CARBON DIOXIDE SPATIAL VARIABILITY AND DYNAMICS IN CENTRAL BRAZIL AGRICULTURAL FRONTIER VIA REMOTE SENSING DATA

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ABSTRACT

The objective of this study was the carbon dioxide (CO_2) spatiotemporal dynamics and related factors assessment during 2015–2018 in the state of Mato Grosso, Brazil. The data were obtained through a temporal series of remote data and multispectral imagery. We observed that forest areas converted to other land uses reached higher values, that characterize with sources, and those the highest and lowest average concentrations of CO_2 are related to the dry and rainy months, respectively, for dry air mole fraction (X_{CO2}) in the atmosphere, which might be the result of differences in the vertical resolution of the CO_2 column and scale. Therefore, both X_{CO2} and CO_2 flux are related land use and land cover changes (LULCC), looking at complex systems that are affected by climatic variables and processes, such as photosynthesis and soil respiration.

Key words — Carbon dioxide, X_{CO2}, land use and land cover.

1. INTRODUCTION

The sustainable expansion of the world economy is directly linked to greenhouse gas (GHG) sources and sinks in production systems [1].

The high rates of GHG emissions related to agriculture come out from the inappropriate use of soil and water resources, the excessive use of agrochemicals, such as fertilizers [2], deforestation, and the use of fire for pasture management, renewal and expansion of areas, and farming activities [3, 4].

Land use and land cover change (LULCC) for commodity production is one of Brazil's main GHG sources, making the country responsible for 2.8% of global emissions [5]. Among its producing regions, the state of Mato Grosso (SMT) is the country's leading agricultural frontier as it is the main commodities producer [6, 7]. In particular, the SMT leads national production in soybeans and animal protein, which are drivers of deforestation, accounting for 22 Mha of pastures and 10.2 Mha of areas cultivated with soybean in 2018 [8].

Given this, it is interesting to highlight the importance of estimating biophysical parameters of vegetations and correlating CO_2 concentrations through geotechnologies.

Therefore, the objective of this study was to use remote sensing approach on CO_2 spatiotemporal dynamics of assessment, from 2015 to 2018 in the SMT.

2. MATERIAL AND METHODS

In this study, column-averaged carbon dioxide (CO_2) dry air mole fraction in the atmosphere, set as X_{CO2} data was based on Orbiting Carbon Observatory-2 satellite, ranging from January 2015 to December 2018.

The enhanced vegetation index (EVI) data were based on the Moderate-Resolution Imaging Spectroradiometer (MODIS) sensor, and rainfall data stem from the Climate Hazards Group InfraRed Precipitation with Station dataset. From Landsat-8 satellite image series, it was possible to distinguish land use and land cover classes, as estimate the CO_2 flux over the study site.

To study the temporal variation of the variables, scatter plots and boxplots were made on the evaluated time series. Furthermore, a heatmap containing Pearson's correlations between variables was made. The statistical analyses were performed using R software [9].

3. RESULTS

A Pearson's correlation analysis was applied to check the relation between X_{CO2} and the other variables (Figure 1). The CO_2Flux (Figure 1) had positive correlations (r = 0.66, 0.68, and 0.44, respectively) with rainfall, SPI, and the EVI, due to the vigor of photosynthetically active vegetation, allowing it to capture the absorption from carbon in the process of photosynthesis and loss through respiration.

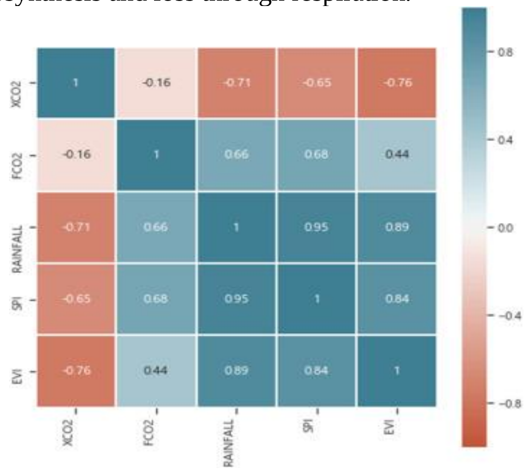

Figure 1. Heatmap of Pearson's correlation matrix for X_{CO2} with CO_2 flux (FCO_2), rainfall, and standardized precipitation index (SPI-12) for the State of Mato Grosso, Brazil.

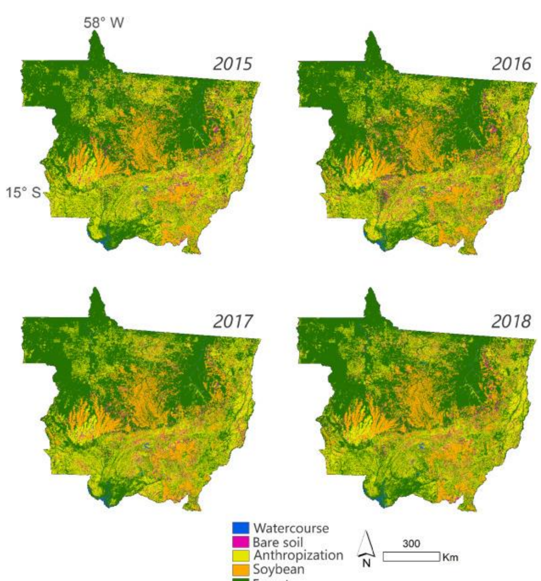

Figure 2. Land use in the State of Mato Grosso, Brazil during 2015, 2016, 2017, and 2018.

The NDFI (Figure 2) showed an expansion in variations in land cover from the exposed soil area (bare soil) to the anthropization area in the southeastern region of the SMT between 2016 and 2017. Meanwhile, in the northeastern region, soybean crop areas were replaced by exposed soil.

In addition, the forest areas underwent significant changes in the southern part of the state, wherein 2015 and 2017 presented least fragmented forest areas than 2016 and 2018. In the northern region, there was an increase in soybean production areas as a result of direct forest replacement and forest/grassland succession.

The annual average rainfall in 2015 was the highest in the northwest region, but gradually shifted to the center and north by 2018. According to the rainfall, 2015 had the worst distribution, 2016 and 2018 had an equal distribution, and 2018 had the highest distribution and volume of rainfall.

The SPI-12 shows varying drought conditions in the SMT during the study period. In particular, the average annual results showed that among the years evaluated, 2015 experienced the most severe drought, while 2018 was the rainier year. The northeast, north, northwest, west, and southwest regions in 2015 presented drought records associated with extreme to moderate droughts, revealing the highest annual drought spatialization, as compared as the next three years. Further, 2018 had the lowest total average annual drought.

The CO_2 flux results showed that the northwest and northeast regions had the lower CO_2flux results, which was consistent for all study years. These regions are characterized by the highest percentages of forest vegetation areas (Figure 3).

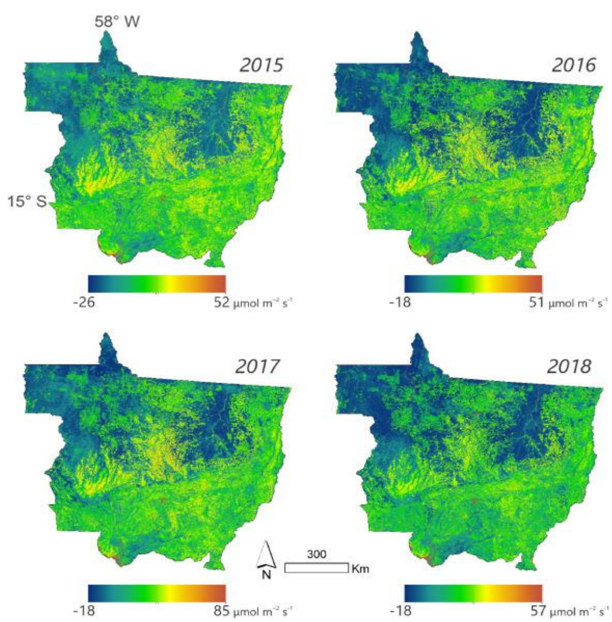

Figure 3. CO_2 flux for the state of Mato Grosso, Brazil for 2015, 2016, 2017, and 2018.

The spatial pattern results of the atmospheric concentration of annual averages of X_{CO2} revealed that the maximum observed values were 402 ppm 405 ppm over the study period (Figure 4). Conversely, in the mid-north regions, the CO_2 flux exhibited opposite behavior, revealing higher amounts and positive values for CO_2. Note that this region is a major soybean producing area in the state, consisting of municipalities such as Sorriso, Sapezal, and Sinop.

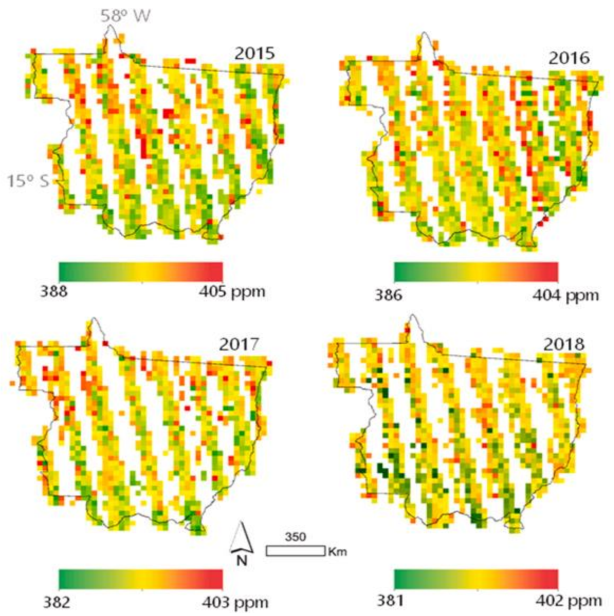

Figure 4. Spatial patterns of atmospheric X_{CO2} concentration for the State of Mato Grosso, Brazil for 2015, 2016, 2017, and 2018.

In the mid-north regions, hotspots were observed in 2015 and 2016. Note that 2015 and 2016 had higher atmospheric spatial patterns of X_{CO2} concentration (ppm) than 2017 and 2018. Further, in the northwest and northeast regions, we observed higher atmospheric spatial concentrations of X_{CO2}. Therefore, the hotspots had lower values in 2018 than the other years, showing a 0.7% reduction in the annual averages of X_{CO2} concentration (ppm), as compared with that of 2015.

4. DISCUSSION

LULC changes are driving factors of the carbon cycle. Specifically, different land uses influence CO_2 absorption and CO_2 flux to the atmosphere [10]. For example, forested areas tend to sequester CO_2 from the atmosphere [11, 12], incorporate carbon into their biomass, and split it into the soil.

Note that the areas in the mid-north of the SMT had a concentration of positive values of the highest annual averages of CO_2 flux, indicating carbon loss to the atmosphere via respiration. Also note that this region has intense farming [13]. Land use change [14, 15], can explain the higher observations of CO_2 fluxes in these areas. In particular, net carbon fluxes from LULC changes accounted for 12.5% of anthropogenic carbon emissions over the last decade [16] (Houghton et al., 2012).

Increase of 3 ppm and 2 ppm in 2015 and 2016, respectively, in the observed maximum annual atmospheric X_{CO2} concentration, as compared with that of 2018, can be attributed to influence of El Niño [17, 18, 19, 20] which contributes to a global increase in atmospheric CO_2 as a response of the terrestrial carbon cycle induced by changing weather patterns [21].

The severe drought observed in 2015 was also the result of El Niño events [18]. Meanwhile, 2018 was an extremely wet year in the central region of the SMT, which ultimately resulted in lower X_{CO2} values.

Chhabra and Gohel (2020) mentioned that high rainfall contributes to vegetation growth and development and increases photosynthetic activity, thus reducing the atmospheric CO_2 concentration. Thus, monthly CO_2 concentration fluctuations can be linked to water vapor content, rainfall, and vegetation cover [22, 23].

5. CONCLUSIONS

Regarding spatial variability, converting forests into other land uses caused increased CO_2 concentrations over the SMT. Similarly, areas with large forest ranges presented lower CO_2 concentrations, mitigating climate change.

Therefore, not only X_{CO2} but also CO_2 concentrations are directly related to LULC in complex systems that are affected by climatic variables and processes, such as photosynthesis and soil respiration.

Thus, we conclude that, remote sensing provides reliable and accessible data for spatio-temporal dynamics of CO_2 monitoring, as detecting possible changes with time series.

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