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Exploring CO_2 anomalies in Brazilian biomes combining OCO-2 & 3 data: Linkages to wildfires patterns

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Abstract

Climate change is a challenge to the global community and one of the causes is the increase of greenhouse gases (GHG) in the atmosphere, especially carbon dioxide (CO_2). The major emission source of this gas into the atmosphere comes from the burning of fossil fuels and biomass burning, on the other hand, the main sink comes from biochemical processes such as photosynthesis. Thus, the observation of CO_2 is a key point to understanding sources and sinks. In this context, The Orbiting Carbon Observatory 2 (OCO-2) and 3 (OCO-3), are a NASA dedicated mission to monitor the column-averaged dry-air mole fraction of carbon dioxide (XCO_2) on a global scale. We combined the OCO-2 and OCO-3 observations to study the spatial distribution of XCO_2 anomalies and how some of these anomalies are related to fire occurrence in the Brazilian Biomes during 2020 and 2021 considering two different seasons, Dry and Wet. The fire occurrence was obtained from Fire Information for Resource Management System (FIRMS) that provides the data from the Moderate-Resolution Imaging Spectroradiometer (MODIS) product of active fires and thermal anomalies at Near-Real Time (MCD14DL, collection 6). The OCO-2/3 observations are affected by cloud formations in wet seasons, we observe that the dry period has more observations. The XCO_2 anomaly values range from $\sim$ 7.0 ppm to -7.0 ppm and mostly positive anomalies occur in Amazon Biome, and this ecosystem has higher average values for all periods ($\sim$0.9 ppm), compared to the other biomes. The fire occurrence was higher in dry periods, especially in 2020 when unprecedented fire outbreaks were registered in Brazil. The most affected biomes were Pantanal, Cerrado, and Amazon. XCO_2 positive anomalies spatially agree with fire foci over some areas, and the correlation values between them ranged from 0.2 to 0.5 depending on the biome and season, and when considering observations with clouds the correlation is slightly higher. We point out for the first time the possibility of using OCO-2 and 3 combined, also, how positive XCO_2 anomalies are related to fire occurrence in different ecosystems and periods, and the role of cloud detection in this relationship.

Keywords: Remote Sensing; Carbon sources; XCO_2 anomalies; Climate Change; Tropical Ecosystems

1. Introduction

Climate change is a great concern globally, having broad effects across social, economical, and environmental sectors, as well as human health (Thomas et al., 2019;

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Tam et al., 2021; Petersen-Rockney, 2022; Mele et al., 2021; Kahn et al., 2021; Drouet et al., 2021; McMichael, 2020; Patz and Thomson, 2018; de Oliveira et al., 2019; Nunez et al., 2019; Habibullah et al., 2022; Malhi et al., 2021; Pereira et al., 2021; Zandalinas et al., 2021). One of the main causes of these changes is the increase in the atmospheric concentration of greenhouse gases (GHG), especially carbon dioxide (CO_2) (Chaves and Pereira, 1992; Davis et al., 2010; Montzka et al., 2011; da Costa et al., 2022a).

The increase in atmospheric CO_2 concentration is mainly attributed to the emission of this gas from the combustion of fossil fuels (Hedelius et al., 2018). However, in Brazil, CO_2 emissions are mostly linked to land use and land cover changes (Azevedo et al., 2018; Silva Junior et al., 2020). In the Brazilian Amazon, the gross emission rates linked to land use change are higher than in other biomes (Garofalo et al., 2022). In general, deforestation and wildfires are related to extensionist agriculture in Amazon and Pantanal for example (Silva et al., 2021; Barbosa et al., 2022; Garofalo et al., 2022; Silveira et al., 2022).

Given the importance that CO_2 concentration has in the global context, space-based satellite missions have been developed to provide global observations of this and other GHGs. Among these missions are the GOSAT and GOSAT-2 (Greenhouse Gas Observing Satellite), launched by the Japan Aerospace Exploration Agency (JAXA) in 2009 and 2018 (Yokota et al., 2009; Imasu et al., 2023), the Orbiting Carbon Observatory −2 and 3 (OCO-2 and OCO-3, respectively), launched by the National Aeronautics and Space Administration (NASA) in 2014 and 2019, respectively (Crisp et al., 2017; Eldering et al., 2019).

All these missions have as one of their goals to estimate the column-averaged dry-air mole fraction of CO_2 (XCO_2) and other GHGs, to understand the carbon cycle, as well the sources and sinks around the world (Crisp et al., 2017; Eldering et al., 2019; Hakkarainen et al., 2019; Araújo Santos et al., 2022). In Brazil, studies have been done to understand how the atmospheric CO_2 cycle is affected by several agricultural and environmental factors (Odorizzi de Campos et al., 2022; Rossi et al., 2022; Morais Filho et al., 2021). Similarly, in Iran, Mousavi et al. (2023) studied the spatiotemporal variability of XCO_2 and how some environmental variables are affecting the CO_2 pattern. They found that in the cold season, the XCO_2 does not decrease due to lesser vegetation cover, and in spring-summer seasons, the XCO_2 has a minimum value. However, those approaches do not identify possible CO_2 sources and sinks.

With these goals in mind, models that address the XCO_2 anomaly are a good indicator of anthropogenic activity (Hakkarainen et al., 2016) and have been related to fossil fuel emissions (Wang et al., 2018; Labzovskii et al., 2019; Zheng et al., 2020; Sheng et al., 2021). This is due that XCO_2 anomalies are a measure of possible sources and sinks of CO_2 (Hakkarainen et al., 2016; Hakkarainen et al., 2019). This direct relationship between anomalies and GHG emissions has been exploited to create models where, for example, CO_2 emissions from fossil fuels are estimated from XCO_2 anomalies (Mustafa et al., 2021; Zhang et al., 2022).

Recent studies have indicated how the negative XCO_2 anomalies would relate to natural processes, such as gross primary production (GPP) (Golkar and Mousavi, 2022; Fu et al., 2022) or related factors, such as Solar-Induced chlorophyll Fluorescence (SIF) (Hakkarainen et al., 2019; Araújo Santos et al., 2022). Meanwhile, Wang et al. (2020) used OCO-2 data to estimate the Australian fires' contribution to the increase of atmospheric CO_2 concentration. Finally, XCO_2 anomalies calculated from OCO-2 data demonstrated similar spatial variation with emissions related to biomass burning in Africa (Hakkarainen et al., 2019), and more recently Souza Maria et al. (2023) using GOSAT, studied the fire foci relation with methane atmospheric concentration.

Wildfires are directly linked to CO_2 emissions to the atmosphere (Aragão et al., 2018), in addition to having other impacts on human health (Urrutia-Pereira et al., 2021; Akdis and Nadeau, 2022) and to the environment (Fonseca et al., 2019; Rossi and Santos, 2020; Guedes et al., 2020). Hence the importance of detecting active fire hotspots and understanding their dynamics (Alencar et al., 2022), especially when we consider that some Brazilian ecosystems have a natural fire cycle and that they can have ecosystem benefits when properly managed (Ramos et al., 2019; Durigan, 2020; Marques et al., 2022).

However, monitoring fires through remote sensing is not a simple task, as this type of observation can suffer from atmospheric correction algorithms for cloud detection (Wooster et al., 2021; Sokolik et al., 2019). In this sense, the Fire Information for Resource Management System (FIRMS) platform provides near real-time data on these fire foci (Giglio et al., 2018; Barbosa et al., 2021), which in the short term helps in fighting these fires (Briones-Herrera et al., 2020; Andrade et al., 2021), but in the long term can be used to understand fire dynamics (da Silva Junior et al., 2020; Alencar et al., 2022; Menezes et al., 2022; Teodoro et al., 2022).

Given the relationship that exists between fire outbreaks with CO_2 emissions, and that positive XCO_2 anomalies indicate potential emission sources, we combined for the first time the OCO-2 and OCO-3 observations aiming to increase the number of observations, especially in periods with high cloud cover, to investigate the XCO_2 anomalies, and how those relate with Fire Foci in Brazilian biomes between 2020 and 2021, years that had an atypical fire incidence in Brazil (Barbosa et al., 2022; Silveira et al., 2022). Complementarily, observations with lower quality (presence of clouds) were used to test whether the relationship with Fire Foci is impacted. Specifically in this work we first analyze the spatial distribution of XCO_2 anomalies over the Brazilian Biomes and the wildfire density distribution, then we assess the similarity between the most fire-affected phytogeographic domain/ ecosystems and the

XCO_2 anomalies, as well as the correlation between the co-located observations.

2. Material and methods

2.1. Study area

Extending across a total area of 8.6×10^6 km^2, owing to the country's continental dimensions and its extensive latitudinal range, approximately 80 % of its territory falls within a tropical climate, with 14 % classified as subtropical, and the remaining 6 % characterized by a semi-arid climate (Alvares et al., 2013). More about the precipitation and temperature distributions can be found in Supplementary Fig. 1.

To gain a deeper appreciation of Brazil's rich environmental diversity, the country is divided into six major geographic regions, known as biomes: Amazon (AMZ), Cerrado (CERR), Pantanal (PNT), Atlantic Forest (AF), Caatinga (CAAT) and Pampa (PMP). These biomes are delineated based on climatic patterns, predominant vegetation, and shared biological and ecological characteristics (Zappi et al., 2015), as further elaborated in the following sections (see Fig. 1).

Each of these biomes is distinctive, encompassing a myriad of ecosystems, and they collectively play an integral role in environmental processes. However, over the past three decades (1985–2017), Brazilian biomes have experienced significant transformations, primarily attributed to deforestation and agricultural expansion (Souza Jr et al., 2020), resulting in a concerning surge in the incidence of wildfires.

2.1.1. Amazon

The Amazon Rainforest (AMZ) stands as Brazil's largest biome and the world's largest tropical rainforest. It is situated in the northern region of Brazil, extending into neighboring South American countries. The Amazon Rainforest is celebrated for its vast expanse and remarkable biodiversity, known as one of the most species-rich terrestrial environments (Hoorn et al., 2010), featuring varied structural characteristics (Myster, 2016). This extensive biome is distinguished by its lush, evergreen tropical vegetation that persists throughout the year. However, during dry periods, it simplifies to a forest with a continuous canopy, with this transition more pronounced from the northeast to the southeast. The Amazon Rainforest is situated in an equatorial climate, characterized by consistently high temperatures and humidity levels year-round. It experiences abundant and continuous rainfall, some regions inside the Amazon can have dry seasons and occasionally punctuated by extended dry periods (Davidson et al., 2012). However, deforestation and land use changes in this biome are

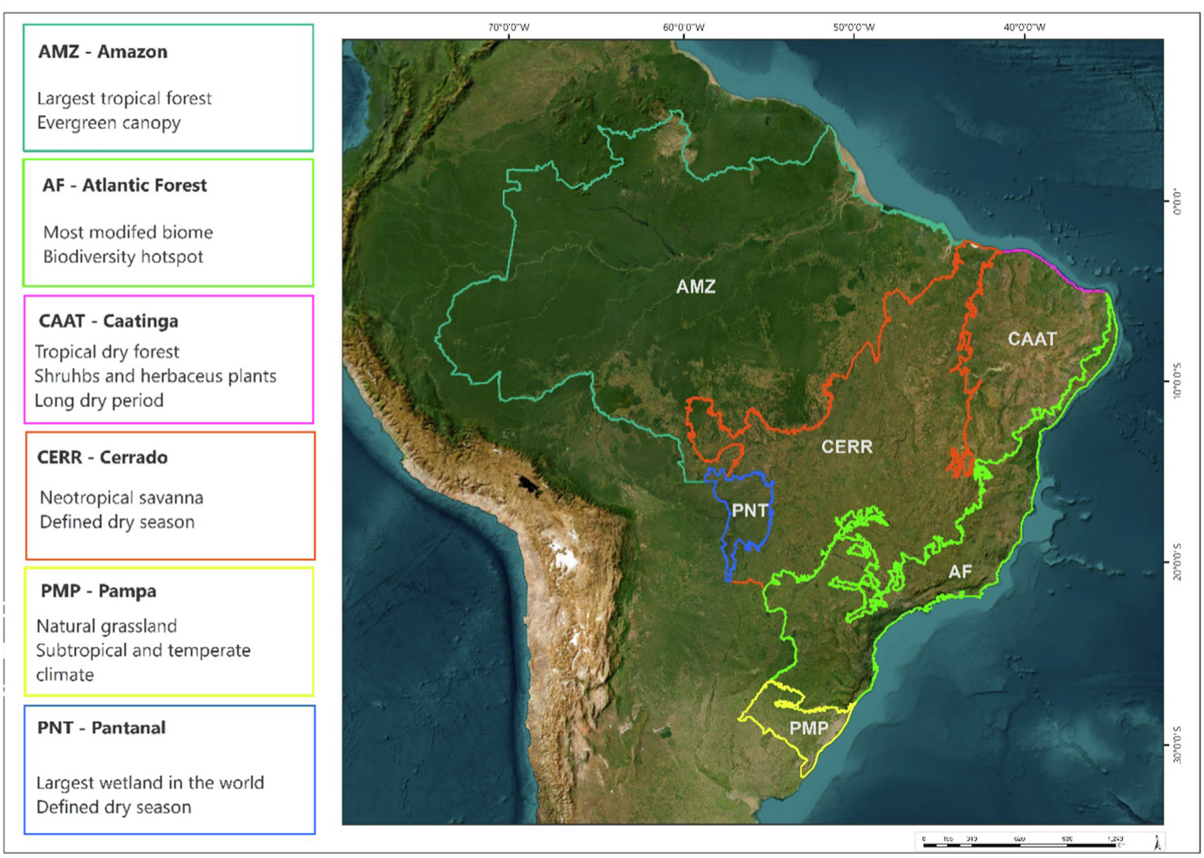

Fig. 1. True color map of Brazil highlighting the major ecosystem domains, the Brazilian Biomes. The text box on the leaf highlights the main characteristics of each biome.

drastically altering its water regime, carbon balance, and biodiversity (Aragão et al., 2014; Aragão et al., 2018; Decaëns et al., 2018; Boulton et al., 2022).

2.1.2. Cerrado

The Cerrado (CERR) the second-largest Brazilian biome, is a Neotropical savanna that extends across the central portion of Brazil. It boasts a wide variety of vegetation and a high degree of endemism, making it arguably the most biodiverse savanna in the world (Klink and Machado, 2005; Wantzen et al., 2012; Reis et al., 2022). The Cerrado's vegetation includes savannas and typical cerrado features, such as scattered trees, shrubs and grasses. This biome exhibits deep-rooted forest patches and transitions into progressively less arboreal formations, leading to nearly treeless grasslands. The Cerrado experiences a tropical seasonal climate with well-defined wet and dry seasons, Notably, the dry season typically prevails from May to September (Hunke et al., 2015).

2.1.3. Atlantic Forest

The Atlantic Forest (AF) is a coastal biome that extends along the eastern coast of Brazil, covering a diverse landscape. It is characterized by tropical and subtropical forests and experiences a humid tropical climate with well-distributed rainfall throughout the year. Historically, this is also the most modified Brazilian biome and it is estimated that today only between 9 and 12 % of the original conformation still exists (Morellato and Haddad, 2000; Vitória et al., 2019). This biome is stratified into small forest fragments in general (Parras et al., 2020; de Mendonça et al., 2022). Within the remnants of its original configurations, the Atlantic Forest (AF) stands out as an incredibly diverse biome, hosting a variety of ecosystems that feature diverse plant structures. These range from evergreen canopies to lowland formations, providing a habitat for approximately 8000 endemic species. It is recognized as one of the world's 25 biodiversity hotspots (Myers et al., 2000; Tabarelli et al., 2005; Vitória et al., 2019; Cantidio and Souza, 2019).

2.1.4. Caatinga

The Caatinga (CAAT) is a semi-arid biome found in the northeastern region of Brazil. characterized by is drought-adapted vegetation, which includes xerophytic plants and shrubs. It is often described as a tropical dry forest dominated by shrubs and herbaceous plants, with a significant number of endemic species (Albuquerque et al., 2012), along with succulent and spiny vegetation (Moro et al., 2016). The region's climate is marked by an extended dry period, which can last from 5 to 11 months depending on the specific area, and on average, the total precipitation volume during the year is less than1000mm (Apgaua et al., 2015; Moro et al., 2016). Recent studies indicate an increase in the degree of severity and extent of arid areas in recent years (Brito et al., 2018; Luiz-Silva et al., 2021).

2.1.5. Pantanal

The Pantanal (PNT) one of the world's largest wetland areas, is primarily situated in the central-western region of Brazil (Schulz et al., 2019). It is a wetland biome characterized by a rich diversity of vegetation, encompassing swamps, seasonal floodplains, and riparian forests. This diverse landscape ranges from floodable grasslands to typical Cerrado vegetation, creating a mosaic of ecosystems (Pott et al., 2011). The Pantanal features a tropical climate with a dry season and a rainy season. In general, the flood flux follows the rainy periods in the region, and the dry season generally occurs between April and September (Marengo et al., 2021). Recently the Pantanal has been suffering changes in land use and unnatural fires (Barbosa et al., 2022).

2.1.6. Pampa

The Pampa (PMP) is a natural grassland biome, known for its variety of grasses, herbs, widely spaced shrubs, and a limited number of isolated trees., (Overbeck et al., 2007; Roesch et al., 2009). Commonly referred to as the "Campos do Sul" due to its location in the southernmost part of Brazil, the Pampa boats a unique climate. It features a combination of subtropical and temperate conditions, characterized by cold winters and hot summers. The Pampa experiences distinct seasons and does not have a defined dry period. Instead, it is subject to seasonal variations, including dry periods during the summer. In general, this biome exhibits well-defined seasons without a specific dry period (Almagro et al., 2020).

2.2. Orbiting Carbon Observatory missions

NASA developed the Orbiting Carbon Observatory (OCO) project to remotely monitor the XCO_2 in the atmosphere on a global scale (Crisp et al., 2004). Currently, there are two missions in orbit, OCO-2 embarked on its own satellite (O'Dell et al., 2018) and OCO-3 aboard the International Space Station (Taylor et al., 2020).

Both missions have similar instrumentation and allow monitoring absorptions in the oxygen band near the 0.76 μm wavelength (O_2 A-band) and the weak and strong CO_2 bands at 1.6 μm and 2.06 μm respectively (Crisp et al., 2012; Eldering et al., 2019). These evaluations are the main parameters of the ACOS algorithm (Atmospheric CO_2 Observations from Space) that estimates XCO_2 (O'Dell et al., 2012; Crisp et al., 2012; O'Dell et al., 2018; Kiel et al., 2019). In addition, the sensors of both missions have a similar footprint with a spatial resolution of < 4 km^2 with one frame consisting of up to 8 footprints (Crisp et al., 2017; Kataoka et al., 2017).

The main difference between OCO-2 and OCO-3 is in the orbit performed, OCO-2 has a Sun-synchronous orbit while OCO-3 has a precessing orbit. Fig. 2 shows the coverage performed in March 2020 over Brazil, exemplifying both missions. While OCO-2 has a polar coverage making observations from 90°N to 90°S, OCO-3 follows a nearly

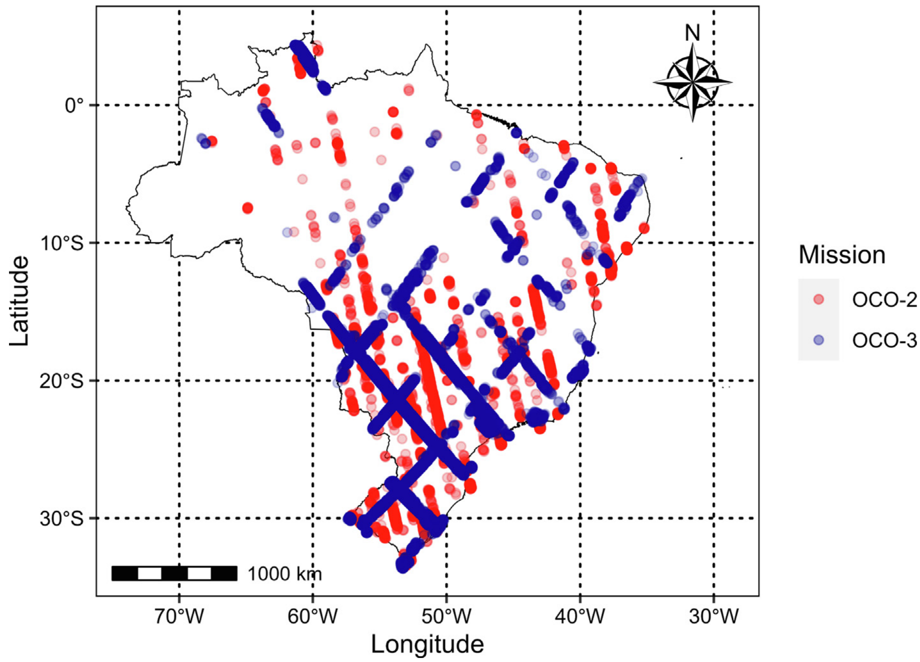

Fig. 2. Good quality observations (quality flag = 0) performed in March 2020 by OCO-2 and OCO-3 in the Brazilian territory.

circular orbit to Earth with latitudinal coverage from 52°N to 52°S (Crisp et al., 2017; Eldering et al., 2019), both covering well the Brazilian territory ranging from ~ 5°N to ~ 33°S (an observation density map is provided in the Supplementary Fig. 2). The sampling gaps, especially over the Brazilian Amazon, are due to cloud cover (O'Dell et al., 2018; Taylor et al., 2020). Furthermore, there is a difference in the revisit time, for OCO-3, the orbit repeats more or less every 3 days, however, the local time of the revisit changes and, only returns to a similar illumination condition in 63 days (Taylor et al., 2020). Meanwhile, the OCO-2 has a revisit period of 16 days with the same local time (Crisp et al., 2017).

In the present work, we use Level 2 version 10 of the Lite Files Full Physics bias corrected for both OCO-2 (https://disc.gsfc.nasa.gov/datasets/OCO2_L2_Lite_FP_10r/summary) and OCO-3 (https://disc.gsfc.nasa.gov/datasets/OCO3_L2_Lite_FP_10.4r/summary) in Nadir, Glint and Target observation modes. We used the observations that passed cloud detection (quality_flag = 0) and also the observations with lower quality (quality_flag $\leq$ 1) during the years 2020 and 2021 for the entire Brazilian territory. These years were chosen for two main reasons: i) The fire incidence was historically higher, and ii) both missions were in orbit and performed observations during the whole year, at the time this study was conducted (June 2022).

2.3. Fire Foci

Fire Foci were obtained from NASA's Fire Information for Resource Management System (FIRMS, https://earthdata.nasa.gov/firms) platform that provides observations of active fires and thermal anomalies from the Moderate-Resolution Imaging Spectroradiometer (MODIS) product MCD14DL (Collection 6). This product consists of daily data in Near-Real-Time (3 h) with a spatial resolution of approximately 1 km, calculated from the swath products (MOD14/MYD14). To reduce the uncertainty of the observations being a fire outbreak, measurements with at least 80 % confidence over the whole Brazilian territory in the years 2020 and 2021 were considered (Giglio et al., 2016; Giglio et al., 2018). The 80 % threshold was used to filter only the highest quality data, nominal quality data (>30 % confidence of being a fire) was not considered. The data was downloaded directly from FIRMS in csv format for the analyzed period (2020 and 2021).

2.4. Anomaly model

There are several anomaly models for atmospheric CO_2 concentration, such as those using statistical metrics (Hakkarainen et al., 2016), those that consider atmospheric transport models using a Gaussian plume model (Wang et al., 2018), or through the Lagrangian particle dispersion method (Schwandner et al., 2017; Wu et al., 2018). The anomaly model used here was proposed by Hakkarainen et al., (2016, 2019), where positive anomaly values (hotspots) are considered potential sources of CO_2 emission to the atmosphere, while negative anomalies (coldspots) are considered possible CO_2 sinks.

$$Xco_{2(anomalies)} = Xco_{2(i,j)} - M_e\left(Xco_{2(j)}\right) \quad (1)$$

where $Xco_{2(i,j)}$ is the i observation of XCO_2 in the day j and $M_e\left(Xco_{2(j)}\right)$ is XCO_2 median in the day j.

This model removes the CO_2 concentration baseline (background) reducing the effect of spatial changes and regional trends in the data, not requiring the introduction of atmospheric transport models, and simplifying data interpretation. This model has been used to study emission sources due to fire and fossil fuel combustion (Mustafa et al., 2021; Zhang et al., 2022) as well as other natural signals (Golkar and Mousavi, 2022; Araujo Santos et al., 2022).

2.5. Temporal and spatial analysis

The data were aggregated into two periods, dry and wet seasons, with the dry period defined as April to September and the wet period composed of observations from January to March and October to December of each year (2020 and 2021), these two periods was defined due to the general climate pattern of Brazil (Alvares et al., 2013).

The Brazilian XCO_2 anomaly pattern was analyzed as averages of each of the six Brazilian biomes in each period and the spatial patterns were generated with a spatial resolution of 0.25°. The XCO_2 uncertainty related to each mission was taken as the daily average of the instrument uncertainty, as well the coefficient of variation was calculated to ensure that both missions had a similar performance, thus allowing to use the datasets as one unique.

Fire Foci probability was calculated using the Kernel density (Eq. (2)). This method identifies the zones where active fire foci occurred in the study periods (Marinho et al., 2021; Oliveira-Június et al., 2021; Barbosa et al.,2021). Such maps were also generated with a spatial resolution of 0.25° in the two annual periods considered (dry and wet), aggregating all fire observations in the analyzed period. The XCO_2 anomalies observations collated with the fire observation were also submitted to this analysis for two reasons: i) detect the probability of a CO_2 source; and ii) reduce unwanted signals.

$$\widehat{f}(x) = \frac{1}{nh}\sum_{i-1}^{n} k\left\{\frac{x - x_i}{h}\right\} \tag{2}$$

where n is the number of observations; h is the bandwidth; k is a density function; x is the coordinate where the function will estimate and x_i is the coordinate observed.

With the elaboration of maps, we performed visual analyses between the distribution of XCO_2 anomalies and Fire Foci. To better understand the relation between both variables, the observations collocated were also submitted to a Speraman's correlation each of the periods and biomes, between the number of Fire foci observed (count) and the maximum values of XCO_2 anomalies (ppm), to evidence the relation between fires outbreaks with anomalies intensity. In the last one, the criteria adopted were only for those observations that passed cloud detection (quality_flag = 0) and then these analyses were remade for the dataset that included the observations that did not pass (quality_flag ≤ 1).

3. Results

3.1. XCO_2 anomaly patterns over Brazil

The daily average of satellite observation uncertainty for OCO-2 over Brazil was ± 0.48 ppm with a maximum of ± 1.1 ppm, presenting a coefficient of variation (CV) of 14.2 % (Fig. 3). The OCO-3 had an average observation uncertainty of ± 0.58 ppm, with a maximum of ± 1.25 ppm and CV of 24.5 % (Fig. 3). In general, the uncertainty associated with the observation was higher during the dry periods for both missions. The Amazon presented higher values of standard deviation (SD) of the XCO_2 anomaly, especially during the humid periods. On the other hand, the Cerrado was the one that presented the lowest SD, occurring in the dry period of 2020.

The anomaly values have a high variation showing extreme values as high as 7 ppm and as low as −7 ppm (Fig. 4). Overall, the highest anomaly values were observed in the year 2020, while the year 2021 presented the lowest (negative) anomaly values (Fig. 4). Amazonia (AMZ) showed the highest average anomalies for all periods analyzed (hotspot), especially in the wet period and in the year 2021, with an average of 0.9 ± 1.6 ppm. Meanwhile, the Pampa (PMP) showed the lowest average anomalies, with negative values, occurring in the dry period of 2021 (-0.9 3 ± 1.2 ppm). Concerning the national maximum and minimum values, the highest value observed was also in the Amazon, around 7.44 ppm during the humid period of 2020, and the lowest observed was in the Caatinga (CAAT) during the dry period of 2021, approximately −7.07 ppm (Fig. 4).

The number of valid observations (quality_flag = 0) was lower during the wet period, especially over Amazon due to the presence of clouds as already pointed out in section 2.2. Note that the central-southern part of the country, where the CERR, AF, and PMP are located, presents a majority presence of slightly negative anomalies (from −1 to 0, more than 30 % of valid observations in each biome). On the other hand, slightly positive anomalies (0 to 1 scales) are more present in the Amazon domains (>30 % of observations). The Amazon was also the biome that presented the most moderately positive anomalies (1 to 3 ppm), representing more than 20 % of observations in this biome, besides presenting the greatest number of observations with anomalies above 3 ppm, considered extreme, compared to all other biome and in the dry period of 2020 had a greater presence of these anomalies above 3 ppm (see Fig. 5).

3.2. XCO_2 anomaly and fire Foci relation

We observed a higher wildfire occurrence density in the Center - North of Brazil, in the dry periods, and in general with a higher frequency in 2020 compared to 2021. The

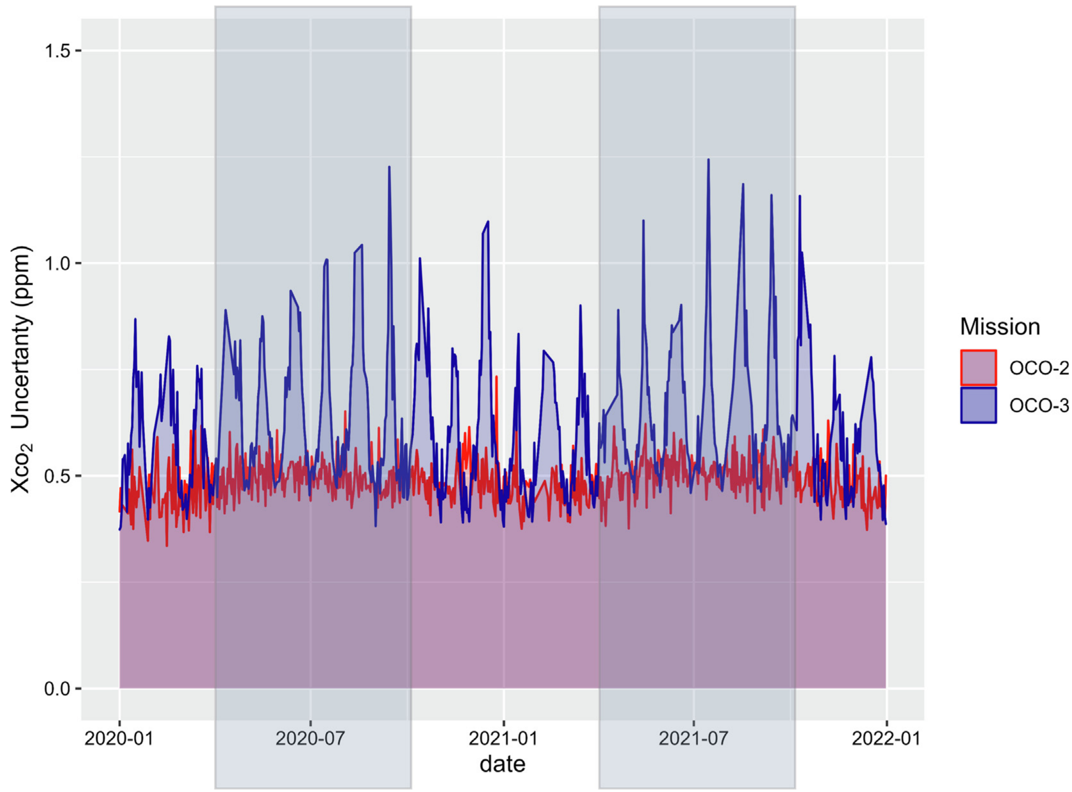

Fig. 3. Daily average observation uncertainty of XCO_2 between January 2020 and December 2021 from OCO-2 and OCO-3 missions, only considering good quality observations (quality flag = 0). The highlighted area represents the dry period.

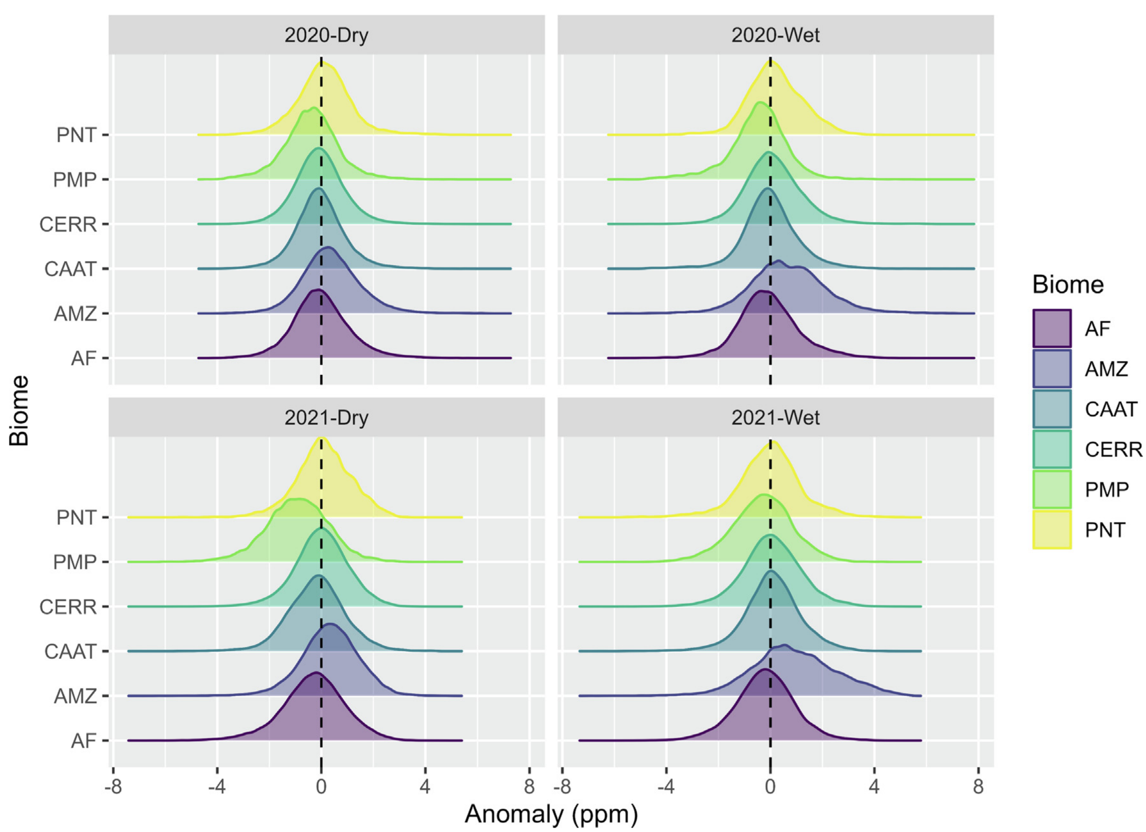

Fig. 4. Density plot of XCO_2 anomalies for each period analyzed in the different Brazilian biomes, only using good quality observations (quality flag = 0). Where AMZ = Amazon, AF = Atlantic Forest, CERR = Cerrado, CAAT = Caatinga, PMP = Pampa and PNT = Pantanal.

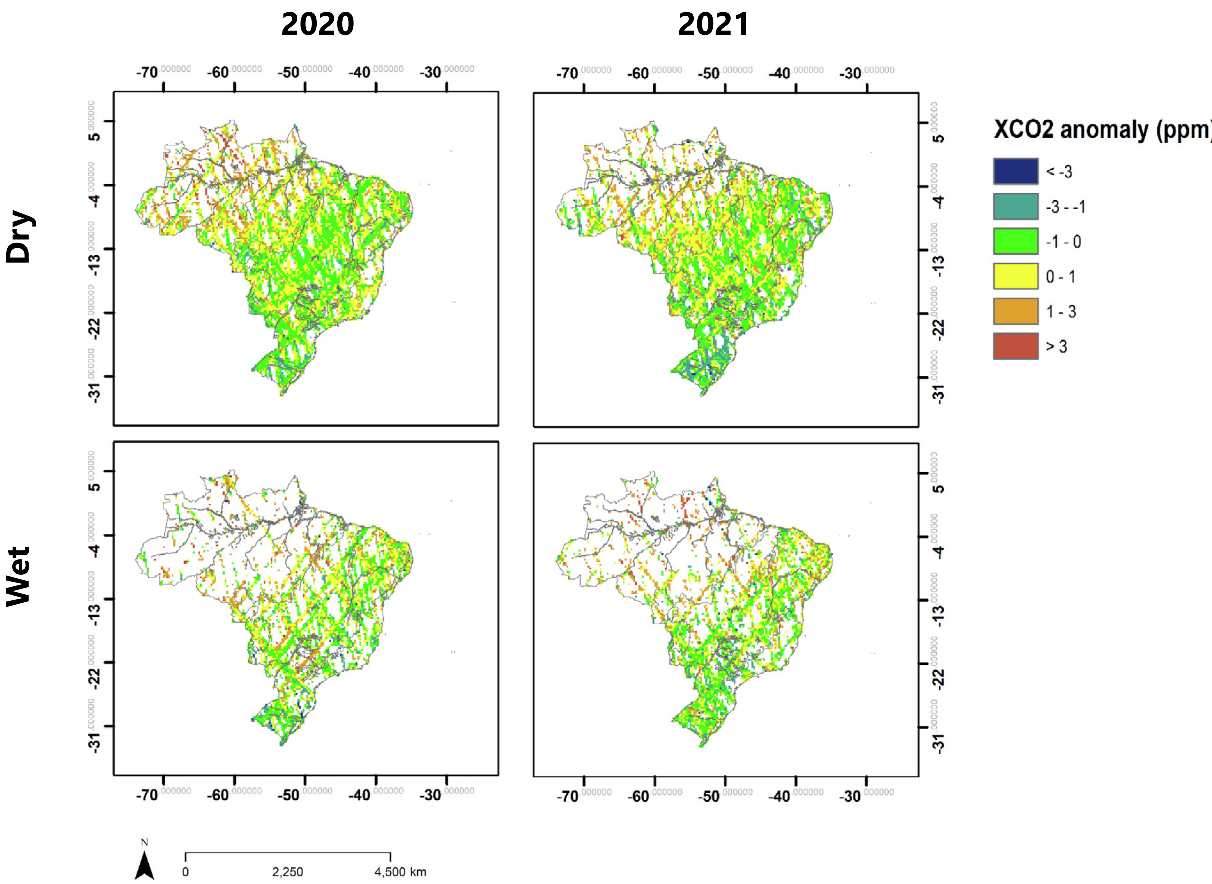

Fig. 5. Spatial distribution of XCO_2 Anomalies (ppm, **left column**) and Fire Foci frequency (**right column**) in the dry and wet seasons of 2020 (**a - d**) and 2021 (**e - h**) in the Brazilian territory, only considering good quality observation (quality flag = 0).

Fire Foci are distributed over the Pantanal, a part of the Amazon, Cerrado, and part of the Caatinga. Concerning the Pampa, no significant Fire Foci were observed during the analyzed period. Similarities were observed in the year 2020 during the dry period in the occurrence of the kernel spatial distributions of XCO_2 anomalies and Fire Foci (Fig. 6). In the Pantanal region, where the density of Fire Foci was greater, we can observe a higher probability of positive XCO_2 anomalies in that region. Such anomalies and fire occurrences are positive (hotspots) and were also observed in the same year over southern Amazonia (Fig. 6). Similarly, this pattern is repeated in the humid period of the same year, with some regions with a high density of Fire Foci coinciding with regions with a higher probability of positive anomalies (Fig. 6).

Positive anomalies also coincide with the high-density regions of Fire Foci, in 2021 in southern Amazon and part of the Pantanal (Fig. 7). Furthermore, during the humid period of 2021, we observe this same pattern at some points between the transition from Cerrado to Caatinga (Fig. 7).

When analyzing all biomes during the dry period, except for the Pampa, showed a significant and positive correlation ($R > 0.2$, $p < 0.05$) between Fire Foci and XCO_2 anomaly (Fig. 8). During the wet period, in general, only the Cerrado, Caatinga, and Pantanal showed a significant correlation ($p < 0.05$); only in the wet period of 2021, the Caatinga's correlation was significant at $p < 0.1$. Considering only the significant correlations, they ranged from proximally 0.2 to $\sim$ 0.5, depending on the Biome and period (Fig. 8).

In general, when we do not filter the data that detected cloud presence (quality_flag $\leq$ 1), the value of the correlations between anomaly and fire outbreaks increases and becomes more significant, especially in wet periods (Fig. 9). However, the observation uncertainties have higher variability (CV $\sim$ 18 % and $\sim$ 30 %, for OCO-2 and OCO-3, respectively) (Supplementary Fig. 3).

4. Discussion

4.1. XCO_2 anomaly pattern across Brazilian biomes

Overall, the uncertainties of the OCO-2 and OCO-3 observations are consistent with previous studies that evaluated the performance of these missions (e.g., O'Dell et al., 2018; Hobbs et al., 2020). The OCO-2 uncertainty reaches up to $\sim$ 1 ppm and for OCO-3 it ranges between 1 and 2 ppm, thus, the OCO-3 has more variability, this is ascribed to the observation strategy that is not always with the same illumination conditions. Despite these differences, the performance is similar which allows us to join the data generated by these missions and, due to this different obser-

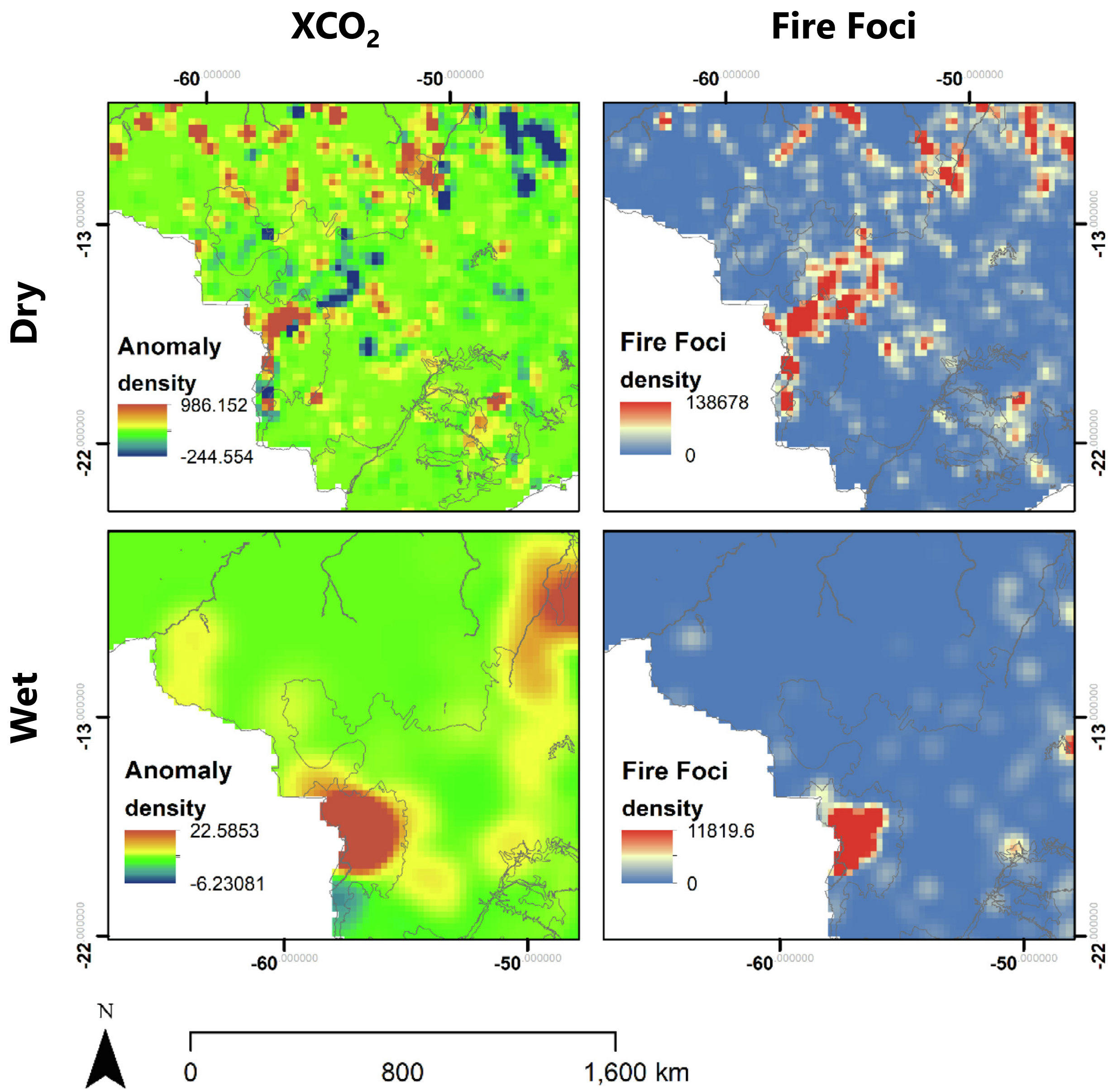

Fig. 6. Spatial variability in some Brazilian regions of the XCO_2 anomalies kernel density and Fire Foci kernel density during the year 2020, where the first row is the dry period and the second is the wet period, and the first column is the XCO_2 density and the second is the Fire Foci only considering good quality observation (quality flag = 0).

vation strategies of the missions give a complementary observation from both missions, covering more area and time than one alone.

Despite the number of observations increasing due to the combined observations, during the months of September-February, there was an increase in cloud cover over Brazil (Prudente et al., 2020), especially over Amazonia (Martins et al., 2018), resulting in a decrease in the number of observations with good quality (quality_flag = 0). Decreases in the number of OCO-2/3 observations have already been reported, with the Amazon region being one of the most affected by cloud cover, especially during wet seasons (O'Dell et al., 2018; Taylor et al., 2020).

As observed by Hakkarainen et al. (2019), positive anomalies over Amazon between 2015 and 2018 are larger compared to other Brazilian biomes, and negative anomalies are more concentrated in the Cerrado, Atlantic Forest, and Pampa domains. Such observation may be related to Amazonia territorial extension, and also because this biome emitted about 2.5 times more than it captured carbon via primary production between 2001 and 2019 (da Silva Junior et al., 2022), having a gross emission of approximately 989 ± 504 Tg CO_2 year^{-1} (Aragão et al., 2018). Other studies also present the biome as an emitter, with a positive balance of ~ 500 Mt CO_2 year^{-1} (Assis et al., 2020). Furthermore, according to Garofalo et al. (2022), the Amazon has higher rates of CO_2 emissions than

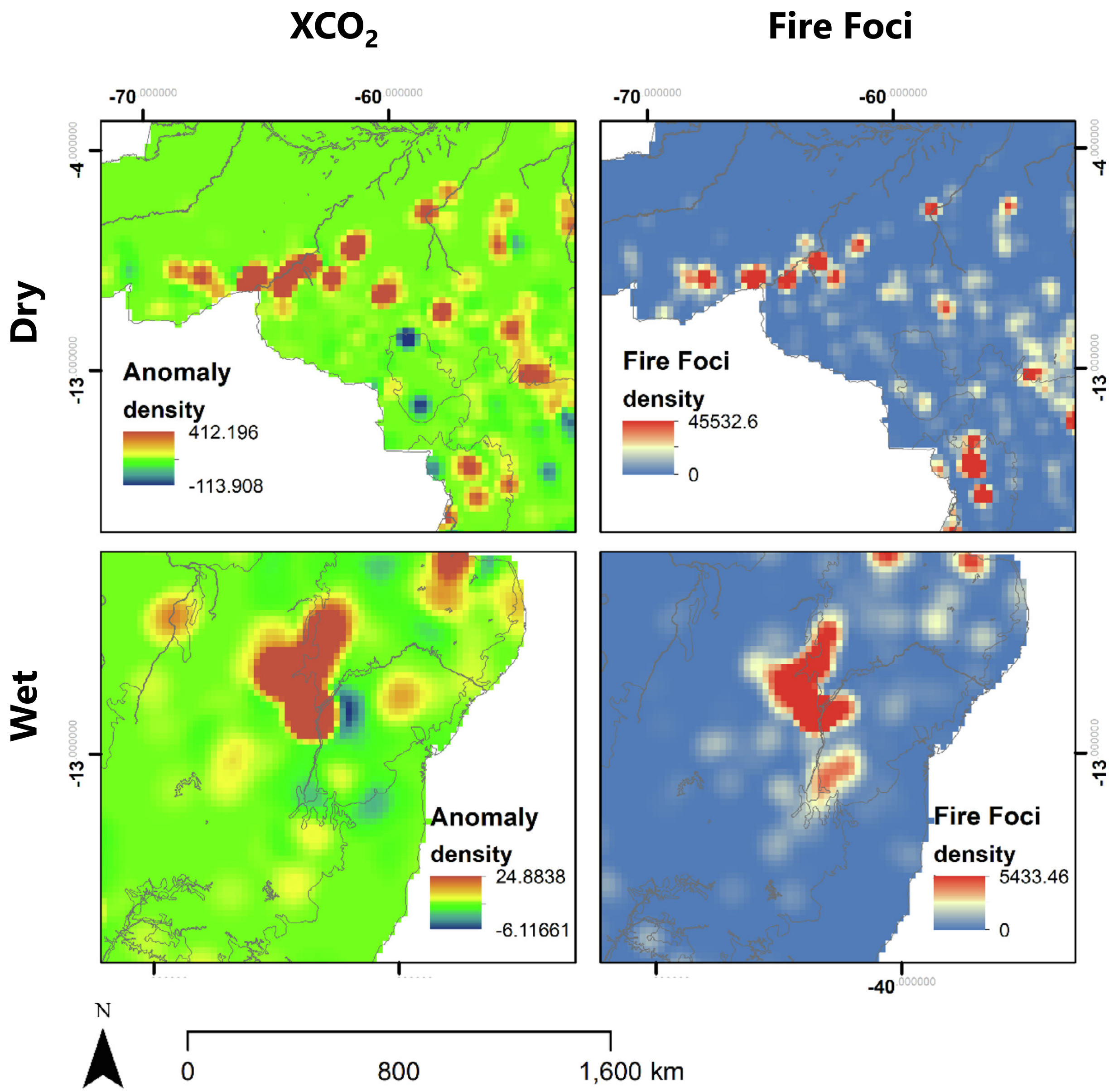

Fig. 7. Spatial variability in some Brazilian regions of the XCO_2 anomalies kernel density and Fire Foci kernel density during the year 2021, where the first row is the dry period and the second is the wet period, and the first column is the XCO_2 density and the second is the Fire Foci only considering good quality observation (quality flag = 0).

CERR, AF, and PMP, this is mainly attributed to land use change and deforestation. On the other hand, Ribeiro et al. (2021) observed, between 2009 and 2015, a positive balance of primary production in the Pampa, characterizing this biome with a negative balance of CO_2, thus a carbon sink.

4.2. XCO_2 anomalies and fire foci relation

The incidence of fire is higher during drier periods of the year, and historically, the regions most impacted by fires are located in the northern and central regions of the country, where the Cerrado, Amazon, and Pantanal biomes domains (da Silva Junior et al., 2020; Alencar et al., 2022; Menezes et al., 2022; Rossi and Santos, 2020; Teodoro et al., 2022). In addition, Silva et al. (2022), using data from MODIS sensors and other satellites, reported a decrease in fires from 2020 to 2021 in the Amazon biome, in agreement with our results, where we observed a decrease in the density of fires between 2020/21, as well as a decrease from dry to wet season.

The areas of fires in the Amazon, in general, are found in the southern part of this biome, near the transition with the Cerrado, this region is known as the arc of deforestation, where is reported an increase in burned areas and fires between 2006 and 2019 (Silva et al., 2021). In 2020, the largest number of fires were recorded since 2010, which were aggravated by agricultural burning and deforestation (Silveira et al., 2022). Similarly, in the Pantanal, a record

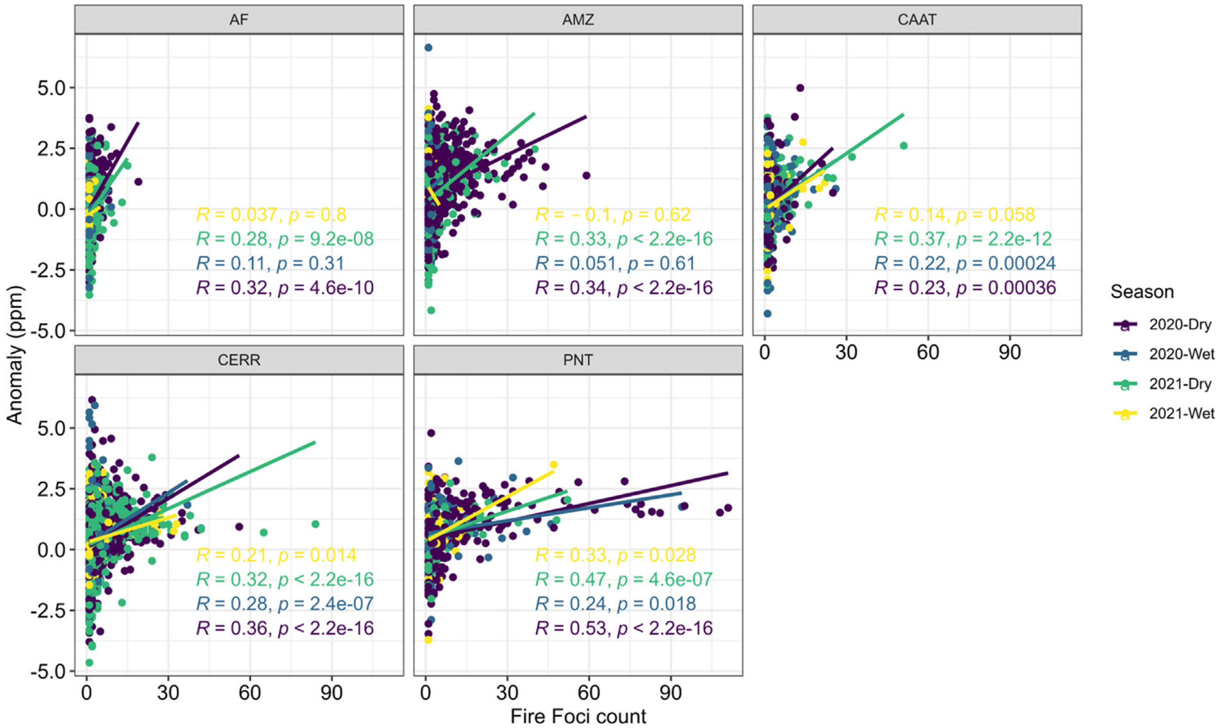

Fig. 8. Scatter plot between XCO_2 anomalies (ppm) and Fire Foci (count) in the different biomes for each season, with Spearman's correlation values inside the panels, only considering good quality observations (quality flag = 0). Where AMZ = Amazon, AF = Atlantic Forest, CERR = Cerrado, CAAT = Caatinga, and PNT = Pantanal.

number of fires were observed in 2020 (200 % higher than the average between 2003 and 2019) and about 40 % of them occurred in forests, which represented a release of 70 Gg C. These fires were mostly associated with human activity, where 70 % of them occurred inside rural properties and 15 % in indigenous lands or protected areas (Barbosa et al., 2022).

In this study, for the first time, the combination of the two NASA missions was used to observe XCO_2 anomalies and how this could be used to understand carbon sources and sinks, specifically in our case fire incidence. Given that fires are closely linked to CO_2 emissions to the atmosphere (Aragão et al., 2018) and that positive XCO_2 anomalies can be indicative of emission sources (Hakkarainen et al., 2016), this corroborates the positive relationships between Fire Foci and XCO_2 anomalies, both over time and spatially, similar to that reported by Hakkarainen et al. (2019) who observed spatial similarity between anomalies and emissions from biomass burning in Africa.

This relationship is most evident precisely in the biomes most impacted by fires (Amazon, Pantanal, and Cerrado) but also with similarities to fire foci over Caatinga and Atlantic Forest. Finally, this relationship is insignificant in the Pampa because this biome is little affected by fires (Oliveira et al., 2022), presenting an almost zero density in all periods studied. Additionally, during dry periods, this relationship is more significant because the seasonality of fire outbreaks is more intense and frequent in this period (Alencar et al., 2022; Menezes et al., 2022). When we consider the observations that did not pass through the cloud mask (quality_flag $\leq$ 1), the relationship slightly increases. This effect may be related to the smoke and aerosols production from fire, which are interpreted as clouds depending on the detection algorithm used (Sokolik et al., 2019; Wooster et al., 2021), such as the case for OCO-2 & 3 (Crisp et al., 2017; O'Dell et al., 2018; Eldering et al., 2019; Taylor et al., 2020).

4.3. Limitations

Although the correlation values can be considered moderate, and even low (less than 0.5), this could be ascribed that positive anomalies are also related to other factors, such as land use changes (Silva Junior et al., 2020; Kondo et al., 2018). However, across the literature, it is not unusual to find a moderated correlation between XCO_2 and other environmental aspects (Parazoo et al., 2013; Albright et al., 2022; Morais Filho et al., 2021; da Costa et al., 2022b; Odorizzi de Campos et al., 2022; Araújo Santos et al., 2022; Jiang et al., 2022).

Moreover, not all anomalies are positive (hotspots), some of them are likely related to CO_2 sinks (Golkar and Mousavi, 2022; Fu et al., 2022; Hakkarainen et al., 2019). Despite we only used collocated observation it is not trivial to exclude all unwanted processes (Gatti et al., 2021; Wu et al., 2021), and the CO_2 vegetation absorption process could explain some of the sink probability observation in our results. All these aspects influence these possible

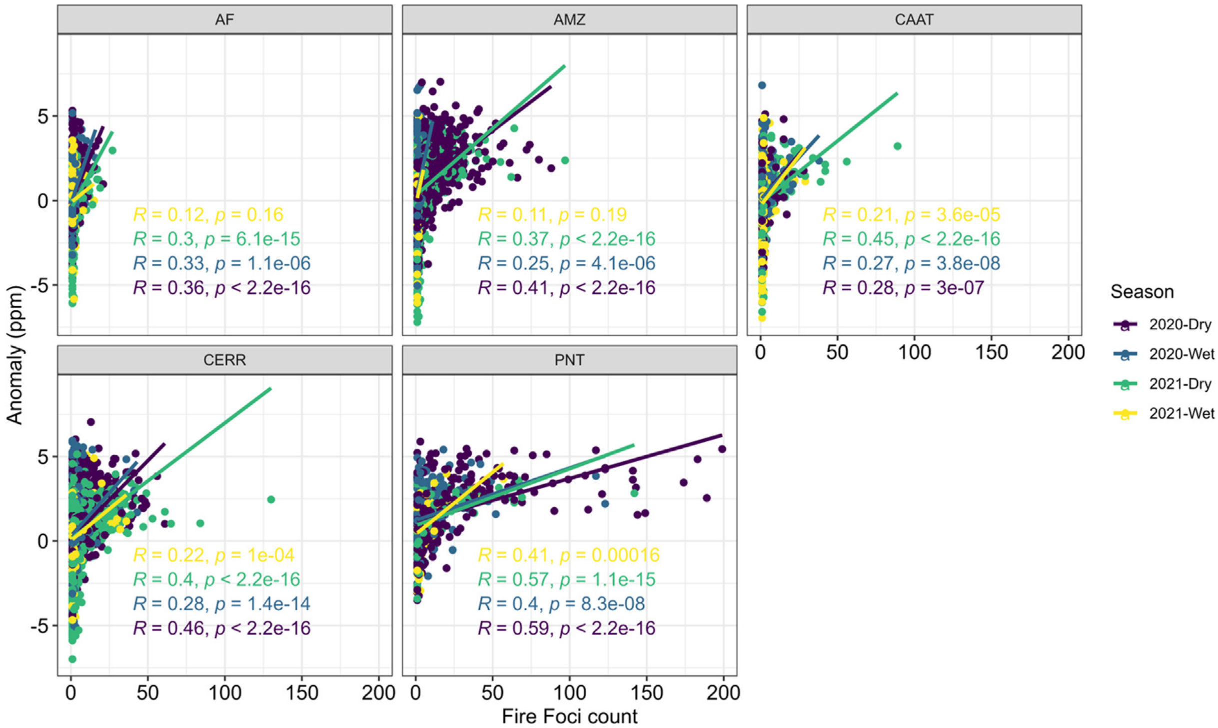

Fig. 9. Scatter plot between XCO_2 anomalies (ppm) and Fire Foci (count) in the different biomes for each season, with the Spearman's correlation values inside the panels, combining good quality observations (i.e., cloud-free, quality flag = 0) and bad quality observations (i.e., with cloud, quality flag = 1). Where AMZ = Amazon, AF = Atlantic Forest, CERR = Cerrado, CAAT = Caatinga, and PNT = Pantanal.

CO_2 sources and sinks, and despite that, in this study, we point to one cause of the positive anomalies and explore the potential of joining data from the OCO-2 and OCO-3 missions.

Another factor that can impact is the different resolutions of the remote sensing products and the different observation strategies (Giglio et al., 2016; Crisp et al., 2017; Eldering et al., 2019), even with those differences being minimized. Furthermore, although there are limitations, our results show an indication of how positive XCO_2 anomalies are related to fire foci, and how cloud detection could improve these results.

5. Conclusion

In general, the positive anomalies are greater in the Amazon biome for the studied period, which is related to territorial extension and the higher emission rates that this biome has been presenting recently. The fire foci had a higher occurrence during dry periods due to the natural variability of occurrence itself, however, we notice that the frequency in 2020 was higher and this is ascribed to the unprecedented fire alarms in Brazil during this period. Furthermore, the most fire-affected regions were the Amazon, Pantanal, and Cerrado.

It was possible to observe similarities between the spatial distribution of Fire Foci and the probability of positive XCO_2 anomalies in some regions of Brazil, corroborated by the positive relationship between Fire Foci and XCO_2 anomalies (R between 0.2 and 0.5). Despite not being a high correlation, they were significant, thus presenting a good indicator of possible sources related to fire occurrence. Moreover, during the dry period the correlations slightly increase, this is attributed to the higher incidence of fires in this period and as a consequence, this indicates a greater potential of CO_2 emission related to fire, especially when the fire isn't properly managed or controlled. Complementarily this relationship was more significant in the biomes most affected by fires. When we consider not only the good-quality observations but also the observations with cloud cover (quality_flag $\leq$ 1) the correlation values increase, this may indicate that the smoke clouds produced by fire may be contained in this classification.

Despite certain limitations linked to the anomaly model adopted, cloud cover itself at certain periods, and unwanted signals, we have shown that it is feasible to combine the OCO missions to improve the spatial coverage of CO_2 observations, we applied this approach to studied the fire foci relation with possible CO_2 sources, however in the future this could be applied to several environmental studies.

CRediT authorship contribution statement

Luis Miguel da Costa: Conceptualization, Formal analysis, Methodology, Data curation, Writing – original draft, Writing – review & editing. **Gustavo André de Araújo Santos:** Formal analysis, Data curation, Writing – review & editing. **Gislaine Costa de Mendonça:** Formal analysis, Data curation, Writing – review & editing. **Luciano de**

Souza Maria: Formal analysis, Data curation, Writing – review & editing. **Carlos Antônio da Silva:** Data curation, Writing – review & editing, Supervision. **Alan Rodrigo Panosso:** Formal analysis, Methodology, Data curation, Writing – review & editing, Supervision. **Newton La Scala:** Conceptualization, Methodology, Data curation, Writing – review & editing, Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.asr.2024.01.016.

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