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JABOTICABAL CAMPUS**

**OBTAINING CARBON FEEDBACKS IN THE BIG DATA ERA:
A PERSPECTIVE TO CENTRAL-NORTH OF BRAZIL**

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Agronomist

2020

**SÃO PAULO STATE UNIVERSITY – UNESP
JABOTICABAL CAMPUS**

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A PERSPECTIVE TO CENTRAL-NORTH OF BRAZIL**

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GUSTAVO ANDRÉ DE ARAÚJO SANTOS – Son of Magno Mansueto dos Santos Araújo and Maria Leônora de Araújo, he was born in Imperatriz - MA, on February 17, 1991. He attended minor elementary school at the Escola Municipal Samaritana and the middle school at the Amaral Raposo State College, in that same school he finished high school in 2008. In August 2010, he joined the Agronomy course at the Center for Agrarian and Environmental Sciences of the Federal University of Maranhão (UFMA-CCAA) campus of Chapadinha. He was a scientific student fellow in three projects. In September 2012, he began his international academic mobility through the Ciências sem fronteiras program at the Instituto Superior de Agronomia in Lisbon - Portugal, with a return in August 2013. In January 2016, he underwent banking for monograph defense, approved as a bachelor's degree in Agronomy. In March 2016, he started the Master's degree in Agronomy (Soil Science), at the Faculty of Agrarian and Veterinary Sciences (FCAV-UNESP), Campus of Jaboticabal-SP. On July 17, 2017, he submitted to the Master's defense, approved as a Master in Agronomy (Soil Science). In August 2017, he started his Ph.D. course in Agronomy (Soil Science) also from FCAV-UNESP. In 2018 he attended the summer school in Data Science at the International Centre for Theoretical Physics (ICTP) in Trieste, Italy, with UNESCO support. In December 18, 2020, he submitted the doctoral thesis to an examination panel, and received his Ph.D. degree in Agronomy (Soil Science) at UNESP/FCAV.

"Educação não transforma o mundo. Educação muda as pessoas. Pessoas transformam o mundo."

Paulo Freire

"You cannot hope to build a better world without improving the individuals. To that end, each of us must work for his own improvement and, at the same time, share a general responsibility for all humanity, our particular duty being to aid those to whom we think we can be most useful."

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I DEDICATE

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OBTAINING CARBON FEEDBACKS IN THE BIG DATA ERA: A PERSPECTIVE TO CENTRAL-NORTH OF BRAZIL

ABSTRACT – With the emergence of the era of earth observation in high resolution, remote sensing data's exponential growth has occurred in recent years. Thus, it is possible to carry out studies to monitor the carbon cycle on a global and regional scale, thus generating carbon feedback that can contribute to climate governance and decision-making to mitigate the effects that cause climate change. Therefore, this study was designed with the purpose of printing feedbacks related to the carbon cycle using Big Data in earth observation using remote sensing and climatic variables obtained by simulation models for the Central-North of Brazil, an important region due to the presence of important biomes such as the Amazonia, Cerrado, Pantanal and Atlantic Forest, besides being one of the most representative regions in the advancement of Brazilian agribusiness. Three studies were carried separately for the following sub-regions: Mato Grosso, Mato Grosso do Sul, and Eastern Amazonia. For each region were discussed different problems. A time series was analyzed from January 2015 to December 2018. The variables X_{CO_2} , Solar-induced fluorescence at 757nm, and 771nm were extracted from Orbiting Carbon Observatory-2 -OCO-2. The NDVI (MOD13A1), EVI (MOD13A1), and evapotranspiration (MOD16A2), data from Moderate Resolution Imaging Spectroradiometer - MODIS and climate variables (precipitation, wind speed, air temperature and relative humidity) as of Prediction of Worldwide Energy Resources - NASA POWER. The data were submitted to descriptive statistics, regression, correlation, temporal analysis and spatial interpolation with the kriging method and hotspots. It was observed that both in biomes and forest areas in Mato Grosso do Sul, the temporal variation of atmospheric CO_2 concentration is mainly governed by photosynthesis ($SIFR^2_{adj.} = 0.07-0.55$; $p < 0.05$, $NDVIR^2_{adj.} = 0.18-0.63$; $p < 0.05$, and $EVIR^2_{adj.} = 0.20-0.49$; $p < 0.05$) and that photosynthesis is positively related to evapotranspiration ($R^2_{adj.} = 0.20-0.44$; $p < 0.001$) and air temperature ($R^2_{adj.} = 0.26-0.44$; $p < 0.001$). In Mato Grosso and Eastern Amazonia, SIF was also an important variable in explaining the temporal variability of X_{CO_2} ($r = -0.84$; $p < 0.01$). However, in these regions, this relationship is also observed spatially. In general, the time variations of X_{CO_2} in the north-central region of Brazil varies between the dry and rainy periods, this was clear in all studies. As for the spatial variation of X_{CO_2} , it varies according to the type of land use and the time of year. Given the results presented in this work, it is clear that the use of big data from remote sensing observations are valuable tools in understanding the carbon cycle since the relationships observed in the intersection of these data generate results that are clearly explained by the physical and biological processes around the soil-plant-atmosphere system.

Keywords: Carbon cycle, Climate Change, MODIS, NASA POWER, OCO-2, SIF

LIST OF ABBREVIATIONS AND ACRONYMS

AIRS-NASA - Atmospheric Infrared Sounder from the National Aeronautics and Space Administration

CH₄ – Methane

CO₂ - Carbon dioxide

COP21 - 21st Climate Conference

DSD - Degree of spatial dependence

ESA - European Space Agency

EVI - Improved Vegetation Index

fAPAR - Fraction of photosynthetically active radiation absorbed by vegetation

GEOS-4 - Global Model and Assimilation Office

GHG - greenhouse gas

GOSAT - Greenhouse Gases Observing Satellite

IBGE - Brazilian Institute of Geography and Statistics

INMET - National Institute of Meteorology

IoT - Internet of Things

IPCC - Intergovernmental Panel on Climate Change

JAXA - Japan Aerospace Exploration Agency

LAI - Leaf area index

LAPIG - Image Processing and Geoprocessing Laboratory

MODIS - Moderate Resolution Imaging Spectroradiometer

N₂O - Nitrous oxide

NASA/POWER - National Aeronautics and Space Administration / Prediction of Worldwide Energy Resources

NDVI - Normalized difference vegetation index

NOAA - National Oceanic and Atmospheric Administration

OCO-2 - Orbiting Carbon Observatory-2

OCO-3 - Carbon Observatory – 3

SCIAMACHY-ESA - Scanning Imaging Absorption Spectrometer for Atmospheric CHartographY from European Space Agency

SIDRA - Automatic Recovery System

SIF - Sun-induced chlorophyll fluorescence

SMAP - Soil Moisture Active Passive

TES - Tropospheric Emission Spectrometer

W m⁻² sr⁻¹ μm⁻¹ – Watt per steradian per square metre per micrometres

X_{CO2} - Column-averaged dry-air mole fraction

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CHAPTER 1 – General considerations

1 INTRODUCTION

Between 1880 and 2012, the average temperature of the planet increased around 0.85 °C. The increase in temperature observed in recent decades is mainly due to increased greenhouse gas (GHG) emissions (Diffenbaugh et al., 2015; Medhaug et al., 2017). The carbon dioxide CO₂ concentrations have increased by about 40% since the beginning of the industrial era. This exponential increase in CO₂ emissions is due to the burning of fossil fuels, deforestation and land-use change (Quéré et al., 2015; Schimel et al., 2015). Given this perspective, numerous studies try to prospect the responses of different regions of the planet under scenarios related to the climate system (Parazoo et al., 2016; Silva Junior et al., 2020)

The soil-plant-atmosphere system is closely related to these scenarios since the biogeochemical cycles of the leading gases responsible for the greenhouse effect pass through the soil, plants and atmosphere, with particular attention to carbon and nitrogen (Finzi et al., 2011). In addition to these, water is also a part of its cycle with in the soil, therefore being a closed, complete and complex system (Seneviratne et al., 2010). Thus, researchers have joined forces to try to understand how climate change can interfere with the ecosystem, seeking alternatives that mitigate the effects of climate change, especially in agriculture (La Scala et al., 2000; Santos et al., 2019; Silva et al., 2019; Xavier et al., 2020).

It is important to emphasize that carbon plays a crucial role in the supply of energy with in the soil-plant-atmosphere system through its cycle (Chapin, Matson, 2011). In this cycle, a series of feedback mechanisms are responsible for the carbon response to the increase in the planet's temperature (NRC, 2003). There is evidence that carbon feedbacks are sensitive to temperature, hydrological cycle and land-use change (Goodwin et al., 2019; Williams et al., 2019). However, these sensitivities are still uncertain due to the uncertainties related to other factors that also influence the carbon cycle, such as nutrient availability like nitrogen (Goodwin, 2019). Besides, the availability of data for significant studies again emerges as a limiting factor.

On the other hand, as the development of technologies aimed at earth observation, especially remote sensing through satellites, a quantity of massive data related to the carbon cycle has been made available in recent decades (Chi et al., 2016; Xu and Xiaoping, 2020), being possible to apply in various fields of science (Silva Junior et al., 2020; Rossi and Santos, 2020; Taylor et al., 2021). The explosion in data generation in the most diverse areas of knowledge has been called the big data era (Chen et al., 2014). This expression is related to the volume, speed, and variety of information produced by different sources in a short time (Lioutas, 2020). A large amount of data generated today is only possible on account to the emergence of technologies such as mobile devices, social networks, satellites, portable sensors, weather stations and model applications for estimated data (Kamilaris et al., 2017; Majumdar et al., 2017)

The advance in data generation has contributed to innovative discoveries in various areas of knowledge in climate science, e.g., the variety and quantity of data have states available in a way never seen before (Shannon, 2019). Furthermore, climate science promises to be one of the largest data sources for data-driven research (Faghmous & Kumar, 2014). According to these authors, it is estimated that in 2010 the available climate data had already reached the volume of 10 Petabytes (1PB= 1.000TB). This number tends to increase exponentially to about 350 Petabytes by 2030. For example, The National Aeronautics and Space Administration (NASA) is considered one of the most important institutions in data generation, being able to generate 12.1TB of data daily through its active missions around Earth and space. Besides, with advances in orbital sensors' development, NASA expects that some of the space agency's missions can generate up to 24 TB a day (Shannon, 2019).

From this perspective, in 2014, NASA launched the Orbiting Carbon Observatory-2 (OCO-2) (Annmarie Eldering et al., 2017). With the launch of the OCO-2 spacecraft, NASA presented the world with an important tool regarding understanding fundamental processes that act on the absorption and emission of CO₂. However, OCO-2 was not the first satellite launched to measure atmospheric CO₂. Before that, we had other sources as the Scanning Imaging Absorption Spectrometer for Atmospheric CHartographY from European Space Agency (SCIAMACHY-ESA) were launched, both able to do this monitoring, but these missions were closed in 2012

(Pan et al., 2021). NASA launched AURA in July 2004 with the Tropospheric Emission Spectrometer (TES) with a better spatial resolution than AIRS and SCIAMACHY. The Greenhouse Gases Observing Satellite (GOSAT) was launched in January 2009 by Japanese national Aerospace (JAXA) to detect CO₂ and CH₄ (Yokota et al., 2009; Frankenberg et al., 2011). However, The OCO-2 was the first to provide the high accuracy, resolution and coverage needed to observe regional carbon sources and sinks. This is due to the OCO-2 ability to make about 16 million measurements each cycle with orbit trails separated by less than 1.5 degrees longitude at the equator (Eldering et al., 2017; Schwandner et al., 2017).

Two of the most important variables measured by OCO-2 are the carbon dioxide (CO₂) column-averaged dry-air mole fraction (X_{CO_2}) and Solar Induced Fluorescence (SIF). X_{CO_2} is the average CO₂ concentration in a column that goes from the earth's surface to the top of the atmosphere (Crisp et al., 2012). SIF is considered the most modern in vegetation analysis via remote sensing because SIF is directly related to photosynthesis's internal mechanisms (Xiao et al., 2019). In this sense, the SIF stands out because it can indicate the photosynthetically active vegetation, unlike other more traditional vegetation indicators such as NDVI, which detect only green leaves' presence (Mohammed et al., 2019).

The understanding of carbon dynamics via remote sensing using various sensors and OCO-2 data has been wide of the world (Gao et al., 2020; He et al., 2020). Zhaleh Siabia et al. (2019) observed in Iran that both soil cover and vegetation cover play essential roles in the spatial distribution of CO₂ and the discovery of carbon dioxide sources and sinks. In India, Chhabra and Gohel, (2019) also observed the importance of vegetation and different soil cover types in controlling atmospheric CO₂ concentrations.

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CHAPTER 5 – Final remarks

The increase in the planet's average temperature in recent decades is tied to the increase in greenhouse gas concentration (GHG) resulting from anthropogenic activities. Therefore, the evidence of the effects of human activities on climate is clear. Given this worrying scenario, the development of research that points to mitigating and adapting to climate change is essential for the survival of the planet.

In this sense, with the emergence of the era of earth observation in high resolution, remote sensing data exponential growth has been occurring in recent years. Given this, remote sensing data is part of the big data era. Thanks to this, monitoring the environment on a large scale has become possible since research has been developed with remote sensing data with different time scales, spatial and sensor types. Many of these studies monitor environmental and atmospheric CO₂ concentrations on a global and regional scale.

In this study, several sources of data were used to obtain carbon feedback. Thus, it was observed that both in biomes and forest areas in the state of Mato Grosso do Sul, the temporal variation of atmospheric CO₂ concentration is mainly governed by photosynthesis (Solar induced chlorophyll fluorescence-SIF, NDVI, and EVI) and that photosynthesis is positively related to evapotranspiration and air temperature. In Mato Grosso and eastern Amazonia, SIF is also an important variable in explaining the temporal variability of X_{CO2}. However, in these regions, this relationship is also observed spatially. In general, the time variations of X_{CO2} in the north-central region of Brazil vary between the dry and rainy periods, this was clear in all studies. As for the spatial variation of X_{CO2}, it varies according to the type of land use and the time of year.

Knowing this dynamic of temporal variation of atmospheric CO₂ in time and space is a powerful tool in decision-making in public policies focused on climate change. Spatial interpolation techniques and the verification of "hot spots" and "hot moments" can contribute to the construction of strategies aimed at mitigating CO₂ emissions in specific locations and periods.

Given the results presented in this work, it is clear that big data and remote sensing are valuable tools in understanding the carbon cycle since the relationships

observed in the intersection of these data generate results that are clearly explained by the physical and biological processes around the soil-plant-atmosphere system.

In this respect, it is essential to emphasize that understanding these relationships is essential in searching for carbon sources and sinks in the biosphere. The search for the balance between carbon emission and absorption in the ecosystem varies according to environmental factors that affect both photosynthesis (carbon uptake) and carbon source.

It is worth stressing that climate change and changes induced by the disturbance of ecosystems can affect photosynthesis processes and breathing differently and, therefore, resulting in the change in the balance of carbon exchanges in ecosystems. An unwanted reduction in carbon capture intensity by ecosystems and forests will bring positive feedback to the carbon cycle, resulting in the increased greenhouse effect and worsening climate change.

Finally, In the next years, new space missions with greenhouse gas monitoring will be launched, such as MicroCarb from the French Government Space Agency and the continuation of the GOSAT mission with the launch of GOSAT-3, both scheduled to launch in 2021. In 2023, the launch of the Geostationary Carbon Cycle Observatory (GeoCARB), his principal goal, will measure the carbon cycle. All of these missions will complement those that already exist, such as OCO-2 / OCO-3, GOSAT-GOSTA-2, SENTINEL-5, MODIS, Soil Moisture Active Passive (SMAP). For this reason, I encourage my colleagues to make massive use of this data so that science can protect society from the effects of climate change through technical strategies.