XCO_2 AND SIF ANOMALIES LINKED TO LAND USE OVER SÃO PAULO- BRAZIL

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ABSTRACT

Climate change is one of the main global concerns today, primarily caused by the emissions CO_2 into the atmosphere. The major emission source of this gas into the atmosphere comes from the burning of fossil fuels and the principal absorption source is photosynthesis. Using Xco_2 and SIF data obtained from the Orbiting Carbon Observatory 2 (OCO-2) between the years 2015 and 2019, we use anomaly models to study their temporal variability in São Paulo - Brazil, and complementarily using the ordinary kriging technique, we analyze the spatial distribution of the anomalies. Our results indicate an inverse relationship between Xco_2 and SIF anomalies, and that the negative CO_2 anomalies (sinks) are concentrated in the forest canopy. In general, we observe that vegetation covers act as CO_2 sinks and that urban environments are a source of emissions in the state of São Paulo.

Key words *— Remote sensing, Climate change, Carbon climate feedback, photosynthesis*

1. INTRODUCTION

Climate change is one of the main global concerns in the current scenario, one of its aggravating factors being carbon dioxide (CO_2) emissions into the atmosphere. These emissions, for the most part, come from the burning of fossil fuels [1], in contrast, plants and soil act as sinks of this gas [2].

Although plants and soil act as sinks, it depends on the intensity of anthropic action on them. Agricultural environments for example, at harvest and planting time, can act as a source of CO_2 to the atmosphere [3]. However, if sustainable practices are used in these seasons to minimize CO_2 emissions, the development phase of the agricultural crop can offset what was emitted by assimilating carbon into its biomass through photosynthesis [4].

Another example is the forests, they store 60% of the terrestrial biomass and their soil carbon stock reaches 40% of the world's stock [5], in this sense, anthropic actions in these environments are extremely harmful, given the amount of carbon that would be emitted [6], in addition to the loss of biodiversity [7].

In this context, the study of anomalies of the average column of CO_2 concentration in the atmosphere (Xco_2) has become a great way to monitor carbon sources and sinks, at globally [8] and regional [9] scales. However, some of this model disregarded atmospheric transport [10], and not further explore is how each use and occupation act on these dynamics.

The studies of anomalies in large areas are possible due to the launch of space missions whose goal was to monitor this gas, such as the case of the Orbiting Carbon Observatory 2 and 3 (OCO-2 and OCO-3) [11, 12]. In addition to enabling Xco_2 monitoring, these two missions also monitor Solar-Induced chlorophyll Fluorescence at 757 nm and 771 nm (SIF) [13].

The relationship between Xco_2 and SIF is widely explored in various contexts and scales, such as on global scales [12] and regional scales [14], in agricultural environments [15] or forests [16], and all these studies point in the same direction, that the relationship between these two variables is inverse Thus, we can assume that the decrease in Xco_2 values and the increase in SIF values are a consequence of photosynthetic activity [15].

Given this, aiming to elucidate the role of forests and agriculture in this context, we investigate how these land uses behaviors as well in other environments, elucidating how photosynthesis influences different land uses and occupations.

2. MATERIAL AND METHODS

2.1 Study area and land use data

The study region is the state of São Paulo, Brazil, which is 2.5×10^5 km^2 in area. The state is composed of different land covers, and this land covers was classified according with Copernicus data [17].

2.2 Data from OCO-2

In this study, we use Xco_2 and SIF_{757} data for the time series from January 2015 to December 2019, with a spatial resolution of 0.25°, product version 9, where these data are already preprocessed before availability, that is, the data already has the bias corrected and with the best coverage quality (quality flag = 0, alert level < 12) [11].

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2.3 Anomalies Models

2.3.1 Xco_2 anomalies

The anomaly model used was proposed by Hakkarainen et al [8], where positive anomaly values (hotspots) are considered as possible sources of CO_2 emission to the atmosphere, and negative anomalies (coldspots), are considered as possible CO_2 sinks, however, because our study is regionalized, unlike the baseline study that was conducted at a global scale, we adapt the formula to our purposes (Eq. 1). Recently Labzovskii et al. [9] also made adaptions in the original formulation for the same reasons:

$$Xco_{2\,(anomalies)} = Xco_{2\,(i,j)} - M_e(Xco_{2\,(j)}) \quad \text{(Eq. 1)}$$

Where $Xco_{2\,(i,j)}$ is the i observation at the year j, and $M_e(Xco_{2\,(j)})$ is the Xco_2 median for the year j.

2.3.2 SIF anomalies

The fluorescence (i.e., SIF) anomaly model adopted was based on the study by Zhang et al. [18]. following the same logic as the Xco_2 anomaly model (Eq. 1), we adapted the original model to an annual scale to make our analyses more realistic.

$$SIF_{(anomalies)} = \frac{SIF_{(i,j)} - \overline{SIF_{(j)}}}{\overline{SIF_{(j)}}} \quad \text{(Eq. 2)}$$

Where $SIF_{(i,j)}$ is the i observation at the year j, and $\overline{SIF_{(j)}}$ is the mean value of fluorescence for the year j.

2.4 Spatial analysis

The spatial variability analysis of Xco_2 and SIF anomalies was calculated by the ordinary kriging (OK) interpolation method, the interpolation was made directly in ArcMap software. The data that constituted the analysis was the general averages for each coordinate over the entire time series.

In addition to kriging, we analyzed the dispersion measures (i.e., mean, standard deviation) of the anomalies for the main land use/cover in the study area. The land-use information was collected through Copernicus dataset.

For this, we used the locations in the kriging that matches with the land use and retrieved these values using the tool extract by mask in the ArcMap software.

3. RESULTS

Concerning the spatial distribution of anomalies, Xco_2 (Figure 1a) has a minimum of -1.65 ppm (coldspot) and a maximum of 1.3 ppm (hotspot) for the entire period analyzed (2015 to 2019), while the anomalies of SIF_{757} (Figure 1b) ranged between 0.45 and -0.47. There is an inversion between the SIF757 and Xco_2 anomalies in certain regions of the state, as in the central region (longitude between 50 and 49 w, latitude ~22 S), while there is a coldspot of Xco_2 in that region we can also observe a positive anomaly of SIF. A little above the highlighted point, there is the presence of a hotspot for CO_2 concentration while for SIF it is a negative anomaly. In the south of the state, the same occurs, with an inverse relationship between the variables, being there a negative anomaly for Xco_2 and a positive for SIF. At the eastern border of the state, from south to north, there is a 'pathway' of Xco_2 hotspots while for some points in this region the SIF shows negative anomalies (Figure 1).

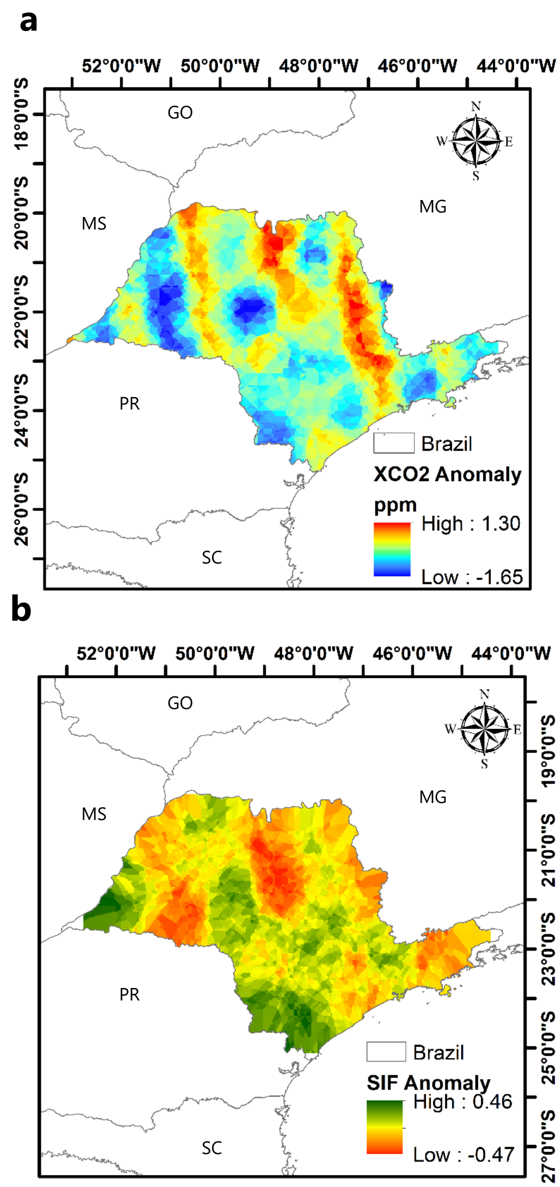

Figure 1. Space patterns of the average Xco_2 (a) and SIF (b) anomalies for São Paulo's State during 2015-2019 using ordinary kriging.

Considering each land use and land cover in the region, the average Xco_2 anomaly, in the whole time-series, for agricultural use is -0.14 ± 0.55 ppm, concerning forest is -0.28 ± 0.49 ppm. For herbaceous vegetation it is -0.28 ±

0.54, in shrubland it is -0.25 ± 0.54 ppm and finally in urban areas, it is 0.03 ± 0.51 ppm (Figure 2a). Concerning the averaged anomalies of SIF in the years analyzed above the land use, in the agricultural environment, the average was -0.02 ± 0.15, for the forest was 0.05 ± 0.16, herbaceous vegetation was 0.02 ± 0.16, concerning shrubs was -0.004 ± 0.15 and in urban use was 0.005 ± 0.15 (Figure 2b).

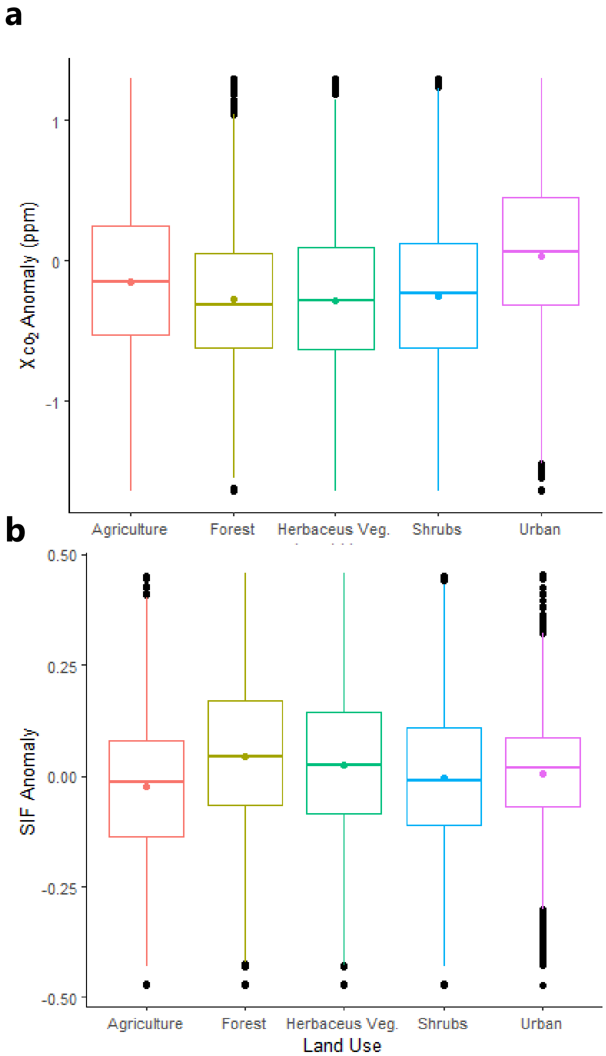

Figure 2. Box plot of Xco_2 and SIF anomalies from 2015-2019 estimated by kriging, considering the main land-use/occupation.

4. DISCUSSION

It can be noted that the forest, in general, is the use that most acts as a carbon sink and at the same time is where the highest average positive anomalies of SIF occur (Figure 2). Forests alone are responsible for 60% of the planet's photosynthesis and terrestrial biomass, carrying out about 30% of primary production [5]. Moreover, due to the stability of this ecosystem, the photosynthetic activity in this environment does not show much variability throughout the [19] making this use one of the most indispensable in the context of CO_2 mitigation.

In the agricultural area, emissions are highly heterogeneous. In the São Paulo state, those areas present greater variability in Xco_2 and SIF anomalies and represent a critical point in the carbon balance, since some of these agricultural uses can be converted into potential carbon sinks [4]. More conscious agricultural production models that the state of São Paulo has adopted since 2012, employing techniques such as no-till farming and ground cover, encouraging the implementation of agroforestry systems in addition to not advancing the agricultural frontier in natural environments, but rather recovering degraded pastures [20,21], provide strategies to control agriculture-related carbon emissions. However, not all areas of agricultural use act as a sink, these areas are possibly regions where management activities are negatively affecting CO_2 assimilation (Figure 1a, and b).

As in other studies, we find that the urban environment is a source of CO_2 in the atmosphere [8, 9]. This result may be related to several factors, the main one being fossil fuel burning [1]. Some actions to reverse this scenario would be the investment in green areas within urban centers [22], other actions can be the replacement of fossil fuels for biofuels such as ethanol, given that Brazil is the second-largest producer of this fuel [21].

5. CONCLUSIONS

The forest is the largest carbon sink among all uses and inversely presents the highest SIF anomalies, demonstrating the importance of maintaining this ecosystem for São Paulo's state in Brazil. The agricultural environment, in general acts as a sink, however in some places and depending on management conditions it can act as a source of carbon. Another key point, is the seasonality, however, due to limitations in the amount of available data it was not possible to study this aspect. Regarding shrubs and herbaceous vegetation, they can be used as a short-medium term strategy for the implementation of green areas in urban environments, aiming to reduce the emissions that this use is responsible for.

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