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Migratory Locust Habitat Analysis With PB-AHP Model Using Time-Series Satellite Images

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ABSTRACT The outbreak of Oriental Migratory Locust(*Locusta migratoria manilensis*) causes devastating disasters to agriculture. With the impact of climate changes and human activities, the distribution of locust habitat (locust habitat is the environment in which locusts live and survive) in China is constantly changing. Monitoring and extracting locust habitat are of great significance for guiding large-scale agricultural production. The occurrence of the locust is closely related to their habitat. Therefore, a comprehensive analysis of habitat factors that affect locust survival is carried out to monitor locust habitat distribution. Besides, the landscape structure also affects distribution. This study explored a model for analyzing multi-temporal Landsat and MODIS images, which combined multiple habitat factors and landscape structure to analyze locust habitat. The locust habitat near North Dagang Reservoir in Tianjin is the research object. First, the habitat factors that affect locust oviposition and growth were analyzed, and vegetation coverage, land cover class, soil moisture, soil salinity, and land surface temperature were selected as five habitat factors. The weights of five habitat factors were evaluated according to the Analytic Hierarchy Process (AHP) model. Then, considering the impact of landscape structure on locust habitat, a moving-window was used to correlate locust habitat factors at pixel scale with locust habitat at patch scale. Finally, the distribution map of the locust habitat at patch scale was generated. The Analytic Hierarchy Process(AHP) was used to compare and test the results. Our research shows that the Patch based - Analytic Hierarchy Process (PB-AHP) can monitor locust habitat. The overall accuracy reached 88%, which is 10% higher than the result based on the Analytic Hierarchy Process(AHP). These results show that the Patch based - Analytic Hierarchy Process (PB-AHP) model has strong robustness and generalization ability in identifying locust habitat and can provide scientific guidance for locust monitoring and control.

INDEX TERMS Locust habitat, landscape, patch based - analytic hierarchy process (PB-AHP), remote sensing.

I. INTRODUCTION

The Oriental Migratory Locust (*Locusta migratoria manilensis*) is a destructive agricultural pest in China [1], [2]. Locust is a major threat to crops such as wheat, maize, rice, and has caused massive economic damage [3], [4]. The outbreak of locust plague could have a significant and negative impact on food security, ecological security, and social stability [5]. In China, the total acreage impacted by locust changed little from 2003 to 2018, at around 667 thousand hectares. In recent years, China has made remarkable gains in controlling locust plague. However, with additional impacts from global warming, drought, environmental changes, and human activities, new locust habitat has been created that does not have adequate monitoring by plant protection departments, which means that sudden locust plagues in the unexpected

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location are a continuous threat [6], [7]. Locust control must be carried out before migration occurs, and having an accurate description of the area needing management is the key to minimizing the harms [8]. As a result, real-time and large-scale quantitative monitoring of locust habitat is indispensable to achieve accurate, effective, and environmentally-responsible prevention and control.

For this research, the study area is located in the Tianjin municipality of China and contains North Dagang Reservoir, Duliujian River, and Lier Bay. This area is a typical locust area in China [9]. The reducing water levels in major rivers and reservoir are and increasing abandoned cropland have provided ideal environments for locust oviposition and growth since the mid-1990s [10], [11]. According to statistics provided by Tianjin Plant Protective Station (TPPS), the annual occurrence area of summer locust in the study area had exceeded 20 thousand hectares since 2000. Locust density in severe plague years was as high as 4-5 thousand per square meter (http://www.tjpps.cn/). Due to the large size of the potential infection area and its unsuitability for human activity, as well as the changing habitat of locust, traditional artificial reconnaissance has become more difficult [12], [13].

Satellite-based remote sensing technology can visualize the large area, provides dynamic, real-time, and periodic observations, and makes it possible and convenient to locust habitat monitoring. Combining the availability of remote sensing data and the physiological mechanism of locust oviposition and growth, it is believed that the current research about locust habitat monitoring based on remote sensing is mainly carried out from vegetation, soil, and climate, mainly including habitat factors such as vegetation coverage, land cover class [14]–[16], soil moisture, soil salinity [17], [18], temperature [19] and so on. In the early stage of locust habitat monitoring, the research was based on the extraction of a single habitat factor using satellite data. For example, Tratalos and Cheke [20] used AVHRR data to obtain the Normalized difference vegetation index(NDVI) and conducted habitat classification research on desert locust. Piou *et al.* [21] found that the use of NDVI at 250 meters resolution, combined with the coherent construction of secondary indicators obtained from NDVI time variation, and can predict the presence of desert locust. Sinha and Chandra [22] found the relationship between areas with high NDVI and locust activity based on a visual approach. Renier *et al.* [23] used MODIS data to develop a dynamic vegetation senescence index to realize near-real-time desert locust habitat monitoring and identify areas that may be effective by locust. Deveson [24] used the one-month positive change in NDVI to measure changes in nymph distributions. Waldner *et al.* [25] used Landsat TM and MODIS data to generate a dynamic vegetation greenness map in Mauritania and monitored desert locust habitat in combination with vegetation coverage. Bolkart *et al.* [26] applied MODIS and Landsat TM images to map locust distribution in the southern part of the Aral Sea and found that locust density was highest in areas with dried reeds, while low or almost no locusts were found in shrub and cropland areas. The above studies revealed certain relationships between habitat factors and locust habitat monitoring, but most of them are based on the monitoring of a single habitat factor. Low *et al.* [27] extracted the inter-annual Enhanced vegetation index (EVI) curve based on images from multi-temporal MODIS data to differentiate land cover classes and consequently drew potential locust habitat.

Besides, some scholars have also comprehensively considered the impact of multiple factors to analyze locust habitat. Huang *et al.* [28] built a model to monitor locust population density by considering the impact of surface temperature, soil moisture, Leaf area index (LAI), and other habitat factors. Shi *et al.* [29] integrated MODIS and Landsat remote sensing images to extract land cover classes, vegetation coverage, and Land surface temperature(LST) to obtain the distribution of locust areas near the North Dagang Reservoir in Tianjin.

On the other hand, the spatial distribution of locust habitat is patchy, and changes in landscape structure can impact geographic patches [29]. This means that the landscape structure of the ecosystem in which locusts live continuously affects the suitability of their habitat [30], [31]. The interaction of all these factors and how to transit from pixel scale to patch scale in this geographic area may affect locust habitat suitability. Monitoring changes in landscape structure through remote sensing data can be extremely useful when trying to extract locust habitat accurately [32], [33]. However, most existing models do not consider the impact of landscape structure on locust habitat. Thus, evaluating the feasibility of using remote sensing data coupled with multiple habitat factors at patch scale to monitor locust habitat is necessary.

In this study, the Patch based - analytic hierarchy process (PB-AHP) model was used to extract landscape structure considering multiple factors, and a locust habitat suitability analysis was completed by analyzing the suitable degree and weight of different habitat factors at patch scale in Tianjin, China. Landsat TM/OLI and MODIS data were used in this study. Specifically, the goals of this article were to: (1) analyze the impacts of multiple habitat factors and landscape structure on the locust habitat, (2) propose a model named PB-AHP to quantify both landscape and multiple habitat factors on locust habitat, and (3) evaluate the performance of the new model. By utilizing remote sensing images to monitor locust habitat, environmentally safe locust prevention and control methods can be developed to guide more effective precision agricultural research and management practices.

II. MATERIALS AND METHODS

A. STUDY AREA

The study area is located in the Binhai New District in southeast Tianjin, China (Fig.1). This study selected an area of 822.23 km^2, which contained the North Dagang Reservoir, Lier Bay, and Duliujian River. This area lies in a northern hemisphere with a monsoon climate of medium latitudes and has four distinctive seasons. The average annual rainfall is

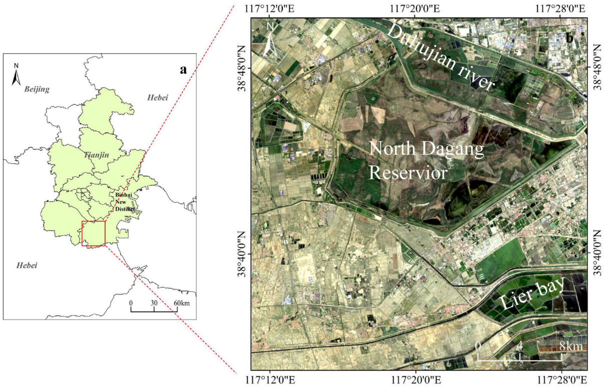

FIGURE 1. The location of Binhai New District in Tianjin (a), the study area (b) in the southeast of Binhai New District covering the typical locust area.

350–620 mm, of which 80% is concentrated from May to September. The annual mean temperature is 12-15° in this area. Bog and fluvo-aquic soils are the most distributed soil types. Enough water resources provide a suitable environment for the local wetland vegetation, which includes reeds such as *Phragmites communis Trin*, *Typha orientalis Presl*, and *Lythrum salicaria* L., with some weeds scattered around, such as *Eehinoehloa crusgall* (L.)Beauv., *Imperata cylindriea* (L.)Beauv., *Cynodon dactylon*(L.)Pars., *Cyperus rotundus*(L.), *Polygonum amphibiuln* L., and *Artemisia spp.* The main crops grown locally include maize, cotton, barley, and sorghum. Locust growth and propagation are helped by less human intervention near wetlands and suitable habitat, which can lead to severe plague in the study area [34].

B. DATA SOURCE

1) SATELLITE DATA

The remote sensing data used in this article are MODIS and Landsat images. Cloud-free Landsat images or few cloud Landsat images (path:122, row:33) were chosen, including TM and OLI images from 2000-2015. Before locust habitat factors were extracted, Landsat images were calibrated using the Fast Line-of-sight Atmospheric Analysis of Spectral Hypercubes module (FLAASH, a module in ENVI 5.3 image processing software) to eliminate the influence of atmospheric and light factors on the objects' reflectance. This module enhanced the image brightness to facilitate information extraction. All parameters for the input FLAASH module are set according to the metafile of the image. Using MODIS(h27v05) products (MOD11A2) from April to May in 2000-2015 to indicate the LST of the study area.

2) STATISTICS ON PLAGUES OF LOCUST

Historical observations of locust occurrence data provided by TPPS from 2000 to 2018, contained the locust occurrence area and locust control area, and locust density in some years. Considering that these data are exclusive, TPPS did not provide specific investigation location or ID numbers.

TABLE 1. The numbers of land cover class reference samples in different years.

Years	Reed and Weed	Pure Reed	Cropland	Water
2000	1437	633	2511	968
2005	1773	1245	1346	900
2010	594	576	2376	800

Due to the particularity of migratory pests, point sample data is difficult to get. Based on locust occurrence area and locust density data provided by TPPS, 10 sample points from each of the four suitable areas in 2002,2006 and 2013 were selected for analysis in this study in combination with textual description information, for a total of 40 sample points per year.

3) LAND COVER CLASS AND DATA

Considering the special ecological environment and locust preferred host selection, four land cover classes were defined: reed and weed, pure reed, cropland, water, and others [29]. "Reed and weed" was defined as weeds and other grasses (rarely) which grew in moist or semi-dry soil, with vegetation coverage ranges between 20% and 70%. These conditions provide a suitable condition for locust reproduction and development. Vegetation coverage of 20-50% is the most suitable for promoting spawning and nymph growth, and 50-70% is ideal for locust migration. "Pure reed" was defined as pure reed vegetation with vegetation coverage of 40-100%. This environment provided plenty of food for locust growth. Low-density areas of 40-50% coverage provide a suitable environment for spawning and nymph growth of locust, while 50-80% coverage denoting high-density areas are ideal for locust migration. "Cropland" was defined as crops with 10-60% vegetation coverage, mainly composed of cotton, barley, corn, peanut, sorghum, a small count of weed and reed. Agriculture and other human activities in the region are frequent make it impossible to provide a suitable environment for locust reproduction and spawning. But this field can provide a destination for migration. "Other" includes bare soil where salt accumulation on the surface and artificial area [29].

Quantitative analysis of locust host species requires a reference land cover dataset. In order to collect these reference data, this study used the national historical land use survey at a 30m spatial resolution (http://www.resdc.cn/) to preliminarily mark the reference pixels in Landsat data. Since historical survey data are not available annually, this study only collected data for the year 2000,2005, and 2010, and evaluated the land cover classification for these three years based on this data.

C. ANALYTICAL METHODS

1) SELECTION AND EXTRACTION OF HABITAT FOACTORS

Based on the analysis of the relationship between locust populations and habitat factors in the study area, five factors related to the suitability of locust habitat were determined, including vegetation coverage, land cover class, soil moisture, soil salinity, and LST.

Multi-temporal Landsat data were used to get vegetation coverage, soil moisture, and soil salinity. The mean vegetation coverage of three phases in the locust critical growth period from May to June was selected as a final variable. The mean soil moisture and soil salinity of three phases from April to May during the locust oviposition period was used as final variables. By calculating the mean value of MODIS(MOD11A2) from April to May, LST was obtained.

$$NDVI = \frac{B_{nir} - B_r}{B_{nir} + B_r} \tag{1}$$

where $NDVI$ represents vegetation coverage, B_{nir} and B_r are the reflectance in the near-infrared band and red band, respectively.

$$TVDI = \frac{T_s - T_{Smin}}{T_{smax} - T_{smin}} \tag{2}$$

$$T_{s\max} = a * NDVI + b, \quad T_{s\min} = c * NDVI + d \tag{3}$$

where $TVDI$ is the temperature vegetation dryness index to represent soil moisture, a, b, c, d are the coefficients of the dry, wet edge fitting equation, respectively.

$$SI = \sqrt{B_g * B_r} \tag{4}$$

where SI is soil salinity index to represent soil salinity, B_g and B_r are the reflectance in the green band and red band.

Before habitat suitability analysis, these data need to be converted into a raster map of corresponding habitat factors. In this study, the spatial analysis tool is used to standardize raster data into numerical data, and each factor is quantified with a score of 0-1. The standardized equation is as follows:

$$x = \frac{S - S_{\min}}{S_{\max} - S_{\min}} \tag{5}$$

among them, S_{min} represents the minimum value of each index in the study area, S_{max} represents the maximum value of each index in the study area.

2) LAND COVER MAPPING

The land cover class map was obtained from Landsat data using a random forest classifier based on seasonal characteristics (SCRF) [27]. Random forest is a classifier that uses multiple trees to train and predict samples. This implementation produces a large number of individual decision trees that are randomly selected from input and training data using bagging or bootstrap [36]. An EVI time series based on Landsat images was as seasonal features of different land cover classes. Because Landsat data is affected by the atmosphere, solar illumination angle, observation angle, and other factors, EVI decreases irregularly. This irregularity affects the accuracy of the time inversion of seasonal characteristics, resulting in the inability to correctly reflect land cover changes [36]. To address this, the Savitzky-Golay (S-G) filtering method was used to reconstruct the EVI time series [37]:

$$Y_j^* = \sum_{i=-m}^{i=m} C_i Y_{j+1} \tag{6}$$

where Y_j^* is the synthetic sequence data, Y_{j+1} is the original sequence data, C_i is the filtering coefficient $(2m + 1)$, and m is half the width of the smoothing window.

Land cover classification accuracy is assessed using a confusion matrix including user, producer, and overall accuracy. The confusion matrix is a comparison array used to indicate the number of pixels classified into a certain category and the number of ground survey pixels. Generally, the columns in the array represent reference data, and the rows represent category data obtained from remote sensing data classification. Overall accuracy is equal to the sum of correctly classified pixels divided by the total number of pixels. Producer accuracy refers to the correct classification percentage of all test samples in a feature category. User accuracy refers to the percentage of each category marked after classification to the exact category in ground survey pixels [38].

The land cover dataset described in section II.B.3) is the training sample and the verification sample of SCRF in this study, the ratio is 7:3. MATLAB 2017a is used to process the SCRF algorithm.

3) LOCUST HABITAT SUITABILITY ANALYSIS BEASED ON AHP MODEL

a: FAOTOR SUITABILITY AT PIXEL LEVEL

Vegetation coverage is the main variable affecting locust habitat. Generally speaking, if the vegetation coverage is too high, the sun will be blocked, and the temperature near the ground will be low, restricting locust feeding and movement and negatively impacting spawning. On the contrary, if the vegetation coverage is too low and the near-ground temperature is relatively high, locust activity increases but is not conducive to overall survival because of insufficient feeding materials and the lack of ideal shelter.

Low-lying and flat wetlands with reed and weed provide an ideal place and food source for locust oviposition and growth [39], [40]. The water resources provide suitable conditions for locust eggs hatching and nymph growth. Pure reed, which has high vegetation coverage, could provide an ideal environment for locust migration [41]. To better link, the types of land cover with locust habitat, the suitability of each land cover class (Table 2) was classified according to the influence of different classes on locust growth. Reed and weed represented the best shelters, followed by water, pure reed, cropland, and other (water affects the suitability of locust habitat in the landscape structure, but water is not locust habitat. The suitability degree of water here is used only for its influence at patch level).

If the soil moisture is high and the soil temperature is low, the development of locust eggs will inevitably be adversely affected. When soil salinity is too high, it is not conducive

TABLE 2. The suitability of each habitat factor at pixel scale.

Factor \ Suitability(M)	1(Poor)	2(General)	3(Good)	4(Optimum)
Vegetation Coverage	<10% or >85%	10%-15% or 75%-85%	50%-75%	15%-50%
Land cover class	other	Cropland	Pure reed	Water, reed and weed
Soil moisture	-	<10% or >25%	19%-25%	10%-19%
Soil salinity	>80%	50%-80%	20%-50%	<20%
LST	<25°C	25°C -28°C	34°C-42°C	28°C-34°C

TABLE 3. Initial weight (obtained by multivariate analysis) and final weight (Obtained by Ahp) of different habitat factors.

Factors	Initial importance	Final weights
Vegetation coverage	0.75	0.29
Land cover class	0.55	0.24
Soil moisture	0.39	0.21
Soil salinity	0.34	0.15
LST	0.29	0.11

to egg hatching, and the growth of halophytes negatively affects locust growth and development [30]. The surface temperature mainly affects the hatching of eggs, and only when the temperature accumulation reaches a certain value can the biochemical reactions needed in the hatching process is completed [29]. Table 2 was used to determine the suitability levels of different habitat factors.

b: DETERMINATION OF FACOTR WEIGHT

The Analytic hierarchy process (AHP) model was used to determine the weight of each habitat factor, which reflects the influence of each factor on locust survival and occurrence. The output of AHP is a set of rankings that can be used to support decision making for many alternatives based on multiple decision factors for each alternative [41]. The model combines each habitat factor [42]. This process consisted of five steps, which included: (1) defining and determining the factors (see in II.C1)); (2) conducting factor importance analysis: based on Landsat data, this study extracted all habitat factors, analyzed the correlation between each habitat factor and the locust area provided by TPPS from 2000-2015, and used the correlation index as the initial importance of each habitat factor; (3) determining the local priority: using the binary comparison method, the priority was calculated before the habitat factor pair to construct the judgment matrix; (4) sorting and calculating the weight of relative importance of all factors to the final goal according to the judgment matrix; (5) conducting the consistency test: when the consistency test result was less than 0.1, the ranking was considered to pass the test.

The habitat suitability index(HSI) for locusts based on the AHP method is as follows:

$$HSI1(x,y) = \sum\nolimits_{t=1}^{n} W_t M_t(x,y) \tag{7}$$

where $HSI1(x,y)$ is the overall score of habitat suitability at pixel scale; W_t is the weight of each factor (Table 3), $M_t(x,y)$ is the suitability at pixel scale of the tth factor, n is the number of factors.

The locust habitat suitability was divided into four categories: Poor locust habitat (POLH), General locust habitat (GELH), Good locust habitat (GOLH) and Optimum locust habitat (OPLH). The HSI of every category is shown in table 4.

4) LOCUST HABITAT SUITABILITY ANALYSIS BEASED ON PB-AHP MODEL

The Patch based - analytic hierarchy process (PB-AHP) model was combined with patch scale modeling to realize more practical monitoring of patchy target objects. To better quantify patch size, we used a moving-window approach which associated the suitability at patch level with the suitability at the pixel level. In order to consider the comprehensive impact of landscape structure on locust habitat, additional information from neighboring pixels in the same window was introduced. The setting of the moving-window involves the choice of its window size. Window size has a significant influence on locust habitat. Too small window size might lead to limited space, which results in failure to form a locust habitat. Too large window size might lead to the scatter of locust growth resource, which is not conducive to locust gathering. This study used Ecognition Developer software to analyze the level of information of the original image objects and the proximity information between the objects. Based on this information, the original image object size was obtained, and combined with land cover classification to determine the size of the patchy habitat target object of locust.

The suitability at patch level was defined as:

$$M_{y,p}(x_{(c+1)/2}, y_{(c+1)/2}) = \frac{\sum_{j=1}^{c}\sum_{k=1}^{c} W_p M_t(x_j, y_k)}{\sum_{j=1}^{c}\sum_{k=1}^{c} W_p} \tag{8}$$

where, $M_{y,p}(x_{(c+1)/2}, y_{(c+1)/2})$ is the suitability degree of each factor at the patch scale; $y = 1, 2, \ldots, 5$, $M_{1,p}$, $M_{2,p}$ and … $M_{5,p}$ represents the suitability of five factors at patch level, respectively; x and y are the numbers of rows and columns in the study area; c is the number of rows and columns of the window, in this study, the optimal size was determined to be 5; $M_t(x_j, y_k)$ is suitability at pixel level, and W_p is the influence of neighboring pixel in the same patch on the central pixel, which could quantify the impact on the landscape.

The weight of spatial distance is expressed by the reciprocal of the spatial distance between surrounding pixels (x_j, y_k)

TABLE 4. Hsi value description.

HSI	Category	Description
0<HSI<=1	POLH	no risk of locust infestation
1<HSI<=2	GELH	a few scattered individuals in a typical locust infestation year
2<HSI<=3	GOLH	a relatively stable and suitable environment for locust breeding
3<HSI<=4	OPLH	the most stable and most suitable breeding environment

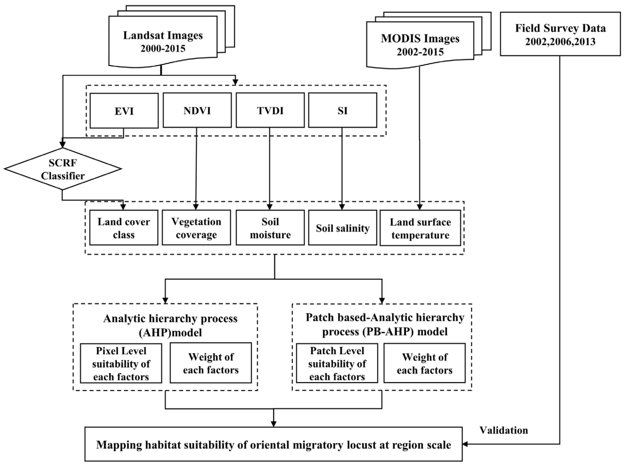

FIGURE 2. Flowchart of the research approach.

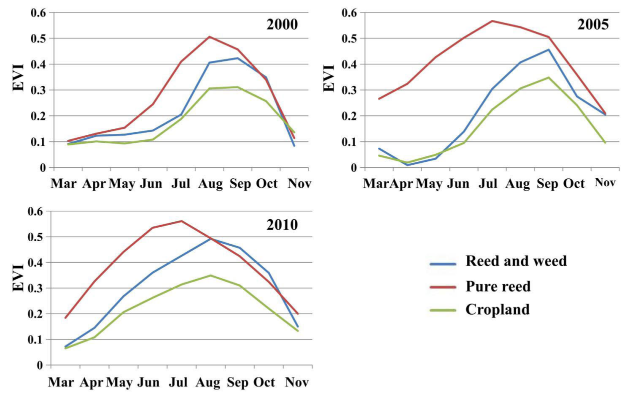

FIGURE 3. EVI series of three land cover classes in 2000, 2005 and 2010.

and the central pixel $(x_{(c+1)/2}, y_{(c+1)/2})$. The specific formula is:

$$W_p(x_j, y_k) = \frac{1}{\sqrt{\left(x_{(c+1)/2} - x_j\right)^2 + \left(y_{(c+1)/2} - y_k\right)^2}} \tag{9}$$

which measures the spatial distance between the calculated pixel and surrounding pixels. Closer pixels normally have higher spatial similarity; therefore, closer pixels should be given a higher weight.

The habitat suitability index of locusts based on the PB-AHP model is as follows:

$$HSI2(x, y) = \sum\nolimits_{t=1}^{n} W_t M_{y,p}(x_{(c+1)/2}, y_{(c+1)/2}) \tag{10}$$

where *HSI2(x,y)* is the overall score of habitat suitability at patch scale; W_t is the weight of each factor (Table 3), $M_{y,p}(x_{(c+1)/2}, y_{(c+1)/2})$ is the suitability at patch scale of the tth factor; n is the number of habitat factors.

The grading index is shown in Table 4 .

III. RESULTS AND DISSCUSSION

A. LAND COVER CLASSIFICATION

The annual EVI curve (Fig.3) reflects the difference in reflectivity between different classes of surface coverage. Although all vegetation classes followed similar seasonal trends, the amplitudes of the curves during the development period showed a significant difference. The average EVI from April to November was calculated, and the EVI curves were used as the SCRF input database to generate land cover data.

The land cover classifications confusion matrix can be seen in Table 5, as well as the overall accuracies of three years (2000, 2005 and 2010) are 93%, 89%, and 93%. Most of the confounding classes were a mixture of reed and weed and pure reed. The SCRF has high precision and can be used to realize land cover classification. Combined with the existing land cover verification dataset and locust habitat suitability dataset, this article drew the land cover classifications in the year 2000, 2005, 2010, 2002, 2006, and 2013. As can be seen from the result, the largest land cover class was cropland, which was mainly distributed in the southwest. The conversion of a land cover mostly occurs between pure reed and mixture of reed and weed, which were observed mostly along major reservoir and rivers (including North Dagang Reservoir, Duliujian River, and Lier Bay). These two classes are also important to cover classes for locust breeding.

The land cover classification result showed that the SCRF was an accurate land cover classifier and can also confirm results from previous research [43]–[45]. Confirming the accuracy of land cover is a crucial step needed to assess ecosystem services such as locust habitat suitability.

B. HABITAT SUITABILITY OF LOCUST

Taking vegetation coverage, land cover class soil moisture, soil salinity and LST as data input, combined with the moving window to establish PB-AHP model to analyze the importance of multiple habitat factors and landscape structure. The traditional AHP model was used to compare and verify the approach. The results revealed that PB-AHP model had higher overall accuracy than AHP model. PB-AHP model had

TABLE 5. Confusion matrix and accuracy of land cover classifications produced by Scrf in 2000, 2005 and 2010.

Years		Reed and weed	Pure Reed	Cropland	Water	UA(%)	OA(%)	Kappa
2000								
	Reed and weed	1258	167	0	12	88	93	0.90
	Pure Reed	126	507	0	0	78		
	Cropland	0	0	2482	29	98		
	Water	13	0	3	952	96		
	PA(%)	90	74	99	95			
2005								
	Reed and weed	1588	182	3	0	89	89	0.88
	Pure Reed	130	982	5	128	78		
	Cropland	0	21	1325	0	98		
	Water	0	94	0	806	90		
	PA(%)	92	76	99	86			
2010								
	Reed and weed	437	150	7	0	73	93	0.89
	Pure Reed	145	431	0	0	70		
	Cropland	13	2	2361	0	93		
	Water	3	0	0	2097	99		
	PA(%)	73	74	99	100			

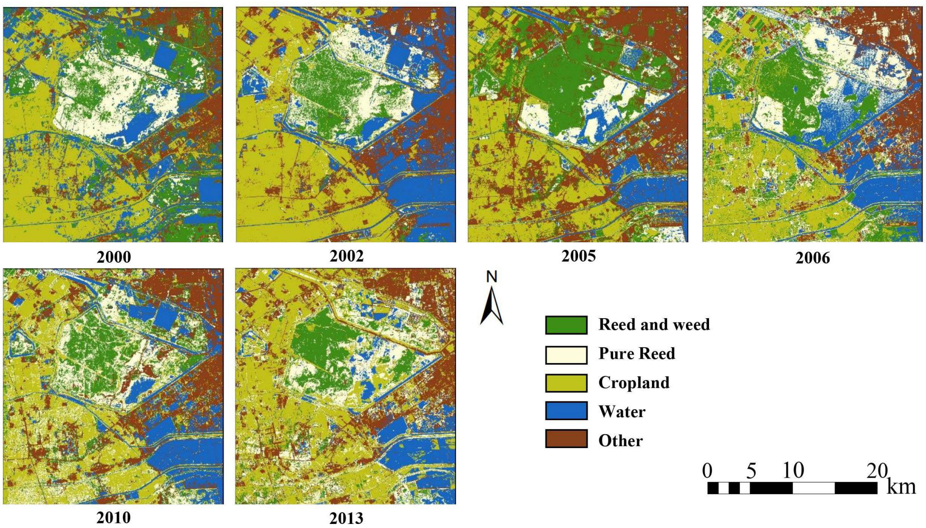

FIGURE 4. Land cover class maps of 2000, 2003, 2005, 2006, 2010 and 2013.

an overall accuracy of 85%, 83% and 88% in the year 2002, 2006 and 2013, respectively. (Table 6).

Fig.5 shows the locust habitat extracted based on the AHP model(left) and PB - AHP model (right). The accuracies of both models were more than 70%, and the results have the same trend, meaning that both models could effectively be used for locust habitat suitability analysis. However, the existence of locust habitat is associative, and locust habitat is affected by the surrounding environment. By introducing quantitative analysis of geographical patches, we were able to give full consideration to the influence of surrounding landscape structure. Therefore, the consistency and integrity of patch-based monitoring results were more comprehensive than pixel-based monitoring results. Accuracy verification results had similar findings. The accuracy based on the PB-AHP model was 88%, which is 10% higher than the results from AHP model. This article provides a quantitative analysis of these two models from three landscape metrics (including mean patch size, patch density, and connectivity, Table 7). Based on the analysis of the area of the study area and the density of locusts obtained from TPPS, the minimum patch size of the locust habitat is 2 km^2. It can be seen from the mean patch area that the locust habitat patch size analyzed by the PB-AHP model is larger than the size obtained based on

TABLE 6. Accuracy verification of habitat suitability analysis results based on Ahp and Pb-ahp models.

		AHP						PB-AHP					
Years		Optimum	Good	General	Poor	UA(%)	OA(%)	Optimum	Good	General	Poor	UA(%)	OA(%)
2002													
	Optimum	7	3	0	0	70	73	8	2	0	0	80	85
	Good	2	7	1	0	70		1	9	0	0	90	
	General	0	1	7	2	70		0	0	8	2	80	
	Poor	0	0	2	8	85		0	0	1	9	90	
	PA(%)	78	64	70	80			89	82	89	82		
2006													
	Optimum	7	3	0	0	70	75	8	2	0	0	80	83
	Good	1	7	2	0	70		0	9	1	0	90	
	General	0	1	8	1	80		0	1	9	0	90	
	Poor	0	0	1	9	90		0	0	1	9	90	
	PA(%)	88	64	73	90			100	75	82	100		
2013													
	Optimum	8	1	1	0	80	78	9	1	0	0	90	88
	Good	0	7	3	0	70		0	8	2	0	80	
	General	0	1	7	2	70		0	0	8	2	80	
	Poor	0	0	2	8	80		0	0	2	8	80	
	PA(%)	100	78	54	80			100	89	67	80		

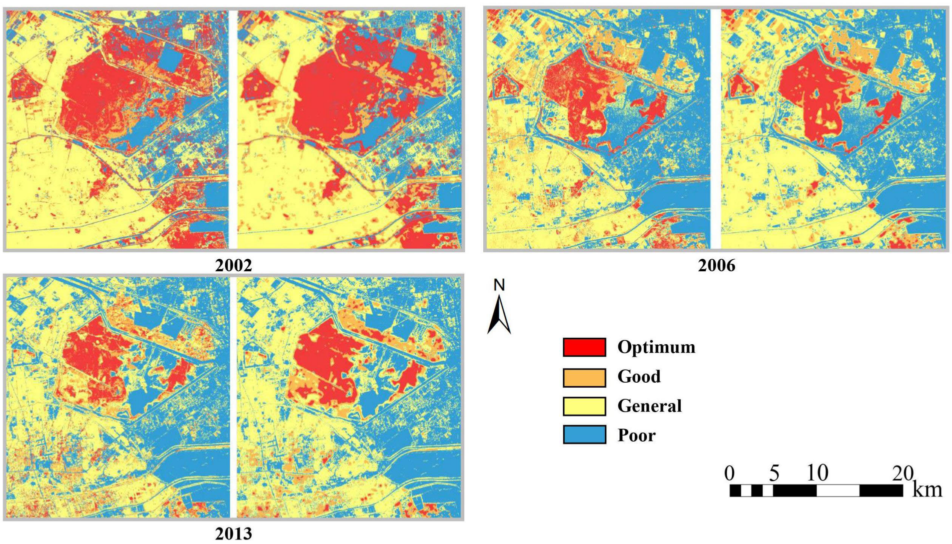

FIGURE 5. Locust habitat map in 2002,2006 and 2013 using AHP(left) and PB-AHP(right) models.

the AHP model, and the mean patch size of four locust habitat classes is greater than 2 km^2, which is consistent with the minimum patch size of locust habitat. The connectivity of the locust habitat analyzed by PB-AHP model is also higher. It is believed that the locust habitat obtained by PB-AHP model is less fragmented. This situation is more realistic and the analysis result is more credible.

Landsat and MODIS data can provide enough data to support the assessment of ecosystems [5], [46]–[49]. Several scholars have studied locust habitat using satellite data. In our research, continuous Landsat and MODIS data ensured successful monitoring of locust habitat factors, thus providing data support for locust habitat suitability analysis. The habitat factors used in locust habitat analysis were determined by comprehensively considering the incubation period and occurrence and development period, combining both host and habitat information. This model was able to evaluate the hatching habitat suitability and reflect vegetation growth and spatial distribution. At the same time, the input values (initial importance) of AHP model were obtained based on

TABLE 7. The landscape metrics of locust habitat obtained by Ahp and Pb-ahp models.

Years		AHP			PB-AHP		
		Mean patch size/km^2	Patch density	CONNECT	Mean patch size	Patch density	CONNECT
2002							
	Optimum	3.45	25.13	0.26	21.80	12.97	0.34
	Good	2.73			9.85		
	General	2.59			3.57		
	Poor	8.76			8.78		
2006							
	Optimum	2.32	36.67	0.20	18.25	13.72	0.31
	Good	1.06			9.28		
	General	3.43			5.57		
	Poor	7.14			7.15		
2013							
	Optimum	0.34	39.05	0.21	2.38	17.16	0.26
	Good	0.77			8.57		
	General	5.04			8.88		
	Poor	3.67			3.68		

correlation analysis between locust area from TPPS data and different habitat factors from 2000 to 2015, which is independent of expert evaluation and improved the objectivity of this method.

Besides, locust habitat occurs in discontinuous patches from the scale of landscapes. These patterns of habitat development depend on the landscape structure. Our research constructed moving windows by analyzing the patch size of the original image to carry out quantitatively analyze the landscape structure so that to map the locust habitat at patch scale and realize the contribution evaluation of landscape structure to habitat suitability classification. Results from this study can effectively restrain the ''salt and pepper'' phenomena by considering the impact of landscape structure on locust habitat and showing the results from combined and related habitat factors. Results from this analysis revealed the relationship between landscape structure and locust habitat and proved that the addition of landscape structure to the model made positive contributions to accurately classifying locust habitat.

The purpose of our research is to improve the accuracy of the locust spatial distribution model by combining landscape structure and coupling multiple habitat factors to meet the current needs of precision agriculture. At the same time, the suitability of each habitat factor was analyzed, and the influence on the landscape structure of the locust ecosystem was considered more comprehensively. In general, this locust habitat suitability analysis model based on satellite data combined with multi-factors and landscape structure performed well, with an accuracy rate of 88%, and was able to generalize automatic locust habitat suitability for years without training data.

The area around North Dagang Reservoir is known to be a locust habitat. Monitoring locust habitat and discussing the landscape pattern and habitat factors that alter it could provide vital support to help agriculture and plant protection in planning and controlling damages from the locust population. Locust habitat maps obtained from satellite data can accurately select the locust control area. Even more importantly, these detailed habitat maps would help redistribute prevention and control treatments more economically and equitably within the study area, reducing waste associated with unoptimized management. These results can also provide a basis for ecological locust control, which helps reduce water pollution and damage to the environment [50]–[52]. While ecological control technology cannot kill locust directly, it uses an ecological transformation to reduce the breeding area, decrease food sources, and control the occurrence area and density. Another aspect is that this multi-year analysis and derived occurrence frequencies of OPLH and GOLH provide the possibility for long-term planning and centralized control measures. At the same time, we can isolate OPLH and GOLH such as North Dagang Reservoir, Duliujian River, and Lier Bay to prevent locust proliferation from ever occurring.

IV. CONCLUSION

Our research validates the potential of earth observation methods to analyze locust habitat in Tianjin. PB – AHP model used in this study analyzed the habitat selection during locust hatching and development, and selected five significant habitat factors, including vegetation coverage, land cover class, soil moisture, soil salinity, and land surface temperature. The inversion result of each factor from 2000 to 2015 was obtained by using the time series from Landsat and MODIS image data. The AHP model was used to obtain the weights of influence for different habitat factors, and the degree of patch scale suitability was obtained through quantitative analysis of landscape structure, allowing the distribution map of locust habitat in the study area to be drawn. The overall accuracy of the model was 88%, which performed 10% better than the traditional AHP model. This study not only confirms the importance of vegetation, soil, and climate for monitoring the locust habitat but also noted the contribution of landscape structure. In addition, this model does not simply determine locust and non-locust areas but quantifies the habitat suitability. This model is strongly generalizable and has significant real-time capabilities for incorporating newly acquired data.

Future work will be a more in-depth study of the relationship between landscape structure, locust habitat, and locust occurrence mechanism. It is necessary to analyze the changes in locust habitat caused by changes in landscape structure and combine with actual control requirements to improve the level of locust monitoring and early warning and establish scientific research results on locust monitoring and early warning to bridge industrial pest control.

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