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Global carbon emission accounting: national-level assessment of wildfire CO_2 emission—a case study of China

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Abstract. Wildfires release large amounts of greenhouse gases into the atmosphere, exacerbating climate change and causing severe impacts on air quality and human health. Including carbon dioxide (CO_2) emissions from wildfires in international assessments and national emission reduction responsibilities is crucial for global carbon reduction and environmental governance. In this study, based on a bottom-up approach and using satellite data, combined with emission factor and aboveground biomass data for different vegetation cover types (forest, shrub, grassland, cropland), the dynamic changes in CO_2 emissions from wildfires in China from 2001 to 2022 were analyzed. The results showed that between 2001 and 2022, the total CO_2 emissions from wildfires in China were 693.7 Tg (1 Tg = 10^{12} g), with an annual average of 31.5 Tg. The CO_2 emissions from cropland and forest fires were relatively high, accounting for 46% and 32%, respectively. The yearly variation in CO_2 emissions from forest and shrub fires showed a significant downward trend, while emissions from grassland fires remained relatively stable. In contrast, the CO_2 emissions from cropland fires showed a clear upward trend. High CO_2 emissions from wildfires were mainly concentrated in the eastern regions of Heilongjiang and Inner Mongolia Provinces in China, accounting for 44% of the total annual emissions. Various factors such as daily cumulative sunshine hours (Spearman's correlation coefficient, forest: -0.41, shrub:0.25; $p < 0.001$) and the normalized difference vegetation index (NDVI; Spearman's correlation coefficient, forest: -0.35, shrub: 0.37; $p < 0.001$), influenced CO_2 emissions from forest and shrub fires. Moreover, temperature (Spearman's correlation coefficient, -0.45, $p < 0.001$) primarily affected CO_2 emissions from grassland fires. The CO_2 emissions from cropland fires negatively correlated with the gross domestic product (GDP) (Spearman's correlation coefficient, -0.52, $p < 0.001$) and population density (Spearman's correlation coefficient, -0.51, $p < 0.001$). China's policy management has been crucial in reducing CO_2 emissions from wildfires. By accurately assessing CO_2 emissions from wildfires, governments worldwide can better set CO_2 reduction targets, take corresponding measures, and contribute to the global response to climate change.

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1 Introduction

To limit the global average surface temperature rise to 1.5 °C higher than preindustrial levels, carbon dioxide (CO_2) emissions must reach net zero by mid-century through various pathways (Rogelj et al., 2018). Globally, wildfires reduce carbon storage in vegetation by approximately 10% from 2001 to 2012 (Lasslop et al., 2020). This significantly impacted the concentration of CO_2 in the atmosphere (Langenfelds et al., 2002; Van Der Werf et al., 2004; Wotawa and Trainer, 2000). The global annual CO_2 emissions from wildfires are approximately 6.5 to 11 billion tons, accounting for approximately one-fifth of the global CO_2 emissions from fossil fuels (Van Der Werf et al., 2010). However, the role of wildfires as a critical factor in carbon sequestration/sources is often overlooked. To mitigate climate change and fully understand the carbon exchange mechanisms between terrestrial ecosystems and the atmosphere, it is essential to consider the impacts of wildfire CO_2 emissions on the Earth system (Chuvieco et al., 2019; Giglio et al., 2018; Kasischke et al., 1995; McGuire et al., 2001; Zhang et al., 2013).

The significant differences in global wildfire CO_2 emissions among countries highlight the complexity of wildfire CO_2 emissions. Extreme forest fires in several countries, such as Australia, Canada, and the United States, often release CO_2 that exceeds the cumulative CO_2 emissions of several years in the same region, significantly impacting the global climate and the environment. Boreal fires, which usually contribute 10% of global fire CO_2 emissions, accounted for 23% in 2021 (0.48 billion metric tons of carbon), marking the highest fraction since 2000 (Zhang et al., 2023). The unprecedented wildfires in Canada in 2023 released significant amounts of air pollutants and greenhouse gases into the atmosphere. Simulation results (Wang et al., 2023) have indicated that these wildfires emitted more than 1300 Tg CO_2 and 140 Tg CO_2 equivalent of other greenhouse gases, including CH_4 and N_2O. The greenhouse gas emissions associated with wildfires exceeded twice the planned cumulative anthropogenic emissions reductions in Canada over a decade. Shiraishi et al. (2021) used a bottom-up approach to estimate CO_2 emissions from catastrophic fires in Australia between 2019 and 2020. The results showed that from March 2019 to February 2020, Australia's annual CO_2 emissions were estimated to be 806 ± 69.7 Tg CO_2 year^{-1}, equivalent to 1.5 times its total greenhouse gas emissions (CO_2 equivalent) in 2017. Phillips et al. (2022) reported that by the middle of this century, wildfires in northern North America could lead to a cumulative net source of approximately 12 billion tons of CO_2, accounting for approximately 3% of the remaining global CO_2 emissions, which is closely related to the temperature targets of the Paris Agreement. In the context of climate change, wildfires are becoming more frequent, and CO_2 emissions from wildfires are often influenced by human intervention. Phillips et al. (2022) found that increasing investment in fire management to avoid CO_2 emissions is equivalent to or lower than other mitigation strategies. Therefore, changes in fire management may impact global atmospheric CO_2 concentrations, and proactive management strategies effectively reduce CO_2 emissions (Kelly et al., 2013; Phillips et al., 2022; Van Wees et al., 2021). However, CO_2 emissions from wildfires are not included in international assessments or national emission reduction responsibilities. Including wildfire CO_2 emissions in international assessments and national emission reduction responsibilities is crucial for global carbon reduction and environmental governance.

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China has released a large amount of wildfire emission inventory, but previous research on wildfire emissions in China has focused chiefly on small-scale and short-term periods (Cao et al., 2005; Huang et al., 2012; Qiu et al., 2016; Tian et al., 2011; Wu et al., 2018). Wang et al. (2008) established an atmospheric pollutant emission inventory of cropland fires in China in 2006 using the emission factor method and analyzed its spatiotemporal distribution characteristics. Wu et al. (2018) estimated pollutant emission inventories from wildfires in central and eastern China from 2003 to 2015 using remote sensing images but did not include the heavily polluted northeast region. In addition, most studies have focused mainly on atmospheric pollutant emissions, with limited research on CO_2 emissions (Jin et al., 2022; Wang et al., 2008; Xie et al., 2024; Yin et al., 2019). Xie et al. (2024) used the GEOS-Chem model to investigate the impact of cropland fires on severe haze events in Heilongjiang Province. They reported high uncertainty in the existing Global Fire Emissions Database (GFED) version 4.1 emission inventory. Van Der Werf et al. (2017) also noted substantial uncertainty in estimating wildfire emissions in existing emission inventories. Therefore, more work must be done to explore the long-term dynamics of wildfire emissions.

This study estimated the CO_2 emissions from wildfires, including forest, shrub, grassland, and cropland fires in China from 2001 to 2022. Also, it explored the factors that may affect the spatiotemporal changes in CO_2 emissions from wildfires. The study results can provide high spatial resolution and long-term wildfire CO_2 emission inventories, which can enhance the accuracy of models assessing the impacts of wildfires on air quality, climate, and human health. Furthermore, this study provides essential scientific support for air pollution control strategies and is a critical foundation for accurately evaluating CO_2 emission reduction targets in various countries.

2 Data and methods

2.1 Study area

China is located in the eastern part of the Eurasian continent on the west coast of the Pacific Ocean. It spans approximately 50 degrees (3-53 °N) from north to south and 60 degrees (73-135 °E) from east to west, with a land area of approximately 9.60×10^6 km^2. There are differences in the distribution of cropland, grassland, shrubs, and forests in China. Croplands are mainly located in the eastern plains and coastal areas, such as Northeast (Heilongjiang, Jilin, and Liaoning), North (Hebei), and East (Shandong, Jiangsu) China, where the terrain is flat and suitable for agriculture. Grasslands are mainly distributed in North (such as Inner Mongolia and Xinjiang) and Southwest (such as the western Sichuan Plateau) of China, forming a vast grassland ecosystem. Shrubs are mainly distributed in mountainous and semiarid areas. Forests are mainly distributed in Northeast (Heilongjiang, Jilin, and Liaoning) and Southwest (Yunnan, Guizhou) China, which have abundant forest resources.

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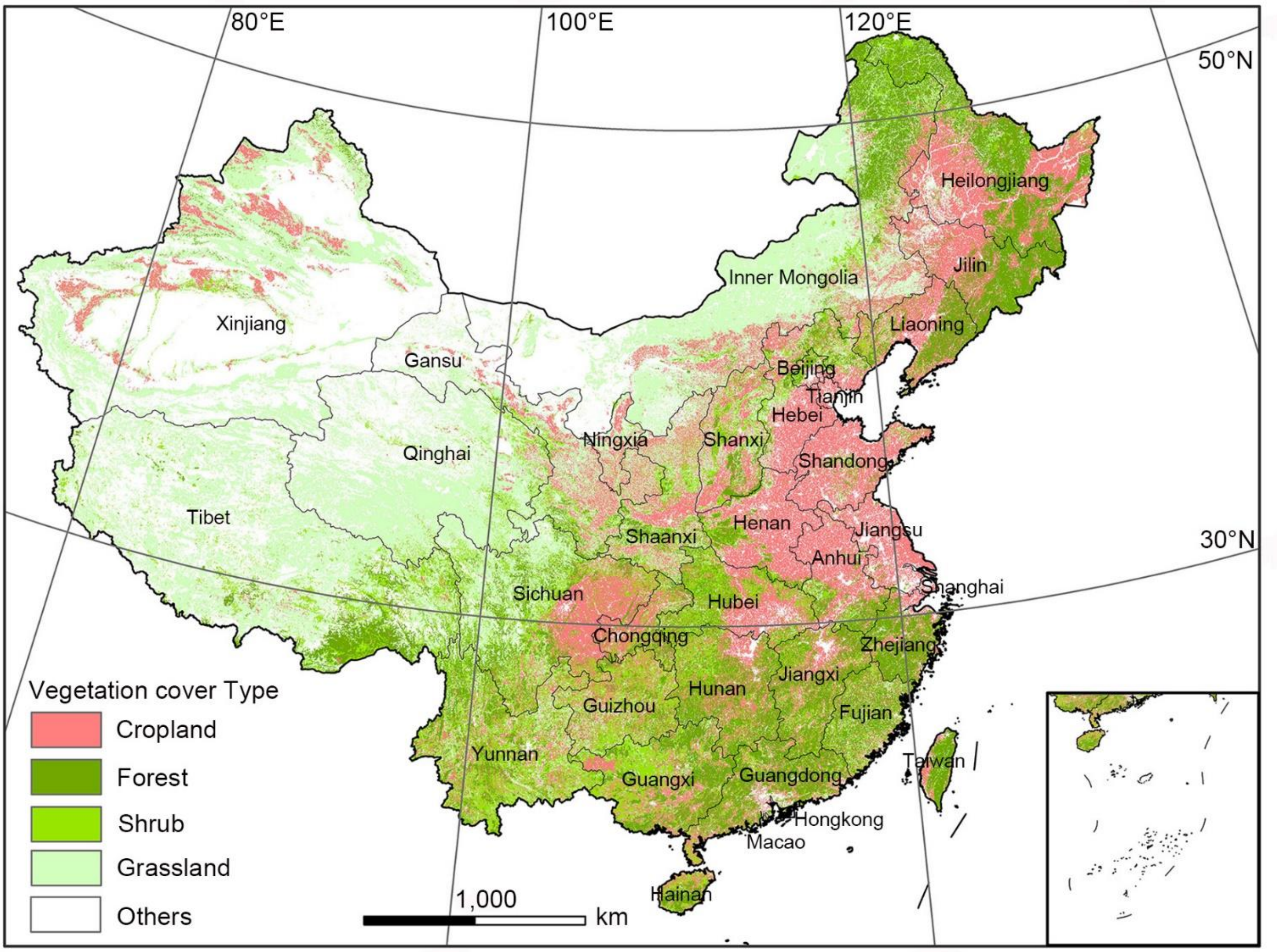

Figure 1: Regional divisions and vegetation distribution in China.

2.2 Data

The burned area data for wildfires with a spatial resolution of 500 m were sourced from MODIS-MCD64A1 burned area product (Giglio et al., 2018). The vegetation cover data were sourced from the China Land Use Land Cover Remote Sensing Monitoring Dataset (CNLUCC), with a spatial resolution of 30 m (Xu et al., 2018). A 1 km harvesting area dataset for three staple crops (e.g., corn, wheat, and rice) in China from 2000 to 2019 was obtained from Luo et al. (2020). Vegetation cover data were combined with fire area data to extract spatial data, including the time and geographic coordinates of fire occurrence, burned area, and vegetation cover types (corn, wheat, rice, grassland, shrub, and forest). The meteorological data were obtained from the Daily Meteorological Dataset of Essential Meteorological Elements of the China National Surface Weather Station (V3.0), and the spatial distribution of the meteorological data was calculated using the Kriging interpolation method in the ArcGIS 10.8 environment. The vegetation cover fraction was sourced from China's

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regional 250 m fractional vegetation cover dataset (Gao et al., 2024a). The normalized difference vegetation index (NDVI) data were sourced from China's regional 250 m normalized difference vegetation index dataset (Gao et al., 2024b).

2.3 Methods

2.3.1 Emission factors

The emission factor refers to the gas released per unit mass of dry combustible material during combustion, typically in grams per kilogram (g kg^{-1}). This is a crucial parameter for calculating gas emissions during biomass burning, such as CO_2, methane (CH_4), and carbon monoxide (CO). Emission factors are influenced by various factors, including the combustibility of tree species, differences in vegetation cover types, and the intensity of flame combustion (Andreae and Merlet, 2001; Lü et al., 2006). To ensure the accuracy of the wildfire emission inventory as much as possible, it is essential to choose appropriate emission factors. This study comprehensively analyzed many studies in the literature to summarize the emission factors of CO_2 generated by wildfires under different vegetation cover types, as listed in Table S1. Finally, the average values from the literature were selected as the emission factors of the different vegetation cover types.

2.3.2 Aboveground biomass

Previous studies have mainly used the aboveground biomass data from Fang et al. (1996) for forests. Forest aboveground biomass data in recent years need to be updated. In this study, the aboveground biomass data of shrubs and forests from 2001 to 2012 were obtained from Su et al. (2016). The data for 2013 to 2022 were obtained from Yan et al. (2023). Grassland aboveground biomass was calculated using the exponential model by Gao et al. (2012):

$$AGB_{grass} = 20.1921 \times e^{3.2154 \times (NDVI)} \tag{1}$$

where AGB_{grass} is the aboveground biomass of grassland (g m^{-2}) based on the average NDVI value of the growing season. The aboveground biomass of cropland was obtained by multiplying the crop-specific yield per unit area by the straw-to-product ratio. The crop-specific yield per unit area (rice, corn, wheat) was derived from the China Statistical Yearbook, while the crop-specific yield per unit area of other crops was defined as the average of rice, corn, and wheat. The straw-to-product ratios for rice, wheat, corn, and other major crops were 1.323, 1.718, 1.269, and 1.5, respectively (Technical Guidelines for Compiling Emission Inventory of Air Pollutants from Biomass Combustion Sources, 2015).

2.3.3 Combustion efficiency

The combustion efficiency of biomass is an essential factor affecting the accuracy of wildfire CO_2 emission estimates. It is influenced by the intensity of fires, wildfire type, moisture content and load of combustibles, and meteorological conditions. Hély et al. (2003) established an empirical relationship between combustion efficiency and vegetation cover fraction (FVC). This relationship was applied in this study to the combustion efficiency calculation for forests, shrubs, and grasslands.

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$$CF = \begin{cases} 0.98 & if\ 40\% \leq FVC\ \ for\ grassland \\ exp(-0.13\ \times FVC) & if\ 40\%\ < FVC\ \leq 60\%\ for\ grassland \\ exp(-1.3\ \times\ FVC) & if\ T_c\ \leq 60\%\ for\ forest\ and\ shrub \\ 0.25 & if\ FVC\ \ > 60\%\ for\ forest \\ 0.3 & if\ FVC > 60\%\ for\ shrub \\ 0.9 & if\ FVC > 60\%\ for\ grassland \end{cases} \quad (2)$$

where CF is the combustion efficiency, and FVC is the vegetation cover fraction. The combustion efficiencies of corn, wheat, and rice were obtained from Zhou et al. (2017), with values of 0.92, 0.92, and 0.93, respectively. The combustion efficiency of other crops was taken as the average value for corn, wheat, and rice (i.e., 0.923).

2.3.4 CO_2 emission estimation

Using a bottom-up approach to estimate China's wildfire CO_2 emissions inventory, the wildfire CO_2 emissions are calculated using the following formula for forest, shrubs, and grasslands:

$$E_i = \sum_{x,i} BA_{x,i}\ \times\ AGB_{x,i}\ \times\ CF_i\ \times\ EF_i \quad (3)$$

where the subscripts x and i represent the location and vegetation cover type, respectively. E_i represents the CO_2 emission, $BA_{x,i}$ is the burned area (ha), $AGB_{x,i}$ is the aboveground biomass (t ha^{-1}), and EF_i is the emission factor. CF_i is the combustion efficiency.

For cropland fires, cropland was further divided into four categories: rice, wheat, corn, and others. The specific calculation formula is as follows:

$$E_j = \sum_{x,j} BA_{x,j}\ \times\ B_{x,j}\ \times\ N_j \times\ CF_j\ \ \times\ EF_j \quad (4)$$

where the subscripts x and j represent the location and type of crop, respectively. E_j represents the CO_2 emissions, $BA_{x,j}$ is the burned area, $B_{x,j}$ is the per hectare yield of crop type j at location x, N_j is the straw-to-product ratio, EF_j is the emission factor, and CF_j is the combustion efficiency.

3 Results and discussion

3.1 Interannual Variation in CO_2 Emissions

The total CO_2 emissions from wildfires in China from 2001 to 2022 were 693.7 Tg, with an average annual value of 31.5 Tg, accounting for 0.46% of the total global emission of All fire types (GFED4, all fire types mean of 7140 Tg from 2001 to 2022, Van Der Werf et al., 2017), and 0.52% of China's fossil fuel emission (approximately 6400 Tg, Shan et al., 2017). CO_2 emissions from wildfires in China were relatively low, decreasing slowly by 0.43 Tg per year (Fig. 2a). CO_2 emissions from cropland and forest fires were relatively high, accounting for 46% and 32%, respectively; shrub fires emissions account for 20%, while grassland fire emissions were the lowest, accounting for only 2% (Fig. 2b).

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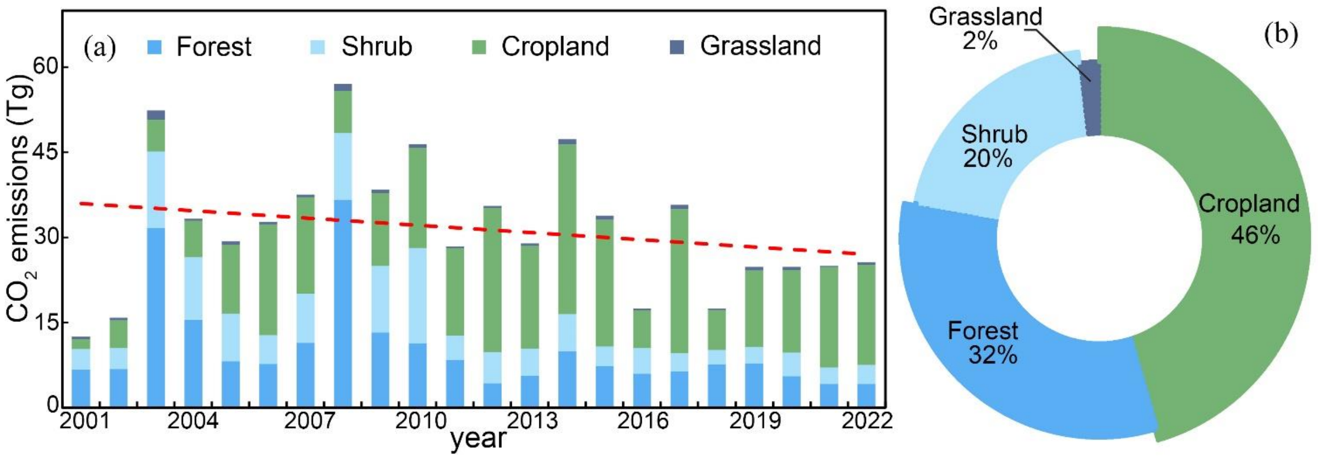

Figure 2: (a) Annual CO_2 emissions within specific vegetation cover types from 2001 to 2022 in China; (b) Contribution of different vegetation cover types to the total CO_2 emissions from 2001 to 2022 in China.

The annual CO_2 emissions from different types of fires showed varying temporal trends. The downward trend for forest and shrub emissions was significant, with a decrease of 0.63 and 0.33 Tg per year, respectively (Fig. 3a and 3b). Such a decline may reflect effective forestry management strategies for forest and shrub fires. In contrast, cropland emissions showed a clear upward trend, with an annual increase of 0.63 Tg (Fig. 3c). This may be related to an increase in agricultural activities, changes in land use, or an increase in cultivation intensity. The emission trend for grassland was relatively stable (Fig. 3d), which might be influenced by a combination of ecological and anthropogenic factors.

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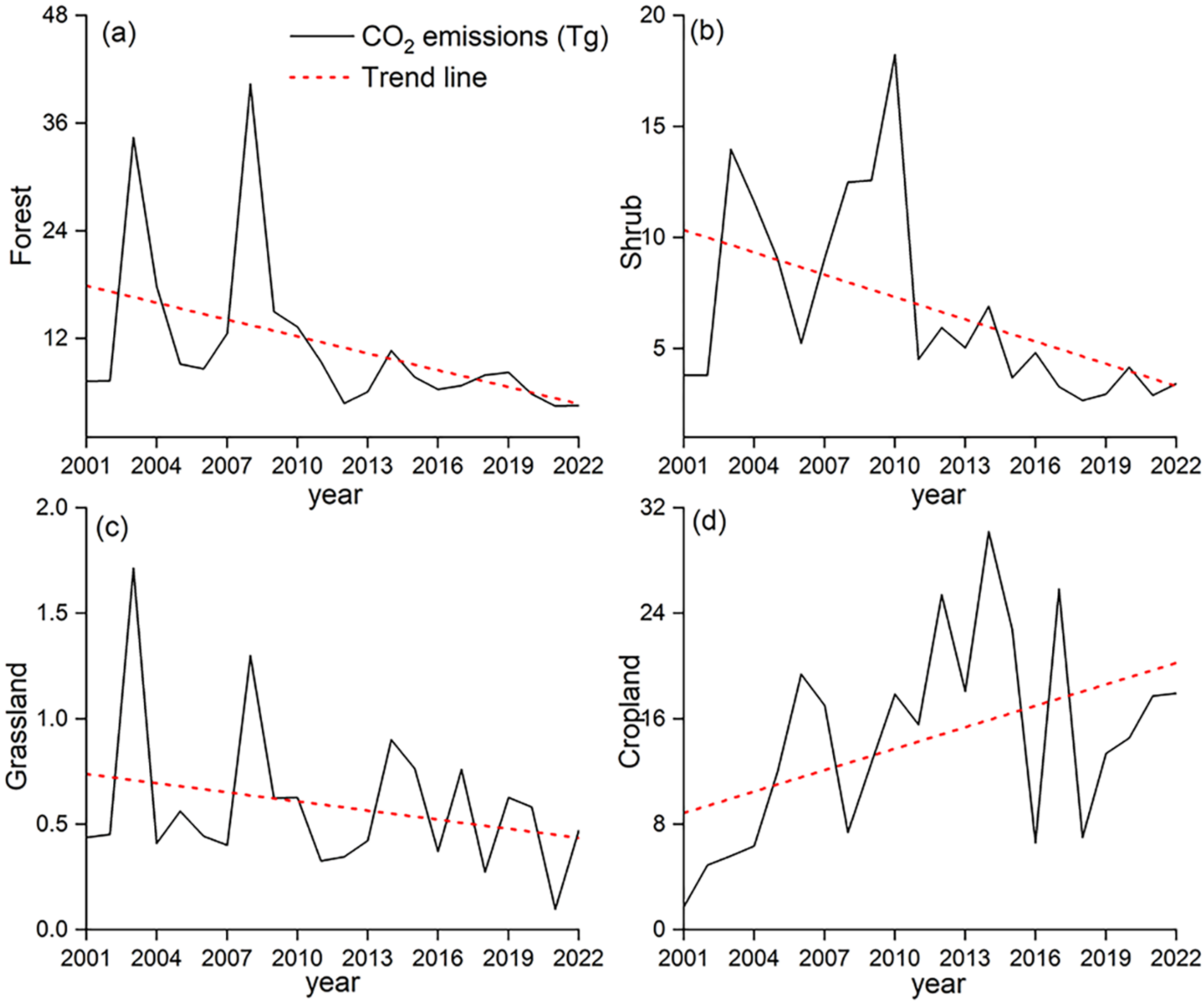

Figure 3: Time series of CO_2 emissions for different vegetation cover types from 2001 to 2022 in China: (a) Forest, (b) Shrub, (c) Grassland, (d) Cropland.

3.2 Monthly Variation in CO_2 Emissions

The CO_2 emissions from different vegetation cover types showed significant seasonal fluctuations, with certain months showing higher emissions than others. Wildfires had lower CO_2 emissions in July and August, which may correspond to the respective wet seasons. Wet conditions usually reduce the occurrence rate of fires (Fig. 4). Forest, shrub, and grassland fires had higher emissions in February, March, and April, possibly related to the dry weather and accumulation of combustible materials in spring, increasing the risk of fires. Cropland fires showed significant emission peaks in April, May, and June. This pattern may be related to specific agricultural activity (such as plowing, sowing, and harvesting) cycles, as cropland fires often occur after harvest when crop residues are burned to prepare for the next planting season. The spatial distribution of forest, shrub, and grassland fire emissions were relatively similar among the different months (Figs. S1-S3). In contrast,

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the spatial distribution of emissions from cropland fires varied significantly across different months and was likely influenced by policy management (Fig. 5). The high emissions of cropland fires in March and April mainly originated from Heilongjiang and Jilin Provinces. The high emissions of cropland fires in May and June mainly came from the Anhui, Henan, 185 and Jiangsu Provinces.

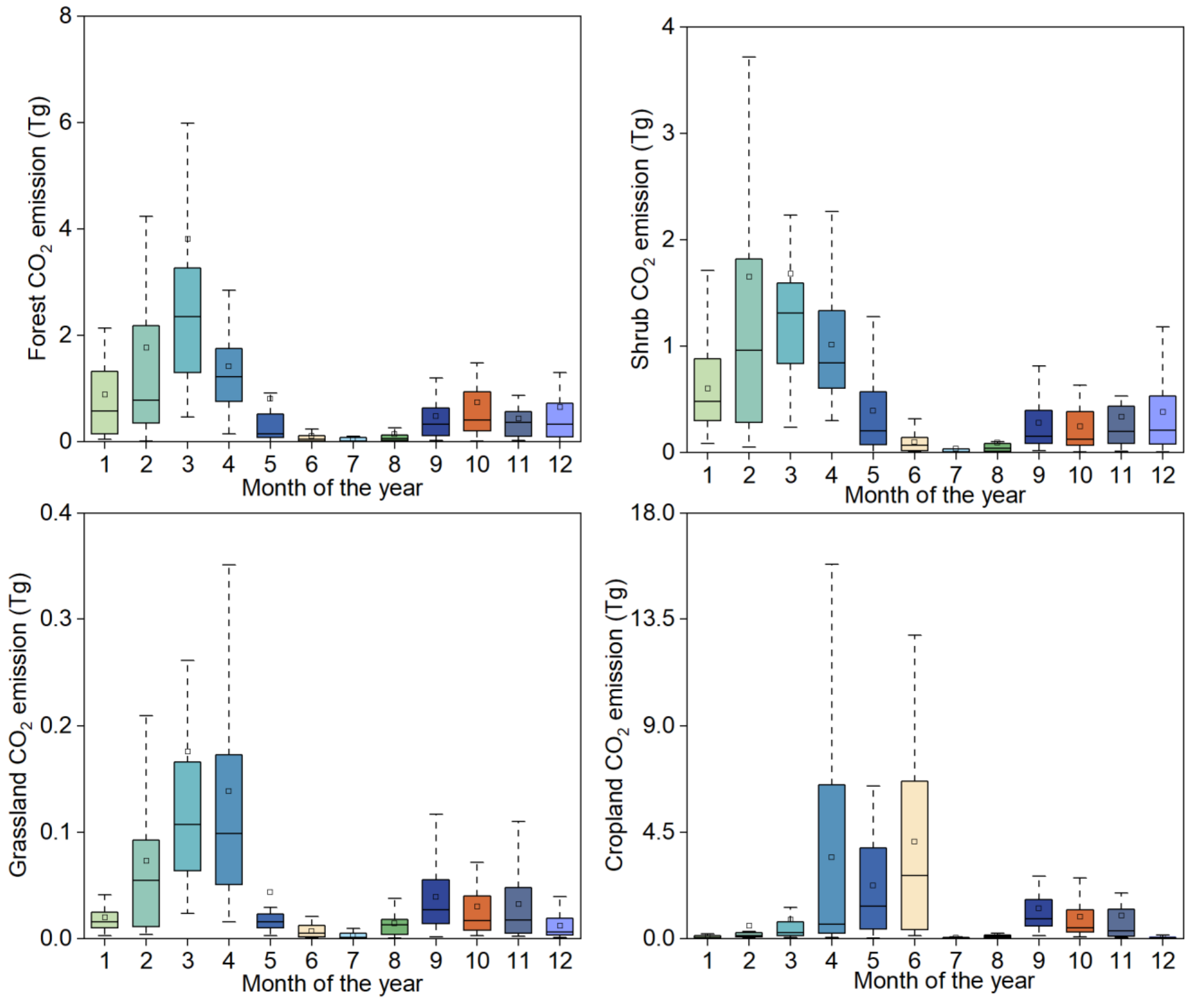

Figure 4: Box plots of CO_2 emissions for specific vegetation cover types per month from 2001 to 2022 in China, showing the median (black line), mean (box), and the range within 1.5 times the interquartile range (IQR): (a) Forest, (b) Shrub, (c) Grassland, (d) Cropland.

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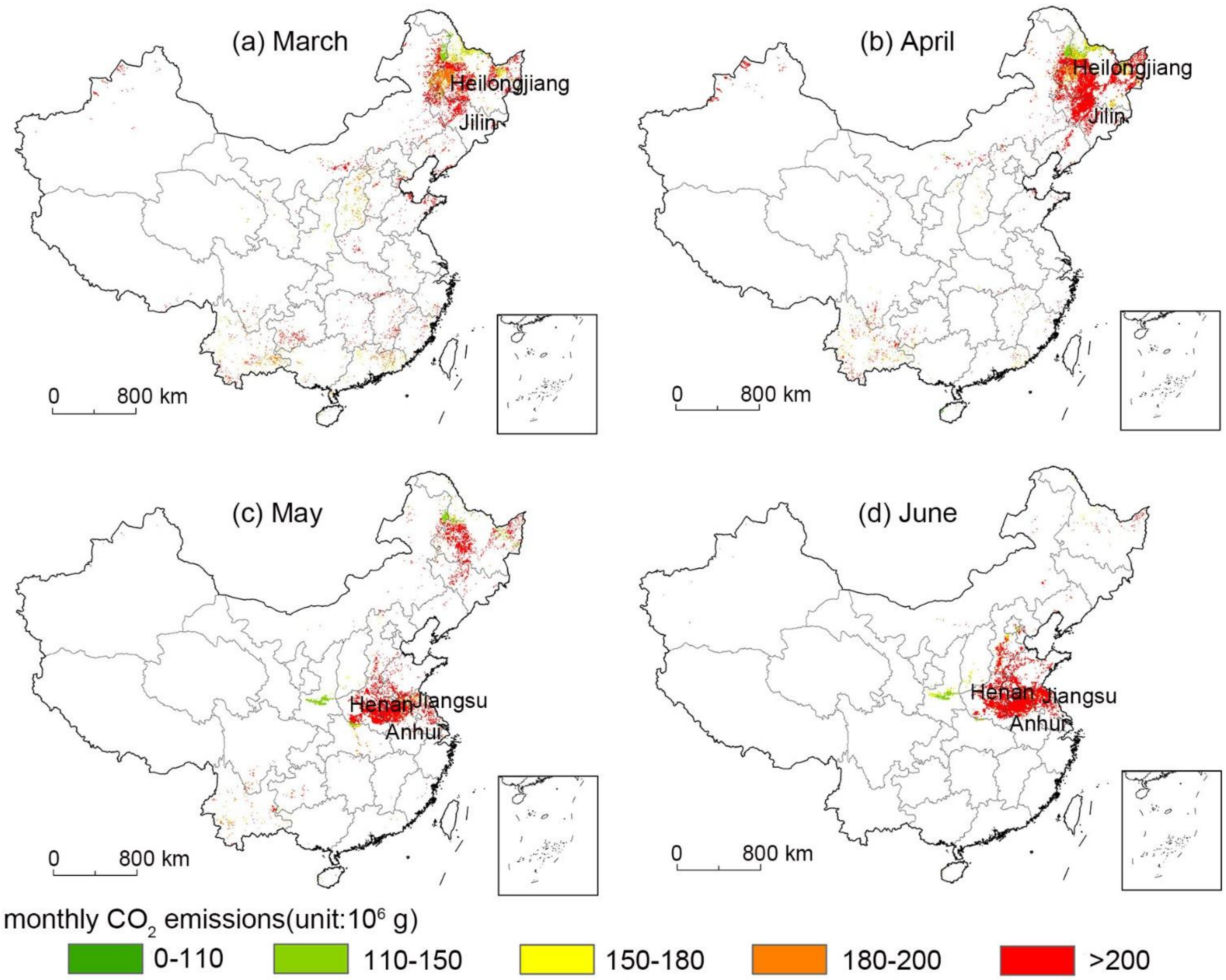

Figure 5: Spatial distribution of monthly CO_2 emissions within cropland fires from 2001 to 2022 in China: (a) March, (b) April, (c) May, and (d) June.

3.3 Spatiotemporal Variations in CO_2 Emissions

Due to differences in geographical location, climate conditions, and population density, the spatiotemporal distribution of CO_2 emissions in each region exhibits heterogeneity (Fig. 6). Overall, the emissions in the northwestern region of China were relatively low. The significant areas with higher emissions were mainly concentrated in China's eastern and central regions (Fig. 6a). The areas with high CO_2 emissions from forest fires were mainly in the northeast and southwest regions (Fig. 6b). The distribution of high CO_2 emissions from shrub fires was relatively scattered. However, there were some concentrated high-emission areas in the western and northeastern regions (Fig. 6c). The emissions from grassland fires were

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generally low and were mainly concentrated in Northeastern China (Fig. 6d). The high-value areas of CO_2 emissions from cropland fires were mainly concentrated in eastern China (Fig. 6e).

The results of the global spatial autocorrelation analysis of CO_2 emissions from wildfires are shown in Table 1. Under different wildfires, the p values were all less than 0.01, with a confidence level of 99%; the Moran's I values were all positive, with a Z score greater than 2.58, indicating a significant positive spatial autocorrelation of CO_2 emissions from wildfires, exhibiting an aggregation pattern in spatial distribution.

Table 1. Global spatial autocorrelation statistics of CO_2 emissions

Vegetation cover type	Moran's I	Z	P	Clustering pattern
Forest	0.052	5.072	0.000	Cluster
Shrub	0.118	8.961	0.000	Cluster
Grassland	0.064	6.632	0.000	Cluster
Cropland	0.281	20.414	0.000	Cluster
All	0.110	8.894	0.000	Cluster

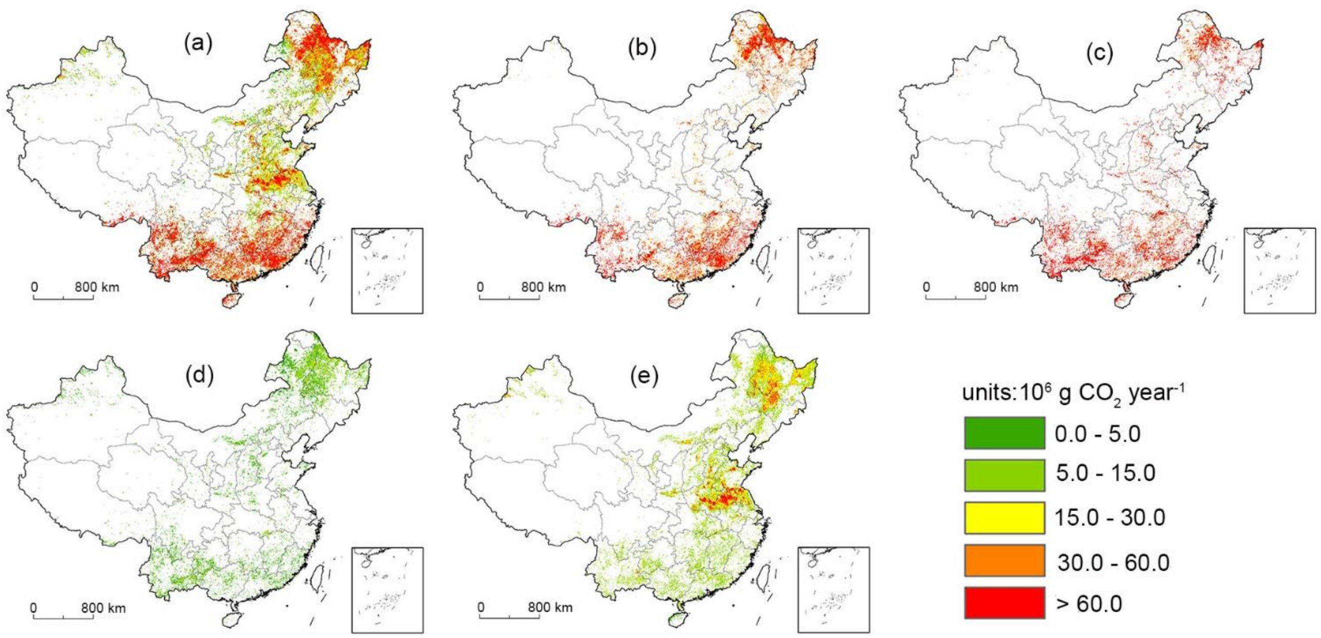

Figure 6: Average annual spatial distribution of CO_2 emissions in China from 2001 to 2022: (a) all fire types, (b) Forest, (c) Shrub, (d) Grassland, and (e) Cropland.

The hotspot analysis of wildfire CO_2 emissions investigated the specific spatial clustering of CO_2 emissions, as shown in Figure 7. In general, the high values of CO_2 emissions were mainly concentrated in the eastern regions of Heilongjiang and Inner Mongolia Provinces in China from 2001 to 2022, with annual emissions accounting for 44% of the total annual

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emissions (Fig. 7a). There was only one high-value aggregation area for forest fires and grassland fires, which is similar to the spatial distribution of total emissions (Fig. 7b and Fig. 7d). The average annual emissions of high-value aggregation areas accounted for 53% and 64% of the total annual emissions, respectively. There were two high-value clusters of shrub fires, one in the eastern regions of Heilongjiang and Inner Mongolia Provinces and the other in the southwestern forest areas, with annual emissions accounting for 25.82% and 40% of the total emissions, respectively (Fig. 7c). There were also two high-risk areas for cropland fires, one in the eastern regions of Heilongjiang and Inner Mongolia Provinces and the other in the eastern and central regions of China, mainly including Shandong, Henan, Anhui, and Jiangsu (Fig. 7e). The average annual emissions accounted for 43% and 48% of the total emissions, respectively. It is worth noting that northeastern China is marked as a high-confidence hotspot area among all fire types, which may indicate the long-term existence of high CO_2 emissions in the region.

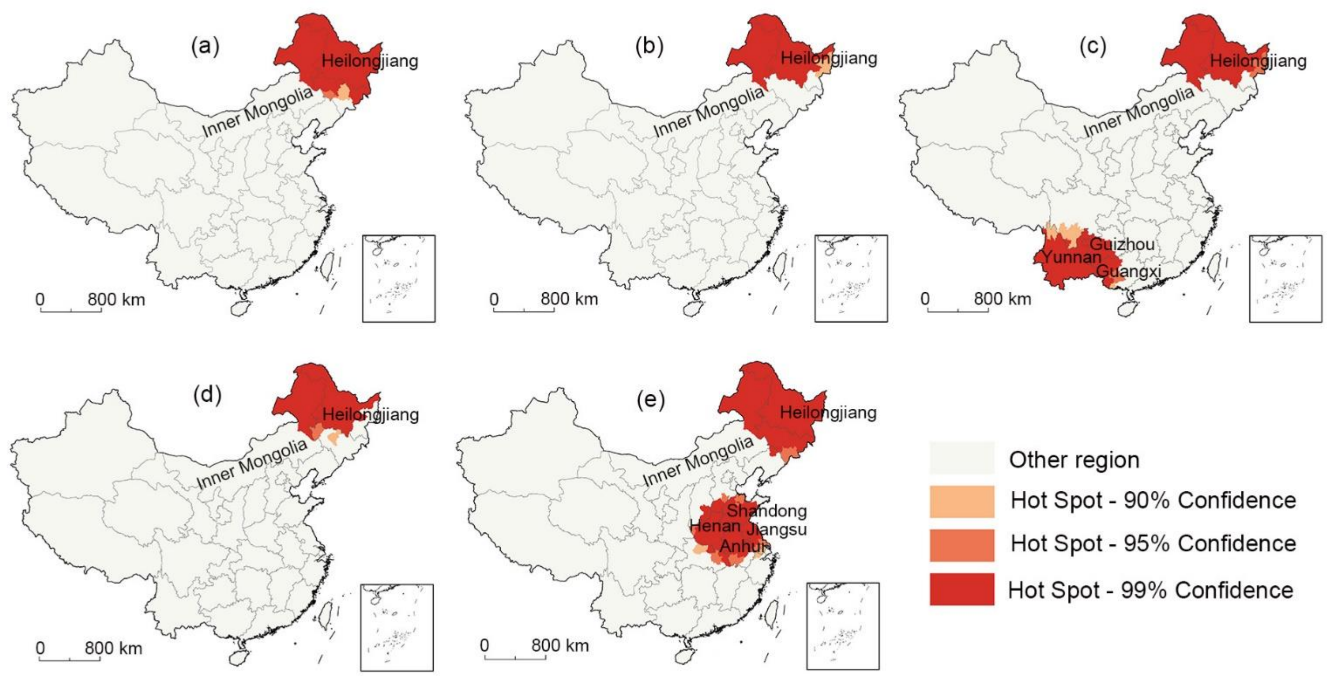

Figure 7: Spatial distribution of CO_2 emission hotspots from 2001 to 2022 in China: (a) all fire types, (b) Forest, (c) Shrub, (d) Grassland, and (e) Cropland.

For emissions from different vegetation cover types, some years and regions exhibit unexpectedly high emissions, potentially caused by special events such as abnormal climate conditions, human activities, and fire management. Figure 8 shows the time series of high-emission regions under the different vegetation cover types from 2001 to 2022. Extreme forest fires occurred in Heilongjiang and Inner Mongolia Provinces in 2003, and the total emissions of these two provinces accounted for 73% of the total emissions in 2003 (Fig. 8a). The high emissions in 2008 were due to forest fires in Inner Mongolia, which accounted for 47% of the total emissions in 2008. Shrub fire emissions peaked in 2003 and 2010 (Fig. 8b).

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The emissions in 2003 occurred mainly in Yunnan, Inner Mongolia, and Heilongjiang, with the total emissions from these three provinces accounting for 63% of the total emissions. The emissions in 2010 occurred mainly in Yunnan and Guizhou, accounting for 78% of the total emissions in 2010. Grassland fire emissions also peaked in 2003 and 2008, with the 2003 main emission areas being Inner Mongolia and Heilongjiang, accounting for 85% of the total emissions for that year. Inner Mongolia was the central emission region in 2008, accounting for 62% of the total emissions for that year (Fig. 8c). Human activities and fire management may affect cropland fire emissions more significantly, resulting in more significant variability in CO_2 emissions across provinces (Fig. 8d). Heilongjiang Province had relatively low emissions from 2001 to 2013, with emissions increasing and trending upward from 2014, where the annual average emissions from 2014 to 2022 were five times greater than the annual average emissions from 2001 to 2013. The primary emission years for the Anhui and Henan Provinces were between 2006 and 2014, with emissions decreasing after 2015. The emission trend in Jilin Province was similar to that in Heilongjiang Province, with higher emissions in recent years. In other regions, CO_2 emissions from cropland fires were relatively high before 2012. After the implementation of China's strict ban on open-air biomass burning in 2012, emissions decreased, showing an overall downward trend.

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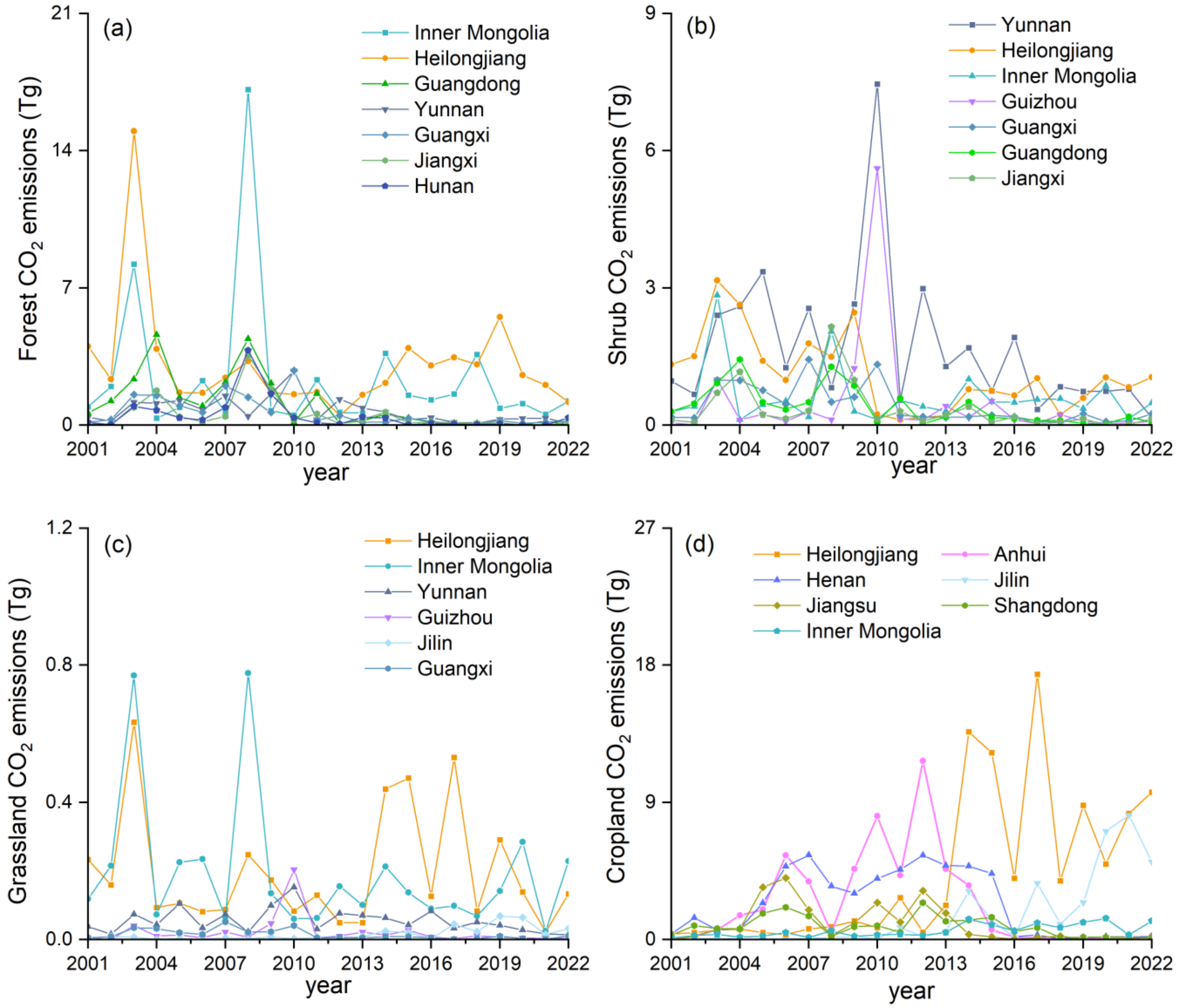

Figure 8: Time series of CO_2 emissions in major regions under different vegetation cover types from 2001 to 2022 in China: (a) Forest, (b) Shrub, (c) Grassland, and (d) Cropland.

The spatial distribution of CO_2 emissions changes over different periods from 2001 to 2022 (Fig. 9). The average annual CO_2 emission from 2001 to 2005 was 28.7 Tg, with CO_2 emission mainly concentrated in the eastern region of China (Fig. 9a). The average annual emissions from Heilongjiang and Inner Mongolia accounted for 42% of the total annual emissions. Compared with 2001-2005, the average annual CO_2 emissions increased from 2006 to 2010 (39.8 Tg), and the high-emission areas increased (Fig. 9b). High emissions still existed in Heilongjiang and Inner Mongolia in the east. However, other provinces, such as Anhui and Henan, began to show higher emissions, mainly due to an increase in cropland fires in these provinces (Figs. S4-S7). The average annual CO_2 emissions decreased from 2011 to 2015 (34.9 Tg). Forest fire

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emissions in Heilongjiang and Inner Mongolia decreased, while cropland fire emissions increased (Figs. S4-S7). High CO_2 emissions from cropland fires still occurred in provinces such as Anhui and Henan (Fig. 9c). The average annual CO_2 emissions from 2016 to 2022 were the lowest of the four time periods (24.4 Tg), with an overall decrease in CO_2 emissions from forest, shrub, and grassland fires (Fig. 9d). CO_2 emissions from cropland fires in various provinces, such as Anhui and Henan, decreased, while high emissions from cropland fires in the eastern regions of Heilongjiang, Inner Mongolia, and Jilin still existed. The average annual emissions from Heilongjiang, Jilin, and Inner Mongolia accounted for 80% of the total annual emissions.

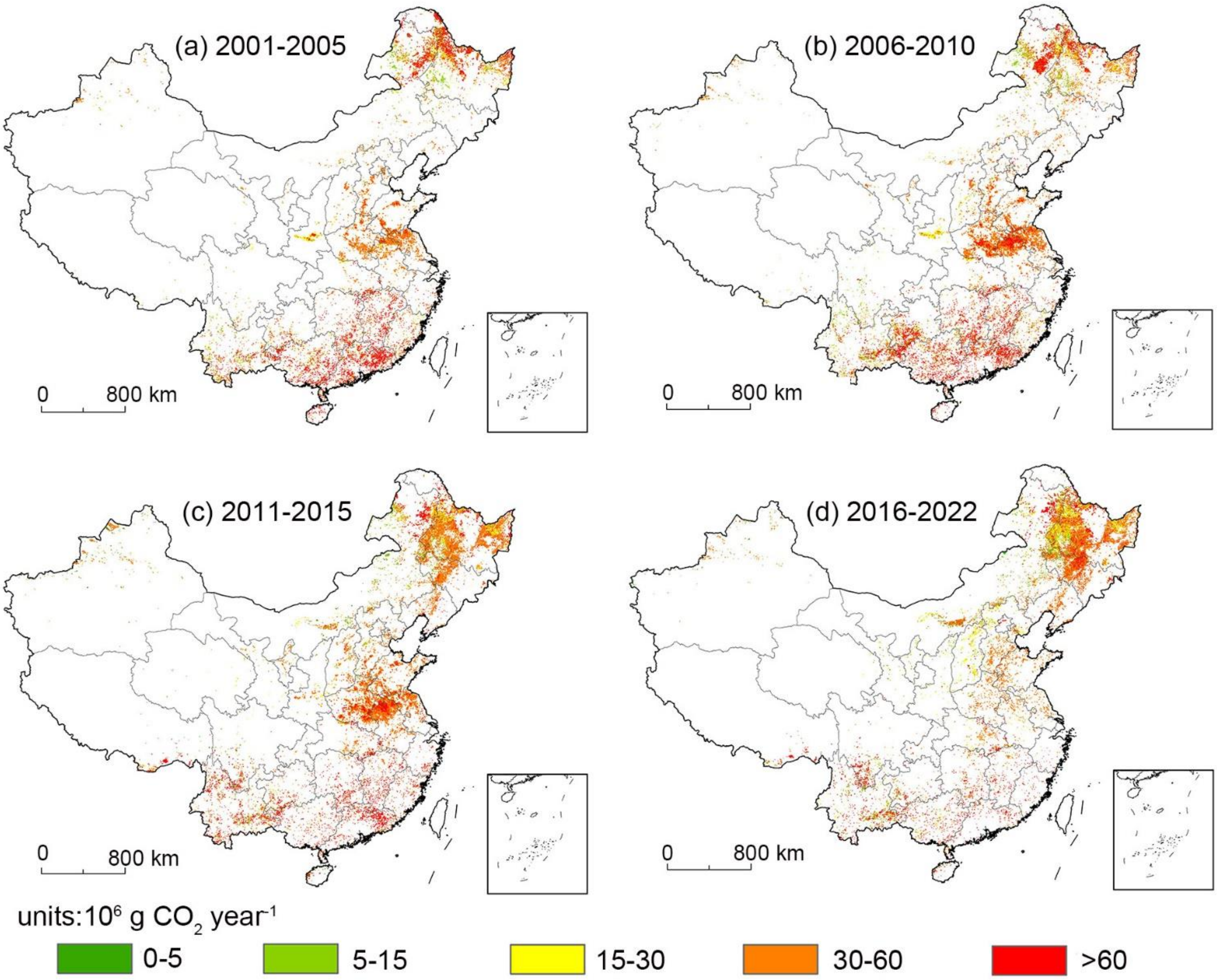

Figure 9: Spatial distribution of annual CO_2 emissions for all types of fires from (a) 2001 to 2005, (b) 2005 to 2010, (c) 2011 to 2015, and (d) 2016 to 2022.

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3.4 The impact of factors on wildfires in China

The factors influencing CO_2 emissions from wildfires are numerous and complex. The Spearman correlation coefficient method was utilized to analyze the connection between CO_2 emissions from wildfires in China and various climate factors, such as temperature, precipitation, relative humidity, wind speed, sunshine, and vegetation factors, including vegetation primary productivity and the NDVI. Additionally, the gross domestic product (GDP) and population density were taken into account (Fig. 10). The main factors influencing CO_2 emissions from forest and shrub fires were daily cumulative sunshine hours (forest:-0.41, shrub:0.25; $p < 0.001$) and NDVI (forest:-0.35, shrub:0.37; $p < 0.001$), while the main factor affecting CO_2 emissions from grassland fires was temperature (-0.45, $p < 0.001$) (Fig. 10a-c). Cropland fires, influenced by human activities, showed a specific negative correlation with GDP (-0.52, $p < 0.001$) and population density (-0.51, $p < 0.001$). At the same time, other factors had relatively small impacts (Fig. 10d). An increase in GDP and population density was often accompanied by better agricultural technology and management practices, including more effective management alternatives to straw burning. Furthermore, changes in fire management may impact CO_2 emissions from wildfires (Gao et al., 2023; Jin et al., 2022; Kelly et al., 2013; Phillips et al., 2022; Van Wees et al., 2021; Xie et al., 2024). Phillips et al. (2022) found that the cost of avoiding CO_2 emissions by increasing investment in fire management is comparable to or lower than that of other mitigation strategies. China's policies have also significantly reduced CO_2 emissions from opening biomass burning fires. Since the forest fire broke out in the Greater Khingan Mountains region of China on May 6, 1987, China has implemented a forest fire prevention and control policy of "prevention first, active elimination." Subsequently, local governments have introduced specific policies on forest, shrub, and grassland fire prevention, successfully reducing the occurrence of forest and shrub fires in China. The research in this paper also showed that the trend in CO_2 emissions from forest and shrub fires had decreased significantly since 2001 (Fig. 3a and 3b). Moreover, Jin et al. (2022) reported that from 2001 to 2019, compared with those of natural wildfires (without strict wildfire management), the average CO_2 emissions generated by wildfires (forest, shrub, and grassland fires) under management policies decreased by more than 80%.

Table 2 Driving factors and sources

Driving factors	Abbreviation	Source
Punctual temperature	tmp	Daily meteorological dataset of essential meteorological elements of China National Surface Weather Station (V3.0)
Relative humidity	rh	
Accumulated precipitation	pre	
Wind speed (2 m)	win	
Daily cumulative sunshine hours	ssd	
Vegetation primary productivity	NPP	MODIS MOD17A3
Normalized Difference Vegetation Index	NDVI	National Qinghai Tibet Plateau Science Data Center
Gross domestic product	GDP	Chen et al. (2022)

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Population density	Pop_den	LandScan Global(https://landscan.ornl.gov/)

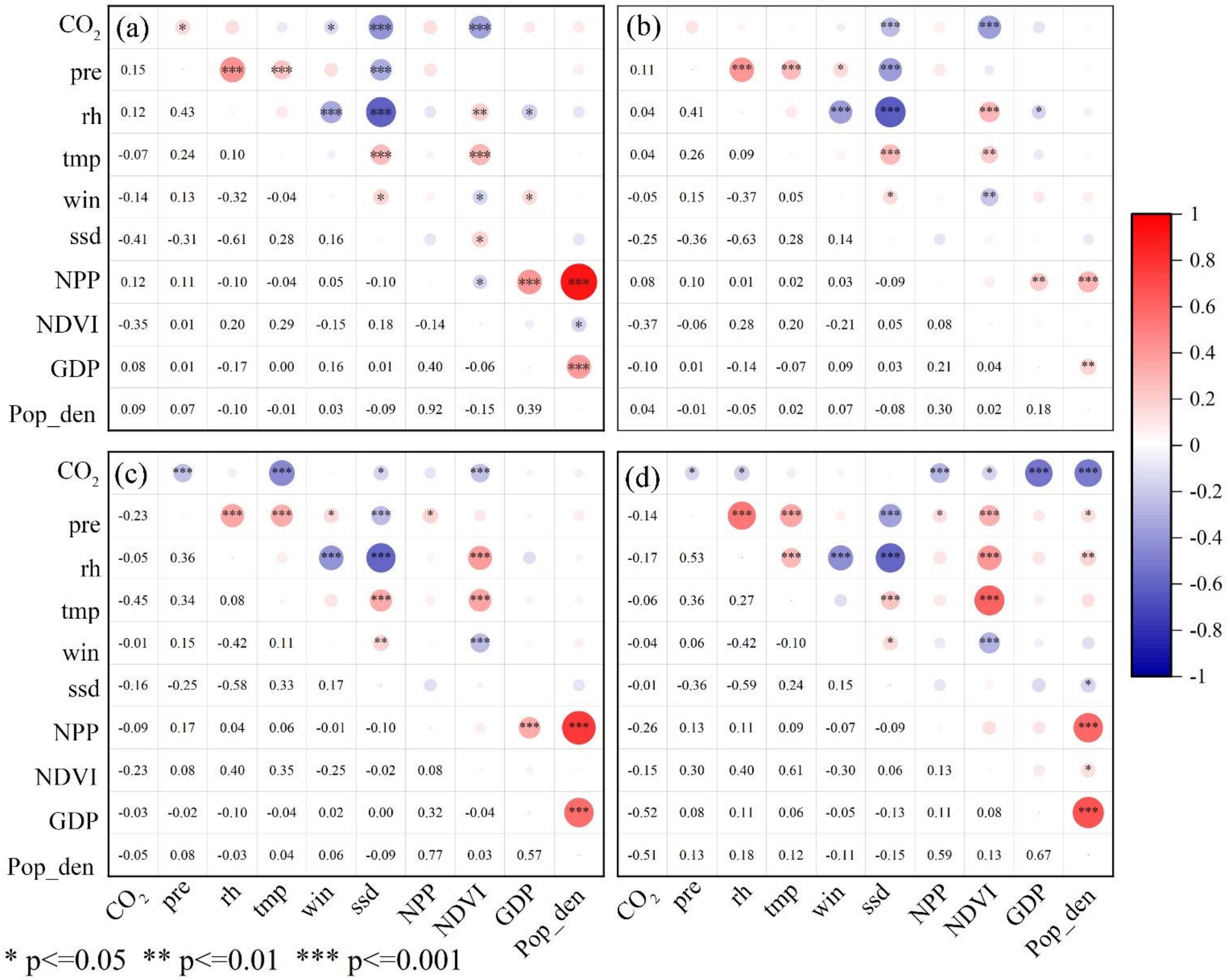

Figure 10: Heatmap of Spearman's correlation coefficients between pairs of variables: (a)forest; (b) shrub; (c) grassland; (d) cropland) See Table 2 for variable descriptions.

3.5 Implications

The burning of agricultural straw in China is a long-standing phenomenon, where burning straw is a traditional method for farmers to deal with waste straw after harvest. In recent years, the frequent occurrence of haze weather has seriously impacted people's production and life. Consequently, the government has introduced multiple policies to strengthen air quality and straw management. Since 2012, following the implementation of policies for air pollution prevention and control,

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CO_2 emissions from cropland fires have decreased (Fig. 7d). However, some provinces, such as Heilongjiang and Jilin, have had higher emissions since 2012 and are on an upward trend (Fig. 7d). In the northeastern region, a large amount of straw is used as the primary non-commercial energy source, leading to serious straw burning issues. Cropland fires in Northeast China mainly occur during the harvest and crop sowing seasons, with peak burning periods in October-November and March-April. Although China has recently prohibited open-air straw burning, this phenomenon persists, indicating that crop straw remains the primary fuel and waste of rural residents. More research is needed to develop new solutions for the sustainable utilization of crop straw in the northeast region, which may help achieve the dual goals of improving air quality and mitigating climate change.

This study holds great significance for atmospheric pollution control management. First, the high spatial resolution and long time series of wildfire CO_2 emissions provide accurate input data for simulating the effects of wildfires on air quality, climate, and human health. This helps to gain a deeper understanding of the impact mechanism of wildfires on the atmospheric environment, providing a reliable foundation for related research. Second, this research has a direct impact on global climate governance. The natural process of carbon emissions from wildfires is essential to the global carbon cycle, with prominent human intervention and control properties. Reducing wildfire carbon emissions is also a potential means of reducing global carbon emissions. However, the current international assessment and national emission reduction responsibilities do not include wildfire carbon emissions or consider measures such as reducing wildfire frequency and intensity through wildfire management. By accurately assessing CO_2 emissions from wildfires, governments worldwide can better set CO_2 reduction targets, take corresponding response measures, and contribute to the global response to climate change.

4 Conclusion

Based on a bottom-up approach and using MODIS fire products combined with emission factors of different wildfires (forest, shrub, grassland, cropland), the dynamic changes in CO_2 emissions in China from 2001 to 2022 were analyzed. Overall, during this period, the total CO_2 emissions from wildfires in China amounted to 693.7 Tg, with average annual emissions of 31.5 Tg. The CO_2 emissions from cropland and forest fires were relatively high, accounting for 46% and 32%, respectively; Shrub fire emissions accounted for 20%, while grassland fire emissions were the lowest, accounting for only 2%. The study revealed that emissions from forest and shrub fires exhibited a significant downward trend. In contrast, emissions from grassland fires remained relatively stable, and cropland fire emissions showed a noticeable upward trend. The emissions also showed different characteristics in different months, with generally lower emissions from all types of fires in July and August. Forest, shrub, and grassland fires had higher emissions in February, March, and April, and cropland fire emissions peaked in April, May, and June, possibly correlated with specific agricultural activities. Spatially, high CO_2 emissions were primarily concentrated in the eastern regions of Heilongjiang and Inner Mongolia, accounting for 44% of the annual average total emissions. Northeast China was also identified as a high-confidence hotspot, indicating long-term high

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CO_2 emissions. Human activities significantly influence CO_2 emissions from cropland fires. Emissions negatively correlated with GDP (-0.52) and population density (-0.51). Various factors, such as accumulated sunshine hours (-0.41, $p < 0.001$) and the NDVI (-0.35, $p < 0.001$), mainly influenced emissions from forest and shrub fires, while temperature (-0.45, $p < 0.001$) primarily affected emissions from grassland fires. China's policy management has been crucial in reducing CO_2 emissions from wildfires. By accurately assessing CO_2 emissions from wildfires, governments worldwide can better set CO_2 reduction targets, take corresponding response measures, and contribute to the global response to climate change.

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Data availability

All the data supporting the findings of this paper can be accessed via the provided links or by requesting them using the contact information provided within those links. The China Land Use Land Cover Remote Sensing Monitoring Dataset (CNLUCC) is sourced from the Resource and Environment Science Data Registration and Publishing System (https://www.resdc.cn/, last access: 4 June 2024). China's regional 250 m fractional vegetation cover dataset, China's regional 250 m normalized difference vegetation index dataset, and The Daily Meteorological Dataset of Essential Meteorological Elements of the China National Surface Weather Station (V3.0) are sourced from the National Tibetan Plateau/Third Pole Environment Data Center (https://data.tpdc.ac.cn/, last access: 4 June 2024). MODIS-MCD64A1 burned area data are publicly available at https://lpdaac.usgs.gov/products/mcd64a1v061 (last access: 4 June 2024). A 1 km harvesting area dataset is available at http://dx.doi.org/10.17632/jbs44b2hrk.2 (last access: 4 June 2024).

Author contributions

The article was written with contributions from all the authors. Xuehong Gong and Yongming Han designed this study; Xuehong Gong, Zeyu Liu, Jie Tian, and Qiyuan Wang collected and organized the data; Xuehong Gong analyzed the data and wrote the original article with contributions from Zeyu Liu, Yongming Han, Guohui Li, and Zhisheng An. Zeyu Liu, Jie Tian, and Qiyuan Wang assisted with the submission of the article. All the authors have given approval to the final version of the article.

Competing interests

The contact author has declared that none of the authors has any competing interests.

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