Novel Approaches for Estimating Personal Transportation Patterns and Emissions

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Disclaimer

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Executive Summary

Accurately estimating transportation-related emissions in a region requires three key components: vehicle composition, emission factors, and vehicle travel activity. Among these, vehicle travel, typically measured as Vehicle Kilometres Travelled (VKT) introduces the greatest uncertainty due to the complexity and variability of travel patterns. This study focuses on identifying and evaluating various VKT estimation methods used in Metro Vancouver. It also proposes a novel methodology to capture regional travel behaviour, particularly under current data limitations.

Five main approaches to VKT estimation were examined: traffic count data, fuel consumption records, odometer readings, travel surveys, and emerging sources such as big data and telematics. Among these, Metro Vancouver currently uses the kilometre accumulation rate (KAR) model, which was developed using data from the AirCare program. Since the program ended in 2014, there has been a growing need for an updated and robust approach to estimating VKT.

In parallel, the study reviewed literature on the travel behaviour of electric vehicles (EVs) and plug-in hybrid electric vehicles (PHEVs). Despite an observed 'rebound effect' due to lower operational costs and increased trip frequencies found in EVs, North American study show that EVs usually travel less each year than internal combustion engine vehicles (ICEVs). Electric cars travel about 7200 km less than ICEV cars which average 18,740 km per year. Electric SUVs travel about 3800 km less than ICEV SUVs which average 20,840 km per year. An energy-based estimate suggests that the average electric vehicle in Canada travels 15,200 km per year, while the average in British Columbia is 13,100 km. The utility factor, which is the share of travel completed in electric mode for PHEVs, was estimated at around 50% in the U.S. and closer to 40% in Canada. This share drops significantly (up to ~11%) when the vehicle ownership changed from personal to company-owned vehicles.

Vehicle registration data from the Insurance Corporation of British Columbia (ICBC) was analyzed to understand the current fleet composition in the region. The historical AirCare dataset was used to identify patterns and key factors affecting VKT. Building on these insights, the study proposes a novel, data-driven methodology for estimating annual VKT. This method leverages limited odometer data collected through ICBC's distance-based insurance discount program, using

statistical reconstruction techniques to overcome sample truncation and better represent full travel patterns.

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1 Introduction

Addressing climate change has become a central priority for governments and policymakers worldwide, driven by the urgent need to mitigate greenhouse gas (GHG) emissions and limit global warming. Accurate estimation of GHG emissions is essential for quantifying a region's contribution to climate change, setting effective reduction targets, and evaluating the success of climate action policies. In Metro Vancouver, transportation is a significant source of GHG emissions, making reliable measurement and monitoring practices critical for informed policy and planning (BC Ministry of Energy and Climate Solutions, 2024; Metro Vancouver, 2023).

Metro Vancouver employs a comprehensive GHG emissions accounting approach, drawing on territorial and consumption-based emissions inventories. The territorial inventory, which is completed annually, captures direct emissions from all sources within the region's boundaries and is fundamental for tracking progress toward local and provincial reduction targets (Metro Vancouver, 2023). This inventory forms the backbone of regional climate action strategies and provides the data necessary for compliance with British Columbia's climate legislation and reporting requirements.

Recognizing the limitations of traditional inventories, which may overlook emissions embedded in imported goods and services, Metro Vancouver also compiles a Consumption-Based Emissions Inventory (CBEI). The CBEI accounts for the full life-cycle emissions associated with the production, transportation, use, and disposal of goods and services consumed within the region, regardless of where those emissions physically occur (Hallsworth Consulting & Sustainability Managers for Metro Vancouver, 2021; Metro Vancouver, 2023). This dual-inventory approach allows for a more holistic understanding of the region's carbon footprint and highlights additional opportunities for policy intervention, such as circular economy initiatives and sustainable consumption strategies (BC Ministry of Energy and Climate Solutions, 2024).

A key methodological challenge in both inventory types, particularly for the transportation sector, is estimating vehicle activity, specifically, the total distance travelled by vehicles, or Vehicle Kilometres Travelled (VKT). Since British Columbia does not maintain a universal odometer reading database for on-road vehicles at the moment, Metro Vancouver must rely on a combination of past odometer readings, regression models, and insurance and registration data to estimate annual VKT. These estimates are a critical input for emissions modelling tools, such as the Motor Vehicle Emissions Simulator (MOVES), which require detailed data on travel activity by vehicle type to produce accurate emissions estimates. This model requires travel activity of 13 vehicle sources to estimate the total GHG emission in the region. Table 1 presents the different vehicle sources used in the MOVES model.

Table 1: Vehicle source types used in MOVES model

Source Type ID	Description
11	Motorcycle
21	Passenger Car
31	Passenger Truck
32	Light Commercial Truck
41	Other Buses
42	Transit Bus
43	School Buses
51	Refuse Truck
52	Single Unit Short Haul Truck
53	Single Unit Long Haul Truck
54	Motorhome
61	Combination Short Haul Truck
62	Combination Long Haul Truck

By integrating these inventories and adopting best-practice methodologies, Metro Vancouver aims to provide transparent, reliable, and actionable emissions data. This data supports regional and municipal climate action planning, informs public policy, and enables ongoing evaluation of progress toward ambitious GHG reduction goals. The following subsections list the best practices used in estimating VKT.

2 Best Practices Scan Estimating VKT

This section outlines the primary methods used to estimate vehicle kilometres travelled (VKT) within a region. These include: the traffic count method, fuel consumption-based estimation, odometer reading analysis, traffic survey approaches, and big data and telematics models. Each of these methods has unique advantages, limitations, and data requirements. Subsections 2.1 through 2.5 provide a detailed discussion of these approaches.

2.1 Traffic Count Method

The use of traffic count data is a foundational approach in transportation planning and is widely adopted in the estimation of VKT across Canada including Alberta, Ontario and Manitoba (City of Calgary, 2010; Government - Manitoba Transportation, 2023; Ontario Traffic Council, 2022). This approach estimates regional VKT by combining traffic volume data collected on road segments with segment lengths, allowing for the calculation of total vehicle travel over time. According to the Transportation Association of Canada, Canadian roads are categorized into six types: freeways, expressways, arterials, collectors, local roads, and public lanes (Transportation Association of Canada, 2019). However, as outlined by the Canadian Institute of Transportation Engineers (CITE), VKT estimation using traffic counts typically focuses only on primary roads, which include freeways, expressways, arterials, and collectors (Canadian Institute of Transportation Engineers, 2012). This exclusion of secondary roads (local roads and public lanes) is primarily due to challenges in data availability, the high number of such roads, and their generally low traffic volumes. Even within the primary road network, estimating VKT on collector roads can be challenging due to limited traffic count coverage and data collection constraints. Thus, a primary limitation of this method lies in its restriction to the primary road network, which may result in underestimation of total regional VKT due to the omission of secondary road contributions. There have been attempts in estimating traffic volumes in these secondary roads using traffic demand modelling (Bsce & Jaeger, 2007). However, that needs in depth data for the Metro Vancouver region.

Recent advancements in data sources, such as STREETLIGHT, offer broader traffic coverage by utilizing anonymized data from cellular devices, and other traffic sensors. While these sources expand spatial and temporal coverage, they introduce a new limitation: the lack of vehicle classification information. Unlike traditional methods that may be augmented by manual classification or registration data, emerging data platforms generally report only aggregate vehicle counts without differentiating between internal combustion engine vehicles (ICEVs), battery electric vehicles (BEVs), plug-in hybrid electric vehicles (PHEVs), or fuel cell electric vehicles (FCEVs). This lack of vehicle-specific detail poses a significant limitation for greenhouse gas (GHG) estimation, as the emission factors vary significantly across vehicle technologies. Addressing this issue would require vehicle classification methods, such as license plate recognition paired with vehicle registration databases. However, such approaches raise privacy concerns, require access to sensitive data, and demand high-resolution video equipment, which could lead to public resistance regarding surveillance and data protection.

Methodology for VKT Estimation Using Traffic Counts

The following outlines the step-by-step methodology for estimating VKT using traffic count data:

1. Calculate the Average Annual Daily Traffic (AADT) for Each Road Segment

$$AADT_i = \frac{\sum(Daily\ traffic\ volumes)}{(Number\ of\ days)}$$

$AADT_i$ = Average Annual Daily Traffic for segment *i*

Daily traffic volumes: Observed daily traffic counts

Number of days: Total number of valid count days

2. Estimate Annual VKT for Each Road Type

$$VKT_j = \sum_{k=1}^{m}\sum_{i=1}^{n}(AADT_i \times \tau_i \times \alpha)$$

$VKT_j = Annual\ VKT\ of\ road\ type\ j$

$\mathrm{m} =$ Number of roads in road type j

$n =$ Number of road segments in road k

$\tau_i =$ Road segment length of section i

$\alpha =$ Daily to annual factor

3. Calculate Total Regional VKT

$$VKT_{Region} = \sum_{j=1}^{4} VKT_j$$

VKT_{Region} = Total VKT for the region

$j = \text{Index of road types (freeways, expressways, arterials, collectors)}$

Challenges in Application

Despite its widespread use, the traffic count method presents several limitations:

1. Incomplete coverage: Roads without traffic counters, particularly local and residential streets, are often excluded, leading to potential underestimation of VKT.
2. Lack of vehicle-specific data: Traffic counters generally do not differentiate between vehicle types (e.g., passenger cars vs. trucks), trip purposes (e.g., commuting vs. freight) and powertrain types (gasoline, electric, hydrogen).
3. Factorial uncertainties: Converting traffic counts to annual VKT estimates requires the application of seasonal, daily, and weekly adjustment factors, introducing a higher degree of uncertainty into the final estimates

2.2 Fuel Consumption-based Estimation

Among the various methodologies available, the fuel consumption-based approach remains a widely used proxy for estimating VKT, particularly in data-limited regions. This method leverages the assumed proportional relationship between fuel consumption and distance travelled, using aggregate fuel sales data to approximate total vehicular activity. While conceptually straightforward and scalable, applying this approach introduces specific challenges and opportunities shaped by the region's geographic, economic, and behavioural characteristics.

Methodological Framework

The core formula for estimating VKT using fuel sales is:

$$VKT = \frac{Total\ fuel\ sales\ (l)}{Average\ fuel\ efficiency\ (l/km)}$$

This method depends on two primary inputs:

- Fuel Sales Data: Typically obtained from provincial tax records, commercial fuel providers, or regional fuel tax systems.
- Average Fleet Fuel Efficiency: Derived from known or estimated fuel economy values across the vehicle fleet, accounting for vehicle class and fuel type.

In Metro Vancouver, fuel sales data are partially available through the British Columbia Ministry of Finance's transit tax database, which provides fuel sales totals at the regional level. However, these data lack resolution at the municipal level. To improve spatial and modal accuracy, the method is often integrated into larger modelling frameworks such as TransLink's EMME travel demand model, which benchmarks and calibrates VKT estimates against fuel sales to address errors introduced by incomplete or inconsistent traffic counts.

Challenges in Application

1. Tourism and through-traffic: Communities located along major transportation corridors, such as the Trans-Canada Highway, may experience inflated fuel sales due to non-resident drivers passing through. This can distort local estimates of fuel-based travel activity. Additionally, variations in land use and community size influence the location and density of gas stations, leading to fuel purchases by vehicles that are registered or primarily operated outside the community.
2. Fuel purchases outside the region: Residents living near the boundaries of Metro Vancouver may choose to refuel outside the region to avoid the additional 18.5 cents per litre gasoline tax collected for Translink (Government of BC, 2025). This behaviour can result in underreported local fuel sales, leading to underestimated VKT within the region, despite travel activity actually occurring inside Metro Vancouver.
3. Vehicle fuel consumption uncertainty: In addition to the range of differences in the manufacturer-specified fuel efficiencies, the fuel efficiencies change due to a wide array

of parameters, including driving habits, built environment and climatic conditions, resulting in higher uncertainty in fuel efficiency estimates

4. Vehicle technological advancements: With the climate action policies, the vehicle fuel efficiencies have greatly improved, and the introduction of hybrid technologies has moved to a separate range further away from basic gasoline vehicles. Hence, the distribution of gasoline sales among these fuel technologies was uncertain.
5. Usage assumptions: Generally, the gasoline sales are attributed to light-duty vehicles, neglecting the use of gasoline in machinery, garden equipment and electricity generators. Historically light-duty vehicles have been estimated to consume the vast majority of gasoline sold in the Metro Vancouver region.
6. Increasing EV population: The shift of light-duty vehicles towards EVs have created a major limitation in estimating VKT using fuel consumption.

2.3 Odometer Reading Analysis Method

Estimating VKT using odometer readings is a direct, data-driven method that has been used for decades in transportation research and policy analysis. This approach utilizes the cumulative distance recorded by vehicle odometers, typically collected during mandatory vehicle inspections, insurance renewals, or dedicated travel surveys.

By comparing odometer readings at two distinct points in time, such as between annual insurance renewals, researchers can determine the actual distance a vehicle has travelled over a defined period. These distances provide a robust estimate of total VKT when aggregated across a fleet or region.

Methodological Advantages

The odometer-based method offers several distinct benefits over alternative VKT estimation techniques:

- Vehicle-Specific Accuracy: Unlike traffic counts or fuel sales proxies, odometer data reflect actual vehicle usage, reducing reliance on assumptions or estimation factors.

- Reduced Sampling Bias: Since data are collected from a wide cross-section of vehicles, the method is less prone to geographic or temporal sampling biases.
- Scalability and Reliability: In jurisdictions where odometer readings are routinely collected, the method provides a cost-effective and scalable dataset for VKT estimation.

Challenges in the application

1. While odometer readings offer a reliable measure of total VKT, they do not indicate where the travel actually occurred. This can cause overestimation when vehicles registered in the region are driven elsewhere. It can also cause underestimation when vehicles registered outside the region are driven within Metro Vancouver. Pacific Analytics suggests using econometric models to address this challenge. In these models, VKT for a vehicle class is estimated using explanatory variables such as vehicle age, fuel prices, income, and other behavioral factors (Pacific Analytics, 2008).
2. Although it can be easier when the odometer readings are routinely collected, it can be challenging when no established programs collect the data from all vehicles.
3. While this method offers significant precision, its effectiveness depends on:
    a. The frequency of data collection
    b. The integrity and consistency of odometer reporting can vary across sources and jurisdictions.
4. Discrepancies in odometer reporting may occur due to delayed data entry, vehicle turnover, or odometer tampering. Therefore, data validation protocols and cross-referencing with other datasets are needed to enhance reliability.

2.4 Using a transport Survey (Trip Diary)

Estimating VKT through trip diary surveys is a well-established method in transportation research and policy analysis. Trip diary surveys collect detailed, self-reported travel data from individuals or households over a specified period, capturing trip-level information such as purpose, mode, distance, and duration. Aggregating these trip distances provides direct estimates of VKT at the individual, household, regional, or population level. This method is widely used in both developed and developing regions because it provides rich, disaggregated data on travel behaviour, mode choice, and the socio-demographic characteristics associated with mobility.

The trip diary approach is particularly valuable in contexts where automated traffic counts, vehicle registration data, or odometer readings are limited, unavailable, or insufficient to capture all modes of travel, especially active and public transport. In Metro Vancouver, the Regional Trip Diary Survey, conducted by TransLink, serves as a core data source for estimating VKT. The latest survey employed a mix of survey, telephone, and app-enabled data collection methods to enhance response rates and minimize biases, such as:

- Underreporting of short or non-motorized trips
- Overrepresentation of certain demographic or modal groups

This data is then analyzed statistically in creating regression models and machine learning models to forecast the travel behaviour of the region in the future (Ali et al., 2024; Cohen et al., 2021; Mahmud et al., 2024).

Challenges in the application

While comprehensive, the trip diary method is subject to limitations, including:

1. Self-reporting biases, such as memory lapses or estimation errors
2. Sampling limitations, which may require post-survey weighting to ensure representativeness
3. Resource intensity is needed for large-scale data collection, processing, and validation. However, advances in mobile apps, GPS integration, and survey automation are increasingly mitigating these limitations and improving data accuracy.
4. Using statistical models that incorporate vehicle type, age, fuel price, income, and regional characteristics to estimate VKT based on survey or sample data. These models can adjust for regional differences and changes in fleet composition, but require robust datasets and careful calibration.

Furthermore, these regression models can be enhanced to analyze the influence of a wide range of factors on VKT, including socio-demographic attributes, economic conditions, transit accessibility, land use and built environment characteristics, as well as vehicle-specific features. Table 2 summarizes the key factors affecting VKT, along with the corresponding studies identified in the literature.

Table 2: Factors affecting VKT

Socio Demographic Factors	
Factor	**Reference**
Age	(Chakraborty et al., 2022; Handy et al., 2005; Kwon, 2022; Simsekoglu, 2018; Zhang et al., 2025)
Gender	(Chakraborty et al., 2022; Handy et al., 2005; Kwon, 2022; Simsekoglu, 2018; Zhang et al., 2025)
Education level	(Kwon, 2022; Simsekoglu, 2018; Zhang et al., 2025)
Employment Status	(Handy et al., 2005; Zhang et al., 2025)
Number of vehicles in house	(Davis, 2019; Handy et al., 2005; Kwon, 2022; Zhang et al., 2025)
Number of members in the household	(Chakraborty et al., 2022; Hasan & Simsekoglu, 2020; Kwon, 2022; Zhang et al., 2025)
Number of children in the house	(Hasan & Simsekoglu, 2020; Kwon, 2022; Zhang et al., 2025)
Unlikeliness to driving	(Boarnet & Crane, 2001)
Economic Factors	
Factor	**Reference**

Income	(Chakraborty et al., 2022; Kwon, 2022; Narváez-Villa et al., 2021; Pickrell et al., 2023; Simsekoglu, 2018; Zhang et al., 2025)
Vehicle ownership status (own, finance, lease)	(Chakraborty et al., 2022; Guo et al., 2016; Zhang et al., 2025)
Electricity cost	(Chakraborty et al., 2022)
Home ownership	(Chakraborty et al., 2022)
Gasoline price	(Gillingham & Munk-Nielsen, 2019; Pickrell et al., 2023)
Dwelling type	(Chakraborty et al., 2022)
Charging opportunity at home	(Chakraborty et al., 2022)
Transit accessibility	
Factor	**Reference**
Density of bus stops near home	(Mahmud et al., 2024)
Proportion of transit riders	(Mahmud et al., 2024)
Train stations within 4km	(Zhang et al., 2025)
Walkability index (Pedestrian friendliness and safety)	(Cervero & Murakami, 2010; Chakraborty et al., 2022; Zhang et al., 2025)
Land use and built environment	
Factor	**Reference**
Traffic conditions	(Sun et al., 2021)
Park and drive facilities	(Narváez-Villa et al., 2021)
Topography features	(Sun et al., 2021)
Residential location (Urban, rural, sub-urban)	(Boarnet & Crane, 2001; Chakraborty et al., 2022)
Population density	(Cervero & Murakami, 2010; Chakraborty et al., 2022)
Logarithm value of population	(Mahmud et al., 2024)

Access to public charging (Public charging points)	(Chakraborty et al., 2022)
Logarithm value of lane miles	(Mahmud et al., 2024)
Proportion of primary roads	(Mahmud et al., 2024)
% of urban areas	(Mahmud et al., 2024)
Unemployment rate	(Mahmud et al., 2024)
Intersection density	(Mahmud et al., 2024)
Supermarkets and grocery stores within 1km	(Zhang et al., 2025)
Vehicle Characteristics	
Factor	**Reference**
Vehicle Type (Electric, PHEV or BEV)	(Chakraborty et al., 2022; Davis, 2019; Réquia et al., 2016; Sun et al., 2021; Zhang et al., 2025; Zhao et al., 2023)
Vehicle size (car, SUV)	(Zhang et al., 2025)
Vehicle base weight	(Narváez-Villa et al., 2021; Zhang et al., 2025)
Vehicle age	(Narváez-Villa et al., 2021; Réquia et al., 2016; Sun et al., 2021; Zhang et al., 2025)
Engine Size	(Narváez-Villa et al., 2021)
EV range	(Chakraborty et al., 2022)

2.5 Big Data and Telematics

Integrating Big Data and telematics into VKT estimation marks a transformative advancement in transportation analytics. These technologies offer real-time, high-resolution, and scalable alternatives to traditional methods such as traffic counts and household travel surveys. By leveraging data from GPS-enabled smartphones, connected vehicles, and fleet telematics systems, transportation professionals can overcome key limitations in spatial coverage, temporal resolution, and reporting accuracy while also reducing monitoring costs.

Enhancements for traffic count-based VKT estimation

Conventional traffic counts rely on fixed sensors (e.g., pneumatic tubes, inductive loops) or manual observations. These are limited in coverage and expensive to maintain, particularly for rural, local, or low-volume roads. Therefore, by using big data, researchers can improve:

- Expanded Network Coverage: GPS data from mobile applications (e.g., Google Maps, Waze) enables continuous monitoring across all roadway types, including those excluded from sensor networks. For example, StreetLight Data uses anonymized location signals to estimate traffic volumes with 85–90% accuracy relative to manual counts (STREETLIGHT, 2019; Turner et al., 2020).
- Dynamic Calibration: Connected vehicle data, such as from Volvo Trucks' 57,000 vehicle telematics dataset, allows real-time validation of traffic patterns and adjustment of seasonal factors (Dahl & Johansson, 2019).
- Cost Efficiency: In regions like Minnesota, Big Data approaches have demonstrated up to 70% cost savings in traffic data collection, as shown in a pilot study by the Texas A&M Transportation Institute and the Minnesota Department of Transportation (Turner et al., 2020).

Enhancements for trip diary-based VKT estimation

Traditional trip diaries, while valuable, are subject to recall bias, underreporting, limited data on trip timing, modal switching and high administrative effort for survey distribution and processing. Therefore, integration of GPS and Telematics provides the following advantages:

- Increased Data Collection: Smartphones and in-vehicle GPS systems automatically capture trip start/end points, routes, duration, and mode, improving data reliability.
- Behavioural Insights via Machine Learning: Advanced models (e.g., gradient boosting, random forest) can classify trip purpose and predict VKT patterns using variables such as time of day, vehicle age, and driver demographics.
- Multi-Modal Capture: GPS data can capture travel coordinates with time and record exact travel routes across all modes, including walking, cycling, and transit. This provides a more

complete view of mobility compared to paper diaries, which only indicate the final destinations.

Challenges in the application

Despite the advantages, use of big data and telematics lead to several challenges including:

1. Privacy Concerns: Telematics data collection involves detailed tracking of location, driving patterns, and behavioral habits, raising risks of privacy invasions and unauthorized surveillance. Users often do not fully understand or consent to the extent of data gathered and its sharing with third parties. Privacy policies can be opaque, leaving consumers little control over their data
2. Bias and Representativeness: Telematics data can be biased toward demographics more likely to use smart devices or participate in telematics programs, leading to underrepresentation of certain groups (e.g., elderly, low-income populations). This skew affects how well data represent overall traffic and travel behavior, complicating extrapolation to broader populations
3. Data Ownership and Sharing Constraints: Ownership of commercial telematics data may be restricted by proprietary concerns or legal constraints. Data sharing between agencies or with researchers is often impeded by confidentiality agreements, limiting full utilization or public release
4. Managing Large, Complex Data Sets: Mobility and telematics data are often large-scale, spatially and temporally complex, requiring advanced analytics and specialized tools for storage, processing, and analysis. Existing tools may not fully support spatio-temporal data aspects, necessitating high technical expertise and advanced infrastructure such as distributed data management systems

3 Review of Current Practices in Metro Vancouver

This section provides insights on the current practices in Metro Vancouver. Discussed in detail under three subsections.

3.1 VKT Estimation Using the AirCare KAR Model

For light-duty vehicles, BC benefited from a comprehensive dataset of odometer readings from the BC AirCare vehicle testing program. The AirCare program was a vehicle emissions inspection and maintenance initiative launched in 1992 in British Columbia's Lower Mainland, including Metro Vancouver and the Fraser Valley Regional District, with the primary goal of improving regional air quality by reducing emissions from on-road vehicles (Taylor Consulting, 2002). The program required that cars and light trucks meet minimum emissions standards before they could be insured, targeting pollutants such as hydrocarbons, carbon monoxide, and oxides of nitrogen. Vehicles that failed the emissions test were either repaired or removed from the road, ensuring that high-emitting vehicles did not continue to contribute disproportionately to air pollution. In addition to its primary role in emissions testing, AirCare also systematically collected annual odometer readings from participating vehicles. This practice resulted in the creation of a comprehensive database of vehicle mileage for the region, covering over a million vehicles and providing valuable data for estimating vehicle use and supporting transportation research. The odometer data enabled comparisons with other vehicle usage surveys and contributed to a better understanding of travel patterns and emissions trends in Metro Vancouver and the Fraser Valley Regional District. Moreover, AirCare accounted for approximately 6% of the light-duty vehicles represented in the Canadian vehicle survey population with about 1.04 million vehicles by 2001 (Wroń, 2001). However, after 22 years of successful operation, the program ended in 2014. As part of the 2015 Metro Vancouver On-Road emissions inventory, a linear km accumulation rate (KAR) relationship for light-duty vehicles was developed using AirCare data up to the program's 2014 end date. Since then, Metro Vancouver has been using the developed KAR relationship to build on-road emission inventories, which were changed from 5-year to annual (for GHGs) starting in 2019. However, the results of this model were validated when creating the 2020 Metro Vancouver On-Road Emission Inventory using the US Department of Transportation

2017 National Household Travel Survey (NHTS, 2017). The AirCare KAR model exhibited a similar magnitude and shape to the other model assessed, and as such, was still deemed to provide a reasonable representation of light-duty vehicle travel distances. The following Table 3 indicates the population weighted fit annual travel distance linear KAR models with vehicle ages (x) for different vehicle types.

Table 3: Linear KAR models with vehicle age

Model (y = mx + c)	**Slope (m)**	**Intercept (c)**
Passenger Cars	-312.8	15501
Passenger Trucks	-400	17383.1
Motorhomes	0	7331.9
Intercity buses	-1159.7	43160.35
Transit buses	0	55715.86
School buses	-406.143	17588.74
Light commercial trucks	-439.09	20728.1
Garbage trucks	-515.51	34887.76
Single unit short haul trucks	-719.85	34587.89
Single unit long haul trucks	-2369.8	63240.45
Combination short haul trucks (Age<4)	-9553.4	94337.19
Combination short haul trucks (Age≥4)	-1499.7	60263.82
Combination long haul trucks	-4500	139150.7

Although the results seem appropriate, the data for the most LDV models are almost a decade old; hence, a novel method of collecting vehicle travel data is necessary. For taxis, buses, trucks, and truck tractors weighing over 8,200 kilograms, as well as commercial trailers and semi-trailers, the British Columbia Ministry of Transportation and Transit conducts Commercial Vehicle Safety and Enforcement (CVSE) inspections up to twice a year (Auditor General, 2018; CVSE, 2025).

These inspections collect odometer readings that enables updating Heavy-Duty Vehicles (HDVs). HDVs include intercity buses, transit buses, school buses, garbage trucks, single-unit short-haul trucks, single-unit long-haul trucks, and long-haul truck combinations, as defined in the MOVES emissions model (Metro Vancouver Regional District, 2024).

In contrast, no comprehensive method currently exists for LDV VKT estimation using regularly updated odometer data. However, since 2019, the Insurance Corporation of British Columbia (ICBC) has begun collecting odometer readings under its optional distance-based discount program. To qualify, vehicle owners must submit annual odometer readings during insurance renewal. Initially, the program was limited to vehicles driving less than 10,000 km per year, which resulted in low participation rates. With the program's expansion to include vehicles travelling up to 15,000 km annually, effective June 1, 2025, it is anticipated that up to 80% of odometer readings for registered LDVs will be captured. However, two time-stamped readings per vehicle are required to calculate annual travel distance. As such, the first usable dataset for VKT estimation will not be available until at least June 1, 2027. Given this delay, an alternative method for estimating VKT at the regional level remains necessary in the interim to support emissions modelling and transportation planning.

Table 4 summarizes the MOVES input data tables generated from the KAR / VKT data, with a description of the data in each table and an overview of the processing approach.

Table 4: MOVES Input Tables Using VKT and KAR Data

MOVES Data Table	Description	Input Processing Approach
sourceTypeYearVMT	Annual VMT calculated through VKT for each MOVES source type.	Annual km accumulation for each model year and MOVES source type was estimated using the KAR models for each source type and model year vehicle counts.
sourceTypeAge	Assigns 4 data fields to each MOVES source type: *relativeMAR*, *survivalRate*,	The linear KAR models for each vehicle source type were normalized, such that the estimated

	functioningACFraction, and *functioningACFractionCV*. The latter 3 use US average defaults for all MOVES modelling, with *relativeMAR* the only location-specific modelling parameter. It is a renormalized representation of the annual Mileage Accumulation Rate (MAR) by source type and model year from 0 to 30 years of age.	annual accumulation was expressed as a fraction of the maximum annual accumulation for the most recent model year within each of 6 Highway Performance Monitoring System (HPMS) vehicle classes. The resultant normalized KAR models within the sourceTypeAge table are used within MOVES to allocate annual travel distance by model year to ensure the same age distribution of VKT as expressed in the KAR models used externally from MOVES to estimate the total annual VKT for each source type.

3.2 Provincial Approach to VKT Estimation

The Province of British Columbia has established a sector-specific GHG reduction target of 27–32% below 2007 levels by 2030. Local governments play a key role in achieving these reductions, particularly in the transportation sector, through commitments outlined in the BC Climate Action Charter. Under the Charter, local governments pledge to achieve carbon neutrality in corporate operations and to report community-wide GHG inventories in support of building energy-efficient communities (Government of BC, 2007). In this context, the Union of BC Municipalities has emphasized the importance of timely and geographically detailed transportation emissions data at the community level.

To support local governments in meeting these commitments, the Climate Action Secretariat (CAS) launched the Community Energy and Emissions Inventory (CEEI) initiative in 2007. This initiative provides a standardized provincial framework for tracking and reporting energy use, GHG emissions, and supporting indicators at a community-wide scale (Ministry of Environment, 2007). More recently, in November 2020, Licker Geospatial Consulting Co. (LGeo) was contracted to enhance BC's provincial GHG inventory alongside a reproducible methodology for annual updates, with a particular focus on emissions from road transportation (Environment and Climate Change Strategy, 2021).

In addition to supporting municipal climate action plans, the improved methodology contributes valuable indicators for transportation policy development at both provincial and local levels. It includes detailed data on vehicle populations by fuel type and class, as well as estimates of fuel consumption (in litre equivalents) and VKT.

VKT Methodology and Data Sources

To estimate VKT, LGeo employed a hybrid methodology using both:

- Bottom-up (disaggregated) sources, such as historical AirCare records, provide odometer data for individual vehicles.
- Top-down sources such as regional trip diary surveys estimate total community-level VKT based on sample travel behaviours.

LGeo derived VKT estimates by vehicle type, community, and year using these inputs. However, VKT remained the most uncertain model input due to incomplete, outdated, and regionally limited data, making it challenging to represent actual driving patterns accurately. Furthermore, the model did not incorporate external behavioural influences such as expanded transit networks or new active transportation infrastructure.

Vehicle Type-Specific VKT Assumptions

- Passenger Vehicles: Trip Diary surveys and AirCare data were the primary data sources.
    - Trip Diaries offered some insights but were constrained by small sample sizes, geographic limitations (mostly southern BC), infrequent data collection, and self-reporting errors.

    - AirCare data (2007–Q1 2014) reflected only driving behaviours of a limited subset of older vehicles in Metro Vancouver. Estimates for newer vehicles were derived using regression techniques and generalized to vehicle archetypes, although these patterns may not reflect usage in other regions.
- Taxis and Limousines: There is no available empirical data on taxi or limousine travel patterns. LGeo employed a basic modelling approach using assumptions about driving duration and average speed. The validity of these assumptions would require future validation through dedicated data collection efforts.
- Public Transit Buses: Only 2019 VKT data were available for public transit buses. This value was assumed to remain constant across all years in the inventory, precluding any analysis of temporal variation in bus service levels or utilization.
- Medium-Duty and Heavy-Duty Trucks (MDTs and HDTs): No community-specific VKT data exists for these vehicle classes. Instead, LGeo used average VKT per vehicle based on provincial-level aggregates provided by Natural Resources Canada (NRCan). This approach does not reflect intra-class variations or regional differences, particularly where multiple vehicle types are grouped under broad categories (e.g., various truck types classified as MDT).

3.3 VKT Estimation Using the TransLink Trip Diary Survey

The Trip Diary is a comprehensive, region-wide travel survey conducted periodically to capture detailed information on residents' travel behaviour, including trip purpose, mode, distance, and frequency. This survey provides a top-down estimate of total VKT by aggregating self-reported trip distances from a representative sample of households across the region. The 2023 Trip diary used a combination of online and smartphone questionnaires from September to December, covering 1.25% of the households of the region (Translink, 2023). This time period was selected specifically to account for normal transportation activities, outside of summer and Christmas holidays, since the purpose of the Trip Diary is to enable regional transportation planning, rather than to calculate total regional VKT.

The Trip Diary survey collects travel data from Metro Vancouver residents, who record all trips taken over a specified period. For each trip, respondents provide details such as the origin, destination, travel mode, and distance. The average trip length for auto drivers, derived from these responses, is used to estimate the daily VKT of Metro Vancouver residents. These trip-level data are then extrapolated to the regional population to estimate total VKT, which can be further normalized by population to provide per capita measures. It's important to note that TransLink's Trip Diary captures only VKT within the region. For example, if a trip starts in Vancouver and ends in Kamloops, any VKT beyond Langley (along Hwy 1) is excluded from the count.

The Trip Diary serves as a critical input for regional transportation and emissions modelling. Its data are used not only for VKT estimation but also to monitor trends in travel behaviour, assess the effectiveness of transportation policies, and inform infrastructure planning. For example, recent Trip Diary results have shown a decline in VKT across Metro Vancouver, reflecting a shift toward shorter trips and increased use of walking and cycling.

Strengths:

- The Trip Diary provides detailed, mode-specific travel data directly from residents, enabling nuanced analysis of VKT by trip purpose and demographic group.
- It captures changes in travel patterns over time, supporting the evaluation of policy impacts and progress toward regional goals.

Limitations:

- As a self-reported survey, the Trip Diary is subject to recall bias and underreporting, which can affect the accuracy of VKT estimates.
- The survey is conducted periodically rather than annually, which limits the granularity of trend analysis.

4 Travel Behaviour of Electric Vehicles

This section presents a detailed review of the literature on the travel behaviour of electric vehicles (EVs). The first subsection examines travel distances of EVs relative to conventional internal combustion engine vehicles (ICEVs), drawing on recent studies that compare real-world usage patterns. The second subsection focuses on plug-in hybrid electric vehicles (PHEVs), reviewing research on the utility factor. Both empirical data and simulation studies are considered to understand how PHEVs are used in practice and the extent of their electrified travel.

4.1 Travel Distance of Electric Vehicle Drivers (Are EVs driven more?)

Understanding the travel behaviour of EV users is critical for shaping transportation policy, planning infrastructure, and advancing climate goals. As EV adoption accelerates, analyzing how these vehicles are used in real-world settings particularly in comparison to ICEVs offers valuable insights for managing emissions, energy demand, and urban mobility systems. This subsection reviews global and Canadian literature on EV travel behaviour, including trip frequency and travel distance.

Globally, research suggests that EV drivers often face travel challenges due to limitations related to battery range and the availability of charging infrastructure (Daramy-Williams et al., 2019; Morton, 2022a, 2022b). Trip planning among EV drivers is frequently shaped by charging availability, which affects route selection and travel timing (Daramy-Williams et al., 2019). Although the province's "Electric Highway" was built by BC Hydro to provide public charging sites within 150 km along major corridors, CBC reports that BC EV drivers still struggle to access sufficient charging stations and call for expanded infrastructure (CBC News, 2025; Yakub, 2025). A "rebound effect" has also been observed, where the low operating cost of EVs may lead to more frequent short trips, potentially reducing the environmental benefits (Morton, 2022a, 2022b). EV drivers also tend to adopt energy-efficient or "eco-driving" styles, encouraged by real-time feedback on energy use and remaining range. Over time, users become more confident managing range constraints and adapt their driving behaviours accordingly. Technological improvements have enhanced EV range, with most models offering 300–400 miles (480–640 km), and premium models exceeding 500 miles (800 km) (Jonas, 2025; Jones, 2023; US DOE, 2022). Nevertheless, for long-distance travel, gasoline vehicles remain preferred due to faster refueling and the broader availability of fuel stations (Jonas, 2025; US DOE, 2022).

Several studies in the United States, particularly in California, have estimated annual EV mileage ranging between 6,300 km and 12,500 km. However, studies reporting higher mileage often had smaller sample sizes (highest being with 2,373 vehicles), limiting the statistical reliability of those findings (Chakraborty et al., 2022; Davis, 2019; Jia & Chen, 2022; Rush et al., 2022; Tal et al., 2020). A study by George Washington University analyzed odometer readings of 12.5 million cars and 11.4 million SUVs across the United States between 2016 and 2022. It found that electric cars traveled approximately 11,530 km per year, which is approximately 7,200 kilometres less than gasoline cars that averaged 18,740 km. Similarly, electric SUVs drove about 17,040 km, while gasoline SUVs averaged 20,840 km (Zhao et al., 2023).

In the Canadian context, similar trends have been observed. A travel diary study in Metro Vancouver found that EV drivers made more trips and relied more heavily on their vehicles than non-EV users, though the study did not confirm higher overall annual mileage (Fassihi, 2018). Interestingly, EV users were more likely to perceive their vehicles as environmentally superior to public transit, whereas non-EV drivers viewed transit more favourably (Fassihi, 2018). A 2024 survey by the Canadian automobile association (CAA) reported that most EV travel in Canada occurs within 100 km of home. BEV drivers reported average weekly mileage of 398 km, while PHEV drivers reported 322 km per week (CAA, 2024). In a separate study estimating travel based on energy consumption, the national average annual distance for electric vehicles were found to be 15,200 km, with British Columbia averaging 13,100 km/year (Cornelis van Kooten, 2024).

Furthermore, literature shows that land use and built environment characteristics have a significant influence on annual travel distance. Given Metro Vancouver's unique climate, urban form, and extensive charging infrastructure, travel patterns may differ from those observed in other regions. Analysis of AirCare odometer readings in Metro Vancouver revealed a strong relationship between vehicle age and annual travel distance, with a consistent linear decline as vehicles age. Since EVs are, on average, newer than gasoline vehicles, they are expected to have higher average annual travel distances. This could suggest that EVs travel more than gasoline vehicles on average. However, when vehicles of the same age are compared, the evidence supports lower annual travel distances for EVs.

In summary, although EV drivers tend to make trips more frequently, they generally travel slightly less distance than gasoline vehicle drivers worldwide. Canadian patterns broadly align with these global findings for trip generation. However, given Metro Vancouver's unique climate, urban form, and proliferation of charging infrastructure may lead to different travel behaviours. There remains a lack of research directly comparing annual travel distances between EVs and gasoline vehicles in Canada, and specifically in Metro Vancouver. Addressing this gap is essential for accurately evaluating the emissions and infrastructure needs of an electrified transport system.

4.2 Utility Share of Plug-in Hybrid Vehicles

Plug-in Hybrid Electric Vehicles (PHEVs) are equipped with an electric motor and an internal combustion engine, allowing them to operate using electricity stored in their battery packs or gasoline. Compared to Battery Electric Vehicles (BEVs), PHEVs typically have smaller battery capacities, ranging from 10 to 20 kWh (Toyota, 2024b, 2024a). While PHEVs can operate in zero-emission mode when powered solely by electricity, they emit GHGs when the combustion engine is in use. Consequently, a critical factor in assessing the environmental performance of PHEVs is the utility factor (the proportion of total distance travelled using the electric motor). Understanding the variability and uncertainty of this metric across different users and regions is essential for accurately estimating emissions.

Several studies have investigated the real-world utility factor of PHEVs. The International Council on Clean Transportation (ICCT) conducted a large-scale empirical study involving over 9,000 PHEVs across Europe (Plötz et al., 2022). The findings revealed that the average electric driving share for privately owned PHEVs was between 45% and 49%, significantly lower than the 70% - 85% utility factors assumed under the Worldwide Harmonized Light Vehicles Test Procedure (WLTP). The disparity underscores the gap between standardized assumptions and actual usage patterns. For company-owned PHEVs, the utility factor was even lower, ranging from 11% to 15%, suggesting that organizational ownership often correlated with heavy mileage influencing usage behaviour (Plötz et al., 2022).

The study also identified electric range as a key determinant of the utility factor. Specifically, a 10-kilometre increase in electric range was associated with a 1% to 7% increase in the share of electric driving. However, this improvement entails trade-offs. Extending electric range typically necessitates a larger battery, which increases the vehicle's curb weight. This increased curb weight, in turn, requires greater system power to maintain performance, leading to higher fuel consumption during non-electric operation. The study found that a 50 kW increase in system power resulted in a 3% to 8% rise in fuel consumption, while a 100 kg increase in curb weight led to a 4% to 6% increase (Plötz et al., 2022).

Similarly, ICCT conducted a global study in 2020 involving over 100,000 PHEVs from China, Europe, and North America, with more than 80,000 vehicles registered in the United States and Canada (Plötz et al., 2020). A significant portion of these North American vehicles belonged to early adopters (consumers who likely had access to home charging infrastructure and engaged in regular charging behaviour). Additionally, the dataset in North America was heavily weighted toward a limited number of model variants, with 21 out of 23 models consisting primarily of the Chevrolet Volt, BMW i3, and Toyota Prius PHEV. The study found that the average utility factor among these early adopters in North America was approximately 54%. A similar utility factor of 53% was observed in Norway. However, utility factors were notably lower in other regions: 43% in Germany and just 26% in China for privately owned vehicles. For company-owned PHEVs, the utility factor was even lower at 24% in the Netherlands and 18% in Germany. However, the utility factor for company-owned vehicles in North America was not measured.

More recently, an analysis by the Pembina Institute (2024) reported that the current utility factor of PHEVs in Canada is estimated at 40% (Pembina Institute, 2024). The study concluded that increasing this figure to 50% would keep Canada on track to achieve its 2030 emissions reduction target of a 40–45% decrease relative to 2005 levels.

The aforementioned increased utility share of the early adopters in the United States and Canada suggests that access to charging infrastructure plays a significant role in determining the utility factor of PHEVs (Plötz et al., 2020). A recent survey conducted by the CAA in 2024, involving over 15,000 PHEV and BEV users across Canada, provides insights into national charging behaviours (CAA, 2024). Among PHEV users, 46% reported charging their vehicles at home using Level 1 chargers. Notably, the use of Level 2 chargers among PHEV users increased significantly, rising from 5% in 2022 to 39% in 2024. For BEV users, home charging with Level 2 chargers was even more prevalent, accounting for 66% of charging, while only 15% used Level 1 chargers at home. None of the PHEV users reported using fast charging stations, primarily due to hardware incompatibility, whereas 10% of BEV users utilized fast chargers. Charging at workplaces and public Level 2 stations remained relatively limited, with 5% of PHEV users and 4% of BEV users charging at their workplaces, and 9% of PHEV users and 5% of BEV users relying on public Level 2 charging stations.

In addition, a significant difference in charging behaviour was observed between residents of single-family homes and those living in multi-unit dwellings. PHEV users' combined share of home charging using Level 1 and Level 2 infrastructure dropped from 90% among single-family homeowners to 66% for those in multi-unit buildings. Similarly, this share declined from 85% to 62% for BEV users. These findings highlight the importance of expanding public charging infrastructure in urbanized and high-density residential areas. Over 30% of PHEV and BEV users living in multi-unit dwellings already rely on public charging facilities, underscoring the need for targeted investment to support equitable access to electric mobility.

5 Data Collection and Analysis

During the study, two main databases were available and accessible. The Insurance Corporation of British Columbia's (ICBC's) publicly accessible data set and the vehicle registration data set collected through the AirCare programme. Insights from each dataset will be provided separately in the following subsections.

5.1 ICBC Vehicle Registration Data

The ICBC maintains a comprehensive dataset compiled through the annual vehicle insurance registration process in British Columbia. This dataset includes fundamental vehicle specifications, such as the Vehicle Identification Number (VIN), model, year of manufacture, and colour, as well as additional information on vehicle usage (e.g., personal or commercial) and geographic identifiers, including the registered postal code of the owner. In 2019, ICBC introduced an optional distance-based insurance discount program, which allowed vehicle owners to submit their odometer readings voluntarily. Under this program, vehicles driven less than 10,000 kilometres annually were eligible for a discount. ICBC states that over 1.4 million customers received distance-based discounts between 2019 and 2025 (ICBC, 2025). Effective June 1, 2025, the annual distance threshold was increased to 15,000 kilometres to make insurance more affordable and accessible (ICBC, 2025). With this expanded threshold, ICBC experts predict that the first set of odometer readings for approximately 80% of the province's vehicle population will be collected by June 2026. However, access to these odometer records is restricted; the data are not publicly available and may only be obtained through a formal data sharing confidentiality agreement with ICBC. Therefore, interested parties, such as researchers or private entities, must obtain access to the dataset in accordance with ICBC's data sharing policies. The following sub sections contains insights obtained from the ICBC public tableau data set.

5.1.1 Vehicle classification

ICBC primarily classifies vehicles based on their intended use, distinguishing between passenger and commercial vehicles. These are further subdivided into classifications such as personal, business, and other users. Additionally, since ICBC offers insurance for a wide range of motor vehicle types, the dataset encompasses diverse vehicle categories. Figure 1 illustrates ICBC's vehicle classification system, highlighting the subset of light-duty vehicles selected for analysis in this study.

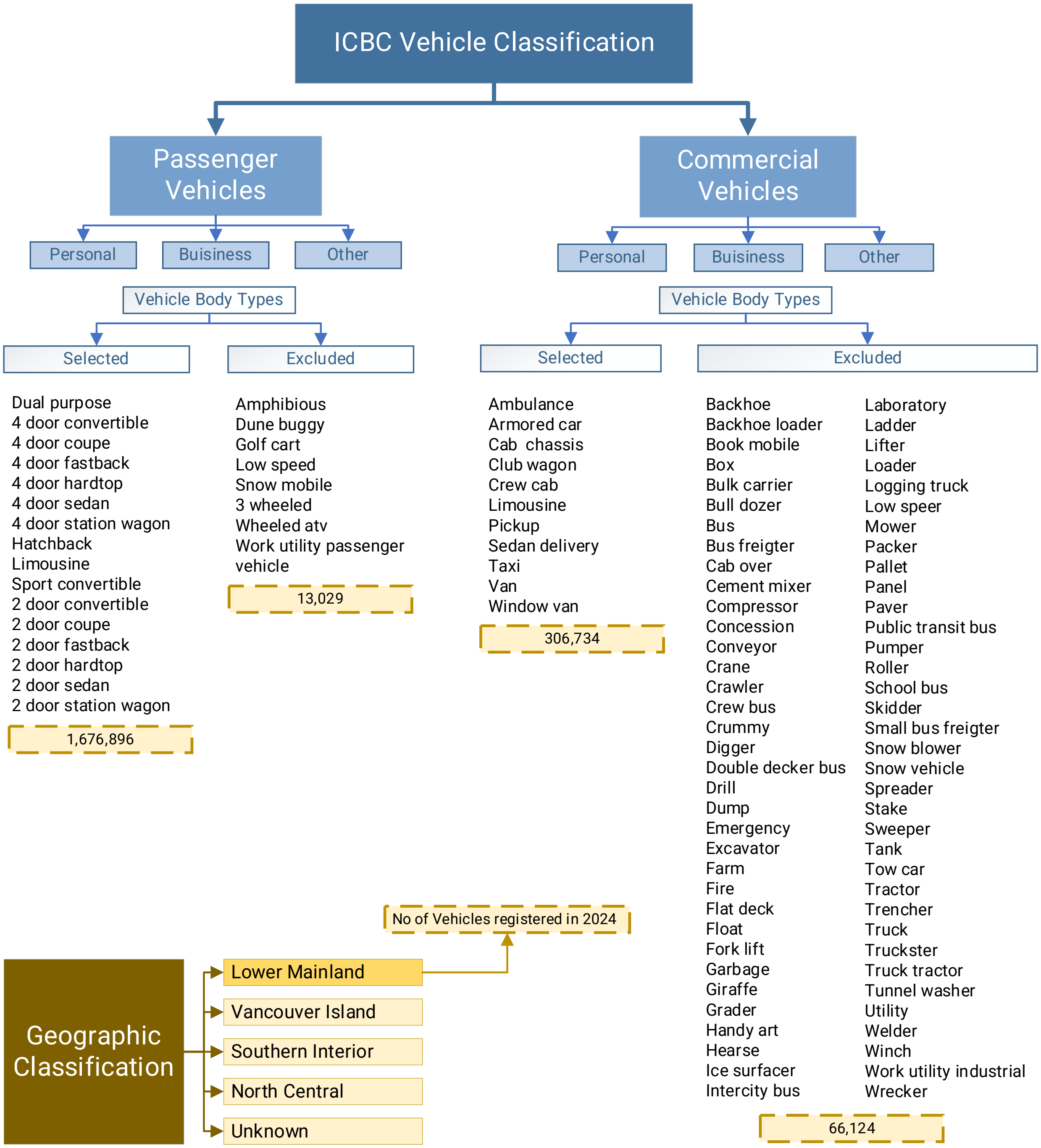


Figure 1: ICBC vehicle classification

5.1.2 Geographic Distribution of the Vehicles

Metro Vancouver comprises 21 municipalities, one electoral area, and one First Nations treaty land (Metro Vancouver, 2025). The ICBC dataset provides vehicle distribution data at the municipal level; however, it only includes the 21 municipalities and does not explicitly report figures for Electoral Area A or the Tsawwassen First Nation treaty lands. Estimating vehicle distribution in these excluded areas can be obtained through spatial analysis using an ArcGIS model based on granular data, such as vehicle registrations by postal code. Within the available municipal data, the distribution of passenger and commercial vehicles across Metro Vancouver is presented in Table 5. It is important to note that some municipalities are aggregated in the ICBC dataset; for example, the City and District of North Vancouver are combined into a single reporting unit, as are the City and Township of Langley. Furthermore, part of Electoral Area A was recorded as UBC in the ICBC dataset, but it was not listed under Electoral Area A due to incomplete information. In addition, vehicles from Tsawwassen First Nation Municipality were counted under Delta Municipality in the ICBC records.

Table 5: Number of registered passenger and commercial light-duty vehicles in 2024

MV Regional District	Passenger Vehicles	Commercial Vehicles
Anmore	1,306	269
Belcarra	357	71
Bowen Island	2,304	761
Burnaby	132,697	21,575
Coquitlam	81,973	11,905
Delta	64,739	13,791
Langley City Langley Township	100,885	28,282
Lions Bay	946	158
Maple Ridge	52,780	15,681
New Westminster	39,263	5,394
North Vancouver City North Vancouver District	82,953	11,844
Pitt Meadows	11,115	2,740
Port Coquitlam	35,383	7,799
Port Moody	19,782	3,079
Richmond	124,804	13,064
Surrey	321,931	53,650
Vancouver	330,760	34,586

West Vancouver	27,041	2,417
White Rock	13,387	1,584
Electoral Area A	-	-
scəẃaθən məsteyəxʷ (Tsawwassen First Nation)	-	-
Total	1,444,406	228,650
% of Lower Mainland	86%	75%

5.1.3 Fuel Type Distribution

According to ICBC's classification, vehicles are categorized into 20 different fuel types, including gasoline, diesel, electric, propane, and natural gas. Table 6 summarizes the number of registered vehicles by fuel type within the Metro Vancouver region, excluding Electoral Area A and the Tsawwassen First Nation treaty lands.

Table 6: Distribution of fuel types in the Metro Vancouver region

	Passenger vehicles	Commercial vehicles
Alcohol	16	3
Butane	14	2
Diesel	18,475	42,851
Diesel Butane	37	16
Diesel Natural gas	16	16
Diesel Propane	11	5
Electric	106,565	3,834
Gasoline	1,220,663	175,285
Gasoline Alcohol	399	73
Gasoline Electric	92,236	5,057
Gasoline Natural gas	309	336
Gasoline Propane	42	470
Heavy-duty hybrid	127	25
Hydrogen	208	2
Multifuel	94	36
Natural gas	80	150
Other	30	1
PHEV	5,043	8
Propane	39	474
Propane Natural Gas	2	6
Total	1,444,406	228,650

As shown in Table 6, although ICBC identifies 20 distinct fuel types, these can be combined into a smaller number of primary fuel categories for analytical purposes. For instance, all diesel-based variants, including diesel, diesel-butane, diesel-natural gas, and diesel-propane, can be grouped under the diesel category, as their primary powertrain is diesel. Similarly, all gasoline-based derivatives are classified as gasoline, except for gasoline-electric vehicles. Vehicles listed as heavy-duty hybrid and multifuel are grouped under the hybrid category. Gasoline-electric and plug-in hybrid vehicles are combined under the PHEV category. Lastly, propane gas variants, alcohol, butane, and other categories were combined under 'other' because of fewer vehicles. The summarized distributions of passenger and commercial vehicles of these combined fuel types within the Metro Vancouver region are presented in Figure 2 and Figure 3.

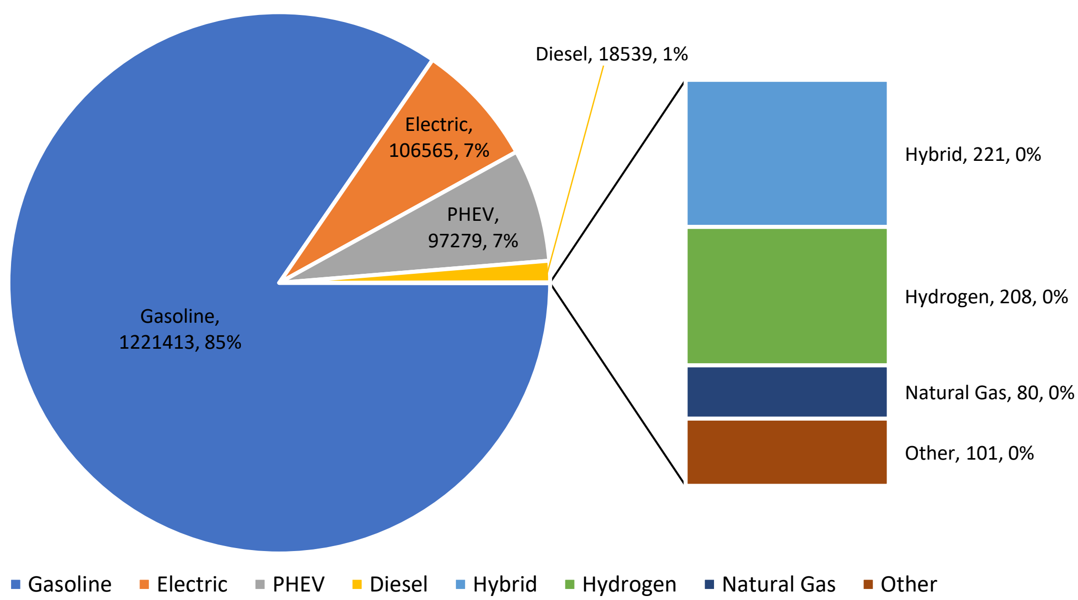


Figure 2: Distribution of fuel type in passenger vehicles

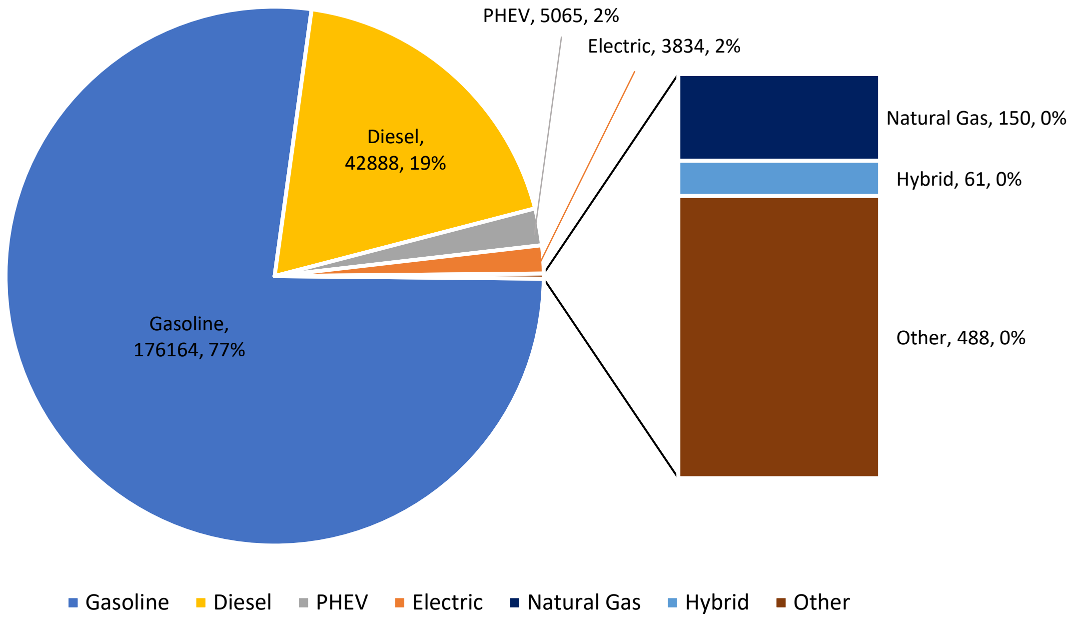


Figure 3: Distribution of fuel type in commercial vehicles

Figure 2 and Figure 3 illustrate that approximately 99% of light-duty passenger vehicles are powered by either gasoline-based or electric-based fuel types. In contrast, around 96% of light-duty commercial vehicles rely on gasoline-based or diesel-based powertrains.

5.1.4 Vehicle Body Style Distribution

According to the ICBC database, there are 24 body styles classified under passenger vehicles and 81 under commercial vehicles, as shown in Figure 1. For the purpose of this analysis, 16 passenger vehicle body styles and 11 commercial vehicle body styles were selected based on their relevance to light-duty vehicles. Table 7 presents the distribution of vehicles across the selected body styles.

Table 7: Body style distribution in passenger and commercial vehicles

Passenger vehicles		Commercial vehicles	
Fourdoorstationwagon	793,284	Crewcab	103,226
Fourdoorsedan	418,470	Pickup	72,230
Hatchback	124,415	Van	49,721
Twodoorcoupe	48,977	Taxi	2,468
Twodoorconvertible	24,569	Limousinecommercial	412

Twodoorstationwagon	6,491	Windowvan	230
Fourdoorfastback	5,687	Clubwagon	168
Twodoorsedan	5,483	Ambulance	103
Fourdoorcoupe	5,252	Armouredcar	66
Twodoorhardtop	3,974	Sedandelivery	15
Dualpurpose	3,810	Cabchassis	11
Fourdoorhardtop	2,019		
Twodoorfastback	1,490		
Fourdoorconvertible	275		
Sportconvertible	168		
Limousinepassenger	42		

5.1.5 Manufacture Year Distribution

The year of manufacture is a key parameter for evaluating the age distribution of the vehicle fleet in Metro Vancouver. Table 6 presents the number of registered passenger and commercial vehicles by model year. Vehicles manufactured before 2000 have been aggregated into a single category, as the majority are considered collector or legacy vehicles with limited participation in regular road use. Notably, the 2024 registered fleet in Metro Vancouver includes passenger vehicles dating back to 1908 and commercial vehicles dating back to 1913.

Table 8: Distribution of vehicle manufacturing years of passenger and commercial vehicles

Year	Vehicle age	Passenger		Commercial	
		No of vehicles	Cumulative %	No of vehicles	Cumulative %
2025	0	19,991	1.4%	996	0.4%
2024	1	98,148	8.2%	13,416	6.3%
2023	2	96,160	14.8%	16,682	13.6%
2022	3	79,284	20.3%	14,764	20.1%
2021	4	78,682	25.8%	12,871	25.7%
2020	5	66,039	30.3%	11,496	30.7%
2019	6	78,542	35.8%	14,446	37.0%
2018	7	86,908	41.8%	14,202	43.2%
2017	8	82,798	47.5%	13,651	49.2%
2016	9	77,751	52.9%	11,228	54.1%
2015	10	74,364	58.1%	10,117	58.5%
2014	11	62,792	62.4%	8,664	62.3%
2013	12	61,032	66.6%	6,872	65.3%

2012	13	52,860	70.3%	6,779	68.3%
2011	14	45,724	73.5%	6,949	71.3%
2010	15	50,997	77.0%	6,588	74.2%
2009	16	41,058	79.8%	4,895	76.4%
2008	17	45,143	83.0%	7,323	79.6%
2007	18	45,371	86.1%	7,570	82.9%
2006	19	35,431	88.6%	6,628	85.8%
2005	20	31,084	90.7%	5,078	88.0%
2004	21	23,709	92.3%	4,128	89.8%
2003	22	21,575	93.8%	3,945	91.5%
2002	23	17,012	95.0%	2,885	92.8%
2001	24	11,646	95.8%	2,254	93.8%
2000	25	9,708	96.5%	1,850	94.6%
Before 2000	25+	50,597	100.0%	12,373	100.0%

To provide a more precise visual representation of the data presented in Table 8, a histogram was developed to illustrate the distribution of vehicle model years with a bin size of 5 years. This histogram is shown in Figure 4.

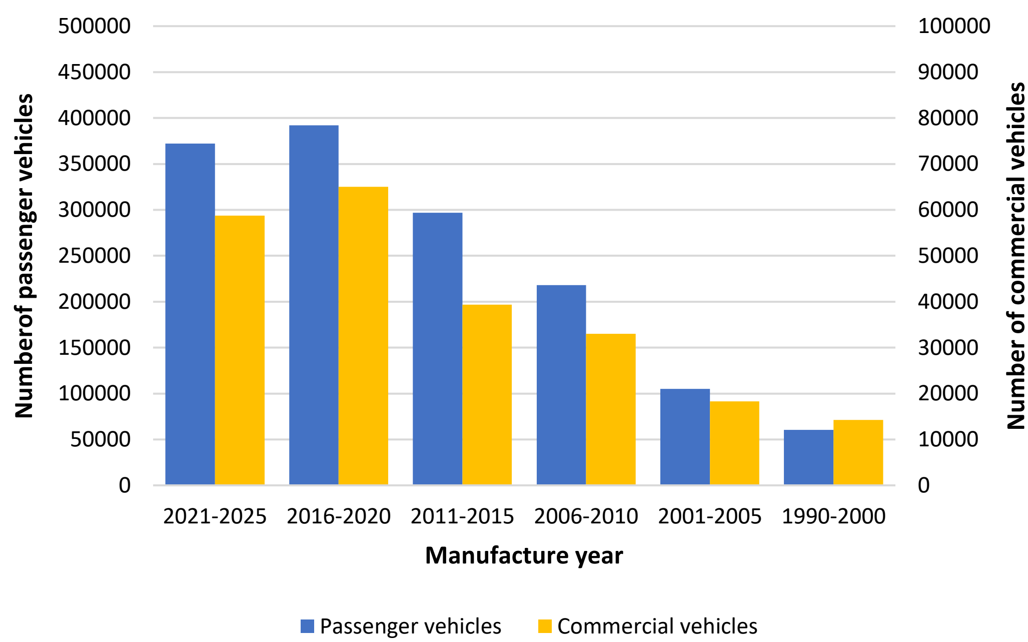


Figure 4: Histogram of the vehicle manufacturing year of passenger and commercial vehicles

Based on Figure 4, the histogram is skewed towards newer vehicles, with most passenger and commercial vehicles being within a 20-year age range. The respective cumulative percentages for vehicles within 20 years are ~89% and ~86% for passenger and commercial vehicles, respectively.

5.1.6 Distribution of Vehicle Use and Owner Type

Vehicles were also classified based on their intended use and type of ownership. Vehicle use was categorized into personal, business, and other. Ownership type was classified as either a person or an external organization. The distribution of vehicle use and ownership is presented in Figure 5 and Figure 6, respectively.

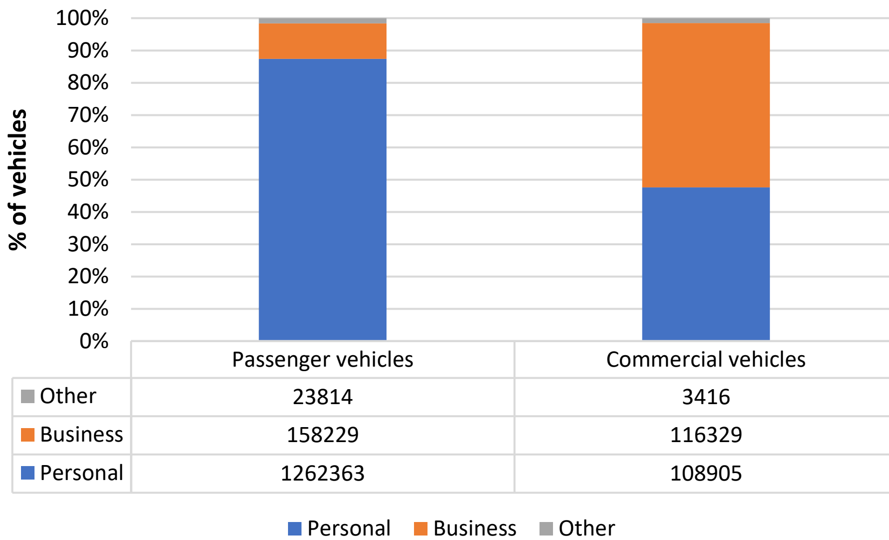


Figure 5: Distribution of vehicle use

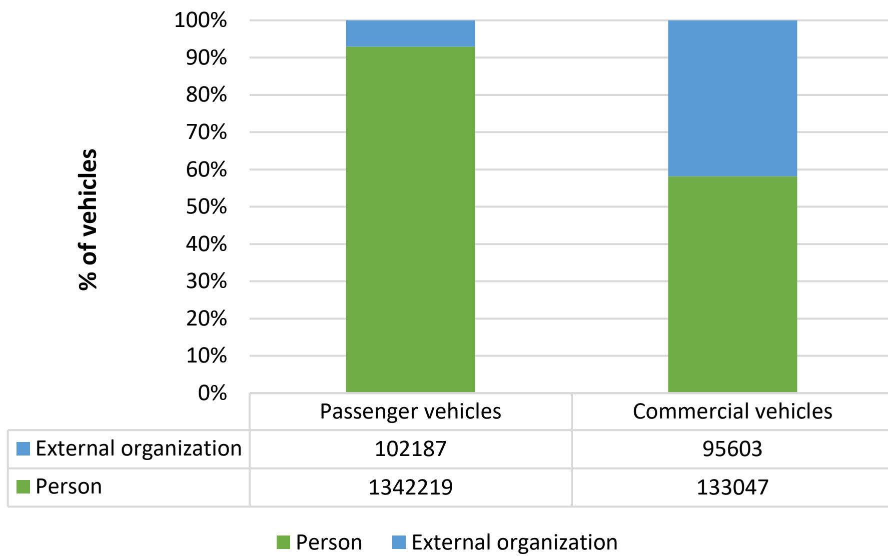


Figure 6: Distribution of vehicle ownership

As shown in Figure 5, approximately 87% of passenger vehicles are designated for personal use, followed by 11% for business purposes and 2% for other purposes. In contrast, among commercial vehicles, 51% are intended for business use, while 48% are used for personal purposes, and 1% are used for other purposes. Figure 6 further reveals that about 93% of passenger vehicles are owned by individuals, with only 7% registered to external organizations. Individual ownership decreases to 58% for commercial vehicles, while ownership by external organizations accounts for the remaining 42%.

5.2 AirCare Program Vehicle Inventory

The AirCare program was a vehicle emissions testing initiative launched in British Columbia in 1992, with the primary objective of improving air quality by reducing emissions from road vehicles, particularly in the Lower Mainland and Metro Vancouver regions (Taylor Consulting, 2002). The program mandated periodic emissions testing for light-duty vehicles, with older vehicles (model year 1991 and earlier) required to undergo annual testing, and newer vehicles (manufactured from 1992 onward) tested biennially following an initial exemption period. AirCare operated entirely on a cost-recovery basis, funded through testing fees without reliance on public tax revenue (NUPGE, 2010).

The program was well-known for its collaboration with the automotive repair industry, ensuring that vehicles failing emissions tests were adequately repaired to achieve measurable reductions in pollutants. AirCare specifically targeted key emissions including carbon dioxide, carbon monoxide (CO), hydrocarbons (HC), nitrogen oxides (NO_x), and particulate matter (Taylor Consulting, 2002). Vehicles were assessed against pass/fail criteria based on their model year and the emissions standards in place at the time of manufacture. In addition to emissions data, the program collected detailed vehicle information, including VIN, make, model, year of manufacture, and odometer readings, thereby creating a comprehensive and valuable vehicle dataset for the region.

The AirCare program was phased out in 2014, having achieved substantial improvements in air quality. Between 1992 and 2014, the aggregated count of measured air quality pollutants from the total light-duty vehicle fleet declined by 89%, largely due to advancements in vehicle technology (CBC, 2012). As a result, the incremental benefits of continuing the program were reduced, while the operational cost remained substantial, approximately $19 million per year (CBC, 2012). With fewer vehicles failing the tests and the cost-effectiveness of the program in question, the BC Government decided to conclude the initiative after 22 years (CBC, 2014) Nevertheless, the database developed through AirCare has proven invaluable for the region's emissions inventories and travel behaviour analysis. It continues to be utilized in the travel pattern prediction KAR model, as further discussed under subsection 3.1.

5.2.1 Introduction to data inventory

The AirCare dataset includes records of vehicle emissions tests conducted between 2002 and 2014. The dataset comprises information from over 7.6 million individual tests, with each row representing a single test event. Each test entry is described across 11 primary columns, which include the following:

- **VIN_HASH** - Representation of the VIN number
- **DATE_TIME** – Date and time of the test
- **VEH_YEAR** – Manufactured year of the vehicle

- **MAKE, MODEL** – Make and Model of the vehicle
- **FUEL** – Fuel type of the vehicle { A= Alcohol, B= Butane, D= Diesel, F= Diesel–Butane, G= Gasoline, H= Gasoline–Alcohol, L= Gasoline-Electric, N= Natural Gas, P= Propane, R= Diesel–Natural Gas, S= Propane–Natural Gas, T= Diesel–Propane, U= Gasoline–Natural Gas, W= Gasoline–Propane, Z= Multi-fuels}
- **VEH_CLASS** – Class of the vehicle {0= Undetermined, 1= Sedan, 2= Station wagon, 3= Minivan, 4= Pickup, 5= Sport/Utility, 6= Full-size van}
- **GVW** – Gross vehicle weight (in kg)
- **LVW** - Loaded vehicle weight (in kg)
- **DAYS_BETWEEN** – Number of days since the previous test
- **ODOMETER** – Odometer reading at the time of test (in km)

The number of data points was too large to conduct the analysis using Microsoft Excel software. Hence, Python coding was used for the analysis. The Python code will be appended as Appendix 1. Descriptive statistics of the Aircare dataset are as follows:

```
=== Number of Unique Values in Text Columns ===
VIN_Hash: 2029754
VEH_CLASS: 6
MAKE: 167
MODEL: 3228
VEH_TYPE: 3
FUEL: 15

Unique values in 'FUEL':
['G' 'P' 'D' ' ' 'W' 'U' 'B' 'N' 'H' 'L' 'Z' 'T' 'S' 'A' 'F']

Unique values in 'VEH_TYPE':
['P' 'T' ' ']

=== Descriptive Statistics for Numeric Columns ===
                 count           mean          std          min  \
VEH_YEAR      7618623.0    1994.434174     7.206786  1901.000000
GVW           2233747.0    2671.233216   737.861342     2.000000
LVW           2322154.0    1940.727133   396.732933   137.000000
ODOMETER      7605227.0  165289.704042  86037.478214     0.000000
DAYS_BETWEEN  5590298.0     588.007775   345.212935     1.000012

                    25%           50%           75%           max
VEH_YEAR    1990.000000   1995.000000   2000.000000   2014.000000
GVW         2268.000000   2699.000000   2903.000000  36044.000000
```

```
LVW              1730.000000    1906.000000    2088.000000  183136.000000
ODOMETER       102000.000000  157000.000000  217000.000000  998000.000000
DAYS_BETWEEN      364.290362     719.869201     741.922934    4704.077176
```

Based on the analysis, although the dataset contains over 7.6 million test records, these correspond to approximately 2 million unique vehicles. The dataset comprises vehicles from 167 manufacturers and 3,228 distinct models, encompassing three vehicle types and 15 fuel types. Vehicles in the dataset were manufactured between 1901 and 2014. The average Gross Vehicle Weight (GVW) was 2,671 kg, while the average Loaded Vehicle Weight (LVW) was 1,940 kg. Odometer readings ranged from 0 to 998,000 km, with an average value of approximately 165,000 km. The time interval between tests ranged from 1 to 4,704 days, with an average interval of 588 days.

5.2.2 Creating Additional Parameters for the Analysis

Although the manufactured year and other vehicle characteristics were provided, it was not possible to analyze the odometer reading with either the date or the manufactured year. Therefore, to analyze the data, several additional columns were created, named VEH_AGE, ODO_DIFF, DAY_DIFF, and Annual Mileage. These columns were created using the following formulas:

VEH_AGE = DATE_TIME - VEH_YEAR

The following were grouped based on the same VIN_HASH, and then the columns were created as follows.

$ODO\_DIFF = ODOMETER_{p,n} - ODOMETER_{p,n-1}$

$DAY\_DIFF = DATE\_TIME_{p,n} - DATE\_TIME_{p,n-1}$

p – VIN_HASH number

n – Test number for each VIN number

$Annual\ Mileage = ODO\_DIFF/DAY\_DIFF$

5.2.3 Impact of Vehicle Age

Vehicle age was identified as a significant factor affecting vehicle travel. Several plots were generated to examine trends related to vehicle age. First, odometer readings were plotted against vehicle age, as shown in Figure 7. Subsequently, annual VKT were plotted with respect to vehicle age, as presented in Figure 8.

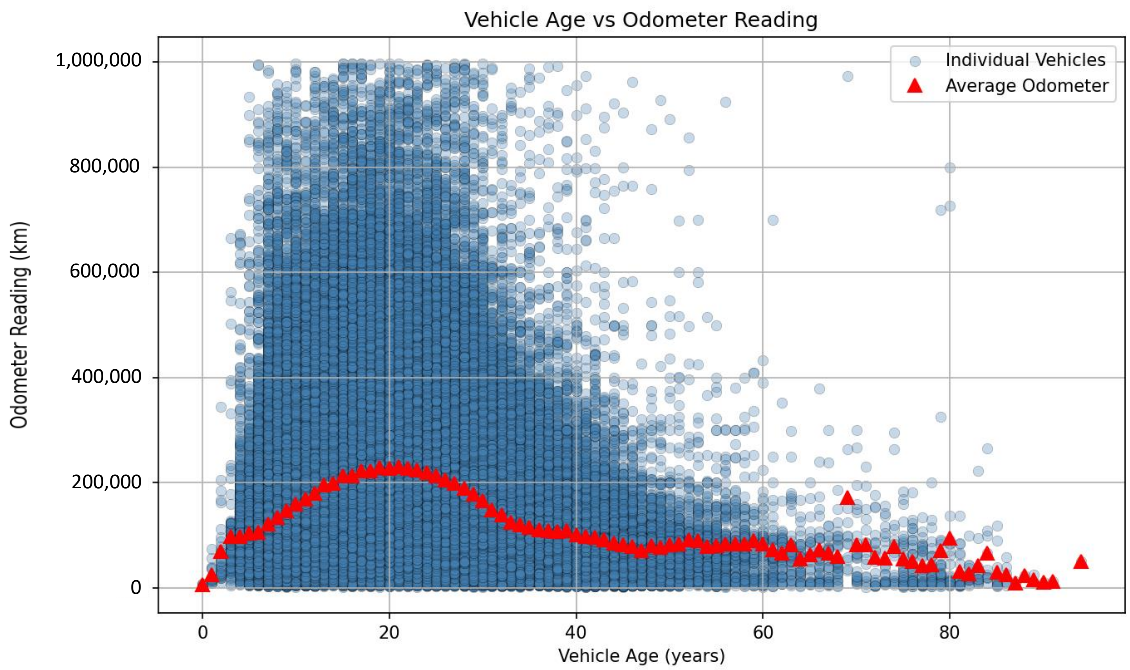


Figure 7: Odometer reading with vehicle age

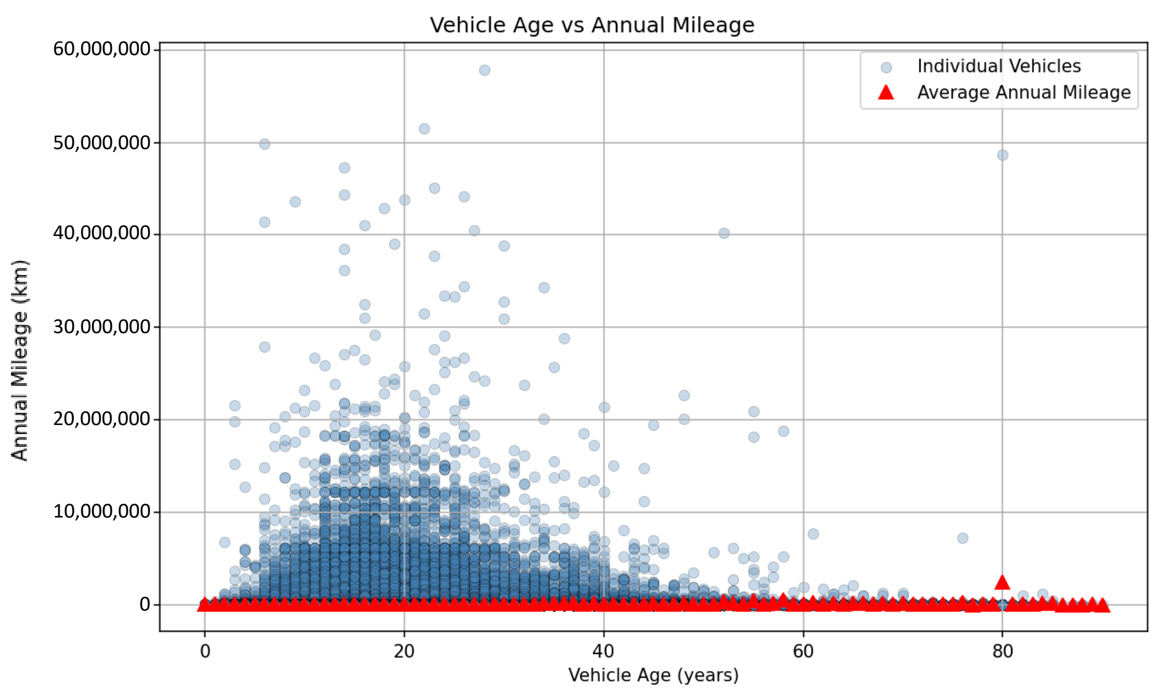


Figure 8: Annual mileage with vehicle age

As shown in Figure 7, average odometer readings generally increase with vehicle age, but begin to decline after approximately 20 years. The decline is likely attributed to the retirement of high-mileage vehicles, leaving a remaining fleet dominated by lower-mileage vehicles, which skews the average downward. A similar pattern is observed in Figure 8, where the scatter plot of annual mileage shows a noticeable decline after 18–20 years of vehicle age. However, due to the presence of extreme values, the average annual mileage trend is not clearly visible. These extreme values are primarily the result of significant outliers, with some vehicles exhibiting annual mileage exceeding 10,000,000 km/year, values that are likely unrealistic and indicative of data quality issues.

To address this, the Interquartile Range (IQR) method was employed to identify and remove outliers. Rather than applying the IQR method to the entire annual mileage dataset collectively, it was applied separately for each vehicle age group. This approach ensured the removal of outliers relative to typical values within each age category, thereby preserving meaningful age-specific trends. Additionally, vehicles older than 40 years were excluded from the analysis due to their irrelevance.

The resulting cleaned distribution of annual mileage by vehicle age is presented in Figure 9.

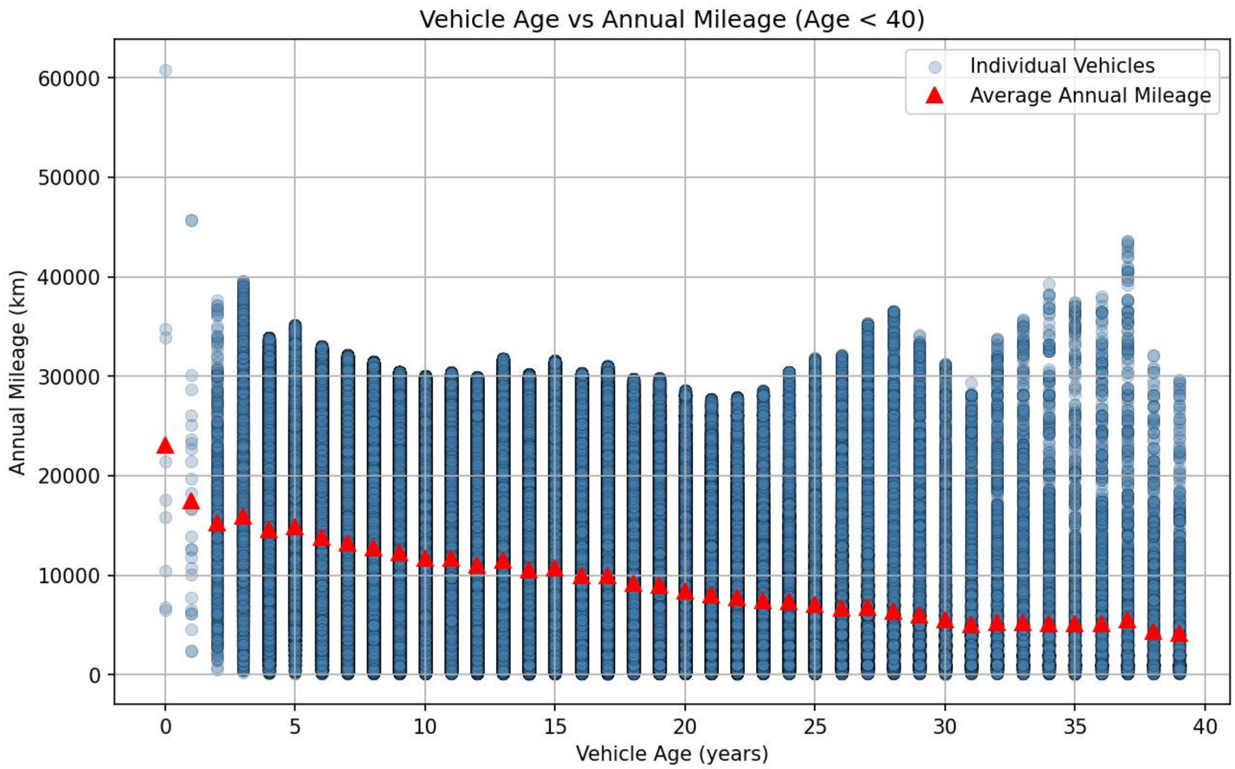
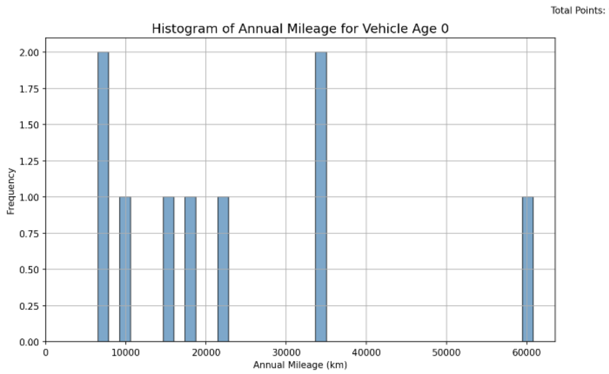
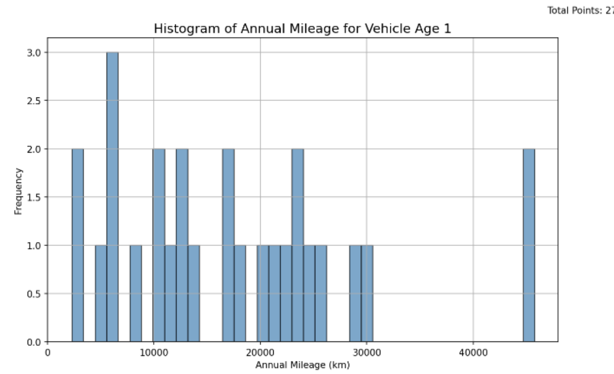
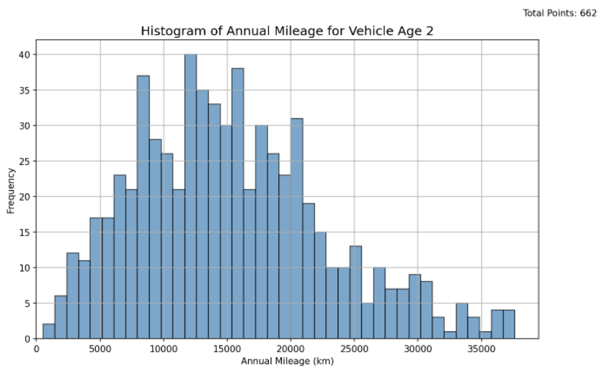


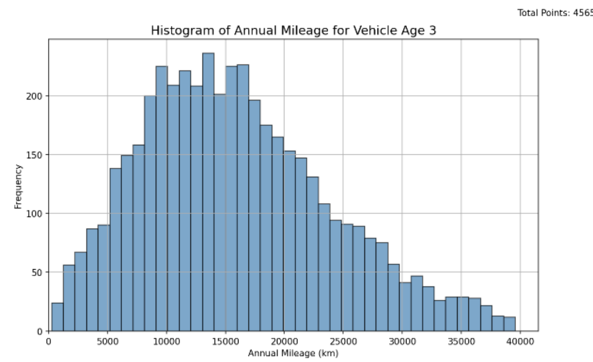
Figure 9: Annual mileage with vehicle age after outlier removal

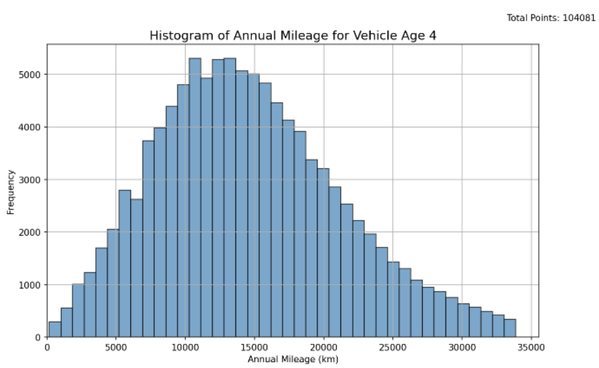
As shown in Figure 9, the application of the outlier removal method successfully constrained annual mileage values to a more practical range, with all values falling below 60,000 km. This data refinement enhanced the credibility of the analysis by eliminating unrealistic values. Additionally, the results revealed a linear decline in average annual mileage with increasing vehicle age. To further explore the distribution of annual mileage across different age groups, histograms were generated for each vehicle age from 0 to 10 years, as well as for ages 15, 20, 25, 30, and 40 years. The resulting histograms are presented in Figure 10.

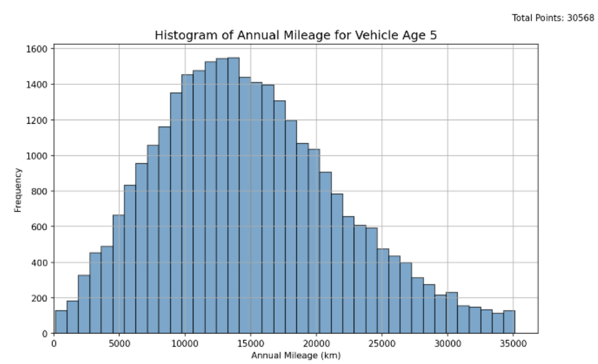

Total Points:
Histogram of Annual Mileage for Vehicle Age 0
Frequency
Annual Mileage (km)

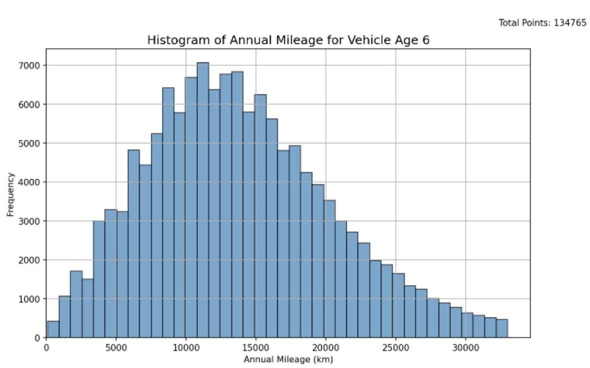

Total Points: 27
Histogram of Annual Mileage for Vehicle Age 1
Frequency
Annual Mileage (km)

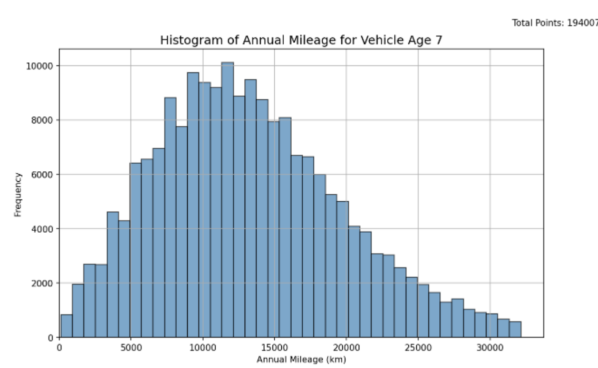

Total Points: 662
Histogram of Annual Mileage for Vehicle Age 2
Frequency
Annual Mileage (km)


Total Points: 4565
Histogram of Annual Mileage for Vehicle Age 3
Frequency
Annual Mileage (km)


Total Points: 104081
Histogram of Annual Mileage for Vehicle Age 4
Frequency
Annual Mileage (km)


Total Points: 30568
Histogram of Annual Mileage for Vehicle Age 5
Frequency
Annual Mileage (km)


Total Points: 134765
Histogram of Annual Mileage for Vehicle Age 6
Frequency
Annual Mileage (km)


Total Points: 194007
Histogram of Annual Mileage for Vehicle Age 7
Frequency
Annual Mileage (km)

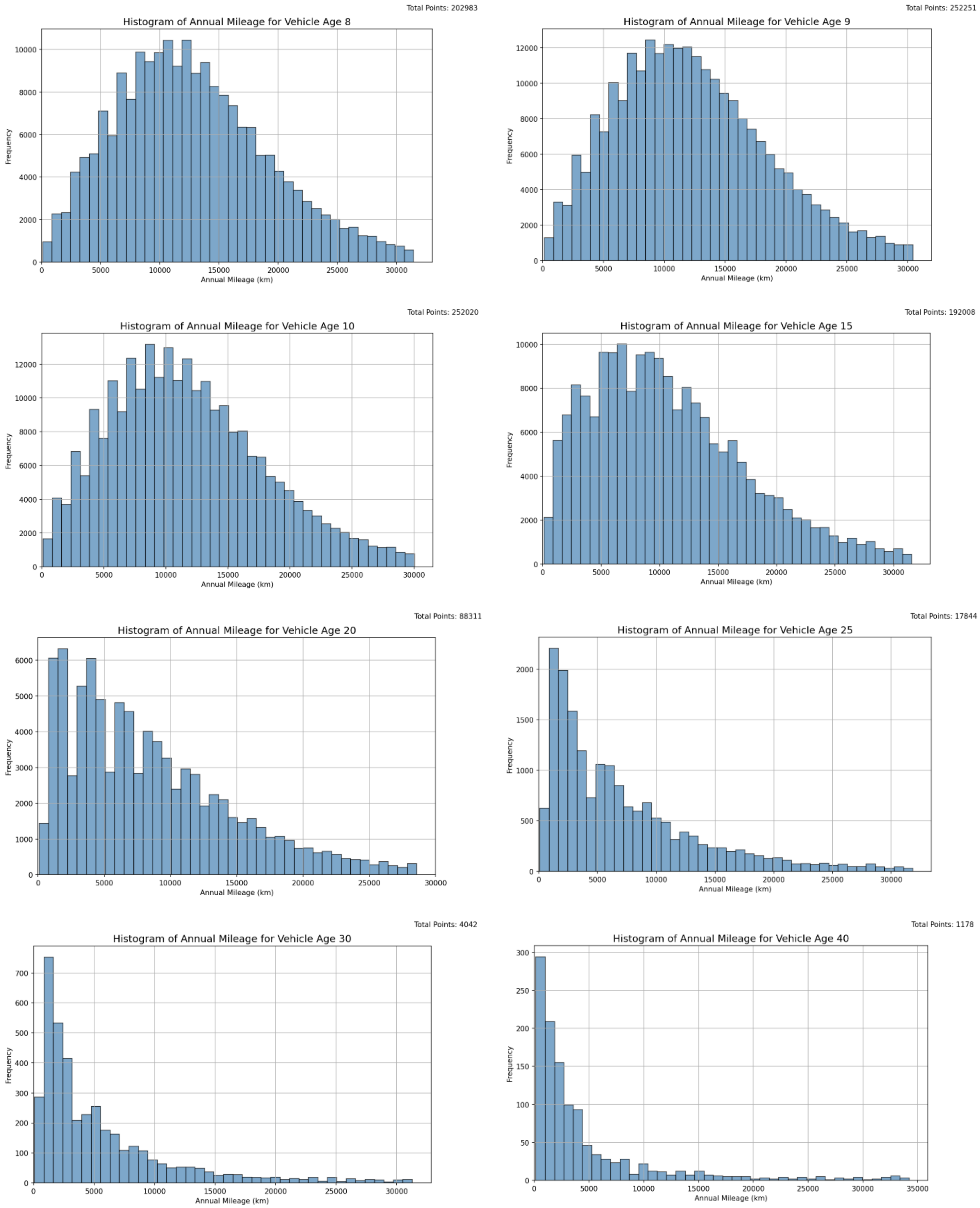


Figure 10: Histograms of annual mileage for vehicle ages (0 to 40)

As shown in Figure 10, the annual mileage distributions generally follow a normal pattern for most vehicle ages, with the exception of ages 0 to 1, where the smaller sample size results in greater variability and deviation from normality. Additionally, a left-skewed distribution is observed across most age groups, and this skewness becomes more pronounced as vehicle age increases. This pattern indicates a progressive shift toward lower modal annual mileage as vehicles age, which is consistent with the linear decline in mean annual mileage illustrated in Figure 9. To further support this analysis, Table 9 presents descriptive statistics for annual mileage by vehicle age, covering vehicles aged 0 to 40 years. The results showed that the standard deviations were very high for vehicles under two years old, mainly due to lower vehicle counts. Even for older vehicles, the standard deviation was more than 45% of the mean and kept increasing with age. This shows that factors other than vehicle age are important for accurately estimating VKT at a detailed level. Examples include location and income. As people in Vancouver tend to have lower VKT due to better transit access and higher density. Wealthier households usually drive more and own more vehicles.

Table 9: Descriptive statistics for annual mileage with vehicle age

VEH_AGE	Count	Descriptive statistics of annual mileage (km)						
		mean	std	min	25%	50%	75%	max
0	9	23123	17549	6518	10429	17590	33871	60833
1	27	17467	11463	2312	8918	16591	23475	45783
2	662	15310	7546	530	9556	14502	19916	37638
3	4565	15916	8018	276	9917	15041	21000	39566
4	104081	14610	6681	159	9720	13998	18895	33885
5	30568	14883	6991	129	9786	14221	19340	35141
6	134765	13826	6587	94	9000	13193	18025	33008
7	194007	13213	6478	120	8454	12552	17381	32135
8	202983	12736	6374	100	8011	12066	16787	31450
9	252251	12256	6226	136	7562	11595	16233	30417
10	252020	11734	6177	110	7048	11032	15638	30020
11	149055	11742	6264	124	7019	11030	15699	30377
12	281961	11041	6194	99	6320	10224	14939	29910
13	190859	11557	6600	95	6545	10705	15643	31816
14	249908	10545	6323	84	5674	9592	14427	30218
15	192008	10793	6596	100	5794	9838	14837	31554
16	197069	9936	6382	101	4986	8878	13774	30359
17	158459	9938	6515	86	4932	8848	13834	31053
18	141513	9237	6308	104	4090	8022	12994	29747
19	110394	9049	6319	104	4011	7892	12790	29804
20	88311	8481	6123	102	3734	7078	12033	28584

21	68042	8093	5987	101	3111	6815	11557	27749
22	54428	7797	5920	90	3017	6232	11085	27923
23	37878	7494	6028	114	2920	5951	10711	28547
24	25428	7343	6171	114	2613	5615	10390	30417
25	17844	7116	6311	93	2080	5069	9946	31836
26	12683	6741	6190	102	2017	4904	9254	32159
27	9224	6782	6666	108	2000	4355	9150	35334
28	6723	6432	6623	113	1968	4022	8836	36596
29	5235	6018	6241	114	1763	3935	8000	34219
30	4042	5519	5808	92	1572	3443	7189	31286
31	3308	5074	5323	138	1145	3067	6804	29368
32	2674	5265	6174	118	1066	3000	6831	33834
33	2284	5278	6412	99	1028	2992	6672	35684
34	1842	5200	6606	113	1031	2839	6166	39247
35	1648	5175	6804	87	1022	2840	6092	37436
36	1660	5169	6692	113	1014	2859	6033	38021
37	1507	5494	8036	108	1003	2296	6033	43641
38	1376	4403	5454	112	1003	2072	5290	32156
39	1264	4176	5157	134	992	2086	5028	29675
40	1178	4592	6214	149	1003	2045	5027	34249

5.2.4 Percentage of Vehicles Below 15,000 km Annual Mileage

The ICBC distance-based insurance discount was first introduced for vehicles that travel less than 10,000 kilometres per year. In 2025, the eligibility limit was increased to 15,000 kilometres. To support this, the share of vehicles with annual mileage below 10,000 and 15,000 kilometres was calculated. This was done for each vehicle age category using the AirCare dataset. The results are shown in Table 10.

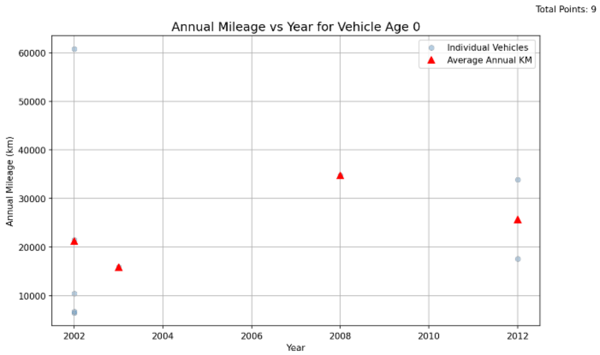
Table 10: Percentage of vehicles with annual mileage less than 15,000 km

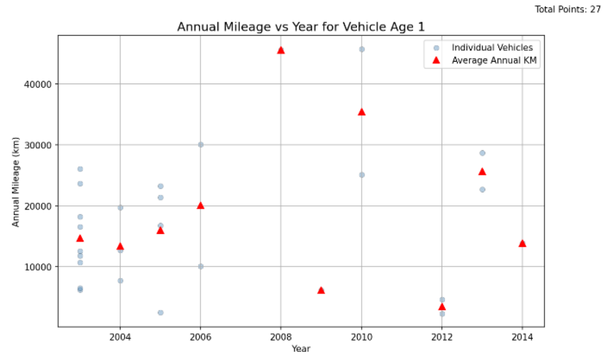
Vehicle age	Total vehicles	Below 10000 km	Percent Below 10000 km	Below 15000 km	Percent Below 15000 km
0	9	2	22.2	3	33.3
1	27	7	25.9	13	48.1
2	662	178	26.9	346	52.3
3	4565	1159	25.4	2267	49.7
4	104081	27441	26.4	58094	55.8
5	30568	7985	26.1	16542	54.1
6	134765	41220	30.6	81216	60.3

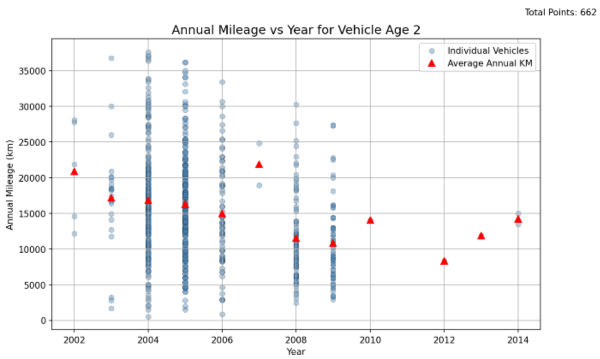
7	194007	66264	34.2	123656	63.7
8	202983	74818	36.9	135237	66.6
9	252251	100106	39.7	174495	69.2
10	252020	108966	43.2	181427	72.0
11	149055	64867	43.5	106993	71.8
12	281961	136433	48.4	212267	75.3
13	190859	87385	45.8	138068	72.3
14	249908	130834	52.4	192737	77.1
15	192008	98204	51.1	145286	75.7
16	197069	111869	56.8	156401	79.4
17	158459	90287	57.0	125378	79.1
18	141513	86769	61.3	115780	81.8
19	110394	68951	62.5	91006	82.4
20	88311	58181	65.9	74654	84.5
21	68042	46305	68.1	58431	85.9
22	54428	38144	70.1	47330	87.0
23	37878	27347	72.2	33097	87.4
24	25428	18598	73.1	22303	87.7
25	17844	13414	75.2	15697	88.0
26	12683	9801	77.3	11374	89.7
27	9224	7140	77.4	8190	88.8
28	6723	5325	79.2	6049	90.0
29	5235	4222	80.6	4744	90.6
30	4042	3396	84.0	3737	92.5
31	3308	2847	86.1	3100	93.7
32	2674	2292	85.7	2476	92.6
33	2284	1952	85.5	2098	91.9
34	1842	1581	85.8	1693	91.9
35	1648	1433	87.0	1525	92.5
36	1660	1441	86.8	1526	91.9
37	1507	1293	85.8	1364	90.5
38	1376	1216	88.4	1293	94.0
39	1264	1131	89.5	1192	94.3
40	1178	1030	87.4	1094	92.9

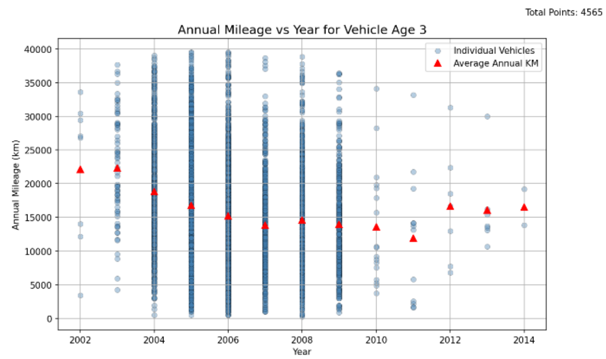
5.2.5 Impact of Measured Date on Annual Mileage

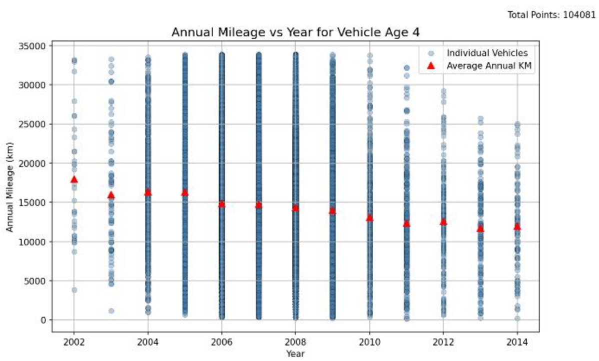
The impact of the time variable on annual mileage was then identified by plotting graphs of annual mileage behaviour for each vehicle age, measured separately for each sampling year.

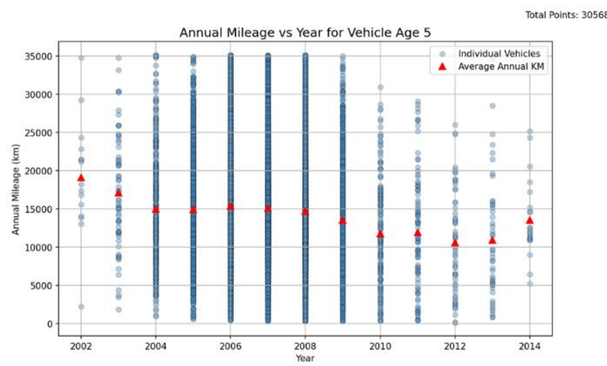

Total Points: 9
Annual Mileage vs Year for Vehicle Age 0
Individual Vehicles
Average Annual KM
Annual Mileage (km)
Year

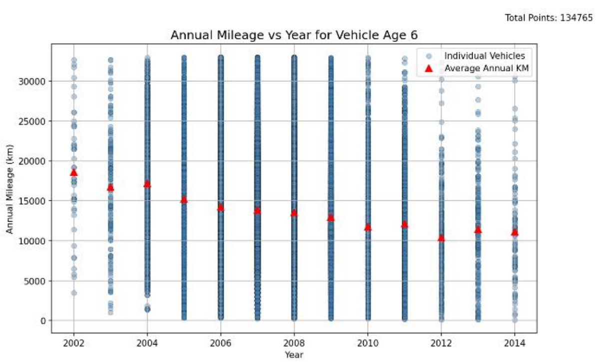

Total Points: 27
Annual Mileage vs Year for Vehicle Age 1
Individual Vehicles
Average Annual KM
Annual Mileage (km)
Year

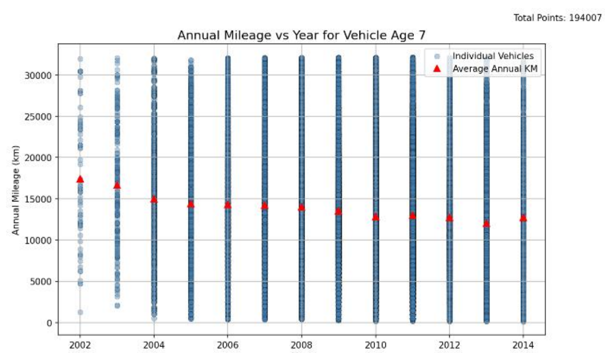

Total Points: 662
Annual Mileage vs Year for Vehicle Age 2
Individual Vehicles
Average Annual KM
Annual Mileage (km)
Year


Total Points: 4565
Annual Mileage vs Year for Vehicle Age 3
Individual Vehicles
Average Annual KM
Annual Mileage (km)
Year


Total Points: 104081
Annual Mileage vs Year for Vehicle Age 4
Individual Vehicles
Average Annual KM
Annual Mileage (km)
Year


Total Points: 30568
Annual Mileage vs Year for Vehicle Age 5
Individual Vehicles
Average Annual KM
Annual Mileage (km)
Year


Total Points: 134765
Annual Mileage vs Year for Vehicle Age 6
Individual Vehicles
Average Annual KM
Annual Mileage (km)
Year


Total Points: 194007
Annual Mileage vs Year for Vehicle Age 7
Individual Vehicles
Average Annual KM
Annual Mileage (km)
Year

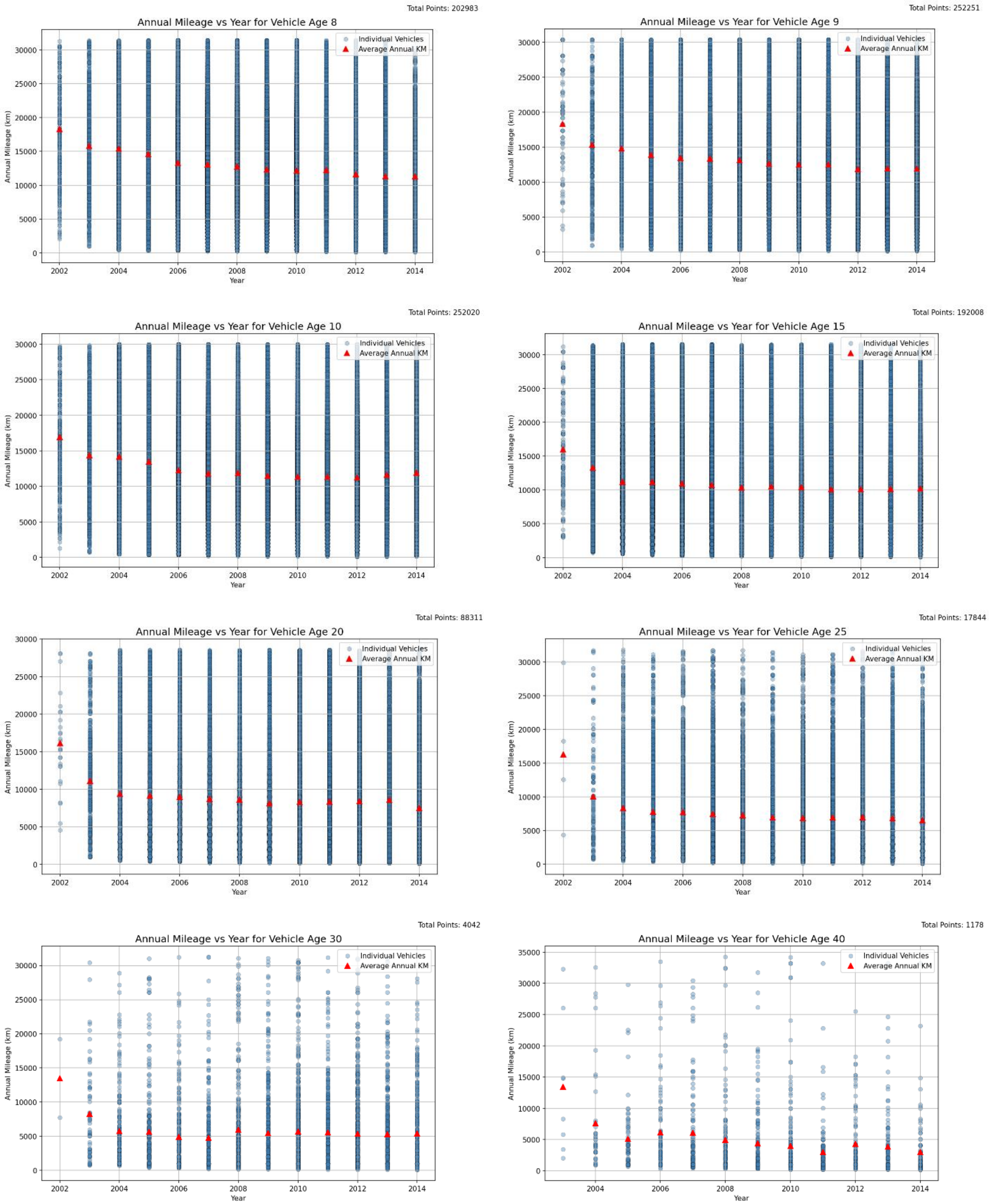


Figure 11: Annual mileage (of individual vehicle) scatter plots with measured year for vehicle ages (0-40)

The number of data points for vehicles aged 0 to 2 years was minimal, resulting in higher variability and less reliable results, as indicated by the scatter plots in Figure 11. For vehicles aged

3 to 5 years, a gradual decline in average annual mileage per vehicle was observed between 2004 and 2014. In contrast, vehicles aged 6 years and older exhibited a slight reduction in annual mileage from 2002 to 2006, followed by a relatively stable trend in subsequent years.

5.2.6 Impact of Fuel Type

Descriptive statistics of annual mileage (in kilometres) were initially generated for each fuel type. The results are presented in Table 11.

Table 11: Descriptive statistics of annual mileage for different fuel types

FUEL	count	mean	std	min	25%	50%	75%	max
Gasoline	3119249	11041	6605	84	5967	10150	15208	118157
Diesel	60087	12064	7315	112	6092	11103	17023	42066
Propane	15533	11256	7438	126	5028	10027	16177	37043
Gasoline – Natural Gas	3332	11227	7294	155	5291	10000	15956	37436
Gasoline – Propane	3016	10554	7139	282	4867	9327	15208	45783
Natural Gas	1004	13169	7655	387	7114	12369	18250	35062
Gasoline – Alcohol	31	11044	7238	899	4993	9432	14689	29040
Uncategorized	25	10999	5429	3810	6509	10910	14661	23804
Multi-fuels	21	8565	6461	501	4348	6527	12412	24421
Butane	17	9744	4826	3495	6456	9100	10735	23485
Diesel – Butane	8	12150	4803	7926	8365	10496	14302	20605
Propane – Natural Gas	6	5520	4461	963	1507	5477	8490	11526
Gasoline – Electric	3	13814	11701	6318	7073	7828	17563	27297
Diesel – Propane	2	9946	882	9322	9634	9946	10257	10569

Subsequently, the mean annual mileage for the top six fuel types, which represent 99.996% of the total vehicle population, was plotted, as shown in Figure 12.

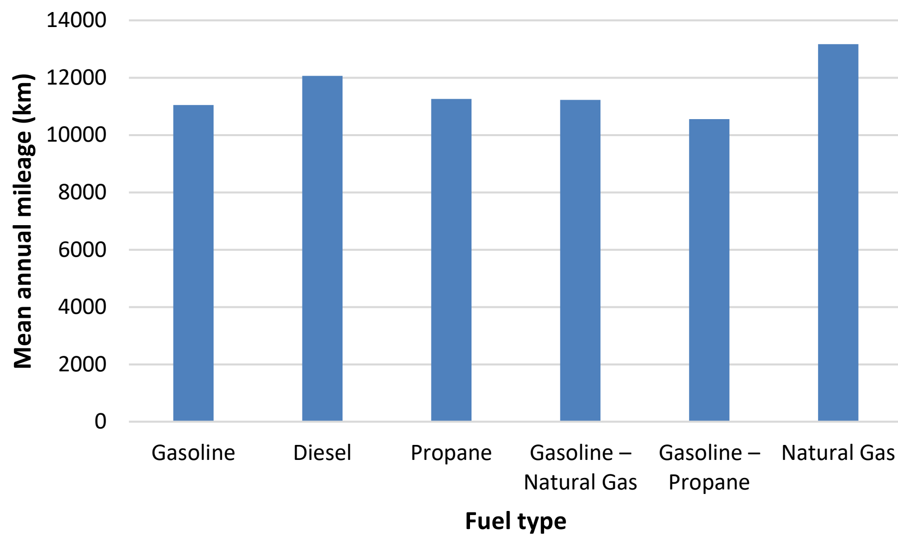


Figure 12: Mean annual mileage for different fuel types

As shown in Figure 12, natural gas vehicles exhibited the highest mean annual mileage, averaging approximately 13,000 kilometres. Diesel vehicles also demonstrated relatively high use, with a mean annual mileage of around 12,000 kilometres, ranking second overall. In contrast, gasoline and propane vehicles showed average annual mileages ranging from 10,000 to 11,000 kilometres. Given the identified relationship between vehicle age and annual mileage, a more detailed analysis was conducted to explore this relationship further. The results are presented in Figure 13, which illustrates annual mileage as a function of vehicle age, categorized by fuel type.

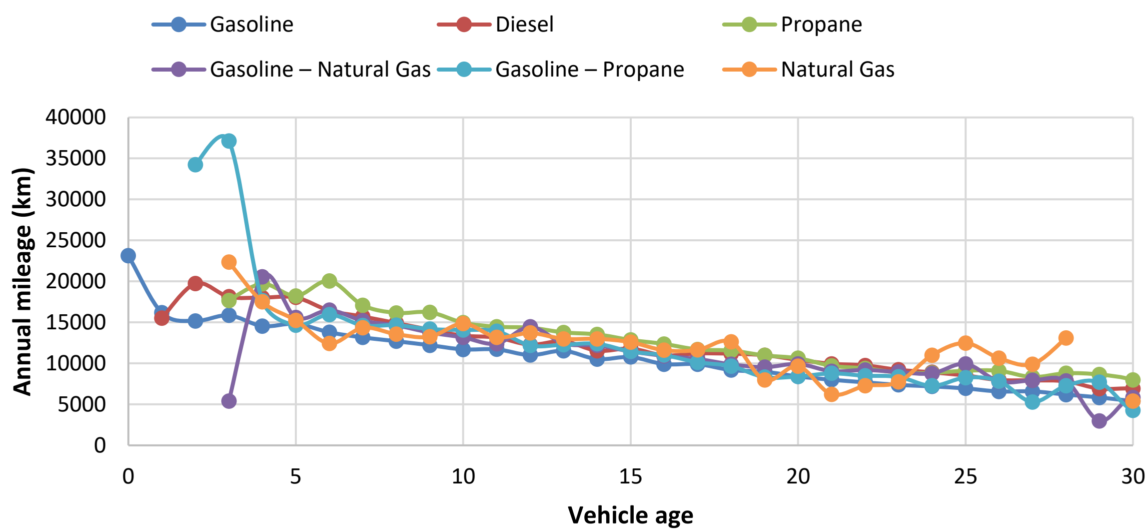


Figure 13: Annual mileage with vehicle age for different fuel types

According to Figure 13, all fuel types exhibit a similar trend in mean annual mileage, characterized by a linear decline with increasing vehicle age. While a few vehicle age categories show elevated or irregular average values, these anomalies are associated with very small sample sizes (typically one or two data points) and are therefore considered statistically insignificant.

6 Novel VKT Estimation Method Framework

Due to current data limitations, odometer readings are not available for every registered vehicle in British Columbia. However, with the continued expansion of ICBC's distance-based insurance discount program, an increasing number of odometer records are expected to become available, enabling the estimation of annual VKT. This section presents a framework for estimating VKT across the Metro Vancouver region, using available odometer data and a method that spatially attributes vehicle travel to the Municipality of registration.

6.1 Define the objective and Scope

Need to define the desired objective and scope for determining VKT. For example we can assume the objective of the framework to estimate the regional light-duty VKT for Metro Vancouver using ICBC odometer data.

6.2 Data Acquisition and Cleaning

To estimate VKT, vehicle registration data from ICBC must be acquired, including odometer readings with corresponding measurement dates. Additionally, vehicle specifications should be obtained, including VIN, year of manufacture, model, fuel type, body style, vehicle usage category, and geographic location (preferably at the postal code level). Once acquired, the dataset must undergo a cleaning process to ensure accuracy and remove erroneous entries. Key categories of outliers include duplicate records, negative odometer readings, and extremely high odometer values. The following subsections describe the approach used for each type of data anomaly.

6.2.1 Removal of Duplicates

To identify potential duplicate entries, a new column "DAYS_BETWEEN" can be created by calculating the difference in measurement dates for each VIN. Rows where the DAYS_BETWEEN value is less than two days are considered duplicates or administrative artifacts and can be removed from the dataset.

6.2.2 Negative Odometer Readings

All odometer readings with values less than zero are physically implausible and are removed through a simple filter condition: Odometer < 0.

6.2.3 Erroneous Odometer Readings

Extremely high odometer values may result from data entry errors or anomalies. Two methods can be used to detect and remove these outliers:

- Fixed Threshold Method: A predefined upper limit (e.g., 100,000 km/year) can be set, beyond which values are excluded from the analysis based on experience.
- Interquartile Range (IQR) Method: This statistical technique calculates the IQR as the difference between the 75th percentile (Q3) and the 25th percentile (Q1) of the data. Outliers are defined as values falling below Q1 – 1.5 × IQR or above Q3 + 1.5 × IQR. This method accounts for data variability and avoids arbitrary cutoffs.

To improve precision, odometer readings can be converted into annual mileage by dividing the distance travelled by the time interval between measurements. The IQR method can then be applied separately for each vehicle age group to screen for unrealistic annual mileage values in an age-specific context. Similarly, age-specific thresholds can be defined for odometer readings.

6.3 Geographical Screening

The ICBC dataset includes vehicle registration information for the entire province of British Columbia, which introduces substantial geographical variation. To narrow the scope of the analysis to Metro Vancouver, a two-stage geographical screening process is required.
First, British Columbia is divided by ICBC into four primary regions:

1. Lower Mainland
2. Vancouver Island
3. Southern Interior
4. North Central

From these, only the Lower Mainland region should be filtered for further analysis.

Second, while the Lower Mainland comprises 53 municipalities, only those located within the Metro Vancouver region are selected for this analysis. Municipality-level filtering is necessary to ensure that VKT estimates accurately reflect travel activity specific to Metro Vancouver. The complete geographical screening workflow is illustrated in Figure 14.

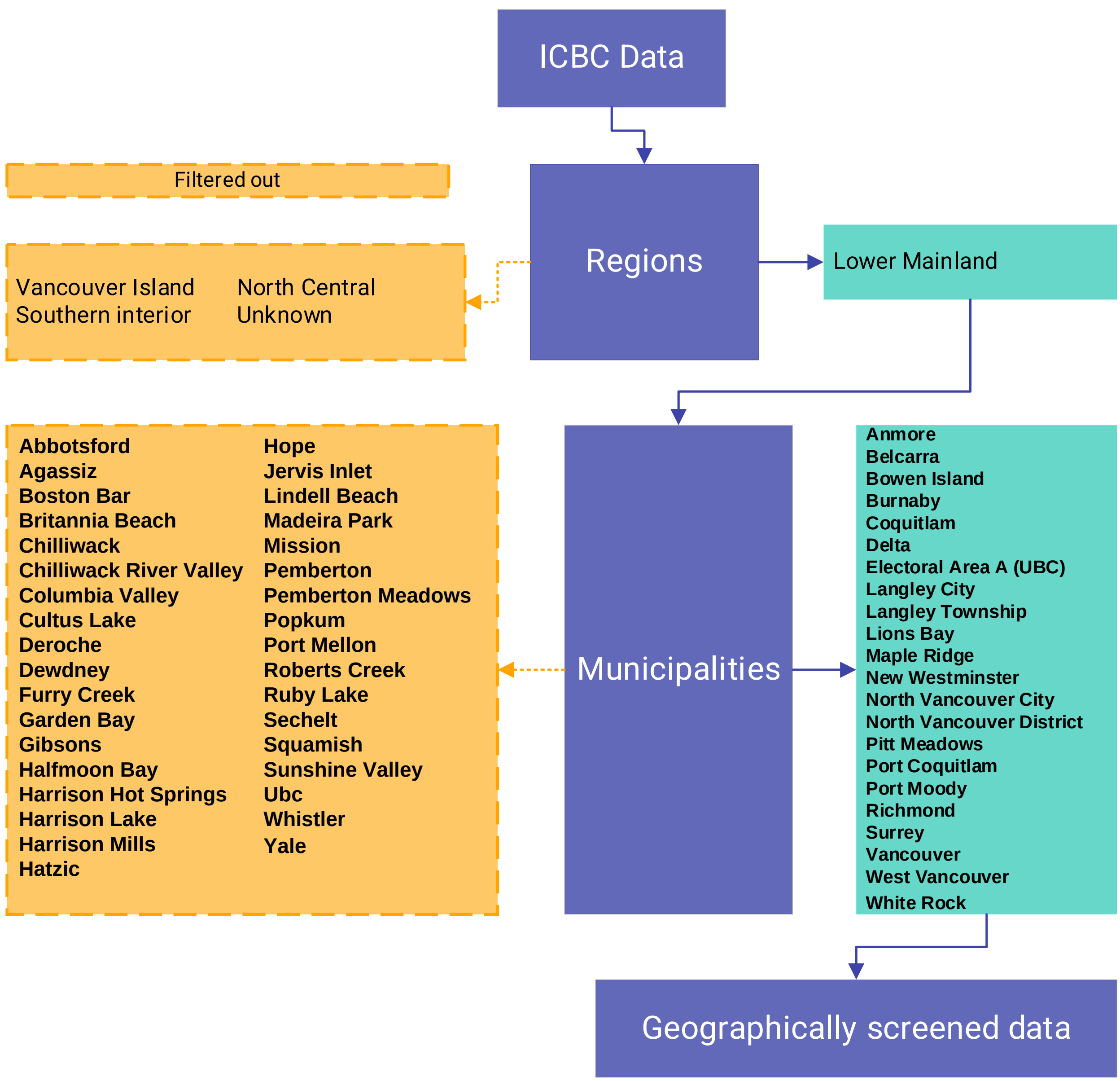


Figure 14: Geographically screening of the data

Furthermore, the data does not account separately for total Electoral Area A (partial data available as UBC) or the Tsawwassen First Nation treaty lands (Included with Delta), and it aggregates the District and City of North Vancouver as well as the City and Township of Langley, limiting the ability to analyze these areas separately. Additionally, if postal code information is available within the dataset, a more precise geographical screening can be conducted using spatial analysis software such as ArcGIS Pro. In this approach, a shapefile containing the administrative boundary of the Metro Vancouver region can be used in conjunction with the ICBC dataset. By performing a Spatial Join using the Geoprocessing Toolbox in ArcGIS Pro, vehicles can be spatially filtered to include only those registered within the defined Metro Vancouver boundary. This method enhances geographic accuracy and ensures that only relevant vehicles are considered in the VKT estimation framework.

6.4 Vehicle Type Screening

ICBC records include vehicle registrations for a wide range of vehicle types, making it essential to perform a detailed screening to isolate the subset relevant to the desired vehicle travel. Initially, vehicles are classified into six broad categories: passenger, commercial, motorcycle, utility trailer, motor home, and commercial trailer. However, these high-level categories encompass a wide variety of vehicle body styles. For example, the passenger vehicle category includes 24 distinct body styles, while the commercial category includes 81. Therefore, to accurately represent light-duty vehicles in the VKT estimation framework, a further screening of body styles within the passenger and commercial categories is required. The vehicle types selected through this screening process are those most representative of light-duty passenger and commercial vehicles. Figure 15 illustrates the vehicle type screening procedure used to define the light-duty vehicle population for this study.

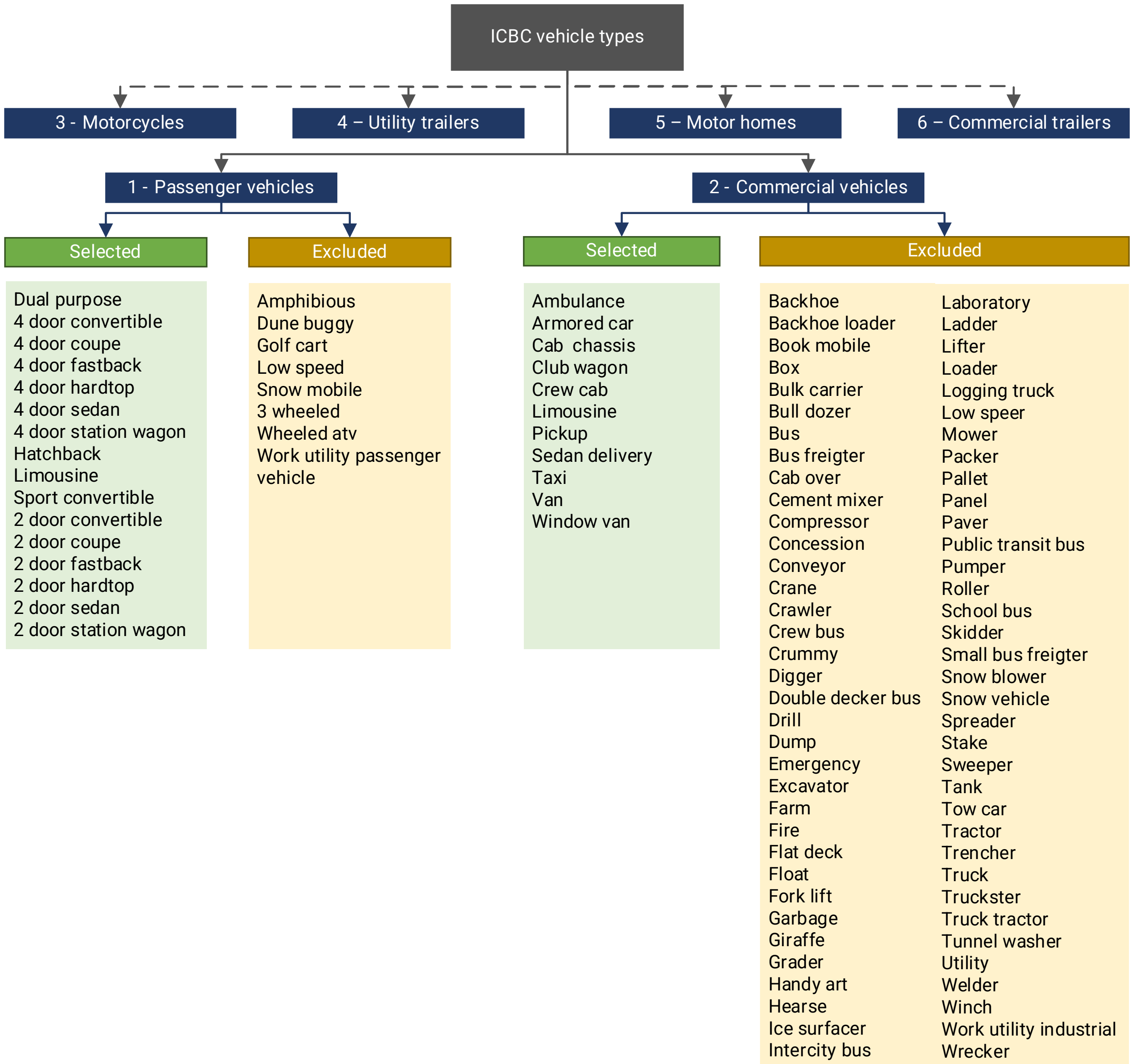


Figure 15: Light-duty vehicle types

6.5 Calculation of the Annual VKT for Each Vehicle

To calculate annual VKT, it is necessary to obtain at least two odometer data points for the same vehicle. This means that each vehicle must have at least two registration records with odometer readings recorded on different dates. It is also important to ensure that all units (such as distance in kilometres and time in days) are consistent across the dataset. The annual VKT can then be calculated using the following equation:

$$Annual\ VKT = \frac{Odometer_{new} - Odometer_{old}}{Measured\ date_{new} - Measured\ date_{old}}\ x\ 365$$

6.6 Vehicle Stratification

To better understand driving patterns across Metro Vancouver, vehicles are stratified based on key characteristics. The distribution of annual VKT is calculated for each combination of these categories. The stratification includes the following:

- Municipality (Municipalities within the Metro Vancouver Region)
- Body type (Coupe, Car, SUV, Truck)
- Vehicle ownership (Passenger or Commercial)
- Fuel type (Gasoline, Electric Vehicle, Hybrid, Plug-in Hybrid Electric Vehicle, Diesel)
- Vehicle age (0-5, 6-10, 11-15, 15-20, 21-25, 26-30, 31-35, 36-40, 40+ years)

This hierarchical grouping enables a targeted analysis. For example, a single branch in the classification tree might represent:

Municipality – Vancouver, Body style – Car, Vehicle ownership – Passenger, Fuel type – Gasoline, Vehicle age – (6-10 years)

For each such branch, the distribution of annual VKT is computed separately along with its descriptive statistics, enabling a granular assessment of vehicle usage patterns across the region. However, depending on data availability and sample size within each group, it may be necessary to reduce the number of stratification variables. If such simplification is required, variables should be removed in the following order: Municipality, then Body type, followed by Fuel type, and finally Vehicle age. Despite this, the goal should be to retain as many characteristics as possible to maintain analytical depth.

6.7 VKT estimation

Spatial aggregation can be conducted in three main steps which are discussed under following subsections.

6.7.1 Identification of Vehicle Counts for Each Stratification Branch

In the first step, the number of vehicles falling under each unique stratification branch defined in the previous stratification tree must be identified and recorded. This involves listing the vehicle counts for every distinct combination of municipality, body style, vehicle ownership, fuel type, and vehicle age.

Examples:

1. Municipality – Vancouver, Body style – Car, Vehicle ownership – Passenger, Fuel type – Gasoline, Vehicle age – (11-15 years) : 120 vehicles
2. Municipality – Vancouver, Body style – Car, Vehicle ownership – Passenger, Fuel type – Gasoline, Vehicle age – (0-5 years) : 12000 vehicles

6.7.2 Reconstructing the Full Annual VKT Distributions for Each Stratification Branch from Truncated ICBC Data

Based on the findings from AirCare data discussed in Subsection 5.2.3, annual mileage for light-duty vehicles in Lower Mainland follows a left-skewed log normal distribution. For vehicles under five years of age, the average mileage was around 14,000 kilometers, with the mileage decreasing slightly as the vehicle age increases. Despite this trend, the dataset also contains vehicles reporting annual mileages of up to 30,000 kilometers. This pattern suggests that the true distribution of annual VKT resembles a log-normal distribution.

However, due to ICBC's distance-based insurance program only applying to vehicles driven less than 15,000 kilometers annually, odometer submissions are expected to be biased. Vehicles driven more than 15,000 kilometers are less likely to report mileage, resulting in a truncated sample.

To address this bias, the following steps are proposed for each stratified data branch:

1. Log Transformation: Take the natural logarithm of the observed (truncated) annual mileage values.
2. Parameter Estimation: Estimate the mean and standard deviation of the logged values.

3. Distribution Reconstruction: Using these parameters, reconstruct the full log-normal distribution for each branch using a statistical function.

This process enables the estimation of the complete VKT distributions, even when the observed data includes only vehicles driven less than 15,000 kilometers annually. The resulting fitted distributions, as illustrated by the red line in Figure 16, represent the inferred complete distribution for each branch. To improve the accuracy of these reconstructed distributions, Maximum Likelihood Estimation (MLE) can be applied. This approach iteratively adjusts the mean and standard deviation of the log-normal model to find the optimal fit, taking into account the effects of truncation.

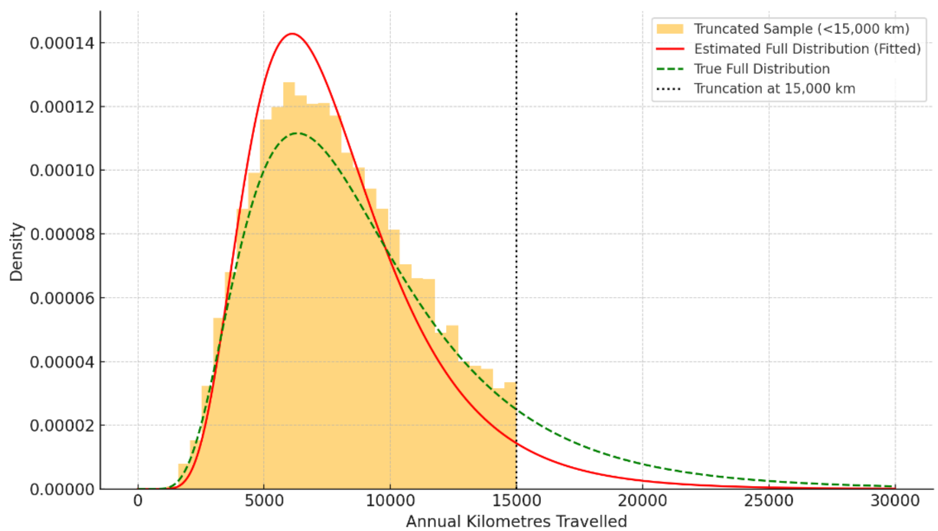


Figure 16: Annual mileage distribution estimation sample

6.7.3 Aggregation of Annual VKT for the Region

To spatially aggregate annual VKT, the first step is to identify all classification branches corresponding to each municipality or region. For example, to estimate the total VKT for the City of Vancouver, all branches classified under "Vancouver" must be extracted from the stratified dataset.

For each of these sub-branches, the reconstructed annual VKT distributions (developed in Section 6.7.2) are modelled. The distributions are then multiplied by the corresponding number of vehicles identified in the same branch (as determined in Section 6.7.1). By summing the estimated VKT across all sub-branches, the cumulative annual VKT for the Vancouver region can be calculated. This process is repeated for each municipality within the Metro Vancouver region, enabling detailed spatial analysis of travel patterns across the region. The following Figure 17 provides the overview of the proposed model framework.

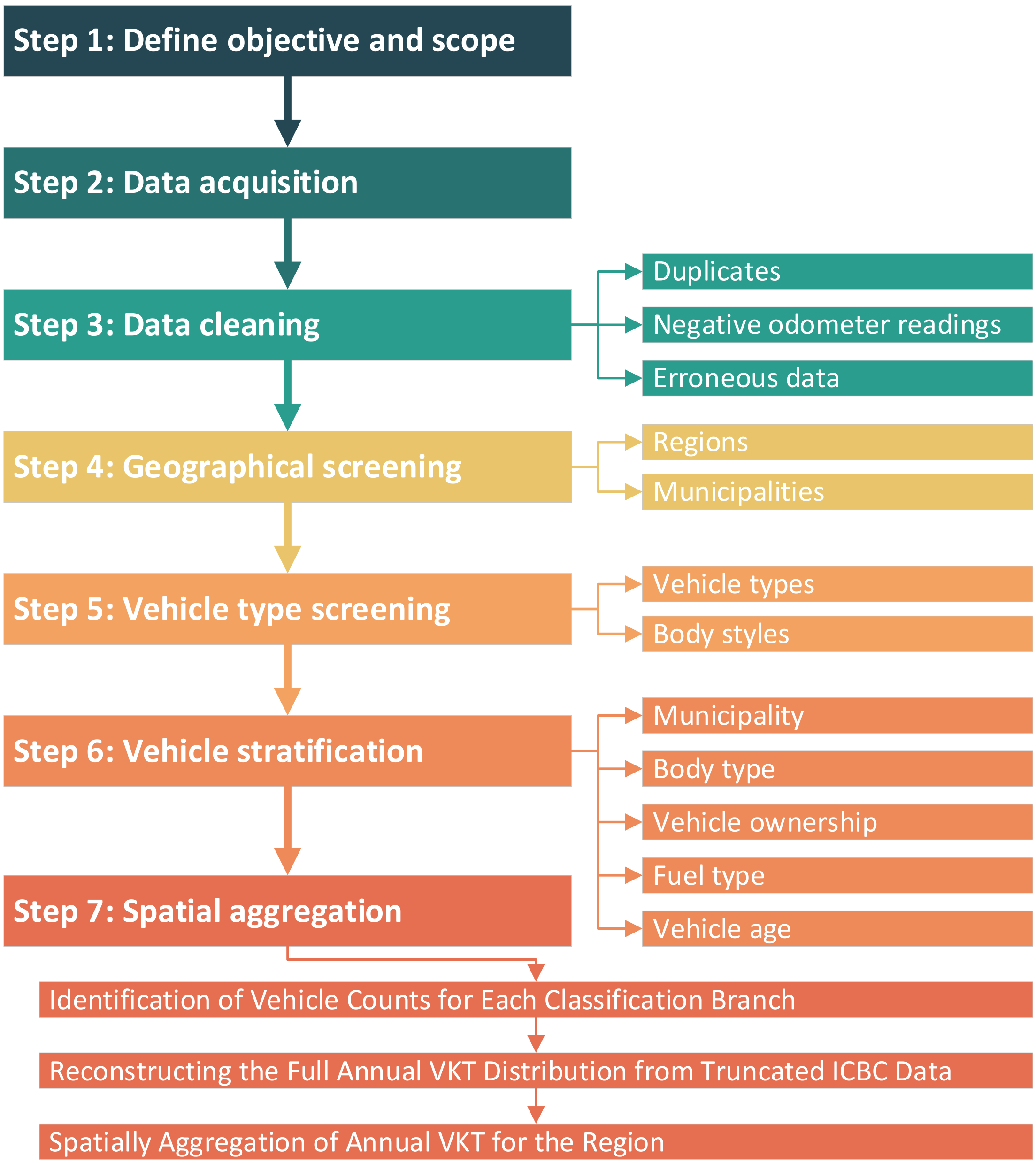


Figure 17: Proposed novel regional VKT estimation framework

Limitations and Directions for Future Research

A key attribution issue in the proposed framework is that vehicle travel is assigned to the municipality of registration rather than where the travel occurs. Metro Vancouver currently uses this approach for GHG emissions on the assumption that the registered address better reflects travel decisions and is more responsive to local transportation policies. For other pollutants (e.g., NOx, PM2.5), emissions are assigned to the road segments where they are emitted. The registration-based approach risks overestimating intra-municipal travel and ignores frequent inter-municipal and inter-regional movements within Metro Vancouver. Spatially aggregated VKT estimates should therefore be interpreted cautiously. Assigning GHGs to the location where travel occurs would require further research.

The methodology could not be fully tested due to data constraints. Estimating annual VKT requires at least two odometer readings per vehicle. ICBC's expanded distance-based insurance program, which began in June 2025, will produce the first reliable set of annual odometer data by mid-2027. While ICBC has offered under-10,000 km annual travel discounts since 2019, this odometer data was not available for the study, preventing validation with real-world measurements. Future research should revisit the methodology once the necessary odometer records are accessible.

The ICBC dataset also has spatial aggregation issues. Certain jurisdictions are merged, such as the City and District of North Vancouver, and the City and Township of Langley, making separate analysis impossible. Data for the Tsawwassen First Nation is included under Delta, and partial data for Electoral Area A is collected under UBC. If ICBC provided registered postal codes, finer spatial disaggregation could be done using GIS techniques.

Alternative VKT estimation methods could also be explored. The 2023 TransLink Trip Diary Survey, which sampled roughly 1.25% of households in the region, could support a machine learning regression model to predict VKT from vehicle characteristics, which could then be applied to the ICBC dataset. This option was considered but not pursued in this study due to limited data access. Fuel consumption–based VKT estimation is another possibility, but it only applies to gasoline vehicles and currently suffers from municipality level fuel data limitations.

Available data covers only provincial fuel consumption, making it unsuitable for estimating VKT at the Metro Vancouver level.

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