Landscape and Urban Planning 254 (2025) 105230

Contents lists available at ScienceDirect

Landscape and Urban Planning

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

Research Paper

Air regulation service is affected by green areas cover and fragmentation: An analysis using demand, supply and flow during COVID-19 quarantine

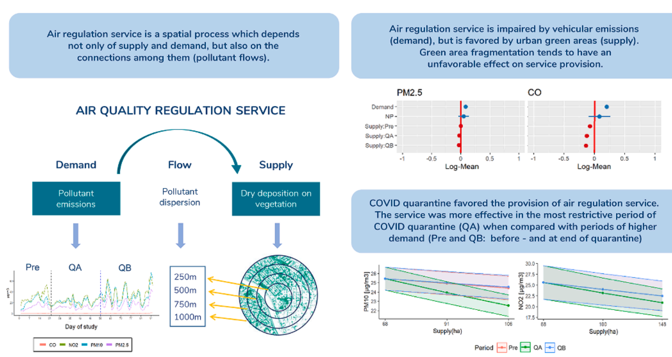
Nataly Andrea Pimiento-Quiroga [a,*], Paula Ribeiro Prist [b], Sergio Ibarra-Espinosa [c,d], Ligia Vizeu Barrozo [e], Jean Paul Metzger [a]

[a] Department of Ecology, Institute of Bioscience, University of São Paulo, Rua do Matão, Travessa 14, 101, São Paulo, SP 05508-090, Brazil
[b] EcoHealth Alliance, 520 8th Avenue ste 1200, New York City, NY 10018, USA
[c] Cooperative Institute for Research in Environmental Sciences, CU, Boulder, USA
[d] NOAA Global Monitoring Laboratory, USA
[e] Departamento de Geografia, Faculdade de Filosofia, Letras e Ciências Humanas, Universidade de São Paulo, SP 05508-080, Brazil

HIGHLIGHTS

- Air regulation services can be improved by increasing green areas amount (supply) and reducing vehicle emissions (demand).
- Fragmentation is important in the provision of air regulation services, with different effects on the pollutants assessed.
- Air regulation service can happen even in distances up to 1 km away from the pollution sources.

GRAPHICAL ABSTRACT



ARTICLE INFO

Keywords:
Green areas
Urban trees
Air pollution
Air quality regulation
Ecosystem services

ABSTRACT

Urban green areas are a potential supplier of air quality regulation service. However, research to date has mostly focused on the effects of the amount of these areas, with few studies evaluating how configuration aspects, such as spatial fragmentation, affect air quality services. Even less is known about how this service varies with decreasing pollutant emissions. Here we fill these research gaps by testing the contribution of green areas composition and configuration in reducing air pollution, before and during the COVID-19 quarantine period, in the largest city of the Global South (São Paulo, Brazil). We relied on a model selection approach using hourly concentrations of different pollutants (CO, NO_2, $PM_{2.5,}$ and $PM_{10,}$) as response variables. As predictors, we consider meteorological variables, the amount and fragmentation of green areas (related to air quality regulation supply), the quantity of vehicle emissions (proxy of demand pressure), all this at different spatial scales (proxy of pollutant flows from emission to supply areas). Our results showed that higher tree cover and lower vehicular emissions decreased concentrations of CO, NO_2 and PM. Air quality regulation was higher in periods of low demand (start of quarantine), when compared to periods of high demand (before and the last part of quarantine). Lower levels of pollutants were associated with greater amounts of green areas at scales of up to 1,000 m from

* Corresponding author.
E-mail address: nataly.pimiento@alumni.usp.br (N. Andrea Pimiento-Quiroga).

https://doi.org/10.1016/j.landurbplan.2024.105230
Received 5 April 2024; Received in revised form 18 August 2024; Accepted 9 October 2024
Available online 30 October 2024
0169-2046/

the air quality monitoring station. This indicates that the presence of green areas can have positive effects on air quality at distances of up to 1,000 m from the sites where pollutants are emitted. Our results show that to enhance air regulation services in large urban areas, it is important to maximize the amount of green areas and minimize their fragmentation, beyond the reduction of vehicular emissions.

1. Introduction

Currently, 80 % of the global urban population is exposed to air pollution levels that exceed acceptable limits, causing 7 million deaths a year (World Health Organization, 2018). Much of this pollution is generated by vehicle emissions, which release nitrogen oxides (NO), sulfur oxides (SO), carbon monoxide (CO), ozone (O_3) and particulate matter (PM) (Popescu and Ionel, 2010) and are responsible for 14 % of global greenhouse gas emissions (IPCC, 2014) and 8 % of $PM_{2.5}$ emissions (Weagle et al., 2018). Despite the establishment of policies to reduce those emissions, continuous urbanization growth –particularly in low- and middle-income countries- is leading to increases in the vehicle fleet, and consequently in pollutants emissions (Kumar et al., 2021). This situation highlights the urgent need to adopt sustainable measures to improve air quality regulation services in urban areas.

Urban green areas can contribute to the provision of several ecosystem services, including air quality regulation (Irga et al., 2015; Roy et al., 2012), and may be a key element to mitigating air pollution impacts. Trees play a recognized role in reducing the effects of air pollution caused by road traffic and industries in residential areas (Krzyżanowski et al., 2005), with estimated economic benefits in reducing human mortality ranging from $1.1 to 60.1 million USD annually (Nowak et al., 2013). This occurs through the process of dry deposition, which reduces the concentration of pollutants through two main mechanisms (i) by intercepting and accumulating particles (PM_{10} and $PM_{2.5}$) on external surfaces, such as leaf pubescence and waxy surfaces (Beckett et al., 2000); and (ii) by capturing pollutant gasses (O_3, NO_2, and CO) inside the leaf stomata (Cieslik et al., 2009). Consequently, higher amounts of green areas with more dense canopy cover are associated with a reduction in particulate matter concentrations, improving air quality (Paoletti et al. 2004; Irga et al., 2015; Shen and Lung, 2016).

The effect of the spatial arrangement of green areas (i.e., their spatial configuration) on air quality regulation service has been less well studied, and with contrasting results. While some studies indicate that higher fragmentation can result in better air quality outcomes (Shi et al., 2019; Wu et al., 2015), others found opposite results (Shen and Lung, 2017, 2016). Configuration aspects, such a higher fragmentation, could decrease the distance between green areas (referred here as "service supply areas"; Villamagna et al., 2013) and pollution sources (i.e., roadways, industries, etc.), reducing the extent of pollutant flows from emission to deposition areas (Metzger et al., 2021), and improving air quality regulation services. Meteorological conditions also have an important effect on air quality regulation services – because factors such as wind speed can determine dilution and dispersion rate of pollutants (Oleniacz et al., 2016) through accumulation or ventilation processes (Seo et al., 2018).

The demand for air quality also affects the provision of regulation services. Demand is typically assessed by combining population density data with air quality standards (Baró et al., 2016; Herreros-Cantis & McPhearson, 2021) or by integrating population exposure and vulnerability to pollutants (Fusaro et al., 2023). Vehicular emission is one of the main drivers to local air quality deterioration (IPCC, 2014), and therefore one of the main factors that increases demand (Larondelle & Lauf, 2016). Ideally, demand assessments should combine population density, air quality standards, and ecological pressures (e.g. pollutant emissions) that interfere with the ecosystem service delivery (Villamagna et al., 2013) and require regulatory attention (Baró et al., 2016).

The provision of air regulation services has three main components: supply (green areas in which dry deposition occurs, i.e. representing the capacity to provide the service of regulating air pollution); demand (related to the population density and the desire for acceptable levels of pollution, below certain thresholds; this demand varies according to the level of air pollution caused by anthropogenic sources, e.g. traffic and industries); and flow of pollutants, which connects pollutant emissions with dry deposition areas through biophysical and meteorological factors. However, frequently only one of these three components (most commonly, supply) is studied in the evaluation of ecosystem service provision (Baró et al., 2016), which may lead to overestimations, or inaccurate assessments of the effect of green areas in the provision of this ecosystem service (Metzger et al., 2021).

The efficiency of the regulation services can also vary with ecological pressures (e.g. high emission of pollutants) that may create inappropriate conditions for service provision by saturating service capacity or by reducing the ecosystem capacity to deliver it (Villamagna et al., 2013). This could happen due to saturation in the stomata's absorption capacity, in the case of gases, or due to a limitation in leaf surface area, in the case of particulate matter. A timely situation to evaluate this effect occurred in 2020, when quarantine policies around the world due the COVID-19 pandemic resulted in a global reduction in pollutants emissions (Loh et al., 2021), which resulted in lower ecological pressure for the air quality regulation service.

The city of São Paulo, one of the biggest megacities in the world, is an ideal system to study the air quality regulation process given its high population density, high levels of air pollution, and extensive tree cover. High pollutant levels in the city are mainly caused by the vehicle fleet, which accounts 96 % of CO, 65 % of NO_x and 40 % of PM emissions (Companhia Ambiental do Estado de São Paulo, 2020). Due to the social distancing policy imposed during the COVID-19 quarantine from 22nd of March 2020, non-essential activities were restricted. As a result, vehicle emissions were reduced, leading to a reduction in the concentration of some pollutants, such as CO, NO_2 and PM (Debone et al., 2020; Freitas et al., 2020). This offered a perfect and unprecedented scenario to study the effects that an abrupt reduction in vehicular emissions (hereafter demand pressure) could have over the air regulation service. In addition, São Paulo has high levels of fragmented and aggregated green areas, which allows for testing of the effect of spatial configuration on air regulation services, a topic that remains poorly understood, especially in tropical regions.

Here we use a novel approach by integrating the three components of air quality regulation (supply, demand, and flows) with meteorological factors with the aim of (1) analyzing the potential of urban green area amount and configuration to improve air quality in the city of Sao Paulo; and (2) evaluating how the reduction in the demand pressures during the COVID-19 quarantine affected the provision of this ecosystem service. We used vegetation quantity, density, and spatial distribution (e.g., fragmentation) to estimate supply, vehicular emissions to estimate demand pressure, and finally different spatial scales (spatial extent of analysis) to capture pollutant flow between emission and deposition areas. Our hypotheses are that the amount of green area will have a positive effect on air quality, with this effect being enhanced by (1) lower demand pressure (i.e. lower vehicular emissions), and (2) areas with lower fragmentation (configurations where higher vegetation density is expected). Furthermore, we hypothesize that a reduction of demand pressure through quarantine could enhance the air quality regulation service delivery, since this alleviates problems of over-demand or ecosystem service saturation. To our knowledge, this is the first study that uses the three components of air quality: regulation service supply, demand and flow, and assesses how the spatial configuration of green areas and abrupt reductions in the quantity of demand affect the provision of this service.

2. Methods

2.1. Conceptual framework

As previously introduced, the provision of the air regulation service has three main components: areas of supply and demand, and the flow linking supply and demand (Fig. 1). To make this scheme operational, we use indicators for each one of these components. Green areas were considered as "supply", because it is where pollutant deposition occurs. The quantity of pollutants emitted by vehicles (the main source of pollutants in the studied system) was considered a proxy for "demand pressure", i.e. of the quantity of pollutants that needs to be removed from the atmosphere to ensure good air quality (the "desired service"). The movement of pollutants from emission areas (i.e., streets) to supply (i.e., green) areas (i.e. "flow"), was assessed across different spatial scales (see section 2.4).

2.2. Study area

The study area encompasses the city of São Paulo, Brazil (Fig. 2), the largest megacity of the southern hemisphere, spanning 1,521 km^2 and with a population of more than 12 million inhabitants (Instituto Brasileiro de Geografia e Estatística, 2022). The city is also the industrial and economical center of the country, accounting for 17 % of its GDP (Silva-Sánchez and Jacobi, 2014), and of South America. The climate is classified as tropical, characterized by a cold and dry season (April to September) and a warm and humid season (October to March) (Andrade et al., 2012, 2017). São Paulo is an ideal place to study air quality regulation services due to its central importance to the economy of Brazil, and the large population affected by pollution health issues (Arbex et al., 2009).

Currently, 48 % of São Paulo is covered by vegetation (Secretaria Municipal do Verde e do Meio Ambiente, 2020), unequally distributed across the regions of the city (Amato-Lourenço et al., 2016). The concentration of vegetation is highest in the South (54.53 %) and the North (41.67 %), while the West (26.69 %), East (16.04 %), and center (15.56 %) regions have less green cover (Secretaria Municipal do Verde e do Meio Ambiente, 2020).

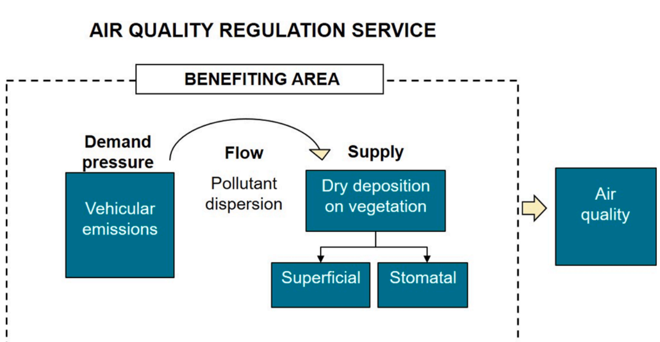


Fig. 1. Simplified scheme showing the processes involved in the air quality regulation service, considering the ecosystem service provision chain (Metzger et al. 2021). Vehicular emissions (here considered a proxy for "demand pressure areas", i.e. areas that put pressure on the air quality regulation service) are dispersed in the air by wind up to certain spatial extents (flow) and a fraction of this is deposited on vegetation (supply areas). This process influences air quality, diminishing pollutants concentrations.

2.3. Air pollution and meteorological data

We obtained hourly air pollution (CO, NO_2, PM_{10}, $PM_{2.5}$) and meteorological data (e.g., wind velocity, air temperature, and relative humidity) from 14 automatic stations (study stations; see Fig. 2 & Table S1) located within the city of Sao Paulo (QUALAR system of CETESB, available at: https://qualar.cetesb.sp.gov.br/qualar/home.do). As CO concentrations were in ppm, we converted them to mg/m^3 using the formula:

*mg/m^3 = concentration in ppm * molecular weight * / 24.45.*

where 24.45 is a constant representing the volume, in liters, of one mole of a gas at standard temperature (25 °C) and pressure (1 atmosphere). The meteorological and air pollution data were obtained between March 1, 2020 to May 31, 2020, corresponding to the periods before and during COVID-19 quarantine, and were divided in three phases: Pre-quarantine (March 1– 21, 2020), Quarantine A (March 22, 2020 to April 24, 2020), and Quarantine B (April 25, 2020 to May 31, 2020), in order to assess the effect of variations in pollutants emissions on the ecosystem service provision. The first phase was delimited to the quarantine start date (March 22, 2020), while the other two quarantine periods were based on Google mobility trends (COVID-19: Relatórios de mobilidade da comunidade, 2022), which showed that the percentage of people staying at home decreased to its lowest mean value since the beginning of quarantine in the weekend of April 25–26, 2020, (Table S2). Thus, Quarantine A represents a more restrictive moment, when people were asked to stay at home, agglomerations were prohibited, and only essential services were available to the public, while Quarantine B represents a more flexible social distancing period.

To identify the days in which dry deposition occurred, we extracted precipitation data. During precipitation events, particles accumulated in vegetation are washed off to the ground surface, with the amount washed off mediated by the magnitude of precipitation (Nowak et al., 2013). As it is estimated that leaves capture about 0.2 mm of precipitation before runoff (Wang, Endreny, & Nowak, 2008), we considered days with precipitation $<$ 0.2 mm as days in which dry deposition occurred, and days with precipitation $>$ 0.2 mm as days without the air regulation service provided by green areas (Nowak et al., 2013). The precipitation data for each CETESB station coordinate was extracted from the Climate Hazards Group Infrared Precipitation with Station data (CHIRPS) of the University of California, with a spatial resolution of 0.05° (~5 km) and a daily temporal resolution.

2.4. Spatial scale (Benefiting area; proxy of flow)

We used a multi-scalar approach to consider the potential of different benefiting areas of the service (which are related to the flow capacities, i.e., the potential of displacement of pollutants from their source to deposition areas), by defining different buffers (250, 500, 750 and 1000 m of radii) around each monitoring station. The scales were chosen according to studies showing that pollutants emitted from vehicular traffic can disperse up to 100 m from urban roads and up to 1000 m from major highways (Hoek et al., 2008; Aguilera et al., 2008; Eeftens et al., 2012). The 1000 m distance was also considered the maximum radii to avoid overlapping between monitoring stations and thus prevents spatial autocorrelation.

The monitoring stations used in the study are spread throughout the city and cover a large area with varying degrees of urbanization and green spaces (e.g. city center, residential and commercial neighborhoods, low and high circulation areas, low, medium and high green cover etc.; See Table S1), thus capturing the spatial heterogeneity that exists in the study area (CETESB 2021). In addition, the different buffers established around each monitoring station, also capture demand heterogeneities, covering both major and minor streets present in that area (with low, medium and high emission areas).

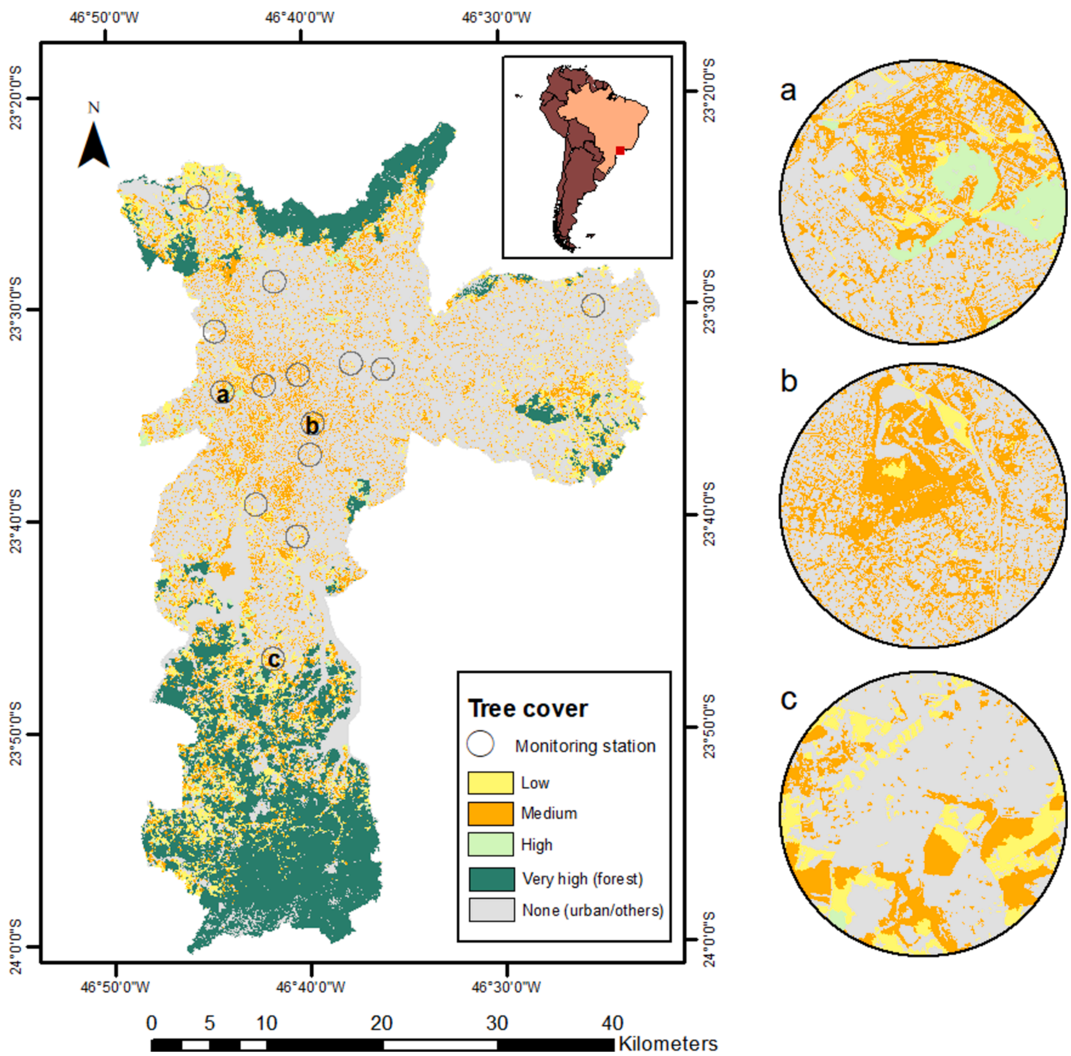


Fig. 2. Spatial distribution of tree cover density (yellow, orange and green pixels), and built-up and other types of areas (aquatic, pastures; gray pixels) in the city of São Paulo. Black circles represent 1000 m buffers around the 14 CETESB's air quality monitoring stations included in the study, with close-up (a-c) around three stations: (a) Cidade Universitária-USP station (West zone); (b) Ibirapuera (South zone); (c) Grajaú-Parelheiros (South zone). The small box on the upper right shows the location of São Paulo's city (red dot) within Brazil (orange) and South America (brown).

2.5. Demand pressure estimation (vehicular emissions)

Vehicular emissions were modeled as a proxy for service demand pressure, by estimating spatial and temporal (hourly) vehicle emissions through the VEIN (Ibarra-Espinosa et al., 2018) R package, available at https://CRAN.R-project.org/package = vein, for the period between March 1 to May 31, 2020. Temporal and spatial disaggregated emissions were estimated following a general approach of multiplication between activities and emission factors (Ibarra-Espinosa et al., 2018), as shown in Eq. (1).

Emission pollutant = $\sum$ activity (AR activity · EF pollutant, activity) (1).

where Emission pollutant for any type of pollutant depends on the activity rate (AR) and the emission factors (EF), which is the mass of pollutants generated according to the level of activity. In the context of vehicular emissions, AR activity represents the number of vehicles multiplied by the distance (km) travelled. EF pollutant activity is the emission factor (g km^{-1}) for pollutants of the vehicles (Ibarra et al., 2018).

For estimating the above components, VEIN uses traffic simulations obtained from the Traffic Engineering Company (CET, https://www.cetsp.com.br/) and the Secretary of Transport and Mobility of São Paulo (SPtrans), data available through direct contact at: http://www.sptrans.com.br/. The simulations take into account emission factors for hot and cold exhaust, evaporative, deterioration and wear emissions. Once we obtained the emissions inventory for the city, we extracted the mean hourly emissions of CO, NO_2, and PM ($_{10}$ and $_{2.5}$) around the 14 study areas, considering the different buffer sizes.

2.6. Supply estimation and configuration

To estimate the amount and configuration of supply areas for the air regulation service, we used vegetation cover mapping from 2020 produced by the city hall (GeoSampa, available at: http://geosampa.prefeitura.sp.gov.br/), and measured the total area of tree cover and the enhanced vegetation index (EVI) for each buffer size. The vegetation map was produced in 2017/2018, covering the entire surface of the São Paulo municipality, including 1,168 km^2 in a scale of 1:1.000 and 359 km^2 in a scale 1: 5,000 (Secretaria Municipal do Verde e do Meio Ambiente, 2020). It is worth pointing out that the city of São Paulo typically experiences minimal landscape changes, and between the creation of the mapping (2016–2017) and our study (2020), green cover changed only 3.6 %. This aspect associated with the high spatial resolution of the mapping, make this the best data available to be used (htt ps://www.prefeitura.sp.gov.br/cidade/secretarias/licenciamento/desenvolvimento_urbano/dados_estatisticos/info_cidade/meio_ambiente/fauna_e_flora/index.php?p = 333887). The original map has 15 classes of vegetation with different degrees of density, which were grouped here into four tree cover categories: low cover (low density tree canopy cover with high openness); medium cover (predominantly arboreal vegetation with closed canopy); high cover (urban and *peri*-urban nuclei of preserved forests); and forests (high density vegetation on advanced and secondary stages); See Fig. 2 & Table S3).

After obtaining the total area of tree cover for each buffer size, we measured the EVI index, to include vegetation density into our estimation of supply (Eq. (2)) as well as potential variations in vegetation foliage due to the transition between seasons (summer − fall) during our study. However, São Paulo's vegetation is mostly perennial, and typically does not present abrupt vegetation changes throughout the year (See table S3). EVI is sensitive to canopy structural variations, which is important for air quality service regulation (Roeland et al., 2019). For EVI estimation, we used the Satveg site (https://www.satveg.cnptia.embrapa.br/satveg/), which uses the product MOD13Q1 (derived from the Terra satellite, starting on 02/18/2000) available in maximum compositions of 16 days, with a spatial resolution of approximately 250 m.

To finally estimate the supply of air quality regulation service, we adapted the pollutant absorption formula proposed by Powe and Willis (2004) to a new supply equation:

Supply = A(m2)* EVI * DV (m/s)* T (s) * P $_{(0 \text{ or } 1)}$ (2).

Where: A is the total area of tree cover (including all types: low, medium, high, and very high density; m^2), EVI is the vegetation index value for the specific spatial scale, deposition velocity is the specific pollutant deposition rate taken from the UFORE-D model ($PM_{10} > PM_{2.5} > NO_2 > CO$; See Table S4; D. Nowak et al., 1998), T is the time step (seconds), and P is the daily precipitation factor (0 when >= 0.02 mm and 1 when <= 0.02 mm; days with and without precipitation, respectively). In addition, to evaluate the effects of spatial configuration, we extracted the number of patches (NP) of green areas for each spatial scale analyzed.

2.7. Statistical analysis

As a first step, we performed a Mantel test, for each one of the pollutants analyzed, with 9,999 permutations, to detect potential autocorrelation. The test revealed no spatial dependence ($p > 0.05$ for all pollutants: $PM_{10} = 0.54$; $PM_{2.5} = 0.85$; $NO_2 = 0.30$; $CO = 0.60$), validating the null hypothesis of spatial independence among air quality stations, for all pollutants and the use of a non-spatial modeling approach. We then compared the levels of pollutant concentrations between the different quarantine levels with an ANOVA test, followed by a post-hoc Tukey's test. Finally, to assess the relationship between pollutant concentrations with supply, demand and flow, we performed a maximum likelihood model selection procedure, considering the second order Akaike's information criteria, corrected for small sample sizes (AICc) (Anderson and Burnham, 2002). In this approach, the lower the AICc, the better the model fits the data. All analyses were made with RStudio 1.4.1717, Fragstats v4.2.1 and ArcGIS 10.5.

Model fitting was done using generalized linear mixed models (lme4 package in R) with a negative binomial distribution. PM_{10}, $PM_{2.5}$, NO_2 and CO concentrations were the response variables, and we included the time of the day within each monitoring station, and the day of the week as random effects. Analyses were performed separately for each pollutant and for each spatial scale. Predictor variables used were: service supply (hourly dry deposition by green areas, calculated according to Eq. (2)), quarantine period (Pre-Quarantine, Quarantine A, and Quarantine B), demand pressure (vehicular emissions), supply configuration (number of green area patches), and meteorology data (relative humidity, wind velocity, and air temperature). Only predictor variables with low correlation values were included in the same model (Pearsońs $r < 0.60$; Zuur, Ieno, Walker, Saveliev, & Smith, 2009). Therefore, models followed the structure: (1) supply: quarantine + (2) demand pressure + (3) meteorological data (wind velocity, relative humidity, or air temperature; or combinations of relative humidity or air temperature with wind velocity; See Table S7) + (4) configuration of supply (number of patches). Supply, demand pressure and meteorological variables were present in every model (See Table S7). In total, we considered 8 models for each spatial scale, with a total of 32 models for each pollutant (e.g., spatial scales were never mixed in the same model, to test for different flow capacities of the pollutants; See Table S8).

3. Results

During the study period, the concentrations of pollutants were higher in the pre-quarantine and quarantine B periods, with significant drops during quarantine A (Fig. 3B & Table S5). The low pollutant concentrations were maintained in the first week of quarantine (days 22 – 28) but started to increase gradually after this period (days 29——35; Fig. 3B), exceeding pre-quarantine concentrations by the end of April into May (days 56 – 63; Fig. 3B) and extending until the end of our study period (May). Vehicular emissions (demand pressure) also showed a decline in the first week of lockdown, particularly in the case of PM_{10} and CO (mostly emitted by automobiles), and secondarily in the case of $PM_{2.5}$. In contrast, NO_2 (mostly emitted by trucks) emissions were low during all the study period, probably because our buffers rarely contained highways within them. As observed with pollutant concentrations, the reduction in emissions only lasted a few days (Fig. 3C; days 22–28). Finally, the average intensity of supply process, given by the average hourly pollutant absorption in green areas (dependent on the deposition rates of each pollutant; See Table S4), were higher and similar for $PM_{2.5}$ and PM_{10}, closely followed by NO_2. In contrast, CO exhibited significantly lower supply levels (Fig. 3D), attributed to its low deposition rate (Table S4).

3.1. Drivers of pollutant concentration

For all pollutants analyzed, the best models selected (AICc < 2; Table 1 & Table 2) contained the interaction of supply with the quarantine period, demand pressure, wind velocity, and relative humidity. Meteorological variables had the greatest effects on pollutants concentrations, followed by demand pressure and supply along the quarantine periods (Fig. 4). Demand pressure had the highest positive effect on NO_2, CO, PM_{10}, and $PM_{2.5}$ concentrations, respectively. The impact of supply on $PM_{2.5}$ during the Pre-quarantine period was non-significant (Fig. 4C-D). For all other pollutants, service supply presented a statistically significant negative effect, with larger effects for the quarantine A period (Fig. 4A-B & 4E-H; Table 1 & Table 2). Despite not being significant for all pollutants ($p < 0.05$), fragmentation (NP) tended to have a positive effect, showing that more fragmented green areas could be associated with increases in pollutants concentrations, except for PM_{10} for which there was an opposite tendency (Table 1). Finally, the pollutant scale of dispersion (flow) for all pollutants was 1,000 m, except for $PM_{2.5}$ for which the 500 m was selected (Table 1 & Table 2; See also Table S8 for a summary of all best models and more details).

For PM_{10}, the best scale selected was 1,000 m, with the two best models showing negative effects for supply by quarantine period, wind velocity, and relative humidity (Table 1). The number of patches was also selected in the models, but presented non-significant effects, while demand pressure presented positive effects. According to our results, an increase in 1 m/h of wind velocity and 20 % in air humidity could result in reduction in ~ 6 μg/(m^3 h) of PM_{10}; planting 23 ha of green areas could reduce 0.5 μg/(m^3 h) of PM_{10} during the pre-quarantine period, 1.5 μg/(m^3 h) of PM_{10} during the quarantine period A, and 0.46 μg/(m^3 h) of PM_{10} during the quarantine B period; while an increase in 33 % in the number of patches could decrease PM_{10} in 1.5 μg/(m^3 h). However, an increase in 29.0 g/(km^2 h) in vehicle emissions could result in an

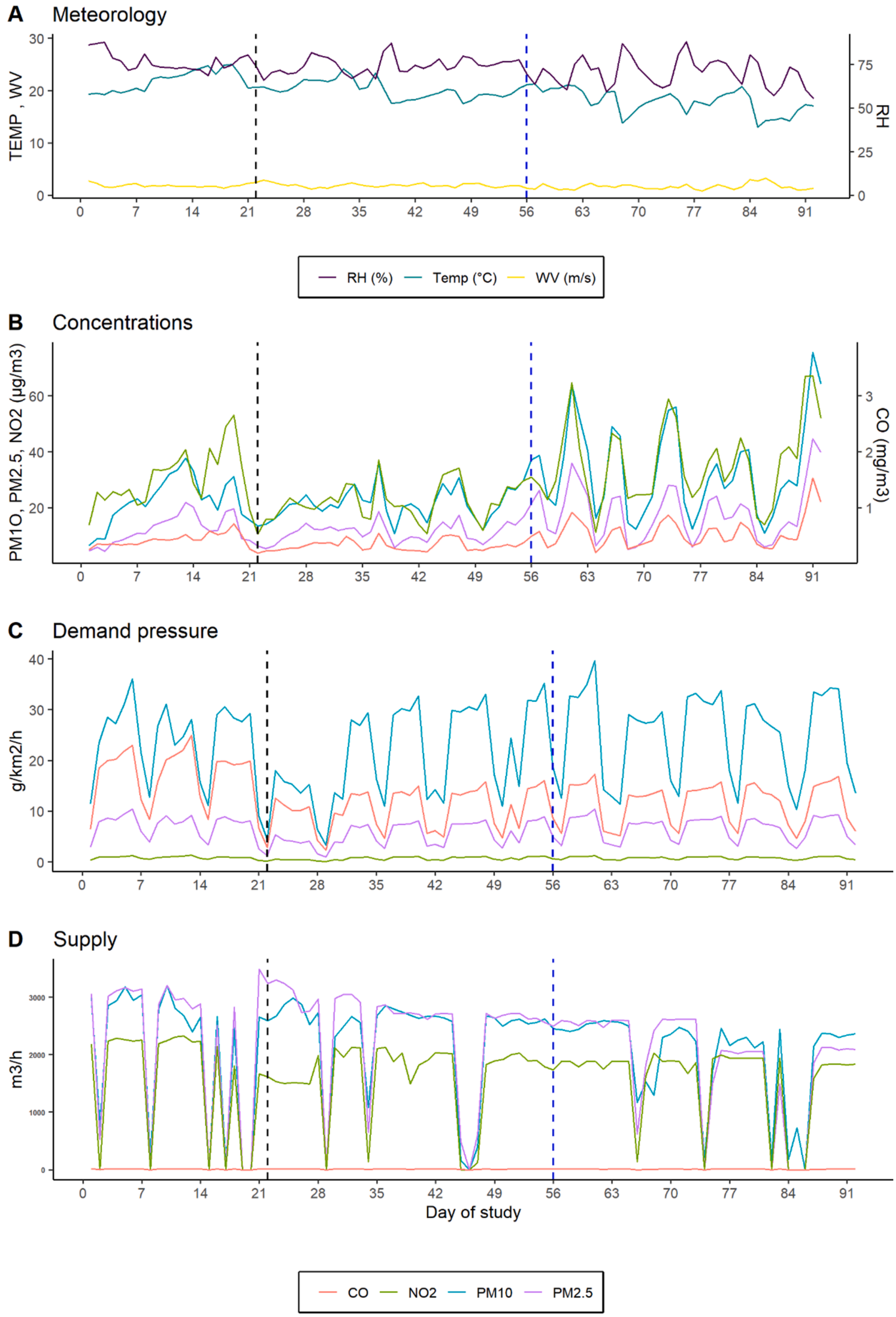


Fig. 3. Mean daily variation in the data for: meteorological variables (TEMP = air temperature, WV = wind velocity (left axis) and RH = relative humidity (right axis) (A); pollutant concentrations of PM_{10}, $PM_{2.5}$, NO_2 (left axis) and CO (right axis) (B); vehicular emissions (C); and potential dry deposition by vegetation (D). Before the dashed black line are the days classified as pre-quarantine, between the black and blue dashed line are the days of Quarantine A, and after the blue line the days classified as Quarantine B. Supply values of 0 are from days with precipitation (days without dry deposition). Supply and demand pressure data in this figure are for the largest spatial scale (1,000 m), which was the most commonly selected scale in the models.

Table 1
Sum of evidence weight of variables, weighted by the number of models in which that variable was present (∑Wi/N), Slope and Standard Error (±SE) of the predictor variables from the best models (ΔAICc ≤ 2) selected to explain pollutant concentrations of PM_{10} and $PM_{2.5}$. Pre = Pre-Quarantine; QA = Quarantine A; QB = Quarantine B. *=variables with significant value (p < 0.05).

Predictor variables and spatial scale	N	**PM_{10}** ∑Wi/N	Slope (±SE)	N	**$PM_{2.5}$** ∑Wi/N	Slope (±SE)
Wind Velocity	24	0.041	−0.284 ± 0.005*	24	0.041	−0.370 ± 0.006*
Relative Humidity	12	0.083	−0.265 ± 0.006*	12	0.083	−0.165 ± 0.007*
Demand pressure (1000)	8	0.121	0.101 ± 0.008*	8		
Demand pressure (500)	8			8	0.080	0.079 ± 0.010*
Number of Patches (1000)	3	0.194	−0.065 ± 0.036	3		
Number of Patches (500)	3			3	0.081	0.047 ± 0.046
Supply(1000):Pre	8	0.121	0.020 ± 0.009*	8		
Supply(500):Pre	8			8	0.080	−0.000 ± 0.012
Supply(1000):QA	8	0.121	−0.060 ± 0.008*	8		
Supply(500):QA	8			8	0.080	−0.027 ± 0.011*
Supply(1000):QB	8	0.121	−0.018 ± 0.009*	8		
Supply(500):QB	8			8	0.080	−0.033 ± 0.012*

Table 2
Sum of evidence weight of variables, weighted by the number of models in which that variable was present (∑Wi/N), Slope and Standard Error (±SE) of the predictor variables from the best models (ΔAICc ≤ 2) selected to explain pollutant concentrations of NO_2 and CO. Pre = Pre-Quarantine; QA = Quarantine A; QB = Quarantine B. *=variables with significant value (p < 0.05).

Predictor variables and spatial scale	**NO_2** N	∑Wi/N	Slope (±SE)	**CO** N	∑Wi/N	Slope (±SE)
Wind Velocity	24	0.041	−0.353 ± 0.004*	24	0.041	−0.382 ± 0.004*
Relative Humidity	12	0.083	−0.128 ± 0.005*	12	0.083	−0.044 ± 0.006*
Demand pressure (1000)	8	0.125	0.214 ± 0.007*	8	0.125	0.209 ± 0.008*
Number of Patches (1000)	3	0.103	0.093 ± 0.142	3	0.113	0.079 ± 0.096
Supply (1000):Pre	8	0.125	−0.064 ± 0.008*	8	0.125	−0.141 ± 0.008*
Supply (1000):QA	8	0.125	−0.101 ± 0.009*	8	0.125	−0.091 ± 0.009*
Supply (1000):QB	8	0.125	−0.064 ± 0.008*	8	0.125	−0.133 ± 0.009*

increment of 2.5 μg/(m^3 h) of PM_{10} concentrations.

For $PM_{2.5}$, the two models selected had scales of 500 m and presented negative effects for supply during quarantine A, supply during quarantine B, wind velocity, and relative humidity, while demand pressure and number of patches had positive effects (Table 1). Supply during the pre-quarantine period also had a negative but non-significant effect ($p > 0.05$). Increasing wind velocity by 1 m/h and air humidity by 17 % could reduce $PM_{2.5}$ in 4 μg/(m^3 h) and 1.96 μg/(m^3 h) respectively. An increase in 11 g/(km^2 h) in the vehicle emissions showed an increment of 1.1 μg/(m^3 h), while planting 15.7 ha of tree cover could decrease in 0.006 μg/(m^3 h) of $PM_{2.5}$ during the pre-quarantine period, 0.34 μg/(m^3 h) during the quarantine period A, and 0.43 μg/(m^3 h) during the quarantine B period.

For NO_2, the spatial scale of 1,000 m was selected in both models, and also presented negative effects for all variables selected with the exception of demand pressure (Table 2). Our models indicated that increases in 1 m/h the wind velocity and 17 % in the relative humidity could reduce NO_2 by 7.52 μg/(m^3 h) and 3.0 μg/(m^3 h) respectively. Planting 32 ha of tree cover could decrease in 2.43 μg/(m^3 h) concentrations of this pollutant during the quarantine A period, and in 1.49 μg/(m^3 h) during the periods of higher demand pressure (pre-quarantine and quarantine B), while increases in 0.7 g/(km^2 h) in the emissions could increase in 6.2 μg/(m^3 h) its concentrations.

For CO, the best spatial scale selected was also 1,000 m, with all variables presenting negative effects while demand pressure and number of patches positive ones (Table 2). In addition, an increase in 1.6 m/h the wind speed and 18 % in relative humidity could decrease concentrations of CO by 0.12 mg/(m^3 h) and 0.01 mg/(m^3 h) respectively. An increase of 12 g/(km^2 h) in pollutant emissions could also increase CO concentrations by 0.09 mg/(m^3 h), while an extra 45 ha of tree cover could result in a decrease of 0.052 mg/(m^3 h) during the pre-quarantine, 0.034 mg/(m^3 h) during the quarantine A period and 0.049 mg/(m^3 h) during the quarantine B period.

3.2. Effects of quarantine on air regulation service

The ANOVA test confirmed the observed differences among the three periods evaluated. In addition, the direction and strength of the effect of the supply on pollutant concentration were dependent on variations in demand pressure (pollutant emissions) caused by the COVID-19 quarantine. The increase in the strength of the negative effect of supply during the first weeks of the quarantine period (except for CO), suggests that the supply service for PM_{10}, $PM_{2.5}$ and NO_2 is enhanced with a reduction in demand pressure (vehicle emissions). When comparing the effects of supply in the three periods analyzed, all pollutant concentrations tended to decrease with higher supply values (greater amount of green areas), and this effect was intensified during the period of lower demand pressure (quarantine A; green line in Fig. 5).

4. Discussion

A literature review indicates that this study is the first to quantify the potential effects of the spatial arrangement of urban green areas and COVID-19 quarantine on an air quality regulation service in the Neotropics, through an approach that simultaneously considers service supply, demand, and flow. As hypothesized, the concentration of pollutants was largely explained by climatic factors (wind speed, humidity) and vehicular emissions. However, factors linked to green area cover and spatial arrangement were also significant, highlighting an opportunity for urban landscape management to consider the provision of air quality regulation services. Our results demonstrate that an increase in the amount of urban green areas could contribute to improve the air quality (especially of NO_2 and PM_{10}). In addition, our results point to the existence of a synergetic effect between the reductions in vehicular emissions and an increase in the provision of the service during the most restrictive quarantine period, which may double the effect of supply reducing NO_2 concentrations and triple the reduction on PM_{10}

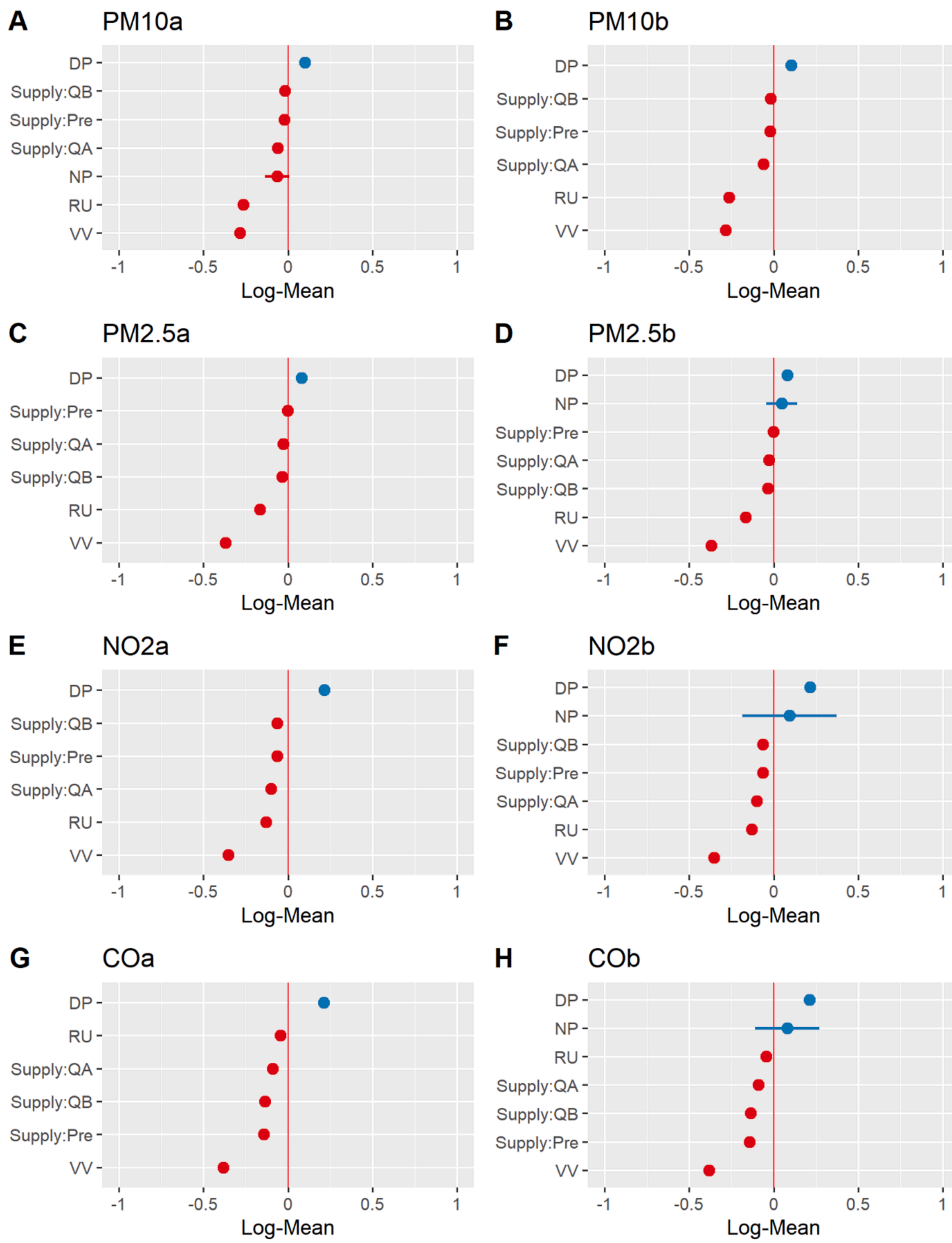


Fig. 4. Parameter estimates of the variables present in the two best selected models ($\Delta AICc \leq 2$) for PM_{10} (A-B), $PM_{2.5}$ (C-D), NO_2 (E-F) and CO (G-H). Positive effects are shown in blue, while negative effects are shown in red. Coefficients whose confidence interval (horizontal lines) crosses the zero line are not significant. DP = Demand pressure, NP = number of patches, Supply: Pre = Effect of supply before quarantine, Supply: QA = effect of supply during Quarantine A, Supply: QB = effect of supply during Quarantine B, VV = Wind velocity, RU = relative humidity.

concentrations, compared to pre-quarantine time. Fragmentation of green areas presented an overall negative, while non-statistically significant, impact on air pollution regulation, once fragmentation was related to higher concentrations of $PM_{2.5}$, NO_2 and CO. Considering the overall trend of fragmentation impairing air quality regulation, we suggest the maintenance or expansion of existing green areas in cities for the mitigation of air pollution, especially in areas with a distance up to 1,000 m of the pollution source, since spatial scales of 500 and 1,000 m of radii explained better pollutants concentrations.

Reducing vehicle emissions significantly improved air quality, leading to a noteworthy reduction in NO_2 and CO concentrations, which is consistent with previous literature findings in São Paulo city (Debone et al., 2020; Freitas et al., 2020; Krecl et al., 2020; Nakada & Urban, 2020). Since vehicle circulation is the main source of pollution in the city, COVID-19 quarantine allowed us to see directly the impacts of vehicle fleet on air quality, and call attention to the importance of creating measures to reduce this kind of emissions. Therefore, urban planning measures such as encouraging the use of cycle lanes, improving public transport services, subsidies for the purchase of hybrid and electric cars and greater support for companies that adopt hybrid/ remote working, among others, are essential for contributing to improving air quality in large urban centers.

Our results corroborate other studies that show a positive effect of greenspaces in improving air quality (Bonilla-Bedoya et al., 2021; Pugh et al., 2012), even for tropical areas (Arroyave-Maya et al., 2019; Bonilla-Bedoya et al., 2021; Ribeiro et al., 2021; Vailshery et al., 2013). However, studies in the northern hemisphere have shown an opposite effect, in which the presence of green areas leads to increases in pollutant concentration, especially along park borders (Xing & Brimblecombe, 2019), which could happen due to a reduced capacity of pollutants to disperse due to the presence of green areas (Janhall, 2015; Viippola et al., 2018). In addition, green areas can release volatile organic compounds (VOCs), which interact with gaseous pollutants forming secondary substances like ozone (Shah et al., 2022), a disservice that can obscure or diminish the perceived benefits of air quality improvement. Therefore, additional field studies in tropical areas should be performed to better elucidate our results.

In this study we found evidence of the benefits of vegetation for the air quality of a megacity. However, the novelty of our study lies in showing that this service is influenced by the spatial arrangement of green areas and can be further enhanced by reducing demand pressures, such as vehicular emissions. We observed an intensification of the service in the period of less demand pressure for almost all pollutants (except CO), which resulted in an increase of the service in comparison with periods with more demand pressure (before quarantine and in the less restrictive quarantine period). The variations in service provision may be explained by shifts in ecological pressures (pollutant emissions), which affect the natural capacity and delivery of a service (Scheffer and Carpenter, 2003; Villamagna et al., 2013), as found experimentally for other regulating ecosystem services like flooding and fire protection (Liu et al., 2023; Sil et al., 2019). We hypothesize that during periods of high demand pressure, the capacity of green areas to absorb or deposit pollutants is quickly exhausted, akin to a funnel system. In such cases, a rapid increase in pollutant emissions could cause green areas to reach saturation and cease absorbing pollutants. This may occur because pollution particles cover the entire leaf surface, reducing and blocking the opening of stomata (Gheorghe & Ion, 2011). However, those hypotheses still need to be tested to elucidate the mechanisms by which the service is improved with a reduction in the vehicular emission.

The observed increase in service provision varied among the different pollutants analyzed. PM_{10} presented the highest service effect during the most restrictive part of quarantine, tripling the reduction in the concentration of pollutants. This is partially related to its high deposition rate in vegetation (Nowak et al., 2013, 1998), which is higher than $PM_{2.5}$'s because larger particles are deposited more quickly than smaller particles (Mcpherson et al., 1994). The lack of reduction in $PM_{2.5}$ concentrations during pre-quarantine, even in areas with high values of supply, contrasts with its strong reduction during quarantine and displays how much a potential overdemand can affect the provision of regulation service for this pollutant. This indicates a potential limit/threshold for the deposition of pollutants in vegetation and supports the hypothesis of the interference of ecological pressures on ecosystem's ability to deliver a service (Villamagna et al., 2013).

In the case of gaseous pollutants, service regulation had a high effect on NO_2, probably because NO_2 is captured within leaf stomata and is converted to nitrate ions that participate in protein build up (Cieslik et al., 2009; Mcpherson et al., 1994), and thus is not resuspended as PM_{10} and $PM_{2.5}$. In addition, the service supply for this pollutant was doubled during the most restrictive period of quarantine, indicating that vehicular emissions in normal conditions (accountable for nearly 65 % of NO_x emissions; Companhia Ambiental do Estado de São Paulo, 2020) can lead to an overdemand situation. Thus, with the reduction in mobility caused by COVID-19 quarantine, we saw experimentally how demand pressure affects the potential service that could be provided by green areas (Villamagna et al., 2013). Lastly, the surprisingly lower effect of supply on CO concentration reduction during periods of lower demand pressure could be due to its low deposition rate (0.002 m s^{-1}), resulting in the dry deposition being more directly affected by the availability of the pollutants concentrations in the air.

The configuration of green areas, particularly its fragmentation, appeared to have a complementary and negative effect on air regulation service, although this was not statistically significant. The more fragmented areas were related to higher concentrations of $PM_{2.5}$, NO_2 and CO, which is a signal that air quality regulation services could be maximized in urban green areas with lower fragmentation, corroborating other studies (Jaafari, Shabani, Moeinaddini, Danehkar, & Sakieh, 2020; Mears, Brindley, Jorgensen, Ersoy, & Maheswaran, 2019; Shen & Lung, 2016, 2017). This effect may occur through the obstruction of pollutant flows at the edges, preventing pollutants from reaching the inner areas of vegetation patches, thus reducing the effect of greenspace cover. A similar trend was observed in the Amazon, where a higher forest cover and lower level of fragmentation were related to lower number of diseases and infections, and is likely related to a higher capacity of larger forest patches to absorb small particles (Prist et al.,

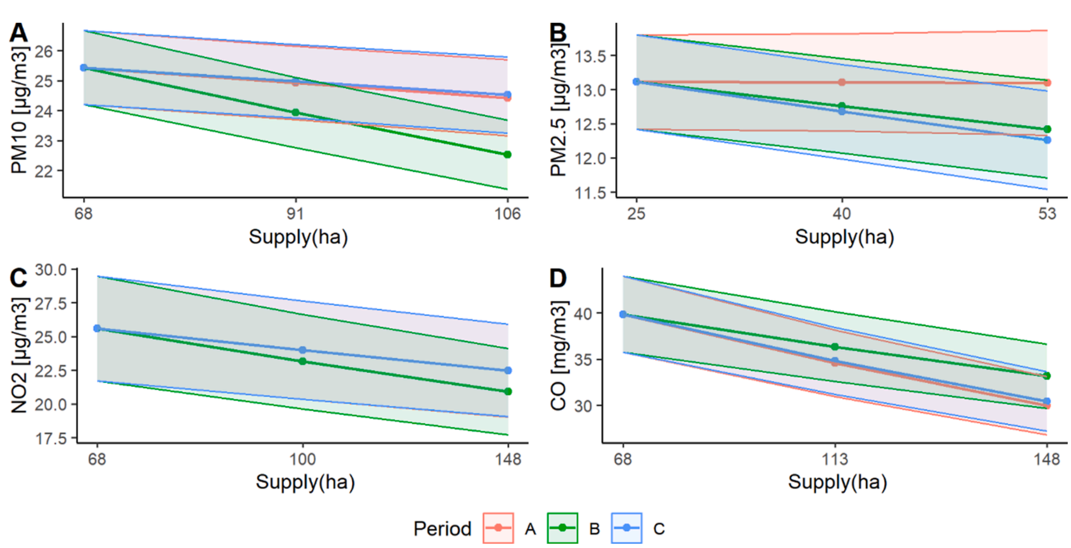


Fig. 5. Effects of supply on pollutants concentrations depending on quarantine time. Periods were defined as: Pre = Pre-quarantine; QA = First part of quarantine (more restrictive); QB = Last part of quarantine (more flexible). PM_{10}, NO_2 and CO values of supply are higher since their spatial scale is of 1,000 m, while $PM_{2.5}$'s is 500 m. SD values were low for all pollutants in all periods evaluated (PM_{10}-Pre = 0,009; PM_{10}-QA = 0,008; PM_{10}-QB = 0,009; $PM_{2.5}$-Pre = 0,012; $PM_{2.5}$-QA = 0,011; $PM_{2.5}$-QB = 0,012; NO_2-Pre = 0,008; NO_2-QA = 0,009; NO_2-QB = 0,008; CO-Pre = 0,008; CO-QA = 0,009; CO-QB = 0,009; See Table 1 & Table 2).

2023). However, for PM_{10}, we observed the opposite trend that a higher fragmentation can be beneficial for decreasing pollutant concentrations. At the landscape level, a higher number of small patches may increase the interaction between deposition (sink) areas and emission (source) areas, thereby enhancing PM (Wu et al., 2015), while at the patch level, dry deposition may be facilitated by a more efficient sweeping of air between vegetation strips (Yazbeck et al., 2021). Therefore, fragmentation might also facilitate pollutant deposition. Thus, new observational studies should be conducted, preferably by controlling compositional aspects (i.e., amount of green urban areas), to be able to reveal the independent effect of fragmentation on air quality services.

While previous studies have shown that the greatest reductions in pollutant concentrations are typically observed at the core of parks (Xing et al., 2019), our results suggest that the benefits of air quality regulation extend much further. Specifically, this service can be effective in areas up to 1,000 m from the pollution source. Our multiscale approach indicated that flow may be occurring on a scale of 500 m for $PM_{2.5}$, and of 1,000 m for NO_2, CO and PM_{10}, which may be related to meteorological variables. Wind velocity, which affects the transport of air pollutants, presented positive effects in our models, suggesting that it can lead to transport and dispersion of the pollutants over kilometers (Seo et al., 2018), reducing pollutant concentrations locally (Irga et al., 2015; Zhang et al., 2015), and affecting the scale of service provisioning (Liu et al., 2016). Furthermore, considering that the transport of pollutants in urban areas is influenced by regional-scale wind flows (ranging from 20 to 2,000 km) (Watson et al., 1988), we believe that the effective range of this air quality regulation service may extend beyond 1,000 m (the largest scale we were able to test; see section 2.4).

The efficiency of flow also depends on the presence of obstacles which can slowdown or prevent the upward movement of pollutants by wind (e.g. buildings, topography, street canyons; Liu et al., 2016; Pugh et al., 2012; Ulpiani, Anne, Di, & Maharaj, 2022), impeding its movement to vegetation and favoring its accumulation. Relative humidity also showed a negative effect on pollutants concentrations (Hart et al., 2021; Kayes et al., 2019), explained by the fact that higher relative humidity favors dry deposition by increasing particle size and thus, raising its deposition rate (Mohan, 2016; Wu et al., 2018). It is important to acknowledge that meteorological variables had the greatest significance in our models for explaining the air regulation service in the city. This was expected since they regulate the dispersion of pollutants to supply areas and their later capture into vegetation.

Finally, although the impact of greenspaces on pollutant concentrations was lower compared to meteorological variables and demand pressures, we believe that our supply values may be underestimated. This is because we used deposition rates from a different biome and did not account for specific factors that can alter deposition, such as terrain, edge effects, and other uncertainties that influence total deposition on vegetation (Saylor et al., 2019). For instance, when we included the Enhanced Vegetation Index (EVI) as a variable in its raw form—rather than within the supply formula—its effect (−0.37) was four times greater than the highest supply effect (Table 2; NO2) and was comparable to the effects of meteorological variables.

4.1. Limitations and uncertainties

The observed effect of vegetation quantity and configuration on the air quality regulation service along different stages of COVID-19 quarantine should be interpreted with caution, considering potential methodological limitations, such as the use of proxies for supply, demand and flow. Firstly, our pollutant absorption estimation (or supply) was calculated using the deposition rates found in studies conducted in the northern hemisphere, which comprise a different forest structure and composition. Vegetation characteristics (such as tree species, diameter at breast height, total height, crown width) are important factors affecting pollutant absorption. Since tropical trees are different from temperate trees by having larger overall diameter, height and width, our assessment of service supply may be underestimated. Moreover, this study does not include important physical phenomena that could affect air quality services, such as the aerodynamic drag of vegetation. A second limitation is the use of only the quantity of pollutant emitted by mobile sources (vehicular fleet) in São Paulo as a proxy of demand pressure, given the prevalence of this type of source. Other sources of pollutants, such as industries, indoor sources, were considered homogeneously distributed over the 14 study stations. Therefore, our demand values may also present an underestimate of reality and some differences among stations in emissions from other sources may have affected our results. Thirdly, this study uses different spatial scales as a proxy for flow, which may not represent the reality of the movement of pollutants, since this flow can depend on atmospheric, relief and even building structure variables, among others. Although our estimated flow (i.e., spatial scales) values are supported by the literature, there are few studies that have tested the dispersion of these pollutants in tropical areas. Therefore, the spatial scales may be higher and more complex than what was considered here. In addition, meteorological variables were not available for all monitoring stations. In case of missing data, we assumed that the microclimate of the nearest station would be similar, and used these values. Despite using most meteorological stations present in the city of São Paulo, and that they are well-distributed and capture the different conditions that exist, extrapolations should be made with caution. Therefore, although the rationale of our analyses and our indicators are well supported by the literature, other studies with more refined measurements of supply, demand, flow and climate are needed to validate these analyses.

4.2. Implications for management

Our study can be used to improve the planning of urban green areas for increased provision of air quality regulation services. Our results show that the amount of green areas is important to guarantee the delivery of the air quality regulation service. Whether by increasing vegetation density in existing green areas or creating new ones (e.g., parks, squares), it is crucial to expand the surface area available for dry deposition. In this case, the more vegetation, the better. Crucially, an increase in the amount of green areas can not only increase the supply, significantly reducing pollution, but also minimize the distances between supply and demand, potentially increasing service flow (Mitchell et al., 2015).

Our results also highlight that green areas can provide this service at distances exceeding 1000 m from the demand areas, and that a less fragmented spatial configuration of those areas would be more beneficial for service provision. Therefore, creating or maintaining large green areas and avoiding their fragmentation in regions up to 1000 m from large polluting sources can contribute to improving air quality in urban areas. However, the spatial arrangement of green areas that maximizes air regulation services may not necessarily enhance the provision of other ecosystem services, such as local climate cooling and urban runoff reduction (Pataki et al., 2011). These factors need to be considered collectively in urban planning, with trade-offs that must be acknowledged when designing urban spaces.

Finally, the provision of air quality regulation services can increase up to threefold during periods of reduced demand pressure. To keep pollutant concentrations within acceptable limits for human health and maximize the benefits of urban vegetation, it is ideal to also implement measures that reduce vehicular emissions, such as enhancing public transportation access and promoting hybrid and remote work options.

5. Conclusions

Our findings highlight the benefits of green areas for air quality regulation in large cities, especially when pollutant emissions are lower, which prevents the saturation of air quality regulation services. Consequently, managing demand pressures, such as vehicular emissions, can enhance the potential for these services. Therefore, programs aimed at reducing pollutant emissions are crucial for improving air quality regulation in megacities.

Increasing the overall amount of green space is essential for enhancing air quality regulation services. While continuous green areas are more effective for the deposition of $PM_{2.5}$, NO_2, and CO, fragmented green areas are valuable for PM_{10} deposition and provide additional ecosystem services, such as urban cooling and cultural benefits. Given that air quality regulation services extend up to 1 km from pollution sources, having green areas located between 500 and 1,000 m from congested roads can significantly contribute to improving air quality and offer potential health benefits.

CRediT authorship contribution statement

Nataly Andrea Pimiento-Quiroga: Writing – original draft, Writing – review & editing, Conceptualization, Methodology, Data curation, Data analysis. **Paula Ribeiro Prist:** Writing – review & editing, Writing – original draft, Supervision, Conceptualization. **Sergio Ibarra-espinosa:** Validation, Methodology, Data curation. **Ligia Vizeu Barrozo:** Supervision, Conceptualization. **Jean Paul Metzger:** Writing – review & editing, Writing – original draft, Validation, Supervision, Methodology, Formal analysis, Conceptualization.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

This work was part of a master degrees' thesis, NPQ was funded by the Coordenação de Aperfeiçoamento de Pessoal de Nível Superior, Brazl (CAPES) – grant 88887.372809/2019-00. JPM was funded by the Conselho Nacional de Desenvolvimento Científico e Tecnológico, Brazil (CNPQ, 309767/2021-0), and is supported by São Paulo Research Foundation, Brazil (FAPESP; Biota Synthesis Project, process n. 2020_06694_8). PRP has the support of Ford Foundation and the National Science Foundation (2225023), United States.

Authorship contribution statement

NPQ, JPM, and PRP conceived and designed the research; NPQ and SIE collected the data; NPQ performed the analysis and wrote the manuscript. All authors edited and approved the manuscript.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.landurbplan.2024.105230.

References

Aguilera, I., Sunyer, J., Fernández-Patier, R., Hoek, G., Aguirre-Alfaro, A., Meliefste, K., Bomboi-Mingarro, M. T., Nieuwenhuijsen, M. J., Herce-Garraleta, D., & Brunekreef, B. (2008). Estimation of outdoor NO x, NO2, and BTEX exposure in a cohort of pregnant women using land use regression modeling. *Environ. Sci. Technol., 42*, 815–821.

Amato-Lourenço, L. F., Moreira, T. C. L., Arantes, B. L. D., Silva Filho, D. F. D., & Mauad, T. (2016). Metrópoles, cobertura vegetal, áreas verdes e saúde. *Estud. avançados, 30*, 113–130.

Anderson, D. R., & Burnham, K. P. (2002). Avoiding pitfalls when using information-theoretic methods. *J. Wildl. Manage.*, 912–918.

Andrade, M. D. F., De Miranda, R. M., Fornaro, A., Kerr, A., Oyama, B., De Andre, P. A., & Saldiva, P. (2012). Vehicle emissions and PM 2.5 mass concentrations in six Brazilian cities. *Air Qual. Atmos. Heal., 5*, 79–88.

Andrade, M. D. F., Kumar, P., Dias de Freitas, E., Ynoue, R., Martins, J., Martins, L. D., Nogueira, T., Perez-Martinez, P., De Miranda, R. M., Albuquerque, T., Teixeira, F. L., Oyama, B., & Zhang, Y. (2017). Air quality in the megacity of São Paulo: Evolution over the last 30 years and future perspectives. *Atmos. Environ., 159*, 66–82.

Arbex, M. A., De Souza Conceição, G. M., Cendon, S. P., Arbex, F. F., Lopes, A. C., Moysés, E. P., & Braga, A. L. F. (2009). Urban air pollution and chronic obstructive pulmonary disease-related emergency department visits. *Journal of Epidemiology and Community Health, 63*(10), 777–783.

Arroyave-Maya, M. del P., Posada-Posada, M.I., Nowak, D.J., Hoehn, R.E., 2019. Remoción de contaminantes atmosféricos por el bosque urbano en el valle de Aburrá Air pollution removal by the urban forest in the Aburra Valley. Colomb. For. 22, 5–16.

Baró, F., Palomo, I., Zulian, G., Vizcaino, P., Haase, D., & Gómez-baggethun, E. (2016). Mapping ecosystem service capacity, flow and demand for landscape and urban planning: A case study in the Barcelona metropolitan region. *Land use policy, 57*, 405–A417.

Beckett, K. P., Freer-Smith, P. H., & Taylor, G. (2000). Particulate pollution capture by urban trees: Effect of species and windspeed. *Glob. Chang. Biol., 6*, 995–1003.

Bonilla-Bedoya, S., Zalakeviciute, R., Mejía, D., Durango-Cordero, J., Molina, J. R., Macedo-Pezzopane, J. E., & Herrera, M.Á. (2021). *Spatiotemporal variation of forest cover and its relation to air quality in urban Andean socio-ecological systems* (p. 59). Urban Green: Urban For.

Cieslik, S., Omasa, K., & Paoletti, E. (2009). Why and how terrestrial plants exchange gases with air. *Plant Biol., 11*, 24–34.

Companhia Ambiental do Estado de São Paulo. (2020). *Qualidade do ar no estado de São Paulo*. Brasil: São Paulo.

Debone, D., Costa, M. V., & Miraglia, S. G. E. K. (2020). 90 days of COVID-19 social distancing and its impacts on air quality and health in São Paulo, Brazil. *Sustainability, 12*, 1–16.

Eeftens, M., Beelen, R., Hoogh, K. D., Bellander, T., Cesaroni, G., Cirach, M., Declercq, C., De, A., Dons, E., Nazelle, A. D., Dimakopoulou, K., Eriksen, K., Fischer, P., Galassi, C., Graz, R., Heinrich, J., Ho, B., Jerrett, M., Keidel, D., Korek, M., Lanki, T., Lindley, S., Madsen, C., Mo, A., Na, G., Nieuwenhuijsen, M., Nonnemacher, M., Pedeli, X., Raaschou-nielsen, O., Patelarou, E., Quass, U., Ranzi, Я. A., Schindler, Å. C., Stempfelet, M., Stephanou, E., Sugiri, D., Tsai, M., Yli-tuomi, T., Varro, J., Vienneau, D., Klot, S. V., Wolf, K., Brunekreef, B., & Hoek, G. (2012). Development of land use regression models for PM2.5, PM2.5 absorbance, PM10 and PM coarse in 20 European study areas; results of the ESCAPE project. *Environ. Sci. Technol., 46*, 11195–11205.

Freitas, E. D., Ibarra-espinosa, S. A., Gavidia-calderón, M. E., Rehbein, A., Rafee, S. A. A., Martins, J. A., Martins, L. D., Santos, U. P., Ning, M. F., Andrade, M. F., & Trindade, R. I. F. (2020). Mobility restrictions and air quality under COVID-19 pandemic in São Paulo. *Brazil*, 1–14.

Fusaro, L., Nardella, L., Manes, F., Sebastiani, A., & Fares, S. (2023). Supply and demand mismatch analysis to improve regulating ecosystem services in Mediterranean urban areas: Insights from four Italian Municipalities. *Ecological Indicators, 155* (September), Article 110928.

Gheorghe, I. F., & Ion, B. (2011). *The Effects of Air Pollutants on Vegetation and the Role of Vegetation in Reducing Atmospheric Pollution*. Economy, Environment and Agricultural Sources: The Impact of Air Pollution on Health.

COVID-19: Relatórios de mobilidade da comunidade, 2022. URL https://www.google.com/covid19/mobility/ (accessed 9.14.22).

Hart, M.A., Maharaj, A.M., Di Virgilio, G., Ulpiani, G., 2021. Schools Weather and Air Quality (SWAQ) –Metadata – Urban Network, Sydney (NSW).

Herreros-Cantis, P., & McPhearson, T. (2021). Mapping supply of and demand for ecosystem services to assess environmental justice in New York City. *Ecological Applications, 31*(6), 1–21.

Hoek, G., Beelen, R., Hoogh, K. D., Vienneau, D., Gulliver, J., Fischer, P., & Briggs, D. (2008). A review of land-use regression models to assess spatial variation of outdoor air pollution. *Atmos. Environ., 42*, 7561–7578.

Ibarra-Espinosa, S., Ynoue, R., O'sullivan, S., Pebesma, E., De Fátima Andrade, M., & Osses, M. (2018). VEIN v0.2.2: An R package for bottom-up vehicular emissions inventories. *Geosci. Model Dev., 11*, 2209–2229.

Instituto Brasileiro de Geografia e Estatística, 2022. IBGE | Cidades@ | São Paulo | São Paulo | Panorama [WWW Document]. URL https://cidades.ibge.gov.br/brasil/sp/sao-paulo/panorama (accessed 9.14.22).

IPCC, 2014. Climate change 2014 mitigation of climate change. Contribution of working group III to the fifth sssessment report of the intergovernmental panel on climate change. Cambridge, United Kingdom and New York, NY, USA.

Irga, P. J., Burchett, M. D., & Torpy, F. R. (2015). Does urban forestry have a quantitative effect on ambient air quality in an urban environment ? *Atmos. Environ., 120*, 173–181.

Jaafari, S., Shabani, A. A., Moeinaddini, M., Danehkar, A., & Sakieh, Y. (2020). Applying landscape metrics and structural equation modeling to predict the effect of urban green space on air pollution and respiratory mortality in Tehran. *Environ. Monit. Assess., 192*, 1–15.

Janhall, S. (2015). Review on urban vegetation and particle air pollution e Deposition and dispersion. *Atmospheric Environment, 105*, 130–137.

Kayes, I., Shahriar, S. A., Hasan, K., Akhter, M., Kabir, M. M., & Salam, M. A. (2019). The relationships between meteorological parameters and air pollutants in an urban environment. *Glob. J. Environ. Sci. Manag., 5*, 265–278.

Krecl, P., Targino, A. C., Oukawa, G. Y., & Casino Junuior, R. P. (2020). Drop in urban air pollution from COVID-19 pandemic: Policy implications for the megacity of São Paulo. *Environ. Pollut., 265*, Article 114883.

Krzyżanowski, M., Kuna-Dibbert, B., Schneider, J. (Eds), 2005. Health effects of transport-related air pollution. WHO Regional Office Europe.

Kumar, P. G., Lekhana, P., Tejaswi, M., & Chandrakala, S. (2021). Effects of vehicular emissions on the urban environment- a state of the art. *Mater. Today Proc., 45*, 6314–6320.

Larondelle, N., & Lauf, S. (2016). Balancing demand and supply of multiple urban ecosystem services on different spatial scales. *Ecosystem Services, 22*, 18–31.

Liu, H. M., Fan, Y. L., & Ding, S. Y. (2016). Research progress of ecosystem service flow. *J. Appl. Ecol., 27*, 2161–2171.

Liu, J., Wang, J., & Tan, Y. (2023). Spatiotemporal pattern and influencing mechanism of the flood-regulating ecosystem service capacity and demand in China's Yellow River basin, 2000–2020. *Journal of Hydrology: Regional Studies*, *45*(October 2022), 101312.

Loh, H.C., Looi, I., Ch'ng, A.S., Goh, K.W., Ming, L.C., Ang, K.H., 2021. Positive global environmental impacts of the COVID-19 pandemic lockdown : a review. GeoJournal 6, 1–13.

Mcpherson, E. G., Nowak, D. J., & Rowntree, R. A. (1994). *Chicago's urban forest ecosystem: results of the Chicago Urban Forest Climate Project* (Vol. 186). Radnor, PA: US.

Mears, M., Brindley, P., Jorgensen, A., Ersoy, E., & Maheswaran, R. (2019). Greenspace spatial characteristics and human health in an urban environment : An epidemiological study using landscape metrics in Sheffield. *UK. Ecol. Indic., 106*, Article 105464.

Metzger, J. P., Villarreal-Rosas, J., Suárez-Castro, A. F., López-Cubillos, S., González-Chaves, A., Runting, R. K., Hohlenwerger, C., & Rhodes, J. R. (2021). *Considering landscape-level processes in ecosystem service assessments* (p. 796). Total Environ: Sci.

Mitchell, M. G. E., Suarez-Castro, A. F., Martinez-Harms, M., Maron, M., McAlpine, C., Gaston, K. J., Johansen, K., & Rhodes, J. R. (2015). Reframing landscape fragmentation's effects on ecosystem services. *Trends Ecol. Evol., 30*, 190–198.

Mohan, S. M. (2016). An overview of particulate dry deposition: Measuring methods, deposition velocity and controlling factors. *Int. J. Environ. Sci. Technol., 13*, 387–402.

Nakada, L. Y. K., & Urban, R. C. (2020). COVID-19 pandemic: Impacts on the air quality during the partial lockdown in São Paulo state. *Brazil. Sci. Total Environ., 730*, Article 139087.

Nowak, D. J., Hirabayashi, S., Bodine, A., & Hoehn, R. (2013). Modeled PM2.5 removal by trees in ten U.S. cities and associated health effects. *Environ. Pollut., 178*, 395–402.

Nowak, D. J., Mchale, P., Ibarra, M., Crane, D., Stevens, J. C., & Luley, C. (1998). Modeling the effects of urban vegetation on air pollution. In *Air Pollution Modeling and Its Application XII* (pp. 399–407). Boston, MA: Springer.

Oleniacz, R., Bogacki, M., Szulecka, A., Rzeszutek, M., & Mazur, M. (2016). Assessing the impact of wind speed and mixing-layer height on air quality in Krakow (Poland) in the years 2014–2015. *J. Civ. Eng. Environ. Archit., 63*, 315–342.

Paoletti, E., Karnosky, D.F., Percy, K.E., 2004. Urban trees and air pollution, in: Konijnendijk, C.C., Schipperijn, J., Hoyer, K.K. (Eds.), Forestry Serving Urbanised Societies. IUFRO World Series, Volume 14. IUFRO Headquarters, Vienna, Austria, p. 407.

Pataki, D. E., Carreiro, M. M., Cherrier, J., Grulke, N. E., Jennings, V., Pincetl, S., & Zipperer, W. C. (2011). Coupling biogeochemical cycles in urban environments: Ecosystem services, green solutions, and misconceptions. *Frontiers in Ecology and the Environment, 9*(1), 27–36.

Popescu, F., & Ionel, I. (2010). Anthropogenic air pollution sources. *Air Qual.*, 1–22.

Prist, P. R., Sangermano, F., Bailey, A., Bugni, V., Villalobos-Segura, M. del C., Pimiento-Quiroga, N., … Zambrana-Torrelio, C. (2023). Protecting Brazilian Amazon Indigenous territories reduces atmospheric particulates and avoids associated health impacts and costs. *Communications Earth and Environment*, *4*(1), 1–12.

Pugh, T. A. M., Mackenzie, A. R., Whyatt, J. D., & Hewitt, C. N. (2012). *Effectiveness of green infrastructure for improvement of air quality in urban street canyons*. Technol: Environ. Sci.

Ribeiro, A., Bollmann, H. A., De Oliveira, A., Rakauskas, F., Cortese, T., Rodrigues, M., Quaresma, C., & Ferreira, M. L. (2021). The role of tree landscape to reduce effects of urban heat islands : A study in two Brazilian cities. *Trees*, 1–14.

Roeland, S., Moretti, M., Amorim, J. H., Branquinho, C., Fares, S., Morelli, F., & Calfapietra, C. (2019). Towards an integrative approach to evaluate the environmental ecosystem services provided by urban forest. *J. For. Res., 30*, 1981–1996.

Roy, S., Byrne, J., & Pickering, C. (2012). A systematic quantitative review of urban tree benefits, costs, and assessment methods across cities in different climatic zones. *Urban For. Urban Green., 11*, 351–363.

Scheffer, M., & Carpenter, S. R. (2003). Catastrophic regime shifts in ecosystems : Linking theory to observation. *Trends Ecol. Evol., 18*, 648–656.

Secretaria Municipal do Verde e do Meio Ambiente, 2020. Mapeamento digital da cobertura vegetal do município de São Paulo. São Paulo, Brasil.

Seo, J., Park, D. R., Kim, J. Y., Youn, D., Lim, Y. B., & Kim, Y. (2018). Effects of meteorology and emissions on urban air quality : A quantitative statistical approach to long-term records (1999–2016) in Seoul, South Korea. *Atmos. Chem. Phys., 18*, 16121–16137.

Shah, A. M., Liu, G., Huo, Z., Yang, Q., Zhang, W., Meng, F., & Ulgiati, S. (2022). Assessing environmental services and disservices of urban street trees. an application of the emergy accounting. *Resources, Conservation and Recycling, 186*(July), Article 106563.

Shen, Y., & Lung, S. C. (2017). Mediation pathways and effects of green structures on respiratory mortality via reducing air pollution. *Sci. Rep., 7*, 1–9.

Sil, Â., Fernandes, P. M., Rodrigues, A. P., Alonso, J. M., Honrado, J. P., Perera, A., & Azevedo, J. C. (2019). Farmland abandonment decreases the fire regulation capacity and the fire protection ecosystem service in mountain landscapes. *Ecosystem Services, 36*(March), Article 100908.

Shen, Y., & Lung, S. C. (2016). Can green structure reduce the mortality of cardiovascular diseases ? *Sci. Total Environ., 566*, 1159–1167.

Shi, Y., Ren, C., Lau, K. K., & Ng, E. (2019). Investigating the influence of urban land use and landscape pattern on PM2.5 spatial variation using mobile monitoring and WUDAPT. *Landsc. Urban Plan., 189*, 15–26.

Silva-Sánchez, S., & Jacobi, P. R. (2014). Implementation of riverside parks in the city of São Paulo – progress and constraints. *Local Environ. Int. J. Justice Sustain., 21*, 65–84.

Ulpiani, G., Anne, M., Di, G., & Maharaj, A. M. (2022). Urban meteorology and air quality in a rapidly growing city: Inter-parameter associations and intra-urban heterogeneity. *Sustain. Cities Soc., 77*, Article 103553.

Vailshery, L. S., Jaganmohan, M., & Nagendra, H. (2013). Effect of street trees on microclimate and air pollution in a tropical city. *Urban For. Urban Green., 12*, 408–415.

Villamagna, A. M., Angermeier, P. L., & Bennett, E. M. (2013). Capacity, pressure, demand, and flow : A conceptual framework for analyzing ecosystem service provision and delivery. *Ecol. Complex., 15*, 114–121.

Viippola, V., Whitlow, T. H., Zhao, W., Yli-Pelkonen, V., Mikola, J., Pouyat, R., & Setälä, H. (2018). The effects of trees on air pollutant levels in peri-urban near-road environments. *Urban Forestry and Urban Greening*, *30*(June 2017), 62–71.

Wang, J., Endreny, T. A., & Nowak, D. J. (2008). Mechanistic simulation of tree effects in an urban water balance model. *Journal of the American Water Resources Association, 44*(1), 75–85.

Watson AY, Bates RR, Kennedy D, editors. Air Pollution, the Automobile, and Public Health. Washington (DC): National Academies Press (US); 1988. Atmospheric Transport and Dispersion of Air Pollutants Associated with Vehicular Emissions. Available from: https://www.ncbi.nlm.nih.gov/books/NBK218142/.

Weagle, C. L., Snider, G., Li, C., Donkelaar, A. V., Philip, S., Bissonnette, P., Burke, J., Jackson, J., Latimer, R., Stone, E., Abboud, I., Akoshile, C., Anh, N. X., Brook, R., Cohen, A., Dong, J., Gibson, M. D., He, K. B., Holben, B. N., Kahn, R., & Keller, C. A. (2018). Global sources of fine particulate matter: Interpretation of PM2. 5 chemical composition observed by SPARTAN using a global chemical transport model. *Environ. Sci. Technol., 52*, 11670–11681.

World Health Organization. (2018). How air pollution is destroying our health. Retrieved from https://www.who.int/news-room/spotlight/how-air-pollution-is-destroying-our-health.

Wu, J., Xie, W., Li, W., & Li, J. (2015). Effects of urban landscape pattern on PM2. 5 pollution—a Beijing case study. *PLoS One, 10*, 1–20.

Wu, Y., Liu, J., Zhai, J., Cong, L., Wang, Y., Ma, W., Zhang, Z., & Li, C. (2018). Comparison of dry and wet deposition of particulate matter in near-surface waters during summer. *PLoS One, 13*, 1–15.

Xing, Y., & Brimblecombe, P. (2019). Role of vegetation in deposition and dispersion of air pollution in urban parks. *Atmospheric Environment*, *201*(August 2018), 73–83.

Yazbeck, T., Bohrer, G., Vines, C., De Roo, F., Mauder, M., & Bakshi, B. (2021). Effects of spatial heterogeneity of leaf density and crown spacing of canopy patches on dry deposition rates. *Agricultural and Forest Meteorology, 306*(May), Article 108440.

Zhang, H., Xu, T., Zong, Y., Tang, H., Liu, X., & Wang, Y. (2015). Influence of meteorological conditions on pollutant dispersion in street canyon. *Procedia Eng., 121*, 899–905.

Zuur, A. F., Ieno, E. N., Walker, N. J., Saveliev, A. A., & Smith, G. M. (2009). *Mixed effects models and extensions in ecology with R* (Vol. 574). New York: Springer.