Detecting and monitoring the progress of powdery mildew disease in squash using hyperspectral imaging and artificial neural networks

Jaafar Abdulridha[1], Yiannis Ampatzidis[2], Pamela Roberts[3], Sri Charan Kakarla[4]

[1] Postdoctoral fellow, Department of Agriculture and Biological Engineering, Southwest Florida Research and Education Center, University of Florida, USA; e-mail: ftash@ufl.edu

[2] Assistant professor, Agricultural and Biological Engineering Department -Southwest Florida Research and Education Center, University of Florida, 2685 SR 29 North Immokalee, FL 34142, USA; e-mail: i.ampatzidis@ufl.edu.

[3] Professor, Plant Pathology Department, Southwest Florida Research and Education Center, University of Florida, USA; e-mail: pdr@ufl.edu

[4] Engineer, Department of Agriculture and Biological Engineering, Southwest Florida Research and Education Center, University of Florida, USA; e-mail: charanksri@ufl.edu

Abstract

Timely disease detection can improve disease management and reduce environmental impact, as applying unnecessary chemical applications could increase the risk of pollution and reduce profit. Herein, different development stages of powdery mildew disease (asymptomatic, early, intermediate, and late stage) were monitored in a squash crop by utilizing hyperspectral imaging (380-1030 nm) in laboratory conditions (the spectral measurements were conducted seven times). Radial basis function network was used to discriminate between healthy and diseased plant and to distinguish the infection level (disease development stage). Since, spectral Vegetation Indices (VIs) have been shown to be useful for monitoring disease development stages, seventeen VIs were selected and evaluated to detect and classify healthy and powdery mildew diseased plants. The best VI that can be used for disease detection was the water index (WI) in early, intermediate and late disease development stage. High classification rates, ranging from 82% - 99% for asymptomatic to late stages, were achieved in disease detection.

Keyword: Disease, powdery mildew, hyperspectral, vegetation indices, classification methods, neural networks.

Introduction

Cucurbita pepo (squash, pumpkin, and gourd) are important and economically profitable vegetable crops. These species are highly susceptible to the powdery mildew (PM) disease caused by the fungus *Podosphaera xanthii* (Cohen et al., 2003). Early disease detection is necessary for the optimal field management of the PM disease. The PM disease must be controlled effectively in order to prevent the spreading of the disease throughout the field and reduce the disease severity.

Disease detection is considered a critical task especially during the early disease development stage(s). Detecting a disease at an early stage might prevent growers from losing the majority of the crops. It can help growers to early detect a disease in small areas and apply precision management practices to control it and avoid spreading in the entire field, which can save time and money.

Visible and near infrared (NIR) spectroscopy is one of the nondestructive methods to detect plant diseases in the laboratory (Abdulridha et al., 2018; Ampatzidis et al., 2017; Luvisi et al., 2016). Several studies utilized this technology in disease and stress detection (Abdulridha et al., 2019a; Harihara et al., 2019). Xu et al. (2007) detected and monitored the leafminer damage in tomato leaves by using NIR spectroscopy (800-2500 nm). The classification was determined in five scales based on the severity level of the disease displayed on the surface of the plant leaves. Abdulridha et al. (2019b) were able to select the best wavelength to detect phytophthora root rot and laurel wilt in avocado trees. The objectives of this study were to: i) evaluate and detect the powdery mildew disease in squash plants in the laboratory, ii) monitor the progress of the powdery mildew disease before and after infection, iii) obtain the optimal wavelength and vegetation indices for disease detection.

Materials and methods

Data collection

Squash leaves (*Cucurbita pepo* 'Yellow Crookneck') were collected before and after natural infection by powdery mildew at University of Florida- Southwest Florida Research and Education Center, in Immokalee, FL. For laboratory measurements, ten leaves were collected at regular intervals to monitor the development of the disease after the infection (April 8, 12, 15, 17, 19, 22, May 1st) (Fig 1). The first set of collected leaves did not show any symptoms, and then the symptoms started to appear gradually after few days.

(a) (b) (c)

Figure 1: Squash plants in different development stages of the powdery mildew disease: a) healthy leaf, b) leaf with early symptoms, c) leaf with late symptoms.

Hyperspectral data collection

A benchtop hyperspectral imaging system, Pika L 2.4 (Resonon Inc., Bozeman MT, USA), was used to collect reflectance data *(*Fig. 2). The Pika L 2.4 is equipped with a 23 mm lens which has a spectral range of 380-1030 nm, 281 spectral channels, 15.3º field of view and a spectral resolution of 2.1 nm.

Figure 2: Laboratory spectral measurements of squash leaves using a benchtop hyperspectral imaging system.

Vegetation indices (VIs)

Seventeen VIs (Table 1) were selected and evaluated to detect and classify healthy and powdery mildew-affected plants. The proposed VIs evaluate the quality and the quantity of the measured vegetation using hyperspectral data. Usually, any spectral measurement would be a combination of reflectance by vegetation, soil, illumination, humidity, temperature, smoke, ecological effect, shadow, soil color and moisture.

Table 1: Vegetation indices utilized in this study.

VIs	Equations and references
Ratio Analysis of reflectance Spectral Chlorophyll-a (RARSa)	$\text{RARSa} = \frac{R675}{R700}$ (Chappelle et al. 1992)
Ratio Analysis of reflectance Spectral Chlorophyll b (RARSb)	$\text{RARSb} = \frac{R675}{(R700 \times R650)}$ (Chappelle et al. 1992)
Water Index (WI)	$\text{WI} = \frac{R900}{R970}$ (Penuelas et al. 1997)
Water Stress and Canopy Temperature (NWI 2)	$\text{NWI2} = \frac{R970-R850}{R970+R850}$ (Babar et al. 2006)
Structure Insensitive Pigment Index (SIPI)	$\text{SIPI} = \frac{(R840-R450)}{(R840-R670)}$ (Penuelas et al. 1995)
Normalized phaeophytinization index (NPQI)	$\text{NPQI} = \frac{(R415-R435)}{(R415+R435)}$ (Barnes et al. 1992)
Normalized difference vegetation index (NDVI 760)	$\text{NDVI 760} = \frac{(R760-R450)}{(R760-R450)}$ (Raun et al. 2001)
Normalized difference vegetation index 850 (NDVI 850)	$\text{NDVI 850} = \frac{(R850-R651)}{(R850+R651)}$ (Raun et al. 2001)
Simple Ratio Index (SR 760)	$\text{SR761} = \frac{R760}{R650}$ (Jordan 1969)
Simple Ratio Index (SR 850)	$\text{SR 850} = \frac{(R850)}{(R650)}$ (Jordan 1969)
Triangle Vegetation Index (TVI)	TVI=0.5[120*(R750-R550)-200(R670-R550)] (Broge & Leblanc 2001)
Modified Triangular Vegetation Index1 (MTVI 1)	MTVI 1= 1.2[1.2*(R800-R550)-2.5 (R670-R550)] (Haboudane et al. 2004)
Renormalized Difference Vegetation Index (RDVI)	$\text{RDVI} = \frac{(R760 - R650)}{(R760 + R650)^{0.5}}$ (Roujean & Breon 1995)
Red-Edge Vegetation Stress Index 1 (RVS 1)	$\text{RVSI 1} = \frac{(R650 + \text{Red Edge } 750)}{2} -$ Red Edge 733 (Merton 1998)
Normalize difference of 750/705	$\text{ND750/705} = \frac{(R750-R705)}{(R750+R705)}$ (Raun et al. 2001)
Modified Chlorophyll Absorption in Reflectance Index (mCARI 1)	mCARI 1= 1.2[(2.5*(R761-R651)-1.3(R761-R581)] (Haboudane et al. 2004)
Anthocyanin Reflectance Index (ARI)	$\text{ARI} = (\frac{1}{R550}) - (\frac{1}{R700})$ (Gitelson et al. 2001)

Data analysis

The M value was used to differentiate between VIs by dividing the difference of mean of two categories (healthy and infected plants) by the sum of the standard deviation (σ) of the two categories (equation 1). There were six disease stages in the laboratory setting, and the M value was calculated to differentiate the results between each individual stage. The M value is generally higher when the standard deviation is low, which leads to the narrowing of the histogram of spectral reflectance which leads to less overlap and good separability (Kaufman & Remer 1994). The M value is considered as a significant discriminant between different vegetation indices. As the value of M value increases, less overlap and better separability is observed (Smith et al. 2007). Furthermore, the Tukey's HSD test (α = 0.01) was used to analyze and evaluate all VIs using the SPSS software.

$$M\ value\ = \frac{(Mean_{Healthy} - Mean_{Infected})}{(\sigma_{Healthy} + \sigma_{Infected})} \qquad (1)$$

Radial basis function network (RBF)

A radial basis function network is a type of artificial neural network. It uses a supervised machine learning to work as a non-linear classifier. In contrast to simple linear classifiers that work on lower-dimensional vectors, non-linear classifiers use advanced functions to go further deep into the analysis. RBF performs classification by measuring the input similarity to examples from the training set. RBF is generally considered a relatively intuitive approach and a better way to address specialized machine learning problems.

Results and discussion

Spectral reflectance of squash leaves collected in laboratory conditions

The squash leaves were collected every 3-4 days, based on the progress of PM disease, and their spectral reflectance was measured in laboratory conditions. The spectral reflectance of leaves across time varied depending on the disease development stage. Fig. 3 shows that the spectral reflectance of leaves was increased in the green and red range gradually as the disease progressed and as the symptoms increased; the spectral reflectance was higher in the late stage of PM disease.

Disease detection accuracies, using the RBF classifier, in initial disease development stages was at 82% and increased gradually to reach 99% in the late disease development stages (Fig 4). The best bands, where the most significant differences could be observed, were selected between 966 nm to 989 nm for PM1, PM2, PM3 and PM4 stages. There was no significant difference between the classification accuracies of these bands, which was tested by using the Tukey's HSD test (Honestly Significant Difference α = 0.01). In the late PM5 stage, the best bands were selected between 1,005 nm and 1,016 nm, while for the very late stage, PM6, the best bands were selected in blue range at 388-398 nm (Table 2).

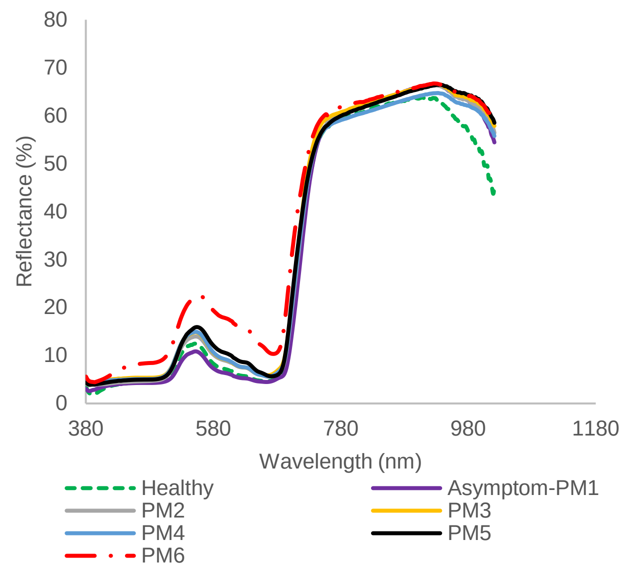


Figure 3: Spectral reflectance signatures of healthy squash plants and powdery mildew-affected plants in different disease development stages.

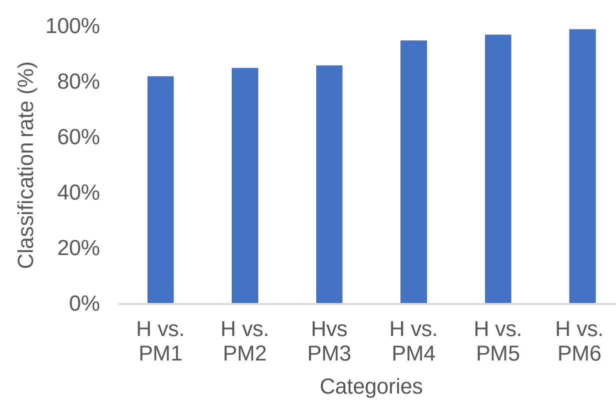


Figure 4: Classification accuracy, using the radial basis function classifier, of health and powdery mildew-affected squash plants in different disease development stages.

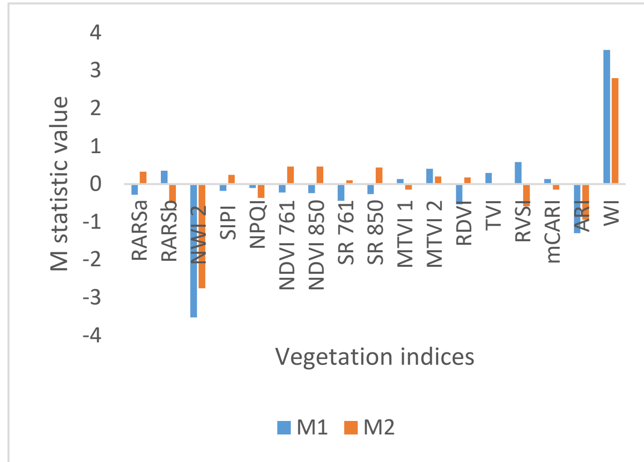
Table 2: The best wavebands selected in laboratory condition based on disease severity; the weight value (classification accuracy) of each band is reported in parentheses. The letter "a" denotes that there is no significant difference between the bands.

Parameters	Best bands selected and their weight value
H vs. PM1	991(100%) a, 976 (100%) a, 978 (99%) a, 992 (99%) a, 989 (98%) a
H vs. PM2	960 (100%) a, 964 (98%) a, 975 (98%) a, 966 (97%) a, 966 (97%) a
H vs PM3	975 (100) a, 964 (98%) a, 975 (98%) a, 966 (97%) a, 966 (97%) a
H vs. PM4	975 (100) a, 964 (98%) a, 975 (98%) a, 966 (97%) a, 966 (97%) a
H vs. PM5	1,012 (100) a, 1,014(99%) a, 1,016 (98%) a, 1,007 (98%) a, 1005 (97%) a
H vs. PM6	388 (100) a, 397 (99%) a, 394 (96%) a, 396 (94%) a, 390 (94%) a

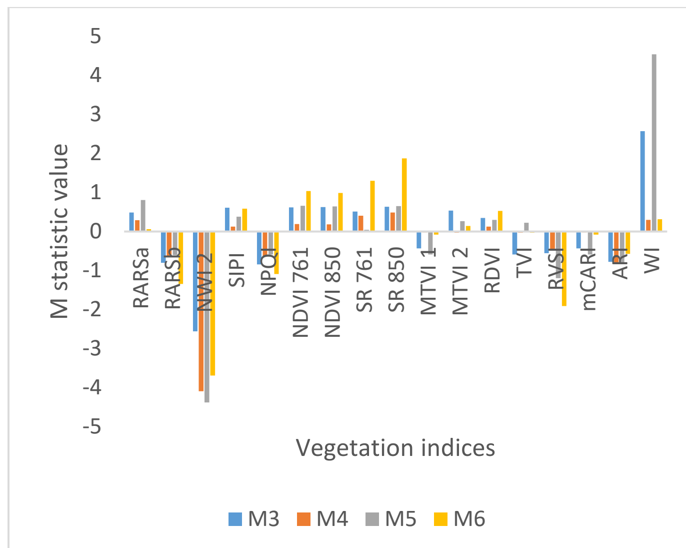
Tukey's HSD test (α = 0.01).

Vegetation indices analysis

The highest M discrimination value for VIs in early PM1 and PM2 stages was observed in the water index (WI) and the Red-Edge Vegetation Stress Index 1 (RVSI 1). Most of the studied VIs in the early stage had a low separation power except the WI, for which the M value was more than 1.0, which indicates a high and good discrimination (de Castro et al., 2015). Fig 5 presents the M value of some of the studied vegetation indices. The best VIs for disease detection varied based on the disease development stage. The M value of the WI increased from 3. 5 in PM1 to 4.5 in PM5, while it reduced to 0.3 in PM6 stage. The M value of the SR850 increased from 0.6 in PM3 to 1.8 in PM6, and the SR761 also increased from 0.6 to 1.8 in PM3 and PM6 stages respectively. This indicates that the WI was the best distinguisher in PM5 stage, and the SR 850 and SR 761 were the best distinguishers in PM6 stage. The least M value among the VIs was observed for the NWI 2 and ARI.



(a)



(b)

Figure 5: M value for some vegetation indices for: a) very early disease stage (PM1 & PM2); b) intermediate and very late stages (PM3-PM6). Data were acquired in laboratory conditions.

Conclusion

The spectral reflectance analysis of squash leaves in indoor conditions was performed to track different PM disease development stages (asymptomatic, early, intermediate and late disease) and to differentiate between each stage of the PM disease. The best bands were selected to differentiate between healthy and PM-affected plants (several disease development stages). Furthermore, a radial basis function classifier was utilized to distinguish the disease severity stages.

The highest classification accuracy (99%) was observed in the very late disease development stage. The most significant vegetation indices that could differentiate between different stages of the disease were the water index (WI) in asymptomatic, intermediate and late stages.

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