ENVIRONMENTAL IMPACTS OF E-SCOOTERS: A CASE STUDY IN THE CITY OF AUSTIN

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16. Abstract

The fourth generation of dockless mobility, which includes dockless bikes and scooters, has been the biggest disruptive force in the bikeshare industry for solving the first-last mile issue of connecting people to/from transit and work or home. High adoption levels combined with little to no regulation regarding usage has raised major concerns for these bikeshare users traveling alongside motorized vehicles. In addition to safety concerns, exposure to traffic-related air pollution (TRAP) is an important factor because these users are directly exposed to vehicular exhaust and have an increased breathing rate while riding, making them more vulnerable to harmful air pollution. Vehicles emit complex mixtures of pollutants that contribute to respiratory and cardiovascular health effects. These health effects are exacerbated for bikeshare users when commuting next to major arterials because they are exposed for longer periods of time (travel times are longer for bikeshare users than vehicle commuters), and pollutant concentrations tend to peak near roadways. Because these modes are utilized to solve the first-last mile issue, they are often rented during morning and evening peak traffic conditions, further increasing user exposure levels. Thus, the routes taken by users and the time of their commute play a major role in evaluating user exposure to traffic emissions. This study aimed to answer key research questions related to the travel behavior patterns and exposure to TRAP for a sample of e-scooter users in the city of Austin. Travel behavior patterns were evaluated through a geospatial analysis of 3.4 million records of dockless trip data collected in 2018 and a brief survey launched in collaboration with the City of Austin. The analysis highlighted two hot spots—the downtown area and the University of Texas-Austin campus located within city limits—and a peak usage period of 12–7 p.m. The survey found that the majority of e-scooter users were White males with an undergraduate degree and full-time employment. Trip length and connection to a transit stop were the key factors influencing the use of e-scooters. E-scooter user exposure to TRAP was obtained by integrating the spatial-temporal dynamics of pollutant concentrations with the real-time commuting patterns of e-scooter users. A chain of modeling components involving the estimation of traffic activities, emissions, meteorology, and pollutant dispersion was used to model the pollutant concentrations. The dynamic emission exposure maps highlighted the key hot-spot routes closer to major highways in the downtown area and during midday and evening peak periods.

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Executive Summary

Dockless mobility has been the biggest disruptive force in the shared mobility industry, solving the first-last mile issue. With high adoption levels combined with little to no regulation regarding usage, dockless bike and scooter users have been traveling alongside motorized vehicles, exposing them to major concerns. Specifically, users are exposed to high levels of traffic-related air pollution (TRAP) due to their direct exposure to vehicle exhaust. With a focus on e-scooter use, this study aimed 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 and the existing vehicle traffic, and the resulting air pollution and exposure.

The availability of high-resolution dockless mobility datasets provided the opportunity to analyze millions of data records to evaluate the temporal and spatial variations of e-scooter trips as well as to understand the TRAP exposure experienced by e-scooter users as they travel along heavily trafficked roadways. Data for 4.1 million e-scooter trips was extracted from the City of Austin dockless bikeshare program. After removing any missing and invalid data records, the resulting dataset consisted of 3.4 million trips. Based on the data analyzed, 56 percent of all scooter trips occurred during a nine-month period from April to December 2018, and 44 percent occurred during a three-month period from January to March 2019. This increase in usage was attributed to the higher e-scooter utilization rate (136 percent increase) in the second year after introducing the e-scooter bikeshare program in the city of Austin.

The hourly variation of e-scooter trips showed the minimum trip count in the early morning (from 5:00 a.m. to 7:00 a.m.) followed by the peak trip count from 12 p.m. to 7 p.m. The hourly variation of e-scooter trips did not follow the expected bimodal peaking pattern (morning and evening periods) typically exhibited in urban traffic. A comparison of the e-scooter trip count data between weekdays and weekends showed a 23 percent higher tendency to use e-scooters over the weekends. These results highlighted the fact that the e-scooters—although intended to solve the first-last mile issue—were being used predominantly for other trips. These findings are in line with other studies that found that e-scooters were predominantly used for errands or recreational purposes rather than connecting to transit stops from home or work.

Survey results indicated that trip length, connectivity to transit, and congestion and parking issues ranked highest as factors influencing the use of e-scooters. The survey found that e-scooters were predominantly used to replace personal vehicles (37 percent), walking or biking (33 percent), and carsharing or ridesharing (10 percent); the remaining 20 percent of respondents would have not made the trip. It was interesting to note that while the usage of personal vehicles and shared ridership decreased, transit usage remained the same despite this new mode's potential to help people connect to transit stops. Although e-scooters reduced vehicle use by about 47 percent, these findings suggested that they could also have a negative impact on overall public health by replacing active modes such as walking or biking.

Spatial analysis of the e-scooter data identified the University of Texas campus and downtown Austin as areas of peak usage. Accordingly, the exposure assessment was conducted for a sample of e-scooter trips that occurred in spring 2018 in these areas. The exposure assessment was conducted through an integrated modeling approach combining e-scooter trip route, traffic emission, meteorological, and pollutant dispersion data. The dispersion model estimated increased fine particulate matter ($PM_{2.5}$) concentrations 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 concentrations computed for different split segments of the trip trajectory. Compared to the concentration estimates, exposure levels varied due to the route taken and the time spent in different locations. The exposure levels 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 trip counts) and evening (attributed to both high trip counts and concentration levels) periods.

This effort reflects one of the earliest studies focused on the intersection between transport geography, environment, and health for 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. Based on the combined modeling and survey findings, e-scooters may not be a sustainable means of transport because they are not being used for commuting or as a first-last mile solution. Although they reduce personal vehicle use, e-scooter users are exposed to high levels of TRAP, and they replace trips that would otherwise have been made using active modes such as walking and biking. In addition, these results combined with previous findings in literature suggested that unless there are efficient charging and recycling strategies, e-scooters may lead to overall higher lifecycle emissions. One limitation of this study included not evaluating the relationship between the dockless trips and other points of interest, such as restaurants, shopping, etc. In addition, this 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 may have altered the usage patterns. The American Meteorological Society/Environmental Protection Agency Regulatory Model (AERMOD) used in this study is a steady-state model capable of modeling only the dispersion of primary pollutants and not the formation of secondary pollutants or the long-range transport of pollutants. This study only evaluated TRAP exposure from current traffic emissions without accounting for the change in emissions due to the reduction in personal vehicle travel or shared ridership. This study also did not include the environmental impacts from the manufacture, operation (i.e., electricity production used to power the e-scooter), or disposal of e-scooters. To get a holistic picture of the environmental impacts of e-scooters, a complete wheel-to-well analysis incorporating the different aspects of e-scooter use—including the manufacture, power usage and impact on the electric grid, and disposal or recycling of e-scooters, as well as their effect on mode shift and emissions—is required.

Acknowledgments

The research team gratefully acknowledges the assistance of the City of Austin Transportation Department especially Jason Redfern, Vo Mary, Dana Hansen, and Tien-Tien Chan, in administering the survey via their newsletters and social media. The authors would like to thank Adam Cohen from the University of California-Berkeley for his feedback on the survey questions and Marcia Walker and Michelle Canton from the Texas A&M Transportation Institute for their assistance throughout the study.

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Background and Introduction

Bikeshare programs have grown rapidly in the recent decade, both in terms of the number of cities offering them and their technology. Bikeshare technology evolution can be broadly classified into four generations:

1. The first generation consisted of docked bikes placed throughout an area that could be freely accessed by the public.
2. The second generation consisted of coin-deposit systems at self-serving docking stations.
3. The third generation consisted of information technology (IT)-based payment systems that used credit/debit cards to track usage.
4. The current and fourth generation is based on smart mobility, combining dockless systems and cellular and global positioning system technologies.

Smart mobility is a new and revolutionary way of thinking about how we get around with zero emissions, zero ownership, and zero accidents. Datasets related to smart dockless bikeshare mobility are increasingly available and serve as valuable sources to better understand populations' behavior and mobility issues in urban areas (Shaheen et al., 2010). This fourth generation of dockless mobility has been the most prominent disruptive force in the bikeshare industry for solving the first-last mile issue. Dockless bikes and scooters can be rented directly through the user's mobile phone application, allowing the user to travel the city streets at around 15 mph (6.7 m/sec). In 2018, electric scooters (e-scooters) replaced pedal-bikes and e-bikes and became the preferred vehicle for dockless vendors (National Association of City Transportation Officials [NACTO], 2018). According to NACTO, cities such as Austin and Santa Monica were some of the earliest adopters of e-scooter programs; such programs have grown in number, making over 85,000 e-scooters available for public usage throughout the country. Early studies on both docked and dockless bikeshare in the District of Columbia, conducted by the Virginia Polytechnical Institute and State University (Virginia Tech), revealed a more accessible, racially diverse set of riders, a higher proportion of women riders, and a lower household income for dockless riders than docked users (Virginia Polytechnical Institute and State University, 2018). This study also showed that bikesharing was much higher in the afternoon than in the morning, and dockless ridesharing yielded a more geographically dispersed pattern. Li et al. (2019) recently analyzed the operating characteristics of a dockless bikesharing system and its activity pattern near metro stations in Nanjing, China (Li et al., 2019). Their analyses revealed different weekend and weekday patterns with two peaks (morning and evening) on weekdays, consistent with the Virginia Tech study. An analysis of dockless bikesharing in Singapore also revealed two peaks in the hourly number of trips and a lower number of trips during weekdays compared to weekends (Xu et al., 2019). A related analysis of the hourly number of trips using dockless bikesharing in Nanchang, China, also showed two daily peaks and found that dockless bike demand increased with the presence of a public transportation stop (e.g., a metro station) (Yang et al., 2019). Contrary to the findings from Yang et al. (2019), a comprehensive study on the temporal and spatial variation of dockless e-scooters in Washington, D.C., revealed that these e-scooters were used mainly for leisure or recreational purposes in addition to commuting to and from work (McKenzie, 2019). Unlike the findings from Li et al. (2019) and Yang et al. (2019), this study showed that the hourly distribution of e-scooters followed a unimodal peaking pattern (McKenzie, 2019).

Most studies on e-scooters have focused on evaluating their travel behavior, leaving a knowledge gap regarding other aspects of e-scooter use. For example, pollutant exposure levels may be of significant concern because the majority of e-scooter users travel along major highways. Many cities lack bike lanes, so users travel on sidewalks or shared lanes with motorized vehicles, decreasing their safety and increasing their exposure to traffic-related air pollution (TRAP). When operated on the sidewalk, e-scooter users risk running into and injuring pedestrians, especially because there are often no requirements for limiting travel speed (Pyzyk, 2018). Although e-scooters are perceived to be an environmentally friendly alternative compared to other forms of transportation, exposure to TRAP is an essential consideration—e-scooter users are vulnerable to harmful air pollutants due to their direct exposure to vehicular exhaust. Further, due to the lack of regulations, these users are traveling along major arterials with or without designated bike paths, thereby exposing them to high emission levels from motorized vehicles. Vehicles emit complex mixtures of pollutants that are found to contribute to various adverse health effects (Mukherjee & Agrawal, 2017; Health Effects Institute, 2010). These adverse health effects cover a variety of morbidity and diseases including but not limited to premature mortality; cardiovascular, respiratory, and birth and developmental effects; and cancer (Adar & Kaufman, 2007; Pearson et al., 2000; Wilhelm & Ritz, 2003). These health effects are exacerbated for e-scooter users when commuting next to major arterials because they are exposed for longer periods of time (travel times are longer for e-scooter users than vehicle commuters), and pollutant concentrations tend to peak near roadways (de Hartog et al., 2010; Hatzopoulou et al., 2013).

While several studies have evaluated exposure levels for bicyclists and pedestrians (Boriboonsomsin et al., 2017; Dons et al., 2011; Hatzopoulou et al., 2011; Lefebvre et al., 2013), limited studies have evaluating e-scooter users and their exposure levels because e-scooters are new, and their usage patterns are unknown. Studies have found that the overall environmental impact caused by e-scooters was lower than the other forms of transportation that they are replacing (Hollingsworth et al., 2019; Moreau et al., 2020). A study by Hollingsworth et al. (2019), based on a comparative evaluation of lifecycle environmental impacts, found that e-scooters were better than personal vehicles but worse than buses with higher ridership. This study's lifecycle global warming analysis found that the highest environmental impacts originated from the materials and manufacturing of the e-scooters (50 percent), followed by the transport of e-scooters to overnight charging stations (43 percent). These impacts decreased with the use of fuel efficient vehicles and fewer trips to collect e-scooters.

Our study aimed to understand the travel behavior patterns and exposure levels experienced by a sample of e-scooter users based on a predictive exposure modeling system for the city of Austin. The travel behavior patterns were evaluated through a combination of geospatial analysis of 3.4 million e-scooter trips in 2018 and a brief online survey launched in collaboration with the City of Austin. Analysis of these data helped to understand the current usage patterns of e-scooters, as well as locations and time periods of peak usage. The predictive modeling system evaluated exposure levels by integrating traffic activity, emissions, dispersion modeling, and spatial interpolation techniques, with e-scooter trip trajectories based on geographic information systems. An exposure concentration map for fine particulate matter ($PM_{2.5}$) was developed based on a sample of e-scooter routes for different time periods in the spring season. The finding helped to highlight the hot spots for peak exposure and variation in exposure levels during different time periods, depending on usage levels and pollutant dispersion. The modeling system and resultant findings can be used to facilitate the planning of city transportation infrastructure and commuter decision-making regarding route and time choice. Section 2 provides an overview of this study's methods, data collection, and analysis. Section 3 presents the case study results. Study conclusions are presented in Section 4.

Materials and Methods

Study Extent

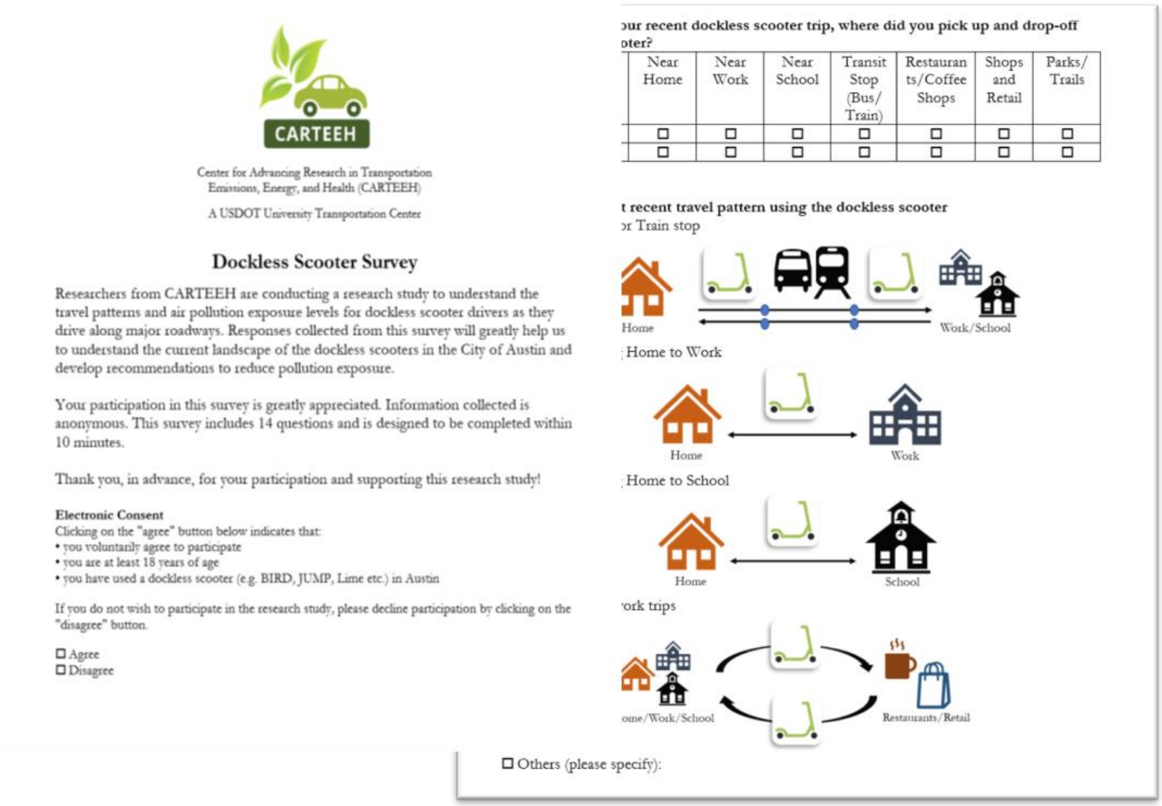
The City of Austin launched a dockless mobility (micromobility) pilot program in early 2018. The Austin Transportation Department expanded the scope of this pilot program to include dockless scooters and e-scooter operators. Based on information obtained from the City of Austin at the time of this study, there were 15,350 scooters and 2,050 bikes available across the Austin area provided by eight operators (Bird, JUMP, Lime, Lyft, OjO, Skip, Spin, and VeoRide). Dockless mobility data (bikes and e-scooters)—providing information about citywide usage, location, and other characteristics of dockless bikes and scooters—were obtained from the City of Austin. The anonymized data included information related to dockless vehicle trips including start and end points of trips, devices used, and distance traveled, as well as monthly summary statistics of the trips made (City of Austin, 2018). Figure 1 shows the key variables included in the dataset. The accessed dataset included 4.1 million records for the dockless mobility system in Austin between March 2018 and early April 2019. The extracted data had a one-minute resolution, and location was identified in terms of geographic coordinates (latitude and longitude). The extracted data were analyzed for missing records and inaccurate information. Records that had invalid latitude or longitude (i.e., associated values were far away from the Austin area, possibly in other states) or had unrealistic trip distances or durations (e.g., 105,219 m or 419,255 sec) were removed. Data were then filtered to include only e-scooter trips with a duration less than 10,000 s and a distance less than 25 km. This process resulted in the removal of 15 percent of the dataset. The final dataset consisted of 3,462,084 records that were analyzed for this study.

Variable Name	Description	Type
ID	A unique ID for each trip. This is an arbitrary sequence and is not derived from any identifier used by the service provider.	Plain Text
Device ID	A unique ID for the device used to complete the trip. This is an arbitrary sequence and is not derived from any identifier used by the service provider.	Plain Text
Vehicle Type	Vehicle type (bicycle or scooter)	Plain Text
Trip Duration	Trip duration, in seconds	Number
Trip Distance	Trip distance, in meters	Number
Start Time	The datetime at which the trip started, in local time (US/Central)	Date & Time
End Time	The datetime at which the trip ended, in local time (US/Central)	Date & Time
Modified Date	The datetime at which the record was last modified (typically the date the data was extracted/loaded from the data provider), in local time (US/Central)	Date & Time
Month	The month # the trip occurred, in local time (US/Central), where 1 = January, etc.	Number
Hour	The hour of the day during which trip occurred, in local time (US/Central).	Number
Day of Week	The day of the week on which the trip occurred, in local time (US/Central), where Sunday = 0, and so on.	Number
Council District	The council district in which the trip started.	Plain Text
Council District	The council district in which the trip ended.	Plain Text
Origin Cell ID	The hexagonal grid cell ID in which the trip started. See dataset description for more	Plain Text
Destination Cell ID	The hexagonal grid cell ID in which the trip ended. See dataset description for more	Plain Text
Year		Number
Start Latitude		Number
Start Longitude		Number
End Latitude		Number
End Longitude		Number

Figure 1. Accessed dockless mobility data structure with 20 variables per trip in Austin.

Survey

A brief online survey designed to understand the usage patterns of e-scooters was launched through social media and newsletters. The survey consisted of 17 questions categorized as: (1) demographic questions related to gender, age, employment, education, and household income; (2) general e-scooter questions related to motivational factors for e-scooter use, use of other modes, and e-scooter use frequency and purpose; and (3) questions regarding their most recent e-scooter trip including pickup/drop-off location, recent travel patterns, time and duration, and use of an alternative mode. The survey was administered through the City of Austin and Center for Advancing Research in Transportation Emissions, Energy, and Health (CARTEEH) newsletters and social media from December 2019 through March 2020. A total of 100 users completed the survey with a response rate of 98 percent. The survey was previously reviewed and approved by the Texas A&M University Institutional Review Board (IRB#: IRB2019-0878). Figure 2 shows a snapshot of the online survey; the full survey questionnaire is included in the Supplemental Material section.


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

our recent dockless scooter trip, where did you pick up and drop-off oter?

	Near Home	Near Work	Near School	Transit Stop (Bus/ Train)	Restaurants/Coffee Shops	Shops and Retail	Parks/ Trails
	☐	☐	☐	☐	☐	☐	☐
	☐	☐	☐	☐	☐	☐	☐

t recent travel pattern using the dockless scooter

or Train stop

Home Work/School

Home to Work

Home Work

Home to School

Home School

ork trips

ome/Work/School Restaurants/Retail

☐ Others (please specify):

Figure 2. Snapshot of the online survey.

Exposure Assessment

Figure 3 shows the modeling framework and key components involved in the exposure assessment. The modeling began with the assembly of base imagery of the case study region. The e-scooter trips made within the case study region were extracted from the City of Austin database. The key data parameters included e-scooter trip start and end locations, distance, and duration. Next, the traffic activities (traffic volume, speed, and vehicle fleet mix) on the major roadways within the case study region were extracted from the regional travel demand model (TDM). The U.S. Environmental Protection Agency's MOtor Vehicle Emissions Simulator (MOVES, version MOVES2014b) was utilized to estimate emissions (U.S. Environmental Protection Agency, 2023a). The MOVES combines site-specific traffic activity data with other local specific information including age distribution, temperature and humidity, fuel supply, and inspection and maintenance parameters. The estimated emissions from the MOVES were then incorporated into an air dispersion model to calculate the pollutant dispersion in the atmosphere based on meteorological and land use parameters.

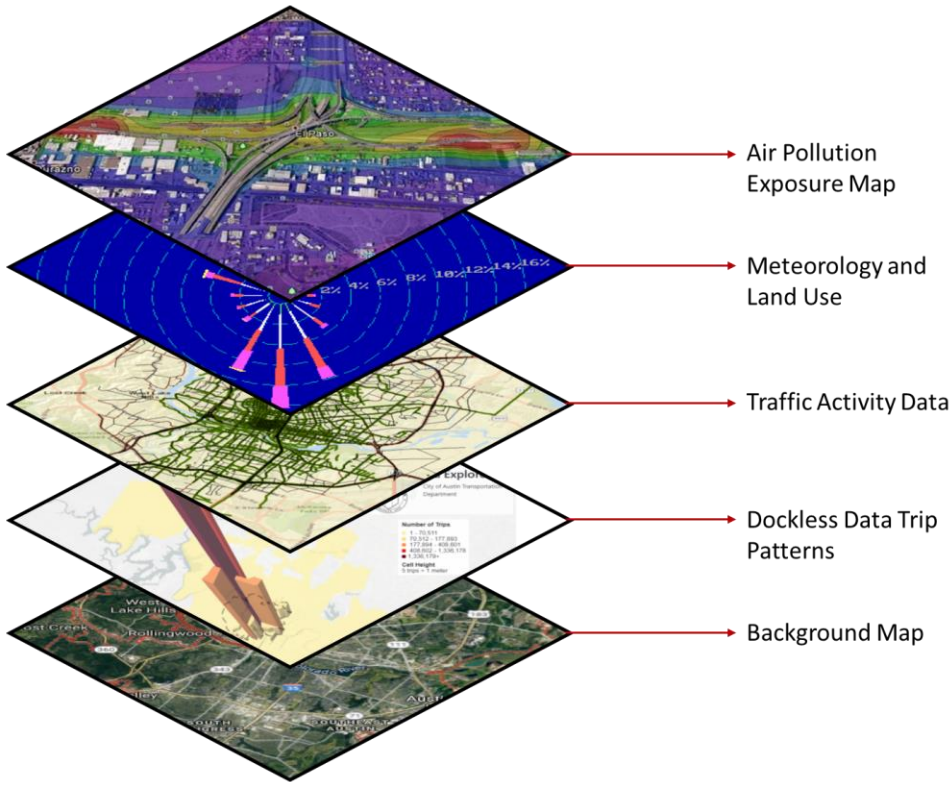


Figure 3. Modeling framework.

The American Meteorological Society/Environmental Protection Agency Regulatory Model (AERMOD) used in this study to simulate air dispersion relied upon the regulatory approved AERMET and AERSURFACE preprocessor models to process the meteorological (MET) and land-use (SURFACE) data, respectively (U.S. Environmental Protection Agency, 2023b). The AERMOD calculates pollutant ($PM_{2.5}$) concentrations from roadway traffic by characterizing the roadway as a series of area sources defined based on the traffic activity, geometry, and area of the roadway link. The AERMOD calculates the resulting $PM_{2.5}$ concentrations at discrete receptor locations placed throughout the modeling domain at hourly averaging periods. A detailed explanation of the different components involved in the modeling framework can be found in Vallamsundar et al. (2016). The resulting spatial and temporal distributions of $PM_{2.5}$ concentration were averaged at the census block level. Next, personal exposure levels experienced by e-scooter users were calculated based on the route taken, time of day, and duration. According to the World Health Organization (1999), personal exposure for an individual at location x, y, z is calculated by determining the concentration the individual is exposed to at that location and time, combined with the amount of time spent in that location. For e-scooter users commuting from location A to location B, personal exposure was calculated by determining the time-weighted concentrations at both locations based on the concentrations and time spent at each location. The total population exposure was obtained by summing the user's exposure levels. Early studies (Duan, 1991; Ott, 1982) mathematically formulated this relationship as follows:

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

where exposure, *E*, is measured as the product of time, *t*, and concentration, *C*, at different locations. Based on this formulation, the e-scooter trip trajectories were split into different segments by the boundaries of the census blocks. Exposure for each split trajectory was calculated by assigning the $PM_{2.5}$ concentration for each census block based on the fraction of time spent in the census block. The total exposure for any given trip was obtained by combining all split trajectories of the trip.

Results and Discussion

Geospatial and Temporal Analysis

Figure 4 shows the spatial distribution of the e-scooter trips. This figure highlights a high density of or high utilization rate for e-scooter trips in the downtown area and near the University of Texas-Austin campus. These hot spots are important because the exposure assessment (described later in the Results and Discussion section) was performed for a sample of e-scooter trips in these areas. The temporal analysis consisted of evaluating the hourly, monthly, and seasonal variations in the e-scooter data from April 2018 to March 2019.

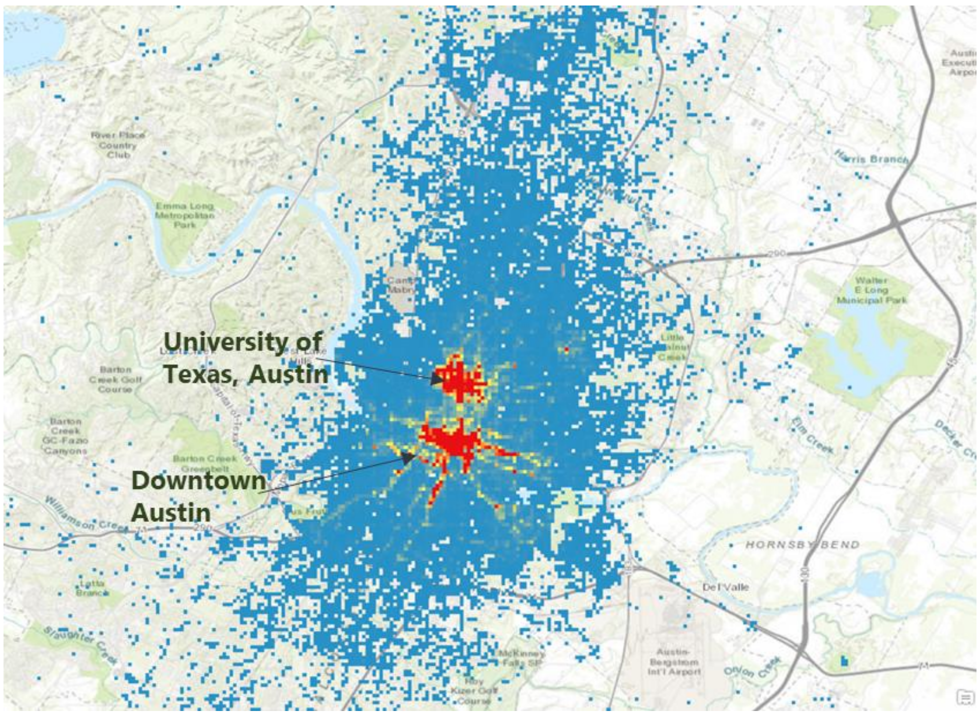
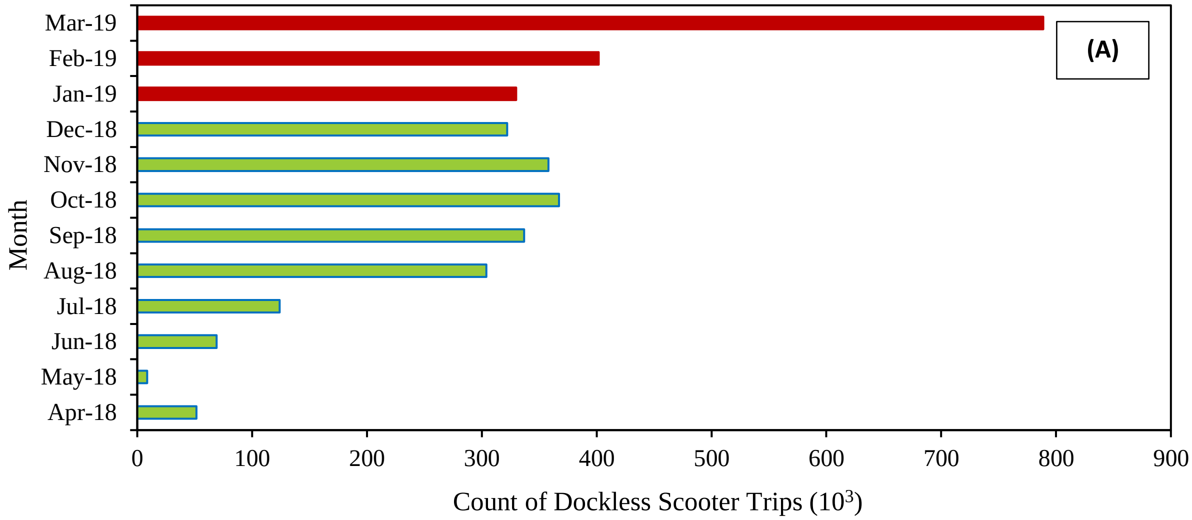


Figure 4. Heat map of e-scooter trip starts.

Figure 5 (Panel A) shows a general increase in trips from August 2018 to March 2019. The slight decrease in scooter trips in December 2018 and January 2019 may be attributed to the holiday season and lower temperatures. The peaking of trips in March 2019 could be attributed to the spring season and events such as the Circuit of The Americas (March 1–3, 2019) the South by Southwest (SXSW) Music, Film, and Interactive Conference and Festival (March 8–17, 2019); and Rodeo Austin (March 16–30, 2019). Figure 5 (Panel B) shows the hourly variations of trip counts for spring (March–May), summer (June–August), fall (September–November), and winter (December–February). A similar trend in the distribution of e-scooter counts was observed for each season, with lower counts observed in the summer. Typically, e-scooter counts were found to increase starting at around 7 a.m., peak from noon to 7 p.m., and decrease at around 10 p.m. The diurnal pattern of the hourly number of e-scooter trips had only one predominant peak for all seasons, which differs from the bimodal (morning and evening) peak demand of the typical urban traffic. This divergence from the typical urban traffic behavior indicated that e-scooters were not being used to only meet first-last mile demands (McKenzie, 2019; Virginia Polytechnical Institute and State University, 2018) but instead were used mostly for other purposes (i.e., errands, directly connecting work to home, and recreational).



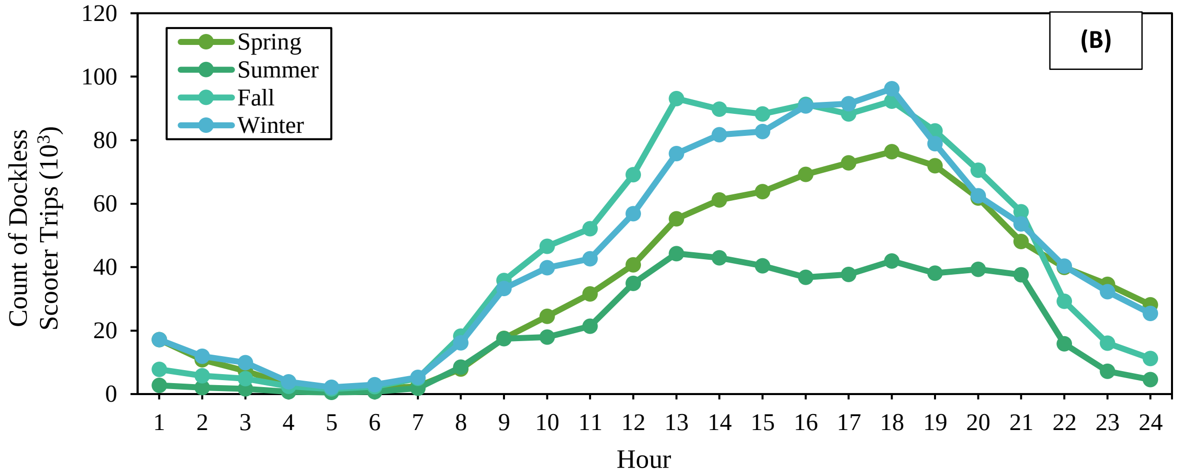


Figure 5. Temporal variations in e-scooter count data.

Figure 6 shows the variations in average e-scooter trip distances and durations over different periods and seasons. The average duration (sec) and distance (m) of e-scooter trips was found to be 687 sec (11.45 min) and 1,495 m (0.93 mi), respectively. Sixty-seven percent of e-scooter trip counts occurred during weekdays and 33 percent occurred during weekends. The proportions of weekdays and weekend days per week (5/7=71 percent weekdays, 2/7=29 percent weekends) were used to normalize these trip count results based on the following factors: 67 percent/71 percent=0.94 for weekdays and 33 percent/29 percent=1.16 for weekends. These results showed a 23 percent higher tendency to use e-scooters over the weekends. The higher trip durations and distances observed during the summer could be attributed to warmer temperatures and summer school breaks.

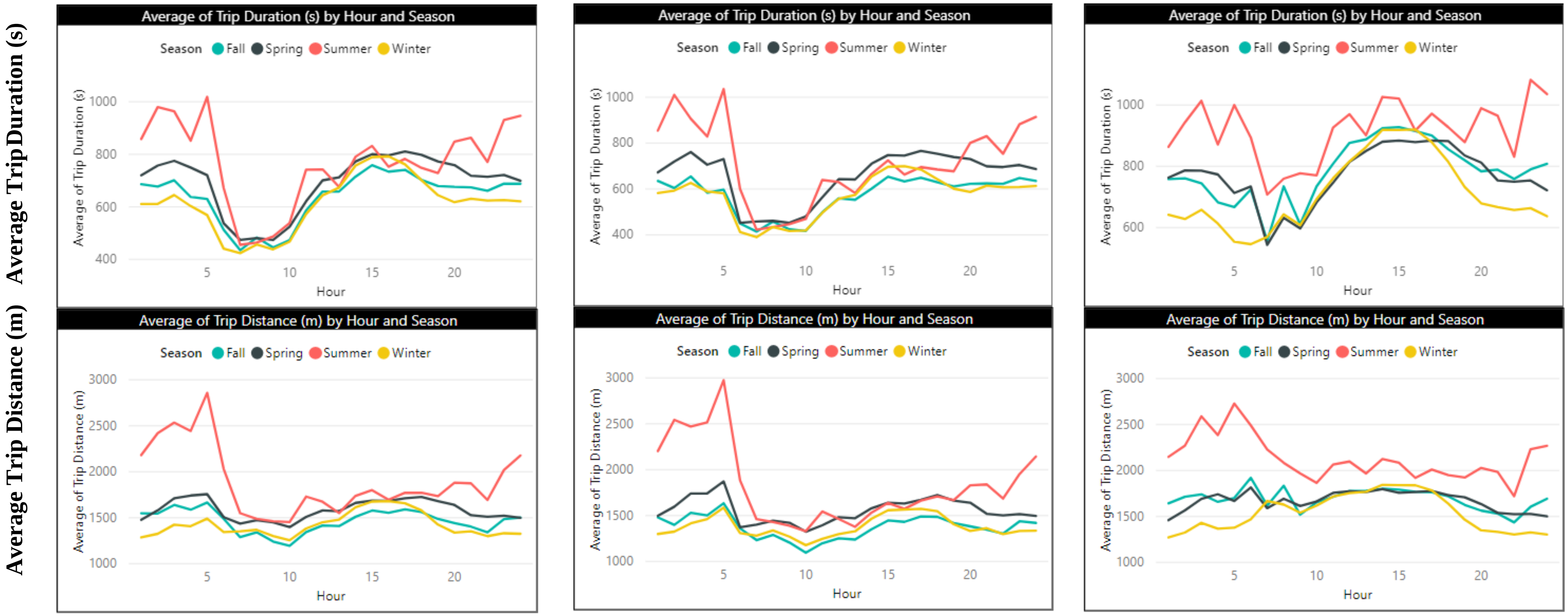


Figure 6. Variations in e-scooter trip distances and durations.

Survey Results

Table 1 summarizes the demographic characteristics of the survey respondents. Predominant survey respondents were male, White or Caucasian, 18–45 years of age, in possession of an undergraduate degree or higher (89 percent), and working full-time (71 percent). Respondents were asked to rank factors that influenced their decision to ride an e-scooter including trip length, connectivity to transit, reduction in air pollution, health concerns, cost, ease of access, congestion and parking issues, and being a scooter enthusiast. The most common factors influencing their use of e-scooters were trip length (50 percent), connectivity to transit (46 percent), and congestion and parking issues (31 percent), as shown in Figure 7. The next question sought to understand the change in usage frequency of other transportation modes—including personal vehicles, walking, personal bikes or scooters, carsharing, ridesharing, and transit—as a result of e-scooter use. Respondents were asked how their e-scooter use affected their use of other modes, on a scale of *much more often* to *much less often*. Figure 8 shows that personal vehicles (50 percent) and ridesharing (53 percent) were used *much less often* and *somewhat less often* due to e-scooter use; transit usage remained the same (49 percent).

Table 1. Demographic Characteristics of Survey Respondents

Demographic Characteristics	Categories	Response Rates
Gender	Male	56%
	Female	44%
Age Group	18–25 years	22%
	26–35 years	27%
	36–45 years	31%
	46–55 years	4%
	>56 years	16%
Race	White or Caucasian	69%
	Black or African American	2%
	Hispanic or Latino	7%
	Asian or Asian American	13%
	Others	9%
Education Level	Less than high school	0%
	High school	11%
	Undergraduate degree	40%
	Master’s degree	33%
	Degree higher than a master’s degree	16%
Employment Status	Student	13%
	Working part-time	7%
	Working full-time	71%
	Retired	9%
Average Household Income	$0–$24,999	6.5%
	$25,000–$49,999	6.5%
	$50,000–$74,999	13%
	$75,000–$99,999	18%
	$100,000–$124,999	16%
	$125,000–$149,999	13%
	$150,000 and up	27%

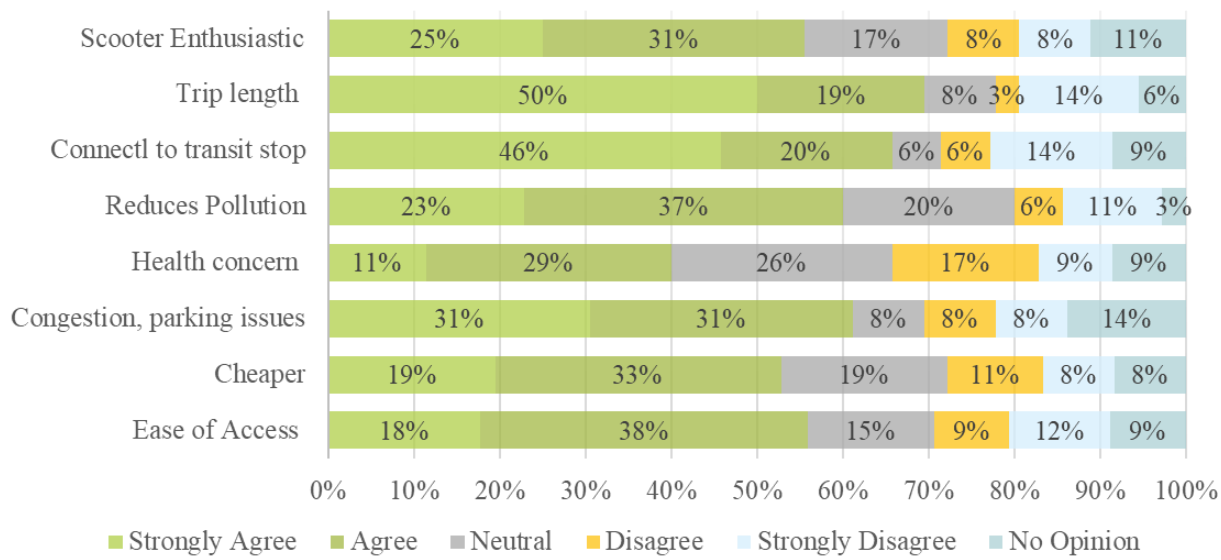


Figure 7. Factors influencing e-scooters use.

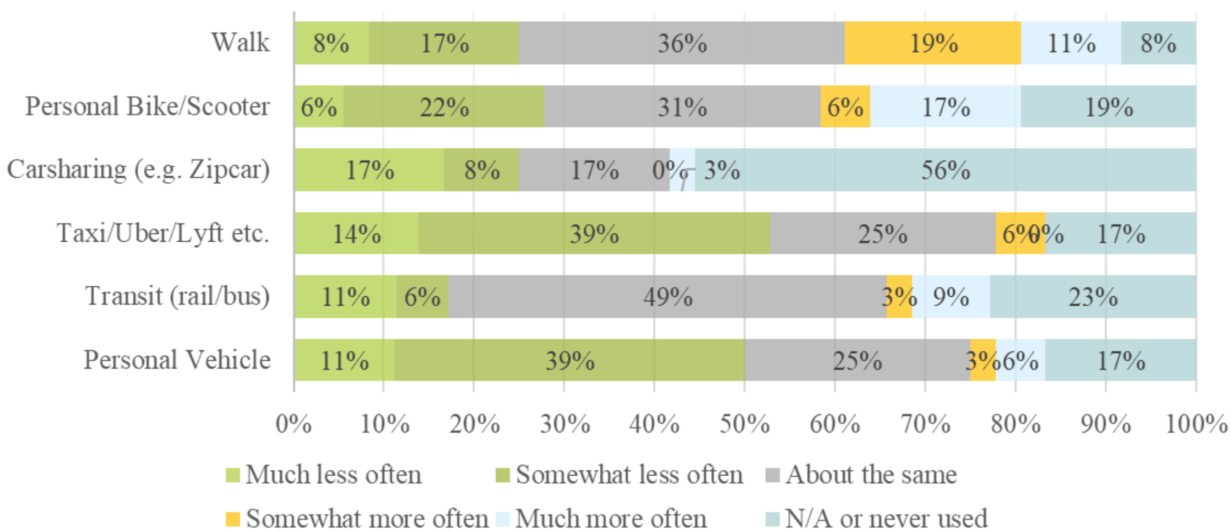


Figure 8. Change in use of other transportation modes due to e-scooter use.

The types of trips made using e-scooters were classified as: (1) trips connecting to a bus/train stop, (2) trips connecting home and work or school, and (3) errands or nonwork trips. Based on the survey responses, 13 percent used an e-scooter to connect to a bus/transit stop, 43 percent used an e-scooter to connect home and work/school, and 44 percent used an e-scooter for errands or nonwork trips. Respondents were asked which alternate mode they would use for these trips if an e-scooter was not available. Figure 9 shows that walking was preferred for trips connecting to a bus/transit stop (33 percent); personal vehicles were preferred for trips connecting home and work/school (43 percent) and errands or nonwork trips (39 percent). Regarding e-scooter pickup/drop-off locations, 45 percent of respondents selected *near home* as the preferred pickup location and 30 percent selected near *restaurants/shops* as the preferred drop-off location. Figure 10 shows the average e-scooter trip distances and durations reported by survey respondents. The predominant average distance and duration was 1–2 mi (47 percent) and 5–20 mins (80 percent), respectively. These survey results were similar to findings obtained from a dockless data analysis performed by the City of Austin. In conclusion, 83 percent of survey respondents found that the use of e-scooters decreased their trip distance and/or their trip time, compared to 17 percent of respondents who found no decrease at all.

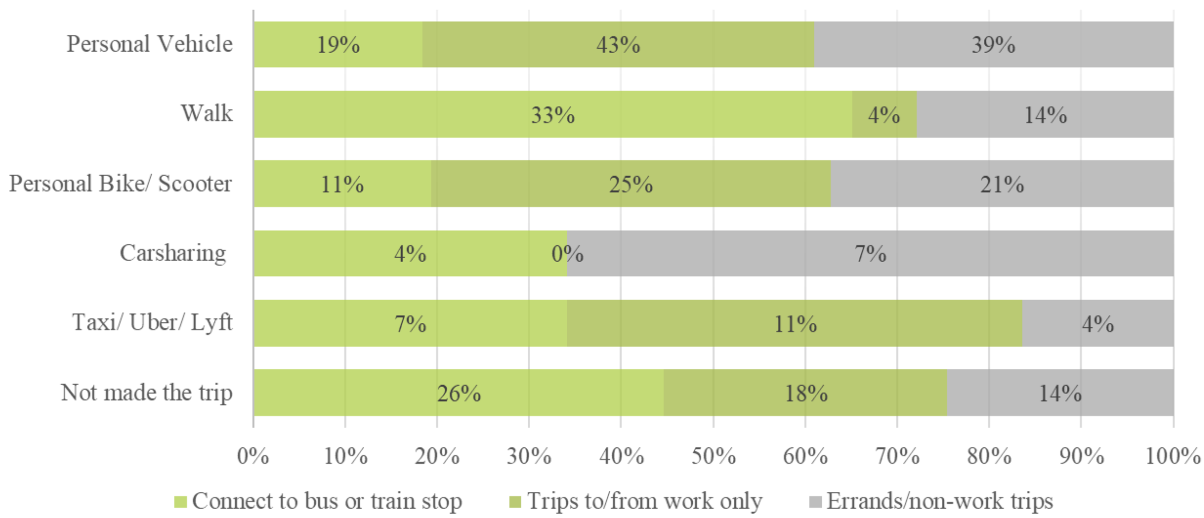


Figure 9. Mode taken if e-scooter option was not available.

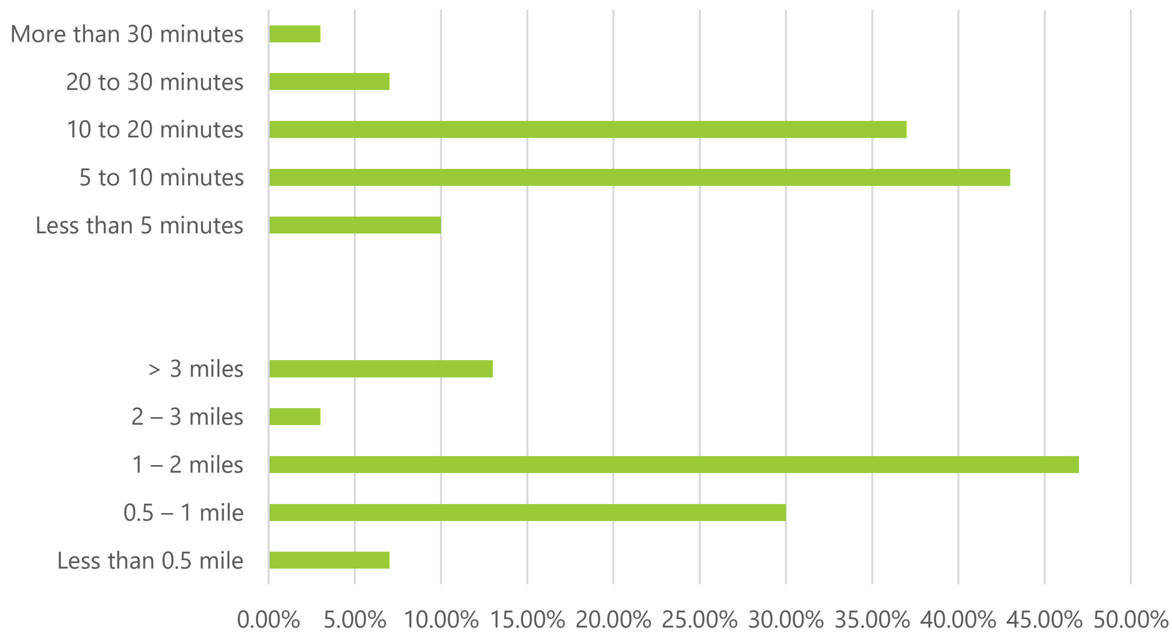


Figure 10. E-scooter trip distances and durations.

Exposure Assessment

Based on the geospatial analysis of the e-scooter trips described previously in the Geospatial and Temporal Analysis section, high-density areas of e-scooter trips in the George and Baker divisions, as shown in Figure 11, were selected for exposure assessments. The case study covered an extent of 3.5 mi by 6 mi, and the e-scooter trip data in these areas accounted for 216,010 trips or 6 percent of the total dockless data obtained from the City of Austin. As a next step, traffic activity data consisting of link-level traffic volumes, speeds, roadway types, and area types corresponding to the case study region were obtained from the Austin Metropolitan Planning Organization's TDM. In addition to traffic activity, other inputs utilized for emission estimation included case study specific vehicle age distributions, temperature and humidity values, fuel supplies, inspection and maintenance parameters, and vehicle fleet mixes for four seasons and four daily time periods (morning peak, evening peak, midday, and overnight) in the spring only. Based on these inputs, the MOVES estimated $PM_{2.5}$ emissions for all emission processes (running exhaust, crankcase running exhaust, and brake and tire wear) at hourly averaging periods for all roadways. The emissions by roadway link, time period, and season produced by the MOVES were incorporated into the air dispersion model (AERMOD) to estimate $PM_{2.5}$ concentrations.

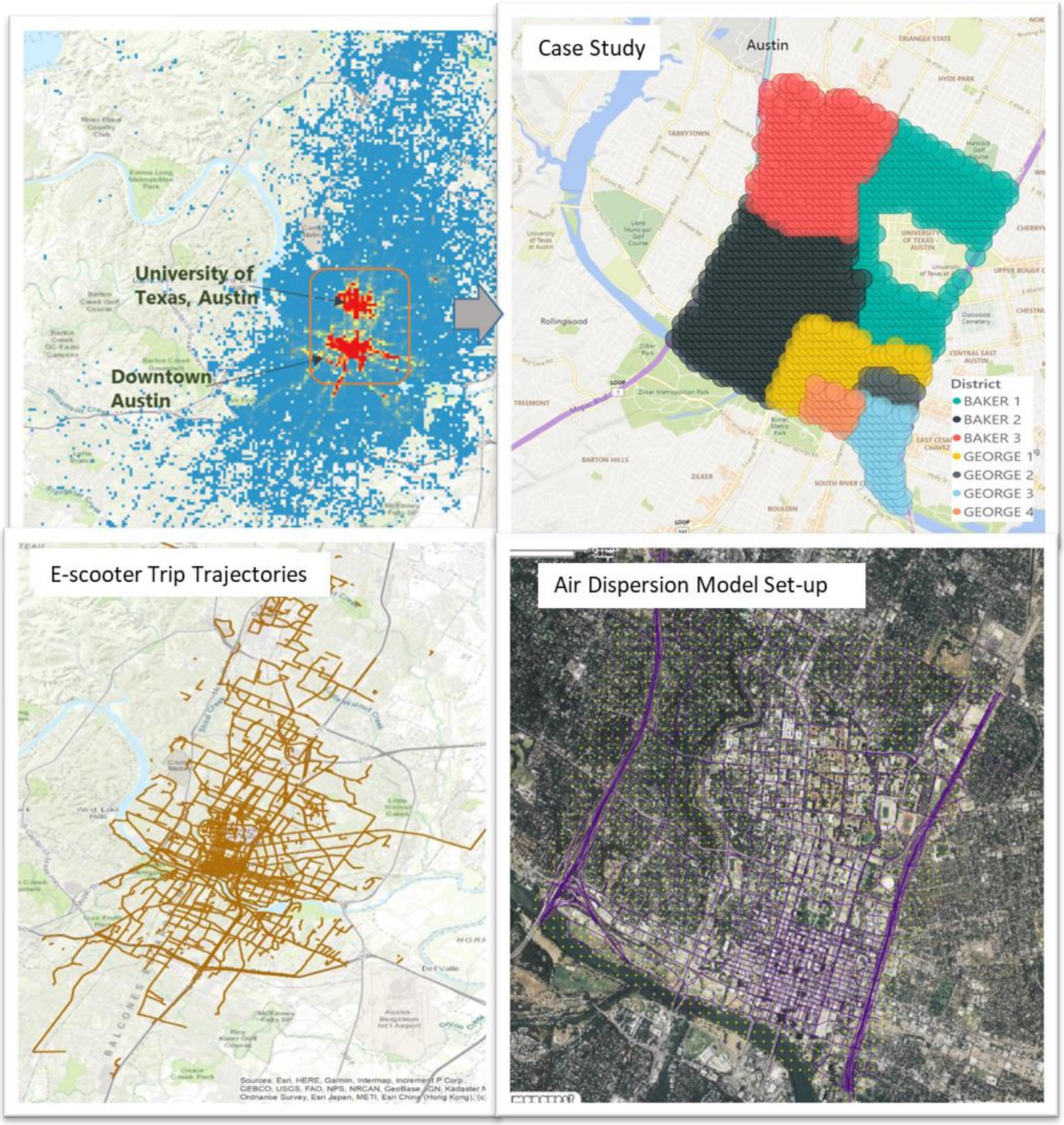


Figure 11. Focused case study area for exposure assessment.

Raw surface and upper meteorological data for the case study region were obtained from the Austin-Bergstrom International Airport and Corpus Christi upper air station, respectively. The raw data were then preprocessed by the AERMET and AERSURFACE models to produce a format compatible with the AERMOD. This meteorological data processing is detailed in Askariyeh et al. (2018). The roadway links in the case study area were characterized as a series of 4,579 area segments in the AERMOD. The $PM_{2.5}$ concentrations were estimated at 1,507 receptors, with finer spacing closer to the roadways and coarser spacing away from the roadways. The resulting $PM_{2.5}$ concentrations were averaged at the census block levels for four different seasons and four daily time periods[1] in the spring season only, as shown in Figure 12. The average hourly $PM_{2.5}$ concentrations ranged between 0.5 and 12.3 μg/m^3. The seasonal variations showed the highest concentrations during the winter season and the lowest concentrations during the summer season. These findings are in line with previous studies that reported higher concentrations due to stable atmospheric conditions and less sunlight, leading to reduced mixing of pollutants and higher concentrations during the late fall and winter season (Askariyeh et al., 2018; Vallamsundar et al., 2016). A similar trend was observed in the concentration heat map for different daily time periods; higher concentrations were observed in the overnight and early morning periods due to reduced sunlight and pollutant dispersion.

Due to the huge number of trip trajectories for the entire period of analysis, exposure assessments were conducted only for spring 2018. Exposure to $PM_{2.5}$ concentrations was estimated by combining the temporal and spatial distribution of $PM_{2.5}$ concentrations with the trip trajectories of e-scooter users. The trajectories were divided into segments based on the census block boundaries. Exposure experienced during an e-scooter trip was determined using the time-weighted concentrations computed for different split segments of the trip trajectory, as described previously in the Materials and Methods section. This process was repeated for all trips within the case study region for the period of analysis. Figure 13 shows the overall exposure levels categorized by the different daily time periods for the spring season. Exposure levels ranged from 1 to 30 μg/m^3 and were higher during the midday and evening periods and near heavily trafficked roadways. Temporal variations in exposure levels followed the temporal variations in concentration distributions, except for during the midday period. A possible explanation for the high midday exposure levels could be the high number of trips during the midday period, as shown previously in Figure 5. Similarly, exposure levels for the overnight period were significantly lower compared to other periods. Although concentration levels were higher during the overnight period, the low number of trips caused the overall exposure levels to remain lower. Th variations between concentrations and exposures highlights the importance of incorporating real-world commuting patterns of people when assessing their exposure rather than using ambient concentrations as a surrogate.

[1] The morning period was 6–9 a.m., the midday period was 9 a.m.–4 p.m., the evening period was 4–7 p.m., and the overnight period was 7 p.m.–6 a.m.

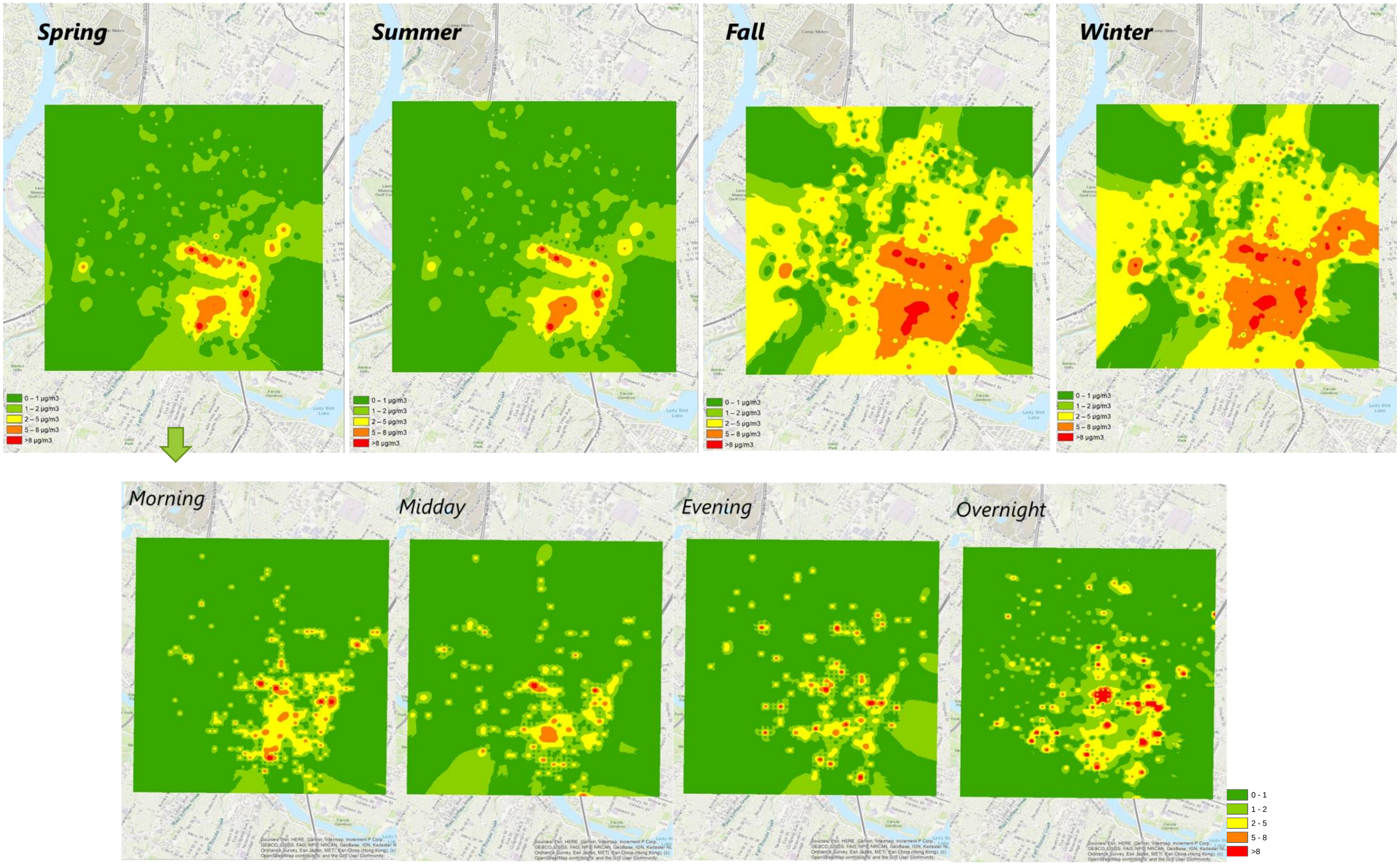


Figure 12. Heat map of $PM_{2.5}$ concentrations.

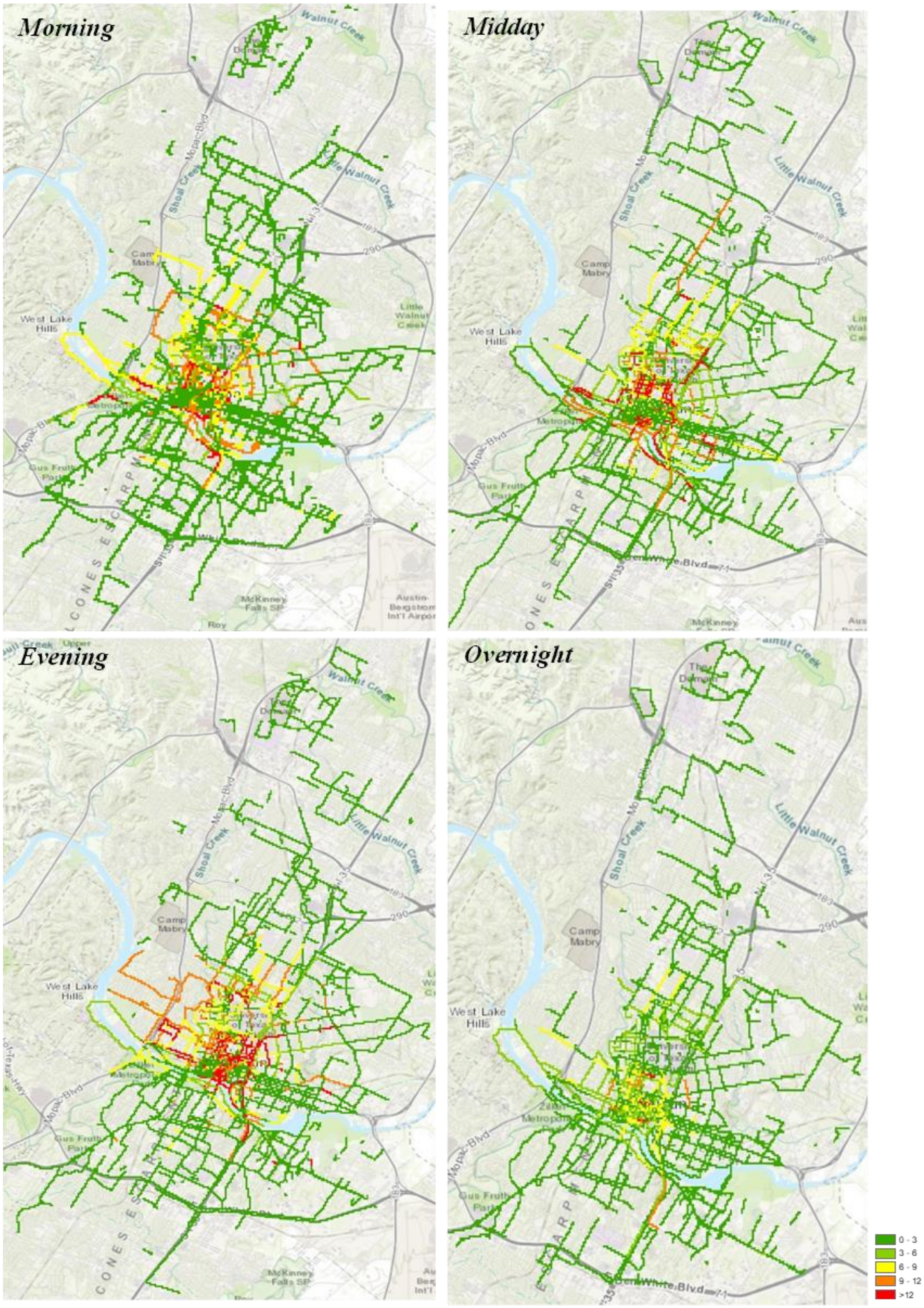


Figure 13. Temporal and spatial distributions of exposure levels.

Conclusions

The fourth generation of dockless mobility is striving 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 and to understand the TRAP exposure experienced by e-scooter users as they travel near heavily trafficked roadways. Data containing 4.1 million e-scooter trips were extracted from the City of Austin's dockless bikeshare program dataset. After removing any missing and invalid data records, the resulting dataset consisted of 3.4 million e-scooter trips. Based on the data analyzed, 56 percent of all scooter trips occurred during a nine-month period (from April to December) in 2018 and 44 percent occurred during a three-month period (from January to March) in 2019. These increased trips (136 percent increase) were attributed to the higher utilization rate of e-scooters in the second year after introducing the e-scooter bikeshare program in the city of Austin. The hourly variations of e-scooter trips showed a minimum trip count in the early morning (from 5 a.m. to 7 a.m.) followed by a maximum trip count from 12 p.m. to 7 p.m., which then decreased until 5 a.m. The hourly variations of scooter trips did not follow the expected bimodal peaking (morning and evening periods) typically exhibited in urban traffic. Comparisons of e-scooter trip count data between weekdays and weekends showed a 23 percent higher tendency to use e-scooters over the weekends.

Survey respondents ranked trip length, connectivity to transit, and congestion and parking issues as important factors influencing their use of e-scooters. Survey respondents used e-scooters mostly to replace their use of personal vehicles for trips connecting home and work/school (43 percent) and for nonwork or errand trips (39 percent), and walking (33 percent) for trips connecting home/work and transit. It is interesting to note that, while the usage of personal vehicles and shared ridership decreased, transit usage remained the same despite this new mode's ability to help people connect to transit stops. These survey results, along with the analysis of e-scooter data, highlighted the fact that e-scooters—although intended to solve the first-last mile issue—are being used predominantly for other trips. Spatial analysis of the e-scooter data identified the University of Texas-Austin campus and downtown Austin as areas of peak usage. Accordingly, exposure assessments were conducted for a sample of e-scooter trips that occurred in spring 2018 in these hot spots. Exposure assessments were conducted through an integrated modeling approach that combined the trip routes taken by e-scooter users and TRAP exposure levels caused by vehicular traffic. The air dispersion model found high $PM_{2.5}$ concentrations during the fall and winter seasons (due to reduced mixing and pollutant concentrations) and during overnight and early morning periods. Dynamic exposure levels were obtained by estimating the time-weighted concentration computed for different split segments of a trip trajectory. Compared to the concentration estimates, exposure levels differed because the route taken and the time spent in different locations were taken into account. Exposure levels followed the temporal distribution patterns of e-scooter usage and concentration levels, with high exposure levels observed during midday (attributed to high numbers of trips) and evening (attributed to both high numbers of trips and concentration levels) periods.

This study is one of the earliest studies targeting a new mode of emerging disruptive transportation. These findings help to understand the travel patterns of e-scooters and their influence on the exposure levels experienced by users during their commute. Because these e-scooters were predominantly rented for other nonwork/errand trips during off-peak periods, user exposure levels were lower than if they were used solely for connecting work/home and transit during peak hours. One limitation of this study included not evaluating the relationship between the dockless trips and other points of interest, such as restaurants, shopping, etc. In addition, this 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 used in this study is a steady-state model capable of modeling only the dispersion of primary pollutants and not the formation of secondary pollutants or the long-range transport of pollutants. This study only evaluated TRAP exposure experienced by e-scooter users from current traffic emissions without accounting for the change in emissions due to the reduction in personal vehicle travel or shared ridership. This study also did not include the environmental impacts from the manufacture, operation (i.e., electricity used to power the e-scooter), or disposal of e-scooters. To get a holistic picture of the environmental impacts of e-scooters, a complete wheel-to-well analysis incorporating the different aspects of e-scooter use—including the manufacture, power usage and impact on the electric grid, and disposal or recycling of e-scooters, as well as their effect on mode shift and emissions from other modes—is required.

Outputs, Outcomes, and Impacts

Research Outcomes

A paper based on this study was accepted for presentation at the 2021 CARTEEH Symposium. A journal paper based on this study is currently under preparation.

Technology Transfer Outputs

Relevant project datasets (appropriately anonymized) will be made available on the CARTEEH Data Hub. The research team also capitalized on opportunities for information sharing and technology transfer with stakeholders in Austin and presented key information about the project to the City of Austin.

Education and Workforce Development Impacts

A Ph.D. student was involved in the data analysis, literature review synthesis, manuscript writing, and documentation.

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Supplemental Information: Online Survey

CARTEEH
Center for Advancing Research in
Transportation Emissions, Energy, and Health
www.carteeh.org
A USDOT University Transportation Center

Dockless Scooter Survey

You are invited to join our dockless scooter research study!

<u>What is the purpose of this study?</u> To understand the usage patterns of e-scooters. The patterns will help us in assessing the air pollution levels for scooter users as they drive along major roadways.

<u>Who can take this survey?</u> You are invited because you live in our study area and have used a dockless scooter. You must be 18 years of age or older to participate. To participate, please check your eligibility by answering the following question under “Informed Consent”

<u>Participation:</u> The survey consists of 17 questions and is designed to be completed within 10 minutes.

<u>Risks:</u> These activities will not pose any risks to you. You can skip any question you do not wish to answer or exit the survey at any point.

<u>Benefits:</u> There are no direct benefits, nor any payment provided for participating in this study.

<u>Privacy:</u> The survey does not collect any personal information that can identify you. You can view the survey host’s privacy policy at https://www.surveymonkey.com/mp/legal/privacy-policy/.

<u>Contact Information:</u> You may contact the study coordinator, Dr. Suriya Vallamsundar, at 1-972-994-2209 or s-vallamsundar@tti.tamu.edu for any questions related to the research study. You may also contact the Human Research Protection Program at Texas A&M University by phone at 1-979-458-4067, toll-free at 1-855-795-8636, or by email at irb@tamu.edu for the following.
- additional help with any questions about the research
- voicing concerns or complaints about the research
- obtaining answers to questions about your rights as a research participant
- concerns in the event the research staff could not be reached

IRB Number:
IRB Approval Date:

Thank you, in advance, for taking part in the study!

Informed Consent
If you want a copy of this consent for your records, you can print it from the screen
If you wish to take part, please click the “I Agree” button and you will be taken to the survey. Clicking on the "I Agree" button below indicates that:
You agree to take part in the survey
You are at least 18 years of age
You have used a dockless scooter in Austin
If you do not wish to take part in the study, please exit survey by clicking on the "I Disagree" button.
☐ I Agree
☐ I Disagree

Questions About Yourself

What is your gender?
☐ Male ☐ Female ☐ Prefer not to answer

What is your age group?
☐ 18-25 years
☐ 26-35 years
☐ 36 – 45 years
☐ 46 – 55 years
☐ > 56 years
☐ Prefer not to answer

What is your highest educational level?
☐ Less than high school
☐ High school
☐ Undergraduate degree
☐ Master’s degree
☐ Degree higher than a master’s degree
☐ Prefer not to answer

Please describe your race/ethnicity
☐ White or Caucasian
☐ Black or African American
☐ Hispanic or Latino
☐ Asian or Asian American
☐ American Indian or Alaska Native
☐ Native Hawaiian or Pacific Islander
☐ Other
☐ Prefer not to answer

What is your employment status?
☐ Student
☐ Working part-time
☐ Working full-time
☐ Retired
☐ Prefer not to answer

What is your average household income?
☐ $0-$24,999
☐ $25,000-$49,999
☐ $50,000-$74,999

☐ $75,000-$99,999
☐$100,000-$124,999
☐ $125,000-$149,999
☐ $150,000 and up
☐ Prefer not to answer

B. Questions about E-scooters in General

To what extent would the following factors ENCOURAGE you to use the e-scooters? Select all that apply.

	Strongly Agree	Agree	Neutral	Disagree	Strongly Disagree	No Opinion
Connect home/work/school to transit stop (bus/rail)	☐	☐	☐	☐	☐	☐
Trip length (e.g., my trip is too short to drive but too long to walk)	☐	☐	☐	☐	☐	☐
Fitness/riding in open air	☐	☐	☐	☐	☐	☐
Reduce pollution from vehicles	☐	☐	☐	☐	☐	☐
Driving in Austin became more difficult (congestion, parking etc.)	☐	☐	☐	☐	☐	☐
Cheaper than taking other modes	☐	☐	☐	☐	☐	☐
Easy access compared to other modes	☐	☐	☐	☐	☐	☐
Excited to try a new mode	☐	☐	☐	☐	☐	☐
Interest in Scooters (bicycles don't work because of physical ability, attire etc.)	☐	☐	☐	☐	☐	☐
Others	☐	☐	☐	☐	☐	☐

Because of using the e-scooters in the last 30 days, how much more or less often do you use each of the following transportation modes? Select all that apply.

	Much less often	Somewhat less often	About the same	Somewhat more often	Much more often	N/A or never used
Personal Vehicle	☐	☐	☐	☐	☐	☐
Transit (rail/bus)	☐	☐	☐	☐	☐	☐
Taxi/Uber/Lyft etc.	☐	☐	☐	☐	☐	☐
Carsharing (e.g. Zipcar)	☐	☐	☐	☐	☐	☐
Personal Bike/Scooter	☐	☐	☐	☐	☐	☐
Walk	☐	☐	☐	☐	☐	☐
Others	☐	☐	☐	☐	☐	☐

Which of the following best describes your riding frequency and purpose for using the e-scooters in the last 30 days? Select all that apply.

	Everyday	A few times per week	Once a week	Less than once a week but more than once a month	Once a month	No activity
Connect to Bus or Train stop	☐	☐	☐	☐	☐	☐
Trips connecting Home to Work	☐	☐	☐	☐	☐	☐
Trips connecting Home to School	☐	☐	☐	☐	☐	☐
To run Errands/ Restaurants/ Shops	☐	☐	☐	☐	☐	☐
Other	☐	☐	☐	☐	☐	☐

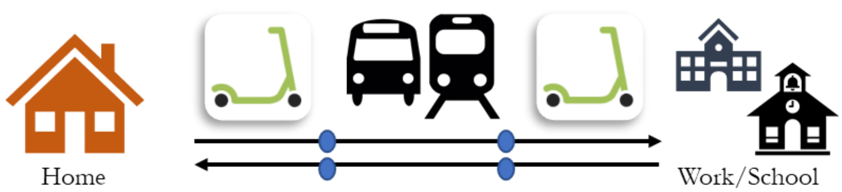
C. Questions about your Most Recent Dockless Scooter Trip

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

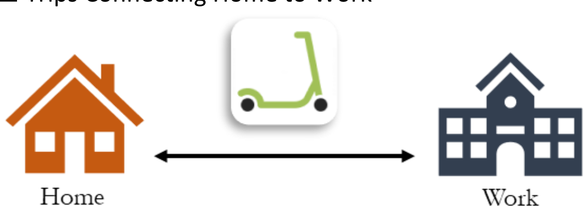
	Near Home	Near Work	Near School	Transit Stop (Bus/ Train)	Restaurants/Coffee Shops	Shops and Retail	Parks/ Trails
Pick-Up	☐	☐	☐	☐	☐	☐	☐
Drop-off	☐	☐	☐	☐	☐	☐	☐

Identify your most recent travel pattern using the dockless scooter

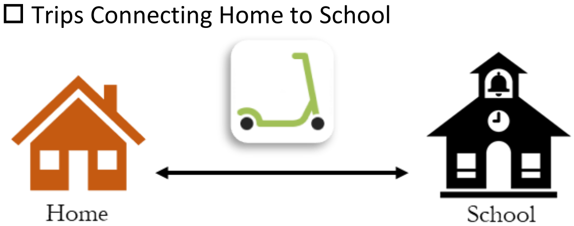
☐ Connect to Bus or Train stop



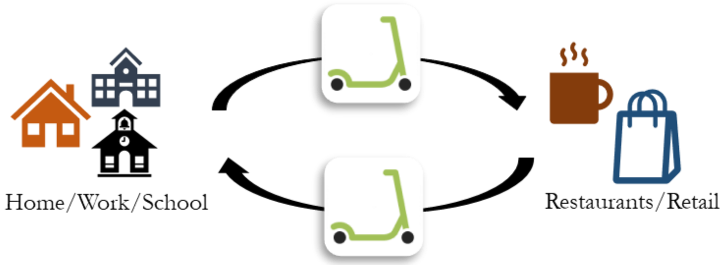
☐ Trips Connecting Home to Work



☐ Trips Connecting Home to School



☐ Errands/ Non-work trips



☐ Others

Thinking about your most recent dockless scooter trip, which mode of transport would you have taken had e-scooters not existed?

	Personal Vehicle	Taxi/ Uber/ Lyft	Carsharin g	Personal Bike/ Scooter	Walk	Not made the trip
Connect to bus or train stop	☐	☐	☐	☐	☐	☐
Trips to/from work only	☐	☐	☐	☐	☐	☐
Errands/non-work trips	☐	☐	☐	☐	☐	☐
Others (please specify):	☐	☐	☐	☐	☐	☐

What times-of-the-day did you travel during your most recent dockless scooter trip?

☐ 7 - 10 AM
☐ 10AM - 1PM
☐ 1 - 5PM
☐ 5 – 8PM
☐ 8PM - 7AM

How far did you travel during your most recent dockless scooter trip? If not sure, provide your best estimate.

☐ Less than 0.5 mile
☐ 0.5 – 1 mile
☐ 1 – 2 miles
☐ 2 – 3 miles
☐ > 3 miles

How many minutes did your most recent dockless scooter trip take? If not sure, provide your best estimate.

☐ Less than 5 minutes
☐ 5-10 minutes
☐ 10-20 minutes
☐ 20-30 minutes
☐ More than 30 minutes

Do you think using the dockless scooter at the start or end of your most recent trip significantly decreased the trip time or distance?

☐ Yes, trip time decreased
☐ Yes, trip distance decreased
☐ Yes, decrease in both
☐ No decrease at all