

# Hyperspectral Discrimination and Response Characteristics of Stressed Rice Leaves Caused by Rice Leaf Folder

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**Abstract.** Detecting plant health condition plays an important role in controlling disease and insect pest stresses in agricultural crops. In this study, we applied support vector classification machine (SVC) and principal components analysis (PCA) techniques for discriminating and classifying the normal and stressed paddy rice (*Oryza sativa* L.) leaves caused by rice leaf folder (*Cnaphalocrocis medinalis* Guen). The hyperspectral reflectance of paddy rice leaves was measured through the full wavelength range from 350 to 2500nm under the laboratory condition. The hyperspectral response characteristic analysis of rice leaves indicated that the stressed leaves presented a higher reflectance in the visible (430~470 nm, 490~610 nm and 610~680 nm) and one shortwave infrared (2080~2350 nm) region, and a lower reflectance in the near infrared (780~890 nm) and the other shortwave infrared (1580~1750 nm) region than the normal leaves. PCA was performed to obtain the principal components (PCs) derived from the raw and first derivative reflectance (FDR) spectra. The nonlinear support vector classification machine (referred to as C-SVC) was employed to differentiate the normal and stressed leaves with the front several PCs as the independent variables of C-SVC model. Classification accuracy was evaluated using overall accuracy (OA) and Kappa coefficient. OA of C-SVC with PCA derived from both the raw and FDR spectra for the testing dataset were 100%, and the corresponding Kappa coefficients were 1. Our results would suggest that it's capable of discriminating the stressed rice leaves from normal ones using hyperspectral remote sensing data under the laboratory condition.

**Keywords:** Hyperspectral remote sensing; Rice crop; Rice leaf folder; Principal components analysis (PCA); Support vector classification (SVC)

## 1 Introduction

Detecting plant health condition plays an important role in controlling disease and insect pest stresses in agricultural crops, which always lead to yield loss and poor quality<sup>[1]</sup>. Although pest damage is predominantly concentrated in patches around original foci, the common protecting practice is still to spray agrochemicals indiscriminately over the entire fields<sup>[2]</sup>. To minimize economic loss and reduce ecological and environmental pressure due to the superfluous input of agrochemicals, it's necessary to accurately know the pest distribution locations and damage degrees caused by disease and insects<sup>[3]</sup> so that the most economical amount of agrochemicals can be applied to the infestation patches. It's a pity that the most common method of damage quantification evaluation is still visual survey<sup>[4]</sup>. However, this technique is subjective, labor-intensive, and time-consuming, and it is impossible to accurately estimate the damaged areas and severity over a wide range<sup>[5]</sup>. Recently, remote sensing techniques have been proved to be effective to monitor insect infestation and disease epidemic in agricultural crops and other plants from ground to satellite platforms, especially in the site-specific crop management of precision agriculture<sup>[6]</sup>.

The current studies have shown that plant spectral properties at visible and near-infrared (NIR) regions vary with the development of specific signatures for a specific stress of a given plant species<sup>[2]</sup>. The reflectance or digital number of healthy plants is low in the visible region (400~700 nm) due to strong pigment absorption, is high in the NIR region (750~1300 nm) for cellular and subcellular structure, and is variable in the shortwave infrared (SWIR) region (1300~2500 nm) because of the presence of water vapor, proteins, and other biophysical and biochemical elements<sup>[2-3, 5]</sup>. In addition to raw reflectance, derivative spectral reflectance and various vegetation indices can also be effective in detecting plant stresses<sup>[6-7]</sup>.

Furthermore, various statistical methods, including cluster analysis<sup>[8]</sup>, decision tree<sup>[9]</sup>, partial-least square regression<sup>[10]</sup>, and principal component analysis (PCA)<sup>[2]</sup>, have been used with various remote sensing data for detecting plant stresses. Among them, PCA is the most widespread method for hyperspectral remote sensing data because it can solve the high dependence and autocorrelation in adjacent wavebands<sup>[11]</sup>. Moreover, the application of artificial intelligence methods including artificial neural networks (ANN) and support vector machines (SVM) in plant stress detection has also been reported recently<sup>[2,12]</sup>. The nonlinear support vector classification machine (viz. C-SVC) had been used to detect the rice health condition at the leaf and canopy levels, which obtained above 85% of the classification accuracy<sup>[12]</sup>.

Rice (*Oryza sativa* L.) is the most important staple food in Asia area and there have been a lot of remote sensing-based researches in rice disease and insect pest damage which harm the leaf lamina, leaf sheath, stem, panicles and other organs<sup>[2,12]</sup>. However, little study was found to discriminate the normal and stressed rice leaves caused by rice leaf folder<sup>[13-14]</sup>. Rice leaf folder (*Cnaphalocrocis medinalis* Guen) is widely distributed between 48° N and 24° S latitude and 0° E to 172° W longitude in the rice growing areas of Asia, Oceania, Australia and Africa<sup>[15]</sup>. The feeding damage caused by rice leaf folder shows up characteristically in pale stripe in the leaf where the chlorophyll-bearing tissues have been eaten away, and only epidermis and cuticle remains. All feeding damage is strictly linear, i.e., occurs in the longitudinal axis of the leaf between the veins.

The purposes of the present study are (1) to analyze the hyperspectral response characteristics of raw and first derivative reflectance (FDR) of normal and stressed paddy rice leaves caused by rice leaf folder, (2) to identify the principal components (PCs) derived from both the raw and FDR spectra, and (3) to examine the capability of SVM in combination with PCA for discriminating normal and stressed rice leaves.

## 2 Methodology

### 2.1 Study Sites

The samples of normal and stressed rice leaves caused by rice leaf folder (*Cnaphalocrocis medinalis* Guen) were collected in three paddy rice fields at the active tillering stage. One field was located near Yundong village (30°12'N, 120°28'E), and the second in Zhangpanqiao Village (30°06'N, 120°15'E), Xiaoshan District, and the last in the Experiment Farmland of Zhejiang University (30°14'N, 120°10'E), China. The sampling date in the former two paddy fields were on July 27<sup>th</sup>, 2007 and the sampling number of normal and stressed rice leaves in all was as equal as 19. The sampling date in the latter and last paddy field was on August 14<sup>th</sup>, 2007 and the sampling number of normal and stressed rice leaves was as equal as 35. The rice cultivar names in the three sites were unknown, but all of them belonged to hybrid and Japonica rice.

### 2.2 Foliar Hyperspectral Reflectance Measurement

The normal and stressed rice leaves caused by rice leaf folder (*Cnaphalocrocis medinalis* Guen), which were verified by plant protection expert, were cut from the rice individuals in the paddy fields. The samples were put into an incubator (25°C) and were transported to the laboratory for further measurements. The foliar hyperspectral reflectance of paddy rice was measured with a portable spectrophotometer (Analytical Spectral Devices Inc., Boulder, CO, USA) through the full wavelength range from 350 nm to 2500 nm. The spectral resolution of the instrument varied from 3 nm less than 1000 nm to 10nm more than 1000 nm, while the spectra were interpolated by the spectrometer software in 1 nm intervals.

Each leaf was positioned on a dark background. The fiber optic sensor with 8° instantaneous field of view (IFOV) vertically pointed to the upper leaf surface about 3 cm height. An incidence angle of 45° was maintained at a standard distance (50 cm). The light source used was one 50 watt halogen lamp. For each paddy rice leaf, a sampling spectrum was made consisting of five readings and four sampling spectra were measured. The average hyperspectra derived from four sampling spectra represented each leaf using ViewSpec Pro (version 5.6.10). All spectral measurements were made relative to a BaSO<sub>4</sub> standard reference-panel, which was observed immediately before and after the spectral measurements of rice leaves.

### 2.3 Foliar Pigment Concentration Measurement

Immediately after foliar hyperspectral reflectance measurements have been taken, the leaves were chipped, weighted and then dipped in 20 milliliter solution (acetone: ethanol: distilled water = 4.5:4.5:1) for 24 hours to extract pigment. The optical density of the extraction solution was measured at 440 nm, 645 nm, and 663 nm by spectrophotometer (Shimadzu UV 2550, Tokyo, Japan). Pigment consists of chlorophyll a (ab. Chl a), Chlorophyll b (ab. Chl b), total chlorophyll (ab. ChlT, which is equal to Chl (a+b)) and Carotenoid (ab. Car) in the study. The formula of pigment concentration (mg/g) was referenced the literature of Tang *et al.*<sup>[16]</sup>. The statistical information of pigment on rice leaves was shown in Table 1.

### 2.4 Data Preprocessing

Firstly, the hyperspectral reflectance was smoothed with a seven step moving average to suppress the instrumental and environmental noise before these data were further analyzed<sup>[5]</sup>. Next, the raw hyperspectral reflectance less than 400 nm and more than 2400 nm were deleted due to severe instrument and system noise. The effective spectral region of FDR ranged from 450 nm to 850 nm. Furthermore, the total dataset was consciously divided into two parts, namely training and testing datasets. The training dataset included the normal and stressed rice leaves caused by rice leaf folder, viz. those leaves which were collected on August 14<sup>th</sup>, 2007. The testing dataset was consisted of those leaves which were collected on July 27<sup>th</sup>, 2007.

Derivative spectroscopy is proposed to tackle analogous problems such as background signals and to solve overlapping problems in spectral features. In practice, the simplest method of finding derivatives is by dividing the difference between successive spectral reflectance by the wavelength interval separating them<sup>[7]</sup>. The FDR spectra can provide the slope information on the rate of change reflectance with respect to wavelength<sup>[17]</sup>. FDR were calculated to analyze the hyperspectral response characteristics of stressed rice leaves caused by rice leaf folder in this study.

### 2.5 Analytical Techniques

Principal component analysis (PCA) is capable of preserving the total variance and minimizing the mean square approximate errors, and it is also used to identify the dominant modes of the original dataset such that the first principal component (PC<sub>1</sub>) accounts for the maximum possible proportion of the variance information of the original dataset, and subsequent principal components (PC<sub>2</sub>, PC<sub>3</sub> ...) account for the maximum proportion of the unexplained residual variance, and so forth<sup>[17]</sup>. The application of PCA has been reported in many studies as an effective data compression technique especially for hyperspectral remote sensing data because it can solve the high dependence and autocorrelation in adjacent wavebands<sup>[11]</sup>. PCs were calculated to represent the hyperspectral features of rice leaves in this study.

Support vector classification (SVC), which is a popular technique for data classification, is one of the most important parts of support vector machine (SVM).

The aim of SVC is to devise a computationally efficient way of learning ‘good’ separating hyperplanes in a high dimensional feature space based on the generalization and optimization theory<sup>[18]</sup>. SVC was conducted in LIBSVM (Library for Support Vector Machines) developed by Chang and Lin<sup>[19]</sup> in our study. The goal of LIBSVM is to help users to easily use SVM as an attached library for SVM. LIBSVM is consisted of *C*-SVC,  $\nu$ -SVC, distribution estimation (one-class SVM), and other models. Thereinto *C*-SVC was adopted in this study. The key parameters of LIBSVM such as kernel function  $\gamma$  and penalty parameter *C* and other parameters are provided with default selections available.

There were two assessment parameters to evaluate the accuracy of *C*-SVC combing with PCA in this study. One is Kappa coefficient which is one measure of the level of agreement. A Kappa coefficient of 1 denotes a full agreement and 0 denotes full disagreement between the actual and predictive classification [20]. The other is overall accuracy (OA) which denotes the agreement probability between the predictive and actual classification for each random sample.

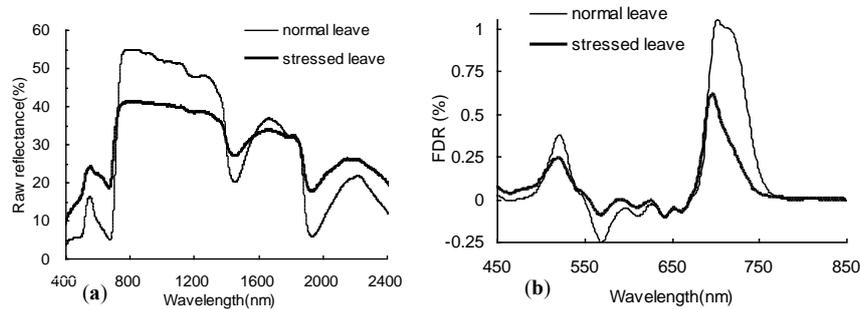
### 3 Results

#### 3.1 Hyperspectral Response Characteristics of Paddy Rice Leaves

Applying hyperspectral remote sensing to precise crop integrated pest management (IPM) is on the basis of spectral response characteristics of paddy rice leaves to crop insect stress in Fig.1. Fig.1 showed the hyperspectral difference was obvious between normal and stressed paddy rice leaves caused by rice leaf folder at the nanometer level because there were evident changes in pigment concentration (Table 1), cell and texture arrangement structure and foliar water content due to the feeding damage caused by rice leaf folder<sup>[15]</sup>. Furthermore, six wavelength intervals (Table 2) had been calculated to simulate the high resolution geometric (HRG) and vegetation (VGT) sensors of Systeme Probatoire d’Observation dela Tarre (SPOT) satellite based on arithmetic mean of hyperspectral reflectance for universal application of SPOT’s image in vegetation monitoring all over the world. The simulated six wavelength intervals clearly indicated the hyperspectral difference between normal and stressed paddy rice leaves from visible spectrum region (PA: 460~690 nm, B0: 430~470 nm, B1: 490~610 nm and B2: 610~680 nm) to NIR (B3: 780~890 nm) and SWIR (1580~1750 nm).

As shown in Fig.1 (a), the raw hyperspectral feature of the normal paddy rice leaves was different from the stressed leaves through the full spectra range (400~2400 nm). Because paddy rice foliar pigment concentration decreased obviously (Table 1), hyperspectral reflectance of stressed leaves increased 2.9, 1.9 and 3.3 times than the normal ones in the visible blue (B0), green and near red (B1) and red (B2) light region (Table 2), respectively. However, the hyperspectral reflectance of stressed leaves decreased 20.7% and 9.7% than the normal ones in NIR (B3) and one SWIR (2.08~2.35 $\mu$ m) region, respectively. But in the other SWIR region, the hyperspectral reflectance increased 28.9% in comparison with the normal ones.

The amplitude of FDR for stressed paddy rice leaves was smaller than that of normal ones as shown in Fig.1 (b). Maybe it's because the stressed paddy rice leaves looked like 'white' color after rice leaf folder fed; the hyperspectral reflectance of the stressed paddy rice leaves had lower change range with respect to wavelengths. Both of the peak wavebands of normal and stressed leaves in the blue light region were located at 521 nm. Same phenomenon occurred in the green light region, the peak waveband (569 nm) of stressed leaves was equal to normal leaves. The red edge position of normal leaves was at 702 nm, but the stressed leaves shifted toward short wavebands about 5 nm.



**Fig. 1.** Average hyperspectral reflectance of rice leaves collected on August 14<sup>th</sup>, 2007.

**Table 1.** Statistical description of paddy rice foliar pigment concentration (Unit: mg/g)\*.

Statistical parameters	Normal rice leaves, N=35			Stressed rice leaves, N=35		
	Chl a	Chl b	Car	Chl a	Chl b	Car
Min.	1.63	0.57	0.60	0.88	0.36	0.35
Mean	2.06	0.71	0.76	1.35	0.52	0.54
Max.	2.53	0.83	0.96	1.90	0.73	0.79
Std. dev	0.19	0.06	0.08	0.25	0.10	0.10
VC	9.2%	8.0%	10.1%	18.7%	18.7%	19.4%

\* The paddy rice leaves were collected on August 14<sup>th</sup>, 2007.

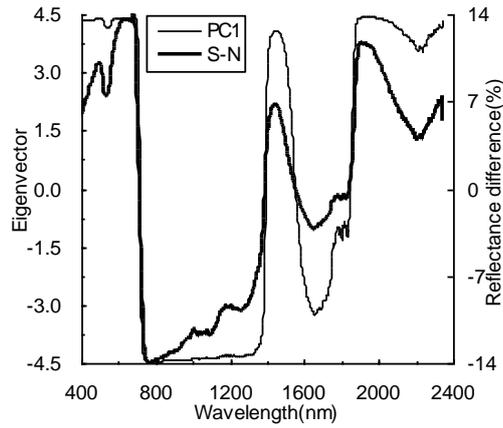
**Table 2.** Average canopy hyperspectral reflectance of rice crops at six wavelength intervals representing the High Resolution Geometric (HRG) and Vegetation (VGT) of SPOT (Unit: %)\*.

Spectra range	July 27 <sup>th</sup> , 2007		August 14 <sup>th</sup> , 2007	
	Normal(n=19)	Stressed(n=19)	Normal(N=35)	Stressed(n=35)
Pan: 490~690 nm	10.1c	22.6a	9.6c	20.9b
B0: 430~470 nm	5.2c	15.0a	5.5c	13.4b
B1: 490~610 nm	12.3c	22.8a	11.6c	21.4b
B2: 610~680 nm	6.8c	22.3a	6.7c	20.1b
B3: 780~890 nm	57.9a	45.9c	54.7b	41.1d
SWIR: 1580~1750 nm	39.2a	35.4b	35.7b	33.2c

\* Reflectance values within a row followed by the same letter are not significantly different from each other by Duncan test at  $\alpha = 0.05$ .

### 3.2 Principal Component Analysis

The first principal component (PC1) explained 72.1% of the variance of the raw hyperspectral reflectance in rice leaves for the training dataset. Fig.2 showed both eigenvector of PC1 and the spectral reflectance difference between the stressed and normal leaves. PC1 had a loading of 0.958 to the reflectance difference of raw spectra between the stressed and normal rice leaves.



**Fig. 2.** Loading plot of the first principal component (PC1) derived from the raw hyperspectral reflectance. S-N meant the hyperspectral reflectance difference between the stressed and normal paddy rice leaves.

The results of the principal component analysis (PCA) revealed that the cumulative contribution of the front three components of the raw hyperspectral reflectance and FDR for the training dataset were 98.1% and 66.2%, respectively (Table 3). Generally speaking, when the cumulative contribution of the front several components is above 80~85%, the remaining components always are omitted in further analysis<sup>[17]</sup>. So the front eighteen components could explain 85.6% of the variance of FDR for training dataset, which were regarded as the principal component spectra (PCs) in this study.

**Table 3.** Percentage of explained variance for the front three PCs (Unit: %)\*.

Spectral types	Training dataset (August 14 <sup>th</sup> , 2007)				Testing dataset (July 27 <sup>th</sup> , 2007)			
	PC1	PC2	PC3	CC	PC1	PC2	PC3	C
Raw	72.1	24.6	1.4	98.1	70.4	26.8	1.6	98.8
FDR	47.9	14.1	4.2	66.2	68.4	11.1	7.6	87.2

\* CC denotes the cumulative contribution.

### 3.3 Results of Support Vector Classification Machine

The nonlinear support vector classification machine (referred to as C-SVC) was used to automatically detect the health condition of paddy rice leaves. The C-SVC model

was built to differentiate the stressed rice leaves from normal ones by using the training dataset consisting of dependent (i.e. normal and stressed rice leaf categories) and independent (i.e. PCs) variables for calibration purpose. The *C*-SVC model was run repeatedly with multifarious sets of values of  $\gamma$  (kernel function) and *C* (penalty parameter) at least three times for cross-validation in order that the optimum classification result could be obtained. When  $\gamma$  was RBF (radial basis function) and *C* was 1, the *C*-SVC model was able to discriminate paddy rice leaves categories without any error. Then the *C*-SVC model was validated by the testing dataset and the classification results were given in Table 4. Not only for the raw hyperspectral reflectance, but also FDR spectra, none of normal or stressed paddy rice leaf was classified mistakenly. The stressed rice leaves had obviously spectral difference from normal ones after the rice leaf folder fed (Fig. 1 and Table 2), which resulted in the perfect classification result by *C*-SVC model integrated with PCA.

**Table 4. Error matrix for C-SVC from the testing dataset with PCs derived from raw and FDR spectra.**

Actual classification	Predictive classification					
	Raw spectra (OA=100%, Kappa coefficient=1)			FDR spectra (OA=100%, Kappa coefficient=1)		
	Normal	Stressed	Total	Normal	Stressed	Total
Normal	19	0	19	19	0	19
Stressed	0	19	19	0	19	19
Total	19	19	38	19	19	38

## 4 Discussions

In this study, *C*-SVC was employed to detect the health condition of paddy rice leaves by integrating it with PCA using raw hyperspectral reflectance and FDR. The results indicated that the stressed rice leaves caused by rice leaf folder presented a higher reflectance in the visible (430~470 nm, 490~610 nm, 610~680 nm) and one shortwave infrared (2080~2350 nm) region, and a lower reflectance in the NIR (780~890 nm) and the other SWIR (1580~1750 nm) region than the normal leaves (Fig.1a and Table 2). These results were consistent with our previous research<sup>[13]</sup>, and were similar to other's results for greenbug-damaged wheat at the leaf or canopy level<sup>[6]</sup>. However, our results were not in agreement with the report from Huang *et al.*<sup>[14]</sup> who concluded that the spectral reflectance of rice leaf decreased in the green (530~570 nm) region with the increase of the damage degrees. Perhaps because in our study the rice leaf folder almost fed on the whole upper surface leaf, there were little pigment concentration in the remaining downer surface leaf than the stressed leaves caused by greenbug<sup>[6]</sup> or rice leaf folder<sup>[14]</sup> in others reports.

FDR spectra were also analyzed from a different view. Perhaps because the stressed paddy rice leaves looked like 'white' color after rice leaf folder fed, the amplitude of FDR for stressed leaves was smaller than that of normal ones (Fig.1 b). Not only the stressed paddy rice leaves, but also the normal ones, the peak wavebands of blue and green spectrum region were located at 521 nm and 569 nm, respectively.

But the stressed leaves shifted toward short wavebands about 5 nm, which suggested that the red light spectrum region was more sensitive to plant pest damage than the blue and green regions. Similar results occurred in other results <sup>[6]</sup>.

The front several PCs were found to be sensitive to the reflectance and digital number of healthy and nonhealthy plants as well as their linear combinations according to current research <sup>[2]</sup>. Same results were also found in this study. PC1 could explain 95.8% of variance in the raw reflectance difference between the stressed and normal rice leaves (Fig.2). The front three PCs would reveal above 85% of cumulative contribution except the FDR spectra of training dataset (Table 3). Subsequently, the classification was almost perfect with the combination of *C-SVC* classifier and PCA for discriminating the stressed rice leaves from normal ones with the obtaining PCs (Table 4). Maybe it's because the stressed rice leaves had obviously spectral difference from normal ones after the rice leaf folder fed (Fig. 1 and Table 2).

## 5. Conclusions

Even though the present study would suggest that it's capable of discriminating the stressed rice leaves from normal ones using hyperspectral remote sensing data under the laboratory condition, this technique is probably still not very practical for detecting the health condition of agricultural crops under the field conditions <sup>[6]</sup>. More external factors, including atmospheric (e.g., illumination, cloudy shadow), edaphic (e.g., soil type, soil moisture), and biotic (e.g., crop variety, leaf area index) conditions as well as field management strategies, coexist at the canopy level <sup>[2]</sup>, which consequentially bring about too much noise in hyperspectral reflectance data and lower classification accuracy for stressed crops and their organs. Therefore, more studies are needed to explore the spectral response characteristics of rice crops under fungi and insect stresses of different levels in outdoor conditions.

The samples of rice leaves only had two levels, namely, normal and stressed rice leaves caused by rice leaf folder. However, the rate of rolling leaf is employed to determine the damage severity caused by rice leaf folder in practice. Future study should include more stress levels in order to discriminate not only the normal rice leaves from the stressed ones but different stress status.

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