Combined Effect of Changes in Transit Service and Changes in Occupancy on Per-Passenger Energy Consumption

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A Research Report from the National Center for Sustainable Transportation

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16. Abstract
Many transit providers changed their schedules and route configurations during the COVID-19 pandemic, providing more frequent bus service on major routes and curtailing other routes, to reduce the risk of COVID-19 exposure. This research first assessed the changes in MARTA service configurations by reviewing the pre-pandemic vs. during-pandemic General Transit Feed Specification (GTFS) files. Energy use per route for a typical week was calculated for pre-pandemic, during-closure, and post-closure periods by integrating GTFS data with MOVES-Matrix transit energy and emission rates. MARTA automated passenger count (APC) data were appended to the routes, and the energy use per passenger mile was compared across routes for the three periods. The results showed that the coupled effect of shift in transit frequency and decrease in ridership from 2019 to 2020 increased route-level energy use for more than 87% of the routes and per-passenger mile energy use for more than 98% of the routes. In 2021, although MARTA service had largely returned to pre-pandemic conditions, ridership remained in an early stage of recovery. Total energy use decreased to about the pre-pandemic level, but per-passenger energy use remained higher than pre-pandemic for more than 91% of the routes. The results confirm that while total energy use is more closely associated with trip schedules and routes, per-passenger energy use depends on both trip service and ridership. The results also indicated a need for data-based transit planning, to help avoid inefficiency associated with over-provision of service or inadequate social distancing protection caused by under-provision of service.

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NCST

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EXECUTIVE SUMMARY

Many transit providers changed their schedules and route configurations during the COVID-19 pandemic, providing more frequent bus service on major routes and curtailing other routes, to reduce the risk of COVID-19 exposure. This research first assessed the changes in MARTA service configurations by reviewing the pre-pandemic vs. during-pandemic General Transit Feed Specification (GTFS) files. Energy use per route for a typical week was calculated for pre-pandemic, during-closure, and post-closure periods by integrating GTFS data with MOVES-Matrix transit energy and emission rates. MARTA automated passenger count (APC) data were appended to the routes, and the energy use per passenger mile was compared across routes for the three periods. The results showed that the coupled effect of shift in transit frequency and decrease in ridership from 2019 to 2020 increased route-level energy use for more than 87% of the routes and per-passenger mile energy use for more than 98% of the routes. In 2021, although MARTA service had largely returned to pre-pandemic conditions, ridership remained in an early stage of recovery. Total energy use decreased to about the pre-pandemic level, but per-passenger energy use remained higher than pre-pandemic for more than 91% of the routes. The results confirm that while total energy use is more closely associated with trip schedules and routes, per-passenger energy use depends on both trip service and ridership. The results also indicated a need for data-based transit planning, to help avoid inefficiency associated with over-provision of service or inadequate social distancing protection caused by under-provision of service.

Introduction

After the outbreak of the COVID-19 pandemic, transit ridership in U.S. cities decreased significantly, since March 2020 (Ahangari et al., 2020). Ridership decline may be attributable to behavioral factors, as mass transportation was considered less safe after the pandemic outbreak (Cho and Park, 2021; Wang and Noland, 2021). However, the influence of the pandemic has not been experienced uniformly across geographic or demographic groups. For example, areas with lower median incomes (Abdoli and Hosseinzadeh, 2021), more essential workers (Hu and Chen, 2021), and vulnerable populations (Liu et al., 2020) were found to maintain higher ridership levels after the pandemic outbreak. Few studies investigated pandemic ridership recovery over time, partly due to the long-lasting impact. Many scholars have suggested that the recovery period of the pandemic will be long (Parker et al., 2021; Petrunenko et al., 2021; Trump et al., 2020; Wang et al., 2021).

Transit energy consumption can be expressed in terms of vehicle energy use and energy use per-passenger-mile. While transit operations tends to have high system-level energy use given the mass of each transit vehicle, the energy use per-passenger-mile tends to be significantly lower for transit vehicles than for personal vehicles given the high passenger loads (Liu et al., 2016). Transportation is usually recognized as a “green” transportation mode, but scholars have highlighted that this can only be achieved at high load factors (Chen et al., 2017; Liu et al., 2016). For example, a study in China found that when the transit load factor declined to below 40% of full load, transit was in fact less energy efficient than the private vehicles operating with carpools (Sui et al., 2020).

This study examines the issues of transit system energy consumption and energy use per passenger-mile in the context of pandemic outbreaks and recovery. The agency selected for this assessment was the Metropolitan Atlanta Rapid Transit Authority (MARTA), the principal transit agency in Atlanta, GA, providing rail and bus transportation services. Since March 2020, MARTA has modified its routes and trip schedules multiple times to cope with changing passenger demand and increasing needs for social distancing. However, the interaction between changing service and shifting demand, and their combined effects on transit-related energy use and per passenger energy use, had not historically been well understood. A number of previous studies have modeled transit emissions on a per passenger per distance basis, primarily using Automated Vehicle Location GPS data (Attanucci and Vozzolo, 1983; Chu, 2010); however, high-resolution GPS data are not available for most transit fleets. Using a more generalizable approach in this study, the research team employed widely-available APC (Automatic Passenger Counter) and GTFS (General Transit Feed Specification) data to model and comparatively analyze the per-passenger energy use pre-pandemic, during-closure, and post-closure.

The objectives of this study were: 1) to demonstrate a set of tools that systematically examine transit emissions (total and per passenger based) at a given cross-section of time; 2) to investigate the system change and resulting emissions change per passenger per mile before and after COVID-19 outbreak, and 3) to provide insights to cause-effect relationships of the transit system operations and transit emission determinants.

Data and Methods

This study used two primary datasets, the General Transit Feed Specification (GTFS) for transit routes and schedules, and the Automated Passenger Counter (APC) data for onboard transit ridership inputs (Chu, 2010). GTFS is a widely used public transportation data specification that allows transit providers to share system information of various attributes (schedules, stop locations, etc.) that can be used in transit and transportation routing app development and in data analysis and predictions. An APC is an automated passenger counting system available from a number of companies that has evolved over three decades to provide demonstrated accuracy in estimating passenger volumes and serves as a reliable substitute for manual counting (Attanucci and Vozzolo, 1983).

This study identifies three weeks in 2019, 2020, and 2021 to represent pre-pandemic, during-closure, and post-closure situations. The first COVID-19 case in Georgia was confirmed in March 2020. In March 2020, companies and schools began suspending in-person meetings and indoor activities became much more restricted. Re-opening did not occur until the spring of 2021, at which time MARTA also largely reverted to pre-pandemic service level (Ryan, 2021). The first complete week of May in each year was selected for the comparison. About one month after the closure started, May 2020 is a good representation of during-closure travel conditions. The first week of May also represents travel conditions that are not influenced by school and college summer breaks and family vacations. MARTA provided both the APC and GTFS datasets for the first complete week (Monday to Sunday) of May in 2019, 2020, and 2021, representing pre-pandemic, during-closure, and post-closure situations, respectively.

The analysis was composed of three modules. First, based on passenger count profiles and stop identification information of the APC data, route-segment level transit inputs were derived to represent observed transit activity. Second, the research team used the TransitSim modeling network (Li et al., 2018), which generates the transit network from GTFS data, integrates Dijkstra's shortest path algorithm for network analysis, and provides the trip distance and average speed for energy and emissions modeling. Third, energy and emissions modeling was performed using MOVES-Matrix, energy use, and emission rate lookup array that provides exactly the same results as the EPA's MOVES regulatory model (Guensler et al., 2016). The following paragraphs of this section introduce each module in more detail.

The research team then analyzed transit bus operations at various levels, defined as follows. *Route* refers to a specific type of bus line configuration (including composition and sequence of stops, driving paths, etc.). Each route usually has multiple *trips* departing at various times of the day according to a fixed schedule (typically repetitive across days). Each specific trip in the schedule on a given day is assigned a "*trip-day*" record. A trip-day is a unique round of bus operations from the first stop to the last stop, along a specific route that contains *n stops* and *(n-1) route segments*. Geographically, route segments are the paths between pairs of adjacent stops. Although the spatial information (distance, etc.) for a specific route segment is the same across various trip-days, schedule-specific information may vary across these trip-days, such as travel time, passenger load, and so on.

Passenger Load Calculations

The research team used Automated Passenger Counter (APC) data to calculate passenger load. In this module, stop-level profiles of raw boarding and alighting counts from APC devices were filtered and processed to provide passenger load information at the route segment level. The outputs of the QA/QC (quality assurance and quality control) process included stop-to-stop route segment information that is ready to be entered into TransitSim network development in the next module.

The following four conditions were accommodated in the QA/QC process. First, dead-heading trips that connect the garage to the first revenue stop were excluded from the APC data, because this study focuses on per passenger energy use and emissions. Second, route segments between two stops were marked as an attribute of the former stop, so that the analyses retained only those stops that had subsequent stops (i.e., the last stop of each route is assigned to the route segment immediately preceding the stop, and the trip segment from the last stop to the garage was discarded). Third, due to what appear to be GTFS specification errors, the operational conditions demonstrated by the APC data do not always match the schedule in the GTFS data. More specifically, a few real-world trips were unreachable in the recorded GTFS route structures due to missing stops and consequently did not correspond to the distance and travel time information from the GTFS-based network analysis. This issue was more severe in 2020. Errors were identified for 155 out of 4,456 route segments in 2020 (likely due to the frequent changes of the on-road schedule that were not included in the GTFS data due to the pandemic), for only 17 out of 9,749 route segments in 2019, and no route segment errors were found in 2021. Given the small number of samples removed in this process, and the relatively large disparity across the years, this research removed any route segments that were of concern in any one year from the data for all three years (120 route segments were identified and removed). Fourth, similar to the third condition, a few stops that were present in the APC data were not recorded in the GTFS profiles, and these stops were removed from all three years. After the data screening process, 96.4%, 94.9%, and 96.2% of data was retained for 2019, 2020, and 2021, respectively, as shown in Table 1. Overall, the samples removed from the analyses were relatively small, and the difference across the years is not disconcerting.

After data filtering, stop-based ridership data was processed into a dataset for each route segment. The dataset for 2019 and 2021 included around 110 routes (in 2020 MARTA condensed these to 43 routes), with approximately 25,000 trip schedules and approximately 60,000 trip-days in each of the one-week study period. Ridership data were processed at trip-day level, to convert a chain of *n* back-to-back stops into a sequence of *(n-1)* connecting route segments (Figure 1), by sorting the stop order (“BLOCK_STOP_ORDER”) attribute in the APC data. Each stop was paired with the immediate next stop to form a route segment (and the next stop was paired with the one further next). Stop-level attributes include boarding and alighting counts, and route segment-level attributes include distance, travel time, and passenger counts, as shown in Figure 1.

Passenger load at route-segment *i* was calculated cumulatively using boarding and alighting counts precedent (from stop *1* to *i*) or subsequent (from stop *i+1* to *n*) to route-segment *i*. In this research, two counting methods were employed; a forward counting (FWC) method and a backward counting (BWC) method. The FWC is the answer to the question "given that the bus is empty when it leaves the garage and arrives at the first stop, how many passengers are present after *i* stops". The FWC calculates passenger loads as the number of passengers initially on the bus (i.e., zero) plus the "net gain" of passengers at every individual bus stop before route-segment *i*. The BWC method answers the question "given that the bus is empty when it leaves the last stop and returns to the garage, how many passengers have to be on the bus to match the passenger changes in the last *n-i* stops". It calculates as the final number of passengers on the bus (i.e., zero) plus the "net loss" of passengers at every bus stop after route-segment *i* (Figure 1). Equations (1) and (2) show the calculation of passenger load using the two methods.

$$FWC_i = \sum_{k=1}^{i} B_k - \sum_{k=1}^{i} A_k \qquad (1)$$

$$BWC_i = \sum_{k=i+1}^{n} A_k - \sum_{k=i+1}^{n} B_k \qquad (2)$$

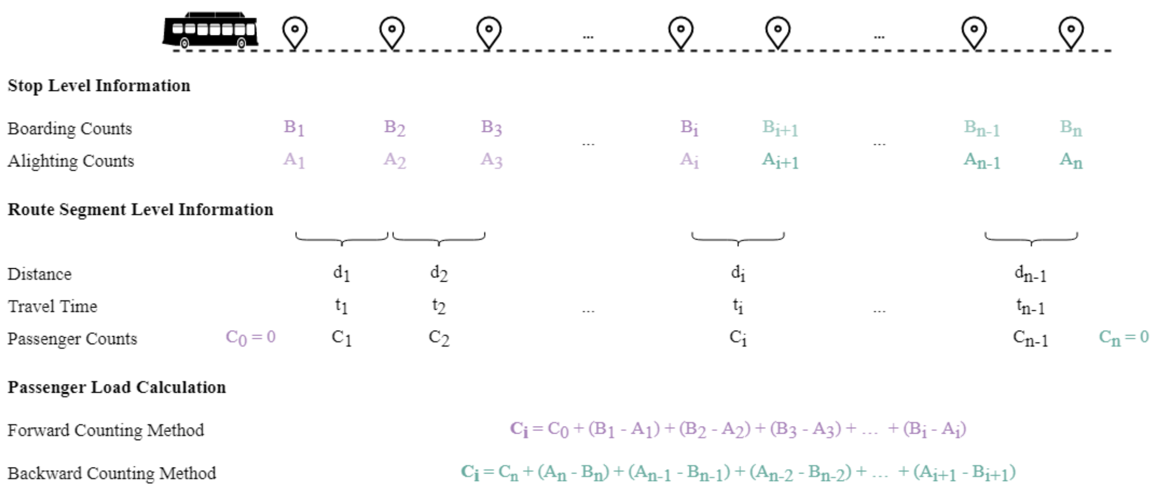


Figure 1. Relationship between stops and route segments for a random trip-day

The last step aims at balancing of APC passenger counts profiles. Despite a reported accuracy for APC data of 90% to 93%, previous studies suggested the need for balancing and correction for systematic and random errors in the counting process (Barabino et al., 2014; Furth et al., 2005; Koutsopoulos et al., 2019; Lebedeva and Mikhailov, 2017; Siebert and Ellenberger, 2020). In an ideal operating condition, for a trip day with *n* stops, the bus is empty when it arrives at the first stop (right before stop *0*, C_0) and when it leaves the last stop (right after stop *n*, C_n) of the journey, as shown in Figure 1 and Equation (3). Therefore, the change in passenger counts and the difference between FWC and BWC at any route segment *i* would be the same, and in ideal operating conditions, they should be both zero, as shown in Equations (4) and (5).

$$C_0 = C_n = 0 \qquad (3)$$

$$\sum_{i=1}^{n} B_i - \sum_{i=1}^{n} A_i = C_n - C_0 = 0 \qquad (4)$$

$$FWC_i - BWC_i = \left(\sum_{k=1}^{i} B_k - \sum_{k=1}^{i} A_k\right) - \left(\sum_{k=i+1}^{n} A_k - \sum_{k=i+1}^{n} B_k\right) = 0 \qquad (5)$$

In reality, the passenger counts can be off by a small amount, due to the movements of the operator and other transit agency staff (Furth et al., 2005), or by a large amount, as the result of systematic and random errors that arise from inaccuracies of automatic counters (Chu, 2010). According to Equation (5), the error at any point *k* in the trip-day will be counted cumulatively in any stop *i* of that trip-day (i.e., same error across the stops of the same trip-day). Therefore, the error in this analysis is denoted as the absolute difference between the sum of boarding counts versus the sum of alighting counts (trip-day level), which is equal to the absolute difference between FWC and BWC (route-segment level). The two representations yield the same number for a given trip-day, as shown in Equation (6).

$$e = |FWC_i - BWC_i| = |\sum_{i=1}^{n} B_i - \sum_{i=1}^{n} A_i| \qquad (6)$$

The cumulative nature of the errors makes the passenger load prone to error propagation, and in such cases, unreasonable numbers may arise (e.g., negative passenger load). The goal of the balancing process is to distinguish between reasonable errors resulting from the normal behaviors of bus operators and passengers versus those that arise from malfunction or miscalibration of the automated passenger counter.

Previous studies adopted various criteria for data balancing, varying from 9% to 15% of error tolerance (Chu, 2010; Furth et al., 2005). In this study, the research team followed a balancing process similar to the approach of Furth et al. (2005) (Furth et al., 2005), and derived two sets of filtering criteria (i.e., a strict scenario vs. a somewhat more relaxed scenario). In the strict scenario, if the difference between the two counts is larger than or equal to ten passengers, the entire trip-day is removed from the analysis for all three years. A route segment receives an error flag if its passenger load is less than or equal to minus five passengers, and the trip-day is removed from the analysis if it contains over three flags (a trip-day typically contains over one hundred route segments). In the more relaxed scenario, trip-days are removed if the difference between the two counts are larger than or equal to twenty passengers. An error flag is only given when the passenger load is less than or equal to minus ten passengers.

For the filtered dataset, passenger load was calculated as the average of FWC and BWC. Passenger loads smaller than zero (but not small enough to be removed) was treated as zero, as shown in Equation (7).

$$C_i = \max\left(0, \frac{FWC_i + BWC_i}{2}\right) \qquad (7)$$

Under the strict scenario, the data balancing process removed 9.1%, 9.6%, and 4.3% of data from 2019, 2020, and 2021, respectively. Under the somewhat relaxed scenario, this process removed 2.2%, 1.7%, and 0.8% of data from 2019, 2020, and 2021, respectively, as is shown in Table 1. Because the analyses in this paper focus on energy use per passenger-mile, it is important to ensure that the data screening criteria do not lead to potential bias in the overall sample, where perhaps a disproportionate number of high-demand routes (full buses), or low-demand routes (nearly empty buses), are removed from the analyses due to APC count error.

Table 1. Data Information and Sample Sizes

	Pre-pandemic		During-closure		Post-closure	
GTFS period	04/09 – 06/01, 2019		04/20 – 05/22, 2020		04/23 – 05/25, 2021	
APC period	05/06 – 05/12, 2019		05/04 – 05/10, 2020		05/03 – 05/09, 2021	
APC Sample Size	2,898,307		2,690,640		2,492,759	
Trips to garage	10,697		7,517		10,616	
Last stops	58,739		52,215		51,949	
Non-reachable stops	33,327		68,349		26,077	
Stops not in GTFS	1,242		8,126		7,056	
APC Sample size after screening	2,794,302		2,554,433		2,397,061	
	96.4%		94.9%		96.2%	
Filtering Scenario	Strict	Relaxed	Strict	Relaxed	Strict	Relaxed
APC Sample size after balancing	2,550,910	2,732,228	2,459,897	2,534,268	2,295,469	2,377,284
	88.0%	94.3%	91.4%	94.2%	92.1%	95.4%

Network Analysis

The research team developed a transit simulation network to model transit operations and obtain parameters needed for energy use and emissions analysis, including link distances and average speed by link. This section introduces the methods used in the network analysis, including network development and analysis on inputs.

As a part of the Roadway Simulator (RoadwaySim) modeling regime developed by Georgia Tech for the ARPA-E TRANSNET project (Li et al., 2016), TransitSim is capable of: 1) developing a transit network for any U.S. city based on standard-format GTFS data; 2) processing transit demand derived from activity-based travel demand models through the simulation network (including park-and-ride and transfers among service providers); and 3) producing link-by-link passenger travel trajectories. The advantage of TransitSim over other built-in transit modules in regional transportation models comes from the level of detail it provides in the results. Instead of aggregated results for overall travel time and distance, TransitSim provides link-by-link travel trajectories that can be easily transformed into a second-by-second passenger travel patterns for use in fine-grained energy and emissions analyses when combined with energy use and emission rates from the USEPA's MOVES model. The TransitSim algorithms can be summarized as follows (Li, 2019; Xu et al., 2018a; Yoon et al., 2005).

- **Pre-process GTFS Data** - Import GTFS inputs, prepare geographic coordinate information, and augment the geographic information with denser reference points;

- **Reconcile schedule and stop information** - Cross-register schedule and geospatial information, to find the exact locations and time of arrival/departure at each stop;
- **Create network links** - Create transit links (or route segments) between stops and road networks, calculate travel time and distance, and code types of links (e.g., walk, transfer, ride, or park-and-ride available);
- **Develop the network graph** - Depending on user specifications, develop transit-only, drive-only, and park-and-ride networks for specified service provider(s);
- **Run O-D pairs** - Conduct a network analysis on origin-destination pairs to find link-by-link travel trajectories.

Because this study focuses on transit-only trips with inputs in route-segment format, the research team reconfigured the TransitSim program to enhance network development efficiency. First, the drive-only and park-and-ride networks were trimmed for these analyses, as the analysis is focused only on the on-transit activities. Second, the network is constructed in a non-schedule-sensitive manner. Due to what appeared to be errors in the GTFS files, the trip identification between APC vs. GTFS datasets did not always match, and the departure and arrival timestamps were missing for more than 75% of the route-segment level inputs. In addition, unlike typical runs of TransitSim scenarios, where the transit schedule has to be checked to minimize wait time, this analysis was based on the recorded observations of transit boarding counts and alighting counts. The network analysis in this module was carried out with a consistent travel time and distance across various schedules ("trips") of the same route. That is, the network for the same route was assumed to remain consistent across time of day. This assumption was verified by comparing the predicted link-by-link travel time and distances versus the real-world profiles of the recorded trips that traverse this link. Less than 0.2% of all links showed non-negligible differences, while 99.8% of the links demonstrated differences smaller than 1%. Hence, this study used the median of all predicted travel time and distances as the parameters for each transit link.

Route-segment level inputs from APC data were entered to TransitSim based on the developed transit network, and the network analysis was conducted at the route level for each route using index matches between APC vs. GTFS data (each route name is coded the same in both datasets). In cases where the route names are coded differently in the two datasets, the route segment was run through the entire network, and a manual verification was conducted to make sure the two datasets landed on the same route. The final output of the network analysis was a dataset with passenger load, travel time, and distance for each route segment per trip-day.

Energy and Emissions Modeling

The emissions and energy use modeling of pre-pandemic, during-closure, and post-closure was performed by implementing MOVES-Matrix, which was developed by Georgia Tech to facilitate rapid applications of energy and emissions modeling using the same outputs as the MOVES regulatory model (Guensler et al., 2016; Vallamsundar and Lin, 2011). By running MOVES about thirty thousand times for a region (specific fuel and inspection and maintenance program), across all combinations of input variables that affect emission rates, a multi-dimensional matrix of 90 billion energy use and emission rates is generated. Users can query the emission rates directly from the matrix, significantly improving run-time efficiency (Guensler et al., 2016). Link-by-link average speed was derived from transit travel time between stops and link distance, and the source type distributions and transit vehicle age distributions were extracted from the fleet composition profiles provided by MARTA.

Because this study focuses on the effects of service and ridership changes on energy use and emissions, analyses should control for any other factors that affect energy use and emissions rates, such as ambient temperature and humidity. The meteorology information is estimated from the National Weather Service Climate Summary of May 2019 (National Oceanic and Atmospheric Administration, 2019), May 2020 (National Oceanic and Atmospheric Administration, 2020), and May 2021 (National Oceanic and Atmospheric Administration, 2021). The average May temperature (70°F) and humidity (70%) in Atlanta is used as meteorology input for MOVES-Matrix (consistent meteorology settings for all periods).

MOVES-Matrix was queried separately for each year to provide the energy use and emissions outputs of CO, NO_x, $PM_{2.5}$, PM_{10}, total gaseous hydrocarbons, and VOC for the analyses. Energy and emissions per passenger mile results are compared in the following section.

Results and Discussion

This section presents and discusses the results of ridership analyses and emissions modeling. The overall changes of transit services, ridership, emissions, and energy use are presented and discussed, and the route-level results are discussed for four representative routes. A discussion of the geographic results is also provided at the end of this section. In this study, all comparisons are presented as percentage change compared to the baseline of 2019 (pre-pandemic).

Overall Characteristics

Figure 2 presents the overall results for both scenarios that employ the strict and somewhat more relaxed data screening criteria. The strict scenario filtered out more trips than the relaxed scenario (leaving 57,488 trips in May 2021 for the relaxed scenario vs. 53,831 for the strict scenario), despite the fact that they retained the same number of routes. The strict scenario removed more observations with higher passenger load, as demonstrated by the average trip passenger load (12.85 passengers in the relaxed scenario versus 12.22 passengers in the strict scenario for May 2019, 6.08 passengers versus 5.68 passengers in May 2020, and 7.94 passengers versus 7.60 passengers in May 2021).

The strict scenario also resulted in higher predictions of emission and energy use per passenger mile (2,730 KJ per passenger mile in the relaxed scenario versus 2,850 KJ per passenger mile in the strict scenario in May 2019), but a lower total emission and energy use (for example, 8.77 billion KJ in the relaxed scenario versus 8.16 billion KJ in the strict scenario in May 2019). This is not surprising, given that the strict data screening criteria removed more of the high occupancy trips from the analysis (i.e., fewer passengers to share the total emissions and energy use). The strict scenario likely filters more records than intended, and can lead to a potential overestimation of modeled energy use and emissions per passenger-mile results. The rest of this section focuses on presenting the results based on the more relaxed APC data screening scenario. Further discussion of the strict vs. more relaxed scenarios is provided at the end of this section.

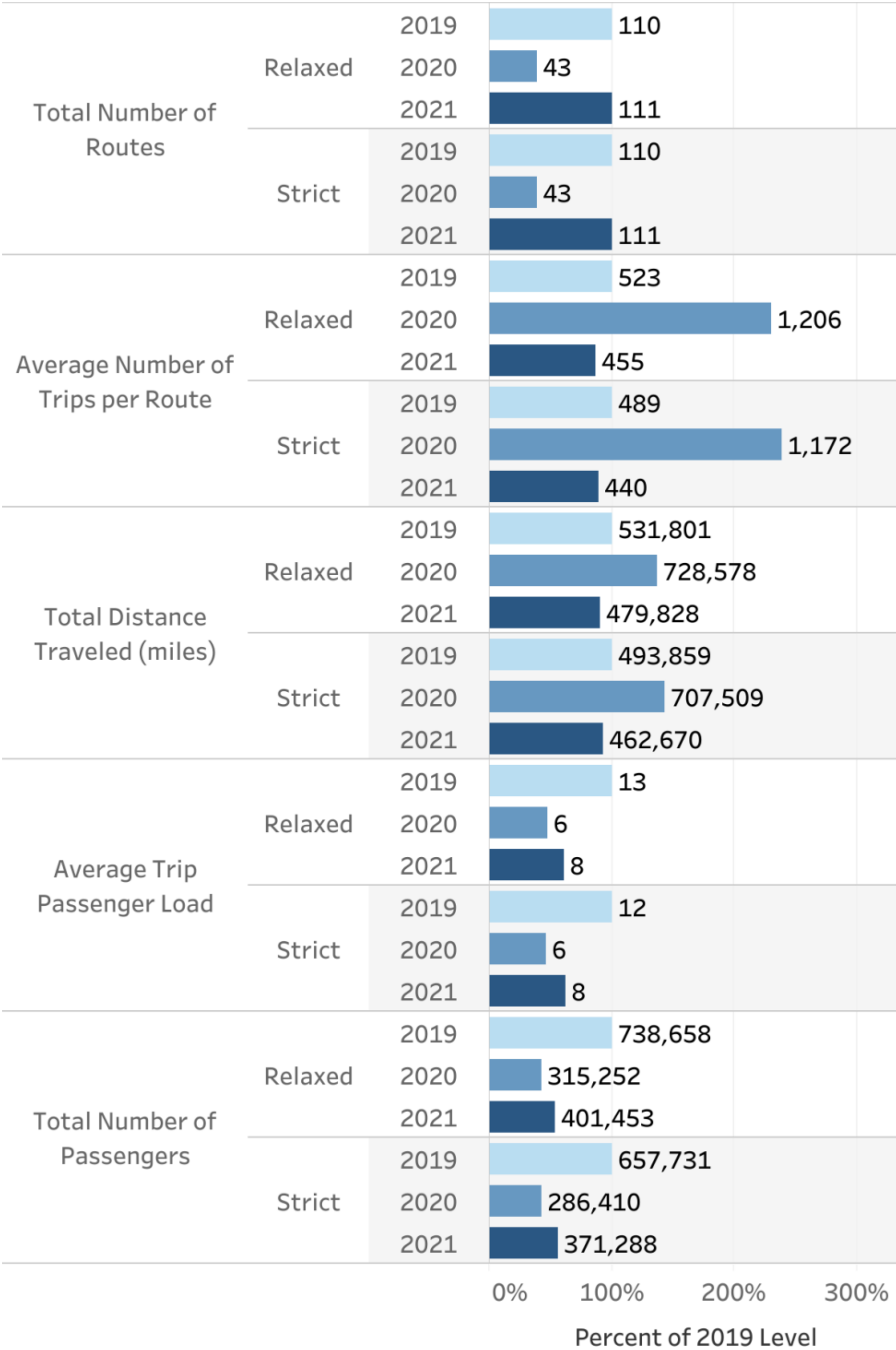


Figure 2. Results of transit operations and ridership changes.

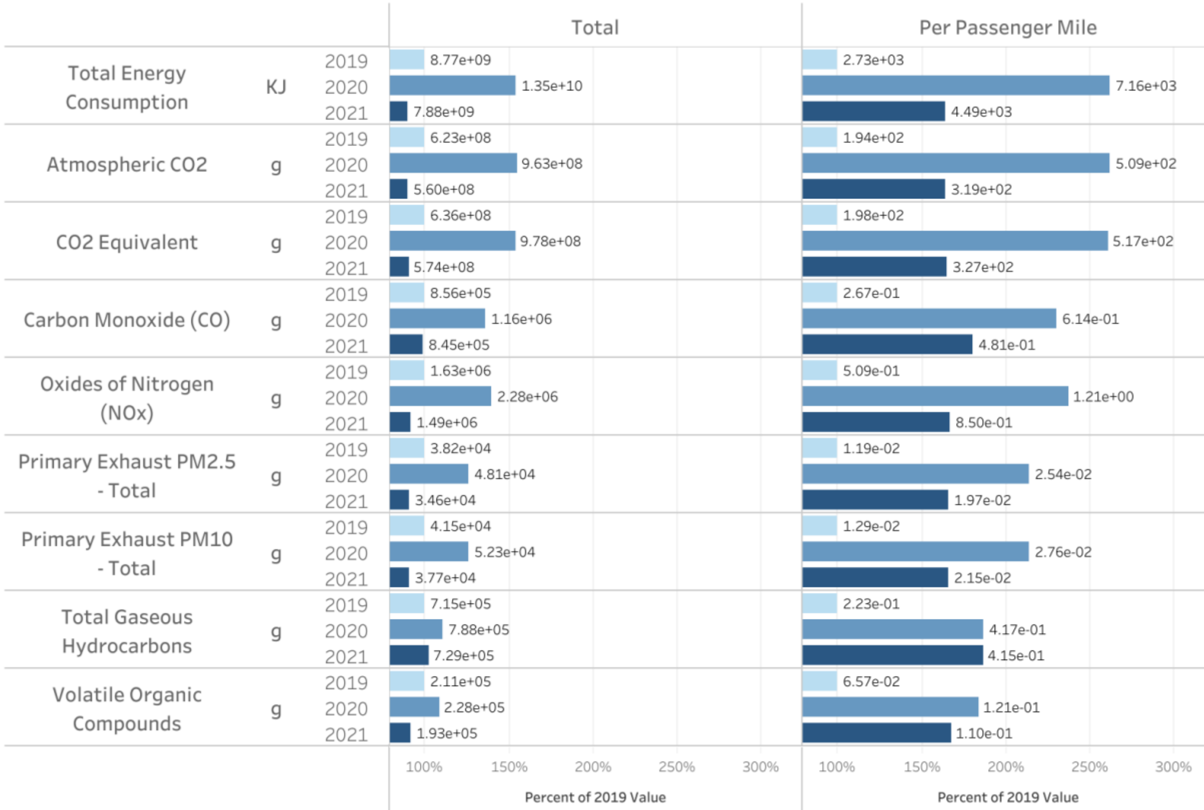


Figure 3. Results of emissions and energy use changes.

MARTA modified its transit service significantly between May 2019 and May 2020, cutting routes and then increasing service frequency on remaining routes, and then reverted to near-original service levels in May 2021. Part of MARTA's focused pandemic response was to decrease the total number of operating routes during the pandemic and increase the frequency of service along the highest passenger load routes to reduce the number of persons on each bus (to reduce potential passenger exposure to COVID-19). The May 2019 seven-day period included 110 routes, while the 2020 pandemic period included only 43 routes, and it increased back to 111 routes in 2021. During the May 2020 pandemic period, as routes decreased, the frequency on the routes that were retained more than doubled. In May 2019, an average route included 523 trip-days in the seven-day period, while this number grew to 1,206 trip-days in May 2020 and then dropped back to 455 trip-days in May 2021. Because these two factors tended to balance each other, the total number of bus trips operating during the study period remained comparable over time, from 57,488 in May 2019, to 51,836 in May 2020, and then to 50,533 in May 2021. In May 2019, MARTA served about 531,801 route-miles in a week, compared to about 728,578 route-miles in May 2020 and about 479,828 route-miles in May 2021. Although the service coverage (routes served) decreased between May 2019 and May 2020, the frequency and route length (mileage) of all remaining routes increased (as seen in Figure 2), and then largely returned to pre-pandemic levels in May 2021.

Most of the routes that were canceled in May 2020 were those with lower passenger loads (ten of the ten with lowest passenger loads were canceled and ten of the ten with highest passenger loads were retained). Passenger loads also dropped abruptly from May 2019 to May 2020, but (unlike transit service) passenger loads did not fully recover in May 2021. In May 2019, the seven-day period served a total of 738,658 passengers, which dropped to 315,252 passengers in May 2020. May 2021 shows an increase in passenger load compared to 2020, 401,453 passengers, but is still a significant decrease compared to 2019, indicating a slow recovery. The average trip load in May 2019 was 12.22 passengers per trip, which decreased to 5.68 passengers per trip in May 2020, and returned only to 7.60 passengers per trip in May 2021 (Figure 2). These results with respect to passenger load recovery are not surprising, given passenger efforts to maintain social distancing, even after the closure ended. The slow recovery could also be due to a decrease in travel demand (or at least the travel demand by transit) itself, given an increased portion of working from home and a higher unemployment rate (less commuting), and given that commuters could divert to other modes of transportations (i.e., passenger cars) to reduce exposure to other people.

As discussed earlier, although the number of transit routes decreased by 60.1%, the frequency of services on the retained routes nearly doubled. The retained routes were also significantly longer (41.8%) on average than the routes that were curtailed, and the route and schedule changes led to an increase of 37.0% in total vehicle-miles-traveled. Hence, total energy use and emissions in May 2020 increased by approximately 50% from May 2019 (13.5B KJ energy use and 963 tons of CO_2e emission in May 2020 compared to 8.77B KJ energy use and 623 tons of CO_2e emission in May 2019). In May 2021, energy and emissions levels returned to near the levels of May 2019 (e.g., 7.88B KJ energy use and 560 tons CO_2e emission in May 2021), as shown in Figure 3. This trend is consistent across energy use and all pollutants.

Energy use and emissions per passenger mile in May 2020 (7,160 KJ energy use and 509g CO_2e per passenger) more than doubled compared to May 2019 (2,730 KJ energy use and 194g CO_2e per passenger). Energy use per passenger decreased in May 2021 (4,490 KJ energy use and 319 g CO_2e per passenger), when transit returned to the original May 2019 schedules, but per passenger energy use and emissions were still more than 60% higher than the original May 2019 levels (Figure 3).

After the COVID-19 lockdown (May 2020), energy use and CO_2e emission per passenger mile were much higher than the national average for transit buses and higher than those of an average single-occupant vehicle. After the lockdown ended (May 2021), passenger loads remained low, and energy use and CO_2e emission per passenger mile were still higher than the national average for transit buses (Davis and Boundy, 2021). According to the Transportation Energy Data Book (Davis and Boundy, 2021), typical transit buses are as energy-efficient as personal vehicles only when typical passenger load is greater than or equal to eight persons per bus (given the mass of the bus vs. the mass of the automobiles). The low passenger load per bus was associated with the need to increase social distancing on each bus, while still providing essential transportation for critical workers.

Changes in system-level energy use and per-passenger energy use differed from year to year. For May 2019 vs. May 2020, system-level energy use increased by 53.9%, while the per-passenger energy use increased by 162.2%. System-level energy use decreased for May 2019 vs. May 2021, while per-passenger energy use increased by 64.4% as passenger ridership was slow to recover. The system-level transit energy use is more closely related to the changes in trip frequency, while per-passenger energy use experiences a combined effect from changes in trip frequency and passenger load.

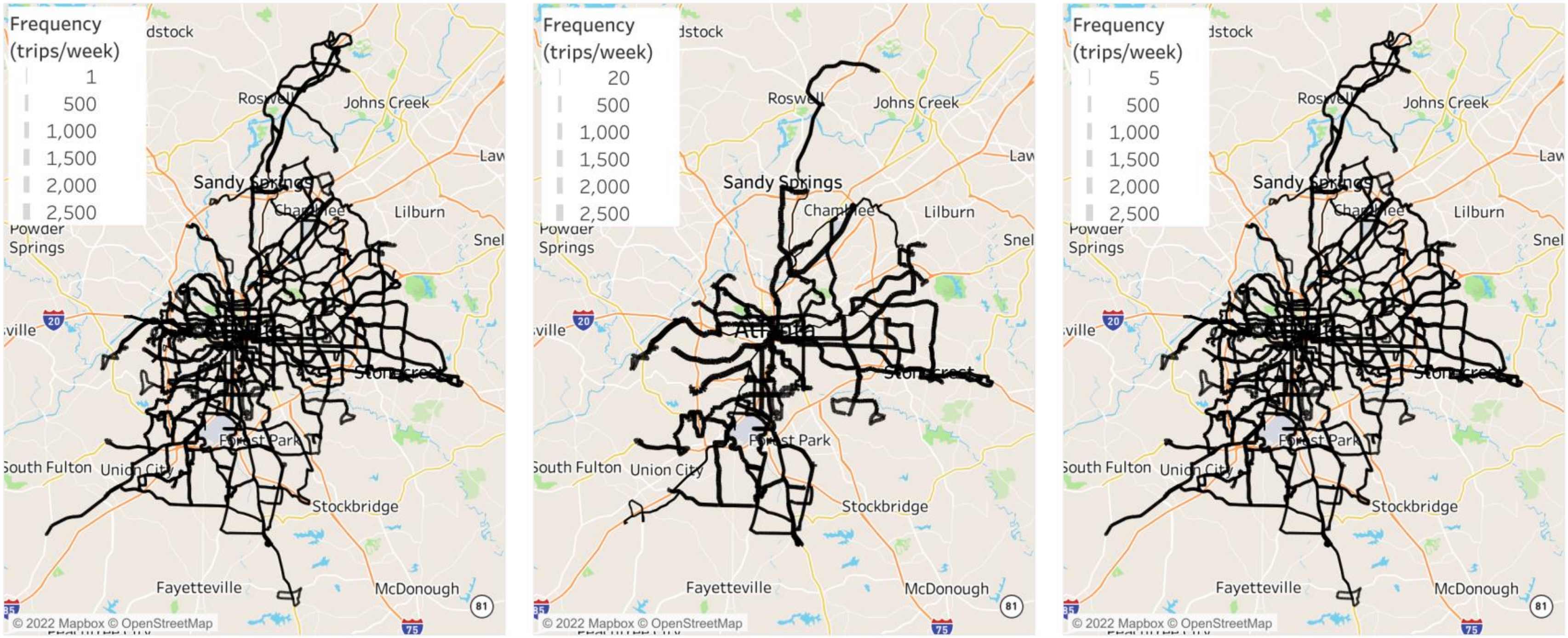
Results by Geographic Location

Taking May 2019 as the baseline condition, the frequency of trips was slightly higher on the northern and western sides of the city than southern or eastern sides. In May 2020, 70 routes were curtailed (63.6% of total routes), with only the main routes in each direction remaining, as shown in Figure 4, and only three additional routes were added. A total of 32 routes (out of the 40 routes that remained) doubled in frequency, 6 remained unchanged, and 2 decreased in frequency, as shown in Figure 5. In May 2021, the frequency of trips was predominately changed back to the original level or dropped below May 2019. Out of the 106 common routes between May 2019 and May 2021, 60 routes had similar frequency (difference in the number of trips less than 10%), 45 routes had lower frequency in May 2021, and only one had a higher frequency in May 2021 (Figure 5a). Routes that experienced the highest decrease in frequency were distributed around the center of the city, and those that experienced increased frequency were in the southern and northeastern peripheral areas.

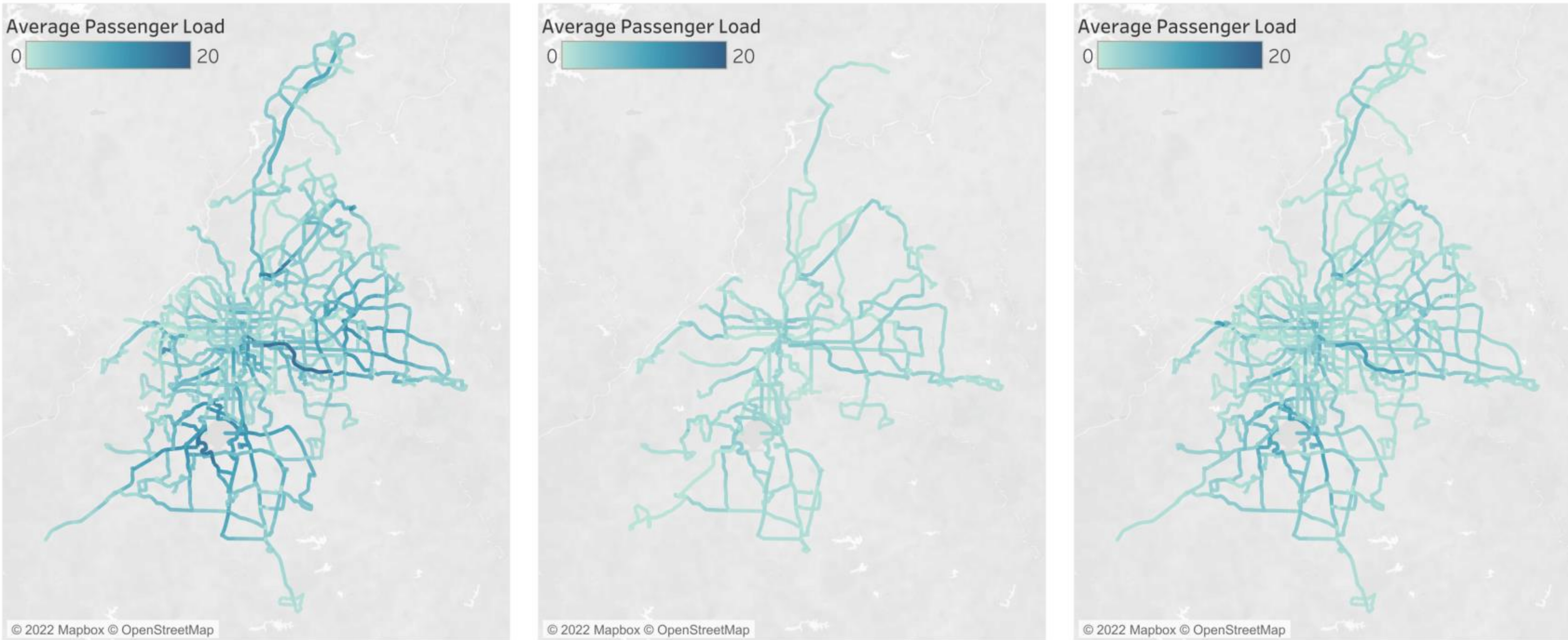
Routes with the highest passenger load in May 2019 continued to carry the highest passenger load in May 2020 and May 2021 (Figure 4). May 2019 and May 2020 shared 40 common routes, and 35 of them experienced a decrease in passenger load, with the northeastern side experiencing the highest drop (Pleasantdale Road Route), followed by areas in the South (Figure 5). May 2019 and May 2021 shared 106 common routes, and 104 of these routes experienced a decrease in passenger load (with 103 having a decrease of larger than 10%) and only two experienced a relatively small (less than 10%) increase. Though a "bounce-back" was observed from May 2020 to May 2021 (Figure 4), the increase was much smaller compared to the decrease associated with the onset of the pandemic. All these results indicate that the passenger load was still in an early stage of the entire recovery process (Figure 5b).

From May 2019 to May 2020, 5.0% of the routes experienced a decrease in energy use, while 95.0% experienced an increase, as shown in Figure 5c. From May 2019 to May 2020, the largest increase in energy use occurred in the far south of the metropolitan area, with the highest increase rate of 537.2%. Two places experienced a decrease in energy use, located around northeastern peripherals and downtown Atlanta, and these overlap with decreased trip frequency. From May 2019 to May 2021, 70.8% of routes experienced a decrease in energy use (81.3% of which were larger than 10%), and 29.2% experienced an increase (9.7% of which were larger than 10%). Some of the routes that experienced the highest decrease in energy use from May 2019 to May 2021 were located around the city center and western fringes (highest decrease of -66.9%), while places that experienced the highest increase were distributed sparsely around the southeastern, southern, and western fringes (with the largest increase being +26.1%). The spatial distributions of the energy use are largely identical to those of the trip frequency in Figure 5, despite the difference in magnitude of change, which again suggests that an increase in trip frequency may be an important factor for the increase in total energy consumption.

From May 2019 to May 2020, 97.5% of routes experienced an increase in energy use per passenger mile (with the highest increase at 504.8%), while only one route experienced a decrease (Peachtree Street Route in Downtown Atlanta, -23.0%). Places that did not see a high increase are located around the southwestern and northeastern sides of the city. From May 2019 to May 2021, 96.2% of routes experienced an increase in per-passenger energy use (with the highest increase of 860.8%), while only 3.8% of routes experienced a decrease. Places that did not experience a high change were located around the northeastern and western sides of the city.



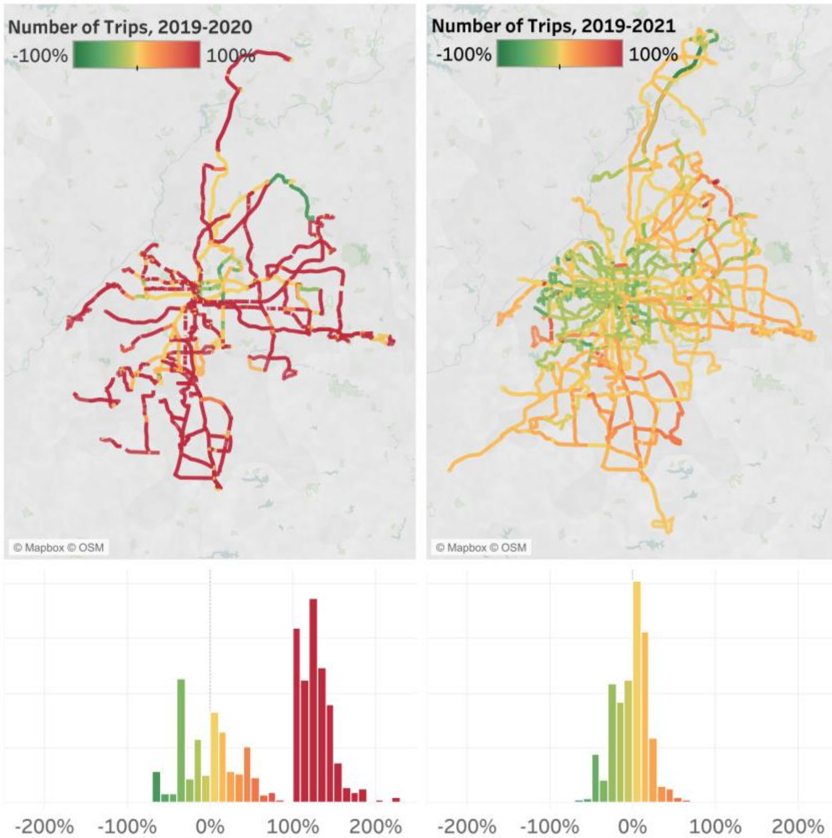
(a). Bus frequency (thickness represents frequency) in 2019 (left), 2020 (middle) and 2021 (right)



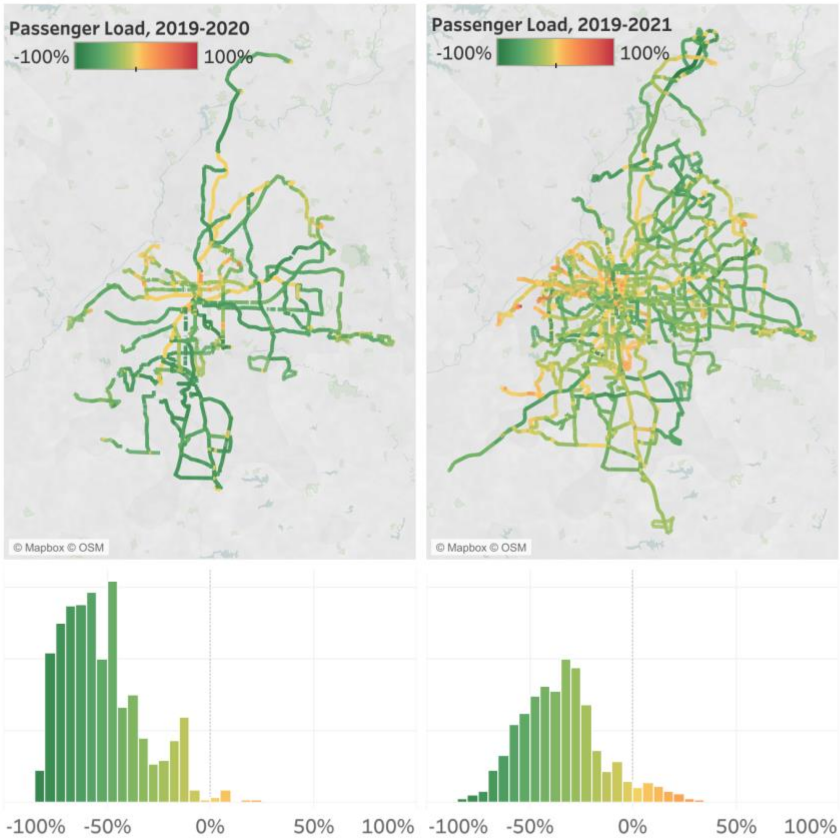
(b). Bus ridership (color represents passenger load) in 2019 (left), 2020 (middle) and 2021 (right)

(c). Energy use per passenger mile (color represents energy use) in 2019 (left), 2020 (middle), and 2021 (right)

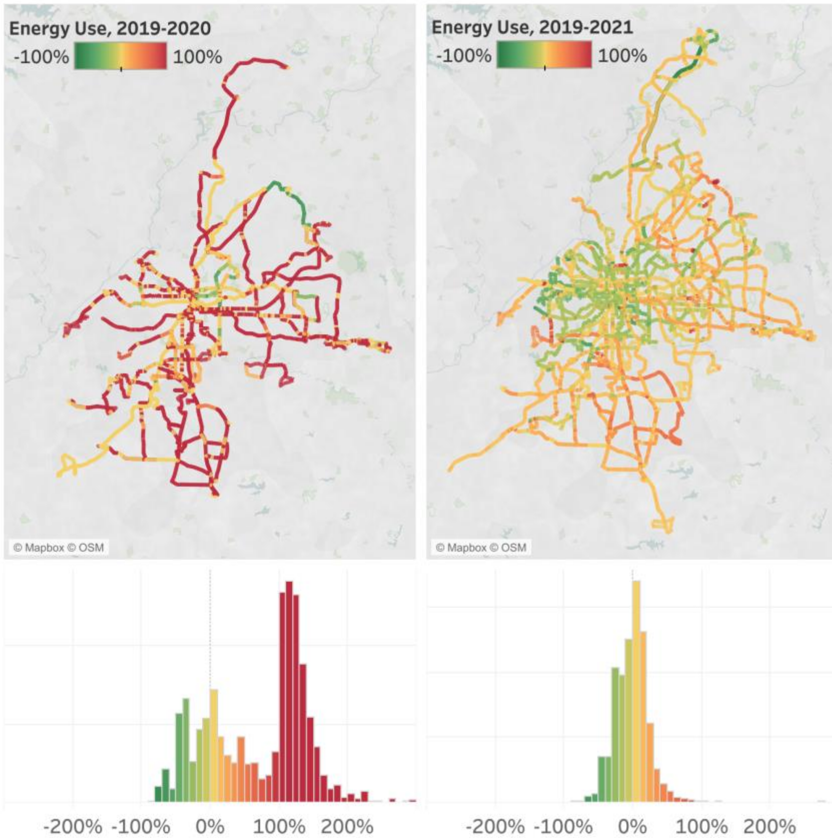
Figure 4. Analysis results across the entire region



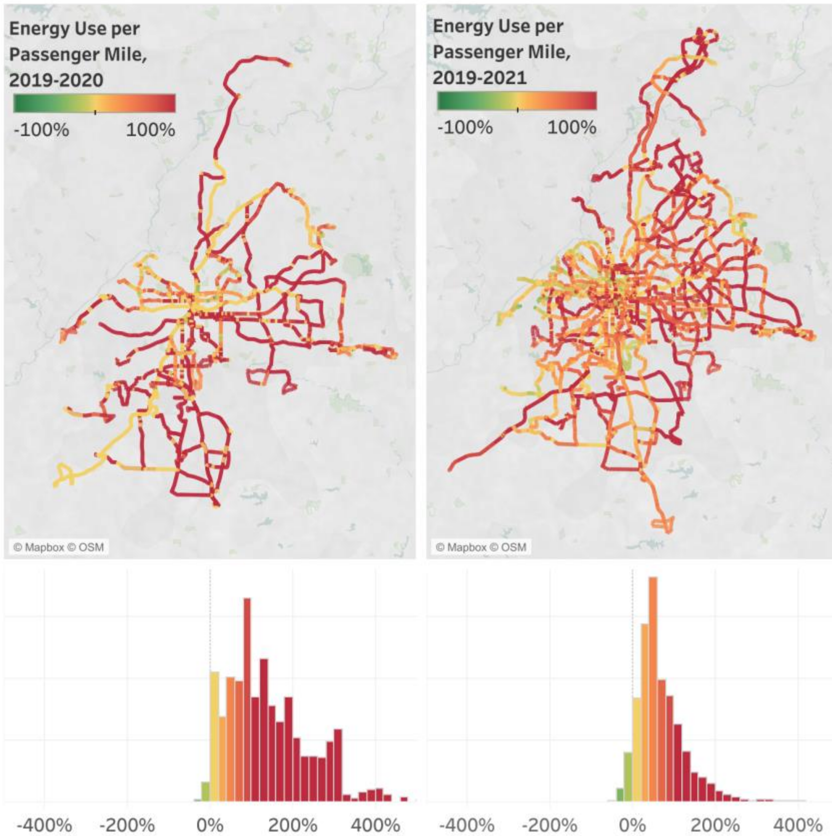
(a). Changes in bus frequency from 2019 to 2020 (left), and from 2019 to 2021 (right)



(b). Changes in passenger load from 2019 to 2020 (left), and from 2019 to 2021 (right)



(c). Change in total energy use from 2019 to 2020 (left), and from 2019 to 2021 (right)



(d). Change in per passenger mile energy use from 2019 to 2020 (left), and from 2019 to 2021 (right)

Figure 5. Changes in (a). Trip frequency; (b). Passenger load; (c). Total energy use; and (d). Per passenger mile energy use (histogram: distribution of changes in each link)

Results for Specific Case Study Routes

In the following section, four representative case study transit routes are selected to present the typical changes. The results for North Decatur Road/Virginia Highland, Campbellton Road, Peachtree Street/Downtown, and Pleasantdale Road, are shown in Figure 6.

North Decatur Road/Virginia Highland ("Decatur") is located on the eastern side of Atlanta and is one of the 67 routes curtailed in May 2020 due to the pandemic. There were multiple other routes serving the same area, and the passenger load of this route was not high in May 2019 (which could be one of the reasons it was curtailed). Trip frequency decreased mildly from May 2019 to May 2021, while passenger load decreased by more than 50%. The predicted total energy use for this route decreased by 25.8% from May 2019 to May 2021, but per passenger mile, energy use nearly doubled (86.5% increase).

Campbellton Road is representative of the majority of the remaining routes, which experienced an increase in bus frequency and a decrease in passenger load. It was also one of the routes with the highest baseline passenger load. The popularity of this route was the likely reason that it was not curtailed and had a doubled frequency from May 2019 to May 2020 (with a decreased passenger load of 64.4%). The total energy use doubled from May 2019 to May 2020, and energy use per passenger mile increased by 107.4%.

Peachtree Street/Downtown is located in Downtown, Atlanta. Similar to Campbellton, this route also experienced an increase in trip frequency, but the average passenger load did not change much from May 2019 to May 2020. The relatively low elasticity of passenger load may suggest a higher dependence of surrounding residents on transit. Similar to Campbellton Road, this route also experienced an increase in total energy use from May 2019 to May 2020. However, the energy use per passenger mile decreased by 23.1% in this period, which was likely related to the fact that the average passenger load did not change much.

Pleasantdale Road is one of only two routes that experienced a decrease in frequency from May 2019 to May 2020. This route is located at the northeastern fringe of the city but it is a major route serving its neighboring area. The frequency and the total energy use both decreased in May 2020, and with a significant decrease in average passenger load, energy use per passenger mile still doubled from May 2019 to May 2020.

Route Name	Year	Total Number of Trips	Average Passenger Load per Trip	Total Energy Use (btu)	Energy Use per Passenger Mile (btu/passenger-mile)
N Decatur Road / Virginia Highland	2018	493	12	88,652,553	4,017
	2020				
	2022	370	5	65,773,136	7,492
Campbellton Road	2018	1,390	20	127,441,482	1,833
	2020	2,773	7	264,277,197	4,880
	2022	1,221	14	112,500,408	2,409
Peachtree Street / Downtown	2018	503	10	63,272,499	8,025
	2020	999	9	197,115,908	6,177
	2022	339	10	41,911,163	6,839
Pleasantdale Road	2018	492	15	60,088,467	3,222
	2020	102	7	21,470,552	6,576
	2022	462	8	59,686,009	3,711

Figure 6. Analysis of four case routes

The four case studies are indicative of how the changes in transit operations during the pandemic led to significant variability in changes in energy use and emissions per capita. Some routes like Campbellton Road may have seen an over-provision of service (to improve social distancing) as passenger loading also dropped, leading to a greater reduction in energy efficiency. Other routes like Peachtree Street/Downtown saw an increase in ridership and may have needed increased service. More nuanced approaches may be needed to balance social distancing, changes in passenger demand, and increased service, especially in neighborhoods that are highly transit dependent.

Limitations and Opportunities for Future Research

The emissions modeling of this study was based on the emission rates from MOVES with default passenger loads; however, emissions and energy use rates do increase with passenger occupancy (which leads to a slightly higher required engine load) (Vallamsundar and Lin, 2011). Figure 7 illustrates transit bus energy use rates vs. passenger load (Xu et al., 2018b). Increases in energy use and emissions are non-trivial, especially when passenger loads drop so significantly, that the research team plans to integrate the effect of passenger load on energy use and emissions in future analyses.

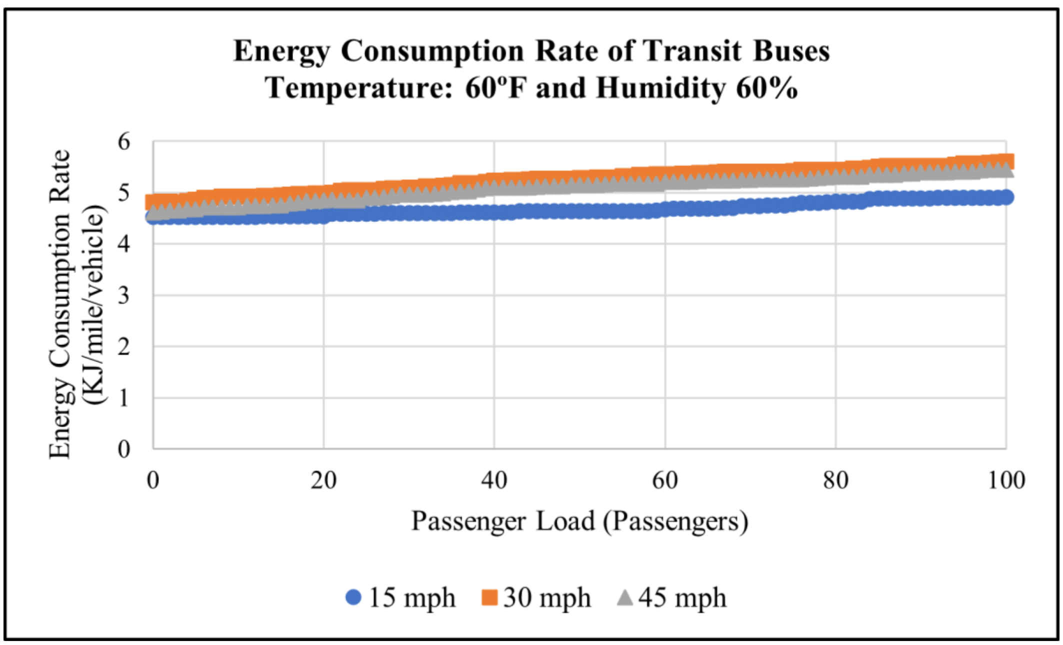


Figure 7. Sensitivity of energy consumption rate on passenger load

Accurate passenger occupancy is critical in any analysis that quantifies energy use and emissions on a per passenger-mile basis. The APC data quality issues that arose in this study are worth noting, in light of the differences in energy use and emissions results per passenger-mile derived from the strict and more relaxed data screening procedures. Removing a disproportionate number of high ridership or low ridership routes, given the correlation of APC accuracy with passenger entry and exit volumes, can bias such results. Without ground truth boarding and alighting data to which APC data can be compared (e.g., manual count confirmations), it is impossible to verify the APC data for any analytical scenario. The research team recommends that research be conducted to develop new QA/QC methods for APC data (which will most likely be combinations of filtering thresholds for specific scenarios) to ensure the accuracy of passenger count data, used in comparative energy analyses across modes, as potential biases may correlated with the amount and rate of passenger ingress/egress activity).

The analyses in this report employed GTFS network and schedule data, which only includes the operating routes. Hence, another limitation of this study is the lack of inclusion of deadheading trips (trips between garage and route locations without passengers, and trips to reposition buses between routes) in the analysis. Deadheading trips contribute a significant portion of energy use and fuel consumption in urban public transit systems (Li, 2019; Nasibov et al., 2013). There are four relevant MARTA bus depots and not routes and their associated buses are necessarily assigned to the closest depot. With service schedule changes during the pandemic, garage locations also likely changed (Li, 2019). Incorporating deadhead segments associated with bus switching between routes mid-day requires access to dispatch bus assignment schedules. Specific routes taken by deadheading buses also cannot be easily inferred. Hence, it is difficult to assess deadheading metrics for emission and energy analysis without AVL data. Future studies should consider including all deadheading trips in the analyses, expanding the existing findings, and presenting a more holistic view of the topic. Assessing the impact of actual route and schedule adherence (and other reliability metrics) on per-passenger energy use and emissions could also be supported once AVL data become available. A logical next step is to extend the current methods and results to a large-scale household-specific datasets that observe transit rider behavior, so that transit performance can be compared across demographic groups. The research team is currently performing a relevant demographic assessment in a follow-on NCST project.

MOVES-based analyses assume that the average bus speed on each transportation link correspond to transit driving cycles embedded within the MOVES model. The MOVES modeling approach is the best currently available in the absence of second-by-second AVL data (Li, 2019; Xu et al., 2018a; Yoon et al., 2005). However, once high-resolution AVL data become available for transit routes in Atlanta, researchers will be able to compare operating mode bin distributions from monitored, second-by-second speed/acceleration data to those that assumed by MOVES via weighting of driving cycles in the MOVES database.

Conclusion and Future Work

This study examined the May 2020 and May 2021 pandemic-related changes in transit service and ridership and their combined effects on energy use and per-passenger energy use for the MARTA system in Atlanta, GA. The General Transit Feed Specification (GTFS) and the Automated Passenger Counter (APC) datasets were used to develop the transit network and derive distance and passenger load information. The outputs were coupled with energy use and emission rates from MOVES-Matrix to assess how transit service and ridership changes impacted energy use and emissions on a per passenger-mile basis.

Compared to the May 2019 pre-pandemic baseline, many routes were eliminated and the frequency of remaining transit services was doubled (to increase social distancing) in the May 2020 pandemic closure period. Transit ridership also simultaneously decreased by approximately 50% in the May 2020 pandemic closure period. In the May 2021 post-closure pandemic period, although the transit service had largely been restored to pre-pandemic levels, the recovery of passenger load was slow and passenger ridership remained well below the pre-pandemic baseline.

Transit energy use in the May 2020 pandemic closure period (13.5B KJ) was approximately twice that of the pre-pandemic period (8.77B KJ). Energy use per passenger-mile during the May 2020 pandemic closure period (7,160 KJ/passenger-mile) was almost four times that of the May 2019 pre-pandemic period (2,730 KJ/passenger-mile). While energy use in the May 2021 post-closure period (7.88B KJ) was more similar to that of the May 2019 pre-pandemic period (8.77B KJ), the energy used per passenger-mile (4,490 KJ/passenger-mile) was still double that of the pre-pandemic period (2,730 KJ/passenger-mile). The results confirm prior research indicating that transit system-level energy use and energy use per passenger-mile depend on different factors. System-level transit energy use tends to be high given the mass of each transit vehicle, but transit provides high energy efficiency per passenger mile at high passenger loads.

The results also suggest that the customer response to changes in transit service differed across routes. As some routes were cancelled and others increased in service frequency, ridership may have shifted across routes. In addition, some routes may have served passengers with more travel flexibility that other routes. During the COVID-19 pandemic, transit agencies faced a difficult tradeoff in selecting which routes to curtail and whch routes to enhance to reduce COVID exposure. More nuanced analysis of the pandemic response, based upon monitored customer ride transactions and rider demographics, might help the agency focus on customers involved in essential services and have little travel flexibility so as to optimize route and service changes in the event of a future pandemic.

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Data Summary

Products of Research

The research team collected no data for this study. The data employed include:

- General Transit Feed Specification (GTFS) Data - Open source and readily available online (link: https://transitfeeds.com/p/marta/65)
- Automated passenger count (APC) Data - Proprietary data procured from MARTA under a specific end-use agreement
- MOVES-Matrix Energy and Emission Rates - Open source data available through NCST at: https://tse.ce.gatech.edu/ncst/movesmatrix

Data Format and Content

- GTFS Data - Standard GTFS format
- APC Data - Proprietary
- MOVES-Matrix Energy and Emission Rates - Text arrays

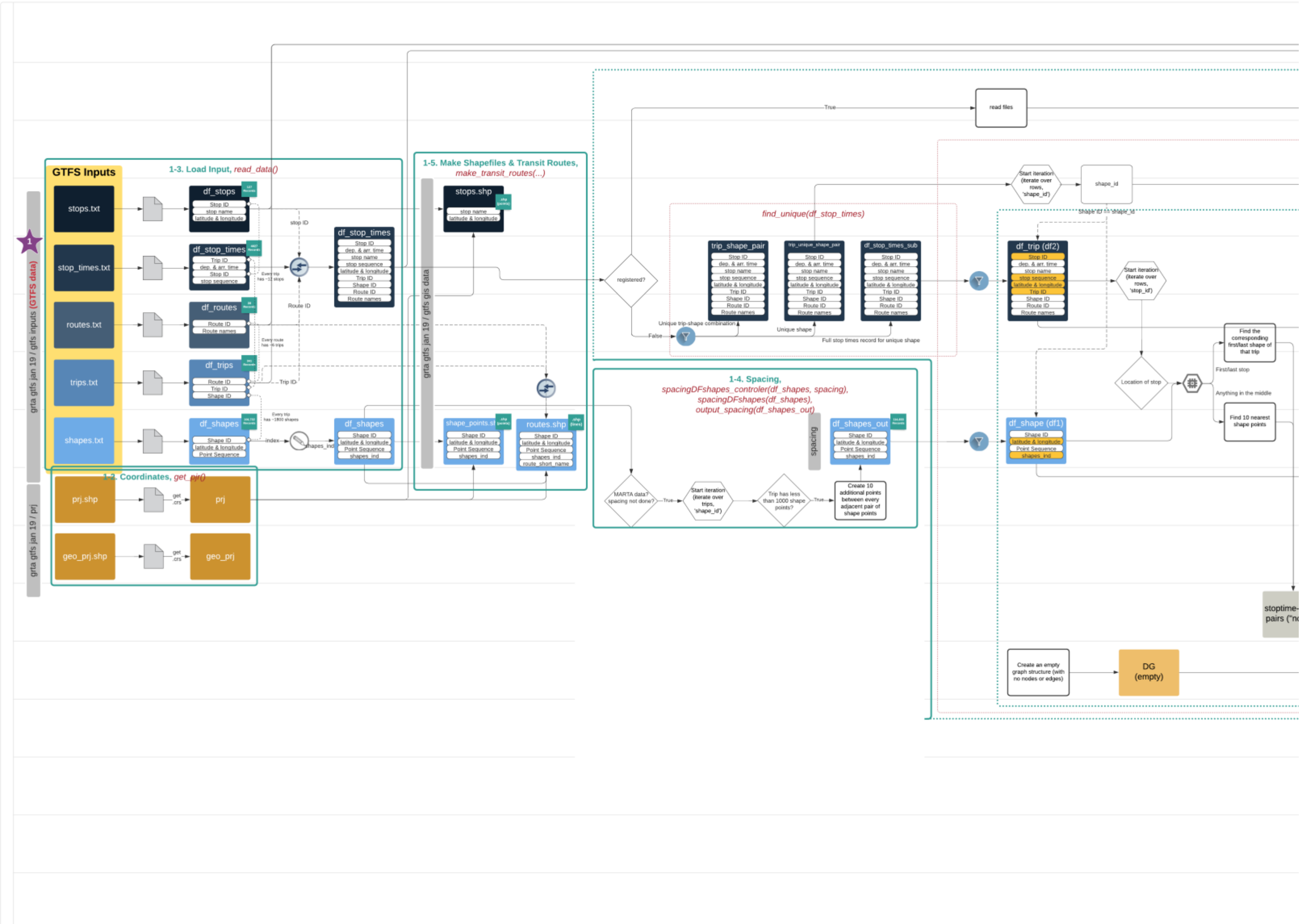
Data Access and Sharing

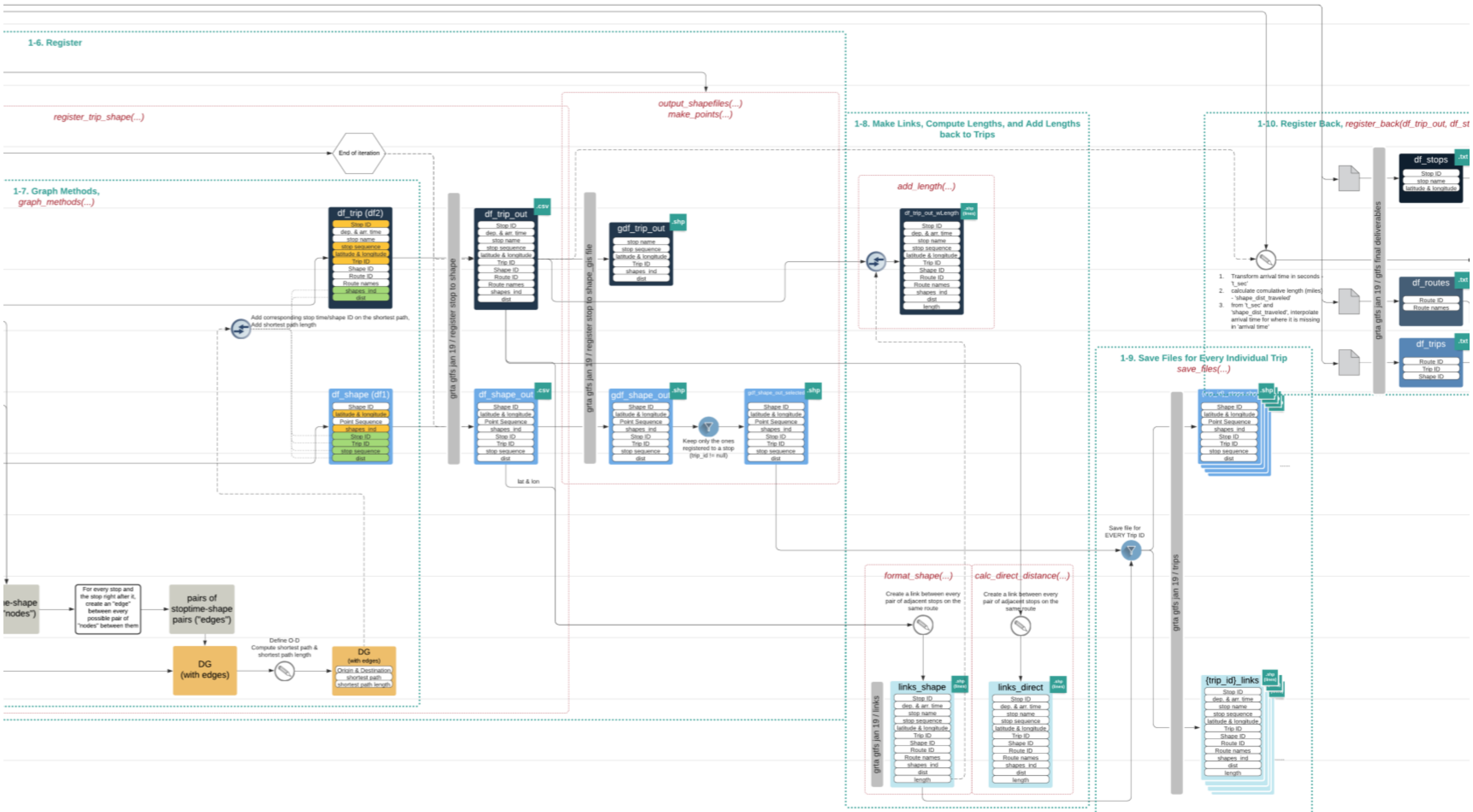
- GTFS Data - Open source available online
- APC Data - Proprietary
- MOVES-Matrix Energy and Emission Rates - Open source data available through NCST at: https://tse.ce.gatech.edu/ncst/movesmatrix

Reuse and Redistribution

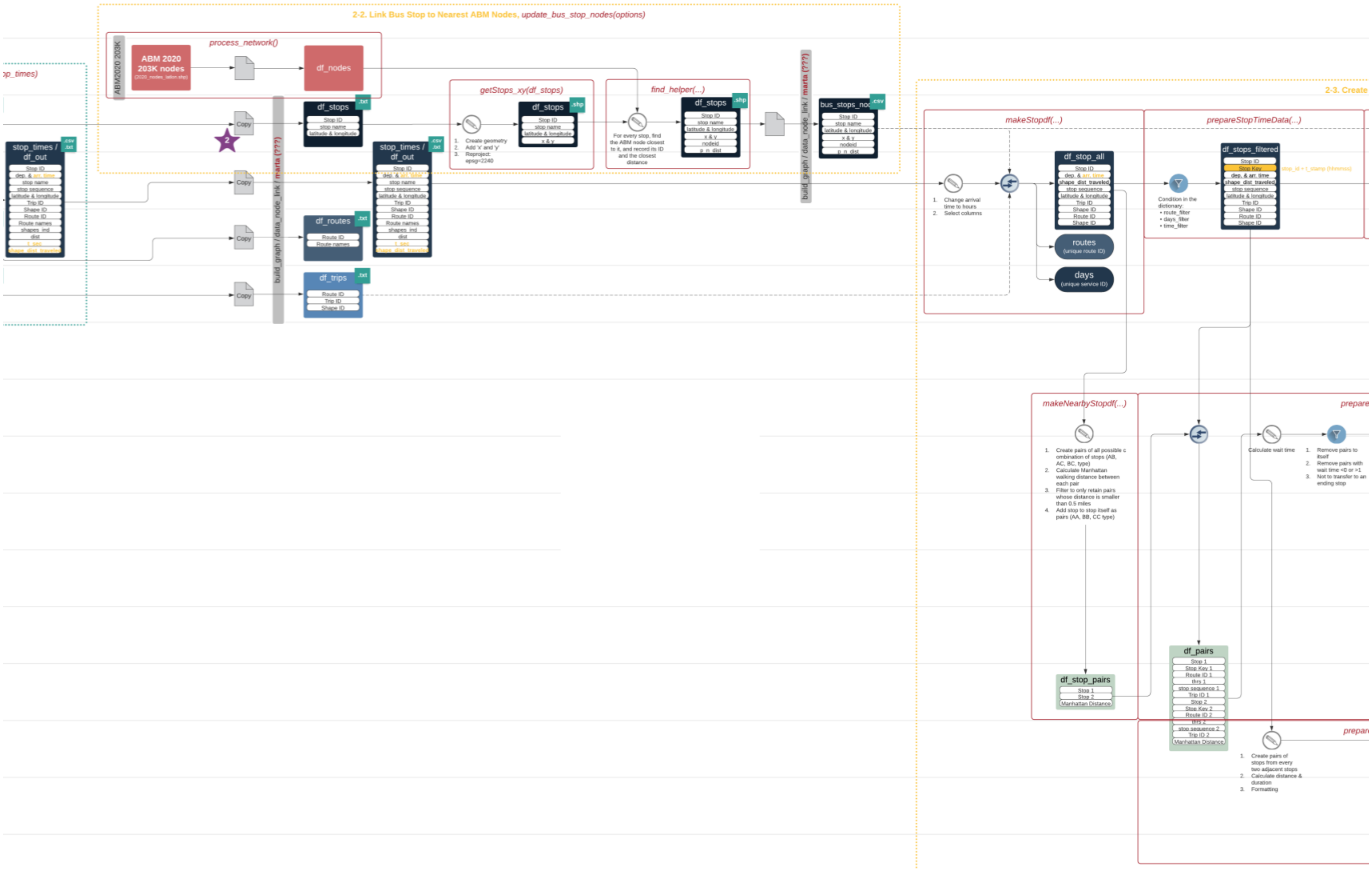
There are no restrictions with respect to re-use and redistribution of the results dataset used to populate the analyses presented in this report and are available through Zenodo (https://zenodo.org/record/7231978#.Y1GseHbMKF4). The GTFS data are public domain. The proprietary MARTA APC data cannot be distributed by the research team and must be obtained from MARTA. MOVES-Matrix data are public domain.

Appendix A - TransitSim Processing Flowchart

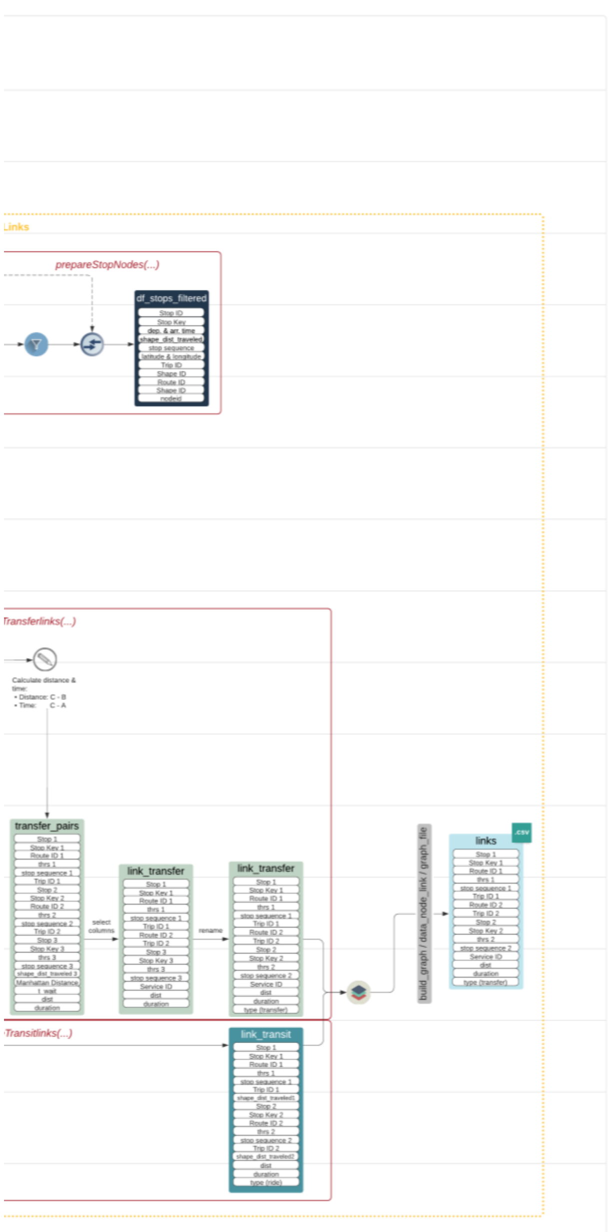




1-6. Register
register_trip_shape(...)
output_shapefiles(...)
make_points(...)
1-8. Make Links, Compute Lengths, and Add Lengths back to Trips
1-10. Register Back, register_back(df_trip_out, df_st
End of iteration
1-7. Graph Methods,
graph_methods(...)
df_trip (df2)
df_trip_out
gdf_trip_out
add_length(...)
df_stops
df_routes
df_trips
df_shape (df1)
df_shape_out
gdf_shape_out
Keep only the ones registered to a stop (trip_id != null)
1-9. Save Files for Every Individual Trip
save_files(...)
Save file for EVERY Trip ID
format_shape(...)
calc_direct_distance(...)
Create a link between every pair of adjacent stops on the same route
links_shape
links_direct
{trip_id}_links
pairs of stoptime-shape pairs ("edges")
DG (with edges)
Define O-D Compute shortest path & shortest path length
lat & lon



2-2. Link Bus Stop to Nearest ABM Nodes, update_bus_stop_nodes(options)
process_network()
ABM2020 203K
ABM 2020 203K nodes
df_nodes
Copy
df_stops
Stop ID
stop name
latitude & longitude
stop_times / df_out
Stop ID
stop name
stop sequence
latitude & longitude
Trip ID
Shape ID
Route ID
Route names
shapes_ind
dist
df_routes
Route ID
Route names
df_trips
Route ID
Trip ID
Shape ID
build_graph / data_node_link / marta (???)
getStops_xy(df_stops)
1. Create geometry
2. Add 'x' and 'y'
3. Reproject: epsg=2240
x & y
find_helper(...)
For every stop, find the ABM node closest to it, and record its ID and the closest distance
nodeid
p_n_dist
bus_stops_no
2-3. Create
makeStopdf(...)
1. Change arrival time to hours
2. Select columns
df_stop_all
dep. & arr. time
shape_dist_traveled
routes
(unique route ID)
days
(unique service ID)
prepareStopTimeData(...)
Condition in the dictionary:
• route_filter
• days_filter
• time_filter
df_stops_filtered
Stop Key
makeNearbyStopdf(...)
1. Create pairs of all possible combination of stops (AB, AC, BC, type)
2. Calculate Manhattan walking distance between each pair
3. Filter to only retain pairs whose distance is smaller than 0.5 miles
4. Add stop to stop itself as pairs (AA, BB, CC type)
df_stop_pairs
Stop 1
Stop 2
Manhattan Distance
Calculate wait time
1. Remove pairs to itself
2. Remove pairs with wait time <0 or >1
3. Not to transfer to an ending stop
df_pairs
Stop Key 1
Route ID 1
thrs 1
stop sequence 1
Trip ID 1
Stop Key 2
Route ID 2
thrs 2
stop sequence 2
Trip ID 2
1. Create pairs of stops from every two adjacent stops
2. Calculate distance & duration
3. Formatting



Links
prepareStopNodes(...)
df_stops_filtered
Transferlinks(...)
Calculate distance & time:
• Distance: C - B
• Time: C - A
transfer_pairs
select columns
link_transfer
rename
link_transfer
build_graph / data_node_link / graph_file
links
.csv
Transitlinks(...)
link_transit

Appendix B - Route-specific data summary

Route Name	year	Total Number of Trips	Average Passenger Load per Trip	Total Energy Use	Energy Use per Passenger Mile
14th Street / Blandtown	2019	552.00	6.28	62,572,502.50	5,795.78
	2020				
	2021	409.00	2.96	46,845,438.67	9,786.71
Alpharetta	2019	447.00	12.18	97,522,392.69	2,692.68
	2020	887.00	3.50	231,169,617.23	8,790.57
	2021	442.00	9.05	99,567,895.92	3,703.83
Atlanta University Center	2019	561.00	6.91	68,704,162.52	9,433.21
	2020				
	2021	402.00	3.58	50,805,257.49	24,454.36
Baker Hills / Wilson Mill Meadows	2019	545.00	2.52	46,237,510.38	12,677.40
	2020				
	2021	287.00	2.18	23,927,667.89	19,738.94
Belvedere	2019	248.00	2.86	27,347,883.99	11,818.37
	2020				
	2021	234.00	1.74	22,215,974.69	18,644.35
Benjamin E Mays Drive	2019	551.00	16.11	109,154,274.67	3,674.17
	2020				
	2021	423.00	6.34	83,751,552.40	8,635.20
Boulder Park Drive	2019	549.00	1.99	50,843,734.53	16,701.61
	2020				
	2021	280.00	3.38	25,538,062.07	16,533.26
Bouldercrest	2019	439.00	14.16	83,717,348.87	2,859.78
	2020				
	2021	435.00	6.10	87,800,770.96	6,886.22
Boulevard / Tilson Road	2019	536.00	9.90	91,281,300.26	3,207.14
	2020				
	2021	398.00	3.99	67,065,942.07	8,079.46
Buford Highway	2019	1,017.00	33.63	132,209,194.85	1,757.54
	2020	2,027.00	11.35	288,282,550.19	4,242.99
	2021	938.00	20.81	126,114,997.18	2,754.08
Camp Creek / South Fulton Parkway	2019	704.00	15.19	130,745,768.44	2,651.60
	2020	1,401.00	4.11	821,399,733.48	8,471.32
	2021	697.00	9.43	136,246,938.07	3,480.13
Campbellton Road	2019	1,390.00	19.77	134,457,881.17	1,933.73
	2020	2,773.00	7.04	273,165,193.89	5,043.86
	2021	1,221.00	13.83	118,694,213.82	2,541.20
Candler Road	2019	953.00	19.49	172,531,948.95	2,192.84
	2020	1,899.00	6.00	766,144,173.80	8,196.56
	2021	893.00	10.53	161,105,895.20	4,499.02
Carroll Heights / Fairburn Heights	2019	533.00	3.26	50,320,620.12	8,160.81
	2020				
	2021	273.00	2.73	25,680,678.88	10,734.99
Cascade Road	2019	1,188.00	12.46	141,947,210.66	3,050.26
	2020	2,369.00	5.27	298,364,909.77	7,735.90
	2021	957.00	10.05	115,393,419.53	3,784.77
Center Hill	2019	542.00	5.71	63,144,539.89	5,533.90
	2020				
	2021	409.00	4.42	47,857,731.41	8,706.54
Cheshire Bridge Road	2019	526.00	6.52	72,914,196.31	8,967.44
	2020				
	2021	353.00	3.25	46,065,070.83	14,550.03

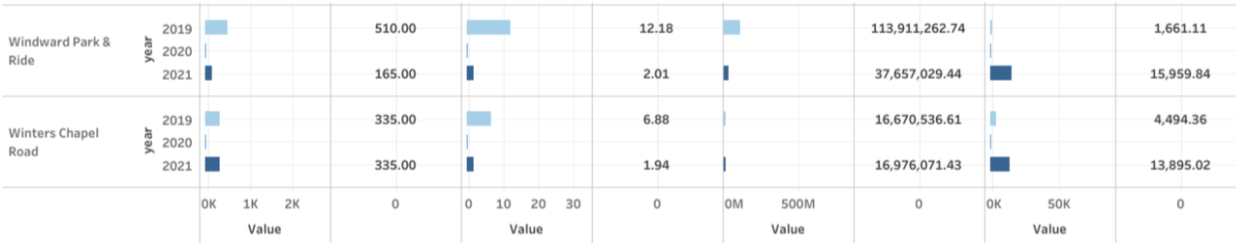
	year				
Church Street	2019				
	2020				
	2021	231.00	3.47	18,447,125.66	8,996.04
Clairmont Road / Howard Avenue	2019				
	2020	887.00	4.52	350,360,807.75	11,686.73
	2021	433.00	8.32	85,533,014.23	5,389.48
Clarkston	2019	471.00	17.94	54,312,703.90	2,151.62
	2020				
	2021	471.00	9.57	57,552,972.04	3,360.97
Cleveland Avenue	2019	1,164.00	16.17	96,252,817.75	2,622.54
	2020	2,321.00	5.03	188,473,470.71	9,537.71
	2021	950.00	13.84	76,268,424.25	3,163.44
Clifton Road / Emory	2019	605.00	14.57	78,223,929.10	3,236.96
	2020	605.00	7.29	200,945,438.61	6,404.11
	2021	452.00	8.42	55,764,996.44	4,215.03
Columbia Drive	2019	463.00	14.00	55,802,856.19	2,993.65
	2020				
	2021	423.00	4.42	54,038,318.13	8,360.94
Conley Road / Mt Zion	2019	269.00	19.05	84,547,077.34	1,527.29
	2020				
	2021	325.00	5.80	106,631,605.12	4,971.33
Covington Highway	2019	656.00	20.35	124,805,935.79	1,756.23
	2020				
	2021	649.00	9.30	130,165,152.31	3,843.21
Defoors Ferry Road	2019	512.00	7.53	65,082,892.95	6,091.79
	2020				
	2021	381.00	4.20	44,810,196.32	7,969.68
Donald Lee Hollowell Parkway	2019	550.00	14.79	67,346,090.34	3,090.77
	2020	1,093.00	8.58	192,335,263.57	5,367.97
	2021	543.00	14.56	65,952,889.02	2,715.40
Dunwoody Village	2019	281.00	5.25	29,457,736.63	6,887.57
	2020				
	2021	281.00	2.00	29,011,961.42	17,804.85
East Holcomb Bridge Road	2019	185.00	2.63	20,253,216.11	9,293.58
	2020				
	2021	185.00	1.19	20,109,937.05	21,064.01
East Ponce De Leon Avenue	2019	660.00	17.33	81,462,178.12	1,787.83
	2020	1,303.00	3.83	176,985,970.21	7,833.72
	2021	648.00	8.29	80,440,366.62	3,501.87
Embry Hills	2019				
	2020				
	2021	332.00	3.66	41,539,366.82	8,182.04
Empire Blvd / Southside Ind Park	2019	621.00	8.52	59,925,321.52	3,473.84
	2020	621.00	5.04	104,149,765.47	6,808.98
	2021	563.00	6.44	56,875,505.43	3,858.72
Fairburn Road	2019	791.00	10.83	83,129,626.17	3,334.28
	2020				
	2021	650.00	4.36	77,677,429.37	8,624.57
Fairington Road	2019	477.00	24.07	94,070,044.63	1,626.36
	2020	947.00	7.92	450,843,600.39	6,369.73
	2021	472.00	11.91	97,215,601.93	3,520.16
Flat Shoals Road	2019	454.00	13.16	57,242,995.48	2,586.73
	2020				
	2021	454.00	8.37	62,610,653.67	4,474.79

Flat Shoals Road / Scofield Road	2019	639.00	13.75	105,887,959.20	2,358.36
	2020				
	2021	559.00	6.51	93,865,491.90	4,946.38
Forest Parkway	2019	279.00	15.84	67,989,190.22	2,308.68
	2020				
	2021	276.00	4.86	67,579,120.30	8,002.63
Fulton Industrial	2019	1,207.00	17.55	168,170,183.17	2,026.66
	2020	2,407.00	8.34	347,779,408.57	4,946.62
	2021	1,207.00	13.44	172,299,754.75	2,598.33
Glenwood	2019	641.00	19.62	136,158,598.55	2,401.44
	2020	1,275.00	7.52	285,724,288.37	6,419.72
	2021	561.00	12.51	116,834,245.66	3,681.94
Grant Park	2019	545.00	5.81	51,658,014.52	7,596.67
	2020				
	2021	283.00	3.15	26,720,545.42	10,212.72
Greenbriar	2019				
	2020				
	2021	419.00	3.82	63,003,677.11	9,059.40
Gresham Road	2019	449.00	8.42	54,113,836.32	3,580.27
	2020				
	2021	419.00	3.62	50,541,590.81	7,353.83
Hairston Road / Stone Mtn Village	2019	440.00	15.45	69,451,054.34	3,116.02
	2020				
	2021	435.00	6.02	70,148,406.55	6,257.45
Haynes Bridge Road / Milton	2019	442.00	11.72	107,253,125.41	2,419.82
	2020				
	2021	432.00	3.06	106,847,378.21	8,576.38
Headland Drive / Main Street	2019	545.00	13.35	78,652,937.62	3,601.76
	2020				
	2021	367.00	5.47	55,235,070.71	8,249.12
Hightower Road	2019	578.00	9.65	53,110,233.18	3,321.73
	2020	1,149.00	7.38	118,959,590.63	4,440.53
	2021	571.00	7.94	52,896,797.73	4,112.71
Hollywood Road / Lucile Avenue	2019	549.00	10.84	74,051,315.36	4,696.13
	2020				
	2021	367.00	5.84	51,069,191.77	7,452.22
Howell Mill Road / Cumberland	2019	714.00	11.95	136,061,349.73	3,473.15
	2020				
	2021	682.00	5.64	126,190,654.95	7,399.62
I-85 Access Road	2019	315.00	13.19	44,047,040.90	2,976.72
	2020				
	2021	315.00	4.36	43,671,405.25	8,159.22
James Jackson Parkway	2019	558.00	6.56	36,640,324.12	4,791.47
	2020				
	2021	563.00	2.10	36,909,417.91	11,879.66
Johnson Ferry Road	2019	165.00	2.73	10,561,568.12	8,599.84
	2020				
	2021	165.00	2.16	10,604,981.37	13,727.81
Jonesboro Road	2019	629.00	18.96	127,787,098.13	2,053.31
	2020				
	2021	625.00	13.75	130,355,173.99	2,826.63
Joseph E Boone Boulevard	2019	760.00	13.18	86,715,473.86	3,319.47
	2020	1,513.00	6.99	247,800,623.57	6,891.66
	2021	638.00	16.28	81,638,132.68	3,655.50

LaVista Road	2019	311.00	11.48	50,968,487.77	3,060.37
	2020				
	2021	309.00	5.01	52,632,150.13	8,365.62
Lawrenceville Highway	2019	536.00	14.21	81,747,124.20	2,699.99
	2020				
	2021	396.00	5.41	60,458,937.63	6,472.53
Lovejoy	2019	110.00	5.15	26,445,640.58	7,187.89
	2020				
	2021	110.00	3.67	27,883,399.15	9,756.93
Lynhurst Drive / Princeton Lakes	2019	547.00	12.75	113,719,575.33	3,275.47
	2020				
	2021	409.00	7.33	84,547,509.31	5,756.83
Marietta Blvd/Joseph E Lowery Blvd	2019	539.00	9.61	74,085,923.52	5,347.07
	2020				
	2021	399.00	5.66	54,585,029.78	7,930.54
Marietta Street / Perry Boulevard	2019	554.00	11.39	96,539,940.96	5,056.21
	2020	1,101.00	6.89	532,193,273.14	9,579.05
	2021	416.00	12.31	73,558,589.89	5,002.62
Martin Luther King Jr Dr/Auburn Ave	2019	542.00	7.54	75,379,017.30	7,869.81
	2020				
	2021	358.00	5.23	48,278,040.19	9,536.17
McAfee / Hosea Williams	2019	326.00	11.06	67,069,499.19	3,931.05
	2020				
	2021	281.00	5.13	57,749,311.17	6,256.43
McDonough Boulevard	2019	845.00	15.31	109,623,923.79	2,249.69
	2020	1,683.00	3.31	316,947,823.08	11,711.84
	2021	661.00	7.70	87,131,166.47	4,874.99
Memorial Drive	2019	605.00	19.49	98,361,102.06	2,470.32
	2020	1,195.00	8.30	339,938,945.31	5,424.94
	2021	594.00	9.88	100,633,297.75	4,402.87
Memorial Drive / N Hairston Road	2019	939.00	20.68	153,176,933.77	2,565.74
	2020	1,863.00	8.81	392,644,590.43	6,919.52
	2021	928.00	13.88	148,753,800.14	3,825.33
Memorial Drive Limited	2019	205.00	11.55	22,609,783.22	2,733.59
	2020				
	2021	135.00	3.31	14,632,161.07	12,198.64
Metropolitan Campus Express	2019	245.00	2.30	13,118,438.91	10,436.44
	2020				
	2021	215.00	0.53	8,709,768.89	87,595.04
Metropolitan Parkway	2019	874.00	14.88	97,132,119.82	2,456.43
	2020	1,741.00	3.75	191,063,973.83	9,924.15
	2021	869.00	9.70	95,102,477.03	3,615.83
Monroe Drive / Boulevard	2019	526.00	9.20	69,598,286.02	5,603.35
	2020				
	2021	395.00	5.13	51,949,437.64	8,299.45
Moreland Avenue	2019	563.00	6.93	48,070,451.96	5,038.86
	2020	563.00	6.03	121,611,116.98	12,920.00
	2021	423.00	4.85	40,215,837.12	7,291.94
Morrow / Jonesboro	2019	505.00	20.32	131,073,996.64	1,757.51
	2020	1,003.00	5.28	717,840,823.95	8,352.36
	2021	505.00	14.67	136,163,105.40	2,672.96
Mount Vernon Highway	2019	95.00	3.87	10,608,914.64	6,741.83
	2020				
	2021	75.00	1.40	7,440,470.86	18,586.68

Myrtle Drive / Alison Court	2019	648.00	10.35	32,580,056.10	3,159.09
	2020				
	2021	548.00	5.03	28,416,120.98	5,573.90
N Decatur Road / Virginia Highland	2019	493.00	11.73	93,533,394.78	4,238.38
	2020				
	2021	370.00	5.39	69,394,332.17	7,904.28
North Avenue / Little Five Points	2019	556.00	12.88	53,206,019.70	4,907.23
	2020	556.00	8.87	81,474,879.62	6,114.40
	2021	556.00	7.49	55,722,637.94	7,888.43
North Druid Hills Road	2019	290.00	11.81	107,300,433.46	5,484.97
	2020				
	2021	280.00	4.53	58,669,129.66	9,100.74
North Point Parkway	2019	416.00	8.71	79,796,431.05	2,529.06
	2020				
	2021	400.00	2.24	77,580,819.54	10,825.14
Northside Drive	2019	553.00	6.96	60,305,437.54	5,326.22
	2020				
	2021	413.00	3.02	46,137,199.01	13,179.43
Oakley Industrial	2019				
	2020	122.00	1.17	38,501,469.89	48,691.81
	2021	182.00	5.18	0.00	
Old Dixie / Tara Boulevard	2019	305.00	24.62	62,086,864.94	1,302.17
	2020	593.00	5.41	256,358,543.95	6,318.88
	2021	298.00	17.51	62,959,871.41	1,754.49
Old Fourth Ward	2019	503.00	5.54	42,124,375.26	11,759.03
	2020				
	2021	264.00	3.03	32,962,757.14	24,542.16
Old National Highway	2019	856.00	21.43	165,671,178.71	1,666.19
	2020	1,705.00	7.63	440,367,199.64	5,222.98
	2021	929.00	15.24	183,159,907.59	2,426.32
Peachtree Boulevard	2019	339.00	5.69	33,124,815.17	5,370.67
	2020				
	2021	322.00	2.16	31,537,322.95	14,168.87
Peachtree Road / Buckhead	2019	1,005.00	15.28	171,328,619.18	4,957.75
	2020	2,003.00	4.19	336,949,222.99	14,592.45
	2021	911.00	10.97	158,896,775.22	6,527.62
Peachtree Street / Downtown	2019	503.00	9.81	66,756,020.69	8,467.25
	2020	999.00	9.13	204,471,861.23	6,407.53
	2021	339.00	9.73	44,218,617.61	7,215.16
Peeler Road	2019	351.00	8.48	41,590,322.06	3,939.30
	2020				
	2021	351.00	2.57	41,707,887.86	12,713.73
Peyton Forest / Dixie Hills	2019	539.00	4.03	60,142,061.07	19,703.79
	2020				
	2021	273.00	3.36	33,252,687.38	25,853.80
Piedmont Road / Sandy Springs	2019	1,013.00	18.86	145,116,886.64	2,234.05
	2020	2,019.00	4.62	301,056,240.74	7,886.30
	2021	924.00	9.78	144,056,850.18	4,285.71
Pittsburgh	2019	552.00	10.38	56,025,769.42	3,725.59
	2020				
	2021	372.00	3.94	38,395,926.94	10,829.93
Pleasantdale Road	2019	492.00	15.43	63,396,688.63	3,399.02
	2020	102.00	6.53	22,270,471.06	6,821.15
	2021	462.00	8.15	62,972,073.33	3,915.27

Ponce de Leon Avenue / Druid Hills	2019	556.00	10.09	48,874,438.82	4,495.05
	2020	556.00	6.71	71,190,848.09	6,038.93
	2021	556.00	5.81	51,767,976.59	7,393.84
Pryor Road	2019	559.00	14.02	76,745,827.14	2,684.61
	2020	1,111.00	6.69	296,989,624.32	6,011.00
	2021	421.00	9.19	57,063,546.55	4,205.31
Rainbow Drive / South DeKalb	2019	607.00	24.40	125,096,287.08	1,071.84
	2020	1,207.00	8.20	754,922,249.45	5,154.79
	2021	612.00	14.89	133,642,456.01	1,737.02
Redan Road	2019	625.00	17.48	109,689,696.73	1,929.59
	2020				
	2021	616.00	6.86	109,662,630.87	5,145.84
Riverdale / ATL Intl Terminal	2019	392.00	20.96	135,890,875.61	1,650.00
	2020	777.00	4.64	777,792,421.64	9,840.99
	2021	392.00	12.35	136,412,234.07	2,971.89
Rockbridge Road / Panola Road	2019	641.00	19.60	161,093,001.92	2,520.88
	2020	1,275.00	8.66	559,768,901.20	6,959.58
	2021	636.00	13.68	158,601,146.61	4,030.88
Roosevelt Highway	2019	502.00	17.11	128,361,408.08	1,985.84
	2020				
	2021	502.00	5.91	131,910,809.03	5,491.35
Roswell	2019	458.00	10.14	75,505,912.93	3,289.70
	2020				
	2021	444.00	4.92	73,463,055.03	7,244.82
Roswell Road / Sandy Springs	2019	534.00	15.83	105,886,206.56	2,735.95
	2020				
	2021	539.00	8.65	107,465,746.71	4,914.15
Shallowford Road	2019	323.00	6.11	29,026,605.00	5,103.39
	2020				
	2021	309.00	3.26	27,229,395.81	9,291.91
Six Flags Over Georgia	2019	301.00	0.88	27,826,831.18	17,434.08
	2020				
	2021	301.00	0.96	27,826,133.55	17,649.61
Snapfinger Woods	2019	472.00	19.38	124,886,388.07	2,665.15
	2020	937.00	8.18	595,736,685.81	6,728.77
	2021	465.00	9.48	119,206,945.73	5,129.56
Sylvan Hills	2019	357.00	10.50	38,744,085.28	3,787.75
	2020				
	2021	343.00	6.37	38,131,189.75	5,382.87
Sylvan Road / Virginia Avenue	2019	372.00	17.55	47,072,311.74	2,954.47
	2020	372.00	9.33	96,582,403.53	4,815.58
	2021	374.00	10.15	50,508,880.36	4,031.38
Tilly Mill Road	2019	390.00	5.51	34,648,668.43	4,695.52
	2020				
	2021	315.00	2.23	27,782,746.06	12,376.85
Upper Riverdale / Southlake	2019	606.00	27.65	115,852,698.35	1,454.79
	2020	1,205.00	7.93	281,916,735.47	5,035.76
	2021	606.00	18.32	127,759,281.42	2,486.30
Venetian Hills / Delowe Drive	2019	563.00	12.61	99,006,551.28	3,508.85
	2020				
	2021	379.00	7.14	67,864,728.99	5,469.68
Washington Rd/Camp Crk Marketplace	2019	571.00	15.60	66,602,810.94	2,270.44
	2020	1,135.00	5.21	142,537,763.28	6,839.45
	2021	578.00	10.65	70,759,870.23	3,312.51


Windward Park & Ride
year
2019
2020
2021
510.00
165.00
12.18
2.01
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1,661.11
15,959.84
Winters Chapel Road
335.00
335.00
6.88
1.94
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0K 1K 2K
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