



Article Forest Damage by Super Typhoon Rammasun and Post-Disturbance Recovery Using Landsat Imagery and the Machine-Learning Method

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Abstract: Typhoon Rammasun landed on the southern coastal region of Guangdong and Hainan Provinces on 18 July 2014, and is the strongest recorded typhoon since the 1970s in China. It caused enormous losses in human lives, property, and crop yields in two provinces; however, its impact on forests and subsequent recovery has not yet been assessed. Here we detected forest damage area and severity from Typhoon Rammasun using Landsat 8 OLI imagery, the Random Forest (RF) machine-learning algorithm, and univariate image differencing (UID) methods, and the controlling factors on damage severity and canopy greenness recovery were further analyzed. The accuracy evaluations against sample plot data indicated that the RF approach can more accurately detect the affected forest area and damage severity than the UID-based methods, with higher overall accuracy (94%), Kappa coefficient (0.92), and regression coefficient ($R^2 = 0.81$; p < 0.01). The affected forest area in Guangdong and Hainan was 13,556 km² and 3914 km², accounting for 13.8% and 18.5% total forest area, respectively. The highest affected forest fractions reached 70% in some cities or counties. The proportions of severe damage category accounted for 20.85% and 21.31% of all affected forests in Guangdong and Hainan, respectively. Our study suggests that increasing tree density and choosing less sensitive tree species would reduce damage from typhoons in vulnerable areas such as fringe, scattered, and high-slope forests. The canopy greenness of damaged forests recovered rapidly within three months for both provinces; however, management strategies should still be applied in the severely damaged areas to sustain forest functions since the persistent forest canopy structure and biomass may require a longer time to recover.

Keywords: typhoon; Rammasun; wind damage; damage severity; machine-learning; Landsat 8 imagery; the southern China

1. Introduction

Many previous studies assessed the impacts of tropical cyclones (e.g., hurricanes and typhoons) on land ecosystems worldwide, especially in areas affected by super strong tropical cyclones, such as in the United States, Mexico, and Asia-Pacific and South American countries. China is frequently affected by typhoons, and is one of the countries most severely affected by typhoons in the Asia-Pacific region. From 2000 to the present, more than 100 strong typhoons have made landfall on coastal cities in China, which have caused enormous losses in human lives, property, and crop yields. For example, the Super Typhoon Saomai landed in Zhejiang Province in 2006, causing 485 deaths and \$3.3 billion USD economic loss [1]. The Super Typhoon Meranti made landfall in Fujian Province in 2016, causing a direct economic loss of \$1.7 billion USD and 28 deaths in Xiamen City alone [2].



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Copyright: © 2022 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (https:// creativecommons.org/licenses/by/ 4.0/). Super Typhoon Lekima landed in Zhejiang Province in 2019, causing 57 deaths and a direct economic loss of \$8.9 billion USD [3]. Most studies on typhoons' impacts in China focused on the physical characteristics, rainfall patterns, wind fields, economic losses, and cropland production losses, while only a few studies have addressed typhoons' impact on forests [4,5].

Typhoons are a tropical cyclone occurring in the western Pacific Ocean, which are characterized by strong winds accompanied by very heavy rainfall, and cause both direct and indirect impacts on forests [6]. Due to different intensities and durations of landfall, damage to forest trees can include uprooting, falling, branch breaking, and massive leaf blowing. This direct damage can also indirectly cause larger areas of tree mortality by overwhelming numbers of fallen trees, soil erosion, landslide, and pests/insects, which in turn may significantly alter the structure, biomass, species composition, and nutrient status of forests [5,7,8]. Many traditional monitoring methods, such as the breaks for additive season and trend monitor (BFAST), univariate image differencing (UID), postclassification comparison (PCC), selective principal component analysis (PCA), and change vector analysis (CVA) [9–16] have been widely applied to assess the impacts of tropical cyclones on forests. In these methods, either two phases or time-series of satellite images were used to compare the differences prior and post a disturbance event. The UID method determines the disturbed grid pixels by applying a threshold and calculating the difference of VIs or spectral reflectance before and after a disturbance event. The UID method only requires two phases of cloud-free satellite images and thus is more widely applied (e.g., [2,17,18]). Wang and Xu [14] compared the UID, PCC, CVA, and PCA methods for detecting forest damage due to Hurricane Katrina and argued that UID and CVA methods performed similarly and were better than PCA, while the PCC method had slightly higher accuracy. The individual vegetation indices (VIs), such as Normalized Difference Vegetation Index (NDVI), EVI (Enhanced Vegetation Index), Normalized Difference Moisture Index (NDMI), Normalized Difference Infrared Index (NDII), as well as Tasseled Cap Greenness, Brightness, and Wetness (TCG, TCB, and TCW) were applied to reflect wind damage on forests [2,10,17–20]. For example, Wang et al. [15] detected forest damage due to Hurricane Katrina using NDVI, EVI, and NDII based on MODIS images, and compared the results with field inventory data. Their study concluded that NDII had higher accuracy than NDVI and EVI, since NDII is more sensitive to canopy water content changes. In contrast, Schultz et al. [16] compared the performance of various VIs in detecting deforestation, and concluded that wetness related VIs (NDWI and TCW) were more accurate than greenness related VIs (NDVI and TCG).

Recently, machine-learning methods, such as Random Forest (RF), Support Vector Machine (SVM), and Convolutional/Artificial Neural Network (CNN/ANN) were introduced and applied in assessing wind damage to forests [9–11,21–23]. For example, Einzmann et al. [21] applied the RF method to detect forest damage, and indicated that RF classifier can accurately (robustness > 90%) detect forest damage severity. Zhang et al. [10] compared the performance of SVM, RF, K-Nearest Neighbor (K-NN), and ANN for detecting forest damage due to hurricanes and argued that RF has the highest robustness. Several studies [23,24] also compared the effectiveness of the traditional methods with the machine-learning methods, and argued that the performance of machine-learning methods was similar to or even worse than the conventional methods. However, some other studies argued that if precise sampling plot data are available, the machine-learning methods could be more accurate because they can integrate multiple VIs, band information, image texture and other auxiliary data and fit the best model to identify the affected forest areas and calculate damage severity, which can avoid the deviations from individual variables [11,25].

Typhoon Rammasun is a super strong typhoon, and landed on Hainan and Guangdong Provinces on 18 July 2014. It is the strongest recorded typhoon that landed in China in the past 40 years. Many studies have assessed forest damage in response to tropical cyclones worldwide. Compared with other countries, China's coastal areas have more complex terrain and vegetation conditions and lack of enough field survey data, which makes it more challenging to study the impacts of typhoons on China's forests. Therefore, only a few studies have addressed the impacts of Rammasun on forest structure and function in some parts of Hainan and Guangdong Provinces [4,5,7]. For example, Xue et al. [26] estimated the damage resistance of different tree species to Rammasun in Wenchang County. Based on statistical data, Zhang et al. [4] assessed the spatial distribution patterns of damage severity of rubber plantation by Rammasun in Hainan. Based on an inventory, Yang et al. [27] also assessed the damage to urban trees by Rammasun in Haikou City of Hainan, indicating that among the investigated trees, the severe and moderate damage rates accounted for about 35.4% and 43.8%, respectively. Qiu et al. [28] compared damage severities of different mangrove communities in response to Rammasun, and concluded that tree types, canopy size, and tree density can significantly affect their responses to Rammasun. According to inventory data, Xue et al. [26] indicated that about 372.65 km² forest area was affected due to Rammasun, resulting in an economic loss of \$0.22 billion USD in forestry sector in Wenchang County of Hainan Province. These existing studies only focused on the economic trees or mangroves, and mainly were based on simple inventory approaches. No studies have been conducted for comprehensively assessing the impacts on all forests at the entire typhoon impacted zones, which further resulted in no regional or national reports on forest damage in response to the super typhoon Rammasun in China. Effective forest recovery management requires precise information on the geographic distribution as well as extent and severity of damage [19].

In this study, our objectives are to (1) evaluate the detection performance and compare the effectiveness of RF method with the UID methods in detecting forest damage area and severity in response to Typhoon Rammaun; (2) assess the forest damage area and severity due to super Typhoon Rammasun in Guangdong and Hainan provinces, (3) identify the main factors affecting forest damage, and (4) monitor forest resilience and recovery after Rammasun. The data and information from this study will not only be useful for national reports regarding the effects of typhoons on forest damage in China but also help policymakers to develop rehabilitation and conservation strategies for reducing forest damage and sustainably manage forests after disturbance.

2. Methods

2.1. Characteristics of Typhoon Rammasun

Typhoon Rammasun formed in the Northwest Pacific Ocean on 9 July 2014, and made repeated landfalls in China and the Philippines, causing significant economic damage and casualties in the coastal areas of both countries. At 15:30 p.m. on 18 July 2014, Typhoon Rammasun made landfall in Wenchang City, Hainan Province, China (Figure 1). At 19:30 p.m. on 18 July 2014, Rammasun landed again on the coast of Longtang Town, Xuwen County, Guangdong Province. It was a super strong typhoon with a maximum wind speed of 60 m/s when landing, which makes it a Category 17 typhoon (the strongest) according to the Chinese GBT 19201-2006 standard or a Category 4 hurricane (Catastrophic degree) according to the Saffir–Simpson Hurricane Scale. Fifty-nine counties and cities in Hainan and Guangdong provinces were affected, causing 56 casualties and total economic losses of approximately \$7 billion USD.

2.2. Study Region

Guangdong Province is located in the southeastern China (20°13′–25°31′N, 109°39′–117°19′E) (Figure 2), covering land area of 179,725 km². Guangdong Province has a subtropical monsoon climate. The mean annual maximum temperature ranges from 28 °C to 29 °C and the minimum temperature ranges from 16 °C to 19 °C, and the mean annual precipitation is from 1300 mm to 2500 mm. Climatic disturbances, such as floods, droughts, and typhoons occurred frequently. The northern part of Guangdong Province is mostly mountains and high hills, and the southern part is mostly plains. The forest cover is 51.26% (10.76 million ha) according to the 8th national forest resource inventory (NFRI) (http://forest.ckcest.cn/sd/si/zgslzy.html; accessed on 1 February 2022).



Figure 1. The administrative boundaries of cities or counties in Guangdong and Hainan Provinces and the path and wind speed of Typhoon Rammasun.



Figure 2. The location of the study region (Guangdong and Hainan Province), and distributions of forests and training and validation plots.

Hainan Province is located in southernmost China $(108^{\circ}37'-111^{\circ}03'E, 18^{\circ}10'-20^{\circ}10'N)$ (Figure 2), with a land area of 35,400 km². It has a tropical monsoon climate, with a mean annual temperature of 22–27 °C and a mean annual precipitation of 1639 mm. Hainan is surrounded by low and flat areas, with a high center and a gradual decline toward the

periphery. Forests are mainly distributed in mountainous areas. The forest cover is 55.38% (2.15 million ha) according to the 8th NFRI.

2.3. Data Sources and Descriptions

2.3.1. Satellite Data

Landsat 8 OLI images were used in this study, which were obtained from the Google Earth Engine (GEE) platform (https://earthengine.google.com/; accessed on 1 February 2022). Due to high rainfall and cloud cover in the study region, we cannot collect a fullcover noise-free image for both provinces right before and after Typhoon Rammasun, so we extended the collection time from 15 May to 15 July 2014 to represent the pre-disturbance conditions, while from 20 July to 20 September 2014 to represent post-disturbance conditions. The Landsat images were already atmospherically corrected using LEDAPS or LaSRC (Surface Reflectance Code) [29,30]. Both algorithms used CFMASK as a built-in cloud detection method and generated QA (Quality Assessment) bands which identify the pixels that exhibit adverse instrument, atmospheric, or surficial conditions. We removed the pixels marked as cloud or other improper objects and fill them with clear pixels from other neighboring months to ensure that only cloud-free images were generated. To reduce the influence of seasonal phenological changes, cloud-free images closer to the outbreak day of Typhoon Rammasun were used. After removing cloud cover pixels, about 70% of the composite pixels were from the Landsat image scenes in the neighboring three months (June, July, and August 2014). The images of other nearest months in the collection time period were used to fill in the missing pixels in sequence.

To characterize forest recovery trajectories after Typhoon Rammasun, all available Landsat 8 OLI images during 15 May to 20 September from 2000 to 2020 were collected. To be consistent, the collected images were all mosaicked to produce an annual time-series composite for the two periods (20 May–15 July and 20 July–20 September) during 2010–2020. All images are identified, processed, and analyzed on the GEE platform.

2.3.2. Training and Validation Plot Data Collection

At present, the training and validation plot data for machine-learning method are generally obtained either through field campaigns (e.g., ground-truth GPS points), or through visually labeling of target classes on pre-existing high-resolution imagery by trained experts (e.g., points or polygons manually drawn on target images) [23,31]. Due to lack of field inventory plot data, the training and validation plot data were visually interpreted based on the high-resolution satellite images. High-resolution satellite images have long been used to collect sampling plot data for training and validation of classified results [23]. On the Google Earth Pro platform, many high-resolution (<5 m) satellite images are available. These images mostly came from WorldView-1/2/3 series, GeoEye-1, SPOT, Pleiades, and Quickbird platforms. We searched for the available high-resolution images before and after Typhoon Rammasun. The changes in reflectance of the high-resolution images were calculated. Based on the changed reflectance and visual interpretation, the affected areas were drawn as polygons (Figure 3). Areas with more pronounced changes are usually selected, where the affected area can be clearly distinguished from the safe area within area of 30 m \times 30 m. The drawn polygons were further aggregated to 30 m \times 30 m spatial resolution to match the Landsat grid pixels. The mean forest canopy damage severity (%) at the 30 m \times 30 m pixels was recorded. We further classified two types of forest status according to the damage severity at these selected grid cells: affected area (>5% canopy loss) and non-affected area (<5% canopy loss). Each 30 m \times 30 m pixel represented a sample plot. Totally, we collected 900 sample plots (600 in Guangdong and 300 in Hainan). Among these plots, 650 were randomly selected as training points for the RF model (450 in Guangdong and 200 in Hainan), 200 of which were assigned damage severity values (120 in Guangdong and 80 in Hainan). The remaining 250 (150 in Guangdong Province and 100 in Hainan Province) were used for validation of the classification results.



Figure 3. Visual interpretation methods for affected forest area and calculation of damage severity based on Google Earth Pro high-resolution images. (a): high-resolution images before Typhoon Rammasun; (b): after Typhoon Rammasun; (c): methods for calculating forest canopy loss rates.

2.3.3. Other Auxiliary Data

Topographic factors such as elevation, slope and aspect were found to significantly influence the damage by typhoons/hurricanes [7,14,15,32,33]. Therefore, we used these data as input variables for the RF mechanism. The high spatial resolution Digital Elevation Model (DEM) data, originally sourced from the NASA/USGS Shuttle Radar Topography Mission (SRTM), was collected from GEE platform using the ee.Terrain.products() function. Other topographic data were calculated from DEM. Due to the lack of good gridded wind velocity data for the typhoon period, we used the distance (km) from typhoon track (typhoon center) to represent the impacts from wind velocity. Using the typhoon track as the centreline, multi-layer buffer zones were set up within the study area. The distances from the typhoon track were further classified into four categories, 0–50 km, 50–100 km, 100–200 km, and >200 km.

In addition, many previous studies also indicated that climatic factors, such as wind velocity and rainfall, can affect damage severity by typhoons/hurricanes [14,15,32–34]. Therefore, we also used wind velocity and rainfall as input variables in the RF model to classify forest damage. Both datasets were collected from the CLDASV2.0 climatic products in China's Meteorological Administration (CMA) website for the period 14-19 July 2014 (http://data.cma.cn/, accessed on 1 February 2022). These climate data have a spatial resolution of 0.0625° at an hourly time step. The data were further downscaled to a 30 m spatial resolution using the inverse distance weighted (IDW) interpolation method. The average wind velocity and the cumulative precipitation during 14–19 July 2014 were used to represent the wind velocity and precipitation, respectively affected by Rammasun. The spatial distributions of elevation and total rainfall are shown in Figure 4. Guangdong Province has lower elevation in the southern and central part and higher elevation in the northern part, while Hainan Province has higher elevation in the central region and lower elevation in the peripheral region. During the Rammasun period (14–19 July 2014), the highest rainfall appeared in the southwestern Guangdong and the eastern Hainan, with the highest rainfall over 250 mm.

2.4. Methods for Detecting Forest Damage Area and Severity

Based on the GEE cloud computing platform, this study used Landsat 8 (OLI/TIRS) surface reflectance data to identify, process, and analyze images from two time periods before and after the outbreaks of Typhoon Rammasun. The methods and work flow were described in detail in our previous study [22]; here we briefly describe the data processing methods.



Figure 4. The digital elevation model (DEM) (m; **Left**) and cumulative precipitation during 14–19 July 2014 (mm; **Right**).

(1) Mask of forest areas

To eliminate the noises caused by non-forest areas, we first mask the forest areas before the classification of affected forest area and damage severity. The RF model with classifier mode (ee.classifier.smileRandomForest() function in GEE) was applied for forest classification. The NDMI (Normalized Difference Moisture Index), NDBI (Normalized Difference Built-up Index), and NDVI (Normalized Different Vegetation Index) indices were used as input variables in the RF model. The classification overall accuracy was 0.92.

(2) The calculations of VIs and image texture variables

According to our previous study, the VIs including NDVI, EVI (Enhanced Vegetation Index), NDII (Normalized Different Infrared Index), CVI (Chlorophyll Vegetation Index), SAVI (Soil-Adjusted Vegetation Index) and NDMI were of the top importance to represent forest damage in responses to typhoon/hurricanes [6,24,35,36]. Therefore, we also used these VIs as inputs to the RF algorithms. In addition to VIs, the image texture information can also be used as input variables in RF model to assisting decision-making. Seven texture variables including CONTRAST, IDM (Inverse Difference Moment), CORR (Correlation), DISS (Dissimilarity), VAR (Variance), ASM (Angular Second Moment) and ENT (Entropy). We applied the Gray-Level Co-occurrence Matrix (GLCM) method to calculate these texture variables in the GEE platform.

(3) Implementations of the UID method

As indicated from many previous studies, the changes in NDVI, EVI and NDII can be used to represent forest damage rates due to typhoons/hurricanes. We applied the univariate image differencing (UID) method to calculate the differences of the VIs (Δ VIs) before and after the Typhoon for comparison with the RF classification/regression algorithm. Based on the importance ranking, we selected three indices, NDVI, EVI, and NDII. Before the calculation of Δ VIs, we applied the LandTrendr de-spiking algorithm to smooth the noises caused by the unreasonable fluctuations of reflectance.

$$\Delta VI = (VI_{after} - VI_{before}) / VI_{before}$$
(1)

(4) Mapping damaged forest area and severity using RF classifier/regressor algorithms

The RF classifier and regressor modes were used to detect damaged forest area and damage severity, respectively. The Random Forest classification algorithm was implemented on the GEE platform (ee.classifier.smileRandomForest()) to detect damaged forest area by typhoons using the sample plot data as training and cross-validation data. After

damaged forest areas have been identified, we further ran the RF algorithm with a regression mode "setOutputMode('regression')". The input variables for RF classifier/regressor included image texture patterns (described above), precipitation, wind velocity, topographic factors (elevation, slope and aspect), reflectance changes in individual bands (from Δ Band1 to Δ Band7) and change in VIs (Δ VI). The importance ranks were listed in (Figure 5), with the highest importance in Δ NDVI, Δ EVI, and Δ Band5. The more detailed methods for RF implementation were described in Zhang et al. [22].



Figure 5. The importance ranks of variables in the Random Forest classifier/regressor models. Note: The importance values are normalized to 0–100; All variables except for precipitation, wind speed, elevation, slope, and aspect are represented by the changes before and after Rammasun.

2.5. Methods for Monitoring Forest Canopy Recovery

The subsequent recovery of damaged forests after Typhoon Rammasun was monitored. As suggested by the importance rank, NDVI and EVI made the highest contributions to the RF model (Figure 5). EVI has a higher sensitivity in densely vegetated areas than NDVI in representing the canopy greenness [37,38]. Considering that recovery becomes slower and less pronounced at later periods than at earlier periods, this study applied EVI rather than NDVI time series to monitor the long-term canopy greenness recovery as well as comparative analyses with other non-disturbed years. The monthly EVI from 2010 to 2020 were computed based on the available Landsat 8 OLI images on the GEE platform. LandTrendr de-spiking algorithm was used to smooth the EVI time series data caused by noises and unreasonable fluctuations.

2.6. Evaluations of Classification Results

The classification results based on RF and UID-VI methods for forest damage area and severity were evaluated against the left 250 sample plot data. The consumer accuracy, producer accuracy, overall accuracy, and Kappa coefficient were used as the evaluation criteria for detected forest damage area (Table 1). The evaluation results indicated that all methods showed high overall accuracy (>87%) and Kappa coefficients (>0.82), with the highest overall accuracy and Kappa coefficient from the RF method. This suggested that RF had a better performance than the UID-VI methods for classifying forest damage in response to Typhoon Rammasun.

Methods	Consumer Accuracy (%)	Producer Accuracy (%)	Overall Accuracy (%)	Kappa Coefficient
RF	93	95	94	0.92
NDVI	91	91	90	0.86
EVI	90	91	89	0.85
NDII	87	88	87	0.82

Table 1. Evaluations results for the detected damaged forest area based on RF and UID-VI methods.

The detected results for forest damage severity were also evaluated using the validation sample plot data. The regular least square method (LSD) was applied to assess the relationships between detected and observed forest damage severity. The results indicated that the fitted slopes for the RF, UID-NDVI and UID-EVI methods were similar and greater than the UID-NDII method; however, the RF method had higher correlation coefficient (R^2) than that of UID-NDVI and UID-EVI methods (Figure 6). On the whole, the RF method had a better performance to detect forest damage severity.



Figure 6. The comparisons between detected and observed forest damage severity (0–1) based on different change detection methods. (**a**): Random Forest method; (**b**): UID method based on NDVI; (**c**): UID-EVI; (**d**): UID-NDII.

To evaluate the performance over spatial scale, we further applied the Intersection over Union (IoU) metric. Intersection over Union is an evaluation metric used to measure the accuracy of an object detector on a particular dataset, which has been widely used to evaluate the extent of overlap between two objects [39]. The greater the region of overlap, the greater the IoU. The IoU can be calculated as a ratio between overlapped area and union area. Through comparisons of the detected forest damage area between RF and UID-VI methods, we found that the IoUs were all greater than 0.52, indicating over 52% agreements of the detected damaged forest areas between these two methods (Table 2). The IoU between RF and UID-NDVI was the highest (0.69), indicating that the spatial similarity was the highest between these two methods.

Table 2. Image overlap and union (IoU) area (grid pixel numbers) and the IoU between RF method and UID-VI methods.

Categories	Overlap	Diff1	Diff2	Union	IoU
RF to NDVI (a *)	$2.95 imes10^6$	$1.29 imes10^6$	$6.14 imes10^4$	$4.30 imes10^6$	0.69
RF to NDVI (b)	$2.04 imes10^7$	$6.14 imes10^4$	$1.29 imes10^6$	$2.18 imes10^7$	0.94
RF to EVI (a)	$2.97 imes 10^6$	$1.36 imes10^6$	$7.42 imes 10^5$	$5.08 imes10^6$	0.59
RF to EVI (b)	$2.01 imes 10^7$	$7.42 imes 10^5$	$1.36 imes10^6$	$2.22 imes10^7$	0.91
RF to NDII (a)	$3.16 imes10^6$	$1.38 imes10^6$	$1.51 imes 10^6$	$6.05 imes 10^6$	0.52
RF to NDII (b)	$1.93 imes10^7$	$1.51 imes 10^6$	$1.38 imes10^6$	2.22×10^7	0.87
D1 1 1 1 1 1 1					

* a: Disturbed forests; b: Undisturbed forests.

These analyses proved that the RF method can more accurately be used to assess forest damage area and severity caused by Typhoon Rammasun. Therefore, the RF was finally chosen as the method in estimating forest damage area and severity in this study. Olofsson et al. [40,41] recommend that land change classification should be accompanied by an accuracy assessment that includes a clear description of the sampling design (including stratified sample size), an error matrix, the area or proportion of area of each category according to the map, and descriptive accuracy measures such as the user's, producer's, and overall accuracy. Their method for accuracy assessment was widely accepted as a better and comprehensive accuracy assessment metric. Following their method, we further developed an error matrix to more comprehensively assess the detection accuracy based on the sample counts for detected forest damage severity categories using the RF regressor mode (Table 3). The assessment results indicated that the user's accuracy of the light damage category was the lowest (66%), while the severe damage category was the highest (86%) among the three damage categories. The producer's accuracy of the moderate damage category was the lowest (59%), while the severe damage category was still the highest (79%). Both the user's and producer's accuracies were the highest for the non-affected forests, resulting in a high overall accuracy (95%) for all detected categories.

Table 3. Error matrix of sample counts (n_{ij}) constructed from the accuracy assessment. Map categories are the rows while the reference categories are the columns. Note: Class 0: no damage (<5% loss), 1: light damage (5–20%), 2: moderate damage (20–50%), 3: severe damage (>50%); Area_{adj}: adjusted area (An unbiased estimator of the map area); ME: margin of error; UA: user's accuracy (commission error); PA: producer's accuracy (omission error); OA: overall accuracy; W_i : the weight of classified area for class i.

Class	0	1	2	3	Total	Map Area (10 ⁵ km ²)	W _i	^{Area} adj (10 ⁵ km ²)	ME (95% CI)	UA	РА	OA
0	111	2	0	0	113	11.94	0.87	11.80	0.30	0.98	0.99	0.95
1	6	65	21	7	99	0.96	0.07	0.93	0.31	0.66	0.68	
2	3	20	95	5	123	0.42	0.03	0.56	0.09	0.77	0.59	
3	2	5	9	99	115	0.37	0.03	0.40	0.06	0.86	0.79	
Total	122	92	125	111	450	13.69	1.0	13.69				

2.7. Analysis Methods

For the detected forest damage severity expressed as a proportion of forest canopy loss (0–100%), which was further reclassified into four categories including no (<5% loss), light (5–20%), moderate (20–50%), and severe (>50%) according to the classification methods of field surveys [4,27,28]. We speculated that severity between 0–5% was caused by system and image errors with high probability; therefore, the category with <5% loss was considered

to be the forest area not affected. The forest damage area and severity were analyzed at grid cell, county, and province scales.

3. Results

3.1. Affected Forest Area and Spatial Patterns

Based on the RF algorithm, this study found that in total 13556 km² of forest in Guangdong Province was affected by Typhoon Rammasun, accounting for 13.8% of the total forest area (Figure 7). The largest affected area was shown in Zhanjiang (1704 km²), followed by Shaoguan (1568 km²), and Maoming (1332 km²) Cities, while the least affected area was located in Shantou (79.5 km²) and Chaozhou (161.5 km²) Cities (Table 4). The affected forest fractions in Zhanjiang (52.24%) and Zhuhai (52.30%) Cities were the highest, while Yangjiang and Zhaoqing Cities were the lowest (<6%). Zhanjiang City had both highest affected area and forest fraction in Guangdong Province mainly because Rammasun first made landfall in this city and the center of typhoon track passed across its southern portion, with mean wind speed of 55 m/s when landing (Figure 1). Additionally, the scattered distribution pattern of forests (less dense) in Zhanjiang made it more vulnerable to external interference. The areas located at the eastern and northern of the province generally had lower impacts since they are far away from the typhoon track.



Figure 7. The spatial distribution of affected forest area and damage severity (0–1) caused by Typhoon Rammasun in Guangdong Province.

City/County	Forest Area	Affected Area	Fraction (%)	Light (%)	Moderate (%)	Severe (%)	
5 5	(KM-)	(KM ²)					
Shenzhen	770	261.48	33.96	67.26	23.27	9.48	
Yangjiang	4955	294.29	5.94	49.20	27.31	23.49	
Shaoguan	10,939	1568.17	14.34	56.72	25.09	18.18	
Zhuhai	354	184.67	52.20	62.96	24.45	12.59	
Shanwei	2257	368.53	16.33	52.52	24.70	22.78	
Guangzhou	2922	521.71	17.86	59.57	24.98	15.45	
Heyuan	8094	999.06	12.34	51.08	27.00	21.92	
Huizhou	6137	966.30	15.74	55.50	26.31	18.20	
Jiangmen	4574	789.11	17.25	61.09	23.71	15.20	
Shantou	358	79.54	22.24	45.70	28.61	25.70	
Zhongshan	352	130.66	37.10	65.59	21.46	12.95	
Foshan	1069	283.78	26.54	74.02	18.41	7.57	
Qingyuan	13,152	1092.32	8.31	51.24	26.34	22.42	
Zhaoqing	11,629	759.96	6.53	48.34	29.55	22.11	
Dongguan	529	202.34	38.25	70.08	19.87	10.04	
Meizhou	10,418	1010.86	9.70	45.84	25.94	28.22	
Maoming	7013	1332.87	19.01	39.29	33.22	27.50	
Zhanjiang	3263	1704.28	52.24	52.29	28.14	19.58	
Chaozhou	1894	161.50	8.53	50.81	24.27	24.93	
Jieyang	2196	357.43	16.27	46.13	27.86	26.01	
Yunfu	5372	487.47	9.07	38.27	33.46	28.27	
Sum	98,248	13,556	13.80	52.20	26.95	20.85	

Table 4. The affected forest area and proportions of different damage severities in cities or counties of Guangdong Province.

Totally, 3914 km² forest area in Hainan Province was affected by Rammasun, accounting for 18.5% of the total forest area (Figure 8; Table 5). Compared with Guangdong Province, Hainan had far less affected forest area, but the affected forest fraction was significantly higher. The largest affected area was located in Haikou (607.2 km²) and Danzhou (545.3 km²) Cities, while the least affected area was located in Sanya City (67.54 km²) and Changjiang County (68.13 km²). The highest affected forest fraction was located in Lingao County (79.39%) and Haikou City (71.33%), indicating most forests in these two regions were affected by Rammasun. Haikou was the second city right after Wenchang stroked by Rammasun and Lingao was also close to the typhoon track (Figure 1). In addition to wind velocity, another reason could be that the rainfall in Haikou and Lingao was among the highest, causing the secondary damage of forests from flooding and landslide. For the entire Hainan, most of the affected forest areas were distributed in the northeast and north where are closer to the typhoon track and at the forest edges where forest coverage (tree density) is lower (Figure 2).

3.2. Forest Damage Severity and Spatial Patterns

The detected forest damage severity was further grouped into four categories. In Guangdong Province, 52.20% (7076 km²), 26.95% (3653 km²) and 20.85% (2826 km²) of the affected forest area were classified in the light (5–20%), moderate (20–50%) and severe (>50%) damage categories, respectively. Most of the severe damage areas were located in the southwest where close to the typhoon track; however, we also found some severe damage areas in the regions far away from the typhoon track, mainly at the forest edges or the scattered forests. The scattered trees and trees at forest edge are more vulnerable to wind damage and the secondary damage to soil erosion due to heavy rainfall. The proportions of moderate damage category varied less (ranging from 18.41 to 33.46%) than the severe and light damage categories in different cities or counties (Table 4). Maoming and Zhanjiang Cities had the largest area in the severe damage category, while the highest proportions of severe damage area were in Yunfu (28.27%), Meizhou (28.22%) and Maoming (27.50%) cities. Although Zhanjiang had the largest affected and severely damage area, the proportion of severe damage was relatively lower (19.58%). This may due to the forest ecosystems had long adapted to wind damage since typhoons more frequently visit this city. Meizhou City had very low affected forest fraction (9.70%) and is located in the eastern Guangdong, but

the complex mountainous terrains and higher forest coverage in the mining area resulted in severe forest damage from landslide or soil erosion due to heavy rain. Maoming City had relatively lower affected forest fraction (19.01%) than Zhanjiang, but it is also close to the wind track (Figure 1) and received higher rainfall (Figure 4), causing higher severely damaged forest fraction.



Figure 8. The spatial distribution of affected area and damage severity (0–1) caused by Typhoon Rammasun in Hainan Province.

City/County	Forest Area (km²)	Affected Area (km ²)	Fraction (%)	Light (%)	Moderate (%)	Severe (%)
Wenchang	1042	306.04	29.37	72.02	9.47	18.50
Dunchang	1021	145.66	14.27	66.25	9.25	24.50
Sanya	1015	67.54	6.65	58.25	23.52	18.23
Qiongzhong	2461	124.54	5.06	61.43	19.08	19.49
Dingan	814	353.99	43.47	71.83	6.73	21.44
Dongfang	1100	82.76	7.52	48.82	34.29	16.88
Haikou	837	597.32	71.34	64.45	10.65	24.90
Danzhou	2079	545.29	26.23	74.68	10.46	14.86
Chengmai	920	371.93	40.43	59.86	13.47	26.67
Qionghai	1222	258.89	21.18	63.63	14.29	22.08
Changjiang	926	68.13	7.36	60.61	18.81	20.58
Lingshui	579	70.99	12.26	60.02	21.59	18.39
Baoting	1932	71.39	3.69	65.78	14.62	19.59
Lingao	480	381.32	79.39	57.05	16.82	26.12
Baisha	1908	181.34	9.50	67.06	13.91	19.02
Ledong	1567	100.88	6.44	62.14	19.50	18.37
Wanning	1258	185.77	14.77	54.13	27.19	18.68
Sum	21,162	3914	18.49	64.90	13.80	21.30

Table 5. The affected forest area and proportions of different damage severities in cities or counties of Hainan Province.

In Hainan Province, 64.87%, 13.82%, and 21.31% of the affected forest area belonged to light, moderate, and severely damage categories, respectively. Most of the severe damage areas were located in the eastern region (especially on the Leizhou Peninsula) where close to the typhoon track, with a few severe damage areas in the regions close to the ocean and at the forest edges or scattered forests. The proportions of severe damage category varied less than the moderate and light damage categories in different cities or counties (Table 5). Chengmai and Lingao Counties had both the largest area and proportions of severe damage category, with 26.67% and 26.12%, respectively. Chengmai had a high affected forest fraction, only lower than that of Haikou City and Lingao County, and it is also close to the typhoon track and had large scattered forest area (Figures 1 and 2), resulting in more severe damaged forest area in this county. Lingao had the highest affected forest area and fraction and the largest fraction of severe damage category, suggesting this county is the most affected region in Hainan. Haikou had the largest affected forest area and fraction, and the proportion of severe damage (24.90%) was relatively high too. Dongfang City had the highest proportion (34.29%) of moderate severity category.

The comparisons between the two provinces indicated that Guangdong had less fraction of severe damage category but had more fraction of moderate damage. There is a more pronounced linear relationship between the extent of forest damage and the distance of the typhoon in Hainan Province than in Guangdong Province, with most of the severe damage being in cities or counties near the typhoon path in Hainan Province. Through accounting for both affected forest area and damage severity, we further calculated that 3.97% of forest canopy was lost in Guangdong Province and 5.09% of the forest canopy was lost in Hainan Province due to Typhoon Rammasun. The damaged forest areas in Hainan were more concentrated at the regions close to the typhoon path, while more scattered in Guangdong, which might be due to differences in elevation (Figure 4) and forest distribution patterns (Figure 2). To explain the spatial change patterns in affected area and damage severity, an analysis on the controlling factors was conducted.

3.3. Controlling Factor Analysis

Our study results indicated a complex spatial pattern in the distribution of forests with different damage severities. Obviously, wind velocity is one of the most important factors affecting the spatial patter of forest damage severity; however, there should be some other factors causing the different severities at the regions with similar wind velocity and explaining the high damage severity over the distant areas. Our results indicated that the wind damage severity declined significantly with the distance from typhoon track when the distance is less than 50 km; however, the damage severity was no longer correlated with wind velocity when the distance is greater than 50 km (Figure 9a), indicating other factors posed predominant impacts on damage severity in these regions. Overall, a negative correlation existed between damage severity and the distance from typhoon track (r = -0.45; Figure 10). The elevation did not have an obvious relationship with damage severity, but the elevation ranging from 1000 to 1200 m showed the highest mean damage severity, and the elevation ranging from 400 to 600 m had the lowest mean damage severity (Figure 9b). A declining tendency for damage severity was found when elevation >1200 m. We further found when the elevation is lower than 1200 m, forest damage severity had no obvious connection with elevation, but a greater damage severity was found when elevation is greater than 1200 m. Overall, a small positive correlation (r = 0.29; Figure 10) was found between elevation and damage severity. Forest damage severity did not show an obvious trend with increasing slopes when the slope is less than 40° ; however, damage severity was significantly lower and declined with slopes when the slope is greater than 40° (Figure 9c). Overall, a small positive correlation (r = 0.18) was found between slope and damage severity. Forest damage severity did not show an obvious trend with increasing precipitation when the precipitation is less than 150 mm (Figure 9d); however, damage severity was significantly higher and slightly increased with precipitation when the precipitation is greater than 150 mm. Overall, a positive correlation (r = 0.30; Figure 10) was found between precipitation and damage severity.



Figure 9. The relationships between forest damage severity (0-1) with elevation, slope, distance from typhoon track and precipitation ((**a**): distance from typhoon track; (**b**): elevation; (**c**): slope; (**d**): precipitation).



Figure 10. The correlation coefficients (*r*) between forest damage severity and various influencing factors in the study region (Y: forest damage severity; X1: elevation; X2: distance from typhoon track; X3: precipitation; X4: slope; X5: aspect).

3.4. Forest Canopy Greenness Recovery after Typhoon Rammasun

We chose EVI as an indicator to represent and assess the forest canopy recovery trajectories after Typhoon Rammasun. The EVI during July-August 2014 were about 10% and 14% lower than the mean EVI in the rest years from 2010 to 2020 in Guangdong and Hainan Provinces, respectively, indicating a significant impact of Typhoon Rammasun on forest canopy in both provinces (Figure 11a,b). However, we found that the EVI fully recovered to pre-damage conditions within about two months in Guangdong Province, while it fully recovered within 3–4 months in Hainan Province. Due to less affected forest fractions and severe damage, the recovery of EVI in Guangdong Province was even faster. We further separately calculated the EVI for forests with different damage severities. In Guangdong Province, the canopy greenness of the severe damaged forests recovered within about 4-5 months, while the light damaged forests recovered within about 2 months. In Hainan Province, the canopy greenness of the severe, moderate, and light damaged forests recovered within 5, 4, and 2 months, respectively. Hainan Province is mostly distributed in the tropical rainforest climate zone, while Guangdong Province is mostly distributed in the southern subtropical climate zone with similar climate to tropical rainforest. Vegetation can maintain a high resettlement or regrowth rate during the entire year; therefore, herbaceous or shrub plants appeared soon to occupy the open gaps created by damaged trees. This suggested that typhoons can only have a shortterm impact on canopy greenness in Guangdong and Hainan Provinces; however, the biomass accumulation and forest height will certainly take longer time to fully recover to the pre-disturbance condition, resulting in long-term impacts on forest biomass and thus carbon stocks.



Figure 11. Landsat-based monthly average EVI for the affected forest areas by Rammasun during 2010–2020 ((**a**): Guangdong; (**b**): Hainan).

4. Discussion

4.1. Comparisons between Different Detection Methods

Different methods for image change detection can cause some uncertainties. Many previous studies applied several algorithms (e.g., LandTrendr, machine/deep learning, CVA and Vegetation Change Tracker (VCT)) and VIs (e.g., NDVI, EVI, NDII, TCW, and TCB) to detect wind damage and post-disturbance recovery, and showed that each of these algorithms or VI was effective [6,9,14,15,19]. To find the best detection method, our study compared the effectiveness between RF and UID-VI methods. The comparisons indicated that the four methods had >87% overall accuracy, >0.82 Kappa coefficients, and >0.5 correlation coefficients (R^2), indicating all methods can be applied for detect forest damage due to Rammasun. The comparison also showed that the RF method had a better performance than the three UID-VI methods, probably because the RF method takes into account the overall variability of all these ΔVIs and the variability generated by other factors. The RF method also previously proved to be more effective than many regular methods [10,11,21,42]. However, the RF method requires sample plot data for training the algorithms, which limits its wide application, and the quality of the training will also affect its accuracy. In addition, we found that the IoU scores between RF and three UID-VI methods ranged from 0.5 to 0.7, indicating good spatial consistence of detected affected forest area using four methods. However, the high un-overlapped fractions also implied a spatial inconsistence or uncertainty for detecting Rammsun's impacts. More field investigation data are needed to further narrow down the uncertainty.

4.2. Comparisons with Other Studies for Damage from Rammasun

There are several studies for addressing the impacts of Rammasun on unique tree species at in parts of or all of Hainan Province, which can provide some indirect evaluations

to our study results. For example, Yang et al. [27] found that the proportions of moderate and severe damage categories accounted for about 43.8% and 35.4%, respectively, for the rubber trees in Haikou City, which were significantly higher than our estimated proportions (10.65% and 24.90%, respectively). This is because the rubber forests are generally planted pure forests, which are more vulnerable to wind damage, resulting in higher fractions of severe and moderate damaged forests. According to field survey data, Zhang et al. [4] estimated the damage severity of rubber forests in Hainan and indicated the very light (0–5%), light (5–10%), moderate (10–20%), severe (20–30%), and very severe (>30%) damage fractions accounted for 19.81%, 26.41%, 14.35%, 19.10%, and 20.33%, respectively. Their fractions for light damage were lower than our estimation (64.90%) and moderate damage fractions were higher than our estimation (13.80%) for all forests. Based on field survey data, Xue et al. [26] indicated that the affected forest area was 372.46 km² in Wenchang City of Hainan, which is consistent with our estimated damage area (306.04 km²). Our study found that affected forest fractions in Lingao, Chengmai, Haikou, and Wenchang of Hainan were 79.39%, 40.43%, 71.34%, and 29.37%, respectively. Based on the field survey data, Zhang et al. [4] also found that the rubber forests in these regions had the highest affected fractions and generally greater than 30%, which is consistent with our study results. Their survey also found that Baoting and other counties at the south had less than 10% rubber forests were affected. We also found Baoting, Ledong, and Sanya had affected forest fractions of 3.69%, 6.44%, and 6.67%, respectively. At the spatial scale, Zhang et al. [4] also indicated that the damage severity in northern and eastern Hainan was generally higher than the south and west, and severe damage also occurred in the regions far away from the typhoon track. Our detected spatial patterns in damage severity were consistent with their conclusions.

4.3. Factors Controlling Forest Damage Severity and Management Implications

In this study, the correlation between damage severity and the factors of interest showed that forest damage severity mainly related to the maximum wind speed, which is consistent with many previous reports (e.g., [6,43]). In addition, the elevation, distance from typhoon track, slope, and precipitation can significantly affect damaged forest area and severity. Our results showed that forest damage severity increased with elevation when elevation is greater than 600 m and less than 1200 m. Our previous study also found the same pattern between damage severity and elevation under the impact of Typhoon Lekima in 2019 in Zhejiang Province [22]. However, our results were opposite with Wang and Xu [14], in which they reported that forests at the lower elevation received higher damage than those at the higher elevation. According to field survey data for Rammasun impacts, Chen et al. [44] indicated that the damage severity increased with slope for rubber forests in Hainan. Based on the field survey data and RF models, another study [43] identified the importance of various factors to the forest damage by Hurricane Irma and Maria and found that slope was also significantly contributed to forest damage. Our study also found that damage severity increased with slope when the slope is less than 40° . Our study further found that damage severity increased with precipitation when the precipitation is greater than 150 mm. Hall et al. [43] also indicated that storm-related rainfall was a stronger predictor of forest damage than maximum wind velocity. The sudden heavy rainfall will result in flooding and thus soil erosion and landslide especially at places with higher elevation and slope, resulting in secondary damage to forests. This suggests that forest managers should pay more attention to forest areas with a high probability of soil erosion and landslide when typhoons are accompanied by heavy rainfall. Recovery management after typhoons should also give priority to these areas [22].

Baldwin et al. [45] indicated that the damage to fringe mangrove forests by Hurricane Andrew was greater. Hall et al. [43] indicated that canopy height was the most important risk factor influencing forest damage. Many previous studies also indicated that taller and larger diameter trees and denser canopies are generally more susceptible to wind damage [14,34,46–48]. Xue et al. [26] and Qiu et al. [28] indicated that tree species, density canopy height significantly affected the rubber forest damage severity by Rammasun. Our study also found that most of the severe damage areas were located in the forest edges and scattered forests where the tree density is lower. These studies suggested that increasing forest density and choosing less sensitive tree species (such as trees with shorter height, slower growth rate, and small-size canopy) would help reduce or avoid damage from typhoons in these vulnerable areas.

4.4. Vegetation Resilience to Wind Damage and Management Implications

Typhoons frequently attack the coastal forests of China, resulting in tree uprooting, and branch, pole, and leaf falling. Therefore, typhoons have a profound and complex impact on the composition of forest ecosystems, the diversity of species and ecological functions, and they can lead to significant changes in microclimate, forest growth, crown density, and biomass accumulation. Compared with a lot of studies focusing on forest damage assessment, the trajectory of recovery has received less attention [6]. Our study found that canopy greenness recovered within three months for both provinces in the subtropical and tropical coastal region, indicating a high resilience of vegetation to typhoon damage. The fast canopy recovery was also observed by Sánchez-Rivera and Gómez-Mendoza [49], who found that vegetation recovered within 2–3 weeks for about 52% of the tropical cyclones and within 4–5 weeks for 38% of the tropical cyclones based on a synthesis for the effects of 21 tropical cyclones in the Yucatan Peninsula, Mexico. Based on field observations, Parker et al. [50] found a steep recovery in NDVI after two hurricanes, and indicated the main reason is new foliage growth from vines and sprouts. Long et al. [19], in which the majority of damaged mangrove in Philippines recovered within 18 months following Super Typhoon Haiyan. Some other studies found longer recovery time. For example, Gang et al. [6] found it took about four years for forests in the northern Gulf of Mexico to recover after Hurricane Katrina. The EVI can effectively reflect the canopy greenness; however, it cannot discriminate the canopy of forest and other vegetation types. The faster EVI recovery may be only caused by the lower canopy vegetation such as vines, shrub, and grass [50]. Therefore, the short recovery period of EVI did not necessarily mean a fast recovery of the forest canopy and biomass. In fact, a long-term period is needed for forest height and biomass recovery especially for the areas with more severe damage. Based on a long-term survey data, Imbert [51] indicated that the inner and tall-canopy stands took as long as 23 years to fully recover the height and biomass after Hurricane Hugo in the Caribbean mangrove forests. Parker et al. [50] found that the weighted canopy height, outer canopy height, and canopy area index were projected to recover after 23.9, 20.4 and 7.4 years, respectively, following Hurricane Patricia, and the projected aboveground biomass recovery time was 14.4 years. They implied that the persistent canopy features (such as canopy cover and production) require decades or even much longer time to recover. More studies are needed to assess the recovery in forest height and biomass based on long-term ground-based observations or other satellite platforms, such as LiDAR sensor [50]. Considering that different aspects of ecosystem structure will recover at different time scales, forest management need to pay special attention to forests with damage in stems, roots, and branches, which will likely take decades to recover in Guangdong and Hainan Provinces. Precise management strategies can alter the forest recovery pathway and accelerate recovery time.

4.5. Uncertainties

Although the evaluation results showed high accuracy, there are some uncertainties in this study. First, the Landsat image quality issue could raise some uncertainties. Due to high rainfall and cloud cover in the study region, few cloud-free Landsat image scenes are available. It is better to use the Landsat images right after and before Rammasun to make the analysis; however, we actually collected the images scenes from 15 May to 15 July and 20 July to 20 September to obtain two full cloud-free composite images representing prior and post-disturbance periods. The natural changes in phenology, tree recovery, and some other disturbance events (such as insects and harvesting) during these long time gaps may greatly compound our research results. Our detected damage area and severity actually included the unidentified other causes, resulting in either overestimation (due to other disturbance events or phenology change) or underestimation (due to forest recovery). This issue also occurred in most previous studies for wind damage detection based on Landsat images since the tropical cyclones mostly occurred in the high rainfall and cloud cover coastal regions [6,17,52,53]. Second, due to lack of field inventory data, the sampling plot data were collected through visual interpretation based on high-resolution images, which could raise some uncertainties in training the RF method and evaluating the detection accuracy. Although the spatial resolution of satellite images used for visual interpretation is generally <5 m, the manual digitizing processes and the attribution to typhoon's damage could cause some errors. Thirdly, although the RF method considered multiple VIs and other auxiliary factors, most of the variables can only reflect the changes in canopy conditions. The created opening due to damaged trees could be rapidly occupied by herbaceous plants in a short period. These herbaceous plants can compensate for the reductions in VIs of trees, resulting in some underestimation of the damage area and severity.

5. Conclusions

Due to complex terrain, weather, and forest conditions in the coastal region, few studies addressed the impacts of typhoons on forests in China. Our study compared the detected damage forest area and severity from different methods and evaluated against sampling plot data. The validation results indicated that the RF machine-learning method can more effectively capture the total affected forest area and their spatial distribution patterns compared with the UID method. The results showed that a large portion of forests (13.8% and 18.5%, respectively) were affected by Typhoon Rammasun in Guangdong and Hainan Provinces. Among which, the severely damaged forests accounted for 20.9% and 21.3% in these two provinces, respectively. The affected forest fractions for some counties/cities reached 70%, indicating a devastating destruction of forest ecosystems in these areas. The affected forest areas were mainly located in the regions close to the typhoon path and the most severely damaged forests mainly distributed at the forest edges or in the scattered forests with lower tree density. Although wind velocity is the main factor controlling the affected forest area and damage severity, other topographic factors and precipitation could also dominantly affect the distribution of damaged forest area especially in the regions distant from the typhoon track. Although a great affected fraction and high damage severity, canopy greenness in the two provinces showed fast recovery within several months; however, the persistent canopy structure (e.g., forest canopy density and forest height) and biomass need to take decades to recover. More studies are needed to explore the long-term recovery of these forest parameters. Although some uncertainties exist, our study can still help inform local governments, the forest sector, and landowners about forest damage severity, its spatial distribution patterns, economic and ecological losses, and major controlling factors, and provide guides to sustainably manage forest ecosystems to reduce typhoons' damage and accelerate post-disturbance recovery.

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