Using SPOT-5 images in rice farming for detecting BPH (Brown Plant Hopper)

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Abstract. Infestation of rice plant-hopper such as Brown Plant Hopper (BPH) (Nilaparvata lugens) is one of the most notable risk in rice yield in tropical areas especially in Asia. In order to use visible and infrared images to detect stress in rice production caused by BPH infestation, several remote sensing techniques have been developed. Initial recognition of pest infestation by means of remote sensing will spread, for precision farming practice. To address this issue, detection of sheath blight in rice farming was examined by using SPOT-5 images. Specific image indices such as Normalized decrease food production costs, limit environmental hazards, and enhance natural pest control before the problem Normalized Difference Vegetation Index (NDVI), Standard difference indices (SDI) and Ratio Vegetation Index (RVI) were used for analyses using ENVI 4.8 and SPSS software. Results showed that all the indices to recognize infected plants are significant at α = 0.01. Examination of the association between the disease indices indicated that band 3 (near infrared) and band 4 (mid infrared) have a relatively high correlation. The selected indices declared better association for detecting healthy plants from diseased ones. Consequently, these sorts of indices especially NDVI could be valued as indicators for developing techniques for detecting the sheath blight of rice by using remote sensing. This infers that they are useful for crop disease detection but the spectral resolution is probably not sufficient to distinguish plants with light infections (low severity level). Using the index as an indicator can clarify the threshold for zoning the outbreaks. Quick assessment information is very useful in precision farming to practice site specific management such as pesticide application.

1. Introduction
Rice is considered as an important crop globally: more than half of the world’s population depends on it for supplying food. In aim of maintaining the crop, several parameters might affect sustainable rice farming which consist of both well-timed and appropriate pest control. The potential of remote sensing makes it useful as a proficient and low-priced system to recognize unhealthy plants in a ground scale, primarily for the reason that infected plants contain various spectral reactions in comparison to healthy ones (18). Few investigations have been undertaken on remote sensing applications for pest control in rice (19). Sensing issues have been discussed in terms of remote sensing methods (2). Most of the research on rice remote sensing was conducted using field zone mapping and production estimating, nevertheless, in order to evaluate plant greener for estimating the growth stage of plants, almost entire works were undertaken by means of hyperspectral remote sensing data. (1, 3, 4, 5, 6, 8 and 9). Several researches (13, 14, and 15) evaluated rice canopy spectra regarding to parameters such as leaf area index (LAI) and airborne phytomass in visible, near infrared and mid- infrared areas. Assessment of plant growth could be achieved by low-cost hyperspectral proximal sensing which evaluate detected data by purpose of measuring rice canopies (6, 7).
However visible light (solar radiation) is absorbed in live green vegetation in the photosynthesis process, but plants scatter (reflect) solar energy at the near infrared waveband simultaneously. This difference in absorption is relatively distinctive in live vegetation and measures the greenness of the plants.

Symptoms of BPH will not be visible from outside in the early stages, but if we enter the field and tap the plants many times, this insect can be seen. They are visible only when the damage is severe, indeed, the plants present a burned up appearance - so called hopper burn - in circular patches. Symptoms of BPH appear more in the later stages of plant growth, when they turn from a green colour to brownish very quickly. Although, nutrient deficiency caused by various reasons are recognized with the plant colour changing, first to dark green and then to yellow or brown, but this mostly happen at an early stage in different parts of the plant, while BPH often affects leaves and chlorophyll content. Morphological plant issues which indicating infection with pests are accessible in two ways: the appearance of the canopy caused by the inner destruction of chlorophyll pigments and then, the tissue construction for photosynthesis and metabolism. Therefore, the unhealthy plants will possess different spectral structures compared to healthy ones. Remote sensing can be used for both discriminating the spectral contrast and recognising the unhealthy plants or patches in the field (19). Rice cultivation around the world could be undesirably affected by pests and diseases. There is a requirement for an agricultural study in both spatial and temporal terms to demonstrate the features and variability of the above mentioned problems. Hence, to address this issue, the existing investigation prepared a pest and disease database for rice by means of satellite imagery and remote sensing analysis in Malaysia. Furthermore, database administration and network knowledge, to detect sheath blight of BPH in the field, will be applied.

2. Detection of crop condition by remote sensing

Functional changes inside vegetation may be seen throughout drought periods. Satellite devices are capable to identify such changes using spectral radiance measurements and applying these records to vegetation indices that are sensitive to the proportion of plant growth, amount of growth and variations of vegetation in terms of moisture stress.

Satellite multispectral sensors that monitor the greenness of vegetation are generated by means of the visible and near infrared (NIR) bands. Reflection of the NIR band in stressed vegetation, which in visible band has no energy absorption, is less than in non-stressed ones. Consequently, for observing the influence of drought on vegetation in moisture stressed and standard crops, wavelengths are more appropriate.

For identifying vegetation situations and moisture stress in vegetation the temporal configuration of NDVI is beneficial. For example, a poor NDVI value reflects rainfall deficiency.

The most critical process and time-consuming scheme in information management-related studies is data collection. Based on a systematic analysis of the current materials, including published and unpublished literature in crop diseases and pests, relevant information was collected for crop diseases and pest classifications from different sources.

3. Methodology

3.1 Study area

Tanjung Karang consists of a small agricultural town sited 7 km north of Kuala Selangor, beyond Pasir Penambang. Most Malays are living in rural areas and are involved in agricultural activities, mainly rice cultivation.
Tanjung Karang Rice Irrigation Scheme is positioned at about 3°25′ to 3°45′N and 100°58′ to 101°15′E in the state of Selangor Malaysia. Rice is grown twice a year mostly from August to January (main or wet season) and February to July (off or dry season).

3.2 Image data collection
SPOT-5 images were collected within 101°12′42.82″N and 3°28′49.88″E at upper left and also 101°13′49.71″N and 3°27′35.57″E at the lower right side. The images had four bands, in green: band 1 (530–600 nm); red: band 2 (610–680 nm), NIR: band 3 (780–1000 nm) and mid-infrared: band 4 (1000-2500nm). Most of the time, at the late growth stage BPH infection is greater. By this means, these dates of imagery were selected which are in both growth stages for comparison. The images were kept as 8-bit digital number (DN) values alternating from 0 to 255. Spatial resolution of the images was 2.5 m.

3.3 Image processing to extract data
Image data were extracted by help of ENVI 4.8 for producing subset captures of the field from the SPOT-5. Initially, BPH sheath blight through the paddy field was detected to identify unhealthy areas; the ENVI spectral utility was applied for data extraction from the subset images. To reduce probable bias, 4-pixel and 8-pixel were verified for arrangements of data extraction for evaluation. Additionally, the 8-pixel scheme was used in the study to extract data.

To apply change detection and threshold methods on multi temporal remotely sensed images, these must first be geometrically registered and radiometrically normalised. Converting DN to radiance was completed and SPOT gain and offset was determined. Among the processes, masking the clouds through subset images was performed.

3.4 Ground Observation
The ground orientation points were estimated through the field trip to the survey zones in the late season, by visiting the farms. Ground observation data was collected on 26 March in the Tanjung Karang area. These factors were used to address the locations where crops had been detected as attacked by BPH, due to SPOT image comparisons.
3.5 Process development to discover disease
Useful and appropriate indicators were identified to improve the technique for image processing. A number of indices such as Normalized Difference Vegetation Index (NDVI), Standard difference indices (SDI) and Ratio Vegetation Index (RVI) were used to isolate infected plants from healthy ones.

3.6 Image index computation
3.6.1 Normalized Difference Vegetation Index (NDVI)
NDVI is an index which provides a measure of vegetation density and condition. It is influenced by the fractional cover of the ground by vegetation, the vegetation density and greenness, and it indicates the photosynthetic capacity of the land surface cover. Its value is always between -1 and +1. Vegetation NDVI in Australia typically ranges from 0.1 to 0.7, with higher values associated with greater density and greenness of the plant canopy. NDVI decreases as leaves come under water stress, become diseased or die. Bare soil and snow values are close to zero, while water bodies have negative values.

The calculation of NDVI for an expected pixel always results in a number that ranges from minus one (-1) to plus one (+1); nevertheless, no green leaves provide a value near to zero; it means that if there is no vegetation the NDVI is shown at zero and if the area holds the maximum likely density of green leaves it is close to +1 (0.8 - 0.9).

The formula for NDVI is:

\[
NDVI = \frac{(NIR - RED)}{(NIR + RED)} \tag{1}
\]

3.6.2 Ratio Vegetation Index (RVI)
The RVI is a modest vegetation index, and is more than 30 years old. The definition of RVI is:

\[
RVI = \frac{NIR}{RED} \tag{2}
\]

RVI distributes the near infrared reflectance values by the visible red reflectance values. The ratio vegetation index is least influenced by soil brightness at LAI greater than three.

3.6.3 Standard difference indices (SDI)
The standard difference index is based on the fact that vegetation condition is closely related to environmental conditions. It displays the effects of climate and insects on vegetation over relatively long periods of time. Low SDI values show poor vegetation condition which could be the result of environmental conditions. Moisture shortage, pests and extreme temperature can cause low values.

The SDI can be expressed as follows:

\[
SDI = \frac{(b_2 - b_p)}{(b_2 + b_p)} \tag{3}
\]

- Where P is the range of bands 1, 3 and 4, and b2 refers to band 2; SDI is the standard difference index. The aim of this part of the study was to look for improved indicators for detecting rice sheath blight via remote sensing, by means of these indices.

3.7 Method development to detect disease
Appropriate indicators were designated to improve the technique for image processing. Various indices such as RI14, SDI14 and SDI24 show better correlations for detecting sheath blight in rice (20).
The following procedures have been used to develop the method:

**Step 1:** Processing the images to recover indices RI14, SDI14 and SDI24.

**Step 2:** The indices have dissimilar measurement components; it is necessary to convert their values into the same scheme for statistical analysis.

In this study the first stage for the conversion was to apply the following formulae:

\[
\text{DRI14} = \frac{\text{RI14} - \text{MRI14}}{\text{SDI14} - \text{MSDI14}}
\]

\[
\text{DSDI14} = \frac{\text{SDI14} - \text{MSDI14}}{\text{SDI14} - \text{MSDI14}}
\]

\[
\text{DSDI24} = \frac{\text{SDI24} - \text{MSDI24}}{\text{SDI24} - \text{MSDI24}}
\]

\[
\text{DNDVI} = \frac{\text{NDVI} - \text{MNDVI}}{\text{NDVI} - \text{MNDVI}}
\]

- In which DSDI14, DRI14, DNDVI and DSDI24 are standardizations of RI14, SDI14, NDVI and SDI24; MRI14, MSDI14, MNDVI and MSDI24 are average of the indices; SSDI14, SRI14, SNDVI and SSDI24 are the standard deviations.

Calculating a new index as a mean of the three designated indices relevant to the formulae is shown below:

\[
\text{SRI} = \frac{\text{DRI14} + \text{DSDI14} + \text{DSDI24} + \text{NDVI}}{4}
\]

- Where SRI refers to Significant Ratio Index. The upper value of SRI shows the greater disease infection rate of the pixel.

For testing the correlation between indices we computed T-test values, using SPSS software.

**4. Results & Discussion**

Unhealthy plants and soil apparently have a spectrum that is noticeably different from the healthy ones; the soil had the highest reflectance in the visible range, and the healthy plants had the lowest. Reflectance for diseased plants was among the reflectance interpretations of soil and healthy ones. Nevertheless, a spectral variance between the infected plants and the healthy ones was minor in identical ranges of the wavelengths. (19).

Table 1 shows the results of statistical analysis using indices, which have been used for differentiating healthy plants from unhealthy ones.

| Image indices | T-test** |
|---------------|---------|
| SDI14         | -7.47***|
| SDI24         | -6.29***|
| RVI14         | -7.44***|
| NDVI          | 8.89*** |

***Significant at \( \alpha = 0.001 \)  
**non-significant
(Table 1) shows that all the indices are significant at $\alpha = 0.01$ and specified definitions to recognize infected plants were assigned. By considering the table results, the NDVI index indicates better correlation compared to the rest.

Statistical analysis were conducted for testing sample based on another set of data derived from ten points on the three different dates; Results were illustrated in following table which shows that NDVI index proves better correlation compared to the others, moreover, similar finding to the training data set was found.

**Table2.** Correlation analysis of indices for 10 points.

| Image indices | T-test$^a$ |
|---------------|-----------|
| SDI$_{14}$    | -5.76***  |
| SDI$_{34}$    | -6.89***  |
| RVI$_{14}$    | -5.80***  |
| NDVI          | 13.24***  |

$^a$Significant at $\alpha=0.001$ $^a$ non-significant

Examination of the association between the disease indices indicated that both band 3 (near infrared) and band 4 (mid infrared) have a relatively high correlation. A similar analysis was extended to a further three images, which generated identical results. Consequently, it was necessary to carefully observe the image indices for further investigation. Four types of image indices were inspected here: ratio vegetation indices, standard difference indices and a normalized difference vegetation index. Rice spectral signs would be closer to the spectra of healthy plants while it had low levels of infection. However, differences between unhealthy plants and healthy ones could be detected, but recognition of infected ones from the others is only possible while the infection levels are above a certain value with larger spectral reactions.

4.1 Association examination for indices

![Figure 2. Correlation between ratio vegetation index and DN.](image)
(Figure 2) demonstrates superior relationships among the ratio indices, healthy and diseased plants for the image of 9 March, 2012. It indicates that the amount of RVI$_{14}$ for unhealthy plants tend to increase.

![Figure 3](image.png)

Figure 3. Correlation between normalized differences vegetation index and DN.

(Figure 3) indicates a significant correlation between infected and uninfected plants for the image from 9 March, 2012. It shows that a higher amount of NDVI belongs to healthy plants.

![Figure 4](image.png)

Figure 4. Correlation between standard differences index and DN.
(Figures 4 & 5) display connections between diseased plants and the standard differences index for the image from 9 March 2012.

An extensive image index was established on the foundation of the selected indices SDI24, RI14, NDVI and SDI14 to organize the images (Figure 6). The images were classified into three types:
healthy to low infection is indicated by the point with RSI < 0, Class 2 refers to low to medium with RSI between 0 and 5, and Class 3 refers to severe infection with RSI > 5. The accuracy of the organization was ~76% which was equivalent to other’s investigations (20).

This misclassification was basically from class 2, containing some low infection samples, which in action may profit pest management in fields to control the disease at early stage. Results showed that there were dissimilarities among the images between early and late growing seasons. Observing particular image indices can conclude that NDVI and SDI indicated better correlations for detecting healthy plants from diseased ones. These types of index could be valuable indicators for a developed technique to detect the sheath blight of rice via remote sensing.

The image demonstrated the spatial spreading of the disease and displayed the likely infection enlargement in the ground. The eastern part of the rice ground was considerably more severely infected by sheath blight than its western half, but overall, infection is spread across the field. Moreover, we observed that the plants beside the levees had the highest levels of infection. This conclusion specifies a variation of the infection and disease growth beside levees. Irrigation and scheme channels for the field are served by means of levees. These probably lead to better conditions for the disease to spread spatially in the field, due to the fact that water constructive organization is suitable for the BPH improvement (11, 16).

With the knowledge that the late growth stage of plant has more severe BPH attacks, and by means of T-test values, the results concluded that 9/10 March had a more severe infestation of the pest.

5. Conclusion
Diseased plants do not display an identifiable spectral variance from healthy plants over a wide range of visible wavelength (18); the SPOT images might not be able to precisely identify the severity of infection at these wavelengths. This infers that they are useful for remote sensing to detect crop disease but the spectral resolution is probably not sufficient to distinguish plants with light infections. In Japan, Yamamoto et al. (1995) utilized infrared thermal images for recognition of rice blast disease by visual examination. The existence of rice blast disease was noticeable in thermal images, but their study did not include quantitative analysis using appropriate indices for more precise identification. Our study showed that SPOT images could be used to demonstrate the coarse scattering of infected plants in the field by recognizing chlorophyll content and the degree of green colour in the leaves. Using the indices as an indicator can clarify the threshold for identifying healthy plants from unhealthy ones. However, a better spectral resolution imagery system is needed (narrower bandwidth and more bands particularly in the infrared range) and in particular, higher spatial resolution.

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