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Publication Date

2022-05-01

DOI

10.1016/j.uclim.2022.101176

Peer reviewed

Urban Climate 43 (2022) 101176

Contents lists available at ScienceDirect

Urban Climate

journal homepage: www.elsevier.com/locate/uclim

Socioeconomic conditions and fossil fuel CO_2 in the Metropolitan Area of Rio de Janeiro

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A R T I C L E I N F O

Keywords:
Radiocarbon dating
Fossil fuel CO_2 mapping
Urban environment
South America
Spatial regression

A B S T R A C T

Worldwide monitoring of fossil fuel carbon dioxide ($FFCO_2$) has been fragmented, and mostly devoted to developed countries. Here we compare a previously published $FFCO_2$ dataset with socio-economic characteristics in order to better tailor $FFCO_2$ urban point-sources for a megacity of the Global South, the Metropolitan Area of Rio de Janeiro (MARJ), Brazil. Evaluations were performed by superimposing maps of the $FFCO_2$ measurements on urban data acquired from the Brazilian Institute of Geography and Statistics, the latest Origin-Destination Survey of the MARJ, and correlation and regression analyses between $FFCO_2$ and socioeconomic variables. While we confirmed that population density and the transportation sector are important drivers of $FFCO_2$ concentrations, the centrality of urban activities within MARJ also creates undesirable clustered zones (e.g., the city centers and the main intercity bridge). At the intra-urban scale, both high- and low-income residents play important roles in $FFCO_2$ levels. For instance, higher-income populations tend to produce more carbon pollution at their own residential areas, where most urban activities are located. Low $FFCO_2$ levels were found in low-income areas with poor infrastructure. However, distance from the city center, age distribution, job availability, lack of basic services, and car ownership force low-income populations to commute through high-traffic areas, adding high $FFCO_2$ levels to the same already clustered places. By integrating $FFCO_2$ monitoring with many socioeconomic variables, we believe that we capture its spatial distribution as well as better understand the causes of its emission patterns. Therefore, future CO_2 monitoring and assessment studies conducted in megacities can benefit from the insights and discussions presented in this study.

1. Introduction

It is widely known that approximately 75% of global CO_2 emissions originate in urban areas (Seto et al., 2014). In recent years, there has been a push to better characterize CO_2 concentrations from those spaces, especially fossil fuel carbon dioxide ($FFCO_2$) and its sources, to help policymakers to better mitigate it.

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https://doi.org/10.1016/j.uclim.2022.101176
Received 15 January 2022; Received in revised form 13 April 2022; Accepted 26 April 2022
Available online 11 May 2022

Cumulative CO_2 emissions and fossil fuel usage can be added up in data inventories, enabling updated budget assessments per energy sector and city. Direct measurements of trace gases, including CO_2, through established monitoring networks (NOAA: www.esrl.noaa.gov) produce a more realistic picture of greenhouse gas (GHG) concentrations at local sites. Fossil fuel-originating CO_2 can be isolated and determined when trace gas measurements are coupled with isotopic analyses of ^{13}C and ^{14}C (Miller et al., 2012; Basu et al., 2020). Alternatively, $FFCO_2$ information at regional or urban scales can be derived by isotopic measurements of ^{14}C from annual plants. Still, $^{14}CO_2$ measurements from either air samples or plant-integrated sources are mostly being used as $FFCO_2$ surface proxy (Battipaglia et al., 2010; Rakowski, 2011; Varga et al., 2019), or to show correlations of $FFCO_2$ with general topographical features, wind patterns, and seasonality (Hsueh et al., 2007, Turnbull et al., 2015, Park et al., 2015, Santos et al., 2019). In some cases, $FFCO_2$ local point-sources (e.g., proximity to roads, industrial clusters, cement complexes, and/or diesel- and coal-powered plants) have been identified (Quarta et al., 2007; Santos et al., 2019; Varga et al., 2019), or were associated with population density and per capita gross domestic product growth (Xi et al., 2013, Varga et al., 2020, Hou et al., 2020).

Although the science of using ^{14}C for $FFCO_2$ attribution and mapping has made remarkable progress toward refining its estimates (Miller et al., 2012; Basu et al., 2020), $FFCO_2$ information derived from isotopes has been highly fragmented (spatially and temporarily) and not necessarily useful in terms of policy change. Decade-long research observations at Salt Lake County, Utah, USA, on air-$^{14}CO_2$ measurements show that major CO_2 increases were attributed to population growth, but urban excesses were not as linear as expected (Mitchell et al., 2018). Moreover, $FFCO_2$ from emerging economies and developing countries has been mostly overlooked (Marland, 2008). Nonetheless, studies forecast that by 2030 over 80% of the world's megacities will be located in developing economies, where massive urbanization (i.e., sprawling) already has been taking shape in a manner distinct from most developed countries. Currently, such growth patterns can be found in most cities in the Global South, but specially in São Paulo and Rio de Janeiro, in Brazil, as well as cities in Africa and Asia (Lagos, Nigeria, and Shanghai, China, respectively). In addition, this type of growth pattern is interconnected with socioeconomic and environmental problems, including increased GHG emissions (Ou et al., 2013). Therefore, for policy-relevant responses, Polloni-Silva et al. (2021) suggest that assessment of CO_2 shifts should be followed by in-depth study of the region studied, such as its socio-economic circumstances. It is thus clear that to ensure effective $FFCO_2$ monitoring and interpretation, so that results can be translated into actions for its mitigation, studies on $FFCO_2$ information acquisition and socioeconomic-related emissions should be linked. Cities that tend to invest in adequate infrastructure, service, and policy plans (Lee and Lim, 2018), followed by nature-based solutions to land use (Pan et al., 2021; Seddon et al., 2020), tend to show economic efficiency and improved urban resilience (Larbi et al., 2021; Yao et al., 2022), and overall reduced GHG emissions (Ou et al., 2013). The aforementioned points call for a more in-depth, multi-criteria analysis of $FFCO_2$ as it relates to public variables impacting urban spaces, and particularly where such an analysis is lacking.

In 2009, Brazil established its National Policy of Climate Change (PNMC). Under this policy, Brazil pledged to reduce GHG emissions by 36.1%–38.9% by 2020, compared to 2005 data. The pledge also included Brazilian urban spaces, where it was estimated that the majority of GHG emissions came from the energy sector (i.e., CO_2 emissions from road transport (39%) and the industrial subsector (27%)). In 2020, metrics on total CO_2 emissions were still at levels similar to those of 2006/2007, slightly over 1300 t/year.[1] Therefore, any reduction would imply stabilization of the share of renewable energy sources in the energy matrix, followed by a decrease in fossil fuel usage (Carvalho et al., 2020). To identify opportunities for reductions, municipalities must first determine the amounts, sources, and causes of emissions. But direct monitoring of $FFCO_2$ at Brazilian cities is scarce (Santos et al., 2019 and references therein) and rarely addresses possible drivers (topography, socioeconomic status, mobility conditions, etc.).

Here, we took advantage of a recent work of Santos et al. (2019), which provided readings of $FFCO_2$ across the Rio de Janeiro state through ^{14}C measurements of Ipê leaves during 2015 (the first of its kind in all of South America). We focused on investigating trends in socio-economic patterns that could be associated with the $FFCO_2$ spikes observed just at the Metropolitan Area of Rio de Janeiro (MARJ). The MARJ alone has already reached the megacity status, with more than 10 million people spread out in a disorganized urban mosaic, similar to many other emerging urban megacities in developing economies.

To better identify $FFCO_2$ urban point-sources and drivers, we use two approaches. First, we visually evaluate socioeconomic conditions in the population across the region with the $FFCO_2$ data by superimposing multiple thematic maps, so as to capture first impressions of the relationships among variables. Socioeconomic information was acquired from the Brazilian Institute of Geography and Statistics (IBGE, 2010) and the latest Origin-Destination (OD) Survey of the MARJ (OD Survey, 2015). Afterwards, we ran a spatial regression model for $FFCO_2$ concentrations, controlling for physical, socioeconomic, and mobility factors, to capture potential underlying patterns that can directly or indirectly influence $FFCO_2$ excesses. Thus, we present our findings considering the population's socioeconomic conditions across the region, as well as its infrastructure and mobility factors. Finally, the paper is summarized by a conclusion and perspectives on our work. In this section, we make brief comparisons with other cities in the Brazilian territory (i.e., Curitiba and São Paulo) as well as other examples worldwide.

2. Study site characteristics

The MARJ has a population of approximately 13 million inhabitants and a population density of 1750 inhabitants/m^2, a high conurbation level and equally high vehicular activity (estimates from the Brazilian Institute of Geography and Statistics, IBGE, for 2021[2]). Besides including the main Rio de Janeiro (RJ) city, with approximately 6.3 million people (Malta and Marques da Costa,

[1] https://plataforma.seeg.eco.br/total_emission (choose CO_2 to single out this pollutant from other GHGs).
[2] https://ftp.ibge.gov.br/Estimativas_de_Populacao/Estimativas_2021/estimativa_dou_2021.pdf

2021), this urbanized area has already incorporated another 21 municipalities over the years (Fig. 1). Thus, it is the second largest urban conglomeration in South America, after the Metropolitan Area of São Paulo, also located in the southeast region of Brazil.

The MARJ's poor infrastructure planning and urban sprawl (a sixfold population increase in just three decades; Da Silveira Pereira et al., 2021) have led to severe social gaps and socio-environmental vulnerabilities (Malta and Marques da Costa, 2021). Urban sprawl occurred from its urban centers to the Southern Zone (along the Atlantic coastline at both sides of the Guanabara Bay; Fig. 1), and later to the Western Zone (along the RJ city seafront, and the swamplands between Pedra Branca and the Tijuca Massifs; Fig. 2A). Urban sprawl promoted the coexistence of richer districts (facing the Atlantic Ocean, with a distinct pattern of segmentation and fragmentation; Glebbeek and Koonings, 2016) side-by-side with several *favelas* or shantytowns (i.e., 763 in RJ city alone; IBGE, 2010). RJ *favelas* can differ significantly from each other. Public policies from the late '80s and '90s implemented street paving and basic services in many surrounding wealthy vicinities (Borba, 2005), allowing for an explosive density growth and greater vehicular traffic.

The region termed Baixada Fluminense (Fig. 1) has not caught up with other parts of the MARJ. It has over 2 million people sprawled within just six municipalities, characterized overall by low-income householders and a lack of access to basic infrastructure, such as land use management and good transportation options, as well as health care and education, green areas, and job opportunities. In contrast, RJ city and the Metropolitan East present a higher socioeconomic status, while Petrópolis city presents a different profile: it is agricultural and somewhat disconnected from MARJ.

The MARJ also presents a complex terrain configuration, with several mountains, hills, valleys, lagoons, and swamplands. The excess of topographical features creates densely populated areas and road corridors (De Farias and de Oliveira, 2013), increasing both air pollutant concentrations (Gioda et al., 2016; De Figueiredo et al., 2019; Ventura et al., 2019) and $FFCO_2$ (Santos et al., 2019).

51% of jobs in the whole MARJ are located in the Central Business District of RJ city, an area which concentrates just 19% of its population (Casa Fluminense, 2017). Monthly income also varies substantially in the MARJ (Table 1), with a large fraction of its population living under poverty conditions (World Bank 2017).

Public mobility and transport sustainability are also very poorly resolved at the MARJ. When comparing the RJ city metro system (42 km) to other developing cities (Beijing,[3] 727 km; and Mexico City,[4] 225 km) we observe its insufficient length and overall concentration in just a few neighborhoods. Similar issues have been observed for the newer Bus Rapid Transit (BRT) and Light Rail Transit (LRT) systems. They also tend to run across the richest neighborhoods, favoring these income populations (Pereira et al., 2019).

Population characteristics of MARJ areas are summarized in Table 1. Overall, the MARJ population has a high proportion of females, youth, and young adults ($<$ 32 years-old), as well as Indigenous and Afro-descendant peoples. High levels of illiteracy and low income remain startling. Moreover, the MARJ still shows a high percentage of unpaved streets, open sewage, and lack of street greenery for a city of this size. Population inequality layers across MARJ's regions and municipalities are summarized in Table 2. In sum, gender, age, income, the unequal distribution of opportunities, and lack of proper infrastructure, together with the MARJ's complex topographic features, tend to result in poor urban mobility conditions (longer commutes and increased traffic jams) (Tables 1 and 2).

Concerning fuel usage, light- and heavy-duty vehicles (commercial, privately owned cars and trucks, or motorbikes) can run on pure hydrous ethanol (E100), gasoline blended with ethanol proportions between 20 and 25% (E20-E25), diesel blended mix (B7 and B10), natural gas (NG) from petroleum wells, or biogas from sugarcane vinasse and bagasse or anaerobic digestion of biomass. These fuels are also used in the city's public transportation: i.e., vans and shuttles, BRT-type (RJ city) or regular buses (remaining MARJ districts), boats, and ferries (Pinguelli et al., 2013; ANFAVEA, 2015). In addition to E100 or 100% biogas, all other types of fuels (even those that are blended) are still highly depleted in ^{14}C (Dijs et al., 2006; Culp et al., 2014) due to the presence of petro-carbon byproducts ($\Delta^{14}C$ of approximately -1000‰), and therefore can directly impact local $FFCO_2$ levels.

Fossil fuel consumption in the MARJ is not limited to the vehicular sector. MARJ has five thermoelectric plants: one in RJ city (Santa Cruz neighborhood), and the remaining four in the Baixada Fluminense (two in Duque de Caxias district, and another two in Seropédica; Fig. 1). These thermoelectric plants are NG-powered (Mendes and Sthel, 2018), thus creating stationary sources of $FFCO_2$ (approximately 28% of total CO_2 emissions; Rio de Janeiro, 2015). Liquefied petroleum gas (LPG) is another source of $FFCO_2$, and it is used for cooking and/or household heating (Bruce et al., 2017). At RJ state, LPG usage is about 50% (Coelho et al., 2018; Butera et al., 2019), with wood or charcoal as secondary energy sources (Jakob et al., 2019). Other fossil fuel stationary sources are the petrochemicals, metallurgical producers, and refineries.

Given fuel-type usage in RJ state alone, it is safe to say that over 55% of it is still from fossil fuel sources, where most of it is destined for the transportation sector (Silva et al., 2020; SEEG, 2021). Therefore, due to fossil fuels' devastating effects on the environment and health (Seto et al., 2014), there is a need to better characterize it in the MARJ, particularly when it comes to its spatial distribution (where most transport-related emissions in the RJ state occur). Moreover, identifying underlying drivers (e.g., socioeconomic factors) affecting $FFCO_2$ would allow policymakers to specifically target its reduction.

3. Methodology

3.1. *Fossil fuel CO_2 distribution map based on $^{14}CO_2$ derived from Ipê leaves*

A $FFCO_2$ distribution map was obtained from a 2015 ^{14}C time-integrated mapping of Ipê leaves, sampled from deciduous perennial

[3] https://www.beijing-visitor.com/beijing-travel/beijing-subway-system

[4] https://mapa-metro.com/en/Mexico/Mexico%20City/Mexico%20City-Metro-map.htm

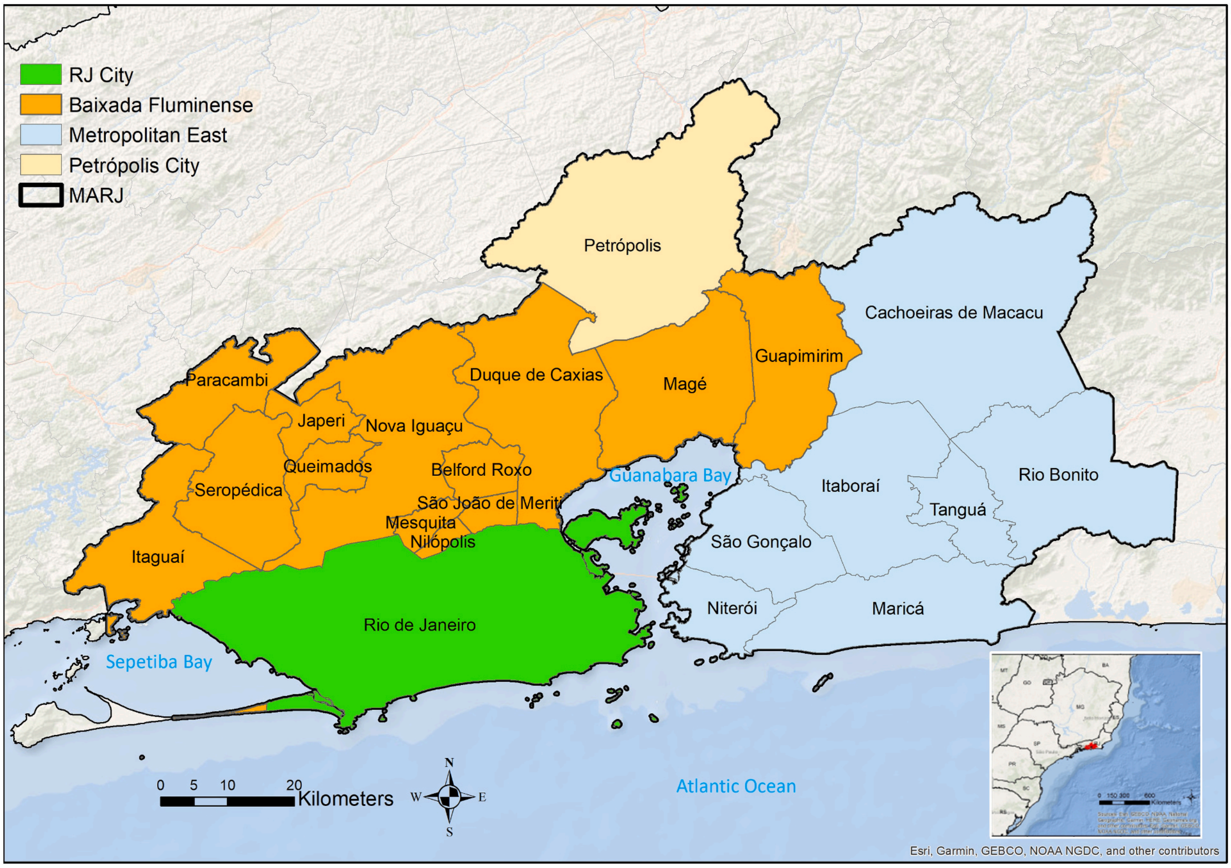

Fig. 1. Metropolitan Area of Rio de Janeiro (with its position in the Brazilian coast – smaller map in bottom right), with its 22 municipalities and subsectors (Rio de Janeiro City, Baixada Fluminense and Metropolitan East). The cities of Cachoeiras de Macacu and Rio Bonito were included in the MARJ in 2013, and Petrópolis in 2018. Source: IBGE (2010).

trees (*Tabebuias*) across RJ state, as detailed in Santos et al. (2019). On this statewide analysis, $FFCO_2$ levels were calculated using relatively coarse-scale ^{14}C data for better coverage of the space studied. Sampling was higher at urban centers and scattered toward inland and coastal areas, as recommended by others (Park et al., 2015). Moreover, vegetation sampling occurred mostly away from highways and known fossil fuel stationary point sources. This measure was performed mostly in open areas, but was nearly impossible at urbanized spaces (an issue also reported by others; Riley et al., 2008).

In the MARJ area (subset reported in this study: Section 4.1, Fig. 2A), Ipê leaf sampling took place at public gardens (i.e., university campuses, natural areas, and city parks), private residences, and sidewalks alongside unpaved and paved roads and close to parking lots. Sampling was impractical in remote locations (with difficult terrain) and in most of the *favelas*. Mature living Ipê leaves (sampled just before abscission and set to dry) were packed in plastic bags and shipped to the W.M. Keck Carbon Cycle Accelerator Mass Spectrometry Facility at the University of California, Irvine (KCCAMS/UCI) for ^{14}C dating by accelerator mass spectrometry (AMS) analysis and other techniques (Santos et al., 2007). Upon ^{14}C-AMS data normalization and corrections (including background), precision and accuracy yield was 2‰. A time-integrated atmospheric $FFCO_2$ map for MARJ state was then derived based on the measurement of $\Delta^{14}C$ (‰) values of Ipê leaves from both urban and cleaner areas. The formulae breakdown and parameter assumptions can be summarized as follows: a $\Delta^{14}C$ shift from 27.1‰ (clean-air background) of approximately 2.5‰ toward negative values corresponds to an input of 1 ppm of $FFCO_2$. The global annual concentration of CO_2 (ppm) for 2015 was obtained from NOAA (www.esrl.noaa.gov) as 400.36 ppm.

3.2. Map production

The database from the latest available Demographic Census of the Brazilian Institute of Geography and Statistics (IBGE, 2010) was obtained for the entire MARJ.[5] Data from the latest Origin-Destination survey in the MARJ (OD Survey of 2015) was obtained through

[5] https://www.ibge.gov.br/estatisticas/sociais/populacao/9662-censo-demografico-2010.html?edicao=10410&t=resultados

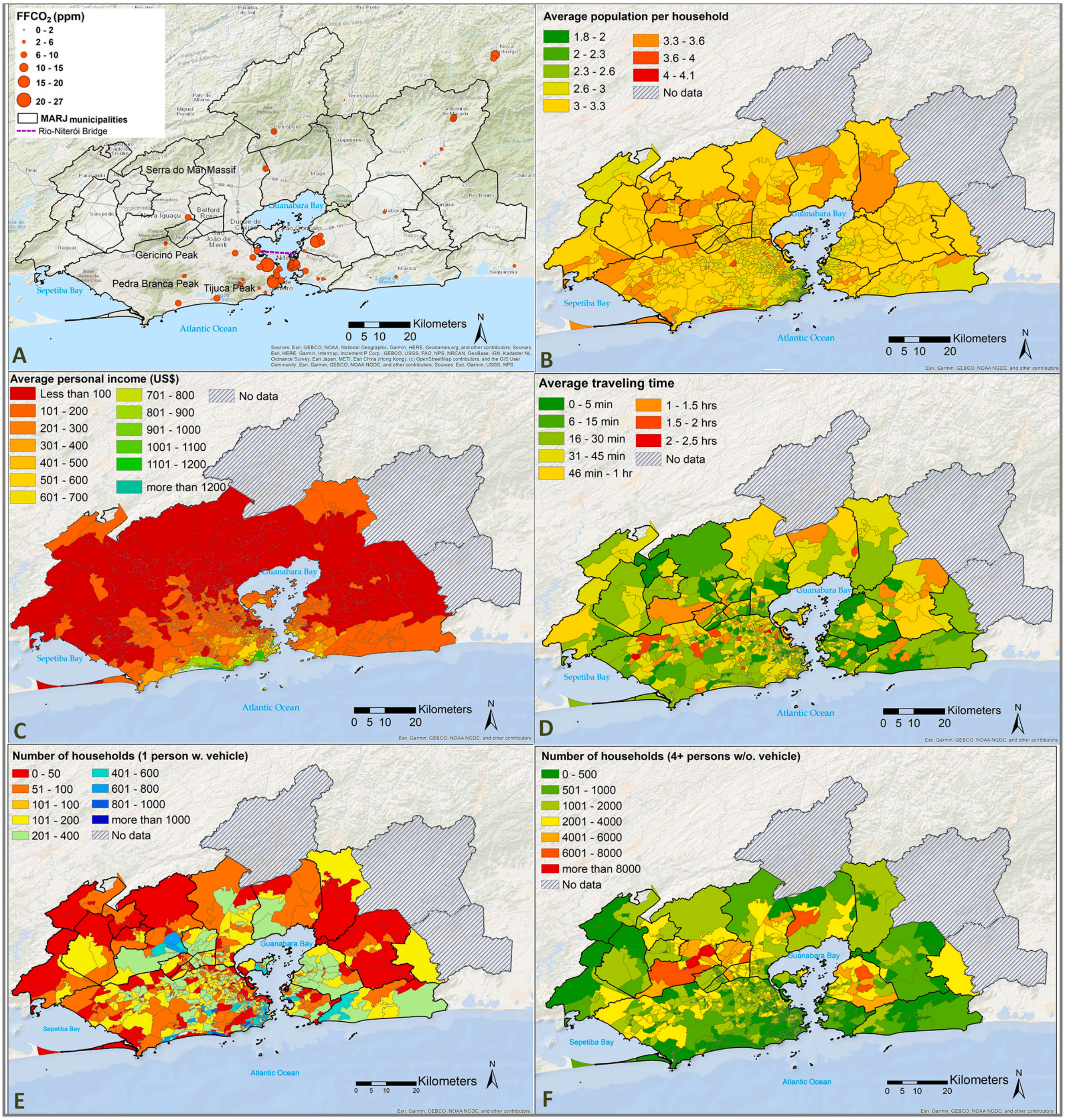

Fig. 2. $FFCO_2$ and socioeconomic data: A) top left: $FFCO_2$ concentrations (bright orange), RJ-Niterói Bridge (purple) and main topographical features in the MARJ; B) top right: average number of people per household; C) center left: average personal income (US$); D) center right: average traveling time of produced motorized trips; E) bottom left: number of households composed of one person with vehicle ownership; F) bottom right: number of households composed of four or more persons without vehicle ownership. Pale blue denotes bodies of water (i.e., Guanabara and Sepetiba Bays as well as the Atlantic Ocean). Source: IBGE (2010) and OD Survey (2015). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

personal communication with the Rio de Janeiro State Government Office. Census data was aggregated to OD zone levels (average population per household and average personal income), allowing us to compare population and income data to mobility data from the OD survey at the same scale. The following variables were then plotted using choropleth thematic classifications (Section 4.1, Figs. 2B-F): number of households with one car and one resident, households with no cars and with four or more residents, and average traveling time of produced motorized trips (trips which start in a given OD zone).

Table 1
Population characteristics and potential drivers of $FFCO_2$.

Data used in the statistical model	Description	Variable type	Average value in the MARJ [a]
number of residents per km^2 [b]	Demographic density	Socio-demographic	2071
income [b]	Average (in the OD zone) of the monthly income of the head of the household		178 USD
% women [b]	–		52%
% illiterate people [b]	–		4%
% residents ≤32 years old [b]	–		51%
% students [b]	–		18%
% Black, brown or Indigenous residents [b]	–		53%
altitude (in meters) [c]	–	Location, topography and greenery	Mostly sea level, peaks at 900 m
% households on streets with trees [b]	–		54%
distance from the city center [c]	Distance (in km) from the city center	Infrastructure and land use	N/A
% households on paved streets [b]	–		74%
streets with open sewage [b]	Existence of streets with open sewage on the OD zone		7%
number of jobs [d]	–		4504 per OD zone
average traveling time [d]	Average time from motorized trips departing from or arriving at the OD zone	Mobility	39 min
number of trips [d]	Number of motorized trips departing from or arriving at the OD zone		40,334 daily trips per OD zone
% households with one car (1 resident) [d]	–		3%
% households with no cars (≥ 4 residents) [d]	–		21%

[a] Mean value for each OD zone (weighted by population size if applicable); [b] IBGE, 2010; [c] Santos et al., 2019; [d] OD Survey, 2015; N/A – Not available; dash in description column implies same as first column.

Table 2
Socioeconomic characterization of MARJ householders by subsector.

Municipality/Subsector	Commute (> 1 h)	Work and live in different cities	Work in RJ city	Income distribution (USD$)*	Income (≥ USD$ 25)*
Rio de Janeiro city	26%	2%	98%	315	5%
Baixada Fluminense	9–54%	17–55%	9–44%	45–145	5–14%
Metropolitan East	8–31%	7–37%	2–24%	51–406	3–14%

* Personal monthly income. Data for 2010, converted to US dollars in 2021 currency. There is no data for Petrópolis city because it was included in the MARJ in 2018; Sources: IBGE, 2010, Casa Fluminense (2017).

3.3. Spatial statistical modeling

We fit a spatial regression model to quantify the relationship between $FFCO_2$ concentration, urban space characterization variables, and socioeconomic variables. Spatial regression is a regression method for studying multiple simultaneous effects from distinct covariates over an outcome (here, $FFCO_2$) when the variables involved exhibit spatial correlation, which typically occurs when data have geographic attributes. The spatial regression models incorporate such inherent spatial correlations, presenting more consistent estimates of the effect of the covariates on the outcome. The interpretation of the coefficients related to the effects of the covariates on the outcome is done in exactly the same way as in linear regression.

We use the Spatial Error Model (SEM), which emerges from the presence of spatial dependence between error terms of neighboring observations, suggesting the hypothesis that unobservable factors that influence the dependent variable are spatially correlated. A Lagrange Multiplier Test for spatial autocorrelation (Arbia, 2014) showed that the SEM is sufficient to remove spatial dependency, so more complex specifications were discarded. The SEM can be mathematically stated as follows:

$$y = X\beta_1 + u, \tag{1}$$

$$u = \lambda Wu + \varepsilon, \tag{2}$$

$$\varepsilon N\left(0, \sigma_\varepsilon^2 I_N\right). \tag{3}$$

Here, X is the matrix of independent variables, and β_1 corresponds to their effect on the dependent variable ($FFCO_2$). The error terms u have a spatial autoregressive specification with a scale parameter λ with $|\lambda| < 1$. W is a weight matrix, such that Wu forms a linear combination of the error terms. We assume that ε follows a multivariate normal distribution with zero mean and a constant diagonal variance matrix $\sigma_\epsilon^2 I_N$, where I_N represents the N-dimensional identity matrix and N is the number of observations.

For the weight matrix, we use inverse distance weighting, with weights for neighbor's i and j given by $w_{ij} = 1/d_{ij}^{\alpha}$, where d_{ij} is the distance between locations i and j, and α is the decay parameter. We test $\alpha = 1$ and $\alpha = 0.25$, corresponding to what we could respectively call *short*- and *long*-range correlations, accounting for qualitatively different situations.

We depart from 17 potentially relevant independent variables (Table 1) and fit all the 131,071 possible specifications (i.e., distinct combinations of the set of independent variables), including up to 17 covariates for each choice of α. Selection rationale is as follows: population density and income have long-term effects on urban GHG emissions (Patarasuk et al., 2016; Baiocchi et al., 2015; Olaniyan et al., 2018; Luo et al., 2021), including $FFCO_2$ (Xi et al., 2013, Wang et al., 2019, Varga et al., 2020, Hou et al., 2020). Some positive or negative drivers of income are illiteracy, age, gender, and race, all of which may impact $FFCO_2$ levels. Altitude (elevation) may be less relevant to urban CO_2 increases due to the relative unlikelihood of its proximity to urban development (Wang et al., 2019). However, we added this variable based on the MARJ urban expansion history, particularly regarding the occupation of *favelas* on hillsides (section 2). The transportation sector and its main factors (high-density urban road, vehicle ownership, commuting patterns), which are known to exert significant effects on GHG emissions (Wang et al., 2017, 2019; Xu et al., 2015), were also added. Last, the number of jobs was included, since work is an activity that drives transportation GHG emissions (Reckien et al., 2007). All the independent variables were measured at the OD zone level.

Considering the limited sample size (72 $FFCO_2$ unique observation sites were used from within MARJ; results from similar geo-locations among the 118 measurements shown in Fig. 2A were averaged), the best fit according to the Akaike Information Criterion[6] (Arbia, 2014) was chosen. Moreover, although MARJ Ipê leaf collection took place mostly inside residential areas, away from freeways and known fossil fuel stationary point sources, we could not explicitly control for these factors at all urban areas (as mentioned in Section 3.1). The absence of potentially relevant variables as independent variables in the model could cause what the statistical theory calls endogeneity, implying potential bias to the estimators of the remaining covariates. In the present case, endogeneity cannot be ruled out, and the parameters could indirectly reflect the effect of relevant variables not explicitly controlled, with which they may be associated.[7] Even so, the estimation of parameters can be very useful, if their interpretation does not neglect the influence that such unnoted factors can exert on the coefficients (Section 4.2).

4. Results and discussions

4.1. $FFCO_2$ and socioeconomic maps

In Fig. 2A, we show the $FFCO_2$ levels derived from $\Delta^{14}C$ (‰) of Ipê leaves in MARJ. This is a subset from Santos et al. (2019). It incorporates both the highest $\Delta^{14}C$ data of 27.1‰ (i.e., zero $FFCO_2$ contribution: our background for clean air of Petrópolis city), and the lowest $\Delta^{14}C$ value of −43.6‰ (i.e., an excess of $FFCO_2$ equivalent to 27.6 ppm), from RJ city center. The latter $FFCO_2$ estimate is slightly higher than that attained for the center of the Los Angeles metropolis (15.1 ± 5.5 ppm) during 2005 and 2006 (Riley et al., 2008), and it is equivalent to the locally added $FFCO_2$ in urban Beijing during May to September of 2009 (25.2 ± 1.0 ppm). Thus, a local contribution of 27.6 ppm to MARJ in 2015 implies that fossil fuel usage remains strong, even though biofuels are largely available to the Brazilian transportation sector (Section 2).

Greater $FFCO_2$ levels (Fig. 2A) were detected in the south-central region of the MARJ, at both sides of Guanabara Bay. These regions show lower average population (Fig. 2B), as well as high income per household (Fig. 2C). They represent the business, education, and entertainment centers of the MARJ, and receive a large number of commuters. Therefore, we believe that we have captured the mobility flow associated with transportation needs (Pereira et al., 2019). After the RJ-Niterói bridge (Fig. 2A) opening in the '70s, four of the seven municipalities at the Metropolitan East side of Guanabara Bay (Maricá, Itaboraí, Tanguá, and São Gonçalo; Fig. 1) experienced intense growth (221% population increase between 1970 and 2010) and urbanization in the form of car-based suburbs (Barandier Jr, 2015).

Similar to RJ city center, Niterói's business center holds a large percentage of formal jobs (more than 30%), universities, and main transportation hubs, such as ferry and bus stations (with more than 300,000 commuters). It is assumed that at least a half million people pass through Niterói's and São Gonçalo's central areas daily (Fig. 2D). Average traveling time for motorized trips seems to show a very heterogeneous pattern in Fig. 2D. But the average commuting time of one-way trip is 39 min (Table 1). This implies that the MARJ population spends a considerable amount of time in traffic jams, particularly for those in the Baixada Fluminense subsector (Fig. 1), where commutes longer than one hour can reach 54% of total trips (Table 2). While overall MARJ's commuters still seem to show a high level of daily public transportation usage (71.5%) versus private cars (28.5%), corroborating our findings (Figs. 2E and F), Barandier Jr (2015) pointed out that motorization by private cars had already increased as much as 27% in just nine years.

Regarding marine traffic, Guanabara Bay operates many marine stations. They all use diesel or crude oil as their main fuel. Marine

[6] The Akaike Information Criterion (AIC) is a popular measure for the goodness of fit of a statistical model, providing a criterion for comparing candidate models. The AIC is based on the likelihood function and the number of model parameters, rewarding models that provide high values of the likelihood function (which roughly indicate how well the model reproduces the observed data) and penalizing the number of parameters entered in the model, favoring simpler models and avoiding overfitting.

[7] Traditional endogeneity tests (such as the Hausman test) rely on the existence of an adequate *instrumental variable,* which is not always possible to find; details on the procedure can be found in Wooldridge (2016). That is probably the reason that such a test is seldom presented. Instead, it is rather more common to argue about the presence/absence of endogeneity, as we did.

traffic emission has been estimated as 6701.4 tons of CO_2 based on ship engine type, load factor, and fuel usage, and it affects mostly the business centers of RJ and Niterói cities (Cepeda et al., 2018). All the aforementioned factors can be observed by the excess of $FFCO_2$ detected in the RJ and Niterói business centers (Fig. 2A), as both sides of the Guanabara Bay show basically the same $FFCO_2$ levels, although the Metropolitan East population (seven cities combined) is at least threefold lower than RJ city alone.

Fig. 2F shows that the high proportion of households composed of four or more persons without vehicle ownership are located mostly in the Baixada Fluminense. Those also coincide with the commuters facing longer traveling times (Table 2). Commuting patterns are probably associated with either unemployment or underemployment conditions, and lack of basic education and career opportunities near the workers' residences (Pereira et al., 2019). Over 2 million people commute to work within RJ city and from its surrounding municipalities (Pacheco et al., 2017; Table 2).

The highest-income region is located at the MARJ southwest (a thin seafront strip at RJ city; Fig. 2C), which shows average to low population per household (Fig. 2B). This small area also shows a high proportion of households composed of one person owning a vehicle (Fig. 2E), and somewhat lower $FFCO_2$ concentrations (Fig. 2A). It is characterized by high-income gated residential areas of high-rise buildings (Glebbeek and Koonings, 2016) with medium to low urban activity.

Regions with many houses composed of four or more persons without a vehicle are mostly located in areas near lower $FFCO_2$ concentrations. These regions coincide with low-income householders (Fig. 2C) and longer traveling times (Fig. 2D), suggesting that poorer populations produce lower per capita $FFCO_2$, at least in their own zones (Fig. 2A).

4.2. $FFCO_2$ and statistical modeling

Table 3 shows the correlation matrix[8] for the selected variables from Table 1. Next, we draw some significances between socio-economic and physical variables with $FFCO_2$. Table 3 shows two distinct groups of variables, negatively and positively correlated to income. High-income zones have a higher proportion of single-person households with a car, and a higher percentage of households on streets with trees, of women, and of households on paved streets, with greater demographic density and areas that show more job offers. The correlation coefficients between these variables and income range between 0.38 and 0.84 (average 0.65). Zones with lower income are those with the highest percentage of Black, brown, or Indigenous residents, of households with four or more residents and no cars, and young residents, and illiterate people, with a higher percentage of streets with open sewage, more distant from the city center, with a greater number of students, and located at higher altitudes. The correlation coefficients between these variables and income range from −0.96 (percentage of Black, brown, or Indigenous residents) and − 0.34 (log altitude), and their average is −0.69, showing the magnitude of these associations.

$FFCO_2$ is positively correlated with the first group (variables positively correlated with income) and negatively correlated with the second (variables negatively correlated with income). It is more strongly correlated with population density (0.5), followed by the availability of jobs (0.43), income (0.28), and the variables paved streets (0.34) and number of households with one car and one resident (0.29). This may imply that some high-income residents live in areas with equally high urban activity (closer to the city center, with more services, more culture, and better infrastructure and employment options). This pattern is in line with the maps shown in Fig. 2, where at some residential areas (i.e., close to center busiest RJ area), specific high-income dwellers tend to be more vehicularly oriented (Figs. 2C and E), which could be associated with higher $FFCO_2$ concentrations (Fig. 2A).

Overall, our correlations support the fact that higher urban activity (intense commerce, transportation demands, etc.) tends to increase $FFCO_2$ levels. In fact, the most important sector for CO_2 emissions in RJ city and state is transportation (about 35% of total CO_2 emissions in the city; Rio de Janeiro, 2015, 2017). However, correlations between urban mobility variables (average traveling time and number of trips) and $FFCO_2$ concentrations are not as strong (0.2 and 0.08, respectively) as those related to income and $FFCO_2$. Here, traffic flow was not used to determine point-by-point fossil fuel emissions, a dataset not yet available in this region. Thus, it is difficult to determine how traffic flow influences specific OD zones that show either high or low $FFCO_2$ levels.

Physical variables such as distance to the city center and altitude show negative correlations to $FFCO_2$: i.e., −0.52 and − 0.6, respectively. The impact of the zones outside the city center is not completely unexpected. However, flat areas away from the MARJ city centers are densely occupied (> 3 residents per household; Fig. 2B), including its hillsides, implying that population density alone is not a main driver of $FFCO_2$ concentrations. Households with no cars (−0.24), high illiteracy (−0.39), and open-air sewers (−0.52) showed negative correlations with $FFCO_2$, suggesting that these dwellers are living in less vehicularly oriented areas, as opposed to the high-income populations, as mentioned above.

Regarding the results of the spatial regression model for $FFCO_2$ (details in Section 3.3), we chose the best fit from all the possible configurations including up to 17 variables (for both choices of the decay parameter). The best fit, presented in Table 4, resulted from decay parameter $\alpha = 0.25$, suggesting long-range spatial correlation. We note that variables not included in the final model should be considered statistically nonsignificant under the presence of the variables in the model.

Wald and LR test the significance of the spatial dependence coefficient in the Spatial Error Model. Table 4 shows that this coefficient is considered nonsignificant by both tests. Considering that those tests are subject to the "type II error",[9] keeping the spatial coefficient should help to avoid bias in the estimation of the remaining coefficients. For assessing robustness of the estimates, we evaluate the

[8] Variables with markedly skewed distributions (such as income, population counts and geographic measurements) typically require logarithmic transformation in regression modeling. The models were fitted using the logarithmic form of the following variables: $FFCO_2$, income, number of jobs, altitude, number of students and distance from the city center. For this reason, we also use this form in calculating correlation coefficients.

[9] A type II error occurs when a test fails to reject a null hypothesis that is actually false.

Table 3
Correlation (derived from matrix between socioeconomic variables from the Census and the OD research and physical variables, including $FFCO_2$ from MARJ (derived from Santos et al., 2019).

	log $FFCO_2$	% households on paved streets	log number of residents per km^2	% women	% households on streets with trees	log income	% households with one car (1 resident)	log number of jobs	average traveling time	number of trips	% illiterate people	% residents ≤ 32 years old	% black, brown or indigenous residents	% households no car (≥ 4 residents)	log altitude	log number of students	log distance from the city center	streets with open sewage
log $FFCO_2$	1,00	0,34	0,50	0,38	0,18	0,28	0,29	0,43	0,20	0,08	-0,39	-0,30	-0,26	-0,24	-0,60	-0,46	-0,52	-0,52
% households on paved streets	0,34	1,00	0,66	0,65	0,28	0,56	0,49	-0,08	-0,29	0,08	-0,62	-0,69	-0,57	-0,61	-0,18	-0,12	-0,22	-0,52
log number of residents per km^2	0,50	0,66	1,00	0,80	0,14	0,38	0,45	0,04	-0,02	-0,01	-0,51	-0,54	-0,44	-0,46	-0,44	-0,19	-0,20	-0,41
% women	0,38	0,65	0,80	1,00	0,48	0,68	0,75	0,20	-0,23	0,00	-0,65	-0,76	-0,71	-0,72	-0,38	-0,39	-0,38	-0,61
% households on streets with trees	0,18	0,28	0,14	0,48	1,00	0,80	0,67	0,32	-0,06	0,03	-0,64	-0,68	-0,74	-0,71	-0,25	-0,41	-0,45	-0,53
log income	0,28	0,56	0,38	0,68	0,80	1,00	0,84	0,27	-0,19	0,17	-0,81	-0,89	-0,96	-0,92	-0,34	-0,38	-0,51	-0,70
% households with one car (1 resident)	0,29	0,49	0,45	0,75	0,67	0,84	1,00	0,27	-0,23	0,25	-0,62	-0,73	-0,81	-0,88	-0,46	-0,44	-0,42	-0,81
log number of jobs	0,43	-0,08	0,04	0,20	0,32	0,27	0,27	1,00	0,01	0,05	-0,14	-0,22	-0,32	-0,25	-0,44	-0,38	-0,41	-0,30
average traveling time	0,20	-0,29	-0,02	-0,23	-0,06	-0,19	-0,23	0,01	1,00	0,00	0,13	0,12	0,25	0,20	-0,19	0,04	0,05	0,26
number of trips	0,08	0,08	-0,01	0,00	0,03	0,17	0,25	0,05	0,00	1,00	-0,15	-0,02	-0,17	-0,19	-0,37	0,13	0,04	-0,18
% illiterate people	-0,39	-0,62	-0,51	-0,65	-0,64	-0,81	-0,62	-0,14	0,13	-0,15	1,00	0,85	0,77	0,73	0,34	0,32	0,50	0,49
% residents ≤ 32 years old	-0,30	-0,69	-0,54	-0,76	-0,68	-0,89	-0,73	-0,22	0,12	-0,02	0,85	1,00	0,89	0,88	0,27	0,33	0,50	0,59
% Black, brown or Indigenous residents	-0,26	-0,57	-0,44	-0,71	-0,74	-0,96	-0,81	-0,32	0,25	-0,17	0,77	0,89	1,00	0,92	0,26	0,31	0,50	0,65
% households with no cars (≥ 4 residents)	-0,24	-0,61	-0,46	-0,72	-0,71	-0,92	-0,88	-0,25	0,20	-0,19	0,73	0,88	0,92	1,00	0,31	0,26	0,36	0,69
log altitude	-0,60	-0,18	-0,44	-0,38	-0,25	-0,34	-0,46	-0,44	-0,19	-0,37	0,34	0,27	0,26	0,31	1,00	0,54	0,31	0,54
log number of students	-0,46	-0,12	-0,19	-0,39	-0,41	-0,38	-0,44	-0,38	0,04	0,13	0,32	0,33	0,31	0,26	0,54	1,00	0,59	0,59
log distance from the city center	-0,52	-0,22	-0,20	-0,38	-0,45	-0,51	-0,42	-0,41	0,05	0,04	0,50	0,50	0,50	0,36	0,31	0,59	1,00	0,63
streets with open sewage	-0,52	-0,52	-0,41	-0,61	-0,53	-0,70	-0,81	-0,30	0,26	-0,18	0,49	0,59	0,65	0,69	0,54	0,59	0,63	1,00

Sources: IBGE, 2010; OD Survey, 2015, Santos et al., 2019.

Table 4
Estimates of the spatial and linear error model coefficients.

Dependent variable: log($FFCO_2$)	Spatial model		Linear model	
	Coefficient	Std. error	Coefficient	Std. error
log number of residents per km^2	0.199***	(0.041)	0.201***	(0.040)
% residents ≤32 years old	0.053***	(0.015)	0.053***	(0.016)
% illiterate people	−0.178***	(0.041)	−0.182***	(0.043)
streets with open sewers	−1.193***	(0.174)	−1.193***	(0.176)
average traveling time	0.017***	(0.004)	0.017***	(0.004)
log number of jobs	0.134***	(0.028)	0.138***	(0.028)
% households with one car (1 person)	−0.126***	(0.031)	−0.128***	(0.033)
Constant	−2.214**	(0.919)	−2.201**	(0.922)
Observations	72		72	
Log Likelihood	−34.496		−35.068	
sigma^2	0.148		0.174	
Akaike Inf. Crit.	88.993		88.137	
Wald Test	1.633 (df = 1)		–	
LR Test	1.144 (df = 1)		–	
R-Squared	–		0.728	
Adjsuted R-Squared	–		0.698	

Note:$^*p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

results of an ordinary linear model as well. Results show that coefficient estimates from the ordinary linear model are very close to the coefficients estimates deriving from the spatial specification (Table 4). Computed standard deviations of the spatial model are also comparable to the linear model ones. Fitting a linear regression is also convenient for it allows assessing the R-squared statistic, which is not generally valid for contexts other than the linear regression. Table 4 shows the R-squared is considerably high (Adjusted R-squared = 0.698).

Also, the interpretation of the parameters depends on the functional form of the regression equation. The dependent variable is in logarithmic form, and we have both log- and level-independent variables. For log-log, we have constant elasticity of y with respect to x_i: increasing x_i in 1% causes an expected percentual change of magnitude approximately equal to β_i in y; for log-level, the expected percentual change corresponds to $100 \times \beta_i$ for each additional unity of x_i. These approximations are not so precise for β_i far from zero ($|\beta_i| > 0.2$). In this case, one can compute the exact percentage change by $(e^{\beta_i} - 1)$ for the elasticity model and $100(e^{\beta_i} - 1)$ for the semi-elasticity. See Wooldridge (2016) for details.

We calculated the effect of demographic density (*log number of residents per km^2*) changes (holding all other predictors constant) on

$FFCO_2$ and found that for each 1% demographic density increase, $FFCO_2$ should increase approximately 0.2%. This finding somewhat agrees with general expectations (Seto et al., 2014), but alone does not help to determine local $FFCO_2$ contributions. Population density has a complex relationship with $FFCO_2$ emissions. In general, a compact city structure can reduce per capita emissions when it is supported by a good public transport network, mixed land use, and other measures in urban planning (Wang and Li, 2021; Xu et al., 2019). Unfortunately, this is not the case for the MARJ, which shows similar problems as less developed regions in China (Liu et al., 2017). Note that here, our evaluations assume that this megacity will continue growing under a business-as-usual scenario. MARJ has a unique landscape, punctuated by a series of hills, and therefore channels most of the traffic to the same routes (Fig. 2A). Without an efficient urban transportation system, the excess of daily traffic jams can just continue increasing transport-related $FFCO_2$ concentrations.

The percentage of residents aged ≤32 years also has an increasing impact on $FFCO_2$ levels: e.g., a 1% rise yields a 5.3% $FFCO_2$ increase, which is consistent with young adults' daily activity patterns (Matz et al., 2015). For instance, young adults often drive their young to school and other activities, as well as themselves to work, school, or recreational places. Therefore, neighborhoods with a greater proportion of younger residents may show higher $FFCO_2$ levels compared to the same neighborhoods with fewer youth and young adults. Moreover, activities at MARJ tend to be concentrated in a few locations (Pereira et al., 2019), creating some mobility demands.

Despite $FFCO_2$ being positively correlated with a younger population, the percentage of illiterate people is ceteris paribus negatively associated with $FFCO_2$ (Table 4). Territories with high percentages of illiterate people showed 17.8% lower $FFCO_2$ concentrations, while OD zones with open sewers showed 69.6% lower $FFCO_2$ than places with proper sewage disposal. These correlations may also imply that illiterate people tend to live and stay away from the business and high-income areas. Lack of basic infrastructure and overall autonomy (such as being able to obtain a driver's license), as well as the lower likelihood of low-income populations spending additional funds on leisure activities, may explain a lower $FFCO_2$ impact at their residential zones.

Average travel time (i.e., average travel time that departs or arrives in the OD zone) shows increasing effects on $FFCO_2$. Hence, a 1% increase on average travel time represents 1.7% more $FFCO_2$. Traffic jam conditions tend to increase pollutant emissions (Ou et al., 2013), but the average travel time at each OD Zone cannot translate automatically into high local $FFCO_2$ concentrations. As previously stated, our work does not include traffic flow data, and therefore, the variable "average travel time" just means that people who live in that OD zone spend extra time in some type of vehicular transport to reach their destination.

Regarding jobs, increasing job offers by 1% should imply an increase of $FFCO_2$ levels by 0.13%. Urban areas with high job availability tend to attract more commuters (Manduca, 2021), which is clearly related to transportation demands in a given zone (Pereira et al., 2019). Finally, for every extra 1% of households with just one person owning a car, the concentration of $FFCO_2$ decreases by 12.6%. This result is somewhat unexpected; especially if those new drivers chose to favor nonrenewable fuels (such as gasoline, diesel, or NG), an increase of $FFCO_2$ would be expected (Fig. 2A and E). On the other hand, locations with intense vehicle use and with populations from lower socioeconomic conditions tend to show high rates of poorly maintained, aged vehicles, which in turn present worse emission factors that can impact pollutant concentration in these locations (Park et al., 2016; Alvim et al., 2017; Helmers et al., 2019). Since income is highly correlated with households with one person and vehicle use in the MARJ (0.84; Table 3), the association captured in our results could stem from the fact that higher-income populations tend to own newer vehicles in good maintenance condition, and therefore with overall better emission factors (CONAMA, 2018). Although MARJ could significantly benefit from lower $FFCO_2$ if all households manage to purchase newer vehicles, this scenario is unlikely to occur anytime soon, due to the ongoing high prices of fuel-efficient vehicles (Bauer et al., 2021).

5. Conclusion and perspectives

In rapidly changing complex urban spaces, finding commonalities that affect GHG emissions (or just $FFCO_2$ concentrations) is challenging. It is difficult to differentiate from a government database alone the consumption of fuel types within political and administrative boundaries (Parshall et al., 2010).

In this work, we combined existing methodologies to better understand the relationships between socioeconomic variables (obtained from official governmental reports) and $FFCO_2$ concentrations (measured by time-integrated $^{14}CO_2$ content in samples of Ipê leaves) across a megacity of the Global South: i.e., MARJ, in Brazil. Fast urbanization processes, and a lack of proper integrated urban planning and policies have brought socioeconomic gaps to MARJ (Malta and Marques da Costa, 2021; Da Silveira Pereira et al., 2021). The topographic features of the MARJ also have led to complicated mobility conditions and unintended traffic concentration (Pereira et al., 2019), leading to high $FFCO_2$ levels at specific zones. Hence, centralized job-house zones can potentially increase on-road $FFCO_2$, an issue that has been identified by others through public database studies of global cities (Song and Gurney, 2020). In this study, we identified high $FFCO_2$ concentrations occurring around the Guanabara Bay, city centers, and the expanded areas near the RJ-Niterói Bridge exits (Fig. 2A), narrow areas (between the mountains and the ocean) with large-scale daily traffic activities. We determined that $FFCO_2$ patterns are location-dependent (a function of centrality) as well as income-related. A large fraction of the MARJ population works away from their residential zones (Table 2), and therefore some type of transportation mode and distance travelled are responsible for higher or lower $FFCO_2$ levels (Fig. 2A, C-F).

High-income residents (Fig. 2C), while in low numbers (Fig. 2B), are somewhat moderate to stronger $FFCO_2$ polluters when high income is related to high urban activity (higher $FFCO_2$ levels were also found in the central/richer districts: the thin seafront strip at RJ city, and central business, educational, and cultural areas of the MARJ districts; Pereira et al., 2019). We also determined that illiterate people and areas with open sewage tend to produce less $FFCO_2$ (Table 4) than the opposite. Nonetheless, lack of basic sanitation and waste management at these areas do not preclude the production of methane (another powerful GHG) at MARJ (Cotovicz Jr et al., 2016). It is desirable for low-income dwellers to eventually improve their quality of life and education, without entailing a significant net increase in $FFCO_2$ concentrations (Galvin and Healy, 2020). Without significant infrastructure changes, and decentralization of jobs and services, our regression analysis reveals the following relationship: For every 1% increase in the population density at MARJ, a 0.2% increase in $FFCO_2$ levels should be observed. This is worrisome, and calls for immediate action.

During the 1960s to 1980s, Brazilian government officials designed plans for urban development in several cities that were experiencing rampant growth, including Rio de Janeiro, São Paulo, and Curitiba. However, only Curitiba city moved forward with its public transportation and land use plans (Follador et al., 2022). It is not within the scope of this study to address why this was the case. However, Curitiba city (4062/km^2 population density; IBGE, 2010) became a worldwide example of sustainable development and urban resilience thanks to an efficient urban planning and bus system (Larbi et al., 2021). Most residents are kept close to amenities and services, and to major bus lines. In addition, Curitiba has invested in expanding urban green spaces, while keeping its overall fuel consumption much lower (Dulal and Akbar, 2013). For instance, rather than gasoline-powered lawn mowers, city parks use animals as lawn mowers.

While it would be difficult for the MARJ to just mimic the Curitiba infrastructure and transportation plans without a proper evaluation (both cities have very different landscape and infrastructure characteristics), evidence shows that urban growth and environmental sustainability are possible once opportunities for and/or constraints against urban sprawling are first identified, and stronger policies to restrict the release of CO_2 are set in motion (Carvalho et al., 2012). Moreover, decentralization efforts regarding jobs and overall services have been implemented in existing cities elsewhere (e.g., in Canada, Duquet and Brunelle, 2020; in Spain, Díaz-Lanchas and Mulder, 2021; and in Indonesia, Trimurni and Mansor, 2020). While the overall results of decentralization attempts have been mixed, successes and pitfalls have been heavily attributed to other factors (e.g., investments and local governance). It is then reasonable to assume that a better spatial distribution, at least of jobs, in the MARJ (Pereira et al., 2019) would decrease transportation demands and lead to lower $FFCO_2$ contributions, as has been found for São Paulo city (Chiquetto et al., 2021). Eventually, better spatial distribution of basic services, schools, commerce, and recreation options, thus affecting all journeys, should follow. Adoption of polycentric development models (e.g., Holden and Norland, 2005; Ou et al., 2019) should help curb overall GHG emissions and also bring a higher quality of life for those living in the MARJ, as well as to others living in megacities of the Global South facing similar issues.

As a spinoff of this study, we have revealed some key factors, especially in regard to the implementation phase and analysis, that may help to improve $FFCO_2$ information acquisition (using isotopes and/or other data collection methods) and statistical modeling. Fig. 2A shows 118 $FFCO_2$ measurements across the MARJ; however, since many results were from similar geolocations, modeling used just 72 $FFCO_2$ unique observations (as sites). Knowing where to implement measurements to optimize CO_2 monitoring will certainly yield better CO_2 metadata (and possibly $FFCO_2$), potentially leading to more accurate interpretation of its increase, which in turn can contribute to the urban policy debate on how to curb $FFCO_2$ concentrations. Regarding the identification of potential $FFCO_2$ drivers for modeling, prior knowledge of population characteristics and regional attributes is paramount. If available, and for a better characterization of $FFCO_2$ data, traffic flow and known fossil fuel stationary sources should be included as well. As mentioned, a traffic flow dataset is not yet available in this region, while known fossil fuel stationary sources were identified just for the large $FFCO_2$ RJ state map of Santos et al. (2019), but difficult to obtain for the MARJ alone. For future studies, in this region or elsewhere, we also suggest the addition of meteorological models, which may add important information on pollutant dynamics. Nonetheless, our results could prove to be very useful for policymakers, not only for controlling $FFCO_2$ levels, but also for guiding policies regarding specific urban management sectors and population sectors toward mitigation options. To the best of our knowledge, these are the first results of this kind obtained for a megacity in South America.

Finally, the significant $FFCO_2$ contribution to urbanized Brazilian megacities is, nevertheless, concerning. Even though Brazilian biofuels are widely used in the transportation sector, fossil fuel emissions from urban spaces remain a challenge that needs to be addressed. This calls for an integrated approach that could be implemented in parallel by combining decentralization of jobs and services, improved public transportation systems, cleaner fuel technologies, newer on-road vehicles, and stronger land use/transportation policies.

Credit author statement

Guaciara Macedo dos Santos: Conceptualization, and acquisition of funding **Guaciara Macedo dos Santos, Júlio Barboza Chiquetto, Alexandre Ribeiro Leichsenring:** Methodology, Formal analysis and interpretation, Writing—original draft, visualization, literature synthesis and discussion.

Declaration of Competing Interest

The authors declare no conflict of interest.

Acknowledgements

This research did not receive any specific grant from funding agencies in the public, commercial, or nonprofit sectors. The authors thank Rodolfo Finatti for his early assistance in the cartographic production. The authors thank two anonymous reviewers for careful reading of our work and their many insightful comments and suggestions.

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