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Crop Disease and Pest Monitoring by Remote Sensing

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Beijing Research Center for Information Technology in Agriculture, Beijing, China

1. Introduction

Plant diseases and pests can affect a wide range of commercial crops, and result in a significant yield loss. It is reported that at least 10% of global food production is lost due to plant diseases (Christou and Twyman, 2004; Strange and Scott, 2005). Excessive pesticides are used for protecting crops from diseases and pests. This not only increases the cost of production, but also raises the danger of toxic residue in agricultural products. Disease and pest control could be more efficient if disease and pest patches within fields can be identified timely and treated locally. This requires obtaining the information of disease infected boundaries in the field as early and accurately as possible. The most common and conventional method is manual field survey. The traditional ground-based survey method requires high labor cost and produces low efficiency. Thus, it is unfeasible for large area. Fortunately, remote sensing technology can provide spatial distribution information of diseases and pests over a large area with relatively low cost. The presence of diseases or insect feedings on plants or canopy surface causes changes in pigment, chemical concentrations, cell structure, nutrient, water uptake, and gas exchange. These changes result in differences in color and temperature of the canopy, and affect canopy reflectance characteristics, which can be detectable by remote sensing (Raikes and Burpee 1998). Therefore, remote sensing provides a harmless, rapid, and cost-effective means of identifying and quantifying crop stress from differences in the spectral characteristics of canopy surfaces affected by biotic and abiotic stress agents.

This chapter introduces some successful studies about detecting and discriminating yellow rust and aphid (economically important disease and pest in winter wheat in China) using field, airborne and satellite remote sensing.

2. Detecting yellow rust of winter wheat by remote sensing

Yellow rust (Biotroph Puccinia striiformis), also known as stripe rust, is a fungal disease of winter wheat (Triticum aestivum L.). It produces leaf lesions (pustules), which are yellow in color and tend to be grouped in patches. Yellow rust often occurs in narrow stripes, 2–3 mm wide that run parallel to the leaf veins. Yellow rust is responsible for approximately 73–85%
of recorded yield losses, and grain quality is also significantly reduced (Li et al. 1989). Consequently, effective monitoring of the incidence and severity of yellow rust in susceptible regions is of great importance to guide the spray of pesticides and to provide data for the local agricultural insurance services. Fortunately, remote sensing technology provides a possible way to detect the incidence and severity of the disease rapidly.

The interaction of electromagnetic radiation with plants varies with the wavelength of the radiation. The same plant leaves may exhibit significant different reflectance depending on the level of health and or vigor (Wooley 1971, West et al. 2003, Luo et al., 2010). Healthy and vigorously growing plant leaves will generally have

1. Low reflectance at visible wavelengths owing to strong absorption by photoactive pigments (chlorophylls, anthocyanins, carotenoids).
2. High reflectance in the near infrared because of multiple scattering at the air-cell interfaces in the leaf’s internal tissue.
3. Low reflectance in wide wavebands in the short-wave infrared because of absorption by water, proteins, and other carbon constituents.

The incidence and severity of yellow rust can be monitored according to the differences of spectral characteristics between healthy and disease plants. In this chapter, we will report several successful studies on the detection and identification of yellow rust in winter wheat by remote sensing.

2.1 Detecting and discriminating yellow rust at canopy level

Hyperspectral remote sensing is one of the advanced and effective techniques in disease monitoring and mapping. However, the difficulty in discriminating a disease from common nutrient stresses largely hampers the practical use of this technique. This is because some common nutrient stresses such as the shortage or overuse of nitrogen or water could have similar variations of biochemical properties and plant morphology, and therefore result in similar spectral responses. However, for the remedial procedures for stressed crops, there is a significant difference between disease and nutrient stresses. For example, applying fungicide to water-stressed crops would lead to a disastrous outcome. Therefore, to discriminate yellow rust from common nutrient stresses is of practical importance to crop growers or landowners.

The specific objectives of this study are to: (1) systematically test the sensitivity and consistency of several commonly used spectral features to yellow rust disease during major growth stages; (2) for those spectral features that are consistently sensitive to yellow rust disease, we will further examine their sensitivity to nutrient stresses to determine whether there are specifically sensitive to yellow rust disease, but insensitive to water and nitrogen stresses.

2.1.1 Materials and methods

2.1.1.1 Experimental design and field conditions

The experiments were conducted at Beijing Xiaotangshan Precision Agriculture Experimental Base, in Changping district, Beijing (40°10.6’N, 116°26.3’E) for the growing seasons of 2001-2002 and 2002-2003. Table 1 summarizes the soil properties including
Crop Disease and Pest Monitoring by Remote Sensing

organic matter, total nitrogen, alkali-hydrolysis nitrogen, available phosphorus and available potassium for both growing seasons. Three cultivars of winter wheat used in 2001-2002 experiment (2002 Exp) were Jingdong8, Jing9428 and Zhongyou9507, while the cultivars used in 2002-2003 (2003 Exp) were Xuezao, 98-100 and Jing411. All the cultivars applied in both growing seasons included erective, middle and loose with respect to the canopy morphology.

<table>
<thead>
<tr>
<th>Items</th>
<th>Disease inoculation experiment</th>
<th>Nutrient stress experiment</th>
</tr>
</thead>
<tbody>
<tr>
<td>Organic matter</td>
<td>1.42% - 1.48%</td>
<td>1.21% - 1.32%</td>
</tr>
<tr>
<td>Total nitrogen</td>
<td>0.08% - 0.10%</td>
<td>0.092% - 0.124%</td>
</tr>
<tr>
<td>Alkali-hydrolysis nitrogen</td>
<td>58.6 - 68.0 mg kg⁻¹</td>
<td>68.8 - 74.0 mg kg⁻¹</td>
</tr>
<tr>
<td>Available phosphorus</td>
<td>20.1 - 55.4 mg kg⁻¹</td>
<td>25.2 - 48.3 mg kg⁻¹</td>
</tr>
<tr>
<td>Rapidly available potassium</td>
<td>117.6 - 129.1 mg kg⁻¹</td>
<td>96.6 - 128.8 mg kg⁻¹</td>
</tr>
<tr>
<td>Cultivars</td>
<td>Xuezao, 98-100, Jing411</td>
<td>Jingdong8, Jing9428, Zhongyou9507</td>
</tr>
<tr>
<td>Treatments</td>
<td>Normal; YR1: 3mg 100⁻¹ ml spores solution; YR2: 9mg 100⁻¹ ml spores solution; YR3: 12mg 100⁻¹ ml spores solution (all treatments applied 200 kg ha⁻¹ nitrogen and 450 m³ ha⁻¹ water)</td>
<td>Normal: 200 kg ha⁻¹ nitrogen, 450 m³ ha⁻¹ water; W-SD: 200 kg ha⁻¹ nitrogen, 225 m³ ha⁻¹ water; W-SED: 200 kg ha⁻¹ nitrogen, 0 m³ ha⁻¹ water; N-E: 350 kg ha⁻¹ nitrogen, 450 m³ ha⁻¹ water; N-D: 0 kg ha⁻¹ nitrogen, 450 m³ ha⁻¹ water; W-SED+N-E: 350 kg ha⁻¹ nitrogen, 0 m³ ha⁻¹ water; W-SED+N-D: 0 kg ha⁻¹ nitrogen, 0 m³ ha⁻¹ water;</td>
</tr>
<tr>
<td>Spectral reflectance measurements (on day after sowing)</td>
<td>207, 216, 225, 230, 233</td>
<td>196, 214, 225, 232, 239</td>
</tr>
</tbody>
</table>

Table 1. Basic information of disease inoculation experiment and nutrient stress experiment

For 2002 Exp, six stress treatments of water and nitrogen were applied, and the treatments were based on local conditions, which usually suffered from yellow rust in the northern part.
of China. Each treatment was applied on 0.3 ha area, and the treatments were 200 kg ha\(^{-1}\) nitrogen and 225 m\(^3\) ha\(^{-1}\) water (slightly deficient water, W-SD), 200 kg ha\(^{-1}\) nitrogen and no irrigation (seriously deficient water, W-SED), 350 kg ha\(^{-1}\) nitrogen and 450 m\(^3\) ha\(^{-1}\) water (excessive nitrogen, N-E), no fertilization and 450 m\(^3\) ha\(^{-1}\) water (deficient nitrogen, N-D), 350 kg ha\(^{-1}\) nitrogen and no irrigation (seriously deficient water and excessive nitrogen, W-SED+N-E), and no fertilization and no irrigation (seriously deficient water and deficient nitrogen, W-SED+N-D). A 0.3 ha reference area (Normal) was applied with the recommended rate which received 200 kg ha\(^{-1}\) nitrogen and 450 m\(^3\) ha\(^{-1}\) water. Three cultivars were evenly distributed in each treatment plot.

For 2003 Exp, according to the National Plant Protection Standard (Li et al. 1989), three levels of concentration of summer spores of yellow rust were applied, and they were 3 mg 100\(^{-1}\) ml\(^{-1}\) (Yellow rust 1, YR1), 9 mg 100\(^{-1}\) ml\(^{-1}\) (Yellow rust 2, YR2) and 12 mg 100\(^{-1}\) ml\(^{-1}\) (Yellow rust 3, YR3), with a dosage of 5 ml spores solution per square meter. The reference area (Normal) that was not inoculated yet was applied with the recommended amount of fungicide to prevent the occasional infection. Each treatment involved 1.2 ha area, with even constitution of three cultivars. All plots in 2003 Exp received the recommended rates of nitrogen (200 kg ha\(^{-1}\)) and water (450 m\(^3\) ha\(^{-1}\)).

2.1.1.2 Canopy spectral measurements

A high spectral resolution spectrometer, ASD FieldSpec Pro spectrometer (Analytical Spectral Devices, Boulder, CO, USA) fitted with a 25 field of view fore-optic, was used for in-situ measurement of canopy spectral reflectance for both 2002 Exp and 2003 Exp. All canopy spectral measurements were taken from a height of 1.3 m above ground (the height of the wheat is 90±3 cm at maturity). Spectra were acquired in the 350-2,500 nm spectral range at a spectral resolution of 3 nm between 350 nm and 1,050 nm, and 10 nm between 1,050 nm and 2,500 nm. A 40 cm × 40 cm BaSO4 calibration panel was used for calculation of reflectance. All irradiance measurements were recorded as an average of 20 scans at an optimized integration time. Prior to subsequent preprocessing, all spectral curves were resampled with 1 nm interval. All measurements were made under clear blue sky conditions between 10:00 and 14:00 (Beijing Local Time).

The spectral measurements were taken 5 times from 196 days after sowing (DAS) to 239 DAS for 2002 Exp, which covered the growth stages of stem elongation, booting, anthesis and milk development. For 2003 Exp, the spectral measurements were taken 5 times from 207 DAS to 233 DAS, which covered the growth stages of booting, anthesis and milk development. The detailed measurement dates for both experiments were given in Table 1. The stem elongation and anthesis stages are essential for the control of yellow rust development, whereas the milk development stage is important for yield loss assessment.

2.1.1.3 Selection of spectral features

The spectral features that we adopted were related to several commonly used vegetation indices (VIs), which were proved to be sensitive to variations of pigments and stresses. Furthermore, in order to conduct a thorough investigation of various types of spectral features, we also included a number of spectral features that were based on derivative transformation and continuum removal transformation (Gong et al. 2002; Pu et al. 2003; 2004). Therefore, the total 38 spectral features are shown in Table 2.
<table>
<thead>
<tr>
<th>Variable</th>
<th>Definition</th>
<th>Description</th>
<th>Literatures</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Derivative transformed spectral variables</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$D_b$</td>
<td>Maximum value of 1st derivative within blue edge</td>
<td>Blue edge covers 490-530nm. $D_b$ is a maximum value of 1st order derivatives within the blue edge of 35 bands</td>
<td>Gong et al., 2002</td>
</tr>
<tr>
<td>$\lambda_b$</td>
<td>Wavelength at $D_b$</td>
<td>$\lambda_b$ is wavelength position at $D_b$</td>
<td>Gong et al., 2002</td>
</tr>
<tr>
<td>SD$_b$</td>
<td>Sum of 1st derivative values within blue edge</td>
<td>Defined by sum of 1st order derivative values of 35 bands within the blue edge</td>
<td>Gong et al., 2002</td>
</tr>
<tr>
<td>$D_y$</td>
<td>Maximum value of 1st derivative within yellow edge</td>
<td>Yellow edge covers 550-582nm. $D_y$ is a maximum value of 1st order derivatives within the yellow edge of 28 bands</td>
<td>Gong et al., 2002</td>
</tr>
<tr>
<td>$\lambda_y$</td>
<td>Wavelength at $D_y$</td>
<td>$\lambda_y$ is wavelength position at $D_y$</td>
<td>Gong et al., 2002</td>
</tr>
<tr>
<td>SD$_y$</td>
<td>Sum of 1st derivative values within yellow edge</td>
<td>Defined by sum of 1st order derivative values of 28 bands within the yellow edge</td>
<td>Gong et al., 2002</td>
</tr>
<tr>
<td>$D_r$</td>
<td>Maximum value of 1st derivative within red edge</td>
<td>Red edge covers 670-737nm. $D_r$ is a maximum value of 1st order derivatives within the red edge of 61 bands</td>
<td>Gong et al., 2002</td>
</tr>
<tr>
<td>$\lambda_r$</td>
<td>Wavelength at $D_r$</td>
<td>$\lambda_r$ is wavelength position at $D_r$</td>
<td>Gong et al., 2002</td>
</tr>
<tr>
<td>SD$_r$</td>
<td>Sum of 1st derivative values within red edge</td>
<td>Defined by sum of 1st order derivative values of 61 bands within the red edge</td>
<td>Gong et al., 2002</td>
</tr>
</tbody>
</table>

| **Continuous removal transformed spectral features** | | | |
| DEP550-750 | The depth of the feature minimum relative to the hull | In the range of 550nm-750nm | Pu et al., 2003;2004 |
| DEP920-1120 | In the range of 920nm-1120nm | | |
| DEP1070-1320 | | | |
| WID550-750 | The full wavelength width at half DEP (nm) | In the range of 550nm-750nm | Pu et al., 2003;2004 |
| WID920-1120 | In the range of 920nm-1120nm | | |
| WID1070-1320 | In the range of 1070nm-1320nm | | |
| AREA550-750 | The area of the absorption feature that is the product of DEP and WID | In the range of 550nm-750nm | Pu et al., 2003;2004 |
| AREA920-1120 | In the range of 920nm-1120nm | | |
| AREA1070-1320 | In the range of 1070nm-1320nm | | |
listed in Table 9 and Table 10. And 2-dimensional feature space coordinates were established with LST as the abscissa and NDWI and MNDWI as the vertical axis, respectively (Figs. 2, 3). LST ranged from 287.5879 to 313.3448, NDWI ranged from 0.0226 to 0.5591 and MNDWI ranged from -0.3402 to -0.1077, respectively.

It is clear that LST was increasing from S0 to S1 to S2. LST was an important driving factor for aphid occurrence and could distinguish wheat non-infected from infested by aphids (Fig. 21 and Table 9). The general trend of NDWI increased firstly and reduced afterward, whereas MNDWI reduced firstly and increased afterward from S0 to S1 to S2.

<table>
<thead>
<tr>
<th>Aphid Damage Degree</th>
<th>LST Minimum value</th>
<th>LST Maximum value</th>
<th>NDWI Minimum value</th>
<th>NDWI Maximum value</th>
<th>MNDWI Minimum value</th>
<th>MNDWI Maximum value</th>
</tr>
</thead>
<tbody>
<tr>
<td>S0</td>
<td>287.5879</td>
<td>296.2498</td>
<td>0.0226</td>
<td>0.4405</td>
<td>-0.3402</td>
<td>-0.1077</td>
</tr>
<tr>
<td>S1</td>
<td>297.8084</td>
<td>306.0133</td>
<td>0.2083</td>
<td>0.5591</td>
<td>-0.6506</td>
<td>-0.3326</td>
</tr>
<tr>
<td>S2</td>
<td>300.5391</td>
<td>313.3448</td>
<td>0.0473</td>
<td>0.4542</td>
<td>-0.4117</td>
<td>-0.1159</td>
</tr>
</tbody>
</table>

Table 9. Minimum and maximum values of LST, NDWI and MNDWI in S0, S1 and S2

<table>
<thead>
<tr>
<th>Aphid Damage Degree</th>
<th>LST Mean value</th>
<th>LST Standard deviation</th>
<th>NDWI Mean value</th>
<th>NDWI Standard deviation</th>
<th>MNDWI Mean value</th>
<th>MNDWI Standard deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>S0</td>
<td>290.8578</td>
<td>1.4740</td>
<td>0.3029</td>
<td>0.0574</td>
<td>-0.2293</td>
<td>0.0296</td>
</tr>
<tr>
<td>S1</td>
<td>299.9236</td>
<td>1.0834</td>
<td>0.3998</td>
<td>0.0587</td>
<td>-0.4940</td>
<td>0.0362</td>
</tr>
<tr>
<td>S2</td>
<td>303.9424</td>
<td>1.7121</td>
<td>0.2979</td>
<td>0.0458</td>
<td>-0.2672</td>
<td>0.0402</td>
</tr>
</tbody>
</table>

Table 10. Mean value and standard derivation of LST, NDWI and MNDWI in S0, S1 and S2

Fig. 21. The distribution of S0, S1 and S2 in the LST-NDWI (left) and LST-MNDWI (right) feature space
3.2.2.2 Discriminating aphid damage degrees using LST and MNDWI

In the 2-dimensional feature space coordinate system that was composed by LST and MNDWI, the S0 samples mainly scattered on the left part of the coordinate system, whereas S1 and S2 samples were distributed on the right part. As shown in Fig. 22, when LST was lower than the certain value, aphid did not occur, suggesting that LST served as a key factor of aphid occurrence and the MNDWI was sensitive to aphid damage degree.

Furthermore, LST₀ and MNDWI₀, which were the cutoff value of threshold values of LST and MNDWI of S0, S1 and S2, were determined by mean values and standard deviations. LST₀ and MNDWI₀ were calculated by formula as follows:

\[
LST₀ = LST_{M1} - 2 \times LST_{SD1}
\]

\[
MNDWI₀ = (M_{M1} + 3 \times M_{SD1}) + \frac{[(M_{M1} + 3 \times M_{SD1}) - (M_{M2} - 3 \times M_{SD2})]}{2}
\]

where \(LST_{M1}\) and \(LST_{SD1}\) are the mean value and standard deviation of LST for S1; \(M_{M1}\) and \(M_{SD1}\) are the mean value and standard deviation of MNDWI for S1; and \(M_{M2}\) and \(M_{SD2}\) are the mean value and standard deviation of MNDWI for S2.

According to Table 3, \(LST₀ = 297.7568\) and \(MNDWI₀ = -0.3866\). Wheat was not infested by aphid when \(LST < 297.7568\), and aphid damage degree was S1 when \(LST \geq 297.7568K\) and \(-0.6506 \leq MNDWI \leq -0.3866\) and S2 when \(LST \geq 297.7568K\) and \(-0.3866 \leq MNDWI \leq -0.1077\) (Fig. 22).

![Fig. 22. Discriminating aphid damage degrees using LST and MNDWI](image)

3.2.2.3 Verification

All survey samples, except 20 samples in the subset selection image were used to test the aphid prediction accuracy of 2-dimensional feature space based on LST and MNDWI (Fig. 23).

The discrimination accuracy was assessed using overall accuracy and kappa coefficient (Table 11). The results showed that the overall accuracy was 84%, and the Kappa accuracy was 75.67%.
3.2.3 Conclusions

This study successfully investigated the relationship between aphid damage degrees and several spectral features, such as NDWI, MNDWI and LST, through 2-dimensional feature space method. The results indicated that LST was the key factor in predicting the occurrence of aphid, and MNDWI was more sensitive to aphid damage degree than NDWI. In the 2-dimension feature space composed by LST and MNDWI, the result showed that S0, S1 and S2 were divided into three regions; S0 was distributed on the left of the space, and S1 and S2 on the right. Further, LST\(0\) and MNDWI\(0\) were calculated according the mean and derivation of S1, S2 as the cutoff value of threshold value to discriminate S0, S1 and S0. Through the verification of discrimination threshold value, it confirmed that the overall accuracy of discrimination was 84% and Kappa coefficient was 0.7567, suggesting that LST and MNDWI were of great potential in discriminating and monitoring the aphid damage degree over a large area, only using thermal infrared band and multi-spectral satellite images.

4. References


Kappa coefficient = 0.7567

Table 11. Error matrices of the verification samples

<table>
<thead>
<tr>
<th></th>
<th>S0</th>
<th>S1</th>
<th>S2</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>S0</td>
<td>17</td>
<td>0</td>
<td>0</td>
<td>17</td>
</tr>
<tr>
<td>S1</td>
<td>2</td>
<td>14</td>
<td>0</td>
<td>16</td>
</tr>
<tr>
<td>S2</td>
<td>4</td>
<td>2</td>
<td>11</td>
<td>19</td>
</tr>
<tr>
<td>Total</td>
<td>23</td>
<td>16</td>
<td>11</td>
<td>50</td>
</tr>
</tbody>
</table>


Haboudane, D., J. R. Miller, E. Pattery, P. J. Zarco-Tejada, & I. B. Strachan. (2004). Hyperspectral vegetation indices and novel algorithms for predicting green LAI of


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Nowadays it is hard to find areas of human activity and development that have not profited from or contributed to remote sensing. Natural, physical and social activities find in remote sensing a common ground for interaction and development. This book intends to show the reader how remote sensing impacts other areas of science, technology, and human activity, by displaying a selected number of high quality contributions dealing with different remote sensing applications.

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