Journal of Transport Geography 105 (2022) 103477

Contents lists available at ScienceDirect

Journal of Transport Geography

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

Exploring the Spatial-temporal dynamics of travel patterns and air pollution exposure of *E*-scooters

Suriya Vallamsundar [a,1,*], Rohit Jaikumar [b], Madhusudhan Venugopal [a]

[a] *Center for Advancing Research in Transportation Emissions, Energy and Health, Texas A&M Transportation Institute, 12700 Park Central, Dallas, TX 75251, United States*

[b] *Center for Advancing Research in Transportation Emissions, Energy and Health, Texas A&M Transportation Institute, 1111 RELLIS Parkway, Suite 3401, Bryan, TX 77807, United States*

ARTICLE INFO

Keywords:
E-scooters
Geospatial analysis
Travel patterns
Traffic-related air pollution
Shared mobility

ABSTRACT

Dockless mobility has been the biggest disruptive force in the shared mobility industry solving the "first-last" mile issue. With their high adoption levels combined with little to no regulation regarding their usage, these users have been driving along with motorized vehicles exposing them to major concerns. The users are exposed to high levels of traffic-related air pollution (TRAP) due to their direct exposure to vehicle exhaust. This study aims to understand the spatial and temporal dimensions of this emerging transportation mode in terms of travel behavior patterns, geographical aspects of travel, interactions between the travel route taken with the existing vehicle traffic, and resulting air pollution and exposure. The travel behavior patterns are evaluated through spatial-temporal analysis of a sample of e-scooter trip data collected in 2018 in the City of Austin and an online travel behavior survey. The analysis identified areas with peak usage, and peak ridership time. The survey results found the e-scooter user demographics to be mostly white males, in the 26–45 age range, with an undergraduate degree and working full-time. Secondly, key responded in influencing the use of an e-scooter are trip length, connectivity to transit, congestion and parking issues, and pollution reduction. Thirdly, e-scooter predominantly replaced personal vehicles and shared ridership in case of home-to-work trips and replaced walking for connecting to transit stops. The exposure to TRAP was obtained by integrating the spatial-temporal dynamics of e-scooter trips with spatial-temporal dynamics of pollutant concentrations modeled from traffic. Exposure analysis found peak exposure levels during midday and evening periods focused in the Central Austin area. This area houses the University of Texas campus and several neighborhoods with lots of shopping, restaurants, bars, and live music avenues. The findings are useful for policymakers and planners when planning for infrastructure changes air pollution control measures, incentive programs, and policies to motivate shared mobility.

1. Introduction

Dockless mobility has been the most prominent disruptive force in the shared mobility industry solving the "first-last" mile issue. Dockless bikeshare considered the fourth generation in shared mobility is based on smart mobility combining dockless systems, and cellular and GPS technology. The datasets related to smart shared mobility are increasingly available and are valuable sources to better understand population behavior and mobility issues in urban areas (Shaheen et al., 2010). The dockless mobility (bikes and e-scooters) can be rented directly through the user's mobile phone, allowing the user to go through the city streets at around 15 miles per hour (6.7 m/s). In 2018, electric scooters, or "e-scooters" replaced pedal bikes and became the preferred vehicle for dockless vendors (National Association of City Transportation Officials (NACTO), 2019). As per the National Association of City Transportation Officials (NACTO), cities such as Austin, and Santa Monica were some of the early adopters of e-scooters that grew in number to over 85,000 e-scooters available for public usage throughout the country. Early studies revealed a more accessible, racially diverse set of riders and a higher proportion of women riders, and a lower household income for dockless riders than docked users (Virgina Polytechnical Institute and State University, 2018). Studies (Xu et al., 2019; Yang et al., 2019) conducted in China, and Singapore have found dockless trips to be higher during weekends compared to weekdays, and an increase in demand with the

* Corresponding author.
E-mail address: suriya.vallamsundar@trinityconsultants.com (S. Vallamsundar).
[1] Present Address: Mobile Source Emissions and Fuel Business Line, Trinity Consultants, 12700 Park Central Dr., #2100, Dallas, TX 75251, United States.

https://doi.org/10.1016/j.jtrangeo.2022.103477
Received 14 April 2022; Received in revised form 10 August 2022; Accepted 11 October 2022

presence of a public transportation stop highlighting their increased use for "first-last" mile connections. Contrary to these findings, a study conducted in Washington D.C. revealed that the e-scooters were used mainly for leisure or recreational purposes (McKenzie, 2019). Similar findings (Foissaud et al., 2022) were reported in a spatio-temporal assessment of e-scooter trips across 4 European cities that found e-scooter users to be mostly tourists, who ride during the daytime, over longer distances at low speeds, around the downtown area and other tourist attractions. Bai and Jiao, 2020 compared the e-scooter usage patterns between Austin, TX, and Minneapolis, MN, and found similar spatial patterns with denser usage patterns focused at the downtown and University campuses in both cities. However, temporal patterns were different with higher usage during afternoons and weekends in Austin, compared to higher usage during evenings and stable patterns across the week in Minneapolis.

Studies have focused on the operational characteristics of e-scooters, and there is a gap in evaluating their environmental and health impact in terms of the exposure levels to air pollution. Key environmental issues evaluated by studies include lifecycle analysis (LCA) and recycling of e-scooters. A study (Hollingsworth et al., 2019) based on a lifecycle global warming analysis found the baseline scenario based on current conditions to result in 65% higher lifecycle greenhouse gas (GHGs) emissions due to the e-scooter use compared to the transportation modes that were being replaced. The study found the likelihood to drop by 35–50% in alternative scenarios evaluated with efficient strategies such as increasing scooter lifetimes and using efficient vehicles and less frequent charging strategies, reducing collection and distribution distances, etc. Similar findings to the baseline scenario were found by a study based in Paris (de Bortoli and Christoforou, 2020) that estimated an additional thirteen thousand tons of GHGs emissions for one million users as a result of e-scooters attributed mainly to the mode shifts from lower-emitting modes. Providing a split between the different components of an LCA, a study (Chester, 2019), found the manufacturing and materials to be the highest attributing factor to lifecycle GHGs emissions, followed by collection, distribution, and charging of e-scooters. All these studies point to the fact that while e-scooters may seem to be a sustainable solution to solving congestion, and last-mile issues and reducing emissions, however, they do not necessarily reduce overall environmental impacts without considering how efficiently they are being collected, distributed, and recycled.

In addition to these environmental issues, the other aspect of e-scooter that has not been evaluated as much as the LCA is the exposure of e-scooter users to traffic-related air pollution (TRAP), as several cities lack bike lanes, forcing users to travel on sidewalks or shared lanes with direct exposure to motorized vehicle emissions. The vehicles emit a complex mixture of pollutants that are found to contribute to various adverse health effects (Mukherjee and Agrawal, 2017; Health Effects Institute (HEI), 2010). These adverse health effects cover a variety of morbidity and diseases including but not limited to premature mortality, cardiovascular, respiratory, birth, and developmental effects, as well as cancer (Adar and Kaufman, 2007; Wilhelm and Ritz, 2003). Commuting next to major arterials is critical because of the peaking tendency of pollutant concentrations near roadways and longer travel time than vehicle commuters (De Hartog et al., 2010; Hatzopoulou et al., 2013). While several studies have evaluated exposure levels for bicyclists and pedestrians (Boriboonsomsin et al., 2017; Lefebvre et al., 2013), there have been limited studies evaluating e-scooter users and their exposure levels since this transportation mode is relatively new, and their usage patterns are yet to be fully understood.

The present study aims to understand the travel behavior patterns and the exposure levels experienced by a sample of e-scooters using a predictive exposure modeling system for the City of Austin in Texas. The travel behavior patterns were evaluated through a combination of geospatial analysis of 3.4 million records of commute data collected and an online survey launched through social media. The exposure to TRAP experienced by the users was evaluated through an integrated modeling platform combining e-scooter trip trajectory data, traffic activities, emissions, meteorology, and pollutant dispersion. An e-scooter trip means a single or one-direction e-scooter movement with an origin and destination within the study area. An exposure concentration map for particulate matter (PM), considered a health marker of exposure to traffic emissions was developed (World Health Organization (WHO), 2003). Finer PM ($PM_{2.5}$) was chosen as it presents a greater health threat than coarser PM because of its small size that allows deeper penetration into the human body (City of Austin (COA), 2018). The finding helped to highlight the hot spots of peak exposure and variation in exposure levels during different periods depending on the usage levels and pollutant dispersion. The modeling system and findings obtained can be used to facilitate the planning of city transportation infrastructure and for commuter decision-making on route and time choice. The paper provides an overview of the methods, data collection, and analysis, followed by results and conclusions drawn from the chosen case study.

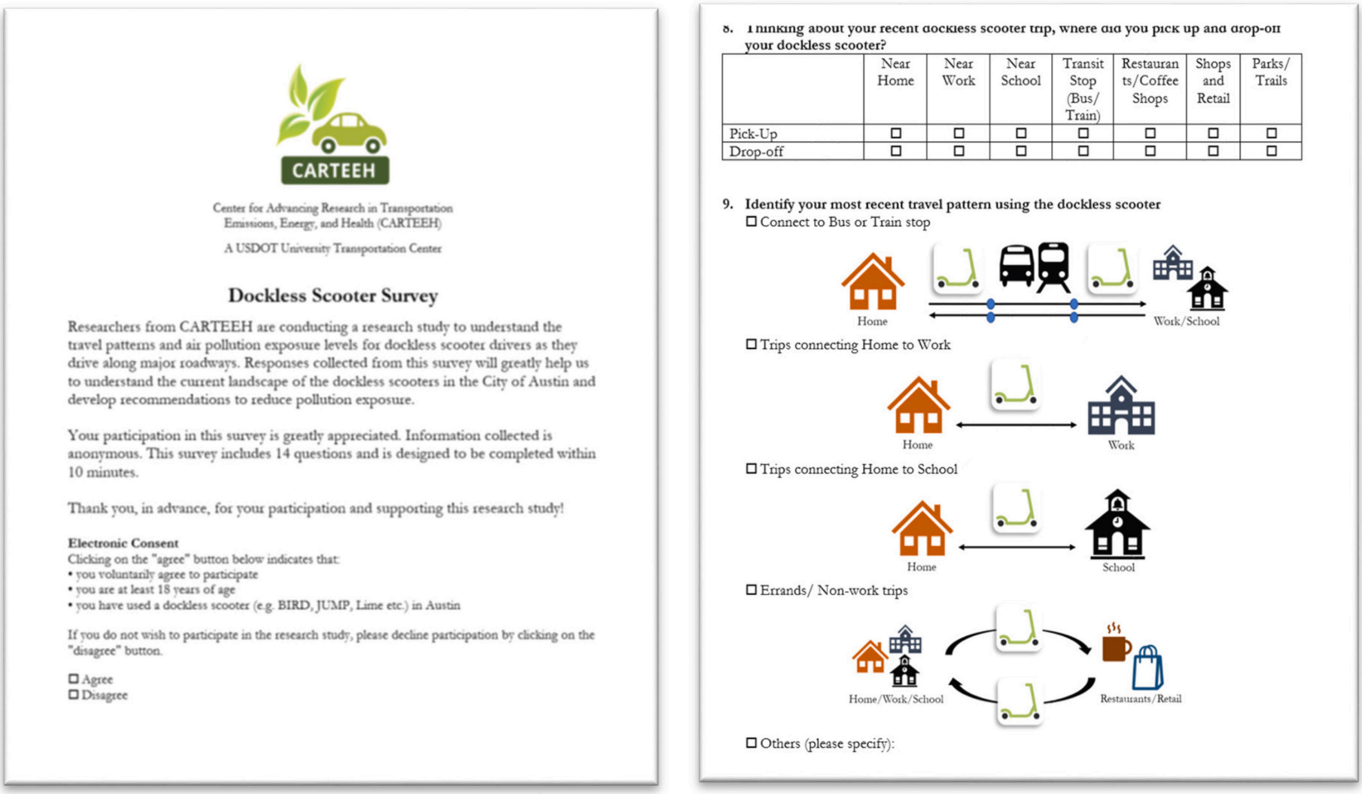
2. Methods

2.1. Study extent and e-scooter trip data

The City of Austin, the capital city of Texas in Travis County is one of the fastest-growing metros in the country. The city houses the University of Texas flagship campus and is also known as the live music capital city of the world due to the major music festivals that are hosted there. In addition to a large number of floating populations, the city has people migrating from other states due to the relocation of several companies to Austin. As per the NACTO 2018 statistics presented, Austin is one of the three U.S cities with the most e-scooter usage (National Association of City Transportation Officials (NACTO), 2019). The climate is characterized by hot, humid, and long summers and short, milder winters. The City of Austin (COA) launched the dockless mobility (micro-mobility) pilot program in early 2018. The Austin Transportation Department expanded the scope of this pilot program to include dockless scooters and e-scooter operators. Based on the information obtained from the COA at the time of this study, there were 15,350 scooters and 2050 bikes available across the Austin area provided by eight operators (Bird, JUMP, Lime, Lyft, OjO, Skip, Spin, and VeoRide). The mobility data obtained provided anonymized information related to the dockless vehicle trips, start- and endpoints of trips, and monthly summary statistics of the trips made, devices used, and distance traveled. The dataset acquired for this study included a total of 4.1 million records that occurred between March 2018 and early April 2019. The key parameters utilized consisted of origin-destination for each trip, trip distance, and duration, start and end time, mode (bike or scooter), etc. Missing and invalid records that did not have a valid latitude or longitude (values far away from the Austin area) and records with unrealistic trip distance and duration were excluded. The data was then filtered to include only e-scooter trips with a duration lesser than 10,000 s (2.78 h) and a distance <15.5 mi (25 km). This process resulted in removing 15% of the dataset acquired. The final data analyzed consisted of a total of 3,462,084 records.

2.2. Survey

An online survey designed to understand the usage patterns of e-scooters was launched through social media. The survey consisted of 14 questions categorized into (A) demographic characteristics, (B) e-scooter questions in general that included information about factors encouraging the use of e-scooters, usage of other modes, riding frequency and purpose, (C) most recent e-scooter trip that consisted of questions related to pick-up/drop-off locations, time and duration and use of an alternative mode corresponding to the most recent trip taken by the respondents. The survey was launched through the COA and other academic institution-related newsletters and social media from December 2019 through March 2020. A total of 100 users completed the



CARTEEH

Center for Advancing Research in Transportation Emissions, Energy, and Health (CARTEEH)

A USDOT University Transportation Center

Dockless Scooter Survey

Researchers from CARTEEH are conducting a research study to understand the travel patterns and air pollution exposure levels for dockless scooter drivers as they drive along major roadways. Responses collected from this survey will greatly help us to understand the current landscape of the dockless scooters in the City of Austin and develop recommendations to reduce pollution exposure.

Your participation in this survey is greatly appreciated. Information collected is anonymous. This survey includes 14 questions and is designed to be completed within 10 minutes.

Thank you, in advance, for your participation and supporting this research study!

Electronic Consent

Clicking on the "agree" button below indicates that:
• you voluntarily agree to participate
• you are at least 18 years of age
• you have used a dockless scooter (e.g. BIRD, JUMP, Lime etc.) in Austin

If you do not wish to participate in the research study, please decline participation by clicking on the "disagree" button.

☐ Agree
☐ Disagree

8. Thinking about your recent dockless scooter trip, where did you pick up and drop-off your dockless scooter?

	Near Home	Near Work	Near School	Transit Stop (Bus/ Train)	Restaurants/Coffee Shops	Shops and Retail	Parks/ Trails
Pick-Up	☐	☐	☐	☐	☐	☐	☐
Drop-off	☐	☐	☐	☐	☐	☐	☐

9. Identify your most recent travel pattern using the dockless scooter

☐ Connect to Bus or Train stop

Home Work/School

☐ Trips connecting Home to Work

Home Work

☐ Trips connecting Home to School

Home School

☐ Errands/ Non-work trips

Home/Work/School Restaurants/Retail

☐ Others (please specify):

Fig. 1. Snapshot of the online survey.
(The online survey administered was used to understand the demographics, and travel patterns of e-scooter users in the City of Austin. Fig. 1 shows a snapshot of the introduction page and questions related to the most recent e-scooter trip taken by the respondent).

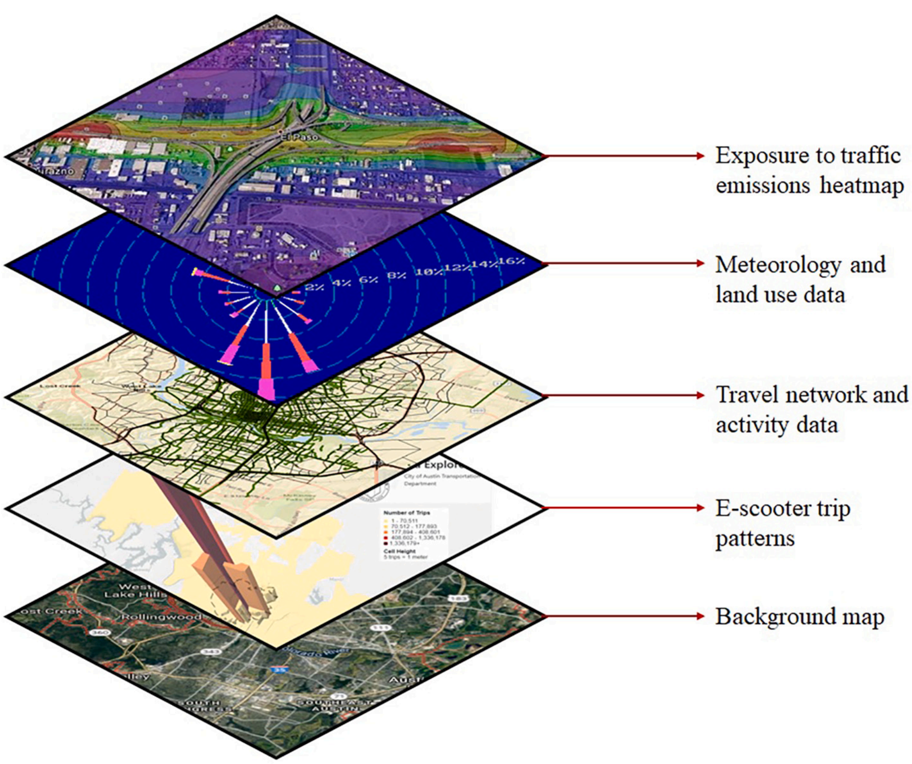


Fig. 2. Modeling framework.
(The modeling framework consists of an integration of different layers of data starting with the background map based on which the e-scooter trip trajectories were generated. Next, the travel network and traffic activities layer was combined with meteorology and land use conditions to estimate the dispersion of the pollutant emissions. The e-scooter trajectories were then combined with spatial and temporal distribution of pollutant concentrations to estimate the personal exposure levels to traffic emissions).

Table 1
Flow of Data between Modeling Components.

Modeling	Model	Input Parameters	Output
Traffic Activities	Austin Regional Travel Demand Model (TDM)	Economic and land use information, transportation network, and demand estimation*	Outputs at the roadway link level consist of average speed and vehicle volume
Traffic-related Emissions	EPA's MOVES2014a Model	Roadway link level inputs (traffic volume, speed, and fleet mix) from TDM. Meteorological, fuel supply parameters, and age distribution from MOVES default database	Outputs consist of total emissions and emissions factors
Pollutant Concentrations	EPA's AERMOD (19191) Model	Surface and upper air data from weather stations processed using AERMOD preprocessors. Emission factors from MOVES model.	Concentration levels obtained at discrete user-defined receptor locations averaged at the census block level
E-scooter Trips	City of Austin dockless mobility database	Trip start and end points, location, and trip duration	Trip information (start and end points, location, and duration) corresponding to case study extent for the period considered were extracted
Exposure Assessment	Exposure assessment formulation where exposure is measured as a weighted product of time and pollutant concentration in different locations	Pollutant concentrations from AERMOD and e-scooter trip trajectory information.	Exposure measured for each e-scooter trip and summed up for all trips corresponding to the case study location and period

* Beyond the scope of this study.

survey. The survey was reviewed and approved by the Texas A&M University Institutional Review Board (IRB#: IRB2019–0878).

Fig. 1 shows a snapshot of the survey.

2.3. Exposure assessment

The exposure modeling framework is shown in Fig. 2. The modeling started with the assembly of base imagery of the case study region. The e-scooter trips were extracted from the COA database and after filtering missing and invalid data resulted in a total of 3.5million trip records. Trip information extracted consisted of trip start and end points, and the duration of the trip. Traffic activities corresponding to traffic volume, speed, and vehicle fleet mix on the major roadways were extracted from Austin's regional travel demand model (TDM) maintained by the Capital Area Metropolitan Planning 3 Organization (CAMPO). The model uses information on economic growth, population, land use information, and existing transportation network to predict the travel demand for existing and future conditions. The model is based on a 4-step methodology of trip generation, trip distribution, mode choice, and trip assignment.

Based on this methodology, the model produces performance measures related to traffic volumes, average speed, and travel time. The Environmental Protection Agency's (EPA) regulatory-approved MOVES2014b model was utilized for estimating emissions. The MOVES model applies a modal-based approach by estimating emissions for each unique combination of operating modes or bins based on vehicle operating conditions and characteristics. The model uses site-specific traffic activity data and combines it with other local-specific information corresponding to age distribution, temperature, humidity, fuel supply, inspection, and maintenance program parameters. These inputs were obtained from the MOVES default database that contains national data based on historic and long-term systematic measurements distributed temporally and spatially to states or counties using

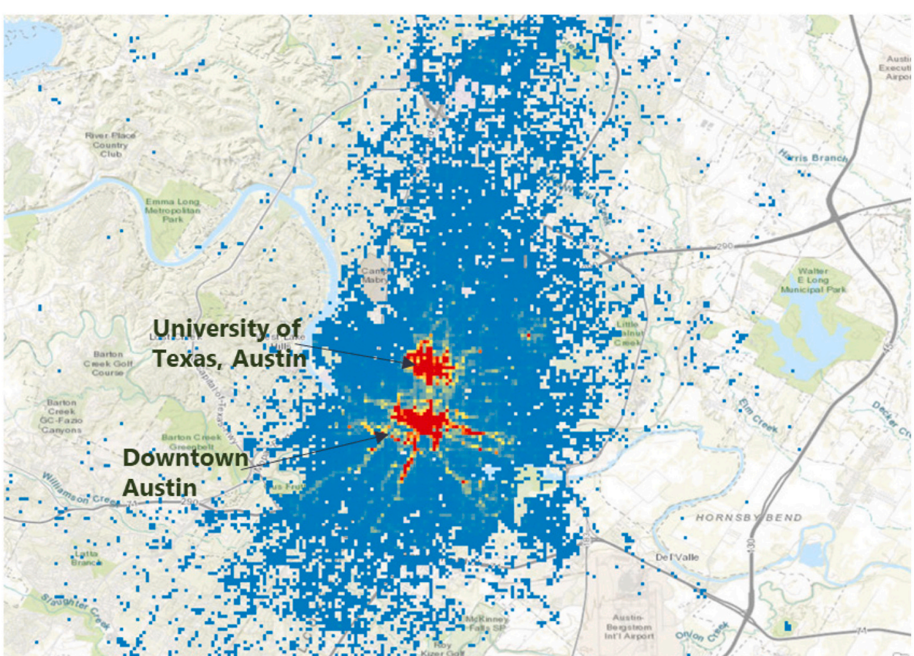


Fig. 3. Heat map of the e-scooter trip starts.
(Heat map of e-scooter trip data highlights clustering of trips starts at the downtown and near the University of Texas, Austin areas. Exposure assessment was conducted for these hot-spot areas).

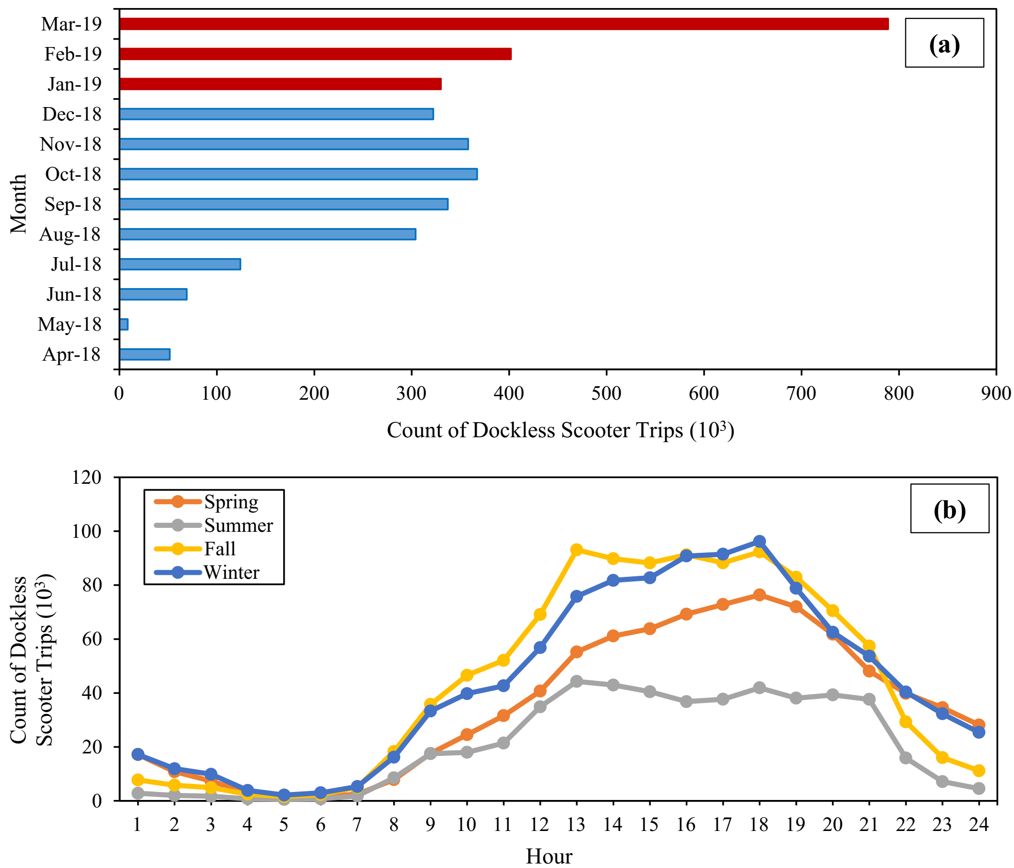


Fig. 4. Temporal variation in the e-scooter data.
(This figure shows the temporal variation of the e-scooter data based on an analysis of 3.5 million trip records. Fig. 4(a) shows the trip data throughout the analysis period from April 2018 – March 2019 since the inception of e-scooters in April. Trips were found to increase from August 2018 with a peaking of trips in March 2019. Hourly variation of trips over seasons (Fig. 4b) presents one predominant peak between 12 pm – 7 pm unlike bimodal peaks observed with typical urban traffic conditions).

allocation factors (Environmental Protection Agency (EPA), 2021). Based on these inputs, the model estimates total emission inventories or emission factors at different geographic scales ranging from national, county, and detailed roadway link levels. For this study, the emission factors were estimated at the roadway link level corresponding to the case study location. The resulting emission factors were then incorporated into an air dispersion model to calculate the pollutant dispersion in the atmosphere based on the meteorological and land use parameters.

Dispersion modeling was conducted using EPA's approved regulatory AERMOD dispersion model, and AERMET and AERSURFACE meteorological preprocesses (Environmental Protection Agency (EPA), 2004). AERMOD calculates the fate and transport of pollutants based on Gaussian formulation and is suited for primary pollutants as it does not account for the chemical transformation or reaction between pollutants. AERMOD is utilized for this study because traffic-related pollutants are typically confined to near emission sources and do not travel far beyond. The model calculates $PM_{2.5}$ concentrations from roadway traffic by characterizing roadways as a series of area sources based on traffic activity, and the geometry of the roadway links. Raw surface and upper air data were extracted from the National Oceanic and Atmospheric Administration (NOAA) and converted into a format compatible with AERMOD using AERMET and AERSURFACE. The $PM_{2.5}$ concentrations were estimated at discrete receptor locations placed throughout the modeling domain over an hourly averaging period.

Early studies (Duan, 1991; Ott, 1982), mathematically established the formulation for exposure as follows:

$$E = \int C(t)dt$$

where E exposure is measured as the product of time t and concentrations C in different locations. Exposure at location x, y, z is calculated by determining the concentration at that location and time combined with the amount of time spent at that location. On the other hand, dynamic exposure for example while commuting from location A to location B is calculated by determining the time-weighted concentration at both locations. A similar approach was adopted for e-scooters by calculating their exposure levels based on the route taken, amount of time spent at each location within the route, total trip duration, and corresponding pollutant concentration at each of those locations. For this purpose, each e-scooter trip was split into trajectories and exposure levels were computed based on the concentration levels at the location of the trajectory and time spent at the location. Total exposure for a given trip was obtained by combining all split trajectories of the trip. Table 1 lists the flow of data between different modeling components involved in exposure assessment. A detailed explanation of the different components involved in the modeling framework can be found in (Vallamsundar et al., 2016).

3. Results

3.1. Geospatial and temporal analysis

The spatial distribution of trips (Fig. 3) highlighted a high density or

Table 2
Demographic Characteristics of Survey Responders in Comparison with the City of Austin.

Demographic characteristics	Categories	Survey Response Rates	City of Austin
Gender (Above 18 yrs)	Male	56%	51%
	Female	44%	49%
Age Group	18–25 years	22%	10%
	26–35 years	27%	29%
	36–45 years	31%	21%
	46–55 years	4%	15%
	> 56 years	16%	25%
Race	White or Caucasian	69%	50%
	Black or African American	2%	7%
	Hispanic or Latino	7%	30%
	Asian or Asian American	13%	9%
	Others	9%	4%
Education Level	Less than high school	0%	
	High School	11%	90% 54%
	Undergraduate degree	40%	
	Master's degree	33%	
	Degree higher than a master's degree	16%	
Employment Status	Student	13%	Not Available
	Working part-time	7%	
	Working full-time	71%	
	Retired	9%	
Average Household Income	$0–$24,999	6.5%	14%
	$25,000–$49,999	6.5%	18%
	$50,000–$74,999	13%	17%
	$75,000–$99,999	18%	13%
	$100,000–$124,999	16%	18%
	$125,000–$149,999	13%	
	$150,000 and up	27%	20%

utilization rate in the downtown area and near the University of Texas at Austin campus.

The temporal analysis consisted of evaluating the hourly, monthly, and seasonal variation of the trips over the period (April 2018–March 2019). Fig. 4 results (Fig. 4a) showed an increase in trips from August 2018 to March 2019. The slight decrease in trips between December 2018 – January 2019 was attributed to the holiday season and lower temperatures. The peaking of trips in March 2019 was due to the starting of the spring season with warmer temperatures and events such as Circuit of The Americas (3/1/2019 to 3/32019), South by Southwest music festival (3/8/19–3/17/19), Rodeo Austin (3/16/19–3/30/19) scheduled around the city. The hourly seasonal variation of trip counts (Fig. 4b) showed the trip counts to increase starting from 7 am, peaking from 12 to 7 pm, and then decreasing at around 10 pm. The diurnal pattern for all seasons exhibited only one predominant peak and differed from the bimodal peak (morning and evening) typical in urban traffic distribution. This divergence from the typical urban traffic behavior indicated that the e-scooters were not only being used to meet the first and last-mile demand *(3, 6)* but also for other purposes (errands, recreational, etc.). This was further exhibited by observing the variation in e-scooter trip distance and duration. 67% of the trips were found to occur during the weekdays versus 33% during the weekends and when normalized by the time distribution of weekdays vs weekends, users have a 23% higher tendency to use e-scooters over the weekends for other purposes compared to weekdays. The average duration and distance were found to be 687 s (11.45 min) and 1495 m (0.93 miles), respectively.

3.2. Survey results

The survey results on the respondent's demographic characteristics (Table 2) highlighted predominant users were male, white, or Caucasian, between 18 and 45 years, mostly with an undergraduate degree or higher (89%), and working full-time (71%). These results in comparison with the overall City of Austin's demographics based on 2016–2020 Census data (Austin, 2022) show the survey respondents predominantly to be mostly male white, between 26 and 45 years of age. This result is probably biased as the survey was administered online through social media and thus might have been frequented by a section of the population having online access and social media.

Responders were asked to rank the factors that influenced their decision to ride an e-scooter. The most responded factor influencing the use of e-scooters corresponded to trip length (69% strongly agreed), connectivity to transit (66%), congestion and parking issues (62%), and pollution mitigation (60%) (Fig. 5a). In terms of usage frequency of other modes, responses (Fig. 5b) exhibited personal vehicle (50%) and ridesharing (53%) to be used much less than due to e-scooters, and transit usage remained the same (49%). The type of trip made using the e-scooter was classified into (1) connecting to a bus/train stop, (2) connecting home to work or home to school, and (3) errands or non-work trips. Based on the responses, it was found that 13% used an e-scooter to connect to a transit stop, 43% to connect home to work/school, and 44% for errands or non-work trips. The responders were asked the mode that would be used for these trips in case an e-scooter was not available. The results (Fig. 5c) highlighted walking to be the most preferred mode for connecting to a transit stop (33%), a personal vehicle for both trips connecting from home to work/school (43%), and errands or non-work trips (39%). Overall, combined for all trip purposes, 33% would have biked or walked, 37% would have taken a personal vehicle, 20% would have not made the trip, and the remaining 10% would have taken carsharing or ridesharing services. These findings were in line with surveys conducted by other studies in terms of modes preferred in the absence of e-scooters. A study conducted in Raleigh, North Carolina (Hollingsworth et al., 2019) found that 49% would have biked or walked, 34% would have used a personal automobile or ride-share service, and 7% of users reported that they would not have taken the trip otherwise, and 11% would have taken a public bus. Comparing these numbers with a study conducted in Portland, Oregon (Portland Bureau of Transportation, 2018), which shows 45% would have biked or walked, 36% would have used an automobile, 8% would not have taken the trip, and 10% would have used a bus or streetcar.

In the case of locations where the e-scooters were picked up and dropped off, survey results found that 45% of responders select "near home" as the pick-up location, and 35% dropped off the e-scooters near "restaurants/shops". The average trip distance was found to be within 1–2 mi (47%) and trip duration between 5 and 20 min (80%). These survey results were found to be comparable with the findings obtained from temporal analysis of the trip data that resulted in an average trip distance of 1 mile and a trip of 12 min. These findings were found to be similar to findings reported by other studies based in the United States (Bai and Jiao, 2020). Noland (2019) based on an assessment of e-scooter tip patterns in Louisville, Kentucky found the average trip distance to be 15.59 min and the average trip duration to be 1.33 miles. Similar findings were reported by Orr et al., 2019 based on Portland's e-scooter trips found the average trip duration and distance to be 14 min and 1.7 miles, respectively. 83% of survey responders found the e-scooters to decrease their trip distance and/or their trip time, compared to 17% who found no decrease at all. Overall, the survey responses highlighted the fact that e-scooters were preferred for a variety of activities including travel to work/school, errands, and recreational purposes, and have reduced the use of personal vehicles and ridesharing, and walking especially for shorter distances and durations.

3.3. Exposure assessment

Based on the geospatial analysis of the e-scooter trips, high-density areas in the divisions of George, and Baker were selected for exposure assessment (Fig. 6 a & b). The case study covered an extent of 3.5mi by 6mi (5.6 km to 9.6 km) and the e-scooter trip data in these areas

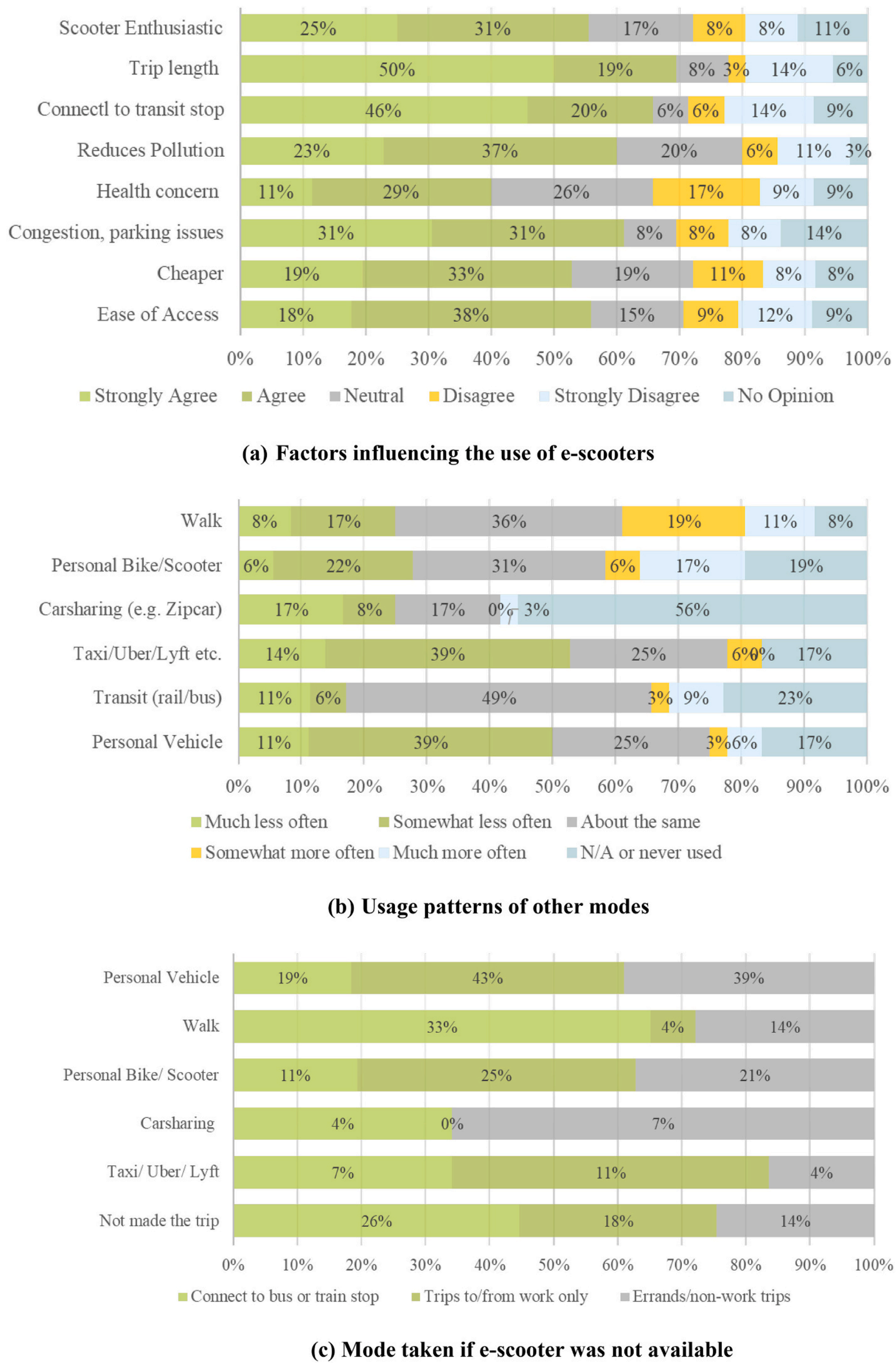


Fig. 5. *E*-scooter survey responses.
(Fig. 5 highlights the survey responses focused on e-scooter travel behavioral patterns corresponding to (a) factors that motivate people to use e-scooters, (b) usage patterns of other models (c) mode taken if e-scooter was not available to help assess the reduction in other modes due to e-scooter usage).

accounted for 216,010 trips or 6% of the total dockless data in the period considered for the study. Based on the trip origin and destination, trip trajectories were generated by applying the Dijkstra algorithm in ArcGIS software. The algorithm breaks the network into nodes and develops the shortest path between the nodes based on constraints imposed such as avoiding freeways, divided highways, and roads that do not permit e-scooters (ArcGIS) (Fig. 6c).

The traffic data corresponding to the travel network covering the case study extent consisted of link-level traffic volumes, speed, and roadway type. The annual average daily traffic (AADT) values for the links modeled in the study ranged from 13,979 to 202,376 with the higher AADT values concentrated at the links of Interstate 35 (I-35) and N-Mopac Expressway close to downtown and the intersection of US290 and I-35. The AADT values were converted into hourly volumes using allocation factors obtained using regional information (Texas Commission on Environmental Quality, 2015). The fleet mix also obtained from regional data consisted predominantly of passenger cars (70%), followed by passenger trucks (17%), and heavy-duty trucks (10%). Other inputs utilized for emission estimation consisting of vehicle age distribution, temperature and humidity, fuel supply, inspection and maintenance parameters, and vehicle fleet mix were obtained from the MOVES default database corresponding to Travis County where the City of

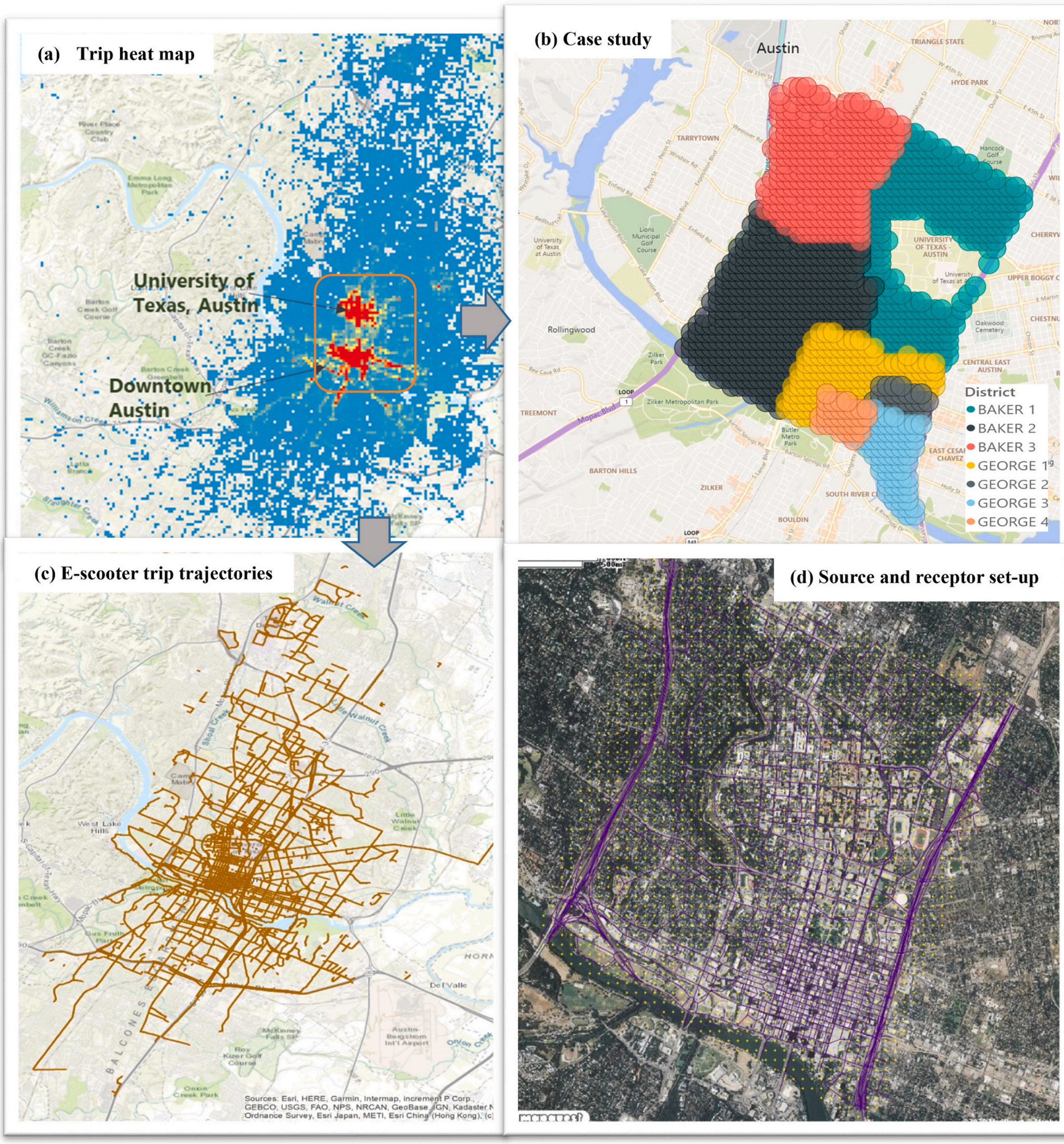


Fig. 6. Exposure assessment model set-up.
(Fig. 6 consists of four components representing the process of model set-up for exposure assessment. Fig. 6a and Fig. 6b showcase the hot-spot locations of e-scooter trips that are selected for exposure assessment. Fig. 6c shows e-scooter trip trajectories generated using ArcGIS, and Fig. 6d presents the source and receptor characterization of the traffic roadway links in the hot-spot locations from which exposure levels experienced by the e-scooter users were calculated).

Austin is located. Based on these inputs, $PM_{2.5}$ emission factors resulting from the vehicle's running exhaust, crankcase running exhaust, brake, and tire wear were estimated using the MOVES model at an hourly averaging period for all roadway links. Emission factors were then normalized by the area of roadway links (in terms of grams/m^2-second) and incorporated into AERMOD.

The raw surface and upper meteorological data for the study region were obtained from Austin Bergstrom International Airport (Station ID: 03904), and Corpus Christi upper air station (Station ID: 12924), respectively. The raw data corresponding to the year 2015 data (which was the latest available at the time of the study) was processed through the AERMET and AERSURFACE preprocessors in a format compatible with AERMOD. The details of meteorological data processing can be found in (Askariyeh et al., 2018). The roadway links in the network were characterized as a series of 4579 area segments Traffic-related pollutant dispersion follows a peaking pattern near the roadway sources before gradually falling off to the background concentration levels. To capture this spatial gradient, receptors were placed at a finer spacing of 25 m closer to the roadway links, and spacing is increased to 50 m, and 100 m with distance from the roadways. This set-up resulted in a total of 1507 receptors placed at an average human breathing height of 1.8 m. The model set-up is shown in Fig. 6d.

The spatial-temporal distributions of $PM_{2.5}$ concentrations averaged at the census block level (Fig. 7) were developed for four time periods.[2]

[2] Morning period corresponds to 6 am to 9 am, midday is considered from 9 am to 4 pm, evening peak from 4 pm to 7 pm, and overnight from 7 pm to 6 am.

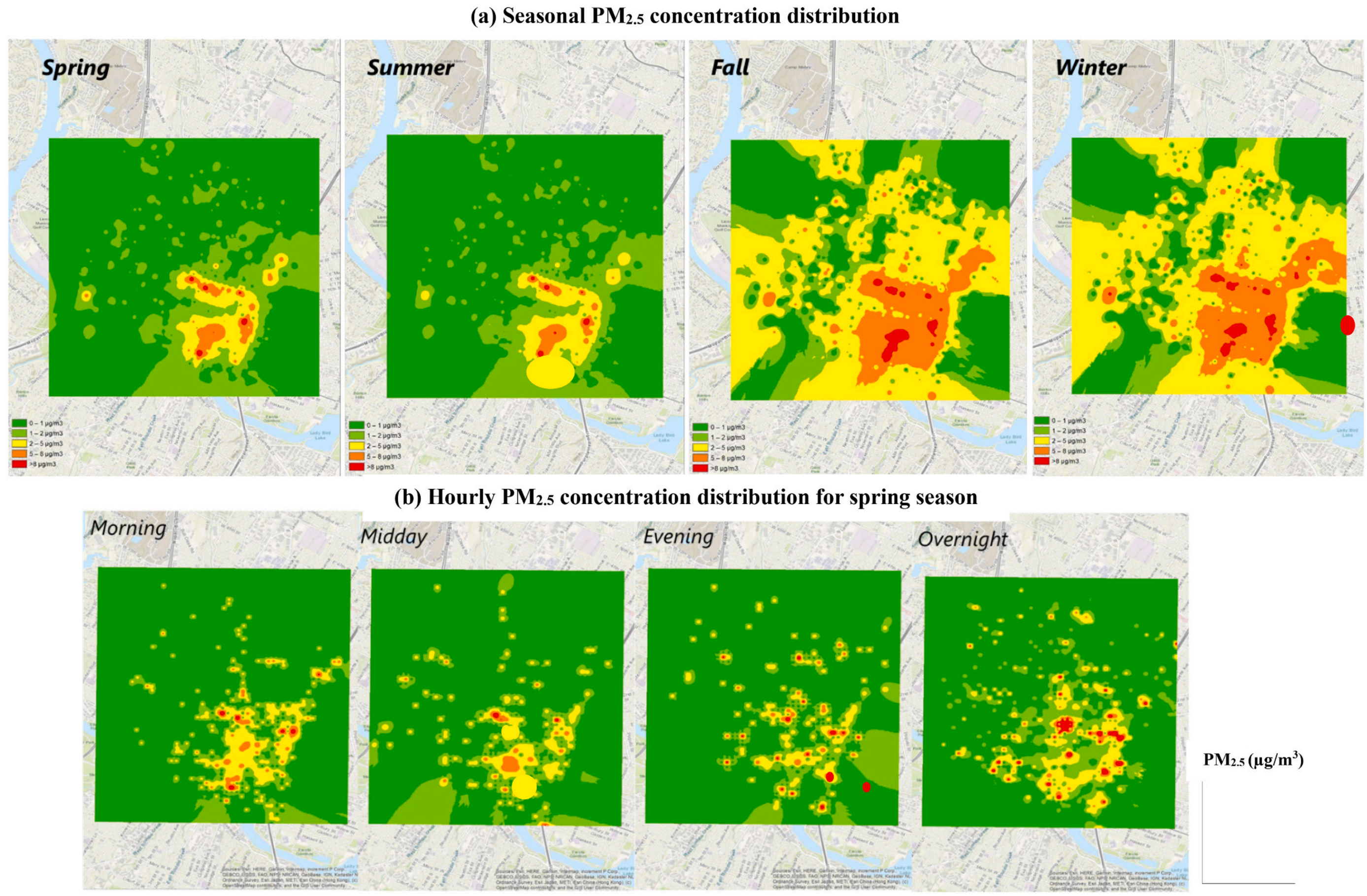


Fig. 7. $PM_{2.5}$ concentration heat map.

Fig. 7a shows the spatial distribution of $PM_{2.5}$ concentrations across the four seasons based on travel network and corresponding traffic activities in the case study region. Higher concentrations were observed during the late fall and winter seasons compared to lower concentrations during summer due to a combination of traffic activities and atmospheric conditions. Fig. 7b shows the hourly concentration distribution for the spring season (for which exposure assessment was conducted). Hourly distribution highlights higher concentrations during overnight and early morning periods compared to lower concentrations during midday hours due to stable atmospheric conditions.

The overall concentration was found to range between 0.45 and 34.16 μg/m^3. The highest emitting links were the ones with the highest traffic volume and concentration was observed to gradually decrease with distance from the roadways. In terms of seasonal variation, higher concentrations were observed during the winter season and the lowest during summer due to stable atmospheric conditions, and less sunlight leading to reduced mixing and higher concentration during the late fall and winter seasons. A similar trend was observed with higher concentrations observed during overnight and early morning periods.

Exposure levels experienced during each e-scooter trip were calculated based on time-weighted concentrations for each split segment of the trip trajectory. To match the spatial resolution of concentrations estimated at the census block, the e-scooter trip trajectories were split into different segments defined by the boundaries of the census blocks. Exposure for each trajectory split was obtained by weighing the pollutant concentration at the split location with the corresponding time spent at that location. This was done because the concentration levels vary based on the location and amount of time spent in that location. The process was repeated for all trips within the case study region for the period of analysis. Total exposure for a given trip was obtained by combining all split trajectories of the trip.

Due to the huge number of trip trajectories over the analysis period, exposure assessment was conducted only for Spring 2018. The overall exposure levels (Fig. 8) were categorized by different periods for the spring season. The temporal variations in the exposure levels were found to follow the temporal variations in the concentration distribution with higher exposures observed during morning and evening periods. However, it was interesting to note the opposite effect for midday (lower concentration but higher exposure due to higher number of trips) and overnight (higher concentration but lower exposure due to reduced trips) periods. Compared to the concentration distribution maps, exposure maps were more focused with higher exposure levels observed near roadway links with high traffic volumes and high e-scooter trips. These links correspond to the Central Austin area that contains the University of Texas campus, Hyde Park, Anderson, North Loop, Brentwood, and Allandale neighborhoods that house several shopping, restaurants, bars, and live music avenues. This highlights the importance of incorporating the location information of people in calculating their exposure rather than basing it on only concentration levels.

4. Summary and conclusions

The fourth generation of dockless mobility is competing to solve the long-standing first-last mile issue in populated urban areas. The availability of high-resolution dockless mobility datasets provides the opportunity to analyze millions of data records to evaluate the temporal and spatial variations of trips as well as to understand the TRAP exposure experienced by e-scooter users as they drive close to heavily trafficked roadways. A total of 4.1 million e-scooter trip data was extracted from the City of Austin dockless bike-share program and after removing the missing and invalid data records, the resulting dataset consisted of 3.4 million data records. Based on the data analyzed, 56% of the entire

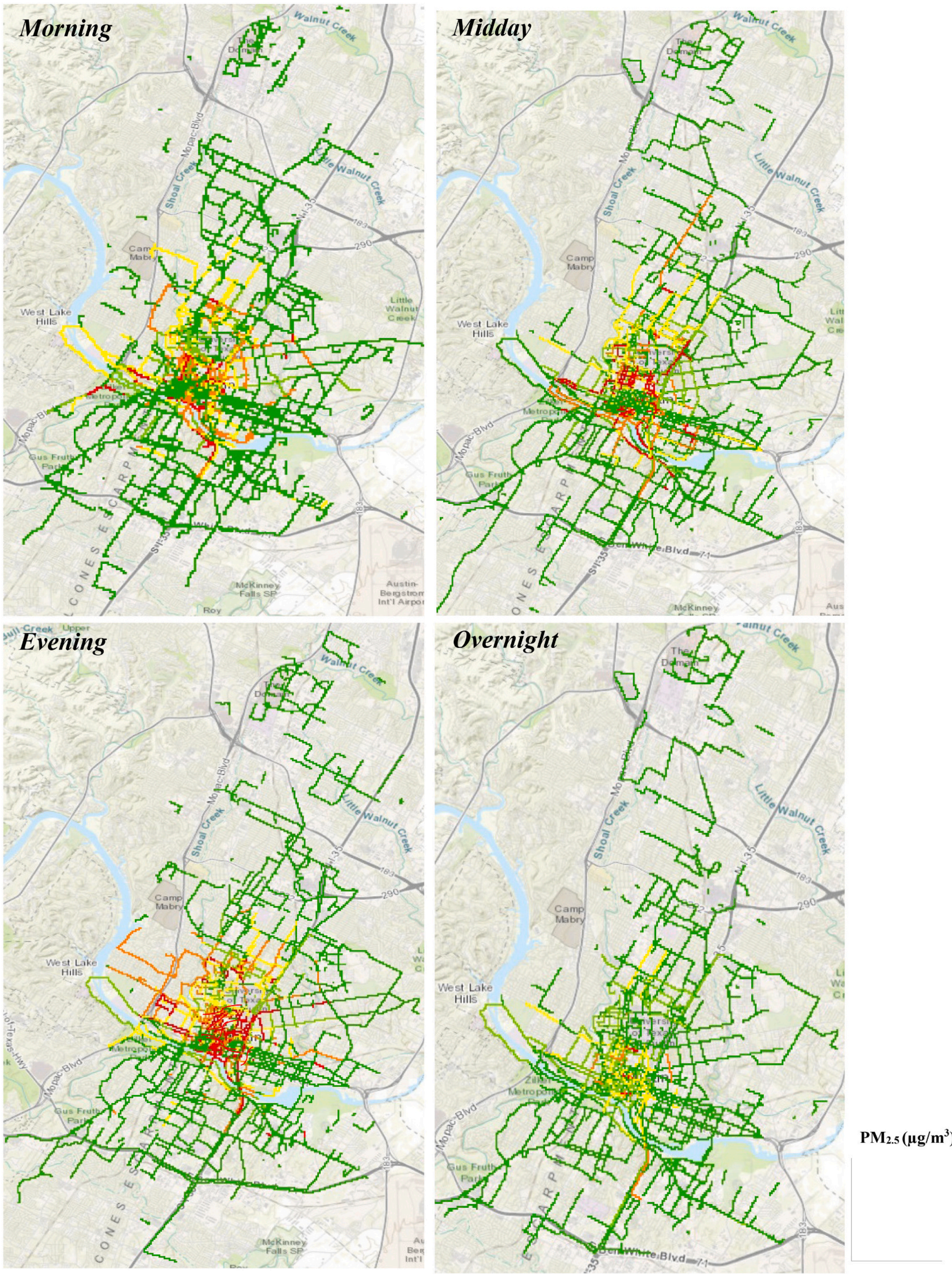


Fig. 8. Temporal and spatial distribution of $PM_{2.5}$ exposure levels for the spring season.
(Fig. 8 exhibits the temporal and spatial distribution of $PM_{2.5}$ exposure levels experienced by e-scooter users in the case study region during the spring season. The distribution highlights higher exposure during midday and evening periods due to a combination of e-scooter trips, traffic activities, and meteorological conditions).

scooter trips occurred during a period of 9 months (April to December) in 2018 and 44% occurred for three months (January to March) of 2019. This was attributed to the higher utilization rate (136% increase) of the e-scooters in the second year of introducing the e-scooter bike-share program in the City of Austin.

The hourly variation of e-scooter trips shows the minimum trip count in the early morning (5:00–7:00 am) followed by the peaking of trips from 12 pm to 7 pm. The hourly variation of scooter trips was found not to follow the expected bimodal peaking (morning and evening periods) typically exhibited in urban traffic. A comparison of the scooter trip count data between weekdays and weekends shows a 23% more tendency to use e-scooters over the weekends. These findings were found to be comparable with findings obtained from a synthesis of the literature on the geospatial analysis presented by Foissaud et al., 2022 that found the peak usage to be during weekends and holidays during midday and evening periods. These results highlighted the fact that the e-scooters although sought to solve the first-last mile issue was being used predominantly for other trips. These findings are in line with other studies (McKenzie, 2019) that found e-scooters to be predominantly used for errands, or recreational purposes rather than connecting to transit stops from home or work.

Survey results ranked the trip length, connectivity to transit, congestion and parking issues, and pollution reduction as high factors that influenced the use of e-scooters. The survey found that e-scooters predominantly replace the personal vehicle (37%), walking or biking (33%), carsharing or ridesharing (10%), and the remaining 20% would have not made the trip. It was interesting to note that while the usage of personal vehicles and shared ridership reduced, transit usage remained the same despite having a new mode to help people connect to transit stops. The findings also highlight that although e-scooters reduce vehicle use, they also could have a negative impact on overall public health by replacing active modes such as walking or biking (Bishop et al., 2011; de Bortoli and Christoforou, 2020).

An exposure assessment was conducted for a sample of e-scooter trips that occurred in Spring 2018. The exposure assessment was conducted through an integrated modeling approach combining the e-scooter trip routes, traffic emissions, meteorology, and pollutant dispersion. The dispersion model estimated increased $PM_{2.5}$ concentration in the fall and winter seasons during overnight and early morning periods due to reduced mixing and pollutant dispersion. The dynamic exposure levels were obtained by estimating the time-weighted concentration computed for different split segments of the trip trajectory. Compared to the concentration estimates, exposure levels were different due to the route taken, and the time spent in different locations. The exposure levels obtained were found to follow the temporal distribution pattern of e-scooter usage and concentration levels with high exposure levels observed during midday (attributed to high trips), and evening (attributed to both high trips and concentration levels) periods.

Limitations of the study include not evaluating the relationship between the dockless trips and other points of interest (such as restaurants, shopping, etc.). The study was based on data collected during the early stages of introducing the dockless e-scooters in the City of Austin, and before the COVID-19 pandemic that might have altered the usage patterns. The AERMOD model used is a steady-state model that is capable of modeling only the dispersion of primary pollutants and not the secondary pollutant formation or long-range transport of pollutants. The study only evaluated the exposure from traffic emissions and not the difference in emissions due to reduction in personal vehicle travel or shared ridership. The study also does not include the environmental impacts from manufacturing, electricity used to power the e-scooter, and disposal. To get a holistic picture of the environmental impacts of e-scooters, a complete wheel-to-well analysis incorporating the different aspects of e-scooters from the manufacturing of the scooters, power usage and impact on the electric grid, disposal or recycling, mode shift, and difference in emissions from other modes caused due to e-scooters is required.

This is one of the early studies that focus on the topic of the intersection between transport geography, environment, and health in an emerging mode of shared mobility. The results help in understanding the travel patterns of e-scooters, and their influence on the exposure levels experienced by the users. According to the survey and modeling results, e-scooter trips mostly replace walking for trips connecting to the transit stop, and personal vehicle for trips to and from home and work. By replacing walking, e-scooters could lead to a sedentary lifestyle leading to adverse health impacts including heart diseases, and diabetes. Alternatively, e-scooters reduce personal vehicle and shared ridership, however, the users are exposed to high levels of TRAP considering their peak usage during midday and evening periods due to the nature of the trips that they are replacing. In summary, based on the study findings, it seems like e-scooters may not be a sustainable means of transport because they are not used as a commute or last-mile solution, they replace trips that would otherwise have been made using active modes, and are exposed to direct vehicular exhaust as they are used for home-to-work trips. Local policymakers could develop policies that limit e-scooter usage during certain periods (off-peak periods when traffic volumes are lower) and restrict e-scooter access to roadways away from heavily trafficked roadways. Other incentives could include subsidizing transit costs for people using active modes or e-scooters to get to the transit stations.

Author contributions

The authors confirm contribution to the paper as follows: study conception and design: Vallamsundar, Jaikumar, and Venugopal; data collection: Jaikumar, Venugopal; analysis and interpretation of results: Jaikumar, and Vallamsundar; draft manuscript preparation: Vallamsundar. All authors reviewed the results and approved the final version of the manuscript.

Funding

Study was funded by the Center for Advancing Research in Transportation Emissions, Energy and Health, Grant Number: 69A3551747128.

Data availability

Data will be made available on request.

References

Adar, S.D., Kaufman, J.D., 2007. Cardiovascular disease and air pollutants: evaluating and improving epidemiological data implicating traffic exposure. Inhal. Toxicol. 19, 135–149. https://doi.org/10.1080/08958370701496012.

Askariyeh, M.H., Vallamsundar, S., Farzaneh, R., 2018. Investigating the impact of meteorological conditions on near-road pollutant dispersion between daytime and nighttime periods. Transp. Res. Rec. J. Transp. Res. Board 2672 (25), 99–110. https://doi.org/10.1177/0361198118796966.

Austin, 2022. Austin and Council District Demographics Dashboard. Accessed at. https://www.austintexas.gov/department/demographics.

Bai, S., Jiao, J., 2020. Dockless E-scooter usage patterns and urban built environments: a comparison study of Austin, TX, and Minneapolis, MN. Travel Behav. Soc. 20, 264–272. https://doi.org/10.1016/j.tbs.2020.04.005.

Bishop, J.D., Doucette, R.T., Robinson, D., Mills, B., McCulloch, M.D., 2011. Investigating the technical, economic and environmental performance of electric vehicles in the real-world: a case study using electric scooters. J. Power Sources 196 (23), 10094–10104.

Boriboonsomsin, K., Luo, J., Org, E., 2017. UC Davis Research Reports Title Biking in Fresh Air: Consideration of Exposure to Traffic-Related Air Pollution in Bicycle Route Planning. Accessed in April 2018 at. https://escholarship.org/uc/item/6qs7m1n0.

Chester, M., 2019. It is a Bird..It is a Lime..It is Dockless Scooters! But Can These Electric-Powered Mobility Options Be Considered Sustainable Using Life-Cycle Analysis? Accessed at. https://chesterenergyandpolicy.com/2019/01/28/its-abird-its-a-lime-its-dockless-scooters-but-can-these-electricpowered-mobility-options-be-considered-sustainable-usinglife-cycle-analysis/.

City of Austin (COA), 2018. Shared Micromobility. Accessed in January 2018 at. https://data.austintexas.gov/Transportation-and-Mobility/Shared-Micromobility-Vehicle-Trips/7d8e-dm7r.

de Bortoli, A., Christoforou, Z., 2020. Consequential LCA for territorial and multimodal transportation policies: method and application to the free-floating e-scooter disruption in Paris. J. Clean. Prod. 273 (10), 122898 https://doi.org/10.1016/j.jclepro.2020.122898.

De Hartog, J.J., Boogaard, H., Nijlan, D.H., Hoek, G., 2010. Do the health benefits of cycling outweigh the risks? Environ. Health Perspect. 118 (8), 1109–1116. https://doi.org/10.1289/ehp.0901747.

Duan, N., 1991. Stochastic microenvironment models for air pollution exposure. J. Expo. Anal. Environ. Epidemiol. 1 (2), 235–257. https://europepmc.org/article/med/1824318.

Environmental Protection Agency (EPA), 2004. Report on User's Guide for the AMS/EPA Regulatory Model – AERMOD. EPA-454-B-03-001.. Office of Air Quality Planning and Standards.

Environmental Protection Agency (EPA), 2021. Overview of EPA's MOtor Vehicle Emission Simulator (MOVES3). EPA-420-R-21-004. Office of Air Quality Planning and Standards.

Foissaud, N., Gioldasis, C., Tamura, S., Christoforou, Z., Farhi, N., 2022. Free-floating e-scooter usage in urban areas: a spatiotemporal analysis. J. Transp. Geogr. 100, 103335.

Hatzopoulou, M., Weichenthal, S., Dugum, H., Pickett, G., Miranda-Moreno, L., Kulka, R., Andersen, R., Goldberg, M., 2013. The impact of traffic volume, composition, and road geometry on personal air pollution exposures among cyclists in Montreal, Canada. J. Expos. Sci. Environ. Epidemiol. 23 (1), 46–51. https://doi.org/10.1038/jes.2012.85.

Health Effects Institute (HEI), 2010. Special Report 17. Traffic-Related Air Pollution: A Critical Review of the Literature on Emissions, Exposure, and Health Effects.

Accessed in May 2019 at. https://www.healtheffects.org/publication/traffic-related-air-pollution-critical-review-literature-emissions-exposure-and-health.
Hollingsworth, J., Copeland, B., Johnson, J.X., 2019. Are e-scooters polluters? The environmental impacts of shared dockless electric scooters. Environ. Res. Lett. 14 (8), 084031 https://doi.org/10.1088/1748-9326/ab2da8.
Lefebvre, W., Degrawe, B., Beckx, C., Vanhulsel, M., Kochan, B., Bellemans, T., Janssens, D., Wets, G., Janssen, S., de Vlieger, I., Int Panis, L., Dhondt, S., 2013. Presentation and evaluation of an integrated model chain to respond to traffic- and health-related policy questions. Environ. Model. Softw. 40, 160–170. https://doi.org/10.1016/j.envsoft.2012.09.003.
McKenzie, G., 2019. Spatiotemporal comparative analysis of scooter-share and bike-share usage patterns in Washington, D.C. J. Transp. Geogr. 78, 19–28. https://doi.org/10.1016/j.jtrangeo.2019.05.007.
Mukherjee, A., Agrawal, M., 2017. World air particulate matter: Sources, distribution and health effects. Environ. Chem. Lett. 15 (2), 283–309. Springer Verlag. https://doi.org/10.1007/s10311-017-0611-9.
National Association of City Transportation Officials (NACTO), 2019. Shared Micromobility in the U.S. Accessed in September 2018 at. https://nacto.org/shared-micromobility-2018/.
Noland, Robert B., 2019. Trip Patterns and Revenue of Shared E-Scooters in Louisville. Transport Findings, Kentucky. https://doi.org/10.32866/7747.
Orr, B., MacArthur, J., Dill, J., 2019. The Portland E-Scooter Experience. TREC Friday Seminar Series.
Ott, W.R., 1982. Concepts of human exposure to air pollution. Environ. Int. 7 (3), 179–196. https://doi.org/10.1016/0160-4120(82)90104-0.
Portland Bureau of Transportation, 2018. 2018 E-Scooter Pilot User Survey Results. Accessed at. https://www.portlandoregon.gov/transportation/article/700916.
Shaheen, S.A., Guzman, S., Zhang, H., 2010. Bikesharing in Europe, the Americas, and Asia. Transp. Res. Rec. J. Transp. Res. Board 2143 (1), 159–167. https://doi.org/10.3141/2143-20.
Texas Commission on Environmental Quality, 2015. 2014 On-Road Mobile Source Annual, Summer Weekday and Winter Workday Emissions Inventories. Texas Commission on Environmental Quality, Austin, TX, USA.
Vallamsundar, S., Lin, J., Konduri, K., Zhou, X., Pendyala, R.M., 2016. A comprehensive modeling framework for transportation-induced population exposure assessment. Transp. Res. Part D: Transp. Environ. 46, 94–113. https://doi.org/10.1016/j.trd.2016.03.009.
Virgina Polytechnical Institute and State University, 2018. D.C. Dockless Bikeshare: A First Look. Accessed in June 2019 at. https://ralphbu.files.wordpress.com/2018/05/dc-dockless-bikeshare_a-first-look_may_10_2018_publication.pdf.
Wilhelm, M., Ritz, B., 2003. Residential proximity to traffic and adverse birth outcomes in Los Angeles County, California, 1994-1996. Environ. Health Perspect. 111 (2), 207–216. https://doi.org/10.1289/ehp.5688.
World Health Organization (WHO), 2003. Health Aspects of Air Pollution with Particulate Matter, Ozone and Nitrogen Dioxide. Assessed in 2012 at. https://www.euro.who.int/__data/assets/pdf_file/0005/112199/E79097.pdf.
Xu, Y., Chen, D., Zhang, X., Tu, W., Chen, Y., Shen, Y., Ratti, C., 2019. Unravel the landscape and pulses of cycling activities from a dockless bike-sharing system. Comput. Environ. Urban. Syst. 75, 184–203. https://doi.org/10.1016/j.compenvurbsys.2019.02.002.
Yang, Y., Heppenstall, A., Turner, A., Comber, A., 2019. A spatiotemporal and graph-based analysis of dockless bike sharing patterns to understand urban flows over the last mile. Comput. Environ. Urban. Syst. 77, 101361 https://doi.org/10.1016/j.compenvurbsys.2019.101361.

Further readings

ArcGIS. Dijkstra's algorithms used by the ArcGIS Network Analyst extension. Accessed at https://desktop.arcgis.com/en/arcmap/latest/extensions/network-analyst/algorithms-used-by-network-analyst.htm.
Capital Area Metropolitan Planning Organization (CAMPO). Regional Travel Demand Model. Accessed at https://www.campotexas.org/regional-transportation-plans/2045-plan/transportation-demand-management-plan/.
National Oceanic and Atmospheric Administration (NOAA). Accessed at https://ruc.noaa.gov/raobs/ for upper air data and ftp://ftp.ncdc.noaa.gov/pub/data/noaa/ for surface data.