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TRAPSim: An agent-based model to estimate personal exposure to non-exhaust road emissions in central Seoul

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ABSTRACT

Non-exhaust emissions (NEEs) from brake and tyre wear cause detrimental health effects, yet their relationship with mobility has not been examined rigorously. We constructed an agent-based traffic simulator to illustrate the coupled problems of emissions, behaviour, and the estimated exposure to PM_{10} for groups of drivers and subway commuters in Seoul CBD. Having calibrated the parameters, the results regarding the air quality revealed that roughly 25–30% of the roadside PM_{10} was significantly higher than the background PM_{10}. Additionally, compared to intra-urban cars, pedestrians who commuted for longer periods of time and were exposed to more ambient particles suffered significant health losses; however, drivers only became aware of the health risk when PM_{10} levels were consistently high for a few days. Compared to the business-as-usual scenario of vehicle entry, a 90% vehicle restriction was able to reduce PM_{10} by 18–24% and cut the percentage of resident drivers who were at risk. However, it was not effective for subway commuters. Using an agent-based traffic simulator in a health context can provide insights into how exposure and health effects can vary depending on the time of exposure and the form of transportation.

1. Introduction

Over the past decades, many urban residents have encountered particulate matter (PM) exposure levels that exceed the limit values established to protect human health. Particulate matter, also referred to as PM_{10} or $PM_{2.5}$, contributed to 4.2 million premature deaths worldwide in 2016 (Wang et al., 2016). Epidemiological studies have found an association between PM and short-term health effects, such as eye, nose, throat, and lung irritation (Laumbach, Meng, & Kipen, 2015; Moreno-Jiménez, Cañada-Torrecilla, Vidal-Domínguez, Palacios-García, & Martínez-Suárez, 2016; Wang et al., 2016), as well as the long-term health effects that allow the toxic components to enter the body, causing oxidative stress that shrinks airways and eventually reduces lung capacity (Khajeh-Hosseini-Dalasm & Longest, 2015).

In 2013, the World Health Organization (WHO) stated that non-exhaust emissions (NEEs) could have caused adverse health effects due to friction between tyres, the road surface, and pavement encrustations in the form of metallic, rubber, carbon black, and other organic substances (Amato, 2018; Kovochich et al., 2021; WHO, R, 2013). This implies that NEEs sources may be to held responsible for the exposure associated with high PM levels in congested urban areas.

To this end, the European Environmental Agency (EEA) is the only institute that assessed traffic-based NEEs based on their research (EMEP/EEA, 2019). The study found that four factors—road wear, brake wear, surface wear, and resuspension—are used to determine NEEs. The emission levels vary depending on the number of vehicles within the unit distance (g/km), their mileage, emission factor, and speed characteristics. While the model is theoretically suitable for scaling the impact of pollution based on the adjustment of vehicle numbers and their journey distance, it lacks the significance of the spatial dynamics of traffic over time. Even though the model provides a thorough overview of the potential pollution that vehicles could emit, it is impossible to understand how the different behaviours of vehicles are likely to disperse more particulates into the local atmosphere which would have

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the greatest impact on human health. Since our mobility ecosystem in urban areas has become increasingly complex, there is a need to build a decentralised tool that can offer better insights utilising autonomous agents to calculate how their local interactions could help a larger goal of pollution mitigation. The potential severity of NEEs for human health has been highlighted by academics and policy professionals in North American and European nations, but laws for NEEs have not yet been developed and calling for more evidence (Air Quality Expert Group, 2019; EMEP/EEA, 2019).

To link the challenges between NEE and the mobility of vehicles and humans, agent-based modelling (ABM) can help connect the problems between NEE and the mobility of vehicles and people at an individual level (Tracy, Cerdá, & Keyes, 2018). ABM is not only specialised in simulating the movement of heterogeneous vehicles and people, but it can also manage how vehicles stop and go, how traffic signals work, and how exposure is measured based on where an agent is located and how much local pollution there is in the area. A promising example is (Gurram, Stuart, & Pinjari, 2019)'s integrated model, which integrated NO_x emission, dispersion, activity patterns of population, vehicle movement, and the exposure to the ambient NO_x based on the time spent in each location. This had not been attempted previously. Other agent-based traffic models have also simulated vehicle emissions caused by urban car traffic using a general programming language (Hofer, Jäger, & Füllsack, 2018) such as SUMO (Anjum et al., 2019; Krajzewicz, Behrisch, Wagner, Luz, & Krumnow, 2015) or MATSim (Hülsmann, Gerike, & Ketzel, 2014).

Given the limited resources available to mimic the agents' attributes and their behavioural patterns, the objective of this paper is to develop an in silico agent-based traffic model that jointly examines the movement of vehicles and individuals, the generation of NEE for vehicles, and estimates the exposure and health effects of individuals. This paper divides the study intentions into three key goals in order to fulfil this goal:

- To characterise the roadside air quality generated by vehicles
- To validate the parameters based on Seoul's Air Quality data from the past 10 years
- To compare the health effects between walking commuters and vehicle commuters
- To apply car-reducing scenarios and identify the characteristics of any improvements

We create TRAPSim, an agent-based model with fine geographical and temporal scales. The reason for developing a finer-scale simulation is to examine the mobility dynamics of the traffic, the generation and dispersion of non-exhaust PM_{10} emissions according to the vehicle's behaviours, and the acute health effects arising from the regular commute patterns.

2. Related works

2.1. Non-exhaust emissions and air quality

The increasing levels of NEEs are mainly caused by the following features. First, the 'stop-and-go' patterns of the traffic allow for more frequent brake pad wear, which increases ambient particle levels (Air Quality Expert Group, 2019). Brake wear emissions are also spatially heterogeneous because the vehicles are expected to slow down when reaching a junction or going downhill (Air Quality Expert Group, 2019; Smit, Ntziachristos, & Boulter, 2010). Second, because aggressive drivers are more likely to accelerate and decelerate more frequently, more particles from their tyres, brake discs, and linings eventually contribute to pollution. Transport for London has mentioned that the Central Business District (CBD) of London is more polluted than the outer areas. Since the average speed of the vehicles does not exceed 20mph, the PM_{10} can vary according to driving behaviour (TfL, 2018). Finally, seasonal impacts are discovered to be necessary for NEEs. In northern Europe, where the roads are regularly icy, studded tyres produce hazardous particles as the metal hits the surface of the road, increasing the amount of dust that is resuspended with the sand (rock salt) that was previously dispersed (Air Quality Expert Group, 2019; Amato et al., 2014; Weinbruch et al., 2014). In arid areas, dust resuspension is in tandem with tyre and brake wear in terms of contributing harmful particulates to the atmosphere (Al-Thani, Koç, Fountoukis, & Isaifan, 2020).

While there have been efforts to reduce the particulate matter from vehicle exhausts, few improvements have been made for non-exhaust particles from tyre and brake wear and dust resuspension. Ferm and Sjöberg (2015) applied an equation of particle emissions based on roadside PM_{10} and NO_x in two Swedish cities to associate ambient PM_{10} (both road and background) with the volume of vehicles. However, they found that it had little relevance. The problem for this study was that the modelled PM_{10} emissions were highly dependent on NO_x because the observed NO_x, which was assumed to have been generated by traffic, had an hourly level variability not seen in PM_{10} observations. The experiment was also site-specific and conducted on a 500 m road. This can either over or underestimate the effects of the road especially when the study domain is small.

Panko, Chu, Kreider, and Unice (2013) discovered a small contribution from non-exhaust particles in French, the US, and Japanese cities (<0.7 μg/m^3 of PM_{10}). Despite being one of the early works on NEE, the selection of locations was biased toward parks, residential areas, or places of worship, which underestimated the effect of NEEs. This is because these areas are mostly far from the road and NEEs are known to be strongly decreased by 150 m (WHO, 2021). Electric vehicles are increasingly seen as an alternative to petrol vehicles, but the findings demonstrated that they emitted more non-exhaust particles due to their heavier weight (Timmers & Achten, 2018).

Perricone et al. (2018) reported that brake wear emissions resulted in 8–27% of the total traffic-related PM_{10} emissions. The airborne particles generated from the friction of brake discs can lead to adverse health effects. The REBRAKE project introduced a concept paper to reduce PM_{10} emissions for car brakes by 50%, leading to a 4–14% reduction in PM_{10}. Other studies are still conducting experiments on the impact of NEE in a restricted environment, such as in a laboratory (Kwak, Kim, Lee, & Lee, 2013) or in tunnels (Kovochich et al., 2021; Lawrence et al., 2013). However, in a laboratory environment, it is easy to measure the emissions due to brake or tyre wear. More importantly, the tests can be time-consuming and may not represent the actual driving conditions well where weather conditions and other compounding factors affect emissions.

From a health perspective, Amato (2018) found that exposure to NEEs is associated with a hospitalisation risk, where the excess risks rose by 4.5% for every extra 1.71 μg/m^3 and 2.1% for cardiovascular admission in the US. Similar risk rates were found in Hong Kong. Signs of oxidate stress resulting from NEEs have been reported in those who have continuously walked near roadsides (Atkinson et al., 2016; Borm, Kelly, Künzli, Schins, & Donaldson, 2007). The consequences of inhaling toxic particles can reduce the size of the airways and eventually impair lung capacity (Khajeh-Hosseini-Dalasm & Longest, 2015).

2.2. Applications of traffic microsimulation

Four research were found to have quantified the population exposure to air pollution based on traffic simulation out of the 30 studies of traffic simulation that were reviewed (Gurram et al., 2019; Hofer et al., 2018; Rech & Timpf, 2021; Yang et al., 2018). The chosen studies are divided into two categories based on whether they involve small- or large-scale simulations in which the agents represent a sample of the population and whether the research area is utilised throughout (see summary at Table 1).

For the small-scale simulation, Yang et al. (2018) used an ABM simulation to look at the cumulative exposure to environmental

Table 1
Literature of the agent-based traffic simulation.

Type	Characteristics	Yang et al. (2018)	Rech and Timpf (2021)	Hofer et al. (2018)	Gurram et al. (2019)
Scale	Large/Small	Small	Small	Large	Large
Tool	Programming Language	NetLogo	NetLogo	Python	MATSim
Pollution	Pollution-related	Yes	No	Yes	Yes
	Source	NO_2	–	CO_2	NO_2
Space	Spatial Area	West Hamburg, Germany	South Augsburg, Germany	Graz, Austria	Tampa, FL, USA
	Spatial Resolution	250 m	Not mentioned	Not mentioned	500 m
Time	Simulation Period	3–4 days	30,000 ticks (8.5 h)	24 h	24 h
	Temporal Resolution	1 min	1 s	1 h	5 s
	Execution time	40 mins	15 mins	3 h	5.2 days
Agents	Type of Agents	Public Transport, Cars, Pedestrians	Bus, Trams, Cars, Pedestrians	Synthetic Population	Synthetic Population dwelling within Tampa
	Number of Agents	8	200 people, 4 cars, 100 cars, 2 buses	Approx. 320,000	2.3 million

stressors, such as temperature and NO_2, in the West of Hamburg. The results showed that the agents' total exposure to NO_2 during the winter was 10–12 times higher than it was in the summer, but that individual temporal at-risk patterns varied depending on the mode of transportation. The Hamburg study only had 8 agents, so switching modes of transportation was extremely unlikely. As a result, once an agent chose a mode of transportation, exposure levels were maintained throughout the entire year. The heatwave parameter, which was thought to enhance stress, had no negative effects on the exposure levels because Hamburg's average temperature did not reach 30 °C regularly.

Rech and Timpf (2021) investigated whether a new bus route promotes satisfaction by comparing the waiting and actual trip times of 200 public transportation passengers with those of private car users. The Augsburg study randomised the agents' points of origin and destination to give the model what appeared to be stochasticity. Although there was a chance that 10–20% of the 200 agents might switch to a new bus lane, this did not significantly alter the output. As with Yang et al. (2018), there were not enough agents to sufficiently reduce the stochasticity of behavioural variability (Miller & Page, 2007).

For the large-scale simulations, Hofer et al. (2018) simulated real-time CO_2 emissions for each road in Graz, Austria, while Gurram et al. (2019) simulated the citizen's potential exposure to NO_2 in Tampa, Florida using MATSim (Multi-Agent Transport Simulation). It took a long time to run the simulation in both investigations since the agents were formed at a 1:1 scale (i.e., one agent was created for each population member). According to the findings of Hofer et al. (2018), the research region released around 1187 t of CO_2 per day, which was only 2% different from the calibration data. A considerable 15–20% reduction in CO_2 emissions was found in the scenario that examined the impact of removing obsolete cars manufactured before 1995 and introducing EVs. However, the scenario that promoted telecommuting and public transportation did not indicate a noticeably lower level of CO_2 emissions. It turned out that this scenario is only effective when the commute is >3 km.

Gurram et al. (2019) found that Tampa city (Florida) was emitting about 20.4 t of NOx per day, with exposures ranging from 0.2 to 145 μg/m^3 and a 99th percentile exposure concentration of 39.9 μg/m^3. The agent-based model was able to capture the immediate rise of NOx with a high-resolution activity-based exposure, in contrast to the CALPUFF dispersion model that was used in their prior study (Gurram, Stuart, & Pinjari, 2015). The results of this study showed that exposure levels varied depending on socioeconomic status: higher exposure was discovered for lower-to-middle income households, people of colour, people of working ages (19–65), and those who lived in urban areas with longer commute times. Overall, integrating the four phases of various simulation platforms is a first for simulation-health research, especially for capturing immediate exposure (hourly intervals) as opposed to aggregate exposure, which hasn't been studied in short-term exposure studies.

Despite the novel construction of a large traffic simulation coupled with the activity and emission models, some points remain problematic. First, the simulation's 24-h time frame was insufficient for determining the longer-term effects of pollution reduction and for capturing the negative effects of various exposures based on people's activity. As gaseous pollutants are variable depending on the weather conditions and the days of the week, a long-term simulation can provide a more accurate estimate of the total negative health impact. Second, the data from the ground truth seemed to match the pollution levels near major thoroughfares or urban centres. Finally, although both research produced pollutions and calibrated them on an aggregated level, the outcomes either neglected or restricted the agent's behaviours. The model developed by Gurram et al. (2019) mobilised all of the population's resident vehicles in accordance with their daily schedules, but as every activity was pre-scheduled, there was no space to evaluate the exposure of trucks or non-resident vehicles. These can also be regarded as particularly troublesome polluters in the city because they caused a 23% discrepancy in NO_x emissions compared to the state estimate.

In summary, it appears that although research into the relationship between vehicle emissions and human exposure is still in its infancy, these studies have sparked the emergence of a brand-new field that integrates individual movements, emissions, and exposure to better comprehend the reality of human exposure. According to evidence from Seoul, commuter vehicles made >6 million trips to and from Seoul. This comprised one-third of all traffic in 2010. Neglecting the quantity of pollutants produced by this group might have led to the omission of a large portion of local emissions that significantly increased ambient pollution. Other types of transportation could seem reasonable to include, but this will largely depend on the simulation capacity.

3. Methods

TRAPSim is simulated on a two-dimensional, continuous space of the CBD of Seoul (16.7km^2). The model has a spatial resolution of 30 m × 30 m and is composed of 155 horizontal and 192 vertical patches (also known as grid-cells). Patches represent the grids of the study area, with each patch attribute comprising the name, code, and PM_{10} concentrations of the subdistrict as well as a Boolean indicator of whether it is indoors or outdoors. Nodes and links are used to represent the streets of the city, with the road links containing road names, speed restrictions, and length and road nodes representing intersections and traffic lights. The only colour changes on the traffic lights are from red to green. Each traffic light changes as the countdown from 10 to 0 progresses, but because each light's starting counter is unique, the signals do not all change at once.

TRAPSim includes the following entities of three mobile agents: (1)

399 resident cars with drivers, (2) non-resident cars,[3] and (3) 1932 subway commuters; and two types of fixed agents: (1) traffic signals, and (2) entry points where the vehicles are fed into the study area. The resident cars accounted for 1% of the total vehicles registered in each sub-district, subway commuters represent 1% of the daily subway passengers, and the number of non-resident cars represent 5% of the traffic. The repository includes a list of the state variables and characteristics that define these entities (Shin, 2021).

The model operates on a discrete timestep (a minute-by-minute) between January 2nd to March 31st, 2018 (127,740 time-steps). In every time step, our model updates the particulates on roads and background areas, the trajectory of subway commuters and resident drivers, and the exposure and health loss in response to the PM_{10} levels exceeding 100 μg/m^3 where the individual is situated. We used a built-in diffusion function in the software for the NEE generation and dispersion that diffuses the particles roughly in line with a Gaussian distribution. The NEE then calculates the roadside PM_{10} using the background PM_{10}.

The execution time spent for a single run on a desktop machine took around 50 min. The model was iterated 20 times to estimate stochastic variability. The parameter space was explored using runs on the Cambridge University HPC cluster. We ran NetLogo (Wilensky, 1999) and R (R Core Team, 2021) because both software are compatible with the Slurm workload manager. However, the main reason is that the local workstations had trouble cleaning the Java caches at each run, which delayed our local PCs after a few iterations.

The detail of the processes is explained in the three modules, Mobility, Pollution generation, and Health (see Fig. 1 for details). The mobility module replicates the agents' daily routines, including where they live and go, which algorithm they are allocated, and which places they will occupy on weekdays and weekends. After the mobility module has started working, three sub-modules of the pollution generation module simultaneously produce ambient PM_{10}, NEE from moving vehicles, and their dispersion and dilution.

3.1. Mobility

3.1.1. Resident vehicles

The pathfinding algorithm is a key function to assign the resident vehicles' origins and destinations. In doing so, we first employed an Origin-Destination matrix to select a portion of the resident vehicles from their sources and distribute it to their destinations (see Shin (2022) for the full matrix). Residents living beyond the study region were not taken into account for additional measurement. The following step is to ask each agent to specify the route once the resident cars' origins and destinations have been assigned in their attributes (see Table 2).

To connect the origin and the destination nodes, we used an A* algorithm (Zeng & Church, 2009). Fig. 2 is an example of an A* algorithm applied to the GIS road network. The network extension *nw* was used. A detailed explanation regarding the A* algorithm and the proof-of-concept example is included (Shin, 2022).

On weekdays, vehicles will travel across road networks to their destination node, halt during business hours, and then travel back to the origin (node) using the same route. However, on weekends, vehicles will travel away from the study area for non-work-related activities, such as shopping, getaways, and places of worship. Every vehicle will halt its travel on weekdays if it approaches its destination node. Following its arrival, the state variable named *timer* starts counting down from ≥480mins, and as soon as the timer reaches zero, the car will start driving back to its original location. All agents are granted an additional 0 to 59 min of fuzziness to departure time, presuming they will be walking to parking lots or needing more time to finish their duties. Each vehicle has a driver whose health will decline if the PM_{10} inside the vehicle is over 100 μg/m^3.

3.1.2. Non-resident vehicles

Contrary to resident cars, non-resident vehicles contribute to pollution inside the study domain rather than having any distinct navigational goals. The vehicles will follow traffic signals and keep their distance from the vehicles in front but will be removed completely when they reach the end of the domain boundary. The randomness of travel directions is to simulate general movement during the vehicle's time in the CBD, in the absence of more detailed data. These vehicles are not initialised but are added when the model is executed.

Vehicles are assumed to have come from the outside. These incoming vehicles make trips to any areas inside the CBD, generating vehicles from the hourly traffic data measured at monitoring stations. Since the spatial extent is restricted to the CBD zone, outbound cars disappear at any endpoint of the road network. Due to the model's low vehicle capacity (up to 2500 vehicle agents), the sample of non-resident vehicles each minute was 5% of the initial volume.

It should be noted that both resident and non-resident vehicles maintain a safety distance of one patch (about 30 m) from the car in front of them. Regardless of the fuel type, vehicles will emit and spread non-exhaust PM_{10} during the voyage. Vehicles are asked to stop in front of the red traffic signal.

3.1.3. Subway commuters

We use a Local Search Algorithm (LSA) for pathfinding for subway commuters (see Fig. 3). LSA is a memory-efficient approach that asks the agent to rewrite the path to reduce additional errors after learning the objective state and the error of distance (also termed error of distance). A* was replaced with LSA because the algorithm that was asked to find the lowest pollution patch between the current step and the final goal kept changing every step, which led to repetitive recalculation on every step, slowing the execution speed.

This study employs a "random-walk" or "hill-climbing search," one of LSA's searching features, in which the agent repeatedly searches the largest value (or smallest value) within the boundary until it finds the goal. The function, however, has a major drawback in that the searching ends either when it reaches the local maximum rather than the global maximum or when there is a vast plateau without a higher surrounding number.

When the simulation commences, the subway commuters are brought to the subway entrances at the hour and minute specified in their state variables. Once the agents arrive at their subway entrances, they walk to their destination buildings using the shortest route.

3.2. Generating non-exhaust emission

Tyre, brake, and road surface wear are the primary causes of non-exhaust emissions (Air Quality Expert Group, 2019; EMEP/EEA, 2019; Kovochich et al., 2021). In order to create tyre wear, brake wear, and road abrasion based on travels, we employed the equation of EMEP/EEA (2019) that generated tyre wear, brake wear, and road abrasion based on trips. The abstract equation is stated as follows:

$$NEE_{Total} = NEE_{Tyre} + NEE_{Brake} + NEE_{Road} \quad (1)$$

The complete equations and definitions are shown in Shin (2022).

One major change from the set of equations is that the emission parameters which were based on g/km were converted to μg/30 m. This alteration was made since the 30-m grid fits the range of the diffusion from tyre and brake wear and it is anticipated that each vehicle commutes along a different path. For instance, when a car drives over a patch, 10 μg of tyre wear, 7 g of brake wear, 10 μg of surface wear, and 3 μg of resuspension are released. At 5 μg, it will likewise be diluted. Therefore, the background PM_{10} concentration plus 25 μg (Tyre + Brake

[3] We clarify that non-resident vehicles are those for which the origin is outside the model domain. Non-resident vehicles enter the study domain according to the hourly vehicle observation data at 10 observation points (the detailed information is included in Shin (2022)).

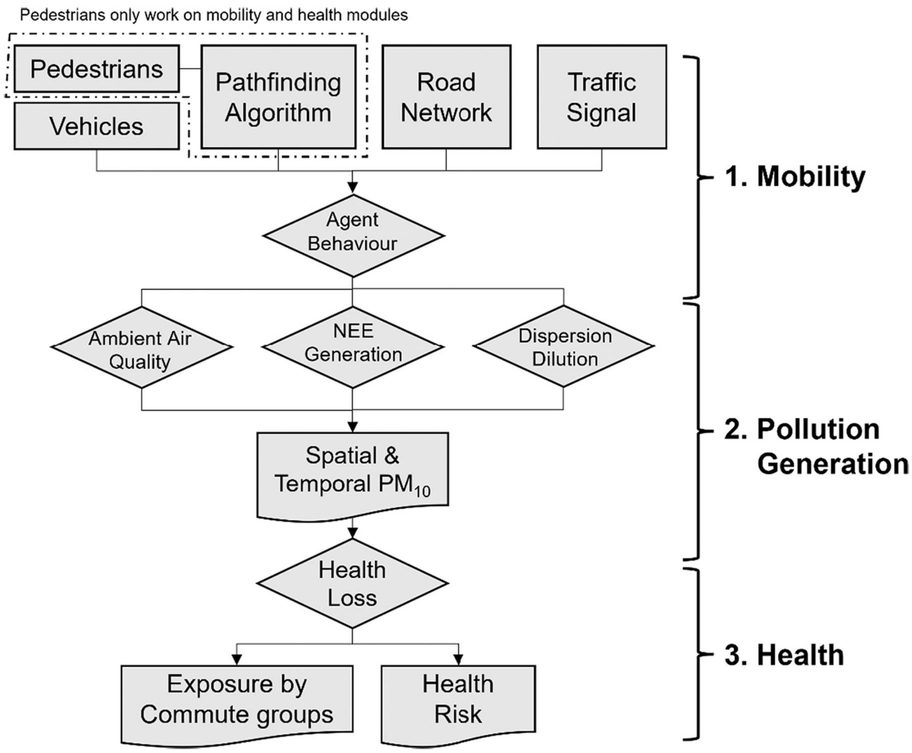

Fig. 1. The overall structure of the simulation in three sections: mobility, pollution generation, and health.

Table 2
Summary of the number of agents and their pathfinding algorithm and used features.

Variables	Vehicles: Resident	Vehicles: Random	Subway
Number of Agents	399	Variable by traffic data	1932
Sample	1% of the total resident vehicles dwelling in CBD	5% of the Traffic monitoring data	Total diurnal population in study area × Proportion of subway commuters in the OD matrix
Algorithm	A* algorithm	Come-in-randomly die-out-randomly	Local search algorithm
Type of space used for trajectory	Road-networks (links)	Road-networks (links)	Patch
Memory of trajectory	Yes	No	No

+ Surface + Dispersion + Dilution) would be the total PM_{10} concentration for that minute. This study also takes into account testing the parameters for dilution and dispersion (see further details in Shin (2022) and Section 4).

3.3. Health loss

The agent's health will decline on the assumption that it encounters over 100 μg/m^3 at which they are currently located.

$$\text{If } PM_{10} \geq 100, dH/dT = -\alpha(H_{max} - H(t)) + H_{recov} \quad (2)$$

In Eq. 2, which we developed in an earlier study (Shin & Bithell, 2019), denotes H_{max} as an agent's health status at the beginning of the simulation. H(t) is the current value at the current timestamp, and H_{recov} is the recovery rate. If the agent is on the patch that exceeds the PM_{10} threshold of 100, its health values would decrease exponentially away

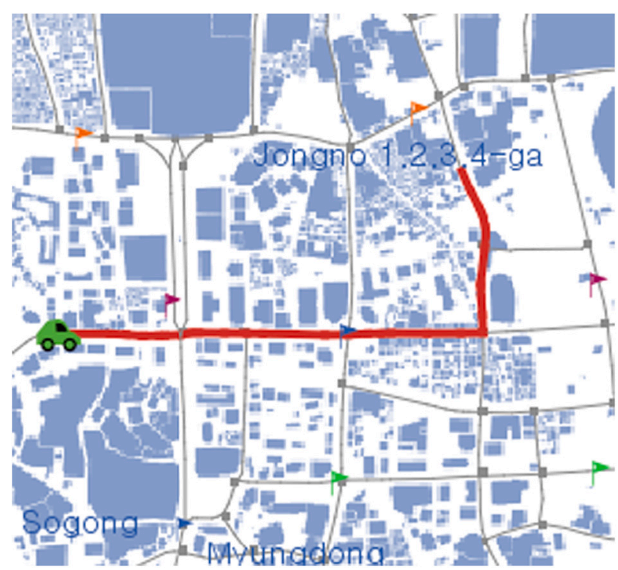

Fig. 2. A is a proof-of-concept model built to test an agent finding the shortest path from the origin (red patch) to its destination (light green patch), and B is the application of the shortest distance on link data.

from their initial value H(0). α determines the rate of change per unit of time during the time when the health impact is relevant. This factor is chosen from a random uniform distribution between zero and a maximum on each tick to account for the reality that individual exposure levels will vary greatly, even within a patch. The term 'at-risk' is defined as the health status of an agent whose health is below 100 (Shin & Bithell, 2019).

While the aforementioned equation is identical to that of Shin and Bithell (2019), there are several measurements in which this study differs. First, the infiltration ratio, often termed the I/O ratio, is used to

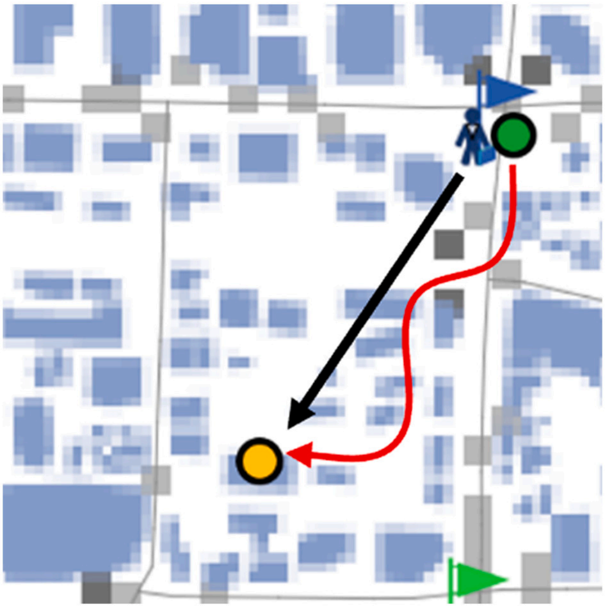

Fig. 3. The person standing next to the starting point (green) moves in a straight line toward the goal point (yellow). In this case, the agent chooses to go toward the target destination, but the route will be created at each stage. In real life, the agents would travel the red route. The difference in arrival time from our experiment comparing the red and black routes was insignificant, but the computational power significantly increased. This led us to select the black line. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

estimate the indoor exposure of individual agents. The infiltration ratio is applied to studies when only one has information about outdoor air pollution but less about indoor air pollution. The ratio, despite the fact that the statistics appear to be rather straightforward, is the result of taking into account the air exchange rate, windows opening, and different types of microenvironments (classroom, home, workplace), as well as seasonality. We simplify the I/O ratio computation procedure by setting the outdoor PM_{10} at 1, changing the in-vehicle status to 0.7, and converting the indoor PM_{10} to 0.2–0.7 because our model pays greater attention to exposure during one's commute routine (Kreider, Unice, & Panko, 2020; Leung, 2015).

The health loss for all agents is applied under the same conditions, yet each agent's means of transportation is different. For subway commuters, everyone has an equal probability of being exposed to the PM_{10} threshold when walking, but the severity of the health damage will depend on how long it takes to get from the subway entrance to the agent's office and how much time is spent outside when the PM_{10} is above 100. Additionally, those working in offices next to roadways may experience worse health problems since roadside pollution can affect inside pollution, such as when windows are opened and closed (Kreider et al., 2020).

All commuters are exposed to 0.2 times the ambient PM_{10} of the provided area if the commuters stay at home between 11 pm and 6 am. Residents are more often exposed to 0.7 times the patch's ambient PM_{10} during transit and 0.2 to 0.7 times that amount when parking their cars at their homes or places of business. Due to the significant load of PM_{10} created by road traffic, it is anticipated that the cars will regularly be exposed to high levels of PM_{10}.

3.4. Policy scenario: Banning vehicles in the CBD

We conduct a 'what-if' scenario to test the effect of vehicle restrictions on air quality improvement. This hypothetical scenario is based on Seoul's "Green Transport Scheme Seoul," which was implemented in December 2019 and attempts to improve air quality by prohibiting high-emission automobiles from entering the central business district. Between 06:00 and 21:00, "Grade 5 vehicles," mainly diesel cars, are prohibited by the local authorities. Violators are subject to an 85 USD fine. This study examined the consequences of preventing car entry on non-exhaust emissions and showed how the situation can benefit people's health.

Second, we test whether maintaining current services or limiting 50% or 90% of the incoming traffic can lower background and roadside PM_{10} levels within the research area. For further context, the model's 100% restriction on incoming traffic means that it only allows resident vehicles to move and generate pollution.

4. Sensitivity test and calibration

Since the fixed monitoring stations provide temporally rich but spatially sparse information, it is essential to examine the uncertainty of vehicle-related parameters that can affect the difference in air quality and health effects. We selected five parameters including non-exhaust emission (NEE), dispersion and dilution (the two are treated as one), the fraction of vehicles, health loss, and walking speed (see Table 3).

We examined each parameter's sensitivity using the one-factor-at-a-time (OFAT) method. The main reason was that there was a memory ceiling that was not sufficient to consider five parameters over 120,000 ticks.

First, we parameterised PM_{10} levels by NEE factors of 1, 5 (baseline), 10, and 20, each of which displayed the N of vehicles that generate non-exhaust PM_{10} emissions (N is the parameter shown in the NEE equations). As the variables increased, the mean PM_{10} levels rose linearly. For example, the mean PM_{10} of Jongno for NEE factors 1, 5, 10, and 20 was 43.4 μg/m^3, 60 μg/m^3, 81.4 μg/m^3, and 123 μg/m^3 respectively. The PM_{10} levels ranged by 12 g/m3 at the highest parameter, NEE 20, with the lowest reading being 122.6 μg/m^3 and the highest reading being 134.1 μg/m^3. The high parameter value can indicate the fluctuation of PM_{10} by road in proportion to the volume of traffic, even though the number of road lanes was not provided.

Dilution, or the time that passes before NEE disappears, was quite sensitive to the settings. The overall PM_{10} grew dramatically by a maximum of 11 μg/m^3 on the parameter 20 as the dilution parameter increased (i.e. the longer the PM_{10} lingers in the atmosphere). This was because the PM_{10} patch (grid) on the road only vanishes when there are no vehicles for 10 min or more, which is impossible other than between 2 and 5 in the morning. On the other hand, the range of dispersion did not appear to have the same impact as dilution. The difference in PM_{10} between 45° and 90° in the baseline scenario was <1 g/m3, even though broader dispersion can increase PM_{10} to neighbouring pavements.

Investigating how PM_{10} varies may change by the rate of car sampling, different sample sizes merely showed a small difference. A 10% sample in Jongno only contributed 1.8 μg/m^3 more than that of 2.5%. Surprisingly, all routes in the 20% sample exhibited less pollution since a significant number of vehicles were prevented from entering the research area due to traffic queues.

Table 3
Summary table of parameters used for sensitivity analysis.

Parameter	Description	Baseline	Min	Max
Non-exhaust Emission (NEE)	Non-emission levels per vehicle	5	1	20
Dispersion	Range of emission	60°	45°	90°
Dilution	Time until the non-emission dilutes	3	3	20
Car sampling	Rate of incoming cars	5%	2.5%	20%
Health loss	Parameter (α) from the health loss equation	0.1	0.03	0.2
Walking speed	Walking speed of subway commuters	0.6–1.0	0.2–0.4	1.6–1.8

The health loss parameter α, an exponential parameter in Eq. 3, was highly sensitive for the at-risk population. Several fluctuations were seen among subway commuters during major pollution episodes, but looking at the peaks of the at-risk population, there was a noticeable increase between $\alpha = 0.1$ and $\alpha = 0.15$ as it resulted in 30% and 100% respectively. Since the rate equation leads to an exponential change in H with α, a small difference between values can change the outcome excessively, despite the support of health recovery. However, the results did not indicate a significant difference when the scenarios with zero vehicles are initialised. This was mostly due to the fact that people avoided heavily polluted areas by walking through quieter areas rather than those close to roads (European Lung Foundation, 2020). Drivers observed a significant shift in the risk population over time, going from 5% to 50% in the range of 0.1–0.15; however, there was also a striking decline (15%) when non-resident vehicles were not present. Even though studies that look at indoor-outdoor pollution ratios have shown that opening a window can contaminate indoor air pollution and can also be a beneficial guideline for vehicles (Kreider et al., 2020), they have not identified any evidence of a high risk connected to particle exposure inside cars.

Slower walking speed resulted in a significant rise in the risk rate, but fast walking only made a small difference. Slow walking (0.2–0.4 patch/min) resulted in a 10% higher risk population in extreme pollution episodes as compared to the standard walking pace of 0.6–1.0 patch/min. Contrarily, over 1.5 patch/min made little change from the baseline speed, indicating that even rapid walking cannot help in avoiding instantaneous exposure to a sudden rise of PM_{10}. The conclusion is necessarily significant because in this case, where exposure to an abrupt rise in pollution is crucial for pedestrians, it may not be assumed that "faster walking and breathing at a greater rate over a shorter time of exposure can greatly minimise the absorption of pollutants."

5. Results

5.1. Comparing air quality between scenarios

Based on different restriction scenarios of traffic entry, it turns out that vehicle restriction improved air quality (see Fig. 4). Compared to Business-as-Usual, restricting 50% of the inbound traffic only reduced PM_{10} by 1.2–2.7 μg/m^3 (2–4%) for the selected roads, while a 90% restriction scenario significantly reduced PM_{10} by 11.4–15.7 μg/m^3 (18–24%). This endorses the study's finding that halving brake disc emissions can reduce ambient PM_{10} by 4–14% (Perricone et al., 2018). This also suggests that a prohibition on driving has enhanced air quality by lowering the total PM_{10} concentration from 60 μg/m^3 to 47 μg/m^3, but more significantly, the reduction was brought about by the elimination of severe levels, which may have prevented immediate harm to human health. The PM_{10} levels did not differ significantly among roads since the model did not account for non-resident vehicles' travel directions or the number of lanes that can influence their trips.

5.2. The spatial distribution of PM_{10} in Seoul CBD

We also compared the spatial distribution of PM_{10} in Seoul CBD. The second of January was chosen as the test date. Overall, the average roadside PM_{10} was at least 25–30% higher than the background PM_{10}, while the maximum PM_{10} levels on the roadways were more than twice as high as those in the background area (see Table 4). The ratio of the roadside to the background, for instance, is 0.75 at Jongno and 0.69 at

Table 4
Summary Statistics of the Modelled PM_{10} in Seoul CBD on 2nd January 2018 (Unit: μg/m^3).

Station	Mean	Median	Min	Max	sd	CI
Jongno	45.8	45.9	19	103	16.6	0.859
Sejong-ro	49.6	50.2	19	93.9	16.5	0.855
Background	31.2	29	19	47.4	8.41	0.435

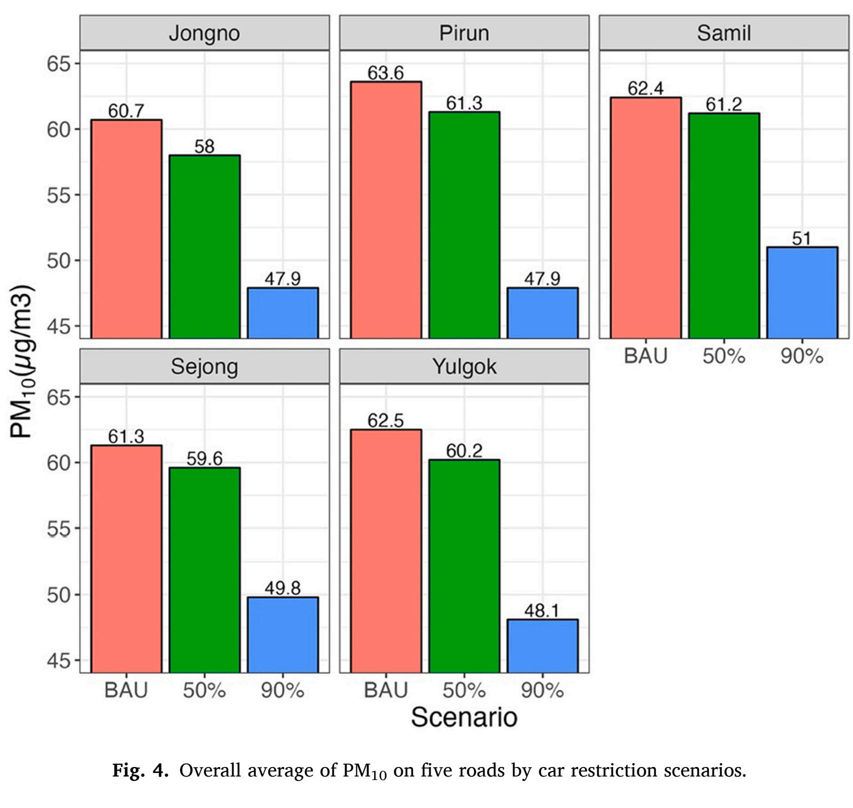

Fig. 4. Overall average of PM_{10} on five roads by car restriction scenarios.

Sejong-ro (see Table 5). This ratio tended to be consistent with the full simulation results.

The daily trend of PM_{10} and its spatial distribution are shown on the hourly averaged map (see Fig. 5A). We discovered that the PM_{10} levels varied from 20 to 90 μg/m^3 when aggregated on an hourly to minutely basis, but that increased traffic to and from offices was associated with higher levels of PM_{10} along the roadsides. Even though there was less congestion in the evening in the upper east part of the CBD, morning and evening rush hours experienced increasing levels of traffic going to and from offices. PM_{10} levels in the upper east and centre road networks declined around 13:00 due to a relatively lower volume. This may be due to the decreased number of inbound vehicles.

Looking at the maximum levels, we discovered that roadways, particularly junctions, experienced over 80 μg/m^3, which was noticeably higher than the background level (see Fig. 5B). This map reveals that junctions in bigger roadways regularly have pollution levels above 100 μg/m^3, even if the upper east was shown to have less pollution in the average figure. It is speculated that the junctions produce more PM_{10} from the driver's stop-and-go behaviour. This is similar to the previous findings that brake emissions vary spatially and tend to escalate when one approaches a junction or a downhill (Air Quality Expert Group, 2019; Timmers & Achten, 2018). Additionally, regions with more traffic signals installed or near the CBD entry points, where many vehicles are trying to enter simultaneously, showed considerably higher PM_{10} levels. This could imply that even on the same day, persons who commute nearby by foot or car have a higher likelihood of being exposed to polluted air. Walking close to intersections where vehicles are more likely to produce particles from their tyres and brake wear requires greater caution.

5.3. Health risk between Subway commuters and drivers

Comparing the temporal at-risk rate between subway commuters and drivers, over 10% of drivers were put at risk on January 23rd 2018. However, when the number of incoming non-resident vehicles was reduced by 90%, the number of resident drivers at risk decreased by 5%, which appeared to be effective (see Fig. 6A). Only a few onsets were seen over the course of the study, except for the extreme pollution occurrences on January 23 and March 26 that had a serious negative impact on the health of the local drivers. By contrast, 10–30% of subway passengers were identified as at-risk groups for each pollution incident, and limits on the entry of vehicles into the CBD did not appear to be successful in reducing the exposure levels (see Fig. 6B). This happened as a result of the model not taking into account the exposure throughout their train ride and most pedestrians walking in the background areas.

6. Discussion and conclusion

This paper constructed a traffic simulation for central Seoul to investigate the coupled problem of NEE and exposure to PM_{10} in groups of pedestrians and resident drivers. Overall, significant extra particulates were found to exist along roadways. Although longer exposure times for pedestrians led to a larger accumulated exposure overall, the majority of drivers were exposed to the highest levels of pollution (>150 μg/m^3), which was largely due to the time spent in congested areas. The health effects, however, depended strongly on how the impact and recovery from exposure were parameterised.

Table 5
Ratio between Background and Roadside Stations.

Station	Back: Road
Jongno	0.75
Sejong-ro	0.69

6.1. The contribution of NEE to ambient PM_{10}

Around 25–30% of the average roadside PM_{10} concentrations were found to be caused by vehicles, with substantially larger contributions on a finer time scale. The volume of traffic that released NEE on roadways was the main cause of the increase in PM_{10}, regardless of the fuel type and mode of power (Air Quality Expert Group, 2019). These results are in line with a case study by Weinbruch et al. (2014), which found that particulate emissions contributed to about 40% of the roadside PM_{10} in the Ruhr. However, because the study combined exhaust and non-exhaust emissions from traffic sources, the rate of roadside PM_{10} may be closer to the results of this study.

6.2. Differences in health effects between pedestrians and drivers

The chief difference between the two groups is the exposure-response to a sudden PM_{10} rise. Even on a highly polluted day, on January 23rd for example, only 7% of resident drivers faced an acute health risk, but practically every subway passenger faced a chance of being ill but quickly recovered once they reached their workplaces. In contrast, when high PM_{10} concentrations persisted for a few days, as they did on March 24 and 25, 88% of drivers experienced a nominal decline in health while 15–30% of pedestrians experienced health hazards as a result of high PM_{10} exposure. This evidence suggests that some susceptible individuals may have severe health hazards from long-term exposure to ambient air pollution, but prolonged exposure to extremely high levels of air pollution caused by vehicle emissions may also result in serious health problems (Laumbach et al., 2015).

Travel time was also an important element that differentiated the exposure patterns. Subway commuters were assumed to travel simultaneously at 6 a.m. from a temporary location and arrive at their final station at various times. The simultaneous effect was modelled by applying a different fraction of PM_{10} to the unknown location, for example, applying 25% of ambient PM_{10} between 10 p.m.–6 a.m., but applying 75% after 6 a.m. The fluctuations in the risk population for subway commuters occurred due to the variation and duration of the commute time. This can add to the research of Gurram et al. (2019) that associated long commute times with higher exposure levels: rural commuters who had long commute times (> 60 min.) experienced 8% greater NO_x exposure than those whose daily travel times were 30 min.

The model parameters showed that drivers just travelling indoors to indoors (for example, from home to car to office) had a different air filtering ratio, which led to the identification of reduced danger for drivers. Cars can operate as a semi-sealed environment to prevent dangerous substances from getting in, which can sometimes be safer than the environment for walkers, even when severe PM_{10} was discovered (Briggs, De Hoogh, Morris, & Gulliver, 2008; Gulliver & Briggs, 2007). However, this argument needs to be carefully examined because some studies insist that professional drivers, including drivers of buses and taxis, face the highest risks related to black carbon and particulates (Moreno-Jiménez et al., 2016; Yamada, Hayashi, & Tonokura, 2016). However, as the current simulation only took indoor activities into account, a more sophisticated behavioural model is required. Nevertheless, the findings can support the benefits of staying inside rather than going outside while the PM_{10} levels are alarmingly high (Laumbach et al., 2015).

6.3. How effective were the scenarios?

In the vehicle restriction scenario, roadside PM_{10} showed a 20% decrease when the majority of cars (90%) were prohibited from the city centre, which is consistent with other estimates of the contribution of NEEs. Despite the fact that less extreme values, primarily due to traffic, were detected, it was nonetheless startling to see an overall drop in all the roads of 10 g/m^3. Similar findings were made in Munich, where PM_{10} within the great ring road was decreased by 2–10% after the Low

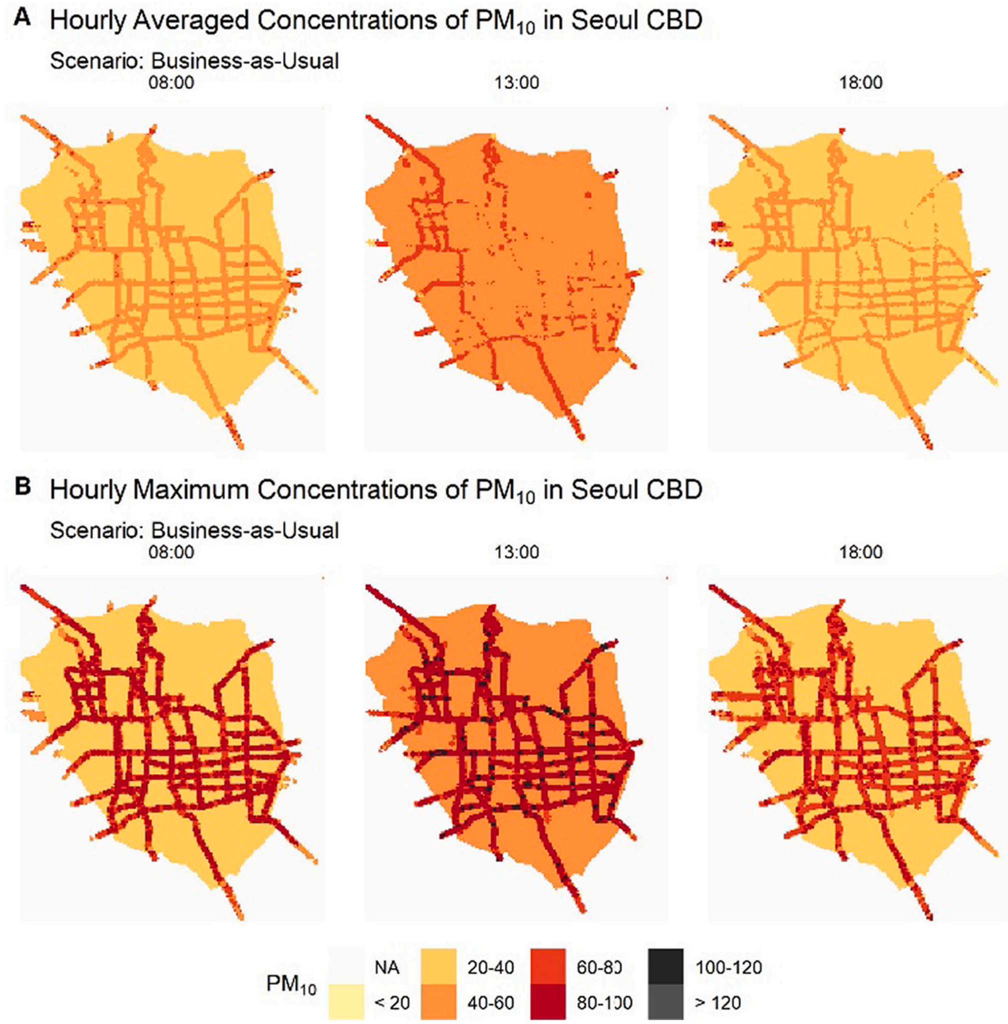

Fig. 5. The modelled results of hourly mean PM_{10} (A) and an hourly maximum of PM_{10} (B) in Seoul CBD on January 2nd 2018 at 08:00, 13:00, and 18:00.

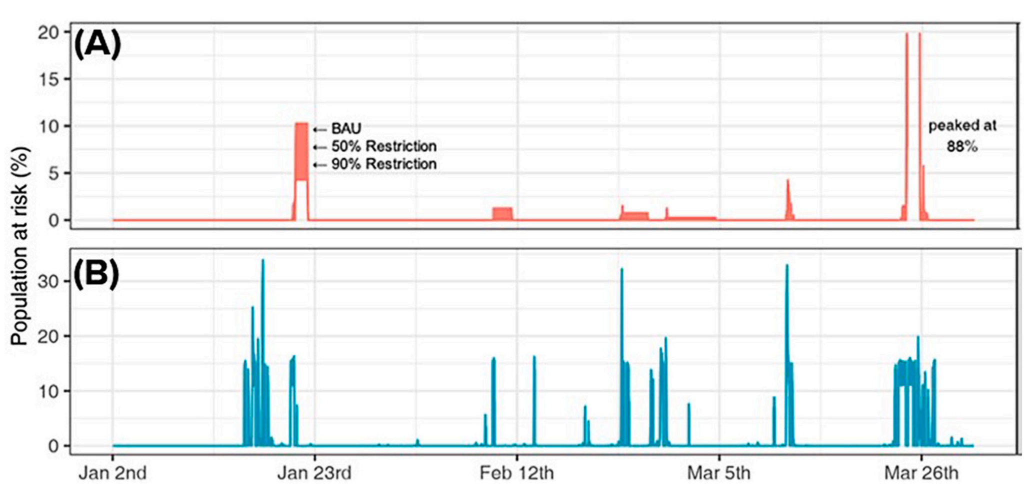

Fig. 6. Health risk of resident vehicle drivers (A) and subway commuters (B).

Emission Zone was put into place (Cyrys, Peters, Soentgen, & Wichmann, 2014), while London had a significant decline in NO_2 but not in particles PM_{10} or $PM_{2.5}$ (Mudway et al., 2019; Wood et al., 2015).

A significant reduction in exposure did not appear to be possible due to changes in pedestrian behaviour (e.g. a smartphone app indicating areas of high PM_{10}). Because the concentration in the background areas was comparable, it was less likely to make a meaningful difference in the outcome for pedestrians who travelled on a day with high pollution levels—unless they stayed at home. Pedestrians who travelled on such a day suffered considerable health damage. While some might argue that exercising outweighs the risks of pollution exposure compared to staying indoors (Tainio et al., 2016), another study disagreed and suggested that when pollution levels are particularly high, people with chronic cardiovascular or pulmonary diseases should avoid pollution exposure (Laumbach et al., 2015). Even though diverse findings lead to unending debates the study's design (long- or short-term, average exposure over time or instantaneous exposure) and the demographics of its subjects need to be carefully considered.

6.4. Strengths and limitations of this study

This study was the first to explore the role of NEEs in conjunction with the detrimental health consequences on a sample of commuters using a microscopic perspective. The creation of brake and tyre wear and the ensuing dispersion that can occur in real life were sufficiently recreated by the application of NEEs on a patch level. Although the equation was cited from studies that used distance-driven indicators (Breuer, Samsun, Peters, & Stolten, 2020; EMEP/EEA, 2019), this study simulates a real-time method of emissions and dispersion from each vehicle to more clearly articulate the causal relationship between the polluters (vehicle emissions) and the susceptible people (drivers and pedestrians).

This study does, however, have some shortcomings. First, this simulation is subject to limitations in terms of the geographic border of Central Seoul and the temporal restriction of January to March. Despite having the highest population disparities between day and night and being known for its excessive traffic, the study region only comprises 2.5% of Seoul. The highest PM_{10} incidents, which happen often, are also known to occur in Seoul during the winter. Hence, this simulation is calibrated to the winter season when the temperature is below 0 °C with less humidity and more heating, thus vehicle's non-exhaust emissions are expected.

Second, the study attempted to simulate the flow of traffic within the spatial domain by using a collective sample of inbound cars, however, due to the coarseness of traffic signal settings and the interactions between vehicles in front of the signal, the traffic could not be properly controlled. The model was given a stop in front of traffic signals and a slow-down function to vehicles ahead of their directions, but because many lanes in the segment were not taken into consideration, more vehicles queued up outside the spatial boundaries.

Third, NEE was dispersed to the neighbouring patches and diluted after a few minutes. However, the current model makes the unrealistic assumption that the airflow is completely steady, stable, and without any breeze. The direction and speed of the wind are taken into consideration as key indicators in the dispersion of pollution in fluid dynamics modelling and atmospheric modelling, such as the ADMS model (Beevers et al., 2013). This is because the wind can influence the patterns and trends of local air movement.

Fourth, even though health loss was parameterised, there is no evidence to imply that the parameter values are justified until they have been calibrated and referenced by other known parameters. The current model evaluated five health loss factors ranging from 0.03 to 0.2 and found that when the values were over 0.15, the acute health risks in every pollution incident were always 100%. This seems unrealistic. Even if the model is merely illustrative, the lack of precise health loss parameters may prevent it from accurately expressing the acute health risks from short-term exposure.

Lastly, the generation of the background PM_{10} values from the study area's two urban background stations. This study only added non-road patches to the simulation from two background monitoring sites, despite the substantial fluctuation in pollution that is predicted in metropolitan areas, particularly where heavy traffic and high-rise buildings trap the airflow. It's likely that this disregarded the geographic variation that personal monitors frequently pick up on (Norton, 2015).

6.5. Future works

Perceiving the severity of NEE to ambient PM_{10}, future research should examine more sophisticated methods of how brake and tyre wear particles are generated and dispersed on roads, as well as whether travelling the shortest distance possible on major roads is preferable to travelling a longer distance but the less congested route in order to lower exposure levels. Immediate improvements can be made in terms of domain expansion to stop cars from idling outside the study area, which will also give a greater possibility for the pollution levels to vary geographically as a result of traffic volume.

There has been a lot of discussion in recent years about whether electric vehicles (EVs), which are heavier than vehicles powered by internal combustion engines (ICEVs), tend to emit more particulate matter on roads (Air Quality Expert Group, 2019; Amato, 2018) or less (OECD, 2020; Timmers & Achten, 2016). Hence, it would be interesting to simulate a 'what-if' model where all cars are electric. This simulation can shed light on how a combination of higher NEE and decreased exhaust emission can alter the quality of the air near roads.

From a health perspective, other working groups in the CBD area may serve as valuable models from the standpoint of health. Taxi drivers, for instance, can be a useful occupation to research because they frequently spend up to 12 h per day driving in Seoul, but little is known about their exposure levels, medical histories, ages, or vastly different work schedules. To better understand if the negative health effects can vary depending on commuting habits and life stages, this study can also look further into travel behaviours by demographic groups.

Data and code availability

The data, codes, and figures are available on our GitHub repository: https://github.com/dataandcrowd/SeoultrafficABM.
Reproducible code for the figures are on the CodeOcean Capsule: doi:10.24433/CO.6287370.v1

Author contribution statement

The authors confirm contribution to the paper as follows: study conception and design: Hyesop Shin and Mike Bithell; data collection: Hyesop Shin; analysis and interpretation of results: Hyesop Shin and Mike Bithell; draft manuscript preparation: Hyesop Shin. All authors reviewed the results and approved the final version of the manuscript.

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. Part of the results were presented in the Proceedings of Social Simulation Conference 2021 (https://link.springer.com/chapter/10.1007/978-3-030-92843-8_26). We have abided by the rules from Springer that we can reuse up to three figures and 400 words from the proceeding.

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