EVALUATION OF VEGETATION INDICES (VIs) TO DETECT TWISTER DISEASE OF ONION USING SENTINEL-2 IMAGERY

Ronaldo Alberto (1), Miguelito Isip (2), Ariel Biagtan (2)

[1] College of Agriculture, Central Luzon State University, Science City of Muñoz, Nueva Ecija, 3120
[2] Institute for Climate change and Environmental Management, Central Luzon State University, Science City of Muñoz, Nueva Ecija, 3120
Email: travert2157@gmail.com; miguelitoisip21@gmail.com; arbiagtan@gmail.com

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ABSTRACT: Traditional plant disease detection is time consuming and costly, thus an inexpensive and faster alternative method of detection is needed to send early warning to farmers to prevent pests and disease infestation and for proper intervention. To provide timely and accurate detection in twister disease of onion, remote sensing was exploited using Sentinel 2 imageries. Vegetation indices (VIs) derived from the VIS-NIR region of the image were evaluated for their capability to detect twister disease. VIs were subjected to regression analysis to evaluate the relationship between vegetation indices and severity index of onion twister disease. Vegetation indices with strong relationship to twister disease were selected and further used in unsupervised ISODATA classification. Overall accuracy of classification generated from vegetation indices were calculated based on confusion matrix using ground truth points collected from field work to identify the most suitable index based on highest overall accuracy. It was found out that NDVI and GNDVI has the highest coefficient of determination (R^2) indicating a strong relationship to the disease severity. Results of the classification show that GNDVI, PSSRa and NDVI obtained the highest overall accuracy. This indicates that these 3 VIs can be used for detection of twister disease in the field since it gives better discrimination and high accuracies. Hence, VI's generated from Sentinel 2 imagery has the potential in detection, monitoring and management of twister disease of onion in the field.

1. INTRODUCTION

Twister disease of onion is caused by a facultative endophyte (living inside the plant) *Gibberella moniliformis.* It is a major onion pathogen in Central Luzon Region, Philippines, mainly in the Province of Nueva Ecija because it is the biggest onion producer in the country. The fungus causes twisting and discolouration of the leaves resulting to elongated neck and slender bulb aside from white, oval, sunken spots on the leaves (Alberto & Aquino, 2010). The disease causes 80-100 percent yield loss resulting to high price and shortages in supply of onion in the market. The traditional way of detecting disease is time consuming and costly. There is a need for alternative method of detection that is inexpensive and can generate faster results in order to address the shorter time from early warning to prevention and treatment.

Remote sensing technology is a useful and effective means of recording the extent of damage by detecting changes in the plant canopy. Such technology may be the only practical means to effectively map disease because of the large numbers of infected areas and their irregular shapes within fields (Yang, 2014). Remote sensing has the potential to be used as an effective and inexpensive technique to identify diseased plants on a field scale, mainly because infected plants have different spectral response compared to healthy plants (Zhang et al. 2002). Remote sensing techniques make use of the characteristics of vegetation spectral reflectance to estimate bio-parameters of the vegetation. A vegetation index can be an indicator to describe the greenness, density and health of vegetation. One way to obtain crop biophysical parameters is ground truth data measurement which takes sample from vegetation. Satellite derived VIs provide another possible way to obtain the biophysical parameters of vegetation over large areas (regional or global scales) while still retaining the high temporal coverage (Frampton et al. 2013).

Vegetation indices are combinations of surface reflectance of two or more wavelength. They highlight a specific property of vegetation which can simplify detection of damage level (Soloviov, 2014). Many different vegetation indices exist and each uses a different set of wavelength measurements for describing physiological attributes of vegetation, looking at either general properties of the plant, or at specific parameters of its growth (Lowe et. al. 2017). A number of vegetation indices has been used for plant disease detection and mapping. Red edge based vegetation indices was used in detecting Ganoderma-infected oil palm trees plantation with 84% overall accuracy

(Shafri and Hamdan, 2009). Ashourloo et al. proposed two indices for wheat leaf rust (*Puccinia triticina*) detection. Both of the proposed indices (LRDSI 1 & 2) have high capability to estimate the leaf rust disease in wheat. Saddik et al. developed spectral disease indices (SDIs) for grapevine disease identification. It was demonstrated that using vegetation indices was, in general, better than using complete spectral data and that SDIs specifically designed for FD performed better than traditional SVIs in most of cases. The precision of the classification is higher than 90%.

The present study aims to evaluate the vegetation indices (VIs) of Sentinel 2 for detection of twister disease of onion. Early detection of twister disease of onion will allow timely disease management resulting to yield loss reduction.

2. MATERIALS AND METHODS

2.1 Study Area

This research was conducted in the Municipality of Rizal, Province of Nueva Ecija (Figure 1) which is comprised of approximately 3.47 Km^2. The study site is located between (121.122407 N, 15.681508E). The area is usually planted with rice followed by onion from November to March.

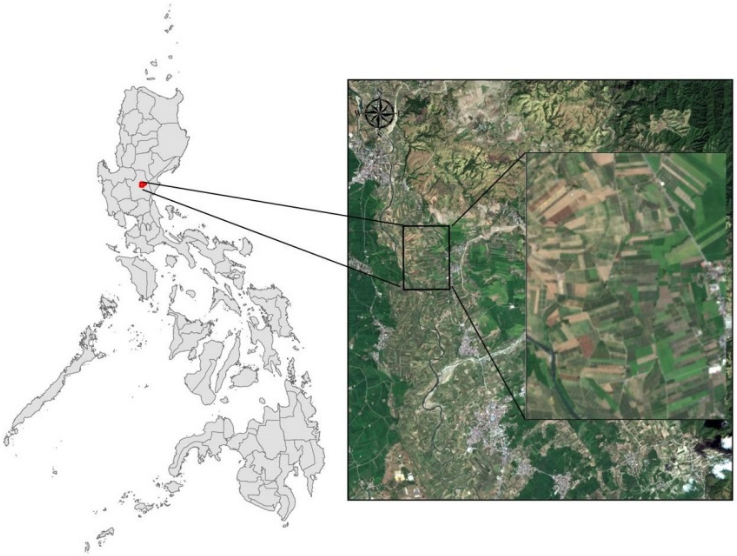

Figure 1. Location of the study area

2.2 Field Data Collection

Field data collection of twister infected onion was carried out during the onion cropping season 2019. Onion fields with early to mid-sign of twister infection were chosen for the study. The geographic location of healthy and infested onion were recorded using handheld GPS (Trimble Geo7x). One hundred (100) plants were randomly chosen and the severity index of twister was calculated following the rating scale developed by Alberto et al. 2018.

2.3 Satellite Image Acquisition

Sentinel-2A MSI image in the study area acquired on February 17, 2019 was downloaded from the Sentinel Science Hub of European Space Agency (https://scihub.copernicus.eu/dhus/#/home). Sentinel-2A has thirteen bands ranging from 443.9 nm to 2202.4 nm including four 10 m visible and near-infrared bands, six 20 m red edge, near infrared and shortwave infrared bands and three 60 m bands visible, near-infrared and shortwave infrared bands. The narrow red edge bands cover spectral regions of 703.9 nm, 740.2 nm and 782.5 nm that can be utilised for monitoring vegetation status (Kumbula et al., 2019).

2.4 Image Pre-processing

Atmospheric correction of Sentinel 2 image was done using Sentinel Application Platform (SNAP 6.0) software with the plugin Sen2cor 2.5.5 in the Sentinel-2A toolbox. The calibrated image was clipped to the study area extent. Bands with 20 m resolution (5, 6, 7, 8a) were re-sampled to 10 meter resolution using the nearest neighbor method.

A total of nine bands were used in generating vegetation indices for detection of onion twister disease as shown in Table 1.

Table 1. Specifications of Sentinel-2 Bands used in this study.

Sentinel-2 Bands	Wavelength (nm)	Bandwidth (nm)
Band 2—Blue	496.6	98
Band 3—Green	560.0	45
Band 4—Red	664.5	38
Band 8—NIR	835.1	145
Band 5—Vegetation Red Edge	703.9	19
Band 6—Vegetation Red Edge	740.2	18
Band 7—Vegetation Red Edge	782.5	28
Band 8a—Narrow NIR	864.8	33

A number of vegetation indices (VIs) were generated using the Thematic Land Processing under the Optical tools of SNAP 6.0 shown in Table 2. The vegetation indices were subjected to regression analysis to evaluate the relationship between vegetation indices and severity index of onion twister disease. Vegetation indices with strong relationship to twister disease were selected and further used in the classification.

Table 2. List of vegetation indices used in the study.

Vegetation Indices	Equation	Reference
SAVI (Soil Adjusted Vegetation Index)	(NIR−R)/(NIR+R)x(1+L)	Huete (1988)
MTCI (MERIS Terrestrial Chlorophyll Index)	(NIR - RE)/(RE - R)	Dash and Curran (2004)
NDI45 (Normalized Difference Index 4 and 5)	(RE1 - R)/(RE1 + R)	Delegido et al. (2011)
NDVI (Normalized Difference Vegetation Index)	(NIR-Red) / (NIR+RED)	Gitelson and Merzlyak (1997)
GNDVI (Green Normalized Difference Vegetation Index)	(NIR - G)/(NIR + G)	Gitelson et al. (1996)
TSAVI (Transformed Soil Adjusted Vegetation Index)	B(NIR−B·R−A)/ RED+B(NIR−A)+X(1+B2)	(Baret and Guyot, 1991)
MCARI (Modified Chlorophyll Absorption in Reflectance Index)	[(RE - R) - 0.2(RE - G)] x (RE - R)	Daughtry et al. (2000)
PSSRa (Pigment Specific Simple Ratio for Chlorophyll a)	(NIR /R)	Blackburn (1998)

2.5 Image Classification and Accuracy Assessment

Eight (8) vegetation indices were used to classify healthy and twister infected onion in the image. Single-band image classification was carried out to assess the capability and sensitivity of each vegetation indices in classifying twister disease of onion. Onion field boundary was used to identify the onion area in the image and non-onion areas were masked out. Unsupervised ISODATA classification was used to identify the twister infected and non-infected zones in the image using ENVI 5.3. The unsupervised method uses the minimum spectral distance to group each pixel into a class based on the spectral bands use in the classification. The process began with arbitrary class means from the image statistics based on the classes specified. It repeatedly performed a classification and recalculated new class statistics, which were then used for the next iteration (Song et al. 2017). 5-10 spectral classes were specified with 100 iterations, after which the classes were group into twister infected and non-infected by visual interpretation method using the identified field observation. Overall accuracy of classification results generated from vegetation indices was calculated based on confusion matrix using ground truth points collected from field work to identify the most suitable index based on highest overall accuracy.

3. RESULTS AND DISCUSSION

3.1 Regression analysis with optimal spectral indices

Regression analysis was performed to assess the ability of vegetation indices in estimating the disease index. Figure 2 shows the results of correlation analysis between each of the 8 spectral indices and disease index. The coefficient of determination (R^2) shows that NDVI (Figure 2A) and GNDVI (Figure 2B) with R^2 of 93.43 and 90.69 has the strongest relationship to the disease severity, this indicates that these two indices has a high sensitivity to twister disease, while, the weakest relationship to the disease severity was observed on TSAVI (Figure 2E) and MTCI (Figure 2C) with R^2 of 0.16 and 0.33 respectively. It was observed that indices with high R^2 such as NDVI, GNDI and PSSRa shows data scattering at lower levels of severity which might affect the classification accuracy of the disease. Ashourloo et al. 2014 stated that the increase in data scattering can cause a decrease in the accuracy of disease severity estimation. Majority of the indices used in this study shows a negative correlation to disease severity index except for TSAVI. This indicates that as the severity of twister increases the vegetation indices values decreases. The result of this study was similar to Ashourloo et al. 2014 where there is a negative relationship between wheat leaf rust and spectral disease indices.

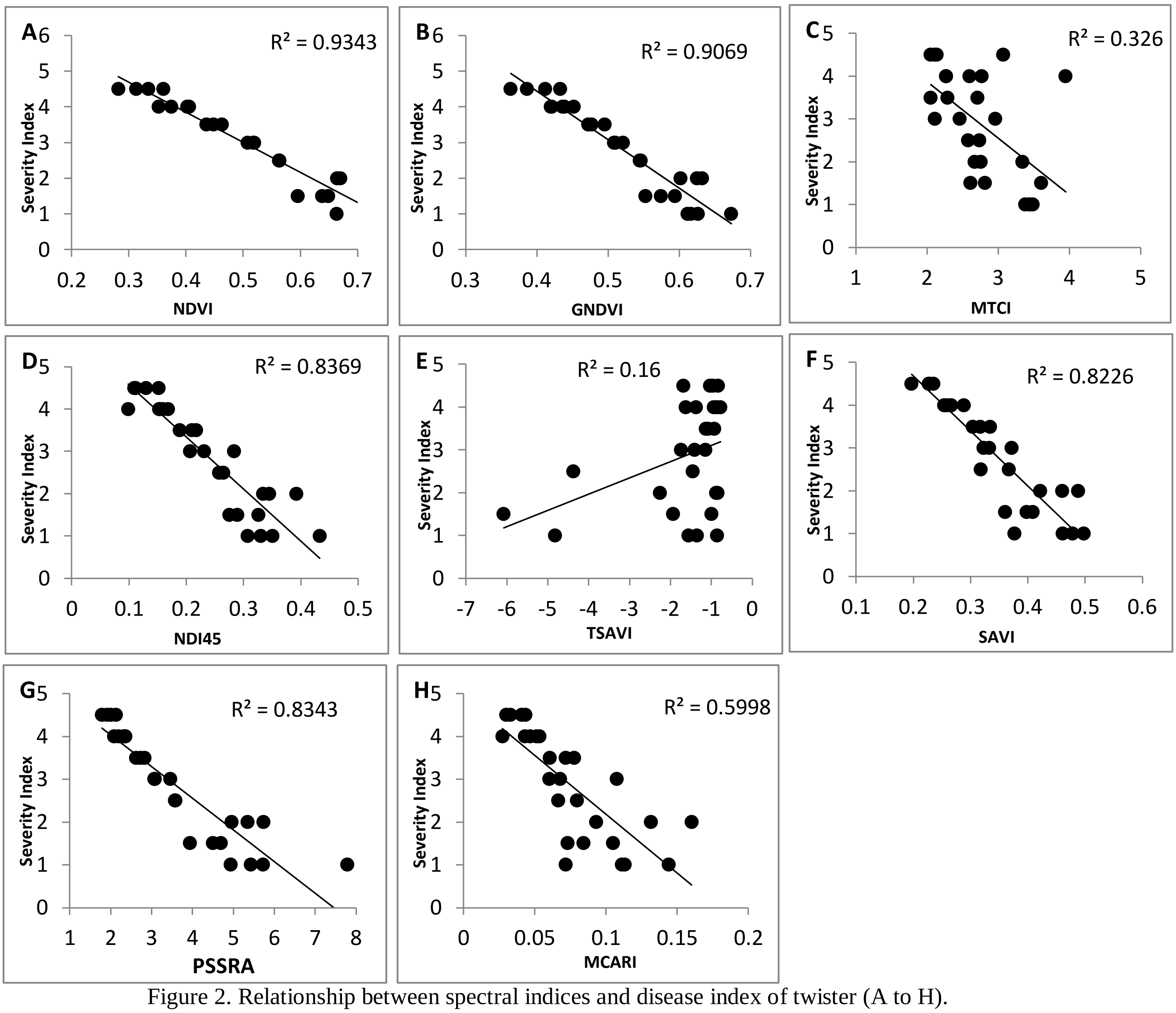

Figure 2. Relationship between spectral indices and disease index of twister (A to H).

3.2 Image Classification and Accuracy

Table 3 shows the overall accuracy of the vegetation indices used in the study. Result shows that GNDVI and PSSRa obtained the highest overall accuracy with 83.33 and 80.95% respectively. While the lowest overall accuracy was recorded in SAVI with 50%. Three (3) out of 6 indices gave better discrimination of healthy and twister infected onion, this indicates that GNDVI, PSSRa and NDVI can be used for detection of twister since they obtained high accuracies. The classification map of healthy and twister infected onion obtained from GNDVI is shown in Figure 3. Healthy onion is presented in green while twister infected onion is presented in yellow. Other features such as soil and trees were masked out from the image and presented in black. The GNDVI was based on the wavelength of Near-infrared (835.1 nm) and Green (560 nm) while PSSRa and NDVI were both based on Near-infrared and Red which relates to plant stress detection. Green Normalized Difference Vegetation Index (GNDVI) is a variation of NDVI which used green reflectance instead of red, and it was argued to be at least five times more sensitive to chlorophyll-a concentration than the NDVI and specifically useful for differentiation in stressed and senescent vegetation (Frampton et al. 2013). This findings support the result of this study since twister disease causes twisting and elongated neck and discoloration of leaves (Alberto et al. 2018). Another characteristic symptom of twister is chlorosis which is characterized by yellowing of leaf tissue due to a lack of chlorophyll. This indicates that GNDVI is sensitive to chlorophyll concentration since it is effective in discriminating healthy and twister infected onion. Results of the study also concurs with the study of Kumbula et al. 2019 where they separated the healthy and unhealthy (stressed) vegetation which were observed in the green peak and vegetation red edge region, hence, vegetation indices such as PVR and GNDVI showed an outstanding performance in detecting the probability of *C. tristis* occurrence. PSSRa and NDVI that produce high classification accuracies were also reported to be one of the best performing VIs in terms of correlation coefficient with respect to canopy chlorophyll content (Frampton et al. 2013).

Table 3. Accuracy assessment of vegetation indices based on confusion matrix

Vegetation Indices	Overall Accuracy
Green Normalized Difference Vegetation Index (GNDVI)	83.33%
Pigment specific simple ratio for chlorophyll a (PSSRa)	80.95%
Normalized Difference Vegetation Index (NDVI)	78.57%
Normalized Difference Index 4 and 5 (NDI45)	52.38%
Modified Chlorophyll Absorption in Reflectance Index (MCARI)	52.38%
Soil Adjusted Vegetation Index (SAVI)	50.00%

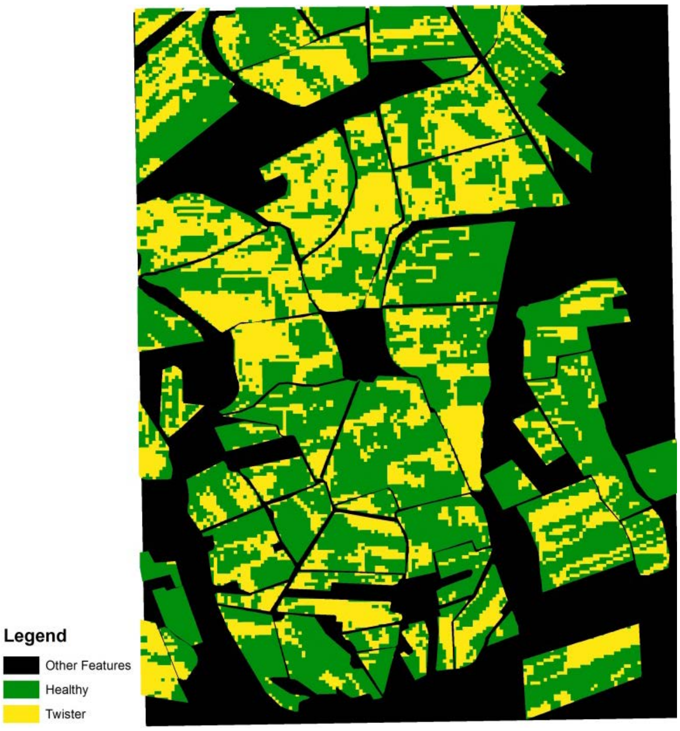

Figure 3. Classification map of healthy and twister infected onion field detected using GNDVI index from Sentinel 2 imagery

4. CONCLUSION

Vegetation indices generated from Sentinel 2 imagery were evaluated in their capability to detect and map the twister disease of onion in the field. Classification accuracy of individual VIs derived from ISODATA classification has been investigated. The results of the study indicate that vegetation indices derived from Sentinel 2 imagery could be used for twister classification which shows satisfactory results. Regression analysis was also performed in each individual VIs to assess the ability of vegetation indices in estimating the disease index. It was found out that NDVI and GNDVI has the highest coefficient of determination (R^2) indicating a strong relationship with the disease severity. It was also found out that the majority of the indices used in this study shows a negative correlation to disease severity index except for TSAVI. Results of the classification showed that GNDVI PSSRa and NDVI obtained the highest overall accuracy. This indicates that this 3 VIs can be used for detection of twister since it gives better discrimination and high accuracies. Hence VI's generated from Sentinel 2 imagery has a potential use in detection, monitoring and management of twister disease of onion.

5. ACKNOWLEDGEMENT

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