https://doi.org/10.25686/7237.2020.6.58835

MONITORING OF FOREST ECOSYSTEMS DISTURBANCES IN MARI EL REPUBLIC

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Natural factors and anthropogenic impact frequently result in different levels of forest disturbances, which have an important influence on forest resource management and climate change. Under the background of global warming, large-scale forest disturbance monitoring and its impact have become the hotspot and the focus of research worldwide. Remote sensing can obtain large-area forest cover data on a regular basis, thus becoming an important means of regular and continuous forest disturbance monitoring. Forest monitoring based on time series data has become the main research method. Therefore, based on in-depth analysis of the relevant methods of forest disturbance monitoring and their indexes, according to time series analysis technique, the author carried out research in Mari El Republic to detect forest disturbances from 10 Landsat images taken between 1985 and 2019. The vegetation index time series methods are adopted to extract the forest disturbance information. Based on the spatial and temporal resolutions of remote sensing data, the laws and driving factors of forest disturbance in the study area were analyzed. The results show that from 1985 to 2019 the number of forest pixels in Mari-El Republic did not change much, and the total area remained floating within a certain range. Forest disturbance pixel number and area of disturbance have an increasing trend year by year, of which the most obvious increase is observed in the period from 2007 to 2011. Finally, the prospects for future research are discussed.

Keywords: *remote sensing, Landsat data, forest disturbance, vegetation index, time series, change detection.*

Introduction

Forest is a type of land ecology system and an essential part of the Earth's biosphere. The carbon recycling and storage of forests play an important role in global land carbon cycle and climate change (He et al., 2001; Schimel, 1995). Due to the occurrence of forest disturbance events such as deforestation, fire (Kurbanov et al., 2017), drought (Millar, Stephenson, 2015) and insect outbreaks (Kautz et al., 2017).The forest communities are replaced by sparse forests, low shrubs and even grasslands, and the carbon originally stored in organisms is re-released into the atmosphere. These events have changed the composition, structure and function of forest systems. It seriously affects the ecological balance and stability of the region and to a certain extent affects the regional and global carbon budget, and may have an impact on the global climate system.

Under the background of global warming, forest disturbance monitoring and its impact have become the hotspot and the focus of research worldwide (Dale et al., 2000). Forest disturbance monitoring research is of great significance for revealing the temporal and spatial evolution of forests. It also provides basic theoretical and technical support for the global forest carbon sink estimation research, and has become an important topic in the field of global change research (Huang et al., 2010). The traditional forest resources and their changes are mainly based on ground surveys, which have problems such as large workload, high labor intensity, high cost, long cycle, low efficiency and poor timeliness. Moreover, the survey accuracy is not high enough to meet the needs of today's monitoring of forest resource changes, especially for large-scale forest disturbance monitoring. Remote sensing, with its wide coverage and repeatable access, can quickly monitor changes that occur, plan forestry activities to care for young plantations, and improve forecasts for the development of forest landscapes and territories (Kurbanov et al., 2010). It also plays an important role in the monitoring of forest changes and disturbances, thus also addressing the above stated problem.

Many experts and scholars have used satellite remote sensing technology to carry out a large number of forest disturbance monitoring studies, and their methods are mainly divided into two categories: threshold segmentation and image classification (Healey et al., 2005). Many researchers point to the need for long-term monitoring and development of technology to assess the ecosystem response to natural disturbances (droughts and fires) from satellite image (Kurbanov et al., 2011).

The purpose of this research is to provide the basis for the local forest protection, and to provide data and support method for forest resource inventory and management.

Study area and materials

The study area Of Mari E;Republic of Russia is located between 45°37' E and 50°12' E, 55°48' N and 57°20' N, where it occupies 23 thousand km2 (fig.1). The territory is a hilly plain with elevation range from 45 to 275 m above the sea level. The climate is moderately-continental with distinct and stable weather in winter and summer and variable weather in spring and fall. The mean annual temperature varies from +2.20 C in the north-eastern part to +3.10 C in the southwest. In recent years, winter months have been warmer than they used to be. The average amount of precipitation is 450-500 mm, including 200-250 mm during vegetation period.

According to a forest resource study conducted in 2017, the forested area of Mari El Republic covers 1,117 thousand ha (Vorobev, Kurbanov, 2017) and the forest cover is 55.4%. The main forest-forming species are pine (*Pinus sylvestris*), spruce (*Picea Abies*), birch (*Betula pendula*), linden (*Tilia cordata*) and aspen (*Populus tremula*). The region can be subdivided into three ecological zones: southern taiga, mixed forest and forest-steppe. The Volga River serves as the natural western border of physiographic and natural conditions. This area has a high rate of forest coverage, and the forest disturbance has changed significantly since 1985 (Kurbanov et al., 2017). Therefore, Mari El Republic serves as a good site for detecting changes in disturbance regimes caused by natural and social conditions, as well forest management policies.

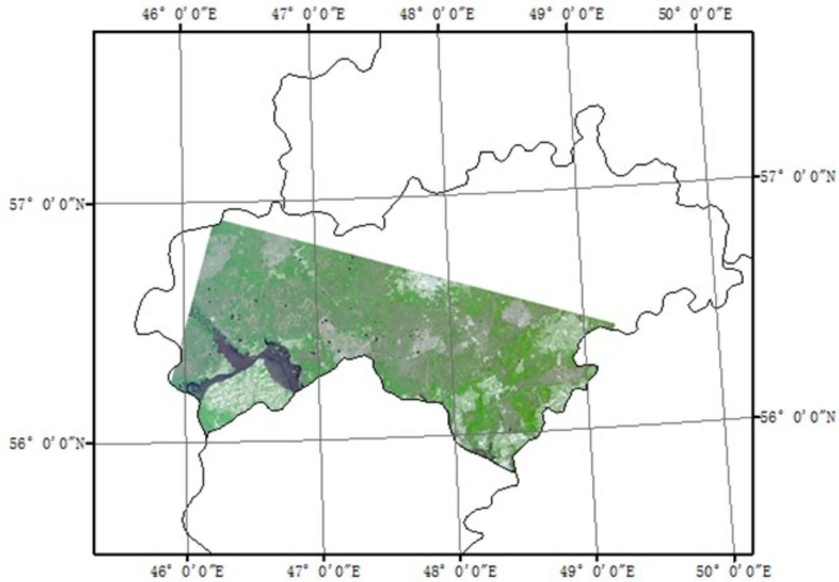

Fig. 1. Location map of study area

Materials and Method

Remote Sensing Images. Landsat remote sensing data acquisition and processing selection during 1985-2019, Landsat images with a spatial resolution of 30 m were used as the main data source to extract forest disturbance information in the study area (Kurbanov et al., 2014). The image data came from the USGS website. The study takes 3-5 years and selects the vegetation growth period (June to early October). In some years, due to cloud coverage, the images are selected for 6 years. A total of 10 scene images were selected as the source data (table 1).

Table 1

Remote sensing data

No.	Date	Sensor	Sources	Level	Cloud/%
1	10.08.1985	Landsat TM	USGS	L1T	0
2	30.05.1988	Landsat TM	USGS	L1T	0
3	25.05.1992	Landsat TM	USGS	L1T	0
4	05.07.1995	Landsat TM	USGS	L1T	1
5	11.06.1998	Landsat TM	USGS	L1T	0
6	29.05.2002	Landsat ETM +	USGS	L1T	2
7	27.05.2007	Landsat ETM +	USGS	L1T	1
8	01.07.2011	Landsat TM	USGS	L1T	0
9	19.05.2013	Landsat OLI	USGS	L1T	0
10	05.06.2019	Landsat OLI	USGS	L1T	2

Preprocessing of Remote Sensing Images. The Landsat ETM images obtained in 2007 have lost data bands. In this paper, the ENVI5.3 plug-in "landsat_gapfill.sav" is used, and the missing bands are repaired by interpolation using a mask. Since the reflectivity of the water body in the fourth band of Landsat is very low, in order to eliminate the influence of directional reflection and prevent the water body from interfering with the recognition of cloud shadows and conducive to radiation calibration and atmospheric correction, before the cloud shadow recognition Water mask. In the study, MNDWI (Wang et al., 2013) was used to extract water. For cloud pixels, this study uses "Fmask 4.0" to extract and make a mask (Qiu et al., 2019). After grinding the cloud and cloud shadow, a certain empty value was generated, which needs to be filled with time interpolation. The Landsat calibration tool of 5.3 was used in conjunction with metadata and data header information to convert the DN value of the Landsat TM/ETM+/OLI data into radiance values. In this radiation calibration, the calibration coefficient proposed in the study (Chander et al., 2009) is used: The Landsat 5/7/8 TM /ETM /OLI image data used in the research institute were using atmospheric radiation correction software Landsat ecosystem disturbance adaptive processing system (LEDAPS).The geometric correction uses the area gray matching method to automatically generate matching points, and adopts the quadratic polynomial method based on control points to complete the geometric correction of the L2 product, so that the registration accuracy is controlled within 0.5 pixels.

Forest extraction. Objects in object-oriented classification technology are represented as collected adjacent pixels, and then through these objects we identify the spectral elements of interest (Walker, Briggs, 2007). This method can make good use of high-resolution panchromatic and multispectral bands with rich color information, multi-segment texture, spatial and spectral information segment and classification of features. The final classification result is highly accurate. At the same time, the final classification result can also be output in the form of a vector. This paper uses the "Feature Extraction" module to extract forest area information from high-resolution panchromatic or multi-spectral data based on image space and image spectral characteristics, that is, object-oriented.

Then the extracted 1985 forest area is used as a mask file for subsequent operations, which can improve the detection accuracy and reduce the amount of calculation. The scale level of this study is 40, the merge level is 85 and the attributes are >0.77 in the spectral mean. There are three pixel values in the output raster image: 0, 1, 2, where the value 1 represents the forest area. The Forest extractions are shown in fig. 2.

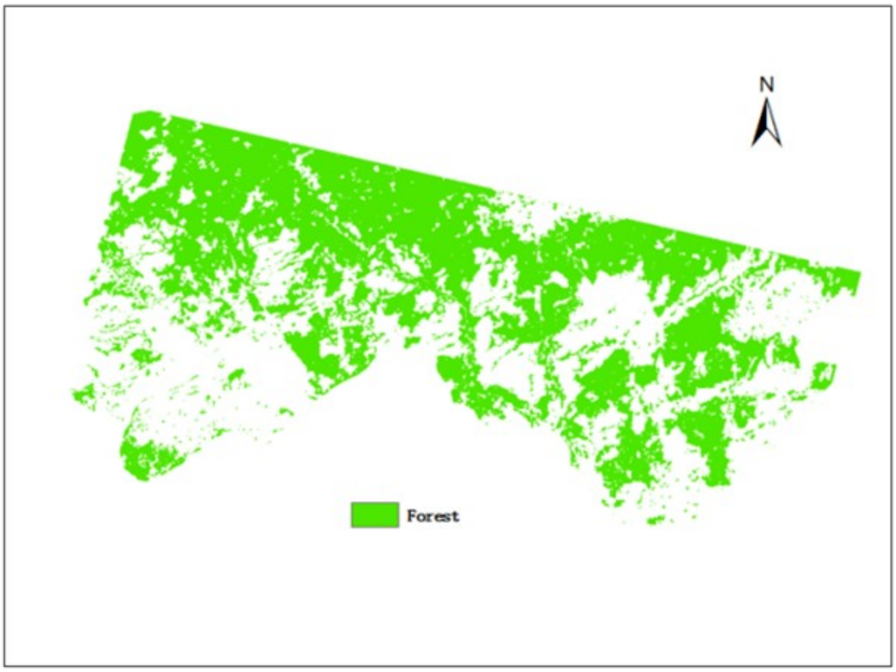

Fig. 2. Forest extractions

Forest canopy change detection. NDVI is an important indicator reflecting the ecological environment and one of the most widely used vegetation indices. However, under sparse vegetation cover conditions, NDVI is susceptible to soil background interference (Wulder et al., 2004), and for dense vegetation, NDVI also exhibits saturation effects (Asrar et al., 1984). Maselli (2004) used NDVI index to conduct long-term monitoring of forest conditions in Mediterranean protected areas and analyzed changes in ecosystem function in the region. Its formula is as follows:

$$\mathrm{NDVI} = \frac{NIR-R}{NIR+R} \,, \tag{1}$$

where R is the reflection value of the red light band, and NIR is the reflection value of the near infrared band.

In this study, the image difference method is used to extract the forest change information using the $NDVI$ interpolation results $\Delta NDVI$ of the two scenes before and after the image. The image after the "i " scene image is the "p " scene image and the formula is:

$$\Delta\mathrm{NDVI} = NDVI_i - NDVI_p$$

Fig. 3. Examples of the ΔNDVI Images

Data standardization. In order to minimize the impact of seasonal changes and directional reflection on the consistency of data, this study uses the mature forest standardization method (Hansen et al., 2008) to standardize the bands and indices used:

$$I_r = \frac{(I - I_\mu)}{I_\sigma} , \tag{3}$$

where I_r is the normalized band or index; I_μ and I_σ are the average and standard deviation of the mature forest area in the band or index, respectively. Among them, the mature forest area is extracted using data, and according to the surface classification system, the part with a pixel value of 1 to 7 is selected as the forest pixel, including evergreen coniferous forest.

Broad-leaved forests, deciduous coniferous forests, deciduous broad-leaved forests, mixed forests, dense shrub forests and sparse shrub forests, the rest non-forest pixels, and forest pixels are extracted through image masks.

Vegetation change tracking algorithm. Vegetation Change Tracker (VCT) is an algorithm for automatic monitoring of forest disturbances based on Landsat time series data at two-year intervals. It fully utilizes time series information to automatically monitor and track land cover changes (Li et al., 2009). Before tracking the vegetation change of the time series index, we selected 4 index values per year, calculated the average value of multiple pixels in the window according to the size of the season setting window and extracted it to obtain the image. We drew the trajectory of the time series of the meta-index, and then tracked the trajectory of the time series of each pixel index, established decision rules according to the time characteristics of the forest change process of the index, and finally determined whether there is forest disturbance in the pixel.

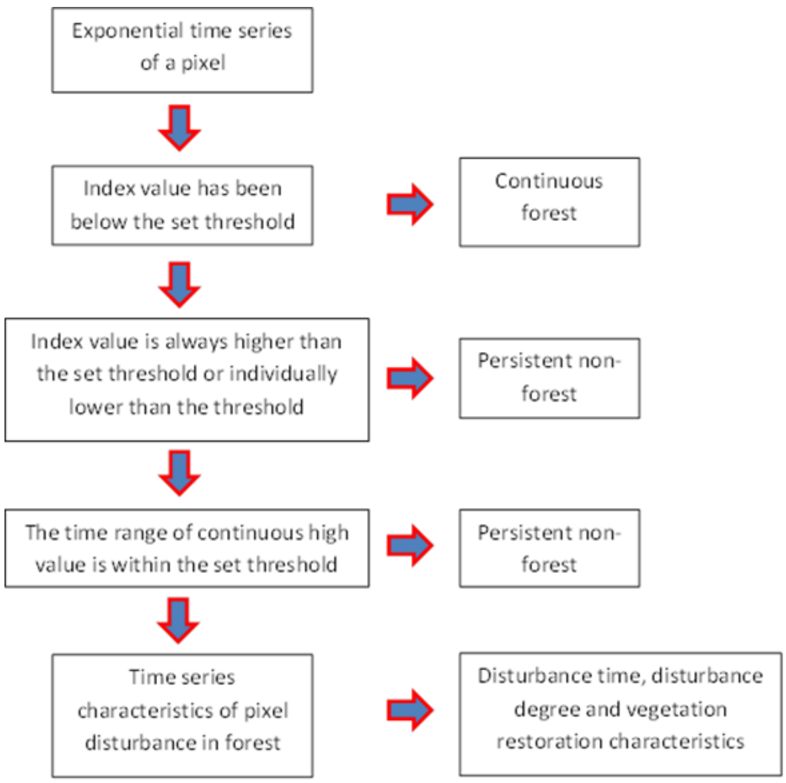

Fig. 4. Major steps and decision rules of VCT algorithm

1) When the forest is not disturbed, the normalized index value only fluctuates around the zero value. The index of a pixel has been at a low (high) value in the time series, and within the set threshold range, then the pixel did not disturb the forest during the monitoring period, and it was determined as a continuous forest.

2) The index value of non-forest pixels is high (low), the continuous non-forest pixels appear in the time series as the index value is always at a high (low) value, and the index of a pixel is in the set threshold in the time series. Outside the range, the pixel is determined to remain non-forest. However, there may also be occasions where the index value is lower (higher) than the threshold for a very small part of the time (Li et al., 2009). When this period of time does not continue for more than a year, the pixel is considered to be a continuous non-forest pixel.

3) The recognition degree of farmland is low, and the index value often shows seasonal fluctuations between high and low values in the time series. The seasonal change is more obvious. The index value is higher in a short period of time. In order to distinguish farmland from disturbing pixels, we used Judging by the time range of continuous high values (Zhao et al., 2015), when the time of continuous high values is within one year, the pixel is considered to be farmland, that is, non-forest pixels, otherwise it is a pixel that has been disturbed. The influence of seasonal fluctuations of index values on the monitoring results of forest disturbances in the time series is reduced.

Extract forest disturbance information. The threshold segmentation method is a common method in image segmentation. This method uses the gray level difference between the target and the background, and then divides the pixel level into different categories by setting a certain threshold, and finally can separate the target and the background.

We used the histogram of the NDVI difference image to find the segmentation threshold. The scene image is composed of multiple forest interference characteristic areas, and the histogram presents a multi-peak phenomenon. Each peak corresponds to a forest interference characteristic area, and the adjacent peak is divided by the valley point convex threshold, by visual method. A, B, and C "inflection points" are visible in the histogram. The pixel values corresponding to these three "inflection points" are segmentation thresholds. Therefore, the forest interference area is divided into slight interference area, medium interference area and severely interference area. [MIN, A]. Slightly disturbance zone, [A, B]: Medium disturbance zone, [B, C]: Severely disturbance zone. After determining the segmentation threshold, we edited and output the gray segmentation results to obtain statistical results, and finally used the 3×3 window to filter the small interference spots, so as to obtain the final forest interference products year by year. Fig. 5, fig. 6 and fig. 7 take Histograms of NDVI 2019-NDVI 2013 as an example, In the example of Histograms of NDVI 2019-NDVI 2013, MIN is -1.9894764, the value of point A is -0.1403, the value of point B is -0.0252, and the value of point C is -0.0109. The other NDVI difference images are defined according to this method. The three "inflection points" A, B, and C have been obtained. The value of the "inflection point" is obtained according to the visual observation of the histogram.

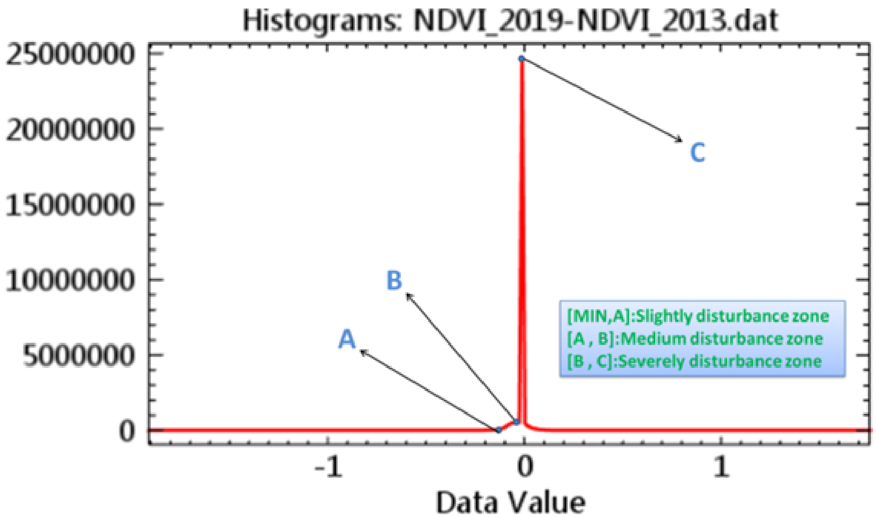

Fig. 5. Histograms of NDVI 2019-NDVI 2013

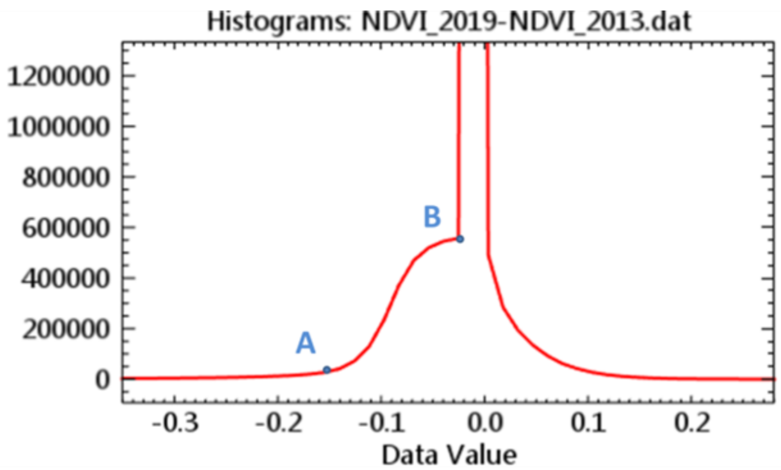

Fig. 6. Detail histogram of NDVI 2019 - NDVI 2013 (1)

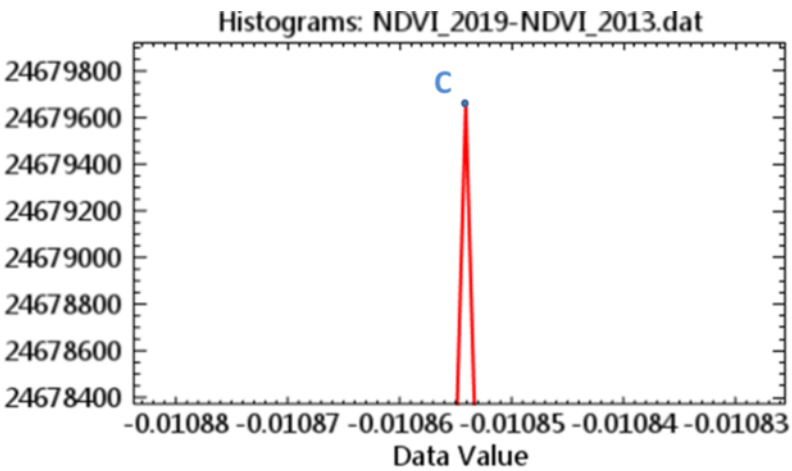

Fig. 7. Detail histogram of NDVI 2019-NDVI 2013 (2)

Accuracy evaluation. In this study, the confusion matrix is used to obtain the detection accuracy. Among them, Overall Accuracy (OA) represents the combination of correctly classified pixels divided by the total number of pixels (Fitzgerald, Lees, 1994). Kappa is a multivariate statistical method for evaluating classification accuracy and it refers to the proportion of errors reduced by the evaluated classification compared to completely random classification The classifier correctly divides the pixels of the entire image into the number of pixels in a specific category and the ratio of the total number of actual references in a specific category is called the mapping accuracy (Manandhar et al., 2009). The ratio of the total number of pixels correctly classified into a specific category is called user accuracy. The calculation is as follows:

$$\mathrm{OA} = \frac{x_{ii}+x_{jj}}{N} \times 100\% \, , \tag{4}$$

$$\mathrm{Kappa} = \frac{N\sum_i^r x_{ii} - \sum(x_i + x_{+i})}{N^2 - \sum(x_{i+} x_{+i})} \, , \tag{5}$$

$$P_{Ai} = \frac{x_{ii}}{x_{+i}} \times 100\% \, , \tag{6}$$

$$U_{Aj} = \frac{x_{ii}}{x_{i+}} \times 100\% \, , \tag{7}$$

where OA is the overall accuracy; in the Kappa coefficient, r is the number of rows of the error matrix; x_{ii} is the value on the i row and i column (main diagonal); x_{i+} and x_{+i} are the sum and the sum of column i; N is the total number of samples; P_{Ai} is the cartographer accuracy of class i ; U_{Aj} is the user accuracy of class j .

Results and discussion

Accuracy evaluation results. The Mari-El forest disturbance monitoring confusion matrix from 1985 to 2019 is shown in table 2. The disturbance points are classified. The number of 326 refers to 386 pixel points, but many non-disturbance points are sacrificed, and 46 are misclassified, which is not stable enough. The overall accuracy for unbalanced classification in Table 3 is 99.26%, and the kappa coefficient is 0. 89, which meets the accuracy requirements of disturbance monitoring.

Table 2

1985 to 2019 Mari-El forest disturbance monitoring confusion matrix

Number of pixels	Disturbed point	Undisturbed point
Disturbed point	326	46
Undisturbed point	53	10935

Table 3

1985 to 2019 Mari-El forest disturbance monitoring accuracy

Project	Disturbed point	Undisturbed point
Cartographer accuracy/%	87.19	99.13
User precision/%	89.2	99.45
Overall accuracy/%	99.26	
Kappa	0.89	

The methods proposed in this study aiming at the characteristics of low spatial resolution and unbalanced classification can not only effectively improve the classification accuracy and solve the problem of unbalanced classification. Iterative training can also provide a more stable and robust monitoring model. In the accuracy test, the kappa coefficient is 0. 89. The plotter precision and user precision of the disturbance point are 87.19% and 89.2% respectively, which shows good stability. Both precisions of the non-disturbance point are above 99%, which guarantees the user precision of the disturbance point and a high kappa coefficient.

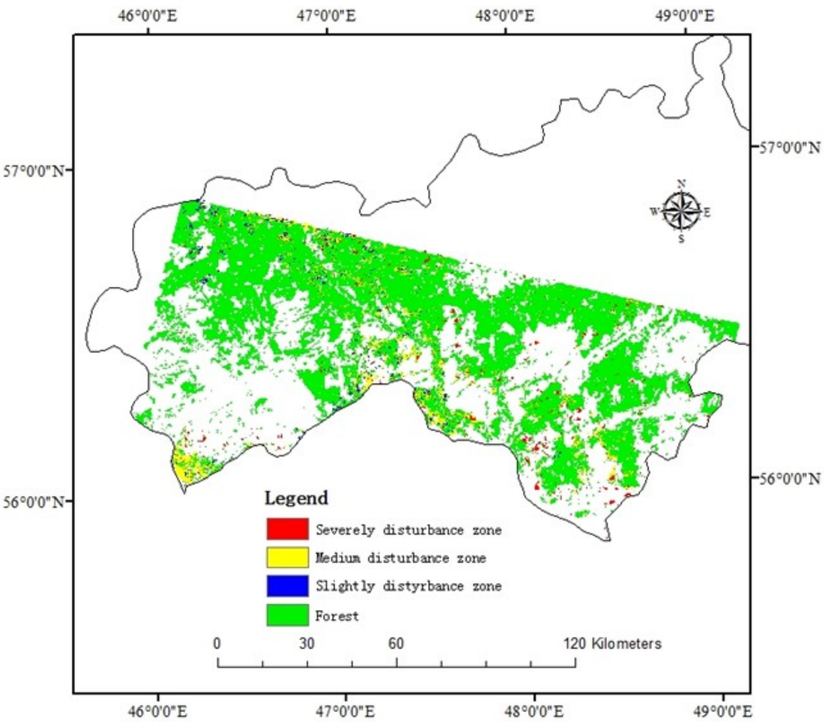

Fig. 8. Mari-El Forest Disturbance Map from 1985 to 2019

Mari-El Forest Disturbance from 1985 to 2019. According to the analysis results of the forest disturbance results map (fig. 8) and the forest disturbance detail map (fig. 9) of the study area from 1985 to 2019, the forests of Mari-El Republic have suffered a large disturbance.

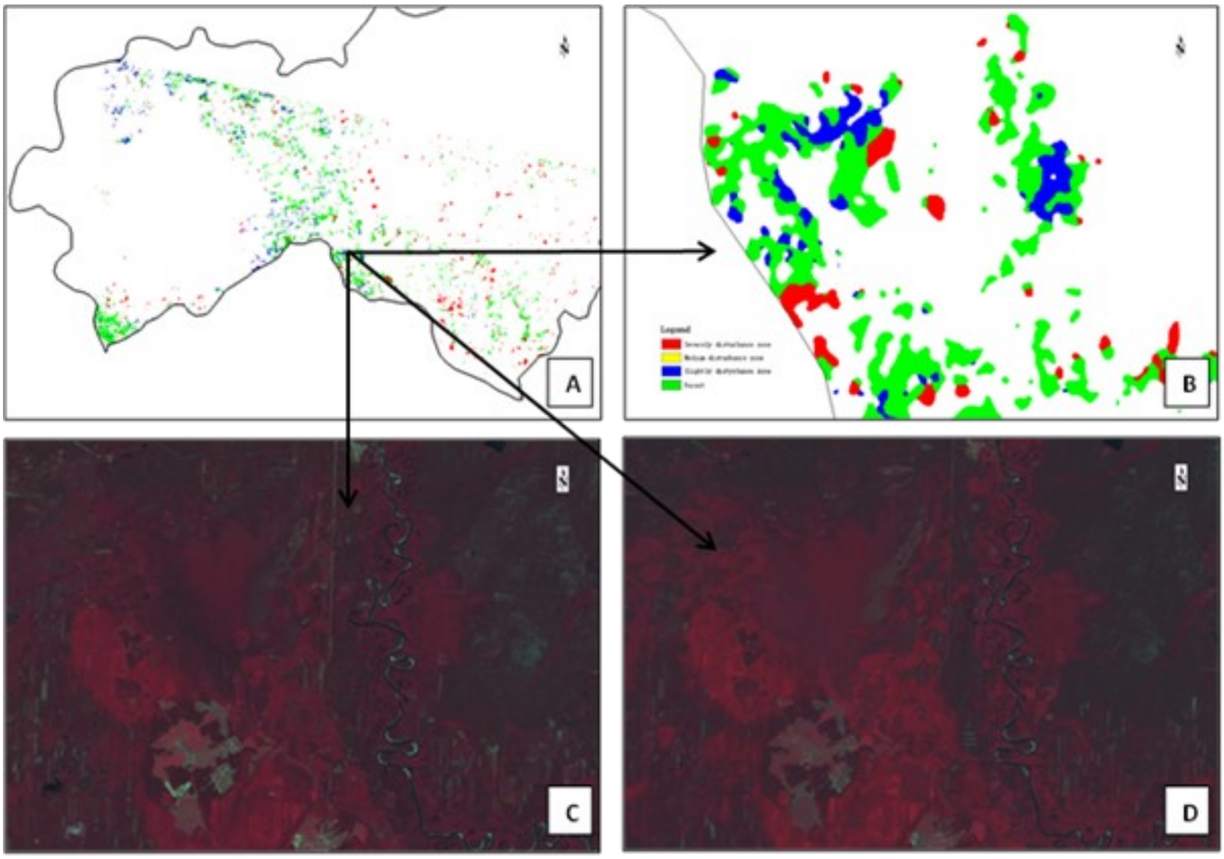

Figure 9. Disturbance maps of Mari El: A) forest disturbance map; B) forest disturbance detail map; C) Landsat CIR map in 2002; D) is Landsat CIR map in 2007

Through the map of forest disturbance changes from 1985 to 2019. It was estimated that from 1985 to 2019, the number of forest pixels in Mari-El Republic did not change significantly, and the total area remained floating within a certain range. Forest disturbance pixel number and area of disturbance have an increasing trend year by year, of which the most obvious increase is from 2007 to 2011. Area of forest disturbance is 1,117.49 km^2, accounting for 8,42% of the total forest area. The annual statistics is shown in Table 4. The highest disturbance accounted for 8.42% in 2007-2011, and the lowest disturbance accounted for 0.41% in 1988-1992.

Table 4

The area of forest disturbance changes in different years

Year	Forest pixel number	Area of Forest, km^2	Area of disturbance, km2	%
2019	14587720	13128.95	375.43	2.86
2013	14405930	12965.34	446.45	3.44
2011	14743575	13269.22	1117.49	8.42
2007	14677232	13209.51	302.35	2.29
2002	14489206	13040.29	278.80	2.14
1998	14009290	12608.36	84.02	0.67
1995	14334776	12901.30	53.93	0.42
1992	14252640	12827.38	52.26	0.41
1988	14405260	12964.73	462.38	3.57

Analysis of the forest disturbances in the Mari El from 1985 to 2019. The forests of Mari-El continued to be disturbed from 1985 to 2019 (Table 5). The forest area transfers changed significantly every two periods. This shows that during this period, the forest is still affected by various factors, and disturbances continue to occur. From the time dimension, the area of forest transfer from 2007 to 2011 is much larger. The loss of forest area is quite serious, mainly due to regional disturbances. Field investigations revealed that a serious forest fire occurred in 2010.

After 2010, the area transferred from the forest showed a downward trend, and the area transferred to forest showed a rapid upward trend, indicating that the local forest restoration and environmental protection policies after the disaster also have a certain inhibitory effect on forest disturbances, which owe to the protection of forest and its ecological environment. Overall, the disturbance mainly occurs when it is mainly logging and forest fires. Therefore, forest disturbance mainly occurs near roads and water areas, and is constrained by terrain and traffic. Urbanization has gradually become a forest disturbance in this area and the driving factor that cannot be ignored.

Table 5

Forest disturbance changes in Mari-El from 1985 to 2019

Year	Severely disturbance zone	Medium disturbance zone	Slightly disturbance zone
2019	0.61	1.18	1.89
2013	1.04	1.77	1.44
2011	4.03	1.18	0.49
2007	1.06	2.29	1.72
2002	1.07	2.64	2.09
1998	0.55	0.23	0.15
1995	0.76	1.87	1.40
1992	1.16	2.87	0.57
1988	1.89	1.37	2.13

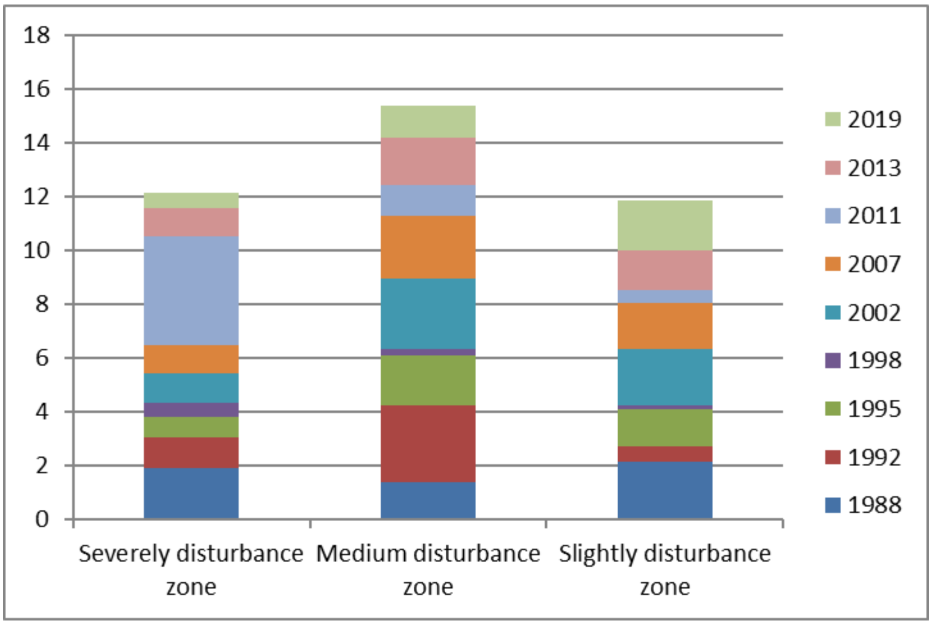

Figure 10. Trend map of forest disturbance Mari-El from 1985 to 2019

Conclusions

This paper reviews and summarizes the update and development of remote sensing data, remote sensing monitoring methods and monitoring indexes of forest disturbances. It summarizes and compares several current disturbance monitoring indexes. And this study is also based on the Landsat TM/ETM+/OLI remote sensing image with a resolution of 30 m, using object-oriented classification method to extract forest area and NDVI image difference method. The research results show that the NDVI image difference extraction forest disturbance method has high accuracy in extracting boreal forests, and has the advantages of simple and convenient operation, and is a cost and time-effective method.

According to the interference monitoring results of Mari-El forests between 1985 and 2019, the forests in this area are still continuously disturbed by various factors. Among them, the disturbances were the largest in 2007-2011 and the least in 1988-2002. The area of thermal forests was year by year. With the decreasing trend, the situation of forest protection is still severe. Since the changes in forest area are closely related to regional and environmental protection policies, according to the continuous increase in forest area in 2011, regional land use and environmental protection policies can suppress the extent of human activities that interfere with forests area. This results in protection and restoration of ecological environment.

The method of automatic extraction of forest samples used in this study can effectively and quickly extract a large number of accurate forest samples, improve the detection accuracy and reduce the amount of calculation for the extraction of forest disturbance areas. It can be used in related research. Although the NDVI image difference extraction method for forest disturbances has a high efficiency and reliable basis for forest disturbance monitoring, it is prone to misdetect agricultural land during the growth period of crops. So the next research needs to consider this aspect. The method is optimized, and the thresholds of forest segmentation in different regions are different. We need to refer to relevant literature and field research to continuously debug to find the optimal threshold, and further clarify the type of forest disturbance in the region and analyze the causes of forest disturbance.

Recommendations

It can be seen that although forest disturbance remote sensing monitoring technology has been well applied in recent years, there are still some shortcomings, and further research can be carried out in the following three aspects:

1) Strengthening the comparative study of the disturbance monitoring index. Due to the fact that the construction methods and theoretical basis of different indexes are different, the monitoring effects for different types of disturbances are also different. Therefore, for the specific forest disturbance types, it is helpful to further distinguish and identify the causes of disturbances by comparing the monitoring effects of different indices.

2) Conducting long-term sequence disturbance monitoring analysis. For a long time, forest disturbance research has been based on the study of changes in remote sensing data of Phase 2 or Phase 3. It is not only time-consuming and laborious, but also has a significant reduction in accuracy during long-term sequence analysis, so that it cannot meet the application requirements. By combining the long-term sequence disturbance analysis method with the appropriate disturbance monitoring index, the monitoring efficiency of forest disturbance can be further improved.

3) Establishing and improving the disturbance monitoring model applicable to regional forests. Frequent changes in forests have caused great disturbances in the estimation of terrestrial carbon sinks, while most of the existing forest carbon stocks use forest resource inventory data, and forest disturbance monitoring based on remote sensing data is underdeveloped. Therefore, it is of great

theoretical significance and practical value to study the disturbance monitoring model applicable to regional forests.

This project/achievement/thesis was funded by "China Scholarship Fund".

This article was completed under the careful guidance of my mentors prof. E.A. Kurbanov, who has given me a lot of help in academic direction determination, topic selection, experimental methods, data processing, theoretical analysis, and finalization of the thesis. During the two-year graduate career, under the guidance of Professor Eldar Kurbanov, I have gained a lot of practical knowledge and techniques, the morality and character of being a person, and more importantly, a serious attitude to everything I do.

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