

The damage of urban vegetation from super typhoon is associated with landscape factors: Evidence from Sentinel-2 imagery

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ABSTRACT

Many studies have investigated the impacts of typhoons on natural vegetation, but the influencing factor of urban vegetation damage from super typhoon is not clear. Therefore, this study investigated the vegetation damage patterns in eight cities affected by Typhoon Mangkhut (the 2nd strongest tropical storm worldwide in 2018) using the normalized difference vegetation index (NDVI) derived from Sentinel-2 images. The vegetation damage maps have an overall accuracy of 97% using the very high-resolution WorldView-3 images as reference data. The results show that (1) The typhoon-induced vegetation damage show high spatial heterogeneity in urban areas and varies with land cover types. Residential greenspace and street trees are more susceptible to typhoon disturbance than natural vegetation. (2) Wind intensity is still an important factor in urban vegetation damage ($r^2 = 0.43$, P value < 0.001). (3) Urban vegetation damage positively relates to vegetation sparseness for all cities ($r: 0.39\text{--}0.89$, P value < 0.01), whereas negatively correlated to the height of surrounding buildings ($r = -0.57$, P value < 0.01), suggesting that both biotic and abiotic factors of the urban environment have influences on the resistance of vegetation to storms. This study provides insights into the resistance and resilience of urban vegetation to strong typhoons that can be used for urban forestry planning and management.

1. Introduction

Typhoons (also known as cyclones or hurricanes, depending on which region the tropical storm hits) are one of the most powerful weather events and can dominate the disturbance regimes of vegetation (Zimmerman et al., 2014). Typhoon-induced vegetation loss not only abruptly influences regional biomass as well as causes a persistent transformation of vegetation composition and structure, altering long-term carbon storage and exchange in terrestrial ecosystems (Fisk et al., 2013; Hutley et al., 2013; Seidl et al., 2017). Urban vegetation grows in settings that are more complicated than natural environments in that it serves both urban aesthetics and ecosystem functions. The disturbance of urban vegetation thus equals both the net primary productivity (NPP) loss of the urban environment and the financial loss; there are even repercussions for personal safety. Investigations of typhoon-induced damage patterns will benefit urban planning by guiding how to improve vegetation resistance to strong typhoons (Jim and Liu, 1997; Jim, 2019).

Previous studies have mainly focused on investigating the impacts of typhoons on natural vegetation and the factors driving these impacts using remote sensing data (Buitre et al., 2019; Helmer et al., 2010; Ibanez et al., 2019; McDowell et al., 2015; Parker et al., 2018; Reiche et al., 2013; Van der Werf et al., 2009). Specifically, vegetation indices derived from satellite images are good indicators of vegetation status (e. g., greenness and vigor) and have become a significant data source for vegetation change detection and analysis (Verbesselt et al., 2012), such as the normalized difference vegetation index (NDVI) (Ayala-Silva and Twumasi, 2004; Chambers et al., 2007; Hu and Smith, 2018), enhanced vegetation index (EVI) (Feng et al., 2018), and normalized difference infrared index (NDII) (Wang et al., 2010). In natural environments, vegetation damage severity largely depends on geographic factors and biotic factors. For instance, a study of several temperate and tropical locations concluded that vegetation damage strongly correlated with the distance from the storm center and the local slope and elevation (Negrón-Juárez et al., 2014). Higher tree mortality was witnessed in tropical rainforests than in temperate forests, which was explained by

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the differences in forest structure (e.g., stem density and the depth of root systems) (Negron-Juárez et al., 2014). Besides forest structure, other variables may also be important, including related variables like forest age and type, as well as climate variables like the amount of rainfall preceding a storm (Feng et al., 2020; Hall et al., 2020).

However, knowledge of typhoon-induced disturbances on natural vegetation may not be applicable in urban environments. On the one hand, the urban landscape has different land surface characteristics compared with natural vegetation. The mosaic of greenspaces and buildings is a distinct landscape characteristic that may influence the spatial pattern of urban vegetation damage induced by typhoons. On the other hand, human intervention, including vegetation planting and clearing, alters species composition, which may in turn impact the response of urban vegetation to disturbance. For instance, over 70% of roadside trees in Guangzhou city are evergreen broadleaf species with large crowns and were planted for shade, while the species that provide functions in parks and institutions are ornamental and were planted for their flowers or fruit (Jim and Liu, 2001). Given that municipal governments have authority to manage urban landscaping in public areas, it is reasonable to hypothesize that the disturbance variation in urban environments relates to urban functions, e.g., the functions that vegetation is planted to serve in a given urban environment. However, knowledge about the spatial pattern of urban vegetation damage caused by strong storms and relationships between damage and urban landscape characteristics is still limited.

To deepen our understanding of the urban vegetation damage caused by typhoon disasters, this study assesses vegetation damage for eight cities in Guangdong Province, China, along the path of a recent super typhoon (Mangkhut, the 2nd strongest tropical storm worldwide in 2018) using Sentinel-2 images. Sentinel-2 images are acquired at a high spatial resolution (10 m) and can therefore be used to quantify urban vegetation with enough spatial detail to assess typhoon impacts. The

objectives of this study are to determine (1) whether typhoon-induced damage is related to urban land cover given different urban backgrounds and (2) whether the pattern of vegetation damage changes with urban landscape pattern. The results of this study provide insight into the response of urban vegetation to the landfall of major typhoons and are essential for improving urban management policies.

2. Materials and methods

2.1. Study area

Eight cities in Guangdong Province, China, located along the typhoon path were selected as the study area (Fig. 1). The cities have different terrains, including the Pearl River Delta (Guangzhou, Dongguan and Jiangmen), the Chaoshan Plain (Chaozhou and Jieyang) and mountainous regions (Meizhou, Maoming and Enping). The eight cities all have a subtropical monsoon climate, with an average annual precipitation of 1500–2000 mm and temperature ranging from 13 °C in January to 28 °C in August. These cities have different distances from the track of Typhoon Mangkhut and thus experienced different wind intensities. Therefore, it is feasible to investigate the influence of different wind speeds on vegetation damage. These cities also have different combinations of natural and planted vegetation (e.g., natural forests and road trees), enabling us to investigate the responses of different vegetation clusters to extreme typhoon events. Because the target of this study was urban vegetation, we considered only the main urban zone and nearby outskirts of each city (red rectangles in Fig. 1) rather than the administrative divisions. Given that the main urban zones of the selected cities have different sizes, and that the urban landscapes vary in other ways, we can also investigate whether the urban vegetation response to typhoons differs by landscape structure.

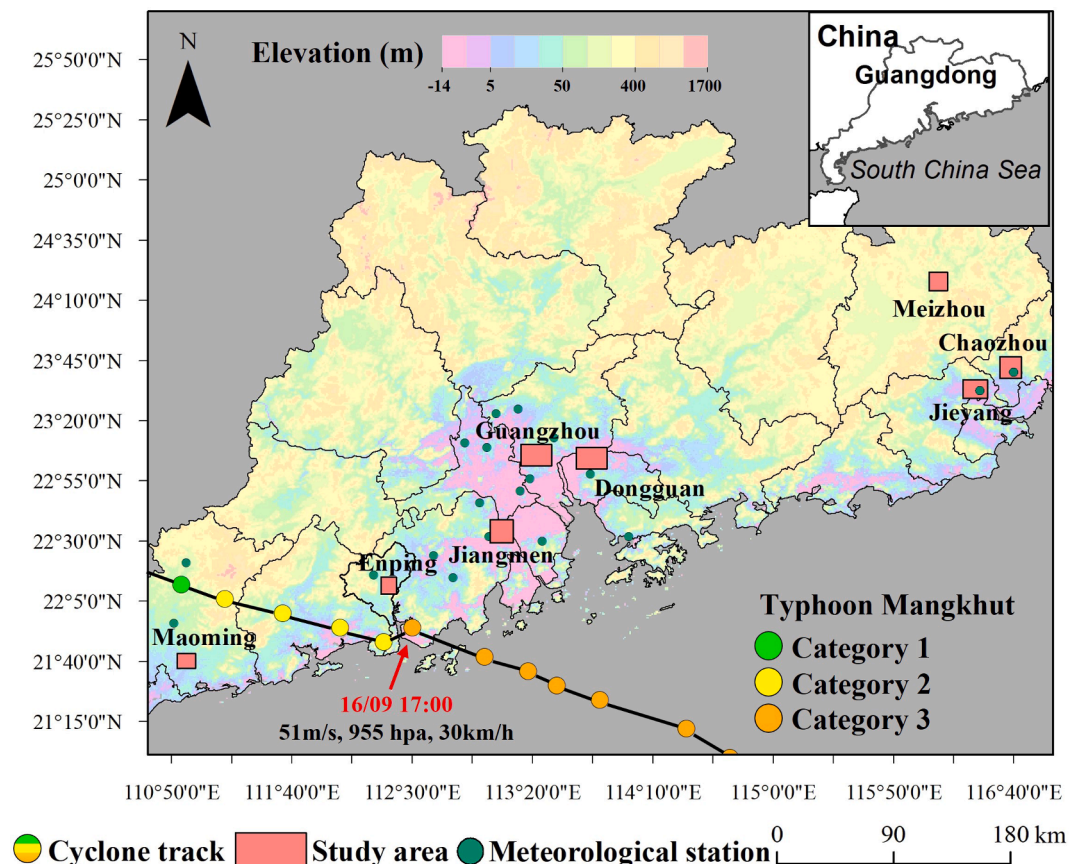


Fig. 1. Eight cities in Guangdong Province, China, close to the track of super Typhoon Mangkhut.

2.2. Dataset

Sentinel-2 images were used to assess the vegetation damage due to its high spatial (10 m) and temporal (5-day revisit cycle) resolutions. This study used a pair of cloud-free images covering the study area acquired before and after typhoon landfall to detect typhoon-induced vegetation change. There were no available cloud-free data in 2018 before the typhoon due to the frequent cloud cover in this subtropical region. Therefore, cloud-free images of the study area in 2017 (one year earlier) were acquired. These images were collected in the same season as the post-typhoon image and provided a good proxy of pre-typhoon vegetation status (Table 1). The post-typhoon images were acquired two to three weeks after the typhoon made landfall. The damage assessments performed using these images reflected post-typhoon human intervention, such as manual removal of the fallen trees. All of the Sentinel-2 images used in this study were L1-C products (top of atmosphere reflectance) obtained from the United States Geological Survey (USGS) Earth Explorer Platform.

Auxiliary datasets, including wind speed records and building layers, were used to describe the typhoon intensity and urban landscape. The hourly wind speed records of 23 meteorological stations were collected from the National Meteorological Information Center of China (<http://data.cma.cn/>), from 0:00 on September 12, 2018, to 09:00 on September 18, 2018 (China standard time, during and after typhoon landfall). The extreme wind speed (EWS) was used to reflect the hourly wind intensities during the period over which the storm was overland, because EWS would gauge the most destructive wind energy during a given period. Most of stations are located close to urban areas even though they are not within the urban cores. One station (Shantou station) was excluded because it is in the cropland. The neighborhood of these stations covers both natural and urban vegetation. Fig. 2 illustrated profiles of hourly extreme wind speed of meteorological stations nearest to each urban core. Geospatial data of buildings of Guangzhou city was collected from the government to derive the building information for our analysis.

2.3. Methodology

Fig. 3 shows the flowchart used to assess typhoon-induced vegetation damage in and around urban areas. The first step is to preprocess the pre- and post-typhoon images, aiming to remove the systematic bias caused by the interannual differences. Second, a pair of Sentinel-2 images was used to extract the urban greenness change based on a vegetation index. Finally, the vegetation loss induced by the typhoon was further analyzed with influential factors including wind speed and urban landscaping.

2.3.1. Remotely sensed vegetation damage mapping and validation

(1) Image preprocessing

The preprocessing of the Sentinel-2 images mainly involved

Table 1
Summary of Sentinel-2 images used in this study.

City name	Orbit code	Pre-typhoon* acquisition date	Post-typhoon acquisition date
Guangzhou	T49QGF		
Dongguan	T49QGF	Oct. 27, 2017	Oct. 07, 2018
Jiangmen	T49QGF		
Meizhou	T50QMM		
Chaozhou	T50QMM	Oct. 24, 2017	Oct. 04, 2018
Jieyang	T50QMM		
Enping	T49QFE	Oct. 27, 2017	Oct. 07, 2018
Maoming	T49QDE	Oct. 25, 2017	Oct. 05, 2018

* Typhoon Mangkhut made landfall on Sept. 16, 2018.

atmospheric correction, image co-registration, data clipping, and relative image calibration. First, Sen2Cor processor was used for atmospheric correction on the downloaded Level-1C data to generate the Level-2A surface reflectance data (Tian et al., 2020). Second, images of the same city were co-registered and clipped to obtain a pair of pre- and post-typhoon images for each city. Third, a relative calibration was implemented by building a linear regression model for each band using samples of invariant objects (e.g., deep water bodies or bright, unvegetated surfaces) (Olsson, 1993; Song et al., 2018) to further remove the minor systematic difference between pre and post-typhoon images.

(2) Vegetation damage mapping

NDVI, the widely used vegetation index in vegetation disturbance detection and analysis, was used in this study to represent vegetation greenness (Ayala-Silva and Twumasi, 2004; Hu and Smith, 2018; Jin and Sader, 2005; Yang et al., 2018). NDVI is demonstrated as an effective indicator of typhoon damages in a previous study (Zhang et al., 2013), and has minimal sensitivity to topography and illumination effects (Chen et al., 2020; Matsushita et al., 2007), which is calculated as follows:

$$NDVI = (NIR - RED) / (NIR + RED) \quad (1)$$

where NIR and RED are the 8th band and the 3rd band of Sentinel-2 L2A images, respectively. For vegetation cover, the NDVI value is usually larger than 0.15 (Eastman et al., 2013; Liu et al., 2015; Yang et al., 2012). In this study, we considered only image pixels with an NDVI value larger than 0.15 to be vegetation. It is reasonable to assume that typhoon damage will not clear all vegetation in a 10×10 m pixel. Therefore, to remove the influence of land cover change from 2017 to 2018, especially urban expansion (e.g., vegetation was changed to build-up due to urbanization), only vegetated pixels (e.g., $NDVI > 0.15$) that existed in both the pre- and post-typhoon images were considered in the subsequent analyses.

Then, the difference between NDVI values post and pre typhoons can be used to quantify the severity of damages. Existing studies often use the direct difference of NDVI to assess the damage of typhoons on dense natural forests (Ayala-Silva and Twumasi, 2004; Bishop et al., 2019; Chen et al., 2020). However, many Sentinel-2 pixels in urban areas are mixed with vegetation and non-vegetation components, so the direct difference would underestimate the damage to vegetation. Therefore, in this study, typhoon-induced vegetation changes were quantified as the relative difference between NDVI values post and pre the typhoon:

$$\Delta NDVI = 100\% \times (NDVI_{\text{post}} - NDVI_{\text{pre}}) / NDVI_{\text{pre}} \quad (2)$$

where $NDVI_{\text{pre}}$ and $NDVI_{\text{post}}$ are the NDVI values of the pixels in 2017 and 2018, respectively. A negative value of $\Delta NDVI$ suggests vegetation loss induced by typhoon damage, while a positive value of $\Delta NDVI$ indicates vegetation gain that suggests vegetation post typhoon is even greener than pre typhoon.

(3) Validation

To validate the reliability of vegetation damage maps derived from Sentinel-2 imagery, the very high-resolution (2 m) WorldView-3 multispectral images were used as reference data. The WorldView-3 image pair was obtained on October 30, 2017, and September 29, 2018, respectively, temporally consistent with Sentinel-2 images. The image extent (Longitude: $114^{\circ}4'E$ – $114^{\circ}13'E$ and Latitude: $22^{\circ}34'N$ – $22^{\circ}40'N$) spatially overlaps with Sentinel-2 image (Orbit number: T49QHF), which locates in Longhua district, Shenzhen, one megacity along the typhoon track. 10- and 2-m resolution images were geo-corrected by manually selected ground control points, and the 2-m resolution images were overlaid with 10 m grids to match the size of Sentinel-2 pixels. By visual inspection of WorldView-3 images, we identified grids with

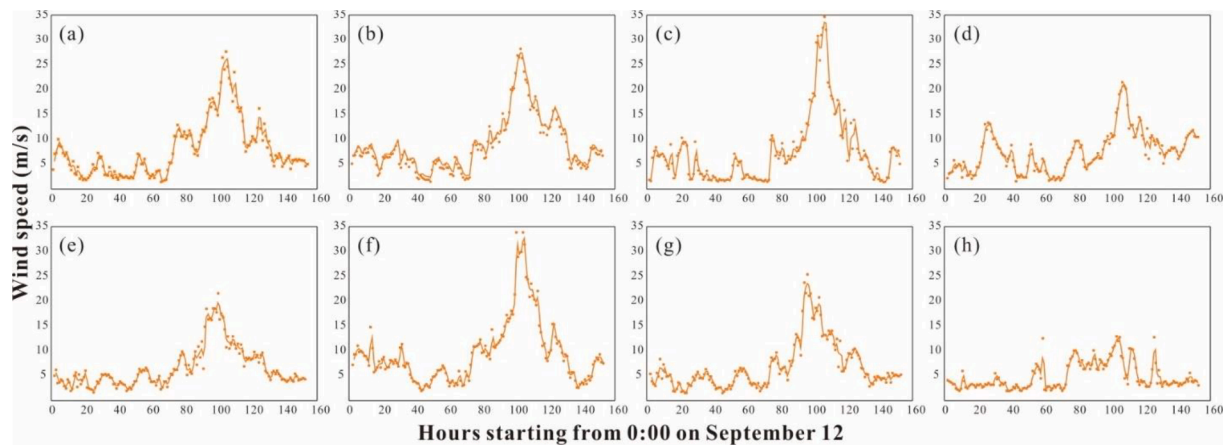


Fig. 2. Hourly extreme wind speed of (a) Guangzhou, (b) Dongguan, (c) Enping, (d) Maoming, (e) Chaozhou, (f) Jiangmen, (g) Jieyang, and (h) Meizhou.

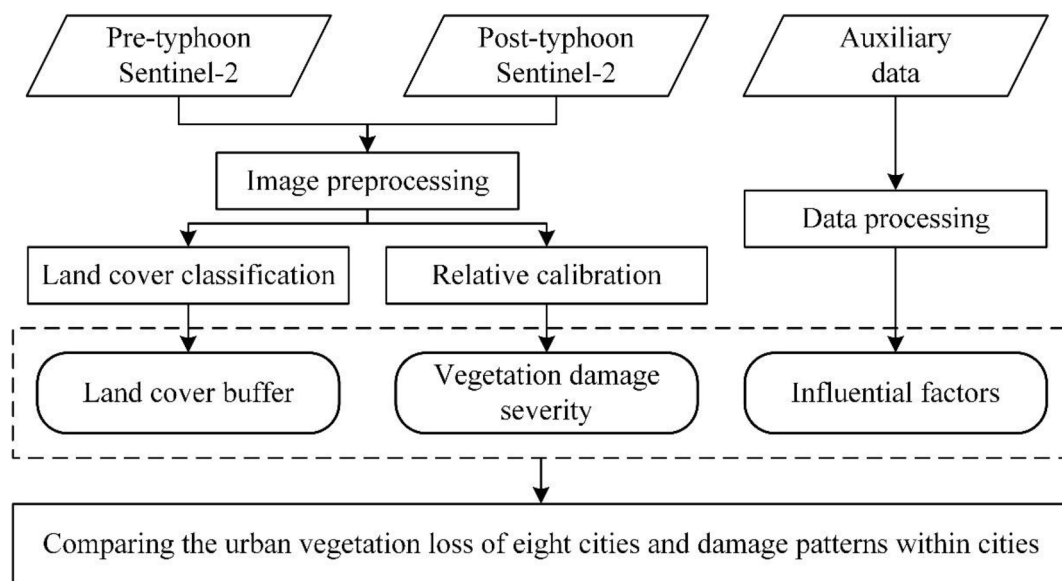


Fig. 3. Flowchart of the process used to investigate the vegetation damage severity and damage patterns of eight cities using Sentinel-2 images.

vegetation damage of different severities as validation samples. A total of 400 samples were manually collected from different parts of the WorldView-3 image. Then, an error matrix was used to assess whether the damage mapping from the Sentinel-2 images agreed with the reference samples from WorldView-3 images.

2.3.2. Analyses of vegetation damage patterns and influential factors

2.3.2.1. Comparing vegetation damage in different land covers. In urban areas, vegetation differs with functions associated with land covers, such as roads, residential communities, and parks. To know the patterns of vegetation damage in different land covers, vegetation pixels were grouped into three major types based on their locations: road trees, residential greenspace, and natural greenspace. In this study, land cover maps were firstly produced by an object-oriented classification approach using eCognition software (Xu et al., 2019) and a supervised classifier, random forest (RF) (Belgiu and Drăgu, 2016). Sentinel-2 images of each city in 2017 were classified into the following classes: built-up, road, bare land, building shadow, crop, grass, or forest (Fig. 4).

The forest and grassland pixels in the land cover maps were further grouped into the three types based on their surrounding land covers, namely, natural vegetation, road trees, and residential greenspace, respectively. Specifically, first, large and intact vegetation patches (e.g.,

city parks) were classified as natural vegetation, to reflect the vegetation damage in natural environment. Vegetation in these areas is distant from artificial land surfaces (roads, buildings) and had little human intervention after typhoons. Next, the remaining vegetation areas were divided into road trees and residential greenspace according to the presence of roads and buildings, respectively. Road trees are any trees planted along the roads. In Sentinel-2 images, vegetation within 10-m distance to the roads was classified as road trees. Residential greenspace was vegetation within a 20-m distance to the built-up area and building shadows. For comparing vegetation damage among vegetation types, the random sampling strategy was employed to select samples to minimize the influence of spatial autocorrelation and biotic factors such as vegetation species, age and health. Spatially adjacent samples were excluded, and the random sampling process continues until enough samples were selected. Lastly, the NDVI losses of samples with these three vegetation types were compared in each city to investigate the association between vegetation damage and land covers.

2.3.2.2. Analysis of influential factors. Based on previous studies of typhoon impact on natural vegetation and on urban wind environment, we selected wind speed, vegetation sparseness, and building height as influencing factors because: (1) wind speed is a dominant factor for natural vegetation damage (Negrón-Juárez et al., 2014); (2) high

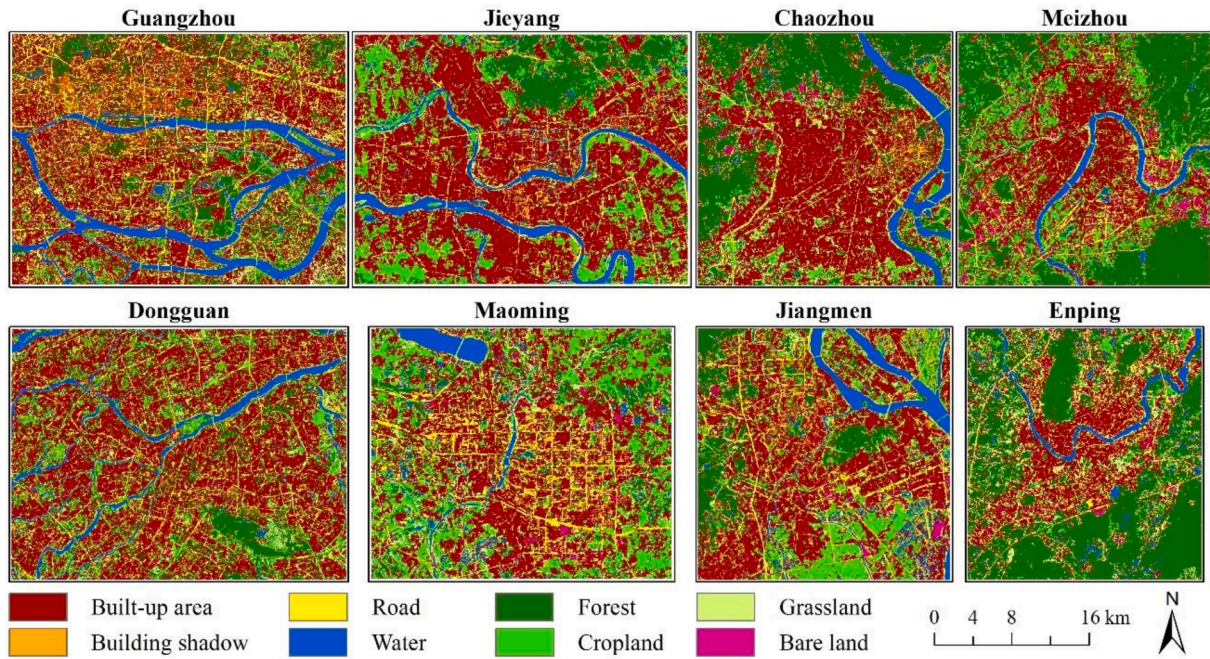


Fig. 4. Land cover maps of the eight studied cities derived from Sentinel-2 images in 2017.

vegetation density may decrease the damage of stems because neighboring trees provide support (Bragg et al., 2003); and (3) studies in the field built environment show that building geometry can lower or enhance the wind velocity (Du and Mak, 2018; van Druenen et al., 2019).

(1) Wind speed

We firstly investigated the relationship between vegetation damage and the wind intensity recorded by meteorological stations. For 23 stations in our study area (Fig. 1), pixel-wise vegetation damages in a 5-km buffer of each meteorological station were averaged to represent the vegetation damage situation for each station. Then, simple linear regression was used to model the relationship between the vegetation damage and the wind speed.

(2) Vegetation sparseness

For urban vegetation pixels (road trees and residential greenspace), vegetation sparseness was calculated by using 5×5 moving windows. Specifically, for the i th vegetation pixel, its vegetation sparseness S_i can be computed according to Eq. (3):

$$S_i = 1 - \frac{\sum A_j/d_{ij}}{\sum 1/d_{ij}} \quad (3)$$

where A_j is an indicator of whether the j th pixel in the moving window is a vegetation pixel. A_j equals 1 if it is vegetation, otherwise it equals 0. The variable d_{ij} is the spatial distance between the j th pixel and the central pixel. S_i ranges from 0 to 1. A value of 0 means all pixels in the moving window are vegetation, while 1 means the central pixel is the only vegetation pixel in the window, e.g., extremely sparse.

(3) Building height

We calculated the mean height of buildings (mBH) in 5×5 windows and assigned this mBH to any central vegetated pixels in a window to reflect the capacity of surrounding buildings to block hurricane winds. To accomplish this, we first generated a 10-meter raster image of

building height that is spatially co-registered with Sentinel-2 image, from the collected geospatial data of building footprints. The value of mBH in 5×5 windows was the calculated:

$$mBH_i = (\sum H_j/d_{ij})/25 \quad (4)$$

where H_j is the building height of neighboring pixel j in the 5×5 windows.

3. Results

3.1. Vegetation damage mapping and validation

Relative changes in NDVI calculated from Eq. (2) were divided into 7 levels to represent the greenness differences pre and post typhoon (Fig. 5), with warmer colors indicating vegetation loss and colder colors suggesting vegetation gain. The results show that the eight cities experienced varying severities of typhoon damage. Cities closer to the typhoon track, such as Enping and Jiangmen, experienced more vegetation damage (Fig. 5). We calculated the percentage of vegetation pixels with NDVI decreases, reflecting the amount of urban vegetation with typhoon-induced damage. Specifically, Enping had the largest percentage of damaged vegetation (61.0%), followed by Maoming (33.6%) and Jieyang (33.5%). Dongguan had the lowest percentage of vegetation influenced by the typhoon (only 17.9%).

Fig. 6 shows three sub-regions of WorldView-3 false-color images taken before the typhoon (in the first column), after typhoon landfall (in the second column), and in the third column, the corresponding NDVI change derived from the Sentinel-2 images. Four types of change in the WorldView-3 images between the two time periods were interpreted for validation, namely, vegetation increase, moderate loss, no change, and dramatic loss (see examples in Fig. 6). Moderate vegetation loss represents those vegetation plots with decreased greenness but without the loss of vegetation coverage in WorldView-3 images, and dramatic vegetation loss denotes vegetation plots with remarkable loss of vegetation coverage in WorldView-3 image (e.g., fallen trees) and with high decrease of NDVI in Sentinel-2 image (the red pixels in Fig. 6(c)). Despite the 10-m spatial resolution of the Sentinel-2 imagery, the derived NDVI changes were consistent with the land surface changes

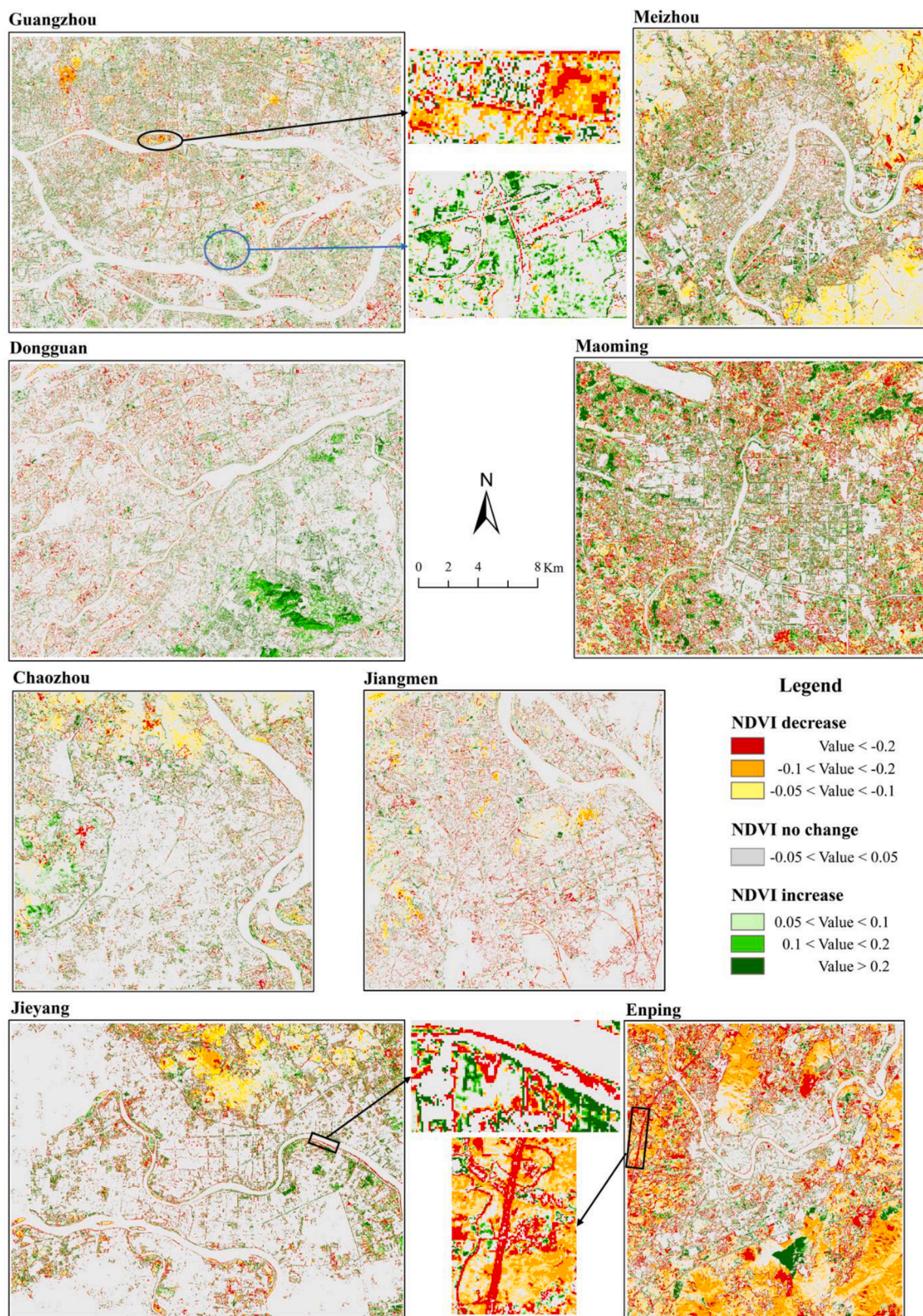


Fig. 5. NDVI change maps of the eight cities along the typhoon track – the black rectangles show the vegetation damage along roads, the black circle shows a city park with decreased NDVI and blue circle highlights a wetland park with increased NDVI after the storm. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

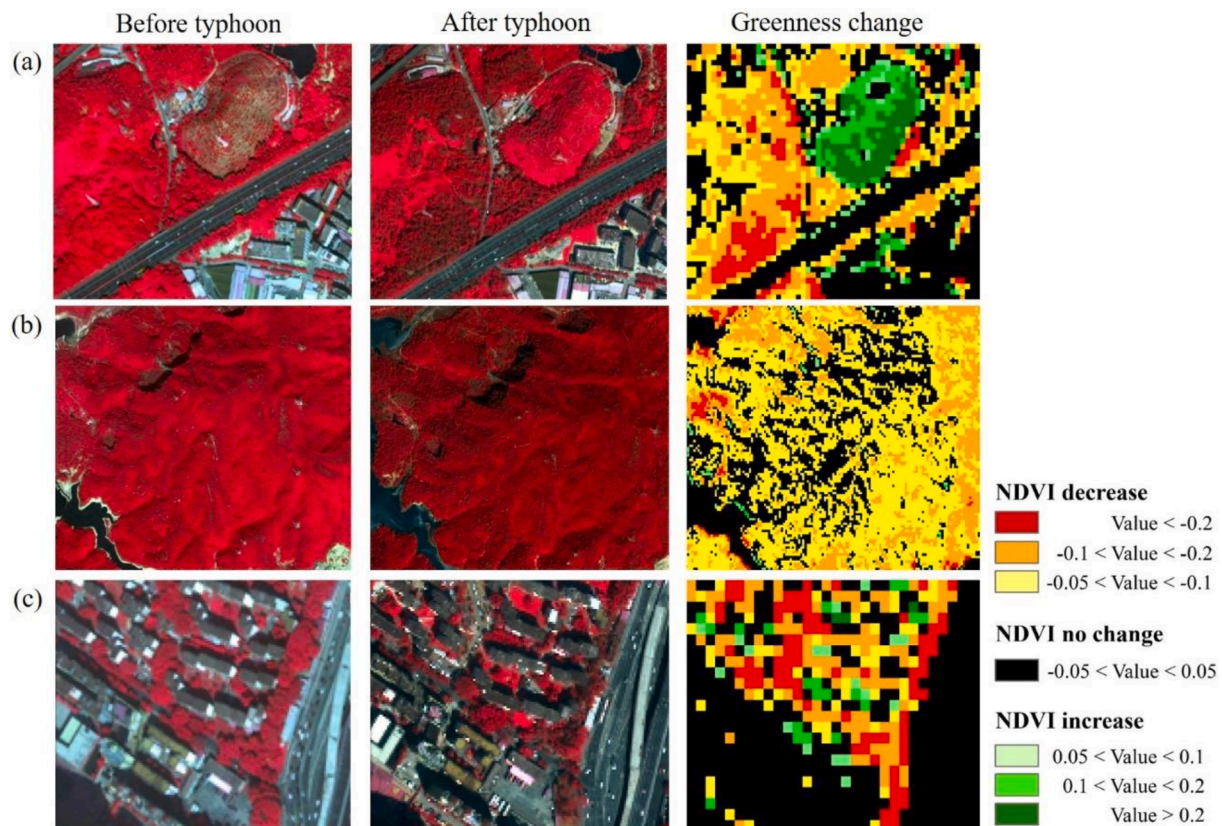


Fig. 6. WorldView-3 images before (the first column) and after Typhoon (the second column) that show the vegetation damage and the corresponding NDVI changes derived from Sentinel-2 images (the third column) in three sites under different situations: (a) both greenness decrease and increase existing, (b) moderate greenness loss in natural forests, and (c) dramatic vegetation loss in a residential community.

observed in the high-resolution images. The overall accuracy reached 97% from the error matrix (Table 2), demonstrating high consistency between the changes in the vegetation damage mapped from Sentinel-2 images and the observed canopy cover changes assessed from WorldView-3 images.

3.2. Comparison of vegetation damage among land cover types

In all eight cities, vegetation damage from the typhoon has high spatial heterogeneity but shows similar land cover-related patterns. Among all cities, the damage of natural vegetation has the smallest percentage (10.1–18.7%), while the damage of road trees and residential greenspace is higher (26.6–37.0%). Van der Waerden's normal scores test (Conover and Iman, 1979) was used to test whether the vegetation damage of road trees and residential greenspace are significantly higher than that of natural vegetation in all cities (Fig. 7). Van der Waerden's normal scores test is a nonparametric significance test method widely used for datasets with abnormal distribution. For each vegetation type, 1% of the total pixels were randomly selected (with the minimum number of 100) and those selected pixels were not spatially

adjacent. This random sampling strategy can minimize the influence of spatial autocorrelation on the significance test. The result showed that road trees and residential greenspace damage were significantly higher than the natural vegetation for all cities (P value < 0.001), suggesting that road trees and residential vegetation were prone to be disturbed by the typhoon.

3.3. Relationship between vegetation damage and influencing factors

3.3.1. Influence of wind speed

The average NDVI losses around each station and EWS has a moderately positive relationship ($r^2 = 0.43$, $n = 23$, P value < 0.001) (Fig. 8). Our results agree with previous studies, including in Puerto Rico (Hu and Smith, 2018) and the US Gulf Coast (Negrón-Juárez et al., 2014). However, the interpretability of the relationship between wind intensity and the vegetation damage severity among the cities in our study was not as high as in a previous study focused on damage assessments on the natural environment of a tropical island (e.g., $r^2 = 0.88$ in Hu and Smith, 2018), suggesting that the urban landscape may also impact the vegetation damage.

Table 2

Confusion matrix of vegetation damage derived from Sentinel-2 images using reference samples selected from WorldView-3 (WV-3) images.

		Mapping results from Sentinel-2				Producer accuracy
		Increase	No change	Moderate vegetation loss	Dramatic vegetation loss	
Reference data From WV-2	Increase	94	4	1	1	94%
	No change	0	100	0	0	100%
	Moderate vegetation loss	0	1	98	1	98%
	Dramatic vegetation loss	0	4	2	94	94%
User accuracy		100%	92%	97%	98%	
Overall accuracy						97%

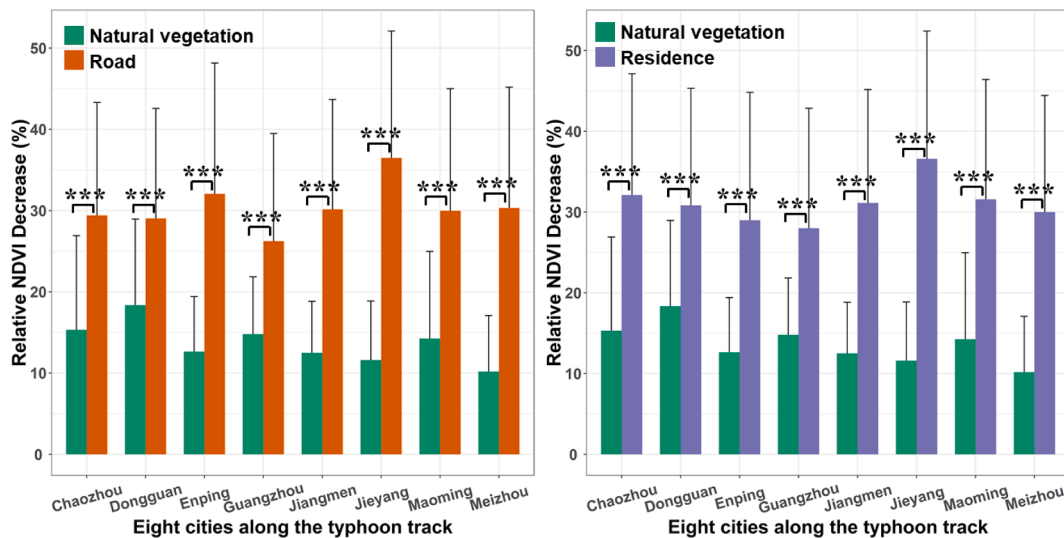


Fig. 7. A comparison of the loss of vegetation greenness between road trees and natural vegetation (left) and between the residential greenspace and the natural vegetation (right) for each city (***)P value <0.001, error bar is the standard deviation).

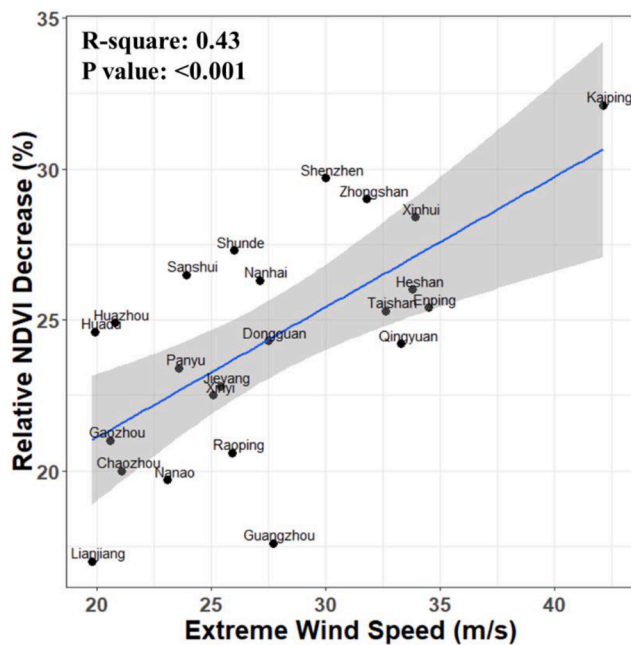


Fig. 8. A scatter plot between the average NDVI decrease versus the wind speed recorded by 23 stations.

3.3.2. Influence of vegetation sparseness and building height

The spatial heterogeneity of vegetation damage in all cities (Fig. 5) implies that the distribution of vegetation may affect the interaction between storms and vegetation. Consequently, the relationship between vegetation damage and vegetation sparseness in all cities was analyzed. To suppress the effect of other variations besides vegetation sparseness, pixels were grouped into bins of vegetation sparseness with 1% intervals. To minimize effects of spatial autocorrelation on the regression, a sample of 100 spatially nonadjacent pixels for each bin was randomly selected. All pixels were used as sample if the pixel number of the bin were <100. The result shows a positive linear relationship between vegetation damage and vegetation sparseness in all cities (Fig. 9). The correlation coefficients range from 0.39 to 0.89 and all are significant (P value <0.01), reflecting that the isolated vegetation was more susceptible to wind attack than clustered vegetation in the urban environment.

Fig. 10 shows a negative relationship between the averaged building height and averaged relative NDVI decrease ($r = -0.57$, $p < 0.01$). Similar to the analysis of vegetation sparseness, we generated bins of building height with 1 m intervals and calculated the mean and standard deviation of relative NDVI loss within each bin, and random pixels in each bin were used for this analysis to reduce the impact of spatial autocorrelation of pixels. Results show that urban vegetation surrounded by taller buildings tends to have lower relative NDVI loss, implying that buildings alleviate the exposure of vegetation to wind attack. However, the effect of low-rise buildings was limited, indicated by the stable NDVI loss when building height is lower than 50 m. In contrast, vegetation surrounded by the supertall buildings was less damaged.

4. Discussion

4.1. Implications for developing cities prone to typhoons

Our result illustrates spatial heterogeneity of vegetation damage induced by typhoons in urban areas, implying a varied resistibility of urban vegetation to strong storms. The findings of this study could help developing cities more resilience to typhoons.

First, we found that vegetation along roadsides and in residential areas is more vulnerable. On the one hand, species of urban trees may not be selected based on their resilience to strong winds (Negrón-Juárez et al., 2014; Ribeiro et al., 2016). Instead, they may be selected for the sake of urban aesthetics. For example, wide crown spread and dense foliage are essential attributes for trees in tropical cities; however, these attributes make species more susceptible to storm damage (C. Y. Jim and Liu, 2001). Thus, multi-stemmed plants with strong root functional traits that have high wind resistance could be a possible candidate for urban greening (Jung-Tai et al., 2017; Su et al., 2020). On the other hand, vegetation regrowth may be faster in natural areas, and in those areas damaged trees were not cleared after the typhoon, with a large pulse of litter to the forest floor. This litter and associated fungi are important sources of nutrients to tropical forest trees after canopy disturbances, such as those from hurricanes. In contrast, removing debris after a disturbance leads to lower long-term productivity (Liu et al., 2018; Lodge et al., 2014); indeed, larger amounts of duff and mulch cover were associated with increased growth rates of urban trees in San Juan, Puerto Rico (Tucker Lima et al., 2013). Our study suggests that human intervention after typhoons (removal of fallen trees, dead branches, and leaves) may have side effects on vegetation restoration in urban areas.

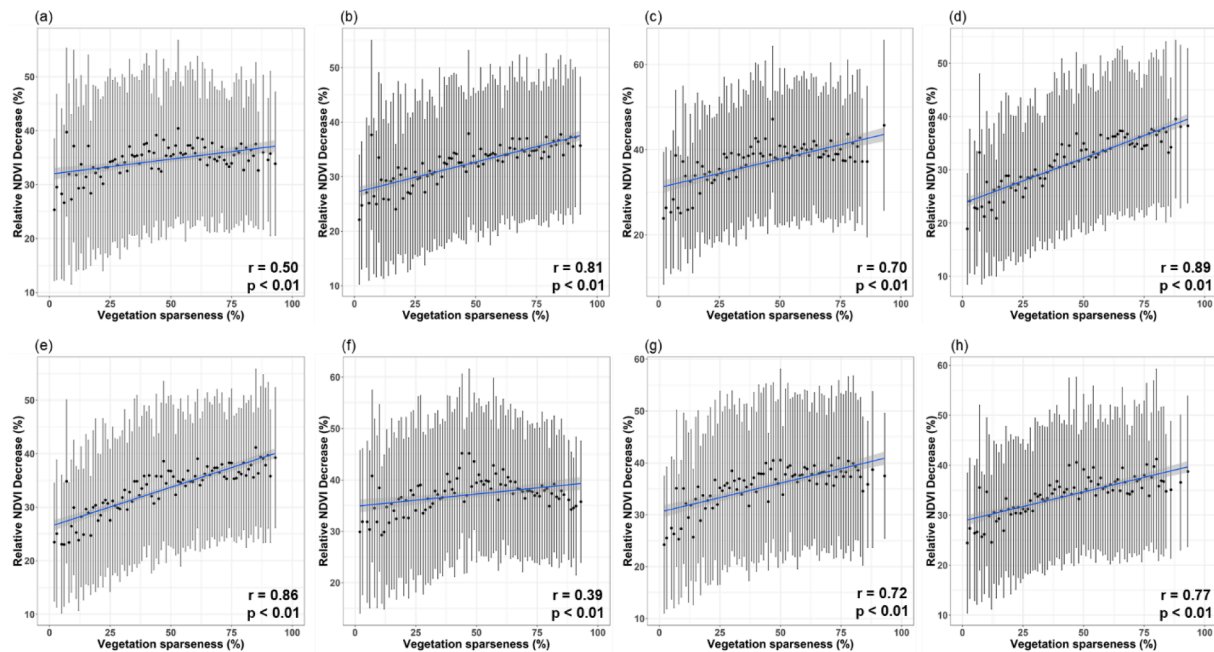


Fig. 9. Relationship between the vegetation sparseness of urban vegetation and relative NDVI loss for (a) Chaozhou, (b) Dongguan, (c) Enping, (d) Guangzhou, (e) Jiangmen, (f) Jieyang, (g) Maoming, (h) Meizhou. The dot means the average NDVI loss in each bin and the error bar represents the standard deviation.

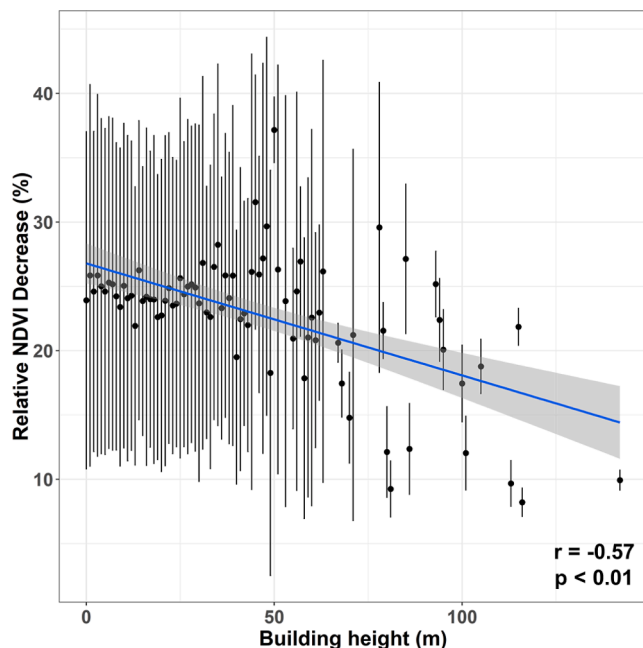


Fig. 10. Relationship between the averaged building height and averaged relative NDVI loss for Guangzhou. The dot means the average NDVI loss in each bin and the error bar represents the standard deviation.

Thus, urban management of post typhoons should consider the strategies for promoting the recovery of green space, e.g., retaining the typhoon-induced vegetation debris, which rarely affects the normal traffic, so that greenness can recover faster.

Second, our study shows that sparser vegetation in urban areas is more vulnerable to typhoons. A possible reason is a trade-off between the space designated for urban afforestation and that for built-up land. In high-density cities, areas with a higher fraction of impermeable surfaces can increase stress on urban vegetation (Mullaney et al., 2015). For example, urban trees may suffer from poor soil conditions, especially

when root growing space is constrained by confined soil volumes. Human activities, including improper transplanting material and process, extensive urban renewal and infrastructure development, may also affect the root systems and lead to lower resistance of trees to storms (Jim and Liu, 1997; Jim, 2019). In future urban planning and management, expanding the soil volume, such as what is known as Soil Area Provision (SAP), in which soil extends from a narrow footpath to the adjoining roadway, forming a soil peninsula (Jim, 2019), is essential to provide more space for root growth and can increase tree resistance to uprooting.

Third, this study reveals that buildings appear to reduce the damage of nearby vegetation, possibly attributed to the weakening effect of building on the wind velocity in the urban environment (Fig. 10). Theoretically, wind intensity directly determines the severity of vegetation damage. Thus, the spatial distribution of satellite-derived vegetation damage is typically consistent with the spatial distribution of wind speed in the natural environment (F. Wang and Xu, 2009; W. Wang et al., 2010). However, there is a lack of evidence on the influence of wind intensity on vegetation damage at street level in urban environment. Although it is difficult to measure the wind speed at a certain position during typhoon landfall, the building height and arrangement can be proxy of factors influencing urban wind velocity, according to the investigation of the ratio of wind velocity at pedestrian level to that at reference point on roof (Horiuchi et al., 2005; Kubota et al., 2008). On the one hand, the average wind velocity is significantly lowered by closely spaced tall buildings in modern megacities (Du and Mak, 2018). On the other hand, taller buildings can cause higher wind speeds in surrounding low-rise urban areas (van Druenen et al., 2019). This effect could also make vegetation located in the low-rise urban area more susceptible to wind attack. This study suggests urban greening should consider the impact of buildings on wind speed to improve the vegetation resistance to storms.

4.2. Limitations

This study has several limitations. First, the pre-typhoon images of the study area were acquired in 2017 (one year earlier). Due to the frequent cloud cover, studies are prone to use the image pair with one-year interval but with the same season for vegetation damage

assessment (Abbas et al., 2020; Feng et al., 2018; Negrón-Juárez et al., 2014; Zhang et al., 2013). Based on the relative calibration and vegetation extraction between pre- and post-typhoon images, the influence of the minor systematic difference and land cover change during one year were largely removed. Second, there were no other significant disturbances during the period we investigated, but another smaller typhoon Hato that made landfall in our study area in August 2017. Given that city governments respond quickly after typhoons, including removing broken trees and replanting new trees (Cheng et al., 1999), we assume that typhoon Hato in August 2017 would not significantly impact our study using the NDVI of October 2017 (two months after typhoon Hato) as the baseline. Third, wind records from only 23 meteorological stations were used to investigate the relationship between wind speed and vegetation damage, which may make the regression between vegetation damage and wind speed less reliable. This relationship needs to be tested with more stations in the future studies. Fourth, biotic factors including vegetation species, vegetation growth state, age, and health may have effects on vegetation losses (Feng et al., 2020; Jim and Liu, 2001; Negrón-Juárez et al., 2014). However, we did not quantify the effect of biotic factors in this study due to the lack of data. To control the influence of biotic factors, we adopted the random sampling strategy and averaged the vegetation loss of all random samples by assuming that vegetation with different biotic factors is evenly distributed in the city. We believe more investigations of the impact of biotic factors would improve our understanding of how urban vegetation responds to super typhoons.

5. Conclusions

The objectives of this study were to assess the vegetation damage in urban areas induced by a super typhoon, Typhoon Mangkhut, and provide insight into the relationships between vegetation damage severity, typhoon wind speed and urban landscape characteristics. Our study demonstrated that sentinel-2 images with a spatial resolution of 10 m can reliably map vegetation damage at fine scales with an accuracy of 97%. The vegetation damage of the eight cities shows significant spatial heterogeneity but similar patterns. For all eight cities, typhoon Mangkhut inflicted remarkable damage on the urban vegetation. The average vegetation damage in cities far from the typhoon track is significantly less than that in stations along the track, confirming that wind speed is an important factor affecting the amount of vegetation in urban areas. The strength of this relationship is much weaker, however, than that of vegetation in natural environments reported by other studies, suggesting that other factors affect the severity of typhoon damage on vegetation. Our study found that typhoon damage was strongly associated with land cover types. We found that vegetation along roads and residential areas where vegetation is mainly artificially planted, is more vulnerable to wind than natural vegetation, and the severity is associated with vegetation sparseness and building height. This study provides insights into urban planning and management for improving the resistance of vegetation in urban systems to super typhoons.

CRedit authorship contribution statement

Shuai Xu: Conceptualization, Methodology, Software, Formal analysis, Investigation, Writing – original draft, Writing – review & editing, Visualization. **Xiaolin Zhu:** Conceptualization, Methodology, Supervision, Resources, Writing – review & editing, Project administration, Funding acquisition. **Eileen H. Helmer:** Conceptualization, Methodology, Writing – review & editing. **Xiaoyue Tan:** Investigation, Writing – review & editing. **Jiaqi Tian:** Investigation, Writing – review & editing, Visualization. **Xuehong Chen:** Investigation, Resources, Funding acquisition.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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