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Original Research

A LandTrendr Algorithm-Based Study of Forest Disturbance from 2000 to 2020 in Jilin Province, China

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Abstract

Forest resources are of great importance for achieving human sustainable development and carbon neutrality goals. Therefore, this study evaluated forest disturbance in Jilin Province, China, from 2000 to 2020 using the LandTrendr algorithm. The results of the study showed that the overall area of forest disturbance was 448.76 km^2 in Jilin Province during the period 2000-2020. Forest disturbance in Jilin Province mainly occurred in Yanbian Korean Autonomous Prefecture and Baishan City. Although forest disturbance changes occurred to varying degrees in all prefecture-level cities, few forest disturbances occurred in the cities of Baicheng City, Liaoyuan City, Siping City and Songyuan City. The main causes of forest disturbance in Jilin Province were annual average temperature, total resources of arable land area at the end of the year, total arable land resources at the beginning of the year, total sown area, rural labor force in agriculture, forestry, fishing and animal husbandry, gross output value of agriculture, forestry, fishery and animal husbandry, annual precipitation, the expansion of construction land and the over-detection of image stitching and thick and dense clouds. This study provides data support for the government to formulate appropriate forest protection policies, and also has implications for monitoring forest dynamics in other regions.

Keywords: Jilin Province, spatiotemporal variation, time-series analysis, LandTrendr algorithm

Introduction

Forests are the largest terrestrial ecosystem on Earth and are an important link in the global biosphere [1-3]. Forests play a vital role in maintaining the earth's ecological balance (e.g., regulating climate, maintaining soil and water) [4-7]. Over the past 30 years, forests have been affected by natural factors such as droughts and typhoons and anthropogenic factors such as the expansion of land for construction, indiscriminate logging, and other human activities, which have produced different degrees of disturbing changes

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and caused irreversible damage to forest ecosystems [8-10]. Scientific studies have shown that increasing forest disturbance changes can weaken forest carbon sinks, which in turn may affect efforts to combat climate change [11, 12].

Jilin province is uniquely located in the central part of northeast China [13]. According to the latest forest resources statistics, Jilin Province has a forested area of 9,560,000 hectares, with 8,431,500 hectares of forested land. Jilin Province possesses a total live wood accumulation of 1.099 billion cubic meters, with a forested land accumulation of 1.096 billion cubic meters and a forest cover of 45.04%. Therefore, it is of great significance to achieve dynamic monitoring of forests in Jilin Province to protect forest resources.

This paper took Jilin Province as the study area to explore the dynamic changes and development trends of its forest ecosystems. Based on a long time series Landsat remote sensing image dataset, the LandTrendr algorithm was used to explore the forest disturbance in Jilin Province from 2000 to 2020 and to analyze the driving forces affecting the area of forest disturbance. The study offers basic data on forest dynamics in Jilin Province, and is also important for the conservation of forest ecosystems in Jilin Province.

Data and Methods

Study Area

As shown in Fig. 1, Jilin Province is located in the geometric center of Northeast Asia, which is made up of Japan, Russia, North Korea, South Korea, Mongolia and Northeast China (121°38′-131°19′E, 40°50′-46°19′N) [14]. Jilin Province covers nine prefecture-level administrative regions, namely Changchun City, Jilin City, Siping City, Liaoyuan City, Tonghua City, Baishan City, Songyuan City, Baicheng City and Yanbian Korean Autonomous Prefecture [15]. The geomorphological form of Jilin Province varies markedly, with the central Dahei Mountain as the boundary, dividing into two major landforms: the eastern mountains and the central and western plains [16].

Datasets

The forest union based on GlobeLand30 data for 2000 and 2020 were used as the forest extent for Jilin Province. Dynamic monitoring of forest disturbance in Jilin Province was carried out using the Landsat series remote sensing image datasets (e.g., Landsat 5 TM, Landsat 8 OLI) from 2000 to 2020. In this case, the synthetic Landsat series remote sensing image datasets were dated to the growing season (i.e., 20 June to 1 September) at latitudes of 25-50 degrees in the Northern Hemisphere. A series of pre-processing operations were performed on all the above remote sensing datasets, including masking cloud pixels, cloud shadow pixels, snow pixels and water pixels [17].

To explore the driving factors of forest disturbance in Jilin Province from 2000-2020, suitable data were selected from the perspectives of anthropogenic and natural factors. From the perspective of anthropogenic factors, relevant data from 2005-2013 for each prefecture-level city in Jilin Province were selected from population, economy, urbanization, transportation and agriculture using the Jilin Provincial Statistical Yearbook (http://tjj.jl.gov.cn/tjsj/tjnj/) for driving force analysis. From the perspective of natural factors,

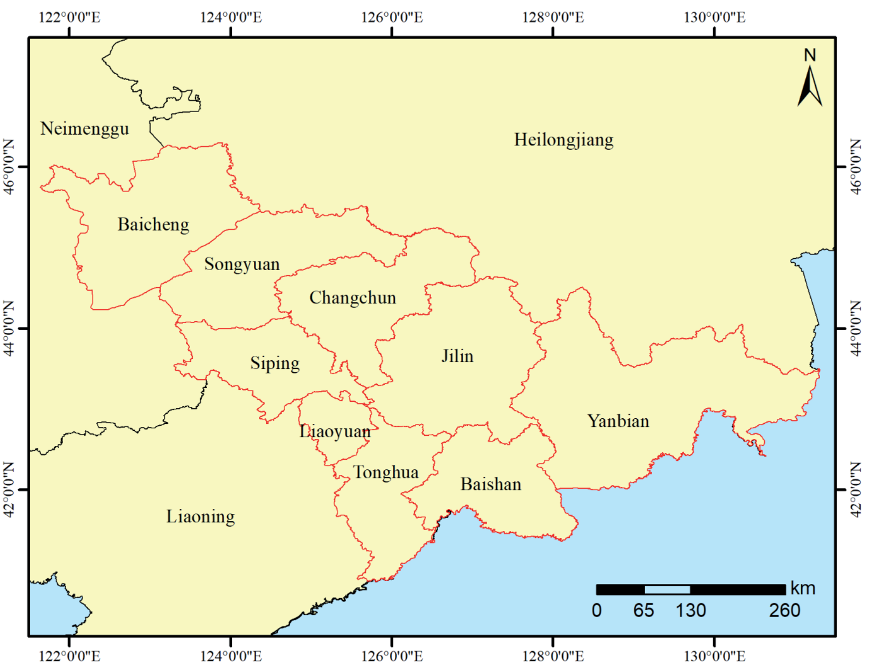

Fig. 1. Geographical location of the study area.

annual average temperature and annual precipitation data from 2000-2015 were obtained from the Resource and Environmental Science and Data Center (https://www.resdc.cn/Default.aspx) and calculated for each prefecture-level city in Jilin Province for driving force analysis.

LandTrendr Algorithm Detects Forest Disturbances

LandTrendr Algorithm is a group of spectral-temporal segmentation algorithms that can be applied to change detection in time series of medium resolution satellite images, mainly the Landsat series of remote sensing images [18]. LandTrendr Algorithm uses spectral indices as a function of time to capture gradual processes (e.g., regeneration) and sudden events (e.g., forest harvesting).

The Normalised Burn Ratio (NBR) index [19] can be used to monitor forest fires and assess their severity [20]. The Normalised Difference Vegetation index (NDVI) [21] can be used to measure vegetation canopy leaf density and greenness and to characterise vegetation growth [22-24]. NDVI index is a useful indicator for monitoring vegetation growth in an ecosystem and is widely used to analyse vegetation change [25, 26]. Many studies have been conducted using the NBR index and NDVI index for forest disturbance monitoring [27, 28]. Therefore, combining the experience of previous studies, NBR index and NDVI index were chosen as the monitoring index for the LandTrendr algorithm with the following equations. Forest disturbance data for Jilin Province were determined by the joint detection of the NBR index and the NDVI index.

$$NBR = \frac{NIR - SWIR}{NIR + SWIR} \tag{1}$$

$$NDVI = \frac{NIR - RED}{NIR + RED} \tag{2}$$

where *NIR* is the near-infrared band; *SWIR* is the short-wave infrared band; *RED* is the red band.

LandTrendr algorithm has a total of nine parameters, namely eight control parameters to adjust

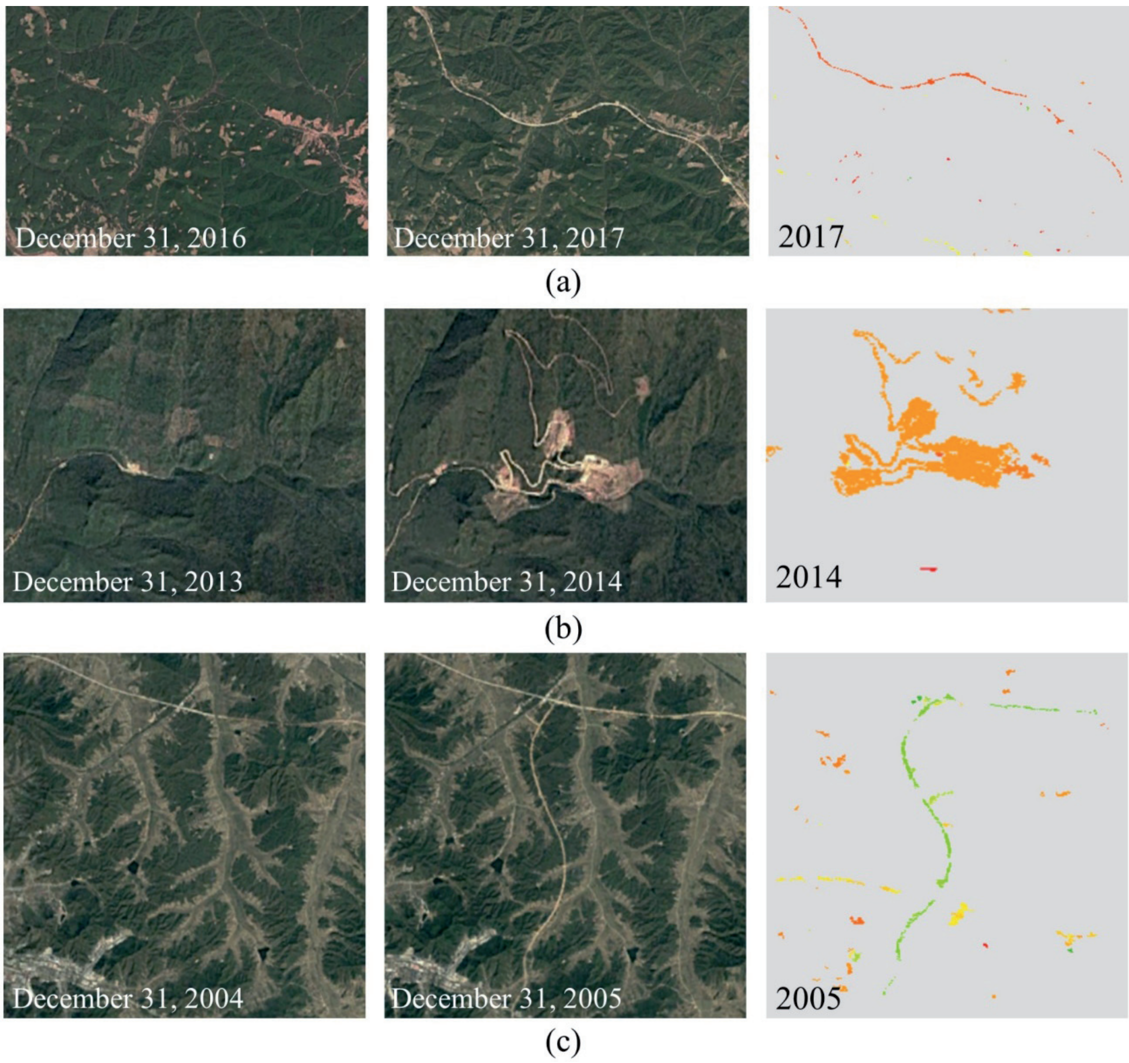

Fig. 2. Results of local forest dynamics change detection in Jilin Province.

how the spectro-temporal segmentation is completed and the annual image collection. Specific information on the parameters selected for this study was as follows: maxSegments was 6, spikeThreshold was 0.9, vertexCountOvershoot was 3, preventOneYearRecovery was true, recoveryThreshold was 0.25, pvalThreshold was 0.05, bestModelProportion was 0.75 and minObservationsNeeded was 6.

Accuracy Evaluation

Appropriate training samples were selected using Google Earth high-resolution remote sensing image history data to evaluate the accuracy of forest dynamics change results in Jilin Province from 2000 to 2020. The overall accuracy and Kappa coefficient were adopted as accuracy evaluation indicators [29-31].

Results

Forest Disturbance Accuracy Evaluation

The Environment for Visualizing Images (ENVI) software was applied to select training samples for accuracy evaluation, including 2980 pixels of changed samples and 3828 pixels of unchanged samples. The overall accuracy of the forest change detection results for Jilin Province was 77.99% with a Kappa coefficient of 0.68. Fig. 2 shows the local detection results of forest disturbance in Jilin Province, and the forest change detection results are generally consistent compared with remote sensing images of the same year.

Spatial and Temporal Distribution of Forest Disturbance in Jilin Province

As shown in Fig. 3a), the forests were mainly concentrated in the southeastern part of Jilin Province, e.g., Jilin City, Yanbian Korean Autonomous Prefecture, Baishan City, Tonghua City, Liaoyuan City. Fig. 3b) shows the spatial and temporal distribution of changes in forest dynamics in Jilin Province from 2000 to 2020. No highly pronounced forest disturbance was found in Jilin Province, and forest disturbance was mainly concentrated in Yanbian Korean Autonomous Prefecture and Baishan City.

Fig. 4 shows the changes in forest disturbance in each prefecture-level city. All prefecture-level municipalities have experienced varying degrees of

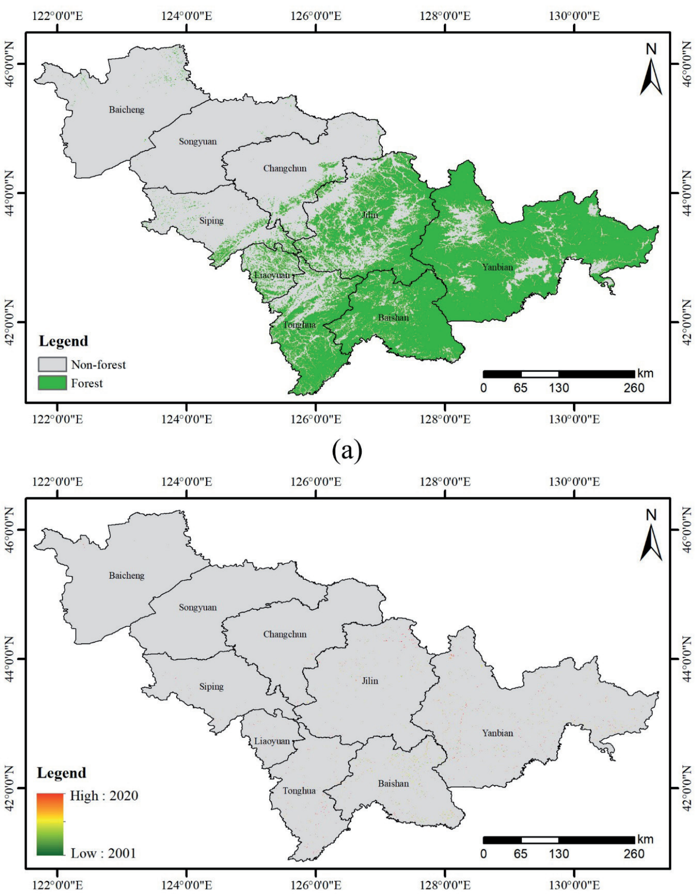

Fig. 3. a) Spatial distribution of the GlobeLand30 forest union for 2000 and 2020 in Jilin Province; b) Spatial and temporal distribution of changes in forest dynamics in Jilin Province from 2000 to 2020.

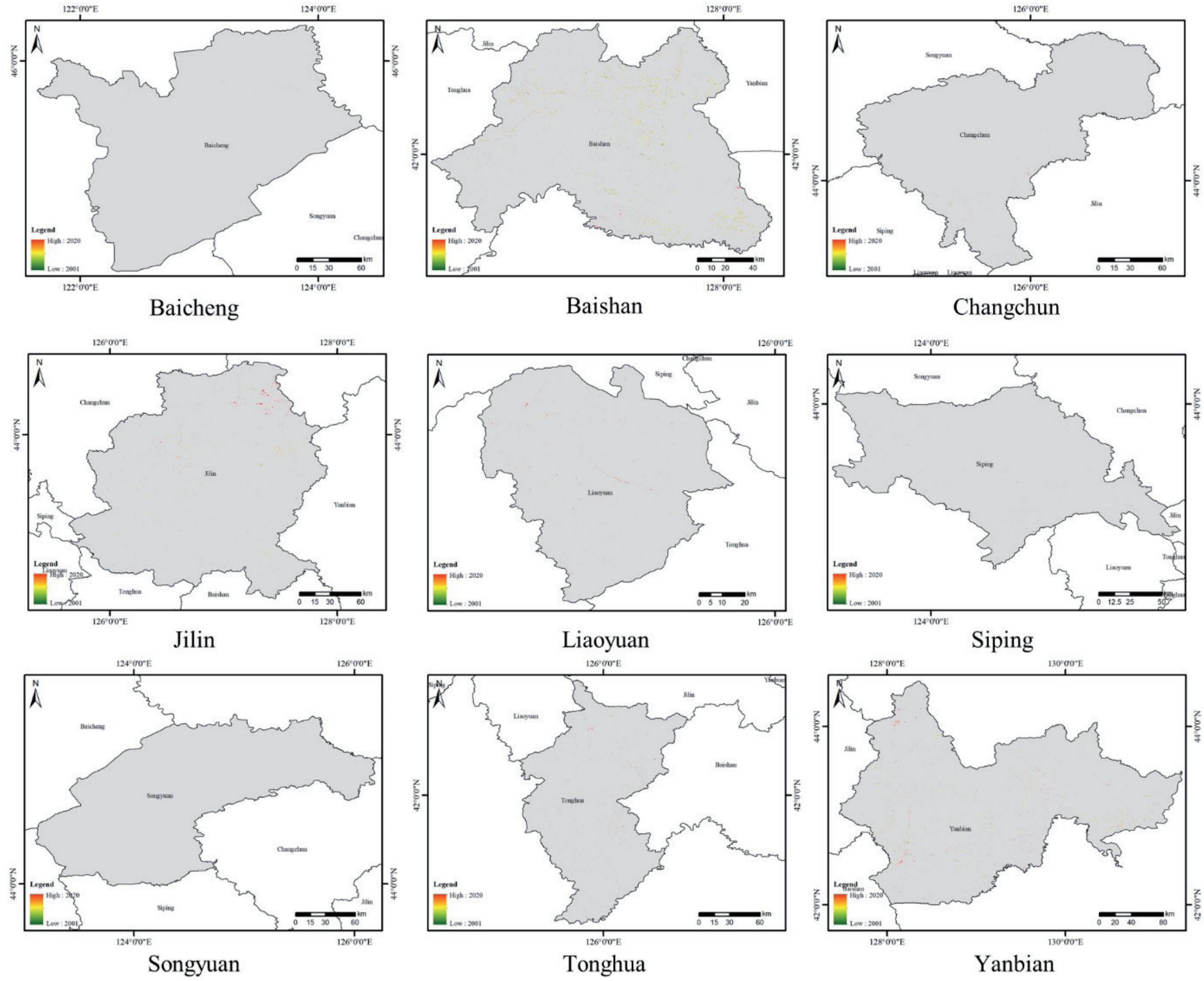

Fig. 4. Spatial and temporal distribution of changes in forest dynamics in prefecture-level cities of Jilin Province from 2000 to 2020.

forest disturbance. As can be seen from Table 1 and Fig. 4, the total area of forest disturbance from 2000 to 2020 was 448.76 km^2. The forest disturbance areas in Jilin Province were not particularly significantly reduced and were all within 60 km^2. Almost no forest disturbance occurred in Baicheng City, Liaoyuan City, Siping City and Songyuan City, all with forest disturbance areas of less than 10 km^2 during the 20-year period. Forest change in Baishan City was approximately 132.11 km^2, with a more dispersed distribution. In Changchun City, forest disturbance covered an area of 10.26 km^2 and was mainly in the southern part of the city. In Jilin City, forest change was located in the north-eastern part of the city, covering an area of approximately 62.19 km^2. Forest change in Tonghua City was mainly focused on the period 2011-2020, covering an area change of 30.22 km^2, with 73.45% of the total forest change in the last decade. During the period 2000-2020, Yanbian Korean Autonomous Prefecture was the city with the greatest forest change in Jilin Province. It had a forest disturbance of 125.98 km^2 in the last ten years, accounting for 68.50% of the total change.

Driving Force Analysis of Forest Disturbance in Jilin Province

As shown in Table 2, from the perspective of anthropogenic factors, the driving factors affecting the area of forest disturbance in Jilin Province were rural labor force in agriculture, forestry, fishing and animal husbandry, gross output value of agriculture, forestry, fishery and animal husbandry, total sown area, total arable land resources at the beginning of the year, total resources of arable land area at the end of the year. The degree of influence was Total resources of arable land area at the end of the year > Total arable land resources at the beginning of the year > Total sown area > Rural labor force in agriculture, forestry, fishing and animal husbandry > Gross output value of agriculture, forestry, fishery and animal husbandry in descending order.

From the perspective of natural factors, forest disturbance area changes in Jilin Province were significantly correlated with annual average temperature and annual precipitation, with forest disturbance area

Table 1. Area changes of forest disturbance by prefecture level cities in Jilin Province

Year \ Area\km^2	Baicheng	Baishan	Changchun	Jilin	Liaoyuan	Siping	Songyuan	Tonghua	Yanbian	Sum
2001	0.8730	12.1752	0.3708	2.3733	0.0531	0.1566	0.0108	1.2915	12.9465	30.2508
2002	0.0027	0.6993	0.0036	0.1224	0.0000	0.0081	0.0000	0.0729	0.7848	1.6938
2003	0.0027	4.3281	0.0171	0.3096	0.0135	0.0000	0.0000	0.6705	2.7486	8.0901
2004	0.0414	6.6726	0.1089	1.9998	0.0414	0.0594	0.0126	0.9351	6.8436	16.7148
2005	0.0009	2.6910	0.1197	1.2636	0.0468	0.0855	0.0036	0.3213	4.1562	8.6886
2006	0.0009	4.1022	0.2952	1.3392	0.0657	0.1521	0.0018	0.3186	4.3695	10.6452
2007	0.0009	9.4050	0.0513	1.7901	0.1602	0.2412	0.0000	1.6731	7.8687	21.1905
2008	0.0162	9.1197	0.2025	2.0754	0.0945	0.0693	0.0279	1.1898	7.6311	20.4264
2009	0.0054	6.4494	1.1358	3.8952	1.6974	1.4274	0.0207	2.8692	4.4334	21.9339
2010	0.0135	10.4292	2.1753	1.8018	0.1971	0.3231	0.0513	1.5786	6.1569	22.7268
2011	0.0405	8.1990	0.2700	4.4865	0.3447	0.2088	0.0045	1.8585	11.3490	26.7615
2012	0.0135	9.3357	0.3105	5.0193	0.3780	0.0990	0.0279	1.3860	11.3634	27.9333
2013	0.0585	1.9134	0.3204	1.5669	0.3033	0.2979	0.0000	1.2024	7.2270	12.8898
2014	0.0891	17.7741	0.6273	6.3756	0.2124	0.7911	0.0000	4.0752	21.2364	51.1812
2015	0.1800	11.6370	0.6687	3.1644	0.7425	1.3041	0.0144	2.2257	12.3372	32.2740
2016	0.1179	3.3426	0.5661	3.7548	0.2628	0.4419	0.0027	3.6774	7.8831	20.0493
2017	0.1530	1.7235	0.3726	1.3626	0.4194	0.9693	0.0000	1.4634	13.5423	20.0061
2018	0.0432	1.8315	0.9252	1.8819	1.3149	0.7254	0.0288	1.1439	9.7839	17.6787
2019	0.3762	4.0203	0.4104	2.6613	0.4293	0.6822	0.0252	4.5333	6.8904	20.0286
2020	0.2754	6.2577	1.3104	14.9463	0.9432	0.8334	0.0252	8.6499	24.3630	57.6045
Sum	2.3049	132.1065	10.2618	62.1900	7.7202	8.8758	0.2574	41.1363	183.9150	448.7679

Table 2. Correlation analysis of forest disturbance factors in Jilin Province.

Category	Driving factors	Pearson correlation coefficient	P	Sig
Population	Population	-0.262	P>0.05	0.018
	Rural labour force in agriculture, forestry, fishing and animal husbandry	**-0.458**	**P<0.05**	**0.000**
Economy	Gross production value	-0.148	P>0.05	0.188
	Gross output value of agriculture, forestry, fishery and animal husbandry	**-0.340**	**P<0.05**	**0.002**
	Fixed Asset Investment	-0.075	P>0.05	0.504
	Gross industrial output value	-0.129	P>0.05	0.250
	Gross output value of the construction industry	-0.097	P>0.05	0.388
Urbanisation	Completed area of housing construction by construction enterprises	-0.124	P>0.05	0.270
Transport	Passenger traffic	0.284	P>0.05	0.010
	Volume of freight transport	-0.126	P>0.05	0.262
Agriculture	Total sown area	**-0.498**	**P<0.05**	**0.000**
	Total arable land resources at the beginning of the year	**-0.529**	**P<0.05**	**0.000**
	Increase in arable land during the year	-0.265	P>0.05	0.025
	Decrease in arable land during the year	-0.136	P>0.05	0.256
	Total resources of arable land area at the end of the year	**-0.536**	**P<0.05**	**0.000**
Climate	Annual average temperature	**-0.563**	**P<0.05**	**0.000**
	Annual precipitation	**0.254**	**P<0.05**	**0.003**

in Jilin Province showing a negative correlation with annual average temperature and forest disturbance area in Jilin Province showing a positive correlation with annual precipitation.

As shown in Fig. 5, the forest changes in Jilin Province were partly due to the conversion of forest to construction land (e.g., roads). Based on the results of the forest change detection, it is evident that forest disturbances in Jilin Province were partly caused by human activities resulting in the expansion of construction land. In addition, there were areas that were part of the over-detection phenomenon, for example, areas of thick and dense clouds or stitching between remote sensing images were also detected as forest changes (see Fig. 6).

Discussion

Causes and Recommendations for Forest Disturbance

It is clear from the findings that climate change is strongly correlated with changes in forest disturbance area, and that demographic, economic and agricultural factors also influence forest disturbance changes. Therefore, mitigating climate change and reducing human expansion and economic and agricultural activities can reduce the possibility of forest disturbance change to a certain extent. In addition, cloud cover in long time series change detection can also affect forest disturbance results.

In order to be able to protect the forests of Jilin Province scientifically and effectively, we should start from the following aspects. Firstly, relevant government departments should take appropriate measures to protect forest resources in areas with high forest disturbance (e.g., Yanbian Korean Autonomous Prefecture and Baishan City), improve the level of forest supervision and slow down the reduction of forest area caused by the expansion of land for construction and agriculture. Secondly, people should raise awareness of forest protection, reduce indiscriminate felling and take care of trees.

In using the LandTrendr algorithm for forest disturbance change studies, appropriate parameters for the study area variables need to be selected. The accuracy of forest disturbance monitoring results can be improved by reducing the generation of pseudo-variation in two ways: (1) Using multiple indexes and multiple wavebands to achieve forest disturbance monitoring. (2) Using longer remote sensing images to synthesize high-quality remote sensing images for forest change detection.

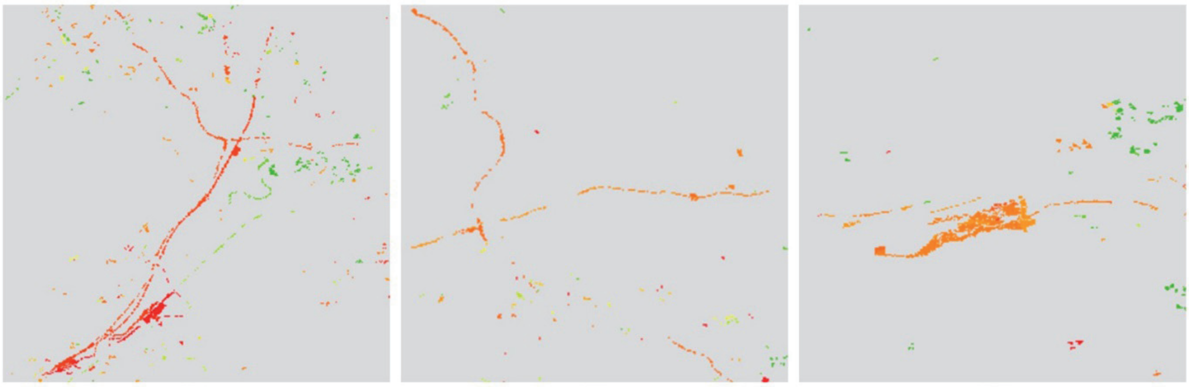
(a) (b) (c)

Fig. 5. Conversion of forests to construction land.

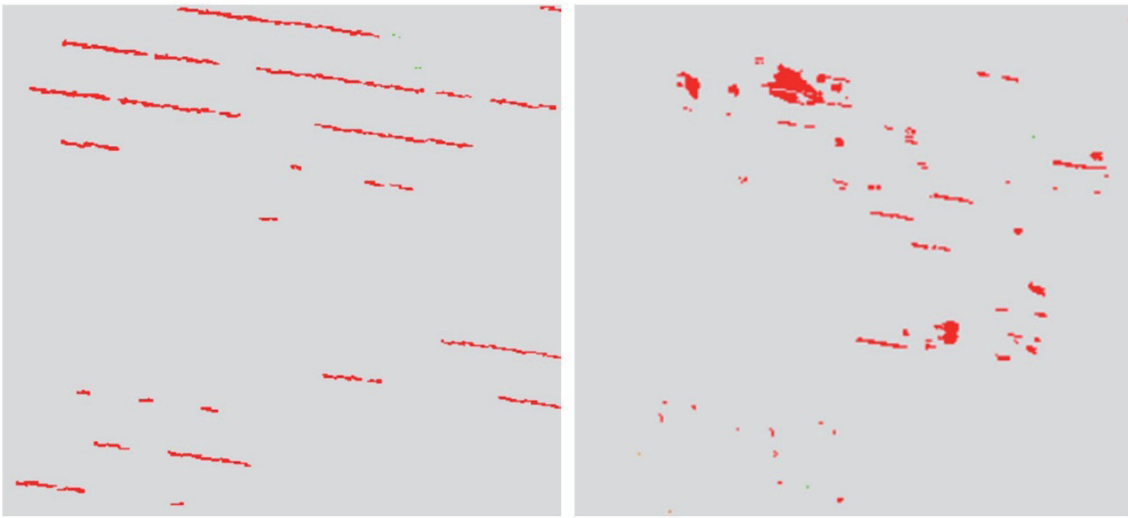
(a) Image stitching (b) Thick and dense clouds

Fig. 6. Forest disturbance over-detection areas in Jilin Province.

Advantages of the LandTrendr Algorithm for Forest Disturbance Studies

The LandTrendr algorithm is an effective way to detect the spatial and temporal distribution of forest disturbance and to obtain the year of disturbance and the amount of disturbance. In this study, the LandTrendr algorithm was used to investigate the forest disturbance in Jilin Province, and two indexes, i.e., NDVI and NBR, were used for forest disturbance detection. Although some areas of false alarms were generated, the false alarms caused by external factors (e.g., image stitching, thick and dense clouds) were effectively reduced compared to a single index, thus making the forest disturbance detection results more reliable. As shown in Fig. 7, although the visual effect of the remote sensing images for 2018, 2019 and 2020 appears to have changed in terms of forest, the combination of the Google Earth high resolution data shows that the green area forest has not changed significantly. NBR index produced pseudo-change in the green area, but the NDVI index had almost no detectable pseudo-change and the final forest disturbance result was the intersection of the NDVI and NBR indexes, thus making the detection result more accurate.

Uncertainty Analysis in Forest Disturbance

This study has been conducted over a relatively long period of time. For long time series studies, Landsat TM/ETM+/OLI series data is the more commonly used data source with a resolution of 30 m [32-35]. However, there are some issues with using the Landsat series satellites during the study. For example, Landsat 7 ETM+ data was used in 2012. It is worth noting that the Landsat 7 ETM+ data had data gaps [36], which in turn affected the change detection results, as shown in Fig. 5. On this basis, problems such as dense clouds in the study area cannot be effectively avoided, which can also affect the results to some extent.

In addition, the LandTrendr algorithm suffers from the following problems. It produced many small ranges

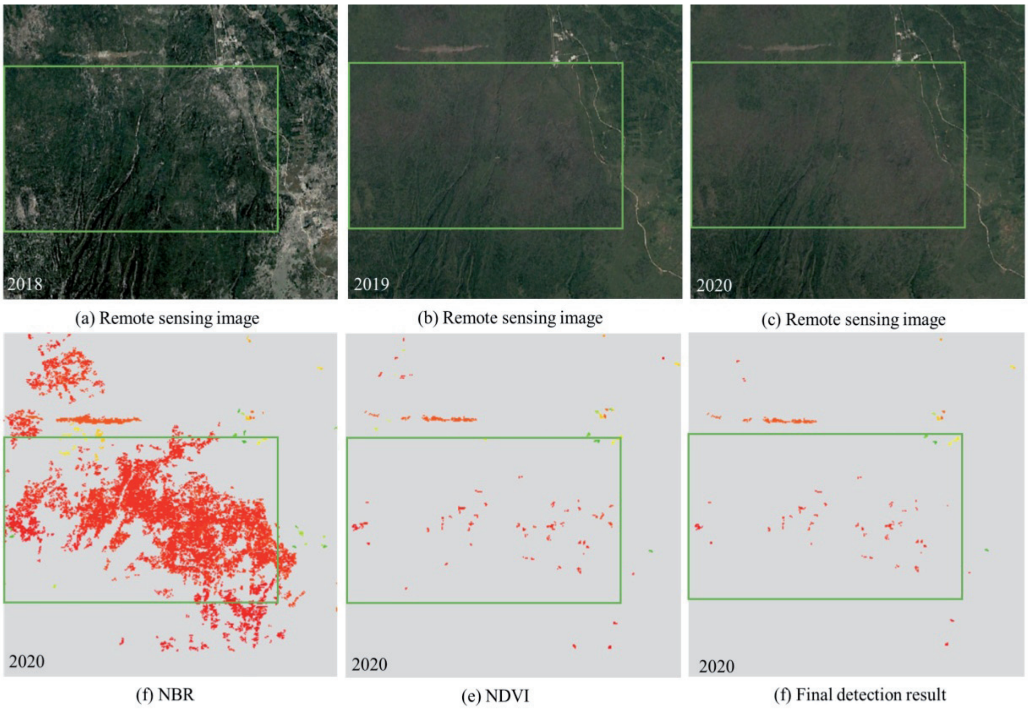

Fig. 7. Forest disturbance detection results for different indexes.

of false detections and less satisfactory results in the first and last years, and did not take spatial correlation into account [37].

Conclusions

This study explored the spatial and temporal distribution of forest change in Jilin Province from 2000-2020 using the LandTrendr algorithm of the GEE platform and analyzed the driving factors that may influence forest disturbance. The results showed the following:

(1) During the study interval, in Jilin Province, the total area of forest disturbance was 448.76 km^2. The area of forest change was small in Baicheng City, Liaoyuan City, Siping City and Songyuan City, and relatively large in Yanbian Korean Autonomous Prefecture and Baishan City.

(2) The factors affecting the change in forest area in Jilin Province were, in descending order, Annual average temperature > Total resources of arable land area at the end of the year > Total arable land resources at the beginning of the year > Total sown area > Rural labor force in agriculture, forestry, fishing and animal husbandry > Gross output value of agriculture, forestry, fishery and animal husbandry > Annual precipitation.

(3) Forest area changes in Jilin Province were partly due to the expansion of land for construction (e.g., roads), as well as over-detection of image stitching and thick, dense clouds. These can be avoided as much as possible by using multiple indicators and multiple bands, or by composing high quality remote sensing images using longer remote sensing images.

This study helps to understand the spatial and temporal distribution of forest change in Jilin Province, while enabling a more targeted approach to forest resource conservation in conjunction with the results of the study.

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Conflict of Interest

The authors declare no conflict of interest.

References

1. CHEN N., QIN F., ZHAI Y., CAO H., ZHANG R., CAO F. Evaluation of coordinated development of forestry management efficiency and forest ecological security: A spatiotemporal empirical study based on China's

provinces. Journal of Cleaner Production, **260** , 121042, **2020**.
2. LU S., TANG X., GUAN X., QIN F., LIU X., ZHANG D. The assessment of forest ecological security and its determining indicators: A case study of the Yangtze River Economic Belt in China. Journal of Environmental Management, **258**, 110048, **2020**.
3. ASKAR A., NUTHAMMACHOT N., SAYEKTININGSIH T., HERMUDANANTO. Assessing land cover changes and co2 emissions in tropical forests, 1998-2016: A case study of the sungai wain protection forest. Polish Journal of Environmental Studies, **28** (5), 3597, **2019**.
4. PEÑUELAS J., SARDANS J. Global change and forest disturbances in the mediterranean basin: Breakthroughs, knowledge gaps, and recommendations. Forests, **12** (5), 1, **2021**.
5. DE FRENNE P., LENOIR J., LUOTO M., SCHEFFERS B.R., ZELLWEGER F., AALTO J., HYLANDER K. Forest microclimates and climate change: Importance, drivers and future research agenda. Global Change Biology, **27** (11), 2279, **2021**.
6. ABDULLAH S., ADNAN M.S.G., BARUA D., MURSHED M.M., KABIR Z., CHOWDHURY M.B.H., HASSAN Q.K., DEWAN A. Urban green and blue space changes: A spatiotemporal evaluation of impacts on ecosystem service value in Bangladesh. Ecological Informatics, **70** , 101730, **2022**.
7. DE LOMBAERDE E., VANGANSBEKE P., LENOIR J., VAN MEERBEEK K., LEMBRECHTS J., RODRÍGUEZ-SÁNCHEZ F., DE FRENNE P. Maintaining forest cover to enhance temperature buffering under future climate change. Science of The Total Environment, **810** , 151338, **2022**.
8. ZHU S., ZHANG Y., ZHANG H., CAO Y., ZHANG G. Progress of researches on monitoring large-area forest disturbance by Landsat satellite images. Remote Sensing for Land and Resources, **26** (2), 5, **2014**.
9. SEIDL R., THOM D., KAUTZ M., MARTIN-BENITO D., PELTONIEMI M., VACCHIANO G., WILD J., ASCOLI D., PETR M., HONKANIEMI J., LEXER M.J., TROTSIUK V., MAIROTA P., SVOBODA M., FABRIKA M., NAGEL T.A., REYER C.P.O. Forest disturbances under climate change. Nature Climate Change, **7** (6), 395, **2017**.
10. TROTTER L., DEWAN A., ROBINSON T. Effects of rapid urbanisation on the urban thermal environment between 1990 and 2011 in Dhaka Megacity, Bangladesh. AIMS Environmental Science, **4** (1), 145, **2017**.
11. SEIDL R., SCHELHAAS M.J., RAMMER W., VERKERK P.J. Increasing forest disturbances in Europe and their impact on carbon storage. Nature Climate Change, **4** (9), 806, **2014**.
12. NABUURS G.J., LINDNER M., VERKERK P.J., GUNIA K., DEDA P., MICHALAK R., GRASSI G. First signs of carbon sink saturation in European forest biomass. Nature Climate Change, **3** (9), 792, **2013**.
13. SHI X., WANG T., CHEN K., CAO X., HE D., XU Z., DENG J. Reliability Analysis and Cumulative Impact Assessment of Forest Ecosystem Services: A Case Study of Jilin Province, China. IEEE Access, **9** , 59160, **2021**.
14. LIU Q., SHAN Y., SHU L., SUN P., DU S. Spatial and temporal distribution of forest fire frequency and forest area burnt in Jilin Province, Northeast China. Journal of Forestry Research, **29** (5), 1233, **2018**.
15. LI J., SHAN Y., YIN S., WANG M., SUN L., WANG D. Nonparametric multivariate analysis of variance for affecting factors on the extent of forest fire damage in Jilin Province, China. Journal of Forestry Research, **30** (6), 2185, **2019**.
16. SHAN Y., WANG Y., FLANNIGAN M., TANG S., SUN P., DU F. Spatiotemporal variation in forest fire danger from 1996 to 2010 in Jilin Province, China. Journal of Forestry Research, **28** (5), 983, **2017**.
17. KENNEDY R.E., YANG Z., GORELICK N., BRAATEN J., CAVALCANTE L., COHEN W.B., HEALEY S. Implementation of the LandTrendr algorithm on Google Earth Engine. Remote Sensing, **10** (5), 1, **2018**.
18. COHEN W.B., YANG Z., HEALEY S.P., KENNEDY R.E., GORELICK N. A LandTrendr multispectral ensemble for forest disturbance detection. Remote Sensing of Environment, **205** , 131, **2018**.
19. VAN WAGTENDONK J.W., ROOT R.R., KEY C.H. Comparison of AVIRIS and Landsat ETM+ detection capabilities for burn severity. Remote Sensing of Environment, **92** (3), 397, **2004**.
20. HISLOP S., HAYWOOD A., JONES S., SOTO-BERELOV M., SKIDMORE A., NGUYEN T.H. A satellite data driven approach to monitoring and reporting fire disturbance and recovery across boreal and temperate forests. International Journal of Applied Earth Observation and Geoinformation, **87** (October 2019), 102034, **2020**.
21. XING H., ZHU L., CHEN B., ZHANG L., HOU D., FANG W. A Novel Change Detection Method using Remotely Sensed Image Time Series Value and Shape based Dynamic Time Warping. Geocarto International, **0** (0), 1, **2021**.
22. GUO J., LI Q., XIE H., LI J., QIAO L., ZHANG C., YANG G. Monitoring of Vegetation Disturbance and Restoration at the Dumping Sites of the Baorixile Open-Pit Mine Based on the LandTrendr Algorithm. International Journal of Environmental Research and Public Health, **19** , 9066, **2022**.
23. RECUERO L., LITAGO J., PINZÓN J.E., HUESCA M., MOYANO M.C., PALACIOS-ORUETA A. Mapping periodic patterns of global vegetation based on spectral analysis of NDVI time series. Remote Sensing, **11** (21), 1, **2019**.
24. PENG W., KUANG T., TAO S. Quantifying influences of natural factors on vegetation NDVI changes based on geographical detector in Sichuan, western China. Journal of Cleaner Production, **233** , 353, **2019**.
25. CHEN B., NIE Z., CHEN Z., XU B. Quantitative estimation of 21st-century urban greenspace changes in Chinese populous cities. Science of the Total Environment, **609** , 956, **2017**.
26. LI J., PEI Y., ZHAO S., XIAO R., SANG X., ZHANG C. A review of remote sensing for environmental monitoring in China. Remote Sensing, **12** (7), 1, **2020**.
27. HISLOP S., JONES S., SOTO-BERELOV M., SKIDMORE A., HAYWOOD A., NGUYEN T.H. A fusion approach to forest disturbance mapping using time series ensemble techniques. Remote Sensing of Environment, **221** (June 2018), 188, **2019**.
28. FU B., LAN F., XIE S., LIU M., HE H., LI Y., LIU L., HUANG L., FAN D., GAO E., CHEN Z. Spatio-temporal coupling coordination analysis between marsh vegetation and hydrology change from 1985 to 2019 using LandTrendr algorithm and Google Earth Engine. Ecological Indicators, **137**, 108763, **2022**.
29. XING H., ZHU L., FENG Y., WANG W., HOU D., MENG F., NI Y. An Adaptive Change Threshold Selection Method Based on Land Cover Posterior Probability and Spatial

Neighborhood Information. IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, **14** , 11608, **2021**.

30. XING H., ZHU L., NIU J., CHEN B., WANG W., HOU D. A land cover change detection method combing spectral values and class probabilities. IEEE Access, **9** , 83727, **2021**.
31. XING H., ZHU L., HOU D., ZHANG T. Integrating change magnitude maps of spectrally enhanced multi-features for land cover change detection. International Journal of Remote Sensing, **42** (11), 4284, **2021**.
32. HANSEN M.C., LOVELAND T.R. A review of large area monitoring of land cover change using Landsat data. Remote Sensing of Environment, **122** , 66, **2012**.
33. WULDER M.A., MASEK J.G., COHEN W.B., LOVELAND T.R., WOODCOCK C.E. Opening the archive: How free data has enabled the science and monitoring promise of Landsat. Remote Sensing of Environment, **122** , 2, **2012**.
34. VIANA C.M., GIRÃO I., ROCHA J. Long-term satellite image time-series for land use/land cover change detection using refined open source data in a rural region. Remote Sensing, **11** (9)**2019**.
35. ZHU L., XING H., HOU D., FENG Y., YANG F., QIU P. A Long-Term Analysis of Spatiotemporal Change and Driving Factors on Poyang Lake during 1987-2019. Polish Journal of Environmental Studies, **30** (5), 4389, **2021**.
36. HOSSAIN M.S., BUJANG J.S., ZAKARIA M.H. Assessment of the impact of Landsat 7 Scan Line Corrector data gaps on Sungai Pulai Estuary seagrass mapping. Applied Geomatics, **7**, 189, **2015**.
37. YAN J., WANG L., SONG W., CHEN Y., CHEN X., DENG Z. A time-series classification approach based on change detection for rapid land cover mapping. ISPRS Journal of Photogrammetry and Remote Sensing, **158** (5), 249, **2019**.