Analysis of Anti-interference Ability of Hyperspectral Sensitive Features to Wheat Powdery Mildew

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Abstract. The development of ground-based, airborne and spaceborne remote sensing has greatly facilitated the identification and diagnosis of various objects. Corresponding algorithms and methods of removing interference from remotely sensed imagery have been proposed. Nevertheless, the studies on anti-interference ability of selected features have not been fully considered. In our study, the hyperspectral reflectance of leaf-scale powdery mildew (Erysiphe graminis) on winter wheat were collected as the testing dataset. A total of seven representative spectral features of Landsat-8 Operational Land Imager (OLI) and GaoFen-1 Wide-Field-View (WFV) was selected, namely, original blue, green, red, near-infrared (NIR) bands and normalized difference vegetation index (NDVI), normalized difference greenness index (NDGI), structure insensitive pigment index (SIPI). Four hyperspectral vegetation indices including red edge (MSR) simple ratio index, NDVI, green band and SIPI were also selected. Three primary background noises including soil, cloud and white poplar (Populus alba L.) were added into the spectral signal. The correlation coefficient (R) between disease severities (0, 1, 2, 3 and 4) and spectral features was used to estimate the anti-interference ability. The results show that there is a generally similar spectral performance for the two sensors, but Landsat-8 OLI is superior to GF-1 WFV in terms of spectral response. The green band was greatly affected with the R values decreasing from 0.77 to 0.35. The MSR and NDVI showed a gradual decrease with the increase of three background noises. The study shows that background noises must be removed when acquiring spectral data and stable spectral features should be also selected by evaluating the anti-interference ability.

1. Introduction
Powdery mildew (PM, Erysiphe graminis) is one of the most serious diseases influencing the yield and quality of winter wheat [1]. Some obvious symptoms can be visually observed when the disease occurs. Pustules with a light white (sometimes light yellow) colour can be observed on wheat leaves [2]. The infection will become more and more serious with the increase of severities. It is highly necessary to estimate the disease epidemic for providing an essential reference for population virulence and cultivar resistance [3]. Traditionally, the severities are evaluated by subjective visual assessment. The identification accuracy and experimental repetition have been greatly affected due to various experiences of phytopathologists. Since the development of remote sensors such as high-resolution digital camera, multi- and hyper-spectral sensors, microwave imaging radiometer, they can be quantitatively determined by image processing and pattern recognition techniques [4].

To extract sensitive features to wheat PM, different approaches have been proposed according to the use of remotely sensed imagery. Zhao et al. proposed an integral method to identify leaf-scale...
wheat PM based on a hyperspectral imaging dataset and machine learning algorithms [2]. Zhang et al. detected the disease damage of PM on leaf level by combining hyperspectral measurements and continuous wavelet analysis [5]. Cao et al. found that the red edge peak (Σdr_{680–760 nm}) was the most sensitive parameter for PM detection by using the correlation analysis [6]. Yuan et al., based on high-resolution SPOT-6 satellite image, mapped the PM disease by performing and comparing three supervised classification methods: artificial neural network (ANN), mahalanobis distance and maximum likelihood (ML) classifier [7]. The above studies show that different sensitive features to wheat PM can be obtained by using a variety of data mining and analysis methods.

In comparison with the extraction of sensitive features, the anti-interference ability of selected features has not been paid sufficient attention. We can image that wheat is planted in the field. It is inevitable that the data acquisition is influenced by a number of background noises. For example, the field is covered by wheat plants and soil at the initial stages (e.g. seedling stage, tillering stage, standing stage). White poplar (Populus alba L.), one of the principal components in natural plant community, generally grows around the wheat field. In addition, there is always some could when collecting the data. To summarize, it is extremely important to explore the anti-interference ability of features modelling the PM, due to the existence of influencing factors. In this study, soil, could and white poplar were added into the spectral signal derived from the original hyperspectral dataset and derived spectral features. The anti-interference ability was evaluated by spectral response and correlation coefficient (R) between disease severities and spectral features.

2. Materials and Methods

2.1. Analysis of Spectral Features of Three Background Noises

Three principle background noises, namely, soil (yellow-brown earths), could and white poplar, were selected by considering the wheat plantation in most regions of China. Their hyperspectral curves were identified from EO-1/Hyperion Hyperspectral Imager (cloud) and United States Geological Survey (USGS) spectral library (soil and white poplar) embedded in the ENvironment Visualizing Images (ENVI, Harris Geospatial Solutions, Inc.) [8]. The reflectance data were resampled to 1 nm and normalized (Figure 1). It can be found that there are significantly different spectral responses in the wavelength ranges of 400–1000 nm. Obviously, white poplar has specific reflectance characteristics of typical vegetation, including green peak, blue and red valleys and high near-infrared (NIR) reflectance. Conversely, there are no obvious spectral features for soil and cloud. In general, they have inverse performance with the increase of wavelengths.

![Figure 1. Comparison of spectral reflectance of three principle background noises.](image-url)
2.2. Generation of Noises
The added noises are divided into random noise and fixed noise. The two parts have the equal weight and three levels of 5%, 10% and 15%. Specific weight of the random noise is generated by the random function shown as follows:

\[ \text{Sig} = (1 - w) \cdot S_0 + w \cdot (N_0 + \text{random()} \cdot N_0) \]  

Where \( \text{Sig} \) denotes the processed signal, \( N_0 \) is the background noise of soil, could or white poplar, \( S_0 \) is the original spectral curve, \( \text{random()} \) is the random function with the range of -1 and 1 and \( w \) is the weight of two noises.

2.3. Comparison between GF-1 WFV and Landsat-8 OLI
When identifying and mapping the regional wheat PM, multispectral remotely sensed imagery is usually used [9]. It is highly necessary to investigate the spectral sensitivity to wheat PM. Here, the Landsat-8 Operational Land Imager (OLI) and GaoFen-1 Wide-Field-View (WFV) were selected to compare their capabilities to identify wheat PM. The band designation and spectral response function (SRF) (Figure 2) were adopted to intercompare the two sensors. The SRFs were respectively derived from the official websites: https://earthexplorer.usgs.gov and http://218.2-47.138.119:7777/DSSPlatform/index.html.

As shown in Figure 2, there are generally spectral similarities for blue, green, red and NIR bands of two sensors. The most obvious difference is that the of GF-1 move towards long wavelength direction. In the NIR wavelengths, GF-1 sensor covers a wider spectral range. Considering the spectral curve shapes, it can be found that the curve of Landsat-8 OLI has a nearly rectangular shape, indicating it has more sensitive response to objects [10]. Consequently, Landsat-8 OLI is superior to GF-1 WVF in identifying the wheat PM.

![Figure 2. Comparison of spectral response function between Landsat-8 and GF-1.](image)

2.4. Signal Generation and Feature Selection
The reflectance means and corresponding integrals to response functions were calculated based on the leaf-scale hyperspectral dataset that were added by the three background noises. To show the capability of identifying wheat PM for different spectral range and response, the input signal is generated by the spectral reflectance that is added by 10% of three noises (Equation 2). Additionally, a total of seven representative spectral features was selected, namely, original blue, green, red, near-infrared (NIR) bands and normalized difference vegetation index (NDVI), normalized difference greenness index (NDGI), structure insensitive pigment index (SIPI) (Table 1).

\[ S_i = 0.7 \cdot S_0 + \sum_{j=1,2,3} N_j \cdot (0.05 + 0.05 \cdot \text{random()}) \]
Here, $S_i$ denotes the input signal, $S_0$ is the original response, $N_j$ is the three background noises, and random () is the random function with the range of -1 and 1.

Table 1. Selected spectral features to monitor wheat PM.

| Spectral feature | Note |
|------------------|------|
| $B$              | The reflectance of blue band (Landsat-8 OLI: 450–515 nm; GF-1 WFV: 450–520 nm) |
| $G$              | The reflectance of green band (Landsat-8 OLI: 525–600 nm; GF-1 WFV: 520–590 nm) |
| $R$              | The reflectance of red band (Landsat-8 OLI: 630–680 nm; GF-1: 630–690 nm) |
| $NIR$            | The reflectance of near-infrared (NIR) band (Landsat-8 OLI: 845–885 nm; GF-1 WFV: 770–890 nm) |
| $\text{Normalized Difference Vegetation Index (NDVI)}$ | $NDVI = (NIR - R) / (NIR + R)$ |
| $\text{Normalized Difference Greenness Index (NDGI)}$ | $NDGI = (G - R) / (G + R)$ |
| $\text{Structure Insensitive Pigment Index (SIPI)}$ | $SIPI = (NIR - B) / (NIR - R)$ |

3. Results and Discussion

3.1. Analysis of Leaf Spectra Caused by Background Noises

The spectral data of leaf-scale wheat are usually influenced by various background noises. As shown in Figure 3, the serration occurred when adding the soil (a), while the overall spectral curves were changed when adding the cloud (b). The phenomena showed that the background noises had significantly affected the leaf spectra.

Figure 3. Performance of spectral reflectance by adding 15% of soil (a) and cloud (b).
Additionally, when adding some background noises, four vegetation indices (VIs) were selected to assess the anti-interference ability of monitoring wheat PM. Four hyperspectral vegetation indices were adopted to test the anti-interference ability, which have been proved to be sensitive to the disease. They were respectively modified red edge (MSR) simple ratio index, NDVI, G and SIPI [11]. The correlation coefficient (R) between disease severities (0, 1, 2, 3 and 4) and four VIs was used to estimate the anti-interference ability. It was obvious that the R values generally showed an increasingly decreasing trend with the increase of weights (Figure 4). In comparison with soil and cloud, the influence of white poplar was smallest due to its similar spectral characteristics with wheat leaf. When analysing the influence for each feature, the G was greatly affected with the R values decreasing from 0.77 to 0.35. The MSR and NDVI showed a gradual decrease with the increase of three background noises.

3.2. Analysis of Band Designations between Landsat-8 and GF-1

Furthermore, the band designations were also compared between Landsat-8 and GF-1. A total of seven commonly used multispectral features including four original bands and three Vis were selected. As shown in Figure 5, there was a similar ability to detect the wheat PM for the two sensors. Nevertheless, there were also some differences for different spectral features. The R values were lower than 0.7 for the four original bands, indicating that the input of background noises significantly decreased the identification capability. There was a large difference for the R of blue band for the two sensors. The NDGI showed a worse performance by comparing the three VIs. The reason could be that the NIR band was not involved in the combination of NDGI [12]. The comparative results showed that GF-1 could be used to detect the wheat PM. Although GF-1 is inferior to Landsat-8 in terms of spectral response and band numbers, but it has a shorter revisiting period. The joint application can be considered in detecting and mapping regional wheat PM.
4. Conclusion
In this study, the non-imaging hyperspectral data of PM-infected winter wheat leaves are used to test of anti-interference ability of spectral features when adding some background noises. Two aspects were adopted to check the study. One was that seven multispectral spectral features of Landsat-8 OLI and GF-1 WVF were used to compare the band designations and SRF. The other is that four hyperspectral VIs derived from non-imaging hyperspectral data were selected to check the anti-interference ability. We find that the input of soil, cloud and white poplar have an obvious influence on spectral response and R values. There is a generally similar performance on characterizing the wheat PM for Landsat-8 and GF-1. In comparison with NDVI and SIPI, NDGI is greatly affected due to the absence of NIR band. The background noises must be removed when using the multi- or hyperspectral remote sensing imagery. In addition, the selection of spectral features is also very important to estimate the disease severities. The anti-interference ability must be also evaluated when applying them to detecting diseases.

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6. References
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