Journal of Transport Geography 121 (2024) 104023

Contents lists available at ScienceDirect

Journal of Transport Geography

journal homepage: www.elsevier.com/locate/jtrangeo

# Please mind the gap: Examining regional variations in private vehicle carbon dioxide emissions and fuel consumption—The case of Australia

Kai Li Lim [a,*], Ying Lu [b], Anthony Kimpton [c], Renee Zahnow [d], Tiebei Li [e], Jago Dodson [e], Neil Sipe [f], Jonathan Corcoran [g]

[a] Dow Centre for Sustainable Engineering Innovation, The University of Queensland, Brisbane, Queensland 4072, Australia
[b] School of Civil Engineering, The University of Queensland, Brisbane, Queensland 4072, Australia
[c] School of Surveying and Built Environment, University of Southern Queensland, Springfield, Queensland 4300, Australia
[d] School of Social Science, The University of Queensland, Brisbane, Queensland 4072, Australia
[e] Centre for Urban Research, RMIT University, Melbourne, Victoria 3000, Australia
[f] School of Architecture, Design and Planning, The University of Queensland, Brisbane, Queensland 4072, Australia
[g] School of the Environment, The University of Queensland, Brisbane, Queensland 4072, Australia

ARTICLE INFO

*Keywords:*
Vehicle emissions
Electric vehicles
Geospatial analysis
Australia

ABSTRACT

This study investigates the geographic and annual variations in carbon dioxide ($CO_2$) emissions and fuel consumption generated by private vehicles across Australia's regions over an 18-year period (2002 to 2020). We examine the influence of vehicle numbers, geography, and time on emissions and fuel consumption using spatial analysis alongside panel regression. Emissions remain relatively high in North Queensland, the Northern Territory, and South West Western Australia and Greater Sydney had steepest decline among the metropolitan regions. Modelling results reveal that higher numbers of internal combustion engine vehicles are positively associated with higher $CO_2$ emissions and fuel usage while higher numbers of electric vehicles are negatively associated. This underscores the importance of targeting high-emission regions for transitioning to electric vehicles. The current study provides empirical insights that hold important implications for policymakers concerning the spatial and temporal trends in private vehicle emissions with the potential to inform low-carbon transport planning.

## 1. Introduction

For Australia to achieve the net zero emissions target by 2035, 76 % of all private car sales need to be electric vehicles (EVs) by 2030 (Rachel et al., 2022). This imminent transition from combustion vehicles to EVs necessitates a huge shift in the infrastructure across the nation. With all Australian States and Territories setting sustainable transport targets and preparing for the EV transition, there is an urgent demand for up-to-date, longitudinal spatial data on private vehicle ownership to map, measure and monitor the regions that remain on-track versus those that are lagging. Curating both this database alongside with the associated tools to analyse and visualise these data are an essential national asset to understand the extent to which Australia will likely meet its national 2035 emission target.

Scholarship examining private vehicle ownership in the context of emission reduction and EV transition has received growing attention from transport scholars. Recent studies have explored factors influencing EV adoption, analysed policies to encourage a transition to EVs, and modelled future EV uptake and associated emission reductions (IEA, 2024). However, longitudinal investigations of geographic variations in vehicle emissions at the national scale remain limited. Existing research on geographic variations in vehicle emissions primarily focuses on specific regions, with studies conducted in Europe (e.g., Kazancoglu et al. (2021), Ghaffarpasand et al. (2020), Krecl et al. (2024)), China (e.g., Guo et al. (2024)) and the United States (e.g., Choma et al. (2020)) examining the influence of factors like urbanisation, fuel economy standards, and vehicle age on emissions across different states or countries. While some research has explored national trends in vehicle emissions (e.g., Choma et al. (2021)), longitudinal studies analysing geographic variations within a single nation remain scarce (with

* Corresponding author.
*E-mail addresses:* kaili.lim@uq.edu.au (K.L. Lim), ying.lu@uq.edu.au (Y. Lu), anthony.kimpton@unisq.edu.au (A. Kimpton), r.zahnow@uq.edu.au (R. Zahnow), tiebei.li@rmit.edu.au (T. Li), jago.dodson@rmit.edu.au (J. Dodson), n.sipe@uq.edu.au (N. Sipe), jj.corcoran@uq.edu.au (J. Corcoran).

https://doi.org/10.1016/j.jtrangeo.2024.104023
Received 4 March 2024; Received in revised form 10 September 2024; Accepted 1 October 2024
Available online 16 November 2024

exceptions like Wen et al. (2023)). This limited understanding hinders our ability to assess the effectiveness of national policies in addressing emission variations across different regions within a country.

What remains far less evident in current scholarship is a national longitudinal understanding of the private vehicle fleet alongside an appreciation of geographic patterns. Underpinning this gap is the general lack of disaggregated, spatially explicit data on private vehicle fleets and their associated emission characteristics. The need for such data and associated analysis of this information is of critical importance as nations around the world seek to rapidly transition their vehicle fleets and meet ambitious emission targets.

The aim of the current study is to examine the evolution of Australia's private vehicle fleet in relation to $CO_2$ emissions and fuel consumption. More specifically, we investigate how private vehicle ownership across Australia's regions has shifted over an 18-year period (2002−2020) and to explore how this has shaped $CO_2$ emissions and fuel consumption. To this aim, we draw on newly released private vehicle registration data from the Bureau of Infrastructure and Transport Research Economics (BITRE) (Australian Government, 2022), and integrate these with information from the Green Vehicle Guide (GVG)[1] (Australian Government, 2023a). By employing spatial analysis alongside panel regression, we first map before modelling regional shifts in $CO_2$ emissions and fuel consumption over 18 years. The goal is to provide up-to-date spatial and temporal insights on private vehicle $CO_2$ emissions and fuel consumption with the capacity to inform emissions reduction policies around Australia's transition to electric vehicles. This longitudinal spatial data allows for the first time, measuring, mapping, and monitoring of private vehicle ownership by make, model, energy use and emissions. Outcomes from our analysis offer new empirical evidence at the national and regional level highlighting trends and tracking progress towards Australia's 2035 net zero target. In doing so we advance current scholarship which has lacked a national level understanding of private vehicle fleet efficiency and emissions over time and across regions.

## 2. Background

Australian cities are among the most car dependent in the developed world outside of the United States. This pattern of dependence on automobiles has been the subject of research and analysis since the 1980s (Newman and Kenworthy, 1989). Such inquiry has identified an array of problems arising from excessive reliance on automobiles, including dependence on fossil fuel imports, congestion, dispersed land-uses, inequitable spatial distributional effects, poor provision of public transport, pollution and perhaps most importantly carbon emissions.

Road transport is one of the worst sectoral contributors to climate forcing (Unger et al., 2010; Australian Government, 2024b), second only to electricity generation. Although the pace of change is not as fast as recommended by climate science to avoid dangerous climate effects there is evidence the transition to non-fossil-fuel electricity generation is accelerating. In Australia there is a rapid shift currently underway as coal-powered electricity generation closes down with new capacity supplied by renewables.

In 2018, Australia's light vehicle fleet was composed predominantly of passenger vehicles, making up 78 % of the fleet, with light commercial vehicles accounting for 17 % and motorcycles for 5 %. This composition reflects a strong preference for petrol engines, particularly in passenger vehicles, where 86 % were petrol-powered (Australian Government, 2021). The Australian market has seen significant growth in SUVs, with their share of the passenger and light commercial vehicle fleet increasing from 17.6 % in 2013 to 25.3 % in 2018. This trend mirrors that of the United States, where SUVs and light trucks have come to dominate the vehicle fleet, representing around 76 % of new vehicle sales as of 2020 (U.S. Department of Energy, 2022). However, the situation contrasts with Europe, where smaller passenger cars remain more prevalent; in 2022, SUVs accounted for approximately 49 % of new car sales in Europe (ACEA, 2023), reflecting a market shaped by higher population densities, narrower roads, and stricter environmental regulations. Japan, on the other hand, features a significant proportion of smaller, highly fuel-efficient vehicles, including Kei cars, which constitute over 30 % of the Japanese vehicle fleet (JAMA, 2023).

In contrast, the uptake of zero carbon emissions motor vehicles (ZEVs) is not occurring at a comparable pace. Most such vehicles are expected to be EVs with a much smaller contribution to fleet decarbonisation by fuel-cell hydrogen vehicles (FCEVs). In 2022 14 % of global vehicle sales were of EVs, predominantly in China. Under its 'stated policies' scenario based implemented policies, the IEA (2023) projects that EVs will comprise 10 per of the global vehicle fleet by 2030 comprising 240 million vehicles.

In 2023, EV sales in Australia surged to nearly 100,000 units, representing 8.5 % of all new vehicle sales. This marked a significant increase from 40,000 in 2022, when EVs made up 3.8 % of total sales, and a far cry from fewer than 5000 EVs sold in 2018, which accounted for just 0.2 % of the market (Electric Vehicle Council, 2024). This growth has been bolstered by government initiatives, such as rebates and incentives, and the introduction of a National Electric Vehicle Strategy (Australian Government, 2023b) and the New Vehicle Efficiency Standard (Australian Government, 2024a). These measures have contributed to a more favourable environment for EV adoption, signalling a shift in Australia's approach to the EV transition. Although Australia has historically lagged in global EV uptake, the recent policy changes and market dynamics indicate a more promising trajectory moving forward. Despite this progress, Australia is still regarded as trailing behind comparable markets like the United States, where EVs accounted for 10 % of vehicle sales in 2023 (IEA, 2024).The US has long benefited from strong federal support, including tax credits and stricter fuel efficiency standards, which have accelerated the adoption of EVs.

Policy debates about the EV transition in Australia have seen significant developments recently. The Federal Government has now introduced the National EV Strategy and is implementing new vehicle efficiency standards, reflecting a more cohesive approach to electrification across the country. However, challenges remain, as the consultation and drafting of these national policies have not fully settled the debates surrounding EV transition.

Meanwhile, state and territory governments have taken proactive steps between 2020 and 2024, developing EV strategies that include a mix of subsidies or rebates for EV purchases, investments in charging infrastructure, transitioning government fleets to EVs, rolling out EV public transport buses, and introducing road user charges to partially offset the loss of federal fuel excise revenue. These strategies are being applied to varying degrees across the country, contributing to the growth in EV adoption.

Regulation of ICEV emissions plays a critical role in the transition to EVs. The New Vehicle Efficiency Standard, which applies at the importation point, remains a federal responsibility. Despite extensive debate in Australia regarding the establishment of fuel economy requirements for conventional vehicles, such policies have only recently begun to take shape. Concerns persist about the potential for "dumping" older, less efficient vehicle models in Australia—models that would not meet stricter fuel economy standards in other countries.

The introduction of the New Vehicle Efficiency Standard represents a significant step forward in Australia's approach to reducing emissions from ICEVs. This standard directly addresses longstanding concerns about fuel economy by implementing regulations like those in other major markets like California. The standard is designed to ensure that new vehicles imported into Australia meet progressively stricter fuel efficiency criteria, helping to prevent the importation of older, less

[1] The Green Vehicle Guide (GVG) is a Federally operated tool comparing the environmental performance and fuel consumption of all light vehicles (up to 3.5 t gross vehicle mass) that have been sold in Australia since 2004.

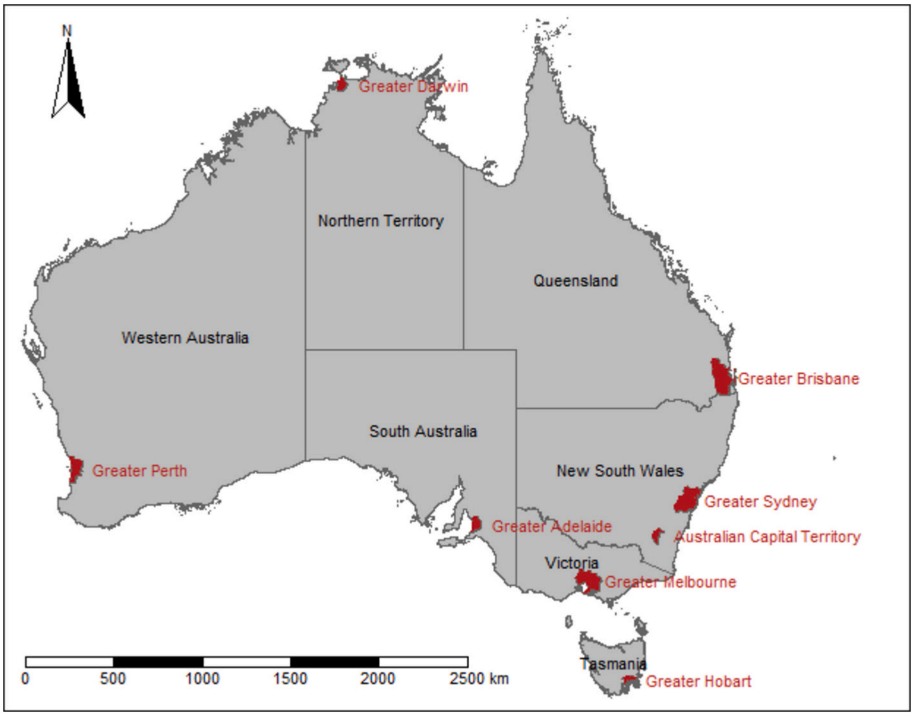


**Fig. 1.** The case study context.

efficient models that would not comply with regulations in comparable international markets.

An important question in the analysis of ICEV fuel economy is the availability of high-quality data that can depict fuel consumption and emissions patterns. Historically, data has been available for research use through the ABS Census of Motor Vehicles (Australian Bureau of Statistics, 2021), which reported detailed data on make and manufacture of motor vehicles based on state and territory registration agency data, disaggregated to the suburban and postcode spatial scales. Since 2021, the ABS no longer publishes this data, a task that has been taken up by the Bureau of Infrastructure, Transport and Regional Economics (Australian Government, 2022), using similar raw data. After a lacuna of almost two years this data is now available for research use. This registration data can be matched to the federal government's 'Green Vehicle Guide' dataset (Australian Government, 2023a), which is a national collation of fuel economy and related data disaggregated by vehicle make, model and variant. This matching augment the vehicle registration dataset and allows for more sophisticated analysis, including spatial analysis at suburb and postcode levels. In addition, this data is available for the period 2002–2020 allowing for both spatial and longitudinal investigation.

While there has been some interest in fuel economy policy issues in Australia the spatial research base on this topic is patchy. Li et al. (2013) investigated socio-spatial fuel efficiency patterns in Brisbane, finding a modest correlation between vehicle fuel consumption and household socio-economic status. Li et al. (2015) found comparable patterns in Sydney to those in Brisbane, whereby wealthier inner urban households tended to own newer more fuel-efficient vehicles whereas lower income outer urban households tended to own older less fuel-efficient vehicles. Similar patterns Li and Dodson (2020) found were also associated with higher commuting cost burdens in Melbourne such that outer suburban residents who used cars tended to face higher commuting costs than those in inner urban areas who were able to access public transport.

The recent availability of disaggregated motor vehicle fuel economy data matched with the green vehicle guide, plus the adoption of more sophisticated computational analysis allows for more comprehensive analysis of fuel economy patterns. The present research initiates this effort by compiling the fuel economy data for the greater capital city and rest of state (or territory) geographies across mainland Australia and Tasmania. With the addition of a temporal dimension, it is possible to observe in detail the fuel economy of motor vehicles over the 18-year period. This comprehensive perspective provides a high-level overview in advance of more detailed post-code level analysis. The remainder of this paper presents the results of our data compilation and spatial analytical approach.

## 3. Case study context

The case study presented in this research focuses on six major metropolitan regions in Australia, namely Greater Perth, Greater Darwin, Greater Brisbane, Greater Sydney, Greater Melbourne, and Canberra, along with the capital city of Tasmania, Greater Hobart. These regions have been selected as they represent key urban centres that are at the forefront of Australia's efforts to transition to a more sustainable and environmentally responsible transportation system (Fig. 1).

1. **Greater Perth:** Greater Perth is the capital and largest city of Western Australia, situated on the country's western coast. As a major economic hub, Greater Perth plays a vital role in the state's economy, and its transportation sector has a significant impact on carbon emissions. The region's efforts towards sustainable transportation are driven by the need to reduce its carbon footprint and contribute to the broader national goal of achieving net-zero emissions by 2035.
2. **Greater Darwin:** Located in the Northern Territory, Greater Darwin is the capital and largest city in the region. The city is known for its unique natural environment and cultural diversity. As the gateway to Australia's northern territories, Greater Darwin's transportation sector faces specific challenges related to long distances, remoteness, and infrastructure development. The case study in this region aims to understand how sustainable transportation solutions can be integrated into its unique urban landscape.
3. **Greater Brisbane:** Greater Brisbane is the capital of Queensland, Australia's third most populous state. The region's transportation

**Table 1**
Multi-field join rate between BITRE Vehicle registrations and GVG vehicle characteristics.

| Multi-Field Join | | | | | | BITRE rows | | BITRE vehicle count | |
|---|---|---|---|---|---|---|---|---|---|
| Number of fields | Model release year | Make | Model | Cylinders | Fuel Class | N | % | n | % |
| 5 | TRUE | TRUE | TRUE | TRUE | TRUE | 1,054,185 | 30.8 | 6,575,292 | 35.5 |
| 4 | TRUE | TRUE | FALSE | TRUE | TRUE | 1,355,742 | 39.6 | 7,593,233 | 41 |
| 3 | TRUE | FALSE | FALSE | TRUE | TRUE | 476,792 | 13.9 | 1,996,880 | 10.8 |
| 3 | TRUE | TRUE | FALSE | FALSE | TRUE | 316,975 | 9.2 | 1,587,460 | 8.6 |
| 2 | TRUE | FALSE | FALSE | FALSE | TRUE | 223,852 | 6.5 | 749,725 | 4.1 |
| | | | | | | 3,427,546 | 100 | 18,502,590 | 100 |

system is vital for supporting economic activities and accommodating a growing population. As one of the major urban centres with high vehicle ownership rates, the study in Greater Brisbane seeks to identify opportunities and challenges in transitioning to electric vehicles and achieving emissions reduction targets.

4. **Greater Sydney:** Greater Sydney is the largest and most populous metropolitan region in Australia, encompassing Sydney, the country's most iconic city. The transportation sector in Greater Sydney is a significant contributor to greenhouse gas emissions, and the study in this region aims to explore how sustainable transportation policies and infrastructure can be effectively implemented to drive the transition towards electric vehicles and sustainable mobility solutions.
5. **Greater Melbourne:** Greater Melbourne is the capital and most populous city in the state of Victoria. The region is known for its vibrant cultural scene, economic diversity, and sprawling urban landscape. As a densely populated urban centre, Greater Melbourne's transportation sector is under scrutiny to contribute to emissions reduction and promote a cleaner and greener future for its residents.
6. **Canberra:** As the capital city of Australia, Canberra plays a crucial role in shaping national policies and initiatives. The region is known for its well-planned urban layout and commitment to environmental sustainability. The study in Canberra aims to understand how policy frameworks and government leadership can drive the adoption of electric vehicles and contribute to the achievement of national emission reduction targets.
7. **Greater Hobart:** Greater Hobart is the capital and largest city of Tasmania, renowned for its natural beauty and unique environmental heritage. The region's transportation system faces the challenge of integrating sustainable mobility solutions while preserving its pristine natural environment. The study in Greater Hobart seeks to explore how electric vehicles can be effectively incorporated into the city's transportation infrastructure and contribute to its emission reduction goals.

The six metropolitan regions represent diverse urban contexts across Australia. This study focuses on these major population centres as they play central roles in Australia's efforts to transition to more sustainable transportation systems. By examining trends and patterns in these urban regions, this study aims to provide insights into the progress and challenges faced in reducing transport-related emissions through electric vehicle adoption and other measures.

The spatial unit of analysis is the postal area (postcode), of which there are 2644 covering Australia (Australian Bureau of Statistics, 2021-2026). Using postal area geography allows for a fine-grained spatial analysis of vehicle emissions and associated trends across the urban and regional areas included in the study. Examining emissions changes at this local level provides a nuanced understanding of where progress is occurring versus lagging across the country.

## 4. Data and methods

To investigate the evolution of the private car fleet's $CO_2$ emissions and fuel consumption across Australia's regions, a data linkage was performed between the BITRE new vehicle registrations and the GVG $CO_2$ emissions and fuel consumption data. However, merging these two datasets posed several challenges due to differences in their coverage and structure.

The BITRE dataset includes vehicle registrations up to January 2023, whereas the GVG dataset only contains data up until 2020. Additionally, the two datasets differ in their classifications of vehicle fuel types. The GVG dataset includes 14 distinct fuel types, while the BITRE registrations categorise vehicles into 4 broader fuel classes. As such, a straightforward merge between the two datasets was not possible without mapping the fields accordingly. This process required careful handling, as certain vehicle makes and models were either discontinued by 2020 (after the GVG data cutoff) or otherwise not listed in the GVG dataset. This resulted in some vehicles being excluded from the analysis, particularly newer models registered after 2020. To maximise the join rate, the 14 fuel types in the GVG were mapped to the 4 broader classes within the BITRE dataset (Appendix A). The key fields used for joining were make, model, model release year, cylinders, and fuel class. As shown in Table 1, progressively dropping certain fields improved the join rate, but not all vehicles could be matched.

An inner join was employed to merge the datasets, ensuring that only vehicles present in both datasets were included in the analysis. Naturally, this led to the exclusion of vehicles for which either dataset did not contain relevant information. In total, 69.2 % of the BITRE rows could not be matched using all five fields, primarily due to unmatched makes and models between the datasets, missing entries for certain vehicle types, and the limited overlap of GVG data ending in 2020. This exclusion is a known limitation of inner joins, and the areas of mismatch between the datasets resulted in data loss.

- **Join Rate:** Table 1 summarises the results of the multi-field join between the BITRE and GVG datasets. When all five fields matched, we were able to successfully join 30.8 % of rows in the BITRE data, covering 35.5 % of registered vehicles. By progressively relaxing the join criteria (e.g., dropping the model field), we were able to join additional rows, reaching 39.6 % of the data with four matching fields and 41 % of the vehicle count.
- **Impact on the Data:** Some vehicles could not be matched due to missing makes or models in either the BITRE or GVG datasets. For example, vehicles registered after 2020 in BITRE naturally had no corresponding GVG data. In total, 69.2 % of the BITRE rows could not be matched using all five fields, but by relaxing the criteria, we were able to assign characteristics to the majority of the data (Table 1). This resulted in the final dataset reflecting a reasonable sample of the overall vehicle fleet, with the majority of unmatched vehicles accounted for through subsequent analytical methods.

To account for vehicles that could not be matched using the full five-field join, we adopted a progressive approach. After progressively relaxing the join criteria, we calculated average $CO_2$ emissions and fuel consumption values from the GVG dataset for the unmatched vehicles (Appendix B). These averages were then applied to the unmatched BITRE records to ensure the analysis captured the best possible estimates for the registered vehicles. This method ensured that the majority of unmatched vehicles were still represented in the final dataset through the application of average characteristics, mitigating the potential bias introduced by data loss. In Appendix C, we show that the average $CO_2$ emissions and fuel consumption per vehicle remained almost perfectly correlated over time, regardless of whether urban or extra-urban running conditions were considered. Thus, for the remainder of the analysis, we focus primarily on $CO_2$ emissions, with the assumption that fuel consumption would yield similar insights. This approach minimised bias introduced by missing data and allowed us to conduct a robust analysis.

The emissions model combines reported $CO_2$ data from the GVG with vehicle registration numbers and characteristics from BITRE. The following assumptions are made:

1) $CO_2$ emissions remain constant over the lifetime of a vehicle.
2) Driving patterns and vehicle maintenance remain constant over the analysis timeframe.

Given the high correlation between fuel consumption and $CO_2$ emissions ($r = 0.999$), we focused primarily on $CO_2$ emissions, assuming that modelling fuel consumption separately would offer limited additional insights. The model does not account for changes in engine wear, congestion, or shifts in consumer behaviour over time, which are acknowledged as limitations.

### 4.1. Limitations

Despite our best efforts to align the datasets and account for missing data, several limitations remain that may impact the accuracy and comprehensiveness of the findings.

Firstly, the analysis is based solely on vehicle registration data and does not take into account how far each vehicle was driven per year, or under what driving conditions (e.g., urban vs rural, traffic congestion, or terrain). This absence of usage data limits the accuracy of the $CO_2$ emission estimates, as vehicles with higher annual mileage would naturally produce more emissions than those driven less frequently. The focus of the analysis is exclusively on new vehicle registrations, meaning that older vehicles already in operation are not included. Therefore, the analysis does not account for the existing vehicle fleet or vehicles that were retired during the study period. As a result, the analysis only captures the emissions of newly registered vehicles, which limits the scope of understanding of $CO_2$ emissions across the entire vehicle fleet in Australia. Older vehicles, which may have higher emissions due to wear and outdated technology, are thus excluded from the dataset.

Another limitation relates to the accuracy of the GVG data. The GVG dataset, which forms the basis of $CO_2$ emission estimates, may have been subject to inaccuracies, particularly with internal combustion engine vehicles, due to cheat devices and software manipulation by manufacturers. Such practices were widely reported in the early 2010s and could affect the reliability of the $CO_2$ and fuel efficiency figures used in this study. Although these limitations are difficult to quantify, we assume that any inaccuracies are distributed evenly across the dataset, thereby minimising systematic bias. Moreover, the dataset ends in 2020, before the significant rise in the adoption of EVs in Australia. As a result, the analysis does not fully capture the impact of the growing EV market on overall $CO_2$ emissions, especially between 2021 and 2023, when key EV policies and incentives were introduced. This gap in the data may lead to an underestimation of the recent shifts in the market towards lower emissions due to the increasing presence of EVs on Australian roads.

Finally, geographical factors such as public transport availability are not accounted for in this analysis, which could affect $CO_2$ emissions in certain postcodes. Regions such as Sydney with well-developed public transport networks may have lower private vehicle usage, and therefore lower per-capita $CO_2$ emissions, compared to areas where private cars are the dominant mode of transport. Moreover, there may be discrepancies between where vehicles are registered and where they are primarily operated, especially for fleet vehicles or individuals who register cars in lower-tax regions but use them in urban areas.

### 4.2. Spatial analysis

To detect and visualise spatial autocorrelation of $CO_2$ emissions across Australian postal areas, the Local Indicators of Spatial Association (LISA) analysis (Anselin, 1995) was selected for its robustness in identifying clusters and outliers in spatial data. LISA allows for a nuanced understanding of how the $CO_2$ emissions of a particular region relate to its surrounding areas. By using this method, we can identify four distinct spatial patterns: High-High (clusters of high emissions surrounded by high-emission regions), High-Low (regions of high emissions surrounded by low-emission areas), Low-High (areas of low emissions surrounded by high-emission regions), and Low-Low (clusters of low emissions). This method offers the advantage of not only detecting global trends but also highlighting significant local variations. The choice of LISA was particularly motivated by its ability to handle the large spatial units of Australia's postal areas, which vary greatly in size, some covering vast rural areas with relatively few vehicle registrations. Specifically, High-High indicates an area with a high level of $CO_2$ emissions surrounded by high $CO_2$ emissions areas. High-Low means an area with a high level of $CO_2$ emissions surrounded by low $CO_2$ emissions areas. Low-High means an area with a low level of $CO_2$ emissions surrounded by high $CO_2$ emissions areas. Low-Low represents an area with a low level of $CO_2$ emissions surrounded by low $CO_2$ emissions areas.

### 4.3. Panel regression

To quantify the relationship between vehicle types (diesel, petrol, EVs, and hybrid vehicles) and $CO_2$ emissions, we employed a panel regression model, accounting for both spatial and temporal variations across Australia's regions from 2002 to 2020. This choice was made to address the complexities of modelling $CO_2$ emissions over time, while controlling for regional characteristics. The panel regression model allows for both fixed and random effects to be estimated, helping to disentangle time-invariant regional differences from national trends in vehicle emissions. Fixed effects models were particularly useful in controlling for unobserved heterogeneity within regions, while random effects models offered insights into the influence of varying vehicle types and other covariates across regions. The equation is shown below:

$$
\begin{aligned}
ln(C_{it}) = {} & \beta_0 + \beta_{DV} ln(DV_{it}) + \beta_{PV} ln(PV_{it}) + \beta_{EV} ln(EV_{it}) + \beta_{HV} ln(HV_{it}) \\
& + \beta_{2003} Y_{2003} + \beta_{2004} Y_{2004} + \beta_{2005} Y_{2005} + \beta_{2006} Y_{2006} + \beta_{2007} Y_{2007} \\
& + \beta_{2008} Y_{2008} + \beta_{2009} Y_{2009} + \beta_{2010} Y_{2010} + \beta_{2011} Y_{2011} + \beta_{2012} Y_{2012} \\
& + \beta_{2013} Y_{2013} + \beta_{2014} Y_{2014} + \beta_{2015} Y_{2015} + \beta_{2016} Y_{2016} + \beta_{2017} Y_{2017} \\
& + \beta_{2018} Y_{2018} + \beta_{2019} Y_{2019} + \beta_{2020} Y_{2020} + \beta_{GA} GA_i + \beta_{GB} GB_i \\
& + \beta_{GD} GD_i + \beta_{GH} GH_i + \beta_{GM} GM_i + \beta_{GP} GP_i + \beta_{GS} GS_i \\
& + \beta_{RNSW} RNSW_i + \beta_{RNT} RNT_i + \beta_{RQ} RQ_i + \beta_{RSA} RSA_i + \beta_{RT} RT_i \\
& + \beta_{RV} RV_i + \beta_{RWA} RWA_i + V_i + \varepsilon_{it}
\end{aligned}
\tag{1}
$$

where $C_{it}$ and $F_{it}$ denote the average $CO_2$ emissions per car on postcode $i$ in period $t$. The vector $\beta_{DV}$, $\beta_{PV}$, $\beta_{EV}$, and $\beta_{HV}$ represent the total number of diesel vehicles, petrol vehicles, EVs and hybrid vehicles respectively on postcode $i$ in period $t$. $Y_{2003} \sim Y_{2020}$ denote the year as dummy variables; $\beta_{GA} \sim \beta_{RWA}$ are the dummy variables indicating if a postcode $i$ is within these Greater Capacity City Statistical Areas (GCCSAs). The random effects estimator assumes that the individual-specific effects $V_i$ are independent of the explanatory variables, while

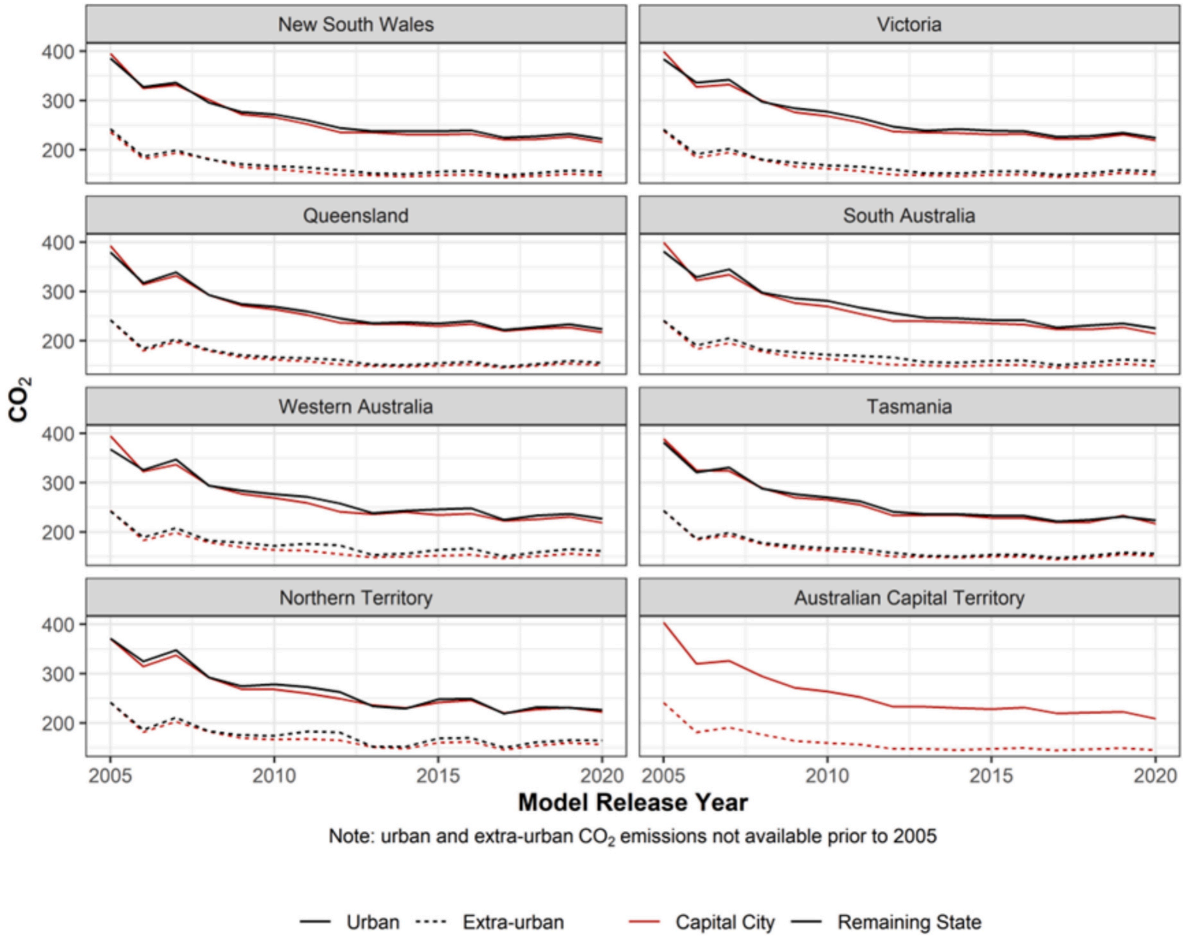


**Fig. 2.** Weighted average $CO_2$ emissions (g/km) by year (2005–2020).

the fixed effectives estimator assumes that there is a correlation between them.

A log-linear form is adopted for the total number of diesel vehicles, petrol vehicles, EVs, and hybrid vehicles, indicating that the coefficients associated with these four variables represent their elasticity. The use of a log-linear form allows for the interpretation of the coefficients as percentage changes in the CO2 emissions.

The panel regression analysis extends beyond a simple cross-sectional model by capturing both longitudinal and cross-regional variations in $CO_2$ emissions. Our use of fixed and random effects estimators ensures that time-invariant regional characteristics, such as geographic constraints or long-standing regional policy differences, do not confound our results. The significance of the Hausman test indicated that fixed effects models provide a more accurate estimation of the data by addressing within-region variations. Additionally, the log-linear form was chosen for its interpretability, allowing us to express the estimated coefficients as elasticities, meaning they reflect percentage changes in $CO_2$ emissions in response to percentage changes in the number of vehicles.

## 5. Results

### *5.1. Descriptive analysis*

Fig. 2 contrasts urban and extra-urban results within Great Capital Cities where urban conditions are more commonplace to the remaining state where extra-urban conditions would be relatively commonplace. This reveals a general decline in average $CO_2$ emissions with sharp decline occurring in 2007 across all states, and further sharp decline within the Northern Territory in 2016. The average $CO_2$ emissions of new cars purchased within Greater Capital City areas are generally lower than the remainder of the state, and this distinction for South Australia, Western Australia and the Northern Territory is especially evident in 2012 outside the greater capital city areas.

Figs. 3 to 5 reveal the spatial trends in $CO_2$ emissions throughout all Australian states. Fig. 3 reveals that there was greater spatial variability in the average $CO_2$ emissions of newly purchased cars in the earlier years however this has declined to a comparable average throughout Australia over time. There is also a general lag within postcodes located further from the capital cities, which is to be expected where a greater proportion of registered vehicles could be larger vehicles to support agricultural activities.[2]

Fig. 4 compares average $CO_2$ emissions against the average from the previous year $\left(\left(Y_{current} - Y_{previous}\right)/Y_{previous}\right)$. The warmer shading for the inland postcodes from 2005 to 2007 explain the sudden rise observed within Fig. 2 around this period and indicate this was spatial dispersed away from capital cities. Further, this countertrend has stopped by 2007 within the eastern states of Queensland, New South Wales, and Victoria. Another key distinction is a widespread decline throughout Australia for 2004, 2008, 2013, and 2017 that could suggest change in vehicle standards or the availability of greater numbers of greener vehicles.

Australian postcodes vary considerably in size with several

[2] Interactive versions of the choropleth maps (Figs. 3 to 5) are available online. Users can interact with these maps, zoom into specific regions, and filter by year to observe temporal and regional patterns in vehicle emissions. Access the interactive maps at https://uq.mu/rl55z.

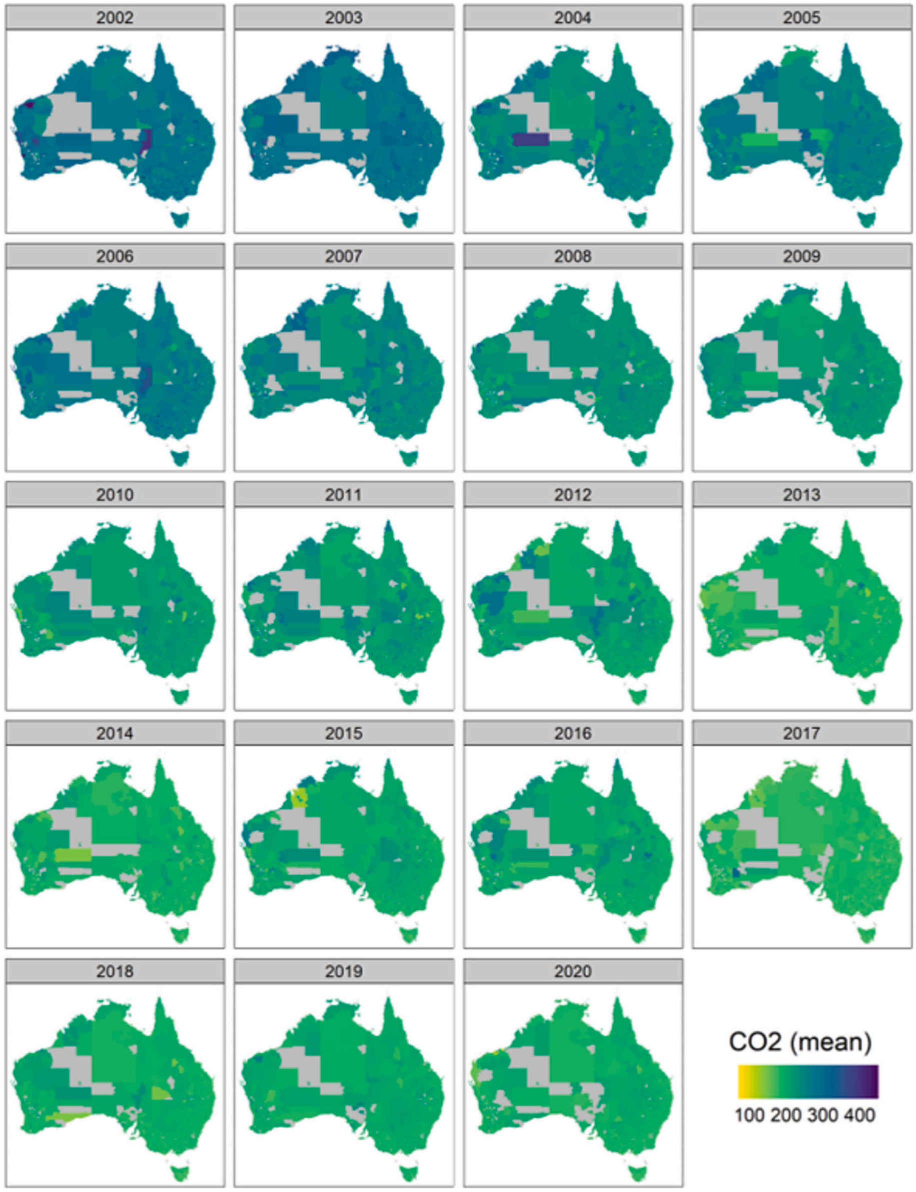


**Fig. 3.** Average $CO_2$ emissions (g/km) by postal area and year (2002 to 2020) throughout Australia.

exceeding the size of countries such as the United Kingdom so a Local Indicators of Spatial Autocorrelation can reveal whether these are likely to be actual spatial trends.

The facet maps in Fig. 5 are predominantly high-high values (orange) which reveals that the average $CO_2$ emissions are higher than expected based upon the nearest neighbouring postcode areas and that this spatial association is statistically significant ($p < 0.1$). These postcodes are typically throughout the eastern states of Queensland, New South Wales, and Victoria. High-low values (purple) are less common and indicate postcode areas where the average $CO_2$ emissions is significantly higher than neighbouring postcodes that generally have lower values—a statistically significant spatial countertrend—and these are predominantly located within Western Australia away from the state capital of Perth. Low-low (green) postcode areas that indicate lower than expected average $CO_2$ emissions are also uncommon but periodically occur throughout the Northern Territory in 2003, 2009, and 2018. Likewise low-high (blue) postcodes areas that indicate lower than expected average $CO_2$ emissions within generally high regions—another statistically significant spatial countertrend—generally occur within the same regions of the Northern Territory. These are sparsely populated postcodes where a relatively small change in car preferences can reflect a large proportion of the population.

Table 2 summarises key vehicle statistics, revealing a steady increase in hybrid and electric vehicle purchases, particularly within Greater Capital Cities, where these vehicles account for a larger proportion of new registrations compared to the rest of the state. Hybrid and electric vehicle purchases are most common in Greater Hobart and the Australian Capital Territory (Canberra).

### 5.2. Panel regression

Table 3 presents the estimation results of the panel regression models. Coefficients for the average $CO_2$ emissions per vehicle across postcode areas are estimated by using the random effects and fixed effects estimators respectively. Similarly, we estimate the coefficients for total fuel consumption across postcode areas using random and fixed effects estimators respectively. The results of the Hausman test are significant, indicating that the fixed effects estimator is the preferred model. Both estimation results (i.e. random and fixed effects models) are presented for robustness checks.

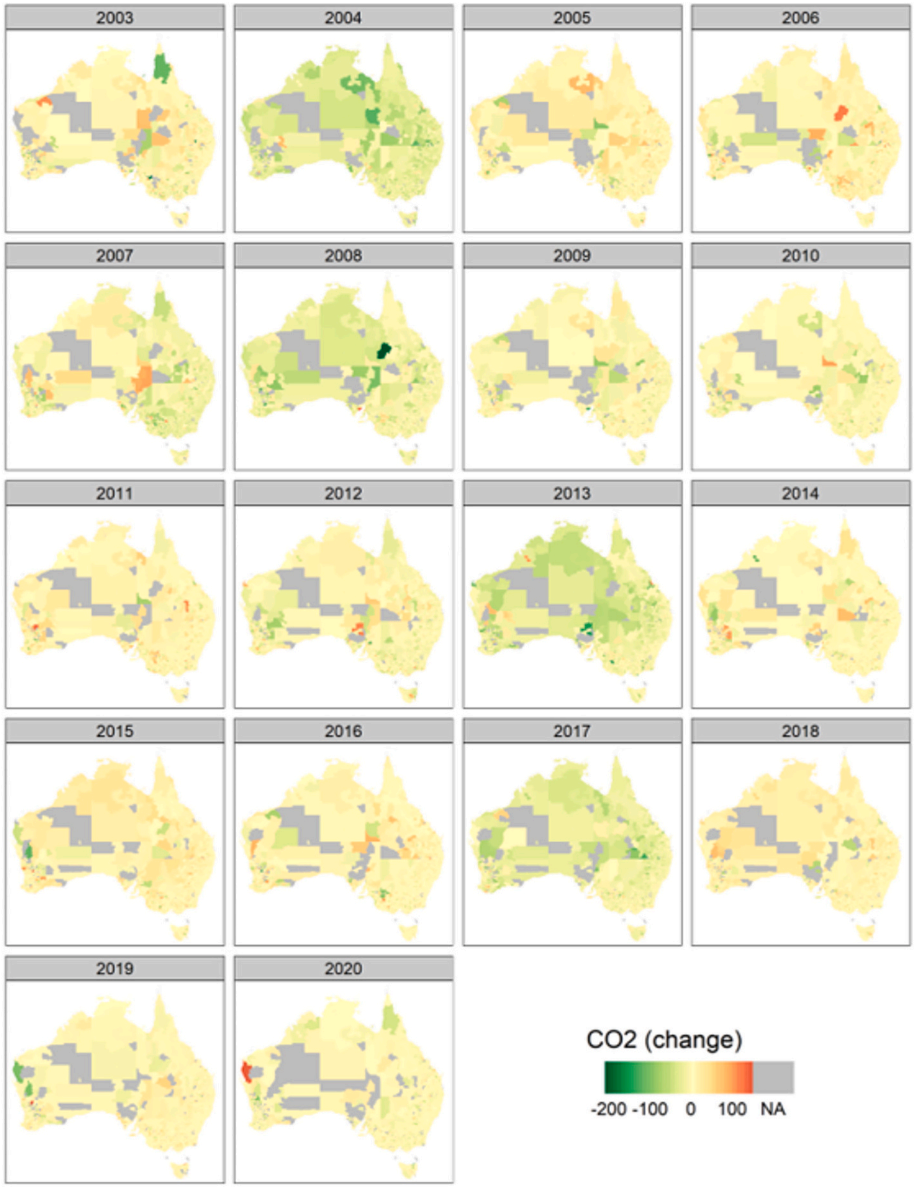


**Fig. 4.** Change to average $CO_2$ emissions (g/km) by postal area and year (2002 to 2020) throughout Australia.

Results indicated that the number of diesel vehicles exhibited a positive relationship with average $CO_2$ emissions per vehicle in both random and fixed effects models. This indicates that $CO_2$ emissions increase with the growing number of diesel vehicles. Specifically, the coefficients of the number of diesel vehicles were 0.020 and 0.016 in the fixed and random effects models, respectively. These findings suggest that a 1 % increase in the number of ICEs result in a 0.020 %–0.016 % increase in the average $CO_2$ emissions per vehicle. These findings are aligned with the existing literature which also identified that the level of $CO_2$ emissions increase with an increase of the number of vehicles (e.g., Jochem et al., 2015; Krause et al., 2020; Gambhir et al., 2015). The number of petrol vehicles, EVs, and hybrid vehicles is negatively related to the average $CO_2$ emissions per vehicle. Given that the petrol vehicles are typically moving towards more fuel-efficient engines, the level of $CO_2$ emissions is decreasing. A 1 % increase in the number of EVs, and hybrid vehicles was found to be related to approximately a 0.006 % to 0.007 % decrease in the average $CO_2$ emissions per vehicle.

The coefficients of year dummy variables indicate an annual decreasing trend of $CO_2$ emissions. Regarding the coefficients for each GCCSA, like the findings presented in the choropleth maps, rural areas such as Rest of Queensland, the Northern Territory, and Western Australia are more likely to emit more $CO_2$ compared to capital cities (e.g., Greater Perth, Greater Brisbane, and Greater Melbourne).

## 6. Discussion and conclusion

The aim of this study was to reveal the annual variations of car $CO_2$ emissions across regions in Australia. Considerable literature concentrates on forecasting car $CO_2$ emissions with few scholars exploring regional patterns in emissions along with their change over time (Rietmann et al., 2020; Krause et al., 2020; Jochem et al., 2015; Zeng et al., 2016). This is despite the importance of such a study in offering the requisite empirical evidence to reveal how net zero emissions targets are tracking across the nation. This current study advances previous research by first mapping annual variations in private vehicle $CO_2$ emissions across regions and second employing panel regression to estimate the association between changes in total vehicle volume and $CO_2$ emissions over an eighteen-year period.

Our findings draw attention to regions of Australia that exhibit consistently high levels of $CO_2$ emissions across the study period.

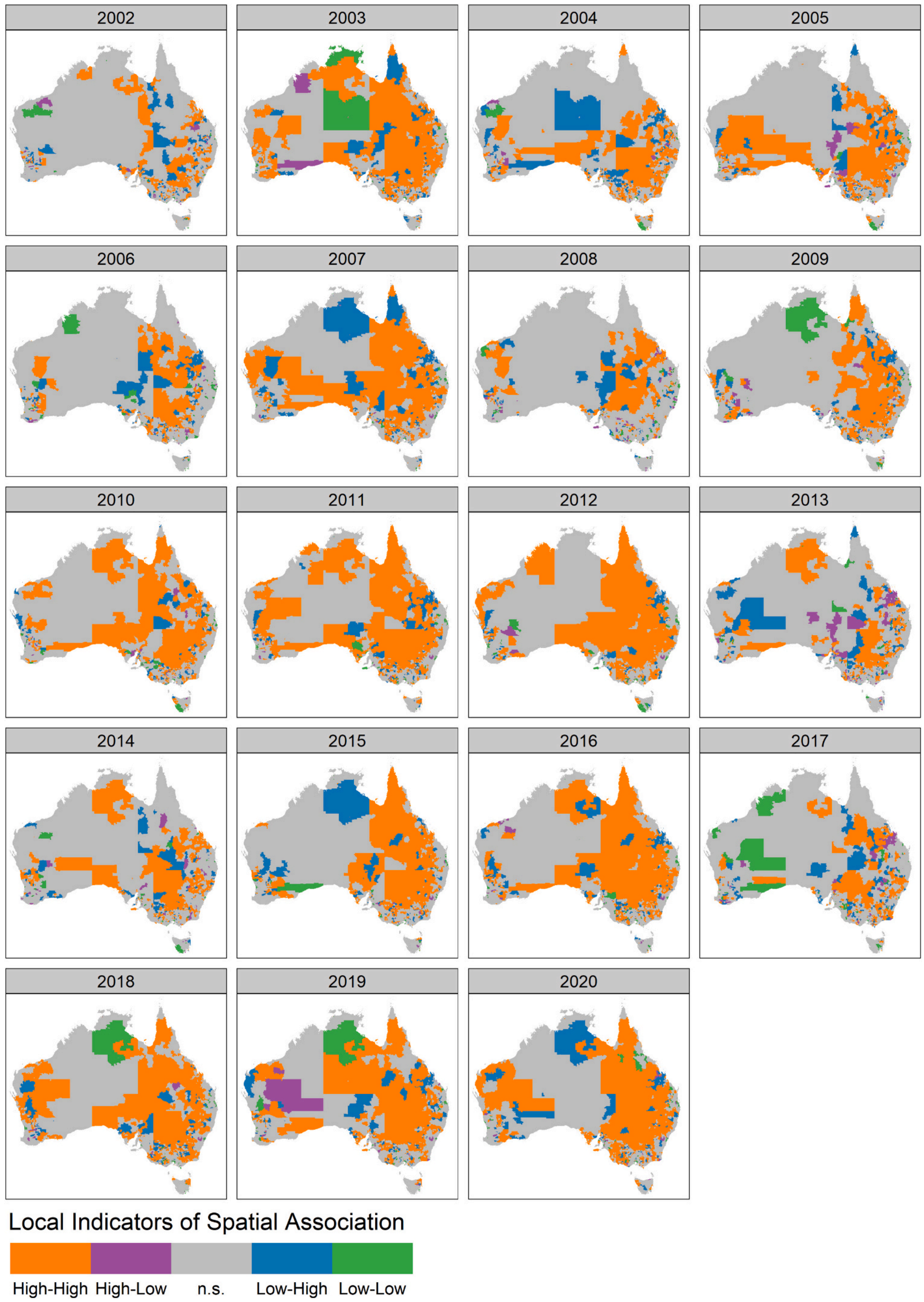


**Fig. 5.** Local Indicator of Spatial Association (LISA) for average $CO_2$ emissions (g/km) by postal area and year (2002 to 2020) throughout Australia.

Specifically, locations in North Queensland, Northern Territory, and south-west Western Australian experienced little decline in $CO_2$ between 2003 and 2020. Indeed, our investigation of proportionate change indicates that these regions experienced increases in $CO_2$ emissions and fuel consumption between 2014 and 2015, 2015–2016, and 2017–2018. Regional, remote and industry driven locations are characterised by higher levels of car dependence, utility, and off-road vehicle registrations which may impede emission reduction through transition to electric or hybrid vehicles. Previous studies have also reported that private vehicle $CO_2$ emissions in remote, rural regions emit more greenhouse gases in Australia (OECD, 2021; Dodson and Sipe, 2007). This highlights the need for innovative approaches to $CO_2$ reduction in non-urban areas and suggests that residential density and transport infrastructure are important considerations when developing strategies to encourage cleaner transport alternatives.

While $CO_2$ emission reduction is uneven across Australia, with some regions lagging behind the rest of the country, we found that overall private vehicle $CO_2$ emissions and fuel consumption have followed a decreasing trend at the national level over the last two decades. The results of this study demonstrate that across Australia as a whole, there is a general decreasing trend in terms of private vehicle $CO_2$ emissions and fuel consumption (Paasonen et al., 2016; Australian Office of Financial Management, 2022; Wadud et al., 2006). The level of average $CO_2$ emissions per vehicle in rural areas (e.g., Rest of Queensland, Western Australia, and the Northern Territory) is relatively higher than the capital cities such as Greater Brisbane, Greater Melbourne, and Greater

**Table 2**
Descriptive Statistics by Model Year and Region.

| Year | Vehicles | Hybrid (%) | Electric (%) |
|---|---|---|---|
| 2002 | 450,821 | 0.03 | 0.01 |
| 2003 | 571,149 | 0.04 | 0.01 |
| 2019 | 1,124,273 | 2.69 | 0.71 |
| 2020 | 982,742 | 6.13 | 0.75 |

| Region. | Total Vehicles | Hybrid (%) | Electric (%) |
|---|---|---|---|
| Greater Sydney | 3,327,377 | 1.82 | 0.17 |
| Greater Melbourne | 3,338,396 | 1.27 | 0.16 |
| Greater Brisbane | 1,830,020 | 1.39 | 0.17 |
| Greater Hobart | 170,464 | 1.29 | 0.26 |
| Australian Capital Territory | 311,194 | 2.16 | 0.28 |

**Table 3**
The estimation results for the total of $CO_2$ emissions and fuel consumption.

| Variables | Average $CO_2$ emissions per car | |
|---|---|---|
| | Random effects | Fixed effects |
| Constant | 5.595*** | |
| ln(Number of diesel vehicles) | 0.020*** | 0.016*** |
| ln(Number of petrol vehicles) | −0.021*** | −0.009*** |
| ln(Number of EVs) | −0.007*** | −0.007*** |
| ln(Number of hybrid vehicles) | −0.006*** | −0.005*** |
| Year (reference: 2002) | | |
| Year 2003 | −0.012*** | −0.014*** |
| Year 2004 | −0.115*** | −0.118*** |
| Year 2005 | −0.095*** | −0.099*** |
| Year 2006 | −0.061*** | −0.064*** |
| Year 2007 | −0.150*** | −0.154*** |
| Year 2008 | −0.202*** | −0.204*** |
| Year 2009 | −0.243*** | −0.244*** |
| Year 2010 | −0.273*** | −0.275*** |
| Year 2011 | −0.285*** | −0.286*** |
| Year 2012 | −0.331*** | −0.332*** |
| Year 2013 | −0.392*** | −0.393*** |
| Year 2014 | −0.395*** | −0.396*** |
| Year 2015 | −0.369*** | −0.370*** |
| Year 2016 | −0.364*** | −0.365*** |
| Year 2017 | −0.431*** | −0.432*** |
| Year 2018 | −0.403*** | −0.403*** |
| Year 2019 | −0.375*** | −0.375*** |
| Year 2020 | −0.400*** | −0.399*** |
| GCCSA (reference: Australian Capital Territory) | | |
| Greater Adelaide | 0.017*** | |
| Greater Brisbane | 0.010** | |
| Greater Darwin | 0.025*** | |
| Greater Hobart | −0.002 | |
| Greater Melbourne | 0.018*** | |
| Greater Perth | 0.025*** | |
| Greater Sydney | 0.005 | |
| Rest of New South Wales | 0.026*** | |
| Rest of North Territory | 0.039*** | |
| Rest of Queensland | 0.033*** | |
| Rest of South Australia | 0.043*** | |
| Rest of Tasmania | 0.010** | |
| Rest of Victoria | 0.034*** | |
| Rest of Western Australia | 0.049*** | |
| Number of groups | 2637 | 2637 |
| Number of observations | 49,215 | 49,215 |
| Hausman test | 885.02*** | |
| R-squared | 0.862 | 0.844 |

Note: *** Significant at 99 % level. **Significant at 95 % level. *Significant at 90 % level.

Adelaide. One likely reason explaining this pattern is that capital cities have higher levels of residential density and accessibility to the public transport system (Wu et al., 2021; Trendle, 2019). This mirrors global patterns in remote and rural regions, as seen in studies conducted in parts of the United States and Europe (Krause et al., 2020).

The geographical disparities in $CO_2$ reductions highlight the need for a more tailored approach to emission reduction in rural and remote areas. These regions face unique barriers, including longer travel distances, limited EV charging infrastructure, and the higher average mileage of vehicles. These barriers are similarly encountered in other rural and remote areas globally, such as parts of California and the southwestern United States, where EV uptake has been slower due to sparse infrastructure and longer driving distances (Robinson and Hardman, 2024). Encouraging EV adoption in these areas will require not only improving infrastructure but also addressing cost considerations and cultural attitudes towards electric vehicles. The introduction of targeted financial incentives, subsidies for EV purchases, and infrastructural support could help mitigate these barriers. Educational campaigns and industry support, particularly in sectors like agriculture that typically rely on larger vehicles, will also be critical in driving the transition to low-emission vehicles.

More broadly, to promote EV uptake across urban and regional locations in Australia, local governments need to systematically design the recharging infrastructure locations with subsidy policy (Li et al., 2018) to ensure highly visible and accessible public charging infrastructure. Large-scale transition to EV use across all regions of Australia is largely contingent upon the development of supportive infrastructure, subsidy and incentive strategies (Heidrich et al., 2017). Promoting EV use in urban areas can help to ensure that decreasing trends in $CO_2$ emissions and energy consumption continue in capital cities of Australia. In urban locations and capital cities, promoting active transport (i.e., walking and cycling) and public transport use can also help to mitigate the emissions and fuel consumption (e.g., Mizdrak et al., 2019; Chapman et al., 2018; Keall et al., 2018).

Our findings align with those from global studies that show $CO_2$ emissions are significantly influenced by vehicle type and usage patterns. In this context, our study advances current scholarship by mapping emissions trends across Australia and highlighting the importance of localised, region-specific policies. Comparisons with other countries suggest that Australia is still trailing behind global leaders in emission reductions. For instance, in Norway and the Netherlands, strong EV uptake combined with comprehensive charging infrastructure has driven substantial emissions reductions (IEA, 2024). The results for Australia show that while metropolitan areas are on track for improvement, rural and remote regions require more aggressive and tailored interventions.

Regarding limitations, the BITRE data contains more granular classification of car makes compared to the GVG data, which provides $CO_2$ emissions and fuel consumption for each make of car. When associating the emissions and fuel consumption information (from the GVG data) with the BITRE data, not all the cars are included when conducting the analysis in this study. This presents a limitation in tracking all vehicles accurately. However, such limitations are not unique to this study, as similar challenges arise in international datasets, such as those used to study emissions differences across U.S. states or between regions within countries like Germany (Jochem et al., 2015). Moreover, other types of emissions are not included in the GVG data such as nitrogen oxides ($NO_x$), particulate matter (PM) and volatile organic compounds (VOC). As thus, future studies are capable to conduct a more accurate analysis if it is plausible to obtain a car information data with various types of emissions and fuel consumption that can be totally compatible with the BITRE data. Further, the current study lacks information in relation to people's perceptions of conventional cars and EVs. Future transportation research can consider people's perceptions of EVs and their attitudes towards the current EVs policy as these attitudinal factors also influence emissions and energy consumption.

In conclusion, this study presents its contributions by conducting a spatial temporal analysis to explore variations in private vehicle emissions and fuel consumption across different regions of Australia over an 18-year period. The findings highlight the uneven progress in reducing transport-related $CO_2$ emissions, with some rural areas lagging behind urban centres. This points to a need for targeted regional emission reduction strategies, including incentives and infrastructure to support EV uptake in high-emitting areas. The utility of this study lies in providing a longitudinal, geospatial perspective on private vehicle emissions, which can inform transport planning and policy aimed at accelerating Australia's transition to low-carbon mobility. While appealing EVs may help mitigate emissions in rural areas, further research is needed to understand the specific barriers and opportunities for cleaner transport in regional contexts. This study offers a foundation and novel dataset to support such investigations.

## CRediT authorship contribution statement

**Kai Li Lim:** Writing – review & editing, Writing – original draft, Validation, Supervision, Project administration, Methodology, Investigation, Funding acquisition, Data curation, Conceptualization. **Ying Lu:** Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis. **Anthony Kimpton:** Writing – review & editing, Writing – original draft, Validation, Methodology, Investigation, Funding acquisition, Formal analysis. **Renee Zahnow:** Writing – original draft, Funding acquisition, Formal analysis, Conceptualization. **Tiebei Li:** Writing – original draft, Investigation, Data curation. **Jago Dodson:** Writing – review & editing, Validation, Supervision, Funding acquisition. **Neil Sipe:** Funding acquisition, Supervision. **Jonathan Corcoran:** Writing – review & editing, Writing – original draft, Supervision, Project administration, Methodology, Funding acquisition.

## Declaration of competing interest

None.

## Data availability

Data is publicly available from the Australian Government.


## Acknowledgments

This project received funding from the Australian Urban Research Infrastructure Network (AURIN). AURIN is funded by the National Collaborative Research Infrastructure Strategy (NCRIS).


## Appendix A. Mapping green vehicle guide fuel type to BITRE fuel class

| Green Vehicle Guide (Fuel Type) | BITRE data (Fuel Class) |
|---|---|
| diesel | diesel |
| pure electric | electric |
| plug-in electric/petrol 95ron | hybrid electric |
| plug-in electric/diesel | hybrid electric |
| plug-in electric/petrol 98ron | hybrid electric |
| electric/petrol 91ron | hybrid electric |
| electric/petrol 95ron | hybrid electric |
| plug-in electric/petrol 91ron | hybrid electric |
| electric/diesel | hybrid electric |
| electric/petrol 98ron | hybrid electric |
| petrol 98ron | petrol |
| petrol 95ron | petrol |
| petrol 91ron | petrol |
| lpg | petrol |

## Appendix B. Green vehicle guide summary

| Model release year | Fuel class | Number of models | $CO_2$ (combined) | | $CO_2$ (extra-urban) | | $CO_2$ (urban) | | Fuel consumption (combined) | | Fuel consumption (extra-urban) | | Fuel consumption (urban) | | Electric range | | Energy consumption | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | mean | s.d. | mean | s.d. | mean | s.d. | mean | s.d. | mean | s.d. | mean | s.d. | mean | s.d. | mean | s.d. |
| 2000 | diesel | 5 | 225 | 0 | – | – | – | – | 8.5 | 0 | – | – | – | – | – | – | – | – |
| 2001 | diesel | 4 | 201 | 29.4 | – | – | – | – | 7.5 | 1 | – | – | – | – | – | – | – | – |
| 2002 | diesel | 28 | 273.1 | 14.2 | – | – | – | – | 10.2 | 0.4 | – | – | – | – | – | – | – | – |
| 2003 | diesel | 35 | 282.5 | 36.8 | – | – | – | – | 10.7 | 1.4 | – | – | – | – | – | – | – | – |
| 2004 | diesel | 64 | 234.9 | 38 | – | – | – | – | 8.9 | 1.5 | – | – | – | – | – | – | – | – |
| 2005 | diesel | 91 | 232.8 | 36.8 | 240.5 | 0 | 329.5 | 0 | 8.8 | 1.4 | 8.9 | – | 12.2 | – | – | – | – | – |
| 2006 | diesel | 162 | 211.8 | 47.5 | 213.7 | 15.9 | 307.3 | 16 | 8 | 1.8 | 8.1 | 0.6 | 11.7 | 0.6 | – | – | – | – |
| 2007 | diesel | 164 | 212.4 | 45.4 | 180.2 | 50.2 | 269.4 | 69.1 | 8 | 1.7 | 6.8 | 1.9 | 10.2 | 2.6 | – | – | – | – |
| 2008 | diesel | 195 | 197.1 | 35.3 | 166.9 | 34.2 | 256.3 | 44.1 | 7.4 | 1.3 | 6.3 | 1.3 | 9.6 | 1.7 | – | – | – | – |
| 2009 | diesel | 242 | 219.9 | 40.7 | 186.3 | 36.7 | 280.9 | 50.2 | 8.3 | 1.5 | 7 | 1.4 | 10.6 | 1.9 | – | – | – | – |
| 2010 | diesel | 256 | 194.1 | 42.2 | 164.3 | 34.8 | 246 | 56.3 | 7.3 | 1.6 | 6.2 | 1.3 | 9.3 | 2.1 | – | – | – | – |
| 2011 | diesel | 182 | 190.5 | 43.2 | 162 | 36.1 | 239.5 | 57.3 | 7.2 | 1.6 | 6.1 | 1.4 | 9.1 | 2.2 | – | – | – | – |
| 2012 | diesel | 202 | 187.6 | 44.4 | 161.4 | 38.4 | 232.4 | 56 | 7.1 | 1.7 | 6.1 | 1.4 | 8.8 | 2.1 | – | – | – | – |
| 2013 | diesel | 189 | 186.5 | 40.5 | 161.9 | 34.5 | 229.8 | 52.6 | 7.1 | 1.5 | 6.1 | 1.3 | 8.7 | 2 | – | – | – | – |
| 2014 | diesel | 156 | 175.7 | 45.3 | 153.4 | 36.9 | 215.2 | 61.4 | 6.7 | 1.7 | 5.8 | 1.4 | 8.2 | 2.3 | – | – | – | – |
| 2015 | diesel | 285 | 183.3 | 38.2 | 161.8 | 32.5 | 220.6 | 48.8 | 7 | 1.4 | 6.1 | 1.2 | 8.4 | 1.8 | – | – | – | – |
| 2016 | diesel | 190 | 179.8 | 40.9 | 159.6 | 34.6 | 216.1 | 54.5 | 6.8 | 1.5 | 6 | 1.3 | 8.2 | 2.1 | – | – | – | – |
| 2017 | diesel | 125 | 160.8 | 33.2 | 144.5 | 26.5 | 188.9 | 45.7 | 6.1 | 1.2 | 5.5 | 1 | 7.2 | 1.7 | – | – | – | – |

(*continued on next page*)

(*continued*)

| Model release year | Fuel class | Number of models | $CO_2$ (combined) | | $CO_2$ (extra-urban) | | $CO_2$ (urban) | | Fuel consumption (combined) | | Fuel consumption (extra-urban) | | Fuel consumption (urban) | | Electric range | | Energy consumption | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | mean | s.d. | mean | s.d. | mean | s.d. | mean | s.d. | mean | s.d. | mean | s.d. | mean | s.d. | mean | s.d. |
| 2018 | diesel | 219 | 186.4 | 30.8 | 165.4 | 26.8 | 223 | 40.2 | 7.1 | 1.2 | 6.3 | 1 | 8.5 | 1.5 | – | – | – | – |
| 2019 | diesel | 133 | 189.8 | 25.6 | 171.9 | 23.1 | 222.3 | 34.7 | 7.2 | 1 | 6.5 | 0.9 | 8.5 | 1.3 | – | – | – | – |
| 2020 | diesel | 126 | 200.8 | 21.1 | 180.8 | 18.3 | 236.8 | 29.2 | 7.7 | 0.8 | 6.9 | 0.7 | 9 | 1.1 | – | – | – | – |
| 2009 | electric | 1 | – | – | – | – | – | – | – | – | – | – | – | – | – | – | – | – |
| 2010 | electric | 2 | – | – | – | – | – | – | – | – | – | – | – | – | 657 | – | 138 | – |
| 2012 | electric | 2 | – | – | – | – | – | – | – | – | – | – | – | – | 162.5 | 17.7 | 154 | 26.9 |
| 2014 | electric | 3 | – | – | – | – | – | – | – | – | – | – | – | – | 287.3 | 186.2 | 160.7 | 34.8 |
| 2015 | electric | 7 | – | – | – | – | – | – | – | – | – | – | – | – | 491 | – | 206 | – |
| 2016 | electric | 15 | – | – | – | – | – | – | – | – | – | – | – | – | 465.3 | 48.5 | 193.4 | 20.8 |
| 2017 | electric | 7 | – | – | – | – | – | – | – | – | – | – | – | – | 473.7 | 65.7 | 176.4 | 25.2 |
| 2018 | electric | 4 | – | – | – | – | – | – | – | – | – | – | – | – | 324 | 81.4 | 156 | 50.7 |
| 2019 | electric | 16 | – | – | – | – | – | – | – | – | – | – | – | – | 506.9 | 112.7 | 177.4 | 31.1 |
| 2020 | electric | 14 | – | – | – | – | – | – | – | – | – | – | – | – | 436.8 | 52.7 | 226.9 | 42 |
| 2003 | hybrid electric | 1 | 106 | – | – | – | – | – | 4.4 | – | – | – | – | – | – | – | – | – |
| 2004 | hybrid electric | 1 | 124 | – | – | – | – | – | 5.2 | – | – | – | – | – | – | – | – | – |
| 2005 | hybrid electric | 2 | 356.5 | 3.5 | – | – | – | – | 15.1 | 0.1 | – | – | – | – | – | – | – | – |
| 2006 | hybrid electric | 3 | 162.3 | 46.3 | 101 | – | 126 | – | 6.9 | 2 | 4.3 | – | 5.2 | – | – | – | – | – |
| 2007 | hybrid electric | 2 | 190 | 41 | 188 | – | 265 | – | 8 | 1.8 | 8 | – | 11.3 | – | – | – | – | – |
| 2008 | hybrid electric | 1 | 186 | – | 170 | – | 217 | – | 7.9 | – | 7.2 | – | 9.2 | – | – | – | – | – |
| 2009 | hybrid electric | 2 | 119.5 | 43.1 | 114.5 | 40.3 | 122.5 | 46 | 5.2 | 1.8 | 4.9 | 1.7 | 5.2 | 1.9 | – | – | – | – |
| 2010 | hybrid electric | 6 | 145.7 | 32.8 | 132.2 | 25.2 | 166.8 | 50.9 | 6.2 | 1.4 | 5.6 | 1.1 | 7.1 | 2.2 | – | – | – | – |
| 2011 | hybrid electric | 3 | 145.7 | 49.1 | 141.3 | 44.6 | 149.3 | 55 | 6.2 | 2.1 | 6 | 1.9 | 6.4 | 2.4 | – | – | – | – |
| 2012 | hybrid electric | 18 | 129 | 39 | 125.1 | 39.5 | 133.9 | 43.8 | 5.5 | 1.7 | 5.3 | 1.7 | 5.7 | 1.9 | 29.7 | 49.7 | 45.7 | 77.4 |
| 2013 | hybrid electric | 12 | 134.7 | 38.2 | 131.2 | 27.5 | 157.9 | 52.3 | 5.7 | 1.7 | 5.6 | 1.3 | 6.7 | 2.3 | 36 | – | 162.2 | – |
| 2014 | hybrid electric | 11 | 97.4 | 56 | 123.4 | 25.6 | 140.6 | 53.3 | 4.1 | 2.4 | 5.1 | 1.2 | 5.9 | 2.3 | 77.8 | 61.9 | 125.5 | 9.9 |
| 2015 | hybrid electric | 16 | 119.6 | 50 | 134.3 | 32.4 | 150.8 | 55.1 | 5 | 2.1 | 5.6 | 1.3 | 6.3 | 2.4 | 41.2 | 9.2 | 150.5 | 41.5 |
| 2016 | hybrid electric | 22 | 90.7 | 67.3 | 139.6 | 41.8 | 173 | 69.5 | 3.8 | 2.8 | 5.9 | 1.8 | 7.3 | 2.9 | 53.9 | 51.8 | 132.9 | 19.2 |
| 2017 | hybrid electric | 19 | 68.6 | 29.7 | 127 | 32.5 | 127.3 | 26.5 | 2.9 | 1.4 | 5.5 | 1.4 | 5.6 | 1.1 | 51.3 | 3.8 | 169.8 | 22.3 |
| 2018 | hybrid electric | 11 | 59.3 | 32.7 | 70 | 47.2 | 105.1 | 18.1 | 2.6 | 1.4 | 3.1 | 2 | 4.6 | 0.8 | 96.9 | 77.8 | 130.4 | 35.9 |
| 2019 | hybrid electric | 29 | 79 | 43 | 107 | 44.7 | 136.4 | 52.8 | 3.4 | 1.7 | 4.6 | 1.8 | 5.8 | 2.1 | 77.1 | 74.9 | 164.6 | 42.4 |
| 2020 | hybrid electric | 22 | 95.4 | 50.7 | 124.3 | 29.4 | 140.9 | 56.4 | 4.2 | 2.2 | 5.4 | 1.3 | 6.2 | 2.4 | 51.8 | 4.5 | 165.3 | 8.2 |
| 1997 | petrol | 6 | 285.3 | 39 | – | – | – | – | 11.9 | 1.6 | – | – | – | – | – | – | – | – |
| 1999 | petrol | 2 | 367 | 103.2 | – | – | – | – | 15.7 | 4.7 | – | – | – | – | – | – | – | – |
| 2000 | petrol | 3 | 237 | 39 | – | – | – | – | 10 | 1.7 | – | – | – | – | – | – | – | – |
| 2001 | petrol | 25 | 212.7 | 62.9 | – | – | – | – | 9 | 2.7 | – | – | – | – | – | – | – | – |
| 2002 | petrol | 220 | 262 | 59.3 | – | – | – | – | 11.4 | 2.7 | – | – | – | – | – | – | – | – |
| 2003 | petrol | 303 | 251.5 | 65.6 | 178 | – | 293 | – | 10.6 | 2.8 | 7.4 | – | 12.2 | – | – | – | – | – |
| 2004 | petrol | 553 | 252.6 | 59.3 | – | – | – | – | 10.7 | 2.6 | – | – | – | – | – | – | – | – |
| 2005 | petrol | 485 | 256.9 | 56.9 | 225.3 | 28.4 | 406.9 | 58 | 10.9 | 2.4 | 9.4 | 1.1 | 17.1 | 2.3 | – | – | – | – |
| 2006 | petrol | 536 | 250.8 | 57.7 | 184.7 | 35.1 | 330.2 | 86.8 | 10.6 | 2.5 | 7.8 | 1.5 | 13.9 | 3.6 | – | – | – | – |
| 2007 | petrol | 402 | 244.6 | 65.5 | 180.9 | 35.2 | 322.9 | 73.7 | 10.3 | 2.8 | 7.6 | 1.5 | 13.6 | 3.1 | – | – | – | – |
| 2008 | petrol | 489 | 243.2 | 66.6 | 181.5 | 42.3 | 327.6 | 91.7 | 10.2 | 2.8 | 7.6 | 1.8 | 13.8 | 3.9 | – | – | – | – |
| 2009 | petrol | 508 | 248.4 | 69.5 | 190.8 | 48.2 | 355.7 | 112.5 | 10.6 | 3 | 8.1 | 2.1 | 15.1 | 4.7 | – | – | – | – |
| 2010 | petrol | 585 | 224.1 | 61.9 | 172.8 | 41 | 314.4 | 100.5 | 9.5 | 2.6 | 7.3 | 1.7 | 13.3 | 4.2 | – | – | – | – |
| 2011 | petrol | 401 | 213 | 64 | 164.3 | 41.9 | 297.1 | 104.3 | 9.1 | 2.8 | 7 | 1.8 | 12.7 | 4.5 | – | – | – | – |
| 2012 | petrol | 488 | 198.2 | 56 | 155.2 | 36.8 | 272.3 | 89.9 | 8.6 | 2.5 | 6.7 | 1.6 | 11.8 | 3.9 | – | – | – | – |
| 2013 | petrol | 487 | 201.1 | 58.9 | 157 | 38.2 | 277 | 95.2 | 8.6 | 2.5 | 6.7 | 1.6 | 11.9 | 4.1 | – | – | – | – |
| 2014 | petrol | 380 | 193.8 | 63.8 | 152.5 | 40.3 | 263.9 | 104.3 | 8.4 | 2.8 | 6.6 | 1.8 | 11.4 | 4.6 | – | – | – | – |
| 2015 | petrol | 543 | 196.6 | 63.2 | 155.8 | 41.8 | 266.2 | 100.1 | 8.4 | 2.7 | 6.7 | 1.8 | 11.4 | 4.3 | – | – | – | – |
| 2016 | petrol | 440 | 181.5 | 49.7 | 145.6 | 32.2 | 243.5 | 81.3 | 7.8 | 2.1 | 6.3 | 1.4 | 10.5 | 3.5 | – | – | – | – |
| 2017 | petrol | 382 | 193.1 | 62 | 154.9 | 41.1 | 259.1 | 99.3 | 8.4 | 2.7 | 6.7 | 1.8 | 11.3 | 4.3 | – | – | – | – |
| 2018 | petrol | 294 | 182.2 | 43.7 | 149 | 31.3 | 241.3 | 69.6 | 7.9 | 1.9 | 6.5 | 1.4 | 10.5 | 3 | – | – | – | – |
| 2019 | petrol | 293 | 192.9 | 56.5 | 156 | 36.3 | 257.5 | 92 | 8.4 | 2.4 | 6.8 | 1.6 | 11.2 | 4 | – | – | – | – |
| 2020 | petrol | 296 | 180.6 | 48.4 | 148.7 | 33.4 | 235.6 | 75.8 | 7.9 | 2.1 | 6.5 | 1.5 | 10.3 | 3.3 | – | – | – | – |

(*continued on next page*)

(*continued*)

| Model release year | Fuel class | Number of models | $CO_2$ (combined) | | $CO_2$ (extra-urban) | | $CO_2$ (urban) | | Fuel consumption (combined) | | Fuel consumption (extra-urban) | | Fuel consumption (urban) | | Electric range | | Energy consumption | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | mean | s.d. | mean | s.d. | mean | s.d. | mean | s.d. | mean | s.d. | mean | s.d. | mean | s.d. | mean | s.d. |
| 2004 | – | 3 | 253 | 5.2 | – | – | – | – | 15.7 | 0.4 | – | – | – | – | – | – | – | – |
| 2005 | – | 8 | 264.4 | 10.1 | – | – | – | – | 16.3 | 0.6 | – | – | – | – | – | – | – | – |
| 2006 | – | 3 | 259.7 | 0 | – | – | – | – | 16 | 0 | – | – | – | – | – | – | – | – |
| 2007 | – | 2 | 258 | 4.2 | – | – | – | – | 14 | 3 | – | – | – | – | – | – | – | – |
| 2008 | – | 2 | 252 | 0 | – | – | – | – | 15.5 | 0 | – | – | – | – | – | – | – | – |
| 2009 | – | 5 | 235.6 | 7.7 | 188.6 | 10.4 | 317.2 | 4.4 | 14.6 | 0.5 | 11.6 | 0.6 | 19.7 | 0.2 | – | – | – | – |
| 2010 | – | 5 | 238 | 19.1 | 188.8 | 17.9 | 323 | 22.4 | 14.7 | 1.2 | 11.6 | 1.1 | 20 | 1.4 | – | – | – | – |
| 2011 | – | 18 | 276.1 | 27.8 | 210 | 16.3 | 390.2 | 54.1 | 17.1 | 1.8 | 13 | 1 | 24.2 | 3.3 | – | – | – | – |

## Appendix C. Relationship between $CO_2$ emissions and fuel consumption for urban, extra-urban, and combined driving conditions

**Key**

- **NA: Not Available**
- **s.d.: Standard deviation**
- **Combined: Combined $CO_2$ emissions or fuel consumption**
- **Urban: $CO_2$ emissions or fuel comsumption in urban conditions**
- **Extra-urban: $CO_2$ emissions or fuel consumption in extra-urban conditions**

| Model Release Year | $CO_2$ and Fuel Consumption | | | Urban and Extra-Urban | |
|---|---|---|---|---|---|
| | Combined | Urban | Extra-Urban | $CO_2$ | Fuel Consumption |
| 1997 | 1.00 | NA | NA | NA | NA |
| 1999 | 1.00 | NA | NA | NA | NA |
| 2000 | 0.94 | NA | NA | NA | NA |
| 2001 | 0.99 | NA | NA | NA | NA |
| 2002 | 0.98 | NA | NA | NA | NA |
| 2003 | 0.98 | NA | NA | NA | NA |
| 2004 | 0.97 | NA | NA | NA | NA |
| 2005 | 0.97 | 0.98 | 0.94 | 0.82 | 0.72 |
| 2006 | 0.98 | 0.99 | 0.97 | 0.91 | 0.89 |
| 2007 | 0.98 | 0.99 | 0.98 | 0.91 | 0.89 |
| 2008 | 0.99 | 0.99 | 0.98 | 0.93 | 0.91 |
| 2009 | 0.98 | 0.99 | 0.97 | 0.95 | 0.93 |
| 2010 | 0.97 | 0.98 | 0.96 | 0.94 | 0.92 |
| 2011 | 0.94 | 0.96 | 0.92 | 0.94 | 0.91 |
| 2012 | 0.97 | 0.98 | 0.95 | 0.93 | 0.90 |
| 2013 | 0.99 | 0.99 | 0.98 | 0.94 | 0.92 |
| 2014 | 0.99 | 0.99 | 0.98 | 0.95 | 0.92 |
| 2015 | 0.99 | 0.99 | 0.98 | 0.94 | 0.92 |
| 2016 | 0.99 | 0.99 | 0.97 | 0.92 | 0.88 |
| 2017 | 0.99 | 0.99 | 0.98 | 0.96 | 0.94 |
| 2018 | 0.98 | 0.99 | 0.96 | 0.90 | 0.87 |
| 2019 | 0.99 | 0.99 | 0.96 | 0.90 | 0.86 |
| 2020 | 0.98 | 0.99 | 0.96 | 0.90 | 0.87 |

## References


ACEA, 2023. The Automobile Industry Pocket Guide 2023/2024. ACEA, Brussels.

Anselin, L., 1995. Local indicators of spatial association—LISA. Geogr. Anal. 27, 93–115.

Australian Bureau of Statistics, 2021. *Motor Vehicle Census, Australia* [Online]. ABS, Canberra. Available: https://www.abs.gov.au/statistics/industry/tourism-and-transport/motor-vehicle-census-australia/latest-release [Accessed 3 Sep 2024].

Australian Bureau of Statistics, 2021-2026. Postal Areas [Online]. Available: https://www.abs.gov.au/statistics/standards/australian-statistical-geography-standard-asgs-edition-3/jul2021-jun2026/non-abs-structures/postal-areas [Accessed 27 Feb 2024].

Australian Government, 2021. Australia's Light Vehicle Fleet – Some Insights. Bureau of Infrastructure and Transport Research Economics, Canberra.

Australian Government, 2022. Motor Vehicles, Australia, January 2022 (First Issue). The Department of Infrastructure, Transport, Regional Development, Communications and the Arts, Canberra.

Australian Government, 2023a. Green Vehicle Guide [Online]. Department of Infrastructure, Transport, Regional Development, Communications and the Arts, Canberra. Available: https://www.greenvehicleguide.gov.au/ [Accessed 1 Aug 2023].

Australian Government, 2023b. National Electric Vehicle Strategy. Department of Climate Change, Energy, the Environment and Water, Canberra.

Australian Government, 2024a. New Vehicle Efficiency Standard Act 2024. In: Department of Infrastructure, T., Regional Development, Communications and the Arts (ed.).

Australian Government, 2024b. Quarterly Update of Australia's National Greenhouse gas Inventory: March 2024. Department of Climate Change, Energy, the Environment and Water, Canberra.

Australian Office of Financial Management, 2022. Australian Government Climate Change commitments, policies and programs [Online]. Available: https://www.aofm.gov.au/sites/default/files/2022-11-28/Aust%20Govt%20CC%20Actions%20Update%20November%202022_1.pdf#:~:text=Emissions%20Reduction%20Target%3A,-%E2%80%A2&text=The%20National%20Greenhouse%20Gas%20Inventory,21.6%25%20lower%20than%202005%20levels [Accessed 18th April 2023].

Chapman, R., Keall, M., Howden-Chapman, P., Grams, M., Witten, K., Randal, E., Woodward, A., 2018. A cost benefit analysis of an active travel intervention with health and carbon emission reduction benefits. Int. J. Environ. Res. Public Health 15.

Choma, E.F., Evans, J.S., Hammitt, J.K., Gomez-Ibanez, J.A., Spengler, J.D., 2020. Assessing the health impacts of electric vehicles through air pollution in the United States. Environ. Int. 144, 106015.

Choma, E.F., Evans, J.S., Gomez-Ibanez, J.A., Di, Q., Schwartz, J.D., Hammitt, J.K., Spengler, J.D., 2021. Health benefits of decreases in on-road transportation emissions in the United States from 2008 to 2017. Proc. Natl. Acad. Sci. 118.

Dodson, J., Sipe, N., 2007. Oil vulnerability in the Australian city: assessing socioeconomic risks from higher urban fuel prices. Urban Stud. 44, 37–62.

Electric Vehicle Council, 2024. Australian Electric Vehicle Industry Recap 2023. Electric Vehicle Council, Sydney.

Gambhir, A., Tse, L.K.C., Tong, D.L., Martinez-Botas, R., 2015. Reducing China's road transport sector CO2 emissions to 2050: technologies, costs and decomposition analysis. Appl. Energy 157, 905–917.

Ghaffarpasand, O., Beddows, D.C.S., Ropkins, K., Pope, F.D., 2020. Real-world assessment of vehicle air pollutant emissions subset by vehicle type, fuel and EURO class: new findings from the recent UK EDAR field campaigns, and implications for emissions restricted zones. Sci. Total Environ. 734, 139416.

Guo, M., Ning, M., Sun, S., Xu, C., Zhang, G., Zhang, L., Zhang, R., Zheng, J., Chen, C., Jia, Z., Liu, Y., Bo, Y., 2024. Estimation and analysis of air pollutant emissions from on-road vehicles in Changzhou, China. Atmosphere 15, 192.

Heidrich, O., Hill, G.A., Neaimeh, M., Huebner, Y., Blythe, P.T., Dawson, R.J., 2017. How do cities support electric vehicles and what difference does it make? Technol. Forecast. Soc. Chang. 123, 17–23.

IEA, 2023. Global EV Outlook 2023. IEA, Paris.

IEA, 2024. Global EV Outlook 2024. IEA, Paris.

JAMA, 2023. The Motor Industry of Japan 2023. Japan Automobile Manufacturers Association, Tokyo.

Jochem, P., Babrowski, S., Fichtner, W., 2015. Assessing CO2 emissions of electric vehicles in Germany in 2030. Transp. Res. Part a-Policy Pract. 78, 68–83.

Kazancoglu, Y., Ozbiltekin-Pala, M., Ozkan-Ozen, Y.D., 2021. Prediction and evaluation of greenhouse gas emissions for sustainable road transport within Europe. Sustain. Cities Soc. 70, 102924.

Keall, M.D., Shaw, C., Chapman, R., Howden-Chapman, P., 2018. Reductions in carbon dioxide emissions from an intervention to promote cycling and walking: a case study from New Zealand. Transp. Res. Part D-Transp. Environ. 65, 687–696.

Krause, J., Thiel, C., Tsokolis, D., Samaras, Z., Rota, C., Ward, A., Prenninger, P., Coosemans, T., Neugebauer, S., Verhoeve, W., 2020. EU road vehicle energy consumption and CO2 emissions by 2050-expert-based scenarios. Energy Policy 138.

Krecl, P., Johansson, C., Norman, M., Silvergren, S., Burman, L., Mollinedo, E.M., Targino, A.C., 2024. Long-term trends of black carbon and particle number concentrations and their vehicle emission factors in Stockholm. Environ. Pollut. 347, 123734.

Li, T., Dodson, J., 2020. Job growth, accessibility, and changing commuting burden of employment centres in Melbourne. J. Transp. Geogr. 88, 102867.

Li, T., Sipe, N., Dodson, J., 2013. Investigating private motorised travel and vehicle fleet efficiency: using new data and methods to reveal socio-spatial patterns in Brisbane, Australia. Geogr. Res. 51, 269–278.

Li, T., Dodson, J., Sipe, N., 2015. Differentiating metropolitan transport disadvantage by mode: household expenditure on private vehicle fuel and public transport fares in Brisbane, Australia. J. Transp. Geogr. 49, 16–25.

Li, Y., Zhang, P.W., Wu, Y.F., 2018. Public recharging infrastructure location strategy for promoting electric vehicles: a bi-level programming approach. J. Clean. Prod. 172, 2720–2734.

Mizdrak, A., Blakely, T., Cleghorn, C.L., Cobiac, L.J., 2019. Potential of active transport to improve health, reduce healthcare costs, and reduce greenhouse gas emissions: a modelling study. PLoS One 14.

Newman, P.W.G., Kenworthy, J.R., 1989. Cities and automobile dependence. England, Ashgate Publishing, London.

OECD, 2021. Regional Outlook 2021 - Progress in the net zero transition [Online]. Available: https://www.oecd.org/regional/RO2021%20Australia.pdf [Accessed 18th April 2023].

Paasonen, P., Kupiainen, K., Klimont, Z., Visschedijk, A., Van Der Gon, H.A.C.D., Amann, M., 2016. Continental anthropogenic primary particle number emissions. Atmos. Chem. Phys. 16, 6823–6840.

Rachel, L., Helen, R., Mudabber, A., 2022. Accelerating EV Uptake: Policies to Realise Australia's Electric Vehicle Potential. Climateworks Centre.

Rietmann, N., Hugler, B., Lieven, T., 2020. Forecasting the trajectory of electric vehicle sales and the consequences for worldwide CO2 emissions. J. Clean. Prod. 261.

Robinson, A.R., Hardman, S., 2024. Cars and Chargers in the Country: Rural PEV Owner Accounts of Charging and Travel in California. UC Office of the President: University of California Institute of Transportation Studies. http://dx.doi.org/10.7922/G2WD3XXX Retrieved from https://escholarship.org/uc/item/9t95p3gk.

Trendle, B., 2019. Public transport access and its implications for household car ownership: a case study of the Sydney greater metropolitan area. Aust. J. Reg. Stud. 25, 196–222.

U.S. Department of Energy, 2022. Transportation Energy Data Book, 40 ed. U.S. Department of Energy, Office of Energy Efficiency Renewable, Energy, Oak Ridge, TN.

Unger, N., Bond, T.C., Wang, J.S., Koch, D.M., Menon, S., Shindell, D.T., Bauer, S., 2010. Attribution of climate forcing to economic sectors. Proc. Natl. Acad. Sci. 107, 3382–3387.

Wadud, Z., Aye, L., Beer, T., Watson, H.C., 2006. Modeling Australian road transport emissions till 2025. J. Civ. Eng. 34, 115–127.

Wen, Y., Liu, M., Zhang, S., Wu, X., Wu, Y., Hao, J., 2023. Updating on-road vehicle emissions for China: spatial patterns, temporal trends, and mitigation drivers. Environ. Sci. Technol. 57, 14299–14309.

Wu, H., Avner, P., Boisjoly, G., Braga, C.K., El-Geneidy, A., Huang, J., Kerzhner, T., Murphy, B., Niedzielski, M.A., Pereira, R.H., 2021. Urban access across the globe: an international comparison of different transport modes. npj Urban Sustain. 1, 16.

Zeng, W.L., Miwa, T., Morikawa, T., 2016. Prediction of vehicle CO2 emission and its application to eco-routing navigation. Transp. Res. Part C-Emerg. Technol. 68, 194–214.