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Analysis of exposure to fine particulate matter using passive data from public transport

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ABSTRACT

The city of Santiago experiences extreme pollution events during winter due to particulate matter and the associated health impact depends on the exposure to this pollutant, particularly to $PM_{2.5}$. We present and apply a method that estimates the exposure of users of the public transport system of Santiago by combining smart card mobility data with measured surface concentrations from the monitoring network of Santiago and simulated concentrations by the CHIMERE model. The method was applied between July 20th and 24th of 2015 to 105,588 users corresponding to 12% of the frequent users of the public transport system and approximately 2% of the total population of Santiago. During those five days, estimated exposure based on measured concentrations varied between 44 and 75 μg/m^3 while exposure based on simulated concentrations varied between 45 and 89 μg/m^3. Furthermore, including socioeconomic conditions suggests an inverse relationship between exposure and income when measured concentrations are used, i.e. the lower the income the higher the exposure, whereas no such relationship is observed when using simulated concentrations. Although only exposure to $PM_{2.5}$ was considered in this study, the method can also be applied to estimate exposure to other urban pollutant such as ozone.

1. Introduction

Air quality (AQ) levels are a societal concern in Santiago, Chile. During winter periods, particulate matter (PM) concentrations, more specifically fine PM ($PM_{2.5}$), exceed daily average thresholds set by Chilean environmental regulation potentially causing harm to human health and impacting the ecosystem (World Health Organization and UNAIDS, 2006). PM causes damage to the respiratory and cardiovascular system, leading to a higher number of hospital consultations, less productivity and premature death (Kim et al., 2015).

The health impact of air pollutants in general, and PM in particular, depends on the exposure to a given pollutant. The personal exposure can be defined as the real exposure as it is experienced by individuals (Dons et al., 2011) and is usually calculated as the average of the concentration at the different places (micro-environments) visited by an individual weighted by the time spent at each place. Therefore, estimating the exposure of an individual requires knowledge of the pollutant concentrations along his/her trajectory and the time spent during the corresponding activity. An accurate exposure estimate takes into account indoor and outdoor air pollution. However, exposure and/or health impact has been estimated using solely outdoor concentrations (e.g. Anenberg et al., 2012).

Concentration of air pollutants can be measured through portable instruments (e.g. Etyemezian et al., 2005; Deville Cavellin et al., 2015) or stationary air quality monitoring stations (e.g. Escudero et al., 2007; Azmi et al., 2010; Mavroidis and Ilia, 2012). In addition, it can also be estimated through chemical transport models (e.g. Draxler and Hess, 1998; Brasseur et al., 1998; Byun and Schere, 2006; Menut et al., 2013),

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which provide information about spatial distribution and composition of PM.

Location of the population and activity patterns may be estimated from sources providing geographic position as a function of time. Previous studies have analyzed this with surveys where participants declare where and when they are doing an activity during a specific day (e.g. Leech et al., 1996; Klepeis et al., 2001; Muñoz et al., 2016; Olguín et al., 2009). Other studies have considered mobile phone data (e.g. Phithakkitnukoon et al., 2010; Alexander et al., 2015), smart card data used in public transport systems (e.g. Devillaine et al., 2012; Ma et al., 2013) and social media data (e.g. Hasan et al., 2013) where a device sends a GPS pulse at regular time intervals.

Various methods have been proposed to estimate human exposure in different environments. Most studies have estimated the exposure to air pollutants using portable instruments during commuting (e.g. Rivas et al., 2017; Salvatierra, 2016; Suárez et al., 2014; Cortese and Spengler, 1976; Violante et al., 2006; Karanasiou et al., 2014). Previous studies have also proposed analyzing exposure by combining mobility patterns estimated with mobile phone data with pollution monitoring from stationary sites (e.g. Liu et al., 2013a,b; Nyhan et al., 2016) and air quality models (e.g. Dewulf et al., 2016; Yu et al., 2018).

In this paper, we present a method to estimate population exposure to $PM_{2.5}$ using public transport data from frequent users to obtain population mobility and air pollutant data from a chemical transport model and observations from stationary monitoring stations. To the best of our knowledge, passive public transport data has not been used for this purpose. Due to the lack indoor concentration measurements, outdoor concentration will be used in this study to estimate exposure. Out of the 18 million total daily trips made in Santiago, 57% are in motorized modes and 51% are in public transport (Muñoz et al., 2016).

2. Data description and methodology

In the following, we present a brief description of Santiago, Chile (Section 2.1), the selected period of analysis with deteriorated air quality levels of $PM_{2.5}$ (Section 2.2), the databases used in this study (Section 2.3) as well as the methodology applied to estimate exposure (Section 2.4).

2.1. The case of Santiago, Chile

Santiago (33.5°S, 70.5°W, 600 m.a.s.l.) is the capital and largest city of Chile encompassing nearly 35% of the country's population with a total of 7.1 million inhabitants (INE, 2017). Nearly 2 million of these are students (MINEDUC, 2018) and 3.4 million people are economically active (INE, 2018). The topography surrounding Santiago basin includes the Chacabuco mountain range to the north, the central Chilean Andes (average height of 4500 m.a.s.l.) to the east, the Angostura de Paine to the south and a coastal range (average height of 1500 m.a.s.l.) to the west.

In winter, thermal inversion together with Santiago's complex topography results in poor ventilation and limited vertical mixing (Muñoz Magnino and Alcafuz, 2012) preventing the dispersion of pollutants and accumulating PM_{10} and $PM_{2.5}$ (Villalobos et al., 2013). This represents a serious air pollution problem and according to the Air Pollution section of the World Bank Development Index report (World Bank, 2010), Santiago's mean annual PM concentrations appear to be one of the highest in South America.

Santiago's total area of 641 km^2 is divided in 34 municipalities and has 11 air quality monitoring stations distributed in different municipalities (Fig. 1). There are notable differences between the municipalities, especially in terms of income, car ownership, household characteristics and mobility patterns (Amaya et al., 2018). In particular, Santiago's Eastern zone, comprised of Providencia, Ñuñoa, Vitacura, Las Condes, La Reina and Lo Barnechea, clusters households with the highest income.

2.2. Study period

The period considered in this study corresponds to the winter week from Monday July 20th to Friday, July 24th, 2015.

During this time, the Ministry of the Environment (MMA, from Spanish *Ministerio del Medio Ambiente*) forecasted two alert episodes (21st and 23rd of July) and two pre-emergency episodes (22nd and 24th of July) according to the national threshold limits (Table 1). Alert episodes entail restrictions that include, among others, suspension of sport activities in schools, prohibition of agricultural burning and residential wood combustion and implementation of license plate restrictions. More restrictive measures are progressively enforced from pre-emergency to emergency based on deteriorated air quality.

During the week of interest, typical synoptic conditions responsible for bad air quality in Santiago were observed on July 20th, 24th and 25th and are associated with the leading edges of coastal lows with downslope flow along the Maipo, bringing down the temperature inversion and reducing the growth of the surface mixed layer (Rutllant and Garreaud, 1995, 2004). Conditions on the 20th correspond to the onset of a period of days with bad air quality. Synoptic configurations on the 24th and 25th are responsible for the pre-emergency observed on the latter (Mazzeo et al., 2018).

The maximum observed daily average concentration of $PM_{2.5}$ by the air quality monitoring network was measured at Cerro Navia (110 μg/m^3 on July 21st) and Pudahuel (105 μg/m^3 on July 23rd) which are located in the north-western zone of the city (Fig. 2). The least affected municipality reported is in the eastern zone in Las Condes (19 μg/m^3 on July 24th). In addition, stations of Cerro Navia and Pudahuel presented daily average $PM_{2.5}$ concentrations corresponding to alert episodes on the 22nd to 24th of July and one pre-emergency episode on the 21st of July.

2.3. Database description

2.3.1. Monitoring station data

Surface concentrations of several air pollutants in Santiago are measured by an air-monitoring network (http://sinca.mma.gob.cl) controlled by the MMA. The network is composed of eleven stations distributed in different zones of the city (Fig. 1). Out of the eleven monitoring stations, four have monitored $PM_{2.5}$ since January 1st, 2000 (La Florida, Las Condes, Pudahuel, Parque O'Higgins) and the rest since May 2008. These stations are located in an urban area and at each station $PM_{2.5}$ is measured using a beta attenuation monitor (Met One BAM-1020) (Liu et al., 2013a,b; SINCA, 2010).

Each station provides hourly concentrations of sulfur dioxide (SO_2), nitrogen oxides (NO and NO_2), carbon monoxide (CO), ozone (O_3) and particulate matter PM_{10} and $PM_{2.5}$. This network also provides temperature, relative humidity, wind direction and wind speed. We note that neither these meteorological parameters nor air pollutants other than $PM_{2.5}$ are used in the present study.

2.3.2. Modeling system

The modeling system used in this study is composed of the meteorological model WRF version 3.7.1 (Skamarock et al., 2008) and the chemical transport model CHIMERE version 2014b (Menut et al., 2013). This modeling system has been extensively validated against measurements in central Chile and is successful in reproducing the main features of the dispersion of $PM_{2.5}$ in Santiago for two winter weeks in 2015 (15th to 28th July) with deteriorated AQ (Mazzeo et al., 2018). The same model configuration adopted by Mazzeo et al. (2018) is used in this study to simulate the dispersion of air pollutants for the period between the 20th and 24th of July. The spatial resolution of the simulated concentrations is 2 × 2 km and the model time step is 5 min. In this study hourly outputs are used.

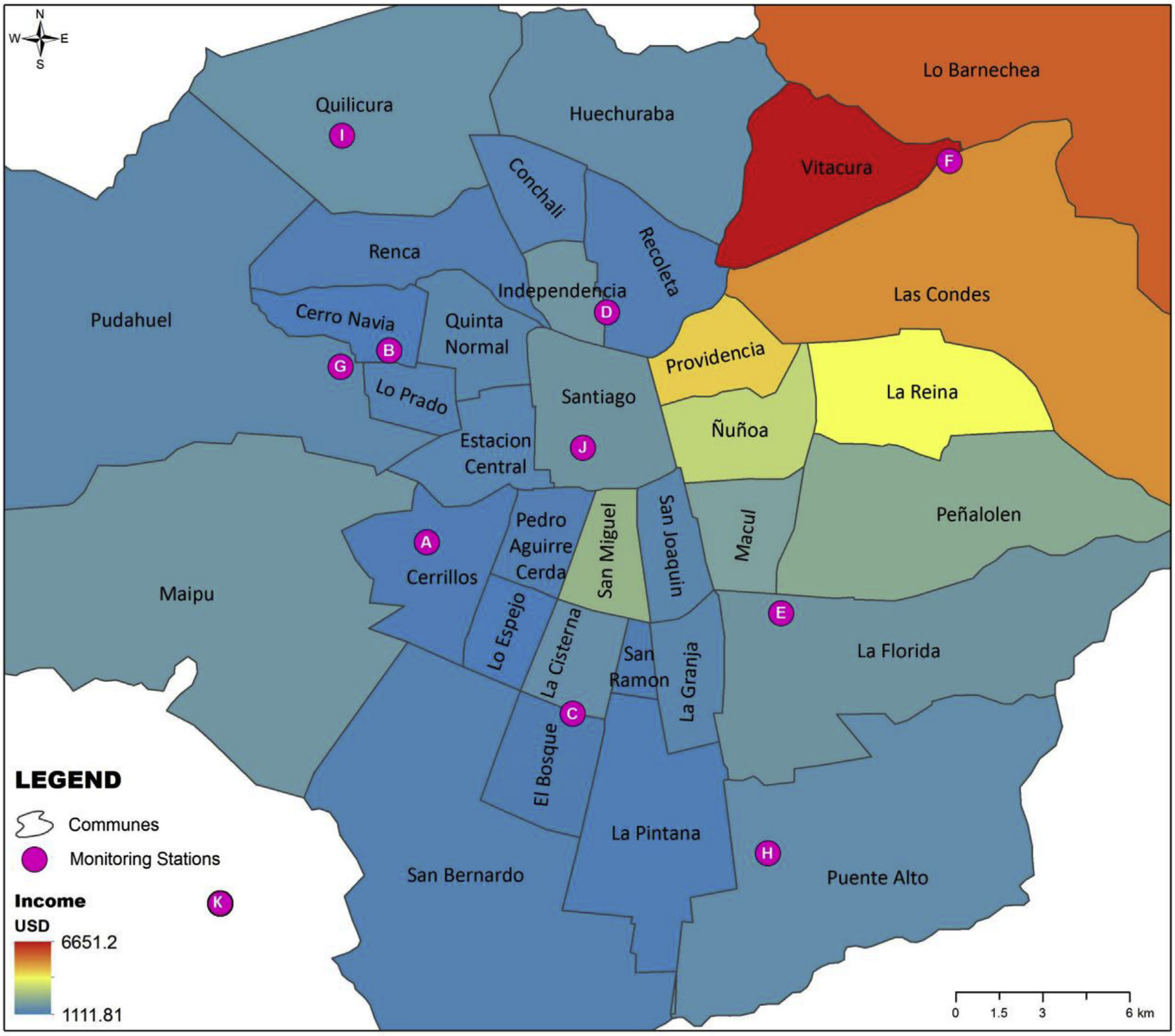

Fig. 1. Santiago's average household income per municipality from higher (red) to lower (blue) income [USD/month −2015]. Location of the eleven monitoring stations are also illustrated (pink dots): Cerrillos (a), Cerro Navia (b), El Bosque (c), Independencia (d), La Florida (e), Las Condes (f), Pudahuel (g), Puente Alto (h), Quilicura (i), Parque O'Higgins (j) and Talagante (k). (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

Table 1
$PM_{2.5}$ concentration levels set by the MMA in Chile. Episodes are declared when a monitoring station with population representativeness measures these average concentrations for 24 h.

Level	$PM_{2.5}$ [μg/m^3]
Good	< 50
Regular	50–79
Alert	80–109
Pre-emergency	110–169
Emergency	> 170

2.3.3. Mobility

Santiago has a multimodal integrated public transport system, known as "Transantiago", including bus and metro since 2007. The system has over 6500 buses all equipped with GPS devices operating in 800 bus lines on a network with over 11,000 stops. Each public transport bus is equipped with a GPS sending pulses every 30 s with the position and time, this estimates the time the bus is at a public transport network bus stop. The data generated by GPS and smart cards while commuting has been used to study the user mobility pattern in the public transport system (Munizaga and Palma, 2012; Devillaine et al., 2012; Amaya et al., 2018). In addition, the integrated Metro network has 6 lines and 118 stations and it is currently expanding with one more line (Gschwender et al., 2016).

The fare collection system is based on a smart card named "bip!". It is the only payment method accounting for the 4.5 million total daily trips in the public transport system. It is required to be validated at the boarding of the bus and metro, thus in a two stage trip the user needs to validate twice. However, it is not required to be validated at the alighting stops.

To estimate exposure, both the boarding and alighting stops of a trip are required. The alighting stop for each trip is estimated combining information from the first validation (from the first trip after alighting) and the line of the given trip (Munizaga and Palma, 2012). Once the alighting stop is identified, the arrival time at the destination, as well as the stops the user passed while travelling, are determined from the stop sequence of the last line used and the bus GPS. The time interval between the moment the user reaches his/her destination and the next validation in the public transport system gives an approximation of the time spent on a given activity. In this study, we assume that each activity is executed in the vicinity of the alighting bus stop until the user travels again.

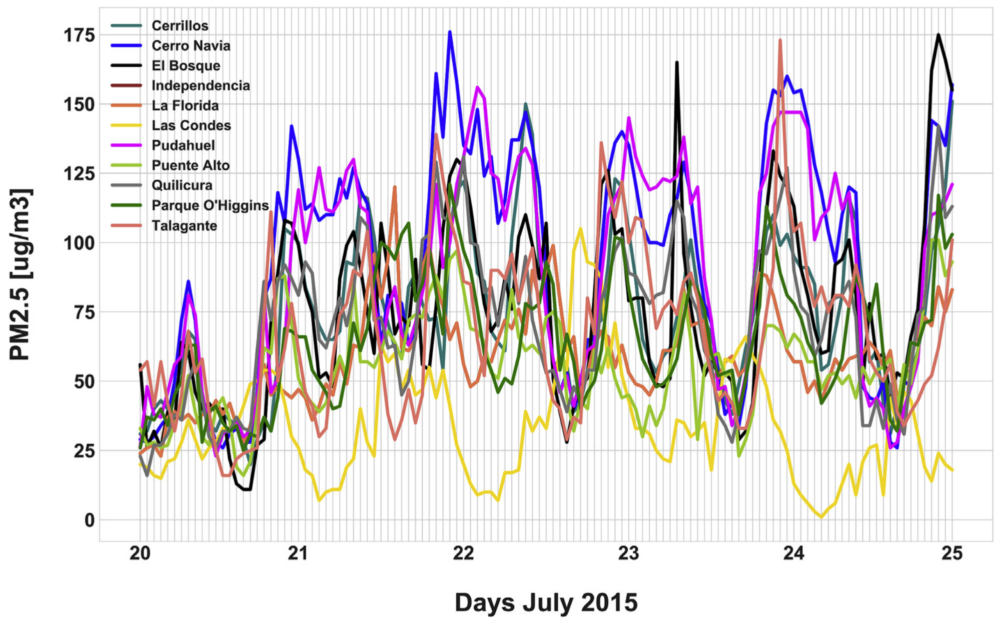

Fig. 2. Hourly $PM_{2.5}$ concentrations from the 20th to 24th of July 2015 at each station of Santiago's air quality monitoring network.

Raw smart card data gathered during the days of interest contains around 22 million trips and 2 million different smartcards. In this study, we focus only on frequent transport users, defined as those that use the public transport system five days within a week (45% of the total smart cards used in a week), which reduces the database to around 900,000 cards. Of these users, the alighting stops, activities and residence could be estimated for 105,588 frequent transport users (1,7% of the population in Santiago and 12% of the frequent transport users during this week) with a total of 1.3 million trips in a week (5,7% of the total trips). These 105,588 constitute the sample used in this study. Out of this sample, 47% travelled twice per day in the public transport system during the week analyzed, of which 52% conducted single trip stages while 48% conducted two trip stages (with one transfer). The sample considers both regular (82%) and student (18%) smart cards with homes mainly located in Santiago municipality (12.6%), Maipú (9%), La Florida (8.3%), Puente Alto (7.7%), Estación Central (6.2%), Lo Prado (5.5%), Las Condes (5.4%), Providencia (4.9%), Pudahuel (4.1%) and Ñuñoa (3.8%).

Activities considered are travel, home, work, school/university (hereafter study) and other. The latter usually related with leisure. Travel is the moment when the user has made a validation in the public transport system until he reaches his destination. The methodology to determine if the user is at home, work, studying or other is based on the smart card type and the duration between validations (Devillaine et al., 2012). Home-based activities are detected if the trip is the last one of the day and the next morning validation is at a close distance from the last alighting stop. Work activities are identified if the card type is adult and the interval between validations is longer than 2 h. Study activities involve validations with a student card and duration longer than 5 h and other activities are assumed when the interval time is between 1 min and 2 h.

The user's residence is estimated by observing the spatial distribution of the first morning validation of the day between 4:00 a.m. and noon. If the bus stops where the first validations are made are within walking distance for at least 3 days, then the user's residence is assigned to the location of these bus stops (Amaya et al., 2018).

Home activities are highly densified in the western (28%) and south-eastern (22%) zones (Fig. 3). Workplaces are mostly located at the center and east, specifically in Santiago (32%), Providencia (22.8%) and Las Condes (12.8%) municipalities. Study places are concentrated near subway lines and located mostly in Santiago (34.5%), Providencia (24.3%) and Las Condes (9.6%).

Time attribution to each activity indicates that students spend 1.5 h more at home on average than the economically active population (hereafter workers) (14 vs. 12.5 h). Work activities are on average 10 h long and study 9 h long. Users residing in central municipalities (Providencia, Santiago, Lo Prado, Ñuñoa, Estación Central and Las Condes) spend on average 36–48 min in transportation, while residents from peripheral municipalities (San Bernardo, Quilicura, La Pintana, Cerro Navia, El Bosque, Lo Espejo, Maipú and Cerrillos) spend around 84–102 min travelling (not shown).

As an example, the data from a typical working day (July 20th), is used to examine the distribution of the five activity types defined above throughout the day. As expected, we observe that home based activities are mainly performed during night time hours contrary to work related activities which start at 9:00 a.m. and finish around 7:00 p.m. (Fig. 4). Study activities are concentrated between 10:00 a.m. and 5:00 p.m. Also, morning and evening travel peaks can be observed at 8:00 a.m. and at 7:00 p.m. when most users travel from home to work in the morning and return in the afternoon, respectively. Time assigned to each activity generally remains unchanged throughout the examined period (see Figure A1 in the appendix).

2.4. Exposure estimation

The exposure during each activity is calculated as the product of the concentration at the nearest bus stop where the activity is conducted and its duration. The concentration at work (or study) and at home is that of the destination bus stop of the corresponding trip whereas during travel it is that of each stop the bus passes by. The duration of activities other than travel (i.e. work, study, home and others) is assumed as the time spent at the alighting stop until the user takes a new trip. Exposure time during travel is assumed as the time between the involved bus stops.

A representation of the methodology to estimate exposure for a given user *i* while travelling is illustrated in Fig. 5. The user starts a trip at the boarding bus stop S_1. After boarding the bus, the user travels and passes by the bus stop S_2. User's destination is located at S_3 where the purpose of the trip is performed. The duration of this trip (D) is from the boarding time at bus stop S_1 to the alighting time at the bus stop S_3. The duration of the activity conducted at S_3 corresponds to the time from arrival at S_3 to the time the user starts a new trip.

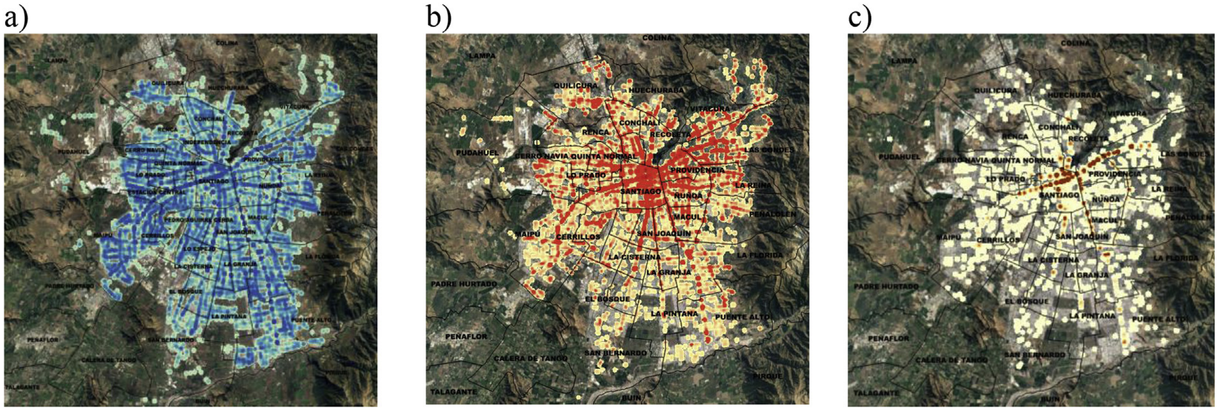

Fig. 3. Heat maps representing the distribution of activities at home at 4:00 a.m. (blue), work at 2:00 p.m. (red) and study at 2:00 p.m. (brown). Darker colors reflect higher density of users. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

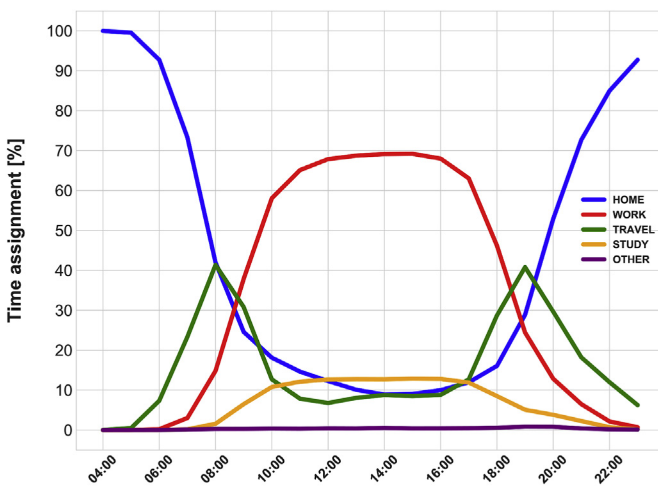

Fig. 4. Time assigned to activities home (blue), work (red), travel (green), study (yellow) and other (purple) during a typical working day. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

The exposure to PM2.5 is estimated using two different datasets; measurements from the monitoring stations (MS) and simulated concentrations from a chemical transport model (CHIMERE). This is done to analyze impact on the exposure estimate from a larger information grouping with the model and compare it to observations from a limited number of stations. The impact of the model bias with respect to observations in estimated exposure is examined in section 5.

The concentration at each bus stop is taken either from the nearest monitoring station (Fig. 5a) or the nearest model grid-point (Fig. 5b). The analysis is also extended by calculating the exposure using synthetic observations at each monitoring station. These correspond to the simulated concentration from the closest model grid-point to the monitoring station (Fig. 5c).

In this study, exposure is estimated using outdoor concentrations since information on indoor air pollution is not available and the estimation is based on the concentration at each bus stop and therefore no specific information exists on the actual place the activity is conducted. In addition, exposure during subway travel was not computed since air pollution information in the underground subway network is not available. Nevertheless, exposure for subway users was calculated during activities (home, work, study and other) using exposure at the alighting station of the metro trip estimated with the methodology proposed by Munizaga and Palma (2012).

3. Results

Average daily exposure (across all users) based on measured concentrations (MS) ranged between 44 and 75 [μg/m^3] whereas exposure estimated with simulated concentrations (CHIMERE) varied between

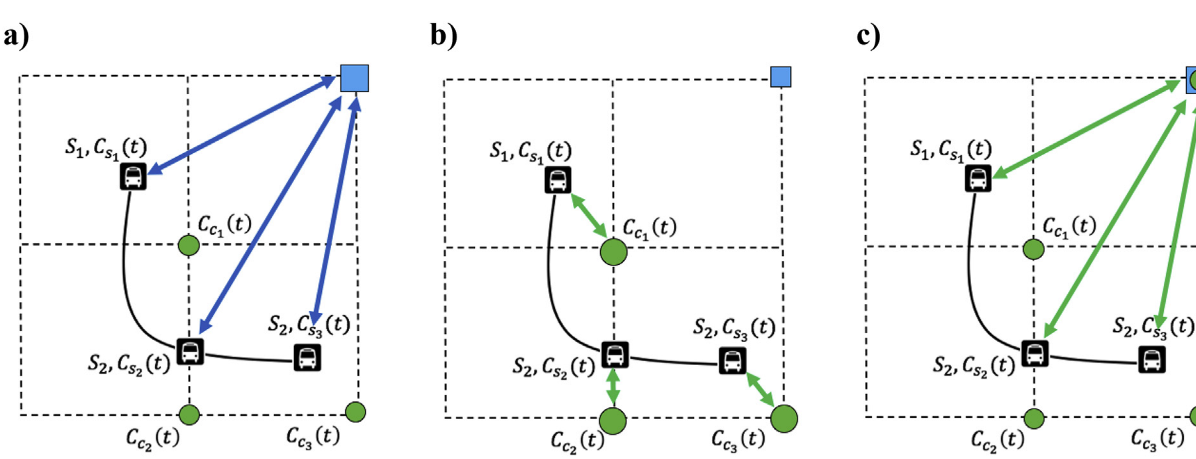

Fig. 5. Illustration of methodology estimating PM2.5 concentration at each bus stop for a user (i) travelling from bus stop S_1 to bus stop S_3 to perform an activity at this bus stop. Trajectory is represented with a solid black line while blue squares correspond to monitoring stations, green dots to CHIMRE concentrations at model grid-points and blue square filled with a green dot to CHIMERE concentration at the nearest monitoring station. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

Table 2
Average daily exposure to $PM_{2,5}$ using both air pollutant data sources.

Day	Average exposure (MS) [μg/m^3]	Average exposure (CHIMERE) [μg/m^3]
20	44	45
21	75	72
22	73	69
23	73	89
24	67	82

45 and 89 [μg/m^3] (Table 2). The difference in average daily exposure between both estimates is larger on more polluted days. For an analysis on the model performance to reproduce the observations we refer to Mazzeo et al. (2018). In that study, the authors examine the model performance to simulate PM2.5 and NOx and explore the impact of mitigation measures based on the reduction of residential and transport emissions to improve air quality for the period considered in the present study. The study shows that reducing transport emissions is more effective in reducing the number of episodes than decreasing residential combustion due to the spatial distribution of the emission sources.

The average daily exposure is now examined based on the thresholds of pollution levels established by the Chilean AQ legislation (Table 1). According to exposure estimates based on MS observations, the population considered in this study was only exposed to Pre-emergency pollution levels (between 110 and 169 [μg/m^3] on a 24-hr average) on July 21st (2% of the users) whereas based on CHIMERE outputs the population was exposed to this pollution level on the 23rd and 24th of July (5% and 1%, respectively) (Table 3). In addition, the percentage of users exposed to Alert levels (daily average concentration between 80 and 109 [μg/m^3]) never exceeded 31% based on MS observations, while the exposure calculated with CHIMERE reached up to 73% of the users on July 23rd. However, while the percentage of users exposed to Alert concentration levels is larger on the 21st and 22nd for MS estimates, the 23rd and 24th estimates based on CHIMERE data suggest a larger number of users exposed to this level of pollution. Both exposure estimates agree that over 80% of the population was exposed to concentrations lower than 50 [μg/m^3] on July 20th, the less polluted day of the week.

For the analysis of hourly exposure, focus will be on the ranges with the largest concentration levels, i.e. between 110 and 169 [ug/m^3] and above 170 [ug/m^3]. These two levels have the largest health impact as well as a larger number of activity restrictions (Mazzeo et al., 2018). According to the exposure estimated with MS data, exposure to concentrations above 170 [ug/m^3] occurred only on the night of the 21st and 24th while according to CHIMERE data this occurred in the morning of the 24th and midnight of the 25th (Fig. 6). Furthermore, on the 21st and 22nd a larger percentage of the population was exposed to concentrations between 110 and 169 [ug/m^3] according to MS data, whereas on the 23rd and 24th more users were exposed to this level of pollution based on CHIMERE data.

Approximately 91% of the estimated average daily exposure was associated with work and home-based activities for both data sets (Fig. 7). Similar results are seen for students in both datasets (see figure A2 in appendix). Due to similar exposure between workers and students, we will focus the remainder of the paper on work related activity. Equivalent figures of student exposure compared to the ones presented hereafter are provided in the appendix.

Although both methods estimate 91% combined exposure at work and home activities, the method using MS data estimates 38% and 53% exposure associated to work and home activities, respectively, whereas the one using simulated data estimates 48% and 43% exposure at work and home, respectively. The difference between both estimates reflects the different concentrations assigned by each method to the bus stop where the activity is conducted. The remaining 9% of the total exposure is associated to travel and other activities.

Average daily exposure estimated with MS data (Fig. 8 A) showed that people with the highest daily exposure were residents from Cerro Navia (92 [μg/m^3]), Pudahuel (90 [μg/m^3]) and Quinta Normal (87 [μg/m^3]) while residents with the lowest exposure were from Lo Barnechea (27 [μg/m^3]), Vitacura (40 [μg/m^3]) and Las Condes (41 [μg/m^3]). However, estimated exposure with CHIMERE data (Fig. 8 B) showed that residents with the highest exposure were from Cerro Navia (92 [μg/m^3]), Pudahuel (92 [μg/m^3]) and Conchalí (89 [μg/m^3]) and those with the lowest exposure were from Lo Barnechea (42 [μg/m^3]), Puente Alto (70 [μg/m^3]) and San Bernardo (68 [μg/m^3]).

The exposure variability with MS data was between 4.6 and 15.9 [μg/m^3] with an average standard deviation of 8.7 [μg/m^3]. Specifically, users from Providencia, Ñuñoa, Macul, Maipú, Independencia, La Florida, Quilicura, Puente Alto, San Joaquín, Conchalí, Recoleta and Cerrillos presented the lowest standard deviations (4.6–6.6 [μg/m^3]), while residents from La Pintana, Renca, P. A. Cerda, Lo Prado, Quinta Normal, La Granja, San Miguel, La Reina, Las Condes, Lo Barnechea and Vitacura presented the largest (9.4–15.9 [μg/m^3]).

CHIMERE results showed a smaller range of exposure standard variations than MS results (9.4–18 [μg/m^3]) with an average standard deviation of 12.1 [μg/m^3]. Users from Lo Barnechea, La Reina, Peñalolén, Vitacura and Las Condes showed the largest variations (ranges between 14.8 and 18 [μg/m^3]) while the rest of the municipalities showed exposure variations from 9.4 to 13.3 [μg/m^3].

The analysis of exposure and the average income in each one of the municipalities of residence suggests a correlation between these parameters for estimates using both datasets; MS and CHIMERE (Fig. 9). While exposure calculated with MS data showed an inverse relationship between these variables, i.e. poorer municipalities are exposed to larger PM2.5 concentrations, the calculated exposure with CHIMERE data showed no such relation.

4. Discussion

The presented research is an exploratory study to estimate exposure to $PM_{2,5}$ of frequent public transport users with two different pollution datasets from Santiago; measured concentrations from monitoring stations of the air quality network of Santiago and simulated concentrations from a chemical transport model (CHIMERE). The method is applied to selected public transport users during a week with deteriorated air quality from July 20th to July 24th, 2015.

In this study, outdoor concentrations are used to estimate exposure during bus trips. No measurements of PM2.5 concentrations were made inside buses during the analyzed period that would allow estimating the bias of this assumption. However, Suárez et al. (2014) measured

Table 3
Percentage of users exposed to the established AQ norms for $PM_{2,5}$ using MS observations (A) and CHIMERE outputs (B).

A

Day	Good	Regular	Alert	Pre-emergency	Emergency
20	89%	10%	0%	0%	0%
21	3%	65%	30%	2%	0%
22	2%	67%	31%	0%	0%
23	5%	82%	13%	0%	0%
24	7%	73%	19%	0%	0%

B

Day	Good	Regular	Alert	Pre-emergency	Emergency
20	82%	18%	0%	0%	0%
21	2%	75%	24%	0%	0%
22	4%	80%	16%	0%	0%
23	1%	22%	73%	5%	0%
24	1%	39%	58%	1%	0%

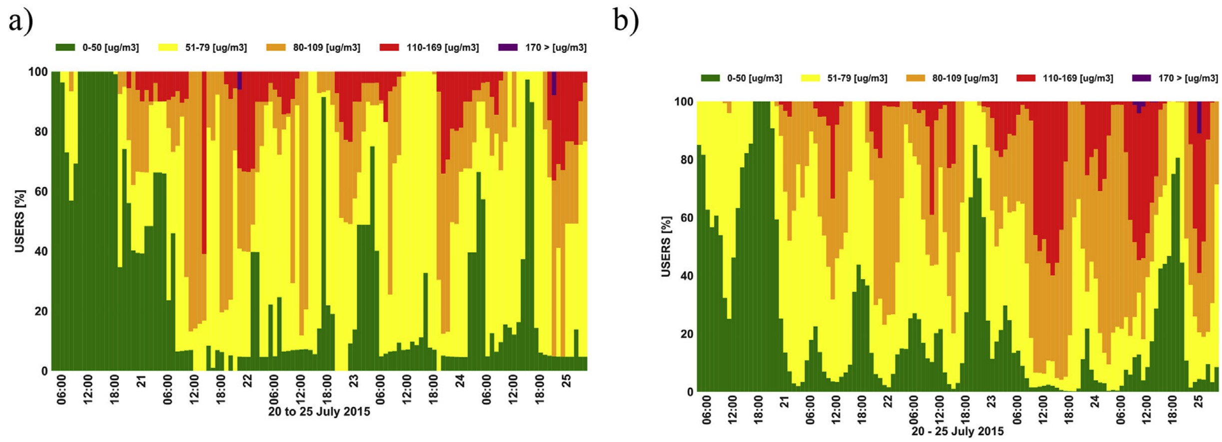

Fig. 6. Percentage of public transport users exposed to different levels of $PM_{2.5}$ from the 20th to 24th of July 2015 based on (A) the monitoring stations and (B) the modeling system.

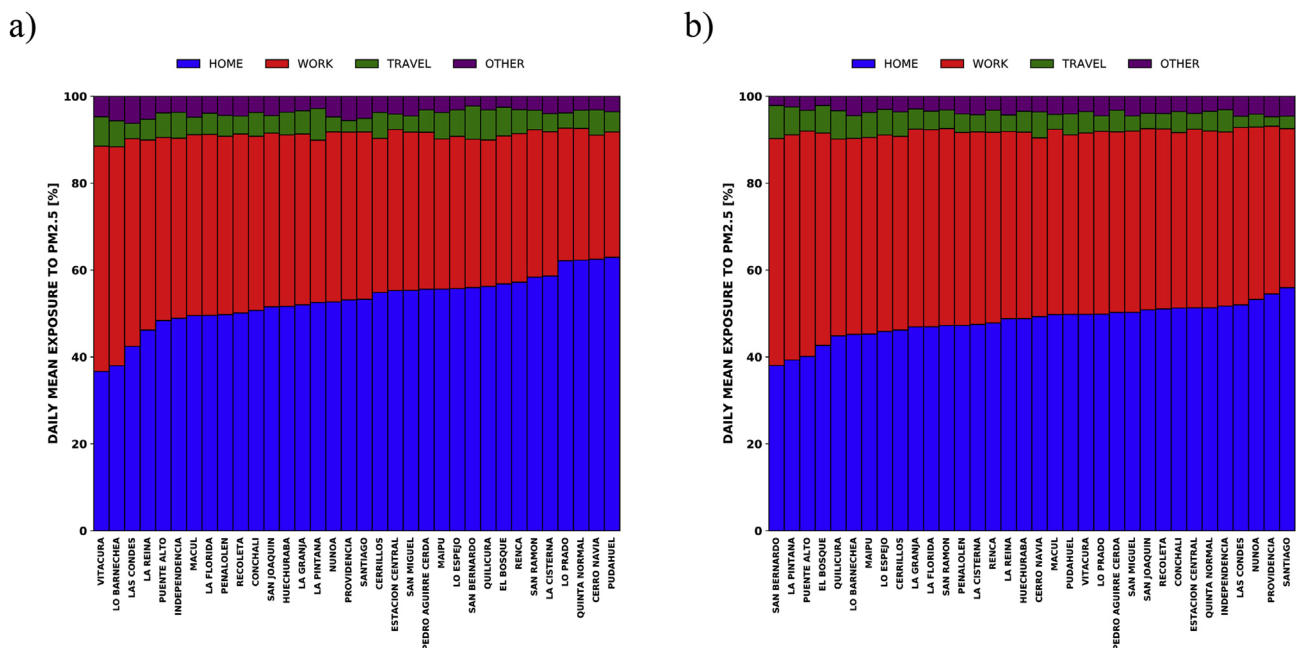

Fig. 7. Activity percentage contribution in daily average exposure to $PM_{2.5}$ grouped by worker's municipality of residence calculated with MS data (A) and CHIMERE data (B).

exposure for different transport modes (bicycle, bus, car and subway) from June 13th to October 13th, 2011 and from March 6th to May 15th, 2012. Their results show that the average exposure inside buses was 60.4 [ug/m^3] while on bicycles it was 50.9 [ug/m^3]. As both trips were made on the same route, the difference in exposure between both transport modes suggests that using outside concentrations to estimate exposure could represent an underestimation of the real exposure inside buses.

In order to disentangle the differences in exposure between the two datasets (MS and CHIMERE), the analysis was extended by calculating the exposure using CHIMERE simulated concentrations at each one of the eleven monitoring stations (CHIMERE-MS henceforth).

The differences between the exposures calculated using MS and CHIMERE-MS (Table 4, second and forth column, respectively) reveals the model bias. The model underestimates the exposure during the first three days while overestimating it during the last two days. Furthermore, smaller differences between the two estimates are seen during these first three days (ranging from 1 to 4 [μg/m^3]) and larger differences occur during the last two days (16 and 14 [μg/m^3]).

The difference between CHIMERE and CHIMERE-MS (Table 4, third and fourth column, respectively) reveal the impact of the density of the monitoring network on the exposure calculation. As both exposures are calculated using model data, the differences lie only in the concentration assigned to each bus stop. We recall that the exposures estimated from concentrations of the monitoring stations (i.e. CHIMERE-MS) are based on the 11 stations spread around the city. Each user is assigned a concentration value from the nearest station at all times, the distance from which may vary throughout the day. Users residing in municipalities near a monitoring station (El Bosque, Independencia, Cerro Navia, Cerrillos, Pudahuel, La Florida, Puente Alto) usually perform daily activities less than 3 [km] away on average (not shown). However, the average distance between users and the closest monitoring station is shown to be over 3 [km] in 20 out of 34 municipalities. On the contrary, exposure estimated based on the simulated concentration fields from CHIMERE are based on a regular mesh with resolution of 2 × 2 km, thus the maximum distance of a user to the closest grid is 1.4 km. Therefore, the present analysis is equivalent to comparing the exposure estimate based on a network of 11 stations with the estimate

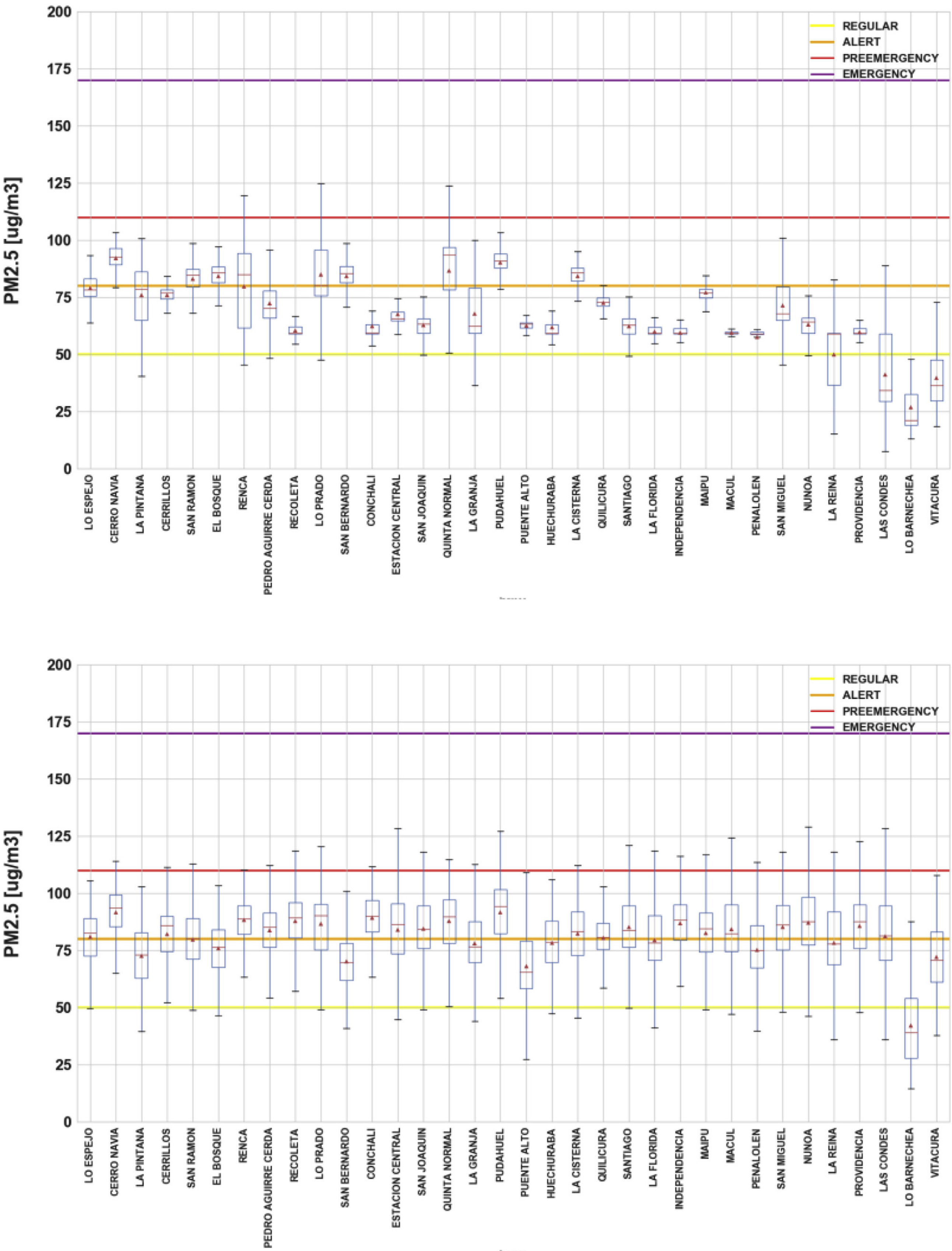

Fig. 8. Average weekly exposure to $PM_{2.5}$ distribution (20th to 24th of July 2015) using AQ monitoring station data (a) and CHIMERE data (b). Results are grouped by user's municipality of residence and sorted from lower (left) to higher (right) income.

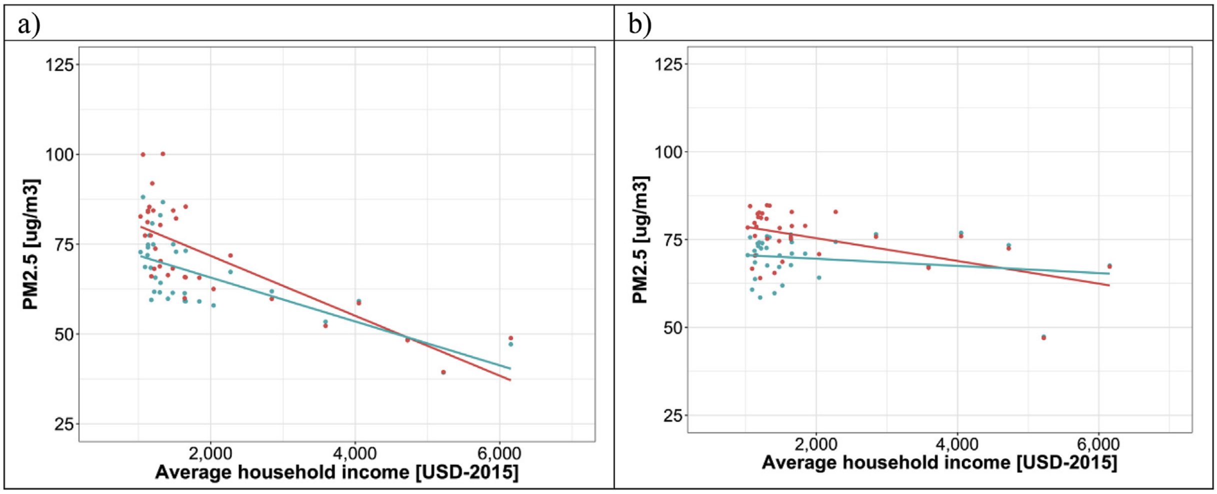

Fig. 9. Linear regression between average household income per municipality and average weekly exposure (green) with MS data (R^2 = 0.51; β = −8.642 × 10^{-6}; ε = +-1.485 × 10^{-6}; t = −5.82) (A) and CHIMERE data (R^2 = 0.04; β = −1.440 × 10^{-6}; ε = +-1.212 × 10^{-6}; t = −1.188.) (B). Statistics of each regression are included where R2 is the correlation coefficient, β is the slope, ε is the error term and t is the significance test. Equivalent linear regression is included (red) when exposure is estimated considering I/O ratios for home and travel activities. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

Table 4
Average daily exposure to $PM_{2.5}$ using both air pollutant data sources.

Day	Average exposure (MS) [μg/m^3]	Average exposure (CHIMERE) [μg/m^3]	Average exposure (CHIMERE MS) [μg/m^3]
20	44	45	43
21	75	72	69
22	73	69	66
23	73	89	86
24	67	82	81

based on a network of multiple stations distributed on a regular grid of 2 × 2 km. In Santiago with an area equivalent to 25 × 25 km this would correspond to a network of 144 stations.

Exposure estimated with the synthetic observations (CHIMERE-MS) is lower than exposure based on data from the "larger network" (CHIMERE) throughout the five days with differences ranging between 1 and 3 [μg/m^3]. This range is comparable to the underestimation observed during the first three days in the case where exposure estimated from observations is compared to estimates based on synthetic observations (MS vs CHIMERE-MS). Although small, this difference suggests an impact on the estimate of the information density or size of the network. This impact is larger, however, when examining the exposure at the municipality level (Fig. 10 vs Fig. 8a and b). In general, a larger variability of exposure for residents of the different municipalities in Santiago is observed when estimating the exposure with a "larger network", in particular for the residents from municipalities with no measuring station. Spatial heterogeneity in exposure is strongly and artificially reduced when estimating exposure with CHIMERE-MS; degrading the model resolution by bringing it to the selected points of the network has the effect of narrowing the intra-communal exposure range to levels comparable to the ones in Fig. 8a. This shows that the narrowness in Fig. 8A is in (good) part the effect of insufficient spatial density of the measurement network, and is not real. Similarly, the (negative) correlation between income and exposure shown in Fig. 9a is also due to the lack of spatial representation of the monitoring stations. Given the spatial correlation of income observed in Fig. 1, highest income municipalities are associated to only one monitoring station with the lowest concentrations throughout most of the week (Fig. 2, Las Condes station). This effect becomes apparent in Fig. 10, where the exposure is estimated with CHIMERE-MS and the decrease in exposure for higher income municipalities can also be observed.

Besides the sources of uncertainty in the estimates discussed above (model bias and network density), there are some additional ones to consider. The time-activity estimation made from travel cards is subject to errors and uncertainty. The different stages of the travel estimation process were validated with exogenous data from surveys and a group of volunteers, revealing that the trip destination was correctly identified in 84% and the purpose of the trip in 79% of the cases (Munizaga et al., 2014). Furthermore, indoor exposure was estimated based on outdoor concentrations, although differences between these two can be significant; indoor/outdoor ratios (I/O ratio) for PM2.5 for different cities in the world range between 0.12 and 3.36 (Chen and Zhao, 2011). Studies conducted in Santiago have estimated the I/O ratios to be 0.95 for high-income households (Rojas-Bracho et al., 2002), 1.08 for public housing and 1.18 for houses in slums (Burgos et al., 2013).

In order to estimate the impact of these I/O ratios on the estimated exposure, these were recalculated at residence and during travel. For home activity an I/O ratio of 0.95 was used for households in high-income municipalities and 1.18 for households in those remaining. The I/O ratio during travel (1.19) was estimated based on the average exposure inside buses (60.4 [ug/m3]) and on bicycles (50.9 [ug/m3]) (Suarez et al., 2014), the latter was used as proxy for outdoor concentration. No equivalent I/O ratio could be found for Santiago in the literature for work, study and other activities. Consistent with the above and regardless of the dataset used, the impact of including the I/O ratios increases the average exposure for low-income municipalities by approximately 6 μg/m^3 and decreases it for high-income ones up to 0.6 μg/m^3 (Fig. 9). We note that when applying the I/O ratios to the exposure computed based on CHIMERE data, a dependency of exposure to household income appears which was not apparent in the ratios without I/O. Similar results were found when applying the same I/O ratios as used for residence (not shown) to work and study.

5. Conclusions

In this study we estimate the $PM_{2.5}$ exposure of 105,588 frequent public transport users in Santiago by combining smart card mobility data with surface concentration data from 11 monitoring stations and simulated concentrations from the CHIMERE model. This method was applied five working days from July 20th until the 24th, 2015, and the activities identified were home, work, study, travel and other.

For the five days, the average exposure estimated with observations ranged between 44 and 75 [μg/m^3] while exposure based on simulated

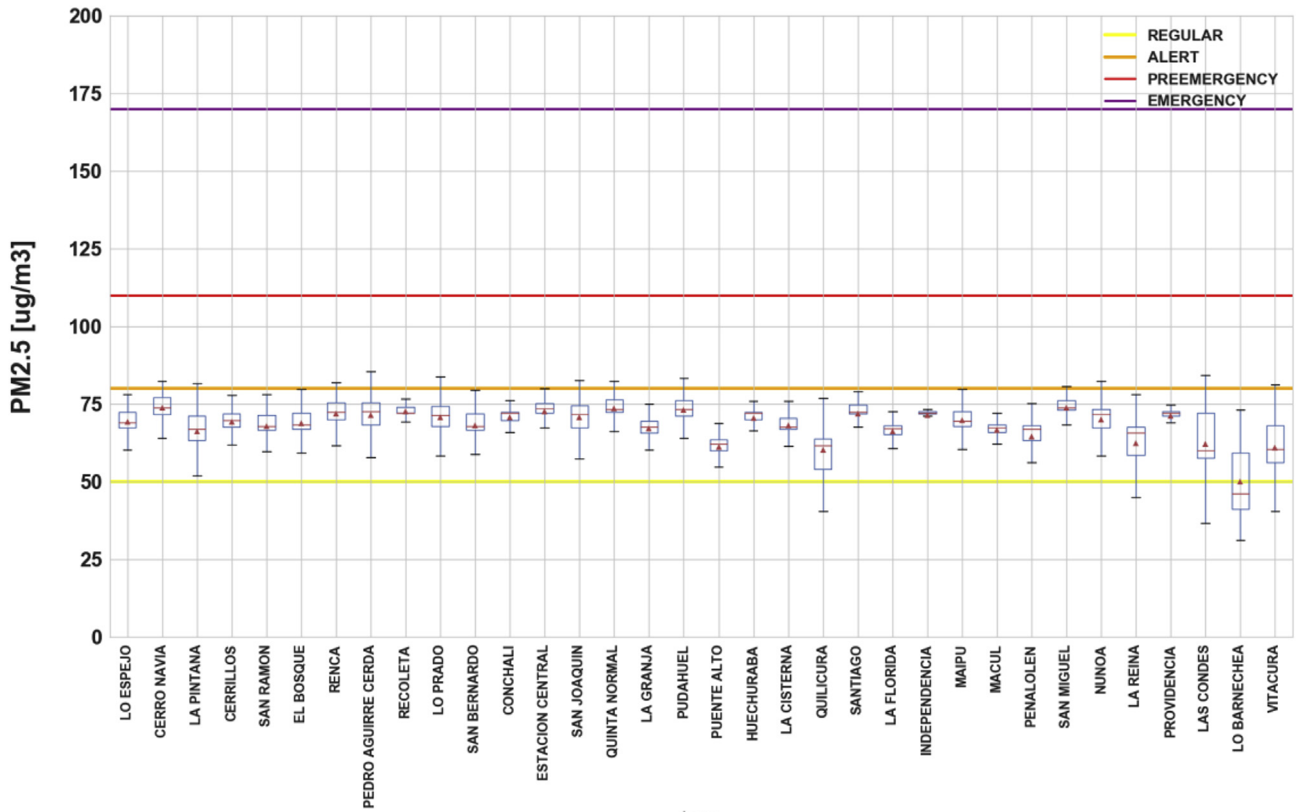

Fig. 10. Average weekly exposure to $PM_{2.5}$ distribution (20th to 24th of July 2015) using CHIMERE data at the monitoring station network location (CHIMERE-MS). Results are grouped by user's municipality of residence and sorted from lower (left) to higher (right) income.

concentrations varied between 45 and 89 [μg/m^3]. Furthermore, the highest average daily exposure estimated with measured concentration was reported on the 21st of July with 2% of the users exposed to concentrations between 110 and 179 [μg/m^3]. In the case of modeled data, highest average daily exposure to $PM_{2,5}$ occurred on the 23rd and 24th of July with, respectively 5% and 1% of the users exposed to the same concentration levels.

Nearly 70% of the total workplaces are in Santiago, Providencia and Las Condes municipalities, thus the larger exposure estimated with CHIMERE at work is mostly due to higher modeled concentrations in these locations. Households, on the contrary, are distributed more evenly than workplaces and are mostly on the periphery. The larger calculated exposure with MS data suggests that the simulated concentrations underestimate the concentrations on the periphery during night hours.

The relationship between user's socioeconomic background and exposure to $PM_{2,5}$ varied depending on the dataset used. An inverse relationship between exposure and income is observed for concentrations of the AQ network: i.e. the lower the income the higher the exposure. In this case, residents from high-income municipalities (Vitacura, Lo Barnechea, Las Condes) reported lower exposures than residents from low-income municipalities (Lo Espejo, Cerro Navia, La Pintana). Exposure calculated using simulated data showed no relationship, suggesting that the exposure to $PM_{2.5}$ is not related to income. Exposure estimations with CHIMERE data showed that the highest exposure affected residents from Las Condes, Pudahuel, Ñuñoa and Cerro Navia and the minimum exposure was estimated in Lo Barnechea, Puente Alto and San Bernardo.

The density of the AQ monitoring network of Santiago has limited impact on the estimated average exposure at the city scale, however it has a strong impact at the communal level. Comparison of the average exposure at communal level between estimates based on observations, model output and synthetic observations revealed that spatial heterogeneity of the exposure estimated with observations is strongly influenced by the density of the measuring network. The consequence being that the health impact in certain communities can be largely underestimated.

Urban features such as street width, building heights, traffic emissions, etc. are responsible for spatial variation of pollutants at scales smaller than the model resolution and are therefore not captured by the model. Yet there are methods that include sub-grid variability and therefore estimate concentrations within the grid cells (Valari and Menut, 2010). These methods were not considered in this exploratory research and could be implemented in the future. Furthermore, no indoor concentrations, neither at home/work nor in public buses were taken during the week considered in this study and therefore, as a first order approximation, outside concentrations were considered to be representative of inside concentrations at home/work as well as during transport. A previous exposure study conducted on different transport modes provides information on the bias introduced by using outdoor concentrations and also suggests that, during commuting, using outdoor concentrations could underestimate the exposure. Furthermore, exposure was recalculated considering I/O ratios from Santiago for home and travel activities increasing exposure in households of low-income municipalities and decreasing it in high-income municipalities.

The methodology presented has the advantage that it allows estimating exposure for a larger sample and on a more regular basis than methods requiring portable instruments to assess population activity pattern and/or measure exposure directly. Even though the exposure is calculated using public transport data, the results can be extended to a larger sample as most of the people that use other transport modes perform them in a similar activity pattern. Although we focus in this work on $PM_{2.5}$, the exposure can also be estimated for other pollutants such as NOx, SO_2, CO, O_3, PM_{10}.

Policies that impact emissions affect the atmospheric concentrations of urban pollutants and thus the exposure to these pollutants. The use of this method for the management of AQ episodes could provide population exposure information and evaluate the impact of different mitigation measures. It would also enable conducting a more realistic assessment of the exposure since the daily activity patterns of the population would be considered instead of the static approach traditionally applied.

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.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.atmosenv.2019.116878.

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