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Modeling net effects of transit operations on vehicle miles traveled, fuel consumption, carbon dioxide, and criteria air pollutant emissions in a mid-size US metro area: findings from Salt Lake City, UT

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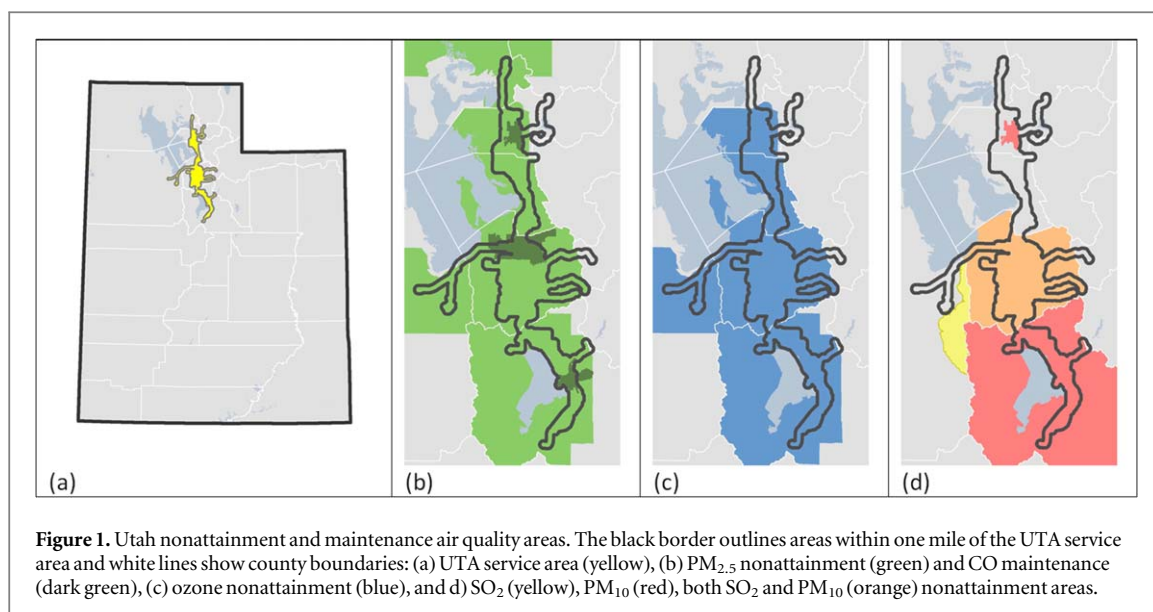
Abstract

The Utah Transit Authority (UTA) serves Utah's Wasatch Front, a rapidly growing conurbation with a current population of ~1.8 M people. UTA uses an electronic fare collection (EFC) system that requires riders to tap on as they enter a bus or train and tap off as they exit, as well as an automated passenger counter (APC) system that counts interruptions of infrared beams across vehicle doorways as riders board and alight. We analyzed EFC and APC data for 2016, along with service schedules and routes from General Transit Feed Specification (GTFS) data, to estimate the impact of UTA on the air quality in its service region by accounting for vehicle miles traveled, gasoline gallons equivalent of fuel consumed, and multiple pollutant species emitted. Buses, light rail, and commuter rail were found to collectively offset approximately 1.5% of the onroad emissions from the counties served by UTA due to transit use replacing single passenger vehicle use. These offsets are not homogeneous; ridership drops significantly (~20%–50% depending on the mode) during the summer months as some of the largest users are educational institutions with noticeable seasonal cycles. Low transit use during the weekend negates some of the air quality benefits as buses and trains travel at lower capacity. Central routes, particularly during peak travel hours provide noticeable congestion, fuel consumption, and pollutant emissions reduction due to trips taken by transit replacing personal vehicles but off-peak, and non-central routes, show lower benefits. Because the light rail is electric, its local air quality benefits are significant due to the electricity being produced primarily outside the airshed. Upgrading the bus fleet to 2010 model, and newer, diesel and compressed natural gas (CNG) buses, as well as modeling an envisioned change to Tier 3 locomotives for the commuter rail system, was found to significantly reduce regional nitrogen oxides (NO_x), fine particulate matter (PM_{2.5}), and sulfur oxides (SO_x) emissions.

1. Introduction

1.1. Motivation

Cities exist to facilitate interactions between people (Bettencourt 2013). Much of this interaction is mediated by movement of people through the urban area, and vehicular mobility has profoundly influenced modern cities. While generating enormous benefits to their populations, vehicular transport also creates well-known problems in cities, including congestion and degraded air quality. Public transit services perform multiple functions in cities. First, transit assists economic activity by enabling mobility of commuters and consumers. Second, transit can strengthen social equity by supplementing mobility options for non-affluent populations. Third, transit can reduce environmental externalities such as congestion and pollution. Rational decision-making in this space is non-trivial. Not only do



planning and operation of transit services demand tradeoffs between these diverse and potentially competing priorities, but evaluating the costs or benefits transit imposes on any one of these priorities can be difficult. In the case of air-quality impacts, the overall impact transit makes on urban air quality is not only a function of transit operations directly (by themselves a complex object of study), but also a function of any unobserved impacts that would be generated by other modes in the absence of transit. Public transit services may reduce emissions from personal vehicles by capturing ridership and thereby displacing personal vehicle trips. A fundamental question here is whether, and to what extent a transit service's operations make a net positive impact on urban air quality.

The Utah Transit Authority (UTA) operates transit services along the Wasatch Front of northern Utah, a conurbation with a current population of ~ 1.8 M persons that is growing rapidly and expected to reach a total population of ~ 2.5 M within the next 30 years (Kem C. Gardner Policy Institute 2017). UTA provides public transit throughout a 7-county area, most of which has significant air quality concerns and is qualified as areas of nonattainment and maintenance for multiple pollutants as seen in figure 1 (Utah Division of Air Quality 2018).

In operation since 1970, the transit operator carries ~ 45 M passengers per year via a network of local and express buses, the TRAX light-rail system, the FrontRunner commuter-rail system, a streetcar line, and a system of on-demand paratransit buses (Utah Transit Authority 2017). As UTA juggles the multiple social goods that transit seeks to promote, this transit authority has worked aggressively over the past two decades to expand the extent and modal diversity of its provided services, and was named 2014 Outstanding Public Transportation System by the American Public Transit Association (American Public Transportation Association 2016).

The geographic, demographic, and ridership heart of UTA's service area is the Salt Lake Valley (SLV), an urbanized airshed with significant air quality problems that houses the state capital, Salt Lake City, and a population of ~ 1.34 M people in 2018. The SLV is bounded by the Wasatch Mountains on the east, the Oquirrh Mountains to the west, and the Great Salt Lake to the northwest. During the winter, meteorological 'inversion' events with warmer air sitting on top of cooler air suppress atmospheric mixing and trap pollutants within the valley, leading to high levels of fine particulate matter ($PM_{2.5}$) (Bares *et al* 2018). During the summer, elevated levels of ozone are a regular occurrence (Horel *et al* 2016). Health concern for this large urban population motivates the question we seek to address in this paper: what are UTA's actual and potential impacts on air quality in the SLV airshed?

1.2. Previous work

The work reported on here draws from and builds on a variety of results from different fields. The current 'big data' era has fed a growing interest in analyzing large-scale properties of human mobility e.g. Brockmann *et al* (2006), and study of patterns in human mobility at the scale of individuals e.g. González *et al* (2008). Such research depends on the existence of large volumes of spatial and temporal data. Two data-capture technologies facilitate unprecedented examination of individual-scale pollutant emissions from mobility. Electronic fare collection (EFC) systems now generate fine-grained data on transit ridership that open up possibilities for analyzing transit-rider travel behavior in new ways; a comprehensive review is given by Pelletier *et al* (2011). Data volume and the nature of spatio-temporal data pose challenges and demand novel analysis methods (Tao *et al* 2014, Chu 2015, Ghaemi *et al* 2015). Availability of fine-grained transit ridership data is increasing; in our study area, UTA uses a smart card system allowing monthly and annual fare-purchasers to 'tap on' and 'tap off' all transit services without holding a ticket or paying a cash fare. Therefore, the mining of EFC data performed in this study required new techniques and sets this study apart from

previous work. Another important component is the automated passenger counter (APC) devices installed on all UTA vehicles. These counters use infrared lights on vehicle doorways to track passenger boarding and alighting, and has also been used in other literature to understand passenger movement (Furth *et al* 2006).

Another technology enabling novel research is the General Transit Feed Specification (GTFS) (Wong 2013). Originally developed by Google in cooperation with Tri-Met, the transit operator in the Portland OR metro area, GTFS is an open data specification for representing movement in time and space of scheduled transit services for a given transit operator. GTFS was originally developed to extend support for internet-based trip-planning to transit modes, but such data is increasingly used to study patterns of access to urban resources such as employment or groceries; e.g. Farber *et al* (2014) and Widener *et al* (2015).

A substantial research literature focuses on the assumed emissions benefits of transit. This literature includes three general methodological approaches: observational studies of pollutant concentration, econometric modeling, and simulation modeling.

1.2.1. Observational studies of pollutant concentration

One way to determine transit's net impacts to air pollutant emissions would be to directly observe mode choice and movement of a region's travelers, as well as directly observing pollutants. In practice this is difficult and expensive to implement—measurement of emissions (or pollutant concentrations) remains expensive and therefore observational data are limited. Also, observing the counterfactual of an avoided auto trip that has been mode-shifted to transit is difficult. For example, Chen and Whalley (2012) used direct observations of pollutant concentrations for 1 year before and 1 year after the opening of a new subway line in Taipei, Taiwan, to investigate transit's impact on air quality. Using Discontinuity Based ordinary least squares regression, they concluded that the sudden (one-day) jump in transit ridership was responsible for reductions in carbon monoxide (CO) and ground-level ozone concentrations. However, this work did not examine carbon dioxide (CO₂), and did not seek to relate the observed emissions benefits to auto trip volume directly, beyond recognizing that the sudden addition of riders to the subway system would have represented a sharp perturbation of the equilibrium auto mode share. Beyond these challenges, a recent review emphasizes the variability in attributes of a marginal transit rider (vehicle efficiency etc) that would influence net influence on emissions as a challenge to estimating such effects (Beaudoin *et al* 2015). These authors conclude that that 'there is very little empirical evidence of the incremental effect that transit supply may or may not have on air quality'. There has been observational work in this vein directly within UTA's service area. Teague *et al* (2015) examined the impact of a voluntary auto trip reduction program in Utah on ground-level ozone concentrations. While these authors found a small but statistically significant reduction, their study design looked only at vehicular trip-making, not potential absorption of avoided auto trips by transit. Additionally, Ewing *et al* (2014) found a decrease in vehicular traffic in an arterial road connecting downtown Salt Lake City to the University of Utah after the extension of the light rail line which led to reduced congestion and potentially lower emissions. Public transportation can thus address an environmental issue by providing a method to mitigate not only air quality pollutants, but also CO₂ and other greenhouse gas emissions from personal vehicles.

1.2.2. Statistical models

Another avenue for investigating the relationships between transit travel, automobile travel, and air quality is econometric modeling. Glaeser and Kahn (2010) modeled emissions from urban areas of the US, including automobile and transit emissions (separately) via regression modeling of data from the 2001 National Household Travel Survey. Model results were associated to tract-level population and housing data and extrapolated up to the county and the metropolitan area. While modeling regional total emissions from both automobile and transit modes, this study did not examine the tradeoffs in mode choice nor in emissions sources or intensities between the two modes. Other econometric studies have attempted to capture these mode transfers. Lalive *et al* (2013) used regression analysis to model the effect of increased passenger rail service on emissions reductions of CO, nitrogen monoxide (NO), nitrogen dioxide (NO₂), sulfur dioxide (SO₂), and ozone (O₃) at the scale of counties for all of Germany and concluded that the rail mode's capture of trips from autos was responsible for declines in pollutant concentration.

Ultimately, however, the spatial granularity of econometric analyses is limited. The capacity of econometric models to extrapolate from samples to populations is linked to the coarse resolution of these studies, where space, time, and individuals are pooled to produce aggregate results. The present study's high spatial and temporal resolution, in conjunction with transit service disaggregation, enables a more detailed analysis at sub-city scales. Furthermore, the increased resolution facilitates the quantification of local-scale air quality effects which are critical in denser urban areas where onroad vehicle emissions dominate pollutant exposure (HEI Panel on the Health Effects of Traffic-Related Air Pollution 2010).

1.2.3. Simulation modeling

Simulation modeling has been used as a way to understand the net influence on pollutant emissions made by the interplay between transit operations and personal vehicle traffic. Griswold *et al* (2014) used a simulation model of an abstract transit system to explore how transit level of service (LOS) impacts rider per-capita emissions. Their model showed that while during peak travel hours per-capita emissions were reduced by using transit, during off-peak hours transit actually *increased* per-capita emissions due to buses or trains. This is due to transit systems operating well below capacity during off-peak hours.

Simulation can also be applied to actual geographic areas, vehicle fleets, or operation cycles. Lau *et al* (2011) modeled direct emissions from the public transit bus fleet of Toronto, Canada, using microsimulation models of bus movements and a passenger learning model that allocated observed demand volume observed at stops according to an agent-based passenger model. Their work explicitly accounted for idling emissions with realistic start-stop drive-cycles and allowed them to examine differences in total and rider per-capita emissions across routes and under scenarios of varying fuel and fleet age. They found that aside from the intuitive impacts of fuel source and vehicle age, per-capita emissions were variable between routes, potentially outweighing those from passenger cars on low-ridership routes. This suggests that service planning (scheduling/routing) may be a tool for transit planners to reduce overall urban emissions.

Waraich *et al* (2016) modeled direct emissions from a system-wide fleet of buses using a microsimulation transportation model. Their work examined the entire bus fleet for Montreal, Canada, using real service schedules and parameterizing fleet characteristics and emissions factors from the actual bus fleet. Ridership was estimated using stop-level regression models of demand and an agent-based model to track boardings and alightings. Like the work of Lau *et al* (2011), these results emphasize the significance of variability in ridership on the question of whether transit provides a net positive or negative impact on emissions but did not attempt to account for net emissions due to avoided auto trips. Ewing and Hamidi (2014) studied the transit multiplier in Portland, Oregon and showed that for every transit mile traveled, 3.04 miles of personal vehicle travel were avoided, due to increased walking trips in compact land use areas near transit stations.

1.3. What does it add to previous studies?

This study builds on previous work in several ways. Here we analyze public transit's impact on mobility-related pollutant emissions, for an entire metropolitan region in northern Utah over a complete meteorological year but resolved finely in numerous dimensions: space (at the grain of individual transit stops), time (at hourly resolution), and mode (separating out bus, light rail, and commuter rail services). The higher resolution of this study permits a more comprehensive and detailed analysis of neighborhood-scale air quality impacts of transit and car trips. This is a critical component for transit system operations decision-making processes as air quality impacts can now be quantified at unprecedented scales. Our approach allows us to capture the strong diurnal and seasonal variability in both ridership and transit operations. This variability is critical from an air quality perspective because of its interaction with the region's significant meteorological fluctuation. We also capture the impacts of service operations changes, which UTA implements three times per year. To our knowledge, this is the first study to model disaggregate vehicle emissions for an entire transit system that combines all the following:

- Utilizes GTFS data to represent the service operator's actual service schedule;
- Reflects actual ridership patterns as captured in EFC data, and corrected scaled up to include system boardings using APC data; and
- Examines the *net* impact of the transit operations, as opposed to direct impacts from the transit fleet only.

Our work provides a comprehensive analysis of UTA's trips by mode, hour, day of week, and location, and represents an upper-bound estimate of the net impact UTA's transit services have on emissions of CO₂ plus three other criteria pollutants.

The paper seeks to answer the following questions:

- What are the spatial and temporal patterns of net impact to emissions of various pollutants (CO₂, CO, NO_x, and PM_{2.5}), attributable to UTA's transit service operations?
- How do UTA's impacts to local pollutant emissions vary by mode (bus, light rail, commuter rail), and which service produces the largest amount of net avoided CO₂ emissions?
- How is the benefit of these avoided net differences in emissions distributed over the regional spatially?

2. Methodology

This study seeks to quantify realized *UTA transit impacts* (passenger miles traveled, fuel consumed, or pollutants emitted) from trips taken via transit modes ('transit' hereafter), hypothetical *avoided automobile impacts* associated with UTA riders ('avoided' hereafter), and *net emissions impacts* from UTA's service operations ('net' hereafter), at an hourly and $0.002 \text{ deg} \times 0.002 \text{ deg}$ resolution for annual, seasonal, and monthly intervals. Estimates for the quantities rely on data supplied by UTA: GTFS feeds and UTA's Transit Emissions Quantifier Tool for the realized emissions, and GTFS feeds together with EFC ridership data for the gross avoided emissions. UTA's Transit Emissions Quantifier Tool is an adapted version of the American Public Transportation Association's Transit Emissions Quantifier Tool v10 (American Public Transportation Association 2017) modified to use Utah vehicle fleet specific emission factors.

2.1. Processing GTFS feed data

UTA's EFC ridership data are aspatial, containing only numeric identifiers for route traveled and origin/destination stations. We used UTA's GTFS feeds to trace each EFC trip's trajectory through space for estimating gross avoided emissions. Similarly, GTFS data was used to trace out UTA's vehicle movements for estimating realized emissions.

GTFS feeds include route information including stop time and location and can be used to generate GIS features depicting the geometry of each transit route. We found the spatial representation of routes in UTA's GTFS data to be inconsistent, which UTA confirmed as a known issue they have since resolved. The problem manifested as occasional missing vertices, resulting in route segments that do not follow roads and instead may cut through the corner of a city block. Although rare, and affecting less than 1% of the routes, this sometimes led to observable errors in the spatial representation of transit routes, particularly on express routes which have fewer stops.

Using ArcMap 10.3.1 (ESRI) and fields joined from the 'shapes', 'trips', 'stops', and 'stop times' tables of a given GTFS feed, we generated a geospatial polyline feature representing the route between adjacent stations for each scheduled vehicle trip. Tao *et al* (2014) refer to such segments as 'mini trips'. The stop sequencing information in the GTFS data then allows us to look up an arbitrary trip origin stop on an arbitrary route and reconstruct the set of stops passed and the path through space traversed to the corresponding trip destination stop. We intersected these mini trips with a grid of rectangular cells representing the modeling grid used in urban atmospheric studies currently being performed at the University of Utah. This finely-resolved regular grid ($0.002 \text{ deg} \times 0.002 \text{ deg}$ or $\sim 200 \text{ m} \times 200 \text{ m}$ in Northern Utah) approximates the scale of a typical city block.

From the intersected mini-trips we constructed a flat table recording origin and destination (O/D) stop id and stop sequence for every successive pair of stops on each route, along with grid cell coordinates and total distance through the grid cell traversed. We used this table to allocate passenger miles implicit in UTA routes or EFC records to the grid. The temporal assignment is to the hourly bin coinciding with the time of trip origination.

UTA publishes updated GTFS feeds multiple times each year, some of which updates correspond with scheduled service changes three times each year on 'change days', and others of which correct errors in earlier versions. For this work we used the earliest feed published post-change day, while watching for feeds with abnormally high numbers of trips. Rides from the EFC data were mapped using the GTFS feed in use by UTA on the date of travel.

2.2. UTA transit emissions

The bus and commuter rail systems produce direct emissions through combustion. The light rail system is electric, and its electrical demand indirectly induces emissions at points of power generation. In this study we estimated both direct and indirect emissions and allocated the direct emissions spatially and temporally using route information as described in section 2.1. We estimated indirect emissions at an hourly resolution but did not allocate them spatially as these emissions are produced outside the study area's airshed. Due to Utah's topography, airsheds are identified as defined valleys surrounded by mountains. Most of Utah's electricity is generated in the central eastern part of the state, well outside the UTA service area. For each trip, all segments were binned to the hour associated with the route's first stop. We independently estimated emission factors based on data from the US Environmental Protection Agency (Lindhjem 1997, United States Environmental Protection Agency 1998, 2005, 2008), and found a close correlation between the emission factors provided by UTA and the United States Environmental Protection Agency (EPA); thus the UTA-provided emission factors were used for this study.

2.2.1. Transit vehicle emission factors

We aggregated UTA's seven largest services into three classes according to emission profiles. We grouped regular Buses, Express Buses, Ski Bus, and Park City Bus as the Bus class. TRAX and Streetcar were grouped as Light Rail, and the FrontRunner constituted the Commuter Rail. Since the light rail is powered by off-site generated electricity, the emission factors for the light rail were obtained based on power plant emission data specific to

Utah. The emissions factors listed for buses in table 1 are disaggregated by bus business unit. Table 1 also contains the sensitivity analysis, or expected future emission factors, due to fleet upgrades.

We estimated bus emissions using GTFS bus trips and emission factors provided by UTA separately for each of four subregional bus ‘business units’: Meadowbrook, Timpanogos, Ogden, and Central. Details on the fleet composition and activity for each business unit is found in table A1. Although the distribution varies by business unit, on average approximately 50% of traveled bus fleet miles are from buses that are from 2010 or newer vintages (considered ‘clean diesel’) and CNG. Commuter rail emissions were estimated using GTFS trip information as well as locomotive emission factors provided by UTA. The commuter rail system uses MPXpress MP36PH-3C locomotives which are rated Tier 0+, the most polluting category of refurbished locomotives (US Environmental Protection Agency 2016b). Light rail indirect emissions are estimated using data on vehicle miles traveled and electricity consumed provided by UTA from UTA’s internal Transit Emissions Qualifier Tool for 2015.

2.2.2. Modeled future transit fleet scenario

A fleet modernization approach for UTA encompasses the replacement of all older buses with either CNG and EPA clean diesel buses (US Environmental Protection Agency 2019), which are defined as buses from 2010 or newer, as well as upgrades to the commuter rail locomotives. UTA’s plan at the time of this study is to upgrade the Central bus fleet to 100% CNG, Ogden and Timpanogos fleet to 100% EPA clean diesel, and Meadowbrook will be 50% CNG and 50% clean diesel (Utah Transit Authority Strategic Planner 2018). Furthermore, the commuter rail locomotives are expected to be changed from Tier 0 + to Tier 3 (US Environmental Protection Agency 2016b). Locomotive tiers correspond to emission standards established by the EPA; Tier 3 locomotives would on average reduce emissions by 50%–70% compared to Tier 0 + locomotives, depending on the pollutant in questions. These fleet upgrades are modeled as a sensitivity analysis test to understand the implications of improved technology on system emissions.

2.3. Avoided emissions

For all observed transit trips we estimate avoided emissions for avoided auto trips that would otherwise take place. We make three simplifying assumptions in this approach. First, we assume each transit trip represents an avoided auto trip that would have been made in a single passenger vehicle had it not used a UTA service. Because of low cross-elasticity of demand between auto and transit modes, this assumption likely overstates gross avoided emissions (Paulley *et al* 2006). That said, a study by the Wasatch Front Regional Council (WFRC), the regional metropolitan planning organization, found that over 87% of total passenger car trips are performed by single occupancy vehicles (Wasatch Front Regional Council 2013), a finding that supports our use of this assumption in this work. Second, we assume that the avoided auto trip would have followed the same route as the UTA service trip observed in the EFC data. Because trips taken using autos are not obliged to follow the fixed routes that trains and busses do, this assumption also likely overstates gross avoided emissions, although this impact is likely to be relatively minor for UTA’s highest-ridership routes (i.e. commuter rail, light rail, and express and arterial bus routes), which follow major commuting routes by design. Finally, as not all riders pay their fare via EFC card we assume that the spatial and temporal distribution of trips by cash fare-payers (and passengers who avoid paying fares altogether) is proportionate with trips by EFC fare-payers. Direct modeling of these effects is beyond the scope of this study, which we believe nonetheless makes a contribution by revealing broad patterns of net emissions impacts from transit services.

2.3.1. UTA’s EFC system

UTA collects rider fares via on-board cash fare collection (bus service), paper tickets purchased prior to boarding (commuter rail and light rail services), and also via an electronic fare collection (EFC) system (all three services), which came on-line on January 1, 2009. Riders using this EFC system pay their fare by placing a card-pass with a magnetic strip against a card reader; we call this ‘tapping on’. Riders paying via EFC are also required to tap off when alighting. The EFC system computes the trip length and charges the cardholder variably by length of trip; if no tap-off is recorded, the cardholder is charged for the maximum trip possible (i.e. to the end of the line) on that route.

For bus services, the EFC card reader is on board the bus, thus allowing the EFC information system to record the card unique ID, the route, plus the unique stop ID and time of boarding or alighting. For commuter rail and light rail services the card reader is on a pedestal at the train station, and therefore records the location (via unique station ID) and time of boarding or alighting, but not (explicitly) the route used. As UTA operated three different light rail routes during our study period and the routes overlap for certain segments, this required us to impute the route travelled on the basis of start and end points together with tap-on/tap-off times. Subject to this caveat, UTA’s EFC data in conjunction with GTFS feeds specifying the geometry and timing of route services therefore allow us to track an (anonymized) rider in space over the length of a trip.

Table 1. Emissions factors used for this study. This table is derived from data provided by UTA's Transit Emissions Quantifier Tool.

	Nitrogen Oxides (NO _x)	Nonmethane hydrocarbons (NMHC)	Carbon Monoxide (CO)	Fine Particulate Matter (PM _{2.5})	Sulfur Oxides (SO _x)	Greenhouse Gas (CO ₂)	Gasoline Gallon Equivalent (GGE)
Current Emission Factors							
Bus – CNG (g/mile)	5.132	0.0475	0.5562	0.1291	0.0137	2,026	126.67
Bus - New Diesel (g/mile)	3.0550	0.0471	0.7978	0.0724	0.0064	1,940	0.88
Central Bus - Diesel (grams/mile)	7.1842	0.1591	1.3868	0.1759	0.0227	2,339	0.88
Meadowbrook Bus - Diesel (grams/mile)	6.3736	0.1830	1.4818	0.1712	0.0207	2,133	0.88
Mt Ogden Bus -Diesel (grams/mile)	9.1470	0.3945	2.5831	0.3900	0.0196	2,013	0.88
Timpanogos Bus -Diesel (grams/mile)	6.7934	0.1746	1.3529	0.1729	0.0195	2,006	0.88
Commuter Rail (grams/mile)	257.09	13.6810	22.6735	13.8347	0.1835	19,032	0.88
Electric Propulsion (g/kWh)	0.9568	0.0070	0.1975	0.0623	0.4372	811.734	33.40
Single Occupied Car (g/mile)	0.8326	0.5427	6.1940	0.0189	0.0070	476.8	0.04149
Sensitivity Test Emission Factors							
New Bus Fleet (grams/mile)	4.2841	0.0472	0.756	0.105	0.00914	1,973	0.88
Tier 3 Commuter Rail (grams/mile)	176.75	5.928	22.6735	5.5339	0.0734	19,032	0.88

UTA also uses infrared automated passenger counter (APC) devices on all UTA vehicles. These systems detect interruptions of an infrared beam across vehicle doorways, thus counting boardings and alightings at every stop without any input from riders. APC data allow us to reconstruct passenger counts for every stop-to-stop segment of a UTA vehicle serving a given route, and from these to calculate total system-wide passenger miles travelled, but they do not support inference of the point-to-point path followed by any single rider.

2.3.2. Nature of EFC data

According to estimates derived from a 2015–2016 onboard survey (Utah Transit Authority 2016), approximately 47% of bus, 45% of light rail, and 53% of commuter rail boardings represent riders paying fares with EFC. However, due to various reasons (e.g. equipment malfunction, failure to tap on/off properly, travel in the downtown free fare zone where no fare or tap on/off is required, etc) the number of recorded EFC trips is smaller than the estimated EFC trips by 37%, 54%, and 15% for the bus, light rail, and commuter rail modes, respectively. We address both of these undercounting issues by scaling observed EFC miles of travel, for each individual transit mode, using annual, mode-specific total passenger miles of travel taken from 2016 APC results. In all following discussion, mention of EFC ridership refers to the upscaled amounts reflecting these APC-derived correction factors. These values are annual averages but can vary across the year due to student ridership decreasing during the summer. Since the APC correction factors are only available at an annual resolution, this estimate may carry a small amount of intrinsic error.

There are two potential sources of bias in EFC data. The first is that several major employers and organizations in UTA's service area provide EFC cards to their employees or students. These organizations include the University of Utah, Intermountain Healthcare, and the Church of Jesus Christ of Latter-day Saints (Mormon), whose international organization is headquartered in the region. This fact likely skews the O/D locations of EFC trips to these larger institutions as their members are likely to use them regularly to commute. The second potential source of bias is that except for higher education students, who are typically lower-income, such programmatic availability of transit passes as an employee benefit likely skews to individuals of higher socioeconomic status. For this study we used data for every EFC boarding and alighting for calendar year 2016.

The EFC data was provided by UTA via monthly files. Each record consists of an EFC card ID, time, date, stop id's for location of tap on, of tap off (if available), and route number (for bus only). Several issues were found and catalogued in the EFC data. One commonly observed problem is incomplete trips, likely the result of riders failing to tap off. Others include incorrect origin and destination stops, inclusion of test routes run for research studies, and origin/destination pairs not found in the GTFS data. We removed all such identified problem trips and their removal was adjusted for by scaling up the EFC data using the APC data, as described above.

2.3.3. Modeling avoided emissions attributable to UTA ridership

The processing methods for avoided emissions from UTA ridership are analogous to those in section 2.2. Each passenger trip listed in the EFC dataset was joined to a specific vehicle trip in the processed GTFS database using the tap on and tap off locations, time of day, and route (if available). Bus and commuter rail trips in the EFC data do not involve transferring since the passenger must exit the vehicle and tap off, thus ending the trip. However, light rail trips may have line transfers which do not necessitate tapping off the first line and tapping on to another line. Therefore, light rail trips that involve tap on and tap off locations that are not in the same line are further disaggregated into two separate trips using a common connection point. Once the UTA vehicle trip carrying the EFC rider was identified, it was decomposed into 'mini-trips' in a similar manner as Tao *et al* (2014). The mini trips were binned to the hour of EFC tap-on and gridded as detailed in section 2.1 above.

Gross avoided emissions were modeled by multiplying miles traveled (binned to the hour and grid cell) by the per-mile emissions from a typical personal vehicle using data provided by UTA based on accepted emission standards (United States Environmental Protection Agency 2005, 2008). This simulates the displacement of a UTA trip by a single-occupancy vehicle.

2.4. Net Impacts

Net impacts from avoided emissions (and other quantities, including passenger miles traveled and fuel consumption) are estimated by subtracting UTA transit impacts from avoided impacts. The subtraction yields a positive value if gross avoided impacts imputed to transit-displaced automobile trips are larger than realized impacts from the UTA system.

3. Results and discussion

3.1. Analysis dimensions

Our analysis is sub-divided into four components:

- (1) Total emissions: This analysis focuses on a system-wide overview without any temporal or spatial disaggregation.
- (2) Spatial patterns: This analysis focuses on annual spatial data.
- (3) Temporal patterns: This analysis focuses on monthly and hourly data without incorporating spatial information.
- (4) Spatiotemporal patterns: This analysis explores both the space and time disaggregation, leveraging the power of the high spatiotemporal dimension available in our datasets and methodology.

For each of these components, we present gross avoided emissions due to transit use (referred to as ‘avoided’), realized UTA system emissions (referred to as ‘system emissions’), and net avoided emissions (referred to as ‘net’) for each mode of transit and emission species.

3.2. Total transit emissions from UTA services

Table 2 shows realized UTA transit emissions derived from the use of 2016 GTFS data and table 1. Energy consumed and emissions generated by the light rail are from off-site facilities; thus, they are calculated, but not counted in estimating on-site system-wide energy demand and emissions. Emissions from a newer, upgraded fleet (‘Sensitivity Test’) show that the greatest benefit would be in bus emissions, where emissions of most species (including $PM_{2.5}$ and NO_x) would be reduced by approximately 50%, while NMHC emissions would be reduced by over 75%. The slight increase in fuel consumption of the new fleet is due to larger numbers of CNG buses which are slightly less fuel-efficient than diesel. Upgraded commuter rail engines would reduce emissions of $PM_{2.5}$ and SO_2 by over 50% and emissions of NO_x by 32%. The upgrade of vehicles on both of these modes would have significant impact on local airshed air quality.

Table 3 lists the 2016 modeled annual vehicle miles traveled, fuel consumed, and emissions replaced due to expanded EFC use for the three largest UTA services. The number of EFC trips we successfully geospatially matched to GTFS routes is 90% which is comparable to the 87%-89% achieved by Tao *et al* (2014). These vehicle miles reflect up-scaling the EFC data with APC scaling factors. The fuel consumption and emissions are calculated using the miles traveled and the emission factors for personal vehicles listed in table 1. Although the light rail system fuel column in table 2 lists kWh, gasoline gallon equivalent (GGE) is used to compare across all fuel types. All three transit modes are responsible for similar avoided miles of single occupancy vehicle travel and resulting avoided fuel consumption and emissions.

Figure 2 and table A2 show the avoided 2016 modeled annual vehicle miles traveled, fuel consumed, and emissions. Figure 2 compares the avoided VMT, fuel consumption, and emissions from the use of UTA’s services against the onroad sector VMT, fuel consumption, and emissions for the seven-county UTA service region (Utah Department of Transportation 2017). Approximately 1.5% of total onroad emissions for the service area are offset due to the use of transit. Within Utah’s Wasatch Front, onroad transportation account for between 25%-50% of pollutant emissions. Therefore, any reduction that can be achieved in this sector is significant in the overall emissions budget. As shown in table 2, the significant potential emissions reductions due to fleet upgrades can substantially improve air quality, particularly for NO_x and $PM_{2.5}$ bus emissions.

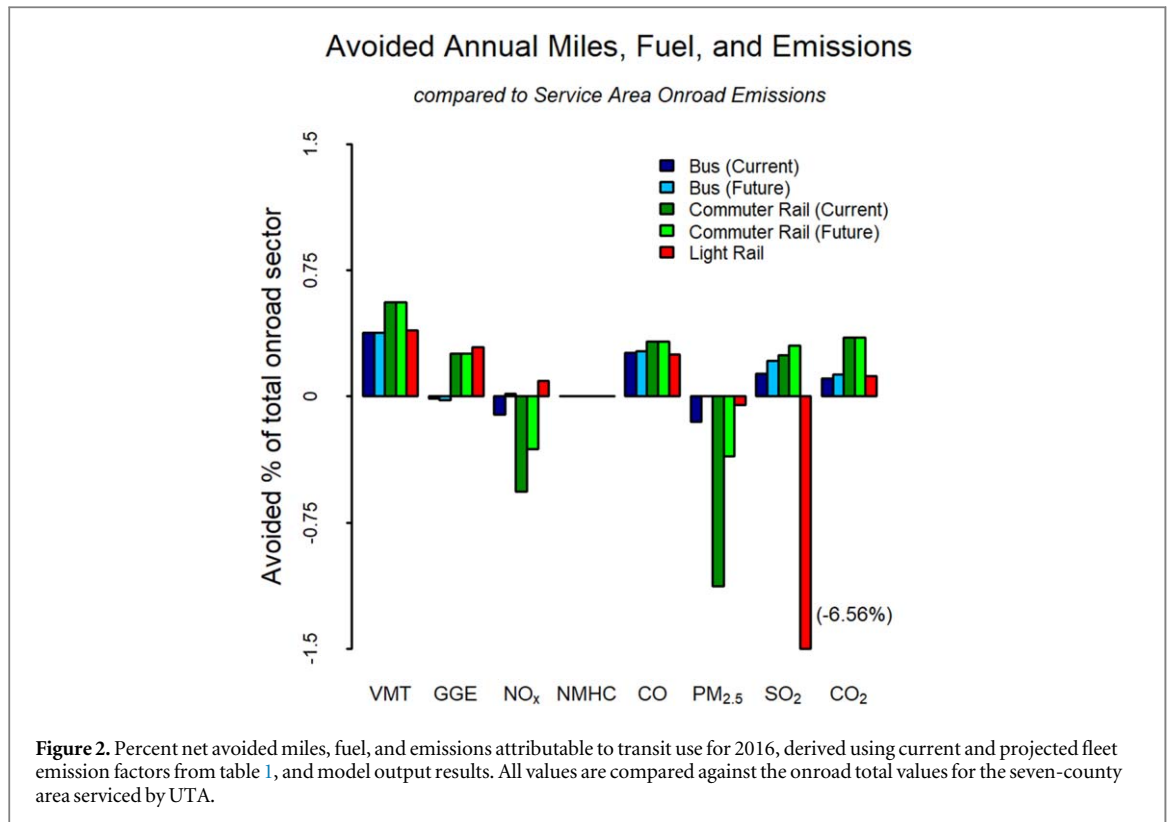
The net impacts values (table A2) were calculated by subtracting realized UTA transit values (table 2) from gross avoided results (table 3). Negative values mean that the UTA system is responsible for more fuel consumption or emissions than if the upscaled EFC trips were replaced by a single-occupancy vehicle. Notably, every UTA mode reduces the miles of travel; however, only the light and commuter rail systems reduce the GGE fuel consumption. Due to the combination of high ridership and cleaner energy generation, the light rail system was found to be the most efficient system for emissions reductions, with the exception of $PM_{2.5}$ and SO_2 emissions. This is because electricity generation in Utah relies on a combination of natural gas and coal (US Environmental Protection Agency 2016a), which emit substantial amounts of $PM_{2.5}$ and SO_2 , but all electricity-related emissions are outside the airshed. While the commuter rail is responsible for a net reduction of most pollutants and fuel consumed, this service is still a net emitter of $PM_{2.5}$ and NO_x . The bus system consumes larger amounts of fuel than it displaces via mode-captured auto travelers and is a net emitter of $PM_{2.5}$ and NO_x . However, since buses share roads with the automobiles whose trips they may displace via mode capture, they are responsible for a significant amount of congestion mitigation, accounting for over 83 million avoided vehicle miles traveled. This study does not quantify the congestion mitigation and increased trip duration effects, which are a non-negligible benefit of the transit system. Since an average bus length is three times that of a personal vehicle, a rough approximation suggests that modal shift from personal vehicle to bus (or other modes of traffic) may lead to a significant reduction in the amount of vehicles of road at any one time, thus reducing congestion at a non-trivial level. The quantifiable benefits of the modest current ridership supports arguments for initiatives to provide incentives for increased transit utilization such as free fares and increased system, while the benefits to air quality arising from a fleet upgrade are also evident.

Table 2. Miles traveled, fuel consumption, and emissions for 2016 UTA transit vehicles derived using emission factors from table 1 and model output results. The top portion shows emission using current emissions factors, the bottom portions shows potential emissions for cleaner vehicles: CNG and 2010 and newer diesel buses, and Tier 3 locomotives. There is no change for light rail emissions. All emissions are in metric tons.

	Vehicle Miles (×1000 miles)	Energy or Fuel (×1000 Gal or kWh)	Nitrogen Oxides (tonne NO _x)	Nonmethane hydro carbons (tonne NMHC)	Carbon Monoxide (tonneCO)	Fine Particulate Matter (tonne PM _{2.5})	Sulfur Oxides (tonne SO _x)	Greenhouse Gas (tonne CO ₂)	Gasoline Gallon Equivalent (x1000 Gal)
Current Emission Factors									
Bus (Diesel/CNG)	18,223	3,798	131.51	3.99	31.16	4.09	0.36	38,029	4,316
Commuter Rail (Diesel - Gal)	1,356	2,506	348.69	18.55	30.75	18.76	0.25	25,813	2,847
Light Rail Elec- tric (kWh)	6,764	40,166	38.43	0.28	7.93	2.50	17.56	32,604	1,202
Sensitivity Test Emission Factors									
Bus (Diesel/CNG)	18,223	3,872	78.07	0.86	13.78	1.91	0.17	35,946	4,399
Commuter Rail (Diesel - Gal)	1,356	2,506	239.72	8.04	30.75	7.51	0.10	25,813	2,847

Table 3. Miles traveled, fuel consumption, and emissions replaced due to EFC use for 2016 derived using emission factors from table 1 and model output results. All emissions are in metric tons.

	Vehicle Miles (×1000 miles)	Energy or Fuel (×1000 Gal or kWh)	Nitrogen Oxides (tonne NO _x)	Nonmethane hydro carbons (tonne NMHC)	Carbon Monoxide (tonne CO)	Fine Particulate Matter (tonne PM _{2.5})	Sulfur Oxides (tonne SO _x)	Greenhouse Gas (tonne CO ₂)	Gasoline Gallon Equivalent (x1000 Gal)
Bus (Diesel/CNG)	101,545	4,213	84.55	55.11	628.97	1.92	0.71	48,416	4,213
Commuter Rail (Diesel - Gal)	125,131	5,192	104.18	67.91	775.06	2.36	0.88	59,663	5,191
Light Rail Elec- tric (kWh)	93,298	3,871	77.68	50.63	577.89	1.76	0.66	44,484	3,871



3.3. Spatial patterns

The spatial pattern of average annual avoided travel for all services is shown in figures 3–5. Figure 3 shows the average annual avoided travel due to bus services. The largest amount of avoided travel due to bus use is found in the most frequently traveled routes, which are generally located in the central parts of cities; in this case Salt Lake City, Provo/Orem to the south, and Ogden to the north. There are some areas in the southwestern part of Salt Lake County that show a negative amount of avoided travel (i.e. more UTA vehicle miles traveled than passenger miles traveled on UTA vehicles). Figure 4 shows the average avoided miles of travel due to commuter rail usage. The commuter rail system reduces miles of travel across its entire length. The smallest reduction is found in the segments leading to the two northernmost stops; otherwise, the reduction is consistent throughout. The average avoided travel from light rail services is shown in figure 5. It is evident from this figure that the largest amount of EFC-observed ride activity takes place in the central north-south trunk line where all three light rail lines travel, followed by the section immediately south where two lines (red and blue) travel jointly. The corridor between downtown and the University of Utah also represents a large amount of avoided travel.

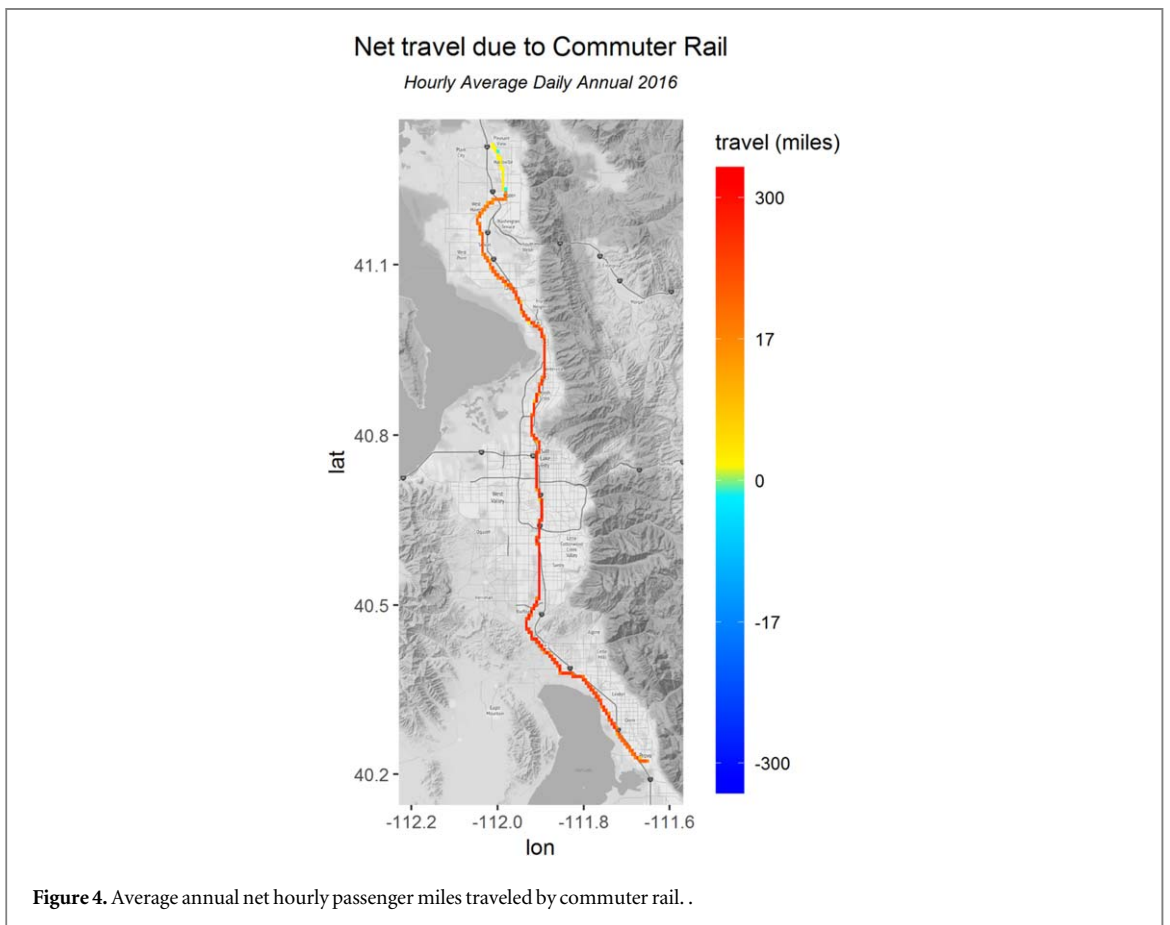
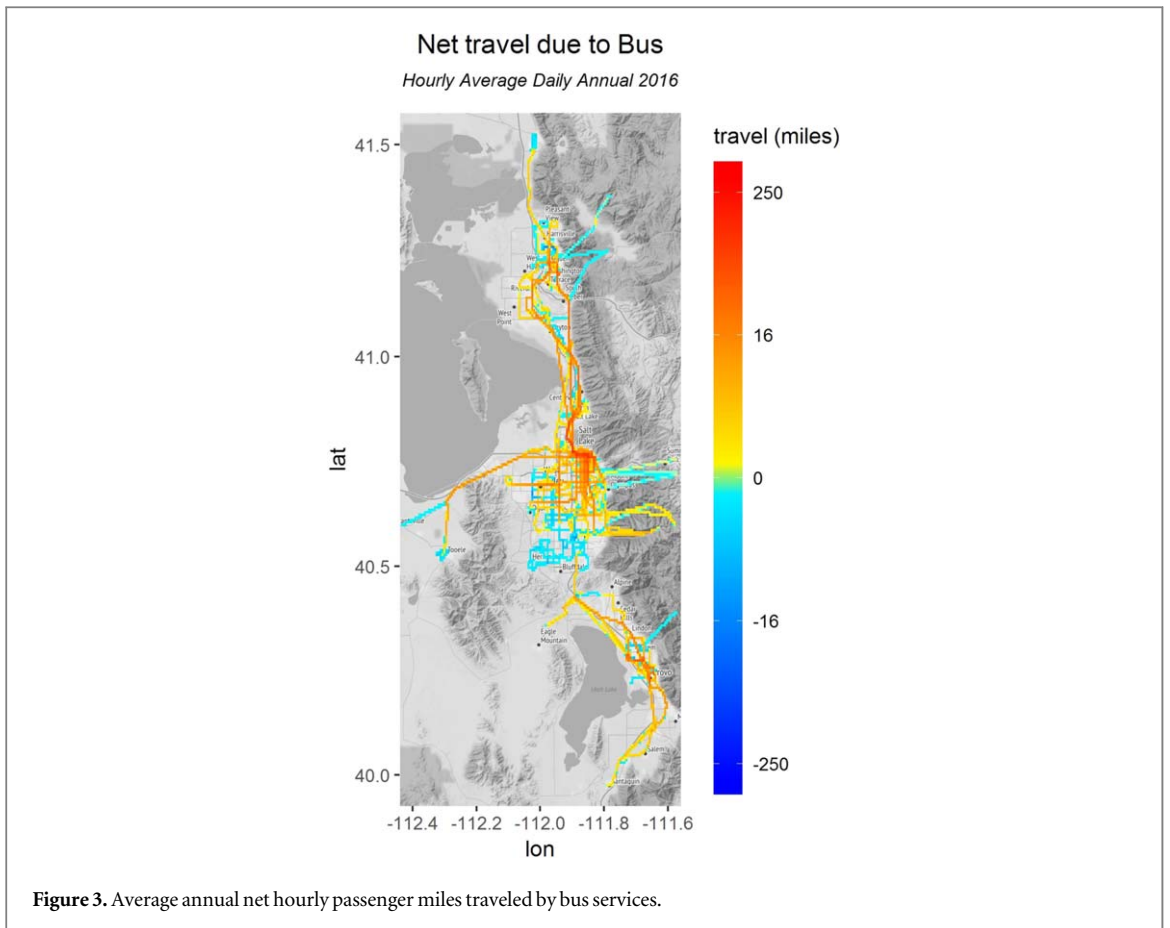
3.4. Temporal patterns

3.4.1. Monthly avoided miles traveled and fuel consumption estimates

Figure 6 shows the average daily avoided miles traveled and fuel consumption due to transit use for 2016 disaggregated by month and day of week. The GTFS data for April 2016 has been found to have trip coding errors which resulted in lower service miles. The drop in July is due to limited service on major holidays: July 4th and Pioneer Day, a Utah State Holiday observed on July 25th in 2016, although the actual holiday is July 24th, which was a Sunday.

The difference between weekdays and weekend days is larger on commuter rail (figure 6(b)) than buses (figure 6(a)). Although many weekday bus routes are not in operation or are less frequent during weekend days, particularly Sunday, the commuter rail does not operate at all on Sunday, and the Saturday service is approximately half of the weekday service.

Multiple bus routes are specifically designed to facilitate school travel, and buses are the main transit mode used by school and university students, which is why the drop during the summer months is more noticeable than for the other two modes of service. Since the University of Utah is the largest provider of EFC cards within the UTA system, the lower number of students during the summer is expected to alter the monthly EFC usage. The light rail (figure 6(c)) shows a similar seasonal pattern as the commuter rail but has a larger amount of EFC riders than all methods on weekends, particularly Sunday. The avoided bus fuel consumption (figure 6(d)) shows a marked decrease during the summer months and December, where the buses become a net positive source of fuel consumption compared to the offset vehicles. This is directly attributable to the decreased



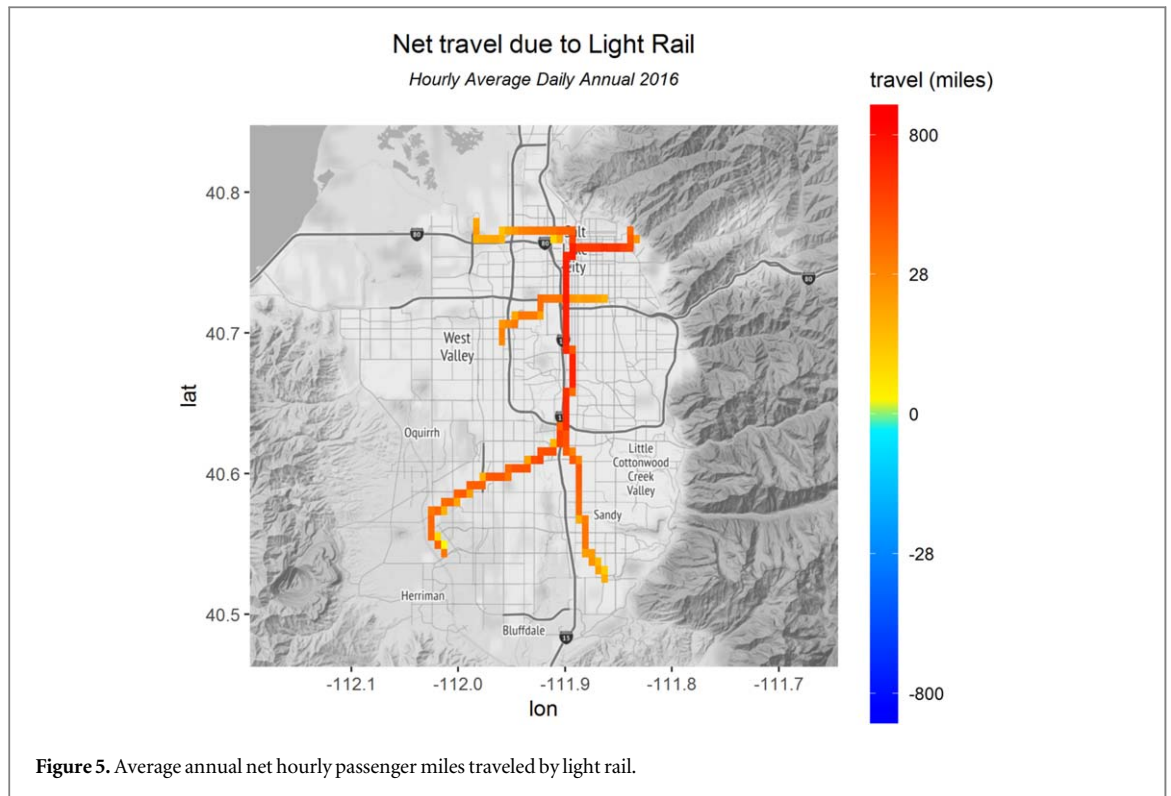


Figure 5. Average annual net hourly passenger miles traveled by light rail.

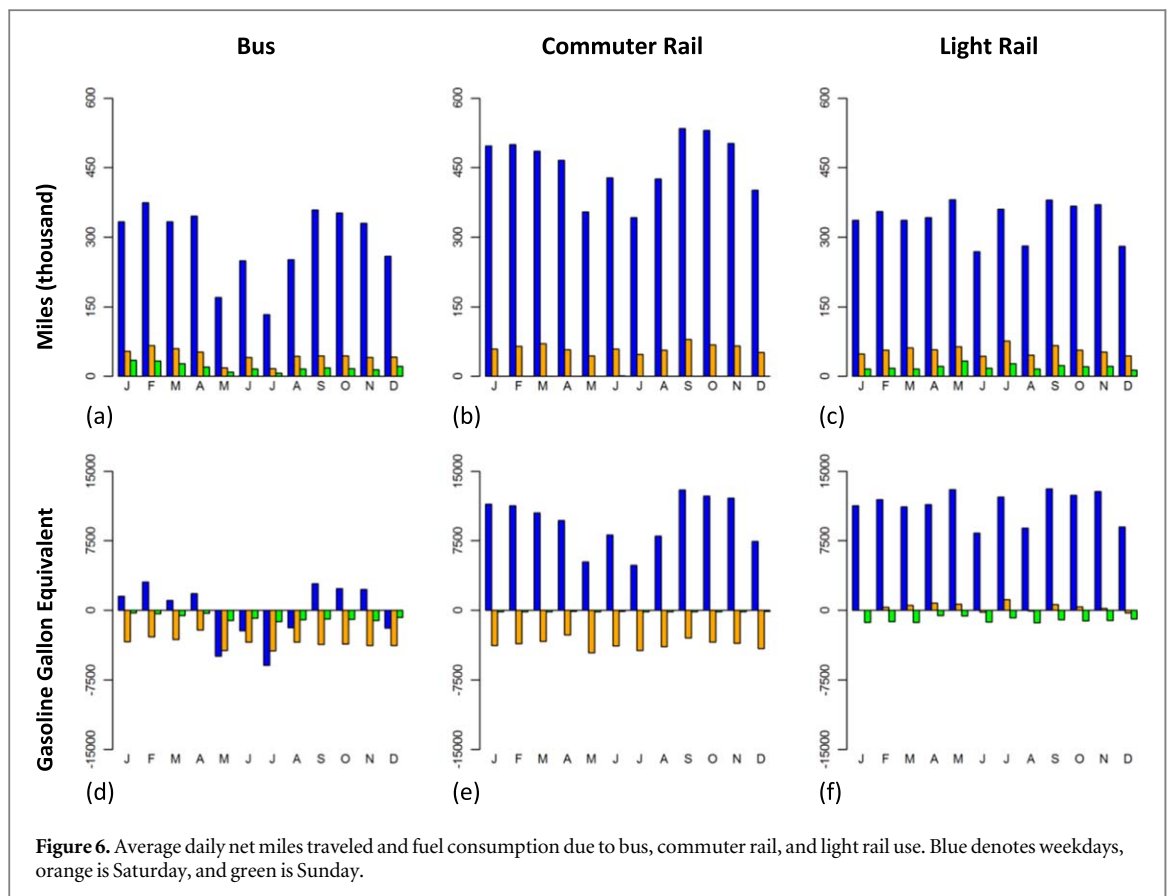
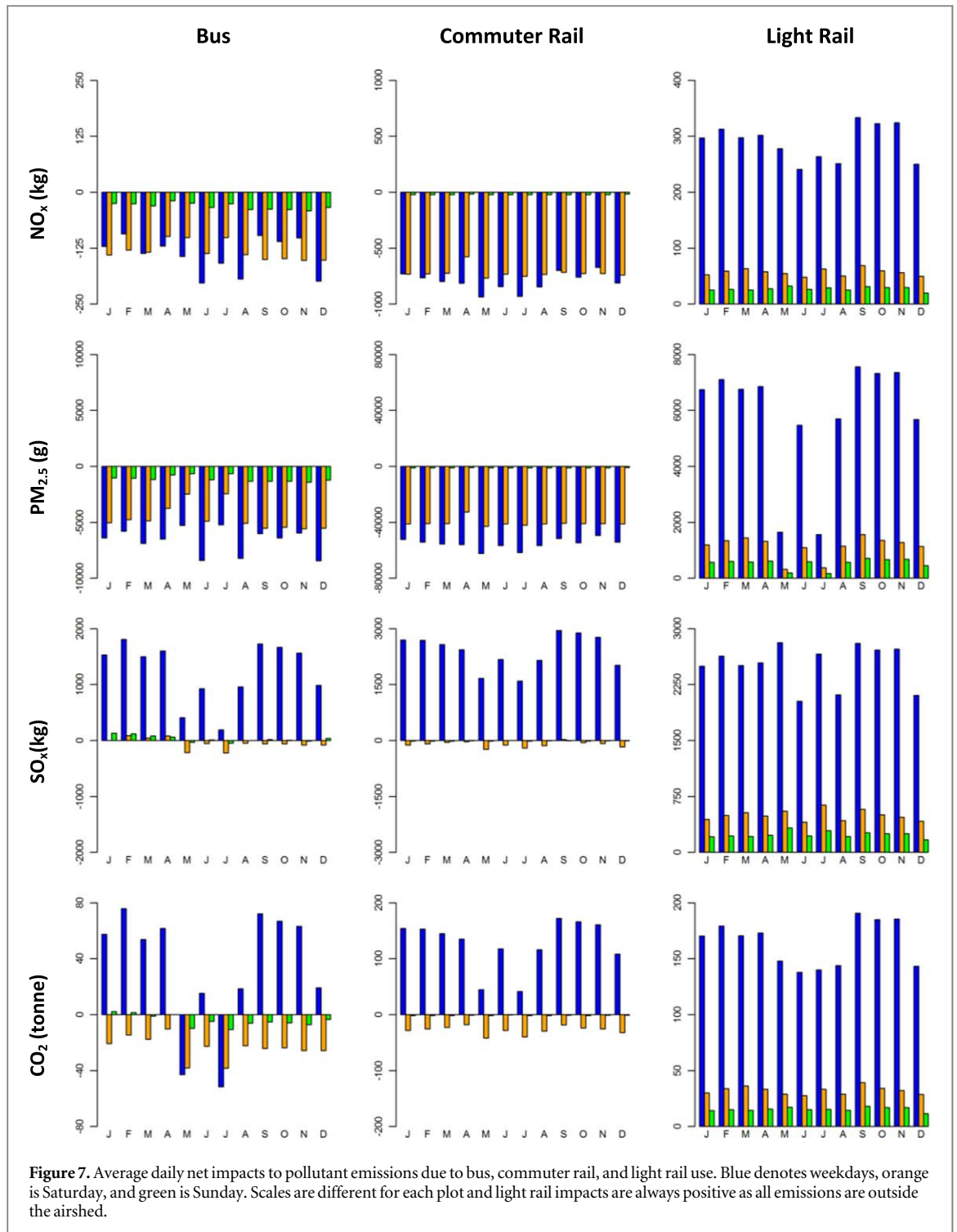


Figure 6. Average daily net miles traveled and fuel consumption due to bus, commuter rail, and light rail use. Blue denotes weekdays, orange is Saturday, and green is Sunday.

ridership, resulting in less EFC avoided travel during these months, as discussed earlier. Since the bus system continues to run at a similar frequency throughout the year, the resulting avoided travel is less during these months. A similar phenomenon is seen in the commuter rail system (figure 6(e)), however, it is much less noticeable. While commuter rail decreases its frequency of service by approximately half, ridership drops to less



than a sixth on Saturdays, compared to weekdays, resulting in this mode becoming a net consumer of fuel compared to offset vehicles. The light rail shows minimal seasonal differences (figure 6(f)) and is a net reducer of fuel consumption on weekdays and Saturdays but is a net consumer on Sundays.

3.4.2. Daily average net emissions impacts

Figure 7 shows the daily average net emissions impacts from all three modes disaggregated by pollutant, month, and day of week. The light rail is shown as a net reducer of all emissions, as expected given that the induced emissions used to generate the electricity for its use are outside the airshed. Due to the significantly larger amount of $PM_{2.5}$ and NO_x that buses and commuter rail emit per vehicle when compared to cars, the effect of avoided trips is minimal, and this figure mostly reflects realized UTA system emissions. The impacts are less negative during weekends because there is less frequent service. Due to the large amount of passenger miles that the bus and commuter rail modes can capture, these modes are generally net SO_x and CO_2 reducers. The

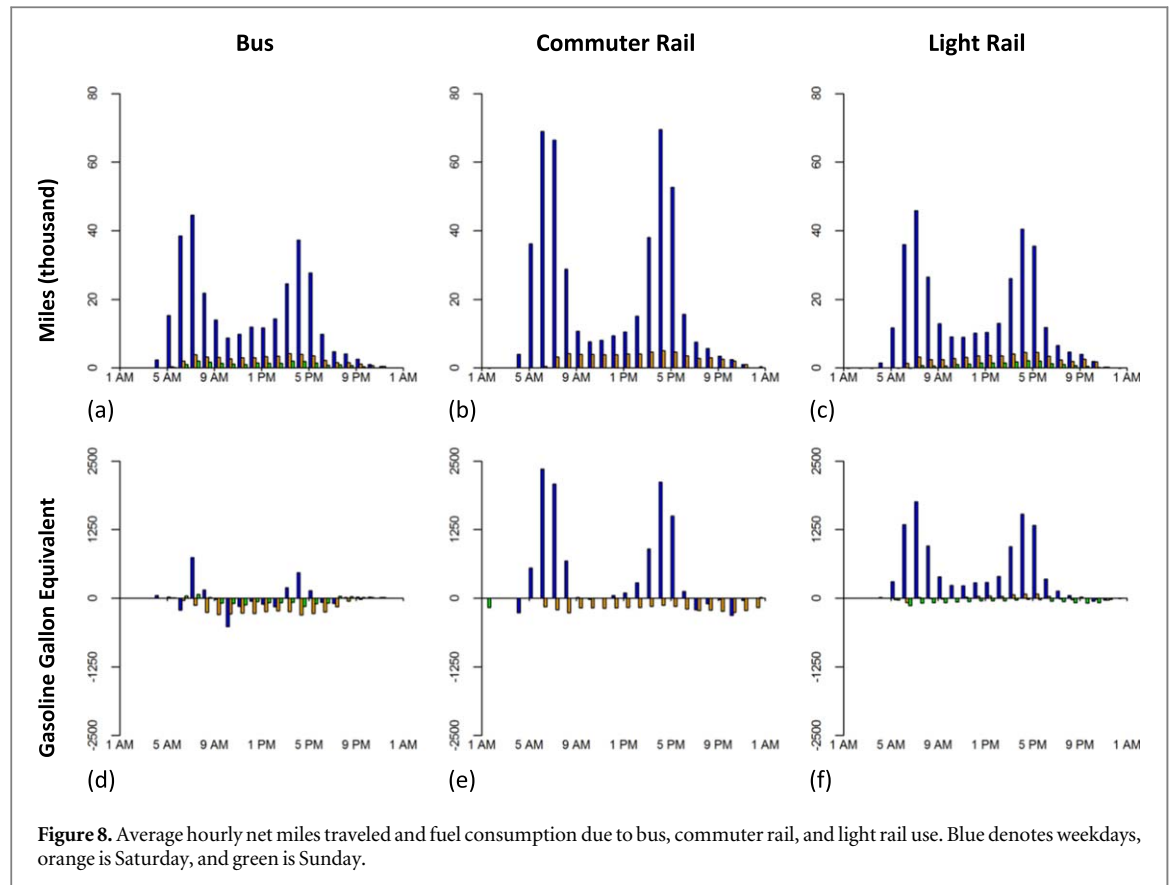


Figure 8. Average hourly net miles traveled and fuel consumption due to bus, commuter rail, and light rail use. Blue denotes weekdays, orange is Saturday, and green is Sunday.

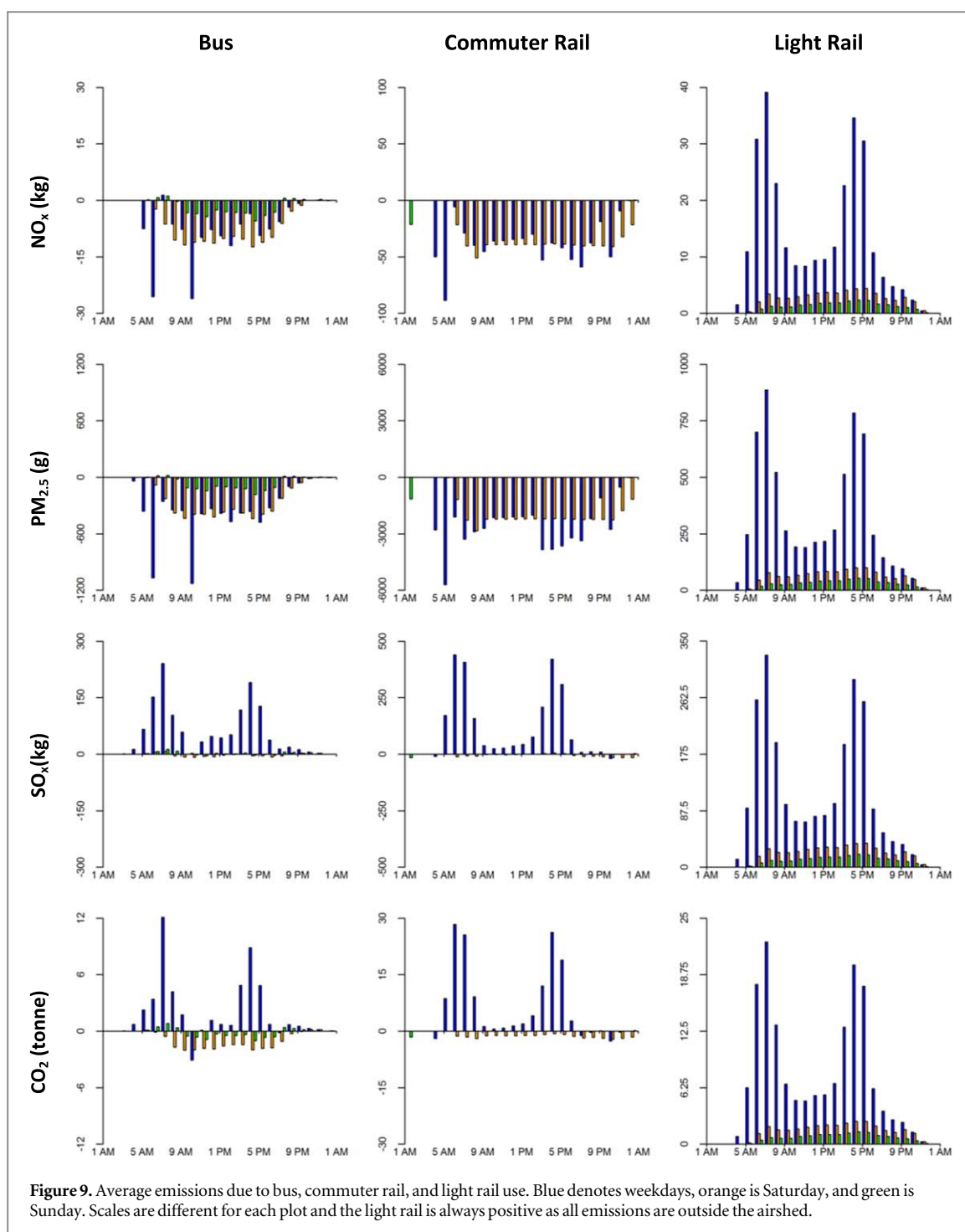
exceptions—Saturdays, and, for buses, the summer months—is because service frequency does not decrease greatly in these times, while EFC ridership does.

3.4.3. Hourly average avoided miles traveled and fuel consumption

Figure 8 shows the hourly distribution of passenger miles avoided and fuel consumption due to transit use for 2016, disaggregated by mode and day of week. Figures 8(a) and (b) show that the bus and light rail systems follow a similar pattern reflecting maximum benefits, in terms of avoided miles of travel, structured by commuting hours. The commuter rail (figure 8(b)) shows a more pronounced pattern than the bus and light rail which is due to its usage primarily as a commuting mode, where bus and light rail modes are more likely to serve discretionary trips and trips taken during the middle of the day. During peak morning and afternoon hours the bus system is a net reducer of fuel consumption (figure 8(d)). However, during the rest of the day, particularly just before and immediately after the morning rush hour, the bus system consumes more fuel than that which would be attributable to displaced personal car trips. This effect is observable for the commuter rail (figure 8(e)) and light rail (figure 8(f)) modes, however these two modes show fewer weekday hours where they are net fuel consumers, and the majority of this negative impact is on weekends, as previously discussed.

3.4.4. Hourly average avoided emissions

Figure 9 shows the hourly distribution for the same mode and fuel or pollutant combination as figure 7. The light rail avoided emissions are all positive since the induced emissions are outside the airshed. Furthermore, since the avoided travel and emissions are all from reduced personal vehicles which model with fixed emission factors, the hourly distributions are identical, only varying in magnitude for each pollutant. Similarly to figure 7, the avoided $PM_{2.5}$ and NO_x from buses and commuter rail is almost always negative, even during the rush hours. This is due to the significantly larger amount of emitted pollutants from these two vehicle types compared to cars. The bus $PM_{2.5}$ and NO_x emissions are somewhat offset on weekdays during the morning rush hour and a midday travel peak lasting into the beginning of the afternoon rush hour. The commuter rail avoided $PM_{2.5}$ and NO_x emissions show a larger negative value just before the morning rush hour, in a similar manner as the bus. This effect is due to the increase in service frequency just before rush hour. The EFC-displaced emissions also offset some of the commuter rail during the morning rush hour and during the midday hours. The avoided SO_x and CO_2 emissions from buses and commuter rail show similar hourly patterns. Because the commuter rail serves commuting mobility, the emissions savings are most clearly observed during the peak hours, while the bus



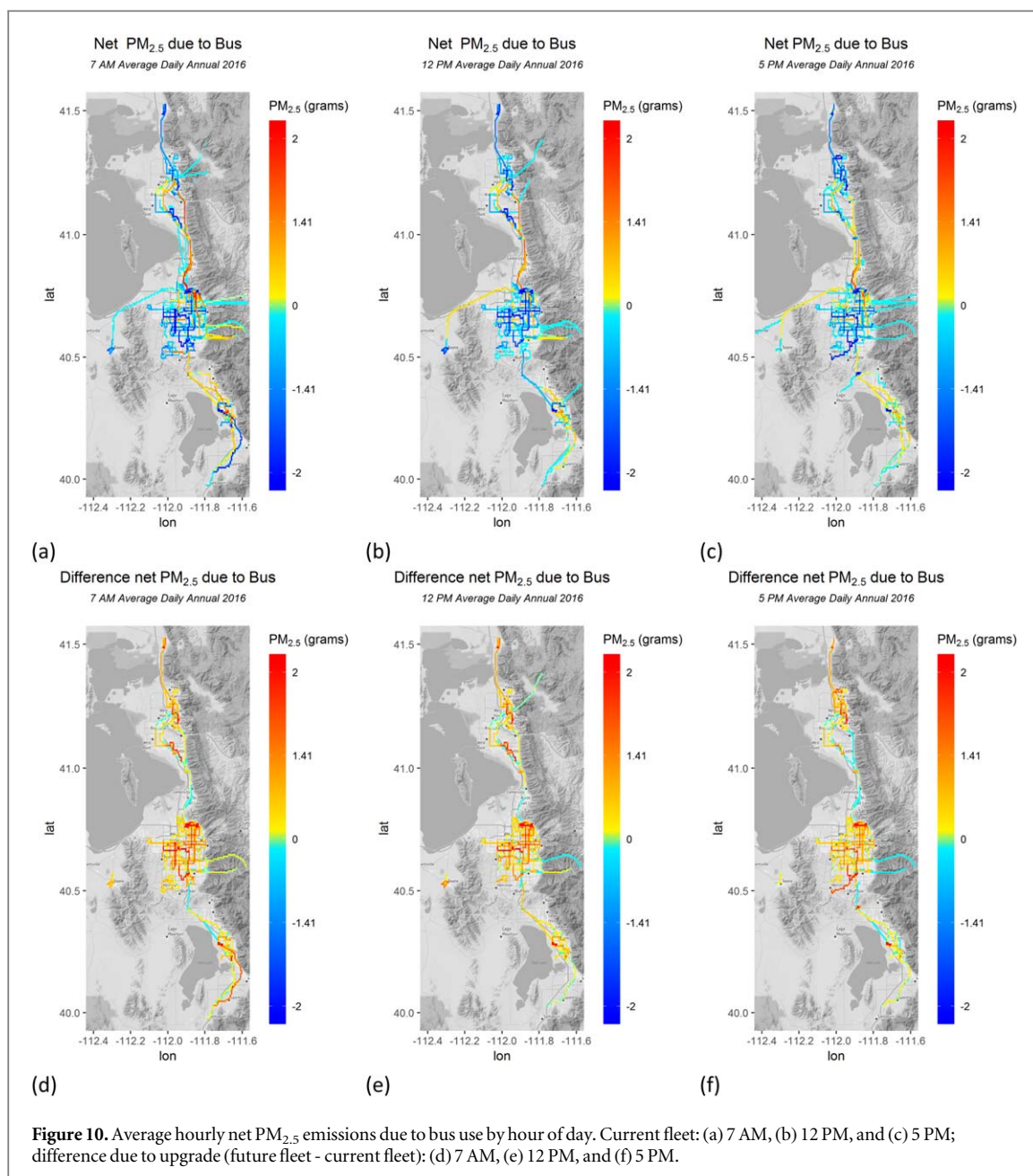
system shows a slightly less pronounced distribution. Weekends, particularly Saturday, as shown earlier, are a net negative throughout the whole day with a stronger signal during the day on buses.

3.5. Spatiotemporal patterns

Leveraging the unique datasets and our novel methodology, we examined realized, gross avoided, and net avoided emissions for all three transit services at high spatial and temporal resolution. Bus service $PM_{2.5}$ emissions are shown in this section for both the current and modeled future fleet, to highlight the impact that cleaner bus fleets may have on emissions, as the majority of UTA’s service area has been designated non-attainment for this pollutant.

3.5.1. UTA bus services $PM_{2.5}$ emissions

Figure 10 shows the average annual hourly $PM_{2.5}$ emissions from bus services by hour of day for the current (figures A1(a)–(c)) and the difference between the current and proposed future (figures A1(d)–(f)) fleets. The extent of the bus routes does not vary greatly during the different hours of the day. However, there are some



commuter routes that are present during the morning and afternoon rush hours—figures A1(a) and (c) - which are not present during the midday hours figure A1(b). It can also be seen that the frequency of bus routes leading to higher $PM_{2.5}$ emissions are concentrated in the central city areas, such as Ogden, Salt Lake City, and Provo/Orem. Although a small seasonal component, the ski bus service can be observed on the northeast section of the midday map (figure A1(b)). The proposed fleet upgrade significantly impacts service emissions since the estimated future bus fleet's $PM_{2.5}$ emission factors are expected to be less than half of the current bus fleet's. This results in markedly lower system emissions across the network.

3.5.2. EFC replaced $PM_{2.5}$ emissions

The average annual hourly replaced $PM_{2.5}$ emissions from bus services by hour of day can be seen in figure A2. Commuter travel is best represented by the elevated travel during the 7 AM and 5 PM commute (figures A2(a) and (c)). The overall spatial pattern shows that travel in the downtown areas of the three large cities, Salt Lake City, Provo, and Ogden, is consistently higher than at other locations. Elevated travel is discernible along the routes connecting Ogden to Salt Lake City during the morning peak hour (figure A2(a)), and even at noon. More generally, midday travel (figure A2(b)) shows a slight attenuation of transit use, particularly in downtown areas.

3.5.3. Avoided $PM_{2.5}$ emissions

Figure 10 displays the average hourly net avoided $PM_{2.5}$ emissions attributable due to bus use by hour of day. Although the bus system does reduce miles traveled, when compared to replacement trips by passenger vehicles, there are marked spatiotemporal differences in $PM_{2.5}$ emissions. During the morning and afternoon rush hours (figures 10(a) and (c)), the bus decreases the net amount of $PM_{2.5}$ emitted in the downtown area and in several of the inter-city transit routes. The afternoon rush hour (figure 10(c)) also shows a net reduction in $PM_{2.5}$ emitted in the southernmost part of the system, from Orem to Santaquin, a town at the extreme southern end of UTA bus service. During the noon hour (figure 10(b)), the bus reduces the amount of $PM_{2.5}$ emitted primarily along the inter-city routes and in some downtown locations. The modeled avoided $PM_{2.5}$ emissions following a bus fleet upgrade result in a net total of nearly zero emissions (figure 2, table 5). The downtown and inter-city corridors result in net $PM_{2.5}$ emissions reductions across all time scales due to bus use. The exurb areas reduce their overall $PM_{2.5}$ emissions, however, not all of them exhibit net reductions because bus system emissions still outpace transit-replaced car use.

4. Conclusions

4.1. Findings

This study resolved the transit system emissions and avoided emissions due to buses, light rail, and commuter rail use at an hourly and $0.002 \text{ deg} \times 0.002 \text{ deg}$ resolution. The high spatial and temporal resolution of our approach allows policy makers and transit planners to assess otherwise unobservable impacts to net emissions stemming from service changes or ridership changes. Our findings support the consideration of policies such as free fare periods, particularly during poor air quality events.

We found significant spatial and temporal differences between the different UTA services and their associated net avoided miles of travel, fuel consumption, and emissions. As expected, the morning and afternoon commute hours result in the largest amount of avoided travel and emissions (figures 6–8). Although there is always a reduction in miles traveled due to transit use, several pollutants emitted by buses and commuter rail are not offset, even during these higher-travel hours. The effect on weekend days is significantly worse since EFC ridership decreases proportionally more than UTA service.

Spatially, the benefits of net avoided emissions from buses were found to be strongest in the central parts of cities and inter-city connecting routes, while the commuter rail had a more homogenous effect throughout its route. Light rail ridership, and offset emissions, was highest in the central trunk line and on the route connecting the University of Utah to downtown Salt Lake City. The electricity necessary to power the light rail was also accounted for and was relatively constant throughout the day; however, as it was generated offsite, the light rail was a net emissions reducer within the UTA service airsheds. If the emissions due to electricity generation were to be accounted for inside these airshed, there would be a negative impact in the air quality due to a net increase in SO_2 emissions (figure 2) as a large fraction of electricity in Utah is generated using coal. However, the other pollutants show a similar decrease as by the bus mode, compared to avoided onroad emissions.

Salt Lake, Utah, Davis, and Weber Counties are Utah's four most populated counties and account for three quarters of the State's total population. These counties encompass the majority of UTA service trips and are also the counties with the most non-attainment or maintenance areas. Since the majority of UTA's service area is in non-attainment for $PM_{2.5}$, an upgrade to a cleaner fleet of buses and commuter rail engines would significantly help offset emissions. All UTA services already reduce VMT and congestion, as well as CO, NMHC, SO_2 , and CO_2 emissions. A fleet upgrade would significantly reduce $PM_{2.5}$ and NO_x emissions, significant contributors to elevated wintertime smog and summertime ozone levels, respectively.

A possible, albeit costly, way to improve UTA's net impact on emissions would be to replace higher-emitting vehicles with newer trains and buses. UTA's bus fleet is systematically being upgraded by replacing older diesel vehicles with newer diesel and natural gas buses. Furthermore, in the near future, some of the newer buses will become electric, thus reducing on-site combustion emissions. Some older buses, which are deployed significantly less as they are near the end of their use, are responsible for as much as twice the emissions per mile traveled than the newer model buses.

Upgrading buses to newer diesel and CNG would turn the bus system from a net contributor of additional NO_x and $PM_{2.5}$ emissions to a net reducer of these pollutants due to avoided car trips. The commuter rail system currently uses Tier 0 + locomotives and upgrading these older locomotives to a more stringent Tier 3 standard has the potential to reduce NO_x emissions by over 30% and $PM_{2.5}$ emissions by more than 60%. Within the confines of this study, these emissions reductions would reduce the commuter rail's net emissions (gross avoided minus realized UTA system) of NO_x and $PM_{2.5}$ emissions by nearly 50% and 70%, respectively. Ultimately, although not explicitly modeled in this study, the conversion of both modes to electric-powered units would significantly benefit the local air quality although the electricity production would affect the air quality of another airshed unless there was a significant shift towards renewable energy sources.

4.2. Limitations

A limitation of the system impact quantification is that light rail trains range from 1 to 4 cars depending on time of day and day of week, with changes to train configurations happening at sub-hourly scale. However, due to lack of available data associating train-set configuration with specific scheduled trips, for the purposes of this study we modeled all light rail configurations as requiring the same amount of electricity, resolved as the total number amount of electricity consumed divided by the number of light rail trips. This yielded train lengths of approximately 2.5 cars. All the trip segments were binned to the hour associated with the route's first stop. This may cause a small discrepancy between the times associated with each trip segment, however, the UTA network is small enough that most trips were found to be less than an hour in duration. The impact of transit use on congestion was not estimated as it would be beyond the scope of this study. It is reasonable to suggest that the impact of transit on congestion is non-negligible as a bus or train car would take up significantly less road space than the estimated number of personal vehicles it would replace.

Avoided auto trips are represented solely by EFC trips which only account for approximately half of UTA's total trips. This has the potential to bias overall trip volumes both spatially and temporally because the non-EFC passengers could have considerably different transit travel behavior compared to EFC users. Since only the largest commercial and educational institutions have programs that provide EFC cards to employees and students, only a segment of the population is captured in this study. Although there is a Salt Lake City resident specific subsidized EFC program ('Hive Pass') other cities in UTA's service area do not have a similar program. Therefore, while scaling factors are used to account for cash-payment trips, these only increase the modeled EFC trips already in place. This is likely to spatially bias trip counts to these larger institutions and undercount areas where cash fares, or other fare media, are predominant. Since these large institutions also follow a traditional 9 to 5 schedule, it is possible that very early or very late trips are underrepresented. More temporally and spatially disaggregated APC data would allow for a better representation of the differences between EFC and cash-payment trips. This could remove some of the potential biases that cannot be accounted in the current form of this study.

Since avoided trips were spatially located following the same route as the transit equivalent of the EFC trip, our methodology has the potential to overestimate some avoided emissions since the most efficient or shortest route for an automobile traveler may not be the one taken by the bus. Alternatively, this may underestimate light and commuter rail avoided emissions because routes of dedicated rights-of-way for these modes could be more efficient than those taken by a private car. It is also unclear whether every transit trip represents an avoided personal vehicle trip. It has been shown that cross-elasticity of demand between auto and transit modes is low, and furthermore, that car trip demand is less responsive to transit trip pricing than vice versa (Paulley *et al* 2006). In this study we simplified the personal vehicle fleet through homogenization (24.1 MPG and associated emissions factors). However, emissions factors vary substantially by make, model, and year of vehicle, which will be strongly controlled by household income (Ferrell and Reinke 2015). This is strongly spatially structured within the UTA service area, and so it is likely that our use of a single 'average' vehicle for modeling avoided emissions substantially over- and under-predicts avoided emissions in various parts of the service area. Additional data estimating the number of miles traveled by sub-groups of vehicles could improve the distribution of emitted pollutants through travel apportionment, however this data is not readily available.

While our work does not capture variability in transit direct emissions attributable to variation in the vehicle fleet or in operational variables such as drive-cycle behavior, we note that such representation comes at a significant cost, involving large-overhead and complex agent-based models e.g. Lau *et al* (2011), (Waraich *et al* 2016). We suggest that future research should investigate the cost/benefit tradeoffs of these respective approaches. While this work does not address drive-cycle behavior, our sensitivity analysis discussed in section 2.2.2 does highlight the potential impacts of cleaner transit vehicles.

Spiller and Stephens (2012) demonstrated that there is significant spatial variability in gasoline price elasticity, with elasticity significantly lower for more rural households. However, while outskirts may show net positive emissions during off-peak hours, public transit serves multiple functions (equity; congestion alleviation; etc), and it is unlikely that UTA could restructure service solely to minimize net carbon emissions. Furthermore Nishiuchi *et al* (2013) found that most riders don't follow a single pattern of daily movement.

4.3. Directions for future research

There are several future research avenues to consider following this study. Because the Wasatch Front experiences two poor air quality seasons a year, the impact poor air quality has on transit ridership is an important question to ask. Is it possible that certain air quality sensitive populations may avoid exposure due to waiting at stops and walking, and are there groups that may take transit more often during poor air quality days to alleviate the impact of single passenger vehicle? The impact of rider behavior as a response to gasoline prices can also be studied since studies found a large drop in vehicle miles traveled by personal vehicles during the 2008 recession. In order to estimate the impact of free (or reduced) fares on valley wide air quality, multiple ridership models could be designed. Since the largest contributors to poor air quality and greatest contributors to personal exposure are personal vehicles, how many car miles of travel need to be removed during poor air quality days to avoid pollutant concentrations from reaching unhealthy levels? While

this study does not quantify the congestion mitigation effect, it is a non-negligible benefit of a transit system and could be a significant benefit of transit usage, particularly during peak traffic hours. In order to answer some of these questions, it would be necessary to understand, given present UTA infrastructure, what is the realistic limit of UTA's capacity to reduce personal vehicle traffic. If used at full capacity, what would be the accompanying emissions reductions? Investigation into these questions would refine the estimate of net impacts this work has produced, and would begin to leverage to public health professionals, transit planners, and policy makers the potential benefits that such an estimate offers.

Acknowledgments

We appreciate assistance in providing data and giving feedback on initial findings from John Close, Kerry Doane, G J LaBonty, Michelle Larsen, Daniel Locke, Ali Oliver, Jerry Van Wie, and James Wadley of the Utah Transit Authority, as well as from Lexie Wilson of the Utah Department of Environmental Quality, Division of Air Quality. None of our findings or conclusions should be interpreted to indicate official positions of either agency.

Appendix

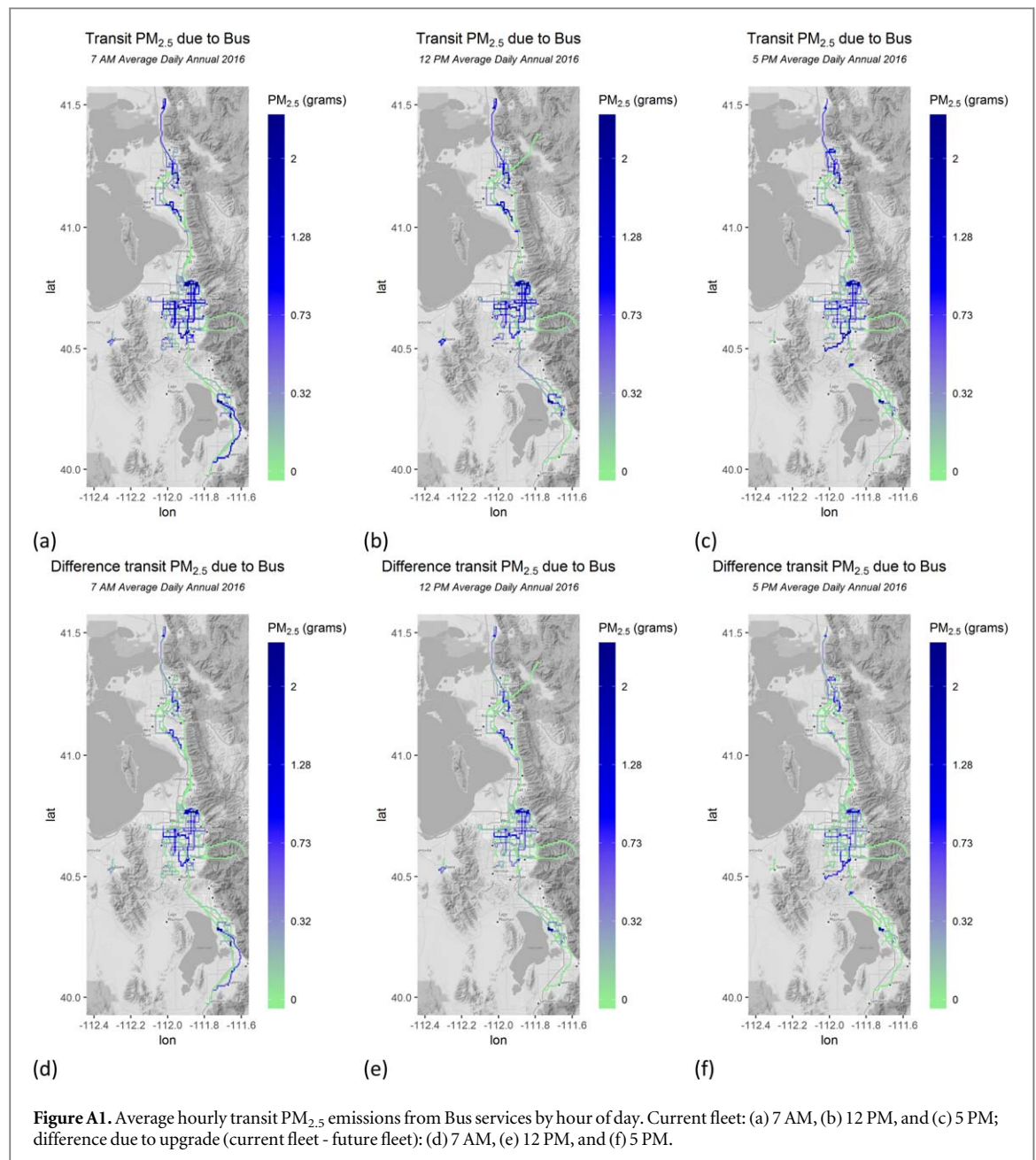
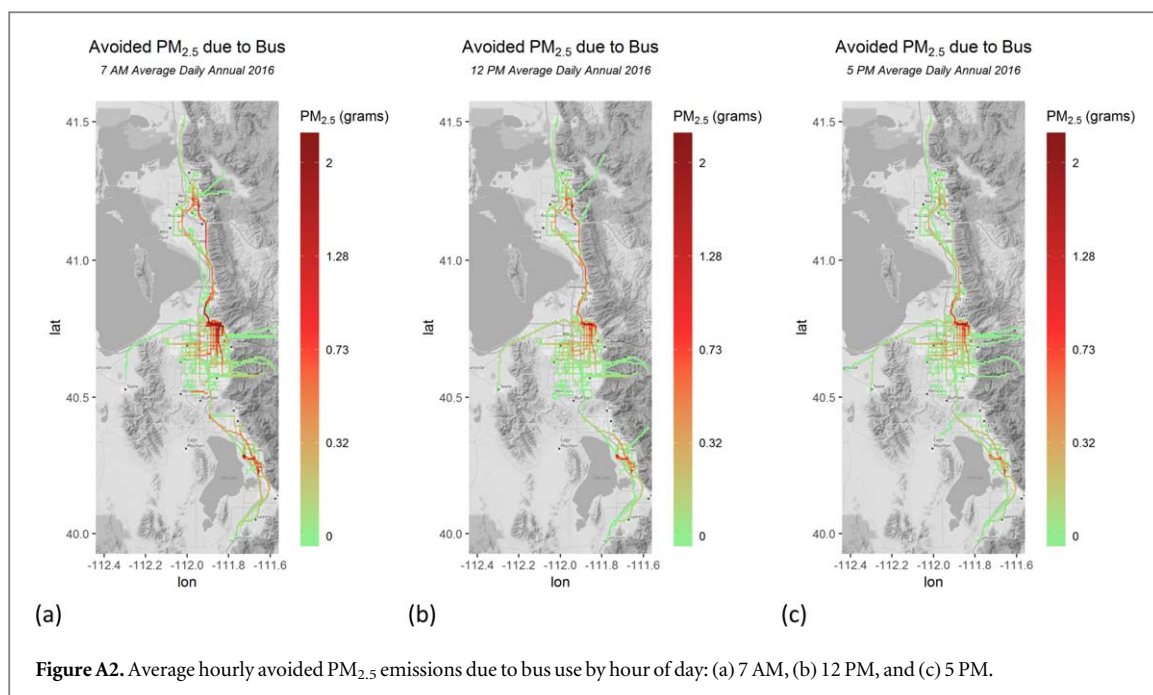


Table A1. Bus fleet composition and activity by business unit. The number of buses, fuel consumed (in diesel gallons equivalent), and miles traveled is disaggregated by bus technology.

Central Bus Fleet			
Manufacturing Year	Number of buses	Fuel Consumption (DGE)	Bus Miles Traveled
1991–1997	0	0	0
1998–2001	20	66,681	269,413
2002–2006	0	0	0
2007–2009	26	170,607	766,973
2010–	0	0	0
CNG 2013 -	47	393,140	1,598,967
Fleet Total	93	630,428	2,635,353
Meadowbrook Bus Fleet			
Manufacturing Year	Number of buses	Fuel Consumption (DGE)	Bus Miles Traveled
1991–1997	0	0	0
1998–2001	50	169,795	731,137
2002–2006	31	150,101	626,056
2007–2009	71	549,605	2,619,681
2010–	97	883,624	4,418,537
CNG 2013 -	0	0	0
Fleet Total	249	1,753,125	8,395,411
Mt. Ogden Bus Fleet			
Manufacturing Year	Number of buses	Fuel Consumption (DGE)	Bus Miles Traveled
1991–1997	11	18,446	79,989
1998–2001	19	89,502	421,014
2002–2006	47	412,618	1,963,117
2007–2009	0	0	0
2010 -	34	334,390	1,876,096
CNG 2013 -	0	0	0
Fleet Total	111	854,956	4,340,216
Timpanogos Bus Fleet			
Manufacturing Year	Number of buses	Fuel Consumption (DGE)	Bus Miles Traveled
1991–1997	0	0	0
1998–2001	11	28,983	140,660
2002–2006	10	78,471	336,557
2007–2009	28	275,500	1,420,854
2010 -	23	176,873	953,487
CNG 2013 -	0	0	0
Fleet Total	72	559,827	2,851,558

Table A2. Net (avoided due to transit use - transit system caused) miles traveled, fuel consumption, and emissions due to transit use for 2016 derived using emission factors from table 1 and model output results. All emissions are in metric tons. Since the light rail consumes electricity but saves gasoline from personal vehicle travel, there is no estimate for net avoided fuel, however, gasoline gallon equivalent (GGE) is used to normalize fuel consumption.

	Vehicle Miles (×1000 miles)	Energy or Fuel (×1000 Gal or kWh)	Nitrogen Oxides (tonne NO _x)	Nonmethane hydro carbons (tonne NMHC)	Carbon Monoxide (tonne CO)	Fine Particulate Matter (tonne PM _{2.5})	Sulfur Oxides (tonne SO _x)	Greenhouse Gas (tonne CO ₂)	Gasoline Gallon Equivalent (x1000 Gal)
Using Current Emission Factors									
Bus (Diesel/CNG)	83,322	414	-46.97	51.12	597.80	-2.17	0.35	10,386	-103
Commuter Rail (Diesel - Gal)	123,775	2,685	-244.50	49.35	744.31	-16.40	0.63	33,850	2,344
Light Rail Elec- tric (kWh)	86,533	NA	39.25	50.35	569.95	-0.74	-16.90	11,880	2,668
Using Sensitivity Test Emission Factors									
Bus (Diesel/CNG)	83,322	341	6.48	54.25	615.20	0.006	0.55	12,470	-186
Commuter Rail (Diesel - Gal)	123,775	2,685	-135.54	59.87	744.31	-5.14	0.78	33,850	2,344



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