scientific reports

Check for updates

OPEN

Life cycle assessment of electric and gasoline vehicles considering grid differences and cold climate in China

Sining Ma[1✉], Zhijian He[2], Amir Hamzah Sharaai[3], Nitanan Koshy Matthew[3] & Nazatul Syadia Zainordin[3]

This study presents a regionally and seasonally resolved life cycle assessment (LCA) comparing battery electric vehicles (BEVs) and gasoline vehicles (GVs) in China, integrating the influence of regional power grid composition and cold-climate effects. Using the ReCiPe 2016 endpoint and IPCC 2021 GWP100 methods implemented in SimaPro with Ecoinvent 3.9.1 data, the analysis quantifies annual and seasonal use-phase emissions across six regional grids. Results show that BEVs emit 25.3% fewer greenhouse gases annually than GVs but cause 2.6 times higher land transformation impacts due to coal-intensive electricity. In Heilongjiang Province, sub-zero conditions reduce BEV charging efficiency to 59% in winter, raising seasonal emissions by up to 70% and lowering the overall GHG advantage to 14.2%. Sensitivity analysis indicates that increasing clean energy penetration reduces human health damage by 15% (DALYs) and resource depletion costs by 91%. The proposed framework uniquely incorporates temperature-dependent performance and regional energy heterogeneity, enabling a more realistic assessment of BEV sustainability under fossil-based and cold-climate conditions. Overall, the findings demonstrate that BEVs consistently outperform GVs in fossil and biogenic emissions but are constrained by land transformation impacts and grid carbon intensity. Achieving genuine zero-emission transport requires coupling BEV promotion with renewable energy expansion and battery efficiency improvements for low-temperature regions.

Keywords Electric vehicles, Life cycle assessment, Environmental impact, Regional energy mix, Cold climate

Transportation is a major contributor to global greenhouse gas (GHG) emissions, and previous research has highlighted its central role in environmental degradation[1]. In response, the electric vehicle (EV) industry has gained strong global momentum, driven by decarbonization and sustainable mobility policies. China—the world's largest EV market—plays a particularly pivotal role in this transition[2]. The government's targets to phase out internal-combustion vehicles by 2035 and to achieve carbon neutrality by 2060 mark key milestones toward sustainable energy use[3]. However, given China's vast territory, uneven resource endowment, and regional disparities in energy structure and climate, ensuring the sustainability of EV promotion across diverse provinces remains a significant challenge. The 2030 strategic directives thus emphasize integrating infrastructure, regulation, and local governance to align EV adoption with regional energy and environmental conditions.

To ensure that electrification contributes effectively to carbon neutrality, EV deployment must be accompanied by green and circular practices. Proactive artificial intelligence (AI) policies have been identified as instrumental in improving economic sustainability, underscoring the positive role of well-targeted government interventions[4]. Moreover, Wang further recommends that governments account for levels of urbanization and sustainable development when formulating AI-based sustainability strategies[5]. Since sustainability trade-offs are highly context-dependent, they require nuanced, region-specific policy approaches—particularly amid rising global protectionism[6]. Evaluating the real sustainability outcomes of such strategies requires quantitative and systematic tools, among which life cycle assessment (LCA) is particularly valuable.

[1]School of Energy and Constructional Engineering, Shandong Huayu University of Technology, Dezhou, Shandong 253034, P.R. China. [2]School of Business and Economics, Universiti Putra Malaysia, Serdang, Selangor, Malaysia. [3]Department of Environmental Management, Faculty of Forestry and Environment, Universiti Putra Malaysia, Serdang, Selangor, Malaysia. ✉email: msncici1234@gmail.com

These evolving policy instruments share a methodological foundation with LCA, which offers a data-driven and evidence-based framework to evaluate the environmental performance of technologies across their entire life span. LCA quantifies environmental impacts from raw material extraction to end-of-life disposal[7]. and it is widely used to compare the sustainability of products, processes, and technologies[8,9]. In this context, LCA provides an ideal approach for assessing the net environmental benefits of EVs, enabling quantitative insight into how policy, technology, and regional energy systems interact to shape sustainability outcomes.

While prior research has examined issues such as EV subsidies, charging costs, infrastructure, and battery recycling, relatively few studies have focused on the use phase, which is the most critical stage for understanding real-world environmental, social, and economic performance[10]. Recent LCAs often generalize results using national averages, overlooking regional heterogeneity in power generation and climate—two factors that fundamentally determine environmental outcomes. The use-phase impacts of electricity generation remain particularly underexplored. Although EVs produce negligible tailpipe emissions, large-scale adoption increases electricity demand, which—depending on the power grid's fuel mix—may lead to substantial non-renewable energy consumption[1]. Consequently, the environmental benefits of EVs vary with grid composition[11]. Consequently, the environmental benefits of EVs vary with grid composition[12]. and overall sustainability depends on the cleanliness of electricity supply. Even when alternative fuels are less carbon-intensive on an energy-equivalent basis, low-efficiency compressed-natural-gas vehicles and heavy BEVs may still exhibit higher well-to-wheel GHG emissions than gasoline vehicles[13]. Thus, BEV promotion must proceed in parallel with the reduction of coal-fired power generation and continual improvement of regional electricity systems[14].

Existing LCA studies show that the use stage of EVs accounts for approximately 85.3% of their total environmental impact, primarily due to electricity consumption[15]. But they not consider temperature and energy component. In China's energy context, EV operation still involves substantial emissions of CO_2 and acidifying gases[16]. Although EVs significantly reduce GHG emissions, they may lead to greater human health and acidification impacts[17]. Conversely, when powered by renewable energy, EVs achieve markedly lower life-cycle emissions[18]. The environmental burden is also affected by battery manufacturing; therefore, attention to the energy intensity of battery systems is essential for accurate LCAs and life cycle cost (LCC) analyses. Lombardi et al. (2017) highlight that efficient battery production and recycling can substantially reduce these effects[19]. Most studies focus on subsidies, charging infrastructure, or battery systems, while fewer address the operational phase—the dominant contributor to life-cycle impacts.

Local climate further influences EV performance. Temperature affects battery efficiency and driving range, thereby altering environmental benefits[20]. Ambient conditions can shape not only operational efficiency but also market acceptance[21,22]. Recent studies have further emphasized that the sustainability of BEVs is highly dependent on regional energy structures and climatic variations[23,24]. However, few have integrated these parameters into a unified life cycle framework—especially in coal-dominated and cold-climate regions where electricity is carbon-intensive and battery efficiency drops sharply. These conditions are particularly pronounced in northern China, making it essential to evaluate EV performance in such contexts.

Heilongjiang Province in Northeast China represents a compelling case. As part of the Northeast Power Grid, it relies heavily on coal-based generation and experiences long, harsh winters. Based on regional meteorological data[25], the winter (December–February) average temperature is − 16.3 °C. These factors amplify electricity-related emissions and degrade battery efficiency, potentially diminishing BEV advantages. Understanding the environmental performance of BEVs under these constraints is thus critical for both regional energy planning and national decarbonization policy.

The objectives of this study are threefold: (1) to quantify the environmental impacts of battery electric vehicles (BEVs) and gasoline vehicles (GVs) during the use phase in Heilongjiang Province, explicitly considering regional electricity generation and seasonal temperature variations; (2) to identify the conditions under which BEVs deliver significant environmental advantages over GVs in coal-based and cold regions; and (3) to propose strategies to enhance BEV sustainability through cleaner energy integration and technological adaptation. The hypotheses of this study are as follows: H1—Regional grid composition and seasonal charging efficiency are the dominant factors shaping BEV sustainability performance; H2—Grid decarbonization and winter-specific efficiency improvements can significantly enhance BEV environmental benefits.

This study advances existing grid-based LCAs by developing a regionally resolved framework that incorporates province-specific power grid data to capture the emission characteristics of the Northeast China Grid. It further integrates temperature-dependent charging efficiency and seasonal variation into the use-phase modelling to reflect real-world performance under cold climates. A dual-method assessment—combining the IPCC GWP100 (V1.02) for midpoint analysis with ReCiPe 2016 (H/A) for endpoint evaluation—provides a multi-level understanding of environmental impacts. Additionally, uncertainty and sensitivity analyses were conducted to test model robustness and identify the most influential parameters. Collectively, these methodological refinements yield a comprehensive and policy-relevant understanding of BEV sustainability in fossil-intensive regions, offering transferable insights for other areas with similar climatic and energy conditions.

Methodology

LCA is one of the most effective approaches for evaluating the resource use and environmental impacts of products across their entire life cycle. A standardized framework has been developed by ISO 14,040[26], which includes four phases: goal and scope definition, inventory analysis, impact assessment, and interpretation, show as Fig. 1. Flow diagram of the LCA framework.

The present study focuses on the use phase of vehicles, which is particularly relevant in regions where power grid structures and climatic conditions exert significant influence on environmental outcomes. The BYD Dolphin and the Volkswagen Lavida were selected as representative models due to their market prevalence and comparable pricing, allowing differences in performance to be attributed primarily to the type of fuel used.

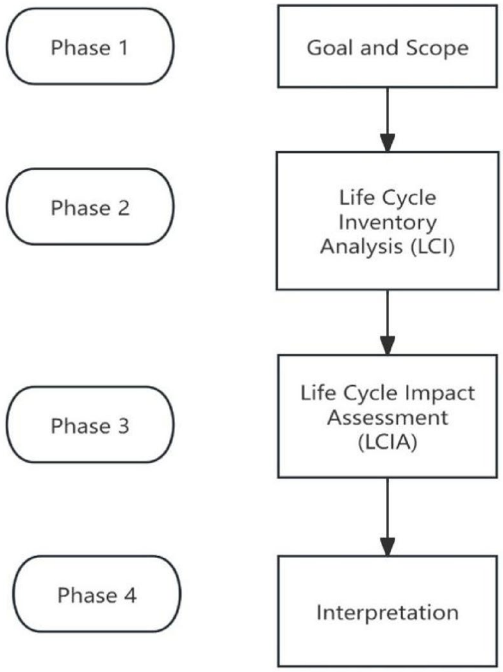

Fig. 1. Flow diagram of the LCA framework.

Goal and scope

The goal of this study is to evaluate the environmental sustainability of BEVs compared with GVs in Heilongjiang Province, China. The analysis focuses on the use phase and quantifies how regional electricity mixes and seasonal temperature variations affect comparative results. A scenario-based LCA was conducted in accordance with ISO 14,040/44 standards.

Gasoline consumption in China is projected to peak around 2025, whereas diesel consumption has largely stabilized. BEVs, which produce zero tailpipe GHG emissions, have become the dominant choice among new energy vehicles. By 2040, it is expected that all private vehicles in China will transition to hybrid electric vehicles (HEVs) and BEVs, with internal combustion engine vehicles becoming the alternative. By 2050, BEVs are projected to constitute approximately 85% of China's total vehicle fleet[27].This optimistic outlook is driven by rapid EV market growth and government initiatives to phase out traditional fuel vehicles. China's EV market is already dominated by BEVs in both private and public sectors[28]. reinforcing the relevance of comparing BEVs and GVs in this study.

This study was carried out in Heilongjiang Province, which is part of the Northeast China Grid. Regional energy structures significantly affect EV sustainability assessments, yet most LCAs rely on average national or developed-region data, which can obscure local differences[11]. China has six major regional power grids[29]. The Northeast, Northwest, and Southwest grids act as sending ends, while North China, East China, and Central China are receiving ends[30]. Regional grids of China and the study area (Heilongjiang) shows in Fig. 2. The Northeast Grid relies heavily on coal-fired power, leading to high fuel consumption and carbon emissions[31]. EV adoption is particularly low in this region, with Heilongjiang ranking last nationwide in sales volume[32]. Figure 3 illustrates China's EV sales volume in 2022.

According to[33], the Northeast Grid covers Liaoning, Jilin, and Heilongjiang Provinces. This study focuses solely on Heilongjiang, which comprises 13 major cities: Da Hinggan Ling, Heihe, Qiqihar, Daqing, Suihua, Yichun, Harbin, Hegang, Jiamusi, Shuangyashan, Qitaihe, Jixi, and Mudanjiang.

Most studies exclude the battery use phase due to the variability of usage conditions and the complexity of technical indicators such as performance and lifespan. However, as this phase constitutes a substantial portion of the vehicle life cycle and is a major source of carbon emissions, it should not be overlooked[34]. During use, lithium battery energy consumption arises mainly from two aspects: additional energy required to carry battery weight and power losses due to less-than-perfect charging and discharging efficiency[35]. According to Burke and Miller (2011), the maximum usable power density of lithium-ion batteries may exceed that corresponding to 95% efficiency, while optimal efficiency is 100%[36].The average temperatures in Heilongjiang Province, − 16.3 °C during the winter months (December–February), 6.0 °C in spring (March–May), 20.5 °C during summer (June–August), and 5.1 °C in autumn (September–November)[25].Temperature strongly influences power demand and range. When below 10 °C, power consumption increases and cruising range declines; the lowest energy use occurs around 10 °C, whereas both higher and lower temperatures cause additional losses[37].A national report on pure EVs showed that energy consumption rose by 4% at 30–35 °C, 40% at 0 °C, and 70% at ≤ − 7 °C, equating to roughly 4% increase per 1 °C drop[38].

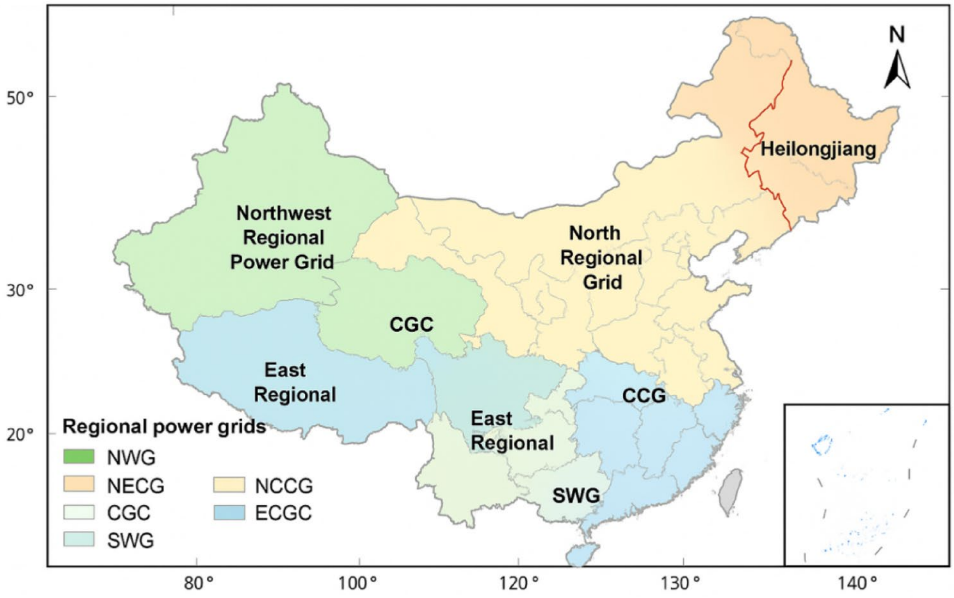

Fig. 2. Regional grids of China and the study area (Heilongjiang).

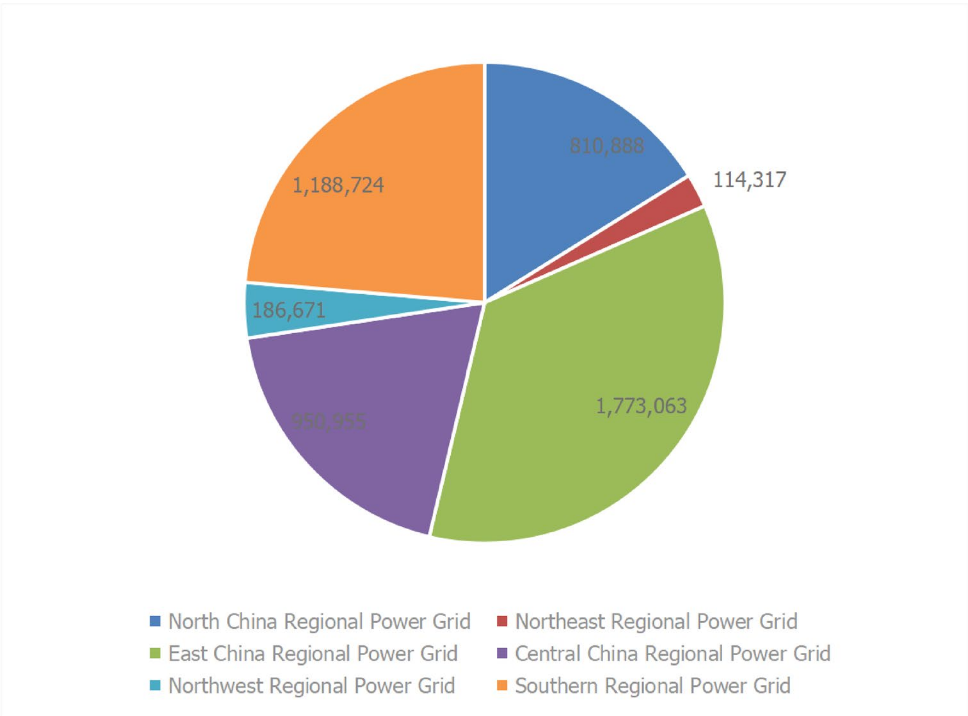

Fig. 3. Electric Vehicle Sales Volume in China in 2022 (in 10 thousand).(Source: New Car Compulsory Traffic Insurance Data).

Based on these findings, this study modeled seasonal variations in Heilongjiang Province. Energy consumption per 100 km increases by 70% in winter (− 16.3 °C, 59% charge–discharge rate), 24% in spring (6.0 °C, 81%), 20% in autumn (5.1 °C, 83%), while summer (20.5 °C) represents the optimal 100% efficiency condition. The annual average is 13.52 kWh/100 km, consistent with Feng et al. (2014) for Harbin's temperature-dependent capacity[36].

The scope of this study, BYD Dolphin (BEV) and Volkswagen Lavida (GV) were chosen as representative models due to their high market relevance and similar pricing. The BYD Dolphin Fashion Edition costs approximately 123,800 CNY, while the Volkswagen Lavida 1.5 L Automatic Wish Edition is priced at about 110,000 CNY[39]. This comparability in cost and performance ensures that observed differences in environmental

Electric vehicle (EV)	2022 Sales (Rank)	2023 Sales (Rank)	Price (10k CNY)	Gasoline Vehicle (GV)	2022 Sales (Rank)	2023 Sales (Rank)	Price (10k CNY)
Wuling Hongguang MINI EV	483 (1)	605 (1)	3.28–9.99	Nissan Sylphy	2,993 (4)	1,369 (6)	10.86–17.49
BYD Qin	177 (4)	330 (3)	12.98–20.99	Volkswagen Lavida	8,177 (1)	2,161 (2)	9.39–15.19
BYD Han EV	136 (5)	164 (5)	20.98–33.18	Toyota Corolla	5,260 (2)	1,978 (3)	10.98–13.68
BYD Dolphin	366 (2)	395 (2)	11.68–13.98	TOYOTA Camry	2,505 (5)	1,446 (5)	17.98–26.98
Tesla (Model 3)	214 (3)	201 (4)	25.99–29.26	Honda Accord	2,428 (6)	1,528 (4)	16.98–25.98
AION.S	7 (6)	2 (6)	13.98–20.29	Volkswagen Sagitar	4,843 (3)	4,521 (1)	12.79–17.99

Table 1. The top six highest-selling vehicle series and total sales volume of EVs and GVs in Heilongjiang Province, China for the year 2022 and January–September 2023. (Source:[40])

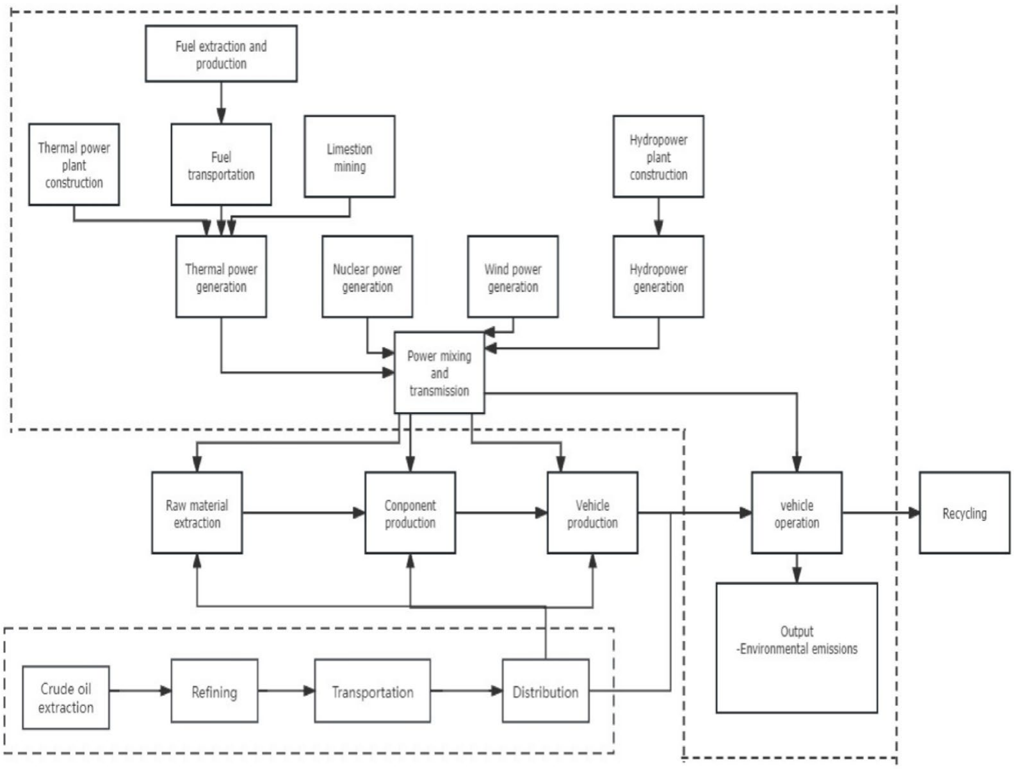

Fig. 4. System boundary of vehicles sustainability analysis study.

impacts can be attributed primarily to fuel type rather than vehicle price or capability. Table 1 summarizes the main features of the selected models.

Functional unit and system boundary

According to the International Organization for Standardization[41], the functional unit (FU) represents the quantified performance of a product system and serves as the basis for comparison in life cycle assessments. In this study, the FU is defined as one vehicle driven 20,000 km per year over a 15-year service life time. This definition reflects typical driving conditions in Heilongjiang Province and enables a consistent comparison of BEVs and GVs. The assumption based average annual mileage of passenger vehicles in China was approximately 19,000 km in 2013[42]. According to the BYD Dolphin's owner manual, maintenance is required every 20,000 km or once per year[43] ; therefore, this study assumes an annual mileage of 20,000 km. Vehicle lifetime and retirement assumptions follow China's auto scrap standards, which initially set a 10-year limit[44] and later extended it to 15 years in 2000. Based on observed survival trends, the service life in this study is assumed to be 15 years, consistent with national averages.

The system boundary of this study is limited to the use phase of the vehicles. For BEVs, this includes electricity generation (upstream) and vehicle operation. For GVs, the boundary covers gasoline refining, distribution, and combustion emissions. Vehicle manufacturing, maintenance, and end-of-life phases are excluded, as the focus of this research is on operational sustainability rather than cradle-to-grave impacts. System boundary of vehicles sustainability analysis study shows in Fig. 4.

Primary data were collected through a consumer survey to capture local driving behaviors, while secondary data were obtained from established databases and government reports. Consumers were considered the only stakeholder group within the use phase.

Life cycle inventory

The Life Cycle Inventory (LCI) stage involves the systematic collection of data for all relevant inputs and outputs associated with a product system, including energy consumption, emissions, and resource use throughout its life cycle[45]. The reliability of LCA results is highly dependent on the quality, transparency, and regional specificity of the underlying data[46]. According to ISO 14,064 standards for greenhouse gas reporting, emissions from fossil fuel combustion and energy production must be documented, as they are directly attributable to the reporting system[47]. Direct emissions occurring during any life cycle stage can contribute significantly to overall impacts[48].

To ensure accuracy, this study prioritised the use of region-specific and up-to-date data, particularly for the Heilongjiang electricity mix. The primary database employed was Ecoinvent v3.9.1 (released January 2023), which provides updated inventories for China's energy grid[49]. These data include electricity inputs from domestic generation and imports, transformation to medium voltage, transmission processes, and direct air emissions (e.g., SF_6 from high-voltage switchgear, allocated to medium-voltage demand). Supplementary data were drawn from government reports and peer-reviewed literature. A summary of the LCI is presented in Table 2. A summary of LCI data quality and representativeness following the ISO 14,040/14,044 framework is reported in Supplementary Table S2.

In Ecoinvent 3.9.1, China's power structure was updated to reflect China's situation in 2020. The State Grid Corporation of China's (SGCC) power structure has been divided into six zones and now better reflects local conditions[49]. This data set includes electricity inputs produced in this country and from imports and transformed to medium voltage, the transmission network, direct emissions to air (SF6 from high-voltage switchgear insulation, allocated to medium-voltage electricity demand).

Given that environmental performance is strongly influenced by local conditions, this study focuses on the power grid composition in Heilongjiang Province, accounting for its coal dependency and extreme seasonal climate effects on BEV efficiency. Sensitivity analyses were conducted for both temperature variations and grid scenarios, enhancing the robustness of the results.

For gasoline vehicles (GVs), the study uses the "petrol, low-sulfur" dataset from Ecoinvent v3.9.1, which covers fuel distribution to end consumers and includes transport processes. Product losses during distribution are assumed negligible and excluded. Tailpipe emissions include CO_2, CH_4, and N_2O, along with hydrofluorocarbon (HFC) releases from air-conditioning systems. However, since CO_2 accounts for 95–99% of total GHG emissions from passenger vehicles, while CH_4, N_2O, and HFCs contribute only 1–5%[50], In line with China's (China 6) GB 18352.6–2016[51], CH_4 and N_2O emissions are not considered, and HFC emissions from air-conditioning systems are also excluded. It is assumed that vehicles comply exactly with National VI B limits, as stricter manufacturer practices would likely impose additional costs[52].

Environmental impacts were assessed using SimaPro, which is recognized for its comprehensive dataset and global application in environmental assessments[54]. The selection of impact categories is a critical step in the LCA methodology. In this study, both midpoint and endpoint indicators were included to provide a robust framework for comparison. Midpoint indicators such as Global Warming Potential (GWP) are emphasized due to their relative certainty, while endpoint categories (e.g., human health, ecosystems, resources) are included to provide integrative perspectives on the overall environmental performance of BEVs and GVs.

Vehicles	Components	Location	Reference	Link
GV	petrol, low-sulfur, in the Global geography	Global geography	Ecoinvent version 3.	https://support.ecoinvent.org/ecoinvent-version-3.0
	One liter of gasoline emits approximately 2,339 g of carbon dioxide from vehicle exhaust.	China	He & Bandivadekar, 2010	https://theicct.org/wp-content/uploads/2022/01/ICCT_fiscalpoliciesES_feb2011_Ch.pdf
	N_2O 20 mg/km	China	Ministry of Environmental Protection General Administration of Quality Supervision, Inspection and Quarantine, 2016	https://www.mee.gov.cn/ywgz/fgbz/bz/bzwb/dqhjbh/dqydywrwpfbz/201612/W020171207355626647621.pdf
BEV	State Grid Southwest (SWG) China Branch input and output	The inventory is modeled for CN-SWG	Ecoinvent version 3.9.1	https://support.ecoinvent.org/ecoinvent-version-3.9.1
	State Grid Northwest China Branch (NWG) China Branch input and output	The inventory is modeled for CN-NWG	Ecoinvent version 3.9.1	https://support.ecoinvent.org/ecoinvent-version-3.9.1
	State Grid Northeast China Branch (NECG)China Branch input and output	The inventory is modeled for CN-NECG	Ecoinvent version 3.9.1	https://support.ecoinvent.org/ecoinvent-version-3.9.1
	State Grid North China Branch (NCGC)China Branch input and output	The inventory is modeled for CN-NCGC	Ecoinvent version 3.9.1	https://support.ecoinvent.org/ecoinvent-version-3.9.1
	State Grid East China Branch (ECGC)China Branch input and output	The inventory is modeled for CN-ECGC	Ecoinvent version 3.9.1	https://support.ecoinvent.org/ecoinvent-version-3.9.1
	State Grid Central China Branch (CCG)China Branch input and output	The inventory is modeled for CN-CCG	Ecoinvent version 3.9.1	https://support.ecoinvent.org/ecoinvent-version-3.9.1

Table 2. Life cycle inventory summary.

Life cycle impact assessment

According to ISO 14,040 (2006), the life cycle impact assessment (LCIA) framework consists of five main steps: classification, characterization, normalization, grouping, and weighting. Among these, classification and characterization are mandatory, whereas normalization and weighting are optional. This study focuses primarily on the classification and characterization of emissions, supplemented by endpoint damage assessment.

Classification involves assigning inventory results to relevant environmental impact categories. In this study, emissions are classified under the Global Warming Potential (GWP) category. Characterization then quantifies contributions to climate change by converting different GHG into carbon dioxide equivalents (CO_2-eq) using established GWP values[55].

The GWP method developed by the Intergovernmental Panel on Climate Change (IPCC) is widely applied in LCA and represents the most scientifically robust approach for climate change assessment[56]. This study adopts the IPCC GWP 100 V1.2 method, which calculates GWP over a 100-year time horizon (GWP100a), ensuring consistency with international practice. All characterization factors, including gas lifetimes, radiative efficiencies, and metrics were implemented (IPCC, 2021) as provided in Supplementary Table S1. Impacts are expressed in kilograms of CO_2-equivalent according to Eq. (1)[57]:

$$GWP = \sum GWP_i \times m_i \tag{1}$$

GWP: total global warming potential (kg CO_2-eq).

GWP_i: characterization factor (global warming potential of substance i relative to CO_2, dimensionless).

m_i: mass of substance i emitted (kg).

where GWP_i is the global warming potential of substance i, and m_i is the mass of substance i emitted.

Beyond climate change midpoints, endpoint impact assessments are also conducted. Endpoints translate midpoint results into quantifiable damages to areas of protection (AoPs), namely human health, ecosystem quality, and resource availability[58,59]. This conversion applies constant midpoint-to-endpoint factors as shown in Eq. (2).

$$CFE_{x,a} = CFm_x \times F_M \rightarrow, E, a \tag{2}$$

$CFe_{x,a}$: endpoint characterization factor for stressor x in area of protection a (e.g., DALY kg^{-1} emission, species·year kg^{-1} emission, or USD kg^{-1} emission).

CFm : midpoint characterization factor (impact per unit emission at midpoint, units depend on impact category)

F_M: conversion factor from midpoint to endpoint for area a (dimensionless)

In line with ISO recommendations, this study applies the ReCiPe 2016 methodology (Hierarchist perspective) to evaluate environmental impacts at both midpoint and endpoint levels[60]. Human health: quantified in disability-adjusted life years (DALYs), representing years of life lost or lived with disability due to environmental burdens. Ecosystem quality: assessed in terms of the potentially disappeared fraction (PDF) of species, expressed as species·year (integrated across terrestrial, freshwater, and marine ecosystems). Resource scarcity: expressed in monetary terms (USD2013 surplus cost), representing the additional future costs of mineral and fossil resource extraction[61].

While midpoint results are emphasized due to their lower uncertainty and stronger causal linkage to emissions, endpoint results are reported as complementary indicators that provide a more tangible perspective on damage outcomes.

Scenario life cycle assessment - comparing BEVs in different power grade emissions

This study conducts a scenario-based LCA to compare the emissions of BEVs and GVs over one year, assuming a driving distance of 20,000 km. The analysis focuses on the effect of regional electricity generation mixes while excluding temperature-related variations. The key parameters selected for the sensitivity analysis were derived from Table 2 (Life Cycle Inventory Summary), which contains the primary operational inputs influencing use-phase emissions. Variations were applied to electricity consumption, grid emission factor, annual mileage, and temperature correction factor, as these variables are expected to exert the greatest influence on the overall results. Used to ensure that comparative outcomes remain consistent under parameter fluctuations.

The source of electricity is a critical determinant of the environmental benefits of EVs. As noted by[62] the dominance of coal in China's power system and its economic competitiveness hinder the ability of the generation mix to fully deliver EV-related emission reductions. Similarly, the sustainability of EVs depends on the cleanliness of the grid, highlighting the importance of region-specific assessments[12].

The Chinese power grid is divided into six major regional grids: The Northeast, Northwest, and Southwest power grids serve as the sending ends, While the North China, East China, and Central China power grids as the receiving ends[29,30]. This study evaluates BEVs within these six regional grids and compares their emissions with those of GVs under identical functional units. The IPCC 2021 Global Warming Potential (GWP) 100 V1.02 method was applied in SimaPro to calculate emissions over one year and 20,000 km of vehicle operation. The comparative assessment framework is expressed in Eq. (2).

By examining regional variations in electricity structure, this scenario analysis provides a comprehensive understanding of how energy mix heterogeneity shapes the relative emissions of BEVs and GVs.

Scenario life cycle assessment- consider temperature effect

A second scenario-based LCA was conducted to analyze the influence of seasonal temperature variations on the emissions of BEVs and GVs in Heilongjiang Province, assuming a one-year driving distance of 20,000 km. The analysis accounts for temperature-dependent charging and discharging efficiencies of BEVs, estimated at 59% in winter, 86% in spring, 100% in summer, and 83% in autumn. Seasonal adjustments to energy consumption were incorporated into SimaPro using the IPCC 2021 GWP 100 V1.02 characterization method. Emissions were compared both seasonally and on an aggregated annual basis, while the comparative framework is expressed in Eq. (1).

To ensure replicability and robustness, all temperature-related parameters and adjustment factors are explicitly listed in the life cycle inventory (Table 2). These values were derived from published field data and technical reports on BEV performance in cold climates, enabling verification and potential recalibration by other researchers.

Temperature is a well-documented determinant of EV performance, influencing both battery efficiency and range[63,64]. Extreme cold conditions increase energy consumption for heating and reduce battery output, thereby diminishing the relative advantage of BEVs[23,65]. By explicitly incorporating seasonal temperature variations into the use-phase modeling, this study provides a more realistic and region-specific assessment of BEV sustainability in cold-climate, coal-dependent regions.

This approach ensures that the analysis captures both the opportunities (e.g., emission reductions under cleaner grids) and the challenges (e.g., performance penalties in winter) associated with BEV adoption in Heilongjiang Province.

Uncertainty and sensitivity analyses of BEVs and GVs

To evaluate the robustness of results, both sensitivity and uncertainty analyses were conducted using SimaPro under the ReCiPe 2016 Endpoint (H) V1.08 / World (2010) H/A method. An uncertainty analysis was performed for both BEVs and GVs to account for fluctuations in energy consumption during vehicle operation and their effects on overall outcomes. Uncertainty analysis was performed through uncertainty analysis of calculation function, Monte Carlo simulation with 1,000 iterations (seed value = 0) to capture the stochastic variability of electricity-related impacts within the Northeast China Grid (NECG). The analysis quantified the uncertainty associated with input parameters, particularly the electricity consumption of BEVs during the use phase.

Sensitivity analysis was designed to examine the influence of grid composition on life-cycle results. The shares of coal, natural gas, hydropower, and wind within the NECG mix were varied by ± 10% from their baseline values to simulate potential decarbonization scenarios. Comparative modeling was implemented using the Ecoinvent 3.9.1 allocation, cut-off by classification datasets—switching between unit-level and system-level boundaries—to assess the sensitivity of environmental outcomes to database assumptions. And, calculation function was used compare. For BEVs, a scenario-based parameter sensitivity analysis was performed by adjusting the energy mix. The baseline scenario was defined by the current composition of the Northeast China Grid, and three additional scenarios were simulated to reflect projected energy development pathways. Scenario 1 and Scenario 2 represent gradual reductions in coal dependence combined with modest increases in cleaner energy sources such as natural gas and wind power. Scenario 3 emphasizes the substitution of coal with nuclear and solar power, thereby accelerating the transition toward a lower-carbon electricity system. These incremental adjustments allowed for the evaluation of system responses to small-scale shifts in energy composition, particularly in terms of carbon emissions, resource consumption, and energy costs.

For GVs, sensitivity analysis was conducted by varying fuel consumption levels to reflect improvements in fuel efficiency, changes in vehicle characteristics, driving conditions, and external environmental factors. These variations in fuel use were modelled to assess their influence on emissions and resource use. Parameter sets were created to represent four alternative scenarios based on Scenario 1: +10% increase in electricity use intensity (1.1× baseline), Scenario 2: +20% increase in electricity use intensity (1.2× baseline), Scenario 3: −10% decrease in electricity use intensity (0.9× baseline), Scenario 4: −20% decrease in electricity use intensity (0.8× baseline).

This combined approach allows identification of the most influential parameters affecting BEV performance under Heilongjiang's regional grid conditions and ensures methodological transparency and reproducibility.

Environmental impact results

Impact assessment characterization

The characterization and endpoint damage results for GVs and BEVs over one year (20,000 km) in Heilongjiang Province are summarized in Table 3. Greenhouse gases (GHGs) absorb infrared radiation and reduce heat loss to space, thereby warming the Earth in a manner analogous to a blanket. The Global Warming Potential

Impact assessment	Damage category	Unit	GV	BEV
Impact assessment characterization	GWP100 - fossil	kg CO_2-eq	4148.85	3099.88
	GWP100 - biogenic	kg CO_2-eq	0.43	0.32
	GWP100 - land transformation	kg CO_2-eq	0.35	0.72
End-point damage assessment	Human health	DALY	0.01	0.01
	Ecosystems	species. yr	0.00	0.00
	Resources	USD2013	652.26	58.06

Table 3. GV and BEV emissions by 20,000 km in Heilongjiang Province impact assessment.

(GWP) indicator is commonly used to compare the warming effects of different gases over a 100-year time horizon[66]. In the context of electric vehicles, GWP and energy consumption are considered the most significant environmental impacts[20]. The GWP indicator set includes GWP-fossil, GWP-biogenic, and GWP-land use and land use change[67].

GWP100 – Fossil. For GVs, the majority of emissions originate from fossil fuel combustion, amounting to 4151.55 kg CO_2-eq, followed by natural gas and petroleum production. For BEVs, the dominant contribution comes from high-voltage electricity production in coal-fired power plants, totaling 3100.08 kg CO_2-eq.

GWP100 – Biogenic. This metric captures the 100-year impact of biogenic carbon emissions. GVs exhibit higher biogenic emissions (0.433 kg CO_2-eq) than BEVs (0.322 kg CO_2-eq). Biogenic CO_2 refers to emissions from biomass sources, which contribute to climate change through both CO_2 and associated gases such as CH_4 and N_2O from biomass burning[68] The higher biogenic emissions of GVs are attributable to petroleum industry activities, including exploration, extraction, and refining, which generate substantial organic waste materials[69].

GWP100 – Land Transformation. This category quantifies the climate impacts of land use change during the vehicle's use phase. BEVs show higher emissions (0.722 kg CO_2-eq) compared to GVs (0.348 kg CO_2-eq). Land transformation refers to the conversion of land from one category to another, such as the establishment of forest plantations on former agricultural land[70]. Such changes can induce radiative forcing and alter climate at local or global scales[71]. The higher BEV values are primarily linked to electricity production processes, particularly hydropower with pumped storage.

Overall comparison. On an annual basis, GVs emit 4149.63 kg CO_2-eq, whereas BEVs emit 3100.92 kg CO_2-eq. This corresponds to an emission intensity of 1.45 kg CO_2-eq per kWh for BEVs and 3.47 kg CO_2-eq per litre for GVs. These findings indicate that BEVs substantially reduce GHG emissions relative to GVs, consistent with previous studies[17,72–74]. However, Wang et al. (2019) found that BEVs' emissions and climate change impacts were significantly higher than those of the ICEVs[16]. Nonetheless, the study had a limitation in that it used foreign data, which might lead to errors in the conclusions. The study by[24] indicates that BEVs fuelled by the current average Chinese energy mix can achieve a 23% reduction in GWP. The lower percentage in NECG may be because of the temperature effect and electricity mix, making EVs less advantageous in this region.

End-point damage assessment

Previous studies[75–77] provide valuable insights into the broader environmental impacts of EVs through LCA. These studies consistently confirm the positive role of EVs in mitigating global warming but also highlight complex trade-offs, such as greater impacts on human health and atmospheric acidification.

Emissions influence multiple environmental mechanisms, including global warming, ozone depletion, ionizing radiation, ozone formation, particulate matter formation, acidification, eutrophication, and toxicity across terrestrial, freshwater, marine, and human systems[78]. These 18 midpoint categories are aggregated into three endpoint damage categories: human health, ecosystems, and resources (Table 3).

Human health. Impacts are expressed in disability-adjusted life years (DALYs), which measure the loss of healthy life years due to disease or disability[79]. Contributing factors include climate change, stratospheric ozone depletion, ionizing radiation, ozone formation, particulate matter formation, human toxicity (carcinogenic and non-carcinogenic), and water use[80]. BEVs show slightly lower health impacts (0.005 DALY) compared with GVs (0.007 DALY). Nevertheless, BEV reliance on coal-dominated electricity in regions such as Heilongjiang may exacerbate particulate matter formation, with associated respiratory risks. Maximizing BEV health benefits therefore requires simultaneous decarbonization of regional power systems.

Ecosystems. Ecosystem impacts are measured in species·yr, representing the potentially disappeared fraction of species integrated over time and space[59]. Results indicate comparable impacts for both vehicles, with GVs affecting 1.38×10^{-5} species·yr and BEVs 1.31×10^{-5} species·yr. For GVs, ecosystem damages are primarily linked to gasoline combustion processes, while for BEVs they stem from electricity production—particularly in coal-intensive grids such as Inner Mongolia. These findings emphasize that decarbonizing electricity supply is essential to reduce the indirect ecological burdens of BEV deployment.

Resources. Resource depletion is quantified in USD2013, representing the additional costs of future extraction[57]. GVs impose substantially higher resource costs (652.69 USD2013) compared to BEVs (58.06 USD2013). For GVs, resource damages are mainly associated with petroleum and gas extraction, whereas for BEVs they arise from coal mining and preparation. The stark reduction in resource damage costs for BEVs underscores their potential economic advantage in reducing societal costs linked to resource depletion.

Results shows, the transition from GVs to BEVs provides a clear environmental benefit in reducing fossil-related emissions and resource consumption, but comes with trade-offs in land transformation emissions. Future sustainability improvements should focus on cleaner energy sources and reducing battery production impacts. However, if the power industry continues to follow the conventional trajectory, a significant amount of the electricity needed to meet the demand for EVs that are replacing GVs will have to be supplied by conventional coal-fired power plants. This, in turn, may have another effect on humans[81]. The studies by[75],[76], and[77] provide valuable insights into the broader environmental impacts of EVs through LCAs. While these assessments confirm the positive impacts of EVs on global warming and other aspects, they also highlight the complex trade-offs, for example, the greater impact of BEVs on human health and atmospheric acidification.

Scenario life cycle assessment - comparing BEVs in different power grade emissions

This scenario aimed to answer How do emissions vary across different power grades of BEVs during their use stage emissions? In this scenario analyze GV and BEV emissions over one year (20,000 km) across different power grids, excluding the effects of temperature.

In the use stage, carbon emissions are closely linked to electricity consumption, which is determined by the energy structure of each grid. Variations in grid composition therefore lead to differences in environmental performance[34]. To evaluate these differences, a damage assessment was conducted using the ReCiPe 2016 Endpoint (H) V1.08 / World (2010) H/A method, comparing process, focusing on three endpoint categories: human health, ecosystems, and resources. The results, illustrated in Fig. 5, compare GV and BEV impacts across the six regional power grids in China.

The findings demonstrate that BEVs consistently have lower environmental impacts than GVs across all categories, regardless of regional grid characteristics. However, the magnitude of these benefits depends on the electricity mix. The Southwest Grid (SWG) performs best due to its high share of renewable energy and efficient generation, while the Northeast China Grid (NECG) performs worst because of its heavy reliance on coal and high fossil fuel intensity. The North China, East China, Central China, and Northwest Grids show intermediate performance, with BEVs outperforming GVs but varying significantly depending on the contributions of coal, natural gas, hydropower, and wind.

These results align with previous studies demonstrating that BEVs powered by renewable-dominant grids are more sustainable than both internal combustion engine vehicles (ICEVs) and BEVs dependent on mixed or fossil-based grids. As emphasized by[12], the sustainability of EVs depends on the of the power grid. Similarly,[82] and[83] highlight that the advantages of EVs are diminished in regions reliant on fossil fuels. underscoring the need for a transition to cleaner energy sources to fully realize the potential of EVs in reducing emissions. BEVs that are powered by renewable energy seem more sustainable than both ICEVs and BEVs that are powered by a mixed energy sources[84].

China's power system remains heavily reliant on thermal generation, which imposes significant upstream energy burdens[62,85]. Nevertheless, BEVs still demonstrate substantial advantages in reducing environmental impacts across all endpoint categories, even under fossil-dominated grids. Petrol vehicles, by contrast, generate higher direct use-phase emissions in every scenario[1].

In summary, while BEVs consistently outperform GVs in terms of emissions, the magnitude of this advantage is strongly conditioned by the electricity mix. Ensuring that EV adoption is accompanied by grid decarbonization will be crucial for achieving meaningful environmental improvements.

BEVs exhibit substantially lower environmental impacts across all categories compared to GVs, regardless of the grid. Their benefits are most pronounced in regions with higher shares of renewable power, such as the SWG, while the NECG shows the weakest BEV performance due to its coal dependency. The North, East, Central, and Northwest grids demonstrate intermediate results, with BEVs consistently outperforming GVs, though with variation depending on the mix of coal, gas, hydropower, and wind. These results agree with[84] who reported that BEVs powered by renewable energy sources are more sustainable than ICEVs or BEVs powered by fossil-dominated grids.

Regional suitability also emerges from the analysis. In coal-reliant regions such as the northwest, northeast, and southern China, hybrid vehicles remain the most cost-effective and environmentally favorable option. Conversely, in developed regions with cleaner energy structures, BEVs achieve greater emission reductions and cost savings. However, the economic competitiveness of coal relative to other generation sources continues to constrain the environmental potential of EV adoption[62].

Overall, although China's power system still depends heavily on thermal generation and results in significant upstream energy consumption[85]. BEVs retain a marked environmental advantage across all impact categories. Petrol vehicles show the highest direct emissions during use[1]. To maximize the long-term benefits of EVs, it

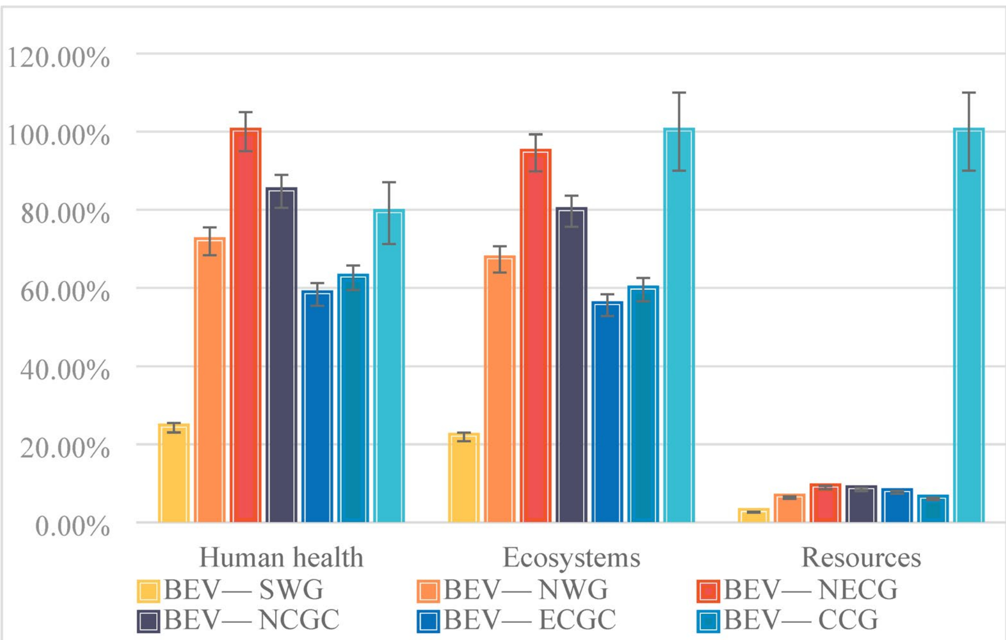

Fig. 5. Comparing the 20,000-kilometer mileage emissions of different power grids EVs and GV.

remains vital to optimize regional power generation portfolios and accelerate the shift toward renewable energy sources[62].

In conclusion, BEVs provide clear emission advantages over GVs, yet the scale of these benefits depends heavily on the electricity mix. Future energy policies should therefore prioritize clean energy expansion to ensure that the transition to EVs leads to genuine environmental improvement.

Scenario life cycle assessment- consider temperature effect

This scenario examines how ambient temperature affects BEV emissions compared with GVs in Heilongjiang Province, within the Northeast Regional Power Grid (NECG). The analysis considers one year of operation (20,000 km) with seasonal variations in charging and discharging efficiencies: 59% in winter, 86% in spring, 100% in summer, and 83% in autumn. Calculations were performed in SimaPro using the IPCC 2021 GWP100 V1.02 characterization method.

The need for region-specific approaches to EV promotion has been emphasized by[86–88] as ambient temperature significantly affects vehicle efficiency and emissions. GHG outcomes depend not only on primary fuel choice but also on upstream emissions throughout the value chain[83].

Fossil emissions. This category quantifies GHG emissions from fossil fuel combustion. As shown in Fig. 6, GVs produce consistently higher fossil emissions than BEVs on an annual basis. However, in winter, BEVs temporarily exceed GVs due to reduced battery efficiency and additional electricity demand for cabin heating[23]. Previous studies reported a 68–80% reduction in BEV driving range under cold conditions with heating use. However, However, due to poor battery performance,[65]. Over a full year, BEVs in Heilongjiang achieve a 14.2% reduction in fossil GWP100 emissions compared with GVs, a figure somewhat lower than the 23% reduction reported for the average Chinese grid[24]. This discrepancy highlights the combined influence of regional climate and energy mix.

Biogenic emissions. Seasonal patterns mirror those of fossil emissions: BEVs emit more than GVs in winter but maintain lower annual totals. Across 20,000 km, BEVs consistently outperform GVs in this category, confirming their environmental advantage despite seasonal inefficiencies.

BEVs consistently exhibit higher land transformation emissions than GVs in all seasons, with annual impacts 2.6 times greater. Land transformation refers to changes in land use (e.g., converting agricultural land to forest plantation[70]. which can affect albedo, evapotranspiration, and greenhouse gas fluxes, thereby influencing climate systems[71]. Land transformation emissions are higher for BEVs than GVs, with the highest contribution coming from electricity production, which is hydro-pumped storage.

Overall assessment. Seasonal climate conditions significantly influence BEV performance, reducing range and increasing winter emissions, as also highlighted by[21,22]. Despite winter disadvantages, BEVs achieve lower annual fossil and biogenic emissions than GVs, though at the cost of higher land transformation impacts. These results confirm that transitioning to BEVs can reduce GHG emissions, but the benefits are maximized only when combined with cleaner energy mixes.

BEVs represent a promising option for mitigating transport-sector emissions[89]. However, their full potential depends on parallel efforts to reduce coal reliance in regional power grids[14]. Policy measures such as lowering tariffs on renewable electricity and incentivizing clean energy deployment are essential. Without such measures, the "zero-emission" label risks reflecting only nominal reductions rather than actual emission cuts[90].

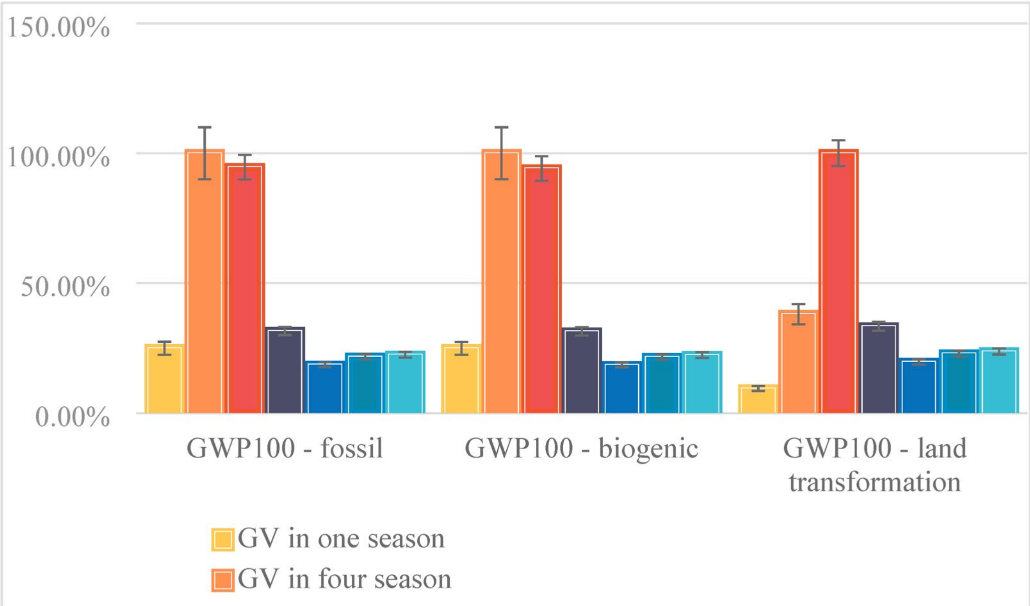

Fig. 6. Comparing process with 20,000-kilometer mileage seasons emissions of BEV and GV.

Uncertainty and sensitivity analyses of BEVs and GVs

The results for BEVs (Fig. 7a) indicate that increasing the share of clean energy sources such as nuclear, solar, and wind consistently improves environmental performance across all impact categories, including human health, ecosystem quality, and resource depletion. The findings of the uncertainty analysis are summarized in Fig. 8, confirming the robustness of these results under parameter variability.

For human health, results show that as the proportion of clean energy increases in Scenarios 1, 2, and 3, impacts measured in DALYs decline significantly. The greatest reduction occurs in Scenario 3, reflecting the large increase in nuclear and solar energy shares. The uncertainty analysis indicates a coefficient of variation (CV) of 22.07%, suggesting moderate variability; although energy supply fluctuations influence health outcomes, uncertainty remains within a manageable range.

For ecosystem impacts, clean energy adoption reduces species·year damage, with Scenario 3 providing the most pronounced improvement. The uncertainty analysis yields a CV of 22.11%, indicating moderate variability but confirming the overall trend that higher clean energy penetration reduces ecological burdens.

For resource consumption, the benefits are most evident in Scenario 3, where nuclear and solar energy minimize fossil resource use. However, uncertainty analysis reveals higher variability, with a CV of 43.72%, reflecting the sensitivity of resource outcomes to the choice of energy technologies employed.

The sensitivity results for GVs (Figs. 7b, 8) show that increasing fuel consumption in Scenarios 1 and 2 worsens human health impacts, as reflected in higher DALY values. Conversely, reducing fuel consumption by 10% or 20% in Scenarios 3 and 4 improves health outcomes. The uncertainty analysis indicates high variability, with a CV of 42.40%, due to factors such as driving conditions and fuel quality.

For ecosystem impacts, fuel use increases ecological damage, with greater species·year losses in Scenarios 1 and 2. Reducing fuel consumption in Scenarios 3 and 4 alleviates these impacts. The uncertainty analysis shows relatively low variability, with a CV of 23.11%, suggesting that ecosystem outcomes are comparatively stable when fuel use decreases.

For resource consumption, fuel use increases demand in Scenarios 1 and 2, while reductions occur in Scenarios 3 and 4, with Scenario 4 showing the greatest improvement. The uncertainty analysis indicates

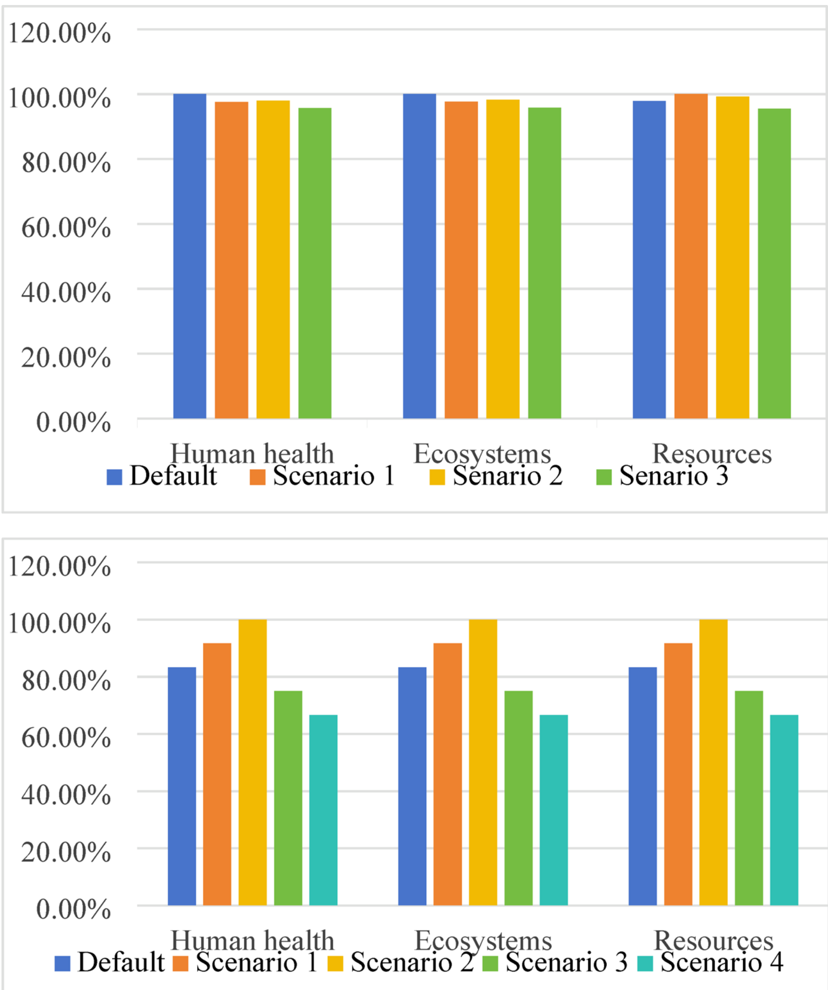

Fig. 7. (**a**) Scenario-based parameter sensitivity analysis was conducted by adjusting the energy mix. (**b**) Scenario-based parameter sensitivity analysis was conducted by adjusting the energy consumption

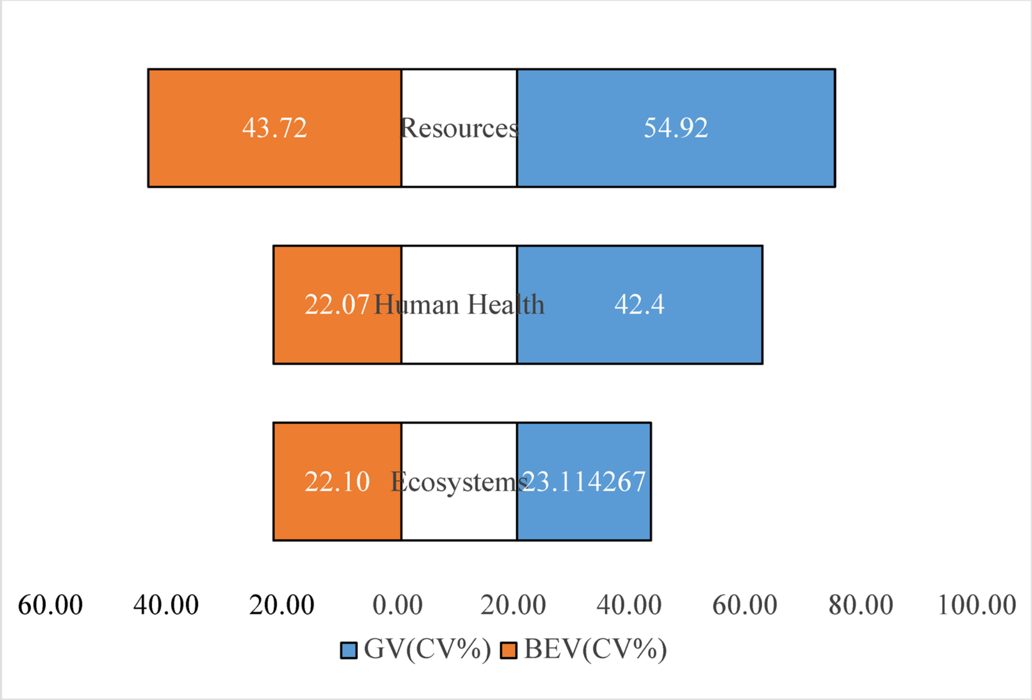

Fig. 8. (**a**) Scenario-based parameter sensitivity analysis was conducted by adjusting the energy mix. (**b**) Scenario-based parameter sensitivity analysis was conducted by adjusting the energy consumption. *Confidence level is 95%.

substantial variability, with a CV of 54.92%, highlighting the strong influence of fuel market fluctuations and extraction costs on resource demand.

In summary, BEVs clearly outperform GVs in terms of environmental and health impacts, as shown in the sensitivity analysis. Scenario 3, with the highest share of clean energy, consistently delivers the best results for BEVs. However, resource consumption for BEVs shows the most variability, with a CV of 43.72%, highlighting uncertainty in resource demand. Human health and ecosystem impact for BEVs are more predictable, with moderate variability. For GVs, reducing fuel consumption leads to better outcomes across all categories, but the uncertainty analysis reveals significant variability in human health (CV = 42.40%) and resource consumption (CV = 54.92%), primarily due to external factors like driving conditions and fuel market prices. These findings emphasize the importance of reducing coal-based electricity for BEVs and fuel consumption for GVs, while managing uncertainties to optimize overall performance.[82] and[83] emphasize that the benefits of EVs are reduced in regions that are dependent on fossil fuels. They stress the importance of transitioning to cleaner energy sources to fully harness the potential of EVs in lowering emissions.

For GVs, reducing fuel consumption leads to better outcomes across all categories, but the uncertainty analysis reveals significant variability in human health (CV = 42.40%) and resource consumption (CV = 54.92%), primarily due to external factors like driving conditions and fuel market prices. These findings emphasize the importance of reducing coal-based electricity for BEVs and fuel consumption for GVs, while managing uncertainties to optimize overall performance.

Despite the narrow difference in DALY (0.005 for BEVs vs. 0.007 for GVs), sensitivity results show a 15% reduction in DALY when renewable energy replaces coal. While species.yr differences are minimal, a shift to cleaner grids reduces impacts by 18%. Significant resource savings (58.06 USD2013 for BEVs vs. 652.69 USD2013 for GVs) emphasize BEVs' sustainability advantage.

Overall, while BEVs are subject to some resource-related uncertainties, provide more stable outcomes compared to GVs in terms of health and ecosystem benefits. For GVs, reducing fuel consumption remains essential, though external factors will continue to introduce uncertainty in resource demand and emissions.

Conclusion and limitations

Conclusion and recommendations: Compared with GVs and BEV generate substantially lower total CO_2 emissions, although they show higher impacts in land transformation. In contrast, BEVs consistently exhibit lower impacts in fossil and biogenic emissions, reflecting their advantage in reducing direct fuel combustion. Approximately 10 kg CO_2-equivalent is produced from either 3 L of gasoline or 7 kWh of electricity, underscoring the relative efficiency of BEVs. When endpoint impacts are considered, BEVs and GVs present broadly similar effects on ecosystems and human health, but BEVs demonstrate significantly greater resource conservation. Within Heilongjiang Province, the Northeast Power Grid (NECG)—heavily reliant on coal—offers the lowest environmental benefits compared with other regional grids. Seasonal analysis further reveals that in winter, BEVs emit more CO_2-eq than GVs because of additional electricity use for battery heating; however, annual BEV emissions remain lower overall. These results confirm that BEVs maintain environmental superiority even under coal-dominated grids, while emphasizing the additional benefits of transitioning toward cleaner energy sources. At a broader level, this work recommends that governments and industries integrate life-cycle-based assessment into transportation planning, prioritize renewable-energy development for vehicle charging, and promote technology adaptation for diverse climatic conditions. The methodological framework presented here can be applied to other regions and emerging markets to support data-driven, region-specific sustainability policies.

Policy Implications: Heilongjiang's coal-dependent grid and cold climate reduce BEV efficiency and offset environmental gains. Local authorities should prioritise grid decarbonisation through wind, nuclear, and biomass integration, improve winter charging efficiency, and support pilot projects on BEV performance under cold conditions. At the national level, EV expansion should align with renewable energy transition and interregional grid balancing. Differentiated electricity tariffs or carbon pricing based on regional emission intensity can guide cleaner energy use, while national standards for cold-climate charging and battery efficiency should ensure consistent decarbonization outcomes.

Key limitations: this study primarily focuses on the use phase, excluding the manufacturing, maintenance, and end-of-life stages, which may lead to an underestimation of upstream and downstream impacts. The analysis is geographically limited to Heilongjiang Province, whose coal-intensive energy mix and severe winters may not represent other regions of China. Furthermore, although scenario and sensitivity analyses were performed, advanced multivariate techniques such as principal component analysis (PCA) could further identify which parameters exert the strongest influence on environmental outcomes. Incorporating such approaches in future work would strengthen model robustness and interpretability.

Future research directions and overall significance: future research should adopt a cradle-to-grave perspective to provide a holistic evaluation of BEV sustainability, integrating production, maintenance, and recycling stages. Expanding the spatial scope to regions with different grid compositions and climatic conditions would improve the generalizability of the findings. Continued innovation in cold-climate battery technologies and the integration of renewable energy sources are essential to optimize the sustainability potential of BEVs. Overall, this study provides critical evidence for coal-dependent and cold-climate regions, demonstrating both the environmental benefits and operational challenges of BEV adoption, and offering guidance for policymakers and industry to advance low-carbon transport and long-term decarbonization.

Data availability

The LCA modelling was carried out using licensed SimaPro software under Universiti Putra Malaysia's official institutional license. Due to database licensing restrictions, the raw inventory data cannot be publicly shared. However, processed datasets and summary results generated during the current study are available from the corresponding author upon reasonable request.

Received: 12 September 2025; Accepted: 29 January 2026
Published online: 02 February 2026

References

1. Shafique, M., Azam, A., Rafiq, M. & Luo, X. Life cycle assessment of electric vehicles and internal combustion engine vehicles: A case study of Hong Kong. *Res. Transp. Econ.* **101112** https://doi.org/10.1016/J.RETREC.2021.101112 (2021).
2. Gan, Y., Wang, M., Lu, Z. & Kelly, J. Taking into account greenhouse gas emissions of electric vehicles for transportation de-carbonization. *Energy Policy*. **155**, 112353. https://doi.org/10.1016/j.enpol.2021.112353 (2021).
3. Xinhua News Agency. *The state council of the people's republic China. Xi Jinping: China's promised time from carbon peak to carbon neutrality is far shorter than the time taken by developed countries* http://www.gov.cn/xinwen/2021-04/22/content_5601515.htm (2021).
4. Wang, Q., Qi, Y. & Li, R. Artificial Intelligence and Corporate Sustainability: Shaping the Future of ESG in the Age of Industry 5.0. *Sustainable Devel.* https://doi.org/10.1002/sd.70200 (2025).
5. Wang, Q., Zhang, F. & Li, R. Artificial intelligence and sustainable development during urbanization: perspectives on AI R&D innovation, AI infrastructure, and AI market advantage. *Sustain. Dev.* **33**, 1136–1156. https://doi.org/10.1002/sd.3150 (2025).
6. Wang, Q., Wang, X. & Li, R. Rethinking sustainability: human development and ecological footprint under deglobalization pressures. https://doi.org/10.1002/sd.70250 (2025).
7. Rajaeifar, M. A. et al. Attributional and consequential environmental assessment of using waste cooking oil-and poultry fat-based biodiesel blends in urban buses: a real-world operation condition study. *J. Homepage: Www Biofueljournal com. Rajaeifar al / Biofuel Res. J.* **15**, 638–653 (2017).
8. Campanario, F. J. & Gutiérrez Ortiz, F. J. Fischer-Tropsch biofuels production from Syngas obtained by supercritical water reforming of the bio-oil aqueous phase. *Energy. Conv. Manag.* **150**, 599–613 (2017).
9. Saranya, G. & Ramachandra, T. V. Life cycle assessment of biodiesel from estuarine microalgae. *Energy Convers. Management: X.* **8**, 100065. https://doi.org/10.1016/j.ecmx.2020.100065 (2020).
10. Sining, M., Sharaai, A. H., Matthew, N. & Zainordin, N. Sustainable development of electric vehicles in china: A bibliometric analysis and systematic review, 2011 onward. *Edelweiss Appl. Sci. Technol.* **8**, 2252–2260 (2024).
11. Liu, K. & Xu, J. Life cycle assessment of driving motor on electric vehicle. *Huanjing Kexue Xuebao/Acta Sci. Circum.* **36**, 3456–3463 (2016).
12. Hsu, T. R. On the sustainability of electrical vehicles. *ArXiv Preprint arXiv*. **1311**, 6015 https://www.researchgate.net/publication/258849529_On_the_Sustainability_of_Electrical_Vehicles#fullTextFileContent (2013).
13. Luk, J. M., Saville, B. A. & MacLean, H. L. Impact of non-petroleum vehicle fuel economy on GHG mitigation potential. *Environ. Res. Lett.* **11**, 044001. (2016).
14. Shafique, M. & Luo, X. Environmental life cycle assessment of battery electric vehicles from the current and future energy mix perspective. *J. Environ. Manage.* **303**, 114050. (2022).
15. Onat, N. C., Kucukvar, M., Tatari, O. & Zheng, Q. P. Combined application of multi-criteria optimization and life-cycle sustainability assessment for optimal distribution of alternative passenger cars in U.S. *J. Clean. Prod.* **112**, 291–307 (2016).

16. Wang, Y., Zhou, G., Li, T. & Wei, X. Comprehensive evaluation of the sustainable development of battery electric vehicles in China. *Sustainability* **11**, 5635. https://doi.org/10.3390/su11205635 (2019).
17. Song, Q. et al. Well-to-wheel GHG emissions and mitigation potential from light-duty vehicles in Macau. *Int. J. Life Cycle Assess.* **23** https://doi.org/10.1007/s11367-017-1424-6 (2018).
18. Ivanov, R. *7th International Conference on Energy Efficiency and Agricultural* Engineering *(EE&AE)* 1–5, https://doi.org/10.1109/EEAE49144.2020.9279077 (2020).
19. Lombardi, L., Tribioli, L., Cozzolino, R. & Bella, G. Comparative environmental assessment of conventional, electric, hybrid, and fuel cell powertrains based on LCA. *Int. J. Life Cycle Assess.* **22**, 1989–2006 (2017).
20. Onat, N. C., Kucukvar, M. & Afshar, S. Eco-efficiency of electric vehicles in the united states: A life cycle assessment based principal component analysis. *J. Clean. Prod.* **212**, 515–526 (2019).
21. Göhlich, D., Ly, T. A., Kunith, A. & Jefferies, D. Economic assessment of different Air-conditioning and heating systems for electric City buses based on comprehensive energetic simulations. *World Electr. Veh. J.* **7**, 398–406 (2015).
22. Ke, W., Zhang, S., He, X., Wu, Y. & Hao, J. Well-to-wheels energy consumption and emissions of electric vehicles: Mid-term implications from real-world features and air pollution control progress. *Appl. Energy*. **188**, 367–377 (2017).
23. Hao, X., Wang, H., Lin, Z. & Ouyang, M. Seasonal effects on electric vehicle energy consumption and driving range: A case study on personal, taxi, and ridesharing vehicles. *J. Clean. Prod.* **249**, 119403. https://doi.org/10.1016/j.jclepro.2019.119403 (2020).
24. Zeng, D. et al. Are the electric vehicles more sustainable than the conventional ones? Influences of the assumptions and modeling approaches in the case of typical cars in China. *Resour. Conserv. Recycl.* **167**, 105210. https://doi.org/10.1016/j.resconrec.2020.105210 (2021).
25. Heilongjiang Meteorological Bureau. *Heilongjiang Province Climate Bulletin*.http://hl.cma.gov.cn/zfxxgk/zwgk/qtxx/202101/t20210122_2638629.html (2021).
26. European Committee for Standardisation. ISO - ISO 14040:2006 - Environmental management — Life cycle assessment — Principles and framework. https://www.iso.org/standard/37456.html (2006).
27. An, F. *et al. A Study on china's timetable for phasing-out traditional ice-vehicles*. https://icet.org.cn/admin/upload/2020072372032769.pdf (2019).
28. Xue, L. *et al. Quantifying the grid impacts from large adoption of electric vehicles in China*.https://wri.org.cn/sites/default/files/2021-11/quantifying-grid-impacts-large-adoption-electric-vehicles-china-CN.pdf (2020).
29. General Office of the State Council of the People's Republic of China. Six major power grids. *The Central People's Govenment of the People's Repu lic of China* https://www.gov.cn/ztzl/2006-07/01/content_324601.htm (2006).
30. China Energy News. Power grid construction continues to improve quality and efficiency (interconnection). *People's Daily Online*. https://english.mee.gov.cn/Resources/publications/Whitep/202012/t20201222_814160.shtml (2020).
31. Cai, B. *et al. China regional power grids carbon dioxide emission factors (2023)*. http://www.caep.org.cn/sy/tdftzhyjzx/zxdt/202310/W020231027692141725225.pdf (2023).
32. China Passenger Car Association-Statistical data. http://data.cpcadata.com/ (2023).
33. Ministry of ecology and environment of the people's republic of China. Emission Reduction Project China Regional Grid Baseline Emission Factors. (2019). https://www.mee.gov.cn/ywgz/ydqhbh/wsqtkz/202012/t20201229_815386.shtml (2020).
34. Wu, W., Cong, N., Zhang, X., Yue, Q. & Zhang, M. Life cycle assessment and carbon reduction potential prediction of electric vehicles batteries. *Sci. Total Environ.* **903**, 166620. https://doi.org/10.1016/j.scitotenv.2023.166620 (2023).
35. Feng, T., Guo, W., Li, Q., Meng, Z. & Liang, W. Life cycle assessment of lithium nickel Cobalt manganese oxide batteries and lithium iron phosphate batteries for electric vehicles in China. *J. Energy Storage*. **52**, 104767. https://doi.org/10.1016/j.est.2022.104767 (2022).
36. Feng, F., Lu, R. & Zhu, C. A. Combined state of charge Estimation method for Lithium-Ion batteries used in a wide ambient temperature range. *Energies* **7**, 3004–3032 (2014).
37. Liu, K., Wang, J., Yamamoto, T. & Morikawa, T. Exploring the interactive effects of ambient temperature and vehicle auxiliary loads on electric vehicle energy consumption. *Appl. Energy*. **227**, 324–331 (2018).
38. Jin, L., Wang, S. & He, H. *Report on Actual Driving Performance, Energy Consumption, Cruising Range and Charging Mode of Guochure Electric Passenger Vehicles*.https://theicct.org/publication/pv-china-real-world-performance-apr23/ (2023).
39. California Primary Care Association. Retail Sales Ranking Express. *California Primary Care Association Offical websit*. http://www.cpcaauto.com/newslist.php?types=csjd&id=2982 (2023).
40. December 2022 Retail Sales Ranking Quick Report. *National Passeng. Cars Association* http://www.cpcaauto.com/newslist.php?types=csjd&id=2982 (2023).
41. International Organization for Standardization. ONORM EN ISO 14040:2021 - Environmental management - Life cycle assessment - Principles and framework.https://webstore.ansi.org/standards/on/onormeniso140402021 (2021).
42. Zhao, D. et al. Report on the Development of China Energy-saving and New Energy Vehicle (). 8 Report on the Development of China Energy-saving and New Energy Vehicle, 8. http://www.catarc.info/attached/file/20180313/20180313161921_3486.pdf (2017).
43. BYD. BYD DolphinOwner's Manual. *Car book* https://www.carobook.com/byd-sms/byd-haitun-owners-manual.html
44. *Ministry of Commerce Standard for Compulsory Scrapping of Motor Vehicles*. https://www.mofcom.gov.cn/dl/file/20211203231250.pdf (2021).
45. International Reference Life Cycle Data System (ILCD). The Specific guide for Life Cycle Inventory (LCI) data sets. builds on the general guide. (2010). https://eplca.jrc.ec.europa.eu/uploads/ILCD-Handbook-Specific-guide-for-LCI-12March2010-ISBN-fin-v1.0-EN.pdf (2010).
46. Yin, R., Hu, S. & Yang, Y. Life cycle inventories of the commonly used materials for lithium-ion batteries in China. *J. Clean. Prod.* **227**, 960–971 (2019).
47. Weng, C. K. & Boehmer, K. Launching of ISO 14064 for greenhouse gas accounting and verification. *ISO Manage. Syst.*https://www.iso.org/files/live/sites/isoorg/files/archive/pdf/en/greenhouse.pdf (2006).
48. Martínez-Blanco, J., Finkbeiner, M. & Organisational, L. C. A. *Life Cycle Assessment: Theory Pract.* 481–498 https://doi.org/10.1007/978-3-319-56475-3_20/COVER/. (2017).
49. ecoinvent v3. 9.1 - ecoinvent.https://ecoinvent.org/the-ecoinvent-database/data-releases/ecoinvent-3-9-1/ (2022).
50. US EPA. O. Greenhouse gas emissions from a typical passenger vehicle. *US EPA* https://19january2021snapshot.epa.gov/greenvehicles/greenhouse-gas-emissions-typical-passenger-vehicle (2016).
51. Ministry of Environmental Protection General Administration of Quality Supervision, Inspection and Quarantine. Limities and measurment methods for emissions from light-duty vehicle (China 6) GB 18352.6–2016. (2016).
52. Mei, X. *Comparative Study on Environmental Impact of Electric Vehicle and Fuel Vehicle* (Tianjin University of Science and Technology, 2022).
53. He, H. & Bandivadekar, A. *Comparative study on fiscal and taxation policies for passenger car CO_2 emission reduction in various countries*. https://theicct.org/wp-content/uploads/2022/01/ICCT_fiscalpoliciesES_feb2011_Ch.pdf. (2010).
54. Lai, X. et al. Critical review of life cycle assessment of lithium-ion batteries for electric vehicles: A lifespan perspective. *eTransportation* **12**, 100169. https://doi.org/10.1016/j.etran.2022.100169 (2022).
55. International Organization for Standardization. ISO 14044:2006(en), Environmental management — Life cycle assessment — Requirements and guidelines. (2006).

56. Hauschild, M. Z. et al. Identifying best existing practice for characterization modeling in life cycle impact assessment. *Int. J. Life Cycle Assess.* **18**, 683–697 (2013).
57. Guinée, J. B. *Handbook on Life Cycle Assessment: Operational Guide To the ISO Standards* (Springer Science & Business Media, 2002).
58. Huijbregts, M. A. J. et al. ReCiPe 2016 v1.1 A Harmonized Life Cycle Impact Assessment Method at Midpoint and Endpoint Level Report I: Characterization. (2017).
59. Huijbregts, M. A. J. et al. ReCiPe 2016 v1.1 A harmonized life cycle impact assessment method at midpoint and endpoint level Report I: Characterization. https://www.semanticscholar.org/paper/ReCiPe-2016.-A-harmonized-life-cycle-impact-method-Huijbregts-Steinmann/b70aeb1db5636d50b32da5ec66e9cba18bae65df (2016).
60. Goedkoop, M. et al. ReCiPe. *A life cycle impact assessment method which comprises harmonised category indicators at the midpoint and the endpoint level* 1, 1–126 (2009). (2008).
61. Huijbregts, M. A. J. et al. ReCiPe2016: a harmonised life cycle impact assessment method at midpoint and endpoint level. *Int. J. Life Cycle Assess.* **22**, 138–147 (2017).
62. Zhang, Y. & Han, Q. Development of electric vehicles for china's power generation portfolio: A regional economic and environmental analysis. *J. Clean. Prod.* **162**, 71–85 (2017).
63. Zhang, C., Zhang, C. & Li, J. Charging and discharging characteristics of lithium-ion batteries for electric transmission armored vehicles. *Power Technol.* **34**, 109–112 (2010).
64. Huo, H., Cai, H., Zhang, Q., Liu, F. & He, K. Life-cycle assessment of greenhouse gas and air emissions of electric vehicles: A comparison between China and the US. *Atmos. Environ.* **108**, 107–116 (2015).
65. Reyes, J. R. M. D., Parsons, R. V. & Hoemsen, R. Winter happens: the effect of ambient temperature on the travel range of electric vehicles. *IEEE Trans. Veh. Technol.* **65**, 4016–4022 (2016).
66. US EPA. O. Understanding Global Warming Potentials. https://www.epa.gov/ghgemissions/understanding-global-warming-potentials (2016).
67. Dodd, N., Donatello, S. & Cordella, M. Level(s) indicator 1.2: Life cycle Global Warming Potential (GWP). (2020).
68. Liu, W. et al. A new integrated framework to estimate the climate change impacts of biomass utilization for biofuel in life cycle assessment. *J. Clean. Prod.* **267**, 122061. (2020).
69. Asim, N. et al. Wastes from the petroleum industries as sustainable resource materials in construction sectors: Opportunities, limitations, and directions. *J. Clean. Prod.* **284**, 125459. https://doi.org/10.1016/j.jclepro.2020.125459 (2021).
70. Mattila, T. *et al. Land Use in Life Cycle Assessment*. http://hdl.handle.net/10138/37049 (2011).
71. Solomon, S. et al. IPCC fourth assessment report (AR4). *Climate change* 374. https://www.ipcc.ch/assessment-report/ar4/ (2007).
72. Petrauskienė, K., Galinis, A., Kliaugaitė, D. & Dvarionienė, J. Comparative environmental life cycle and cost assessment of Electric, Hybrid, and conventional vehicles in Lithuania. *Sustainability* **13**, 957. https://doi.org/10.3390/su13020957 (2021).
73. Bao, Y. et al. Global research on the air quality status in response to the electrification of vehicles. *Sci. Total Environ.* **795**, 148861. https://doi.org/10.1016/j.scitotenv.2021.148861 (2021).
74. Evtimov, I., Ivanov, R., Stanchev, H., Kadikyanov, G. & Staneva, G. Life cycle assessment of fuel cells electric vehicles. *Transp. Probl.* **15** (3), 153–166 (2020).
75. Shi, X., Wang, X., Yang, J. & Sun, Z. Electric vehicle transformation in Beijing and the comparative eco-environmental impacts: A case study of electric and gasoline powered taxis. *J. Clean. Prod.* **137**, 449–460 (2016).
76. Boureima, F. S. et al. Comparative LCA of electric, hybrid, LPG and gasoline cars in Belgian context. *World Electr. Veh. J.* **3**, 469–476 (2009).
77. Abdul-Manan, A. F. N. Uncertainty and differences in GHG emissions between electric and conventional gasoline vehicles with implications for transport policy making. *Energy Policy*. **87**, 1–7 (2015).
78. Rashedi, A., Khanam, T., Jeong, B. & Hussain, M. Evaluation of environmental sustainability matrix of deepgen tidal turbine. *Ocean Eng.* **266**, 113031. https://doi.org/10.1016/j.oceaneng.2022.113031 (2022).
79. WHO. Indicator Metadata Registry Details. *The global health obserbatory*https://www.who.int/data/gho/indicator-metadata-registry/imr-details/158 (2023).
80. Bałdowska-Witos, P., Tomporowski, A. & Bieliński, M. Using the LCA method to develop the production of pigment for processing plastics. *Materials* **16**, 5524. https://doi.org/10.3390/ma16165524 (2023).
81. Council, C. E. China would optimize power source structure and distribution: Planning of power sources for the 12th Five-Year National Plan. *Research Group on Planning China's Power Sector in the 12th Five-Year National Plan (Ed.). China Electricity Council, Beijing.(in Chinese)* https://www.china5e.com/news/news-142508-1.html (2011).
82. Moro, A. & Lonza, L. Electricity carbon intensity in European member states: impacts on GHG emissions of electric vehicles. *Transp. Res. Part. D: Transp. Environ.* **64**, 5–14 (2018).
83. Al-Buenain, A. et al. The adoption of electric vehicles in Qatar can contribute to net carbon emission reduction but requires strong government incentives. *Vehicles* **3**, 618–635 (2021).
84. Wilken, D. et al. Multidimensional assessment of passenger cars: comparison of electric vehicles with internal combustion engine vehicles. *Procedia CIRP*. **90**, 291–296 (2020).
85. Wang, K. et al. Analysis and countermeasures of china's green electric power development. *Sustainability* **13**, 708. https://doi.org/10.3390/su13020708 (2021).
86. Yuksel, T., Tamayao, M. A. M., Hendrickson, C., Azevedo, I. M. L. & Michalek, J. J. Effect of regional grid mix, driving patterns and climate on the comparative carbon footprint of gasoline and plug-in electric vehicles in the united States. *Environ. Res. Lett.* **11**, 044007. (2016).
87. Meyer, N., Whittal, I., Christenson, M. & Loiselle-Lapointe, A. The Impact of Driving Cycle and Climate on Electrical Consumption & Range of Fully Electric Passenger Vehicles. *A EVS26 - International Battery, Hybrid and Fuel Cell Electric Vehicle Symposium* https://tc.canada.ca/en/programs/non-funding-programs/ecotechnology-vehicles-program/impact-driving-cycle-climate-electrical-consumption-range-fully-electric-passenger-vehicles (2018).
88. Holland, S. P., Mansur, E. T., Muller, N. Z. & Yates, A. J. Are There environmental benefits from driving electric vehicles? The importance of local factors. *Am. Econ. Rev.* **106**, 3700–3729 (2016).
89. Koroma, M. S. et al. Life cycle assessment of battery electric vehicles: implications of future electricity mix and different battery end-of-life management. *Sci. Total Environ.* **831**, 154859. https://doi.org/10.1016/j.scitotenv.2022.154859 (2022).
90. Andersson, Ö. & Börjesson, P. The greenhouse gas emissions of an electrified vehicle combined with renewable fuels: life cycle assessment and policy implications. *Appl. Energy*. **289**, 116621. https://doi.org/10.1016/j.apenergy.2021.116621 (2021).

Acknowledgements
We are grateful to our colleagues and peer reviewers for their constructive feedback, which significantly enhanced the quality of this manuscript.

Author contributions
Conceptualization, M.S.N and H.Z.J.; methodology, M.S.N and H.Z.J.; writing—original draft, M.S.N and H.Z.J.; writing—review & editing, M.S.N and H.Z.J.; funding acquisition, M.S.N and H.Z.J.; resources M.S.N and H.Z.J.;

supervision, A.H.S., N.K.M., and N.S.Z.

Declarations

Competing interests
The authors declare no competing interests.

Additional information
Supplementary Information The online version contains supplementary material available at https://doi.org/10.1038/s41598-026-38471-1.

Correspondence and requests for materials should be addressed to S.M.

Reprints and permissions information is available at www.nature.com/reprints.

Publisher's note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.