PREDICTING WHEAT APHID USING 2-DIMENSIONAL FEATURE SPACE BASED ON MULTI-TEMPORAL LANDSAT TM

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ABSTRACT

Aphid (*Hemiptera: Aphididae)* outbreaks appear in wheat (*Triticum aestivum L.*) planting area in China, and had significant economic impacts on wheat. It has severe impact on both winter wheat yield and grain quality. The aim of this study was to monitor and predict of wheat aphid by analyzing the relationship between land surface temperature (LST), modified normalized difference water index (MNDWI) and the occurrence and prevalence of aphid in wheat. The results showed that LST was an important driving factor for occurrence of aphid, and MNDWI was sensitive to aphid damage degree. Meanwhile, a 2-dimensional feature space was established based on LST and MNDWI derived from Landsat TM images, and discrimination model of aphid damage degrees was established according to the distribution of samples in the feature space. It was verified that the overall accuracy of discrimination model is 82.5%, and kappa accuracy is 73.88%.

Index Terms**—**Winter wheat, Aphid, land surface temperature (LST), Modified normalized difference water index (MNDWI)

1. INTRODUCTION

Aphid *(Hemiptera: Aphididae*) is considered as one of the most destructive insects of wheat and appears almost every year. It is reported that aphid infestation has a severe impact on both quality and yield of winter wheat [1]. Therefore, predicting the incidence of aphid and aphid damage degree on a spatial large scale and in real time and consequent use of this information to facilitate timely making preventive strategies is critical to enhance the viability of wheat production industry in China, particularly for guiding variable spraying. Until now, Prediction models of aphid occurrence and damage degree have been mainly based on metrological data, such as temperature and relative humidity [2], which is based on spot scale and has no spatial distribution information [3]. Fortunately, satellite imagery provides spatially continuous observations of those variables on a large scale [4]. Luo et al. investigated the relationship between LST and incidence of wheat yellow rust, and found that LST was a critical driving factor to occurrence of wheat yellow rust [5].

In the study, the paper was to propose predicting methods of aphid damage degrees based on 2-dimensional feature space established by the land surface temperature (LST) and modified normalized difference water index (MNDWI) derived from Landsat TM.

2. MATERIALS AND METHODS

2.1 Field inventory and data preprocessing

Field inventory was carried out respectively on May 4, May 6, May 20, May 21, June 3 and June 4, 2010, in Shunyi District (116°28′—116°58′E, 40°00′—40°18′N) and Tongzhou District (116°32′—116°56′E, 39°36′—40°02′N) of Beijing, China. Based on the combination of representative sampling and random sampling scheme, a total of 140 sample plots with size of 0.09ha (30m×30m) were collected (Fig. 1). These sample plots had different site conditions, plant densities, and management conditions. The survey items included center geographical coordinates of sample plots and aphid density.

Every sample covered with 1m^2 area, and ten tillers in each sample plot were randomly selected and aphids were counted on them. Subsequently, total aphids on 10 tillers were counted, and aphid densities were estimated as follows: total aphids /10tillers. The survey results could be divided into three aphid damage degrees according to aphid density, including S0: aphid density was zero and no damage to wheat, S1: aphid density was about from one to five and damage degree to wheat was slight, S3: aphid density was more than five and damage degree to wheat was severe.

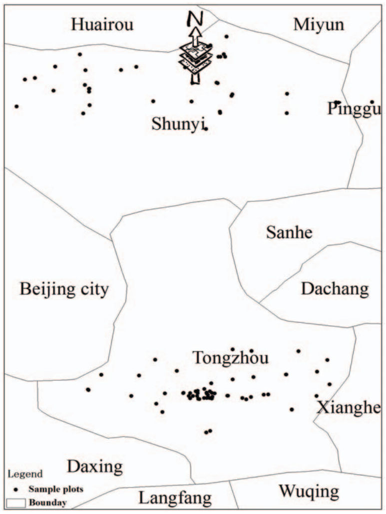

Fig. 1 Study area and distribution of sample plots

2.2 Satellite image acquisition and preprocessing

Three Landsat-5 Thematic Mapper (TM) images (path 123/row 32) were acquired on May 4, May 20 and June 5, 2010, respectively. And all images were more than 90% cloud-free. Landsat-5 TM images were spectrally corrected to reflectance using the Landsat TM calibration tool and FLAASH (Fast line-of-sight Atmospherics Analysis of Spectral Hypercubes) was used to correct the image for atmospheric effects [6] in ENVI 4.5 (ITT Industries, 2008). The Landsat-5 TM images were geometrically corrected versus a reference IKONOS image (equivalent scale map 1:10000) of the same area. The root mean square error (RMSE) did not exceed 0.3 pixels, which was considered adequate for the purpose of the study.

2.3 Derivation of LST and MNDWI from Landsat 5 TM

MNDWI was proposed by Xu [7] and proven to be a better index for the extraction of water information from remote sensing imagery than the normalized difference water index (NDWI). MNDWI can be expressed as follows:

$$MNDWI = \frac{R_{GREEN} - R_{SWIR}}{R_{GREEN} + R_{SWIR}}$$

Where R_{GREEN} , R_{SWIR} are the reflectances or radiance in green band (TM2) and short-wave infrared band (TM5).

LST was derived from the thermal infrared band (10.4-12.5μm) of Landsat-5 TM using generalized single-channel algorithm developed by Jiménez-Muñoz and Sobrino [8, 9]. Surface emissivity (ε) and atmospheric water vapor content (*w)* were important parameters in the algorithm. In the study, *w* was derived from the reflectance of band 2 and band 19 of MOD02 (MODIS Level-1BCalibrated Radiances) [10], and ε was calculated by vegetation coverage [11].

NDWI, MNDWI and LST of all sample points were calculated and extracted form Landsat TM images.

2.5 Method for measurement accuracy

One basic accuracy measurement is the overall accuracy indicator, which is calculated by dividing the correctly classified pixels by the total number of pixels checked. The Kappa coefficient is a measure of overall agreement of a matrix. And it is introduced to the remote sensing community in early 1983[12] and has become a widely used measure for classification accuracy. In contrast to overall accuracy, the Kappa coefficient takes also non-diagonal elements into account [13]. The Kappa coefficient is always calculated by the formula:

$$K = \frac{N\sum_{i=1}^{r} X_{ii} - \sum_{i=1}^{r} X_{i} + X_{+i}}{N^2 - \sum_{i=1}^{r} X_{i} + X_{+i}}$$

where *r* is the number of rows and columns in error matrix, *N* is the total number of observations, X_{ii} is the observation in row *i* and column *i*, X_{i+} is the marginal total of row *i*, and X_{+i} is the marginal total of column *i*.

3. RESULTS

3.1 2-dimensional feature space based on LST-MNDWI

The mean values and standard deviations of LST and MNDWI with aphid damage degrees of wheat sample plots were listed in Table 1. And a 2-dimensional feature space coordinate was established with LST as abscissa and MNDWI as the vertical axis (Fig. 1).

Table 1 Mean values and standard derivations of LST and MNDWI in S0, S1 and S2

Aphid damage degree	LST		MNDWI	
	Mean value	standard deviation	Mean value	standard deviation
S0	290.8265	1.2295	-0.2245	0.0266
S1	299.7326	0.7202	-0.5007	0.0306
S2	303.6126	1.0583	-0.2474	0.0291

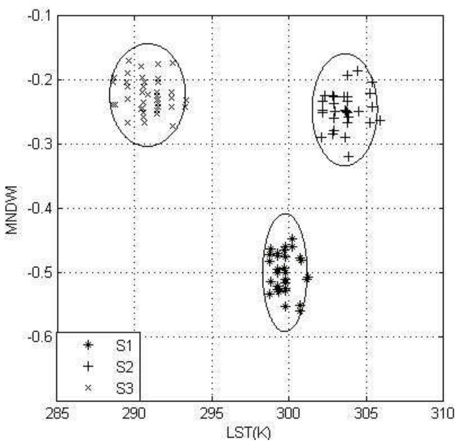

Fig. 2 2-dimensional feature space based on LST and MNDWI

The trend of LST increased from S0 to S1 and then to S2, and it was an important driving factor for aphid occurrence, which could distinguish uninfected wheat from the infested (Fig.2 and Table 1). Besides, the general trend of MNDWI decreased firstly and increased afterward from S0 to S1 and then to S2

3.2 Prediction models of wheat aphid based on 2-dimensional feature space

In the 2-dimensional feature space coordinate based on LST and MNDWI, the samples were divided into three classes and they distributed in different regions. According to the distribution of samples, three models of aphid damage degree were established. They were three ellipses with the mean value as center, multiple of standard derivation of LST and MNDWI as the long axis and the short axis of the ellipse. The equations were calculated as follows:

$$E_1:\ (\frac{x_1-290.8265}{3\times 0.0266})^2+(\frac{y_1+0.2245}{2\times 1.2295})^2=1$$

$$E_2:\ (\frac{x_2-299.7326}{3\times 0.0306})^2+(\frac{y_2+0.5007}{2\times 0.7202})^2=1$$

$$E_3:\ (\frac{x_3-303.6126}{3\times 0.0306})^2+(\frac{y_3+0.2474}{2\times 1.0582})^2=1$$

If the wheat point was outside the ellipses, we could discriminate its class according to the minimum distance between point and ellipses.

3.3 Verification

40 survey samples except for building up the models were used to test the prediction model accuracy (Fig. 3).

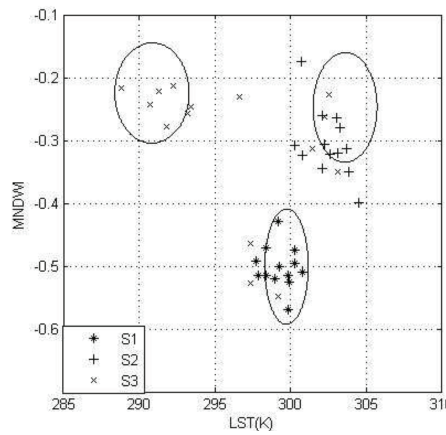

Fig. 3 Scatter of verification points in 2-dimensional feature space

Classification prediction of verification samples were assessed using overall accuracy and Kappa coefficient (Table 2). The results showed that the overall accuracy was 82.5%, and Kappa accuracy was 73.88%.

Table 2 The Error Matrices of verification samples

	S0	S1	S2	Total
S0	8	3	3	14
S1	0	13	0	13
S2	0	1	12	13
Total	8	17	15	40

Kappa coefficient = 0.7388

4. DISCUSSION

Plant diseases and pests are governed by a number of factors, such as temperature, humidity, field management, enemies, etc. However, the habitat factors are the major driving factors for the development and prevalence of diseases and pests [14], there is no exception for the aphid. The weather station can only offer points data, while remote sensing has been proven to be a promising means for acquiring spatially continuous observations over large area [15]. It is rare that the LST derived from remote sensing data is used to forecast the development of aphid damage degree.

The paper was trying to analyze the relationship between LST, MNDWI and aphid occurrence and damage degree, and present a method that could forecast the aphid occurrence and damage degree using 2-dimensional feature space established by LST and MNDWI derived from Landsat TM. The study showed that aphid occurrence and prevalence had the relationship with LST and MNDWI. In the 2-dimensional feature space, wheat sample points were divided into three regions according to aphid damage degree (S0, S1, and S2). And LST increased from S0 to S1 and then to S2, while the general trend of MNDWI decreased firstly and increased afterward from S0 to S1 and then to S2. Three ellipses model was established according to distribution of sample points of S1, S2 and S3, respectively. The verification results showed that the overall accuracy was 82.5%, and Kappa accuracy was 73.88%, so the ellipses model could predict the aphid damage degree.

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