Desert locust plague monitoring using time series satellite data

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Abstract: Desert locust has caused great losses to food security in East Africa and Southwest Asia since its outbreak in 2019. This study selected six locust damaged countries (India, Pakistan, Ethiopia, Kenya, Somalia, and Yemen) as the research object. The vegetation coverage curves in these six countries from February 2000 to June 2020 were obtained based on the remote sensing data. Then, the desert locust damage area is monitored by determining determine the locust damage threshold of different vegetation cover types (cropland, grassland and shrub) based on the change of vegetation coverages. The results showed that desert locust caused serious damage to vegetation. By the end of June 2020, Desert Locust harmed vegetation area of 1058.3 thousand hectares, 792.9 thousand hectares, 1137.5 thousand hectares, 936.8 thousand hectares, 780 thousand hectares and 763.5 thousand hectares in India, Pakistan, Ethiopia, Kenya, Somalia and Yemen, respectively. The research results laid the foundation for real-time, rapid, and large-scale monitoring of locust plague dynamics, and provide a scientific basis for reasonable and economic prevention of locust plague.

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1 Introduction

Desert Locust (*Schistocerca gregaria*) is a major threat for global agriculture because of its abilities to eat crops and travel long distances[1-6]. The desert locust has ravaged the Horn of Africa and Southwest Asia from Year 2019, which poses serious damage to agricultural production and food security of many countries. The locust plagues are particularly serious in some countries such as Pakistan, Ethiopia, Kenya, Somalia, Yemen and India[7-11]. The swarms have brought a heavy blow to the agricultural and pasture production in these areas. Therefore, the frequency and severity of locust plague have been the focus of the world. Locust plague monitoring could provide a scientific basis for the formulation of prevention and control strategies in key locust damaged areas[12,13].

The main objective of this study was to evaluate the potential of remote sensing data to identify locust damage and realize desert locust damage monitoring at large scale by this technique. Traditional ground survey methods cannot obtain data for over large and inaccessible areas to accurately analyze locust dynamics and determine the best implementation period of control measures[14-16]. Remote sensing technology can quickly obtain continuous information on the temporal and spatial vegetation changes in large areas[17-21].

The commonly used methods for locust plague damage remote sensing monitoring are based on vegetation indexes such as Leaf area index (LAI) or Normalized difference vegetation index (NDVI). By comparing the changes in vegetation before and after the locust plague, the occurrence degree, scope and level of plague were judged, the area where the vegetation index declined was determined as the plague damaged area, and the damaged levels were classified according to the degree of decline[22-24]. For example, Ji et al.[25] compared the NDVI of the reed area before and after the occurrence of the locust plague based on the multi-temporal MODIS remote sensing data and found the critical value of NDVI for different locust damaged levels, and correspondingly determined the severely damaged area and the moderately damaged area of the locust plague. Zha et al.[26] proposed a time filtering method based on continuous MODIS data to realize locust plague severity monitoring over times. Zha et al.[27] constructed a Locust density index (LDI) model based on the NDVI difference using multi-temporal Landsat TM data, and distinguished and classified the occurrence level of locust based on this model. Deveson et al.[28] monitored the decline in vegetation caused by the occurrence of the Australian plague locust

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(*Chortoicetes terminifera*) based on NDVI, and found that seasonal rainfall and binary habitat stratification are important explanatory factors for locust monitoring. Eltoum et al.[29] combined MODIS and ground survey data to realize vegetation changes caused by the desert locust plague in Sudan using Enhanced vegetation index (EVI) data. Some scholars built a monitoring model of vegetation loss caused by locust plague based on ground hyperspectral remote sensing data[30,31]. With the development of remote sensing technology, some scholars have also applied UAV hyperspectral data to locust plague monitoring. For example, Song et al.[32] and Zheng[31] used UAV hyperspectral imagers to collect locust-damaged reed canopies to assess the loss of reeds and realized locust damage monitoring.

Existing studies are mainly based on pre-disaster and post-disaster images to monitor the damage of locust plague to a single vegetation type in a small area. These studies require clear damage dates and relevant ground survey data, which are more difficult to apply to large-scale, multi-vegetation types of locust plague monitoring research. In response to this problem, our study used MODIS remote sensing data to extract and analyze the monthly maximum NDVI time series curves and climate changes of different countries and different vegetation cover types in the past 20 years. The countries in study area were divided into two types of vegetation with periodicity and vegetation without periodicity. The desert locust plague damage models were constructed for different types. And the desert locust damaged area monitoring was realized by the desert locust plague damage threshold selected based on the distribution of the model result histograms.

2 Materials and methods

2.1 Study area

Six countries are included in our study area, i.e. India, Pakistan, Ethiopia, Kenya, Somalia, and Yemen. India is a country in South Asia. Main agricultural products in India include rice, wheat, oilseed, cotton, jute, tea, sugarcane, and potatoes[33]. Pakistan is in the northwestern part of the South Asian subcontinent. Agriculture occupies an important position in national economy of Pakistan, which accounts for about 25% of its GDP. Most parts of Pakistan have a subtropical climate, characterized by hot and dry climate and little rainfall. The main crops in Pakistan include wheat, rice, millet, sorghum, and corn. Ethiopia is in the center of the Horn of Africa. It is a large country in animal husbandry, with suitable grazing land covering more than half of the country area. Kenya is in eastern Africa and the whole territory is in the tropical monsoon zone. The main crops are corn, wheat, rice, sorghum, cassava, etc. Somalia is located on the Somali Peninsula in the easternmost part of Africa. Most of the region has a subtropical and tropical desert climate, and the southwest has a tropical grassland climate, with high temperatures all year[34]. Somalia has 8.2 million hectares of cropland, accounting for 13% of Somalia's land area. Yemen is located at the southwest of the Arabian Peninsula, and its agricultural population accounts for about 71% of Yemen's population. Agricultural products mainly include cotton, coffee, sorghum, millet, corn, barley, beans, sesame, and tobacco. These six countries have been the main endangered countries of the desert locust plague since 2019. They are mainly in southwest Asia and the Horn of Africa. In 2018, tropical cyclones caused an abnormal increase in rainfall in East Africa. The heavy rainfall generated before the locust eggs hatch accelerated the growth of vegetation and provided favorable conditions for locust hatching, which led to the outbreak of the desert locust plague in these six countries[35].

2.2 Data and Processing

The remote sensing data used in this study includes MODIS-NDVI (MOD13Q1) product February 2000 to June 2020. They were used to monitor the changes of vegetation to realize the locust plague monitoring. Global land cover data (30 m) provided by the National Earth System Science Data Sharing Service Platform (http://www.geodata.cn/) was used to get vegetation coverage. Greenness data (http://iridl.ldeo.columbia.edu/maproom/Food_Security/Locusts/Regional/greenness.html) and Rainfall data (https://sharaku.eorc.jaxa.jp/GSMaP/) in Asia and Africa since 2000 were used to get locust breeding area. The occurrence records of desert locust in these six countries (http://www.fao.org/ag/locusts/en/info/info/index.html) and crop planting calendar (http://www.fao.org/agriculture/seed/cropcalendar/welcome.do) provided by Food and Agriculture Organization of the United Nations (FAO) were used to provide prior knowledge for analyzing the area affected by the desert locust plague (Table 1, Figure 1).

Table 1 Number of locust occurrence records in six countries

Country	Number of locust occurrence sample
India	1132
Pakistan	832
Ethiopia	460
Kenya	5151
Somalia	660
Yemen	218
Total	8453

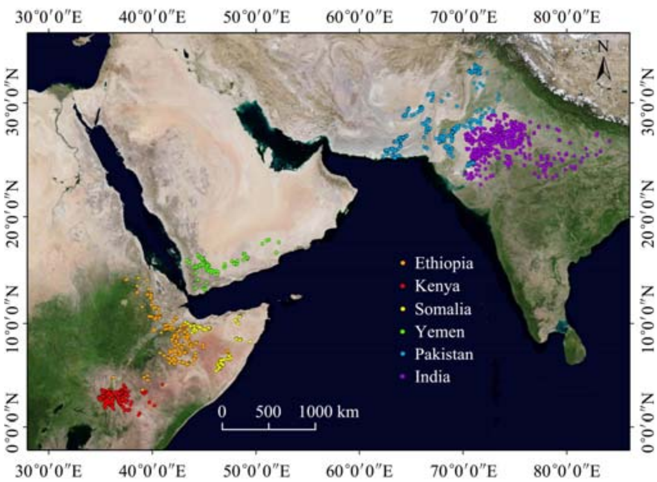

Figure 1 Locust occurrence records in six countries

2.3 Desert locust plague monitoring models

The priori regions where locust plagues might occur were determined by the ground survey point data provided by FAO. On this basis, this study realized locust plague monitoring using vegetation coverage curves analysis in six key countries. Because different vegetation cover types have different vegetation growth conditions and tend to be damaged by locusts, the vegetation types in study area were divided into cropland, grassland and shrub based on the vegetation coverage data of these six countries. In order to extract the areas damaged by locust plague, NDVI was used to characterize the growth status of vegetation. Based on MODIS remote sensing data, the monthly maximum NDVI curves from February 2000 to June 2020 are extracted. And combined with global land cover data, and the NDVI change trends of three vegetation cover types were analyzed. The NDVI curves of different vegetation cover types in these six countries could be divided into two categories: vegetation growth with certain periodicity and vegetation growth without periodicity.

For countries with obvious periodicity of NDVI curves(Pakistan, India and Ethiopia), this study calculated the difference between the maximum NDVI in June of different vegetation types in 2020 and the mean maximum NDVI in June from 2000 to 2018 to extract the vegetation changes caused by locust plagues. NDVI in Year 2019 was not considered as a reference year because the desert locust plague has endangered the growth of vegetation in study area and vegetation growth cycle has been destroyed in 2019. Equation is shown in (1).

$$NDVI_{DIF1(2020,k)} = NDVI_{(2020,k)} - \frac{\sum_{y=2000}^{2018} NDVI_{(y,k)}}{19} \tag{1}$$

where, k represents the month of monitoring, which is equal to June in this study; $NDVI_{DIF1(2020,k)}$ is the difference between the maximum NDVI of three countries in June, 2020 and the mean maximum NDVI in June the nineteen years from 2000 to 2018. $NDVI_{(2020,k)}$ is the maximum NDVI in June, 2020; $\frac{\sum_{y=2000}^{2018} NDVI_{(y,k)}}{19}$ is the mean value of maximum NDVI in June from 2000 to 2018,y represents the year.

Since the NDVI curves of Kenya, Yemen, and Somalia did not have obvious periodicity, it is impossible to calculate the difference using Equation 1 to obtain the vegetation change areas. This study analyzed the rainfall and temperature data of these four countries and found that these three countries had the same rainfall and high temperature conditions at Year 2018 and 2020. On this basis, it is possible to simulate the vegetation growth in four countries in Year 2020 without locust damaged, and then, the impact of locust plague on vegetation could be calculated:

$$NDVI_{DIF2(2020,k)} = NDVI_{(2020,k)} - \left(\frac{NDVI_{(2018,k)} - NDVI_{(2018,k\text{-}1)}}{NDVI_{(2018,k\text{-}1)}} \times NDVI_{(2020,k\text{-}1)}\right) \tag{2}$$

where, $NDVI_{DIF2(2020,k)}$ is the difference between the maximum NDVI of three countries in June of 2020 and maximum NDVI forecasting data of three vegetation types in 2020 which is not damaged by locust plague; $NDVI_{(2020,k)}$ is the maximum NDVI in June 2020; $\frac{NDVI_{(2018,k)} - NDVI_{(2018,k\text{-}1)}}{NDVI_{(2018,k\text{-}1)}}$ is monthly seasonal trends in 2018.

Due to the different NDVI values and different locust damaged level of three vegetation types (cropland, grassland, shrub), NDVI difference images were directly divided into thresholds to monitor locust damage areas was unreasonable. This study combined global land use data, and extracted these three types separately and drew their difference histogram distribution, to extracted the areas damaged by locusts based on the thresholds of different vegetation coverage types combined with the mean and standard deviation.

3 Results and discussion

This study monitored desert locust damages based on the changes in vegetation using MODIS remote sensing data. There are many vegetation indexes used to characterize the changes in green vegetation coverage, such as NDVI, EVI, and Ratio Vegetation Index (RVI)[36-39]. According to the different vegetation cover types and growth conditions in study area, the selected vegetation index is different. For example, RVI is very sensitive to vegetation with high coverage and has a good correlation with biomass, but it cannot identify differences in vegetation density. NDVI is the best indicator of plant growth status and preparation space distribution density. When the vegetation coverage is less than 80%, the NDVI has a linear relationship with the prepared biomass. When the vegetation coverage is greater than 80%, the sensitivity of NDVI to vegetation detection decreases. According to the characteristic that the vegetation coverage in our study area is less than 80% on average, NDVI was chosen as the vegetation index to monitor the occurrence of locust plagues in this study.

NDVI curves from February 2000 to June 2020 for cropland, grassland and shrub in six countries were extracted from time series MODIS data. The NDVI curves of Pakistan, India and Ethiopia had obviously similar peaks, troughs and trends every year, which indicated that the vegetation growth of these three countries had obvious periodicity in the past 20 years (Figure 2, Figure 3 and Figure 4). While, the NDVI curves of Kenya, Yemen and Somalia have low similarities in different years, which indicated that the vegetation growth in these countries did not have obvious periodicity (Figure 5, Figure 6 and Figure 7). And then, two locust plague monitoring models were constructed to calculated the difference between the maximum NDVI in June 2020 and the mean maximum NDVI June of Year 2000-2018 in the three countries of India, Pakistan, and Ethiopia, and the difference between the maximum NDVI in June 2020 and the NDVI in the predicted non-plague in the three countries of Kenya, Somalia and Yemen (Figure 8). On this basis, this study analyzed the histogram distribution of NDVI difference images of different vegetation cover types and found that the distribution conforms to the normal distribution. The mean value plus or minus the mean square error method was used to select the desert locust damage threshold for different vegetation types to achieve locust damaged area monitoring.

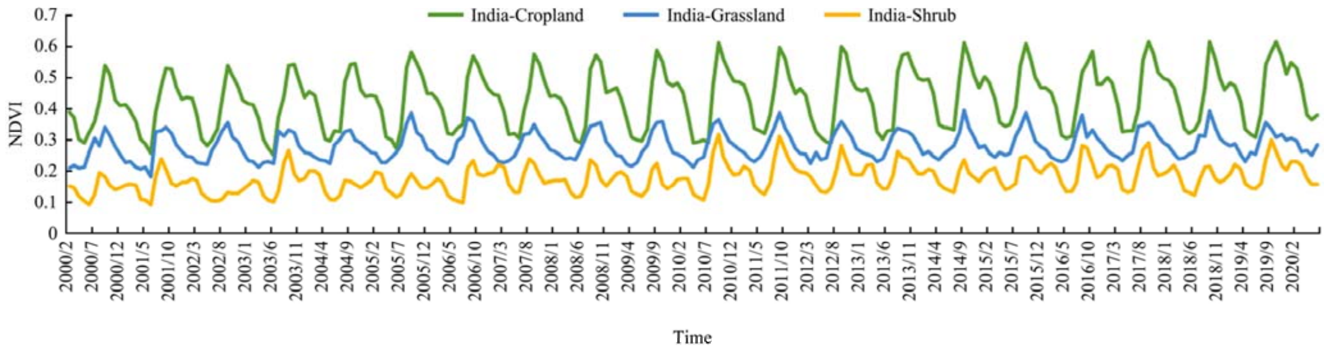

Figure 2 NDVI curves of different vegetation cover types in India from February 2000 to June 2020

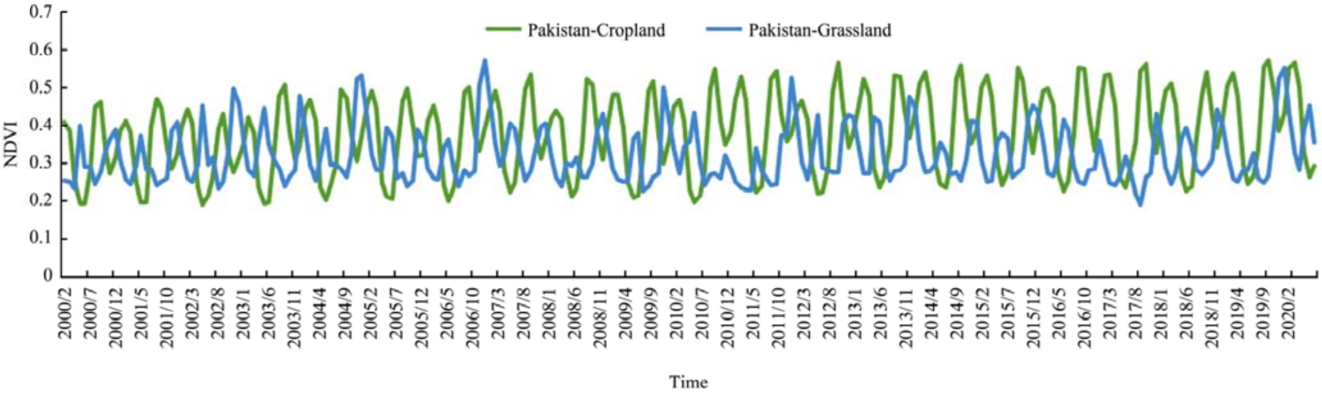

Figure 3 NDVI curves of different vegetation cover types in Pakistan from February 2000 to June 2020

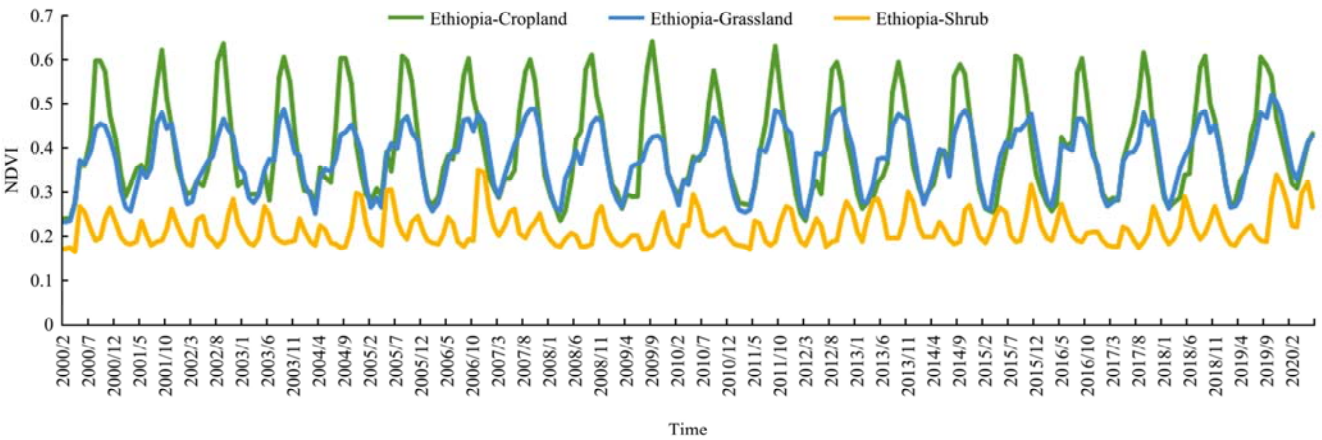

Figure 4 NDVI curves of different vegetation cover types in Ethiopia from February 2000 to June 2020

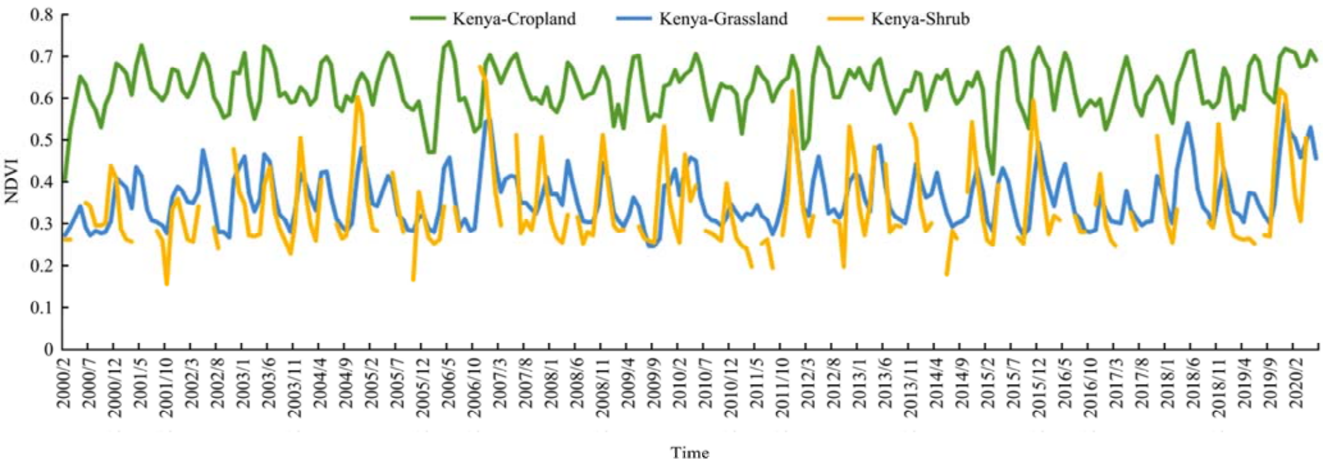

Figure 5 NDVI curves of different vegetation cover types in Kenya from February 2000 to June 2020

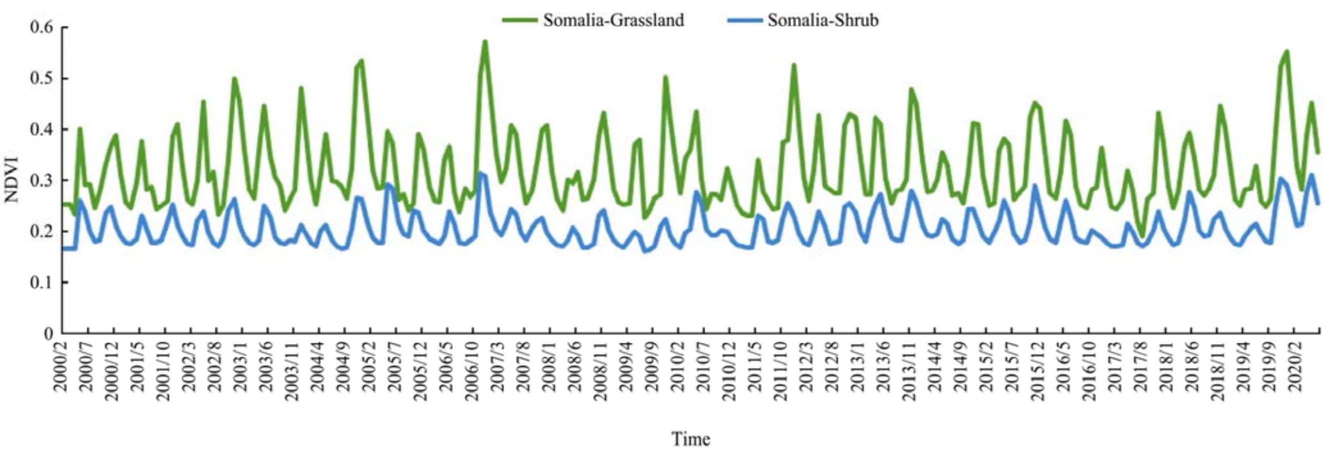

Figure 6 NDVI curves of different vegetation cover types in Somalia from February 2000 to June 2020

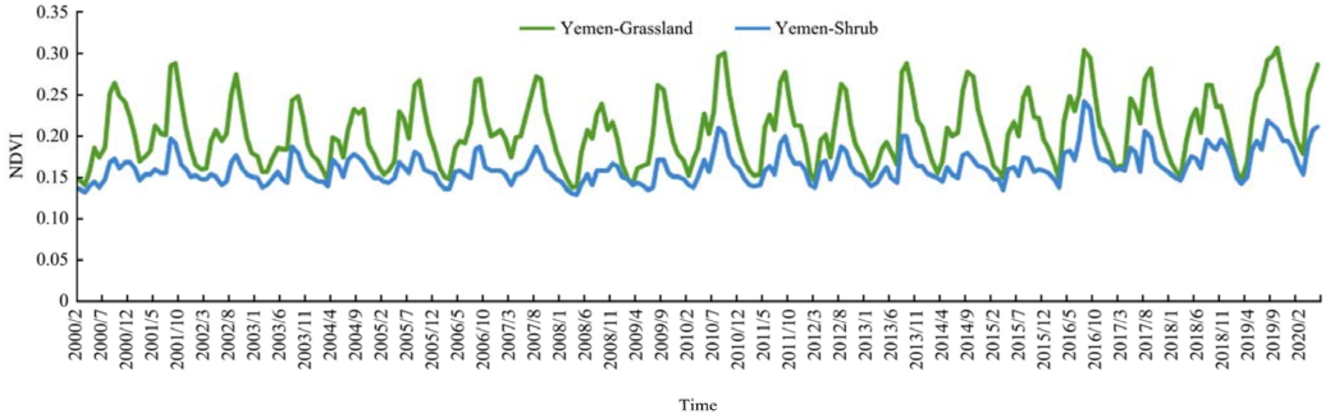

Figure 7 NDVI curves of different vegetation cover types in Yemen from February 2000 to June 2020

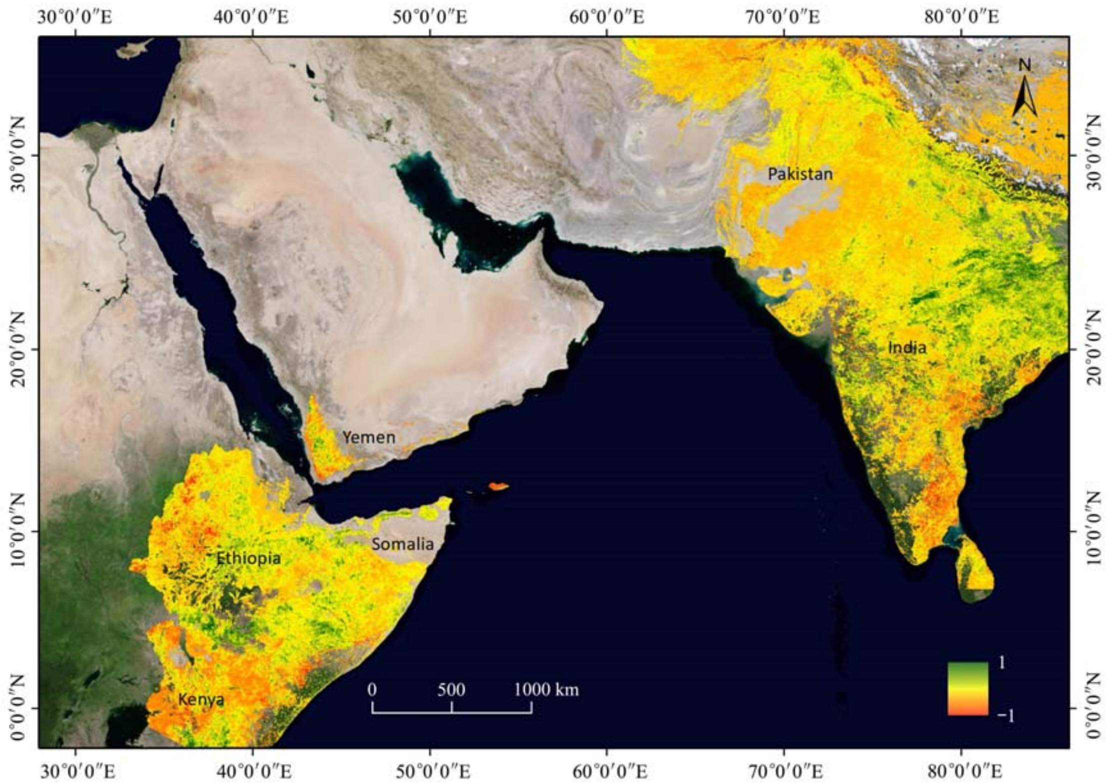

Figure 8 NDVI difference images in Asia and Africa in March of Year 2020 and Year 2000-2018

By the end of June 2020, desert locust in India harmed about 1058.3 thousand hectares of vegetation area, including 450.9 thousand hectares of cropland, 320.6 thousand hectares of grassland, and 286.8 thousand hectares of shrub, accounting for 0.2%, 0.7% and 1.6% of the total cropland, grassland, and shrub in India, respectively. The main vegetation cover types in Pakistan include grassland and cropland. By the end of June 2020, desert locust in Pakistan harmed about 792.9 thousand hectares of vegetation area, including 455.2 thousand hectares of cropland and 337.7 thousand hectares of grassland, accounting for 1.8% and 3.5% of the total cropland and grassland in Pakistan respectively. The main locust damaged vegetation cover types in Ethiopia include cropland, grassland and shrub. By the end of June, desert locust in Ethiopia harmed about 1137.5 thousand hectares of vegetation area (including 304.8 thousand hectares of cropland, 364.5 thousand hectares of grassland, and 468.2 thousand hectares of shrub), accounting for 1.3%, 2.1% and 0.6% of the total cropland, grassland, and shrub, respectively. The main plague-affected vegetation cover types in Kenya include cropland, grassland and shrub. The vegetation area harmed by locust in Kenya had reached 936.8 thousand hectares, including 86.7 thousand hectares of cropland, 492.8 thousand hectares of grassland and 357.3 thousand hectares of shrubs, accounting for 1.7%, 2.5%, and 1.0% of the total cropland, grassland, and shrub in Kenya, respectively. The main plague-affected vegetation cover types in Somalia include cropland, grassland and shrub. The result shows that desert locust in Somalia harmed about 780 thousand hectares of vegetation area by the end of June (including 1.6 thousand hectares of cropland, 154.7 thousand hectares of grassland and 623.7 thousand hectares of shrub), accounting for 1.6%, 4.0% and 1.4% of the total cropland, grassland, and shrub in Somalia, respectively. The main plague-affected vegetation cover types in Yemen include cropland, grassland and shrub. Desert locust in Yemen harmed about 763.5 thousand hectares of vegetation area (including 143.8 thousand hectares of cropland, 47.9 thousand hectares of grassland, and 571.8 thousand hectares of shrub), accounting for 14.3%, 8.3% and 10.1% of the total cropland, grassland, and shrub, respectively (Table 2, Figure 9).

Table 2 Damage area and proportion of cropland, grassland and shrub in study area (thousand hectares)

Country	Damage area	Cropland		Grassland		Shrub	
		Damage area	Damage proportion	Damage area	Damage proportion	Damage area	Damage proportion
India	1058.3	450.9	0.2%	320.6	0.7%	286.8	1.6%
Pakistan	792.9	455.2	1.8%	337.7	3.5%	-	-
Ethiopia	1137.5	304.8	1.3%	364.5	2.1%	468.2	0.6%
Kenya	936.8	86.7	1.7%	492.8	2.5%	357.3	1.0%
Somalia	780.0	1.6	1.6%	154.7	4.0%	623.7	1.4%
Yemen	763.5	143.8	14.3%	47.9	8.3%	571.8	10.1%

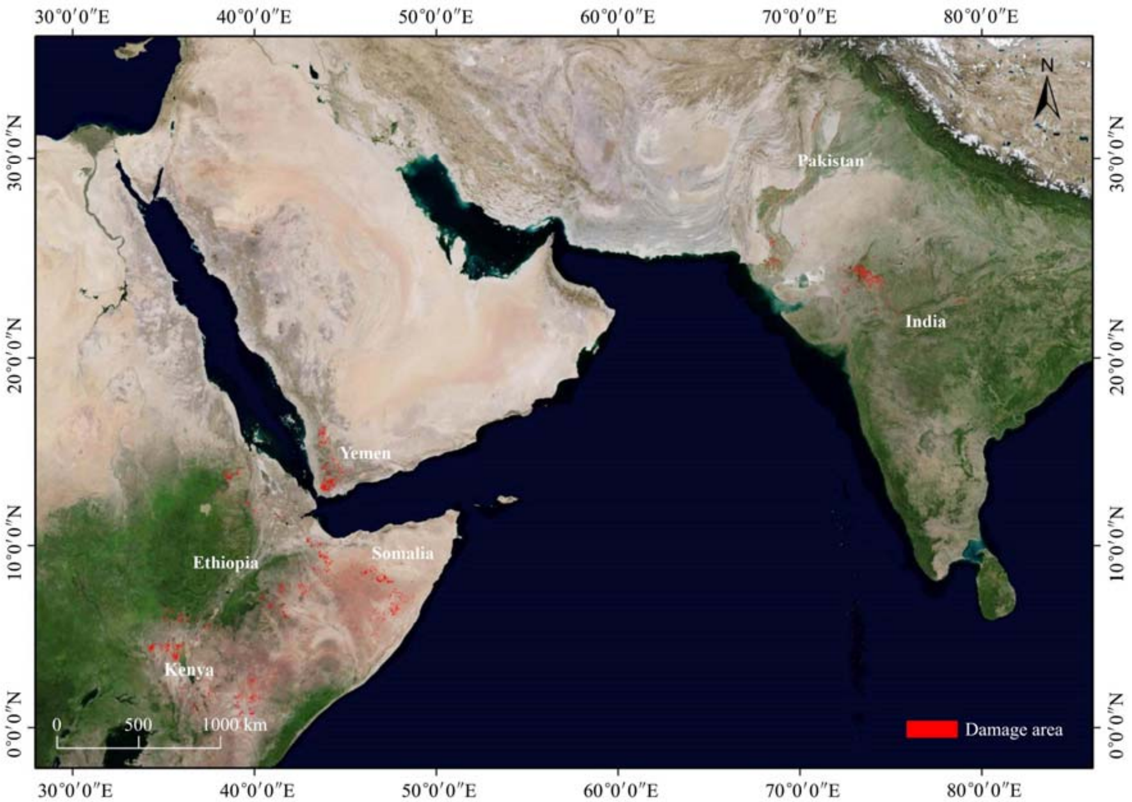

Figure 9 Damage area of study area in June 2020 using remote sensing data

4 Conclusions

This study extracted and analyzed NDVI curves in different countries uses MODIS data. Two desert locust monitoring models were constructed for years of vegetation growth with periodicity and non-periodicity. The locust damage thresholds were selected for different vegetation types in different countries combined with the histogram distribution of the monitoring model results and land cover data, which could be used desert locust damage monitoring in June 2020 for India, Pakistan, Ethiopia, Kenya, Somalia and Yemen. The monitoring results are highly consistent with those provided by relevant agricultural information websites, which proves that MODIS remote sensing data and NDVI have certain potential in the monitoring and evaluation of large-scale desert locust plagues. And these models are superior to previous traditional measurement methods in terms of monitoring speed, detection scale and cost. Desert locust continuous, rapid and high-precision monitoring using remote sensing and other high-tech technologies could provide a scientific basis for the precise control of desert locust plagues. The desert locust plague has erupted on a large scale In Year 2019. The scope and area of occurrence have continued to expand, and the damage has become more and more serious. The results of this study have been adopted by FAO as one of the references for the prevention and control of desert locust plagues in Asia and Africa to ensure food security.

Although the models proposed in this study can be used to monitor large-scale desert locust plague, the coupling with locust development and climate change is not deep enough. In the future, we will further dig deeper into the growth and development mechanisms of vegetation under abnormal climates and the occurrence and development mechanisms of locusts. And combine them to innovate and build an intelligent monitoring model for desert locust plague that is universal in time and space.

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[References]

[1] Anderson N L. Some relationships between grasshoppers and vegetation. Annals of the Entomological Society of America, 1964; 57(6): 736–742.

DOI: 10.1093/aesa/57.6.736

[2] Duranton, J. F.; Lecoq, M. Le Criquet Pèlerin au Sahel; Comité permanent inter-etats de luttecontre la sécheresse au Sahel: Ouagadougou, Brukina Faso, 1990.

[3] Cherlet M, Mathoux P, Bartholomé E and Defourny P. SPOT VEGETATION contribution to desert locust habitat monitoring// Proceedings of the VEGETATION 2000 Conference. 2000; Italy: Lake Maggiore: 247–257.

[4] Ould Baba, M. Biogéographie du Criquet pèlerin en Mauritanie, Fonctionnement d'une Aire Grégarigène et Conséquences sur L'organisation de la Surveillance et de la Lutte Anti-acridienne.Master Thesis, École Pratique des Hautes Études, FAO, Rome, Italy, 2001.

[5] Cissé S, Ghaout S, Babah Ebbe M A, Kamara S and Piou C. Field verification of the prediction model on desert locust adult phase status from density and vegetation. Journal of Insect Science, 2016; 16(1): 74. DOI: 10.1093/jisesa/iew046

[6] Murali Sankar P and Shreedevasena S. 2020. Desert locusts (Schistocerca gregaria) – A global threatening transboundary pest for food security. Research Today, 2(5): 389–391.

[7] Cressman K. Desert Locust Guidelines 3. Information and forecasting. Desert Locust Guidelines, 2001; 29–31.

[8] Meynard C N, Leco, M, Chapuis M and Piou C. On the relative role of climate change and management in the current desert locust outbreak in East Africa. Global Change Biology, 2020; 26(7): 3753–3755.

[9] Joshi M J, Raj V P, Solanki C B and Vaishali V B. Desert Locust(Schistocera gregaria F.) outbreak in Gujarat (India). Agriculture and Food: E-Newsletter, 2020; 2(6): 691–693.

[10] FAO. Locust watch, Food and Agricultural Organization of the United Nations. Desert Locust Bulletin, 2019; 483: 1–8.

[11] FAO. Desert Locust. Rome: Author. 2020; Retrieved from http: //www.fao.org/locusts/en/.

[12] Adriaansen C, Woodman J D, Deveson E and Drake V A. Chapter 4.1 - The Australian Plague Locust—Risk and Response. In: Shroder J.F., Sivanpillai R. (Eds.), Biological and Environmental Hazards, Risks, and Disasters. Elsevier, 2016; 67–86.

[13] Ciancio A and Mukerji K G. Integrated management of arthropod pests and insect borne diseases. Berlin: Springer Netherlands, 2010; 163–183.

[14] Latchininsky A V. Locusts and remote sensing: A review. Journal of Applied Remote Sensing, 2013; 7(1): 5099.

[15] Araujo Picoli M C , Camara G , Sanches I , et al. Big earth observation time series analysis for monitoring Brazilian agriculture. ISPRS Journal of Photogrammetry and Remote Sensing, 2018; 145PB(NOV.): 328–339.

[16] Cressman, K. Chapter 4.2 - Desert Locust. In: Shroder J.F., Sivanpillai R. (Eds.), Biological and Environmental Hazards, Risks, and Disasters. Elsevier, 2016; 87–105.

[17] Hü C, ttich, Herold M , et al. Indicators of Northern Eurasia's land-cover change trends from SPOT-VEGETATION time-series analysis 1998-2005. International Journal of Remote Sensing, 2007.

[18] Robbins P F , Chhangani A K , Rice J , et al. Enforcement Authority and Vegetation Change at Kumbhalgarh Wildlife Sanctuary, Rajasthan, India. Environmental Management, 2007; 40(3): 365–378.

[19] Beatriz Martínez, María Amparo Gilabert. Vegetation dynamics from NDVI time series analysis using the wavelet transform. Remote Sensing of Environment, 2009; 113(9): 1823–1842.

[20] Zhou Q, Li B , Chen Y . Remote Sensing Change Detection and Process Analysis of Long-Term Land Use Change and Human Impacts. Ambio, 2011; 40(7): 807–818.

[21] Jia W, Zhao S, Liu S. Vegetation growth enhancement in urban environments of the Conterminous United States. Global Change Biology, 2018.

[22] Bryceson K P. Digitally processed satellite data as a tool in detecting potential Australian plague locust outbreak areas. Journal of Environmental Management, 1990; 30(3): 191–207. DOI: 10.1016/ 0301-4797(90)90001-D.

[23] Ji R, Xie B Y, Li D M, Li Z and Zhang X. Use of MODIS data to monitor the oriental migratory locust plague. Agriculture, Ecosystems and Environment, 2004; 104(3): 615–620. DOI: 10.1016/j.agee.2004.01.041.

[24] Chen J, Ni S X and Li Y M. LAI retrieval of reed canopy using the neural network method. Remote Sensing for Land and Resources, 2008; (2): 62–67.

[25] Ji R, Zhang X, Xie B Y, Li Z, Liu T J and Liu C. Use of MODIS data to detect the Oriental migratory locust plague: a case study in Nandagang, Hebei Province. Acta Entomologica Sinica, 2003; 46(6):713–719.

[26] Zha Y, Gao J, Ni S X and Shen N. Temporal filtering of successive MODIS data in monitoring a locust outbreak. International Journal of Remote Sensing, 2005; 26(24): 5665–5674. DOI: 10.1080/ 01431160500196349

[27] Zha Y, Ni S X, Gao J and Liu Z B. A new spectral index for estimating the oriental migratory locust density. Photogrammetric Engineering and Remote Sensing, 2008;74(5): 619–624. DOI: 10.14358/PERS.74.5.619

[28] Deveson E D. Satellite normalized difference vegetation index data used in managing Australian plague locusts. Journal of Applied Remote Sensing, 2013; 7(1): 075096. DOI: 10.1117/1. JRS. 7. 075096

[29] Eltoum M, Dafalla M and Hamid A. Detection of change in vegetation cover caused by desert locust in Sudan//SPIE Proceeding Asia Pacific Remote Sensing. 2014; Beijing, China: SPIE.

[30] Zhao F J. The Application of Hyper Spectra in Locusts Monitor on Grassland. Beijing: Chinese Academy of Agricultural Sciences, 2014, 15–20 (In Chinese).

[31] Zheng X M. Monitoring Oriental Migratory Locust damage based on multi-platform remote sensing techniques. Hangzhou: Zhejiang University, 2019, 23–26 (In Chinese).

[32] Song P, Zheng X, Li Y, Zhang K and Wang X. Estimating reed loss caused by Locusta migratoria manilensis using UAV-based hyperspectral data. Science of The Total Environment, 2020; 719: 137519.

[33] Ghosh S, Roy A. Desert Locust in India: The 2020 invasion and associated risks. EcoEvoRxiv, 2020.

[34] Owidhi M A. Climate Change and Agriculture in Kenya. Sustainable Bioresource Management, 2020.

[35] Bag, H. and Bhoi, L. Desert Locust and Climate Change: A Risk for Agriculture. Biotica Research Today, 2020; 802–804.

[36] Park, J, Ryu K. Variation Characteristics of Vegetation Index(NDVI) Using AVHRR Images and Spectral Reflectance Characteristics. Journal of Environmental Ences, 2005; 19(1): 90–96.

[37] Zhou G, Wang H and Sun Y, et al. Lithologic classification using multilevel spectral characteristics. Journal of Applied Remote Sensing, 2019; 13(1): 1–12.

[38] Tahir M N, Naqvi S Z A, Lan Y B, Zhang Y L, Wang Y K, Afzal M, et al. Real time monitoring chlorophyll content based on vegetation indices derived from multispectral UAVs in the kinnow orchard. Int J Precis Agric Aviat, 2018; 1(1): 24–31.

[39] Tahir M N, Lan Y B, Zhang Y L, Wang Y K, Faisal N, Shah M A A, et al. Real time estimation of leaf area index and groundnut yield using multispectral UAV. Int J Precis Agric Aviat, 2020; 3(1): 1–6.