Automatic System for Crop Pest and Disease Dynamic Monitoring and Early Forecasting

Yingying Dong, Fang Xu, Linyi Liu, Xiaoping Du, Binyuan Ren, Anting Guo, Yun Geng, Chao Ruan, Huichun Ye, Wenjing Huang, and Yining Zhu

***Abstract*—Infected areas and damage levels due to crop pest and disease have been growing seriously according to the climate change. We aim to develop an automatic system to provide national pest and disease dynamic monitoring and early forecasting products, by integrating multisource information (Earth Observation, meteorological, ecological, entomological, and plant pathological, etc.) and cutting edge research on pest and disease modeling to support decision making in the sustainable management of pest and disease. First, we selected the sensitive indexes for pest and disease habitat monitoring and early forecasting, and then optimized the forecasting model's parameters to enhance its applicability in national level. Second, we developed an automatic system based on web GIS platform to efficiently realize the national pest and disease dynamic habitat monitoring and early forecasting. Finally, we released the pest and disease forecasting thematic maps. China's national disease wheat yellow rust (*Puccinia striiformis*) and national pest oriental migratory locust (*Locusta migratoria manilensis (Meyen)*) are taking as the experimental objects. Based on the developed system, we forecasted the infected areas of rust and locust in China, in 2019, with these R-square values are higher than 0.87. This system would not only promote the efficacy of pest and disease management and prevention by improving accuracy of monitoring and forecasting, but also help to reduce the amount of chemical pesticides, which could thus guarantee food security and agriculture sustainable development in China.**

***Index Terms*—Pest, disease, monitoring, forecasting, system.**

I. Introduction

AGRICULTURAL systems are facing a growing challenge of pest and disease threats by climate change [1], [2]. Ground monitoring of disease severity and pest population density, and meteorological-based disaster forecasting are normally used by the plant protection department of the government. But, they could not meet the requirements of scientific control for timely and spatially continuous information on pest and disease occurrence and development over large areas. Remote sensing technology as a rapid acquisition of national observation has been widely used in the research field of precision agriculture, especially for crop pest/disease spectral features extraction, habitat monitoring, and infected areas and damage levels forecasting. Many methods and algorithms are constructed and validated in leaf level, canopy level, and regional level, providing meaningful work for national crop pest and disease mapping [3]–[7]. Besides, the development of big earth data and artificial intelligence provides powerful way for big data analysis and information mining [8]. Then, how to effectively gather multisource data and analysis models in an intelligent system to provide time series pest and disease habitat monitoring and early forecasting spatial products at national level are the current research trend in agriculture remote sensing.

Existed research have made some achievements in the agricultural system construction. RustTracker is a global wheat rust monitoring system supported by the wheat rust disease global programme of Food and Agriculture Organization of the United Nations (FAO) to release wheat rust annual report and global warning [9], [10]. FAO developed the eLocust system to record field observations during survey in all locust affected African and Asian countries, and alerted the danger of desert locust invasion with the early warning systems by comprehensive analysis of ground surveys, meteorological data, and remote sensing data [11], [12]. Shelestov *et al*. [13] built a geospatial information system for agricultural monitoring to realize automatic data retrieval and business-logic analysis with remote sensing satellite data and products. Oki *et al*. [14] constructed an agricultural monitoring system based on remote sensing images and field server camera data, which could be applied to crop fertilizer management and crop production forecasting. Zhang *et al*. [15] developed a WebGIS-based monitoring information system based on PHP platform to analyze and visualize real-time filed survey, also middle-term-scale prediction of rice pest and disease. Peng *et al*. [16] built a GIS-based apple disease and pest management information system, including basic database, pest/disease diagnosing and predicting functions, and information releasing functions. Zhao *et al.* [17] designed an agricultural disease and pest image remote transmission system to improve

Manuscript received February 28, 2020; revised June 29, 2020; accepted July 15, 2020. Date of publication July 31, 2020; date of current version August 13, 2020. This work was supported in part by the National Key R&D Program of China under Grant 2017YFE0122400, in part by the Beijing Nova Program of Science and Technology under Grant Z191100001119089, in part by the National Natural Science Foundation of China under Grant 41801338, and in part by the Youth Innovation Promotion Association CAS under Grant 2017085.
(Corresponding authors: Wenjiang Huang; Yining Zhu.)

Yingying Dong, Xiaoping Du, Huichun Ye, and Wenjing Huang are with the Key Laboratory of Digital Earth Science, Aerospace Information Research Institute, Chinese Academy of Sciences, Beijing 100094, China (e-mail: dongyy@radi.ac.cn; duxp@radi.ac.cn; yehc@radi.ac.cn; huangwj@radi.ac.cn).

Fang Xu and Yining Zhu are with the Beijing Advanced Innovation Center for Imaging Technology, School of Mathematics, Capital Normal University, Beijing 100048, China (e-mail: aaronxf1314@163.com; ynzhu@cnu.edu.cn).

Linyi Liu, Anting Guo, Yun Geng, and Chao Ruan are with the Key Laboratory of Digital Earth Science, Aerospace Information Research Institute, Chinese Academy of Sciences, Beijing 100094, China, also with the University of Chinese Academy of Sciences, Beijing 100049, China (e-mail: liuly35@radi.ac.cn; guoanting12@126.com; gengyun@radi.ac.cn; 474048903@qq.com).

Binyuan Ren is with the National Agricultural Technology Extension and Service Center, Beijing 100125, China (e-mail: renbinyuan@agri.gov.cn).
Digital Object Identifier 10.1109/JSTARS.2020.3013340

data transmission efficiency and quality for field management. These systems for crop or fruit pest and disease monitoring and forecasting mainly take field survey data and meteorological data as the key inputs, while sampling maps, qualitative trend prediction maps and loss assessment charts as the outputs. In addition, the update frequency of the regional situation of pest/disease is annual or growing seasonal. Aim to provide timely national pest/disease early forecasting information for field management scheme design to ensure food security, quantitatively habitat monitoring, and dynamic forecasting of the pest and disease infected areas and damage levels during the crop growth period are needed.

In order to support decision making in the sustainable management of national pest and disease, we brought together and produced cutting edge research to provide dynamic habitat monitoring and early forecasting information of crop pest and disease in national level, by integrating multisource datasets, such as Earth Observation-EO, meteorological, ecological, entomological, and plant pathological, habitat monitoring and pest/disease forecasting algorithms and models, computing platform and automatic system development technologies. The following research is conducted in the article work, including:

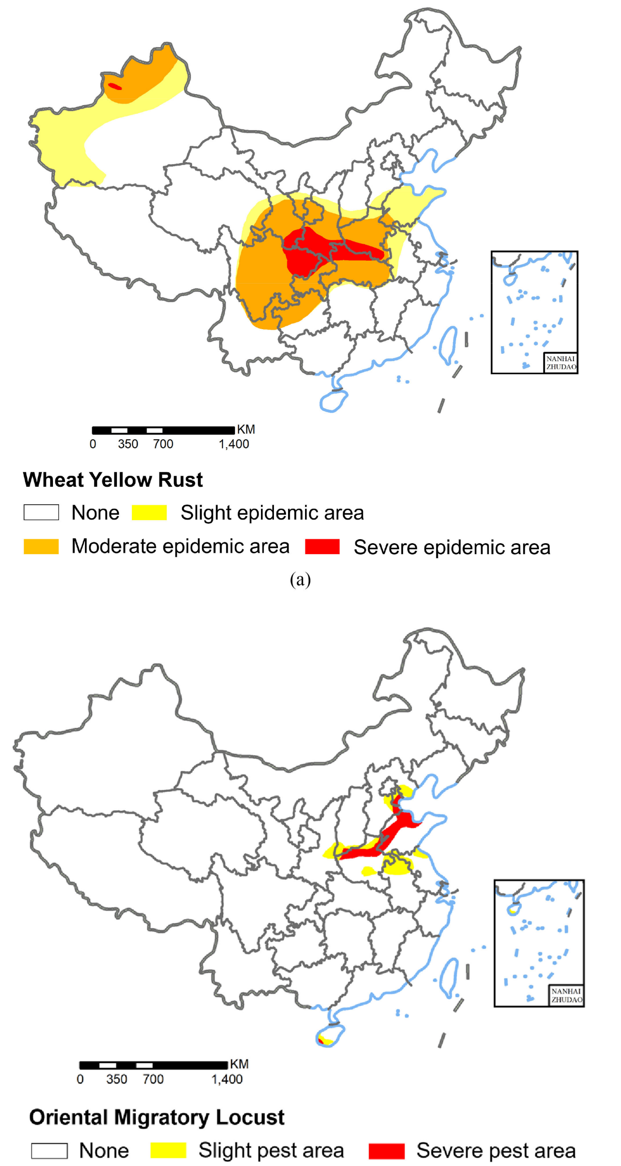
1) sensitive indexes for pest/disease habitat monitoring and early forecasting are constructed and selected based on pest/disease spectral response mechanism and environmental features to promote pest/disease occur and development;
2) pest/disease forecasting model construction, and model's parameters optimization based on historical data and optimization method, also validation are conducted;
3) an automatic system is developed based on WebGIS platform to effectively gather datasets and models, to realize dynamic pest/disease habitat monitoring and forecasting; and
4) pest/disease thematic maps are produced to show spatial distribution, infected areas, and damage levels in national level.

We selected China's national disease—a fungal disease wheat yellow rust (*Puccinia striiformis*), and national pest—a serious insect pest oriental migratory locust (*Locusta migratoria manilensis (Meyen)*) as our experimental objects. Then, we dynamically forecasted the rust and locust infected areas and damage levels in China, in 2019, with our developed system and outputted the time series thematic maps to support pest/disease management and prevention.

II. Data And Methods

A. Study Area and Dataset

Wheat yellow rust and oriental migratory locust are taking as our objects. These two national disease and pest occur every year in China, causing yield loss by 10% to 30% when severe. For wheat yellow rust, its main occur areas are shown in Fig. 1(a). Three different epidemic areas are listed. For the severe epidemic area of rust, it mainly distributed in Shaanxi, Sichuan, Gansu, Chongqing, Henan, Hubei, and Xinjiang provinces. For the moderate epidemic area of rust, it mainly distributed in Henan, Hubei,



(b)

Fig. 1. Main areas of wheat yellow rust and oriental migratory locust in China. (a) Wheat yellow rust. (b) Oriental migratory locust.

Shaanxi, Shanxi, Gansu, Ningxia, Qinghai, Sichuan, Yunnan, Guizhou, Chongqing, and Xinjiang provinces. For the slight epidemic area of rust, it mainly distributed in Shandong, Anhui, Hebei, Henan, Shaanxi, Ningxia, Gansu, Qinghai, and Xinjiang provinces. For, oriental migratory locust, its main occur areas are shown in Fig. 1(b). The locust areas are mainly distributed in Shandong, Henan, Hebei, Anhui, Shaanxi, Tianjin, Jiangsu, Hainan, Shanxi, Guangxi, and Liaoning provinces, in which the beach, river beach, and lake beach areas are normally the severe pest areas. Most of the pest areas have two locust generations per year, i.e., summer locust and autumn locust, which are the most important locust distributed in China and caused more serious damage. Then, we selected these two generations for remote sensing habitat monitoring and forecasting.

The data used for rust and locust habitat monitoring and forecasting include spatial data and attribute data. For spatial data, they include land-use data with 30 m spatial resolution, administrative division data, wheat planting area, locust area, and remote sensing data including MODIS surface reflectivity (MOD09A1), normalized difference vegetation index (NDVI) (MOD13A2), land surface temperature (LST) (MOD11A2), landsat and sentinel images. For attribute data, they include tables and documents, in which, the tabular data mainly refer to meteorological data including rainfall, mean daily temperature, wind direction and speed, and ground data of pest and disease occur from field survey, and the documents include files or information of rust and locust occurrence from the official website of Ministry of Agriculture and Rural Affairs of China and China statistical yearbook.

B. Crop Pest and Disease Monitoring and Forecasting Models

To dynamically monitor the habitat of rust and locust, and forecast disaster infected areas and damage levels, we first constructed the sensitive indexes for rust and locust, respectively, and then developed the forecasting models.

For wheat yellow rust, it is a major wheat disease occur every year in China, and the most important period of rust is its spring epidemic during March to May. This time is not the main affecting time of wheat aphid, so rust and aphid could be distinguished. Then, the spatial distribution of rust in China is taken as prior knowledge as shown in Fig. 1(a), which could be used to distinguish diseases occurring at the same time, such as wheat Fusarium head blight and wheat powdery mildew. And, tens of years meteorological data analysis could help to distinguish drought and rust, while for nutrition stress it is normally not widely happen at national level. In addition, according to tens of years field survey collected by the plant protection department of National Agricultural Technology Extension and Service Center, it is not popular that many pests and diseases occur at the same time and same location at national level [18].

Wheat yellow rust forms yellow stripes or oval-shaped spots on the leaves of wheat, which results in leaf yellowing, chlorophyll content and water content reduction. Then wheat rust index (WRI) is constructed based on plant senescence reflectance index (PSRI) (1) and red-edge vegetation stress index (RVSI) (2) to monitor wheat yellow rust, for which WRI (3) could consider wheat growth, chlorophyll content and their variation characteristics. Then, integrated with disease habitat information including land surface temperature (LST, MODIS product), rainfall and wind (meteorological data), also historical data, Disease Index (DI) (4) is constructed for wheat yellow rust habitat monitoring based on our previous teamwork [19]–[24].

$$\mathrm{PSRI} = (R_R - -R_B)/R_{\mathrm{NIR}} \tag{1}$$

$$\mathrm{RVSI} = ((R_{712} + R_{752})/2) - R_{732} \tag{2}$$

$$\mathrm{WRI} = f(\Delta\mathrm{PSRI}, \Delta\mathrm{RVSI}) \tag{3}$$

$$\mathrm{DI} = g(\mathrm{WRI}, \mathrm{LST} - \mathrm{LST}_{\mathrm{avg}}, R - R_{\mathrm{avg}}, W) \tag{4}$$

where, R_R, R_B and R_{NIR} are the reflectance of red, blue, and near infrared (NIR) bands, and R_{712}, R_{752}, and R_{732} are the reflectance of 712, 752, and 732 nm bands. LST is LST while $\mathrm{LST}_{\mathrm{avg}}$ is the average historical LST. *R* is rainfall while R_{avg} is the average historical rainfall. ΔPSRI is the difference between PSRI and PSRI of health wheat, while ΔRVSI is the difference between RVSI and RVSI of health wheat. *W* is wind direction and speed. *f* and *g* are constructed with regression model support vector machine, based on field survey data for model training and parameters optimization. The data range of DI is 0% ∼ 100%. When $0 < \mathrm{DI} \leq 30\%$, the damaged level of rust is slight, $30\% < \mathrm{DI} \leq 60\%$ is moderate, and $\mathrm{DI} > 60\%$ is severe. In which, the classification of different rust damage levels is according to China's "Rules for investigation and forecasting of wheat yellow rust" (GB/T15795-2011). As given in Table I, the levels 1 and 2 refer to the slight occurrence of wheat rust, the level 3 refers to moderate, and levels 4 and 5 refer to severe.

TABLE I
WHEAT YELLOW RUST FIELD INVESTIGATION INDICES

Index	Level				
	1	*2*	*3*	*4*	*5*
Disease index	$0.001<Y\leqslant5$	$5<Y\leqslant10$	$10<Y\leqslant20$	$20<Y\leqslant30$	$Y>30$
The rate of disease field / %	$1<R\leqslant5$	$5<R\leqslant10$	$10<R\leqslant20$	$20<R\leqslant30$	$R>35$

Y is the disease index, which is used to reflect the severity of disease occurrence. The calculation formula is $Y = F*D*100$, F is the disease leaf rate, and *D* is the average severity of the disease leaf. *R* is the disease field rate, referring to the percentage of the number of damaged fields in the total fields.

For oriental migratory locust, it is a major pest occur every year in China, there are two locust generations, i.e., summer locust mainly during May to early July and autumn locust mainly during middle July to September. The spatial distribution of locust in China is taken as prior knowledge as shown in Fig. 1(b). Locust habitat and its spread area are relatively stable in China, and locust is absolutely the main pest in these areas [25]. And, tens of years meteorological data analysis could help to distinguish drought and locust, while for nutrition stress, the vegetation changes caused by nutritional stress are relatively slow compared to locust bites. Locust eats leaves and stems of vegetation, which results in vegetation canopy and leaf area index reduction. Then, locust Index (LI) is constructed based on NDVI (5) and modified soil adjusted vegetation index (MSAVI) (6) to monitor locust, for which LI (7) could consider crop canopy cover, soil background information and their variation characteristics. Finally, integrated with pest habitat information including MODIS LST product and wind (meteorological data), also historical data, pest index (PI) (8) is constructed for locust monitoring. ΔNDVI is the difference between NDVI and NDVI of health vegetation, while ΔMSAVI is the difference between MSAVI and MSAVI of health vegetation. Where, *f* and *g* are constructed with regression model support vector machine, based on filed survey data for model training and parameters optimization. The data range of PI is 0% ∼ 100%. When $0 < \mathrm{PI} \leq 30\%$, the damaged level of locust is slight, $30\% < \mathrm{PI} \leq 60\%$ is moderate, and $\mathrm{PI} > 60\%$ is severe. In which, the classification of different locust damage levels are according to China's "Technical Specification for the Investigation and Forecast of *Locustamigratoriamanilensis* (Meyen)" (GB/T 15799-2007). As given in Table II, the levels 1 and 2 refer to the

TABLE II
ORIENTAL MIGRATORY LOCUST FIELD INVESTIGATION INDICES

Index	Level				
	1	*2*	*3*	*4*	*5*
Index of occurring (L)	$L \leqslant 0.1$	$0.1<L \leqslant 0.25$	$0.25<L \leqslant 0.56$	$0.56<L \leqslant 0.9$	$L>0.9$
The rate of damaged area (%, P)	$P \leqslant 30$	$30<P \leqslant 50$	$50<P \leqslant 70$	$70<P \leqslant 90$	$P>90$
Average density of the oriental migratory locust larva (head/m^2, d)	$0.2 \leqslant d<0.3$	$0.3<d \leqslant 0.5$	$0.5<d \leqslant 0.8$	$0.8<d \leqslant 1$	$d>1$

Damaged levels of locust decided by the index of occurring (L).

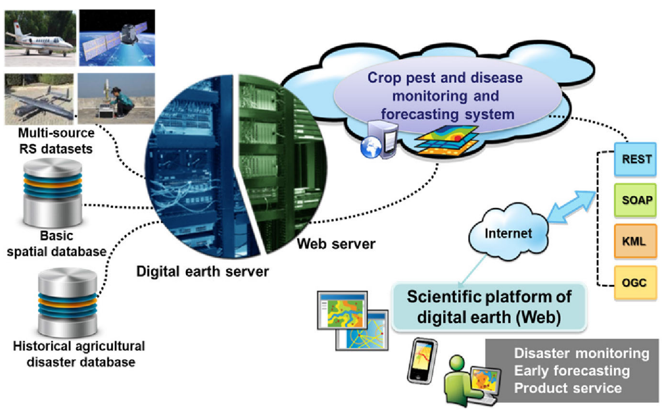


Fig. 2. Framwork of crop pest and disease monitoring and forecasting system.

slight occurrence of locust, the level 3 refers to moderate, and levels 4 and 5 refer to severe.

$$\mathrm{NDVI} = (R_{\mathrm{NIR}} - R_R)/(R_{\mathrm{NIR}} + R_R) \tag{5}$$

$$\mathrm{MSAVI} = ((2R_{\mathrm{NIR}} + 1) - (\mathrm{sqrt}((2R_{\mathrm{NIR}} + 1)^2 - 8(R_{\mathrm{NIR}} - R_R))))/2 \tag{6}$$

$$\mathrm{LI} = f(\Delta\mathrm{NDVI}, \Delta\mathrm{MSAVI}) \tag{7}$$

$$\mathrm{PI} = g(\mathrm{LI}, \mathrm{LST} - \mathrm{LST}_{\mathrm{avg}}, W). \tag{8}$$

III. System Design and Implementation

Based on the multisource data and forecasting models, we developed an automatic system for national crop pest and disease habitat monitoring and forecasting, to dynamically produce thematical maps providing infected areas and damage levels to support agricultural decision making.

A. System Framework

The framework of crop pest and disease monitoring and forecasting system is shown in Fig. 2 . The system was developed on the scientific platform of digital earth that complies with the Java 2 Platform Enterprise Edition specification, to build a three-layer browser/server (B/S) network architecture, including data layer, application layer and client layer. Compared with the client/server (C/S) architecture, the B/S architecture adopts a browser-based solution strategy, which could effectively reduce the difficulty and cost of system maintenance and expansion.

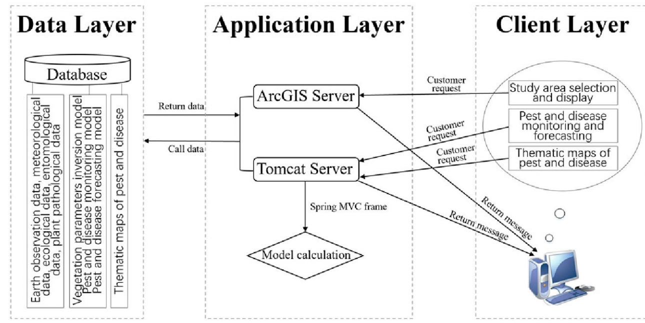


Fig. 3. Data layer, application layer, and client layer of the system.

The client of the B/S architecture does not need to install the required software to run the system on their own computer and could access the system services provided by the network server just through a browser. The B/S system architecture shown in Fig. 3 is as follows.

1) Data Layer: This layer is mainly used to store data, models, and products. The data include spatial data and attribute data listed in session A of part II. And three databases, i.e., multisource remote sensing database, basic spatial database, and historical agricultural disaster database, are constructed to manage different kinds of data. The models include pest and disease forecasting models proposed in session B of part II. The products include the dynamic thematical maps of pest and disease forecasted infected areas and damage levels.

2) Application Layer: The application layer or Web server is the pivotal part of the crop pest and disease monitoring and forecasting system. This layer is mainly responsible for HTTP requests received from the client layer (Web browser), and then selecting corresponding servers to process different types of requests. For the requests related to geographic information display, they would be handled by the ArcGIS Server, while for the requests related to model calculation, they would be handled by the Tomcat server through building Spring MVC framework. The application layer will first call the multisource data of the study area, including earth observation data, meteorological data, ecological data, entomological data and plant pathological data, and then call the pest and disease habitat monitoring and occurrence forecasting model according to the client's request, and return thematic maps of pest and disease forecasting to the client interface for display at last.

3) Client Layer: The client layer or Web browser is mainly responsible for providing the system's user interface, responding to user instructions, and completing the related functions of user interaction. The client layer includes the response and display of processing interface controls, the selection of crop pest and disease habitat monitoring and early forecasting models, and the display of system service products, such as pest and disease dynamic forecasting thematic maps.

In summary, these three layers of the B/S architecture system are interrelated. First, the client layer collects user requests and transfers them to the application layer. Then the application layer calls the corresponding data and models from the data layer for data analysis and processing according to user requests and saves the results in the data layer. Finally, the application layer feeds back the user requests response to the client layer.

B. System Database

Large amounts of multisource data are involved in the crop pest and disease system. Due to the need of high efficiency of data transfer, SQL Server was selected to build the system database to realize storage and management of multisource data and disaster spatial service products. The SQL Server database engine not only provides safe and reliable storage functions for the massive multi-source data and pest/disease forecasting products, but also improves the storage efficiency with its improved data compression performance.

The databases of this system include spatial database, attribute database and web front-end related files. Among them, the spatial database is mainly used to store data related to spatial analysis and visualization. The attribute database is mainly used to store and manage descriptive data related to habitat monitoring and early forecasting of crop pest and disease. The system uses webpage access, and the front-end related files include page style CSS files, functional design JS files, and pest/disease products JPG, PNG, TIF, and PDF files. Considering the data storage and calling efficiency, the system stores TIF files in the spatial database, and other front-end related files are stored in the spatial database in the form of location indexes.

C. System Function

The functions of the crop pest and disease monitoring and forecasting system include basic functions and application functions. The basic functions include view zooming, roaming, and moving, information query, operation help, and other basic map operation functions. The application functions include study area selection, parameter inversion, pest, and disease habitat monitoring and occurrence forecasting, and products output. The details are as follows.

1) Basic Function: In the system, geographic data management, mapping, editing, and data uploading and calling of map services are realized with ArcGIS Server. Taking the release of pest/disease forecasting thematic map for example, first, the map was opened in ArcMap. Then, the map was conducted with coordinate processing, rendering and other basic graphical operations, and send to server through internet along with the setting of service name, general parameters, maximum, and minimum cache proportions. Finally, an automatic uploading map service mode was developed with python to improve operating efficiency. For the uploaded map service, users could access it through internet standard resource address uniform resource locator, which declared in the map control, and display it on the front-end interface of the system in form of layer overlaying.

2) Application Function: The application functions include six modules, i.e., research area selection, parameter extraction, pest and disease habitat monitoring, pest and disease occurrence forecasting, disaster information query and product output. For the research area selection module, it provides users the selection of study area and available data. The system supports nationwide data selection from April to August in 2019 now. For the parameter extraction module, it provides vegetation index calculation and temperature analysis. The system supports the calculation and analysis of PSRI, RVSI, NDVI, MSAVI, and LST required for habitat monitoring and forecasting of rust and locust. For the pest and disease habitat monitoring module, it supports habitat monitoring of rust and locust, including calculation and analysis of WRI, LI, temperature, precipitation, and wind speed and direction. For the pest and disease occurrence forecasting module, it supports the calculation of DI for rust and PI for locust, and the analysis of meteorological numerical forecasting products. For the disaster information query module, it supports the query and statistical analysis of the forecasted infected area and damage levels of pest/disease in specific time and area. And, the query result will appear in the lower right corner of the browser in the form of a pop-up box. If there is no data in this area, a prompt box with no data information will pop up. For the product output module, it includes the pest and disease thematic map, supporting the operations of map display, zooming, and saving.

3) Technical Realization: To improve the model calculation efficiency, the system calculates the model online by utilizing the Java language within the spring MVC framework. For the Spring MVC framework, it is mainly composed of five parts, i.e., dispatcher servlet, handler mapping, handler adapter, handler, and view resolver. We wrote two XML files, one is used to configure the dispatcher servlet and address access, and the other is used to configure the handler mapping, handler adapter, handler, and view resolver. It should be noted that the handler mapping and the handler adapter should be used correspondingly, and the jar package required by the Spring framework and the javaidlb.jar required by Java to call Interactive data language into the project should be imported at the same time. The call and calculation of the model includes the following steps. First, the compiled model is used as a handler which is executed by the handler adapter under the instruction from the dispatcher servlet. Then, the handler runs the corresponding program to process the model and data and returns the result to dispatcher servlet. Finally, the view resolver will translate the result into the real view name, by which the result could be accessed by view address to promote model efficient calculation.

D. Results

Based on the system, we forecasted the infected areas of wheat yellow rust in China during April to May and oriental migratory locust during June to August 2019.

1) Wheat Yellow Rust Application: In March 2019, the average temperature of the winter wheat planting areas in China reaches 5.6 °C, which is 1.5 °C higher than previous years, and the average precipitation reached 30 mm, which is similar with that in previous years. In early April 2019, the temperature in Southern and Western China are higher than that in previous years, while the precipitation was higher in the middle and lower reaches of the Yangtze River basin, the Jianghuai, and the southern Huanghuai wheat planting areas. These environmental conditions are suitable for rust development. According to our

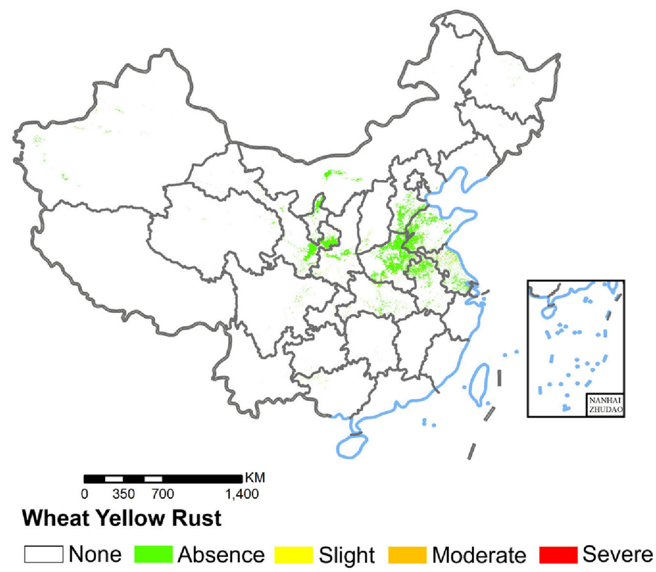


Fig. 4. Remote sensing forecasting of wheat yellow rust in April.

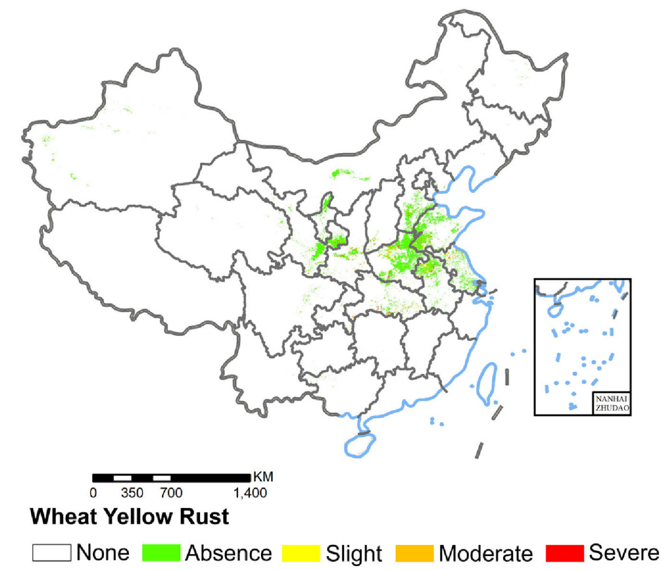


Fig. 5. Remote sensing forecasting of wheat yellow rust in May.

TABLE III
STATISTICS OF WHEAT YELLOW RUST FORECASTED INFECTED AREAS AND DAMAGE LEVELS IN APRIL

Region	Area / Thousand hectares			
	Absence	*Slight*	*Moderate*	*Severe*
East China	8499.3	21.3	20.7	14.7
North China	3561.4	9.3	5.3	3.3
Central China	6665.9	22.7	12.7	8.7
Northwest China	3353.3	11.3	6.7	4.7
Southwest China	1816.0	8.7	2.7	1.3

TABLE IV
STATISTICS OF WHEAT YELLOW RUST FORECASTED INFECTED AREAS AND DAMAGE LEVELS IN MAY

Region	Area / Thousand hectares			
	Absence	*Slight*	*Moderate*	*Severe*
East China	8357.3	126.0	48.7	24.0
North China	3503.3	28.7	26.7	20.6
Central China	6552.7	98.7	40.0	18.6
Northwest China	3293.3	26.7	34.0	22.0
Southwest China	1794.0	10.7	14.0	10.0

TABLE V
STATISTICS OF SUMMER LOCUST FORECASTED INFECTED AREAS AND DAMAGE LEVELS

Province	Area / Thousand hectares			
	Absence	*Slight*	*Moderate*	*Severe*
Shandong	66.1	88.1	60.8	3.1
Henan	94.0	76.7	12.7	2.0
Hebei	74.2	69.6	12.3	3.6
Anhui	36.6	27.6	1.2	0.2
Shaanxi	19.2	29.0	6.8	0.0
Tianjin	25.9	14.4	7.4	0.8
Jiangsu	19.3	20.8	2.3	0.1
Hainan	30.9	1.7	0.0	0.0
Shanxi	22.0	8.1	1.5	0.4
Guangxi	10.5	1.3	0.1	0.0
Liaoning	1.0	0.8	0.0	0.0

system output of rust forecasting, we found that, the affected areas of rust are estimated to reach around 0.2 million hectares in April, mainly in Northwest China, East China, and Central China. Specifically, the rust is estimated to be severely occur in southwest Gansu and southern Henan, moderately occur in central Henan, and slightly occur in southwest Shandong, northern Anhui, and northern Jiangsu. The specific distribution of infected areas and damage levels of rust in April is shown in Fig. 4 and Table III.

In May 2019, the national averaged temperature of the wheat areas reaches 16.8 °C, which is 0.6 °C higher than that in previous years, and the precipitation of winter wheat regions of China reaches 80 mm, which is 15% more than that in previous years. Environmental conditions are conducive to the further spread of rust. As shown in our system forecasting result in Fig. 5 and Table IV, the affected areas of rust are estimated to reach around 0.5 million hectares. Specifically, the rust is estimated to be severely occur in northern regions of Jiangsu and northern regions of Anhui; moderately occur in eastern regions of Gansu, central and southern regions of Henan, southern regions of Hubei and southern regions of Anhui; slightly occur in eastern regions of Sichuan, central regions of Shaanxi, southern regions of Shanxi, southern regions of Hebei and southern regions of Shandong.

Compared to the field survey data of national rust occur in May from the plant protection department of National Agricultural Technology Extension and Service Center, the difference between real rust infected areas and our estimated infected areas is 40 thousand hectares. And, the spatial distribution of our estimated result is consistent with the field survey.

1) Oriental Migratory Locust Application: In June, the infected areas of summer locust are estimated to reach around 0.5 million hectares in these eleven provinces shown in Fig. 6 and listed in Table V. In Shandong province, the summer locust is estimated to moderately occur mainly in coastal locust area

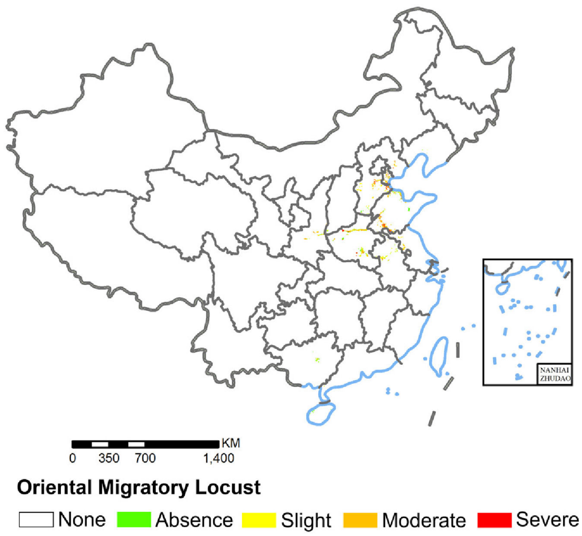


Fig. 6. Remote sensing forecasting of summer oriental migratory locust.

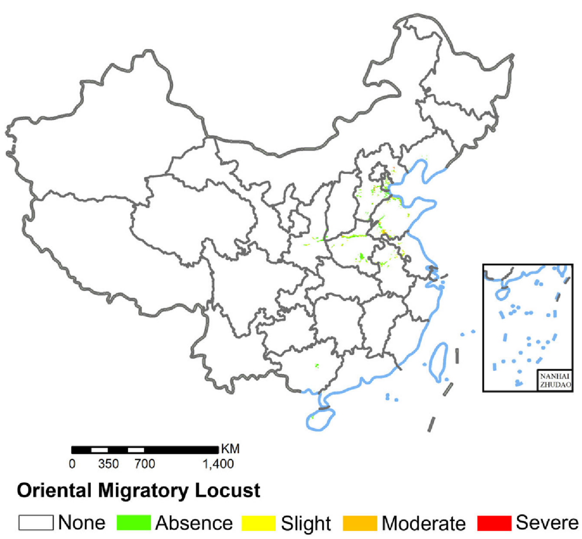


Fig. 7. Remote sensing forecasting of autumn oriental migratory locust.

TABLE VI
STATISTICS OF AUTUMN LOCUST FORECASTED INFECTED AREAS AND DAMAGE LEVELS

Province	Area / Thousand hectares			
	Absence	*Slight*	*Moderate*	*Severe*
Shandong	90.2	63.7	49.5	2.8
Henan	118.6	51.1	12.1	1.3
Hebei	76.0	67.8	12.3	3.3
Anhui	37.0	26.6	1.1	0.2
Shaanxi	17.2	27.6	6.5	0.0
Tianjin	27.9	10.6	8.6	0.8
Jiangsu	21.5	16.8	2.5	0.1
Hainan	29.6	1.2	0.0	0.0
Shanxi	24.1	6.1	1.2	0.3
Guangxi	10.3	0.6	0.0	0.0
Liaoning	1.0	0.8	0.0	0.0

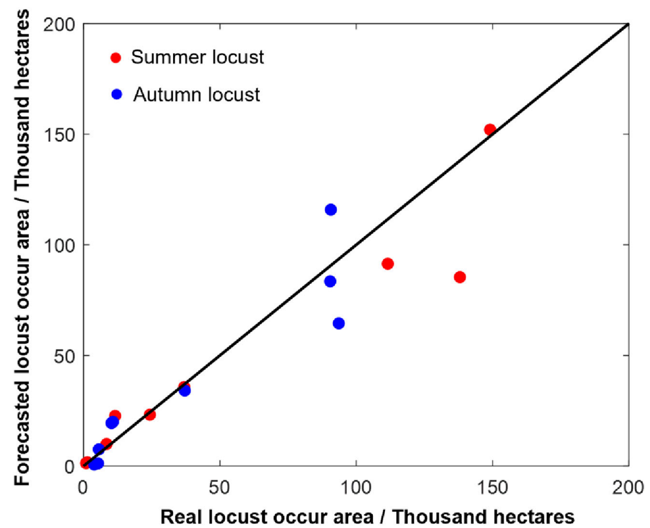


Fig. 8. Comparison of the forecasted locust occur area and real locust occur area in eleven provinces of China.

and riverine locust area of Dongying, Heze, and Jining districts. In Henan province, the summer locust is estimated to severely occur mainly in riverine locust area along the Yangtze River, within Puyang, Xinxiang, and Zhumadian districts. In Hebei province, the summer locust is estimated to moderately occur mainly in coastal locust area of Cangzhou, Tangshan, Langfang, and Baoding districts. In Anhui province, the summer locust is estimated to slightly occur mainly in Bengbu, Chuzhou, and Fuyang districts. In Shaanxi province, the summer locust is estimated to slightly occur mainly in Weinan, Xian, and Xianyang districts. In Tianjin district, the summer locust is estimated to severely occur mainly in Dagang reservoir, Duliujian spillway, and Lier bay. In Jiangsu province, the summer locust is estimated to slightly occur mainly in Huaian, Suqian, and Xuzhou districts. In Hainan province, the summer locust is estimated to slightly occur mainly in Dongfang district and Ledong Li Autonomous county. In Shanxi province, the summer locust is estimated to slightly occur mainly in Yuncheng district. In Guangxi province, the summer locust is estimated to slightly occur mainly in Laibing district. In Liaoning province, the summer locust is estimated to slightly occur mainly in Huludao.

In August, the infected areas of autumn locust are estimated to reach around 0.4 million hectares in these eleven provinces shown in Fig. 7 and given in Table VI. In Shandong province, the autumn locust is estimated to severely occur in Kenli, Dongying, and Hekou counties, and moderately occur in Jining and Dongying districts. In Henan province, the autumn locust is estimated to be slightly occur in most parts, moderately occur in Luoyang, Zhumadian, and Xinxiang districts, and severely occur in Sanmenxia district. In Hebei province, the autumn locust is estimated to severely occur in Huanghua and Qianxi counties, and moderately occur in Cangcounty. In Anhui province, the autumn locust is estimated to slightly occur mainly in Huoqiu and Funan counties. In Shaanxi province, the autumn locust is estimated to slightly occur mainly in Dali, Heyang, and Huayin counties. In Tianjin district, the autumn locust is estimated to severely occur mainly in New Binhai, Jizhou, and Wuqing districts. In Jiangsu province, the autumn locust is estimated to slightly occur mainly in Xuyi, Sihong, and Pei counties. In Hainan province, the autumn locust is estimated to slightly occur mainly in Dongfang district and Ledong Li Autonomous county. In Shanxi province, the autumn locust is estimated to slightly occur mainly in Yongji, Wanrong, and Ruicheng counties. In Guangxi province, the summer locust is estimated to slightly occur mainly in Laibing district. In Liaoning province, the autumn locust is estimated to slightly occur mainly in Suizhong county of Huludao.

Compared to the field survey data of national locust occur in June and August from the plant protection department of National Agricultural Technology Extension and Service Center in Fig. 8, we found that the R-square values for summer locust and autumn locust are 0.92 and 0.87, respectively. And, the spatial distribution of our estimated result is consistent with the field survey.

IV. Discussion and Conclusion

Crop pest and disease monitoring and forecasting in national level is very important for agricultural field management and plant protection. To achieve the national dynamic habitat monitoring and pest/disease occurrence forecasting, we developed an automatic system to efficiently gather multisource data, disaster monitoring and forecasting models and algorithms, and thematic maps. For the system, the internet, remote sensing, and GIS technologies are gathered comprehensively to construct different function modules with high cohesion and low coupling relationship. That could help to achieve the efficient calculation of models required for pest/disease habitat monitoring and early forecasting, reducing the cost of data storage and calculation of the system. The users could simply access our system through a web browser without the installation of required software for system running. Our system supports the users to select their interesting areas, extract pest/disease environmental parameters, monitor pest/disease habitat, and forecast infected areas and damage levels dynamically. Also, products services of pest and disease thematic maps are provided to users. Our system would not only promote the efficacy of pest and disease management and timely prevention by improving accuracy of monitoring and forecasting, but also help to reduce the amount of chemical pesticides by providing time series early forecasting thematic maps. Our system could provide technical support to guarantee food security and agriculture sustainable development in China.

With the development of big earth data [26], [27], the system still needs further improvement in the database construction. Facing the massive information sources in the era of big data, how to use communication technology to quickly obtain massive multisource data, and incorporate deep learning and other artificial intelligence technologies to achieve efficient information mining, and to achieve rapid and high-precision extraction of disaster information is the future research hotspot [28]–[30]. In addition, continuously optimizing the degree of automation and intelligence of the system and achieving its stable business operation is important to support green plant protection in China.

Acknowledgment

We thank Hong Chang, Qiong Zheng, Yue Shi, Huiqin Ma, *et al.* for the field work of wheat yellow rust and oriental migratory locust.

References

[1] J. Pretty, "Intensification for redesigned and sustainable agricultural systems," *Science*, vol. 362, no. 23, 2018, Art. no. eaav0294.

[2] S. Devi, "Locust swarms in East Africa could be "a catastrophe" *Lancet*, vol. 395, 2020, Art. no.10224.

[3] J. C. Zhang *et al.*, "Monitoring plant diseases and pests through remote sensing technology: A review," *Comput. Electron. Agriculture*, no. 165, 2019, Art. no. 104943.

[4] H. Al-Saddik, A. Laybros, B. Billiot, and F. Cointault, "Using image texture and spectral reflectance analysis to detect yellowness and ESCA in grapevines at leaf-level," *Remote Sens.*, vol. 10, no. 4, 2018, Art. no. 618.

[5] L. Yuan, R. L. Pu, J. C. Zhang, J. H. Wang, and H. Yang, "Using high spatial resolution satellite imagery for mapping powdery mildew at a regional scale," *Precis. Agriculture*, vol. 17, no. 3, pp. 332–348, 2016.

[6] F. Löw, F. Waldner, A. Latchininsky, C. Biradar, M. Bolkart, and R. R. Colditz, "Timely monitoring of Asian migratory locust habitats in the Amudarya delta, Uzbekistan using time series of satellite remote sensing vegetation index," *J. Environ. Manage.*, vol. 183, pp. 562–575, 2016.

[7] W. J. Huang *et al.*, "New optimized spectral indices for identifying and monitoring winter wheat diseases," *IEEE J-Stars*, vol. 7, no. 6, pp. 2516–2524, Jun. 2014.

[8] H. D. Guo, "Big Earth data: A new frontier in Earth and information sciences," *Big Earth Data*, vol. 1, no. 1-2, pp. 4–20, 2017.

[9] 2019. [Online]. Available: https://rusttracker.cimmyt.org/

[10] 2020. [Online]. Available: http://www.fao.org/agriculture/crops/thematic-sitemap/theme/pests/ wrdgp/en/

[11] 2020. [Online]. Available: http://www.fao.org/ag/locusts/en/info/info/index.html

[12] K. Cressman, "Role of remote sensing in desert locust early warning," *J. Appl. Remote Sens.*, vol. 7, no. 1, 2013, Art. no. 075098.

[13] A. Y. Shelestov, A. N. Kravchenko, S. V. Skakun, S. V. Voloshin, and N. N. Kussul, "Geospatial information system for agricultural monitoring," *Cybern. Syst. Anal.*, vol. 49, pp. 124–132, 2013.

[14] K. Oki, S. Mitsuishi, T. Ito, and M. Mizoguchi, "An agricultural monitoring aystem based on the use of remotely sensed imagery and field server web camera data," *Gisci. Remote Sens.*, vol. 46, pp. 305–314, 2009.

[15] G. F. Zhang, X. D. Liu, Y. Q. Zhu, and B. P. Zhai, "An open WebGIS-based monitoring system on crop pests and diseases," *J. Nanjing Agricultire Univ.*, vol. 32, pp. 165–169, 2009.

[16] Z. Peng, G. Liu, M. Z. Li, and D. L. Li, "Management information system for apple diseases and insect pests based on GIS," *Trans. CSAE*, vol. 12, pp. 150–154, 2006.

[17] M. X. Zhao and J. C. Liu, "Design of agricultural disease and pest image remote transmission system," *Rev. Faculty Agronomy*, vol. 36, no. 5, pp. 1626–1636, 2019.

[18] 2019. [Online]. Available: https://www.natesc.org.cn/

[19] A. T. Guo *et al.*, "Identification of wheat yellow rust using spectral and texture features of hyperspectral images," *Remote Sens.*, vol. 12, no. 9, 2020, Art. no. 1419.

[20] Q. Zheng *et al.*, "Identification of wheat yellow rust using optimal three-band spectral indices in different growth stages," *Sensors*, vol. 19, no. 1, 2019, Art. no. 35.

[21] Y. Shi *et al.*, "Wavelet-based rust spectral feature set (WRSFs): A novel spectral feature set based on continuous wavelet transformation for tracking progressive host-pathogen interaction of yellow rust on wheat," *Remote Sens.*, vol. 10, no. 4, 2018, Art. no. 525.

[22] J. C. Zhang *et al.*, "Impact of spectral interval on wavelet features for detecting wheat yellow rust with hyperspectral data," *Int. J. Agriculture Biol. Eng.*, vol. 11, no. 6, pp. 138–144, 2018.

[23] Q. Zheng, W. J. Huang, X. M. Cui, Y. Shi, and L. Y. Liu, "New spectral index for detecting wheat yellow rust using Sentinel-2 multispectral imagery," *Sensors*, vol. 18, no. 3, 2018, Art. no. 668.

[24] D. M. Chen, Y. Y. Shi, W. J. Huang, J. C. Zhang, and K. H. Wu, "Mapping wheat rust based on high spatial resolution satellite imagery," *Comput. Electron. Agriculture*, vol. 152, pp. 109–116, 2018.

[25] Y. Shi, W. J. Huang, Y. Y. Dong, D. L. Peng, Q. Zheng, and P. Y. Yang, "The influence of landscape's dynamics on the Oriental Migratory Locust habitat change based on the time-series satellite data," *J. Environ. Manage.*, vol. 218, pp. 280–290, 2018.

[26] H. D. Guo, Z. Liu, H. Jiang, C. L. Wang, J. Liu, and D. Liang, “Big Earth Data: A new challenge and opportunity for Digital Earth’s development,” *Int. J. Digit. Earth*, vol. 10, no. 1, pp. 1–12, 2017.
[27] M. Sudmanns *et al.*, “Big Earth data: Disruptive changes in Earth observation data management and analysis?,” *Int. J. Digit. Earth*, vol. 13, no. 7 pp. 832–850, 2020.
[28] G. Maral, M. Bousquet, and Z. Sun, *Satellite Communications Systems: Systems, Techniques and Technology*. Hoboken, NJ, USA: Wiley, 2020.
[29] S. Vivek and V. A. Jesma, “The changing phase of agriculture: Artificial intelligence,” *Agriculture Int.*, vol. 6, no. 1, pp. 33–38, 2019.
[30] N. E. M. Khalifa, M. Loey, and M. H. N. Taha, “Insect pests recognition based on deep transfer learning models,” *J. Theor. Appl. Inf. Technol.*, vol. 98, no. 1, pp. 60–68, 2020.

Yingying Dong received the B.S. degree in information and computation science from Shandong Normal University, Shandong, China, in 2006, the M.S. degree in mathematics of computation from Capital Normal University, Beijing, China, in 2009, and the Ph.D. degree in agricultural remote sensing and information technology from Zhejiang University, Zhejiang, China, in 2013.

Her research interests include research and application in vegetation remote sensing.

Fang Xu received the B.S. degree in applied mathematics from Qilu Normal University, Shandong, China, in 2014, and the M.S. degree in statistics and information from Capital Normal University, Beijing, China, in 2017.

Her research interests include development and application of agriculture system.

Linyi Liu received the B.S. degree in geographic information system from the Capital Normal University, Beijing, China, in 2015, and the Ph.D. degree in cartography and geography information system from the University of Chinese Academy of Sciences, Beijing, China.

His current research interests include crop disease monitoring, remote sensing, and geographic information system development.

Xiaoping Du received the B.S. degree and M.S. degree in computing science and technology from the China University of Geosciences, China, in 2001 and 2004 respectively, and the Ph.D. degree in GIS from the University of Chinese Academy of Sciences, in 2015.

From 2016 to 2018, he was a Postdoc with the German Aerospace Center (DLR). His research interests include digital earth, geospatial big data, and remote sensing for natural disasters and environment monitoring.

Binyuan Ren received the M.S. degree in Agricultural insects and disease control from Nanjing Agricultural University, Nanjing, China, in 2014.

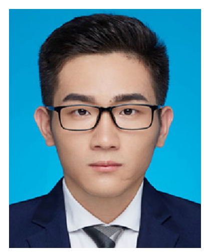
His research interests include crop pests and disease monitoring and forecasting, and crop pests and disease control technique extension.

Anting Guo received the M.S. degree in agricultural informatization from Henan Agricultural University, Zhengzhou, China, in 2017. He is currently working toward the Ph.D. degree in cartography and GIS with the University of Chinese Academy of Sciences, Beijing, China.

His research interests include remote sensing monitoring of crop pests and diseases.

Yun Geng received the B.E. degree in computer science and technology from Beijing Forest University, Beijing, China, in 2017. She is currently working toward the Ph.D. degree with the Aerospace Information Research Institute, Chinese Academy of Sciences, Beijing, China.

Her current research interests include migratory locust monitoring and forecasting, remote sensing, and geographic information system development.



Chao Ruan received the Graduate degree in signal and information processing from Anhui University, Anhui, China, in 2019. He is currently working toward the Ph.D. degree in cartography and GIS with the University of Chinese Academy of Sciences, Beijing, China.

His research interests include remote sensing forecasting of crop pests and diseases.

Huichun Ye received the B.S. degree in agricultural resources and environment from Huazhong Agricultural University, China, in 2008, and the Ph.D. degree in soil science from China Agricultural University, China, in 2014.

His research interests include research and application in vegetation remote sensing.

Wenjiang Huang received the Ph.D. degree in cartography and GIS from Beijing Normal University, Beijing, China, in 2005.

He is currently a Professor with the Key Laboratory of Digital Earth Science, Aerospace Information Research Institute, Chinese Academy of Sciences, Beijing, China. His research interests include quantitative remote sensing research and application in vegetation.

Yining Zhu received the B.S. degree in information and scientific computing from Beijing Information and Technology Institute, in 2006, the M.S and the Ph.D. degree in mathematics and information technology from Capital Normal University, Beijing, China, in 2009 and 2012, respectively.

He was a Postdoc at the Peking University, Beijing, China, from 2013 to 2014. He is currently an Associate Professor with the School of Mathematical Science, Capital Normal University. His current research interests include image reconstruction, deep learning-based artifact correction, and image processing.