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Review

Methods, Progress and Challenges in Global Monitoring of Carbon Emissions from Biomass Combustion

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Abstract: Global biomass burning represents a significant source of carbon emissions, exerting a substantial influence on the global carbon cycle and climate change. As global carbon emissions become increasingly concerning, accurately quantifying the carbon emissions from biomass burning has emerged as a pivotal and challenging area of scientific research. This paper presents a comprehensive review of the primary monitoring techniques for carbon emissions from biomass burning, encompassing both bottom-up and top-down approaches. It examines the current status and limitations of these techniques in practice. The bottom-up method primarily employs terrestrial ecosystem models, emission inventory methods, and fire radiation power (FRP) techniques, which rely on the integration of fire activity data and emission factors to estimate carbon emissions. The top-down method employs atmospheric observation data and atmospheric chemical transport models to invert carbon emission fluxes. Both methods continue to face significant challenges, such as limited satellite resolution affecting data accuracy, uncertainties in emission factors in regions lacking ground validation, and difficulties in model optimization due to the complexity of atmospheric processes. In light of these considerations, this paper explores the prospective evolution of carbon emission monitoring technology for biomass burning, with a particular emphasis on the significance of high-precision estimation methodologies, technological advancements in satellite remote sensing, and the optimization of global emission inventories. This study aims to provide a forward-looking perspective on the evolution of carbon emission monitoring from biomass burning, offering a valuable reference point for related scientific research and policy formulation.

Keywords: biomass combustion; carbon emissions; satellite remote sensing; bottom-up method; top-down method

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Citation: Qu, G.; Shi, Y.; Yang, Y.; Wu, W.; Zhou, Z. Methods, Progress and Challenges in Global Monitoring of Carbon Emissions from Biomass Combustion. *Atmosphere* **2024**, *15*, 1247. https://doi.org/10.3390/atmos15101247

Academic Editor: Stephan Havemann

Received: 6 September 2024
Revised: 12 October 2024
Accepted: 16 October 2024
Published: 18 October 2024

1. Introduction

Biomass burning represents a significant source of global carbon emissions, exerting considerable influence on the global and regional carbon cycles [1]. This combustion process exerts a significant influence on carbon stocks and alters the biomass composition and structure of terrestrial ecosystems, thereby affecting their material cycle and energy flows [2]. Concurrently, the greenhouse gases (GHGs), pollutant gases, trace gases, and aerosols released into the atmosphere during combustion exert a significant influence on the global and regional atmospheric GHG balance, the radiation balance, the atmospheric environment, and air quality.

As indicated in the 2023 Global Carbon Budget report, global CO_2 emissions reached 40.9 Gt in 2023, with an atmospheric CO_2 growth rate of 5.1 Gt yr^{-1}, resulting in a global average atmospheric CO_2 concentration of 419.3 ppm (parts per million) [2]. In addition to fossil fuel combustion and land-use change, biomass burning represents a significant source of CO_2 emissions (Figure 1). As indicated by the Global Fire Emissions Database 4.1s [1], global CO_2 emissions from biomass burning fires between 1997 and 2023 amounted to 7.19 Gt CO_2 yr^{-1}, with 2023 CO_2 emissions reaching 8.43 Gt [2,3]. As stated in the Blue Book of Carbon Emissions Research from Forest Fires (2023), published by the Chinese Academy of Sciences, global forest fires emitted 33.9 Gt of CO_2 between 2001 and 2022. This resulted in an increase of 4.35 ppm in the atmospheric CO_2 concentration [4]. In the case of the extreme 2023 wildfire season in Canada, the direct CO_2 emissions from forest fires exceeded 1.5 Gt, which is higher than the total combined CO_2 emissions from forest fires in Canada over the past 22 years (1.374 Gt) [1,5]. The accurate quantification of carbon emissions from biomass burning is of critical importance for the comprehension of the carbon cycle in terrestrial ecosystems and is fundamental for the elucidation of global and regional carbon balances. Furthermore, carbon emissions from biomass combustion represent a crucial input parameter for atmospheric chemistry transport models [6]. The establishment of accurate and reliable biomass combustion carbon emission inventories has the potential to enhance the precision and reliability of model simulations. It is therefore of great significance to the carbon cycle of terrestrial ecosystems and GHG emission reduction that scientific and effective accounting of biomass burning carbon emissions be carried out.

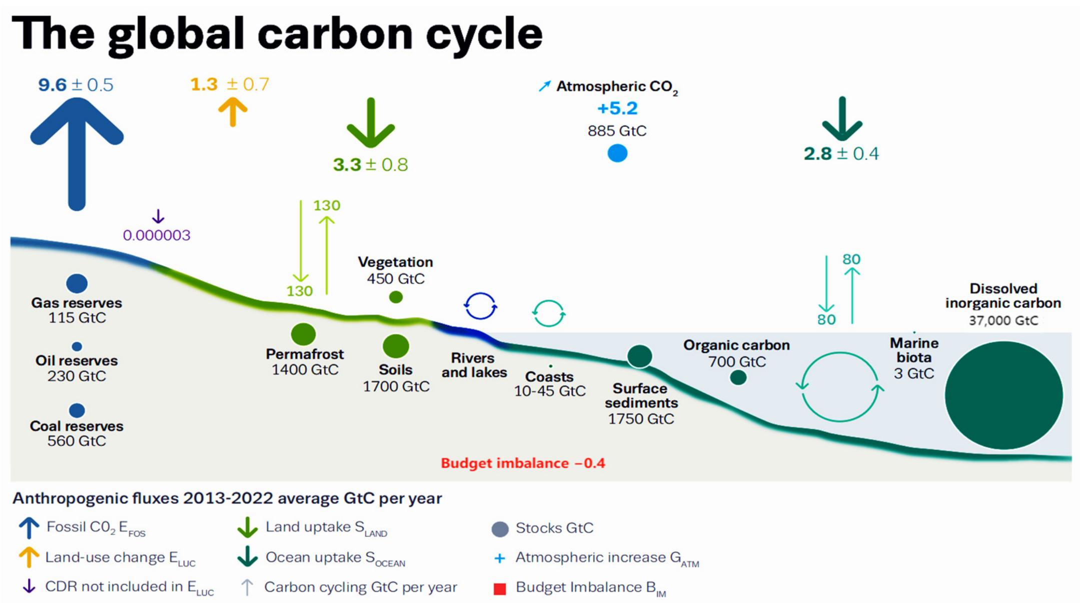

Figure 1. Equilibrium carbon balance between human activities, atmosphere, and natural ecosystems for the 10-year period 2013–2022 [2].

The phenomenon of biomass burning, which encompasses a range of activities, including forest fires, grassland fires, crop residue burning, household fuelwood burning, and domestic waste burning, is distinguished by several characteristics. These include periodicity, randomness, the presence of multiple point sources, and a wide range, which collectively pose significant challenges to effective monitoring. There are numerous parameters that must be considered when estimating carbon emissions from biomass combustion. The discrepancy in the estimation accuracy of each data source is evident, and this significantly impacts the precision of carbon emission estimation. Furthermore, the influence of emission source intensity and meteorological conditions introduces additional complexity and uncertainty to the factors affecting biomass combustion, which presents a significant challenge to accurately estimating biomass combustion carbon emissions [7–10].

The accurate accounting and inventorying of carbon emissions represents a significant challenge within the broader field of atmospheric environmental science and global carbon cycle research. Long-term, high-resolution, and multi-scale biomass burning carbon emissions constitute an essential foundation for identifying GHG sources, supporting model simulations, interpreting observations, and formulating emission reduction and control programs. This study provides a comprehensive and systematic review of the current global biomass burning carbon emission monitoring methods, offering a detailed analysis of the latest developments and challenges in their applications. It also present a structured overview and future outlook for biomass burning carbon emission monitoring research while simultaneously providing theoretical insights that can inform a further understanding of the scientific issues related to the carbon cycle in terrestrial ecosystems, remote sensing monitoring and inversion of biomass burning carbon emissions, as well as GHG emission reductions.

2. Analysis of the Current Situation and Limitations of Bottom-Up Monitoring Methods

The bottom-up method is a terrestrial ecosystem-based approach that estimates carbon emissions by multiplying data on biomass burning activities (fire points, vegetation indices, biomass, etc.) by emission factors for different types of fires. This method remains the most prevalent approach for estimating GHG emissions, as adopted by the Intergovernmental Panel on Climate Change (IPCC) and numerous national governments.

2.1. Land Ecosystem Process Modeling

The precision of fire carbon emission estimates can be enhanced by optimizing and refining input parameters, including fire area, combustible biomass, combustion efficiency, and emission factors. The main equation used in this model is:

$$\frac{dC_{bio}}{dt} = GPP - R_a - LF - CE \tag{1}$$

where the carbon emissions from fire (CE) are calculated as:

$$CE = \sum_{i=1}^{n} BA \times F \times CF \times EF \tag{2}$$

In this equation, BA represents the burned area, F represents the fuel biomass, CF is the combustion factor, and EF is the emission factor.

These equations provide a comprehensive framework for estimating fire-related carbon emissions and serve as the basis for the enhanced model algorithms described below. (1) The use of enhanced model algorithms has led to an improvement in the precision of remote sensing inversion products pertaining to fire area. For instance, the MCD64A1 dataset is a newer satellite product designed for more accurate fire area detection. Compared to the earlier MCD45A1 dataset, the relative error of MCD64A1 has been reduced from 27.9% to 17.9% [11]. (2) Ecosystem process models may be employed to simulate the spatial distribution of fuel-based biomass, thereby replacing the land-use-type-based uniform biomass [12]. For instance, based on the global fire emissions database derived from the CASA (Carnegie–Ames–Stanford Approach) biogeochemical model, as documented by van der Werf et al. (2017) [1], the BEAMS-Fire (Biosphere model integrating Eco-physiological And Mechanistic approaches using Satellite data-Fire) ecosystem model was employed to simulate the biomass of diverse forest types in Southeast Asia, subsequently enabling the estimation of carbon emissions [13]. (3) The application of vegetation indices and moisture conditions allows for the quantification of burning factors for different burn types in different pixels. This, in turn, enables the establishment of a correlation between the burn factor of each vegetation type and the moisture content of combustible materials under different moisture conditions [14]. This approach allows for the simulation of spatio-temporal patterns and changing characteristics of global burn factors, as well as the accurate reflection of combustion ratios of different combustible material types under different moisture conditions. (4) The emission factors of different vegetation types in various regional contexts, along with their spatio-temporal dynamic changes, are quantified through field surveys and indoor experimental analyses [15].

The aforementioned models and methods have enhanced specific input parameters of the biomass burning emission inventory model, thereby reducing the uncertainty in biomass burning emission estimates. However, these methods typically improve only one or a few parameters independently, and few studies have systematically optimized all of these improvements in a unified manner. For instance, the MCD64A1 dataset improves the accuracy of burned area detection, while the CASA model enhances the precision of carbon emission estimates by optimizing biomass and fuel load parameters. While each method contributes to different aspects of fire carbon emission modeling, there remains significant potential for further improving the overall accuracy of these simulations.

2.2. Emission Inventory Method

The emission inventory method is a methodology proposed by the IPCC for the estimation of GHG emissions. As outlined in the emission inventory list, the functional relationship between activity data and emission factors is established for each fire type, thereby enabling the estimation of emissions [2]. The primary equation utilized in this model is as follows:

$$CO_{2biomass} = \sum_{i=1}^{n} BA_i \times F_i \times CF_i \times EF_i \tag{3}$$

where BA_i represents the burned area for the *i*-th type of biomass burning, F_i is the fuel biomass for the iii-th type, CF_i is the combustion factor, and EF_i is the emission factor.

Tsinghua University has developed the Multi-resolution Emission Inventory for China (MEIC), a multi-scale emission inventory model for China. A unified source classification and grading system and an emission factor database have been constructed, and real-time dynamic calculation and online downloading of emission inventories have been realized. However, the scale of concern in the inventory is unbalanced, with a paucity of research at the mesoscale. The NCAR developed the FINN (Fire Inventory from NCARv2.5) model fire emission inventory [15], which estimates high-resolution global open biomass burning emissions and provides high-resolution input parameters for global and regional atmospheric chemistry models and air quality simulations [16]. The European Commission has developed the Emissions Database for Global Atmospheric Research (EDGAR) carbon emissions inventory, which is based on the IPCC algorithm and provides a global database for anthropogenic greenhouse gas emissions. However, it lacks natural source emissions from biomass burning. Subsequently, Gong and Shi employed the emission inventory method to estimate methane emissions from biomass burning in China and constructed a high spatio-temporal resolution emission inventory dataset, thereby furnishing scientific and effective data support for effective monitoring and the control of methane [17]. Furthermore, the research team utilized the emission inventory method to calculate CO_2 emissions from open biomass burning in Northeast China over an extended period and developed a high-resolution monthly biomass burning emission inventory for the region spanning from 2001 to 2017.

The construction of emission inventories is contingent upon the data obtained from biomass burning activities and the emission factors for the various types of fires in question. The data are typically acquired through statistical, testing, or experimental monitoring, which are inherently subjective, uncertain, and subject to a certain lag. The inaccuracies associated with data, such as fire points, biomass, and emission factors, which are inherent to this method, are propagated throughout the emission inventory calculation process. This introduces an inherent uncertainty to the emission inventory and compromises the precision of emission estimates.

2.3. Fire Radiation Power Method

The fire radiation power (FRP) method employs real-time observations of fire points from platforms such as satellite remote sensing to ascertain the radiative energy of a fire. The carbon emissions resulting from the combustion of biomass are calculated by multiplying the rate of biomass consumption by a conversion factor. The fundamental equation employed in the model can be stated as follows:

$$FRE = \int_0^{24} FRP_{peak}\left(b + e^{-\frac{(t-h)^2}{2\sigma^2}}\right) dt \times CR \times EF \tag{4}$$

where FRP_{peak} is the peak fire radiative power and b represents the background power. t is time, h is when the peak occurs, and σ sigmaσ reflects the fire's duration. CR converts fire radiative power into burned biomass, while EF converts burned biomass into carbon dioxide emissions.

This method addresses the limitations of the conventional biomass burning emission estimation approach, which is based on the combustion area and unable to monitor carbon emissions from minor fire sources. This method meets the criteria for dynamic emission inventories and high-resolution datasets, as exemplified by the Global Fire Assimilation System (GFAS) [18]. In a study conducted by Fu et al., the FRP method was employed for the estimation of biomass burning emissions in the North China Plain [19]. The resulting estimates were then compared with those obtained through the use of a terrestrial ecosystem model, specifically the Global Fire Emission Database (GFED) approach. It was determined that the GFED significantly underestimated the carbon emissions from biomass burning in the North China Plain due to the absence of identification and monitoring of minor radiating fire points [19]. Ruecker et al. employed this methodology to estimate fuel consumption per unit area on the fire front and combined it with the diffusion rate to obtain the fire intensity and spread rate of Baalam in the Sahel [20]. This approach enabled the successful estimation of carbon emissions from biomass burning in this region. Zhou et al. developed a methodology based on the FRP method for estimating carbon emissions from the open burning of straw in various regions of China [21]. This approach demonstrated a high degree of consistency with field survey results, with a correlation coefficient of 0.70. This method offers a more precise and timely estimation of emissions from straw open burning. In a recent study, Lv et al. employed the fire radiation power to estimate open biomass burning in the Heilongjiang River Basin [22]. They also established a high-spatial-and-temporal-resolution daily 1 km long time series emission inventory from 2003 to 2020. Wan et al. employed MODIS fire counts and the FRP method, integrated with empirical data from the Tropospheric Sounding Instrument (TROPOMI), to elucidate the carbon emissions from forest fires in Australia during the early months of 2020 [23]. Integrating TROPOMI-derived NO_2 and CO data with MODIS data led to a notable improvement in estimation accuracy, with the explained variance for NO_2 increasing from 40% to 56% and for CO from 35% to 51%. This was particularly evident in the estimation of emissions from savanna and temperate forest fires.

The FRP method is a monitoring technique that assesses carbon emissions from the standpoint of energy consumption and biomass combustion conversion efficiency. However, during the process of satellite identification and the quantification of fire points, there are significant fluctuations in the daily cycle parameters of fire radiation power intensity, which presents a challenge in continuously observing local fire point areas. This can result in errors of omission. Furthermore, the fire radiation power conversion factor is derived from traditional empirical statistics, which introduces a lag that affects the real-time and precise estimation of carbon emissions from diverse fire types.

As the bottom-up approach relies primarily on the IPCC inventory method, it is challenging to accurately capture the dynamic changes in emission sources due to the lag in updating statistical data and emission factors. Furthermore, there is a lack of third-party independent verification of "sky-ground-space" data, which could enhance the reliability of the results. This results in considerable discrepancies between the various carbon emission inventories. Furthermore, the definition standards and statistical quality of activity data vary from country to country, which makes it unfeasible to effectively establish a reliable global biomass burning emission inventory.

3. Analysis of the Current Situation and Limitations of Top-Down Monitoring Methods

The top-down method is a research approach that takes the atmosphere as its object of study. It is based on observations of GHG concentrations and meteorological field data, including ground observations, aerial surveys, and satellite data. It employs a combination of atmospheric chemical transport models and diffusion models to indirectly simulate carbon emission fluxes at varying scales. The top-down method relies, in part, on the emissions data obtained through the bottom-up method. However, it also incorporates information on atmospheric CO_2 concentrations derived from ground, airborne, or satellite observations. The method can be used to invert carbon emissions from biomass burning at the point, regional, and global scales. This allows for a more accurate estimation of carbon emissions than traditional survey and statistical methods while also reducing the uncertainty introduced by artificial factors such as parameter settings.

3.1. Gaussian Plume Model

The Gaussian plume model is a widely utilized tool for simulating the transport and diffusion processes of point source emissions. By combining real-time updated remote sensing data from carbon satellites with the Gaussian plume model, it is possible to identify the plumes of CO_2 emissions from point sources (forests, grasslands, etc.) of ground biomass burning. This allows for the conversion of these emissions into CO_2 emissions, which can then be used to assess the emission characteristics of different biomass burning sources and to update and optimize existing emission inventories. A case study illustrating this application is shown in Figure 2.

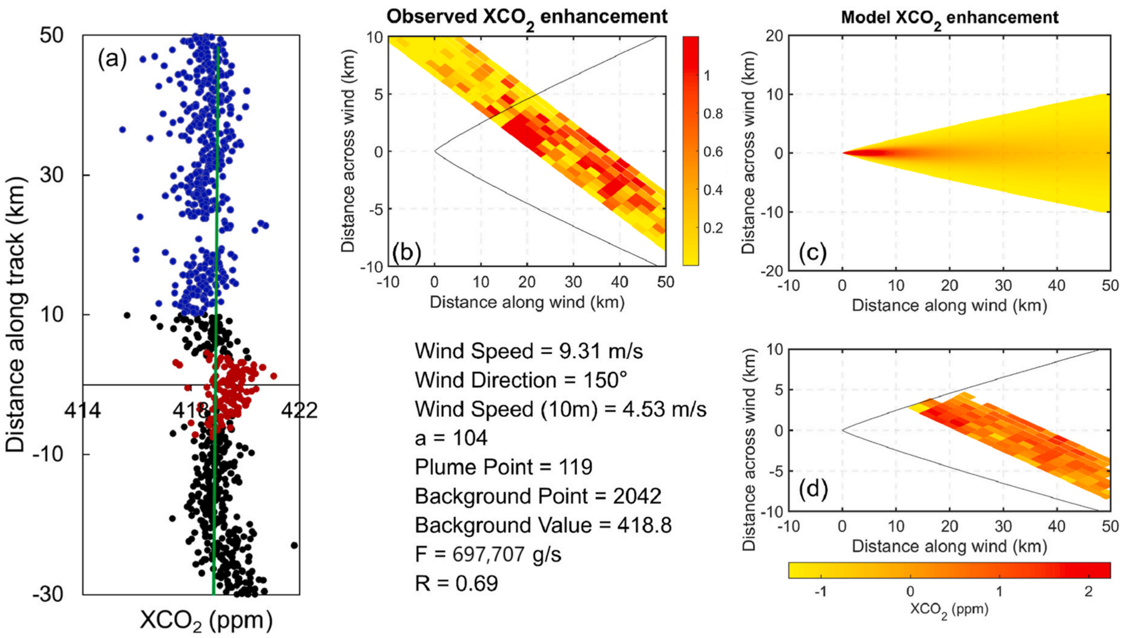

Figure 2. Illustration of emission estimation using the Gaussian plume model for Zouxian on 19 January 2021. (**a**) Background value map showing plume (red), background (blue), and reference points (black). (**b**) Observed XCO_2 enhancement with the plume area identified. (**c**) Simulated X CO_2 enhancement from the Gaussian plume model. (**d**) Simulated X CO_2 enhancement overlaid on OCO-3 satellite data [10].

Presently, atmospheric CO_2 concentration data obtained from GHG satellite observations, including the Greenhouse Gasses Observing Satellite (GOSAT), Orbiting Carbon Observatory-2 (OCO-2), and the Carbon Dioxide Observation Satellite (TanSat), are extensively utilized for remote sensing estimation and inversion of carbon emissions from substantial point sources such as biomass burning and coal-fired power plants [24]. Bovensmann et al. were the first to propose that remote sensing satellites can detect strong local and regional point source CO_2 emissions and quantify them [7]. Subsequently, Nassar et al. employed the Gaussian plume model in conjunction with OCO-2 data to quantify CO_2 emissions at the scale of a single facility (power plant), and the findings demonstrated a notable correlation between remotely sensed carbon emissions and daily reported emissions [25]. Krings et al. employed in situ airborne remote sensing CO_2 measurements and inverse Gaussian plume models to ascertain the emission source location and the CO_2 emissions from the plume overlap [26]. Zheng et al. employed OCO-2 satellite data in conjunction with a Gaussian plume model to ascertain CO_2 emissions from multiple point sources in China [27]. The resulting total emissions exhibited a high degree of concordance with those reported in other anthropogenic emission inventories, particularly with the MEIC, showing 27.1% higher estimates during the cold season and 5.2% lower estimates during the warm season. The results also aligned reasonably with global inventories such as the EDGAR inventory and the Open-Source Data Inventory for Anthropogenic CO_2 (ODIAC). Nassar et al. enhanced the quality of the OCO-2 satellite data and the input parameters required by the Gaussian plume model by incorporating higher-resolution ERA-5 wind data, implementing sub-footprint fitting for improved plume modeling, and adopting a new automated background selection method specifically for wind speed and background values [25]. They also inverted CO_2 emissions from large point sources in various regions, including the United States, Poland, Russia, and South Korea. Guo et al. integrated CarbonSat observation data and optimized the background value determination submodule of the Gaussian plume model to achieve the remote sensing inversion of carbon emissions from very large, extremely large, and large point sources in China [10]. This approach provides insights and data support for the remote sensing inversion of carbon emissions from biomass burning and multi-source carbon emissions.

The integration of Gaussian plume models and carbon satellite data can enhance the temporal and precision capabilities of bottom-up models. Nevertheless, the low resolution of carbon satellite data and the impact of environmental noise (e.g., clouds and precipitation) continue to present challenges in terms of identifying biomass burning emission sources and accurately determining atmospheric background concentrations. For instance, sensors such as OCO-2 and GOSAT have low resolutions that prevent them from capturing smaller farmland fires and transient fire points with low emission intensities, resulting in an underestimation of emissions.

3.2. Lagrange Particle Diffusion Model

The Lagrangian atmospheric transport model employs a particle tracking approach to estimate the concentration distribution of pollutants at varying locations and times. This methodology entails monitoring the movement of individual or collective pollutant particles in both space and time. The model can provide information regarding the dispersion of pollutants from their source to the area of influence, as well as the temporal evolution of these pollutants. It is a commonly utilized methodology in gas dispersion simulation studies within a specified area [28].

In a recent study, Wu et al. employed an enhanced Lagrangian particle dispersion model (X-STILT) to extract amplified XCO_2 signals from XCO_2 data obtained from the OCO-2 satellite [29]. The X-STILT workflow is illustrated in Figure 3. Heymann et al. employed the X-STILT model to invert the XCO_2 data from the OCO-2 satellite, thereby retrieving CO_2 emissions from fires in Indonesia [8]. These emissions were approximately 30% lower than those obtained using GFAS1.2 and GFED4. In a comparative study conducted by Kiel et al., the XCO_2 enhancements observed by OCO-3 were contrasted with the CO_2 simulated by X-STILT [9]. The findings indicated that the model demonstrated superior capability in capturing the XCO_2 gradients within urban areas. By employing X-STILT's distinctive time-reversal methodology to attribute the observed XCO_2 enhancements to disparate emission sources at the surface, the researchers discovered that the discrepancy between the satellite-observed XCO_2 enhancement values and those derived from the X-STILT model is typically less than 1 ppm. Roten et al. employed OCO-3 satellite data to monitor one source identified by OCO-3 and then extrapolate other sources to minimize the computational burden associated with X-STILT calculations [30]. They applied the algorithm to OCO-3 data for two cities, namely Los Angeles and Salt Lake City. The time required to identify CO_2 sources was reduced by 62% and 78%, respectively. In a recent study, Wu et al. employed the Lagrangian atmospheric transport model to assess the efficacy of the MicroCarb satellite in estimating carbon emissions [31]. Additionally, they evaluated the impact of varying meteorological conditions, including cloud cover and changes in biological flux, on carbon emissions in two major urban centers: Paris and London.

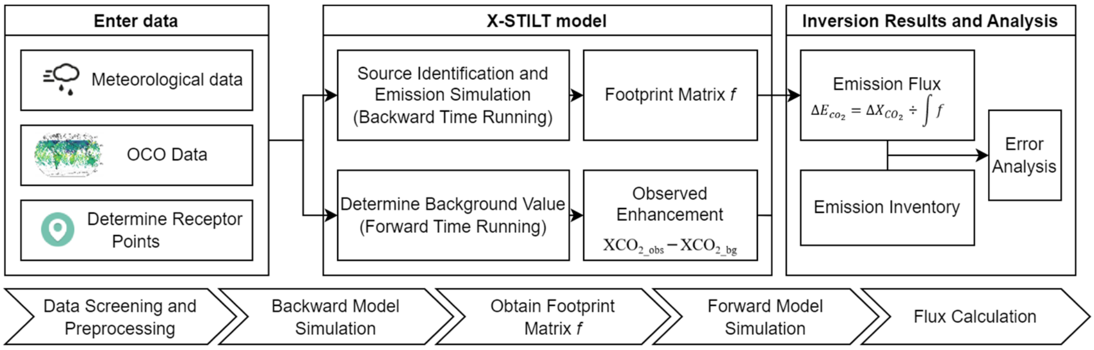

Figure 3. X-STILT model CO_2 emission inversion flowchart (XCO_2_obs: satellite-observed value; XCO_2_bg: model-calculated background value; *f*: footprint value).

The X-STILT model represents an extension of the traditional surface-based receptor method to an air-column-based receptor scheme. This is based on satellite observations, meteorological data, and an a priori emission inventory. The model quantifies regional carbon emissions by simulating regional plume diffusion using meteorological data and combining this with enhanced values extracted from satellite observations of XCO_2 concentration data. Nevertheless, the inversion of carbon emissions from biomass burning remains uncertain due to the influence of factors such as the spatial resolution of meteorological data, the quality of satellite data, and emission inventories. Furthermore, due to the inherently unstable meteorological conditions at the regional scale, the X-STILT model is not suitable for simulations at this scale.

3.3. GEOS-Chem Model Inversion

Atmospheric chemistry transport models have increasingly become a standard tool for investigating global and regional changes in atmospheric CO_2 concentrations. GEOS-Chem is a three-dimensional global atmospheric chemistry transport model developed by Harvard University in the United States. The model is capable of simulating the concentration distribution and evolution process of various atmospheric components based on the physical and chemical effects of atmospheric composition and its transport process. It has been employed extensively in the domain of atmospheric chemistry transport research [32]. The CEOS-Chem nested technology route is illustrated in Figure 4.

Wu et al. constructed an inversion model using GEOS-Chem coupled with the ensemble square root Kalman filter (EnSRF) to estimate both the global and China's terrestrial carbon fluxes for 2019. Their findings showed that the global terrestrial and oceanic carbon sinks accounted for 2.12 and 2.53 Pg C per year, respectively, which corresponds to 21.1% and 25.1% of global fossil fuel CO_2 emissions. [33]. In a study published in 2021, Fu et al. employed the GEOS-Chem model to investigate the responsiveness of CO_2 concentrations in East Asia to interannual fluctuations in sources and sinks [19]. Their findings indicated that alterations in biomass burning emissions may account for up to 7% of the observed variability, corresponding to a range of 0.8–1.2 ppm. Dong et al. discovered through GEOS-Chem simulations that the biomass burning emission inventory in northern Eurasia was overestimated due to the utilization of emission factors based on US vegetation types [34].

This further underscores the necessity of verifying and enhancing biomass burning emission inventories. Lutsch et al. demonstrated through a comparison of GEOS-Chem model simulations using GFASv1.2 as a priori parameters with infrared measurements that the GEOS-Chem model underestimated the transport of wildfire emissions to the Arctic [35]. Palmer et al. employed a combination of the GEOS-Chem model and inversion algorithms to infer posteriori fluxes from NOAA and GOSAT data, utilizing prior emission inventories [36]. The researchers discovered that biomass burning in the tropical regions has been the primary driver of changes in carbon concentrations since the 2014/2016 El Niño event. Su et al. quantified the impact of biomass burning carbon emissions on global atmospheric CO_2 concentration changes on the grid-scale based on the GEOS-Chem model [3]. Their findings indicate that biomass burning can lead to an increase of 2.4 ppm in the global average atmospheric CO_2 concentration each year. Xie et al. estimated the carbon emissions from biomass burning in winter agricultural fires in Heilongjiang Province, China, using the GEOS-Chem model [32]. They then combined these data with heavy haze events in Northeast China to conduct a quantitative traceability analysis.

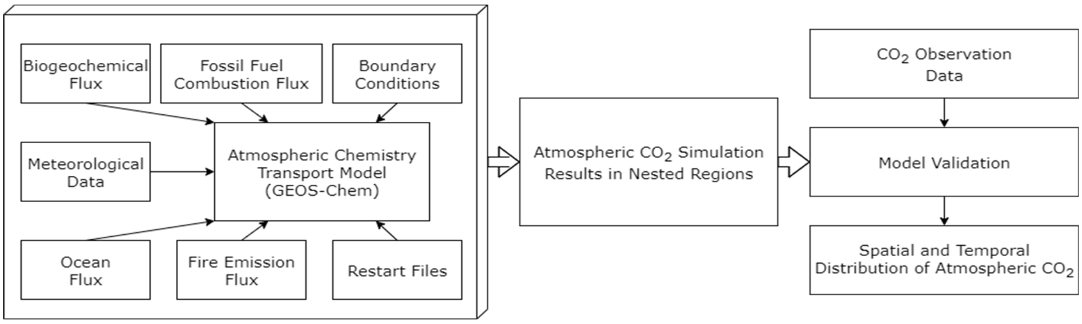

Figure 4. The CEOS-Chem nested technology route.

The GEOS-Chem model is capable of simulating the impact of biomass burning emissions on the dynamic changes in atmospheric CO_2 concentrations on a range of spatial scales (from regional to global). The model can be used as a forward model to assimilate multi-source observational data based on Bayesian principles to invert and obtain high-precision posterior biomass burning emission inventory data, thus enabling the quantification of the global carbon flux from biomass burning in real time [37]. However, the accuracy of the inversion is largely dependent on the precision of the a priori emission inventory, the timeliness of the observational data, and the accuracy of the inversion algorithm [38].

The objective of the top-down method is to reduce the discrepancy between the simulated and observed CO_2 concentrations with respect to spatial and temporal scales. However, the accuracy of the a priori emission inventory and the complexity of the model parameterization scheme have a significant impact on the accuracy of the simulation results. Despite the potential for real-time detection across a vast geographic area, satellite remote sensing is constrained by the influence of complex meteorological conditions, including cloud cover, precipitation, and aerosol pollution. The assimilation and inversion of global carbon emissions from biomass burning is hindered by several issues, including low data utilization, an uneven spatial and temporal distribution of data, and insufficient inversion accuracy. These challenges contribute to an increased level of uncertainty in the process.

4. Trends and Prospects of Carbon Emission Research on Biomass Combustion

The following sections outline key methods for enhancing the precision and reliability of biomass burning emission monitoring through remote sensing technologies:

4.1. High Precision of Data and Multi-Source Fusion

(1) The acquisition of high-precision observational data: The advent of remote sensing technology has allowed for the utilization of high-resolution satellite data, exemplified by MODIS (Moderate Resolution Imaging Spectroradiometer) and VIIRS (Visible Infrared Imaging Radiometer Suite), a standard practice for the monitoring of carbon emissions from biomass burning [39]. However, the limitations of a single data source have prompted researchers to gradually shift their attention to multi-source data fusion, which can enhance spatial and temporal resolution by integrating data from disparate sensors, including the GOSAT, OCO-2, and TROPOMI. For example, the high-resolution column-averaged carbon dioxide concentration (XCO_2) observations from the OCO-2 satellite of the National Aeronautics and Space Administration (NASA) are a valuable resource for estimating the spatial and temporal distribution of fire emissions [40]. (2) Integration and validation of multi-source data: By integrating ground-based observations (e.g., TCCON), airborne sensor data, and satellite remote sensing data, researchers can construct more comprehensive and accurate biomass burning emission inventories. This multi-source data integration approach has been widely employed in global carbon budgets, facilitating more reliable estimates through comparison and validation. For instance, the integration of TCCON ground-based measurements with satellite data (e.g., GOSAT) has been shown to markedly reduce satellite observation errors [39].

4.2. Model Optimization and Introduction of New Algorithms

(1) Model parameter optimization: It is acknowledged that traditional emission inventory models, such as the GFED and the GFAS, are not without uncertainty when applied globally. This is primarily due to the manner in which the model parameters are set. In recent years, researchers have reduced these uncertainties by incorporating additional measured data into the model calibration process and utilizing more sophisticated combustion efficiency and emission factor formulas. By constructing the CASA model, improving the fuel consumption parameter settings, and accurately estimating the net primary productivity of vegetation, Fu et al. were able to reduce the emission estimation error of the GFED4 model by 15% [41]. (2) The introduction of new algorithms: The rapid development of big data and machine learning techniques has created new avenues for research on carbon emissions from biomass burning. The application of machine learning algorithms to historical fire data enables more precise forecasting of future fire occurrences and associated emissions. Xu et al. implemented a deep learning model (YOLOv5n-CB) for real-time forest fire monitoring, improving detection accuracy and speed [42]. This supports the role of machine learning in enhancing fire detection and biomass burning emission tracking. Farahmand et al. introduced the Fire Danger from Earth Observations (FDEO) system, which uses satellite data and machine learning to predict wildfire danger by up to two months in advance. This highlights how advanced algorithms improve fire prediction and emissions forecasting [43].

4.3. Detailed Regional Studies and Applications on a Global Scale

(1) Regional-scale research: In light of the findings of global-scale research, regional-scale research has gradually become a focal point in its own right. For example, studies on biomass burning emissions in the Amazon rainforest and Sub-Saharan Africa have not only revealed the characteristics of burning emissions in different ecosystems but also provided a scientific basis for environmental protection and policy formulation in these regions [3]. Wiedinmyer et al. employed the regional model NCAR to simulate fire activity in Sub-Saharan Africa and indicated that these fires were responsible for 25% of global atmospheric CO_2 concentrations [44]. (2) Application and extension at the global scale: While regional studies are indispensable, the prevailing emphasis in the context of global climate change research remains on the application of these findings to the monitoring of carbon emissions on a global scale. Global biomass burning emission inventories, such as GFED and FINN, have been implemented globally and provide fundamental data support

for global carbon cycle research. It is imperative that future research endeavors to enhance the precision of these inventories and integrate a greater quantity of real-time observational data [39].

4.4. Assimilation Technology and Dynamic Monitoring

(1) Application of data assimilation techniques: By employing atmospheric chemistry transport models (e.g., GEOS-Chem) and data assimilation techniques, researchers can integrate multi-source observational data with model simulations to generate high-precision post-processing emission inventories. This method has the additional benefit of correcting systematic errors in the model and improving the accuracy of carbon emission estimates. For instance, the GEOS-Chem model, when used in conjunction with OCO-2 satellite data, enables the real-time updating of fire emission estimates, thereby markedly enhancing the responsiveness to sudden fire occurrences [3]. (2) Realization of dynamic monitoring: The dynamic monitoring of biomass combustion emissions has become a more feasible undertaking with the advent of near real-time data processing and analysis systems. In recent years, dynamic monitoring systems have been employed to facilitate rapid responses to emergencies such as forest fires and to generate emission estimates within a short period of time. Such systems have been implemented for the monitoring of forest fires in the United States and Australia, thereby markedly enhancing disaster response capabilities [39].

4.5. Interdisciplinary Cooperation and International Collaboration

(1) Interdisciplinary collaboration: The study of carbon emissions from biomass burning is a complex undertaking that requires the expertise of numerous disciplines, including ecology, meteorology, remote sensing technology, and atmospheric chemistry. Additionally, it necessitates the integration of social and economic considerations. Future research will increasingly prioritize interdisciplinary collaboration, with the integration of knowledge and technology from diverse fields facilitating more comprehensive carbon emission monitoring and assessments. For example, the study conducted by Liousse and colleagues integrated atmospheric chemistry, social economics, and remote sensing technology to develop a comprehensive methodology for estimating emissions from biomass burning [45]. (2) International collaboration and data sharing: In the context of globalization, international collaboration in the study of biomass burning emissions is of particular importance. The establishment of a global observation network and data sharing platform enables researchers from disparate countries to collaborate on addressing the challenges of global climate change. As evidenced by the Sixth Assessment Report (AR6) of the IPCC and the research of He et al., international collaboration and data sharing can markedly enhance the precision of global carbon emission monitoring, thereby facilitating countries' collective efforts to tackle climate change [46].

5. Conclusions

Significant progress has been made in monitoring global carbon emissions from biomass burning over the past few decades. Nevertheless, current research continues to encounter certain challenges, including the absence of consistent monitoring techniques, constraints in spatial and temporal resolution, and shortcomings in satellite remote sensing technology. Despite these issues, the introduction of new algorithms, the optimization of models, and the strengthening of interdisciplinary collaboration across field like ecology, meteorology, atmospheric chemistry, and remote sensing, as well as international cooperation and data sharing, are expected to result in a significant improvement in the accuracy and reliability of monitoring carbon emissions from biomass burning. Future research should further integrate multi-source data, promote innovation in satellite remote sensing technology, and optimize global carbon emission inventories to achieve more accurate assessments and predictions of global carbon cycles and climate change. These advances will not only provide more robust data support for scientific research but will also serve as crucial reference points for the development of global GHG emission reduction policies, thereby facilitating global efforts to address climate change.

Author Contributions: Conceptualization, G.Q. and Y.S.; formal analysis, G.Q., Y.Y. and Z.Z.; investigation, G.Q., Y.Y. and W.W.; resources, Y.S.; writing—original draft preparation, G.Q.; writing—review and editing, G.Q. and Y.S.; supervision, Y.S.; project administration, Y.S.; funding acquisition, Y.S. All authors have read and agreed to the published version of the manuscript.

Funding: This research is supported by the National Key Research and Development Program of China (2023YFB3907404), the FY-3 Lot 03 Meteorological Satellite Engineering Ground Application System Ecological Monitoring and Assessment Application Project Phase I (ZQC-R22227), the National Natural Science Foundation of China (42071398), and the Academic Innovation Project of Harbin Normal University (Grant: HSDBSCX2021-104).

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: No new data were created or analyzed in this study. Data sharing is not applicable to this article.

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

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