Postprint: Mapping and Analysis of Disturbance and Recovery in Southern Plantation Forests Using Long-Term Landsat Time Series Imagery

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Abstract

Based on Landsat imagery from 1986 to 2011, and taking Fogang County, Guangdong Province—a southern plantation forest distribution region—as a case study, this study utilized the Landsat Ecosystem Disturbance Adaptive Processing System (LEDAPS) to preprocess and generate standard surface reflectance data, constructing a Landsat Time Series Stack (LTSS) for the LandTrendr algorithm to monitor long-term temporal changes in plantation forest disturbance and recovery. The study analyzed the interannual variation, magnitude, and duration of forest disturbances over 24 consecutive years, validated the accuracy of disturbance identification by the algorithm, and explored the driving forces of plantation forest disturbance. The results indicate that forest disturbances in Fogang County were relatively severe, generally around 1000 hm². In the years 1987, 2002, 2004, 2005, 2006, 2007, and 2009, the disturbed area exceeded 2000 hm², with the disturbed areas in 1987 and 2007 reaching over 6000 hm². Compared with the changes in forest disturbance, the forest recovery area in Fogang County showed relatively stable temporal variation. Through trend analysis of forest disturbance and recovery areas in Fogang County, it was found that from the late 1980s to the 1990s, the areas of forest disturbance and recovery were generally smaller than those after 2000, with more moderate trends than those after 2000. Starting from 2000, the forest disturbance area gradually increased, with the overall trend in area change higher than that of forest recovery, although forest recovery area still showed improvement. Specifically, forest disturbances lasting 1 year accounted for approximately 38% of the area, those lasting 2 years about 28%, those lasting 3 years about 25%, and those lasting 4 years about 7%, indicating mainly short-term acute disturbance events. Additionally, the areas of forest disturbance and recovery lasting more than 4 years in Fogang County did not exceed 100 hm². Before 2000, the areas of sustained disturbance and acute disturbance were comparable, showing relatively flat changes; after 2000,

the area of acute disturbance far exceeded that of sustained disturbance, reaching a maximum of approximately 2800 hm^2, although both showed fluctuating upward trends. In two selected 4 km^2 sample plots, visual validation methods based on image spectral identification and comparison with disturbance records showed that the algorithm results were relatively consistent with real surface interpretation information, with an error of approximately 0.1 km^2. Automated monitoring of forest disturbances using long-term time series remote sensing imagery is essential, and the derived qualitative, spatial, and quantitative information lays the foundation for sustainable forest management on one hand, and provides effective data support for evaluating forest productivity and forest carbon storage on the other.

Full Text

Mapping Disturbance and Recovery of Plantation Forests in Southern China Using Yearly Landsat Time Series Observations

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Abstract

Yearly Landsat imagery from 1986 to 2011 of a typical plantation region in Fogang County, Guangdong Province, southern China, was used as a case study. The Landsat Ecosystem Disturbance and Adaptive Processing System (LEDAPS) algorithm was implemented to generate standard surface reflectance images and construct a Landsat time series stack (LTSS). The LTSS was fed to the Landsat-based detection of trends in disturbance and recovery (LandTrendr) algorithm to monitor long-term changes in plantation disturbance and recovery, followed by intensive validation and continuous 24-year change analyses on annual change, disturbance amount, and disturbance duration. Validations derived from two chosen sample plots of 4 km^2 indicated that the LandTrendr-based mapped disturbance results strongly agreed with those derived from visual interpretation of pre- and post-disturbance multispectral images and visualization of local disturbance documents, with an error of 0.1 km^2.

Results indicated that forest disturbances in Fogang County were relatively drastic. An annual disturbance of 1000 hm^2 was witnessed for most years of the study, and annual disturbance exceeding 2000 hm^2 occurred in 1987, 2002, 2004, 2005, 2006, 2007, and 2009. Particularly, disturbances in 1987 and 2007 exceeded 6000 hm^2. In comparison to forest disturbance, forest recovery areas were relatively stable. Through trend analysis of forest disturbance and recovery in Fogang County, forest disturbance and recovery areas mapped in the late

1980s through 1990s were less than those mapped after 2000, and the trend was lower than that after 2000. Since 2000, forest disturbance areas have gradually increased, with a slight increase in forest recovery, but the overall magnitudes of forest disturbance exceeded those of forest recovery.

The area of forest disturbance with a duration of 1 year accounted for 38%, 28% for a duration of 2 years, 25% for a duration of 3 years, and 7% for a duration of 4 years; these disturbances were classified as abrupt and short-term disturbance events. Gradual forest disturbance and recovery events for a duration over 4 years existed, but the overall areas were less than 100 hm^2/a, and were highly different from the areas of abrupt disturbance events. Prior to 2000, abrupt and gradual disturbance areas were almost equal, with a gentle change. After 2000, abrupt disturbance areas were greater than those of gradual disturbances, with a maximum of 2800 hm^2, and both abrupt and gradual disturbances showed an undulatory increasing trend.

Based on the history and status of forest disturbances in Fogang County, the factors contributing to the environmental disturbance of forest plantations were analyzed to develop effective forest management strategies and countermeasures. The current study demonstrated the need to use dense time series images to map forest disturbance and recovery events in plantation forests. This approach could provide qualitative, locational, and quantitative forest change results for land use decision-makers and conservation communities, enabling the strategic development of sustainable forest management and providing effective data support to evaluate forest productivity and carbon storage.

Keywords: plantation; Landsat dense time series; LandTrendr; forest disturbance and recovery; dynamic monitoring; driving forces; Southern China

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Introduction

Disturbance is the primary driver of dynamic change in forest ecosystems, altering stand species composition and structure [1-3]. Typical natural disturbances and post-disturbance regeneration events affect forest carbon sinks [4], with disturbance status influenced by varying degrees under different landscape changes [5]. Forest harvesting, as an important component of anthropogenic disturbance and landscape dynamics, affects forest carbon storage on one hand, while being closely associated with forest cover, topography, and socioeconomic factors on the other [6]. The implementation of large-scale afforestation and reforestation programs has given China the world’ s largest plantation area, accounting for 1/4 of global plantation area [7], and the existence of these plantations has increased forest carbon storage [8]. In southern China, afforestation and reforestation activities are among the main causes of regional carbon sink changes [9]. Fast-growing and high-yield plantation construction plays an important role in alleviating timber demand and improving economic and ecological benefits, and has been listed as a national production base with pivotal significance [10].

However, during plantation establishment, species selection primarily considers fast-growing characteristics, resulting in plantations that generally suffer from single species composition, poor structure and function, and frequent pest and disease occurrences, leading to rapid, short-rotation characteristics in southern China's forests [11-12]. Developing scientifically reliable methods to monitor the spatiotemporal patterns of forest disturbance or recovery is crucial for healthy plantation management and has profound significance for carbon accounting [9,13]. Relying solely on two or three phases of long-interval imagery [14-15] often fails to fully capture the frequent harvesting and post-harvest regeneration activities that occur in southern plantations.

In recent years, satellite remote sensing technology development, particularly time series remote sensing data, has provided data support for forest disturbance monitoring and has been successfully applied [16]. However, how to quickly and effectively identify forest disturbance or recovery phenomena with different durations and geographical distributions remains a technical challenge. Although some automated forest change analysis algorithms [17-21] provide powerful tools for near-real-time monitoring of forest ecosystems, few methods can monitor both short-term forest changes and detect continuous forest changes using time series data [22-23] while fully utilizing the temporal and intensity characteristics of different disturbance types. The LandTrendr algorithm [20] has been successfully used for forest disturbance monitoring in the Pacific Northwest region [19-20,24], but studies using nearly continuous time records to monitor plantation disturbance or recovery distribution in southern China have not been reported. Continuous plantation disturbance and recovery data records are of great value for regional forest management, policy formulation, ecosystem conservation and restoration, biodiversity protection, and carbon evaluation in southern China.

The main objectives of this study are: (1) to analyze the spatiotemporal patterns of forest disturbance and recovery in Fogang County, Guangdong Province, based on long time series remote sensing image data stacks from different sources using the Landsat LandTrendr algorithm, including forest disturbance year, amount, and duration; and (2) to validate the mapping accuracy of forest disturbance and recovery using existing imagery, historical data, and field survey records.

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1. Study Area and Data

Fogang County is located in central Guangdong Province, on the edge of the Pearl River Delta, in the southeastern corner of Qingyuan City. Most of the county' s mountainous and hilly areas are covered by plantations, with dominant species including eucalyptus, lychee, and longan fruit trees. Currently, fast-growing commercial forests and economic forests dominate the county' s forest landscape. This study selected one scene covering most of Fogang County (path/row: p122r043) as the study area (hereinafter referred to as Fogang County)

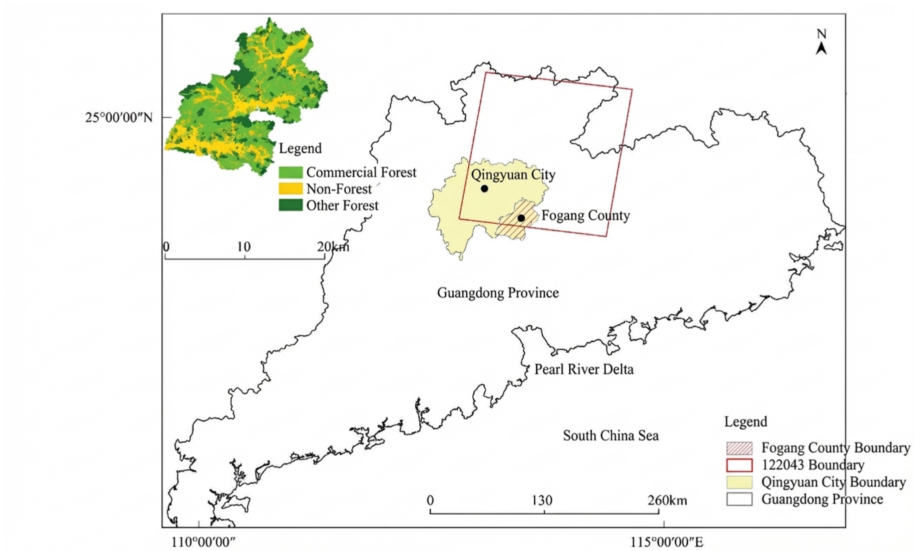

Figure 1: Figure 1

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FIGURE:1 Geographical location of the study area

The Landsat TM/ETM+ remote sensing images used in this study were obtained from the United States Geological Survey' s Earth Resources Observation and Science (USGS/EROS) Center, purchased from the Chinese Academy of Sciences' Earth Observation and Digital Earth Center (BJGS), or freely obtained from the Geospatial Data Cloud. Image acquisition dates were selected during peak growing seasons to minimize phenological effects on spectral identification. Regarding cloud cover, since obtaining completely cloud-free imagery is difficult, we ensured minimal cloud cover while maintaining a certain proportion of high-quality data within the time series. For low-latitude areas, acquisition dates could be extended to late October. Table 1 describes the remote sensing data used in the analysis.

The Guangdong Provincial Forestry Ecological Planning and Design Institute provided Fogang County' s forest resource database for 2005 and subcompartment data for 2011 to identify forest types and different land cover types. Google Earth high-resolution images were used to understand field conditions. Field surveys and consultation of local historical records and relevant personnel revealed extensive forest harvesting and some disaster phenomena in the region.

TABLE:1 Description of remotely sensed images used in the current analysis

2. Research Methods

2.1 Atmospheric Correction Data from the two sources were standardized using LEDAPS to construct the LTSS, as specifically described in Shen et al. [25]. To further ensure the effectiveness of spectral identification, cloud and shadow masking was performed based on target images requiring repair and cloud-free reference images. Reference images were integrated to create an average reference image, which was then compared with target images. Cloud and shadow masking was performed through artificially set thresholds, requiring at least one reference image to ensure image clarity or effective cloud masking. Cloud masking primarily utilized band 6, while shadow masking mainly used band 2. When pixel values were below the threshold, they appeared yellow on the image, indicating areas requiring masking.

2.2 Spectral Index Selection Based on previous research [20], the Normalized Burn Ratio (NBR) demonstrates maximum sensitivity for capturing disturbance events and has a higher probability of matching disturbances compared to Normalized Difference Vegetation Index (NDVI) and Tasseled Cap Wetness index [19,26]. This index uses the difference-to-sum ratio of near-infrared (NIR) and short-wave infrared (SWIR) to monitor disturbances:

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

NIR reflects healthy green vegetation, while SWIR reflects rocks and bare soil. Healthy forests have high NIR and high SWIR values, showing lower NBR values. After forest disturbance, SWIR values increase. Image data in the time series stack were transformed and matched pixel-by-pixel with cloud mask data, and these time series source data were used for algorithm segmentation.

2.3 Time Series Segmentation Algorithm and Filtering The core of the LandTrendr algorithm is time series segmentation, using each pixel in the time series to identify changes. Small variations are filtered to increase the signal-to-noise ratio. The first step defines segmentation endpoints determined by vertex years. The second step uses flexible mixing of point-to-point or regression lines to obtain the best linear trajectory. The algorithm produces annual source data, vertex-corresponding years, and NBR values for each point in the segmentation, which are used for subsequent mapping algorithms. Annual fitted NBR values describe the trajectory [FIGURE:2].

FIGURE:2 Threshold settings for cloud and shadow screening

The process identifies 25 vertices and unchanged values. A regression model based on surface data is used to assess vegetation cover proportion and generate disturbance magnitude values [20]. Considering this regression model was built for different vegetation cover and density in the Pacific Northwest region, adjustments were made to adapt to the vegetation characteristics of the current study area. Disturbance duration values range from 1-25 years, determined by the number of years corresponding to NBR values. Parameter settings are shown in Table 2.

TABLE:2 Parameters used in LandTrendr processing

2.4 Forest Disturbance Mapping Disturbance maps were created based on annual disturbance magnitude and duration images. A minimum mapping unit of 0.1 km² was used to ensure disturbance patches were sufficiently large to avoid validation difficulties across broad areas while capturing most forest harvesting activities. When multiple disturbances occurred, the disturbance patch was classified based on the sum of patch area and relative disturbance magnitude products to balance different disturbance magnitude events. Patches with the highest values were considered primary disturbances, and those with lower values were secondary disturbances. Finally, random forest classification [27] was applied using forest training samples obtained through manual interpretation. Pixels that remained forest throughout the time series were extracted, and the final disturbance map filtered out any disturbances in non-forest pixels.

The algorithm monitors abrupt or continuous disturbances. Disturbance patterns with the largest changes within 4 years are defined as abrupt disturbance or recovery, while those with changes over 4 years are defined as gradual disturbance or recovery. The algorithm processes entire images, and forest areas identified in the mask are used to cut the disturbance result image to the study area boundary.

FIGURE:3 Workflow for detecting forest disturbance and recovery events using LandTrendr segmentation algorithm

2.5 Forest Recovery Mapping To obtain post-disturbance forest recovery, this study calculated two indicators of vegetation recovery: absolute and relative indicators. The absolute indicator relates to disturbance, while the relative indicator is the recovery indicator. The formulas are as follows:

$$\Delta NBR_{regrowth} = NBR_{fitted,t5} - NBR_{fitted,t0}$$

where $NBR_{fitted,t5}$ and $NBR_{fitted,t0}$ represent fitted NBR values after disturbance occurrence and at the vertex defining the start of recovery segmentation, respectively. $\Delta NBR_{disturbance}$ represents forest loss caused by disturbance before the time series began. The denominator changes during disturbance segmentation.

2.6 Forest Disturbance Product Validation The LandTrendr algorithm produced a map of the year with greatest disturbance change in Fogang County.

When pixels experienced multiple disturbances, only the most significant change was recorded, representing the primary disturbance in that area. Typical areas generally contain both primary and secondary disturbances (stand-replacement events). After disturbance, pixels no longer appear as forest pixels in Landsat images. Secondary disturbances show greater brightness after disturbance compared to before, with reduced greenness but remaining forest pixels. Primary disturbances typically reflect regional disturbance events, while secondary disturbances are mainly low-magnitude events generally occurring after primary disturbances.

Given that forest recovery requires a long process and validation data is difficult to obtain, this study temporarily did not consider forest recovery validation. Two typical areas in Fogang County were selected to validate disturbance mapping using Landsat imagery from corresponding disturbance years. Disturbed areas were overlaid onto each image in the time series stack, and validation was performed by comparing visually interpreted disturbance areas with algorithm-derived areas. Validation materials primarily came from visual interpretation of existing Landsat images and high-resolution Google Earth images, supplemented by field survey data containing subcompartment areas.

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3. Results

3.1 Validation of Forest Disturbance Products Validation based on image spectral visual interpretation and comparison showed that typical disturbance areas could be easily identified. In one 4 km² sample plot, the primary disturbance occurred in 2002, 2005, 2006, and 2007, with some disturbances also occurring in other years but not as primary disturbances. The visually interpreted disturbance area was 0.8768 km², while the automated disturbance mapping in the primary disturbance year map showed 0.7659 km². In another sample plot, primary disturbances occurred in 2002, 2005, 2007, and 2008, with disturbances each year but those in 2005 and 2007 being primary disturbances, consistent with the algorithm' s definition. The visually interpreted area was 0.3165 km², while the automated mapping showed 0.2511 km². These results indicate that visual interpretation results have some error compared with LandTrendr algorithm-filtered disturbance images [FIGURE:4].

FIGURE:4 Visual validation of forest disturbance using Landsat images

3.2 Temporal Distribution Characteristics of Maximum Forest Disturbance and Recovery The forest greatest disturbance year map

shows the year of maximum change for each pixel. When pixels experienced multiple disturbances, only the most significant change from segmentation start to end is displayed. Continuous forests have been masked, with different colors representing different disturbance year distributions. This study characterized

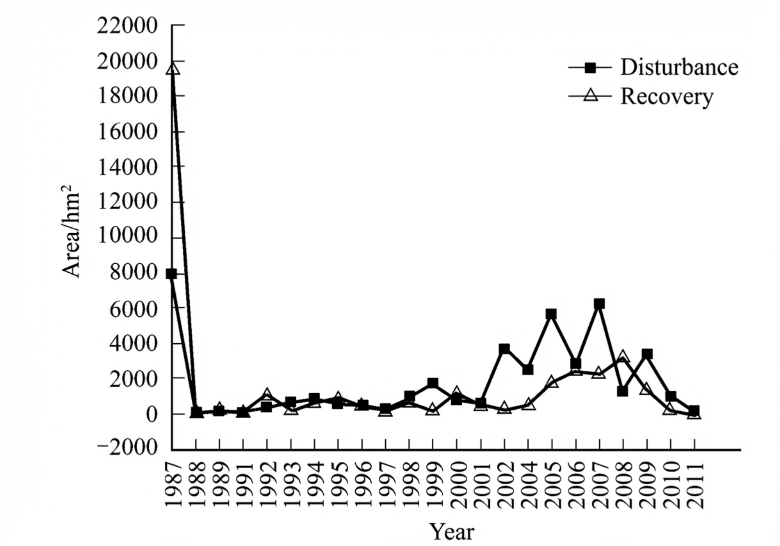

Figure 2: Figure 5

annual forest disturbance and recovery areas at the pixel scale, revealing drastic forest disturbance in Fogang County.

FIGURE:5 Fogang County forest greatest disturbance year map

Annual disturbance area exceeded 1000 hm² for most years, with 1987, 2002, 2004, 2005, 2006, 2007, and 2009 exceeding 2000 hm². Disturbances in 1987 and 2007 reached 6000 hm². Forest recovery areas showed relatively stable temporal variation. Trend analysis of forest disturbance and recovery areas in Fogang County indicated that areas from the late 1980s through the 1990s were generally smaller than those after 2000, with flatter trends. Since 2000, forest disturbance areas have gradually increased, with slight increases in forest recovery, though overall disturbance magnitudes exceeded recovery

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FIGURE:6 Temporal features of forest disturbance and recovery areas detected over Fogang County

Disturbed pixels were combined into adjacent patches with a minimum area of 0.1 km² to calculate areas of different disturbance durations. Results show forest disturbance area in Fogang County generally decreases with increasing duration, mainly occurring within 1-2 years, with 1-year duration accounting for the highest proportion. This indicates that forest disturbances in Fogang County are primarily abrupt, short-term events

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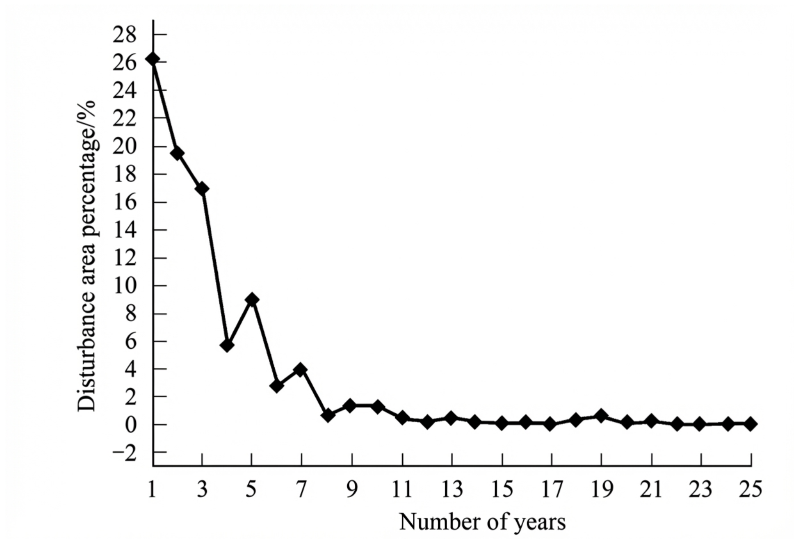

Figure 3: Figure 6

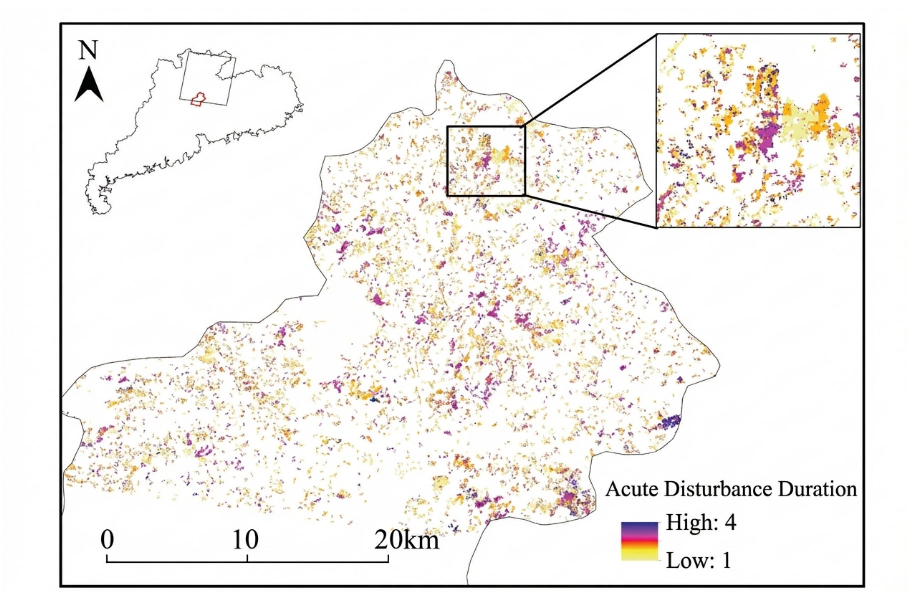

Figure 4: Figure 7

FIGURE:7 Fogang County forest disturbance area changing with duration

3.3 Spatial Distribution Characteristics of Maximum Forest Disturbance Forest disturbance in Fogang County shows strong spatial distribution patterns

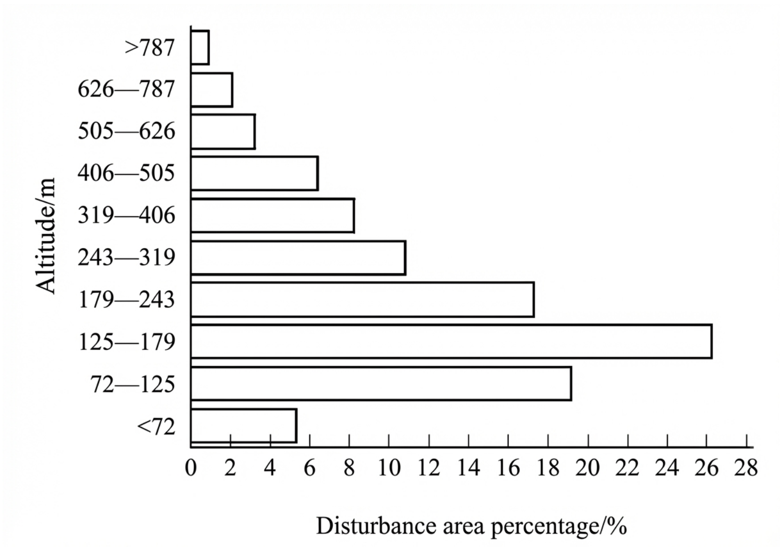

Figure 5: Figure 8

. As elevation increases, the percentage of disturbed area shows a clear decreasing trend. The largest disturbance distribution occurs at elevations between 125-179 m. Only 0.96% of forest disturbance area occurs above 400 m elevation.

FIGURE:8 Fogang County forest disturbance area changing with altitude

3.4 Abrupt Forest Disturbance Pattern Analysis Primary and secondary abrupt disturbance events were identified . Before the 1990s, primary disturbance areas were significantly smaller than after 2000. Primary disturbance areas in 2005, 2007, and 2009 exceeded 2000 hm^2, showing frequent occurrence. This pattern aligns with the short-rotation characteristics of fast-growing plantations in Fogang County, showing disturbances occurring approximately every two years, particularly evident before 2000. Abrupt disturbance duration distribution shows varying annual proportions, with 1-year and 2-year durations being most common, indicating numerous short-term disturbance events

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TABLE:3 Area of forest major and minor disturbance

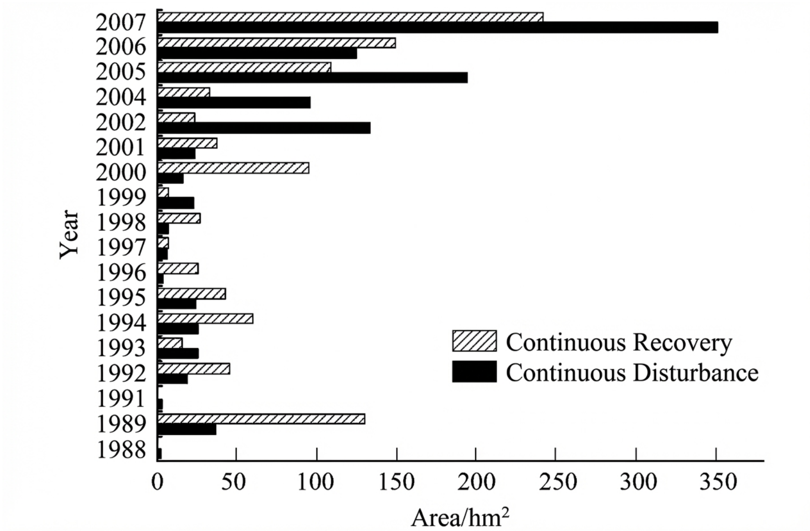

Figure 6: Figure 9

FIGURE:9 Fogang County abrupt disturbance changing with duration

3.5 Gradual Forest Disturbance and Recovery Pattern Analysis Gradual forest disturbance and recovery exist in Fogang County but cover small total areas. After 2000, gradual disturbance areas show fluctuating increases, reaching maximum values of 380 hm² and 220 hm² in 2007. Before 2000, gradual recovery areas were larger than gradual disturbance areas, indicating forest cover growth and regeneration. After 2007, gradual recovery areas increased, showing forest growth status. Comparison of abrupt and gradual disturbance areas shows they were nearly equal before 2000, but after 2000, abrupt disturbance areas far exceed gradual ones, with both showing fluctuating trends [FIGURE:10, FIGURE:11].

FIGURE:10 Comparison of gradual forest disturbance and recovery areas in Fogang County

FIGURE:11 Comparison of abrupt and gradual disturbance areas in Fogang County

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4. Discussion

4.1 Driving Force Analysis Fogang County represents a typical plantation distribution area with extensive artificial forests. The severe forest disturbance is mainly caused by abrupt disturbance events such as plantation harvesting, slash burning, urban construction along roads and rivers, and severe climate impacts. These findings align well with forest resource surveys and subcompartment records.

The 1980s forestry policy in Guangdong Province led to large-scale afforestation. In 1995, Fogang County implemented fast-growing eucalyptus plantation programs. When these plantations reached maturity, large amounts of timber were harvested for further afforestation, and pre-plantation slash burning generated extensive disturbance events [28-31]. After 2000, urbanization development accelerated, and forests near roads and rivers were continuously encroached upon, causing drastic forest area reduction and fluctuating disturbance increases [32]. In 2005, extensive fire scars were distributed, indicating intensive slash burning. The 2008 ice and snow disaster caused severe forest damage, and subsequent rapid forestry recovery policies facilitated forest restoration.

4.2 Preprocessing and Algorithm Analysis The LandTrendr algorithm performs different types of filtering at the pixel scale, ensuring the identifiability of disturbance patch areas and helping monitor typical disturbance events. Fast-growing plantations are suitable for mid-low elevation areas that are easy to manage and transport. The higher the elevation, the lower the probability of forest disturbance. However, some data quality issues existed: 1987 data contained anomalies and could not correctly identify surface features, causing obvious misclassification of disturbance and recovery.

In driving force analysis, not all possible natural and anthropogenic driving factors were considered, and no quantitative relationships were established—only qualitative analysis was performed. While the algorithm monitors disturbance year and amount, it can identify disturbances occurring within specific years and distinguish primary and secondary disturbances, particularly abrupt versus gradual disturbances. However, it captures only maximum disturbances based on magnitude and area, omitting some subtle disturbances.

The algorithm requires Landsat time series data stacks, where image registration quality and data format affect subsequent algorithm accuracy. Original data came from different sources with inconsistent processing and archiving methods, requiring standardization that inevitably introduces errors. Artificial threshold setting during parameter configuration also introduces result errors. The algorithm requires imagery dates distributed throughout the year, but obtaining such specific dates while ensuring good data quality is impossible. Monthly deviations create phenological effects, and 1-2 year intervals prevent good capture of missing year information, affecting interannual disturbance monitoring results.

4.3 Validation Method Analysis Foreign validation techniques are relatively mature [17,19,33]. Tools like TimeSync can automatically obtain interpretation results for comparison with algorithm segmentation [19,34]. However, due to lack of historical ground data, forest resource data, and high-resolution imagery in China, these methods were not promoted in this study. Validation results showed disturbance monitoring tended to be smaller than visual interpretation, mainly because the algorithm is more sensitive to forest disturbance monitoring in high-density coniferous forest areas, with limitations in non-pure coniferous areas causing misjudgment [35]. Despite identification deficiencies, monitoring results remain referencable.

4.4 Algorithm and Technology Application Analysis Forest disturbance characteristics include duration, frequency, and area [36]. Due to lack of continuous annual disturbance type and biomass historical statistics, this study could only monitor abrupt and gradual disturbance durations, with insufficient positioning of specific disturbance types, intensity, and causes [1,5-6]. This study explored automated monitoring technology for forest disturbance and recovery in southern plantation areas. Although initial domestic use of the LandTrendr algorithm faced technical and data selection difficulties, integrating and improving preprocessing techniques successfully enabled disturbance mapping. Qualitative driving force analysis based on quantified forest changes can provide forest disturbance and recovery history and constitutes a key component for future evaluation of forest carbon storage and biodiversity protection under climate change, providing reference for automated analysis of long-term forest disturbance and recovery changes in China.

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Figures

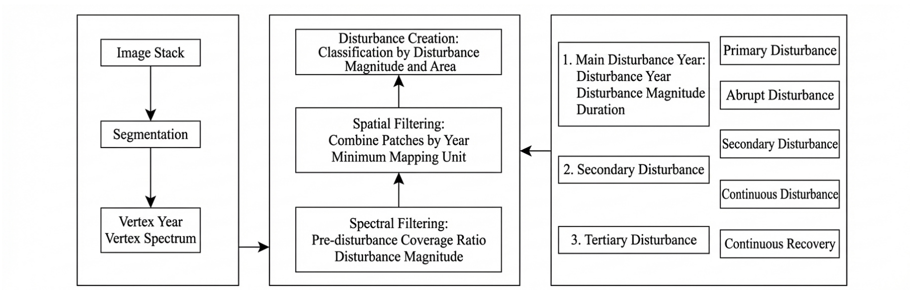

Figure 7: Figure 3

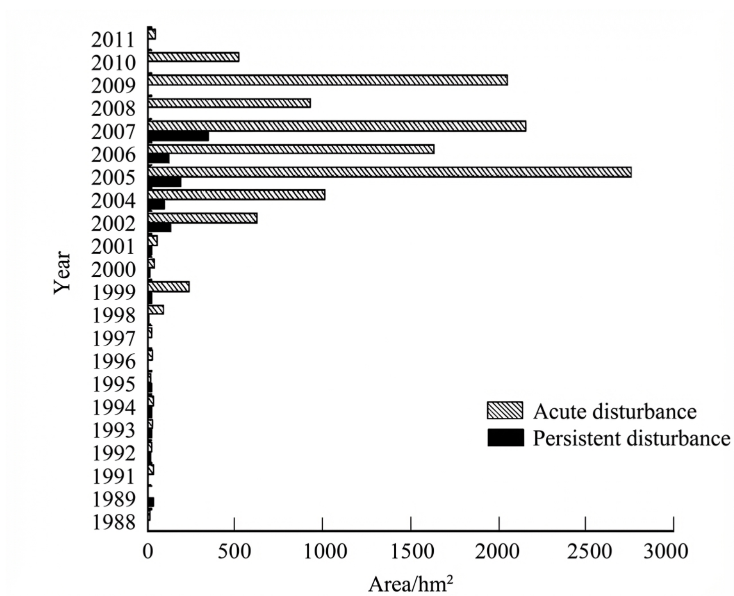

Figure 8: Figure 10

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