

RESEARCH ARTICLE

Assessing the Direct Impact of Typhoons on Vegetation Canopy Structure and Photosynthesis

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Typhoons are undergoing changes in frequency, intensity, and landward movement due to climate change, placing coastal vegetation ecosystems at heightened risk. These ecosystems provide critical ecological, social, and economic functions, making accurate assessment of typhoon impacts essential for effective management and disaster risk reduction. Traditional methods for assessing typhoon impacts on large-scale vegetation often compare pre- and post-typhoon satellite images. These do not account for natural variations in plant life cycles or interannual variations in environmental conditions, potentially leading to inaccurate assessments of typhoon-induced vegetation damage and recovery. This study proposes a novel framework for quantifying typhoons' immediate and long-term impacts on vegetation canopy structure and photosynthesis. We developed random forest models based on satellite-observed leaf area index (LAI) and environmental data during typhoon-free periods to simulate LAI under non-typhoon conditions. The simulated LAI time series was then compared with the satellite-observed typhoon-affected LAI to assess the typhoon-induced canopy loss and recovery, which was then used to estimate the typhoon-caused photosynthesis loss and recovery with 2 widely used light-use efficiency models. The framework was applied to 3 super typhoons that traversed the Greater Bay Area. Typhoons Nida, Hato, and Mangkhut caused canopy losses in 76.58%, 61.25%, and 89.67% of vegetated regions, respectively, leading to direct cumulative gross primary production losses of 0.36, 0.22, and 0.50 Tg C. The proposed framework establishes a pivotal foundation for future modeling and assessment of direct vegetation damage attributed to typhoons, providing scientific support for vegetation management and disaster risk reduction in coastal areas.

Introduction

Terrestrial ecosystems, serving as crucial components of the global carbon cycle, are profoundly influenced by climate change. This influence encompasses both gradual climatic and environmental shifts [1–3], as well as extreme climate events [4]. Among these extreme events, tropical cyclones (also known as typhoons or hurricanes) can cause substantial damage to vegetation [5,6]. The impact of these events may potentially counteract the potential increased carbon uptake from favorable environmental changes (e.g., global warming and rising CO₂ concentration) [7]. Therefore, elucidating the dynamics of vegetation responses to

extreme climate events and their underlying mechanisms is critical for understanding how terrestrial ecosystems react to climate change on a broader scale.

Over the past decades, typhoons have increased in magnitude, and intense typhoons have become more frequent [8]. They have also tended to migrate toward coasts [9]. The increasingly destructive typhoons further coincide with the fact that a substantial portion of their coverage is situated within the tropical and subtropical zones [10], which are crucial for global biomass stock and carbon sink [11,12]. More often than not, typhoon occurrences also coincide with the growing season when vegetation sustains its photosynthetic peak [13,14]. All

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these coincidences lead to a projection that the influence of typhoons on terrestrial ecosystems would inevitably intensify [15].

Intensifying typhoons can alter the vegetation canopy structure and the photosynthetic capacity, primarily through mechanical disruption from gale-force winds [16]. The vegetation canopy is disproportionately exposed to typhoons, suffering from varying levels of defoliation [17], which will subsequently diminish its carbon sequestration capacity [18]. Research has demonstrated the substantial impact of typhoons on carbon dynamics, with studies showing that Taiwan's annual carbon sequestration rate could potentially double in the absence of typhoon disturbances [19], while in other regions, such as longleaf pine woodlands, typhoons have been observed to transform these ecosystems from carbon sinks into net carbon sources [20]. Typhoons' effects on vegetation encompass a complex process, involving both immediate destruction and long-term consequences. The initial damage can be exacerbated by time-lagged impacts and delayed mortality [21]. Furthermore, when the recovery period exceeds the interval between major typhoon disturbances, rapid nutrient depletion may occur, impeding growth or inducing mortality in affected plant communities [22].

Despite increasing attention to the impacts of typhoons on vegetation [6,23], quantitative assessment of typhoon-induced vegetation losses remains a persistent challenge. While advancements in remote sensing technology facilitate timely disaster assessments over multiple spatial scales [24], extensive cloudiness around the typhoon event introduces new complications [17,25]. Large-scale evaluations of vegetation response to typhoons usually rely on analyzing changes in satellite-observed spectral information before and after typhoon events to quantify vegetation loss [26,27]. However, the remote sensing data used in the traditional methods were typically collected either month away from the typhoon event [28] or in the same period of different years [29], which can introduce substantial noise in the assessment. Vegetation exhibits substantial variability, with increases of up to 30% in the normalized difference vegetation index (NDVI) observed over a single month, driven solely by plants' internal phenological processes [30]. Interannual variations in environmental conditions can also lead to substantial interannual variability in vegetation. For instance, favorable environmental conditions can result in end-of-season gross primary production (GPP) being nearly 50% above average [31], and extreme events may induce even greater changes [32]. In contrast, during the landfall of Typhoon Herb, one of the most intense typhoons in Taiwan in the late 20th century, the associated NDVI decline was less than 0.1 [33]. These facts make the accurate assessment of the typhoons' effects on vegetation extremely challenging, as the signal (impacts of typhoons on vegetation) is smaller than the noise (changes in vegetation caused by plant's internal rhythm and environmental variations).

To address these challenges, this study proposed a novel framework to quantify the direct impacts of typhoons on vegetation canopy structure and photosynthesis. Here, direct impacts are defined as changes in vegetation canopy and subsequent alterations in photosynthesis that result solely from the mechanical forces exerted by typhoons. Leaf area index (LAI), defined as half of the total green foliage per unit ground horizontal surface area, is a fundamental indicator of vegetation canopy structure. It serves as an effective indicator for quantifying canopy loss. We employed random forest (RF) models with multiple environmental variables that well capture the inter- and intra-annual variations in vegetation to simulate LAI under

a non-typhoon scenario. The simulated LAI was then compared with observed LAI (typhoon-affected) to characterize the effects of typhoons on vegetation canopy structure. Furthermore, GPP, representing the total carbon assimilated by plants through photosynthesis, was chosen as a key measure of ecosystem productivity. We used 2 widely used light-use efficiency (LUE) models to estimate the trajectories of GPP under both typhoon and non-typhoon scenarios, allowing for the assessment of typhoon's impact on vegetation photosynthetic capacity. Building upon the proposed framework, this study also examined the legacy effects of typhoons and the subsequent recovery of vegetation following typhoon impacts. By quantifying both the immediate and long-term impacts of typhoons on vegetation canopy structure and photosynthetic capacity, this study contributes to a more robust methodology and comprehensive understanding of how extreme climate events affect terrestrial ecosystems, ultimately providing valuable insights for predicting ecosystem resilience and developing effective management strategies in the face of global climate change.

Materials and Methods

Study area

The Guangdong–Hong Kong–Macao Greater Bay Area (GBA), encompassing 9 cities within Guangdong Province along with Hong Kong and Macao, represents a rapidly developing metropolitan cluster in the world (Fig. 1). It is characterized by high vegetation coverage dominated by evergreen species and a subtropical climate. Due to its proximity to the South China Sea, the GBA is prone to frequent typhoons. The unique blend of all these factors makes the GBA an ideal site for exploring typhoon's effects on vegetation dynamics.

Study data

Typhoon track data

The International Best Track Archive for Climate Stewardship (IBTrACS) database constitutes a comprehensive global cyclone repository documenting detailed cyclone information (available at <https://www.ncei.noaa.gov/products/international-best-track-archive>). This study obtained the position and intensity information of typhoons and the maximum extent of the 34-kt (R34), 50-kt (R50), and 64-kt (R64) wind radii [34]. To focus on typhoons with notable impacts on GBA vegetation over the past 20 years, we carried out an initial identification of typhoon impacts. First, typhoons with tracks crossing the GBA were identified. For each identified typhoon, the difference in LAI between the post- and pre-typhoon periods was calculated. This difference was then compared with the LAI difference during the same period in other non-typhoon years. A typhoon was considered to have a substantial impact on GBA vegetation if, within 24 d after the disturbance, the observed LAI difference was lower than the first quartile of LAI differences observed during the same period in other reference years. Based on this criterion, the 3 most damaging typhoons were identified: Typhoon Nida (landfall on 2016 August 2), Hato (2017 August 23), and Mangkhut (2018 September 16) (Fig. S1).

Satellite-based LAI product

The moderate resolution imaging spectroradiometer (MODIS)-derived LAI product (MCD15A2H) with 500-m spatial and 8-d temporal resolution is well suited for timely post-disaster assessments over large regions. However, a statistical analysis

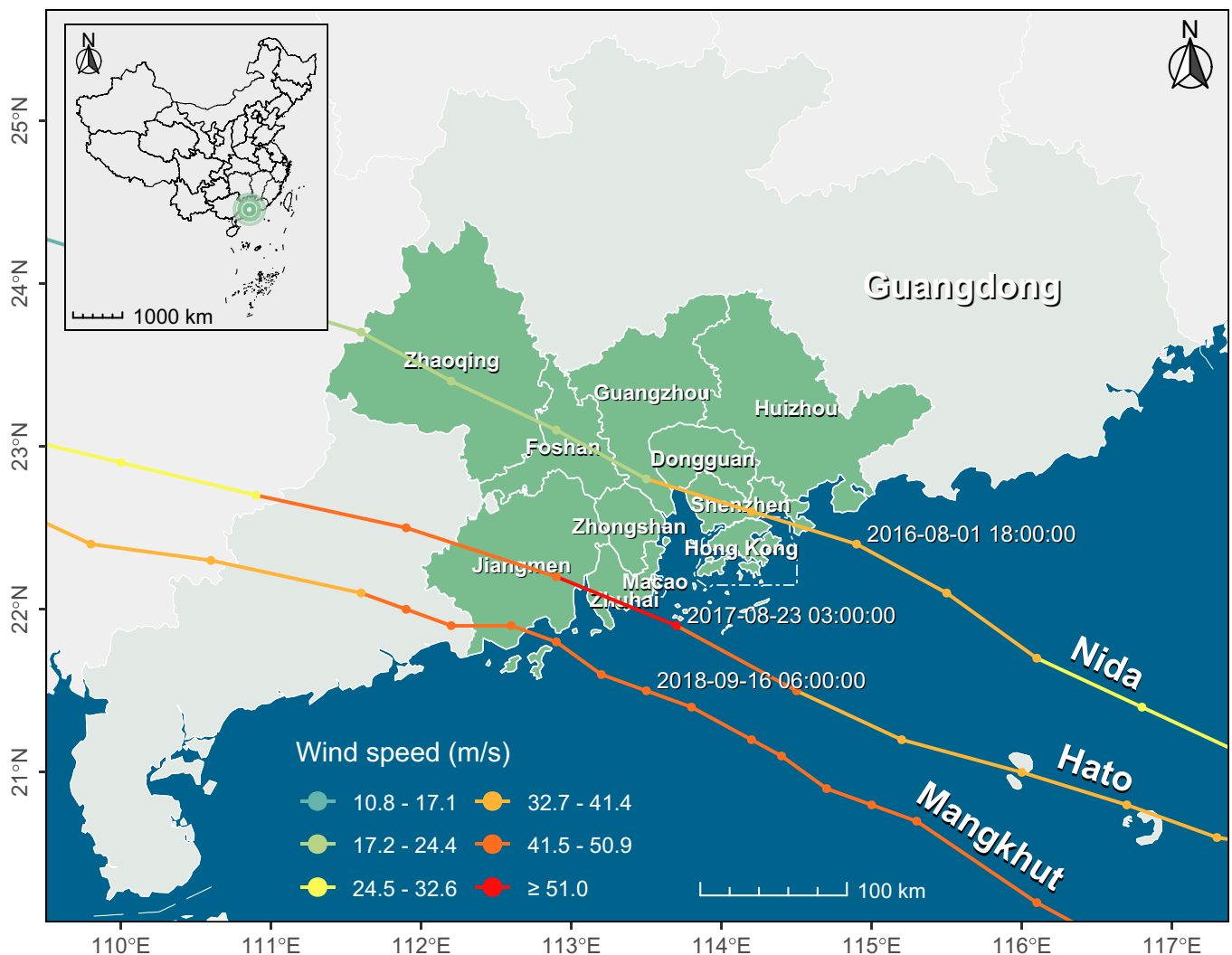


Fig. 1. Study area and tracks of super typhoons Nida, Hato, and Mangkhut. Wind speeds are illustrated by colors along typhoon tracks.

of the quality control information (QC) for vegetation areas within the GBA revealed that while 65.08% of the data meet “relatively high quality” standards ($QC < 32$, the main algorithm used without saturation), only 38.18% are of the highest quality ($QC \leq 2$, using the main algorithm without cloud or saturation) (Fig. S2). To address the issue of lower-quality data, Yuan et al. [35] introduced a modified spatiotemporal filtering method, which performs simple data assimilation for lower-quality observations, followed by Savitzky–Golay filtering to enhance the product. The reprocessed LAI has shown marked performance improvements [36,37] and has been widely used in vegetation monitoring, as well as in land surface and climate modeling [14,38]. In this study, we utilized the reprocessed LAI with an 8-d temporal and 500-m spatial resolution for 2003–2020 (<http://globalchange.bnu.edu.cn/research/laiv061>).

Meteorological data

We considered a series of meteorological factors that could drive LAI and GPP variations, including temperature, radiation, precipitation, vapor pressure deficit (VPD), and CO_2 . Daily air temperature, precipitation, downward shortwave radiation, 2-m dew point temperature data, as well as volumetric soil water

content at depths of 28 to 100 cm were acquired from the ERA5-Land dataset (<https://doi.org/10.24381/cds.e2161bac>). Air temperature and dew point temperature were used to calculate VPD [39]. Additionally, daily atmospheric CO_2 concentration was obtained from historical observations at Mauna Loa Observatory, Hawaii (<https://gml.noaa.gov/ccgg/trends>).

Auxiliary data

The MODIS MCD12Q1 product supplies yearly land cover data at a 500-m resolution (<https://lpdaac.usgs.gov/products/mcd12q1v061>). We re-categorized woody savannas and savannas in MCD12Q1 to savannas, and combined croplands and cropland/natural vegetation mosaic into croplands. To minimize the impact of land cover classification errors and account for regional land cover changes, the study period (2003–2020) was divided into three 6-year intervals. For each pixel, the dominant land cover type within each interval was determined based on the majority classification. The GBA featured 5 main vegetation types: evergreen broadleaf forests (EBF), savannas (SAV), grasslands (GRA), croplands (CRO), and permanent wetlands (WET) (Fig. S3). GPP data from MOD17A3HGF products (<https://lpdaac.usgs.gov/products/mod17a3hgf061>),

with 500-m spatial and annual temporal resolution, were used to compare with model-simulated GPP.

All the abovementioned data, except for the typhoon track data, were unified to a 0.01° spatial and 8-d temporal resolution. Regarding land cover data, the predominant type within each grid was designated as the definitive classification. Other datasets were downscaled via bilinear interpolation and upscaled via block averaging.

Overall workflow

The workflow consisted of 2 main steps (Fig. 2). First, RF models were constructed based on a series of explanatory factors to simulate LAI under non-typhoon scenarios. By quantitatively comparing simulated LAI with observed typhoon-affected LAI, the impact of typhoons on vegetation canopy structure was assessed. Second, the simulated non-typhoon LAI time series, along with the observed typhoon-affected LAI, were input into the LUE models. GPP under both scenarios was thus estimated and compared, characterizing the impact of typhoons on vegetation photosynthesis.

Quantifying typhoon's impact on vegetation canopy structure

The RF model was selected due to its robust ability to manage intricate and nonlinear interactions among variables, making

it well-suited for capturing complex patterns in the LAI. In RF models, the explanatory variables included 20 factors: environmental factors (temperature, radiation, precipitation, VPD, and CO₂) from the preceding 3, 2, and 1 months, along with spatial information (longitude, latitude), temporal information (Julian day), vegetation type, and the multi-year mean LAI. These factors can either drive vegetation dynamics or capture vegetation growth status in a specific location [3,40]. The multi-year mean LAI was calculated with a 5-year window centered on the target year. To evaluate the model's performance, we designated 15 years between 2003 and 2020 (excluding 2016, 2017, and 2018) as reference years. For cross-validation, each year's data was sequentially chosen as the testing sample, with the remaining 14 years' data serving as the training set (Fig. S4). Model accuracy was evaluated using the coefficient of determination (R^2) and the root mean square error (RMSE) based on cross-validation, repeated iteratively for each reference year. After confirming the RF model's ability to capture vegetation canopy dynamics, we used data from all 15 reference years to simulate LAI time series under non-typhoon scenarios from typhoon occurrence to the end of the following year.

With RF-simulated LAI, this study quantified the typhoon-induced vegetation canopy damage based on both direct (ΔLAI) and relative ($\Delta\text{LAI}\%$) LAI differences defined as follows:

$$\Delta\text{LAI} = \text{LAI}_{\text{obs}} - \text{LAI}_{\text{sim}} \quad (1)$$

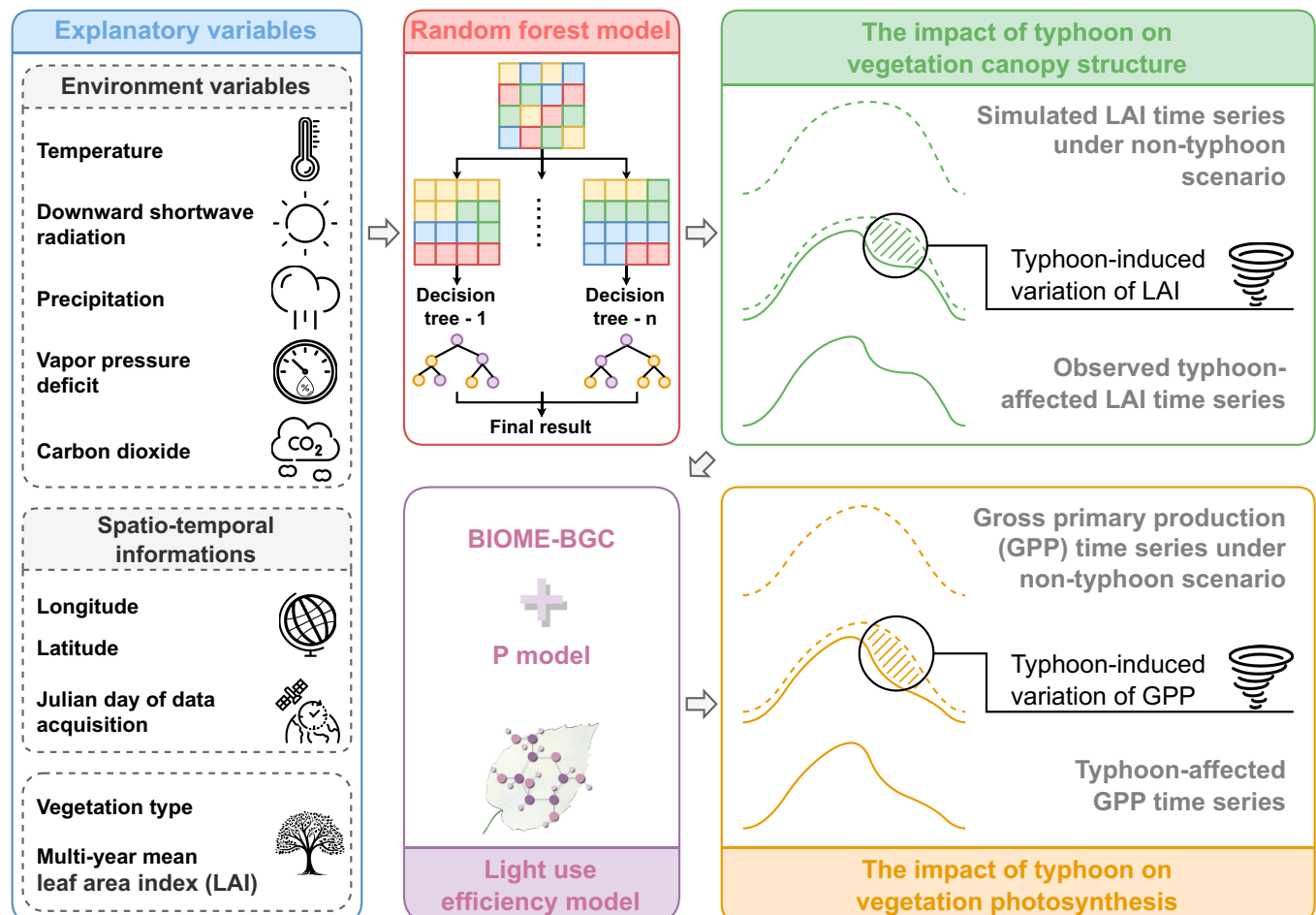


Fig. 2. Overall workflow of this study.

$$\Delta LAI\% = \frac{LAI_{obs} - LAI_{sim}}{LAI_{sim}} \times 100 \quad (2)$$

where LAI_{obs} and LAI_{sim} represent observed typhoon-affected LAI and RF-simulated LAI for non-typhoon scenarios, respectively.

The relative LAI difference was introduced because the direct difference may not fully capture typhoon's impacts on vegetation canopy. In sparse vegetation, a small ΔLAI may signify substantial canopy loss, whereas in dense vegetation, the reverse holds [41]. Vegetated areas showing $\Delta LAI\% < -15\%$ were considered severely damaged [42]. Total leaf area change was calculated by multiplying ΔLAI by the land area.

Quantifying typhoon-induced loss of photosynthetic capacity

The reduction in vegetation photosynthetic capacity attributable to the typhoon was proxied by the loss of GPP within regions experiencing vegetation canopy loss. This study employed LUE models to estimate GPP based on vegetation canopy conditions and environmental parameters. In particular, 2 well-established and extensively utilized models, namely, the Biome-BioGeochemical Cycles (BIOME-BGC) model and the P model, were selected [43,44]. For the P model, the required environmental variables included temperature, radiation [used to calculate photosynthetic photon flux density (PPFD)], VPD, and CO_2 concentration. The unit cost ratio (β) was set to 146, with additional parameters following the BRC ("Bernacchi") setup as described by Stocker et al. [43]. In the case of the BIOME-BGC model, the required environmental inputs included temperature, radiation, soil water content, and CO_2 concentration. The maximum LUE (ϵ_{max}) for different biomes was sourced from Zhao and Running [45], with ϵ_{max} set to 1.268 for evergreen broadleaf forests, 1.239 for woody savannas, 1.206 for savannas, 0.860 for grasslands, 0.680 for permanent wetlands, and 1.044 for croplands. LAI_{sim} and LAI_{obs} were taken as model inputs to obtain the GPP under non-typhoon and typhoon scenarios, respectively. In regions with canopy damage ($\Delta LAI < 0$), we computed the direct (ΔGPP) and relative ($\Delta GPP\%$) GPP loss:

$$\Delta GPP = GPP_{S1} - GPP_{S0} \quad (3)$$

$$\Delta GPP\% = \frac{GPP_{S1} - GPP_{S0}}{GPP_{S0}} \times 100 \quad (4)$$

where GPP_{S0} and GPP_{S1} denote the GPP under non-typhoon and typhoon scenarios, respectively.

To quantify cumulative GPP losses at the pixel scale, we defined canopy recovery time as the interval from the typhoon event until the observed LAI exceeded the simulated LAI. An upper threshold for recovery time was set, marking when 95% of affected pixels had recovered.

Results

LAI simulation and GPP estimation

RF models demonstrated high effectiveness in capturing LAI variations, with R^2 values exceeding 0.89 and RMSE below $0.59 \text{ m}^2 \text{ m}^{-2}$ (Fig. S5). The models performed best for WET and GRA, achieving average R^2 values of 0.95 (0.93 to 0.96) and 0.94 (0.93 to 0.95), with corresponding RMSE of 0.14 (0.12 to 0.17) $\text{m}^2 \text{ m}^{-2}$ for WET and 0.14 (0.13 to 0.16) $\text{m}^2 \text{ m}^{-2}$ for GRA.

The model performance was relatively weaker for EBF, with an average R^2 of 0.74 (0.59 to 0.82) and RMSE of 0.68 (0.53 to 0.84) $\text{m}^2 \text{ m}^{-2}$. Moreover, the simulated LAI curves for the major vegetation types exhibited distinct seasonal and interannual variability (Fig. S6). The accurate simulation of LAI established a reliable foundation for subsequent GPP estimation. Additionally, we assessed the performance of the LUE models. Given the absence of observational data for GPP in non-typhoon scenarios, the evaluation primarily centered on GPP estimates derived from observed LAI data under typhoon conditions. GPP derived from the BIOME-BGC model ($R^2 = 0.81$ to 0.82) and the P model ($R^2 = 0.83$ to 0.84) exhibited comparable and strong correlations with MODIS GPP for 2016–2018. The RMSE for the P model ranged from 293.31 to 330.02 $\text{g C m}^{-2} \text{ year}^{-1}$, while that for the BIOME-BGC model ranged from 289.86 to 311.11 $\text{g C m}^{-2} \text{ year}^{-1}$ (Fig. S7).

Typhoon's impact on vegetation canopy structure

Following Typhoon Nida, Hato, and Mangkhut, observed LAI was lower than RF-simulated LAI under non-typhoon scenarios (Fig. 3), indicating canopy damage caused by the typhoons. Additionally, about 1 month after the disturbance, the typhoon-induced canopy damage reached its maximum extent. It took approximately 48, 40, and 64 d, respectively, for the regional vegetation to recover to the normal level, defined as the first instance where the observed LAI was no longer significantly lower than the simulated LAI, or when the magnitude of the effect size (absolute value of Cohen's d) of their difference was less than 0.2 (Fig. 3).

The extent and severity of canopy loss varied spatially. Typhoon Nida caused canopy loss ($\Delta LAI < 0$) in 76.58% of vegetated areas and severe loss ($\Delta LAI\% < -15\%$) in 14.12% of the area. For Typhoon Hato, these ratios were 61.25% and 4.26%, respectively. Notably, Typhoon Mangkhut exhibited the most substantial impact, with an area ratio of 89.67% for canopy loss and 17.00% for severe loss (Fig. 4). Total leaf area loss induced by Typhoon Nida, Hato, and Mangkhut was 13,242.74, 6,097.38, and 13,641.72 km^2 , respectively. Despite a consistent proportional difference in the extent of damaged areas (Fig. S8B), average $\Delta LAI\%$ within affected areas decreased with increasing distance from the coastline (Fig. S8C).

The typhoon-induced GPP loss

During the recovery of vegetation canopy, all regions with canopy damage from typhoons experienced cumulative GPP losses (Fig. 5). Typhoon Nida caused a direct cumulative GPP loss (ΔGPP) of 0.36 Tg C (averaged from the BIOME-BGC model and P model), with a mean relative loss ($\Delta GPP\%$) of -3.38% . Typhoon Hato resulted in a cumulative loss of 0.22 Tg C, featuring a mean $\Delta GPP\%$ of -2.88% . Typhoon Mangkhut caused the most substantial cumulative GPP loss of 0.50 Tg C with a $\Delta GPP\%$ of -4.34% . Furthermore, the spatial heterogeneity of typhoon-induced photosynthesis losses became evident upon analysis. We computed the cumulative loss of photosynthetic capacity for all pixels experiencing canopy losses following each typhoon disturbance. The representation of these findings employed the median, accompanied by the 10th and 90th percentiles. The mean values of the P model and BIOME-BGC model indicated that Typhoon Nida, Hato, and Mangkhut led to cumulative GPP losses of 10.76^{30.51}_{2.44} (Median^{90th percentile}_{10th percentile}), 7.33^{24.38}_{1.20}, and 12.59^{36.29}_{2.09} Mg C, respectively, with the corresponding relative losses of 2.68^{6.66}_{0.78}%, 1.96^{6.27}_{0.40}%, and 3.28^{9.16}_{0.67}%. Moreover,

a noticeable reduction in $\Delta\text{GPP}\%$ was observed with increasing distance from the coastline (Fig. S8D). Particularly, Typhoon Mangkhut caused about 6.13% relative cumulative GPP losses in coastal areas (within 50 km of the coastline), which is more than 4 times the reduction in the 200- to 250-km buffer zone ($\Delta\text{GPP}\% = 1.40\%$). Typhoon Nida showed smaller regional differences, but the 0- to 50-km zone still experienced double the relative cumulative GPP losses compared to the 200- to 250-km zone.

Typhoon-induced vegetation damage under varied exposure levels and vulnerabilities

Utilizing data on canopy structure alterations after 3 typhoons, we investigated the magnitude of vegetation canopy damage across varying degrees of exposure. The distribution patterns of relative canopy loss ($\Delta\text{LAI}\% < 0$) and severe relative canopy loss ($\Delta\text{LAI}\% < -15\%$) were similar along the wind radius, distance from the typhoon track, elevation, and aspect (Fig. 6). Within the 64-kt wind radius, vegetation canopy experienced the most pronounced impacts, with the mean $\Delta\text{LAI}\%$ for damaged vegetation reaching -12.45% . Damage was less severe within the 50- and 34-kt wind radii, with mean $\Delta\text{LAI}\%$ of -8.37% for R50 and -5.57% for R34 (Fig. 6A). Concerning spatial proximity, vegetation damage decreased with increasing distance from the typhoon track

(Fig. 6B and F). The highest (>500 m) and lowest (<10 m) elevations suffered the most pronounced vegetation damage (Fig. 6C and G). Moreover, vegetation on the eastern, southeastern, and southern slopes incurred the greatest damage (Fig. 6D and H).

Given the potential variations in vulnerability to typhoon disturbances across diverse vegetation types, we analyzed vegetation damage severity by type. Evergreen broadleaf forests showed the most pronounced direct LAI loss (Fig. 7A), but the relative canopy loss was not as severe due to their dense canopy (high LAI) (Fig. 7B). In contrast, nonforest vegetation types such as permanent wetlands and grasslands experienced lower direct canopy losses (Fig. 7A) but higher relative canopy losses, indicating substantial damage to their simpler canopy structures (Fig. 7B). Simulated GPP from LUE models indicated that typhoon-induced photosynthetic capacity losses in evergreen broadleaf forests were comparatively lower than those observed in nonforest vegetations (Fig. 7C to F).

Discussion

Improved assessment of typhoon-induced vegetation losses and post-typhoon recovery

The unique feature of our methodology is that it simulates vegetation canopy structure (LAI) in non-typhoon scenarios. Current

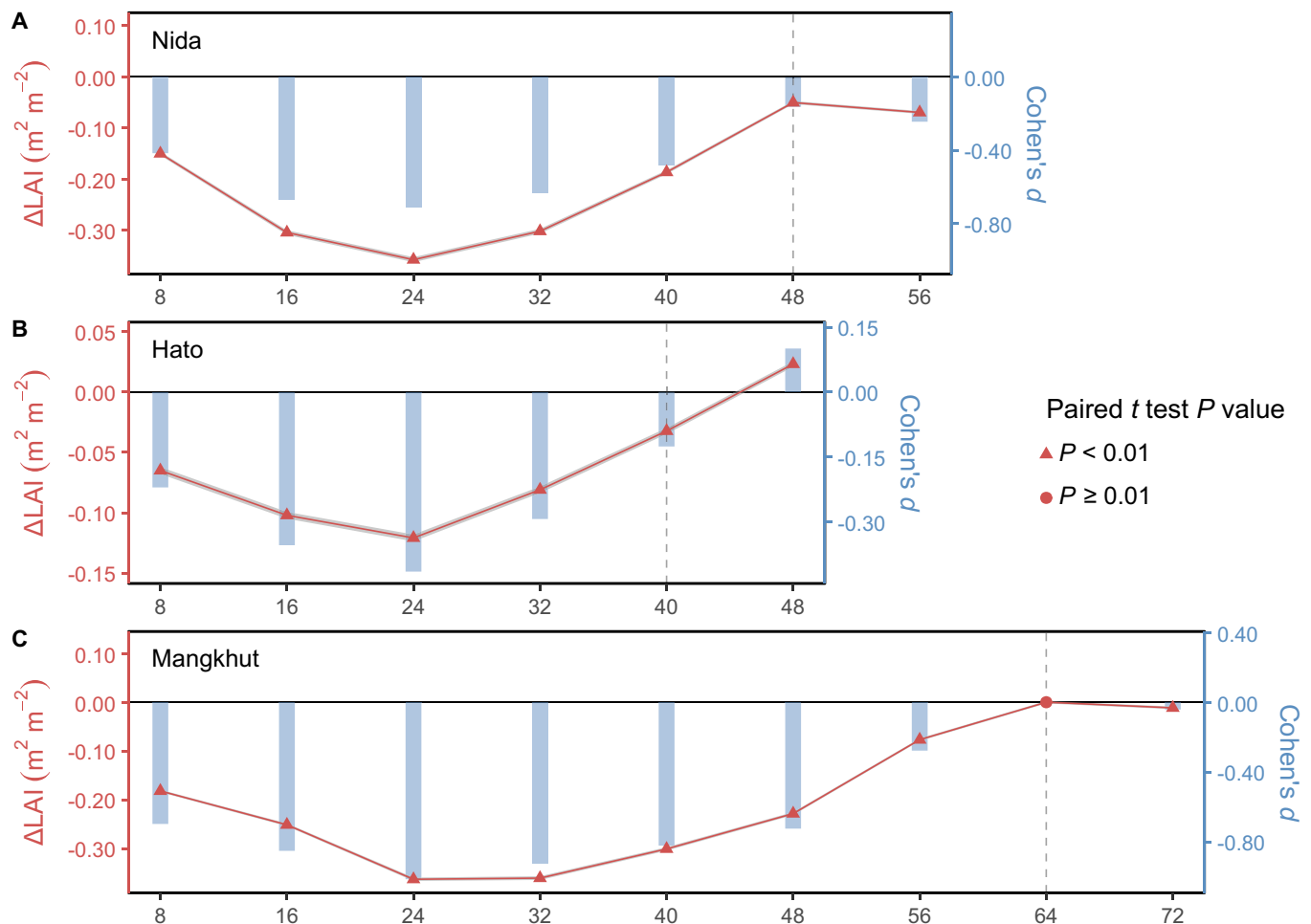


Fig. 3. Differences between observed and simulated leaf area index (ΔLAI) after disturbances of super typhoons (A) Nida, (B) Hato, and (C) Mangkhut. Comparisons of differences were conducted using paired t tests. The red line indicates the mean differences, while the shaded areas represent the confidence intervals of these differences. The blue bars illustrate the Cohen's d effect size. The gray dashed lines mark the time taken for vegetation recovery, defined as the point at which the observed LAI is no longer significantly lower than the simulated LAI or the absolute value of Cohen's d falls below 0.2.

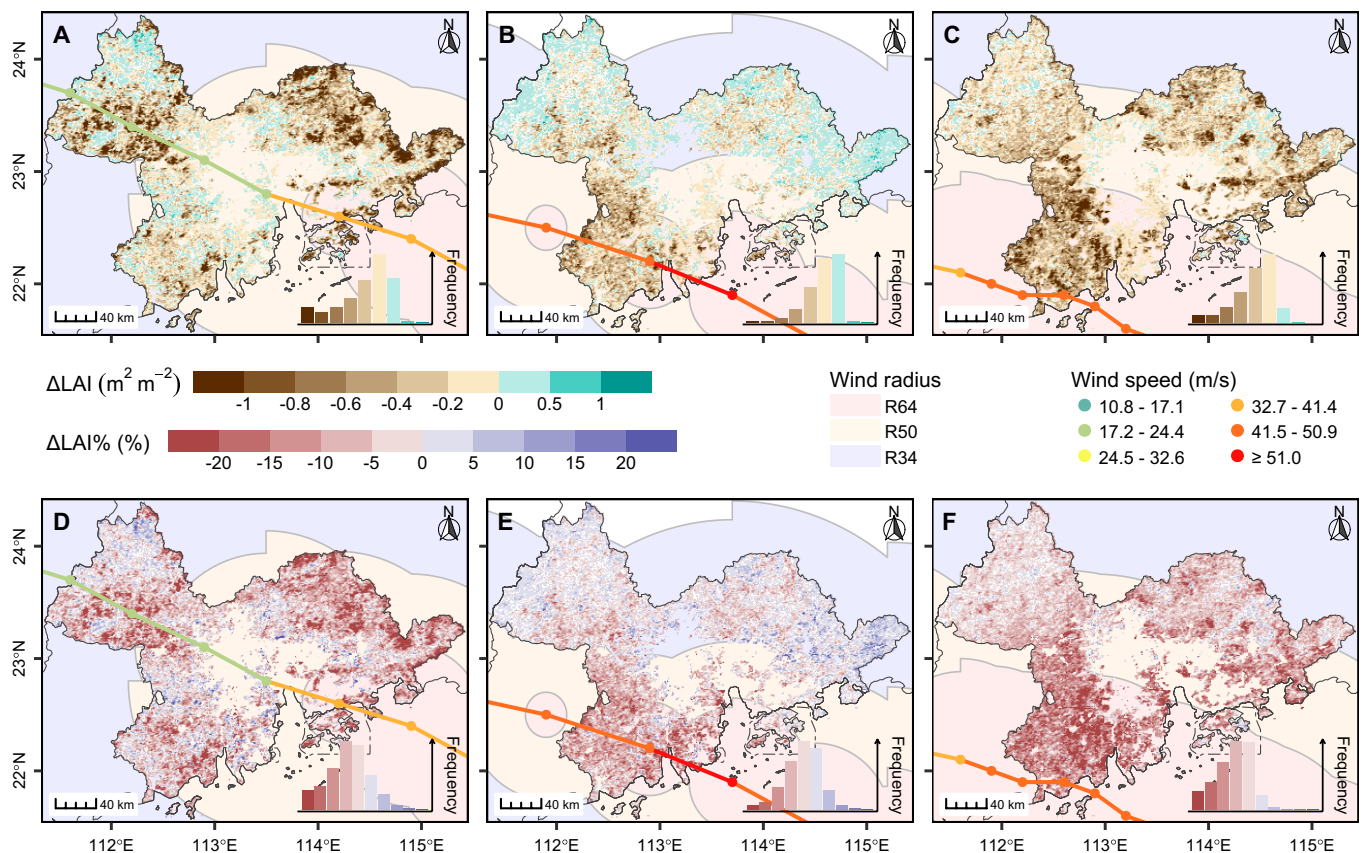


Fig. 4. Spatial patterns of LAI differences in the first month after super typhoons Nida, Hato, and Mangkhut: (A) to (C) show direct LAI differences (ΔLAI), and (D) to (F) show relative LAI differences ($\Delta\text{LAI}\%$). Colored lines with dots represent typhoon tracks. Background colors represent the maximum extents of the 34-kt (R34), 50-kt (R50), and 64-kt (R64) wind radii. Areas where the absolute value of $\Delta\text{LAI}\%$ is less than 1% are indicated in white.

detection of typhoon-induced vegetation damage at the regional scale relies on cloud-free satellite observations before and after typhoon events [17,46] (Fig. 8) but always suffers from data availability issues due to cloud cover [25]. Consequently, there is often a long time gap between typhoon events and observations, which incorporate considerable information on vegetation phenology [23,47]. Studies have also attempted to employ data obtained in the same period of neighboring years (Fig. 8). Nevertheless, this approach fails to account for intra-annual variability in vegetation and inter-annual variability in environmental conditions [41,42]. Different from these conventional methods, our approach avoided the long-time gap between typhoon events and observations by LAI simulation. The simulation was based on a machine learning model driven by a series of explanatory variables considering spatial, temporal, and, most importantly, factual environmental information. This guaranteed that the simulated LAI was comparable to observed values. The continuous and consistent simulated LAI time series facilitated distinguishing vegetation canopy damage from vegetation phenology and climate fluctuation. Furthermore, our methodology extends beyond LAI simulation. Given sufficient observational data, it can be adapted to detect variations in other vegetation indices, offering a highly versatile framework for post-disaster damage assessment.

We applied and compared 3 methodologies to detect the impact of 3 typhoons on LAI (Fig. 9). Spatially, our method detected LAI changes that align more closely with typhoon paths and wind radii compared to the 2 traditional approaches. Specifically, areas closer

to the typhoon paths and those affected by stronger wind radii exhibited greater LAI loss. Additionally, in terms of magnitude, Typhoon Hato hit the GBA in August 2017 with wind speeds exceeding 51 m/s, resulting in substantial canopy structure loss ($\Delta\text{LAI} = -0.05^{0.19}_{-0.39} \text{ m}^2 \text{ m}^{-2}$), as detected by our approach (Fig. 9B). In contrast, the 2 traditional methods indicated regional increases in LAI, suggesting positive typhoon-induced impacts. Method 1 (Fig. 8, $\Delta V_1 = V_{\text{post}} - V_{\text{pre}}$) revealed a ΔLAI of $0.03^{0.20}_{-0.12} \text{ m}^2 \text{ m}^{-2}$ (Fig. 9E), but the overall increase in LAI during the growing season may have masked the damage signal (Fig. 9J). Method 2 (Fig. 8, $\Delta V_2 = V_{\text{post}} - V_{\text{mean}}$) showed a regional ΔLAI of $0.15^{0.94}_{-0.24} \text{ m}^2 \text{ m}^{-2}$ (Fig. 9H), yet the considerably higher LAI in 2017 compared to adjacent years raises concerns about the validity of the detection (Fig. 9J).

Exposure and vulnerability influence typhoon-induced vegetation loss

The inherent characteristics of typhoons such as track and intensity shape the spatial extent of impacts and determine exposure levels. The wind speed of typhoons has been reported to comprise 20% of forest disturbances [27]. Elevated levels of disturbance have also been observed close to the hurricane track [48]. Consistent with previous studies, our results indicated that regions exposed to higher wind speeds and closer proximity to typhoon tracks typically exhibited more pronounced losses (Fig. 6A, B, E, and F). Despite minimal track overlap with the GBA, Typhoon Mangkhut's extensive size

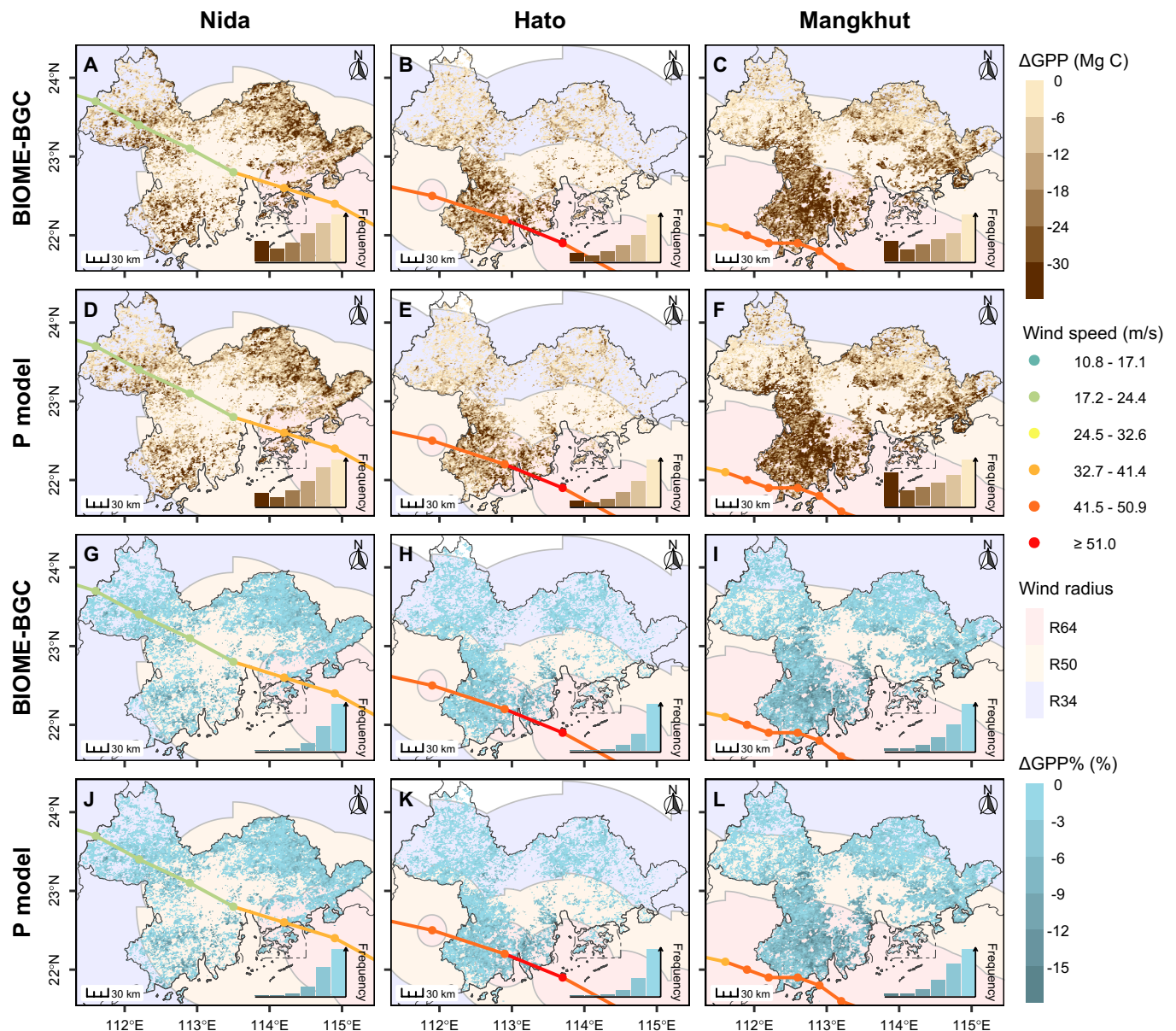


Fig. 5. Spatial patterns of cumulative GPP losses after super typhoons Nida, Hato, and Mangkhut: (A) to (F) show direct cumulative GPP losses (ΔGPP), and (G) to (L) show relative cumulative GPP losses ($\Delta GPP\%$). Subplots (A) to (C) and (G) to (I) illustrate GPP derived from the BIOME-BGC model, while (D) to (F) and (J) to (L) depict GPP derived from the P model. Colored lines with dots represent typhoon tracks. Background colors represent the maximum extents of the 34-kt (R34), 50-kt (R50), and 64-kt (R64) wind radii.

and high intensity caused a pronounced impact, inducing canopy loss in 89.67% of the vegetation-covered area (Fig. 4). Topography plays another role in the extent of vegetation's exposure to wind and the alteration of local wind patterns [29]. GBA is geographically located along the southern coast of China mainland. Typhoons affecting this region primarily originate in the oceans to its southeast (e.g., the South China Sea). The directional pattern leads to a higher potential of exposure to strong winds on the eastern, south-eastern, and southern slopes (Fig. 6D and H). Moreover, windward slopes are also more susceptible to heavy rainfall accompanying typhoons.

Divergent structural characteristics across distinct vegetation types may contribute to variations in their vulnerability to typhoon disturbances [49,50]. Forests were noted to manifest the most noteworthy direct alteration in LAI (Fig. 7A). This

observation aligned with earlier research, emphasizing that stands characterized by higher structural complexity tended to undergo more pronounced damage [51]. Potential explanations for this phenomenon include the increased density and height of trees within complex stands, making them more susceptible to breakage. This heightened vulnerability may trigger a potential “domino effect”, wherein the fracture of trunks may harm the roots and canopy of adjacent trees. Nevertheless, the examination of alterations in relative LAI yielded distinct findings. Our findings were similar to prior research, demonstrating that sparse forests and cultivated croplands were more susceptible to strong winds and heavy rains associated with typhoons [52]. Ecosystems with simpler canopy structures and shallower roots, such as shrubs and grasslands, may incur substantial canopy loss subject to typhoon events. For these ecosystems, even a small loss of canopy structure can pose a challenge to the stability of

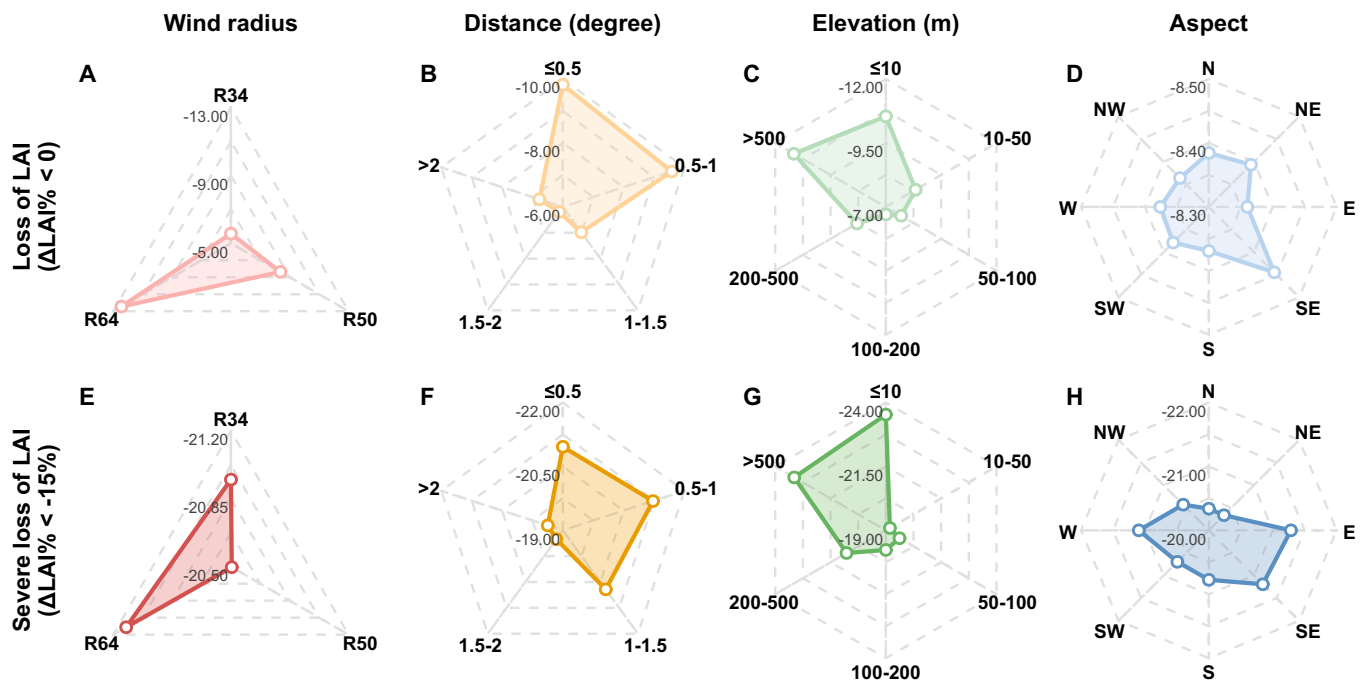


Fig. 6. Distribution of vegetation canopy loss (proxied by LAI) across wind exposure and topographic factors. R34, R50, and R64 represent the maximum extent of the 34-, 50-, and 64-kt wind radii. (A to D) LAI loss (<0%) by wind radius, distance from the typhoon track, elevation, and aspect. (E to H) Severe LAI loss (<-15%) by the same factors.

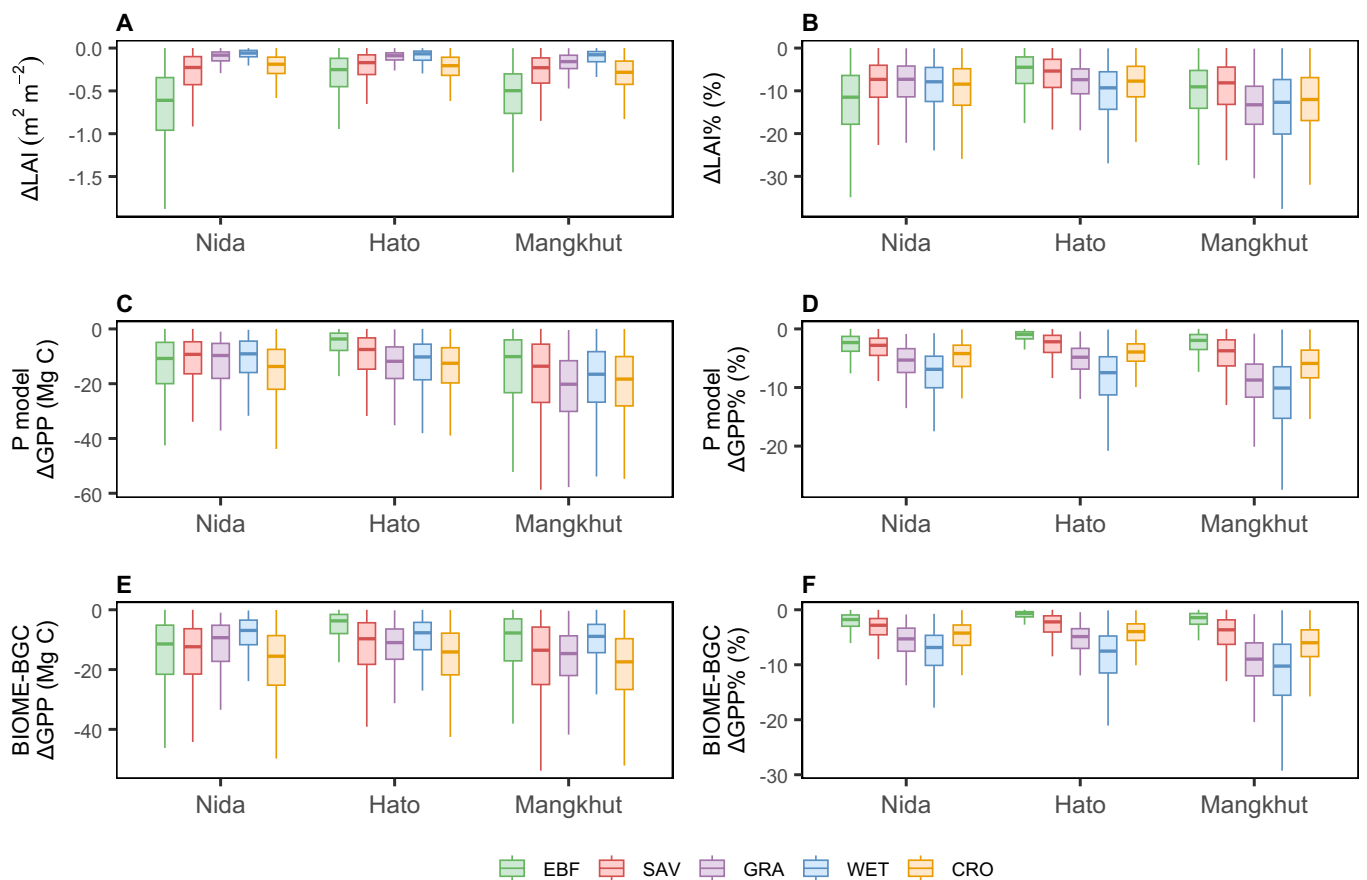


Fig. 7. Distribution of typhoon-induced loss in vegetation canopy structure (proxied by LAI) and photosynthetic capacity (proxied by GPP) across various vegetation types. Statistical analysis was conducted within regions experiencing vegetation canopy loss ($\Delta\text{LAI} < 0$). Subplots (A) and (B) depict direct and relative differences in LAI, (C) and (D) represent direct and relative differences in GPP calculated by the BIOME-BGC model, while (E) and (F) denote direct and relative differences in GPP from the P model. EBF, evergreen broadleaf forests; SAV, savannas; GRA, grasslands; CRO, croplands; WET, permanent wetlands.

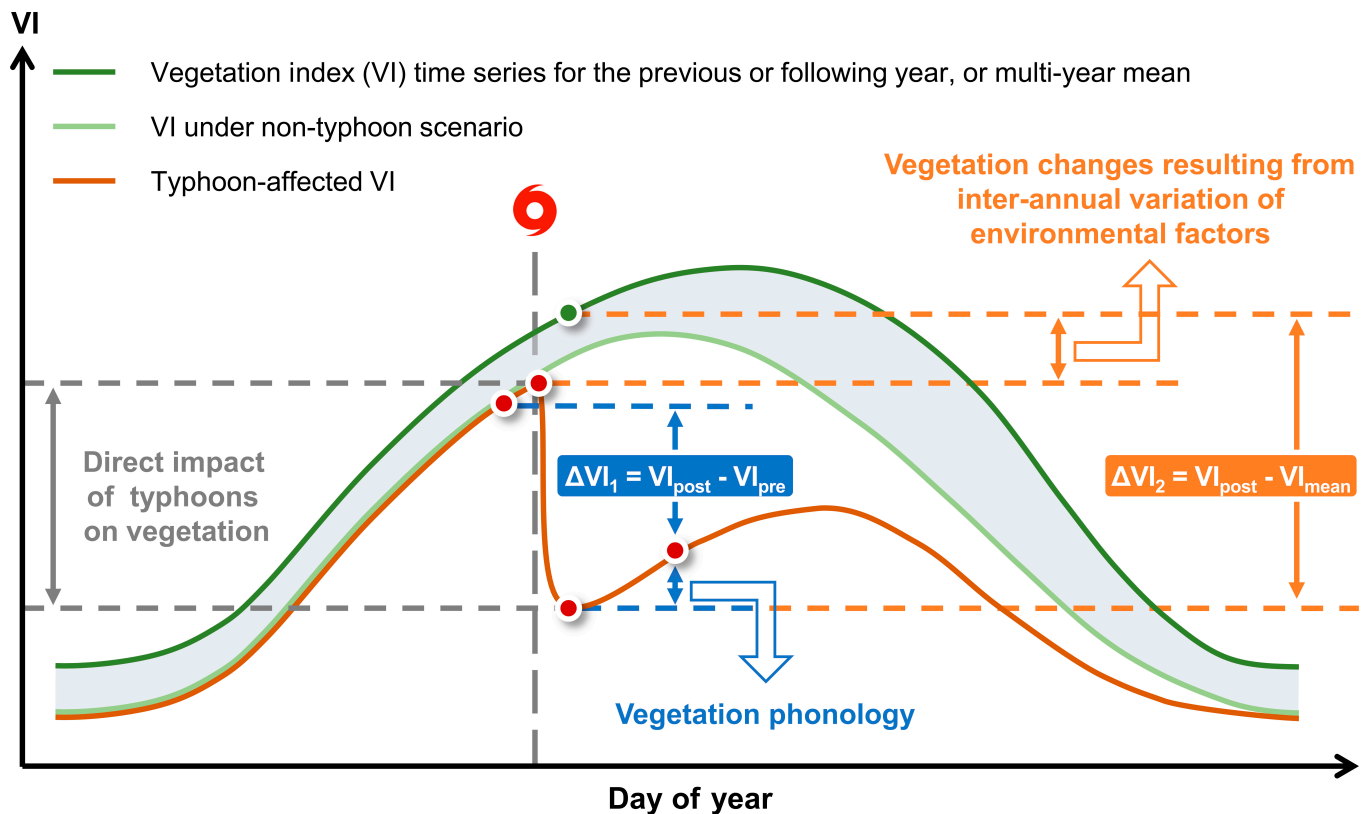


Fig. 8. Schematic diagram illustrating methods in assessing the impact of typhoons on vegetation. The difference between the 2 gray dashed lines represents the typhoon's direct impact on vegetation. Blue lines correspond to the first assessment approach, wherein the typhoon's impact on vegetation is calculated as differences between the pre- and post-typhoon vegetation index (VI). Yellow lines represent the second assessment method, involving the computation of differences between post-typhoon VI and VI from corresponding periods of neighboring years (either the year preceding or following the typhoon occurrence, or a multi-year average).

the entire ecosystem. Nevertheless, existing research on vegetation damage caused by typhoons predominantly focuses on forest ecosystems. More vulnerable nonforest ecosystems have received less attention.

Resilience of vegetation following typhoon disturbance

Vegetation resilience is contingent upon the extent of damage incurred. Although the average LAI loss from Typhoon Mangkhut was comparable to that from Typhoon Nida, the overall recovery time after Mangkhut was approximately half a month longer. This finding hints at the possibility that Typhoon Mangkhut might have caused more severe physical damage, such as stem snapping and uprooting. Other critical determinants of vegetation resilience include the timing and meteorological characteristics of the typhoon [53]. Typhoon Nida and Hato occurred in early August, coinciding with the peak of vegetation growing season, allowing for quicker recovery due to favorable temperature and humidity conditions for leaf and branch regeneration. In contrast, Typhoon Mangkhut occurred at the end of the growing season, when less favorable conditions led to a longer recovery period.

Uncertainty and limitations

Despite our efforts, certain limitations inherent in the study should be acknowledged. First, our investigation centers on quantifying physical canopy losses, yet it lacks an in-depth examination of biochemical properties. Relying solely on

canopy physical losses to assess the influence of typhoons on vegetation functions and activities, such as photosynthesis, may inherently possess limitations. Future research should delve more deeply into the effects of climate extremes on vegetation physiological attributes for a comprehensive understanding of their effects. Second, regarding the modeling of vegetation conditions under non-typhoon scenarios, our model is constructed based on observed LAI data. In regions characterized by prolonged cloud cover, the quantity and quality of these observational datasets may influence the accuracy of the simulations. Increasing availability of satellite data is expected to enhance the frequency and quality of observations, which will help mitigate these challenges. Furthermore, the performance of RF models could be further improved by incorporating extra determinants such as landforms [42] and landscape patterns [41]. Currently, these data are unavailable in satisfactory spatiotemporal resolution. Moreover, challenges exist in directly assessing the reliability of our results due to the absence of in situ observational data and the limitations of satellite data caused by cloud cover. Although growth and damage censuses are valuable and have long served as a cornerstone of ecological research, they are labor-intensive and site-specific, hindering a comprehensive understanding of pre- and post-typhoon vegetation dynamics [48]. Furthermore, the pre-disaster investigations require reliable typhoon forecasting, which poses challenges in regions devoid of well-established long-term observations. Last, while we have detected ecosystem impacts from specific typhoons, such localized damage assessments may not be extrapolated to

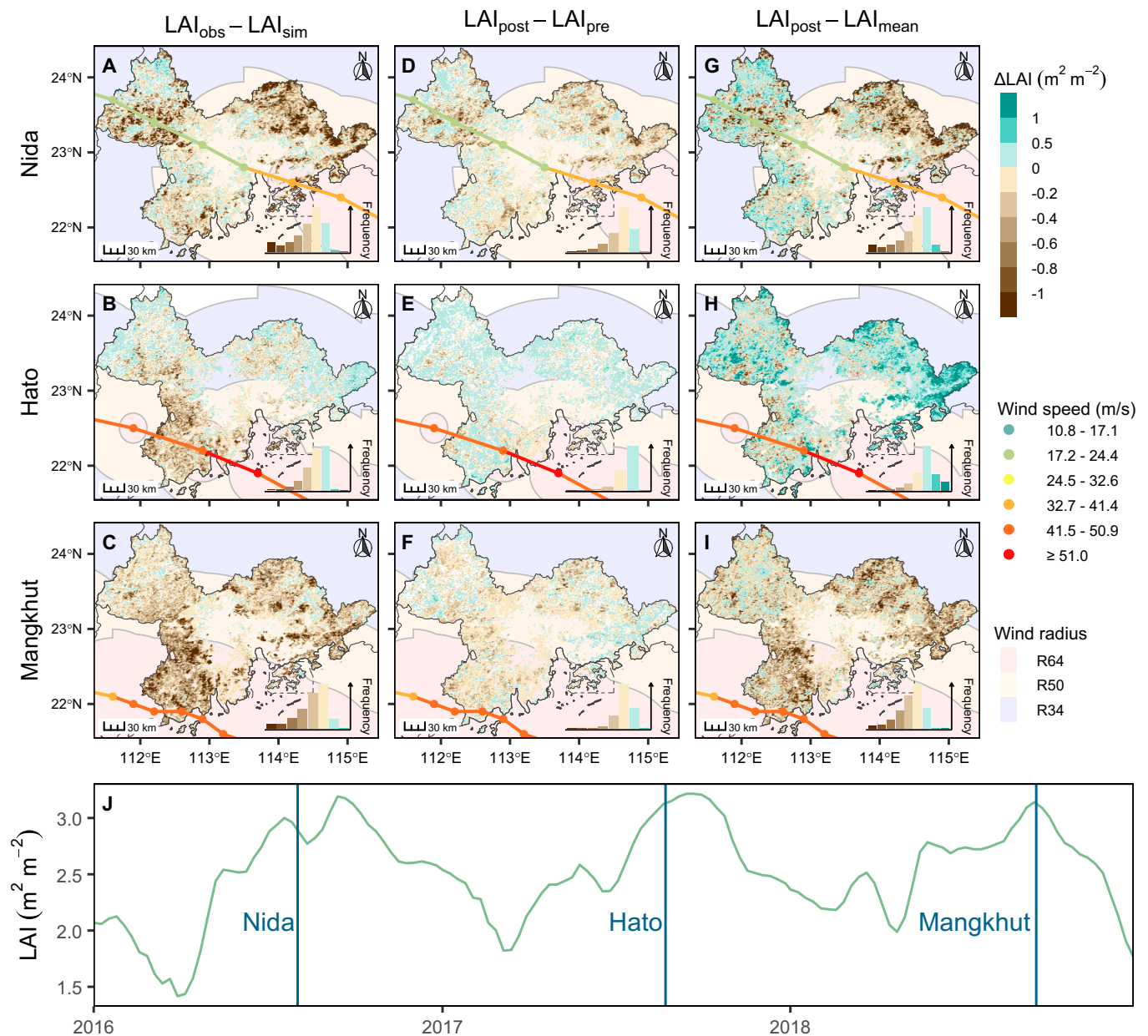


Fig. 9. Spatial patterns of typhoon-induced changes in LAI (ΔLAI), assessed using (A to C) the new framework proposed in this study, i.e., the difference between post-typhoon LAI and simulated LAI, and (D to I) 2 conventional methods. The traditional approaches include (1) the difference between post- and pre-typhoon LAI within the same year and (2) the difference between post-typhoon LAI and the LAI of the 2 adjacent years. The first 3 rows show the detection results for super typhoons Nida, Hato, and Mangkhut, respectively. (J) Time series of mean regional LAI in the study area from 2016 to 2018.

broader scales due to varying sensitivities and resilience levels among different ecosystems [17]. In future work, an integrated assessment of typhoon impacts in a broader context is needed.

Conclusion

This study presents an innovative and comprehensive framework for assessing typhoon impacts on both vegetation canopy structure and photosynthetic activity. By integrating satellite-based observations, RF modeling, and LUE models, our approach yields a more nuanced and accurate assessment of typhoon-induced changes in vegetation dynamics. This methodology not only disentangles the direct effects of typhoons on vegetation, accounting for inherent canopy structure variability

and interannual environmental fluctuations, but also elucidates the long-term legacy effects and subsequent recovery patterns. The proposed method was utilized to investigate the impact of 3 notable typhoons in the 21st century—Nida, Hato, and Mangkhut—on the vegetation of the GBA. These typhoons resulted in vegetation canopy losses covering 76.58% (Nida), 61.25% (Hato), and 89.67% (Mangkhut) of the vegetated region of the GBA. The recovery of the vegetation canopy took approximately 1 to 2 months following the disturbances. Additionally, the mechanical damage inflicted by the typhoons on the canopy structure led to a sustained negative impact on the carbon uptake capacity. Specifically, Typhoon Nida, Hato, and Mangkhut caused cumulative GPP losses of 0.36, 0.22, and 0.50 Tg C, respectively, in areas with canopy loss. Furthermore, we conducted a comparative

analysis of our novel framework in relation to conventional approaches. We noted a notably higher regional LAI in 2017 compared to adjacent years, coinciding with Typhoon Hato's occurrence during the vegetation growth period. Consequently, both commonly used methods underestimated the extent of damage, indicating positive typhoon-induced impacts on vegetation ($\Delta\text{LAI} = 0.03^{0.20}_{-0.12}$ and $0.15^{0.94}_{-0.24} \text{ m}^2 \text{ m}^{-2}$). Our framework effectively identified substantial typhoon-induced damage to vegetation ($\Delta\text{LAI} = -0.05^{0.19}_{-0.39} \text{ m}^2 \text{ m}^{-2}$). Additional research is also needed in the future to delve deeper into the mechanisms driving the extent of typhoon impacts on vegetation and to help formulate practical recommendations to mitigate typhoon-induced damage.

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Data Availability

All data are from publicly available sources and are detailed in Materials and Methods.

Supplementary Materials

Figs. S1 to S8

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