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Long-term commuting times and air quality relationship to COVID-19 in São Paulo

P.J. Pérez-Martínez [a,*], J.A. Dunck [a], J.V. de Assunção [b], P. Connerton [b], A.D. Slovic [b], H. Ribeiro [b], R.M. Miranda [c]

[a] School of Civil Engineering, Architecture and Urban Design, University of Campinas, Rua Saturnino de Brito, 224, Cidade Universitária Zeferino Vaz, 13083-889 Campinas, Brazil

[b] Department of Environmental Health, School of Public Health, University of São Paulo—USP, São Paulo 01246-904, Brazil

[c] School of Arts, Sciences, and Humanities, University of São Paulo, Rua Arlindo Béttio, 1000, Ermelino Matarazzo, 03828-000 São Paulo, Brazil

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ABSTRACT

The Coronavirus Disease 2019 (COVID-19) epidemic is an unprecedented global health crisis and the effects may be related to environmental and socio-economic factors. In São Paulo, Brazil, the first death occurred in March 2020 and since then the numbers have grown to 175 new deaths per day in April 2021, positioning the city as the epicenter of the number of cases and deaths in Brazil. São Paulo is one of the largest cities in the world with more than 12 million inhabitants, a fleet of about 8 million vehicles and frequent pollutant concentrations above recommended values. Social inequalities are evident in the municipality, similarly to other cities in the world. This paper focuses on transportation activities related to air pollution and associated with cardiovascular and respiratory diseases especially on people who developed comorbidities during their whole life. This study relates travel trip data to air quality analysis and expanded to COVID-19 disease. This work studied the relationship of deaths in São Paulo due to COVID-19 with demographic density, with family income, with the use of public transport and with atmospheric pollution for the period between March 17th, 2020 and April 29th, 2021. The main results showed that generally passenger kilometers traveled, commuting times and air quality related diseases increase with residential distance from the city center, and thus, with decreasing residential density. $PM_{2.5}$ concentrations are positively correlated with COVID-19 deaths, regions with high urban densities have higher numbers of deaths and long-distance frequent trips can contribute to spread of the disease.

1. Introduction and literature review

Responsible for over 4 million premature deaths per year, outdoor air pollution is among the top five risk factors for mortality globally (Cohen et al., 2017). The straightforward approach to public policy aimed at this problem is to reduce exposure to pollution to protect public health (Landrigan et al., 2018). In large cities, traffic is a major source of air pollution (Jimenez and Bronfman, 2012; Molina and Molina, 2004) and tackling traffic-related pollution is essential to promote air quality and protect public health (Watts et al., 2015). The main pollutants related to vehicle traffic and monitored by environmental companies are hydrocarbons (HC), fine particulate matter ($PM_{2.5}$), inhalable particulate matter (PM_{10}), carbon monoxide (CO), nitrogen compounds (NO, NO_2) and ozone (O_3). In the Metropolitan Region of São Paulo vehicles are responsible for 96% of CO, 73% of HC, 65% of NO_x, 11% of SO_x and 40% of particulate matter (CETESB, 2020a).

Particulate matter is one of the most harmful pollutants for human health. Particles with a diameter between 10 and 15 μm do not penetrate in the lungs due to curvature of the respiratory system, mucus and high relative humidity. But with the decrease in particle diameter, the capture efficiency increases. In addition to anthropogenic pollution, natural processes can generate particles that are harmful to health, including those known as respiratory disorders and psychic changes that have been linked to increased air pollution (Snow et al., 2018). There are several studies analyzing the number of deaths avoided when the concentration of pollutants decreases, especially due to mass public transport use (Leirião and Miraglia, 2019; Da Silva et al., 2012).

Most of the current knowledge on air pollution effects on human health come from cohort studies, where long-term exposure to air pollution is assessed at place of residence based on site monitors, land

* Corresponding author.
E-mail address: pjperez@unicamp.br (P.J. Pérez-Martínez).

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use regression models or distance from a busy road (Andersen et al., 2012; Chen et al., 2017; Turner et al., 2011). Air pollution effects are dose-dependent (Fay, 2019; Schwartz et al., 2008). Predicted levels are usually based on one or very few years of air quality data and do not account for changes in residential address throughout one's life or commuting exposure during the day, which can lead to exposure misclassification and bias. To date, personal monitoring was ideal for exploring differences in pollution exposure levels by type of activity, but not feasible for large cohorts given the high costs involved and the difficulties of managing these systems long-term. Still, personal monitoring studies have shown that exposure levels differ by type of activity, dominant transport mode and social income classes, and related time spent in traffic accounts for the highest levels of exposure during the day (Blangiardo et al., 2011; Dons et al., 2014; Lane et al., 2015), suggesting that reducing commuting time might reduce exposure dose, especially for low income classes (Brunekreef et al., 2009). Uncontrolled urban sprawl and low quality public transport services lead to higher commuting times, especially for low-income people, who generally have less support to seek out care for respiratory diseases (Zhao, 2015). However, the contribution of traffic congestion to air pollution exposure in large cities remains unknown.

A paper recently showed a precise method to address long-term exposure to air pollution at the individual level by analyzing the concentration of black spots directly in postmortem lungs (Takano et al., 2019). The study was based on autopsies authorized by family members, since autopsy is not mandatory in São Paulo for all undefined natural deaths. These kinds of studies are currently complemented with research related to the COVID-19 epidemic, which show strong relationships between long-term high pollutant concentrations and virus impacts on respiratory and cardiovascular diseases (Connerton et al., 2020; Wu et al., 2020). Another important aspect of the knowledge of pollutant concentrations is that cities with high concentrations of pollutants, especially particles, have been greatly affected by the COVID-19 pandemic. Studies suggest that the pollutants may influence the spread of the virus (Zoran et al., 2020). In particular, Wu et al. (2020) found that an increase of just 1 $\mu g/m^3$ in $PM_{2.5}$ is associated with an 8% increase in the COVID-19 mortality rate; likewise, Coker et al. (2020) found a positive association of ambient $PM_{2.5}$ concentration on excess mortality in Northern Italy related to the COVID-19 epidemic. Their estimates suggest that a one-unit increase in $PM_{2.5}$ concentration ($\mu g/m^3$) is associated with a 9% (95% confidence interval: 6–12%) increase in COVID-19 related mortality. Additional studies specifically discussed the relationship between COVID-19 and air pollution from traffic, using the urban environments as observatories to test the correlation between traffic, pollution and public health throughout lock-down scenarios (Chen et al., 2021; Gama et al., 2021; Travaglio et al., 2021).

São Paulo is a 12 million inhabitant city where transportation is the main source of air pollution, having high concentrations of $PM_{2.5}$ and O_3 and frequently exceeding air quality standards (Pérez-Martínez et al., 2015). The city combines notable socioeconomic inequalities, ethnic diversity and high-quality data and could be considered a laboratory for urban policies aimed to promote urban health, particularly transportation-based policies. From a global perspective, São Paulo is not among the most polluted cities in the world (WHO, 2018) but ranks 5th among the most congested cities (INRIX, 2019), which increases the dose of air pollution that some residents of São Paulo are exposed to, especially in the city's peripheral regions (Pérez-Martínez et al., 2020a). The city of Patna in India ranks 5th in pollution levels (fine particulate annual mean in $\mu g/m^3$) and is more than 8 times more polluted than São Paulo (144 vs 17 respectively) but is smaller in population (2 vs 12 million).

Traffic is an important source of pollution in large cities and high levels of congestion might lead to underestimation of the exposure dose of residents. It may have an important impact in cities where air pollution is not the highest in international rankings, but where congestion is a major factor, which is the case of São Paulo and other megacities. In São Paulo, the transport sector is the most important source of air emissions (around 80%); followed by industrial sectors (which have been removed from the city over the decades), particulate matter resuspension and secondary aerosols (CETESB, 2020a). In this paper we use retrospective origin and destination (O/D) mobility and socio-demographic data (IBGE, 2020; METRO-SP, 2019; METRO-SP, 2017) to show that time and distance traveled while commuting in traffic are important factors in São Paulo.

It is generally understood that COVID-19 illness is more likely to be deadly for individuals with particular medical preconditions (e.g. obesity, cancer, chronic kidney and pulmonary diseases and type 2 diabetes) as well as for senior citizens (Ribeiro et al., 2020). Individuals exposed to transport systems and adverse environmental conditions over many years throughout their lifetime are more likely to develop certain respiratory system preconditions, increasing their likelihood of getting severely ill from COVID-19. The first hypothesis of this paper is that individuals living at the same location (who are therefore exposed to the same residential levels of pollutants) but who spent more time in traffic and traveled longer distances, receive higher doses of air pollution and are more likely to develop cardio and respiratory diseases, making them more vulnerable to die from COVID-19. The second hypothesis in this study is that individuals more exposed to different transport systems are more (or less) likely to contract COVID-19.

We now have the opportunity to test the two hypotheses in São Paulo, Brazil, by analyzing the relationship between COVID-19 mortality and potential endogenous variables. It is challenging to associate mortality with traffic induced air pollution, considering most COVID-19 deaths are individuals with particular medical preconditions and elderly people who probably do not commute as much as young adults.

2. Data and methods

In this study we used a broad set of data from several sources combined with COVID-19 related health data from the Municipality of São Paulo (MSP): number of deaths due to the Pandemic registered in São Paulo until 29th April 2021 (Prefeitura de São Paulo, S.M. da S, 2021). We analyzed long-term mobility data from the Origin and Destination (OD) survey from the Metro Company (METRO-SP, 2019) and socio-demographic data from the Brazilian Institute of Geography and Statistics during the period 1967–2017 (IBGE, 2020). Our research relies on municipality micro-regions, as cross-sectional levels, based on Transport Area Zones (TAZs) and Public-Health Area Zones (PAZs). We consider all different databases homogenized to the same spatial resolution: there is a direct correspondence between TAZs and PAZs. We also used long-term (2015–2019) air-quality data from the São Paulo Environmental Company (CETESB, 2020b) using the control network and the online platform QUALAR (CETESB, 2021). CETESB's stations measure, among other pollutants, concentrations of long-term particulate matter ($PM_{2.5}$) and nitrogen oxides concentrations (NO_X) in the Metropolitan Region of São Paulo (MRSP). We interpolated these concentrations to common TAZs using inverse weight distance (IWD) and aggregating statistical techniques to produce high-resolution cross-sectional data for the period 2015–2019. Therefore, all the variables used in this research are either aggregated or disaggregated to the same local micro-level to analyze the relationship between COVID-19 deaths and independent explanatory variables: mobility, sociodemographic profile, age and air quality.

2.1. Regional data and COVID-19 scenarios

We looked at the mobility patterns across the studied region during the first months of the epidemic's initial wave in March 2020. Firstly, we estimate monthly deviations in bus passenger trips, vehicle flows and congested kilometers. Deviations from month *i* (January 2020 to April 2021) are estimated using 2019 baseline records:

$$d_i = \frac{(\text{month}_i - \text{month}_{i,2019})}{\text{month}_{i,2019}} \quad (1)$$

The total number of bus passenger trips per month were obtained from transit operators (SPTRANS, 2021). More than 210 million passengers used regional buses every month in 2019. Light and heavy-duty vehicle flows (LDVs and HDVs) and the monthly average of daily traffic in both egress/access directions from/to São Paulo match the vehicle counts for the main highway in the region (Bandeirantes SP-348). In 2019, the Bandeirantes highway registered an annual average daily traffic (AADT) of ~110 thousand vehicles per day, 18% of which were HDVs (DER, 2021). The congested kilometers, expressed as total length of busy roads, represent monthly averages of daily congestion rates (CET, 2021). In MRSP, ~ 90 km of congested roads were estimated every day in 2019. We also estimated the monthly average NO_x concentrations to evaluate the direct impact of transport activities. These values, expressed in μg per m^3, correspond to CETESB's air quality network which covers the MRSP – Metropolitan Region of São Paulo (CETESB, 2021). In this case, the monthly concentrations are compared with the mean values of the five preceding years (2015–2019). During this period, the average NO_X in the region was 46.3 μg/m^3.

Finally, the former deviations are compared with the number of monthly COVID-19 deaths registered in São Paulo from March 2020 to April 2021 (Fig. 1). In the Municipality of São Paulo, more than 27 thousand people have died from COVID-19 (sum of confirmed and suspected deaths) since the beginning of the epidemic's initial rate of 64 deaths per day (Prefeitura de São Paulo, S.M. da S, 2021). We also relate the Covid-19 data with the transit occupation and isolation rates during these months. Occupation rates, expressed as passengers per operated bus, represent how transit operators are adapted to COVID-19 scenarios. An average of ~34 passengers travel in every bus under normal conditions (Prefeitura de São Paulo, S.M., da M. E T, 2021). Isolation rates, expressed as the percentage of people with restricted mobility, represent georeferenced data from telecommunication records (respecting the privacy of users, the information is aggregated and anonymized). Georeferenced data are grouped to develop public policies that improve measures of social isolation to confront the coronavirus. ~ 18 to 25% of population had restricted mobility under normal conditions (Paulo, 2021; SIMI-SP, ABR, I, 2021).

2.2. Sociodemographic local data

This section describes the variation of local mobility patterns and socioeconomic differences across the TAZs and PAZs. The local OD survey collects data on the mobility patterns of more than 30,000 households in the MRSP. The survey considered 517 TAZs in 39 municipalities of which 342 are in the São Paulo Municipality (METRO-SP, 2019). Around 100,000 individuals from these households were asked to record their travel trips registering all transportation modes: private vs public and motorized vs non-motorized trips. In their travel diaries, the individuals recorded their trips, geo-referenced by the coordinates of the origin and destination, throughout a working day. The number of passenger trips, extended by a statistical expansion factor, are transformed into passenger kilometers traveled (PKT) multiplying the trips by the orthodromic distances (Chatman, 2008).

The sociodemographic data include the total population and the urban density in each TAZ in terms of inhabitants/km^2. Epidemiological studies have found good agreements between high population densities and COVID-19 cases, a pattern likely related to closer human contact while performing activities, especially in small households in the peripheral areas of the municipalities (Cole et al., 2020; Liang et al., 2020). The mean income of the population, in Brazilian Real/month, and the employment rate, in number of jobs/inhabitant, are also tested to account for the vulnerability of poor and unemployed people to COVID-19, as the reviewed literature indicates a higher impact among these groups (Ribeiro et al., 2020). The final socioeconomic variable considered was the share of people older than 60 years old among the total population, which was tested to study the influence of the pandemic on the elderly population.

Our model includes the motorization index, expressed in numbers of cars/1000 inhabitants. Since our data is spatially organized, we consider the borders of the TAZs and PAZs and the centroid distances to capture the cross-sectional interactions between the local micro-regions. Therefore, we include a spatial weight matrix as a lagged variable to capture spillover effects due to the virus spreading among contiguous areas. We also split up the municipality into macro-regions according to distance from the center of the business district (CBD) to detect potential contagion from daily commuters. A variable was built for the four macro-regions: CBD, expanded CBD, outside city marginals and outside

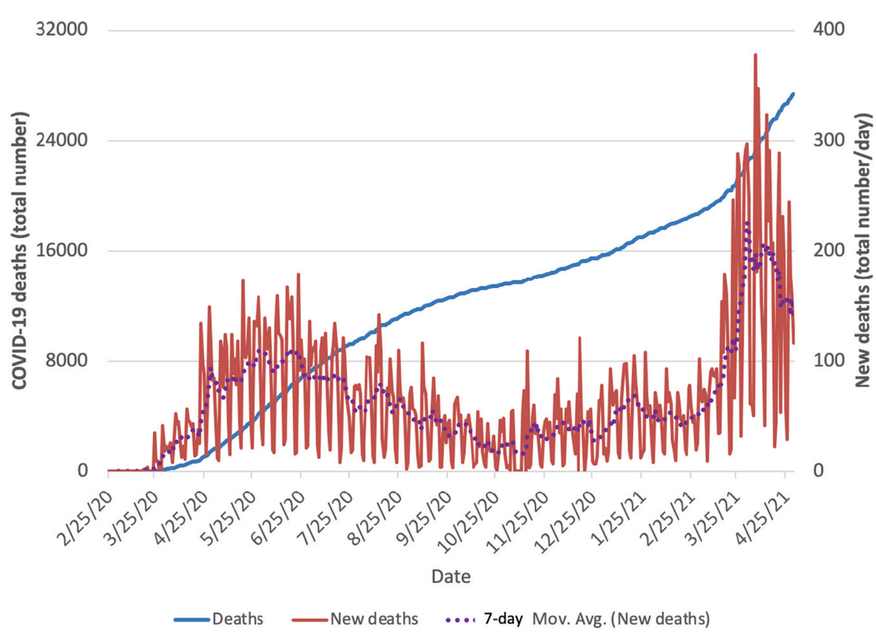

Fig. 1. COVID-19 deaths in São Paulo during the period 25th February 2020 – 29th April 2021: total sum of confirmed deaths (blue curve) and daily number of deaths (red curve). Notes: the dashed blue line represents 7-day moving average of new deaths. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

the Rodoanel ring.

Concentrations of $PM_{2.5}$ (in μg/m^3) are measured by the CETESB air quality monitoring network at a total of 23 stations (CETESB, 2021). These measurements have been extrapolated at a resolution of 100 m and finally aggregated to the TAZs/PAZs using the mean grid-cell concentrations within each micro-region. Using long-term data, we remove the bias due to annual oscillations, which better considers the lasting human exposure to high concentrations (Takano et al., 2019).

The COVID-19 health data used in this paper was provided by the São Paulo Secretary of Health (Prefeitura de São Paulo, S.M. da S, 2021). The Secretary collects the data from the local public health centers (PAZs) and relates to the residence of each person. The data are corrected for potential discrepancies: incorrect attribution of cases and deaths to COVID-19 disease and time correction of the delays between hospitalization, deaths and attributed cases. Since the number of COVID-19 cases is widely underestimated in Brazil due to the low number of applied tests compared to other countries, we decided to only use the number of deaths as a unique dependent variable for the sake of completeness and robust statistics. We assume that the number of COVID-19 deaths is better estimated than the number of cases, as described in recent studies conducted in the region (e Silva et al., 2020; Fernandes et al., 2021). There may be an under notification of COVID-19 deaths (~20% of suspected deaths over total). COVID-19 figures in reviewed studies have revealed that vulnerable people with deficient primary health conditions are likely to be more affected by the pandemic (Cole et al., 2020; Wu et al., 2020). Considering most COVID-19 deaths are of elderly people who probably do not commute as much as young adults, it is challenging to associate COVID-19 mortality with traffic related air pollution. Our spatial data permit control for these strata at the municipality level, representing the peripheral micro-regions of São Paulo. COVID-19 data consider the period from the first confirmed case in São Paulo in 25th February 2020 until the second plateau of the epidemic was reached at the end of April 2021 (Fig. 1).

2.3. Spatial model

This section describes the model employed to understand the differences in socio economical and mobility patterns throughout São Paulo. We studied the temporal and spatial influence of socioeconomic and land use variables on air quality, COVID-19 deaths and related PKT. We are not only interested in knowing the differences between transit/private oriented mobility and urban population growth by geo-referenced transport area zones but also in understanding changes in travel behavior (i.e. asking whether private driving has begun to decrease due to transit development and traffic restrictions in central areas). In this sense, disaggregated mobility data are necessary to identify temporal and spatial trends driven by transportation policies.

The spatial error model estimated the absolute number of deaths at daytime t and transport area zone/health area i, up until 29th April 2021 across 342 TAZs/PAZs, using COVID-19 records from the total municipal health information network, which occurred during the weeks after the first death related to the virus appeared on 17th of March 2020. In order to investigate the relationship between COVID-19 deaths, air-quality, socio-demographic and mobility variables, the following regression model was applied to the 342 TAZS/PAZs:

$$D_{t=29th\ April\ 2021,i} = a_0 + M_i^{'} a_1^M + S_i^{'} a_2^S + a_3 C_i + \delta_r + \rho \varpi_i R_i + \lambda \varpi_i \varepsilon_i + \mu_i \qquad (2)$$

where $D_{t,i}$ refers to the number of deaths from COVID-19 in TAZ i as of 29th April 2021; a_0 (intercept) and a_j are regression coefficients obtained by maximum likelihood estimation. M_i' and a_1^M represent the vector and regression coefficients of the mobility variables: number of trips using public transport (1000 trips/day/ region), public transport share on total motorized trips (%), public transport traveled distance (1000 pkt/day/region) and traveled distance by all transport modes (1000 pkt/day/km^2). S_i' is a vector of socio-demographic records, which may impact COVID-19 deaths and a_2^S are the regression coefficients related to: urban density (inhabitants/km^2), income (Brazilian Real/month/inhabitant), employment rate (number of jobs/inhabitant), motorization index (number of cars/1000 inhabitants) and share of population older than 60 years (%). C refers to annual long-term concentrations of $PM_{2.5}$ (μg/m^3) averaged over the period 2015–2019 in TAZ i. The term δ_r represents metropolitan level fixed effects for each of the 4 macro-areas dividing the metropolitan region of São Paulo: center business district (CBD), expanded business district, areas between the main metropolitan access/egress highways "marginals" and the external ring "Rodoanel" and areas outside the external ring. The centroid distance of each TAZ from the CBD also acts as a fixed effect. The final selection of independent variables was performed starting from some other variables in an original model that were dismissed because they were not statistically significant. In the model selection, testing was performed and careful consideration was given to ensure there were no strong correlations between independent variables.

Finally, we consider a spatially lagged variable of R_i residuals - predicted in a first stage considering the same variables included in Eq. (2) - and a spatial error term ε_i, using a spatial weight matrix ϖ_i with an order of contiguity equal to one (Anselin and Rey, 2014). The residual variable works as a control variable perpendicular to the other explanatory variables and represents the exogenous variables not considered in the model. The statistical significance of the residual coefficient (*Rho*) gives additional information about the endogenous nature of the explanatory variables (Cole et al., 2020). The model produces consistent unbiased estimates and improves the classic statistical model that uses ordinary least squares (OLS) statistics. The consideration of the lagged residual variable and error term is expected to improve the *R-square* of the model.

3. Results and discussion

3.1. Mobility analysis and COVID-19 scenarios

The long-term trend in São Paulo is towards decreasing public transport and increasing private transport (METRO-SP, 2017). However, the mobility reaches a threshold regarding private transport due to public transportation policies and active restrictions on private mobility (especially in the central regions). Fig. 2 shows the distribution of the number of trips (31% cars and 26% buses) and passenger kilometers (37% private cars and 38% buses) in MRSP. The share of non-motorized trips (35%) and passenger kilometers related to public transport (62%) indicate the potential of the mobility system to further reduce CO_2 and pollutant emissions (METRO-SP, 2019). A maximum spatial-budget value of ~20 PKT/person/day was reached and income group differences in time and spatial budgets are decreasing over the years. The overall mobility increased during the period 1997–2017 coupled with pollutant concentrations and related cardio and respiratory diseases.

The motorization index, per capita number of cars, increased with the growing mobility, a trend which appeared separately for different income groups. In São Paulo, the total mobility of high-income grouping is about 1.5 times the mobility of low-income classes (3.6 vs. 2.2 trips/person/day). Also the time budget (expressed in minutes) of high-income classes is about 1.5 times the time budget of low-income groups (113 vs. 78 min/person/day). Similarly, the space budget (expressed in PKT) of high-income classes is ~2 times the space budget of low-income groups (18 vs. 10 PKT/person/day), although differences are lower and decreasing over time (METRO-SP, 2017). Households with higher incomes have higher temporal and spatial budgets compared to low-income households (427 vs. 298 min/household/day and 67 vs. 37 PKT/household/day), although the differences between income groupings are also decreasing over time.

Studying differences between transport modes, the motorized mobility of high-income groupings is ~3 times higher than low-income groupings (3.1 vs. 1.0 trips/person/day). The private mobility of high

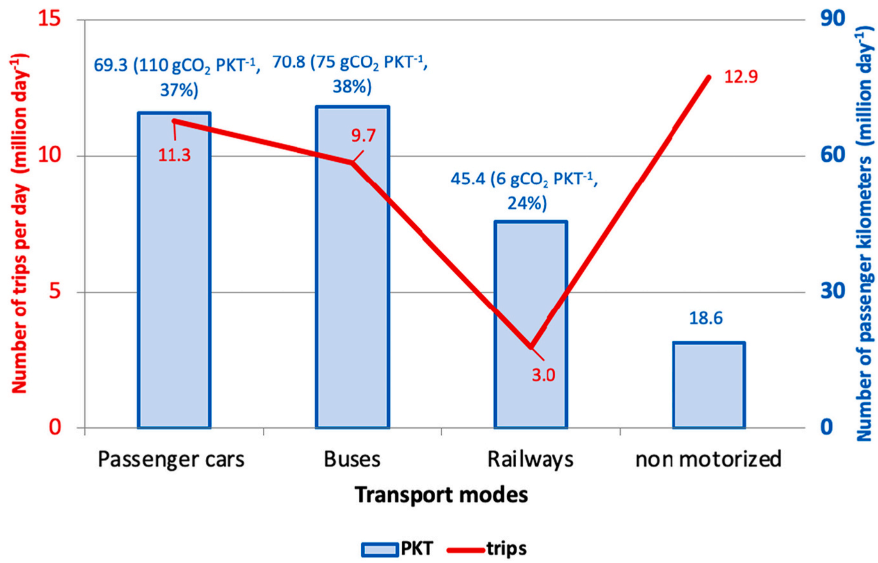

Fig. 2. Total number of trips and passenger kilometers traveled (PKT) per day in the Metropolitan Region of São Paulo by different transport modes (METRO-SP, 2019): passenger cars, buses, railways and non-motorized (walk and bicycle). Mean CO_2 emission rates (in gCO_2 eq./PKT) and motorized vehicle's shares of PKT (in parentheses).

income classes represents >25% of the mobility of this group (<10% for low income classes). Oppositely, the non-motorized mobility of low-income classes represents >50% of the mobility of this group (<8% for high income classes). Currently, the immobility of low-income classes is similar to the immobility of high-income classes (~25%). In the past, immobility for males was lower than for females but has been equal as of 2017. Studying differences between activities, the educational mobility of low-income classes is similar to the educational mobility of high incomes. The working mobility is decreasing through time.

The fact that wealthy central regions present higher mobility - overall transport distances, times and trips - leads to a more detailed analysis of long-distance commuting to work. In this sense, major transit flows during working days could act as a spreading vector of COVID-19 from the city center to the periphery. Fig. 3a and b show the spatial distribution of main transit corridors, vehicle flows and hotspots of passenger boarding counts associated with the main public transport terminals and hubs. However, according to Vasconcellos (2001), traffic related pollutant emissions per person/day of private transport of high income classes are ~8 times higher than car emissions of low income classes (241 vs. 31 g CO person/day). While emissions from public transport of low income classes are similar to emissions of high income classes (~ 2 g CO/person/day), emissions from private transport of high income classes are ~100 times higher than emissions from public transport (~ 13 times higher than public transport among low income classes).

Decreasing emissions from private cars is crucial to reducing air pollution effects and mortality (Beelen et al., 2008; Dons et al., 2011). Investments in public transport facilities and high quality services, such as high capacity electrified metro lines, are needed to reduce long-term pollutant emissions (Pérez-Martínez et al., 2020b). Transport emissions from private cars in São Paulo, and associated air quality concentrations, largely affect transit users, increasing their probability to develop respiratory system preconditions and their risk for several chronic diseases associated with aggravated COVID 19 (Kephart et al., 2021). Therefore, we can conclude from our model results that there is a possible correlation between diseases such as COVID-19 deaths and long-term exposures to pollutants (i.e. $PM_{2.5}$ and NO_X).

Fig. 4 shows the monthly deviations of bus passenger trips, NO_X concentrations, LDV and HDV flows and congested kilometers compared with the number of COVID-19 deaths. During the initial months of the epidemic, bus passenger flows decreased ~70% coupled with 42%, 55%, 18% and 94% reductions of NO_X, LDVs, HDVs and congestion, respectively. These reductions were the direct consequence of mobility restrictions established in São Paulo to battle the COVID-19 disease, which showed an initial peak in June 2020 with an average of 96 deaths per day. The isolation rate increased from 25% to 52% during this period: more than half of the citizens experienced restricted mobility during the first peak. The transit vehicle occupation rates decreased to a minimum of 25 passengers per operated bus, down from the normal rate of ~34 passengers (−25%), showing transport policies towards social distancing and influence of the new Delta variant in March and April 2021.

The reduction of COVID-19 to ~25 deaths per day led to a reopening of economic activities by the end of the year 2020. NO_X concentrations and LDV flows almost recovered the prior pre-pandemic values (HDV flows even increased compared to 2019 by 20%). Bus passengers and congestion values recovered from the 40% and 20% reductions in regard to the baseline period. Transit occupation values increased to normal operating values and isolation rates remained at a constant value of 42% (increment of 68% respect 25% corresponding to restricted mobility under normal conditions). We can observe that in October of 2020, NO_X concentrations returned to near-baseline level. In São Paulo, this pollutant predominately results from heavy truck and bus emissions (CETESB, 2020b); although bus circulation rates did not recover to baseline levels, the circulation of trucks increased during the economic reopening period.

There was an overall reduction of the mobility patterns corresponding to new mobility restrictions linked to different peaks of COVID-19 deaths at the beginning of the year 2021. In April 2021, the epidemic reached a maximum peak of 175 new deaths per day. Responding to new peaks, different mobility restriction policies were applied from January 2021 onwards and deviations of NO_X concentrations, vehicle and truck flows and congestion fell to 0.38, 0.29, 0.19 and 0.59, respectively. Bus passengers slightly decreased their activities and deviations fell under 40% (corresponding to a new decrease of the occupation rates to 26 passengers per vehicle).

3.2. *Differences between TAZs*

Table 1 shows the descriptive statistics of our local data. During the reviewed period, starting with the first death on 17th March 2020 until

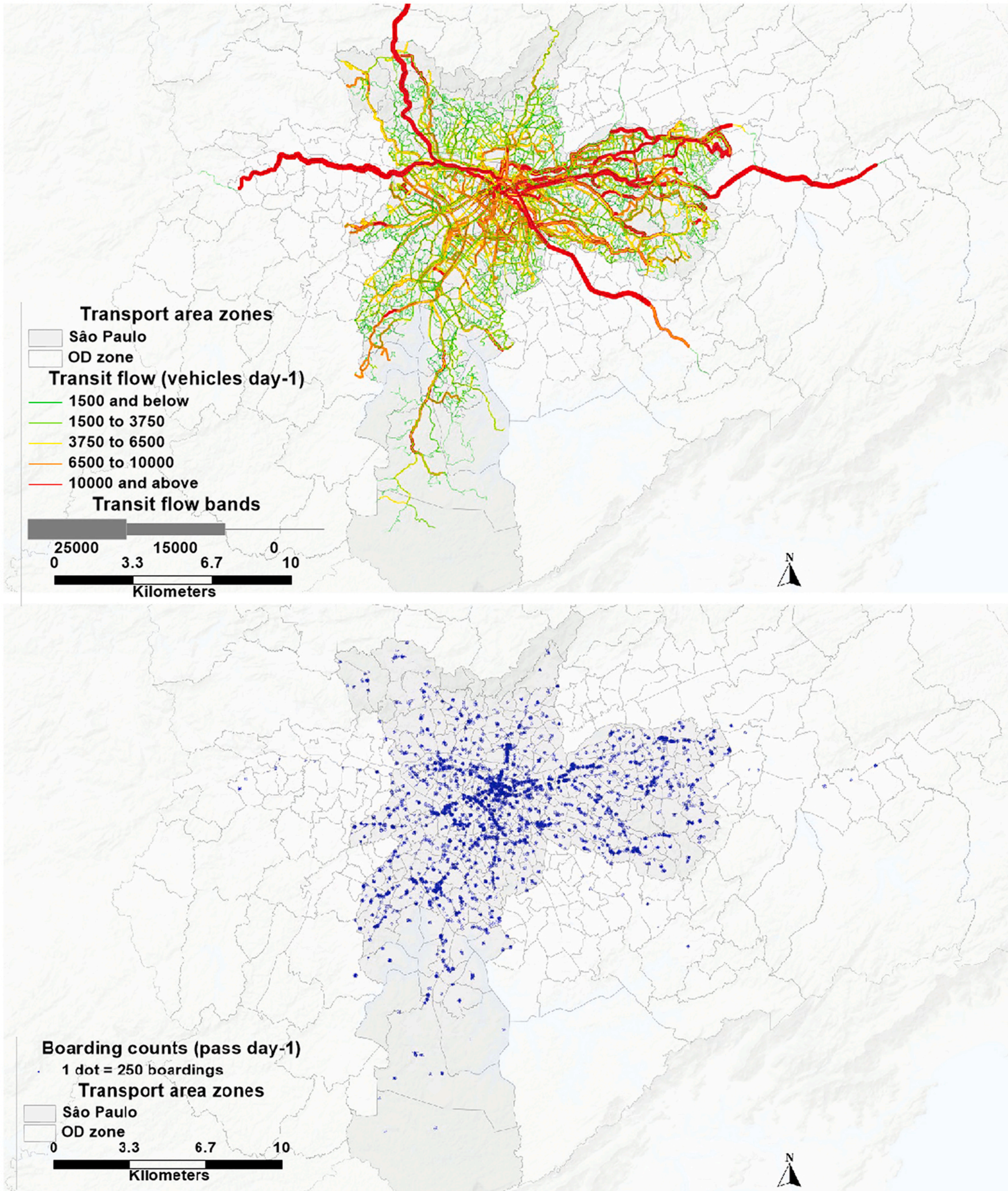

Fig. 3. Transit flows (vehicles/day) during working days operating in São Paulo (Fig. 3a) and related boarding passenger counts per day (Fig. 3b). Notes: ranges for each level of flows in Fig. 3a are presented in the legend of the graphs together with the traffic flow bands graph according to statistical quintiles. Dots in Fig. 3b represent the locations of the representative public transport stops, stations and terminals with appropriate mobility data (hotspots). The limits of the transport area zones in the Metropolitan Region of São Paulo are plotted.

the second peak of the epidemic was reached on 29th April 2021, 111 deaths were registered on average across the 342 micro-regions (maximum 460). These micro-regions have an average urban density of 12,134 inhabitants/km^2. The sizes of the regions vary from vast areas in the periphery to small areas in the city center and the associated average density presents a large variation (standard deviation of 7309 inhabitants/km^2). On average, 17.5% of the population is over 60 years old. The median income in São Paulo is 1264 Brazil Real/inhabitant/month (~250 US$, standard deviation 1036) and the median employment rate is 0.5 jobs/inhabitant (standard deviation 2.9). The mean motorization index, 241 cars/1000 inhabitants, presents a smaller variation across sections (standard deviation 121) compared to the other sociodemographic variables.

Regarding mobility data, we report a median annual value of 25,190 public transport trips/region/day (standard deviation 20,850), showing large cross-sectional variations. The public transport share of total motorized trips presents an average annual value of 39.5% (maximum 72.3% in CBD). The average public transport related distance is 7.1 km/trip (maximum 17.9). We studied the deviation of passenger kilometer traveled distances (PKT) using public and private transport modes: 229,796 average public transport PKT/region/day (standard deviation 209,087) and 143,394 average all modes PKT/km^2/day (standard deviation 111,193).

Air quality data expressed in terms of $PM_{2.5}$ concentrations present

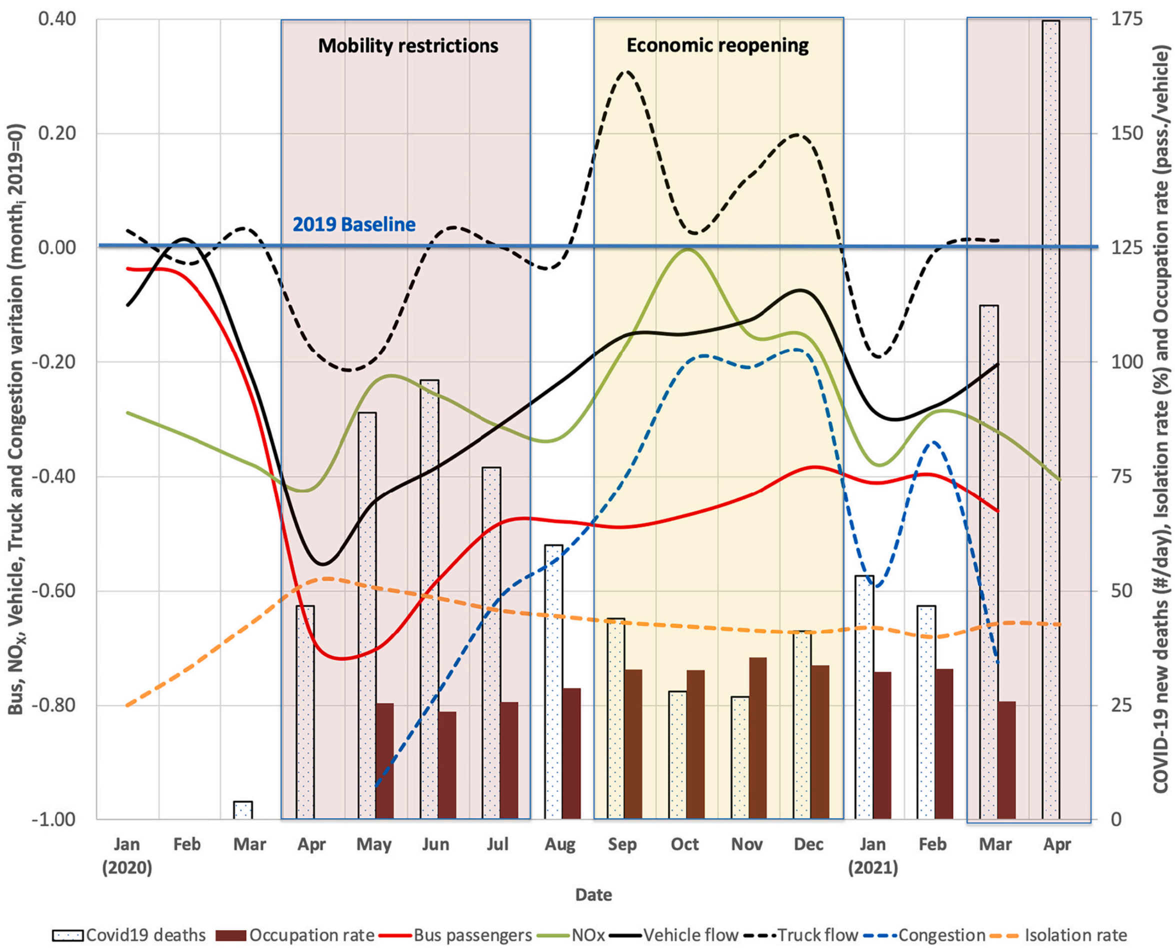

Fig. 4. Monthly deviations of bus passenger trips, NO_x concentrations, vehicle and truck flows and congested kilometers compared with Covid-19 deaths, bus occupation and isolation rates during the months since the beginning of the epidemic in São Paulo city. Notes: deviations of month *i* (January 2020 – April 2021) are estimated from 2019 baseline records (*deviation month*$_i$ = *(month*$_i$ - *month*$_{i,2019}$*)/month*$_{i,2019}$); red and yellow vertical shaded bars represent the months with some mobility restrictions and reopening of the economic activities, respectively. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 1
Descriptive statistics (n = 342).

Variable	Mean	Std.	Median	Max
COVID19-deaths (number/period until 29th April 2021)	111.1	93.3	86.6	460.3
Public transport trips (1000/day/region)	30.3	20.8	25.0	116.6
Public transport share (% motorized trips)	39.5	10.6	39.3	72.3
Public transport trip distance (km/trip)	7.1	3.0	6.5	17.9
Public transport PKT (1000 pkt/day/region)	230	209	177	1533
All modes PKT (1000 pkt/day/km^2)	143	111	116	817
Urban density (inhabitants/km^2)	12,134	7309	11,750	42,793
Income (Brazil Real/inhabitant/month)	1658	1036	1264	5333
Employment rate (jobs/inhabitant)	1.2	2.9	0.5	39.9
Motorization index (cars/1000 inhabitants)	241	121	224	574
Old people (% more than 60 years)	17.5	6.7	17.2	38.6
Long-term mean $PM_{2.5}$ (μg/m^3)	16.9	1.0	16.9	19.5

an average value of 16.9 μg/m^3, a standard deviation of 1.0 and a maximum of 19.5. The values of the long-term averages in all the micro-regions are above the levels recommended by the World Health Organization (5 μg/m^3). Finally, we estimate the number of air quality diseases related to PKT, number of COVID19 related deaths/PKT, using the appropriate individual levels of exposure to pollution (number of COVID-19 related diseases/pollutant concentration), accounting for vehicle type, time spent and distance traveled in different daily activities of the dominant vehicles used in each passenger trip (concentration of pollutant/PKT and number of COVID-19 related diseases/PKT). For private transportation, we can use adequate pollutant emission rates from the State Environmental Company (CETESB, 2020a), applied to an average vehicle fleet in São Paulo. In the case of public transportation, buses and metropolitan modes, we use private data from the local transit companies (METRO-SP, 2017; SPTRANS, 2018).

Fig. 5 shows the spatial distribution of daily PKT for household individuals in the Metropolitan Region of São Paulo by different motorized transport modes: private vehicles (cars and motorcycles), rail transport modes and buses. We used a diffusion Kernel smoothing technique to interpolate daily PKT from all the surveyed values (n = 115,587) by dominant transport mode (Fig. 1, **Supplementary Material**): 62,391, 15,202 and 37,994 individuals for private vehicles, rail modes and transit buses, respectively. Ranges for each level of PKT are presented in the legend of the graphs (189–2240 and 85–850 km). Fig. 5 shows the map of PKT in the city of São Paulo matched to the geo-referenced location of the residences of ~100,000 surveyed individuals in Fig. 1 **(Supplementary Material)**. Regions near the central business district (CBD) have low PKT. High PKT regions, shown as the surfaces in red colors, are large throughout the entire periphery indicating pendular commuting trips. The legend of the figure shows the São Paulo Municipality road network, the underlying 342 TAZs and the interpolated PKT Quintiles (in passenger kilometers/day by dominant transport mode).

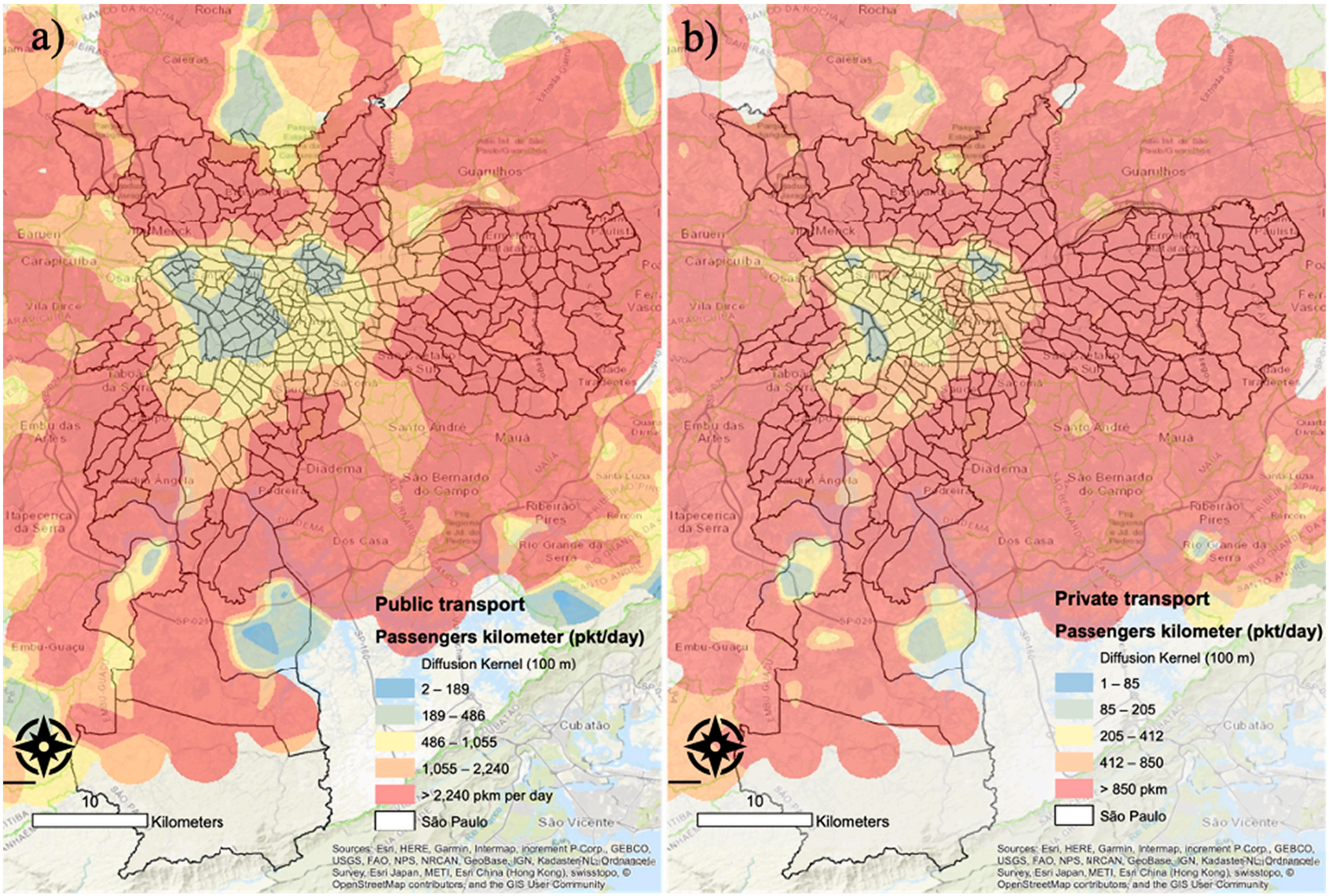

Fig. 5. Passenger kilometer traveled (PKT, km/day) in São Paulo (2017) by dominant transport mode: public buses (Fig. 5a) and private-owned transport vehicles (Fig. 5b). Ranges for each level of PKT are presented in the legend of the graphs. Notes: The limits of the transport area zones in the municipality of São Paulo are plotted. Individual PKT data were multiplied by sampling expansion factors and interpolated by quintiles using diffusion Kernel smoothing techniques. The size of the grid employed to fit the surfaces was 100 m (1,298*825 cells).

The spatial variations reflect the differences between central and peripheral areas and complement the differences in COVID-19 deaths.

Fig. 6a shows the spatial distribution of long-term air pollution ($PM_{2.5}$) concentrations (2015–2019) in São Paulo. Fig. 6b shows household PKT from the 2017 Metrô travel survey, aggregated by TAZs. Eastern areas have high pollutant concentrations and public transport related PKT. Oppositely, central regions have low PKT values and better atmospheric conditions. Low $PM_{2.5}$ concentration areas, in blue, are largely, but not exclusively, on the urban central fringe of the western regions. The public transport travel distances are negatively correlated with human wages and employment rates, reflecting a different pattern between the central and suburban regions (Fig. 6c). Peripheral regions also present high values of urban density (> 10,000 inhabitants/km^2, Fig. 6d) and long travel distances associated with public transport commuting trips. The share of public transport among the total number of motorized trips in the periphery is not different compared to the central regions, showing the increasing importance of private transportation in the suburbs using old cars and technologies. This circumstance is corroborated by the increment of the motorization index in some regions on the suburban fringe and the increasing share of public transport in the central regions. In São Paulo, central regions also present a higher number of trips in all transport modes due to non-commuting and commercial activities (Fig. 6e). The citizens in these wealthier areas use new transportation facilities, such as new metro lines and high-capacity infrastructures, combined with novel technologies and services, such as the transportation network companies (TNCs). Finally, Fig. 6f includes the spatial pattern of COVID-19 deaths per thousand inhabitants to compare with the distribution of the other explanatory variables. Peripheral regions suffer the most from the impact of the epidemic.

Overall, the distribution of public and private hospitals plays an important role in determining access to healthcare, with private healthcare systems being more common in higher-income areas (generally located near the center of the city of São Paulo), while outskirt regions depend heavily on public hospitals. Regarding COVID-19 deaths and healthcare, it should be noted that Intensive Care Unit (ICU) capacity was shared between private and public systems (Li et al., 2021), and that temporary hospitals were constructed to increase ICU capacity specifically for COVID-19 hospitalizations, making it difficult to determine the degree to which the distribution of these systems influenced the spatial distribution of COVID-19 deaths.

3.3. Model results

The basic descriptive statistics of Table 1 are compared and fit to a spatial error model using regional public health COVID-19 measurements as the dependent variable and socio-demographic, mobility and long-term air quality parameters as the explicative variables. Table 2 shows the results of the model using Eq. (2) and the columns present the estimates of COVID-19 deaths for $PM_{2.5}$ and the other descriptive variables.

$PM_{2.5}$ concentrations are positively correlated with COVID-19

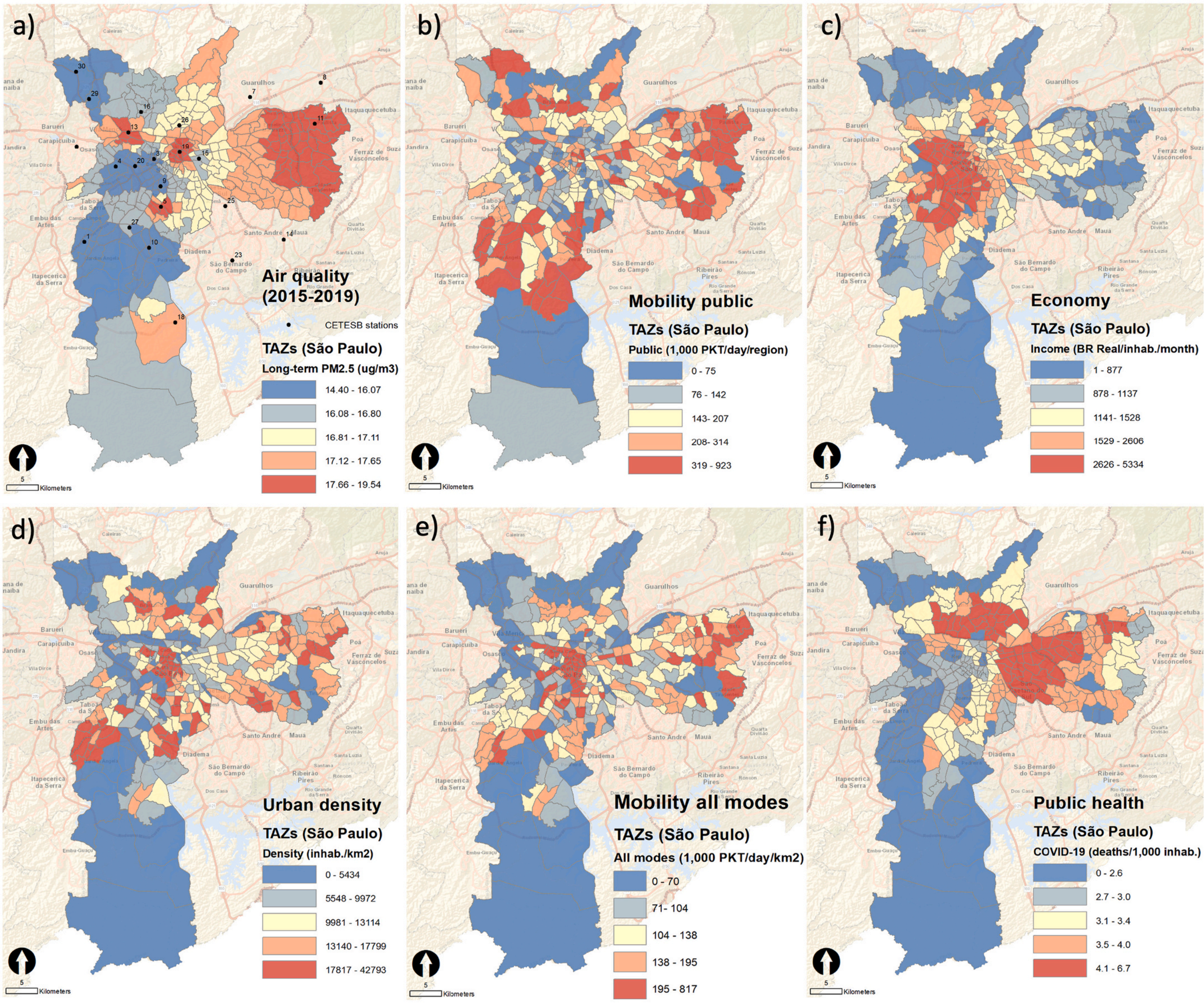

Fig. 6. a) Long-term $PM_{2.5}$ concentrations (μg/m^3), b) passenger kilometers traveled in public transport (1000 pkt/day/region), c) income (Brazil Real/inhabitant/month), d) urban density (inhabitants/km^2), e) overall mobility (1000 pkt/day/km^2), f) COVID-19 deaths in São Paulo during the period 17th March 2020 – 29th April 2021 (total deaths/1000 inhabitants/region). Notes: ranges for each level of the variables are presented in the legend of the graph according to statistical quintiles. Dots in Fig. 6a represent the locations of the representative CETESB's stations with appropriate long-term air quality data.

deaths. Keeping the other explanatory variables constant, an increment in the pollutant concentration of 1 μg/m^3 is associated with 7.3 more deaths (standard error 4.1 and $p < 0.1$), similarly to the 8% increase obtained in the USA (Wu et al., 2020). Analyzing the other variables and focusing on statistically significant relationships, we find that regions with high urban densities have higher number of COVID-19 deaths compared to low density regions: an increment of 1000 inhabitants/km^2 is coupled with 4.8 more deaths (standard error 0.5 and $p < 0.01$). Regarding Eq. (2), in order to support the interpretation of the beta coefficients of Table 2 in absolute terms and in the case that there are no integers (i.e. 4.8 more deaths from COVID-19 in a mean average of 111.1 deaths per transport area zone), the model can offer the results also in relative terms (so-called Relative Risks RR and Attributable Risks AR); that is to say, a y % increment in the number of deaths can be interpreted as a direct consequence of an x increase in the explanatory variable i, holding the other variables constant.

We also find that average income is negatively related to COVID-19 deaths - an increment of the mean monthly wage of 100 Brazil Real (~20 US$) is associated with 2.4 less deaths (standard error 0.6 and $p < 0.01$) - while the motorization index has positive correlation (0.8 more deaths vs. 10 cars/1000 inhabitant increment). As it was expected, the share of people over 60 years old has a positive association, although not statistically significant in the model. This variable was included because it is understood to be a relevant factor, especially considering the importance of older populations as a risk group and the unavailability of a vaccine for the period considered in the study.

Regarding the mobility indicators, we discovered that a 10% increase in public transport share of motorized trips is related to 21.6 less deaths (standard error 3.0 and $p < 0.01$). Conversely, the increase of PKT related to public transport trips is also associated with COVID-19: 17.2 more deaths per increment of hundred thousand kilometers per region and day (standard error 3.2 and $p < 0.01$). The increase of PKT related to all transport modes is associated with a decrease of COVID-19 deaths: 31.2 less deaths per increment of hundred thousand passenger kilometers per km^2 and day (standard error 3.3 and $p < 0.01$). The "all transport modes" variable includes walking and cycling, which helps clarify the difference of the sign between the two PKT indicators. People could reduce their chance of dying from COVID-19 just by adding kilometers

Table 2
Spatial error model ($n = 342$).

Independent variable	COVID-19 Deaths (until 29th April 2021)		
	Estimate (SE)	z-value	Probability
Constant	−14.21 (72.46)	−0.20	0.84
Public transport trips (1000/day/region)	1.67 (0.29)***	5.68	0.00
Public transport share (% motorized trips)	−2.16 (0.30)***	−7.20	0.00
Public transport PKT (10,000 pkt/day/region)	1.72 (0.32)***	5.39	0.00
All modes PKT (10,000 pkt/day/km^2)	−3.12 (0.33)***	−9.53	0.00
Urban density (1000 inhabitants/km^2)	4.77 (0.45)***	10.69	0.00
Income (100 Brazil Real/inhabitant/month)	−2.42 (0.57)***	−4.21	0.00
Motorization index (10 cars/1000 inhabitants)	0.84 (0.44)*	1.89	0.06
Old people (% more than 60 years)	0.25 (0.61)	0.41	0.69
Long-term mean $PM_{2.5}$ (μg/m^3)	7.34 (4.06)*	1.81	0.07
Lag Residual - Rho (ρ)	0.17 (0.05)***	3.43	0.00
Lambda (λ)	0.50 (0.06)***	7.68	0.00

Notes: Robust standard errors in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The control variable included in the estimation is the proximity to the CBD (Praça da Sé). All modes variable includes walking and cycling.

traveled in non-motorized means during frequent short-time trips (i.e. less than 15 min). There would be a drop in cases if this replacement were done on a large scale, thus decreasing the concentrations of pollutants. Non-motorized trips represent an alternative to motorized journeys for distances under 2 km, especially in central wealthier areas. Oppositely, passengers from peripheral regions have limited alternatives to transit to perform frequent pendular motorized trips. In these regions, the high volume of long-distance trips may have a strong influence on the epidemic's development.

Although there is a relationship between public transport use and COVID-19, in terms of number of trips (1.7 more deaths per 1000 trip increment, $p < 0.01$) and associated traveled distances, there is also a positive influence of public transport's share of total motorized trips, especially related to short-distance non-commuting trips. In this sense, Table 2 shows a positive parameter in the motorization index variable (combined with a negative one in the public transport share variable). There is a need to encourage the use of public transport while also disincentivizing the use of private transport in all the regions of the city. For instance, transport policies related to the 15-min city, which encourages employees to work and socialize close to their places of residence, can contribute to the reduction of traveled distances in all motorized transport modes. The model indicates a negative relationship between public transportation/non-motorized modes and likelihood to die from COVID-19, with the use of private automobiles showing an increasing risk. Even though the model finds strong correlation between dependent and independent variables, this does not imply causality. This finding highlights the need for further studies to illuminate how these transportation modes (or their associated lifestyles) may be associated with differing virus transmission rates or increased susceptibility to develop severe symptoms.

On one hand, the model identifies possible relationships between individuals' mobility patterns and the development of several respiratory preconditions that can increase the risk of a fatal response to developing COVID-19 (addressed in the first hypothesis in the introduction). On the other hand, the model shows that long distance commuters are more likely to die from COVID-19, but at the same time, individuals who travel long distances in all other modes (including private motorized and active transport such as walking and cycling) are less likely to die from such disease. In this paper, we detect long-distance pendular commuting trips from distributions of income and demography among TAZs: low income classes living at the periphery and economic opportunities at the central regions (Fig. 6). Individuals from central regions carry out several trips during the day, adding up to a considerable daily trip distance across all modes. Mobility patterns also affect pandemic spreading (addressed in the second hypothesis in the introduction).

Motorization rates are becoming less independent of income and peripheral TAZs are acquiring old cars from other areas; for this reason we grouped the motorization index and income in the final model. We are including both public transport passenger-kilometers traveled PKT and PKT across all modes to distinguish between different mobility patterns in the periphery and central areas. Public transport and private automobile PKT were strongly correlated as shown in Fig. 5.

4. Conclusion

In summary, we performed an econometric analysis of socio-economic variables such as use of public transport across different modes, urban density, family income, employment rate, motorization index, age and $PM_{2.5}$ concentration, for the period 17th March 2020–29th April 2021, in order to verify the possible relationship among the variables and SARSCoV-2, COVID-19 deaths in São Paulo city, Brazil. We used a São Paulo-based case study to explore the relationship between residential locations, on household patterns of passenger kilometers of traveled distance (PKT), and COVID-19 deaths. Long-term mobility data from origin and destination (OD) surveys in São Paulo showed that with increases in less pollutant private transport and use of high-capacity infrastructures, the overall reduction in air pollution concentration levels creates a more uniform spatial profile of air-quality related diseases in the city center. However, this pattern differs across the São Paulo microregions and increases in commuting distances and use of low-capacity public transport in the periphery creates a more heterogeneous high profile of diseases.

Due to the recent nature of the study, mobility data for the pandemic period at the TAZ level is not yet available. In the model of this paper, it is assumed that the data from the OD survey represents long term trends and that peoples' habits in São Paulo tend to recover rapidly over a short period of time after the reopening of economic activities (as it was shown in Fig. 4). Mobility patterns have also changed during the pandemic, especially through March/June 2020 months, since the local, state and federal governments imposed some mobility restrictions coinciding with the peaks of the pandemic (Connerton et al., 2020). Even though we had little mobility forced restrictions in São Paulo, we can assume that some population segments, especially wealthy people, changed their mobility patterns considerably (traveling less as a measure of self-protection or even replacing transit with private or non-motorized trips). The fact that the recovery of transit during the reopening months was less accentuated than the private transport supports this assumption.

In this work, using available OD mobility data, we tested how individuals more exposed to certain transport systems are more likely to die from COVID-19, as a possible result of having developed certain preconditions which made them more vulnerable to this disease (our first hypothesis). It should be noted that one limitation of this study was the use of total COVID-19 death numbers, which were not adjusted for population in each PAZ. The decision to use the unadjusted values provided more compatibility with the model, given that our study does not aim to make comparisons between cities and focused instead on transport routes and mobility dynamics, which influence COVID-19 deaths differently. Long-term outcomes have already shown that passenger kilometers, commuting times and air pollution related diseases increase with residential distance from the city center. Passenger trips alone, however, do not account for the air-quality related disease profiles in the region's central business district where the use of private cars dominates (and non-motorized trips) and diseases decreased over time. Higher fringe disease values are a function of both increased passenger kilometers traveled and commuting times. The long-term OD travel data would need to be adjusted using scenario data during the COVID-19 months to test whether individuals more exposed to different transport systems are more (or less) likely to contract COVID-19 (second hypothesis). Transit operators reduced the occupancy rates by ~25% during the epidemic peaks (Fig. 4). In future communications, we will need to test these scenarios to have concluding results about the influence of different transport systems on the spreading of the disease.

The results of our study agree with the outcomes of the reviewed literature (Beelen et al., 2008; Brunekreef et al., 2009). In São Paulo, the PKT and air-quality related diseases, by dominant transport modes using household (HH) mobility data of individuals, increased with distance from the central business district (CBD) and decreased with urban density (number of inhabitants/km^2). Oppositely, the traffic and related environmental problems are still more concentrated in the central regions of São Paulo, decreasing with CBD and increasing with urban density, respectively. However, air quality is also becoming more degraded within the peripheral regions of RMSP.

Overall, spatial differences between PKT and air pollution related diseases are due to differences in the use of transport modes - private versus public vehicles - showing that the choice of the transport mode is a key mobility indicator. A higher share of public transport appears in the peripheral regions, leading to lower vehicle traffic and resulting emissions per km^2 compared to the inner parts of the metropolitan region. Increases in commuting distances and the use of low-capacity public transport in the periphery (such as vans and micro buses) creates a more heterogeneous high profile of diseases. The distribution of the modal choice is heavily influenced by the income levels in São Paulo, with wealthy households of the city center using more private vehicles, which are less efficient (per person) in terms of energy consumption, pollutant emissions and contribution to air pollution related diseases.

The observed reductions in air pollution levels in São Paulo during the past years (CETESB, 2020b; CETESB, 2021) are desirable but not enough to protect the health of people residing in the city. Growth management plans, combined with strategies to reduce emissions, reducing traffic commuting times is crucial to prevent air pollution related diseases in megacities; transport and urban policies in the future are expected to reduce commuting times and distances. Over time, investments in high capacity public transport infrastructures will shift passengers from private cars and diesel buses to efficient railways resulting in air quality related disease reductions.

The paper presents rich data and visualization on the travel trips and mobility in São Paulo. Although this information can be expanded to the air quality analysis, it does not need to be associated with the COVID-19 disease exclusively and could be extrapolated to other respiratory and cardiovascular diseases. Additional reliable information on transport related cardiovascular diseases with air quality are needed to develop appropriate mobility policies.

The current levels of air pollution in the city require measures that reduce the number of motorized trips and congestion, such as reducing the distances to be covered, policies that induce more efficient public transport and lowering emissions from freight transport (Pérez-Martínez et al., 2020a). Our findings reinforce the need for policies that decrease commuting times and distances to reduce exposure of their residents together with policies aimed at directly reducing pollution levels without increasing the use of private transport.

The circumstances of the COVID-19 pandemic served as a living laboratory to investigate transportation and mobility dynamics through sociodemographic lens, highlighting how the unequal access to transportation services impacted exposure to both particulate matter and to COVID-19. The results are in line with other works, which have investigated the disproportionate impact of the virus on poorer and communities of colour in São Paulo, for example (Li et al., 2021). Ultimately this calls attention to the urgent need to expand access to quality transportation services and increase active mobility infrastructure.

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CRediT authorship contribution statement

P.J. Pérez-Martínez: Conceptualization, Data curation, Formal analysis, Methodology, Project administration, Writing – original draft, Writing – review & editing. **J.V. de Assunção:** Data curation, Formal analysis, Methodology, Writing – original draft, Writing – review & editing. **P. Connerton:** Formal analysis, Validation, Writing – original draft. **A.D. Slovic:** Data curation, Formal analysis, Investigation, Writing – original draft, Writing – review & editing. **H. Ribeiro:** Investigation, Visualization, Writing – original draft, Writing – review & editing. **R.M. Miranda:** Formal analysis, Investigation, Methodology, Writing – original draft, Writing – review & editing.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jtrangeo.2022.103349.

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