Research on Diagnosis Characteristics of Wheat Powdery Mildew Under Different Severity Grading Standards

Dongyan Zhang, Xun Yin, Fengfang Lin, Linsheng Huang, Jinling Zhao, Yu Liu, Wei Ma and Qi Hong

April 28, 2019

Research on Diagnosis Characteristics of Wheat Powdery Mildew Under Different Severity Grading Standards

1st Dongyan ZHANG
Anhui Engineering Laboratory of Agro-Ecological Big Data. Anhui University
Hefei, China
zhangdy@ahu.edu.cn

2nd Xun YIN
Anhui Engineering Laboratory of Agro-Ecological Big Data. Anhui University
Hefei, China
1426951361@qq.com

3rd Fenfang LIN
School of Geography and Remote Sensing, Nanjing University of Information Science & Technology
Nanjing, China
linfenfang@126.com

4th Linsheng HUANG
Anhui Engineering Laboratory of Agro-Ecological Big Data. Anhui University
Hefei, China
linsheng0808@163.com

5th Jinling ZHAO
Anhui Engineering Laboratory of Agro-Ecological Big Data. Anhui University
Hefei, China
aling0123@163.com

6th Yu LIU
Anhui Engineering Laboratory of Agro-Ecological Big Data. Anhui University
Hefei, China
1459949374@qq.com

7th Wei MA
Beijing Research Center of Intelligent Equipment for Agriculture
Beijing, China
maw@nercita.org.cn

8th Qi HONG*
Anhui Engineering Laboratory of Agro-Ecological Big Data. Anhui University
Hefei, China
116378253@qq.com

***Abstract*—Wheat powdery mildew (*Blumeria graminis Dc.speer*) is one of the most devastating crop diseases in the globe. Thinking of economic effective and environmental protection value, early detection of the severity of wheat powdery mildew can provide important information and technical support for disease prevention. In this study, the wheat leaves infected powdery mildew were chosen as observation objects, the obtained hyperspectral imagery data was pre-processed by reflectance calculation and noise elimination. After the disease-infected samples with different severities were divided into three-levels, four-levels, and five-levels, the effects of samples classification on identification of the disease were explored. Subsequently, the Relief-F algorithm was used to screen the sensitive bands of the disease in the early and mid-late growth stages, to observe the wavelengths change of disease identification in different developmental periods. The results showed that the sensitive bands of disease detection respectively locate at 700 nm and 680 nm for the early and mid-late growth stages, and the position of sensitive wavelength moves toward the short-wave direction as the disease worsens. On the basis, Calculating the powdery mildew disease index (PMDI) and nine kinds of common vegetation indexes, to compare their effects on disease identification, the study found that when the samples were divided into four levels, the determination coefficient R^2 of PMDI is the highest. For the early and mid-late infection stages, the R^2 are respectively 0.763 and 0.766. Furthermore, the corresponding SVM models were established in the different developmental periods, the classification accuracy of the early growth and mid-late stage are 90.63%, 84.62% respectively. The above results show that PMDI calculated by the sensitive band screening has good effective on identifying the severity of the disease, especially there is a good potential at the early growth stage.**

Keywords—Sensitive band, Vegetation index, SVM, Wheat powdery mildew

I. Introduction

In recent decades, due to the global warming leading to the outbreak of crop pests and diseases frequently, this has become an important factor influencing food production and quality worldwide. Hyperspectral imaging remote sensing, combing image and spectra as one, has attracted the attention of scientists around the world. It was widely used to research on diagnostic mechanism of crop pests and diseases, and serve agricultural production [1]. At present, this technology has been used for monitoring the cotton root rot [2], wheat stripe rust [3], powdery mildew [4], etc., and there are great research progresses. Wheat powdery mildew, as one of the most popularly diseases affecting China's food security, at the beginning it occurs in the middle and lower layers of plants. As the severity of the disease increases gradually, this disease appears obviously on the canopy. Currently, the diagnostic mechanism of the disease has been explored by scientists and researchers in the nation and overseas. Zhang et al. analyzed the leaf spectroscopy of wheat powdery mildew, the result indicated that the ranges of 512~634 nm and 692~702 nm were the sensitive to the disease [5]. Yuan et al. screened the sensitive bands of wheat powdery mildew and wheat strip rust by correlation analysis and independent T test, found that two spectral ranges including 665~684 nm and 718~726 nm were obvious bands to differentiate the two kinds of diseases [6]. Guan et al. employed an optimized spectral index to identify different diseases of winter wheat, the final recognition results were respectively 86.5%, 85.2%, 91.6% and 93.5%, for the healthy, stripe rust, powdery mildew and aphid leaves [7]. Meanwhile, the study evaluated the severity of the disease based on canopy spectrum, obtained the determination coefficient of R^2 =0.811 [8]. The results of above researches were acquired based on the samples from middle to late growth stage, and there were no more attentions at early developmental period. However, a fewer researchers began to pay attention to the problem. Huang et al. studied the diagnosis methods of wheat powdery mildew at early growth stage. The R^2 and RMSE of prediction model were 0.886 and 3.553, respectively, indicated that the proposed method can effectively identify the disease [9]. Lin et al. classified the severity of wheat powdery mildew into four grades to construct and evaluate the PMI index, the model accuracy of R^2=0.80 displayed that the PMI index is feasible for disease identification at early growth stage [10]. However, it is not explored that when sample classification of the disease is different, whether this will affect the results of disease diagnosis. Focusing on the problem, the aim of this study is that (i) Selecting and determining the sensitive bands of wheat powdery mildew in the early and mid-late infection stages, provides data support for calculation of disease index and verify the application potential. (ii) Exploring the influence of sensitive bands on disease identification under different samples grades standards, provides some technical supports for accurate identification and spray-prevention of wheat powdery mildew.

II. DATA COLLECTION AND ANALYTICAL APPROACH

A. Data collection

In this study, hyperspectral images of the disease-infected leaves were collected by ImSpectorV10E-QE imaging spectrometer, which is linear array scanning mode with spectral range 326.7-1098 nm, spectral resolution 2.8 nm, and the pixel size of CCD camera is 1344×1024. During the data collection, to reduce the influence of visible light, the imaging spectrometer was put into a black cabinet, the lens vertically downward, and four halogen lamps around the cabinet was condensed to the bottom center position, and then the leaf sample was placed on the black cloth at the bottom of cabinet. The key parameters, the height of 40 cm and exposure time of 18 ms were adjusted for the spectrometer, to guarantee each image was captured clearly.

B. Classifying disease degree and disease index calculation

The a-component and b-component in the Lab color space were used to set the automatic threshold to extract the leaf area, and then applied the super-red color feature 2R-G-B to segment the lesion on the leaf [11], finally the formula (1) utilized to calculate the disease index (DI) and was as follows:

$$\mathrm{DI} = \frac{S_{lesion}}{S_{leaf}} \tag{1}$$

In the formula, S_{lesion} is the pixel size of the lesion, S_{leaf} represents the pixel size of the entire blade, and DI shows the severity of the disease, meaning the ratio of the lesion to the whole leaf.

The classification of the severity of wheat powdery mildew in this study referred to the national agricultural industry standard (NY/T613-2002) "Standards for the investigation of wheat powdery mildew", and also combined with grading research of reported literatures [12], the samples of the early and mid-late infected stages were divided into three grades, four grades and five grades, respectively. The aim is that thinking of different samples classification, to research which classification level is more conducive to the disease identification by hyperspectral remote sensing. Among them, the three-level severity was divided into level 0 (<5%), level 1 (<40%), and level 2 (<100%), which was shown in Table. 1.

TABLE I. STATISTICS OF THREE-LEVEL SAMPLES

Three levels	**Early samples**	**Mid-late samples**
0%-5%	74	18
5%-40%	47	30
40%-100%	7	56

The four-level severity was divided into level 0 (＜5%), level 1(＜20%), level 2(＜50%), and level 3(＜100%), as shown in Table. 2.

TABLE II. STATISTICS OF FOUR-LEVEL SAMPLES

Four-levels	**Early samples**	**Mid-late samples**
0%-5%	74	18
5%-20%	26	16
20%-50%	22	18
50%-100%	6	52

The five-level severity was divided into level 0 (＜3%), level 1(＜10%), level 2(＜20%), level 3(＜30%), and level 4(＜100%), as shown in Table. 3.

TABLE III. STATISTICS OF FIVE-LEVEL SAMPLES

Four-levels	**Early samples**	**Mid-late samples**
0%-3%	68	10
3%-10%	18	15
10%-20%	14	9
20%-30%	14	8
30-100%	14	62

C. Spectral data preprocessing

Reflectance conversion. The hyperspectral image measured in the laboratory is the raw image of DN value. In the study the relative reflectance of the leaf sample was calculated by the ratio of the DN values of samples to the reference plate [13].

Noise elimination. The imagery cube acquired by the imaging spectrometer contains both the spectral information of each pixel and the image information at the specific band. The spectral image is often affected by objective factors such as uneven distribution of light intensity and dark current in the camera, resulting in noise signal interferences sensitive feature extraction [14]. In the study, the normalized method was used to eliminate the effect of noise on the sensitive wavelength screening.

D. Analytical approach

1) Relief-F algorithm

The Relief-F algorithm is extended by Kononenko and can solve the multi-classification and regression problems [15], was used to screen the sensitive bands of wheat powdery mildew in this work. The algorithm is commonly used to deal with regression problems where the target attribute is a continuous value, as well as the data missing problem. The basic idea of the algorithm is to assign weight values to each feature in the feature set, iteratively update the weights, and then select feature subsets according to the weights, so that good features gather similar samples and discrete heterogeneous samples. Supposed there are K kinds of classes label on the data set, records the training data set as D={(x_1,y_1),(x_2,y_2),⋯,(x_n,y_n)}, where $x_i \in R^p$ is the sample feature space, $y_i \in R^k$ is the sample category space. If the sample x_i belongs to class K, it is denoted as $y_i(k) = 1$, if not, it is recorded as $y_i(k) = 0$. Therefore, the data set D can be regarded as consisting of a p × n feature matrix and a k × n label matrix. Finally, the Relief-F algorithm updates the sample weight value by the formula (2).

$$\mathrm{W(A)} = \mathrm{W(A)} - \sum_{j=1}^{k} diff(A,R,H_j)/(mk)$$

$$+\sum_{C\notin class(R)} \left[\frac{p(C)}{1-p(class(R))}\sum_{j=1}^{k} diff(A,R,M_j(C))\right]/(mk) \quad (2)$$

The class(R_i) represents the class label owned by the sample R_i, diff(A, R_1, R_2) is the distance of samples R_1 and R_2 above feature A, $P(C)$ is the class C target, and $M_j(C)$ represents the j-th nearest neighbor sample in the class C∉class(R), m shows the number of iterations.

2) Vegetation index

The powdery mildew disease index (PMDI) is calculated using the difference of two bands and the selected weighted band [10]. The process is that the sensitive band was screened by the Relief-F algorithm to take out the single band, which has the highest correlation with the disease levels was records as R_i. The R_m and R_n were those bands from the best and worst weighted wavelengths (10%), respectively. The PMDI index is shown in formula 3

$$\mathrm{PMDI} = \frac{R_m - R_n}{R_m + R_n} + n * R_i \quad (3)$$

Where, n is a single band coefficient.

This study also chosen nine vegetation indices, commonly used to diagnose the crop disease (Table. 4) to verify the application potential of the PMDI index, especially the disease index was calculated after Relief-F algorithm screening sensitive bands in the early and mid-late infected stage, respectively.

TABLE IV. VEGETATION INDEXES AND FORMULAS [16-24]

Vegetation indexes	References	Formulas
NBNDVI	Thenkabail, et al. ,2000	$(R_{850} - R_{680})$ / $(R_{850} + R_{680})$
PRI	Camon, et al. ,1992	$(R_{570} - R_{531})$ / $(R_{570} + R_{531})$
TVI	Broge and Lebanc ,2001	$0.5 \times [120 \times (R_{750} - R_{550}) - 200 \times (R_{670} - R_{550})]$
TCARI	Haboudane, et al. ,2002	$3 \times [(R_{700} - R_{670}) - 0.2 \times (R_{700} - R_{550}) \times (R_{700}/R_{670})]$
MCARI	Daughtry, et al. ,2000	$[(R_{701} - R_{671}) - 0.2 \times (R_{701} - R_{549})]/(R_{701}/R_{671})]$
RVSI	Merton and Huntington, 1999	$[(R_{712} + R_{752})/2] - R_{732}$
PSRI	Merzlyak, et al. ,1999	$(R_{680} - R_{500})$ / R_{750}
NDVI	Rouse, et al. ,1973	$(R_{840} - R_{675})$ / $(R_{840} + R_{675})$
SIPI	Peñuelas, et al. ,1995	$(R_{800} - R_{445})$ / $(R_{800} - R_{680})$

3) SVM

The Support Vector Machine (SVM) theory is first proposed by Vapnik in 1995 [25]. It is a machine learning method based on the theory of statistical VC dimension and structural risk minimization. It has unique advantages in solving non-linear, small-sample and high-dimensional data, and overcomes problems such as “dimensional disaster” and “over-learning”. As an excellent small sample machine learning method, SVM is widely used in pattern recognition and regression analysis. The successful application of kernel technology has greatly improved the classification performance of SVM. In this study, the radial basis function (RBF) was used as the kernel function in SVM to establish a classification model of wheat powdery mildew.

III. RESULTS AND ANALYSIS

A. Sensitive bands screening for diagnosis of wheat powdery mildew under different severity grades

Table 5 shows that when the severity grades were classified as three types, the positions of sensitive bands and the relationships between them and DI are different in the early and mid-late growth stages. It can be seen that the sensitive wavelengths are 699 nm, 700 nm and 701 nm in the early stage of the disease, which locate in the range of red edge. In the mid-late growth stage, the positions of wavebands change from 680 nm to 682 nm, which belong to the red absorbed valley. On the whole, as the deepening of the disease, there is an obvious “blue shift” for the sensitive wavebands. The above changes can be explained that white spots on the leaf become more as the severity of powdery mildew increases, then causes the changes of internal chlorophyll contents, water and cellular activity in disease-infected leaves. It is indicated that the developmental periods of powdery mildew brings about positions change of sensitive wavelengths.

TABLE V. SELECTION OF SENSITIVE WAVELENGTHS UNDER DIFFERENT DISEASE LEVELS AND GROWTH STAGES

Results	Three types		Four types		Five types	
	Early	*Mid-late*	*Early*	*Mid-late*	*Early*	*Mid-late*
Sensitive band	699 nm	682 nm	701 nm	681 nm	700 nm	680 nm
R^2	0.648	0.697	0.763	0.766	0.749	0.636
RMSE	0.358	0.422	0.45	0.58	0.722	0.887

In this study, samples with different disease severities were divided into three categories, including three-levels, four-levels and five-levels. The details were shown in Table 1, Table 2 and Table 3, respectively, to investigate that whether the severity grading is related to identification accuracy of wheat powdery mildew. As shown in Table 5, under the four-level classification, the relationship based on above sensitive wavelengths is most relevant to DI in the early infected stage. The coefficient of determination R^2 and RMSE are 0.763 and 0.450, respectively. In the mid-late growth stage, the R^2 is 0.766 and the RMSE is higher than those of the early stage. Furthermore, in the early infection stage of the disease, the R^2 of the five-level classification is higher than that of three-levels. On the contrary, the R^2 is lower in the mid-late developmental period, but the RMSEs of the five-levels are high in all growth stages.

B. Determination of optimal disease indices

Based on above sensitive wavebands, the PMDI indexes in the early and mid-late disease-infected stages were calculated to verify its application potential by comparing with other nine vegetation indices commonly used in crop disease identification. Table 6 shows that PMDI index has the highest R^2 and the lowest RMSE in the three levels classification, especially the results of four-levels are the best. It was further found that other vegetation indices including MCARI, SIPI, NBNDVI and NDVI also have the higher diagnostic accuracy. Combined with main wavelengths of these indices construction, they basically close to 680 nm and 700 nm. There is a similar result with PMDI index, this demonstrates that the result of PMDI is accepted and reliable. In addition, Newton et al. analyzed the spectral reflectance of barley canopy infected by powdery mildew, and found that the prediction model with the ratio of the reflectance of two wavebands was better than one with single waveband [26]. Yuan et al. used leaf spectrum and FLDA discriminant model to distinguish the wheat powdery mildew and stripe rust. The result showed that the overall accuracy of the model was over 80% [6]. The above studies mainly focused on diagnosis of powdery mildew in the middle and late growth stages, and there was few were reported in the early developmental period of crop diseases. In this study, the PMDI index was used to diagnose wheat powdery mildew at early growth stage. The result showed that the accuracy of model was high with the R^2=0.763 under four levels classification. It can be concluded that PMDI index has application potential in early detection of the disease.

TABLE VI. STATISTICAL ANALYSIS OF DIFFERENT VIS

Vegetation indexes	Three Levels				Four Levels				Five Level			
	Early		*Mid-late*		*Early*		*Mid-late*		*Early*		*Mid-late*	
	R^2	*RMSE*	R^2	*RMSE*	R^2	*RMSE*	R^2	*RMSE*	R^2	*RMSE*	R^2	*RMSE*
NBNDVI	0.637	0.364	0.686	0.430	0.738	0.473	0.755	0.594	0.679	0.817	0.624	0.904
PRI	0.600	0.392	0.654	0.452	0.703	0.503	0.717	0.638	0.659	0.842	0.575	0.961
TVI	0.578	0.392	0.646	0.457	0.672	0.529	0.717	0.638	0.600	0.913	0.585	0.950
TCARI	0.385	0.473	0.027	0.757	0.403	0.714	0.023	1.185	0.443	1.076	0.013	1.465
MCARI	0.645	0.360	0.536	0.523	0.719	0.490	0.572	0.784	0.721	0.762	0.487	1.056
RVSI	0.453	0.447	0.498	0.544	0.543	0.625	0.568	0.788	0.487	1.032	0.427	1.116
PSRI	0.447	0.449	0.522	0.531	0.512	0.646	0.585	0.772	0.437	1.082	0.451	1.093
NDVI	0.636	0.364	0.679	0.435	0.736	0.474	0.748	0.602	0.677	0.820	0.616	0.914
SIPI	0.639	0.363	0.695	0.424	0.731	0.479	0.762	0.585	0.668	0.831	0.643	0.881
PMDI	0.648	0.358	0.697	0.422	0.763	0.450	0.766	0.580	0.749	0.722	0.636	0.887

C. Construction of recognition model based on SVM

The SVM identification models of powdery mildew were established and shown in Figures 1, 2 and 3. The samples were divided into calibration set and test set by the Kennard-stone algorithm [27], which is better than random and systematic samplings. It was seen that the accuracy of the models under the four-level classification was higher than those of three-levels and five-levels in two developmental periods of the disease. Obviously, the accuracy is as high as 90.63% in the early stage of the disease, which is much better than the accuracy of 84.62% at the mid-late growth stage.

Furthermore, it was pointed out that the accuracies of classification models under three grading categories are different in the early stage of the disease, changing from 71.88% to 90.63%. In the mid-late growth stage of the disease, the accuracy of models has also large difference. The above results may be caused by uneven sample distributions from different severity grades, so the further experiments should be done and verify this result.

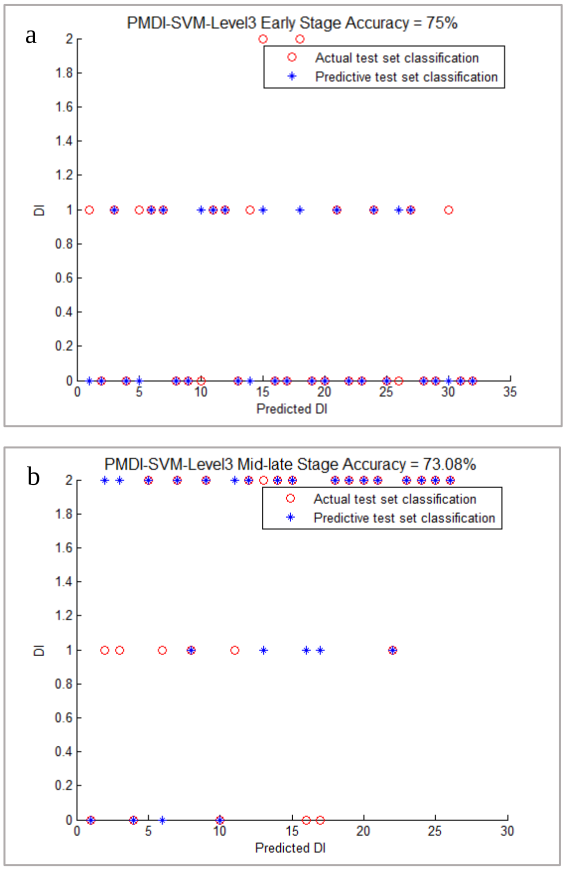
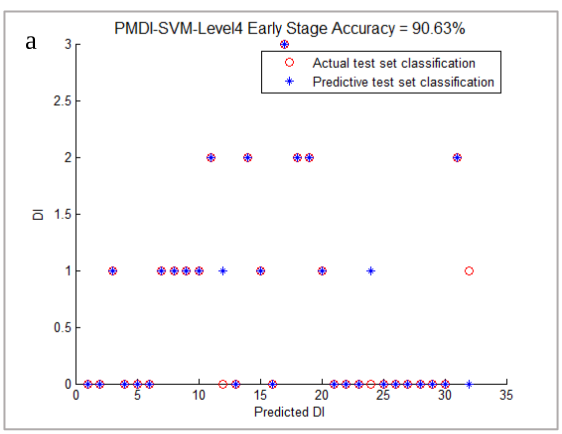


Fig. 1. The model accuracies of early (a) and mid-late (b) stages under the three-level classification



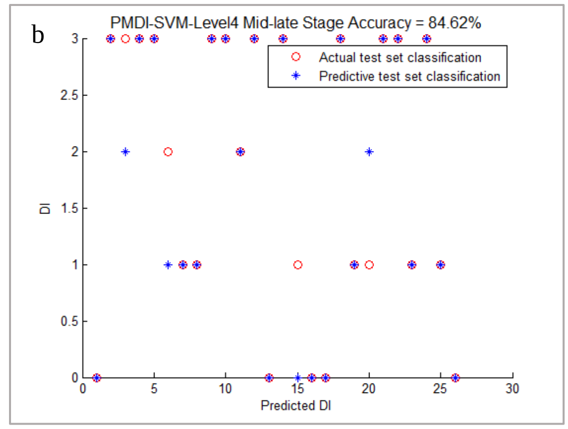


Fig. 2. The model accuracies of early (a) and mid-late (b) stages under the four-level classification

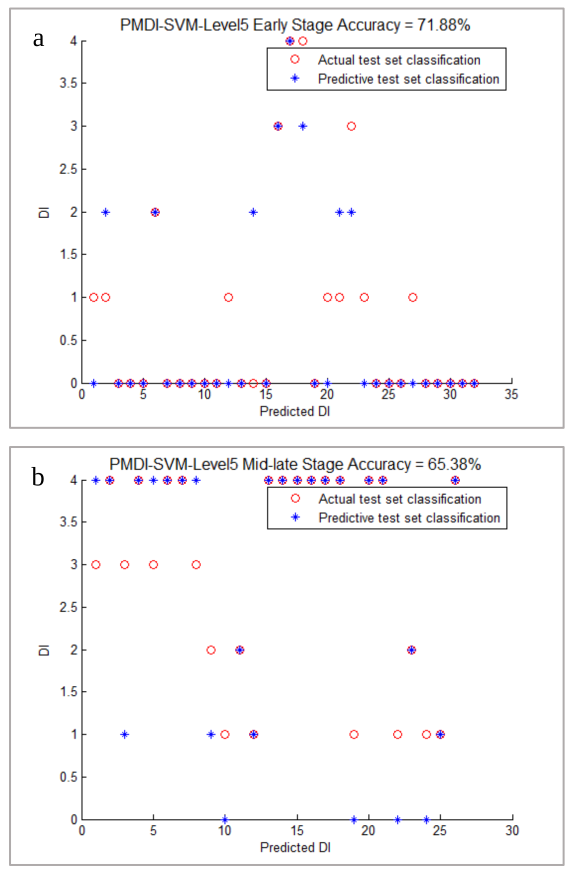


Fig. 3. The model accuracies of early (a) and mid-late (b) stages under the five-level classification

IV. Conclusion

It was explored that whether sensitive wavebands by the Relief-F algorithm were same under different disease grading standards. Then, PMDI indexes were calculated by these bands, to assess the identification ability of wheat powdery mildew in early and mid-late growth stages. Some results were obtained:

(1) Sensitive wavebands of the disease selected by the Relief-F algorithm locate at 700 nm in the early infection stage,

while that of mid-late growth stage is 680 nm. A “blue shift” phenomenon of wavelengths appears with the deepening of the disease. And these wavelengths have few changes under different severity grading standards.

(2) Compared with 9 common vegetation indices, the PMDI index shows good identifying ability to the disease in the early and mid-late growth stage. Furthermore, the result indicated that the recognition model has application potential in the early infection stage of wheat powdery mildew.

However, the above results were obtained in the case of one year's samples and one variety. This needs further to verify by many factors such as various varieties, different years and environments.

V. ACKNOWLEDGEMENT

This research was financially supported by the National Natural Science Foundation of China (Grant No. 2016YFD0200608), the National Key Research and Development Program of China (Grant No. 41771463, 41771469) and the Anhui Provincial Science and Technology Major Project (Grant No.16030701091).

REFERENCES

[1] A. Apan, A. Held, S. Phinn and J. Markley, "Detecting sugarcane ‘orange rust’ disease using EO-1 Hyperion hyperspectral imagery", International Journal of Remote Sensing, vol. 25, no. 2, pp. 489-498, 2004.

[2] C. Yang, J. Everitt and C. Fernandez, "Comparison of airborne multispectral and hyperspectral imagery for mapping cotton root rot", Biosystems Engineering, vol. 107, no. 2, pp. 131-139, 2010.

[3] D. Ashourloo, M. Mobasheri and A. Huete, "Evaluating the Effect of Different Wheat Rust Disease Symptoms on Vegetation Indices Using Hyperspectral Measurements", Remote Sensing, vol. 6, no. 6, pp. 5107-5123, 2014.

[4] X. Cao, Y. Luo, Y. Zhou, X. Duan and D. Cheng, "Detection of powdery mildew in two winter wheat cultivars using canopy hyperspectral reflectance", Crop Protection, vol. 45, pp. 124-131, 2013.

[5] J. Zhang, R. Pu, J. Wang, W. Huang, L. Yuan and J. Luo, "Detecting Powdery Mildew of Winter Wheat Using Leaf Level Hyperspectral Measurements", Computers and Electronics in Agriculture, vol. 85, pp. 13-23, 2012.

[6] L. Yuan, J. Zhang, J. Zhao, W. Huang and J. Wang, "Differentiation of Yellow Rust and Powdery Mildew in Winter Wheat and Retrieving of Disease Severity Based on Leaf Level Spectral Analysis", Spectroscopy and Spectral Analysis, vol. 33, no. 6, pp. 1608-1614, 2013.

[7] Q. Guan, "Inversion of Leaf Area Index of Winter Wheat and Spectral Recognition of Diseases", Post-Graduate, AnHui University, 2014.

[8] L. Huang, Q. Zhang, D. Zhang, F. Lin, C. Xu and J. Zhao, "Early diagnosis of wheat powdery mildew based on Relief-F band screening", Infrared and Laser Engineering, vol. 5, pp. 210-217, 2018.

[9] Y. Fan, X. Gu, S. Wang, G. Yang and L. Wang, "Analysis of Canopy Spectral Characteristics of Winter Wheat Powdery Mildew and Disease Index Inversion", Journal of Triticeae Crops, vol. 37, no. 1, pp. 136-142, 2017.

[10] F. Lin, D. Wang, D. Zhang and X. Yang, "Evaluationof Spectral Disease Index PMI to Detect Early Wheat Powdery Mildew using Hyperspectral Imagery Data", International Journal of Agriculture and Biology, vol. 20, no. 9, pp. 1970-1978, 2018.

[11] J. Zhang, J. Meng, B. Zhao, D. Zhang and J. Xie, "Research on the Chlorophyll Content(SPAD)Distribution Based on the Consumer-Grade Modified Near-Infrared Camera", Spectroscopy and Spectral Analysis, vol. 3, pp. 737-744, 2018.

[12] W. Shen, Y. Li, W. Feng, H. Zhang and Y. Zhang, "Inversion model for severity of powdery mildew in wheat leaves based on factor analysis-BP neural network", Transactions of the Chinese Society of Agricultural Engineering, vol. 22, pp. 183-190, 2015.

[13] Y. Lei, D. Han, Q. Zeng and D. He, "Grading Method of Disease Severity of Wheat Stripe Rust Based on Hyperspectral Imaging Technology", Transactions of the Chinese Society for Agricultural Machinery, vol. 5, pp. 229-232, 2018.

[14] H. Qiao, Y. Zhou, Y. Bai, D. Cheng and X. Duan, "The primary research of detecting wheat powdery mildew using in-field and low altitude remote sensing", Acta Phytophylacica Sinica, vol. 4, pp. 341-344, 2006.

[15] I. Kononenko, "Estimating attributes: Analysis and extensions of RELIEF", Machine Learning: ECML-94, vol. 784, pp. 171-182, 1994.

[16] P. Thenkabail, R. Smith and E. Pauw, "Hyperspectral vegetation indices and their relationships with agricultural crop characteristics", Remote Sensing of Environment, vol. 71, no. 2, pp. 158-182, 2000.

[17] J. Gamon, J. Peñuelas and C. Field, "A narrow-waveband spectral index that tracks diurnal changes in photosynthetic efficiency", Remote Sensing of Environment, vol. 41, no. 1, pp. 35-44, 1992.

[18] N. Broge and E. Leblanc, "Comparing prediction power and stability of broadband and hyperspectral vegetation indices for estimation of green leaf area index and canopy chlorophyll density", Remote Sensing of Environment, vol. 76, no. 2, pp. 156-172, 2001.

[19] D. Haboudane, J. Miller, N. Tremblay, P. Zarco-Tejada and L. Dextraze, "Integrated narrow-band vegetation indices for prediction of crop chlorophyll content for application to precision agriculture", Remote Sensing of Environment, vol. 81, no. 2-3, pp. 416-426, 2002.

[20] C. Daughtry, "Estimating Corn Leaf Chlorophyll Concentration from Leaf and Canopy Reflectance", Remote Sensing of Environment, vol. 74, no. 2, pp. 229-239, 2000.

[21] R. Merton, J. Huntington, "Early simulation results of the ARIES-1 satellite sensor for multi-temporal vegetation research derived from AVIRIS", Proceedings of the Eighth Annual JPL Airborne Earth Science Workshop, Pasadena, CA, USA, pp. 9-11, 1999.

[22] M. MERZLYAK, A. GITELSON, O. CHIVKUNOVA and V. RAKITIN, "Non-destructive optical detection of pigment changes during leaf senescence and fruit ripening", Physiologia Plantarum, vol. 106, no. 1, pp. 135-141, 1999.

[23] J. Rouse, R. Haas, J. Schell and D. Deering, "Monitoring vegetation systems in the Great Plains with ERTS", Nasa Special Publication, vol. 1, pp. 309-317, 1974.

[24] J. Penuelas, F. Baret and I. Filella, "Semiempirical indexes to assess carotenoids chlorophyll-a ratio from leaf spectral reflectance", Photosynthetica, vol. 31, no. 2, pp. 221-230, 1995.

[25] V. Cherkassky, "The Nature Of Statistical Learning Theory~", IEEE Transactions on Neural Networks, vol. 8, no. 6, pp. 1564-1564, 1997.

[26] A. NEWTON, C. HACKETT, R. LOWE and S. WALE, "Relationship between canopy reflectance and yield loss due to disease in barley", Annals of Applied Biology, vol. 145, no. 1, pp. 95-106, 2004.

[27] R. Kennard and L. Stone, "Computer Aided Design of Experiments", Technometrics, vol. 11, no. 1, pp. 137-148, 1969.