EXTRACTION OF ONION FIELDS INFECTED BY ANTHRACNOSE-TWISTER DISEASE IN SELECTED MUNICIPALITIES OF NUEVA ECIJA USING UAV IMAGERIES AND OBJECT BASED IMAGE ANALYSIS

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ABSTRACT: Remote sensing is one of the advanced technologies that can be used in early detection, mapping and spatial tracking of pests and disease infestations. This technology can give an updated information on the geoinformation and plant health status of the areas by conducting image analysis and classification processes using imageries captured by satellites and Unmanned Aerial Vehicles (UAV). Anthracnose-Twister disease is one of the destructive diseases of onion in the Philippines caused by fungi *Colletotrichum gloeosporioides* and *Gibberella moniliformis.* The manifestations of this disease in onion areas are very visible in aerial imageries captured by UAV's, thus, these imageries were utilized in extracting infected onion areas in the fields. To map out the affected areas, Object Based Image Analysis (OBIA) was performed in aerial imageries captured by the UAV's. Vegetation indices generated from the RGB and NIR bands were used as image layers and the Support Vector Machine as the classifier. The Support Vector Machine (SVM) was used to generate geophytopathological maps showing the actual picture and health status of onion fields with 85+% accuracy. The OBIA using SVM was effective in extracting infected onion areas using different vegetation indices, thereby, creating geophytopathological maps pin pointing the infected and the non-infected fields in the areas. These, maps were turned over to the decision makers and extension workers to raise the level of awareness on the infestation and used as monitoring tool in disease spread prevention as well as in planning for disease and pesticide management and environmental protection.

1. INTRODUCTION

Onion is one of the high-value and profitable crops in the Philippines (Cleland et. al., 2007) and it is usually planted after rice during the dry season (Alberto et. al, 2001). However, this crop is very susceptible to anthracnose-twister infection which lowers the net income of the farmers. Anthracnose-twister disease is one of the common infection in onions in the Philippines. This disease is characterized by curling, twisting, and chlorosis of the onion leaves, abnormal elongation of the necks, and formation of slender bulbs. Some diseased plants rot before harvest while others decay rapidly when stored. The causal organisms were identified as *Colletotrichum gloeosporioides* and *Gibberella moniliformis* which is suspected to be the cause of twisting and abnormal neck elongation due to excessive accumulation of gibberellins in onions (Alberto, 2014). The manifestations of this disease in onion areas are very visible in aerial imageries, thus, these imageries can be utilized in extracting infected onion areas in the fields.

Remote sensing is one of the advanced technologies that can be used in early detection, mapping and spatial tracking of pests and disease infestations. Remote sensing technology offers an effective method for tracking phenological changes such as leaf green-up and autumn coloring from regional to the global scale (Motohka et. al., 2010). Thus, this technology can give an updated information on the geo-information of plant type and health status on fields by conducting image analysis and classification processes using imageries captured by satellites and Unmanned Aerial Vehicles (UAV).

The images captured by the satellite and UAVs are datasets that can be utilized in resource mapping. These datasets can generate Vegetation Indexes (VIs) which can be used to determine the health and strength of vegetation, vegetation density, with the aim to obtain those formulas that get more reliable information about vegetation based on remotely sensed values (Suarez et. al., 2017). Vegetation Indices are commonly used in extraction and classification process in mapping techniques like supervised classification (Wan et. al., 2018). Supervised classification is one of the classification process of Object Based Image Analysis (OBIA) which involves pixels being grouped into objects based on spectral similarity and classified to the nearest possible classifications (Blaschke, 2009). OBIA has an alternative and automated classification process using Support Vector Machine (SVM). Support Vector Machine is a machine learning algorithms that utilizes and analyzed the characteristics and scientific patterns of chosen features to create new examples based on the probable similarities of the objects (Pradhan, 2012). Therefore, the images captured by the satellite and UAVs can be used in generating informative maps for agricultural purposes using the VIs and OBIA process.

To address the problems dealt by the anthracnose-twister in the onion fields, this study can give valuable outputs following the methods/techniques in remote sensing and image classification, and with the aid of Geographic Information System (GIS) technology. GIS offers useful and practical technique in investigating the intensity in different area, which can be completed with minimal cost and time (Shojaei et. al. 2018)(Cheshmidari et. al., 2017). The GIS tool is essential in analyzing disease data which is associated with geographic locations and can generate spatial distribution, spread and occurrence of plant diseases (Alberto et. al., 2018).

Furthermore, the maps that can be produced can be utilized in the Integrated Pest Management (IPM). IPM involves integrating multiple control methods based on site information obtained through inspection, monitoring, and reports in a specific areas (Yan et. al., 2017). This study aims to develop a method in extracting onion areas infected with anthracnose-twister disease and generate maps thru the use of remote sensing technology and image classification using OBIA.

2. MATERIALS AND METHODS

2.1 Study Area and Image Acquisition

Three pilot areas of onion fields infected with anthracnose-twister located each in the municipalities of Cuyapo, Guimba and Laur were selected as study areas. Data acquisition of multispectral images was done during the onion season using UAV mounted with multispectral camera sensor. Flight missions were done during daytime (10:00 AM – 2:00 PM) to avoid overshadowing of the trees to the onion fields. The mounted camera sensor can capture 4 bands each flight, namely; RED, GREEN, RED EDGE, and NIR. In addition, field sampling was done by recording GPS points for different classes present in the pilot sites, which includes; grass/weeds, infected onion area, healthy onion area and soil. A total of 20 points for each classes were gathered during the field survey.

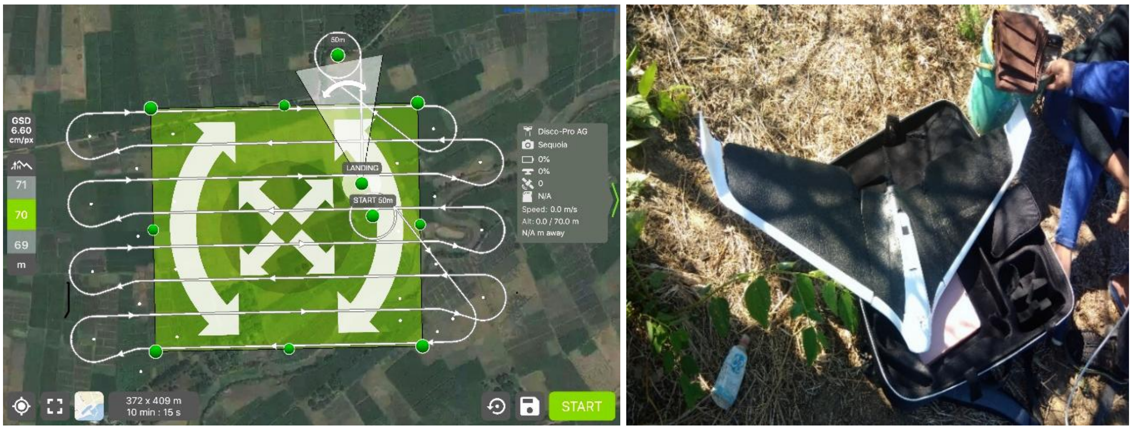

Figure 1. Mission planner using PIX4D and Parrot Disco Ag Pro (UAV)

2.2 Generation of Vegetation Indices

The images captured by the UAV were loaded to PIX4D software to generate the necessary derivatives for image analysis. Five (5) spectral indices were generated using the software such as; Soil Adjusted Vegetation Index (SAVI), Normalized Difference Vegetation Index (NDVI), Green Normalized Differentiation Index (GNDVI), Chlorophyll Index Red Edge (CIRE), Normalized Difference Red/Green Redness Index (NGRDI).These vegetation indices were computed using the software by utilizing the available spectral bands (Red, RE, Green, and NIR). Table 1 shows the vegetation indices equations.

Table 1. Vegetation Indices equations.

Vegetation Indices Layers	Equation	Reference
NDVI (Normalized Differentiation Vegetation Index)	(NIR-RED) / (NIR+RED)	(Rouse et al. 1973)
SAVI (Soil Adjusted Vegetation Index)	1.5*(NIR-RED) / (NIR+RED+0.5)	Huete (1988)
GNDVI (Green Normalized Difference Vegetation Index)	(NIR-GREEN) / (NIR+GREEN)	(Gitelson et al. 1998)
CIRE (Chlorophyll Index Red Edge)	(NIR/RED EDGE) - 1	(Xie et al. 2018)
NGRDI (Normalized Difference Red/Green Redness Index)	(GREEN-RED) / (GREEN + RED)	(https://www.indexdatabase.de/db/i-single.php?id=390)

2.3 Object Based Image Analysis Classification Process

2.3.1 Segmentation Process

The vegetation indices generated from the multispectral bands had undergone image analysis and segmentation processes. A set of rule based algorithms were used for preliminary process and segmentation process to separate the objects based on the heterogeneity within the layers. Two types of segmentation algorithms were used in the process; (a.) separate the onion fields in large scale by utilizing an available thematic layer which digitized from ArcMap using chessboard segmentation and (b.) segment the separated onion fields into smaller objects using multiresolution segmentation for the classification process (Table 2).

Table 2. Multiresolution segmentation parameters.

Scales Used : 1	
Thematic Layer Used: No	
Weights of Layers: CIRE: 2 GNDVI: 0 NGRDI I: 1 NDVI: 1 SAVI: 2	
Shape: 0.2	**Compactness:** 0.6

2.3.2 Separability and Threshold (SEaTH)

To avoid the time-consuming, trial-and-error practice for seeking significant features for optimal class separation in object-based classification the SEaTH stool was used to determine the best layers and features for the process (Nussbaum et. al., 2006). It is based on the *J-Value* of Jeffries Matusita distance with a scale of 0-2, wherein the highest scale gives better separability. The samples for each classes; (healthy onion area, infected, soil areas, and grass/vegetation areas) gathered during the field activities were used as reference samples for the SEaTH tool. The vegetation index layers with respective features which obtained *J-Value* of 1.5+ based on the reference samples were used as parameters in the image classification process. Table 3 shows all parameters that were used for the selection of best layers and features using SEaTH tool.

Table 3. Vegetation Indices and Features

Vegetation Indices Layers	Features
CIRE	Mean
GNDVI	Mode
NGRDI	Skewness
NDVI	Standard Deviation
SAVI	Texture (GLCM)

2.3.3 Support Vector Machine Classification and Accuracy Assessment

Support Vector Machine was first introduced as a machine learning algorithm for classification which perform regression rules from the data that can be used to learn polynomial, radial basis function, and multi-layer perceptron as a classifier (Osuna et. al., 1997). SVM classifier is said to be competitive and best machine learning algorithms in classifying high-dimensional data sets (Huang et. al., 2002).

Support Vector Machine (SVM) classifier was used to extract onion fields infected by anthracnose-twister disease. The segmented objects from multi-resolution segmentation had undergone the process, wherein the best vegetation indices with respective features based on separability calculated by the SEaTH tool were utilized as the parameters for the process.

Accuracy assessment was used to evaluate the performance of the SVM classifier. A set of 20 points for each class were validated and applied as classified samples for the accuracy assessment. The standard accuracy for passing the evaluation is set to 80% above.

3. RESULTS AND DISCUSSION

3.1 Determination of Best Features for Extraction

Selection of best VI's layers and respective features is important in an extraction process, however, different indices and feature subsets are needed to characterize certain disease (Rumpf et. al., 2009). The SEaTH tool offers the best solution to carry out the selection, because of its capability to calculate the thresholds which allows the maximum separability of the sample objects or features (Nussbaum et. al., 2006). Table 4 shows matrix of the VI's and features with best separability and threshold based on the J-values of *Jefrries-Matusita* scale (0-2). The table reveals that both Mean and Mode features for all VI's have good separability among the classes, while features; Standard Deviation, Skewness, and Texture (GLCM), were obtained lower *J-values*, showing no significant impact for the separability.

Table 4. Separability assessment performed using SEaTH Tool

	SOIL				INFECTED				GRASS	
HEALTHY	Mean NDVI	1.99	Mode (Min) GNDVI	1.9	Mode (Min) NDVI	1.88	Mean GNDVI	1.77	Mean SAVI	1.53
	Mode (Min) NDVI	1.99	Mean GNDVI	1.9	Mean NDVI	1.86	Mode (Min) SAVI	1.65		
	Mean SAVI	1.96	Mean NGRDI	1.7	Mode (Min) GNDVI	1.85	Mean SAVI	1.63		
	Mode (Min) SAVI	1.93	Mode (Min) NGRDI	1.56						
GRASS	Mean SAVI	2	Mean GRVI	1.98	Mean SAVI	1.99	Mean GNDVI	1.96		
	Mean NDVI	2	Mean GNDVI	1.97	Mode (Min) SAVI	1.99	Mode (Min) NGRDI	1.91		
	Mode (Min) NDVI	1.99	Mode (Min) GNDVI	1.96	Mean NDVI	1.99	Mean GRVI	1.9		
	Mode (Min) SAVI	1.99	Mode (Min) NGRDI	1.96	Mode (Min) NDVI	1.99	Mode (Min) CIRE	1.65		
					Mode (Min) GNDVI	1.96	Mean CIRE	1.59		
INFECTED	Mean SAVI	1.83								
	Mean NDVI	1.76								

**All features which includes: Mean, Mode, Standard Deviation, Skewness, Texture (GLCM), for all VI's were calculated by the SEaTH tool.*

Based on the results of SEaTh tool, the NDVI shows the highest separability of healthy onion from soil and infected areas, while SAVI for the grass/vegetation. NDVI is commonly used as VI for vegetation because the response variables of this index is the plant "greenness" or photosynthetic activity while SAVI a type of vegetation index that account for the variation in soil type and soil properties (Olukayode et. al., 2018). The GNDVI shows good separability in terms of vegetation, this is due to higher sensitivity for chlorophyll concentration at the green spectrum from 540nm – 570nm (Gitelson et. al., 1998). In addition, NGRDI also shows positivity for extraction, from the study of (Elazab et. al., 2015), this VI is superior from NDVI in explaining growth patterns of canopies for grassland and rice fields, thus, the unique values of this VI is good in separating onion and grasses based on the crop canopy. On the other hand, the CIRE VI has a considerable j-value wherein this index shows good response in chlorophyll and Nitrogen value which can be use in estimation which characterized from the red-edge and NIR region (Schlemmer et. al., 2013).

Moreover, these VIs are the commonly response base on the chlorophyll content of the plant but characterized in different regions of the spectral bands.

3.2 Classified Maps using Different Vegetation Indices and SVM

The vector files that were exported from the eCognition software which was generated using SVM classification process had undergone smoothening and laid-out into maps in ArcMap software. Results shows the final map of extracted onion fields with anthracnose-twister in a pilot site in the municipalities of Cuyapo (A), Guimba (B), and Laur (C) Nueva Ecija, the map includes classes namely: healthy onion area, infected with anthracnose-twister onion area, soil areas, and grass/vegetation areas.

Figure 2. Image classification using SVM in different pilot sites in the municipalities of Cuyapo (a), Guimba (b), and Laur (c), Nueva Ecija

Table 5 shows the overall assessment on the generated maps using the UAV and SVM as a classifier. The data shows that a total of 30.26 ha of onion area has been covered by the flight for the three pilot sites. The pilot site in Cuyapo has an onion area of 8.54 ha wherein 1.63 ha or 19.08% of the total area as classified as infected area. On the other hand, the onion area of Guimba had 2.94 ha calculated as infected area or 24.80% of the 11.84 ha of the total area. Moreover, the municipality of Laur was identified to have the highest infected area of 4.93 ha or 57.72% of the 9.88 ha total onion area.

Moreover, the average accuracy of the image classification performed using the Support Vector Machine as classifier is 90.75%.

Table 5. Overall assessment of the anthracnose-twister infection on the 3 pilot sites

Pilot Sites	Total Onion Area (Ha)	Infected Area (Ha)	Percent Infected	Classification Acc. (%)
Cuyapo	8.54	1.63	19.08 %	80.85 %
Guimba	11.84	2.94	24.80 %	96.00 %
Laur	9.88	4.93	57.72 %	95.40 %
Total	30.26	9.5	31.39 %	**Avg. 90.75 %**

4. CONCLUSION

The process of image classification using Object Based Image Analysis and multispectral images captured by UAV was proven to be effective in extracting infected onion areas with anthracnose-twister disease. The set of algorithms used in the classification process provides satisfying results. The chessboard and multi-resolution segmentation processes were found to be one of the important factors in the classification process since it helped the algorithms to get the best averages in heterogeneity and patterns of the segmented objects. On the other hand, the different set of features and vegetation indices calculated by the SEaTH tool provides excellent image classification using SVM.

In addition the generated maps shows the infection caused by the anthracnose-twister in the pilot sites in the municipalties of Cuyapo, Guimba, and Laur, wherein 1.63 ha, 2.94 ha, and 4.95 ha revealed as the affected area, respectively. Moreover, the whole classification was able to produce a high accuracy greater than the standard 80% and be able to lay out into final map products. The results of this study can be a very important tool for detection and spatial tracking of various diseases aside from Anthracnose-Twister in the near future, following the advancement of technologies towards agriculture. By simply launching an Unmanned Aerial Vehicle (UAV) with an available camera sensors, the datasets captured will be able to create datasets and generate informative maps that will used by decision makers, agricultural planners and farmers as well.

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