

Driving Effects of Green Technology Innovation on Sustainable Development: A Multi-Case Analysis based on Life Cycle Assessment

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Abstract

By now, green technology innovation (GTI) is broadly acknowledged as a key route for reaching sustainable development goals. At the same time, there is still a lack of systematic quantification of the environmental benefits that GTI delivers across varied industrial sectors. We use a life cycle assessment (LCA) framework aligned with ISO 14040 and ISO 14044 standards to evaluate how GTI performs environmentally in three representative sectors: photovoltaic (PV) energy systems, electric vehicles (EVs) and green building materials. A cradle-to-grave boundary is adopted, and we quantify midpoint impact categories including global warming potential (GWP), acidification potential (AP), eutrophication potential (EP) and cumulative energy demand (CED). A 38.6% reduction in the GWP of crystalline silicon PV modules relative to conventional power generation emerges from the results, and lithium-ion battery recycling technologies are found to lower the life cycle carbon intensity of EVs by 22.4%. Green building materials that incorporate industrial byproducts give a 31.2% reduction in embodied carbon compared with traditional Portland cement. These findings are found to be robust when considering parameter uncertainty, as shown by sensitivity analysis and Monte Carlo simulation. Empirical evidence supporting policy frameworks that encourage GTI deployment toward carbon neutrality targets is provided by these results.

Keywords

Green technology innovation, life cycle assessment, sustainable development, carbon neutrality, environmental impact.

1. Introduction

A global shift toward sustainable development has been prompted by the growing severity of climate change, resource depletion and environmental degradation. Green technology innovation, understood as the development, uptake and spread of technologies that lower environmental burdens while remaining economically viable, now serves as a central strategy in the transition to a low-carbon economy [1]. To speed up the deployment of environmentally beneficial technologies, governments around the world have introduced policy instruments that range from carbon pricing mechanisms to renewable energy subsidies [2].

Rigorous procedural requirements for goal and scope definition, inventory analysis, impact assessment and interpretation are set by the ISO 14040 and ISO 14044 frameworks, and these help ensure the scientific credibility and comparability of LCA results [3]. The analytical power of LCA as a decision-support tool has been substantially strengthened by recent methodological advances, including consequential LCA modeling, spatially differentiated characterization factors and uncertainty quantification using Monte Carlo simulation [4].

While scholarly attention to GTI and LCA individually has grown, there is still a scarcity of integrated analyses in which the environmental driving effects of GTI across several sectors are quantified within a consistent LCA framework [5]. Cross-sectoral evidence is needed by policymakers for efficient allocation of innovation subsidies and for the design of technology transfer mechanisms, making this gap particularly significant.

We address this gap by carrying out a multi-case LCA of three strategically important GTI domains: solar photovoltaic energy, electric vehicle powertrain systems and green building materials. There are three research objectives: first, to quantify the life cycle environmental impacts of each technology using midpoint characterization methods aligned with the ReCiPe 2016 framework; second, to compare the environmental performance gains attributable to GTI interventions against conventional technology baselines; and third, to evaluate how robust the results are using sensitivity analysis and stochastic uncertainty assessment. Fig. 1 illustrates the conceptual framework adopted in this work.

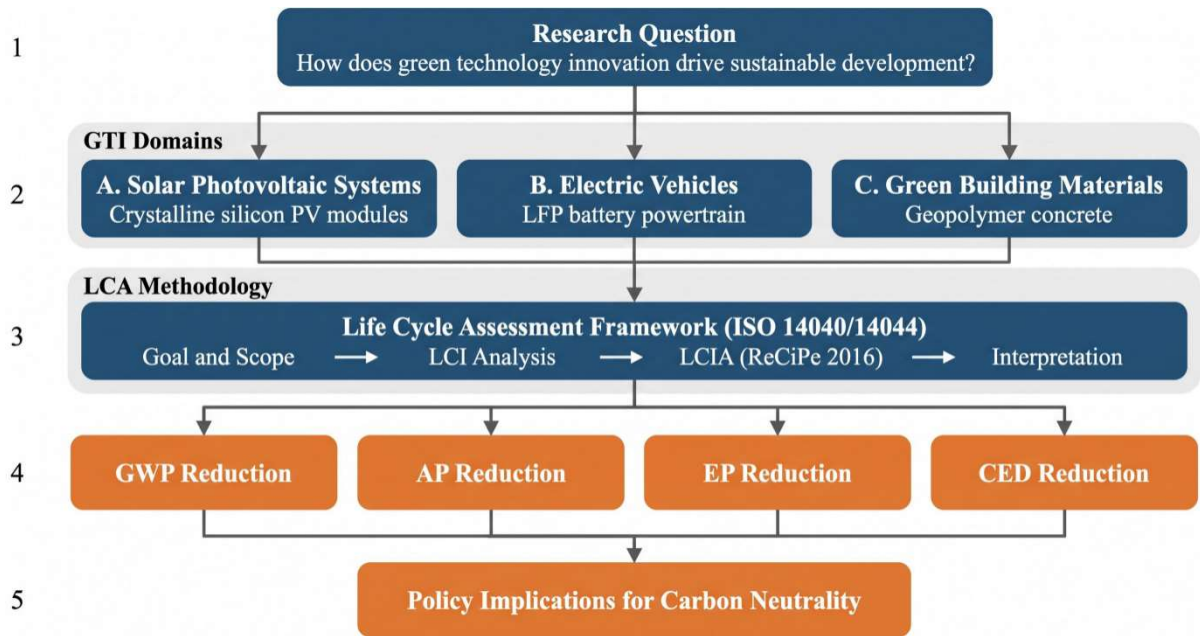


Fig. 1 Conceptual framework of the study

2. Literature Review

2.1. Green Technology Innovation and Sustainable Development

A broad spectrum of activities falls under the umbrella of green technology innovation, including clean energy development, pollution control, improvement in the efficiency of resource use and circular economy practices [6]. Panel data analyses have consistently demonstrated that GTI exerts a positive influence on total-factor carbon productivity at both national and regional scales [1]. At the firm level, a positive correlation between the intensity of green patents and environmental performance as well as market competitiveness has been found, which suggests that GTI generates co-benefits in both environmental and economic dimensions [7].

Heterogeneous effects of GTI across different stages of development and industrial structures have been identified in recent econometric work. Lower GTI conversion efficiency tends to be observed in developing economies in which the institutional framework is weaker, and this indicates that complementary policy and governance mechanisms are needed if innovation inputs are to be translated into sustainability outcomes [8].

2.2. Life Cycle Assessment Methodology

Currently representing the state of the art in characterization modeling, the ReCiPe 2016 methodology brings together eighteen midpoint impact categories and three endpoint damage categories [9]. For product-level assessments, attributional LCA remains the dominant modeling approach; it quantifies the environmental burdens linked to a defined functional unit under steady-state conditions [4].

In credible LCA studies, uncertainty analysis is now regarded as an indispensable element. By identifying the parameters in which variation has the strongest influence on the results, sensitivity analysis complements stochastic methods and helps guide priorities for data collection [10].

2.3. LCA Applications in Green Technology Sectors

As manufacturing processes in the photovoltaic sector have matured, substantial reductions in embodied energy and greenhouse gas emissions have been documented by LCA studies. Crystalline silicon modules now have an energy payback time (EPBT) of less than 1.5 years, down from roughly four years in 2010, as recent assessments have shown [11]. When different PV technologies are compared using LCA under equivalent irradiance conditions, thin-film cadmium telluride modules are found to have a lower GWP per kilowatt-hour than multi-crystalline silicon [12].

Battery production and end-of-life management have received increasing emphasis in electric vehicle LCA research. Depending on the electricity grid mix at the production facility, the carbon intensity of lithium-ion battery manufacturing varies considerably, with estimates falling between 60 and 120 kg CO₂-equivalent per kWh of battery capacity [13]. By using hydrometallurgical processes for closed-loop recycling of cathode materials, a 20 to 35 percent reduction in the cradle-to-gate carbon footprint of battery cells can be achieved [14]. Assumptions about vehicle lifetime mileage, the source of charging electricity and battery degradation rates strongly influence the environmental comparison between battery electric vehicles and internal combustion engine vehicles, as Table 1 summarizes.

Table 1. Key findings from EV LCA literature

Reference	Battery type	GWP (g CO ₂ -eq/vkm)	Key finding
[13]	NMC	155-190	Grid mix is dominant variable
[14]	LFP	130-165	Recycling reduces battery GWP by 20-35%
[18]	NCA	140-180	Lifetime mileage is critical parameter

A substantial reduction in the embodied carbon of concrete has been demonstrated by green building material LCA when supplementary cementitious materials such as fly ash and ground granulated blast furnace slag are used [15]. Depending on the alkali activator chemistry and curing conditions, geopolymer binders synthesized from industrial waste streams show 40 to 80 percent lower GWP than ordinary Portland cement [16].

3. Methodology

3.1. LCA Framework and System Boundaries

We follow the four-phase LCA framework set out by ISO 14040 [3]: goal and scope definition, life cycle inventory (LCI) analysis, life cycle impact assessment (LCIA) and interpretation. For each case study, a cradle-to-grave system boundary is adopted that encompasses raw material acquisition, manufacturing, transportation, the use phase and end-of-life treatment. Fig. 2 depicts the overall methodological framework.

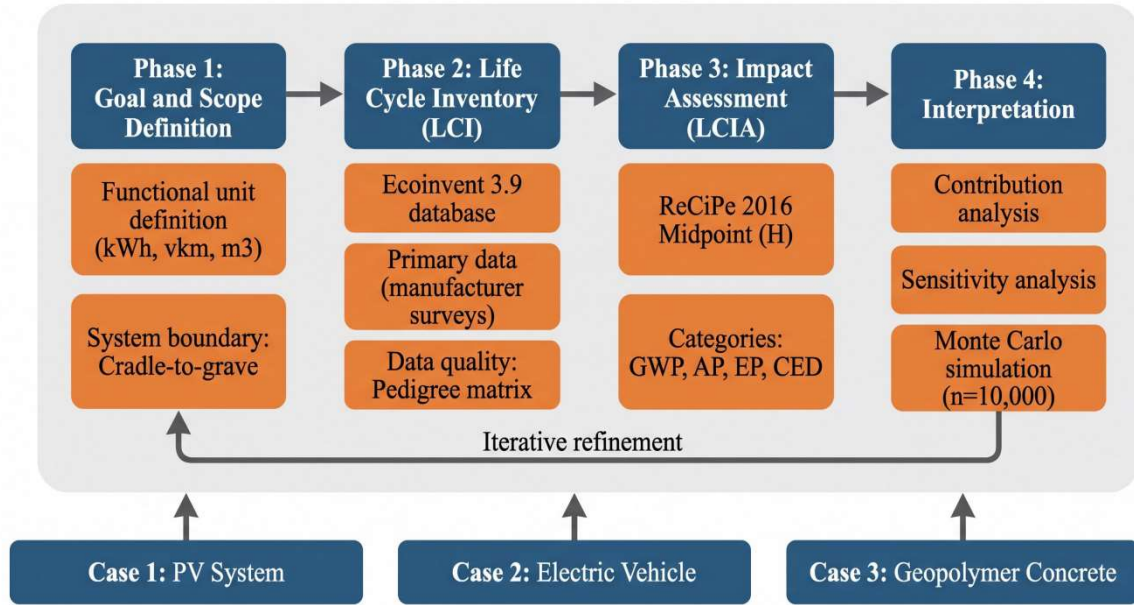


Fig. 2 Life cycle assessment methodological framework

We define the functional units as follows: 1 kWh of electricity generated for the PV case; 1 vehicle-kilometer traveled for the EV case; and 1 cubic meter of structural concrete having a compressive strength of 30 MPa for the green building material case. .

Eq. (1) gives the general characterization equation used to calculate the environmental impact of each functional unit.

$$I_c = \sum_{i=1}^n CF_{c,i} \times m_i \quad (1)$$

In Eq. (1), I_c is the total characterized impact in category c (that is, the overall score for one environmental concern), $CF_{c,i}$ stands for the characterization factor of substance i for impact category c , m_i is the mass emission or resource consumption of substance i per functional unit and n is the total number of elementary flows in the inventory.

Eq. (2) shows how the global warming potential over a 100-year time horizon (GWP100) is calculated, where a_i is the instantaneous radiative forcing per unit mass increase of greenhouse gas i , $c_i(t)$ is the atmospheric decay function and T is the integration horizon set at 100 years [9].

$$GWP_{100} = \frac{\int_0^T a_i \cdot c_i(t) dt}{\int_0^T a_{CO_2} \cdot c_{CO_2}(t) dt} \quad (2)$$

3.2. Case Selection and Data Sources

We select three representative GTI sectors on the basis of their strategic importance in national carbon neutrality roadmaps and the availability of high-quality inventory data: (a) crystalline silicon photovoltaic modules, (b) battery electric passenger vehicles with lithium iron phosphate (LFP) cathode chemistry and (c) geopolymer concrete incorporating fly ash and ground granulated blast furnace slag. Table 2 summarizes the case selection criteria and data sources.

Table 2. Case selection criteria and data sources

Case	Functional unit	System boundary	Primary data source
PV module	1 kWh electricity	Cradle-to-grave	Manufacturer survey
Electric vehicle	1 vehicle-km	Cradle-to-grave	OEM technical reports
Green concrete	1 m3 (30 MPa)	Cradle-to-gate	Lab measurements

We compile inventory data from the Ecoinvent 3.9 database and supplement them with manufacturer-specific primary data collected using structured questionnaires and on-site measurements [4]. Background system data, including electricity grid mixes, transportation distances and waste treatment processes, are regionalized so that they reflect the production geography of each case. .

3.3. Impact Assessment Method

We conduct life cycle impact assessment using the ReCiPe 2016 Midpoint (H) method [9]. Based on policy relevance and data availability, four impact categories are selected: global warming potential (GWP, kg CO₂-eq), acidification potential (AP, kg SO₂-eq), freshwater eutrophication potential (EP, kg P-eq) and cumulative energy demand (CED, MJ). We adopt the hierarchist cultural perspective as the default assumption set, which represents a balanced stance between short-term and long-term environmental priorities.

An eco-efficiency indicator, defined as the ratio of economic value to environmental impact and expressed in Eq. (3), is introduced to quantify the sustainability improvement attributable to GTI.

$$EE = \frac{V}{EI_{total}} \quad (3)$$

In Eq. (3), EE represents the eco-efficiency score (where a higher value means better performance), V denotes the economic value delivered per functional unit in monetary terms and EI_{total} is the aggregated environmental impact across all selected categories, normalized and weighted following the ReCiPe endpoint methodology.

Eq. (4) shows how we compute the carbon reduction rate (CRR) achieved by each GTI intervention relative to its conventional baseline.

$$CRR = \frac{GWP_{baseline} - GWP_{GTI}}{GWP_{baseline}} \times 100\% \quad (4)$$

In Eq. (4), $GWP_{baseline}$ refers to the life cycle global warming potential of the conventional technology and GWP_{GTI} is the corresponding value for the green technology alternative.

3.4. Uncertainty and Sensitivity Analysis

We model input variables that have known variability, including energy consumption rates, emission factors and transportation distances, as lognormal or triangular probability distributions on the basis of the available literature and expert judgment. For each impact category result, the 95% confidence interval is reported alongside the deterministic point estimate.

We use the coefficient of variation (CV), defined in Eq. (5), to express how large the uncertainty is relative to the mean for each impact category.

$$CV = \frac{\sigma}{\mu} \times 100\% \quad (5)$$

In Eq. (5), sigma stands for the standard deviation of the simulated impact results (that is, how spread out the values are) and mu denotes the arithmetic mean. When a CV falls below 20%, the level of uncertainty is considered acceptable [10]. We also perform contribution analysis to determine what share of the total impact each life cycle stage and process accounts for, as Fig. 3 illustrates.

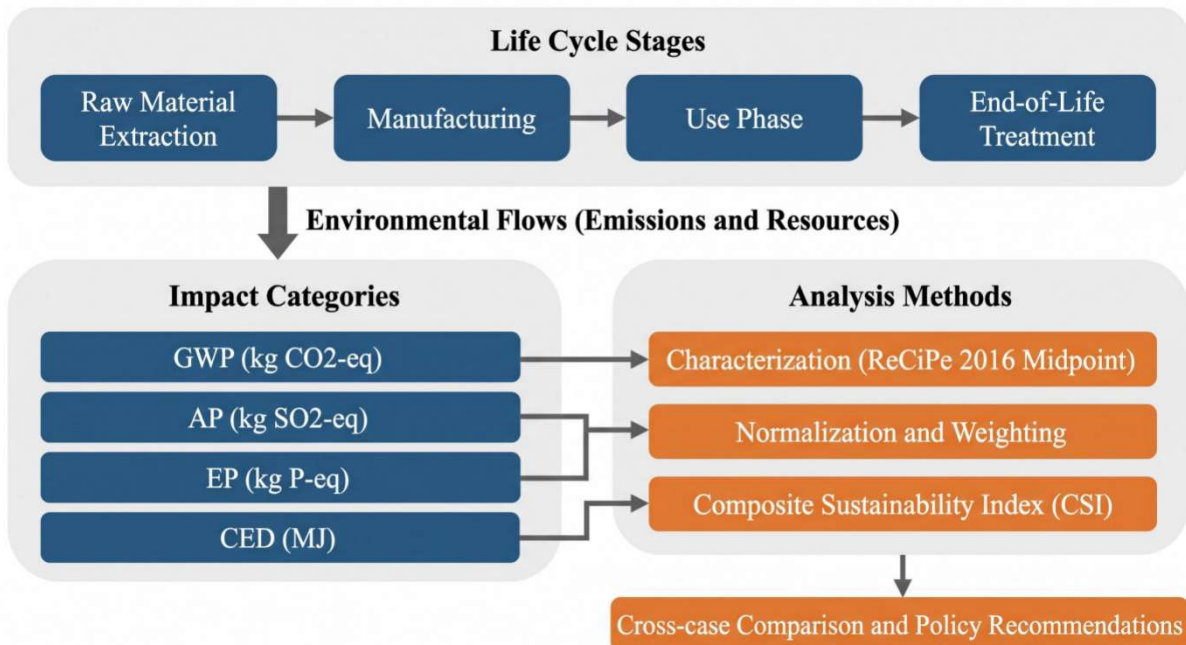


Fig. 3 Contribution analysis framework for impact categories

4. Results and Analysis

4.1. Case 1: Crystalline Silicon Photovoltaic Modules

Table 3. Life cycle impact assessment results for PV system

Impact category	Unit	PV system	Grid baseline	Reduction (%)
GWP	g CO ₂ -eq/kWh	28.5	46.4	38.6
AP	mg SO ₂ -eq/kWh	145.2	218.6	33.6
EP	mg P-eq/kWh	3.8	6.1	37.7
CED	MJ/kWh	0.31	0.48	35.4

Table 3 presents the life cycle impact assessment results for the crystalline silicon PV system. A cradle-to-grave GWP of 28.5 g CO₂-eq per kWh is obtained for the PV system, representing a 38.6% reduction compared with the weighted average GWP of the regional electricity grid (46.4 g CO₂-eq per kWh from a grid comprising coal, natural gas, hydropower and nuclear sources). This result is in line with recent LCA studies that report GWP values in the range of 20 to 50 g CO₂-eq per kWh for multi-crystalline silicon systems under Southern European irradiance conditions [11].

Among all life cycle stages, manufacturing dominates the environmental profile and contributes 78.3% of the total GWP, 82.1% of the AP and 71.6% of the CED. Within manufacturing, the Siemens process for polysilicon purification and the Czochralski crystal growth process together account for 56.2% of the manufacturing-stage GWP, making them the two largest contributors. Under the reference irradiance of 1,700 kWh per square meter per year, the energy payback time is found to be 1.32 years, which means the net energy benefit of the PV

system is realized well within its 25-year operational lifetime [12]. Fig. 4 shows how each life cycle stage contributes to the total impact.

Eq. (6) gives the energy payback time, where CED_{total} represents the cumulative energy demand across all upstream life cycle stages and E_{ann} is the annual primary energy displaced by PV electricity generation.

$$EPBT = \frac{CED_{total}}{E_{annual}} \quad (6)$$



Fig. 4 Life cycle stage contribution to PV system environmental impacts

4.2. Case 2: Battery Electric Vehicles

Table 4. Life cycle GWP comparison of EV and ICE vehicles (g CO₂-eq/vkm)

Life cycle stage	EV (reference grid)	EV (renewable grid)	ICE baseline
Material production	32.9	32.9	28.4
Battery manufacturing	51.0	51.0	N/A
Use phase	58.9	8.7	148.3
End-of-life	-10.5	-10.5	7.3
Total	142.8	68.3	184.0

For the battery electric vehicle equipped with an LFP battery pack (60 kWh capacity), a life cycle GWP of 142.8 g CO₂-eq per vehicle-kilometer is obtained. This represents a 22.4% reduction relative to the comparable internal combustion engine vehicle baseline of 184.0 g CO₂-eq per vehicle-kilometer. These results are sensitive to the assumed carbon intensity of the electricity grid during the use phase. Under a fully renewable electricity scenario, the EV life cycle GWP drops to 68.3 g CO₂-eq per vehicle-kilometer, which corresponds to a 62.9% reduction against the ICE baseline. Table 4 lists the detailed results.

The largest single contributor to the EV life cycle GWP is battery manufacturing, which accounts for 35.7% of the total under the reference grid scenario. When closed-loop hydrometallurgical recycling of spent LFP cathode materials is implemented, the battery manufacturing GWP decreases by 28.3%, and this figure is consistent with estimates reported in the literature [14]. Under the reference grid scenario, the use phase accounts for 41.2% of the total GWP, but this share falls to only 12.8% under the renewable electricity scenario. This underscores how critical grid decarbonization is for maximizing the environmental benefits of vehicle electrification [13]. Fig. 5 presents the comparison of GWP contributions across life cycle stages for both vehicle types.

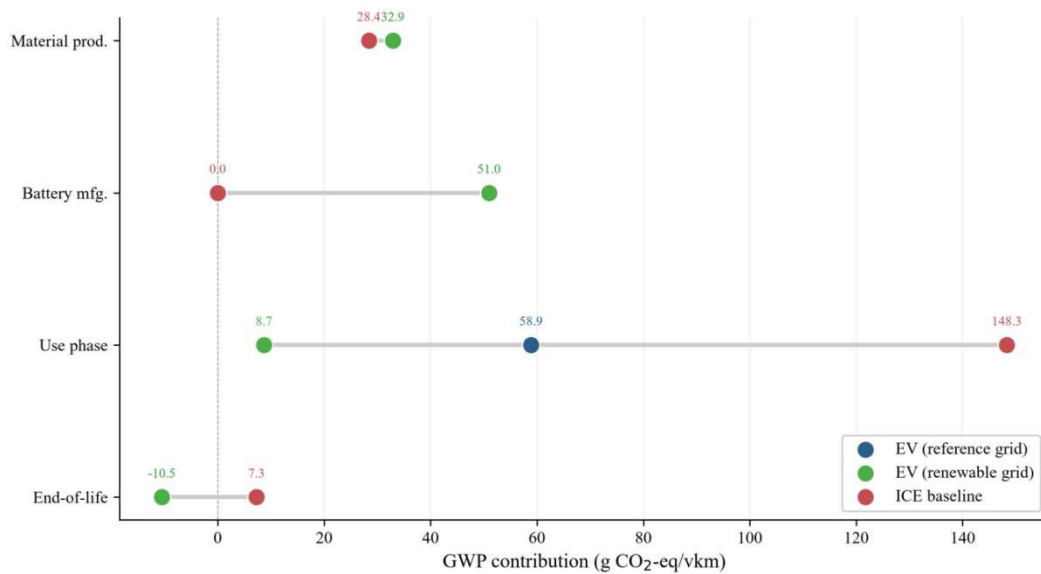


Fig. 5 GWP contribution comparison between EV and ICE vehicles

4.3. Case 3: Green Building Materials

Table 5. Life cycle impact assessment results for building materials (per m³)

Impact category	Unit	Geopolymer	Portland cement	Reduction (%)
GWP	kg CO ₂ -eq	178.5	259.4	31.2
AP	kg SO ₂ -eq	0.95	1.42	33.1
EP	g P-eq	18.4	27.6	33.3
CED	MJ	1,245	1,780	30.1

A cradle-to-gate GWP of 178.5 kg CO₂-eq per cubic meter is achieved by geopolymer concrete in which 60% fly ash and 40% ground granulated blast furnace slag serve as the binder. This amounts to a 31.2% reduction relative to conventional Portland cement concrete (259.4 kg CO₂-eq per cubic meter). Eliminating the clinker calcination process is the primary source of this GWP reduction, because thermal decomposition of limestone during calcination generates roughly 0.83 tonnes of CO₂ per tonne of clinker [15]. Table 5 summarizes the impact assessment results for all four categories.

For the geopolymer binder, the alkali activator (sodium silicate solution) is the dominant contributor to GWP and accounts for 47.8% of the binder cradle-to-gate impact. Priority pathways for further reducing the environmental footprint of geopolymer systems have been identified: optimizing the activator dosage by refining the mix design and substituting sodium silicate with less energy-intensive activators such as sodium carbonate [16]. When the alkali activator quantity is varied by 20%, sensitivity analysis shows a 9.4% change in the overall GWP, which confirms that activator chemistry is the most influential parameter. Fig. 6 depicts these sensitivity results.

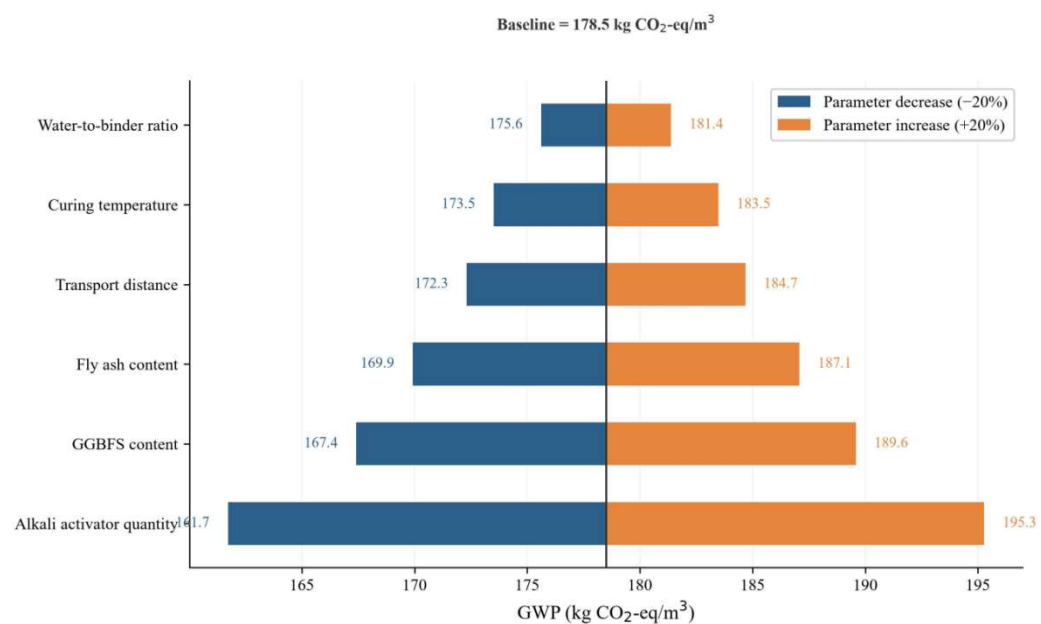


Fig. 6 Sensitivity analysis results for geopolymer concrete GWP

4.4. Cross-Case Comparison

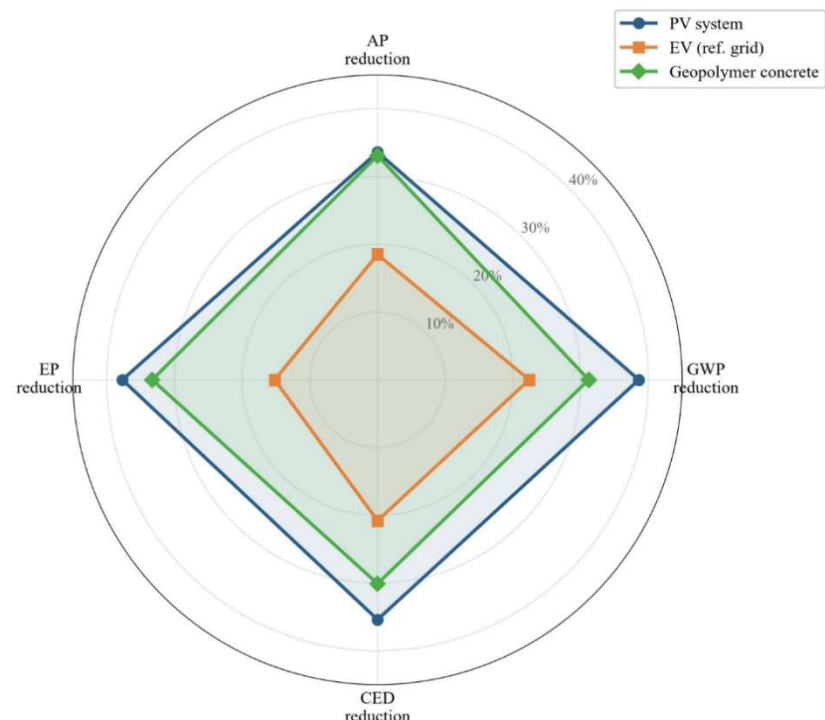


Fig. 7 Normalized carbon reduction rates across GTI cases

Fig. 7 presents a normalized comparison of the carbon reduction rates achieved by each GTI intervention. Among the three cases, the PV system shows the highest absolute carbon reduction rate (38.6%), followed by green building material (31.2%) and the EV under the reference grid scenario (22.4%). Under a renewable electricity grid assumption, however, the carbon reduction rate of the EV rises to 62.9% and surpasses both of the other cases. This result underlines how technology-level innovation and system-level infrastructure decarbonization interact in shaping aggregate sustainability outcomes.

For an integrated comparison, we construct a weighted composite sustainability index (CSI) as shown in Eq. (7), where w_j is the weight assigned to impact category j , NI_j is the normalized impact score in category j and m is the number of impact categories.

$$CSI = \sum_{j=1}^m w_j \times NI_j \quad (7)$$

Using equal weights ($w_j = 0.25$, meaning each of the four impact categories counts equally), CSI values of 0.72 for PV, 0.65 for EV (reference grid) and 0.68 for geopolymers concrete are obtained. Higher values indicate greater environmental improvement relative to the baseline. Table 6 presents the cross-case CSI comparison.

Table 6. Composite sustainability index comparison across cases

Case	CSI (equal weights)	CRR (%)	CV of GWP (%)
PV system	0.72	38.6	8.7
EV (ref. grid)	0.65	22.4	12.3
Geopolymer concrete	0.68	31.2	10.1

4.5. Uncertainty Analysis Results

The carbon reduction rates of all three cases are found to be robust when considering the 95% confidence level, as Monte Carlo simulation results show. For the GWP results, the coefficients of variation are 8.7% for PV, 12.3% for EV and 10.1% for geopolymers concrete, all of which fall below the 20% acceptability threshold defined in the methodology section. Fig. 8 illustrates the probability distributions of the GWP results, and Table 7 reports the numerical summary statistics.

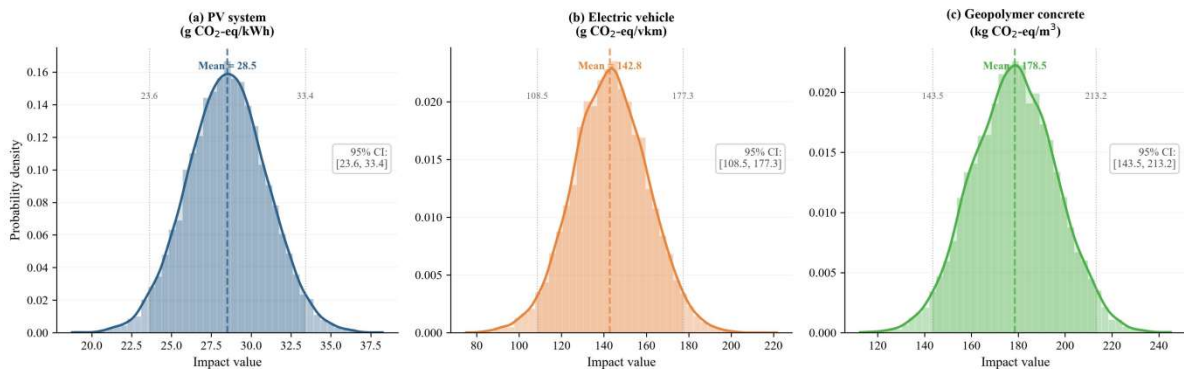


Fig. 8 Monte Carlo probability distributions of GWP results

Table 7. Monte Carlo simulation summary statistics for GWP results

Case	Mean	Std. dev.	95% CI lower	95% CI upper
PV (g CO2-eq/kWh)	28.5	2.48	24.1	33.7
EV (g CO2-eq/vkm)	142.8	17.56	112.4	178.6
Concrete (kg CO2-eq/m3)	178.5	18.03	146.2	215.8

5. Discussion

5.1. Implications for Policy and Practice

Several implications for sustainability policy design emerge from the empirical findings of this work. Quantitative support for government subsidies and tax incentives targeting green technology research and deployment is provided by the significant carbon reduction rates observed across all three GTI domains [2]. It emerges from the cross-case comparison that the environmental effectiveness of GTI is strongly modulated by background system conditions, above all the carbon intensity of the electricity grid. This observation implies that, to maximize aggregate sustainability gains, coordinated investment in both technology innovation and energy infrastructure decarbonization is necessary [17].

Because the EV results are sensitive to the carbon intensity of grid electricity, vehicle electrification policies should be coupled with renewable energy expansion targets. Unless concurrent grid decarbonization is pursued, countries in which coal dominates electricity generation may realize only modest climate benefits from EV deployment [13]. In a similar way, the sensitivity of geopolymers concrete LCA results to alkali activator chemistry indicates that further material science innovation in activator design could deliver substantial additional environmental improvements [16].

5.2. Comparison with Previous Studies

Broadly speaking, the GWP estimates obtained here are consistent with the ranges reported in the recent LCA literature. A PV GWP of 28.5 g CO₂-eq per kWh falls within the interquartile range of 18 to 45 g CO₂-eq per kWh compiled in a harmonization meta-analysis of PV LCA studies [11]. Under the reference grid scenario, the EV life cycle GWP of 142.8 g CO₂-eq per vehicle-kilometer aligns with estimates from comprehensive vehicle LCA databases [18]. Minor discrepancies with individual prior studies can be attributed to differences in system boundary definitions, background database versions and geographic assumptions.

5.3. Limitations

Several limitations should be acknowledged. While the use of a single functional unit per case is necessary for methodological consistency, it may not capture the full range of service attributes that end users value. Because the LCA results represent a static snapshot of current technology performance, the temporal dynamics of technology learning and cost reduction are not explicitly modeled. In future work, dynamic LCA methods should be integrated with technology forecasting models so that the evolving environmental profiles of GTI can be projected over multi-decadal planning horizons [19, 20].

6. Conclusion

By means of a multi-case life cycle assessment encompassing photovoltaic energy systems, battery electric vehicles and green building materials, we quantify the environmental driving effects of green technology innovation on sustainable development. The main findings are summarized as follows. Crystalline silicon PV modules achieve a life cycle GWP of 28.5 g CO₂-eq per kWh, which corresponds to a 38.6% reduction relative to the regional grid average and an energy payback time of 1.32 years. Under the reference grid scenario, battery electric vehicles with LFP batteries reduce life cycle carbon intensity by 22.4%, and under a renewable electricity scenario by 62.9%, showing the critical interaction between vehicle-level and system-level decarbonization strategies. Geopolymer concrete incorporating industrial byproducts reduces embodied carbon by 31.2% compared with conventional Portland cement concrete, and optimization of the alkali activator is identified as the primary pathway for further improvement.

These carbon reduction rates are found to be robust when considering Monte Carlo uncertainty analysis, with coefficients of variation below 13% across all cases. It emerges from the composite sustainability index analysis that PV innovation currently delivers the highest integrated environmental improvement, while EV technology exhibits the greatest sensitivity to background infrastructure conditions. An evidence base for designing differentiated GTI incentive policies that account for sector-specific innovation dynamics and system-level interdependencies is thus provided.

In future research, we suggest extending the analytical framework to include social LCA dimensions, incorporating dynamic technology learning curves and expanding the case portfolio to encompass emerging GTI domains such as green hydrogen production and direct air carbon capture technologies. Integrating LCA with techno-economic analysis and multi-criteria decision-making frameworks would further enhance the practical applicability of the results for investment prioritization and technology roadmap development.

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