-space configurations that separate each class.

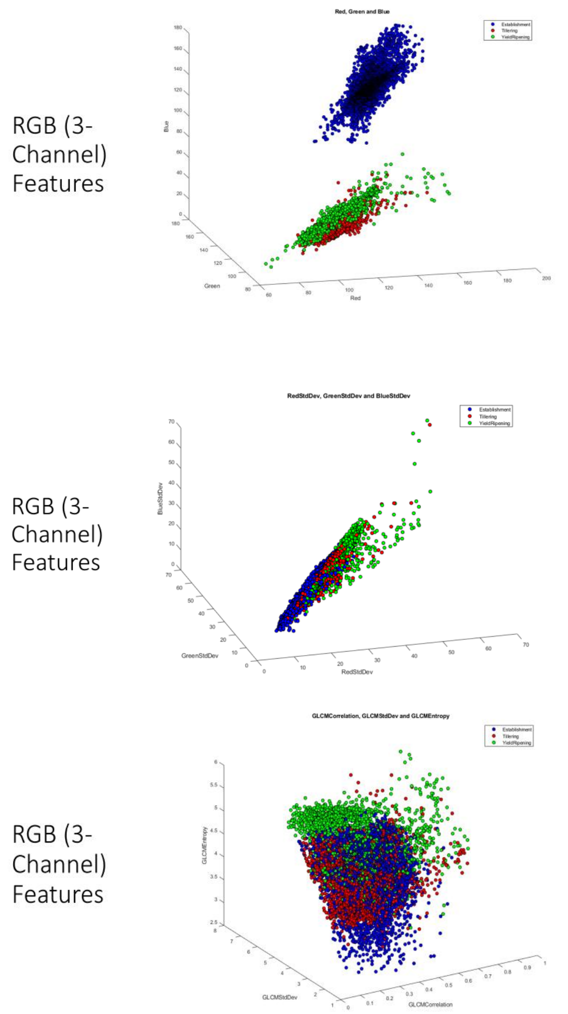


Fig. 7:**Feature-space plots for the Growth stages of sugarcane.**

Gray-level co-occurrence matrix (GLCM) uses texture features which could separate them further.The basis of GLCM textural feature was on the Red band. Detailed derivations and mathematical formulation of these features are described in the eCognition reference book [18]. Shown in figure 8 are the 3D plots of the samples in the best feature-space configurations that separate each class using GLCM.

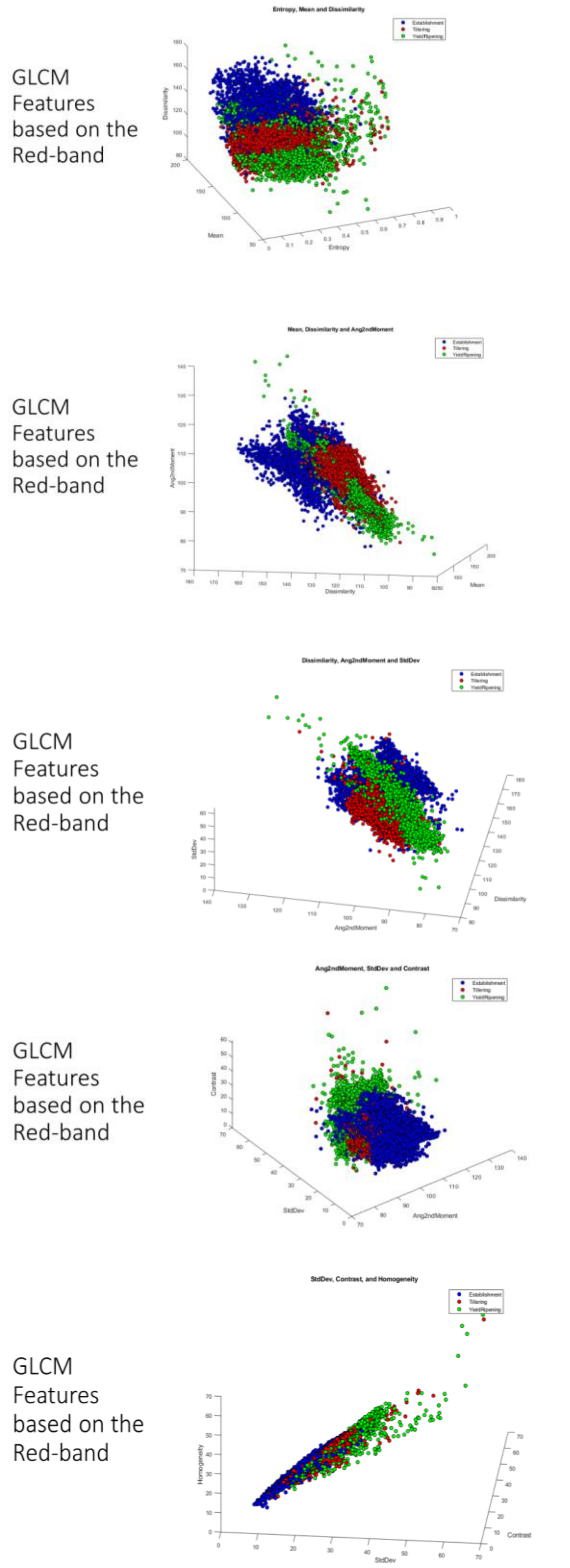
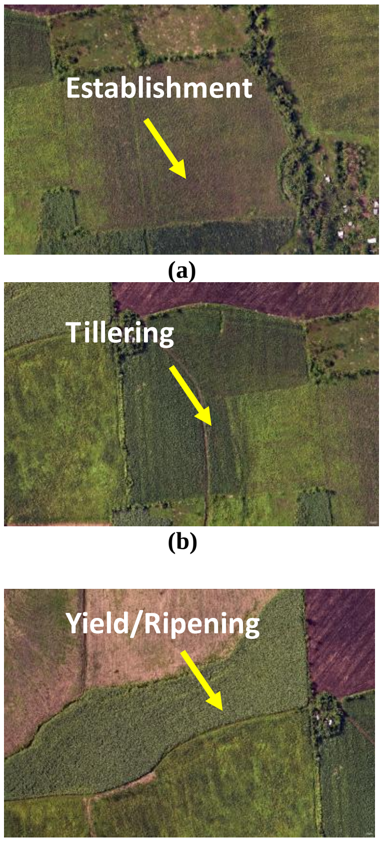


Fig. 8:**Feature-space plots for the Growth stages of sugarcane using GLCM features on the Red-band**

b). Sample Collection

Based on the spectral characteristics of each growth stage, we collect samples from the orthoimages. However, during the sample collection, it shows that the sugarcane at Yield Formation and Ripening stages are very difficult to distinguish from each other visually on the orthoimages. Three sets of samples collection on the image representing sugarcane at (1) Establishment; (2) Tillering, and (3) Yield Formation and Ripening stage. During the establishment phase, sugarcane young seedlings are so small that planting lines are still visible in an aerial image. The brownish colour of the ground is still clear as shown in Figure 9. During the tillering stage, sugarcane leaves seems dark green, seedlings crowd each other out and the planting lines become less visible. During the Yield formation and Ripening Stage, the top leaves of the plant become Pale Green in colour ("Laya") and the texture becomes much different from the tillering stage as the plants leaves become more "crowded". The planting lines are no longer visible.

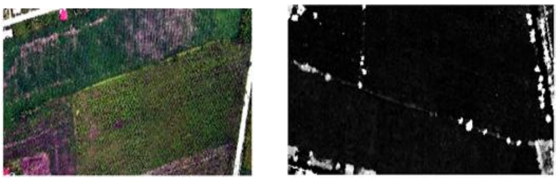


(c)

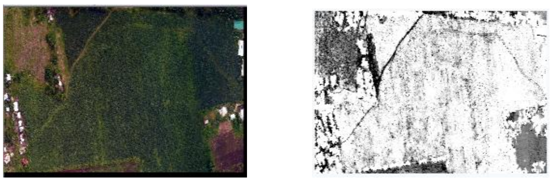
Fig. 9:**(a) Establishment, (b) Tillering and the (c) Yield/Ripening Stages of Sugarcane**

c). Image Segmentation

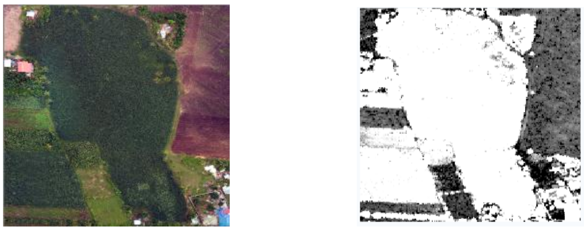
This paper highlights the classification of a certain class of vegetation objects having a height of 0.25 to 2 meters in the LiDAR nDSM. Classification of the image objects were done by developing rule sets in eCognition. This class was referred to as class "Medium Elevation" in this paper. Subclasses of this class are the growth stages of sugarcane. Segmentation was based on LiDAR nDSM and orthoimages. The feature used in RGB was texture information which was observed by visual inspection. The nDSM and orthoimages (RGB) were used in segmentation to produce the classified image for the sugarcane growth stages as shown in Figure 10. Samples were then collected for each of the growth stages (establishment, tillering and yield formation/ripening). Rule set was developed in eCognition software version 9.0 to classify the growth stages. A sample rule set is shown in Figure 11.



Establishment Stage



Tillering Stage



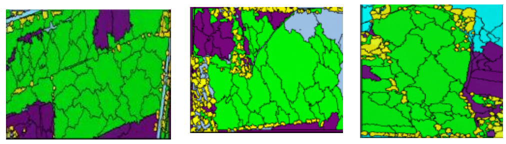
Yield Formation / Ripening Stage

Fig. 10: **Samples of the growth stages of sugarcane**

Fig. 11: **Rule set developed to classify the growth stages of sugarcane**

d). Classification Result

The classified images and the accuracy assessment are shown in Figure 12. A high overall accuracy of 80.3 % was obtained with a KIA of 54.2 % for the establishment stage as shown in table 1. The tillering stage has an accuracy of 92.2% and a KIA of 82.9% as shown in table 2. The yield formation / ripening stage have an accuracy of 82.8% and a KIA of 58.6% as shown in table 3. Shown in Figure 13 is the land cover classification map.



Establishment Stage Tillering Stage Yield Formation / Ripening Stage

Fig. 12: **Classified image of growth stages of sugarcane**

TABLE I
Accuracy Assessment result of establishment stage of sugarcane

	Confusion Matrix		
User class/Sample	Establishment	Shrub	Sum
Establishment	42	9	51
Shrub	5	15	20
Sum	47	24	
Accuracy			
Producer	0.8936170	0.625	
User	0.8235294	0.75	
Hellden	0.8571429	0.6818182	
Short	0.75	0.5172414	
KIA Per Class	0.6223404	0.478	
Totals			
Overall Accuracy	0.8028169		
KIA	0.5406654		

TABLE II
Accuracy Assessment result of tillering stage of sugarcane

	Confusion Matrix		
User class/Sample	Tillering	Shrub	Sum
Tillering	39	3	42
Shrub	2	20	22
Sum	41	23	
Accuracy			
Producer	0.9512195	0.8695652	
User	0.9285714	0.909	
Hellden	0.9397590	0.8888889	
Short	0.8863636	0.8	
KIA Per Class	0.858	0.8012422	
Totals			
Overall Accuracy	0.9218750		
KIA	0.8286938		

TABLE III
Accuracy Assessment result of Yield formation / Ripening stage of sugarcane

	Confusion Matrix		
User class/Sample	Yield formation /Ripening	Shrub	Sum
Yield formation/Ripening	36	7	43
Shrub	3	12	15
Sum	39	19	
Accuracy			
Producer	0.923	0.6315789	
User	0.8372093	0.8	
Hellden	0.878	0.7058824	
Short	0.7826087	0.5454545	
KIA Per Class	0.7025641	0.503	
Totals			
Overall Accuracy	0.8275862		
KIA	0.5863053		

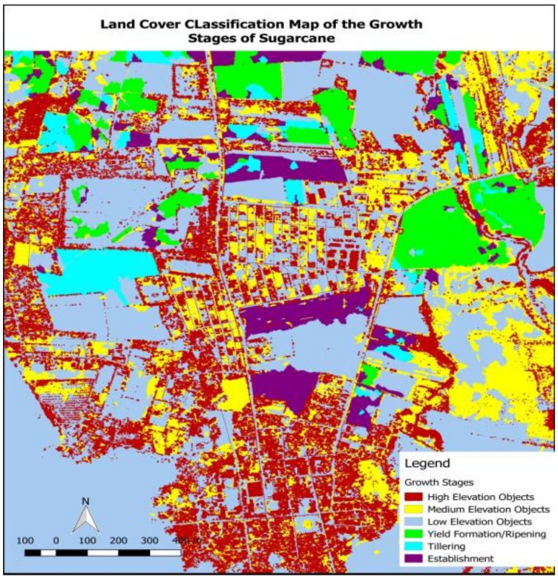


Fig. 13:**Land cover classification map of the growthstages.**

IV. CONCLUSION

This study was able to demonstrate an object-based classification of the sugarcane growth stages using spectral signatures, LiDAR data sets, Orthoimages and SVM. Segmentation and rule-based classification was done using eCognition. Combining these techniques and technologies, high accuracies was obtained for the different growth stages of sugarcane. Establishment stage is 80%, Tillering stage is 92% and Yield Formation/Ripening stage is 83% accuracy. With the high accuracy results proves that using these techniques and technologies are reliable in the classification of the growth stages of sugarcane. This can contribute to the regional and global scale of providing information on sugarcane growing areas and growth conditions.

Further research with additional samples is necessary for a precise result. Data that will be used in the process is necessary because the workflow is dependent on the images provided by LiDAR or any other remote sensing technology.

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