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Air quality and greenhouse gas implications of autonomous vehicles in Vancouver, Canada

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ABSTRACT

This study explores vehicle fleet emissions changes due to connected and autonomous vehicle (CAV) diffusion, over the years 2030 and 2040 in Metro Vancouver, using the US Environmental Protection Agency's MOtor Vehicle Emission Simulator (MOVES). Impacts were assessed across scenarios with varying future vehicle kilometers traveled (VKT), transit use, fuel-type, and diffusion rate. In all models, greenhouse gas emissions (GHGs) were reduced due to increasing electric vehicles, though reductions varied. At best, CAVs decreased GHGs by 20% compared to no-CAV conditions in 2040. At worst, we model a 6% decrease in GHGs if autonomy provokes increased use of personal vehicles (Motor City scenario), even with 85% electric vehicles. An overall reduction in emissions is seen for other pollutants, with the exception of PM, ranging from emissions reductions of up to 20% (PM exhaust) to an increase in emissions by 30% ($PM_{2.5}$ brakewear) in 2040. Increased VKT per CAV had the most significant impact.

1. Introduction

Connected and autonomous vehicles (CAVs) are soon to become a part of our roadways. Much like the introduction of the automobile, they are predicted to massively transform urban mobility (Cutean, 2017; Rodier, 2018; Stern et al., 2019; WSP, 2019; Greenblatt and Shaheen, 2015). However, there are large uncertainties surrounding exactly what this future will look like. It is projected that CAVs will provide numerous benefits such as improved traffic flows, increased safety, reduced costs, an overall decrease in emissions, reduced urban parking capacity, new potentials for car sharing and ride splitting, and increased mobility for non-drivers. On the other hand, increased use of autonomous vehicles could present a variety of issues. Some of the most discussed concerns include: a potential increase in vehicle-use and therefore increased congestion, pollution, and parking demand issues; data management and privacy issues; the resilience of connectivity infrastructure; an increase in urban sprawl; increased maintenance and ownership needs and costs; social equity concerns; and legal issues in vehicular collisions (Fagnant and Kockelman, 2015; Litman, 2019; Stern et al., 2019; WSP, 2019). These unknowns are especially concerning with regards to the creation of locally-applicable policy and laws surrounding increasingly automated roadways. A lack of location-specific literature and the difficulty in estimating the impacts of autonomous drivers further contributes to the deficiency of concrete evidence to support decision-making in this field. Therefore, exploratory studies and predictive models are very important in current policy discussions.

It is estimated that autonomy can result in a change to emissions through mechanisms such as driving habits, vehicle-to-vehicle communication, and new drivers on the road, such as seniors or those with visual impairments (California Air Resources Board, 2018; Schoen et al., 2013; Sinha and Labi, 2007; Wimmer and Schnessl, 2006). Wadud et al. (2016) estimates an overall change in vehicle operational energy consumption by -45% to +60%. This large uncertainty is due to the fact that the magnitude and species

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of emissions vary with vehicle design, type of driving, frequency and duration of use (changes in the frequency and distance of habitual commutes), and the behavior of the larger vehicle fleet (combined autonomous and human-driven vehicles) (Sinha and Labi, 2007; Wadud et al., 2016; Smith, 2016). In general, findings surrounding the impacts of autonomous vehicles on air pollution are divided (Crayton and Meier, 2017). Some argue that the smoothing of drive cycles and traffic waves could result in a decrease in vehicle emissions (Liu et al., 2017; Rodier, 2018; Mersky and Samaras, 2015; Stern et al., 2019). Existing technologies such as cruise control or "eco mode" are examples of these smoothing effects. Eco modes largely improve fuel efficiency by limiting the throttle response, and therefore the "severity" of acceleration, while cruise control helps to maintain a constant speed, reducing the frequency of accelerations (Hunting, 2017). Human efforts to drive in an eco-friendly manner (by staying within speed limits, anticipating stops, and moderate acceleration) have been shown to reduce emissions levels by up to 10% (Barkenbus, 2010). For autonomous vehicles, drive cycles can be further optimized through a 100% adoption rate of these identified eco-driving techniques (Anderson et al., 2016; Wadud et al., 2016). Using a simulation of link-based driving behaviors of traffic fleets in Austin, Texas, Liu et al. (2017) estimated that the smoothing effect of autonomous vehicles could result in a decrease in emissions by up to 14%. In that study, CAV driving patterns were approximated to be smoother than human ones through the application of spline functions to a standard EPA driving cycle. Bose and Ioannou (2003) estimate that the automation of acceleration cycles can result in a 28.5% reduction in fuel consumption, and up to 60.6% reduction in fleet-wide pollution levels when diffusion (on-road percentage) of semi-automated vehicles reaches 10% of the fleet. Given the smoothing-effect of CAVs, more efficient route choices, and the ability to increase capacity on roadways through a decrease vehicle spacing (due to the quicker reaction time of an autonomous driver), many predict that traffic flows will improve, with the potential to reduce congestion by up to 60%, depending on CAV diffusion rates (Fagnant and Kockelman, 2015; Shladover et al., 2012). This is due to the communication of braking and acceleration cycles between vehicles, a process known as platooning (Fagnant and Kockelman, 2015). Wadud et al. (2016) estimate that platooning has the potential to decrease energy consumption by approximately 25%. Stern et al. (2019) studied the emissions of a small fleet of vehicles, finding that an overall dampening of traffic waves results in reduced acceleration and deceleration cycles (lower vehicle specific power) and less time spent idling. This resulted in predicted emissions reductions between 15% (for carbon dioxide, CO_2) and 73% (for nitrogen oxides, NO_x) for a 5% penetration of autonomous vehicles in stop-and-go traffic conditions. An additional area of uncertainty in these findings is if traffic-smoothing affects gasoline and diesel-powered vehicles equally; there is limited information in the literature, but Liu et al. (2017) found that diesel vehicle drive cycle smoothing resulted in smaller reductions in VOCs, $PM_{2.5}$, CO, and NO_x compared to ethanol.

Others suggest that an increase in vehicle use and therefore vehicle kilometers traveled (VKT) will likely result in an increase in air pollution (Fagnant and Kockelman, 2015; Heinrichs, 2016; Rodier, 2018). It has been suggested that autonomy will increase user willingness to be on the road more frequently and for longer periods of time, as time normally spent driving could be used for other activities like working or resting (Fagnant and Kockelman, 2015; Heinrichs, 2016; Rodier, 2018). Additionally, driverless vehicles will open up mobility options for previously restricted groups, such as those with motor disabilities, young people, and the elderly. While this provides social benefits, these factors could increase the number of vehicles on the road, and therefore increase congestion by an estimated +/−2% at peak hours, and +/−1% overall (Maciejewski and Bischoff, 2018). However, this increase in VKT could be mitigated by car sharing and ride splitting/pooling (Rodier, 2018).

Given that automated vehicles are already being tested on roads, there is an urgent need to understand the air and climate impacts of these technologies. To provide guidance for CAV policymakers, this paper models the potential air quality impacts of increasing market penetration of CAVs through a local sensitivity analysis of identified CAV-related emissions inputs, and scenario-testing encompassing in Metro Vancouver, British Columbia, Canada, based on the regional transit operator's proposed future transportation scenarios.

2. Methodology

2.1. Study scope

This study covers early rates of CAV penetration in the geographic area of Metro Vancouver, a metropolitan area in the southwestern corner of mainland British Columbia, Canada. Unless otherwise noted, this paper uses the term "CAV" to describe vehicles with full levels of automation (levels 4–5), as outlined by the SAE's classification system for driving automation: all dynamic driving tasks are performed by an automated system, in all roadway and environmental conditions that can be managed by a human driver (WSP, 2019) (see also: Glossary). Metro Vancouver consists of 21 municipalities, one electoral area, and one treaty First Nation. The study covers the years 2030 and 2040, with a baseline comparison model from the year 2020. Given the area's future targets for vehicle electrification, it is assumed all CAVs will be electric vehicles. Therefore, micro-scale emissions changes in CAVs were predicted to be seen in processes that differ by driving habits, such as brake wear, tire wear, and number of starts. CAVs are likely to transform vehicle use and ownership, especially with the growth of mobility-as-a-service (MaaS) platforms and use of shared AVs (Stocker and Shaheen). As detailed in full in the Glossary, these platforms use technology and software to allow users to access multimodal transportation on demand, without needing to use a personal vehicle (KPMG et al., 2018). One example is the widely popular e-hailing app, Uber. It is predicted that while individually owning an autonomous vehicle will initially be more expensive than an average car, subscribing to autonomous MaaS platforms will be cheaper than current human-operated alternatives (Keeney, 2017; Litman, 2019). Therefore, CAVs will most likely emerge as vehicle fleet types that are characterized by repeated or previously set routes: transit, taxis or e-hail companies, and car sharing (Lang et al., 2017; Ticoll, 2017; Stocker and Shaheen). Accordingly, on-road light-duty vehicles and transit buses were modeled. Due to the complexity of creating a MaaS demand model and large uncertainties, autonomous taxiing is not directly considered in this study, however VKT changes due to e-hailing and ride splitting are included. Vehicle design (form and weight) also plays a large part in vehicle emissions (Sinha and Labi, 2007). However, since future autonomous vehicle forms are unknown, and our focus is on early diffusion stages, the effects of vehicle design are not considered here. Additionally, the potential for accelerated aging of CAVs (due to longer periods of use than a personal vehicle) was considered to be negligible. The study considers the emissions of autonomous passenger vehicles, indirectly including the effects of empty driving due to uncertainties surrounding the effects of vehicle decision-making on fuel efficiency. One study found that control strategies that do not focus on efficiency can degrade fuel economy by up to 3%, while efficiency-focused algorithms can increase it by up to 10% (Mersky and Samaras, 2015). Given that there is lack of clarity on the autonomous vehicle models that will be available in the future, the effects of empty driving were only considered indirectly by the different increases in VKT per vehicle in the different scenarios (see Table 4, column "MaaS VKT").

Given models of commercial CAVs in development, it is assumed that electric autonomous light-duty vehicles replace gasoline, ethanol, diesel, hybrid, electric passenger vehicles in proportion to the current powertrain mix. The same assumption was applied to all diesel, hybrid diesel, natural gas, and gasoline buses; however, MOVES does not allow for the modeling of electric buses (largest vehicle size that can be modeled in MOVES as fully-electric is a light-duty truck), so it was assumed autonomous populations were dispersed across all bus types. The pollutants and greenhouse gases modeled include carbon monoxide (CO), nitrogen oxides (NO_x), methane (CH_4), benzene, volatile organic compounds (VOCs), atmospheric carbon dioxide (CO_2), total energy consumption, total CO_2 equivalents, and PM_{10} and $PM_{2.5}$. MOVES does not account for emissions from generation of electricity, only from tank-to-wheels operation (US EPA, 2019). However, in British Columbia, over 98% of electricity generation is from renewable sources (in 2018: 91% hydro, 6% geothermal/biomass, 2% natural gas, 1% wind, <1% other), so these impacts are expected to be minimal (Canada Energy Regulator, 2019).

2.2. Future climate considerations

With the effects of climate change quickly intensifying, Metro Vancouver is projected to experience increased annual temperatures, dryer summers, and higher levels of precipitation in winter months (Province of British Columbia, 2016). For the purpose of this study, we used Weather Shift's weather files, which correspond to the IPCC's 50th percentile predictions (IESVE, 2019). Future weather models are important in emissions modeling as colder temperatures are strongly correlated with increased tailpipe emissions, and were previously found to be underestimated in vehicle emissions modeling using the US Environmental Protection Agency (US EPA) MOVES model, especially for formaldehyde-to-toluene emissions ratios (Jobson and Huangfu, 2016).

2.3. Fuel type

In addition to a reduction in fuel consumption, autonomous vehicles provide potential for alternative fuels (including electric vehicles). Autonomy could make it easier for vehicles to self-refuel (for electric vehicles refuel is synonymous with recharge), and therefore could refuel more often, allowing for the use of technologies such as hydrogen fuel cells, or electric vehicles with smaller and more affordable batteries (Anderson et al., 2016; Wadud et al., 2016). Given announced climate policies in the City of Vancouver, this study will assume that all CAVs will be electric vehicles. Therefore, the scope can be further refined, and emissions differences at the CAV-vehicle-level can be assumed to be solely due to non-tailpipe emissions (such as brake wear and tire wear). Effects on tailpipe emissions are assessed for the whole fleet based on traffic pattern flow changes with CAV diffusion. In this study, we assume that CAVs will recharge no more than normal for an electric vehicle, and that recharging stations will be widely available throughout Metro Vancouver (negligible additional VKT to travel to a charging station).

2.4. Diffusion timing for autonomous vehicles

It has been suggested that CAVs will follow the S-shaped diffusion path that is often characteristic of new technologies and products: initial gradual growth, rapid adoption, and then saturation at about 70%–100% of market share (Litman, 2019; McKinsey, 2016). As shown in Table 1, there seems to be a general trend in the literature suggesting significant market penetration in North America to occur in the 2040s to 2050s, with initial introduction in the 2020s to 2030s (Cutean, 2017; KPMG et al., 2018; Litman, 2019; Madlani and Orlowski, 2018; McKinsey, 2016). Electric and autonomous technology use will likely be centered in dense, high-income cities with well-established transportation systems, established concerns and targets for emissions, and where technology costs represent a lower proportion of municipal income. In this context, we hypothesize that Metro Vancouver's urban centers are a potential area of early adoption (McKinsey, 2016).

2.5. The MOVES model

Emissions were estimated using the US EPA's Motor Vehicle Emission Simulator (MOVES), a modeling system designed to estimate exhaust and evaporative emissions, as well as brake and tire wear emissions from all on-road vehicles at multiple scales. It is based on millions of the US EPA's emission test results and a vast selection of published studies (US EPA, 2017). It is a publicly-available model that has become a popular choice for macroscopic vehicle emissions studies (Stern et al., 2019; McMaster Institute for Transportation & Logistics, 2014). For a given time, location, vehicle type, activity type, and emission process, the MOVES model follows the following generic framework:

Table 1
Level 4-5 CAV diffusion projections based on literature.

Study	Year	Percent Vehicle Fleet		
		Low-disruption	Medium-disruption	High-disruption
McKinsey (2016)	2030	0%	15%	55%
	2040	10%	90%	100%
Litman (2019)	2030	15%	15%	
	2040	30%	30%	
	2050	40%	45%	
Ticoll (2017)	2030	30% of taxi/transit fleets		
	2040	Automated mass transit accounts for most personal trips		

1. Calculate the total activity of emissions sources (vehicles) in a given geographic area
2. Distribute the total activity into "Source and Operating Mode Bins", defining levels and types of emissions for each emission process (different types of emissions for each source-type in different roadway situations)
3. Calculate the emission rate given fuel types and meteorological data
4. Aggregate emission rates across bins

This process is summarized by Eq. (1), where i is the use type (i.e., a certain vehicle being used for a certain activity type) and n is the number of operating mode bins (Koupal et al., 2003):

$$\text{Total Emissions}_i = \text{Total Activity}_i \times \sum_{j=1}^{n} \text{Emission Rate}_{i,j} \times \text{Bin Distribution}_{i,j} \tag{1}$$

Total emissions are the result of the summation of the above equation for the total population of vehicles over the time span specified by the user. In MOVES, emission rates for each vehicle and activity type differ by location, time of day, day of the week, season, year, road type, vehicle age, fuel type, operating mode, and vehicle-specific power. These emissions rates are then adjusted based on temperature and humidity levels (Koupal et al., 2003; NRC, 2001). The modeled emissions processes include running exhaust, start exhaust, extended idling (referred to as "hotelling" for trucks with a refrigeration load), evaporative emissions (permeation, vapor venting, and liquid leaks), refueling (vapor loss and spillage), crankcase emissions, tire wear, and brake wear. The model's outputs included total emissions, miles, populations, cold-starts and hours on the road.

2.6. Scenario development

Irrespective of the emergence and diffusion of CAVs, Vancouver's mobility ecosystem will change with increases to population, a rise in electric vehicles on the road, increased use of car share and e-hailing companies, and a planned increase in transit services following the city's 2040 transportation plans.

Metro Vancouver's population is projected to reach 3.6 million by 2050, a 33% increase from current populations (City of Vancouver, 2012), which is estimated to be equivalent across all municipalities of Metro Vancouver. Vehicle fleet sizes will follow this growth, with vehicle density (light vehicles per capita) remaining at about 50%–80% of the population in the United States and Europe (Ramanathan, 2000; Davidson, 2015). In 2017, vehicle density in British Columbia's Lower Mainland (which includes Metro Vancouver), was at about 65.8%, and is assumed to remain constant throughout the study (ICBC, 2020; Province of British Columbia, 2020).

Due to growing concerns about environmental impacts, legislation has passed in BC requiring that 100% of new vehicle sales (for lease or purchase) be zero emission by 2040 (The Canadian Press, 2019). According to Vancouver's Renewable City Strategy, by 2050, new light-duty vehicle sales will be 30% conventional hybrid, 45% plug-in hybrid, and 25% electric vehicle (City of Vancouver, 2016). Baseline (non-CAV) populations in 2030 and 2040 were interpolated assuming this goal is reached and that new vehicle sales and replacements follow current trends (Table 2).

The City of Vancouver's Transportation 2040 plan and Metro Vancouver Future of Transportation 2040 plan set out a precedent to achieve lower levels of personal-vehicle use through the densification and diversification of urban areas, and the growth of the region's transit network (City of Vancouver, 2012; Metro Vancouver, 2011). The City of Vancouver hopes to reduce VKT by 20% from 2007 levels, with at least two thirds of all trips on foot, bike or transit (City of Vancouver, 2012). Currently, about half of trips in Metro Vancouver are by personal vehicle, 45.5% by auto driver, and 6% as passenger trips (McElhanney, 2019). It was found that transit ridership is primarily affected by population sizes, employment levels, and gas prices (McElhanney, 2019).

With the emergence of CAVs, modality choices can be greatly disrupted (Greenblatt and Shaheen, 2015), potentially affecting Vancouver's plans for a transit-heavy transportation future. The local public transit operator, TransLink, has explored the potential effects of CAVs at a conceptual level, determining four possible scenarios, described in Table 3. These conclusions closely resemble the possible futures put together by Heinrichs (2016), who completed an in-depth literature review exploring the relationships between land use and autonomous vehicles. The selection of scenarios in this study are based on the relative magnitude of change (as outlined by TransLink) for modality choices, vehicle ownership, new user groups, and changes in cost (TransLink, 2016). In these scenarios, fuel-type switching was not considered for comparability between findings.

Table 2
On-road Population distribution for baseline model conditions.

Vehicle Class	Power train	2020	2030	2040
Passenger Car[a]	Gasoline	92.5%	86%	80%
	Diesel	5%	4%	3%
	Ethanol (E-85)	1%	2%	3%
	Fully Electric	1.5%	7.8%	14%
Bus[b]	Gasoline	9.8%	9.8%	9.8%
	Diesel	80.5%	80.5%	80.5%
	Natural Gas	9.8%	9.8%	9.8%

[a]MOVES does not separately model hybrids/plug-in hybrids, these are included in the 'fleet average' gasoline and diesel emissions for each model year in MOVES (US EPA, 2019).
[b]MOVES cannot model fully electric buses (US EPA, 2019).

Table 3
Future scenarios after introduction of AVs in Metro Vancouver (TransLink, 2016).

	Vehicle Occupancy	
	Single Occupancy	Multi-Occupancy
Multi-modal trips	**Uncoordinated Mobility:** Mass-transit is prominent. 'Last-mile' trips are provided by many mode connected to mass transit in urban areas and suburban centers. Private vehicle ownership remains high outside of urban centers.	**Coordinated Mobility:** Mobility, rather than a transportation mode, is bought. Modes integrate seamlessly and operate under a public transportation system umbrella. The efficiencies of the core support the 'last-mile' trips at the periphery.
Auto-dependent mobility	**Status Quo:** More personally owned vehicles and urban congestion. People commute longer distances potentially changing patterns of density. Public transit remains viable.	**Motor City:** Cars remain prominent but they are shared vehicles (as e-hail or subscription fleets or individually owned vehicles). Transit use and services have declined. Parking is now located in large facilities outside the core.

A scenario-based analysis was conducted by testing the set of possible diffusion scenarios as presented in Table 3 (TransLink, 2016). This method of global sensitivity analysis encompasses interactions between variables, and ensures that the validity of the interval of inferences is narrow enough to be useful (Leamer, 1985). The baseline CAV model scenarios were based on findings from a literature review and the Vancouver 2040 transportation plan. They are organized by year, CAV adoption/diffusion levels both overall and for CAVs integrated into MaaS platforms, modality choice (level of transit and shared CAV use), vehicle ownership, and changes in VKT per CAV, which reflect potential changes in vehicle usage due to reduced costs, ride splitting and car sharing, and increased acceptance of longer commutes with the elimination of the burden of driving. The scenarios are defined in Table 4.

These scenarios are compared to baseline no-CAV data and regional emissions goals in 2030 and 2040. The 2030 and 2040 "No CAV" baselines are based on the 2020 baseline, with inputs adjusted for projected population changes and future vehicle and fuel sales. The 2030 and 2040 Regional Emissions Goals are based on regional emissions percent reduction targets as stated in the 2015 Lower Fraser Valley Air Emissions Inventory applied to our 2020 baseline. To develop the 2020 baseline, we first re-created Metro Vancouver's 2015 estimates with the 2015 Metro Vancouver MOVES model inputs to confirm proper operation of MOVES. We then updated the 2015 MOVES inputs to 2020 numbers where available (e.g., changing vehicle fleet mix, population etc.), and ran MOVES again with these 2020 inputs. The output from MOVES was compared to the 2020 CO_2-eq emissions projections provided in the most recent Metro Vancouver reporting from 2018 (Metro Vancouver, 2018); these numbers agreed within 10%. We also sanity-checked our baseline estimated with Metro Vancouver staff.

2.7. Data collection and processing

Collected data for this study were processed to reflect the Metro Vancouver transportation network in the years 2020, 2030, and 2040. Baseline inputs were based on MOVES inputs from a 2015 study of Metro Vancouver emissions (Metro Vancouver, 2018). These were altered and scaled based on current and future projections of: (1) weather, from Natural Resources Canada weather files and IESVE projected weather; (2) populations, scaled based on overall Metro Vancouver population projections; (3) VKT, scaled linearly by population change, assuming a 3% decrease in total VKT due to Metro Vancouver initiatives (McElhanney, 2019); and (4) fuel type usage fractions, following the projections of electric vehicle population changes based on future policies. Data processing was primarily completed with Excel-based modeling and Python scripts. It was assumed that road type distributions, population distributions and density, and VKT distributions (the fraction of kilometers traveled by each vehicle type) remained the same from

Table 4
Definition of City of Vancouver scenario ranges used in this study.

Year	Scenario	Tot. Diff.[a]	MaaS share[b]	MaaS VKT[c]	Transit[d]	Δ VKT/CAV[e]	Δ Car/MaaS Car[f]	Net VKT Effect[g]
2020	Baseline	0%	–	–	17%	–	–	–
2030	Status Quo	1%	–	–	17%	–	–	–
	Motor City	15%	10%	+103%	10%	+9%	−11	+10%
	Uncoordinated Mobility	10%	10%	+54%	18%	+9%	−11	–
	Coordinated Mobility	15%	10%	+5%	25%	+9%	−11	−10%
2040	Status Quo	10%	5%	–	17%	–	–	–
	Motor City	85%	25%	+103%	3%	+9%	−11	+60%
	Uncoordinated Mobility	45%	25%	+54%	18%	+9%	−11	+12.5%
	Coordinated Mobility	85%	25%	+5%	33%	+9%	−11	−35%

[a]% vehicle fleet.
[b]% vehicle fleet that is part of a MaaS platform.
[c]% change in VKT by a shared CAV.
[d]% of trips taken on transit.
[e]% change in VKT by the CAV fleet due to increased willingness to drive.
[f]Reduction in # of individually-owned passenger vehicles per vehicle in a MaaS platform.
[g]Overall impact on region-wide VKT.

2015 data. Population inputs were cross-checked with local government databases (ICBC, 2020; TransLink, 2019; BC Stats, 2019). The MOVES default vehicle age distribution data, and a ramp fraction of 8% of VMT was used in all models for both rural restricted roads and urban restricted roads, as is the default in the MOVES model (Koupal et al., 2003). The validity of inputs was determined through the calibration of the 2020 baseline model to Metro Vancouver's estimations of CO_2 emissions in 2015 projected to 2020, with an error margin of 10%. Metro Vancouver estimates of 2030 reductions in emissions are drawn from the 2015 Lower Fraser Valley Air Emissions Inventory and Forecast. Not all pollutant species are considered individually in this study, so reductions in CH_4 and benzene are assumed to be similar to emission reductions in overall greenhouse gases, and VOCs, respectively, and cause greater uncertainties in the validity of these projections as a method of comparison for study findings.

The findings of past agent-based models of CAVs were compiled to develop a large-scale MOVES study, following the methodologies of similar studies, such as Wadud et al. (2016), Chen et al. (2019), Auld et al. (2017), Brown and Dodder (2019), Greenblatt and Saxena (2015), and Liu et al. (2017). Specifically, models at a micro and macro scale were combined. The micro-scale analysis encompasses emissions at the vehicle level, due to emission differences from a reduction in cold starts and accelerations. The macro-scale model (or fleet level) analyzes potential changes in traffic patterns, due to overall traffic smoothing, and changes in vehicle kilometers traveled (VKT) due to VKT per capita changes, MaaS platform use, new users, and modality choices.

To model fleet-level emissions, MOVES input files for speed distributions and VKT by vehicle type were altered. The findings from Maurer et al. (2016) and Stern et al. (2019) were used to estimate changes in speed distributions, again scaling changes in speed as a function of the percentage of CAVs in the vehicle fleet according to Eq. (2). Traffic flow (or capacity) for a single lane is a function of distance between vehicles, length of the vehicles, and average speed of the fleet. Maurer et al. (2016) describe capacity (C_m) with mixed autonomous and human drivers according to Eq. (2).

$$C_m = \frac{\upsilon}{\eta^2 \upsilon T_{aa} + \eta(1-\eta)\upsilon T_{ah} + (1-\eta)\upsilon T_{hx} + L} \tag{2}$$

where υ is the average fleet velocity, η is the percent of the fleet that is autonomous vehicles (diffusion level), T_{aa} is the distance time-lag between two CAVs, T_{ah} is the distance time lag of a CAV behind a human driver, and T_{hx} is the distance time lag of a human behind any vehicle. Making the assumptions that the vehicles in this fleet are realistic passenger vehicles, the values for T_{aa}, T_{ah}, T_{hx} can be set as 0.5 s, 0.9 s, and 1.15 s respectively, and L is assumed to be 21 m. To determine the scale factors for the MOVES speed distributions (speed bins), capacity was calculated for each bin's average velocity and increasing levels of diffusion (0%–85%). As all other variables remained constant, other than speed, capacity and diffusion; it can be assumed that the increase in capacity is proportional to an increase in speed relative to the 0% CAV case. These factors were used to scale speed bin distributions for the MOVES inputs. These scale factors were used as a multiplier for the MOVES speed bin inputs (expressed as a percentage of time at which vehicle kilometers are within each speed bin). Due to a lack of published studies, we assumed smoothing of drive cycles impacted all vehicles equally. It can be seen in Fig. 1 that speeds begin to have a noticeable impact on fleet behavior after the 5% diffusion point.

VKT was scaled based on variable inputs of modality choices and direct changes in VKT habits. If there was a shift towards transit, VKT was removed from passenger vehicles and no change in transit bus VKT was made, assuming that transit routes (while accounting for population increases) would have the capacity to meet extra demands of modality changes.

At the vehicle scale, since it was assumed that all CAVs would be electric, only tire wear and brake wear were adjusted across the scenarios. The change in brake wear emissions with CAV diffusion were found following the findings of Liu et al. (2017). A spline function was used, with a smoothing factor of 0.22999 to model the driving cycle of an autonomous vehicle in regular traffic conditions. Based on a US EPA study, Eq. (3) was used to estimate the brake wear emissions of an autonomous vehicle for all of

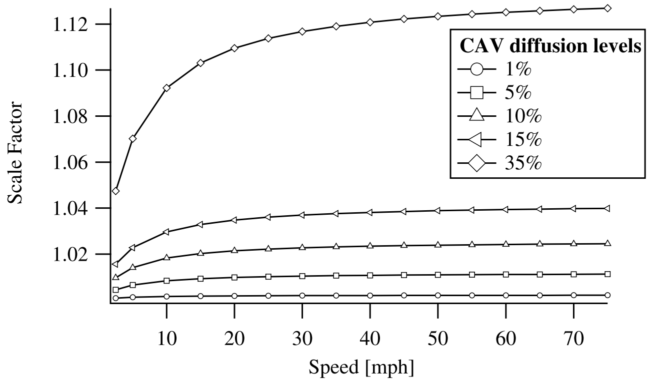

Fig. 1. Change in Average Fleet Speed due to Presence of Autonomous Vehicles.

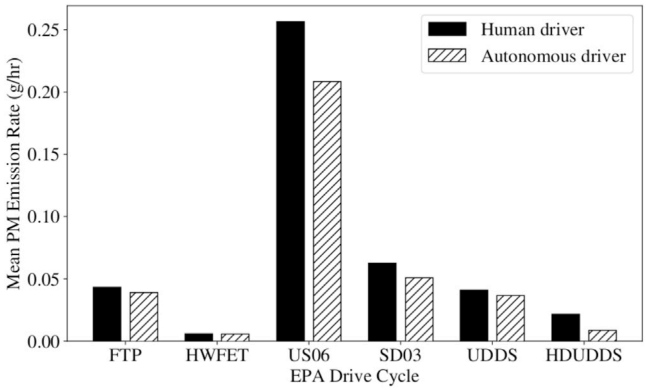

Fig. 2. Changes in brake wear due to autonomy for US EPA Drive Cycles.

the EPA's driving cycles, which assumes that $PM_{2.5}$ emissions are proportionate to brake wear. It can also be assumed that the mass fraction of particles below $PM_{2.5}$ in PM_{10} is 0.125 (US EPA, 2014).

$$E_{PM_{2.5}} = 0.1872a^3.195 \tag{3}$$

where $E_{PM_{2.5}}$ is the emissions of $PM_{2.5}$ in g/h, and a is the deceleration rate in $\mathrm{m/s^2}$. These changes can be seen in Fig. 2.

MOVES outputs for passenger cars were scaled by the average of the urban driving cycles (STP, UDDS, and SD03) and a highway cycle (HWFET), resulting in a 10.2% and 4.0% decrease in emissions for CAVs in urban and highway environments, respectively. Transit bus outputs were scaled by the average emissions decrease of the urban and urban heavy-duty driving cycle (HDUDDS). It was found that due to the usual stop–start patterns of a transit bus at intersections and in traffic (bus stops assumed unchanged), emissions could be decreased by 35.7%. The aggressive cycle (US06) was not considered as it is assumed that autonomous vehicles would not drive aggressively. These changes were assumed to be proportional to the chosen autonomous vehicle fleet size.

Tire wear emissions were explored in the same manner as brake wear emissions, but changes were found to be insignificant, as the US EPA's model for tire wear is based on speed (rather than acceleration), which does not change at the vehicle level in this study. As such, creating a model for vehicle-level tire wear changes with autonomous vehicles was outside of the scope of this study.

Due to limitations of the MOVES model, the emissions reduction at the vehicle level were partially calculated in post-processing. This was completed by analyzing the output of the baseline tests for vehicle types in 2030 and 2040 (no CAVs). For brake wear emissions, with x as the ratio of autonomous vehicles in the total fleet, x_{bus} is the fraction of transit buses that are autonomous, P_j is a vehicle fleet population, m_i is the mass of pollutant, and i is the pollutant type ($PM_{2.5}$ and PM_{10}). The reduction of emissions for passenger vehicles is based on road type, denoted by w_i. The total reduction in brake wear PM emissions were calculated using Eqs. (4) and (5).

$$m_i = w_i \frac{xP_{Total} - P_{Bus}x_{bus}}{xP_{Total}} \times m_{i,Passenger} + 0.3568\frac{P_{Bus}x_{bus}}{xP_{Total}} \times m_{i,Bus} \tag{4}$$

$$m_{i,Bus}\begin{cases} 0.3, & \text{if year} = 2030 \\ 1.0, & \text{if year} = 2040 \end{cases} \text{ and, } w_i\begin{cases} 0.1023, & \text{if road type} = \text{urban} \\ 0.0398, & \text{if road type} = \text{highway} \end{cases} \tag{5}$$

Following the findings of Ticoll (2017), Eqs. (4) and (5) assume that transit fleets will be 30% autonomous by 2030, and fully autonomous by 2040.

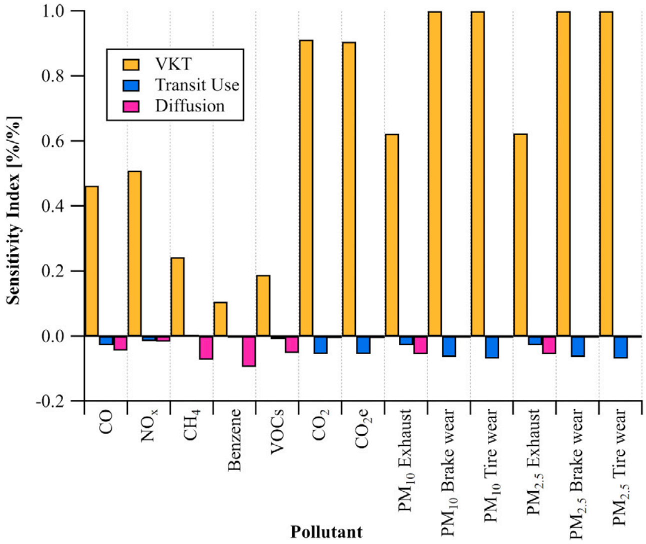

Fig. 3. Emission sensitivity coefficients of CAV-related variables.

2.8. Sensitivity analysis

It is likely that the largest impacts on emission levels will be modality choices and VKT per capita, rather than CAV populations and simply the physical presence of autonomous vehicles. As user habits are not linearly related to CAV diffusion, we use a sensitivity analysis to understand the range and scale of impacts that CAVs could have on future emissions, and to identify the CAV-related changes that have the most influence. A local sensitivity test was completed with the commonly used finite difference approximation technique, or the one-at-a-time (OAT) method, allowing for an understanding of the potential that individual input parameters have to affect a model's output, while minimizing the number of model runs (Yan et al., 2014; Travesset-Baro et al., 2016).

The sensitivity of an input, S is found using Eq. (6) as follows: (1) the MOVES model is run for a baseline case, in this case for the year 2030, where I is set at a neutral value with no effects of CAVs, defined as I_0, providing a baseline emissions estimate, $E(I_0)$;(2) I is changed by a given amount (δI), which was defined as $\pm x\%$ of I_0, and new input files for the MOVES model are produced through an Excel-based conversion workbook; (3) the total emissions are found for $E(I_0+\delta I)$ and $E(I_0-\delta I)$ (when applicable); (4) and finally, the sensitivity coefficient, S is found (Yan et al., 2014; Travesset-Baro et al., 2016):

$$S_{E,I} = \frac{E(I_0+\delta I) - E(I_0-\delta I)}{2\delta I} \tag{6}$$

The normalized sensitivity coefficient, $S_{E,I,norm}$ is less dependent on the chosen value of δI, providing a measure of percent change in $E(I)$ given a one percent change in I. It is defined in Eq. (7).

$$S_{E,I,norm} = \frac{E(I_0+\delta I) - E(I_0-\delta I)}{2\delta I} \times \frac{I_0}{E(I_0)} \tag{7}$$

The following variables were identified for the sensitivity analysis: diffusion of CAVs [%, which encompasses changes in speed, vehicle starts, and brake wear; mode choice [% of trips on transit]; change in vehicle kilometers traveled [% change from baseline projection]. The model was run for $\pm 1\%$ transit and VKT, and diffusion was changed by $\pm 5\%$ where $E(I_0)$ was found for a diffusion level of 5%. Factors that are indirectly related to CAVs, but influence the potential range of inputs include the year of analysis, which in turn influences levels of electric vehicle diffusion and weather inputs. As these factors were deemed uncontrollable, they were not considered in the sensitivity analysis. The analysis was completed for the year 2030.

3. Results and discussion

3.1. Local sensitivity analysis

The sensitivity of CAV-related variables is summarized in Fig. 3. VKT sensitivity coefficients are positive, as an increase in VKT will result in an increase in emissions, while transit-use and diffusion are correlated with a decrease in emissions. Changes in VKT due to behavioral transportation changes (such as and increase in vehicle use due to increased productivity during commutes) had the largest effect on emissions, especially for CO (0.46), NO_x (0.51), CO_2 (0.91), and PM species (1.0 for PM_{10} and $PM_{2.5}$ exhaust and brake wear). Effects of modality choices and low-level diffusion appear to have little effect on overall emissions, however diffusion seems to affect CO (−0.04), methane (−0.07), benzene (−0.1), and VOCs (−0.05), and PM exhaust species (−0.07 and −0.06 for

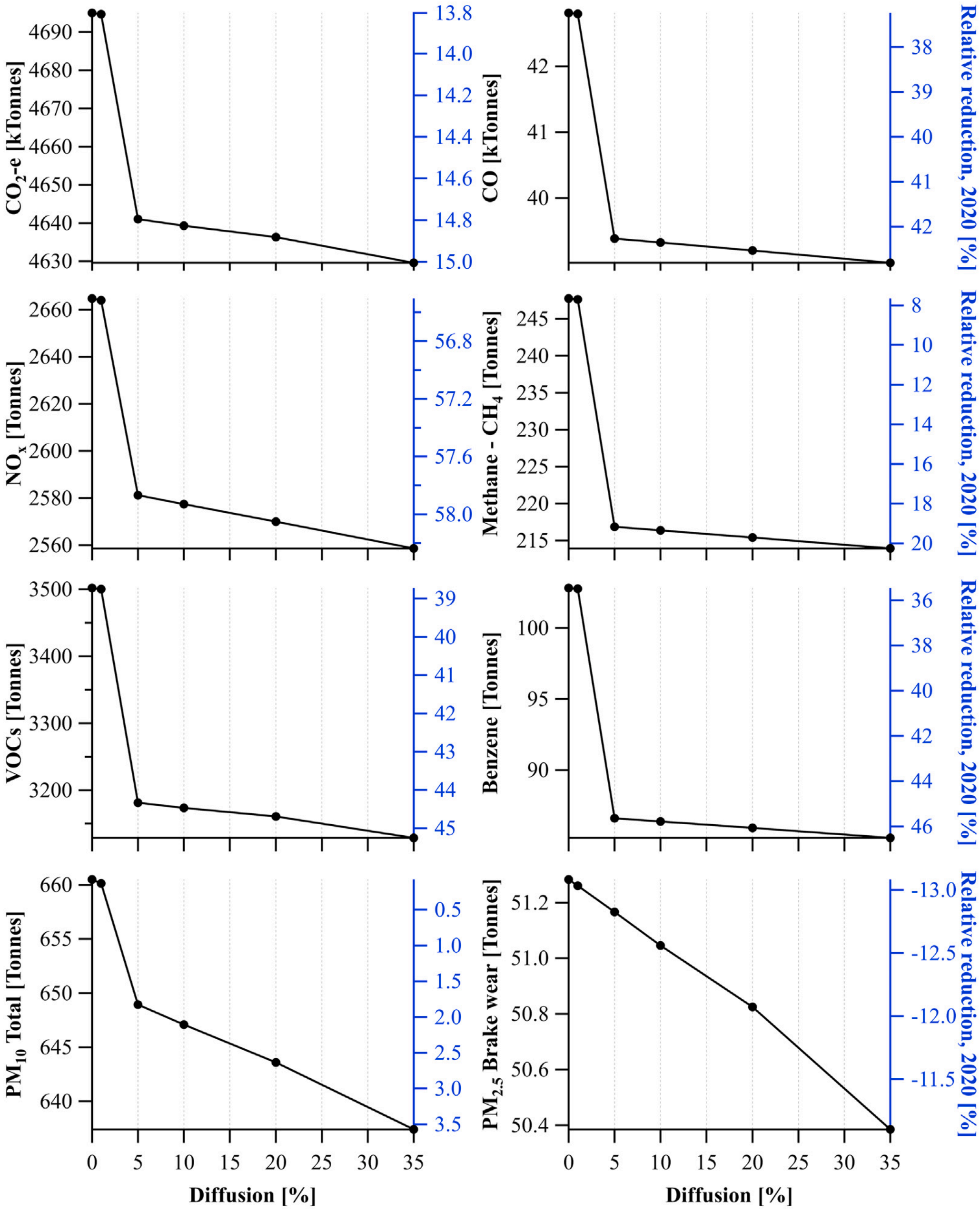

Fig. 4. Expected effects of CAV diffusion on emissions (based on 2030 Metro Vancouver projections).

PM_{10} and $PM_{2.5}$, respectively). Transit had measurable impacts on total CO (−0.03), CO_2 (−0.05), PM exhaust emissions (−0.06 for PM_{10} and $PM_{2.5}$), and PM brake wear emissions (−0.07 for PM_{10} and $PM_{2.5}$).

The greatest potential in emissions savings is from VKT habits. VKT per capita is largely related to land-use diversity and socioeconomic factors (Woldeamanuel and Kent, 2014), so it is exceedingly difficult to model future of VKT without an understanding of how CAV diffusion levels and urban form are related. At low diffusion levels, autonomy on the road will have negligible impacts on vehicle fleet emissions, and VKT choices have the potential to make the greatest impacts. However, it is unlikely that CAVs will have significant impacts on modality and VKT habits until the technology is more widespread, with the potential to affect psychological factors that govern transportation choices (such as a willingness to commute longer or increased use of ride-sharing).

Eliminating effects from VKT changes to further understand the effects of diffusion as an independent variable holding all other variables constant, MOVES was run at increasing levels of diffusion in the light-duty vehicle fleet only, from 0%–35%, for the year 2030 (Fig. 4). The left axis is the total modeled emissions for the year 2030 for the given diffusion level, while the right axis

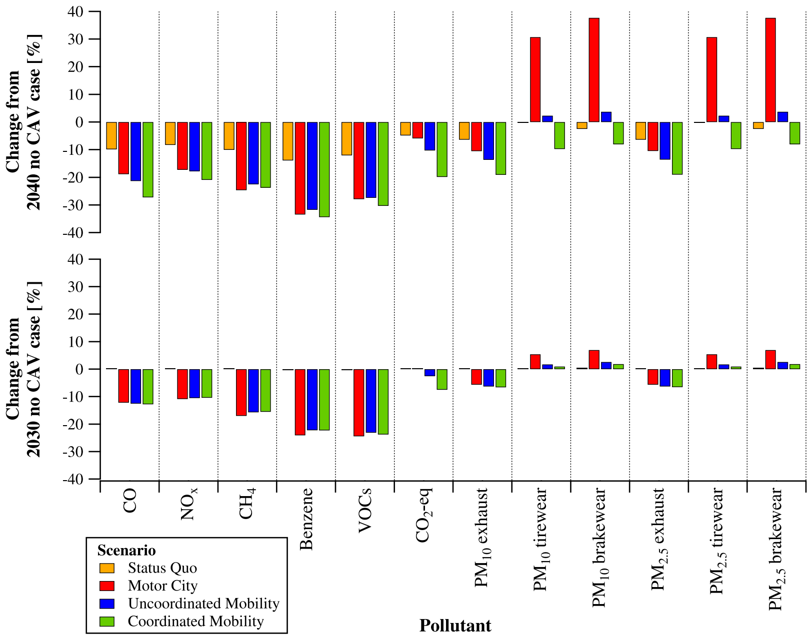

Fig. 5. Expected emissions changes due to autonomous vehicle diffusion in Metro Vancouver across the four scenarios outlined in Table 4.

represents this value as a relative reduction from projected 2020 emissions. As only CAV diffusion levels were altered, it can be assumed that these results also somewhat reflect the effects of autonomy on emissions at the vehicle level. It was found that with increasing diffusion, CAVs incur the most changes from about 1%–10% diffusion, after which impacts plateau, with the exception of PM_{10} and $PM_{2.5}$ emissions. Due to the direct relationship between CAV populations and brake wear emissions (rather than fleet-behavior), it can be seen that brake wear emissions follow a relatively linear path. In this assessment, CAV diffusion has the largest impact on methane (8%–20%), benzene (35%–46%), and VOC emissions (39%–45%).

It can be seen that there is a threshold just before 5% diffusion in which autonomy begins to have a measurable effect on emissions, likely due to the fact that traffic-smoothing effects are largely realized after the 5% diffusion point (see Figs. 4 and 1). Although many studies do not consider the impacts of CAVs under 10% diffusion, Chen et al. indicate a similar threshold, with autonomy impacting fuel consumption at an approximate diffusion rate of 5% (Chen et al., 2019). Others have found that energy efficiency can be impacted at low penetration levels (Vahidi and Sciarretta, 2018). However, it was found that fuel consumption begins to be significantly impacted at above a 50% diffusion rate in mixed stop-and-go traffic, when considering effects of traffic-smoothing and platooning of CAV fleets of 10%–100% of vehicle populations (Rios-Torres and Malikopoulos, 2018). Conlon and Lin (2019) found that GHG emissions were only reduced at over 30% diffusion rates, however they were impacted at at least 10% diffusion (Conlon and Lin, 2019).

3.2. Scenario testing

With an understanding of the scale of impact for different emissions mechanisms of CAVs, the TransLink-based scenarios were modeled, with findings depicted in Figs. 5 and 6.

Fig. 5 presents the percent change of emissions species from CAV diffusion, based on non-CAV conditions in the same year. We observe that in every scenario, CAVs are more likely to decrease VOCs, NO_x, benzene, CH_4, CO, and PM tailpipe emissions, or result in negligible change. There is a general decrease in emissions for most pollutant species due to the impacts of increased electric vehicle integration in future years. The exception is brake wear $PM_{2.5}$. Although brake wear PM emissions significantly decrease at the vehicle level for CAVs (see Fig. 4), there seems to be little impact when considering entire vehicle fleet emissions due to the fact that PM emissions increase with temperature (Garg et al., 2000) and VKT may increase substantially.

As effects of platooning and speed changes are magnified between 2030 and 2040, it can be concluded that emissions changes due to overall fleet behavior (or traffic-smoothing effects) are dominant for species in which quantities vary widely between scenarios. For example, the relative decrease in PM exhaust is approximately 6%–19% for CAV diffusion over 5%, with more significant changes occurring after and including 45% diffusion (the 2030 Status Quo conditions represent a 1% diffusion level which was proven to have little impact on emissions in the sensitivity analysis). This suggests that these emissions reductions stem from simply the presence of CAVs on the road the associated accelerated integration of EVs. However, PM_{10} brakewear emissions have the potential to increase relative to baseline emissions in the 2040 Motor City scenario, or decrease in the Coordinated Mobility scenario, indicating the importance of vehicle-sharing and fleet behavior on emissions.

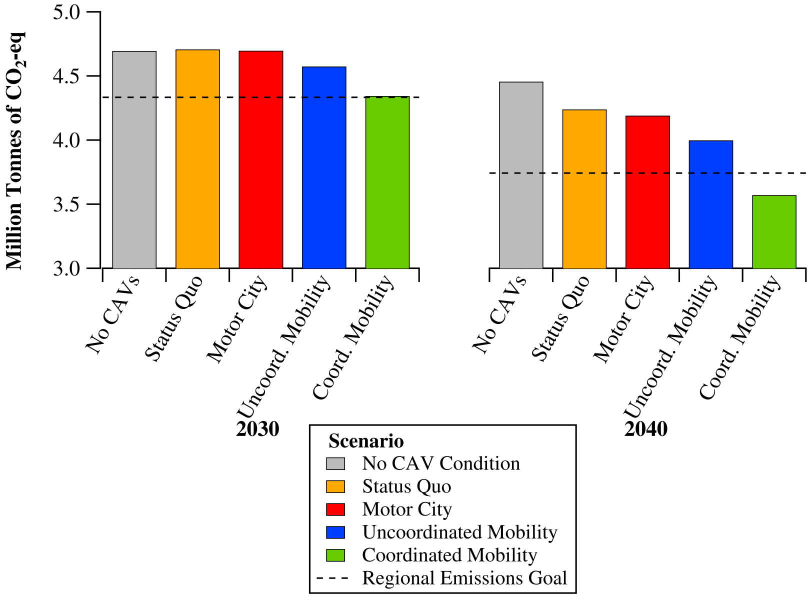

Fig. 6. Expected range of emissions due to autonomous vehicle diffusion in Metro Vancouver.

Fig. 6 shows projected CO_2-eq emissions, a proxy for GHG emissions (Delcan, 2007) for the years 2030 and 2040, with comparisons to non-CAV conditions and the regional emissions goals for each year (Metro Vancouver, 2018). Although the increasing use of EVs results in an overall decrease in GHG emissions, initial results indicate an increased probability for emissions to exceed regional GHG goals (which are based on planned increasing use of EVs, reduced VKT, and increased transit use). This occurs in most scenarios, with the exception of Coordinated Mobility. Unsurprisingly, the largest savings for all pollutants are seen in the Coordinated Mobility scenario, likely due to the integrated use of transit and MaaS multimodal subscription platforms. This again suggests that CAV overall diffusion has less of an impact than user mobility decisions, and emphasizes the importance of city planning as CAVs are integrated into the fleet. Furthermore, this emphasis on planning decisions suggests EV adoption policies alone will not enable us to meet our GHG targets, as we assume all light-duty CAVs will be EVs in this study and this assumption generally accelerated the rate of EV adoption in the region.

4. Conclusions

There is a substantial uncertainty as to how autonomous vehicles will affect transportation habits and traffic patterns, even at low levels of diffusion. Therefore, this paper has attempted to understand the scale of what is possible. The results suggest that CAVs have the potential to significantly impact future emissions, in both positive and negative ways. The changes due to CAV diffusion are most significant between 1%–5% diffusion levels, where the rate of emissions savings is highest. However, indirect effects on the vehicle fleet, due to user choice and city planning (as illustrated in ‘Motor City’ vs ‘Coordinated Mobility’) dominate emissions changes past this point. CAVs have the potential to decrease GHG emissions (CO_2-eq) by an additional 20% compared to no-CAV conditions in 2040, due to integrated transit-use and shared CAVs. On the other hand, we estimate only a 6% decrease in GHG emissions will occur if autonomy provokes increased use of personal vehicles (Motor City scenario), even with 85% of fleet using electric vehicles. An overall reduction in emissions is seen for other pollutants, with the exception of PM species, ranging from emissions savings of up to 20% ($PM_{2.5}$ exhaust) to an increase in emissions by 30% ($PM_{2.5}$ brakewear) in 2040. The sensitivity analysis confirmed the significant impact of VKT habits on emissions. Understanding mechanisms of impact can help inform areas of focus for future emissions and CAV-related policy planning. As the societal/psychological impacts of CAVs have the largest potential for impact (especially in early diffusion stages), it is imperative that emission reductions strategies be approached from a systems-level (Taiebat et al., 2018).

There are a number of limitations of this model. As the MOVES model is complex and inflicts a high computational cost (12 h per run), the number of model runs was restricted. Additionally, the MOVES model does not allow for the alteration of vehicle specific power at the county-level (this is only possible at the project, or link level), which limits the ability to model the true effects of traffic smoothing. Furthermore, the EPA’s methodology for calculating tire wear did not allow for the measurement of PM emission reductions at the vehicle level for autonomous vehicles. An improved model for calculating tire wear emissions as they relate to accelerations and stops would eliminate this issue. Finally, it is assumed that all CAVs would be EVs due to specific policy plans in Metro Vancouver. However, the possibility of using alternative fuels in autonomous vehicles are often proposed (Wadud et al., 2016), which could prove to have further effects on emissions.

The results of this study are based solely on the findings from the MOVES model at a county scale. It is suggested that similar methodologies be applied to other emissions modeling software to assess the validity of these findings. Additionally, with further model runs (and perhaps models), a more robust sensitivity analysis (such as the use of a Monte Carlo simulation Yan et al., 2014; Travesset-Baro et al., 2016) could address the non-linearity of variables, as well as spatial uncertainties that arise among different types of urban areas. Finally, the study of smaller geographic areas could increase the robustness of this model, and allow for more precise emissions estimates. Specifically, this would allow for an understanding of the relationship between land-use (and road) types and emissions effects, and provide the opportunity to explore the contested issue of MaaS platforms and effectively consider effects of ride splitting and car sharing. For example, land use regression could be used to estimate demand predictions in certain areas within the study region, to understand the density and distribution of MaaS demand in different locations.

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Appendix. Glossary

- **Car sharing**: Access to vehicles by joining an organization that provides and maintains a fleet of cars and/or light trucks (SAE International, 2018b).
- **Connected and autonomous vehicle (CAV)**: In this paper we define CAVs as any vehicles with Level 4 or Level 5 automation (see below).
- **Diffusion**: The percentage of on-road vehicles of a certain type/classification.
- **E-hailing**: A for-hire transportation service where rides are dispatched on-demand using a smartphone app (SAE International, 2018b). Like Uber, these apps can be used for individual taxiing as well as ride splitting or ride pooling.
- **Level 4 automation**:' 'High Driving Automation". An automated driving system (ADS) can perform all driving tasks, but only under certain conditions; the ADS cannot be engaged outside of those conditions. When ADS is engaged, the human driver does not need to pay attention, nor do they need to be ready to take over if necessary — they become a passenger. Outside of those conditions, the human driver needs to take control (SAE International, 2018a).
- **Level 5 automation**: "Full Driving Automation". An ADS can drive the vehicle under all conditions. The human occupants are not expected to take over when provided with a request to intervene; they are passengers and never need to be involved in driving (SAE International, 2018a).
- **Market share**: The percentage of new vehicles sold of a certain type/classification.
- **Mobility as a Service (MaaS)**: A mobility distribution model that meets a person's end-to-end transportation service needs over one e-hailing platform. In this paper, MaaS refers to the provision of multiple autonomous transportation options such as mass transit, car sharing, ride-hailing and taxiing that can be managed through a single smartphone app (Spulber and Dennis, 2016). In this paper, MaaS refers to an autonomous vehicle passenger fleet, with services of ride splitting, car sharing, ride-hailing and taxiing, that can be accessed through an e-hailing app. Transit is considered separately.
- **Ride sharing**: Carpooling. When parties needing to travel in similar routes combine trips in one vehicle.
- **Taxiing**: A passenger car mobility service that transports a single party at between desired pickup and drop-off locations.

References

Anderson, J., Kalra, N., Stanley, K., Sorensen, P., Samaras, C., Oluwatola, O., 2016. Autonomous vehicle technology: A guide for policymakers. In: Autonomous Vehicle Technology: A Guide for Policymakers. RAND Corporation, Santa Monica, Calif., http://dx.doi.org/10.7249/rr443-2.

Auld, J., Karbowski, D., Sokolov, V., 2017. Assessing the regional energy impact of connected vehicle deployment. Transp. Res. Proc. 00 (00), URL www.sciencedirect.comwww.elsevier.com/locate/procedia2214-241X{%}0Awww.elsevier.com/locate/procedia.

Barkenbus, J.N., 2010. Eco-driving: An overlooked climate change initiative. Energy Policy http://dx.doi.org/10.1016/j.enpol.2009.10.021.

BC Stats, 2019. BC population projections. URL https://catalogue.data.gov.bc.ca/dataset/bc-population-projections.

Bose, A., Ioannou, P.A., 2003. Analysis of traffic flow with mixed manual and semiautomated vehicles. IEEE Trans. Intell. Transp. Syst. 4 (4), 173–188. http://dx.doi.org/10.1109/TITS.2003.821340.

Brown, K.E., Dodder, R., 2019. Energy and emissions implications of automated vehicles in the U.S. energy system. Transportation Research Part D: Transport and Environment 77, 132–147. http://dx.doi.org/10.1016/j.trd.2019.09.003, https://pmc/articles/PMC6961821/?report=abstracthttps://www.ncbi.nlm.nih.gov/pmc/articles/PMC6961821/.

California Air Resources Board, 2018. Brake & tire wear emissions. In: Vehicle Emissions Research Program. URL https://ww2.arb.ca.gov/resources/documents/brake-tire-wear-emissions.

Canada Energy Regulator, 2019. Provincial and territorial energy profiles – british columbia. In: Provincial and Territorial Energy Profiles. URL https://www.cer-rec.gc.ca/en/data-analysis/energy-markets/provincial-territorial-energy-profiles/provincial-territorial-energy-profiles-british-columbia.html.

Chen, Y., Gonder, J., Young, S., Wood, E., 2019. Quantifying autonomous vehicles national fuel consumption impacts: A data-rich approach. Transp. Res. A 122, 134–145. http://dx.doi.org/10.1016/j.tra.2017.10.012.

City of Vancouver, 2012. Transportation 2040 moving forward. Transportation 2040 1–99, URL https://vancouver.ca/files/cov/transportation-2040-plan.pdf{%}0Ahttp://vancouver.ca/files/cov/Transportation{_}2040{_}Plan{_}as{_}adopted{_}by{_}Council.pdf.

City of Vancouver, 2016. Vancouver's EV Ecosystem Strategy. (November), City of Vancouver, pp. 1–78.

Conlon, J., Lin, J., 2019. Greenhouse gas emission impact of autonomous vehicle introduction in an urban network. Transp. Res. Rec. 2673 (5), 142–152. http://dx.doi.org/10.1177/0361198119839970, URL https://doi.org/10.1177/0361198119839970.

Crayton, T.J., Meier, B.M., 2017. Autonomous vehicles: Developing a public health research agenda to frame the future of transportation policy. Journal of Transport and Health 6 (April 2017), 245–252. http://dx.doi.org/10.1016/j.jth.2017.04.004.

Cutean, A., 2017. Autonomous Vehicles and the Future of Work In Canada. Information and Communications Technology Council (ICTC), Ottawa, Canada, p. 14, URL https://www.ictc-ctic.ca/wp-content/uploads/2018/01/ICTC{_}-Autonomous-Vehicles-and-The-Future-of-Work-in-Canada-1-1.pdf.

Davidson, K., 2015. Has demand for autos reached a peak in the developed world? URL https://www.schroders.com/nl/nl/particulieren/nieuws-marktinformatie/markets/the-end-of-the-road-has-the-developed-world-reached-peak-car/.

Delcan, 2007. Guidelines for Quantifying Vehicle Emissions Within the Ministry's Mutiple Account Evaluation Framework. Technical Report, BC Ministry of Transportation, pp. 1–18.

Fagnant, D.J., Kockelman, K., 2015. Preparing a nation for autonomous vehicles: Opportunities, barriers and policy recommendations. Transp. Res. A 77, 167–181. http://dx.doi.org/10.1016/j.tra.2015.04.003.

Garg, B., Cadle, S., Mulawa, P., Groblicki, P., Laroo, C., Parr, G., 2000. Brake wear particulate matter emissions. Environ. Sci. Technol. 34 (21), 4463–4469. http://dx.doi.org/10.1021/es001108h, URL https://pubs.acs.org/sharingguidelines.

Greenblatt, J.B., Saxena, S., 2015. Autonomous taxis could greatly reduce greenhouse-gas emissions of US light-duty vehicles. Nature Clim. Change 5 (9), 860–863. http://dx.doi.org/10.1038/nclimate2685, URL www.nature.com/natureclimatechange.

Greenblatt, J.B., Shaheen, S., 2015. Automated vehicles, on-demand mobility, and environmental impacts. Curr. Sustain./Renew. Energy Rep. 2 (3), 74–81. http://dx.doi.org/10.1007/s40518-015-0038-5, URL https://doi.org/10.1007/s40518-015-0038-5.

Heinrichs, D., 2016. Autonomous driving and urban land use. In: Maurer, M., Gerdes, J.C., Lenz, B., Winner, H. (Eds.), Autonomous Driving: Technical, Legal and Social Aspects. Springer, Berlin, Heidelberg, pp. 213–231. http://dx.doi.org/10.1007/978-3-662-48847-8.

Hunting, B., 2017. What is eco mode and how does it work? URL http://knowhow.napaonline.com/eco-mode-work/.

ICBC, 2020. Vehicle Insurance Policies in Force. Technical Report, ICBC, Vancouver, BC, pp. 1–28.

IESVE, 2019. Weathershift data files. URL https://www.iesve.com/support/weatherfiles/weathershift.

Jobson, T., Huangfu, Y., 2016. Impact of Cold Climates on Vehicle Emissions: The Cold Start Air Toxics Pulse. Technical Report, Washington State University, Pullman, WA, pp. 1–38.

Keeney, T., 2017. Mobility-As-a-Service : Why Self-Driving Cars Could Change Everything. Technical Report, ARK Invest, New York, URL http://research.ark-invest.com/hubfs/1{_}Download{_}Files{_}ARK-Invest/White{_}Papers/Self-Driving-Cars{_}ARK-Invest-WP.pdf.

Koupal, J., Cumberworth, M., Michaels, H., Beardsley, M., Brzezinski, D., 2003. Design and implementation of MOVES: Epa's new generation mobile source emission model. Int. Emission Invent. Conf. d, 1–15.

KPMG, AVIN, Ontario, 2018. Driving Ontario Forward: The Car of the Future. Technical Report, (June), Ontario Centres of Excellence.

Lang, N., Rüßmann, M., Chua, J., Doubara, X., 2017. Making autonomous vehicles a reality: Lessons from boston and beyond. URL https://www.bcg.com/en-ca/publications/2017/automotive-making-autonomous-vehicles-a-reality.aspx.

Leamer, E.E., 1985. Sensitivity analyses would help. Am. Econ. Rev. 75 (3), 308–313.

Litman, T., 2019. Autonomous vehicle implementation predictions: Implications for transport planning. In: Transportation Research Board Annual Meeting, Vol. 42. pp. 36–42. http://dx.doi.org/10.1613/jair.301, arXiv:9605103.

Liu, J., Kockelman, K.M., Nichols, A., 2017. Anticipating the emissions impacts of smoother driving by connected and autonomous vehicles, using the MOVES model. Int. J. Sustain. Transp. 1–22.

Maciejewski, M., Bischoff, J., 2018. Congestion effects of autonomous taxi fleets. Transport 33 (4), 971–980. http://dx.doi.org/10.3846/16484142.2017.1347827.

Madlani, N.K., Orlowski, L., 2018. The Road Ahead For Autonomous Vehicles. S&P Global, p. 2018.

Maurer, M., Gerdes, J.C., Lenz, B., Winner, H., 2016. Autonomous driving: Technical, legal and social aspects. In: Autonomous Driving: Technical, Legal and Social Aspects. Springer, pp. 1–706. http://dx.doi.org/10.1007/978-3-662-48847-8.

McElhanney, 2019. 2018 Vancouver Panel Survey Report. McElhanney, pp. 1–118, URL https://vancouver.ca/files/cov/2018-transportation-panel-survey.pdf.

McKinsey, 2016. Automotive revolution - perspective towards 2030. In: Auto Tech Review, Vol. 5. Technical Report, (4), McKinsey & Company, pp. 20–25. http://dx.doi.org/10.1365/s40112-016-1117-8.

McMaster Institute for Transportation & Logistics, 2014. Estimating Vehicular Emissions for the Toronto and Hamilton Census Metropolitan Areas: A report prepared for Environment Canada. (June), McMaster University, pp. 1–81, URL http://mitl.mcmaster.ca/reports/MITL{_}Emissions{_}Toronto{_}Hamilton{_}July.pdf.

Mersky, A.C., Samaras, C., 2015. Fuel economy testing of autonomous vehicles. Transp. Res. C (65), 31–48. http://dx.doi.org/10.1016/j.trc.2016.01.001, URL http://repository.cmu.edu/cee.

Metro Vancouver, 2011. Metro Vancouver 2040: Shaping Our Future. (1136), Metro Vancouver, Vancouver, Canada, pp. 1–80, URL.

Metro Vancouver, 2018. 2015 Lower Fraser Valley Air Emissions Inventory and Forecast Final Report and Summarized Results. (March), Metro Vancouver, Vancouver, Canada, pp. 1–20, URL http://www.metrovancouver.org/services/air-quality/AirQualityPublications/2015LowerFraserValleyAirEmissionsInventory.pdf.

NRC, 2001. Evaluating vehicle emissions inspection and maintenance programs. In: Evaluating Vehicle Emissions Inspection and Maintenance Programs. National Academies Press, http://dx.doi.org/10.17226/10133.

Province of British Columbia, 2016. Impacts of climate change. In: Climate Adaptation & Awareness. URL https://www2.gov.bc.ca/gov/content/environment/climate-change/adaptation/impacts.

Province of British Columbia, 2020. Population estimates. URL https://www2.gov.bc.ca/gov/content/data/statistics/people-population-community/population/population-estimates.

Ramanathan, R., 2000. Link between population and number of vehicles. Evidence from Indian cities. Cities 17 (4), 263–269. http://dx.doi.org/10.1016/S0264-2751(00)00022-6.

Rios-Torres, J., Malikopoulos, A.A., 2018. Impact of partial penetrations of connected and automated vehicles on fuel consumption and traffic flow. IEEE Trans. Intell. Veh. 3 (4), 453–462. http://dx.doi.org/10.1109/TIV.2018.2873899.

Rodier, C.J., 2018. Travel Effects and Associated Greenhouse Gas Emissions of Automated Vehicles. Institude of Transportation Studies, University of California, Davis, URL https://rosap.ntl.bts.gov/view/dot/35517.

SAE International, 2018a. Taxonomy and definitions for terms related to driving automation systems for on-road motor vehicles. http://dx.doi.org/10.4271/J3016_201806, URL https://doi.org/10.4271/J3016_201806.

SAE International, 2018b. Taxonomy and definitions for terms related to shared mobility and enabling technologies. http://dx.doi.org/10.4271/J3163_201809, URL https://doi.org/10.4271/J3163_201809.

Schoen, L.J., Alspach, P.F., Arens, E.A., Aynsley, R.M., Bean, R., Eddy, J., Int-hout, D., Khalil, E.E., Simmonds, P., Stoops, J.L., Turner, S.C., Walter, W.F., Hall, R.L., Anderson, J.R., Barnaby, C.S., Bruning, S.F., Clark, J.A., Emmerich, S.J., Ferguson, J.M., 2013. Thermal environmental conditions for human occupancy. ASHRAE Stand. 2013 (55).

Shladover, S.E., Su, D., Lu, X.-Y., 2012. Impacts of cooperative adaptive cruise control on freeway traffic flow. Transp. Res. Rec.: J. Transp. Res. Board 2324 (1), 63–70. http://dx.doi.org/10.3141/2324-08, URL http://journals.sagepub.com/doi/10.3141/2324-08.

Sinha, K.C., Labi, S., 2007. Air quality impacts. In: Transportation Decision Making: Principles of Project Evaluation and Programming. John Wiley and Sons, pp. 251–285. http://dx.doi.org/10.1002/9780470168073.

Smith, C., 2016. Turning Transportation - Challenges and Opportunities Presented to the City of Vancouver by Autonomous Vehicles Greenest City Scholars Report. University of British Columbia, Vancouver, BC, pp. 1–93.

Spulber, A., Dennis, E.P., 2016. The Impact of New Mobility Services on the Automotive Industry. Technical Report, Center for Automotive Research, Ann Arbor, URL www.cargroup.org.

Stern, R.E., Chen, Y., Churchill, M., Wu, F., Delle Monache, M.L., Piccoli, B., Seibold, B., Sprinkle, J., Work, D.B., 2019. Quantifying air quality benefits resulting from few autonomous vehicles stabilizing traffic. Transp. Res. D 67, 351–365. http://dx.doi.org/10.1016/j.trd.2018.12.008.

Stocker, A., Shaheen, S., 2017. Shared automated mobility: Early exploration and potential impacts. http://dx.doi.org/10.7922/G2NG4NSQ, URL https://escholarship.org/uc/item/5d55s8sp#author.

Taiebat, M., Brown, A.L., Safford, H.R., Qu, S., Xu, M., 2018. A review on energy, environmental, and sustainability implications of connected and automated vehicles. Environ. Sci. Technol. 52 (20), 11449–11465. http://dx.doi.org/10.1021/acs.est.8b00127, URL https://pubs.acs.org/sharingguidelines.

The Canadian Press, 2019. B.c. introduces law to require cars, trucks sold by 2040 be zero emission. In: CBC News. URL https://www.cbc.ca/news/canada/british-columbia/b-c-introduces-law-to-require-cars-trucks-sold-by-2040-be-zero-emission-1.5093110.

Ticoll, D., 2017. Harnessing the Mobility Revolution to Build the Canada That We Want. University of Toronto, Toronto, Canada, pp. 1–7.

TransLink, 2016. The future of driving: Policy Directions for Automated Vehicles and New Mobility Services in Metro Vancouver. (August), TransLink, Vancouver, Canada, pp. 1–28, URL http://buzzer.translink.ca/wp-content/uploads/2016/09/Future-of-Driving-Policy.pdf.

TransLink, 2019. Fleet and technologies. URL https://www.translink.ca/About-Us/Corporate-Overview/Operating-Companies/CMBC/Fleet-and-Technologies.aspx.

Travesset-Baro, O., Gallachóir, B.P.Ó., Jover, E., Rosas-Casals, M., 2016. Transport energy demand in andorra. Assessing private car futures through sensitivity and scenario analysis. Energy Policy 96, 78–92. http://dx.doi.org/10.1016/j.enpol.2016.05.041.

US EPA, 2014. EPA Brake and Tire Wear Emissions from On-road Vehicles in MOVES2014. Technical Report, US EPA.

US EPA, 2017. Dynamometer drive schedules. In: Vehicle and Fuel Emissions Testing. URL https://www.epa.gov/vehicle-and-fuel-emissions-testing/dynamometer-drive-schedules.

US EPA, 2019. How can hybrid and electric vehicles be modeled in MOVES? In: MOVES and Related Models. URL https://www.epa.gov/moves/how-can-hybrid-and-electric-vehicles-be-modeled-moves.

Vahidi, A., Sciarretta, A., 2018. Energy saving potentials of connected and automated vehicles. Transp. Res. C 95, 822–843. http://dx.doi.org/10.1016/j.trc.2018.09.001, URL http://www.sciencedirect.com/science/article/pii/S0968090X18305199.

Wadud, Z., MacKenzie, D., Leiby, P., 2016. Help or hindrance? The travel, energy and carbon impacts of highly automated vehicles. Transp. Res. A 86, 1–18. http://dx.doi.org/10.1016/j.tra.2015.12.001.

Wimmer, A., Schnessl, E., 2006. Effects of Humidity and Ambient Temperature on Engine Performance of Lean Burn Natural Gas Engines, Vol. 2006. American Society of Mechanical Engineers, Internal Combustion Engine Division (Publication) ICE, http://dx.doi.org/10.1115/ICEF2006-1559.

Woldeamanuel, M., Kent, A., 2014. Determinants of per capita vehicle miles traveled (VMT): The case of California. J. Transp. Res. Forum 53 (3), 35–46. http://dx.doi.org/10.5399/osu/jtrf.53.3.4240.

WSP, 2019. Ontario CAV ecosystem analysis. (June), pp. 0–42, URL https://www.oce-ontario.org/docs/default-source/publications/avin-ecosystem-analysis-final-report-2019.pdf?sfvrsn=2.

Yan, F., Winijkul, E., Bond, T.C., Streets, D.G., 2014. Global emission projections of particulate matter (PM): II. Uncertainty analyses of on-road vehicle exhaust emissions. Atmos. Environ. 87, 189–199. http://dx.doi.org/10.1016/j.atmosenv.2014.01.045.