

Article

Applicability Assessment of GFED4 and GFED5 on Forest Fires in Chinese Mainland and Its Fire-Scale Patterns Change

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Highlights

What are the main findings?

- GFED4 shows strong agreement with statistical data of forest burned areas in China, especially in high-fire years and spring.
- A clear decline in large-fire burned area, while a significant increase in small fires.

What is the implication of the main finding?

- GFED4 provides reliable monitoring of large forest fires, while GFED5 is essential for detecting small fires.
- The GFED burned area products require additional validation across multiple global regions.

Abstract

The GFED (Global Fire Emissions Database) series products are widely used in global fire research, yet their applicability in mainland China remains insufficiently evaluated. Additionally, large fires and small fires are rarely studied separately. This study first evaluates GFED4's applicability for monitoring forest fire burned areas in Chinese mainland (2001–2015) through multi-temporal (annual, seasonal, and monthly) and multi-spatial (national, regional, provincial, and 0.25° grid) analyses, using Pearson correlation (CC), root mean square error (RMSE), and mean error (ME) alongside official statistical data. Then, the forest fire-burned areas of small fires were extracted based on the difference between GFED4 and GFED5. The results show that GFED4 exhibits strong consistency at the national level and in key fire-prone regions such as Northeast, North, and Central South China, especially during high-fire years and in spring. However, systematic overestimation occurs in the Northwest, while underestimation or seasonal bias is observed in parts of East and Southwest China. The results show a clear decline in large-fire burned area, but a significant increase in small fires, particularly in Northeast, Central South, and East China. Spatial analysis indicates small fires exhibit strong clustering (Moran's $I = 0.270$, $p < 0.01$), whereas large fires are spatially dispersed. The study concludes that GFED4 is reliable for monitoring large fires in forested zones but should be applied cautiously in non-forested and small-fire-dominated regions.

Keywords: forest fires; GFED4; GFED5; applicability assessment; spatiotemporal variation

Academic Editor: José Manuel Fernández-Guisuraga

Received: 27 August 2025

Revised: 10 October 2025

Accepted: 14 October 2025

Published: 16 October 2025

Citation: Wang, X.; Di, Z.; Zhang, S.; Meng, H.; Tian, X.; Xie, M.

Applicability Assessment of GFED4 and GFED5 on Forest Fires in Chinese Mainland and Its Fire-Scale Patterns Change.

Remote Sens. **2025**, *17*, 3461.

<https://doi.org/10.3390/rs17203461>

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1. Introduction

Wildfire represents one of the most critical natural disturbance processes globally, exerting profound impacts on carbon cycling, ecosystem structure, biodiversity, and human societal security [1–3]. In recent years, under the combined effects of global warming and intensified human activities, both the frequency and intensity of wildfires have shown sustained increases [4–6]. Research indicates that wildfires annually affect several hundred million hectares of land surface while emitting 5–8 Gt CO₂ [7,8], establishing them as a significant driver of global change. As a key component of wildfire systems, forest fires demonstrate distinct spatial concentration within specific climatic zones and geomorphic regions, carrying substantial ecological and socioeconomic consequences [9–11]. This spatial clustering underscores the necessity for long-term, systematic, and regionally specific monitoring and assessment of forest fire dynamics—an endeavor carrying both fundamental scientific value and practical significance.

With the advancement of remote sensing technologies, global fire monitoring systems have become increasingly sophisticated, forming an integrated data pipeline that combines satellite-based fire detection, burned area estimation, and emission modeling [12–20]. A series of freely available global BA products—such as MODIS-derived MCD64A1 [21,22], ESA’s FireCCI [23], and the Global Fire Emissions Database (GFED) series [24,25]—have greatly facilitated fire research at regional to global scales. Among these, GFED stands out due to its integration of burned area, emissions, and biogeochemical modeling, and has been widely applied in climate change assessments, carbon cycle studies, and ecosystem disturbance analyses [26–28].

The GFED series has undergone continuous refinement. GFED4, released in 2013, is based on MODIS MCD64A1 Collection 5.1 and is particularly effective in capturing large-fire events (>100 ha) with high consistency across broad spatiotemporal scales [29–31]. In contrast, the recently released GFED5 incorporates high-resolution data from Landsat and Sentinel-2, significantly improving the detection of small-scale and short-duration fires that were previously omitted [32,33]. This technological evolution underscores the need to evaluate the performance and limitations of different GFED versions across diverse ecosystems.

Global fire datasets exhibit distinct characteristics in their application across different research domains internationally. The GFED series products have been deeply integrated into multidisciplinary research paradigms globally, providing critical emission inputs for global aerosol modeling and atmospheric chemistry research in the atmospheric sciences [34,35], while also finding applications in public health studies that assess mortality risks from landscape fire smoke [36,37]. In ecological studies, they serve as important basis for understanding ecosystem carbon cycles and vegetation dynamics through fire disturbance analysis [27,28]. Furthermore, research on regional air quality management has demonstrated the value of GFED data in quantifying population exposure to fire-induced pollution [38], while climate science research on fire-climate feedback mechanisms also widely relies on such global products [39]. In contrast, the application of GFED series products in China remains relatively limited, primarily focusing on regional-scale fire risk assessment [11] and emission inventory development [40], with insufficient research from a global perspective to deepen understanding of product performance. This application disparity highlights the necessity of systematically evaluating global fire products using China’s unique geographical environment.

Beyond application comparisons, another critical aspect lies in dataset validation. International research has established relatively comprehensive verification systems. For the MCD64A1 product, Hall et al.’s evaluation in Ukrainian farmlands showed its superiority over FireCCI51 [41], while Katagis et al.’s research in Mediterranean ecosystems confirmed its reliability [42]. Additionally, validation work by Boschetti et al. in North American forests [43], Hawbaker et al. in fragmented landscapes [44], and Roteta et al. in

African savannas [45] collectively built a cognitive framework for understanding global fire product performance. Examining the domestic research landscape, although valuable explorations have been conducted by Jiao et al. in Sichuan Province [46], Zhao et al. in northwestern Yunnan mountainous areas [47], and Wang et al. in three major forest regions [48], these studies are all constrained by spatial scope, failing to form a systematic evaluation covering all major eco-regions in Chinese Mainland, particularly leaving a research gap in comparative studies between the new-generation GFED5 and GFED4 products.

Understanding fire dynamics also requires examining the fundamental drivers, particularly in fire-climate relationships. The international academic community has developed relatively mature theoretical frameworks. Research by Abatzoglou and Williams revealed important mechanisms through which climate change regulates fire activity by affecting fuel aridity and fire weather conditions [49], while Andela et al. demonstrated the dominant role of human activities in global burned area changes [50]. Additionally, large-scale climate patterns such as El Niño/Southern Oscillation have been shown to drive pan-tropical fire activity through teleconnection mechanisms [51]. These studies provide theoretical foundations for understanding fire dynamics at global scales. In the Chinese context, related research shows distinctive regional characteristics: Liu et al. found obvious latitudinal gradients in the relationship between fire risk and climate factors in northeastern forest regions [10], Tian et al.'s research indicated that southern forest fires are more susceptible to seasonal climate variations [52], while Wang et al. revealed the differential effects of human activities on fire dynamics across different ecological regions [53]. These research differences emphasize the urgent need to evaluate global fire products based on China's unique climate-vegetation-human activity complex system.

Synthesizing the domestic and international research landscape, this study identifies three critical research gaps: First, although GFED series products are widely used globally, they still lack systematic applicability evaluation in Chinese Mainland, with existing research limited to local regional applications. Second, GFED5 as a new-generation data product shows improvements in detection capability compared to GFED4, particularly in enhanced detection of small fires in Chinese regions, yet this remains inadequately validated. Third, there is insufficient research utilizing China's authoritative forestry statistics from a regional "ground truth" perspective to deepen understanding of global product performance.

Addressing these research gaps, the innovation of this study is mainly manifested in three aspects: establishing a multi-scale validation framework covering China's major eco-regions to achieve the first systematic evaluation of GFED4 and GFED5 in mainland China; innovatively utilizing the difference between GFED5 and GFED4 to quantify the contribution of small fires, providing new perspectives for understanding fire dynamic changes in China; and leveraging China's comprehensive forestry statistical observation network to enhance understanding of GFED series products' global performance from regional validation data perspective. These innovations not only help promote scientific application of GFED products in Chinese regions but will also provide important references for regional adaptability research of global fire products.

Therefore, to address these research gaps and leverage the proposed innovative approaches, this study systematically evaluates the performance of GFED4 and GFED5 products across the Chinese mainland through the following methodological framework: By integrating provincial forest fire records from the *China Forestry Statistical Yearbook* (CFSY) (2001–2015), we implement a comprehensive assessment across three temporal scales (annual, seasonal, and monthly) and four spatial scales (national, six subregions, provincial, and 0.25° grid). To quantify the discrepancies between GFED4 and official statistics, we employ statistical metrics including correlation coefficient (CC) [54], root mean square error (RMSE) [55], and mean error (ME) [56]. Building on this foundation, the introduction of GFED5 products enables the establishment of a comparative framework that

distinguishes “large fires vs. small fires,” thereby facilitating the analysis of spatiotemporal variations across different fire intensity levels. Furthermore, for interannual trend analysis, the non-parametric Mann–Kendall test [57] is applied to detect significant trends in burned area time series, with Sen’s slope estimator [58] used to quantify the magnitude of changes. Finally, Moran’s I [59] and Local Indicators of Spatial Association (LISA) [60] are employed to identify spatial clustering patterns of burned areas. The findings provide theoretical foundations and methodological references for the scientific application of GFED products in China, their localized refinement, and forest fire monitoring practices.

2. Materials and Methods

2.1. Study Area

The study area (Figure 1) comprises six regions in China: Northeast China (NE), North China (NC), East China (EC), Northwest China (NW), Southwest China (SW), and Central South China (SC). The specific provincial compositions of each region are detailed in Table 1. Among these, NE, SW, and SC exhibit the highest forest coverage, collectively accounting for over 60% of the nation’s total forest area and representing the most fire-prone zones. In contrast, NW has sparse vegetation and the lowest fire frequency.

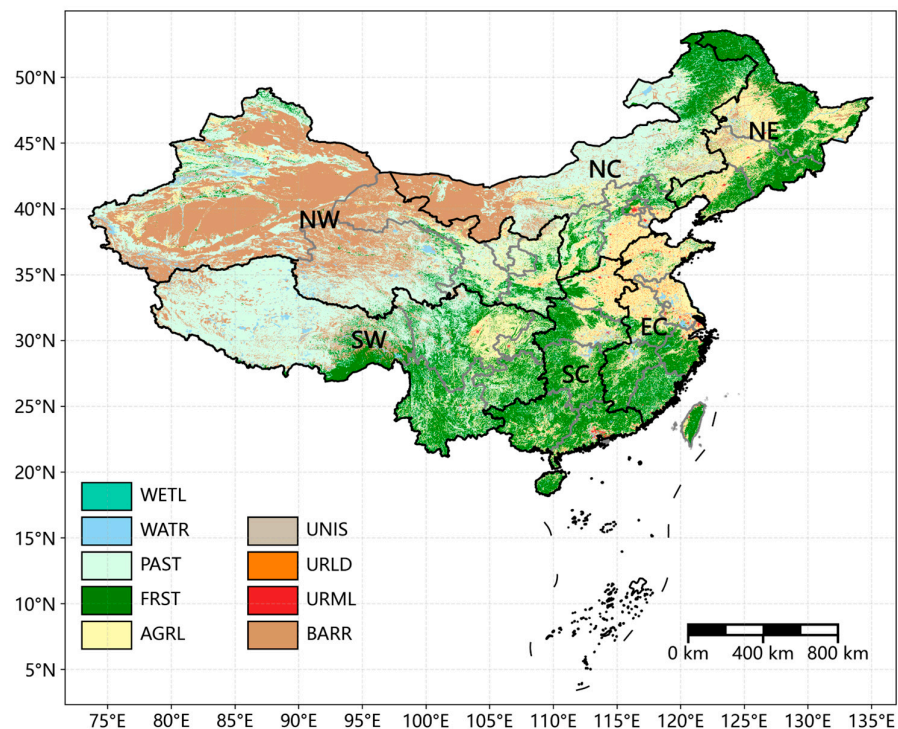


Figure 1. Overview of the study area in China. The map divides the Chinese mainland into six major regions: NE (Northeast China), NC (North China), NW (Northwest China), SW (Southwest China), EC (East China), and SC (Central South China). Land cover types are classified as: AGRL (cropland), FRST (forest), PAST (grassland), WATR (water bodies), WETL (wetland), BARR (barren land), URML (urban land), URLD (rural land), and UINS (other built-up land).

Table 1. Regional division scheme of the study area.

Region Name	Abbreviation	Provinces/Autonomous Regions/Municipalities
Northeast China	NE	Heilongjiang, Jilin, Liaoning
North China	NC	Beijing, Tianjin, Hebei, Shanxi, Inner Mongolia
Northwest China	NW	Shaanxi, Gansu, Ningxia, Qinghai, Xinjiang
Southwest China	SW	Sichuan, Chongqing, Guizhou, Yunnan, Tibet
East China	EC	Shanghai, Jiangsu, Zhejiang, Anhui, Fujian, Jiangxi, Shandong
Central South China	SC	Henan, Hubei, Hunan, Guangdong, Guangxi, Hainan

2.2. Data

2.2.1. Statistical Data

The forest fire data were obtained from the *China Forestry Statistical Yearbook* compiled by the National Forestry Administration [61]. This annual publication provides provincial-level statistics on forest fire occurrences from the previous year, including burned area, affected forest area, number of fire incidents, and other relevant information. The dataset does not contain spatial information. The data can be downloaded from <https://www.hceis.com/default.aspx> (accessed on 24 January 2025).

This dataset provides statistics collected through administrative reporting systems. Its definition of a “forest fire” is based on formal investigations and typically includes incidents that meet specific criteria, such as exceeding a minimum burned area threshold. The primary metrics include the total burned area, the affected forest area, and the number of fire incidents, aggregated at the provincial level.

The dataset used in this study covers the period from 2001 to 2015, providing a consistent monthly time series for analysis. To facilitate a multi-scale comparative analysis, the original monthly data were further aggregated into seasonal totals (e.g., Spring: March–May) and annual totals.

2.2.2. Product Data

The Global Fire Emissions Database (GFED) is a collaborative effort developed by Vrije Universiteit Amsterdam, NASA Goddard Space Flight Center, and other institutions. Its data sources and algorithms have undergone multiple iterations and updates. The GFED dataset provides globally gridded estimates of monthly burned area, emissions of various trace gases and aerosols, contributions from different fire types, and biosphere fluxes. In this study, both GFED4 and GFED5 datasets were obtained from official sources. GFED4 data can be downloaded from https://daac.ornl.gov/VEGETATION/guides/fire_emissions_v4.html (accessed on 15 January 2025), and GFED5 data can be downloaded from <https://zenodo.org/records/7668424> (accessed on 15 January 2025). The fundamental definition of burned area in GFED is derived from satellite remote sensing observations. Specifically, the burned area estimates are primarily obtained by detecting changes in surface reflectance characteristics from moderate-resolution imaging spectroradiometer (MODIS) instruments aboard NASA’s Terra and Aqua satellites. This satellite-based approach provides a consistent, globally applicable method for identifying fire-affected pixels, which forms the spatial foundation for subsequent emissions modeling. The emissions estimates are then calculated by combining the burned area data with information on vegetation biomass, combustion completeness, and emission factors.

The monthly burned area data from GFED used in this study were also aggregated to seasonal and annual scales for analysis.

The main characteristics and differences between GFED4 and GFED5 are summarized in Table 2. GFED4 is constructed based on the MODIS MCD64A1 Collection 5.1 burned area product and features high consistency across large spatial scales and long-term comparability, making it well-suited for fire trend analysis from regional to global scales [48]. It is particularly effective in detecting large fires (>100 ha). For instance, Vetrita

et al. [30] evaluated fire detection accuracy in tropical peatland and non-peatland areas and found that the performance of MCD64A1 Collection 6 was optimal when small burns (<100 ha) were excluded, highlighting GFED4's strong representation of large fire events. In contrast, GFED5 integrates high-resolution satellite data from Landsat and Sentinel-2 for correction, significantly improving its ability to detect small-scale fires [32,48]. As a result, the total burned area estimated by GFED5 is generally closer to actual fire occurrence. The systematic enhancement in GFED5's detection capability primarily stems from its improved sensitivity to these smaller fire events. Therefore, the difference in burned area between GFED5 and GFED4 (i.e., GFED5 – GFED4) can be attributed largely to the contribution of small-scale fires that are captured by GFED5 but omitted by GFED4. Based on this rationale, we operationally define “large fires” as those detected by GFED4 with burned areas typically exceeding 100 ha, while “small fires” are defined as those represented by the GFED5-GFED4 residual with burned areas generally below the 100 ha detection threshold of GFED4's underlying algorithm [24]. Consequently, this study treats the forest burned area derived from GFED4 as a representation for large-scale forest fires, while the difference between GFED5 and GFED4 (i.e., GFED5 – GFED4) is used to quantify the contribution of small-scale forest fires.

Table 2. Comparison of GFED4 and GFED5 burned area products.

Aspect	GFED4	GFED5
Data source	MODIS MCD64A1	MODIS MCD64A1
Temporal resolution	Monthly	Monthly
Time span	1997–2016	1997–2020
Spatial resolution	0.25°	0.25°
Data format	HDF	NetCDF
Data content	Monthly burned area	Monthly burned area
Burned area detection algorithm	Based on NBR (Normalized Burn Ratio)	Corrected using high-resolution data
Omission error correction	Correction factors by region, season, and vegetation type	Direct calibration with high-resolution reference data
Commission error correction	Not explicitly corrected	Non-burned areas in MODIS adjusted using high-resolution data
Cropland fire treatment	Simplified estimation method	New estimation method using high-resolution data
Peatland and deforestation fires	Limited processing	Effectively addressed using high-resolution data
Accuracy of burned area estimation	Conservative estimate; may underestimate small fires	Higher accuracy; better reflects contribution from small-scale fires

2.2.3. LUCC Data

The Land-Use and Land-Cover Change (LUCCC) data were used to extract forest fire burned areas from the total burned area across all land cover types. The land use data used were from the 2010 dataset, with a spatial resolution of 1 km. The data were obtained from <https://www.resdc.cn/> (accessed on 4 April 2024).

2.3. Research Method

2.3.1. Statistical Metrics

To quantitatively assess GFED4 product performance, we conducted multi-scale (temporal/spatial) validation by comparing satellite-derived burned areas with official statistical yearbook records. Three statistical metrics were employed: Pearson's correlation coefficient (CC), Root mean square error (RMSE), Mean error (ME). The mathematical formulations of these metrics are presented in Table 3.

Table 3. Statistical metrics formulation.

Metrics	Formula	Optimal Value
Correlation Coefficient (CC)	$CC = \frac{\sum(G_i - \bar{G})(O_i - \bar{O})}{\sqrt{\sum(G_i - \bar{G})^2 \sum(O_i - \bar{O})^2}} \quad (1)$	1
Root Mean Square Error (RMSE)	$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (G_i - O_i)^2} \quad (2)$	0
Mean Error (ME)	$ME = \frac{1}{n} \sum_{i=1}^n (G_i - O_i) \quad (3)$	0

Note: G_i and O_i denote satellite products and statistical yearbook data, respectively. $\bar{G}$ and $\bar{O}$ represent their mean values.

2.3.2. Linear Trend Analysis

A linear regression model based on the least squares method was established to analyze the interannual trend of burned area (y) over time (x , year):

$$y = kx + b \quad (4)$$

The slope “ k ” in the equation represents the mean annual change rate (ha/yr), while the intercept “ b ” indicates the estimated baseline burned area at the starting point of the time series. This method was applied to quantify change rates at three spatial scales: national, regional, and grid levels.

2.3.3. Mann–Kendall Nonparametric Test

To identify localized significant trends in forest fire burned areas, we conducted pixel-by-pixel trend significance detection (2001–2015) for gridded data ($0.25^\circ \times 0.25^\circ$). The test statistic is calculated as follows, where X_i and X_j represent the burned area values at time i and j (with $i < j$) within the time series, respectively:

$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^n \text{sign}(X_j - X_i) \quad (5)$$

$$\text{sign} = \begin{cases} +1, & \text{if } (X_j - X_i) > 0 \\ 0, & \text{if } (X_j - X_i) = 0 \\ -1, & \text{if } (X_j - X_i) < 0 \end{cases} \quad (6)$$

$$Z = \begin{cases} \frac{S-1}{\sqrt{\text{Var}(S)}} & \text{if } S > 0 \\ 0 & \text{if } S = 0 \\ \frac{S+1}{\sqrt{\text{Var}(S)}} & \text{if } S < 0 \end{cases} \quad (7)$$

Statistical significance was assessed at $\alpha = 0.05$ (two-tailed), with the following decision criteria: (1) $Z > 1.96$ ($p < 0.05$) indicated a significant increasing trend; (2) $Z < -1.96$ ($p < 0.05$) represented a significant decreasing trend; and (3) values within $[-1.96, 1.96]$ ($p \geq 0.05$) suggested no significant trend. The null hypothesis of no trend was rejected when $|Z| > 1.96$.

2.3.4. Spatial Autocorrelation Analysis

Spatial autocorrelation analysis is a statistical testing method that includes both global and local hypothesis testing approaches.

(1) Global Spatial Autocorrelation

Global spatial autocorrelation measures the spatial distribution characteristics of attribute values across a study region, quantifying the similarity of attribute values among spatially proximate or adjacent units. This analysis is primarily conducted using the global Moran's I index, calculated as follows:

$$I = \frac{n \sum_{i=1}^n \sum_{j=1}^n W_{ij} (x_i - \bar{x})(x_j - \bar{x})}{\sum_{i=1}^n \sum_{j=1}^n W_{ij} \sum_{i=1}^n (x_j - \bar{x})^2} \quad (8)$$

where x_i and x_j represent the burned forest area of province "i" and "j", respectively; $\bar{x}$ denotes the mean burned area across all provinces; W_{ij} is the spatial weight matrix element between provinces; and "n" indicates the total number of Chinese mainland provinces.

(2) Local Spatial Autocorrelation

To better characterize local spatial clustering patterns, we employed the local indicator of spatial association (LISA), specifically the local Moran's I index, which quantifies the similarity/correlation between a spatial unit and its neighbors to identify spatial clusters (hot/cold spots), outliers, and spatial heterogeneity. Essentially decomposing the global Moran's I into individual spatial units, LISA provides localized refinements of the global pattern through the following calculation:

$$I_i = \frac{(x_i - \bar{x}) \sum_{j=1}^n W_{ij} (x_j - \bar{x})}{\sum_{i=1}^n (x_i - \bar{x})^2} \quad (9)$$

where all variables maintain the same definitions as in the global Moran's I calculation.

3. Results

3.1. Evaluation of GFED4 Applicability for Forest Fire Burned Areas in China

3.1.1. Annual-Scale Analysis

Figure 2 shows the annual average burned forest area across six regions of Chinese mainland. The primary forest fires were concentrated in Northeast China (NE), which had the largest annual average burned area (127,021 ha). North China (NC), Southwest China (SW), and Central South China (SC) followed, with burned areas around 30,000 ha. East China (EC) had an annual average burned area of 19,496 ha, while Northwest China (NW) recorded the smallest extent (1258 ha).

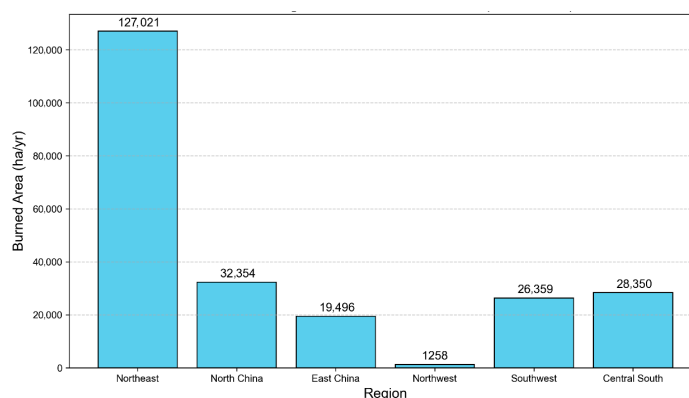


Figure 2. Annual average forest fire burned area for different regions in China (2001–2015).

Figure 3 presents the interannual variations in forest fire burned areas in Chinese mainland and its six subregions from 2001 to 2015, with the corresponding statistical metrics summarized in Table 4. At the national scale, GFED4 data exhibited strong consistency with statistical yearbook records, showing a high correlation coefficient of 0.832. Both datasets captured the pronounced peak during the high-fire year of 2003 particularly well. The model demonstrated relatively small simulation errors, with a root mean square error (RMSE) of 15.336 (10^4 ha) for Chinese mainland, indicating GFED4's reliable performance at the annual scale nationwide.

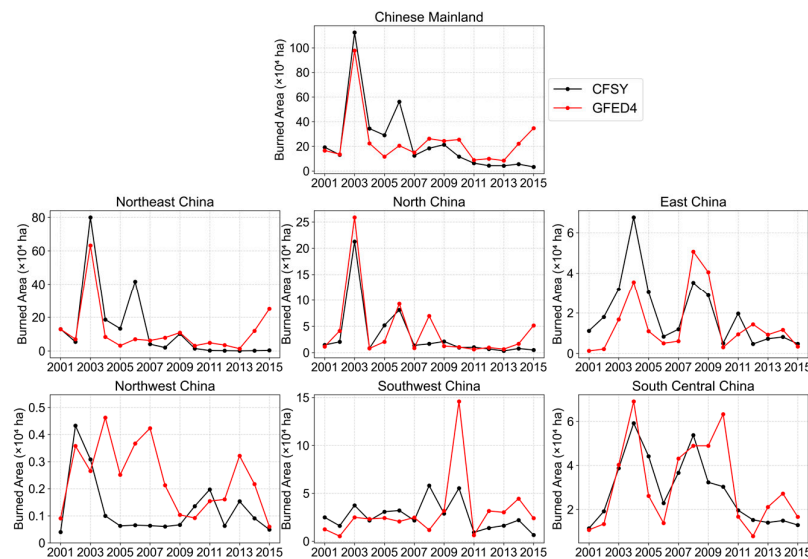


Figure 3. Interannual variations in forest burned area in Chinese mainland and its subregions.

Table 4. CC, RMSE, and ME of annual burned area (2001–2015).

Region	CC	RMSE($\times 10^4$ ha)	ME($\times 10^4$ ha)
China Mainland	0.832	15.340	0.348
Northeast China	0.790	12.975	−0.947
North China	0.943	2.432	0.947
East China	0.695	1.323	−0.485
Northwest China	0.262	0.179	0.11
Southwest China	0.488	2.861	0.445
South Central China	0.782	1.224	0.279

At the regional scale, GFED4 showed good temporal agreement with statistical data in Northeast China (NE), North China (NC), and Central South China (SC), with correlation coefficients exceeding 0.78 (reaching 0.94 in NC). In these regions, the model performed better for high-fire years while slightly overestimating burned areas during low-fire years. In contrast, the correlations were weaker in other regions: 0.695 for East China (EC), 0.488 for Southwest China (SW), and only 0.262 for Northwest China (NW), representing the poorest agreement among all regions.

Regarding simulation errors, Northeast China had the largest RMSE (12.98×10^4 ha), while other regions showed smaller errors below 2.9×10^4 ha, with Northwest China having the minimal error of merely 0.18×10^4 ha. This spatial pattern of errors strongly correlated with the total burned areas in these regions. As shown in Figure 2, the annual average burned area in Northeast China reached 127,021 ha, whereas Northwest China had only 1258 ha—less than

1% of the Northeast's total. For mean errors (ME), negative biases were observed in the eastern regions (NE and EC), while other regions showed positive biases.

In summary, GFED4 showed generally good correlation with statistical yearbook data for annual burned areas in China, particularly in Northeast, North, and Central South China. The spatial distribution of simulation errors, with the largest in Northeast and smallest in Northwest China, was closely related to regional differences in total burned area magnitude.

3.1.2. Seasonal-Scale Analysis

Figure 4 compares the seasonal mean burned areas between GFED4 and statistical yearbook data across Chinese mainland and its six subregions. The results demonstrate generally consistent seasonal patterns between the two datasets, particularly in identifying major fire seasons.

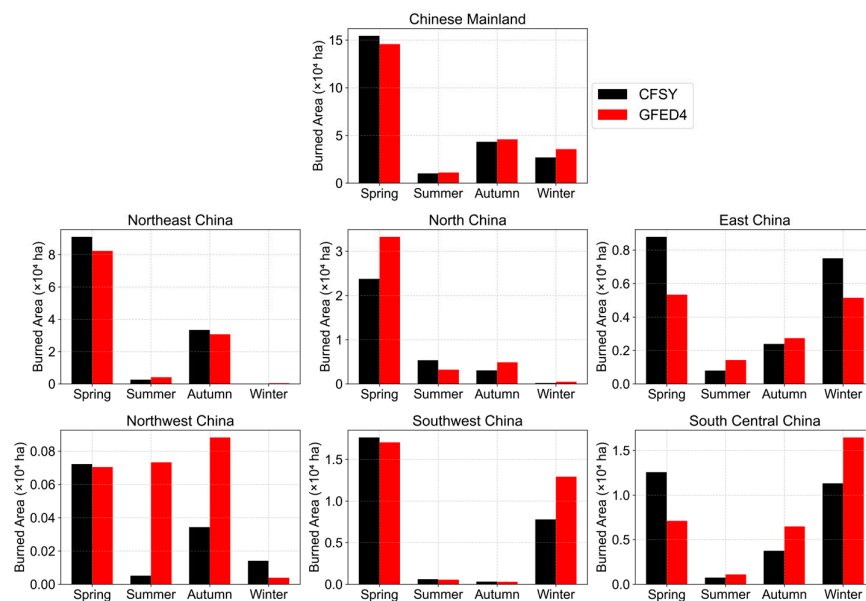


Figure 4. Seasonal mean burned area in Chinese mainland and its subregions.

At the national scale, both GFED4 and statistical records showed peak burned areas in spring, reflecting China's concentrated fire activity during this season. Relatively lower values occurred in autumn and winter, with GFED4 exhibiting slightly higher estimates than statistical data, possibly indicating greater sensitivity to localized fires. Summer displayed the minimal burned areas with minor discrepancies between datasets, suggesting GFED4's stable performance during low-fire periods.

Regionally, all areas exhibited high fire activity in spring, while winter fires were primarily concentrated in East China (EC), Central South China (SC), and Southwest China (SW). Summer consistently showed the lowest fire occurrence across all regions.

GFED4 performed most reliably in high-fire regions, including Northeast China (NE), North China (NC), Central South China (SC), and Southwest China (SW), accurately capturing both the timing and intensity of primary fire seasons. Moderate agreement was observed in East China (EC), with GFED4 slightly underestimating spring fires while overestimating autumn-winter activity. In Northwest China (NW) where seasonal fires were extremely weak, GFED4 systematically overestimated burned areas across all seasons, suggesting limitations in satellite-based fire detection for this region.

In summary, GFED4 demonstrated the strongest performance in spring simulations, while exhibiting regional variability during summer and autumn that may require further optimization based on fire type classification.

Table 5 presents the simulation performance metrics of GFED4 across seasons for Chinese mainland and its subregions. Regarding correlation coefficients (CC), the Central South China (SC) demonstrated the most stable performance, with CC values exceeding 0.7 for all four seasons, indicating GFED4's robust capability in capturing this region's seasonal fire characteristics. In contrast, Northwest China (NW) showed the weakest overall correlations, with maximum CC reaching only 0.31 and even displaying negative values in some seasons. Northeast (NE) and North China (NC) exhibited good agreement during spring, summer and autumn, but notably poorer performance in winter. East China (EC) showed its lowest correlations in summer, while Southwest China (SW) had relatively low CC values in spring and autumn.

Table 5. Seasonal statistical indicators for Chinese mainland and its subregions.

Season	Region	CC	RMSE($\times 10^4$ ha)	ME($\times 10^4$ ha)
Spring	China Mainland	0.888	12.392	−0.870
	Northeast China	0.843	11.997	−0.869
	North China	0.949	2.388	0.949
	East China	0.706	0.856	−0.345
	Northwest China	0.049	0.082	−0.002
	Southwest China	0.136	1.598	−0.060
	South Central China	0.749	0.850	−0.544
Summer	China Mainland	0.757	0.802	0.102
	Northeast China	0.822	0.372	0.155
	North China	0.643	0.911	−0.211
	East China	0.083	0.249	0.062
	Northwest China	−0.329	0.111	0.068
	Southwest China	0.609	0.109	−0.007
	South Central China	0.734	0.121	0.034
Autumn	China Mainland	0.769	4.303	0.262
	Northeast China	0.702	4.306	−0.278
	North China	0.490	0.510	0.180
	East China	0.755	0.217	0.034
	Northwest China	0.311	0.136	0.054
	Southwest China	0.076	0.045	−0.002
	South Central China	0.838	0.499	0.274
Winter	China Mainland	0.764	2.388	0.854
	Northeast China	0.074	0.083	0.044
	North China	0.042	0.081	0.028
	East China	0.809	0.588	−0.237
	Northwest China	0.141	0.017	−0.010
	Southwest China	0.854	1.624	0.514
	South Central China	0.872	0.913	0.515

For root mean square error (RMSE), the magnitude generally corresponded with burned area size across regions and seasons. Larger burned areas typically resulted in higher RMSE values. Spring, having the most extensive burned areas, consistently showed the highest RMSE across nearly all regions, reflecting error accumulation at larger burned areas. Secondary peaks occurred in autumn for NE, and in winter for EC, SW and SC, aligning with these regions' seasonally elevated (but spring-subordinate) fire activity levels.

The bias analysis revealed systematic underestimation (negative bias) during spring in most regions. Other seasons predominantly showed positive biases, suggesting GFED4's tendency to overestimate burned areas outside spring.

3.1.3. Monthly Scale Analysis

Figure 5 presents the monthly distribution characteristics of forest fire burned areas across Chinese mainland and its six subregions from 2001 to 2015. Overall, GFED4 and statistical yearbook data exhibit high consistency in monthly fire trends at both national and regional scales. For instance, bimodal distribution patterns are clearly observed in the national totals, Northeast China (NE), Northwest China (NW), and Central South China (SC), while unimodal distributions predominantly occur in North China (NC), East China (EC), and Southwest China (SW). The peak months show generally less than two months' difference between GFED4 and statistical data, indicating GFED4's reliable capability in capturing seasonal fire dynamics.

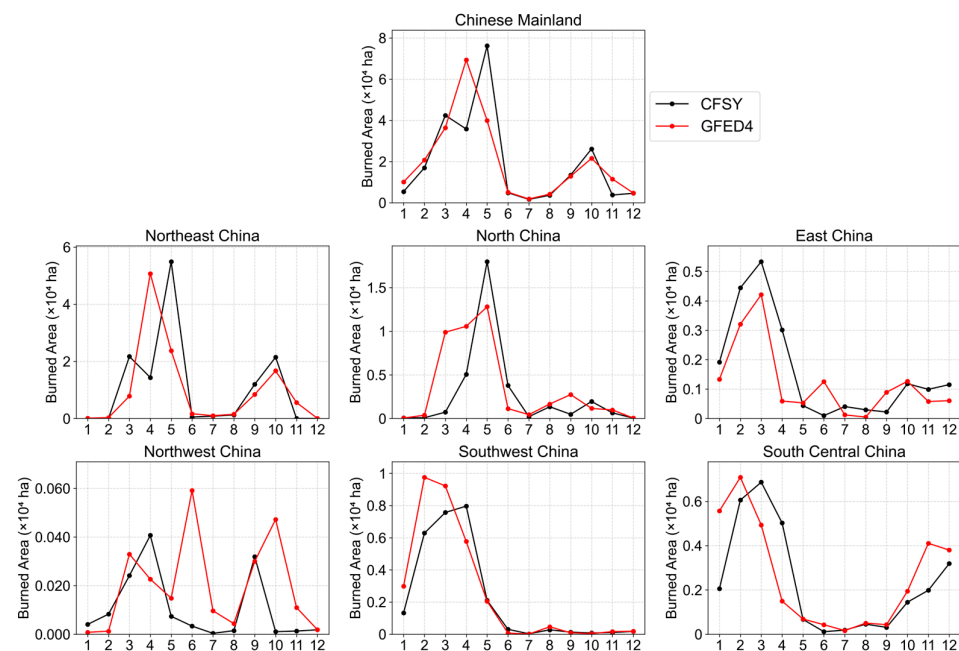


Figure 5. Monthly mean burned area in Chinese mainland and its subregions.

Regionally, the monthly burned area distribution in Northeast China (NE) most closely resembles the national pattern, with primary peaks concentrated during March to May and secondary peaks appearing in September to October. Northern regions (including NE, NC and NW) typically show primary peaks from March to May, while southern regions (such as EC, SW and SC) exhibit slightly earlier primary peaks, mainly occurring between January and April. Additionally, secondary peaks can be observed during September to October in NE and NW, and from October to December in SC, revealing that fire activity remains relatively active in southern regions during late autumn to early winter, with the secondary peaks appearing slightly later compared to northern regions.

3.1.4. Provincial Scale Analysis

Figure 6 displays the spatial distribution of correlation coefficients (CC), root mean square errors (RMSE), and mean errors (ME) between monthly burned area from GFED4 and statistical yearbook data across China's provincial administrative divisions.

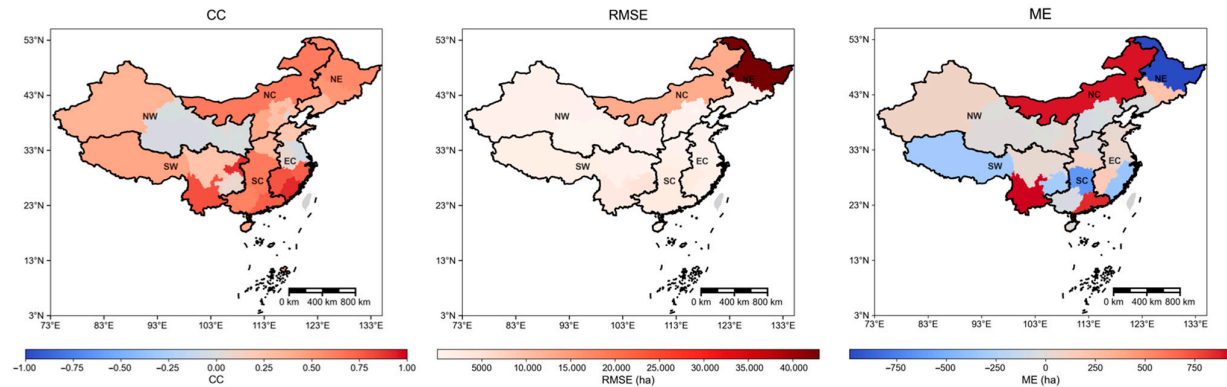


Figure 6. Spatial distribution of statistical metrics.

Provinces with higher CC values (indicating better agreement between datasets) are primarily concentrated in southern Southwest China and southern East China, including Zhejiang, Jiangxi, Fujian, Guangdong, Yunnan, and Chongqing. In contrast, provinces with lower CC values, mainly located in central-southern Northwest China and northern East China including Qinghai, Gansu, Guizhou, Ningxia, Shaanxi, Anhui, and Jiangsu, show poorer consistency between GFED4 and statistical records.

The RMSE values are notably higher in Inner Mongolia and Heilongjiang (both exceeding 12,000 ha), while remaining below 3000 ha in all other provinces.

For ME, most provinces range between -250 and 250 ha/month. However, Heilongjiang and Hunan exhibit significantly negative ME values, indicating systematic underestimation of monthly burned areas in these provinces. Conversely, Inner Mongolia, Yunnan, and Guangdong show pronounced positive ME values, reflecting GFED4's tendency to overestimate burned areas in these regions.

3.2. Spatiotemporal Differentiation Characteristics of Large and Small Fires

3.2.1. Definition of Large and Small Fires

Figure 7 displays the spatial distribution of annual mean forest fire burned area in Chinese mainland from 2001 to 2015, as estimated by GFED5, GFED4, and their difference (GFED5-GFED4), corresponding to total fires, large fires, and small fires, respectively. Previous validation has confirmed the consistency between GFED4 and CFSY data. Unlike GFED4, GFED5 incorporates Landsat and Sentinel-2 high-resolution satellite data for calibration, significantly improving its detection capability for small-scale fires. As a result, GFED5 provides more accurate estimates of total burned area that better reflect actual fire conditions.

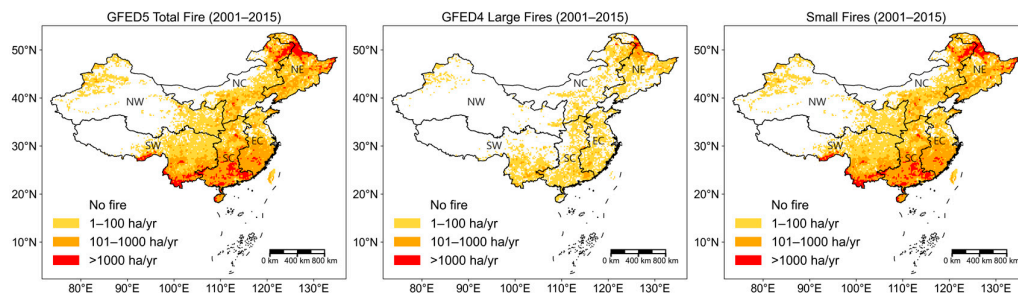


Figure 7. Annual mean forest fire burned area with a spatial resolution of 0.25° grid.

Based on the differences between these two versions, we use GFED4-derived forest burned area as an indicator of large forest fires, while the difference between GFED5 and GFED4 (GFED5-GFED4) quantifies the contribution of small-scale forest fires. This approach allows for separate characterization of large and small fire regimes across China's forest landscapes.

In the GFED5 total fire distribution, forest fires occur across most of China with varying intensities. Areas with annual burned areas exceeding 1000 ha/yr are mainly concentrated in northern Northeast China, southern Southwest China, and southern Central South China. Large fires show distinct spatial clustering in eastern and southern China, particularly in northern Northeast China, southern Southwest China and southern Central South China, while being relatively scarce in western regions. Small fires exhibit a more widespread distribution than large fires, closely following the spatial pattern of total fires, with both showing higher activity in China's northern and southern extremities and relatively lower occurrence in central regions.

3.2.2. Spatiotemporal Variation Characteristics of Large and Small Fires

Figures 8 and 9 present the annual trends of large fires (GFED4) and small fires (GFED5-GFED4) across Chinese mainland and its subregions, respectively. The results reveal distinct spatiotemporal patterns:

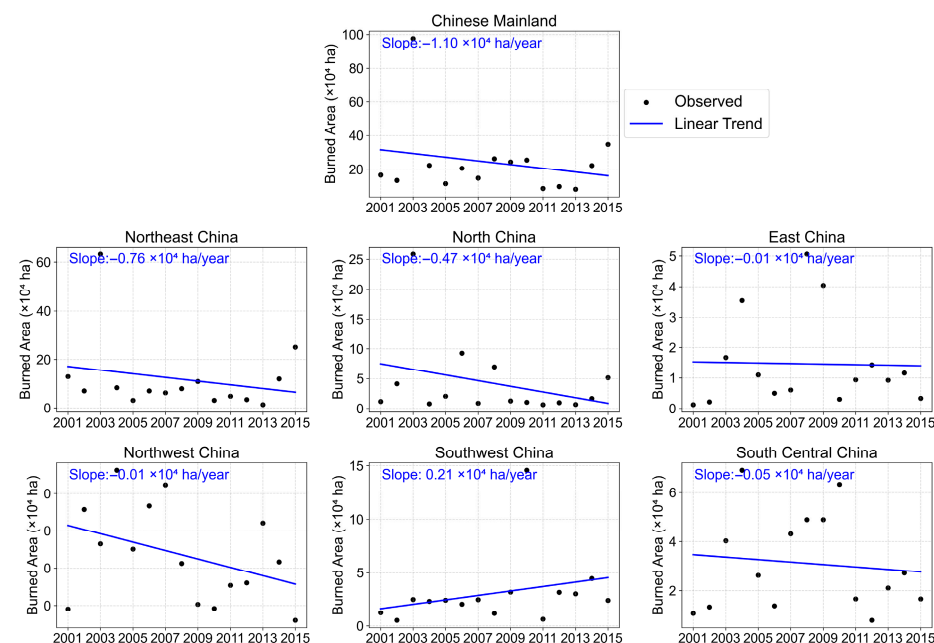


Figure 8. Trend analysis of large fire-burned area.

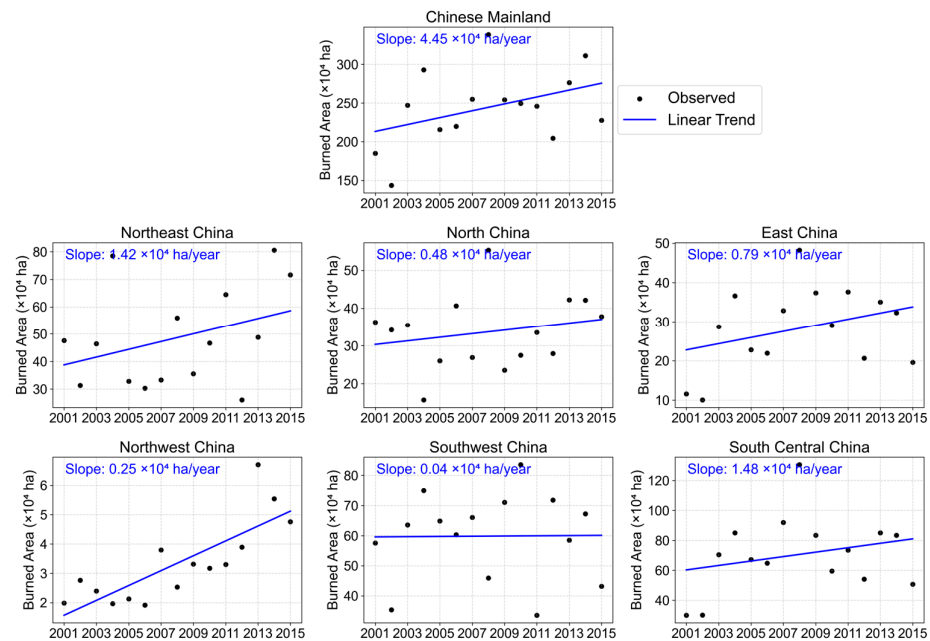


Figure 9. Trend analysis of small fire-burned area.

At the national scale, large fires exhibited an overall declining trend, particularly pronounced in Northeast China (NE) and North China (NC). In contrast, Southwest China (SW) showed a slight increase in large fire activity during the study period.

In contrast, small fires exhibited a more pronounced increasing trend, with a national-scale slope of 4.45×10^4 ha/year. The most significant increases occurred in Central South China (SC), Northeast China (NE), and East China (EC). Although Southwest China (SW) showed relatively stable small-fire activity, it still maintained a slight upward trend.

Figure 10 further displays the spatial distribution of annual trends for large and small fires at the 0.25° grid scale, clearly revealing their distinct spatial patterns of change. Large fires generally exhibit a “decreasing at both ends, increasing in the middle” spatial pattern. Specifically, significant decreasing trends are observed mainly in northern Northeast China (northern Heilongjiang and northeastern Inner Mongolia), southern Southwest China (southern Yunnan), and southern Central South China (Guangdong and Guangxi), with only some areas passing significance tests. In contrast, increasing trends dominate central Northeast China (southern Heilongjiang and Jilin) and central Southwest China (northern Yunnan), with most areas showing statistically significant increases. Additionally, central–northern Central South China and East China display a mosaic of increasing and decreasing trends, though increasing areas predominate.

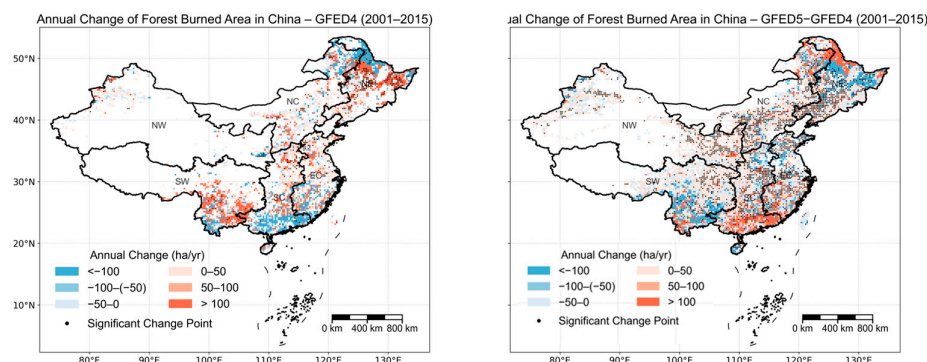


Figure 10. Annual burned area change in 0.25° grids for small and large fires.

Small fires overall demonstrate an opposite trend pattern to large fires, characterized by “increasing at both ends, decreasing in the middle”. Unlike large fires, most areas showing increasing trends for small fires pass significance testing. Furthermore, increasing trends of small fires are observed in Northwest China and eastern Southwest China—two regions completely devoid of large fires.

Figure 11 displays the interannual variations in large-fire proportions (2001–2015) for the top five provinces with the highest large-fire occurrence: Heilongjiang, Xinjiang, Jilin, Shaanxi, and Inner Mongolia.

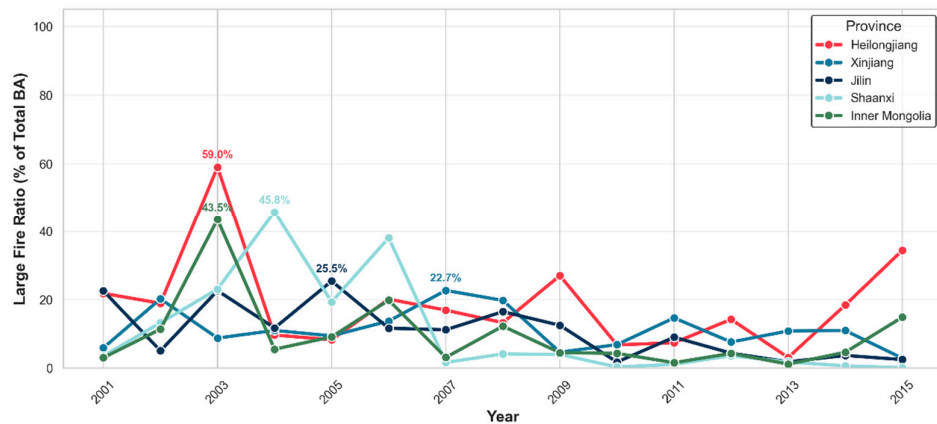


Figure 11. Temporal variations in large-fire proportion for the top five provinces.

Overall, these provinces exhibited a consistent pattern of initial increase followed by subsequent decrease in large-fire proportions during this period. Heilongjiang reached its peak large-fire proportion of nearly 60% in 2003, gradually declining to approximately 30% by 2015. Xinjiang’s maximum proportion of about 23% occurred in 2007, followed by a decrease to nearly 0% in 2015. Jilin showed a peak of around 25% in 2003 before gradually declining to about 10% in 2015. Shaanxi reached its maximum proportion of approximately 45% in 2007, then progressively decreased to nearly 0% by 2015. Similarly, Inner Mongolia peaked at about 43% in 2003 before dropping to around 15% in 2015.

Figure 12 presents the interannual variations in small-fire proportions (2001–2015) for the top three provinces with the highest small-fire occurrence: Jilin, Hebei, and Guangdong.

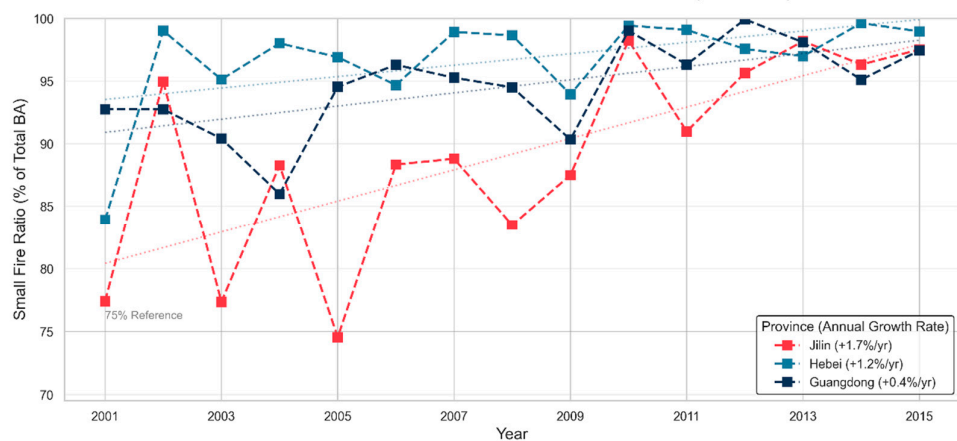


Figure 12. Temporal changes in small-fire proportion for the top three provinces.

Jilin exhibited a fluctuating upward trend, with its small-fire proportion increasing from approximately 77% in 2001 to nearly 98% in 2015, representing an annual growth rate of +1.7%/yr. Hebei showed similar fluctuations, rising from about 84% to 99% over the same period (+1.2%/yr). Guangdong demonstrated a more stable increase from 90% to 95% (+0.4%/yr).

Collectively, all three provinces displayed increasing trends in small-fire proportions during 2001–2015, with Jilin and Hebei showing particularly marked increases. By 2015, these provinces had reached exceptionally high small-fire proportions (>95%).

3.3. Spatial Autocorrelation

3.3.1. Global Spatial Autocorrelation Analysis

Figure 13 presents the spatial distribution characteristics of annual mean forest fire burned area across Chinese provinces (2001–2015), with spatial autocorrelation measured by Moran's I.

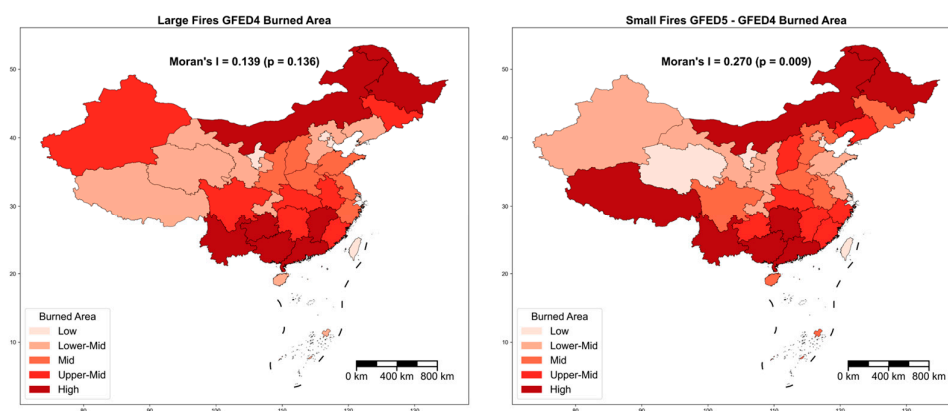


Figure 13. Global spatial autocorrelation analysis on provincial forest fire burned area.

The left panel shows large fires (GFED4) with a Moran's I of 0.139 ($p = 0.136$), indicating weak spatial clustering that is not statistically significant. This suggests large fire-burned areas are relatively dispersed across space.

The right panel illustrates small fires (GFED5-GFED4) exhibiting significant spatial autocorrelation (Moran's I = 0.270, $p = 0.009$), indicating strong and statistically validated clustering patterns among adjacent provinces. Geographically, small fires demonstrate pronounced spatial heterogeneity, with marked high-value clustering in Central South (SC) and Northeast (NE) China, contrasting sharply with persistently low values in Northwest (NW) and select areas of Southwest (SW) China. These findings underscore that small fires possess more distinct regional signatures than their large-fire counterparts.

3.3.2. Local Spatial Autocorrelation Analysis

Figure 14 displays the LISA (Local Indicators of Spatial Association) clustering patterns of annual forest fire burned areas across Chinese provinces from 2001 to 2015. For large fires (left panel), the analysis identifies Xinjiang, Gansu, Shanxi, Tianjin, and Shandong as forming a significant “low-low” cluster, indicating these provinces and their neighboring areas all exhibited relatively low large-fire burned areas. Meanwhile, Inner Mongolia appears as a “high-low” outlier, suggesting it had higher large-fire activity compared to its surrounding provinces where burned areas were lower.

The spatial autocorrelation patterns of small fires (right panel) show some similarities but with notable differences. Guangxi emerges as a distinct “high-high” cluster, demonstrating that both the province itself and its adjacent areas experienced consistently high

small-fire burned areas. Inner Mongolia again appears as a “high-low” anomaly, maintaining its pattern of elevated fire activity relative to neighboring regions. Conversely, Gansu, Shanxi, Shandong, and Liaoning form a “low-low” cluster, where these provinces and their immediate surroundings all showed lower levels of small-fire activity.

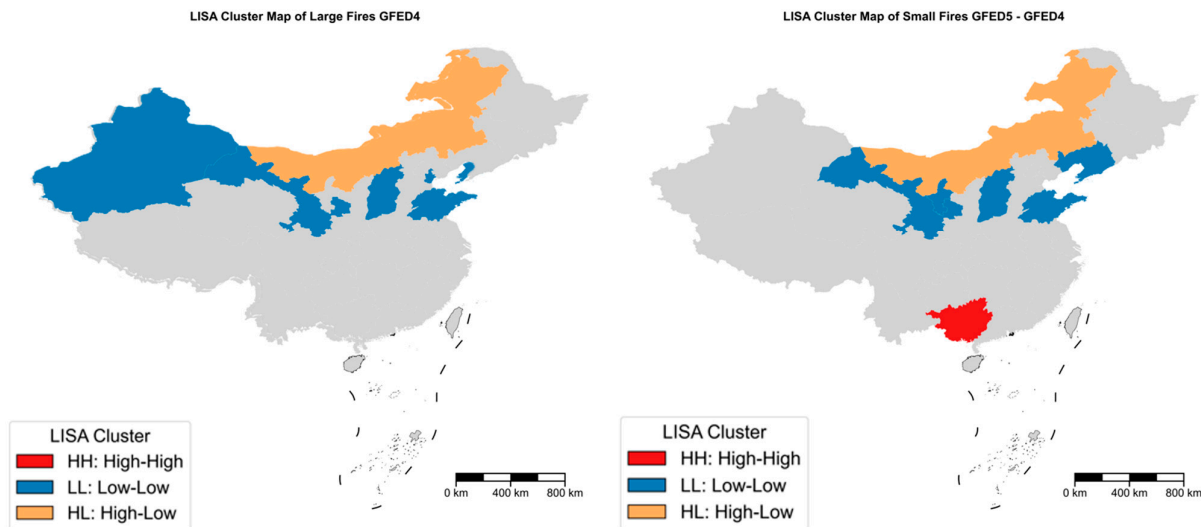


Figure 14. Local spatial autocorrelation analysis on provincial forest fire burned area.

4. Discussion

4.1. Feasibility Analysis of GFED4 for Representing “Large Fires”

GFED4 and GFED5 exhibit significant differences in fire detection capabilities and modeling approaches, which provide a scientific basis for classifying fire intensity (e.g., “large fires” vs. “small fires”). GFED4 primarily relies on MODIS active fire data (MCD14ML) and fire duration models to estimate burned area. Its algorithm is particularly sensitive to high-intensity, long-duration fires with concentrated spatial coverage (i.e., “large fires”), but has limited detection capacity for low-intensity, short-duration, or spatially dispersed small fires (e.g., agricultural burning or scattered forest fires). This limitation stems from GFED4’s core product MCD64A1 Collection 5.1, which has a minimum detectable burn size of approximately 40 ha in agricultural environments [24]—far exceeding the actual scale of many agricultural waste burning events. Such scale mismatch leads to systematic underestimation of small-scale agricultural fires by GFED4. However, the underdetection of small fires is not limited to croplands; the system also shows reduced efficiency in detecting low-intensity surface fires in fragmented forests or grassland ecotones. In contrast, while GFED5 also uses MCD64A1 as its foundation, it incorporates two key improvements: (1) integration of VIIRS 375 m thermal anomaly data, and (2) application of biome-specific dynamic correction factors derived from high-resolution remote sensing data (Landsat-8/9, Sentinel-2) to calibrate commission and omission errors. These enhancements significantly improve GFED5’s capability to capture small and short-duration fires [31].

The results of this study demonstrate that GFED5 consistently records higher total burned areas than GFED4 across Chinese mainland, with particularly pronounced differences in regions like Yunnan and Heilongjiang. These areas experience numerous small-scale fires that GFED4 frequently misses due to detection limitations. GFED5’s integration of high-resolution Landsat and Sentinel-2 data enables systematic correction of these omission errors, granting it superior capability in identifying small-fire events.

Supporting evidence shows that approximately 60% of GFED5's additional burned area detection comes from fires smaller than 21 hectares—below the minimum detectable size for a single MODIS pixel [31]. Such small fires are systematically underrepresented in GFED4 due to spatial resolution constraints [62,63], consistent with previous research indicating that the global cumulative burned area from these relatively small fires may be substantial [29].

Therefore, based on the differences in fire detection mechanisms, comparative burned area results, and supporting literature, the classification scheme using GFED4 to represent “large fires” and GFED5-GFED4 to characterize “small fires” is well-grounded both theoretically and empirically for Chinese mainland. In this study, “large fires” are operationally defined as those represented by GFED4 data, typically with burned areas exceeding 100 ha, while “small fires” are characterized by the GFED5-GFED4 residual, generally corresponding to burned areas below the approximately 100 ha detection threshold of GFED4's underlying algorithm.

However, the applicability of GFED4 exhibits significant regional disparities, as evidenced by its systematic overestimation and poor correlation ($CC = 0.262$) in Northwest China (NW). To investigate the potential for misclassification between forest and non-forest fires (e.g., in savannas or grasslands), which represents a key source of uncertainty in satellite-based fire monitoring in heterogeneous landscapes, we conducted a critical supplementary analysis: we re-extracted the forest burned area using GFED's built-in land cover distribution data (landcoverdist). As shown in Figure A1, this method did not improve the agreement with official statistics; in fact, it led to a considerable degradation in performance. Specifically, the correlation coefficient for NW plummeted from 0.262 to -0.111 . A similar, though less dramatic, decline in performance was observed across other regions as well. This counterintuitive result demonstrates that the challenge in arid regions like NW is not primarily due to a straightforward misassignment of savanna or grassland fires to the forest category. Instead, it points to more fundamental limitations, likely rooted in the spectral confusion between burned scars and prevalent non-vegetated surfaces (e.g., bare soil) in arid environments, which affects the core burned area detection algorithm of MCD64A1 before any land cover attribution takes place. A detailed comparison of the two extraction methods across all regions is provided in Appendix A. Therefore, while the classification scheme using GFED4 for “large fires” is well-grounded overall, its application in arid and semi-arid regions of China requires caution due to these inherent product limitations.

4.2. Discussion on Causes of Regional and Seasonal Fire Variations

Forest fires in China exhibit significant spatiotemporal heterogeneity, characterized by a distinct pattern of high incidence in spring, concentrated regional distribution, and pronounced north–south differences. This spatial and temporal variation arises from the complex interplay of multiple factors:

(1) Regional Variations in Climate and Weather Conditions

China's vast territory spans from boreal to tropical zones, resulting in significant regional differences in temperature, precipitation, and relative humidity under the influence of monsoon systems. These climatic factors directly affect the probability and intensity of forest fires.

For example, northeastern and northern China experience dry and windy springs, where lightning strikes and agricultural land-clearing activities frequently trigger large-scale fires [64]. In contrast, southern regions (e.g., Central South and Southwest China) are more influenced by human-controlled burning and agricultural fires, leading to widespread but smaller-scale fires from early spring to winter.

Furthermore, the increasing frequency of extreme weather events—particularly droughts and heatwaves—has significantly elevated fire risks across multiple regions [3].

(2) Variations in Land Use and Vegetation Structure

The fuel foundation for wildfires is closely linked to land cover types. In Northeast China, particularly the Greater Khingan Mountains region, vast tracts of natural coniferous forests dominate the landscape. Species such as Mongolian Scots Pine (*Pinus sylvestris* var. *mongolica*), Dahurian Larch (*Larix gmelinii*), and Dahurian Rhododendron (*Rhododendron dauricum*) exhibit pronounced flammability due to their fuel properties [10]. Studies have confirmed that these species contribute significantly to high fire probability zones [65], characterized by intense, long-lasting fires that represent major wildfire risks in the region.

In contrast, southern regions such as Southwest and East China are characterized by broadleaf forests, shrublands, and agroforestry mosaics, where diverse land use types and high vegetation fragmentation lead to discontinuous fuel distribution. Fire sources in these areas predominantly stem from agricultural activities, including crop residue burning and field margin clearance, resulting in generally low-intensity fires that typically manifest as small-scale, short-duration surface fires or agricultural burns. Due to poor fuel connectivity and limited fire spread potential, these fires seldom develop into high-intensity forest fires, instead exhibiting high frequency but limited spatial impact.

This divergence in vegetation structure and land use patterns is a key factor contributing to the pronounced regional differences in fire intensity, scale, and seasonal distribution across China.

(3) Human Activities and Fire Management Differences

Human activities account for an extremely high proportion of forest fire causes in China, with significant regional differences in fire control policies, agricultural practices, population density, and economic development levels. Research indicates that in the Greater Khingan Range region, fires are primarily influenced by human activities, especially in areas with high infrastructure density such as transportation networks, where fires occur frequently. In contrast, in subtropical regions like Fujian, fires are more driven by climatic factors, with high temperatures during the fire season being the main trigger [53].

This suggests that different ecological regions should adopt differentiated management strategies based on the dominant fire factors: in northern China, the focus should be on controlling human-induced ignition sources, while in southern China, more effort should be made to enhance fire risk warnings under extreme weather conditions. Furthermore, as socio-economic development continues, the impact of human activities on forest fires is gradually increasing, which poses greater challenges for national fire prevention and control in the future.

An additional compelling aspect of China's fire dynamics is the opposing trends observed for large and small fires [66]. On the one hand, the decline in large, high-intensity fires—especially in regions such as the Greater Khingan Range—can be largely attributed to the effectiveness of national fire management policies, including stricter fire suppression measures, improved monitoring systems, and large-scale afforestation and fuel reduction programs [65]. These efforts have substantially reduced the occurrence and spread of catastrophic wildfires. On the other hand, the increase in small-scale fires, particularly in southern and eastern China, is closely linked to widespread human activities such as agricultural burning, crop residue disposal, and land management practices [66,67]. These activities generate frequent but localized surface fires that seldom escalate into large-scale forest fires. Moreover, the influence of climate change—manifested in longer dry seasons, more frequent droughts, and rising temperatures—has further

amplified the likelihood of such small fires, especially in regions where human ignitions are abundant [10,68].

Together, these opposing trajectories highlight the dual role of human intervention: while policy interventions have effectively suppressed large fires, everyday agricultural activities and changing climatic conditions continue to sustain or even increase the prevalence of small fires [10,67]. Importantly, this shift in fire dynamics also has implications for carbon emission estimates. Accurate quantification of burned area is essential for reliable fire emission assessments. Although each small fire consumes relatively little biomass, their rising frequency means they may collectively contribute substantially to cumulative carbon emissions [67]. Neglecting these high-frequency, low-intensity fires could therefore lead to systematic underestimation of future fire-related emissions in China [65]

(4) Fundamental Challenges of Satellite Fire Monitoring in Arid Regions

The supplementary analysis presented in Appendix A, which showed degraded performance when using GFED's built-in land cover data, underscores that the limitations identified in Northwest China are not merely issues of post-detection classification but stem from inherent challenges in satellite-based fire monitoring in arid and semi-arid regions. These challenges are rooted in the fundamental physics of remote sensing and the design of global algorithms.

Firstly, the sparse and fragmented vegetation cover results in fires that are typically low in intensity, small in size, and highly discontinuous. These fire characteristics often fall below the confident detection threshold of MODIS-based products, leading to significant omission errors [69]. Concurrently, the spectral signature of a burned area in such environments is often weak and can be indistinguishable from other prevalent surface features, such as bare soil, shadowed terrain, or mineral exposures. This spectral ambiguity frequently leads to commission errors, where these non-burned surfaces are misclassified as burns by the MCD64A1 algorithm [70].

Secondly, global burned area algorithms are primarily tuned and validated for ecosystems with higher biomass and more contiguous fuel beds [71], such as boreal forests or tropical savannas. Their performance inherently degrades in arid landscapes where the signal-to-noise ratio is low, and the spectral-temporal characteristics of "burning" are less distinct.

Therefore, the performance decline observed when applying GFED in Northwest China is systemic. Future studies utilizing such datasets in similar arid regions must account for these inherent uncertainties. For more accurate monitoring, it is strongly recommended to supplement global products with regional calibration using higher-resolution satellite data (e.g., Landsat, Sentinel-2) or local ground truthing to correct for both omission and commission errors [45].

4.3. Research Limitations

In this study, the estimation of forest burned area based on GFED4 and GFED5 was conducted by multiplying the total burned area of each grid by the forest coverage ratio within that grid. This approach relies on the fundamental assumption that fires are distributed uniformly across different land use types in proportion to their areal share—that is, the probability of burning in forests, grasslands, croplands, etc., is proportional to their respective area ratios. However, this assumption may not hold in reality. The occurrence and spread of fires are driven by multiple factors, such as climatic conditions, fuel characteristics, and intensity of human activities [72]. Different land cover types exhibit significantly different burning probabilities. For instance, in areas with high fuel loads (e.g., dense coniferous forests), fires are more likely to ignite and spread rapidly, while in regions such as paddy fields and wetlands—even if they cover large areas—the fire risk is relatively low. As a result, the linear area-based allocation method may lead to over- or

underestimation of the actual forest burned area in certain regions [25]. Furthermore, compared to GFED4, the GFED5 product detects more burned area across the country. This is largely due to its incorporation of higher-resolution active fire data and improved fire detection algorithms, which enable the identification of more small-scale and short-duration agricultural fire events. However, under the estimation method used in this study, these additional agricultural burned areas were also proportionally allocated to forested areas within the grid. As a result, the forest burned area estimated from GFED5 appears significantly larger than that from GFED4. This discrepancy may not fully reflect actual changes in forest fires themselves, but rather stem partly from the categorical mechanism and underlying assumptions of the methodology.

To further assess the potential magnitude of this bias, we conducted a sensitivity analysis using nine 0.25° grids in Liaoning Province where cropland coverage exceeded 80% and forest cover was less than 10% (Figure 15). In these cropland-dominated grids, actual forest burning was negligible, but the proportional allocation method still assigned a portion of the total burned area to forests. The results showed that the mean annual difference in forest burned area between the allocation method and the actual situation was 14.497 ha, compared with a mean annual total burned area of 768.839 ha across all land cover types in the same grids (Figure 15). This corresponds to a deviation of 1.756%. These results suggest that, at least for GFED4, the proportional allocation approach introduces only a limited level of bias in cropland-dominated regions. This test does not fully account for the differences between GFED4 and GFED5, as the additional burned area detected by GFED5 largely originates from small-scale agricultural fires, but it reflects the quantify the uncertainty of the uniform allocation algorithm to forest burned area.

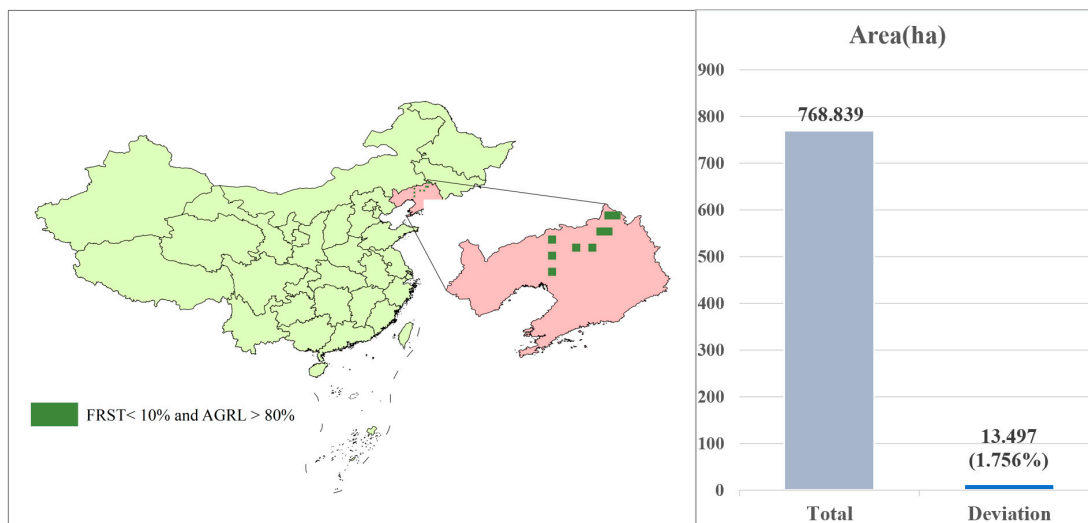


Figure 15. Study area and results of the sensitivity analysis. The map shows the Chinese mainland in green, with the focus area of Liaoning Province magnified in pink. Green grids represent cells with cropland coverage greater than 80% and forest coverage less than 10%.

5. Conclusions

This study utilized burned area data from GFED4 and GFED5, land use data, and China forest statistical yearbook data. It first systematically evaluated the applicability of GFED4 in estimating forest burned area across Chinese mainland from 2001 to 2015. Subsequently, based on discrepancies between GFED4 and GFED5, small fires were identified and extracted, while GFED4 data were categorized as large fires. Using this classification,

the spatiotemporal characteristics of large and small fires were investigated. The main conclusions are as follows:

- (1) GFED4 demonstrates good applicability at the national level and in major fire-prone regions. On a national scale, GFED4 shows high consistency with the interannual variation trend of statistical data ($CC = 0.83$) and accurately captures the characteristics of high-fire years (e.g., 2003). In high-frequency fire regions such as Northeast China, North China, and South Central China, GFED4 performs particularly well, with correlation coefficients generally exceeding 0.78. North China achieves the highest agreement ($CC = 0.94$). However, GFED4 exhibits systematic overestimation in the arid Northwest region, reflecting the product's broader challenges in accurately mapping fires in non-forested, arid ecosystems. In contrast, it shows significant underestimation in parts of East and Southwest China.
- (2) GFED4 performs best on the temporal scale in spring, while regional variations are observed in summer and autumn. During spring, GFED4 demonstrates the highest accuracy in capturing fire activity patterns across the country and in most regions (e.g., Northeast China, North China, and South Central China), with correlation coefficients exceeding 0.84. In contrast, its performance declines in summer and autumn, particularly in regions such as Northwest and East China, where lower fire intensity leads to increased fluctuations or misjudgments. Monthly scale analysis indicates that GFED4 effectively reproduces the “bimodal” distribution pattern of forest fires in China (peaks in March–May and October–November). However, deviations in peak magnitude persist in certain regions, such as East and Northwest China.
- (3) Spatially, GFED4 performs better in southeastern China but shows limited applicability in the northwest. At the provincial scale, GFED4 exhibits strong agreement with statistical data in southeastern provinces (e.g., Guangdong, Fujian, Yunnan), while its performance is poorest in arid northwestern regions (e.g., Xinjiang, Gansu, Qinghai). Grid-scale analysis further reveals that large fires are predominantly concentrated in Northeast, Southwest, and Central-South China, whereas small fires are widely distributed across the country. However, GFED4 demonstrates notably limited capability in detecting small-fire events.
- (4) Large fires show a declining trend, while small fires increase significantly with notable regional variations. From 2001 to 2015, the burned area of large fires in Chinese mainland generally decreased, particularly in Northeast and North China. In contrast, the burned area of small fires increased markedly at a rate of 4.45×10^4 hectares per year, with the most pronounced growth observed in South Central, Northeast, and East China. Provincial statistics indicate that small fires account for over 70% of the total burned area nationwide. In recent years, provinces such as Jilin, Hebei, and Guangdong have even recorded small fires constituting more than 95% of their total burned area, highlighting that small fires have become the dominant form of forest fires in China.
- (5) Small fires exhibit stronger spatial clustering characteristics. Spatial correlation analysis reveals that large fires are relatively dispersed in distribution (Moran's $I = 0.139$, $p = 0.136$), while small fires demonstrate significant positive spatial autocorrelation (Moran's $I = 0.270$, $p < 0.01$). Distinct high-value clusters of small fires are observed in South China, Northeast China, and Central China.

Author Contributions: Conceptualization, X.W. and Z.D.; methodology, X.W.; validation, X.W.; formal analysis, X.W., H.M. and S.Z.; data curation, X.T., H.M. and M.X.; writing—original draft preparation, X.W.; writing—review and editing, X.W., S.Z. and Z.D.; supervision, Z.D. and S.Z. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the Open Fund of State Key Laboratory of Remote Sensing and Digital Earth (Grant No. OFSLRSS202421) and the Natural Science Foundation of Hunan Province (Grant No. 2023JJ30484).

Data Availability Statement: No new data were created or analyzed in this study.

Acknowledgments: Both GFED4 and GFED5 burned area datasets were obtained from official sources (GFED4: https://daac.ornl.gov/VEGETATION/guides/fire_emissions_v4.html; GFED5: <https://doi.org/10.5281/zenodo.7668423>). LUCC data were obtained from <https://www.resdc.cn>.

Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

AF	Active Fire
BA	Burned Area
ESA	European Space Agency
FireCCI	Fire Climate Change Initiative
GABAM	Global Annual Burned Area Map
GBA2000	Global Burned Area 2000
GFED	Global Fire Emissions Database
GFED4	Global Fire Emissions Database Version 4
GFED5	Global Fire Emissions Database Version 5
GLOBSCAR	Global Burnt Scar satellite product
JRC	Joint Research Centre
L3JRC	Level 3 JRC burned area product
Landsat	Land Satellite
MODIS	Moderate Resolution Imaging Spectroradiometer
NASA	National Aeronautics and Space Administration
NBR	Normalized Burn Ratio
VIIRS	Visible Infrared Imaging Radiometer Suite
EC	East China
NC	North China
NE	Northeast China
NW	Northwest China
SC	South Central China
SW	Southwest China

Appendix A: Supplementary Analysis on Forest Burned Area Extraction Methods

To investigate the weak performance in Northwest China, we compared our primary method (using an external land use dataset) with an alternative method using GFED's built-in LandCoverDistribution (landcoverdist). The results showed that the built-in data performed worse: in Northwest China, the correlation coefficient (CC) decreased from 0.262 to −0.111. This pattern held across most regions. This finding indicates that the core issue lies not in land cover classification, but in fundamental limitations of the burned area detection algorithm in arid environments, justifying the use of the external dataset in our main analysis.

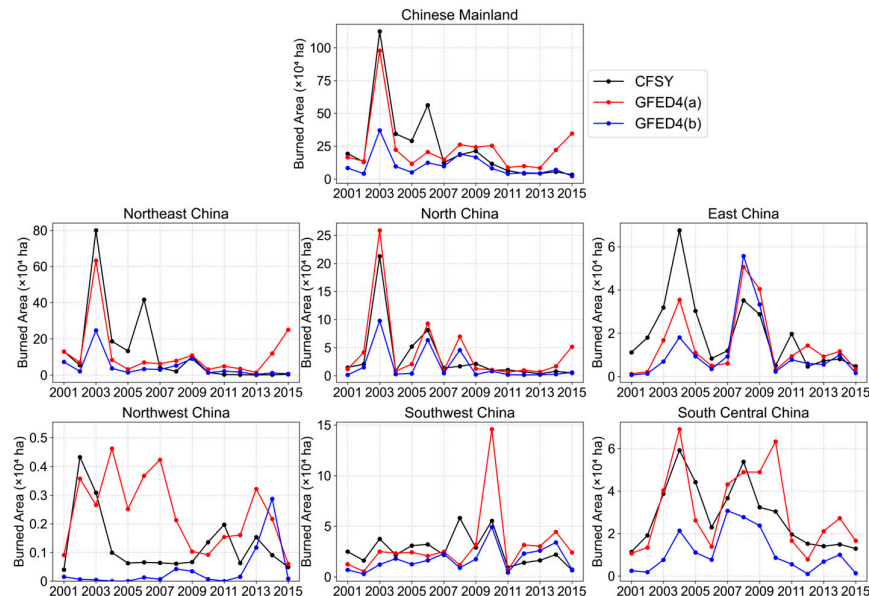


Figure A1. Comparison of forest burned area estimates across China and its six subregions derived from two extraction methods: (a) using an external land use dataset, and (b) using the built-in Land-CoverDistribution (landcoverdist) from the GFED dataset.

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