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How Do Emission Factors Contribute to the Uncertainty in Biomass Burning Emissions in the Amazon and Cerrado?

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Abstract: Fires drive global ecosystem change, impacting carbon dynamics, atmospheric composition, biodiversity, and human well-being. Biomass burning, a major outcome of fires, significantly contributes to greenhouse gas and aerosol emissions. Among these, fine particulate matter ($PM_{2.5}$) is particularly concerning due to its adverse effects on air quality and health, and its substantial yet uncertain role in Earth's energy balance. Variability in emission factors (EFs) remains a key source of uncertainty in emission estimates. This study evaluates $PM_{2.5}$ emission sensitivity to EFs variability in Brazil's Amazon and Cerrado biomes over 2002–2023 using the 3BEM_FRP model implemented in the PREP-CHEM-SRC tool. We updated the EFs with values and uncertainty ranges from Andreae (2019), which reflect a more comprehensive literature review than earlier datasets. The results reveal that the annual average $PM_{2.5}$ emissions varied by up to 162% in the Amazon (1213 Gg yr^{-1} to 3172 Gg yr^{-1}) and 184% in the Cerrado (601 Gg yr^{-1} to 1709 Gg yr^{-1}). The Average peak emissions at the grid-cell level reached 5688 Mg yr^{-1} in the "Arc of Deforestation" region under the High-end EF scenario. Notably, the $PM_{2.5}$ emissions from Amazon forest areas increased over time despite shrinking forest cover, indicating that Amazonian forests are becoming more vulnerable to fire. In the Cerrado, savannas are the primary land cover contributing to the total $PM_{2.5}$ emissions, accounting for 64% to 80%. These findings underscore the importance of accurate, region-specific EFs for improving emission models and reducing uncertainties.

Keywords: biomass burning; emission factors; uncertainties; modelling; remote sensing; Amazon; Cerrado

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1. Introduction

Fires are a key component shaping global landscapes, ecosystems, and the atmosphere, and impacting human well-being. They lead to environmental damage, air pollution, human mortality, and economic losses [1], especially in fire-sensitive regions. Fires can threaten species with extinction and are transforming terrestrial ecosystems by causing habitat loss and fragmentation [2–4], contributing to the shift of carbon sinks into carbon sources, including in regions of Amazonia [5], changing the atmospheric composition [6] and thus degrading the air quality [7], harming human health from increased exposure to smoke pollution [8,9], and resulting in economic losses [10,11]. They are also a burden to local communities [12] that might lead to human migration [13]. However, in fire-prone ecosystems like savannas, including the Cerrado biome in Brazil, where fire is a natural and essential process for nutrient cycling, vegetation dynamics, and biodiversity, strict zero-fire policies can be counterproductive and disrupt the ecological balance [14].

Fires are explained by climatic variability in a large fraction (~77%) of the world's burnable regions [15], although human activities and fire–human–climate interactions have been gradually impacting fire regimes [1]—especially in the tropics. Fire activity has increased across many parts of the world, including both fire-prone and fire-sensitive regions, where models predict longer fire seasons and increased fire weather days amplified by dynamic fire–atmosphere interactions and the increased fuel availability caused by drought [16]. Therefore, the likelihood of extreme wildfires has been increasing worldwide [17–19].

Biomass burning (BB) is a major and direct consequence of fires, characterised as a key component of the Earth system that affects carbon stocks, vegetation dynamics, atmospheric emissions, biodiversity, and land use and land cover (LULC) changes [20]. BB smoke spreads throughout the troposphere, even reaching remote regions [21], and has been linked to reductions in global terrestrial productivity [22]. For example, biomass burning aerosols from the Amazon have been observed to cross the Andes and disperse over the Pacific Ocean, highlighting the long-range transport of these particles [23]. Considering this, and the dynamicity of fires, orbital remote sensing combined with modelling remains the most viable approach to estimate BB emissions, and their impacts, on regional to global scales [18,24–30].

Progress has been made in estimating BB emissions. This includes the development of several global inventories [29,31–34] and regional tools for generating emission fields, such as the PREP-CHEM-SRC in South America [35,36]. Additional advancements have focused on improving accuracy through increased spatial resolution [25], the integration of data from sensors onboard both polar and geostationary satellites [37], and enhanced modelling of the fire diurnal cycle [36]. Improvements have also been made in incorporating LULC information [38] and refining surface parameters [39] in these models. Yet, the substantial variability among these estimates remains [40–42]. Discrepancies among BB emissions inventories stem from the distinct approaches available to estimate them (burned area or Fire Radiative Power—FRP), models, input data, and parametrizations [20,41,43].

LULC-based emission factor values (EFs—mass emitted of a gas or aerosol species in relation to the burned biomass) are required to estimate BB emissions independently of the approach or model used. However, the influence of EF values on estimated emissions remains uncertain. Accordingly, in this study, we have performed a sensitivity analysis aimed at understanding these uncertainties using the PREP-CHEM-SRC emissions preprocessor tool [35,36]—focusing on the Brazilian biomes, that are severely impacted by fires, Amazon and Cerrado. This tool allows us to run such sensitivity analysis, as opposed to the analysis-ready global BB emission inventories, such as the Global Fire Emissions Database (GFED) [33]. We ran the PREP-CHEM-SRC tool over a 22-year time series (2002–2023) under four EF scenarios, using the values proposed by Andreae and Merlet [44] and the updated estimates by Andreae [45]. While Andreae and Merlet [44] provided a foundational dataset by compiling EFs from available studies at the time, Andreae [45] significantly advanced this work by conducting an extensive review of over 370 experiments. This update not only expanded the range of ecosystems and combustion conditions covered but also included average EF values per LULC type along with standard deviations, enabling a more detailed representation of the variability. These improvements allow for the identification of low-end and high-end EF values, offering greater accuracy and a better understanding of uncertainties compared to the earlier dataset. Our analysis focused on fine particulate matter ($PM_{2.5}$) emissions, as aerosol estimates are subject to greater uncertainties compared to gases [31]. $PM_{2.5}$ emissions are critical for air quality monitoring, prediction, and assessment, as well as for regional and global climate modelling, where they influence radiative forcing and cloud formation processes [6,21,46,47]. To contextualize our findings, we also compared our results with the GFED4.1s [33], the most widely used BB emissions inventory globally, which serves as a key input for these applications.

2. Materials and Methods

2.1. Biomass Burning Emissions in the Study Area

The combination of the Amazon and Cerrado biomes (Figure 1) accounts for 61% of the $PM_{2.5}$ emitted from BB in South America [48]. Therefore, fires are a common occurrence in both biomes, as also evidenced by aerosol transport studies linking biomass burning in the Amazon to long-range effects [23]. The Amazon is a moist tropical forest that is naturally difficult to ignite, whereas the Cerrado is a vast and biologically diverse tropical savanna composed of grasslands, savanna formations, and woodlands, where natural lightning-ignited fires are frequent during the transition between the dry and rainy seasons [49]. With the increase in deforestation that happened in Brazil during 2019–2022 [50], fires have increased in parallel, especially in areas of primary vegetation [51]. Even with the decrease in deforestation in the Amazon since 2023, fires, which prevent regrowth across 56–82% of the potential natural forest area after complete deforestation [52], are still raging in response to the 2023/24 extreme drought event [51,53,54]. This event has been associated with increased emission of particulate matter and degraded air quality locally [7], contributing to Manaus, the capital of the Amazonas state, having the second worst air quality in the world in October 2023 [55]. Such characteristics make the Amazon and Cerrado an ideal study area for understanding the impacts of the EFs on the final estimate of $PM_{2.5}$ emitted from BB.

2.2. PREP-CHEM-SRC Emission Pre-Processor Tool

Though there are several global BB inventories available nowadays, including the GFED [33], Global Fire Assimilation System (GFAS) [31], Fire Energetics and Emissions Research (FEER) [32], VIIRS-based Fire Emission Inventory version 0 (VFEIv0) [34], and Global Emissions Inventory from Open Biomass Burning (GEIOBB) [29], we still need to produce regional-scale estimates as BB emissions are spatially heterogeneous and may exhibit regional patterns that differ from global trends [57]. Moreover, regional models also offer more reliable parametrizations [38].

South America, which contributes approximately 15% of global $PM_{2.5}$ emissions from biomass burning [33], benefits from a specialized emissions pre-processor tool, PREP-CHEM-SRC, designed to estimate emissions from various sources, including BB, anthropogenic sources, biogenic sources, and volcanoes, across the continent [35]. This tool, available at http://brams.cptec.inpe.br/downloads/ (accessed on 25 February 2025), was initially developed to provide inputs for the CATT-BRAMS regional atmospheric model system for integrated air quality and weather forecasting [58] but was adapted to improve the representation of BB in other models, such as WRF-Chem [59].

PREP-CHEM-SRC enables emission estimates across flexible projections and spatial resolutions, with multiple models integrated into the tool [35]. For example, when BB is the emission source, the user can choose between the burned area approach (3BEM model) or the FRP approach (3BEM_FRP model) [36]. The current version of the 3BEM_FRP model, used in our runs as discussed below, includes several improvements over previous versions, such as new annual LULC maps based on MapBiomas [38], the representation of the fire diurnal cycle [60], and updated emission coefficients from the FEER product [32]. These and other customizable configurations make PREP-CHEM-SRC ideal for running sensitivity analyses, in contrast to the more rigid, analysis-ready global BB inventories. It has been extensively employed to quantify and identify spatial and temporal patterns of BB emissions in South America [36,40,60], the Amazon [61–63], and the Cerrado [38,48].

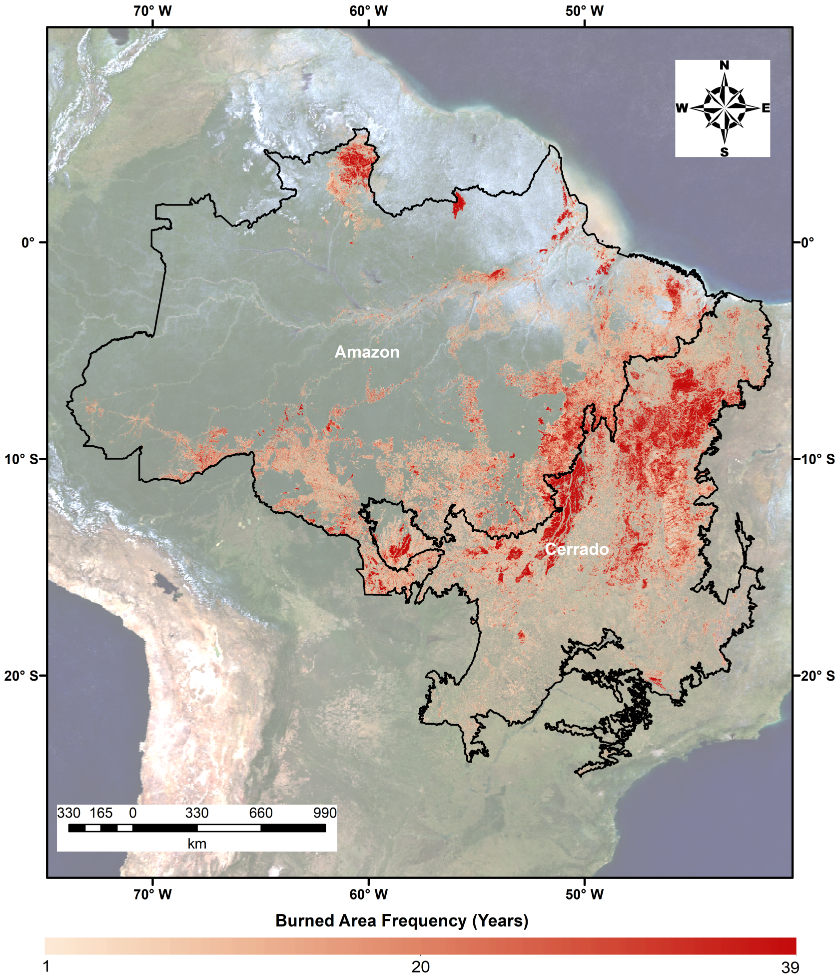


Figure 1. The location of the study area—the Brazilian Amazon and Cerrado biomes—highlighting the burned area frequency (number of years when a 30 m pixel burned between 1985 and 2023 according to the MapBiomas Fogo product [56] Collection 3). The base map is a mosaic of MODIS images, the MOD09GA product, spanning from January 2022 to August 2024. The colour composite is R1G4B3.

2.3. PREP-CHEM-SRC Runs

We ran PREP-CHEM-SRC under four distinct EF scenarios. The EFs are defined as follows [64]:

$$EF^e = \frac{M^e}{B_b} \tag{1}$$

where EF^e (g kg^{-1}) represents the emission factor for a given species, M^e (g) is the total mass emitted of that species, and B_b (kg) is the total burned biomass.

The Original (Ori) EF scenario is based on the values made available by Andreae and Merlet [44]. These are the EF values used in the freely available version of PREP-CHEM-SRC. As a key advance in this work, we apply revised EFs from the latest literature review by Andreae [45], who analysed over 370 studies that estimated EF values per LULC and compiled them into average values, and identified the standard deviation (SD) of those values. Here, we quantify emissions of $PM_{2.5}$ under Average (Avg), Low-end (Loe) and High-end (Hie) EF scenarios, which relate to the average, average minus 1 SD, and average plus 1 SD values of the EF reported by Andreae [45], respectively. The EF values considered in the four EF scenarios (Original, Average, Low-end, and High-end), are shown in Table 1. Following PREP-CHEM-SRC, BB events occurring in the remaining LULCs use the EF values assigned to the Savanna LULC. EF values in PREP-CHEM-SRC are stored in a lookup table that includes all species and LULC categories. Each species' EF value is assigned based on the LULC of the grid cell. In our runs, we updated this lookup table three times to represent the scenarios based on work by Andreae [45].

Table 1. Emission factor values, per Land Use and Land Cover, adopted in the four scenarios. Ori = Original; Avg = Average; Loe = Low-end; and Hie = High-end.

	$PM_{2.5}$ Emission Factors (g kg^{-1})			
Land Use and Land Cover	**Ori**	**Avg**	**Loe**	**Hie**
Tropical Forest	9.4	8.3	5.0	11.6
Extratropical Forest	15.7	18.4	3.2	33.6
Savanna	4.0	6.7	3.4	10.0
Croplands	4.0	8.2	3.8	12.6

Our model runs treated BB as the sole active emission source in PREP-CHEM-SRC and South America as the adopted domain—represented by a regular grid of 0.1° (~11 km) covering the continent. Moreover, all input data and parameters, including FRP estimates from MODIS active fires and LULC classifications, remained unchanged across runs, except for the EF values. This allows us to isolate the impact of EF variability, providing critical insights into how much emission estimates fluctuate solely due to differences in EF selection, independent of other potential sources of uncertainty. We chose the FRP approach to estimate BB emissions—3BEM_FRP model implemented on PREP-CHEM-SRC [36]—due to its minimal input data requirements when compared to the burned area approach, making the impact of the EFs on the final estimate of BB emissions more discernible. The 3BEM_FRP input data consisted of the FRP associated with the active fires detected by the Moderate Resolution Imaging Spectroradiometer (MODIS) sensors—products MOD14 and MYD14 [65].

After processing, our outputs were the daily mass of various species of trace gases and aerosols emitted from BB, including $PM_{2.5}$, for each cell of the 0.1° grid spanning South America, covering the period from 2002 to 2023. To simulate combined active fire detection from sensors onboard polar and geostationary satellites, we increased daily emissions by 4%, following Pereira et al. [36]. Then, the daily $PM_{2.5}$ estimates were aggregated to produce annual estimates and clipped to the boundaries of the Amazon and Cerrado biomes, as defined by the Brazilian Institute for Geography and Statistics (IBGE), to align with this study's objectives. Further details on the applied method can be found in de Oliveira et al. [63] and Mataveli et al. [38]. PREP-CHEM-SRC and 3BEM_FRP are comprehensively described in Freitas et al. [35], Pereira et al. [40], Santos et al. [60], and Pereira et al. [36]. The last study also validated the estimates and benchmarked them against global BB emissions inventories. Our scenarios' annual estimates were compared to GFED4.1s; the processing of this global BB emissions inventory, available at https://www.geo.vu.nl/~gwerf/GFED/GFED4/ (accessed on 25 February 2025), consisted of aggregating the $PM_{2.5}$ monthly estimates into yearly rasters and clipping them to the delimitation of the Amazon and Cerrado biomes.

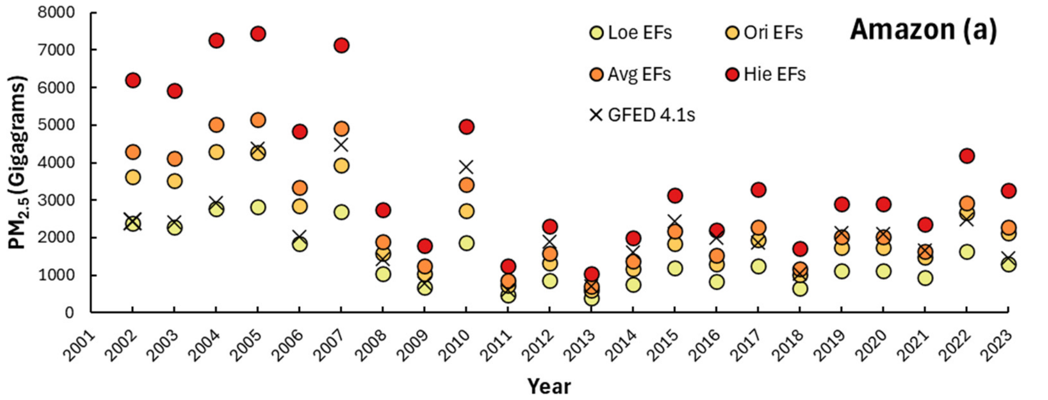
We also investigated how different LULC categories contribute to $PM_{2.5}$ emissions across the study area. For this analysis, we utilized annual LULC maps described by Mataveli et al. [38], which provide the original LULC information used to run the 3BEM_FRP model. This ensures consistency with the spatial resolution of the annual emission estimates. These maps aggregate the original LULC classes into four categories (Forest, Savanna, Croplands, and Other LULCs) [38]. They facilitated a detailed assessment of LULC dynamics, identifying the major categories that contribute to total $PM_{2.5}$ emissions from BB.

3. Results

Figure 2 shows the time series of the $PM_{2.5}$ emitted annually from BB in the Amazon and Cerrado biomes during 2002–2023 under the four distinct EF scenarios, as well as the GFED 4.1s estimates. Based on these results, we quantified the impact of EF variability on $PM_{2.5}$ emissions from BB in the Amazon and Cerrado biomes. In the Amazon, the annual average $PM_{2.5}$ emissions varied by 162% depending on the EF values used. This percentage represents the difference between the lowest and highest emission estimates, where the Low-end EF scenario resulted in an annual average of 1213 Gg yr^{-1}, while the High-end EF scenario reached 3172 Gg yr^{-1}. The percentage change was obtained by comparing the increase from the lowest estimate to the highest relative to the lowest value ((Hie scenario − Loe scenario)/Loe scenario) × 100). A similar result was observed in the Cerrado, where the emissions varied by 184%, with values ranging from 601 Gg yr^{-1} in the Low-end EF scenario to 1709 Gg yr^{-1} in the High-end EF scenario. When comparing, in the Amazon, the annual average $PM_{2.5}$ emission from the Average EF scenario with the Original EF scenario, where the EF values are the same for both the Croplands and Savanna LULCs, the $PM_{2.5}$ estimates were 17% higher with the average EFs (annual average of 2192 Gg yr^{-1} and 1872 Gg yr^{-1}, respectively). In the Cerrado, this difference was higher, reaching 50% (1155 Gg yr^{-1} and 772 Gg yr^{-1}, respectively). In relation to the GFED 4.1s, which uses EF values from Akagi et al. [64] and estimates emissions based on the burned area estimates from Giglio et al. [66], we observed that its $PM_{2.5}$ estimates are always comprised between the Low-end and High-end EFs scenarios estimates and closer (but lower) to the annual average emission of the Average EF scenario in both the Amazon and Cerrado biomes, which corresponds to an annual average emission of 1869 Gg yr^{-1} and 978 Gg yr^{-1}, respectively. Though, interannually, the GFED 4.1s estimates range more widely than our estimates (e.g., they are usually lower than the Average EF scenario in the Amazon but in 2010 they were higher).

These results highlight the significant influence of EF selection on emission estimates, emphasizing the need for careful consideration of EF variability in BB inventories. In the Amazon, annual $PM_{2.5}$ emissions based on Low-end EFs ranged from 395 Gg in 2013 to 2821 Gg in 2005, while High-end EFs led to values between 1039 Gg in 2013 and 7457 Gg in 2005. Similarly, in the Cerrado, emissions varied from 165 Gg in 2009 to 1568 Gg in 2010 under Low-end EFs, whereas High-end EFs resulted in a range of 467 Gg in 2009 to 4497 Gg in 2010.

Figure 3 illustrates the percentual contribution of different LULC categories to total $PM_{2.5}$ emissions associated with BB in the Amazon and Cerrado biomes from 2002 to 2023. The results shown in this figure were extracted from the Average EF scenario, as it represents the results obtained in all scenarios. Forests are the primary LULC category responsible for emissions in the Amazon, accounting for at least 62% of annual total $PM_{2.5}$ estimates. This share has risen over time, reaching 89% in 2021, despite shrinking forest area, as detailed in the description of the LULC maps [38]. This indicates that the remaining forests may be becoming more vulnerable to fire, highlighting the increase in forest degradation in the Amazon [67]. By contrast, savannas, the second-largest source, show a declining trend, dropping from 37% in 2002 to just 11% in 2021. In the Cerrado, savannas are the primary contributors to annual total $PM_{2.5}$ emissions, accounting for 64% to 80% of the total emissions. Forests contribute between 11% and 24%. In both LULCs, no consistent trend of increase or decrease was observed over the study period. Notably, the contributions from other LULC categories are proportionally higher in the Cerrado compared to the Amazon, reflecting the diverse land-use practices and more fragmented landscapes characteristic of this biome.



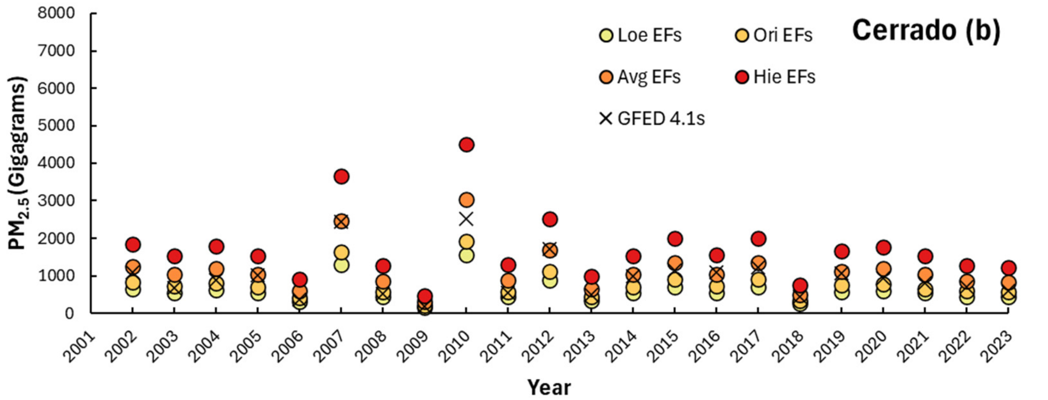
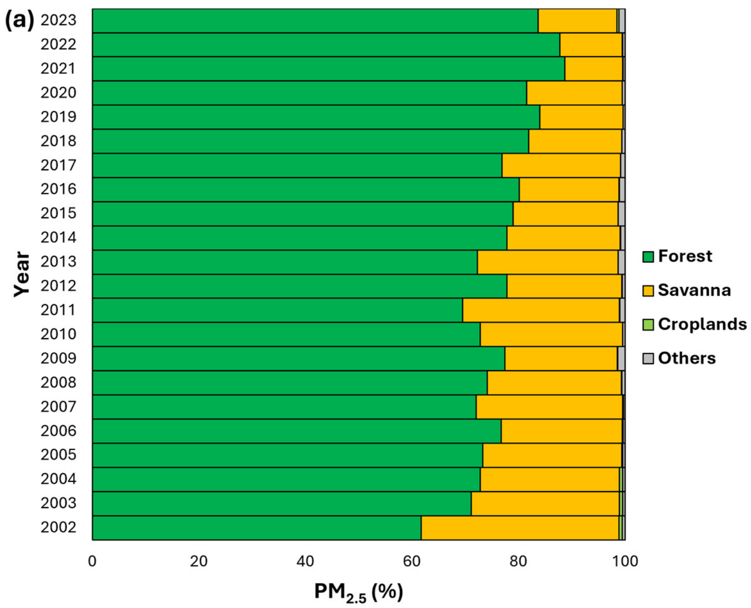


Figure 2. Annual emission of fine particulate matter ($PM_{2.5}$) associated with biomass burning in the Amazon (**a**) and Cerrado (**b**) biomes during the 2002–2023 period under the four distinct Emission Factors scenarios, as well as GFED4.1s estimates. Ori = Original; Avg = Average; Loe = Low-end; Hie = High-end.



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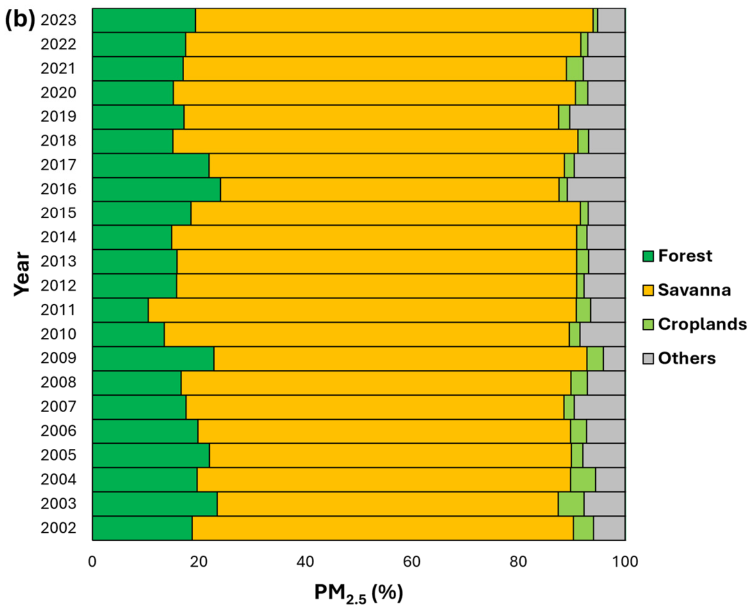
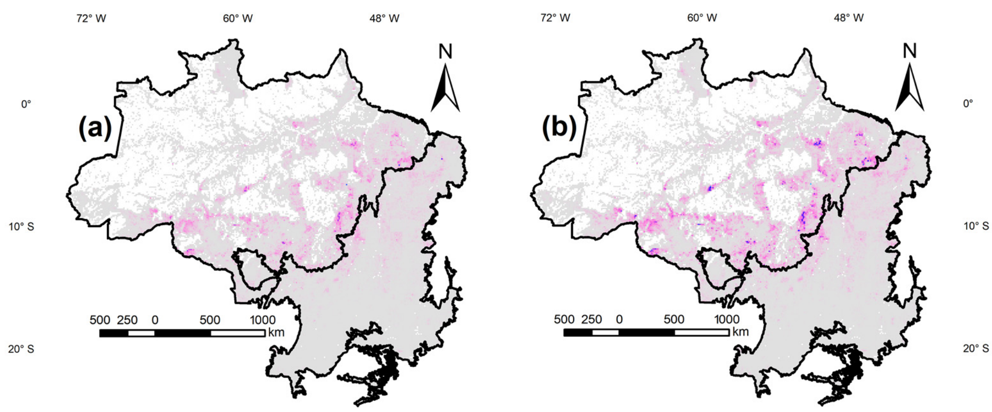


Figure 3. Percentage contribution of different Land Use and Land Cover categories to the total annual $PM_{2.5}$ emission associated with biomass burning in the Amazon (**a**) and Cerrado (**b**) biomes during 2002–2023. Results were extracted from the Average EF scenario.

The spatial distribution of the annual average emission of $PM_{2.5}$ associated with BB across the study area under the four EF scenarios over the 2002–2023 period is shown in Figure 4. While the spatial distribution of emissions remains consistent across all scenarios, the magnitude of the emission values varies, as expected, since the EFs were the only parameter modified during the PREP-CHEM-SRC runs. This highlights the significant influence of EFs on emission intensity without altering spatial patterns. Grid cell-based annual average estimates reached 5688 Mg yr^{-1} in the High-end EF scenario and only 1934 Mg yr^{-1} in the Low-end EF scenario—a difference of 194%. Highest values and largest differences among scenarios occurred in the ecotone between the Amazon and Cerrado biomes, as well as in the region known as the "Arc of Deforestation", where a larger concentration of colours varying from dark blue to dark red is observed. This was expected because these areas concentrate most of BB activity in the study area and are dominated by anthropogenic activities. Particularly, the EFs used in the runs varied significantly for Savanna (including pasturelands) and Croplands LULCs, as shown in Table 1, which influenced the magnitude of the values observed in these regions.



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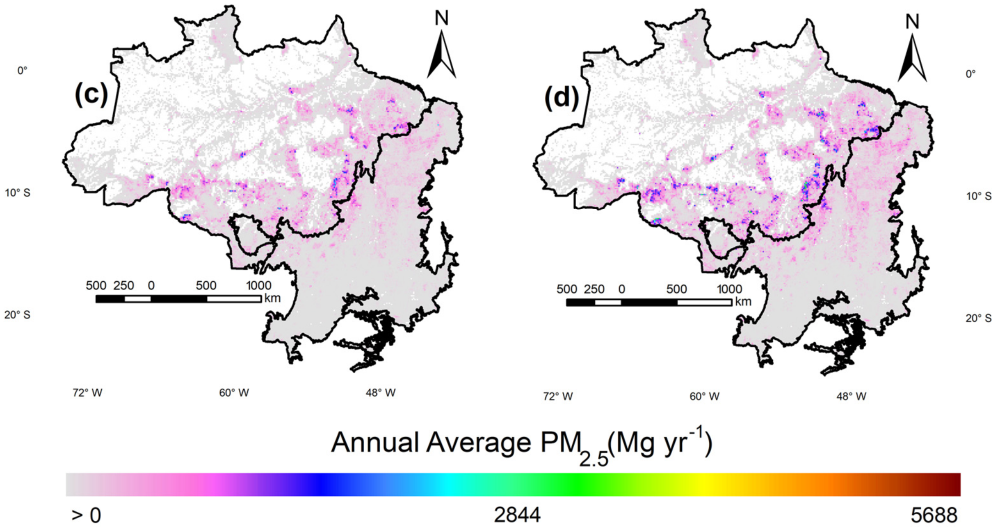

Figure 4. Spatial distribution of the annual average emission of fine particulate matter ($PM_{2.5}$) emitted from biomass burning, between 2002 and 2023, under four Emission Factors (EFs) scenarios in the Amazon and Cerrado biomes—Low-end EFs (**a**), Original EFs (**b**), Average EFs (**c**), and High-end EFs (**d**).

4. Discussion

Modelling aerosol emissions from BB is often associated with substantial uncertainties [31]. Reducing these uncertainties is crucial for improving the reliability of global and regional climate models, particularly their ability to accurately represent aerosol-related radiative forcing and its impacts on the climate system [6]. Additionally, accurate estimates of aerosol emissions, such as $PM_{2.5}$, are essential for advancing air quality modelling, enabling better prediction and assessment of air pollution levels and their impacts on human health and ecosystems [68,69]. By quantifying the influence of EFs on BB emission estimates, our findings contribute to constraining uncertainties in $PM_{2.5}$ emissions for South America. These region-specific results enhance understanding of emission dynamics and serve as a benchmark to assess the performance of climate and air quality models in capturing variability in aerosol emissions. Furthermore, accurate BB emission estimates are critical for informing international climate policy. Reliable data empower policymakers to evaluate the effects of different policy choices, such as fire management and mitigation strategies, enabling informed decisions and targeted actions at both regional and global scales [38].

The identified variation of up to 162% in the Amazon and 184% in the Cerrado raises uncertainties about which EF values should be used to estimate BB emissions. Most LULC-based EF values currently available are generalized and do not account for the specific characteristics of local vegetation [44,45,64,70]. Moreover, the seasonality of the vegetation impacts on fire intensity and combustion efficiency, making the EFs vary over time [71]. Seasonal EFs can address this gap and are already available for certain species, though not for $PM_{2.5}$, in specific regions like savannas [72]. Other studies are developing global databases with seasonal estimates of fire characteristics, including EFs and fuel loads, which hold promise for replacing static EF values in models like 3BEM_FRP [30,73,74].

Until these novel methods for estimating EFs become available, the Average EF scenario proposed by Andreae [45] remains the most robust option for integration into PREP-CHEM-SRC. Adopting these values increased $PM_{2.5}$ emissions, on average, by 17% in the Amazon and 50% in the Cerrado when compared to the Original EF scenario (EF values adopted in the freely available version of PREP-CHEM-SRC). This is positive as a previous validation study based on the 3BEM_FRP model outputs showed an underestimation of $PM_{2.5}$ concentration in the study area—especially in the Cerrado [36]. Underestimating BB emissions is observed in all inventories, including GFED. For instance, carbon emission estimates from GFED5, the updated version of the inventory currently under development, are approximately 50% higher than those from GFED4 [75]. This increase is primarily due to an improved representation of global burned area, which is 61% larger than in GFED4 [66,75]. Additionally, GFED5 accounts for the spatial and temporal variability of EFs in savannas by incorporating the values proposed by Vernooij et al. [72]. Therefore, GFED5 estimates in the Amazon and Cerrado biomes will probably match those from our Average EF scenario. Another approach worth testing to improve 3BEM_FRP emissions estimates is the use of ensemble runs that combine multiple proposed EF values.

The observed increase in $PM_{2.5}$ emissions occurring in the Forest LULC in the Amazon over time, despite a reduction in forest area, was particularly intriguing (Figure 3). This suggests that the remaining forests are becoming more vulnerable to fire. Forest degradation, primarily driven by fire, is a growing issue in the Amazon, potentially contributing more to carbon emissions than deforestation during drought years [76]. The rise in fire vulnerability is further amplified by the fact that fire-induced tree mortality in primary forests often exceeds 50% of the above-ground biomass [77], leading to long-term reductions in carbon stocks and significant impacts on the global carbon cycle. The main protection against fire for Amazonian forests is their ability to create a moist sub-canopy microclimate, which helps contain and recycle moisture within the ecosystem [78]. However, prolonged droughts, such as those in 2010 and 2015–2016, reduce this moisture retention capacity, making forests more flammable and increasing fire susceptibility [79]. Additionally, droughts contribute to forest fragmentation, which further elevates the likelihood of wildfires [67]. As drought events in the Amazon become more frequent and intense, as exemplified by the 2023/24 drought [54], the risk of wildfires is expected to rise, exacerbating the impacts of forest degradation. Recent studies showing an increase in forest fires, despite decreased deforestation, support this finding, highlighting the amplified and far-reaching consequences of these fires at both local and broader scales [7,51,53]. The patterns observed in the Cerrado were consistent with our expectations, showing a concentration of $PM_{2.5}$ emissions in the Savanna LULC and a decreasing contribution from the Forest LULC over time, consistent with the findings from previous studies [38,48].

The uncertainties related to the input data used in the 3BEM_FRP model must also be considered. These include the omission of small-scale or low-intensity fires and detection failures caused by cloud cover or thick smoke in MOD14 and MYD14 products [43]. Cloud obscuration alone accounts for approximately 11% of all active fire omissions detected by coarse-resolution sensors in Amazonia [80]. As a result, emission estimates derived solely from MODIS active fire products likely underestimate the total emissions, particularly in regions with persistent cloud cover or frequent low-intensity fires that remain undetected. To correct this bias, a 4% adjustment coefficient was applied to scale up emissions [36]. This coefficient was derived by running the 3BEM_FRP model with MODIS active fires as the input data and then comparing it to a run that incorporated FRP data from both polar-orbiting (e.g., MODIS) and geostationary (e.g., Spinning Enhanced Visible and Infrared Imager—SEVIRI) sensors [36]. While this coefficient accounts for all of South America, including our study area, it may vary within the continent. Future efforts could refine biome-specific adjustment factors. This is particularly crucial as the MODIS sensors are expected to cease operations by the end of 2025, affecting BB emission estimates since most regional and global inventories currently rely on MODIS. To maintain the consistency of emission estimates and preserve a time series spanning over two decades, MODIS-based emissions will need to be harmonized with data from other sensors, such as the VIIRS [81].

These findings underscore the need to validate BB emission estimates. Equally important is determining how best to conduct validation experiments. Usually, BB inventories, which inherently have high uncertainties as evidenced by our results, are often used as inputs for models like the CCATT-BRAMS [58] and WRF-Chem [82] to estimate the concentration and transport of emissions in the atmosphere [6,21,36,41,59,71]. These model outputs are then compared to reference datasets, such as aerosol loads from orbital sensors [83], ground-based networks like the AErosol RObotic NETwork (AERONET) [84], or data from field campaigns, including the South American Biomass Burning Analysis (SAMBBA) experiment [40,59]. However, using this approach, it is not possible to disentangle the uncertainties arising from the BB inventories from those associated with the concentration and transport models. Additionally, emission concentration comparisons are often aggregated over large areas [41], which hinders the precise identification of spatial patterns. This underscores the importance of developing consistent global BB databases based on field measurements, which can serve as reference datasets to validate regional and global BB inventories derived from remote sensing and modelling.

5. Conclusions

This study provides a comprehensive evaluation of the impact of EFs on BB emission estimates, focusing on the Amazon and Cerrado biomes over a 22-year period (2002–2023). By analysing four distinct EF scenarios, we quantified the significant variability introduced by different EF values, which reached 162% in the Amazon and 184% in the Cerrado for $PM_{2.5}$ annual average emissions. This underscores the critical role of accurate EF selection in reducing uncertainties in BB emission estimates.

Our findings also highlighted notable biome-specific patterns. In the Amazon, forests accounted for the majority of $PM_{2.5}$ emissions, with their contribution increasing over time despite a reduction in the forest area. This indicates that the remaining forests are increasingly affected by fires. In the Cerrado, the savannas were the dominant source of emissions, with stable contributions over the study period, reflecting the biome's characteristic land-use practices and fire dynamics.

The comparison of the GFED 4.1s estimates with those from the PREP-CHEM-SRC revealed that the GFED 4.1s emissions consistently fell between the Low-end and High-end EF scenarios. The Average EF scenario, which produced emissions 17% and 50% higher than the Original EF scenario in the Amazon and Cerrado, respectively, aligns closely with the expected values for future BB inventories like the GFED5.

Our results emphasize the urgent need for localized and temporally dynamic EF values to improve BB emission models. While the adoption of globally averaged EF values serves as a reliable interim solution, emerging efforts to incorporate seasonal and regional EF variations offer a promising path forward. Furthermore, the growing acknowledgment of BB emission underestimations across inventories, including the GFED, highlights the importance of enhancing both EF databases and methodologies to ensure more accurate and actionable outputs.

Finally, this study reinforces the necessity of validating BB emission estimates using independent, high-resolution datasets derived from field measurements, remote sensing, and ground-based networks. Addressing the challenges of disentangling uncertainties in BB inventories from those in transport and concentration models requires concerted efforts to develop global BB databases rooted in observational data. These efforts will significantly improve the reliability of BB emission estimates and their integration into climate and air quality models, ultimately supporting more informed policy decisions for mitigating the impacts of BB.

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