A Hybrid LCA–Statistical Framework for Plant-Level Cement Embodied Carbon Quantification: Methodology Development and Application to Data-Scarce Regions

Abstract

Purpose. Embodied carbon (EC) assessment in cement production is hindered by data scarcity in emerging economies where plant-level operational data are limited or proprietary. This study develops, operationalises, and validates a hybrid life cycle assessment (LCA) and statistical framework for plant-level EC quantification in data-scarce contexts through structured primary data collection, stoichiometric process modelling, regression-based statistical analysis, and identification of dominant decarbonisation leverage points.

Design/methodology/approach. A structured questionnaire-based survey administered to a leading cement manufacturing plant in Qatar provided primary operational data. Process-based LCA (cradle-to-gate, modules A1–A3; ISO 14040/44; EN 15804+A2) was coupled with multivariate regression modelling in the Statistical Package for the Social Sciences (SPSS). Stoichiometric mass and energy balances together with Intergovernmental Panel on Climate Change (IPCC) and World Business Council for Sustainable Development (WBCSD) calcination protocols were operationalised to quantify emission contributions. One-at-a-time sensitivity analysis (±10% parameter variation) identified dominant decarbonisation leverage points, and predictive equations were validated against published international ordinary Portland cement (OPC) benchmarks.

Findings. The framework yields an embodied carbon intensity of 652 kg CO2e per tonne of OPC for the case-study plant (cradle-to-gate, A1–A3), with calcination dominating (81%), followed by fuel combustion (12%) and electricity (5%). Sensitivity analysis confirms the clinker-to-cement ratio and CaO content as the strongest decarbonisation levers: a 10% clinker-ratio reduction yields approximately 62 kg CO2e per tonne. Statistical models ($R^2 > 0.9$) validate the predictive equations and confirm the framework's ability to generate decision-ready emission curves for clinker substitution, fuel switching, and grid decarbonisation scenarios. The Qatar benchmark sits in the lower-mid range of international OPC values, attributable to natural-gas firing and moderate electricity intensity. To the authors' knowledge this is the first published plant-level OPC embodied carbon value for Qatar and the wider Gulf Cooperation Council (GCC) region.

Practical implications. The framework transforms static LCA into dynamic decision-support for clinker substitution scenarios, low-carbon procurement screening, and regulatory compliance, with documented protocols enabling replication across facilities and regions.

Social implications. The study establishes Qatar's first comprehensive plant-level EC benchmark, supporting Qatar National Vision 2030 decarbonisation commitments and demonstrating pathways for data-scarce regions to participate in global net-zero cement initiatives.

Originality/value. This study advances embodied carbon assessment by showing how stoichiometric rigour can be maintained while enabling statistical scenario analysis in data-limited industrial contexts. The framework provides the first plant-level EC benchmark for Qatar and offers a replicable methodology for emerging cement markets lacking comprehensive operational databases.

Keywords: Life Cycle Assessment (LCA); Embodied Carbon; Cement Production; Predictive Modelling; Process-Based Assessment; Statistical Analysis; Decarbonisation; Qatar.

Abbreviations

A1–A3	Cradle-to-gate life cycle modules (raw material supply, transport, manufacture)
CaO	Calcium oxide
CCUS	Carbon capture, utilisation and storage
CEM	Cement type designation under EN 197-1
CKD	Cement kiln dust
CO_2	Carbon dioxide
CO_2e	Carbon dioxide equivalent
DEFRA	Department for Environment, Food and Rural Affairs (UK)
EC	Embodied carbon
EF	Emission factor
EN 15804	European standard for Environmental Product Declarations of construction products
EPD	Environmental Product Declaration
FU	Functional unit
GCC	Gulf Cooperation Council
GGBS	Ground granulated blast-furnace slag
GHG	Greenhouse gas
GSAS	Global Sustainability Assessment System (Qatar)
GWP	Global warming potential

ICE	Inventory of Carbon and Energy
IPCC	Intergovernmental Panel on Climate Change
ISO	International Organization for Standardization
LC³	Limestone calcined clay cement
LCA	Life cycle assessment
LCI	Life cycle inventory
MgO	Magnesium oxide
NCV	Net calorific value
OAT	One-at-a-time (sensitivity method)
OLS	Ordinary least squares (regression)
OPC	Ordinary Portland cement
SCM	Supplementary cementitious material
SPSS	Statistical Package for the Social Sciences
VIF	Variance inflation factor
WBCSD	World Business Council for Sustainable Development

1. Introduction

The building and construction sector is at a critical juncture in global climate mitigation, accounting for roughly 40% of annual carbon emissions and 36% of energy use worldwide (Kandiyil et al., 2025). The construction sector is recognised as one of the most carbon-intensive industries worldwide, accounting for a substantial share of global greenhouse gas (GHG) emissions (De Wolf, Pomponi and Moncaster, 2017; Röck et al., 2020). Cement alone contributes approximately 7–8% of anthropogenic CO2 emissions, largely due to the calcination of limestone and the high clinker content in ordinary Portland cement (OPC) (Barcelo et al., 2014; Barbhuiya, Das and Adak, 2024). While global studies have examined embodied carbon in cement, regional gaps persist, particularly for the Gulf states and Qatar, where construction demand is high yet data availability remains limited (Biswas et al., 2017; Al-Nuaimi, Banawi and Al-Ghamdi, 2019; Al Jundi and Chaudhry, 2025; Kandiyil et al., 2025).

A significant portion of this impact arises from embodied carbon (EC), defined as the emissions associated with manufacturing materials and construction processes, which create an immediate carbon spike at the construction stage that cannot be retroactively mitigated (Kandiyil et al., 2025). Within this context, cement production stands out as one of the largest single industrial contributors to greenhouse gases, responsible for approximately 8% of global CO2 emissions (Barbhuiya, Das and Adak, 2024). Reducing the carbon intensity of cement and concrete has therefore become a paramount challenge in advancing sustainable construction.

Existing LCA studies frequently rely on generic international databases such as the Inventory of Carbon and Energy (ICE) (Hammond and Jones, 2011) or ecoinvent (Swiss Centre for Life Cycle Inventories, 2020). These do not capture regional factors such as Qatar's reliance on natural gas for both electricity and kiln firing, nor the specific logistics of raw material sourcing (Andric and Al-Ghamdi, 2020; Al-Nuaimi, Banawi and Al-Ghamdi, 2019). As a result, embodied carbon benchmarks are often poorly aligned with local conditions.

This study addresses these shortcomings by conducting a process-based LCA of OPC production at a cement plant in Qatar, structured in accordance with ISO 14040/44 (ISO, 2006a, 2006b) and EN 15804+A2 (Mineral Products Association, 2019). The analysis is complemented by sensitivity testing and predictive regression modelling, offering both transparent quantification and enhanced predictive capability. The study pursues three objectives. First, it establishes a robust Qatar-specific embodied carbon benchmark for cement using primary plant-level data. Second, it identifies the most influential process parameters governing cradle-to-gate emissions through structured sensitivity and statistical analysis. Third, it provides methodological insights, packaged as a hybrid LCA and statistical framework, that are transferable to other data-scarce regions and relevant to global decarbonisation efforts.

2. Literature Review

Cement manufacture is one of the largest single industrial sources of CO_2 due to process calcination emissions and fuel combustion. Updated global inventories show that cement process emissions alone reached approximately 1.45 to 1.50 Gt CO_2 in 2016 to 2018 (about 4% of fossil-fuel emissions) and have risen cumulatively to more than 38 Gt since (Kandiyil et al., 2025; Barbhuiya, Das and Adak, 2024). Within project-stage LCAs, cement is typically the dominant contributor to concrete's cradle-to-gate (A1–A3) global warming potential (GWP) because clinker production releases stoichiometric CO_2 when $CaCO_3$ decomposes to CaO and CO_2, while kilns also require high-temperature thermal energy, historically from fossil fuels (Barcelo et al., 2014; Scrivener, John and Gartner, 2018).

Decarbonisation pathways therefore span clinker-factor reduction with supplementary cementitious materials (SCMs) such as fly ash, slag, and calcined clays, including limestone calcined clay cement (LC^3); fuel switching and efficiency improvements; alternative fuels with high biogenic content; electricity decarbonisation via cleaner grids; process innovation through novel clinkers such as belite-ye'elimite/CSA systems; and carbon capture utilisation and storage (CCUS) at kiln stacks (Scrivener, John and Gartner, 2018; Barbhuiya, Das and Adak, 2024). Among these, lowering clinker content delivers immediate GWP reductions at scale because it directly targets the process-emission term. LC^3 has emerged as a promising mainstream solution in developing regions given clay availability and moderate calcination temperatures (Dhandapani, 2020; Nguyen, 2020; Mañosa, 2024; Hosen and Chen, 2025). Where SCM supply is constrained, performance-based specifications and optimisation of mix design, rather than prescriptive cement contents, can realise additional reductions for a given mechanical performance (Habert and Roussel, 2009; Wałach, 2023).

Process-based LCA of cement typically includes raw material extraction and processing (A1), inbound transport (A2), and manufacture (A3), quantified via mass and energy balances and stoichiometric models for calcination (WBCSD/CSI, 2011). Comparisons across databases and studies show wide numerical dispersion driven by site-specific kiln chemistry, fuel mix, electricity mix, and clinker ratio (Hammond and Jones, 2011; Röck et al., 2020; Teng, 2023). Recent national and sectoral inventories and United States life-cycle inventories also report cradle-to-gate concrete footprints strongly governed by cement input and clinker factor; transport (A2) is smaller, but long import distances for gypsum and iron ore can still be material in regional contexts (Hottle and Bare, 2022; Biswas et al., 2017).

For calcination, the customary approach multiplies clinker production by CaO and MgO fractions (IPCC method) using ratios 44/56 and 44/40.3 respectively to convert to CO2, adjusted for cement kiln dust (CKD) bypass and non-recycled dust fractions. Fuel emissions scale with energy input and fuel emission factor (EF), for example approximately 56 kg CO2 per GJ for natural gas, and electricity scales with the site-specific grid EF (WBCSD/CSI, 2011, 2013). Reported cradle-to-gate emission factors for OPC typically fall in the range of approximately 550 to 900 kg CO2e per tonne of cement depending on clinker ratio and energy mix (Barcelo et al., 2014; Scrivener, John and Gartner, 2018; Hottle and Bare, 2022). The lowest values are associated with efficient kilns, lower clinker factors, clean grids, and use of alternative fuels; the highest arise from high-clinker cements with coal or petcoke firing and carbon-intensive grids.

A recurring challenge is the inter-database variability of material emission factors (for example ICE v2/v3, ecoinvent, GaBi, OneClick LCA datasets, and national LCIs). Studies have documented significant spread due to different system boundaries, background datasets, electricity mixes, and allocation rules (Tait and Cheung, 2016; Teng, 2023; Chen et al., 2025). For Gulf projects, reliance on European averages can misrepresent A2 and A3 contributions, including marine imports, grid intensity, and fuel mix (Al Jundi and Chaudhry, 2025). Consequently, primary plant data, including kiln feed, chemistry, dust and bypass rates, fuel and electricity use, and explicit transport, remain critical to reduce uncertainty and to create country-specific factors aligned with EN 15804 and ISO 14040/44 (Kandiyil et al., 2025). The present study directly addresses these limitations by collecting primary plant-level kiln chemistry, fuel consumption, CKD management, and transport data from a Qatar-based facility, thereby replacing generic background datasets with process-specific inputs traceable to actual production conditions. This approach generates a Qatar-anchored emission factor grounded in WBCSD and IPCC Tier 3 methods, overcoming the systematic uncertainty arising from reliance on European or global average datasets.

In the Gulf, concrete supply chains exhibit distinctive characteristics: heavy reliance on imported gypsum and certain minerals, abundant limestone but variable clay suitability, hot climates with high operational energy demand for buildings (and therefore growing interest in embodied emissions as operational energy decarbonises), and nascent but increasing availability of Environmental Product Declarations (EPDs) (Biswas et al., 2017; De Wolf, Pomponi and Moncaster, 2017; Al-Nuaimi, Banawi and Al-Ghamdi, 2019; Al Jundi and Chaudhry, 2025). Gulf-States EPD case studies for concrete demonstrate the sensitivity of cradle-to-gate GWP to cement constituents and transport routes, and call for regionalised datasets to supplement generic databases (Biswas et al., 2017). Parallel work on Qatar's construction material sourcing under supply disruptions (Al-Nuaimi, Banawi and Al-Ghamdi, 2019) shows that route choices and border constraints can materially affect embodied impacts in practice. While much of the regional literature has focused on operational energy and cooling demand (Andric and Al-Ghamdi, 2020), the growing proportion of upfront embodied emissions in near-zero-operational buildings (Röck et al., 2020) has refocused attention on cement and concrete LCAs and SCM adoption suited to local geology, for example calcined clays and ground limestone. These regional specificities, including gas-based electricity, imported gypsum and iron ore, and nascent EPD adoption, make a process-level, primary-data-driven LCA indispensable for Qatar's cement sector and underpin the methodological choices and system boundary of the present study.

Beyond point estimates, sensitivity and statistical or predictive modelling are increasingly used to explore how clinker ratio, CaO and MgO, CKD losses, fuel EF, grid EF, and transport propagate to A1–A3 totals (Habert et al., 2020; Röck et al., 2020; Hottle and Bare, 2022). Regression and machine-learning approaches have been applied to optimise mixes and anticipate GWP under varying constraints, with recent studies coupling optimisation and prediction to recommend low-GWP formulations (Xing, 2023; Salgado et al., 2025; Arvizu-Montes et al., 2025; Iqbal and Noureldin, 2025). Despite this trend, peer-reviewed examples that tightly integrate process-based LCA with statistical models for cement, rather than for concrete mix portfolios, remain comparatively scarce, especially in Gulf contexts. This study operationalises these insights using a one-at-a-time (±10%) sensitivity design on clinker factor, clinker chemistry (CaO and MgO), energy, and logistics, and couples the process LCA with SPSS regression. For electricity, fuel, and transport, deterministic log–log identities (coefficients approximately 1.000; $R^2 = 1.000$) are confirmed, while for calcination a multiple regression on clinker output and CaO/MgO is estimated with $R^2 \approx 0.94$, with CKD terms retained for completeness. This integration enables transparent prediction curves that directly tie policy levers, such as clinker substitution and grid EF, to cradle-to-gate GWP, leaving a gap this work helps to fill. Unlike mix-design optimisation studies (Xing, 2023; Chen et al., 2025) that apply regression to concrete formulations, this study integrates statistical modelling directly with a process-based cement LCA, targeting the upstream production stage (A1–A3) rather than concrete mix performance. Uniquely, it combines stoichiometric IPCC and WBCSD calcination protocols with SPSS regression to yield predictive emission curves tied to kiln chemistry parameters (CaO%, MgO%, CKD fractions), namely plant-specific parameters unavailable in generic databases. This integration provides a methodological bridge between deterministic process accounting and statistical decision-support not previously demonstrated for cement production in the Gulf region.

The synthesis above reveals four persistent and interrelated gaps that the present study is designed to address. First, virtually all existing Gulf cement LCAs rely on generic international databases (ICE, ecoinvent, GaBi) rather than plant-specific kiln chemistry and CKD or bypass accounting, introducing systematic regional misspecification; this gap is closed through primary plant-level data collection. Second, while regression and machine-learning methods have been applied to concrete mix optimisation (Xing, 2023; Chen et al., 2025; Arvizu-Montes et al., 2025), tightly integrated combinations of process-based cement-production LCA with statistical predictive modelling remain scarce in the Gulf; this gap is addressed by coupling SPSS regression with stoichiometric LCA. Third, standardised, auditable A2 transport modelling for Qatar-specific raw-material sourcing routes is largely absent from the peer-reviewed literature; this gap is partially addressed here using DEFRA and IPCC emission factors. Fourth, policymakers and certification schemes lack plant-level, verified emission factors and scenario curves for Qatar; this gap is filled by generating the first comprehensive Qatar-specific OPC benchmark and regression-derived decarbonisation curves.

Collectively, these gaps justify the hybrid LCA and statistical framework proposed in this study, which uniquely combines the rigour of ISO 14040/44-compliant process-based LCA with the predictive flexibility of SPSS multivariate regression, applied to primary operational data from Qatar's cement sector.

3. Methodology

3.1 Goal, Scope and Standards

This study quantifies the cradle-to-gate embodied carbon (Global Warming Potential, 100-year horizon) of cement production and develops a predictive modelling framework that links process parameters to carbon emissions. The system boundary is shown in Figure 1. The assessment follows the principles and requirements of ISO 14040/14044 and reports impacts consistent with EN 15804 (modules A1–A3) using

IPCC AR5 characterisation factors. The functional unit (FU) is defined as 1 tonne of OPC at the factory gate.

The system boundary encompasses all upstream and manufacturing stages relevant to cement production: raw material extraction and pre-processing (A1), inbound transport of inputs (A2), and cement manufacture (A3), including calcination, kiln-fuel combustion, and purchased electricity. Downstream stages (A4 to C) and capital goods were excluded, in line with EN 15804 recommendations, unless already embedded within background datasets.

The cradle-to-gate system boundary (A1–A3) was selected for three reasons. First, it encompasses all processes within the cement manufacturer's direct operational control, namely raw material extraction (A1), inbound transport (A2), and manufacture including calcination, kiln-fuel combustion, and electricity (A3), thereby capturing the full scope of actionable mitigation at the plant level. Second, this boundary is defined by EN 15804+A2 product category rules for cement and cementitious materials, ensuring that the resulting emission factor is directly comparable with industry EPDs (Mineral Products Association, 2019). Third, it aligns with the WBCSD Cement CO2 and Energy Protocol, which delimits its accounting scope at the factory gate and is the primary international standard for cement-sector carbon accounting (WBCSD/CSI, 2011). Module A4 (transport from factory gate to site) was excluded because it is project-specific, dependent on contractor logistics, and outside the manufacturer's direct control, a boundary choice consistent with published OPC LCAs (Hottle and Bare, 2022; Barcelo et al., 2014).

A key feature of this research is the use of comprehensive primary industrial data obtained through a structured questionnaire-based survey of a leading cement plant in Qatar. The survey instrument was specifically designed for this study to capture process-level details such as kiln-feed composition, clinker-to-cement ratio, fuel and electricity consumption, and CKD management. The methodology thus integrates empirical data collection with process-based life-cycle modelling and statistical analysis, offering a robust and transferable framework that can be applied across different regional contexts. Details of the data acquisition, validation, and confidentiality procedures are presented in the next section (Data Sources and Quality Assurance).

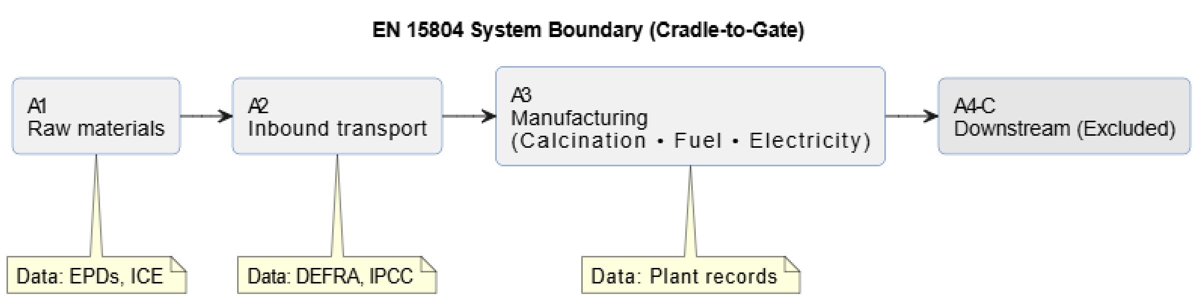

Figure 1. System boundary for cradle-to-gate (modules A1–A3) OPC production.

3.2 Data Sources and Quality Assurance

3.2.1 Case Study Description

Qatar's cement manufacturing sector is concentrated around two major producers that together meet the bulk of national demand. The case-study facility is one of these two principal plants and is among the largest OPC manufacturers in the country. Further plant-level identifying detail is withheld in this publication under a non-disclosure agreement; the disclosed operational characteristics are sufficient to support methodological transparency without compromising commercial confidentiality. The Qatar cement market is estimated at approximately 7.5 million tonnes of annual consumption (IMARC Group, 2025), of which the case-study plant represents a substantial share. The plant operates a modern dry-process rotary kiln system fuelled primarily by natural gas, which is Qatar's dominant industrial energy source. The plant operates exclusively on OPC (CEM I equivalent) production, with no supplementary cementitious materials (SCMs) incorporated into the cement blend during the study period. Raw materials are predominantly sourced domestically (limestone), with supplementary imports of gypsum and iron ore via sea freight. Purchased electricity is drawn from the Qatar national grid, which operates predominantly on natural gas. CKD management follows the plant's standard operational practice of partial recycling. Data were collected across five operational years (2020 to 2024) under a confidentiality agreement; specific production volumes and company identifiers are withheld in this publication but were used in mass-balance and statistical calculations.

3.2.2 Data Collection Approach

The primary data-collection instrument was a structured technical questionnaire comprising approximately 30 items organised across five thematic modules: (i) raw material inputs, quantities, and clinker-feed composition; (ii) fuel types, consumption quantities, and net calorific values (NCVs); (iii) electricity consumption and grid parameters; (iv) clinker production rates, cement blending ratios, and CKD management; and (v) inbound transport distances, material sourcing origins, and logistics modes. The full questionnaire is provided as supplementary material accompanying this article so that the protocol can be reapplied by other researchers. The study employed a targeted industrial case-study design rather than a broad-sample survey, consistent with the aim of generating process-specific, plant-level data unavailable from generic databases. Accordingly, the questionnaire was administered to a single leading cement manufacturing facility in Qatar, identified through professional industry networks and academic collaboration.

The questionnaire was pre-tested with three technical representatives at the facility, including a kiln process engineer, a quality assurance manager, and an environmental compliance officer, to verify terminology accuracy, data availability, and feasibility before formal deployment. Following pilot refinement, the final instrument was administered over a four-month period. Completed responses were provided by three senior technical personnel across kiln operations, quality control, and sustainability functions. Annual input and output data covering five consecutive calendar years (2020 to 2024) were collected, with each year constituting one observation in the regression dataset (N = 5). Multi-year data were essential to capture inter-annual variability in kiln chemistry and production output, strengthening the robustness of regression coefficients.

The questionnaire was developed in consultation with academics, LCA experts, and industry engineers to align with ISO 14040/44 and the WBCSD Cement CO2 and Energy Protocol. It covered annual input and output parameters across all relevant processes, including raw-material quantities, fuel and electricity consumption, kiln-feed chemistry (CaO, MgO), clinker production, cement blending ratios, and CKD management. Additional sections addressed material sourcing routes, transport distances, and operational practices affecting process efficiency. Responses were collected through confidential industry collaboration, supported by follow-up communications and, where necessary, on-site technical verification of plant logs and process reports. Data collection spanned several months to accommodate internal approval procedures and quality checks by the participating facility.

3.2.3 Data Validation and Confidentiality

All primary data were anonymised to maintain commercial confidentiality. Specific production volumes and company identifiers are withheld in this publication but were used internally to conduct mass and energy balance calculations. To ensure accuracy, each data entry was validated through triangulation that compared plant-reported figures with independently available EPDs, published emission factors, and engineering consistency checks (for example, stoichiometric CO2 output from CaO and MgO composition, and thermal balance for fuel inputs).

Secondary datasets were used selectively to fill background processes, for example electricity grid mix, and upstream material emission factors were drawn from authoritative sources such as ecoinvent, ICE, and the WBCSD database.

A qualitative pedigree-style data-quality assessment was applied across five conventional dimensions: (i) reliability, (ii) completeness, (iii) temporal representativeness, (iv) geographic representativeness, and (v) technological representativeness, consistent with the ecoinvent pedigree-matrix approach (Swiss Centre for Life Cycle Inventories, 2020). The assessment functioned as a reporting tool: any data entry that did not meet acceptable representativeness on any individual dimension was flagged for cross-verification before inclusion in calculations. Entries that could not be validated were either excluded or substituted with conservative secondary estimates from published EPDs or WBCSD protocol default values. This approach ensures methodological conservatism by allowing only data that meet the minimum quality standard to enter the quantitative models.

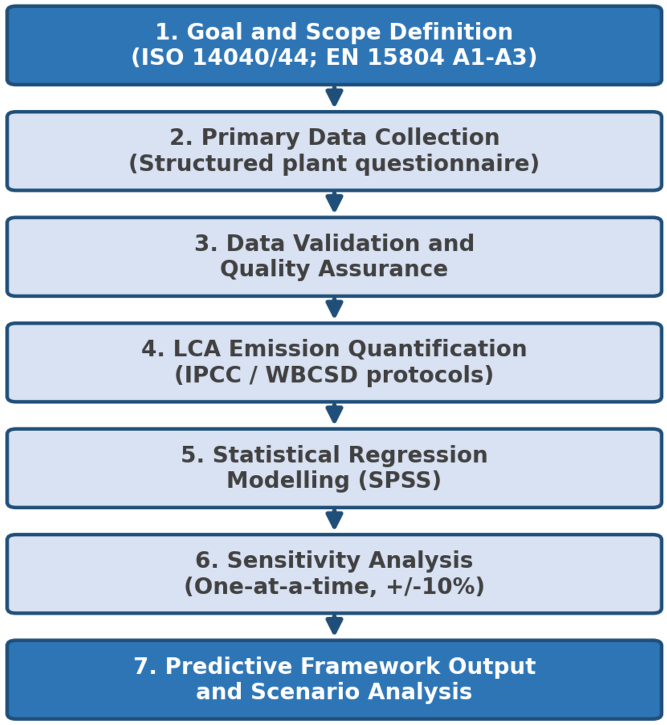

Figure 2. Research workflow for the hybrid LCA and statistical framework. The workflow proceeds sequentially through seven stages: (1) goal and scope definition, (2) primary data collection, (3) data validation and quality assurance, (4) LCA emission quantification, (5) statistical regression modelling, (6) sensitivity analysis, and (7) predictive framework output and scenario analysis.

Ethical Compliance

The study adhered to institutional ethics and data-protection requirements. Participation by the industrial partner was voluntary, based on mutual understanding of the research objectives and strict adherence to data confidentiality. The results are presented in aggregated or normalised form per functional unit, ensuring that no commercially sensitive information can be traced to the company.

3.3 Emission Quantification Models: Life-Cycle Inventory and Carbon Footprint Calculations

The life-cycle inventory aligns with EN 15804 module boundaries and is normalised to the functional unit.

3.3.1 Raw Material Extraction (A1)

Annual quantities (t yr−1) for limestone, clay or shale, iron ore, recycled inputs, and gypsum are multiplied by source-specific cradle-to-gate emission factors (kg CO2e t^{-1}). Quarrying, crushing, screening, and grinding are included per data source.

3.3.2 Inbound Transport (A2)

For each stream, tonne-kilometres are computed from mass and distance by mode; emissions use mode-specific emission factors (for example heavy goods vehicle and bulk carrier). Multimodal routes (ship and truck) are aggregated.

3.3.3 Calcination Emissions (A3)

The following stoichiometric equation quantifies process CO2 from carbonate decomposition during clinker production. This deterministic relationship is used because calcination CO2 is governed by the molar conversion of CaCO3 to CaO and CO2, and MgCO3 to MgO and CO2, with stoichiometric ratios (44/56 for CaO and 44/40.3 for MgO) directly converting clinker chemistry into process emissions:

$$CO2 = Mclinker \times (0.785 \times WCaO + 1.091 \times WMgO)$$

where CO_2 is the stoichiometric process CO_2 from calcination (kg CO_2 per tonne of clinker); $M_{clinker}$ is the mass of clinker produced (tonnes; for the per-tonne functional unit, normalised by cement output); W_{CaO} is the mass fraction of CaO in clinker (dimensionless, 0 to 1; typically 0.60 to 0.67 for OPC); W_{MgO} is the mass fraction of MgO in clinker (dimensionless, 0 to 1; typically 0.01 to 0.05 for OPC); 0.785 is the stoichiometric ratio 44/56 (CO_2 released per unit CaO mass); and 1.091 is the stoichiometric ratio 44/40.3 (CO_2 released per unit MgO mass).

CKD and bypass corrections use reported non-recycled CKD, the fraction of original carbonate retained in the CKD, and the fraction calcined.

3.3.4 Fuel Combustion Emissions (A3)

Emissions are computed from measured natural-gas use and its net calorific value (NCV) with the IPCC factor for gas combustion (t CO2 per TJ), including unit conversions from Nm3 where applicable.

3.3.5 Electricity Emissions (A3)

Plant kWh is multiplied by the national grid emission factor (kg CO2e per kWh). For Qatar, the grid EF is 0.431 kg CO2 per kWh.

Cut-off and allocation rules: no multi-output allocation is required at the cement kiln; CKD treatment follows the WBCSD protocol. Cut-offs apply only where upstream datasets already include capital goods.

3.4 Sensitivity Analysis Design

Parameters for sensitivity analysis were selected based on three criteria: (i) their explicit inclusion as primary input variables in the WBCSD and IPCC Tier 3 cement CO2 accounting protocol (WBCSD/CSI, 2011), ensuring alignment with internationally recognised emission accounting standards; (ii) their demonstrated influence on cradle-to-gate global warming potential in peer-reviewed literature (Barcelo et al., 2014; Scrivener, John and Gartner, 2018; Hottle and Bare, 2022), confirming that variation in these parameters materially affects emission outcomes; and (iii) their operational controllability, where each parameter represents a lever that plant management can feasibly adjust through procurement, process optimisation, or capital investment. Parameters that are fixed by chemistry or externally determined (for example, IPCC atmospheric characterisation factors and fixed stoichiometric molecular-weight ratios) were excluded. The clinker-to-cement ratio and clinker CaO content were prioritised as primary levers given their dominant influence on the calcination emission term; fuel, electricity, and transport parameters were included as secondary levers reflecting energy and logistics decisions.

A local sensitivity analysis was undertaken to evaluate the influence of key modelling parameters on the calculated carbon footprint. Each parameter was perturbed independently while holding others constant, consistent with a one-at-a-time (OAT) sensitivity method. The relative percentage change in cradle-to-gate embodied carbon (kg CO2e per tonne of cement) was then recorded. This approach enabled the identification of parameters exerting the greatest leverage on the result, thereby highlighting priority areas for decarbonisation strategies and for improving data accuracy. Results are reported in Section 4 as both a tornado chart and tabular values. Table 1 summarises the design.

Table 1. Sensitivity analysis design: key parameters, baseline values, variation ranges, and rationale.

Parameter	Unit	Baseline value	Variation range	Rationale
Clinker-to-cement ratio	ratio	0.95 (95% clinker)	+10% capped at 1.00; −10%	Reflects potential shifts through SCM substitution; upper bound physically constrained (see note).
Clinker chemistry: CaO	% mass	63.3	±10% relative	Captures variability in raw-meal chemistry.
Clinker chemistry: MgO	% mass	4.5	±10% relative	Captures variability in raw-meal chemistry.
Natural-gas EF	kg CO_2 per Nm^3	2.13	±10% relative	Represents uncertainty in fuel composition.
Grid electricity EF	kg CO_2 per kWh	0.431	0.30 to 0.60	Covers low- to high-carbon grid scenarios.

Transport intensity	t·km per t	Baseline distances	±10% relative	Simulates alternate sourcing and logistics routes.
CKD parameters	kg per t and fractions	Plant-specific	±10% relative	Reflects variability in carbonate content and calcining.

Note. Baseline clinker-to-cement ratio of 0.95 reflects the case-study plant's OPC formulation. A +10% relative variation yields a theoretical value of 1.045, which exceeds the physical maximum of 1.00 (100% clinker by mass) and is therefore physically impossible. In the sensitivity analysis the upper bound is capped at 1.00, consistent with a 100%-clinker cement, the absolute physical maximum. Because the plant already operates at 0.95, the operationally meaningful and policy-relevant sensitivity direction is downward (clinker reduction via SCM substitution): the −10% scenario (0.855) corresponds to approximately 14.5% SCM substitution, consistent with a CEM II/A-type blended cement. Results are reported for both bounds; the upper bound should be interpreted as the marginal sensitivity approaching, not exceeding, the physical ceiling.

3.5 Statistical Regression Modelling

To complement the deterministic life-cycle assessment, statistical modelling was performed in IBM SPSS Statistics (v.25) using the baseline dataset and systematically generated sensitivity scenarios. The workflow followed in SPSS is summarised in Figure 3. The dependent variable was defined as the cradle-to-gate embodied carbon intensity (kg CO2e per tonne of cement), while independent variables represented key process drivers: clinker-to-cement ratio, clinker chemistry (CaO% and MgO%), kiln-fuel consumption, electricity use (via the grid emission factor), and transport intensity.

A multiple linear regression approach was applied to quantify the relationship between these predictors and the total embodied carbon. Standard diagnostic procedures were used to evaluate model robustness, including checks of goodness-of-fit (R^2, adjusted R^2), multicollinearity (variance inflation factor), and statistical significance of coefficients (p-values). For relationships that are strictly proportional by design, such as electricity and transport emissions, log–log specifications were estimated to confirm the deterministic identities.

Model validation was based on the internal scenario dataset. Predictive accuracy was assessed by comparing regression-predicted values against deterministic calculations across all scenarios. Residual analysis confirmed that model assumptions of linearity and homoscedasticity were not violated. The regression confirmed that clinker ratio and clinker chemistry are the most influential predictors of cement's embodied carbon, aligning with the sensitivity analysis and the stoichiometric process calculations.

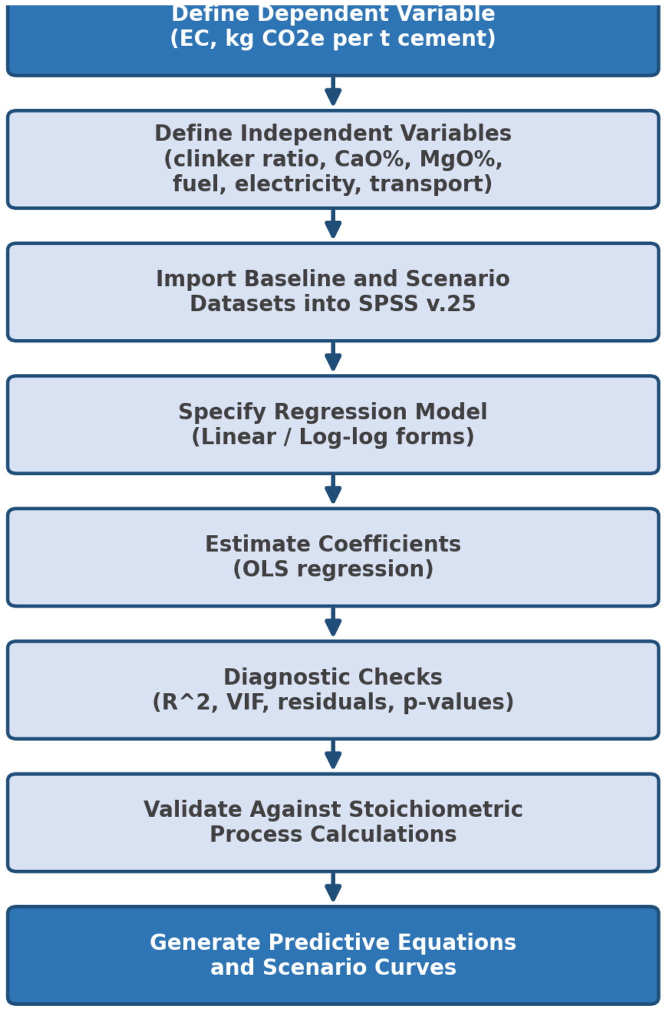

Figure 3. Workflow of the SPSS-based statistical regression modelling. The flow chart shows the sequential steps followed in SPSS: defining the dependent and independent variables, importing the baseline and scenario datasets, specifying the regression form, estimating coefficients via ordinary least squares, running diagnostic checks, validating against stoichiometric calculations, and generating predictive equations and scenario curves.

4. Results and Discussion

4.1 Embodied Carbon Intensity Benchmark

Applying the hybrid LCA and statistical framework to the case-study plant yields a cradle-to-gate embodied carbon (GWP, 100-year, IPCC AR5) of 652 kg CO2e per tonne of OPC (functional unit: 1 t OPC; EN 15804 modules A1–A3). This value represents, to the authors' knowledge, the first published plant-level OPC embodied-carbon benchmark for Qatar and for the wider Gulf Cooperation Council region, which until now have lacked a verified, primary-data-based emission factor for cement production. Stage contributions show a strongly skewed profile: calcination dominates at approximately 81%, kiln-fuel combustion contributes approximately 12%, purchased electricity approximately 5%, and upstream A1 and A2 processes together account for less than 3% (Table 2). This partitioning matches the mechanistic expectation for clinker-rich OPC, in which process CO2 from carbonate decomposition controls the footprint.

The benchmark is computed output of the integrated process-based LCA model developed in this study, derived by substituting primary plant-reported operational data into the governing equations for calcination, fuel combustion, electricity, raw material extraction, and transport (Table 9). The result lies in the lower half of the published cradle-to-gate range for gas-fired, high-clinker OPC plants, which is typically reported in the interval 600 to 720 kg CO2e per tonne (Barcelo et al., 2014; Hottle and Bare, 2022; Scrivener, John and Gartner, 2018). Its position is consistent with Qatar's reliance on natural gas, which has a lower emission factor than coal or petroleum coke, and a moderate grid emission intensity. The benchmark therefore fills a documented evidence gap for the GCC and provides a reference point against which future plant-level and policy assessments in the region can be calibrated.

The full integrated equation used to derive this benchmark is presented in Section 4.4.6; for clarity its constituent terms are summarised below:

$$\mathrm{EC(A1–A3) = EC(A1) + EC(A2) + EC(A3, calc) + EC(A3, fuel) + EC(A3, elec)}$$

$$\mathrm{EC(A1)} = \Sigma\ (\mathrm{m_i} \times \mathrm{EF_i\text{^}A1})$$

$$\mathrm{EC(A2)} = \Sigma\ (\mathrm{TKm_j} \times \mathrm{EF_j\text{^}A2} \times 10^{-3})$$

$$\mathrm{EC(A3, calc)} = 1000 \times \mathrm{r\_cl} \times [\mathrm{w\_CaO} \times (44/56) + \mathrm{w\_MgO} \times (44/40.3)] \times (1 - \mathrm{f\_CKD,ret}) + \Delta\mathrm{\_CKD}$$

$$\mathrm{EC(A3, fuel)} = \mathrm{F\_MJ} \times \mathrm{EF\_fuel} \times 10^{-3}$$

$$\mathrm{EC(A3, elec)} = \mathrm{E\_kWh} \times \mathrm{EF\_grid}$$

where m_i is the mass of each raw material (kg per tonne of cement); $EF_i^{\wedge A1}$ is the emission factor for raw-material extraction and processing (kg CO_2e per kg); TKm_j is the tonne-kilometres for transport route j (t·km per t); $EF_j^{\wedge A2}$ is the transport emission factor for mode j (kg CO_2e per t·km); r_{cl} is the clinker-to-cement ratio (dimensionless); w_{CaO} and w_{MgO} are the mass fractions of CaO and MgO in clinker (dimensionless); $f_{CKD,ret}$ is the fraction of CKD returned to kiln (dimensionless); Δ_{CKD} is the correction term for calcined non-returned CKD (kg CO_2e per tonne); F_{MJ} is the kiln fuel energy input (MJ per tonne of cement); EF_{fuel} is the fuel emission factor (kg CO_2e per GJ; 10^{-3} converts MJ to GJ); E_{kWh} is the purchased electricity (kWh per tonne of cement); and EF_{grid} is the grid electricity emission factor (kg CO_2e per kWh).

4.2 Emission Component Analysis

Table 2. Contribution of each process stage to the carbon footprint of OPC cement (functional unit: 1 t cement; modules A1–A3).

Stage (EN 15804 module)	Process description	EC contribution (kg CO_2e per t)	Share of total (%)
A1 — Raw materials	Quarrying and processing of limestone, clay, iron ore, and gypsum	14.20	2.20
A2 — Transportation	Trucking of local clay and limestone; shipping and trucking of iron ore and gypsum	1.70	0.30
A3 — Process (calcination)	CO_2 from decomposition of $CaCO_3$ and $MgCO_3$ in kiln feed, corrected for CKD losses	525.40	80.60
A3 — Fuel combustion	Scope 1 emissions from natural-gas combustion in kiln and calciner	80.90	12.40
A3 — Electricity use	Scope 2 emissions from purchased electricity (Qatar gas-based grid)	29.70	4.60
Total (A1–A3)	**Cradle-to-gate embodied carbon**	**652.00**	**100.00**

Note. Values are rounded to two decimal places. EC = embodied carbon; CKD = cement kiln dust; A1–A3 = EN 15804 cradle-to-gate modules.

The magnitude and the A3 dominance are consistent with international OPC ranges and with Gulf plants operating exclusively on natural gas. Qatar's figure lies at the lower end of global OPC values, largely due to the gas-based energy mix; nevertheless, the absolute process burden remains high, underscoring the structural role of clinker calcination, as shown in Figure 4.

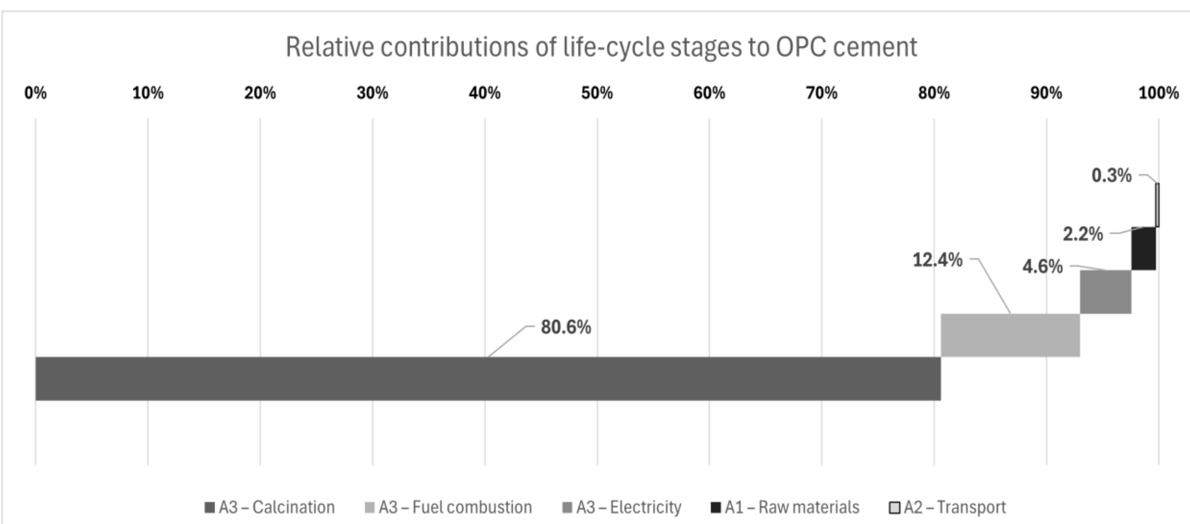

Figure 4. Relative contributions of life-cycle stages (A1–A3) to the cradle-to-gate carbon footprint of OPC cement (kg CO_2e per tonne; baseline 652 kg CO_2e per t). Bars show absolute contribution; percentage labels show share of total. Calcination (A3) dominates at approximately 81%, confirming process chemistry as the principal mitigation lever for the case-study plant.

4.3 Local Sensitivity Analysis of Process Parameters Influencing Embodied Carbon

To evaluate the robustness of the baseline cradle-to-gate carbon footprint, a structured one-at-a-time (OAT) local sensitivity analysis was performed on key process parameters influencing the embodied-carbon model. Each variable was perturbed by ±10% around its baseline value while all other inputs were held constant. This approach, recommended by ISO 14044 (ISO, 2006b) for testing the influence of assumptions on life-cycle results, provides a transparent and computationally efficient means of screening main-effect sensitivities (Hamby, 1994; Saltelli, Chan and Scott, 2008). The ±10% range was chosen as a realistic representation of operational and measurement uncertainty typically encountered in plant-reported data, sufficiently broad to reveal dominant drivers without generating implausible boundary conditions (Lloyd and Ries, 2007).

The results in Table 3 and Figure 5 indicate that the clinker-to-cement ratio exerts the strongest leverage on total embodied carbon, producing approximately ±9.5% change in EC for ±10% variation in the ratio. Clinker chemistry, particularly the CaO and MgO contents, shows the next-highest influence (approximately ±8%), reflecting the direct stoichiometric control of calcination emissions. Energy-related factors such as the natural-gas emission factor and grid electricity intensity display moderate sensitivity (approximately ±1%), while upstream raw-material and transport parameters contribute negligibly (less than 0.5%). The CKD-related parameters produced variations below 0.2% and were therefore omitted from graphical presentation for clarity. Overall, the OAT analysis confirms that process chemistry and clinker substitution dominate uncertainty and mitigation potential, whereas energy-mix and logistics changes play only marginal roles in the present gas-fired Qatari context.

Table 3. Sensitivity analysis results: impact of ±10% variation in parameters on embodied carbon (baseline EC = 652 kg CO_2e per t).

Parameter tested	EC at −10% (kg per t)	EC at +10% (kg per t)	ΔEC (kg per t)	% change vs baseline	Relative influence
Clinker-to-cement ratio	590.00	714.10	−62 / +62	−9.50% / +9.50%	Highest
Clinker CaO content	599.20	703.00	−53 / +51	−8.10% / +7.80%	High
Clinker MgO content	599.20	703.00	−53 / +51	−8.10% / +7.80%	High
Fuel EF (natural gas)	644.70	660.10	−7 / +8	−1.10% / +1.20%	Moderate
Electricity EF (grid)	649.30	655.00	−3 / +3	−0.40% / +0.50%	Low

Raw material factors (A1)	650.50	653.40	−1 / +1	−0.20% / +0.20%	Very low
Transport intensity (A2)	651.80	652.10	−0.20 / +0.10	−0.03% / +0.02%	Negligible

Note. CKD-related variations (mass, carbonate content, calcination fraction) were also perturbed by ±10%, but changes in overall EC were below 0.2% and are therefore omitted for clarity. EC = embodied carbon; EF = emission factor; A1 = raw-material extraction; A2 = inbound transport.

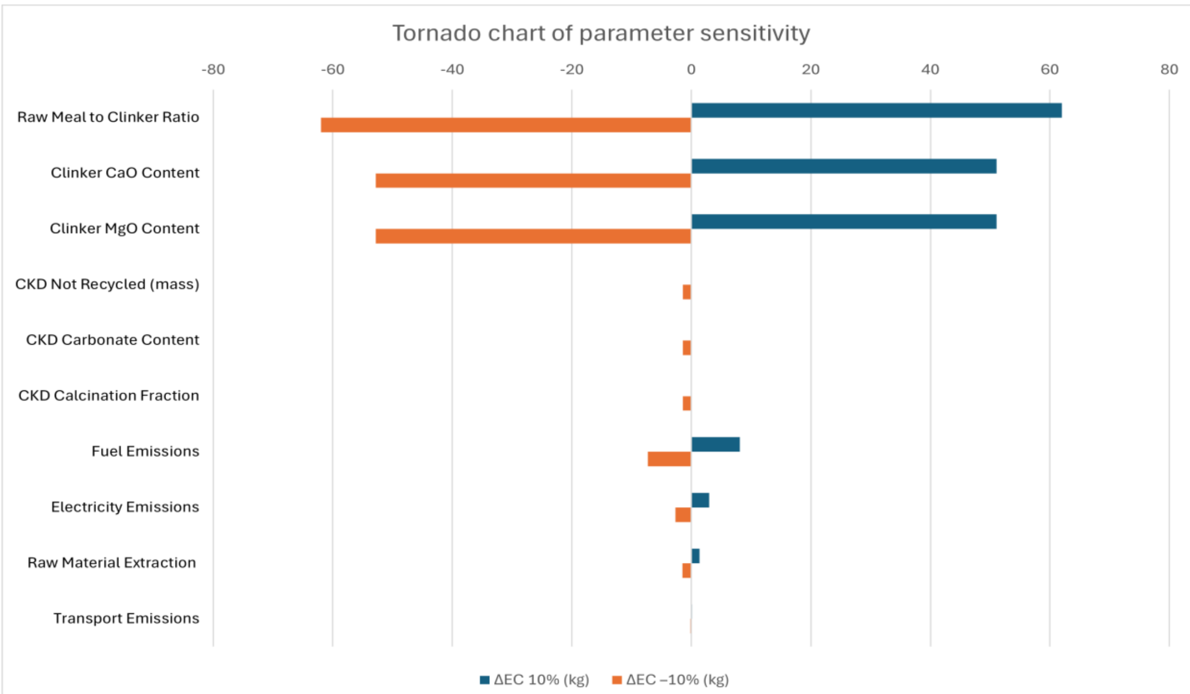

Figure 5. Tornado chart of parameter sensitivity for ±10% one-at-a-time variation around the baseline EC of 652 kg CO_2e per tonne of OPC cement. The y-axis lists tested parameters in descending order of influence; the x-axis shows the absolute change in cradle-to-gate EC (kg CO_2e per t) relative to baseline. Bars to the left indicate decreases (−10% input) and bars to the right indicate increases (+10% input). The clinker-to-cement ratio is the dominant mitigation lever; chemistry variability (CaO and MgO) is the next-order driver via calcination stoichiometry; energy-related uncertainties are modest; and A1 and A2 effects are negligible at plant scale.

4.4 Regression-based Predictive Modelling (SPSS)

Regression models were estimated on the combined baseline and scenario dataset to provide predictive equations and statistical corroboration of process relationships.

4.4.1 Calcination / Process CO_2 Model

The following multiple regression equation predicts annual process CO2 emissions from cement calcination using clinker chemistry (CaO%, MgO%) and CKD parameters as predictors. This statistical model is used because calcination, the dominant emission source (approximately 81% of total EC), is governed by plant-specific kiln chemistry that varies inter-annually, necessitating a regression approach rather than a fixed emission factor.

A multiple linear regression of annual process CO2 on clinker production, CaO%, MgO%, and CKD terms showed a strong fit ($R^2 = 0.939$; adjusted $R^2 = 0.894$; p(model) < 0.001). Clinker production and CaO and MgO were statistically significant ($p < 0.05$), reflecting stoichiometric control of CO2 release; CKD covariates were not significant but were retained for completeness. Model predictions were within approximately 1 to 2% of manual stoichiometry across scenarios. Table 4 shows the regression details and Figure 6 compares regression-predicted with manually calculated process CO2 emissions across sensitivity scenarios.

Table 4. SPSS regression coefficients for the calcination CO_2 prediction model.

Predictor	B (unstandardised)	Std. Error	Beta (std.)	t	Sig. (p)	VIF
(Constant)	−762,675.449	186,046.076	—	−4.099	0.003	—
CaO (%)	7,464.286	1,227.818	0.529	6.079	<0.001	1.000
MgO (%)	62,400.253	17,116.437	0.317	3.646	0.007	1.000
CKD (t per year)	0.291	4.090	0.006	0.071	0.945	1.000
Fraction original CKD	7,691.200	107,928.647	0.006	0.071	0.945	1.000
Fraction calcined CKD	3,460.994	90,169.039	0.003	0.038	0.970	1.000
Clinker (t per year)	0.542	0.063	0.748	8.591	<0.001	1.000

The regression model confirms that clinker production volume and CaO and MgO content are the strongest predictors of process CO2 emissions, consistent with chemical stoichiometry. The relatively minor role of CKD terms reflects the low proportion of dust in the dataset. The high coefficient of determination ($R^2 \approx 0.94$) and low multicollinearity (VIF < 2) indicate that the model is statistically robust and suitable for use as a predictive tool in embodied carbon assessments.

$$CO_2\_process\ (t/yr) = -762{,}675.449 + 7{,}464.286 \cdot CaO\% + 62{,}400.253 \cdot MgO\% + 0.291 \cdot CKD\_t/yr + 7{,}691.200 \cdot FracOrigCKD + 3{,}460.994 \cdot FracCalcCKD + 0.542 \cdot Clinker\_t/yr$$

where $CO_2\_process$ is the annual calcination CO_2 emissions (tonnes CO_2 per year); CaO% is the CaO content of clinker (% by mass; typically 60 to 67% for OPC); MgO% is the MgO content of clinker (% by mass; typically 1 to 5% for OPC); CKD_t/yr is the annual mass of non-recycled cement kiln dust (tonnes per year); FracOrigCKD is the fraction of original carbonates remaining uncalcined in CKD (dimensionless, 0 to 1); FracCalcCKD is the fraction of original carbonates that have been calcined in CKD (dimensionless, 0 to 1); and Clinker_t/yr is the annual clinker production volume (tonnes per year). The intercept (−762,675.449) is the regression constant with no standalone physical interpretation. All coefficients were estimated using SPSS ordinary least squares regression on five annual observations. Dependent variable: *CO_2_process* (t per year).

It is important to note that supplementary cementitious materials (SCMs), including fly ash, ground granulated blast-furnace slag (GGBS), and calcined clay, were not utilised at the case-study plant during the study period. The facility produced exclusively ordinary Portland cement (OPC; CEM I equivalent) with no SCM substitution incorporated into the cement blend. Accordingly, the calcination regression model was developed within the operational envelope of this OPC-only production context, and SCM substitution rate is not included as a regression predictor because it has no observed variation in the dataset. The clinker-to-cement ratio in the sensitivity analysis (Table 1) implicitly simulates future SCM-substitution scenarios by modelling emission outcomes at lower clinker fractions; however, these projections extend beyond the observed regression domain and should be interpreted as scenario projections rather than direct model predictions calibrated on SCM-inclusive data. Before applying this framework to blended-cement facilities, the regression model should be recalibrated with SCM substitution rate and SCM type included as additional predictors.

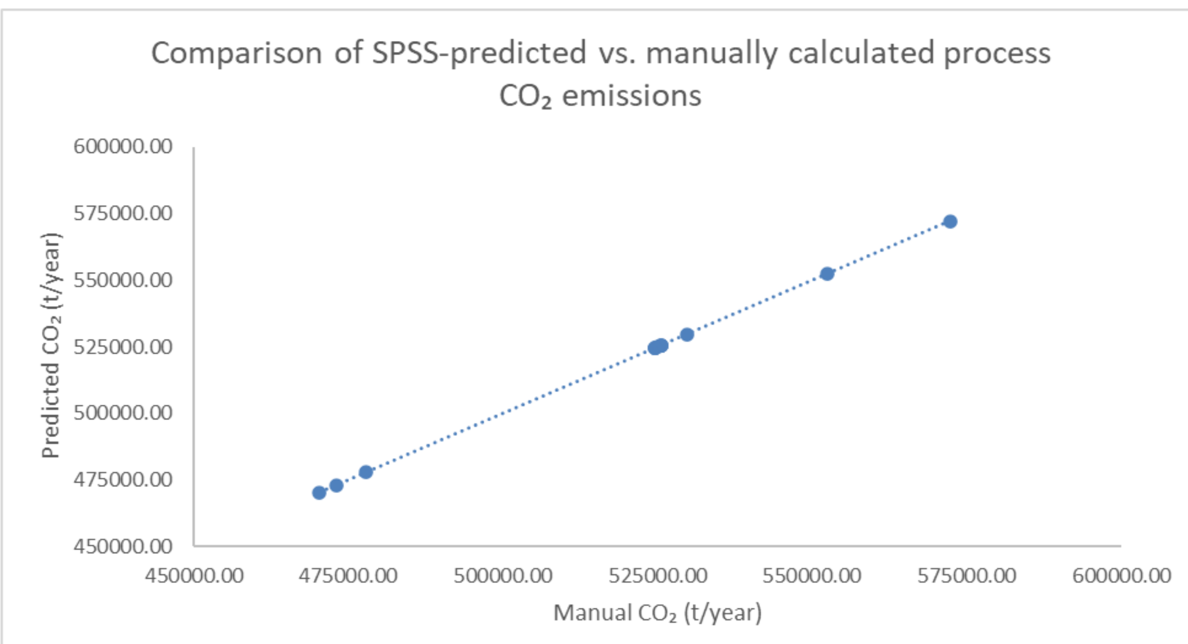

Figure 6. Comparison of regression-predicted with manually calculated process-CO_2 emissions across sensitivity scenarios. The x-axis shows manually calculated CO_2 (kg per tonne of cement) using the stoichiometric IPCC method; the y-axis shows the SPSS regression-predicted value. Points fall close to the 1:1 identity line, with R^2 = 0.939, confirming the regression model reproduces stoichiometric outputs within approximately 1 to 2%.

4.4.2 Statistical Modelling of Electricity-Related Emissions

The following deterministic identity quantifies scope 2 electricity emissions and is corroborated by a log–log regression to confirm proportionality with respect to electricity demand and grid emission factor.

Electricity consumption in cement manufacturing contributes indirectly to embodied carbon through scope 2 emissions. For the Qatari case study, baseline electricity use corresponds to approximately 29.7 kg CO2e per tonne of cement (functional unit, cradle-to-gate).

To assess the responsiveness of emissions to electricity consumption and the grid emission factor, a log–log regression model was estimated in SPSS. The dependent variable was the natural logarithm of annual CO2 emissions, while predictors were the logarithms of electricity consumption and EF. The regression achieved perfect explanatory power ($R^2 = 1.000$; adjusted $R^2 = 1.000$), reflecting the deterministic nature of the equation, as shown in Table 5.

Table 5. SPSS regression coefficients for electricity-related emissions (log–log model, functional-unit basis).

Predictor	B	Std. Error	t	Sig. (p)
Constant	≈ 0 (n.s.)	—	−0.103	0.922
ln(Electricity)	1.000	≈ 0.000	75,250,154.425	<0.001
ln(EF)	1.000	≈ 0.000	79,668,144.609	<0.001

The governing equation used to quantify this parameter is:

$$CO_2\_electricity = Electricity \times EF$$

where *CO_2_electricity* is the scope 2 electricity emissions (kg CO_2e per tonne of cement); Electricity is the purchased electricity per tonne of cement (kWh per tonne); and EF is the grid emission factor (Qatar) = 0.431 kg CO_2 per kWh. This identity is confirmed by log–log regression with coefficients ≈ 1.000 and R^2 = 1.000.

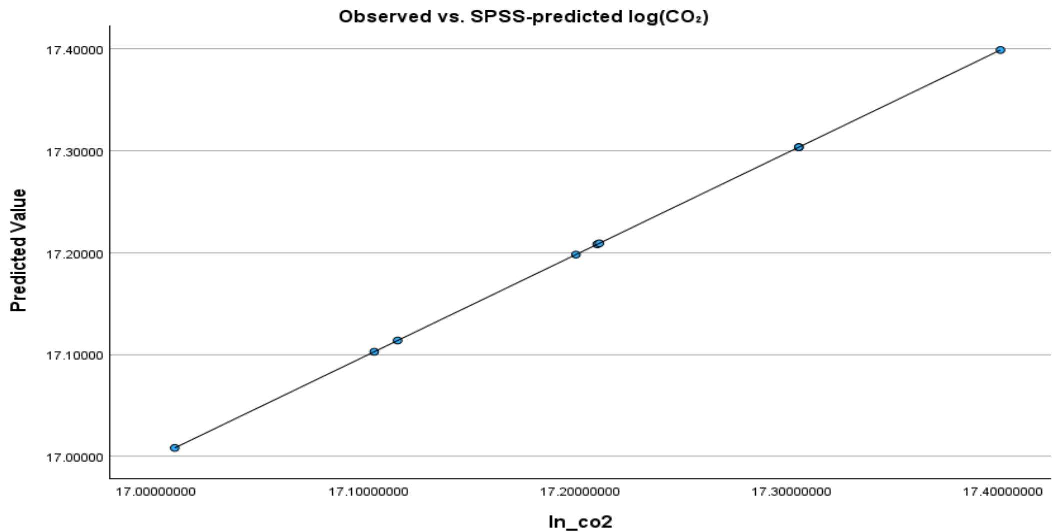

Figure 7. Observed with SPSS-predicted ln(CO_2) emissions across electricity consumption and grid-EF scenarios (Qatar, cradle-to-gate). The x-axis shows observed ln(CO_2); the y-axis shows model-predicted ln(CO_2). Points lie on the 1:1 identity line, confirming exact proportionality of electricity-related emissions to both demand and EF. Both axes are on a natural-log scale.

4.4.3 Statistical Modelling of Fuel-Combustion Emissions

The following log–log identity quantifies kiln fuel-combustion emissions; the deterministic relationship between fuel quantity, energy density, and emission factor is confirmed via SPSS regression with a perfect fit.

Fuel combustion was the second-largest contributor to the carbon footprint of Qatari OPC cement, accounting for approximately 80.9 kg CO2 per tonne of cement (≈12.4% of total cradle-to-gate emissions). The SPSS regression analysis reproduced this contribution with a perfect fit ($R^2 = 1.000$), confirming the deterministic relationship between fuel use, energy density, and emission factor. Scenario testing showed proportionality: a ±10% variation in inputs translated directly into ±10% change in emissions. The observed and predicted values aligned exactly, with negligible residuals, demonstrating both statistical robustness and physical validity. While fuel-related emissions are non-trivial, their influence remains modest relative to calcination, implying that major decarbonisation gains must come from reducing clinker factor and addressing process emissions, with efficiency improvements or fuel switching providing incremental benefits (Table 6).

Table 6. SPSS regression coefficients for the fuel-combustion CO_2 prediction model. Dependent variable: ln(CO_2).

Predictor	B (unstandardised)	Std. Error	Beta (std.)	t	Sig. (p)
(Constant)	−6.908	0.000	—	−53,099,885.3	<0.001

ln(Fuel)	1.000	0.000	0.577	14,046,371.6	<0.001
ln(NCV)	1.000	0.000	0.577	14,046,371.6	<0.001
ln(EF)	1.000	0.000	0.577	14,046,371.6	<0.001

The regression coefficients confirm the deterministic identity of fuel-combustion emissions. Each predictor (fuel consumption, net calorific value (NCV), and emission factor (EF)) has a coefficient of 1.000 with extremely high statistical significance ($p < 0.001$), reflecting direct proportionality. The intercept (−6.908) corresponds to the unit-conversion factor ln(0.001) from MJ to GJ. The perfect model fit ($R^2 = 1.000$) in Figure 8 indicates that fuel-related CO2 emissions scale linearly with fuel quantity, energy content, and EF, with no unexplained variance. The SPSS model therefore validates the LCA calculation method and confirms that any variation in fuel inputs translates directly into proportional changes in fuel-related embodied carbon. The following equation quantifies fuel-combustion emissions based on fuel input, energy density, and emission factor:

$$\ln(CO_2\_fuel) = -6.908 + \ln(Fuel) + \ln(NCV) + \ln(EF)$$

where *CO_2_fuel* is the annual kiln-fuel CO_2 emissions (tonnes CO_2 per year); Fuel is the annual fuel consumption (Nm³ or t natural gas); NCV is the net calorific value of natural gas (MJ per Nm³); EF is the fuel emission factor (kg CO_2 per GJ; ≈56 for natural gas); and −6.908 ≈ ln(0.001), the unit-conversion constant from MJ to GJ. Equivalent linear form: *CO_2_fuel* = Fuel × NCV × EF × 0.001.

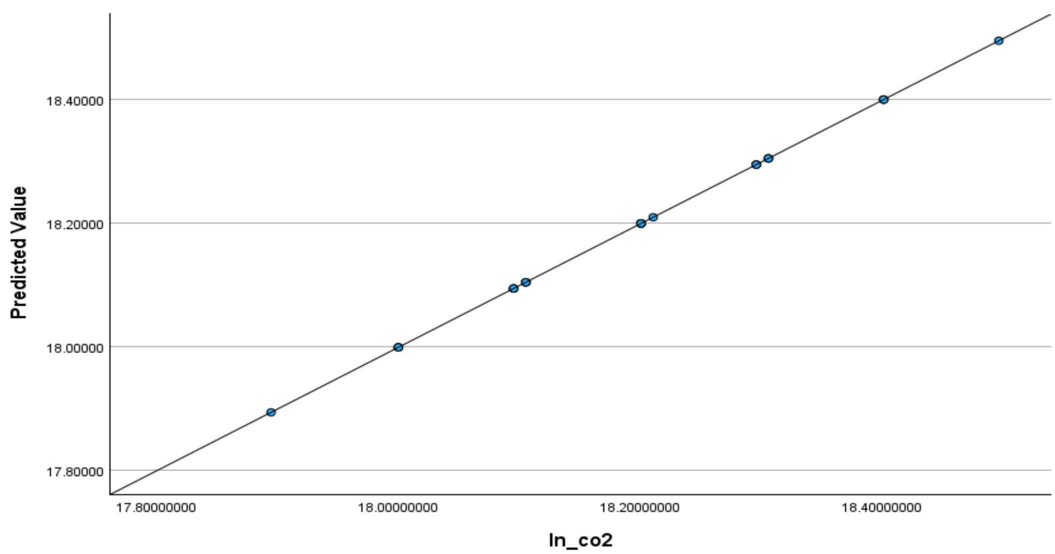

Figure 8. Observed with SPSS-predicted ln(CO_2) emissions for kiln fuel combustion. The x-axis shows observed ln(CO_2); the y-axis shows predicted ln(CO_2). Points lie exactly on the 1:1 identity line ($R^2 = 1.000$), confirming proportional scaling of fuel CO_2 with fuel quantity, NCV, and EF.

4.4.4 Statistical Modelling of Raw Material Extraction and Processing Emissions

The following equation quantifies module A1 emissions from raw-material extraction and processing; the regression confirms the deterministic mass-times-EF relationship with a small additive adjustment for iron-ore inputs.

Raw-material extraction and processing (module A1) made only a modest contribution to the carbon footprint, at approximately 14.2 kg CO2e per tonne of cement (≈2.2% of total A1–A3 emissions). This reflects quarrying, crushing, and grinding of limestone, clay, and minor imports of iron ore and gypsum. Compared with calcination and fuel combustion, A1 emissions are small, yet they remain non-negligible given supply-chain dependencies and import distances.

Regression analysis in SPSS (Table 7) confirmed that embodied carbon is essentially a direct function of the quantity of each material multiplied by its emission factor, with iron ore exerting a slightly higher relative impact. Model fit was exact ($R^2 = 1.000$), validating the deterministic relationship. Figures 9 and 10 illustrate the dominance of limestone due to mass share, while iron ore and gypsum contribute disproportionately per unit mass. Scenario testing (±10%) showed that limestone drives overall variation, whereas changes in clay, recycled content, or transport distances exert negligible influence. Although A1 accounts for only a small share of the cradle-to-gate footprint, its material-level differences are non-trivial and justify inclusion in regional embodied-carbon databases, especially to capture variability in imported inputs.

Table 7. SPSS regression coefficients for raw-material emissions (A1 stage).

Predictor	Coefficient (B)	Significance (p)
Constant	0.000	—
QE (Quantity × EF)	1.000	<0.001
Iron ore	+0.067	0.049
Clay or shale	n.s.	1.000
Gypsum	n.s.	1.000
Recycled material	n.s.	1.000

Note. n.s. = not statistically significant. QE = quantity × emission factor.

$$\text{Emissions\_A1 (t/yr)} = 1.000 \cdot QE + 0.067 \cdot D\_IronOre$$

where Emissions_A1 is the annual raw-material extraction emissions (tonnes CO_2e per year); QE is the product of material quantity and its emission factor (tonnes CO_2e per year); D_IronOre is a dummy variable for iron-ore inclusion (1 if iron ore is used, 0 otherwise); and $R^2 = 1.000$.

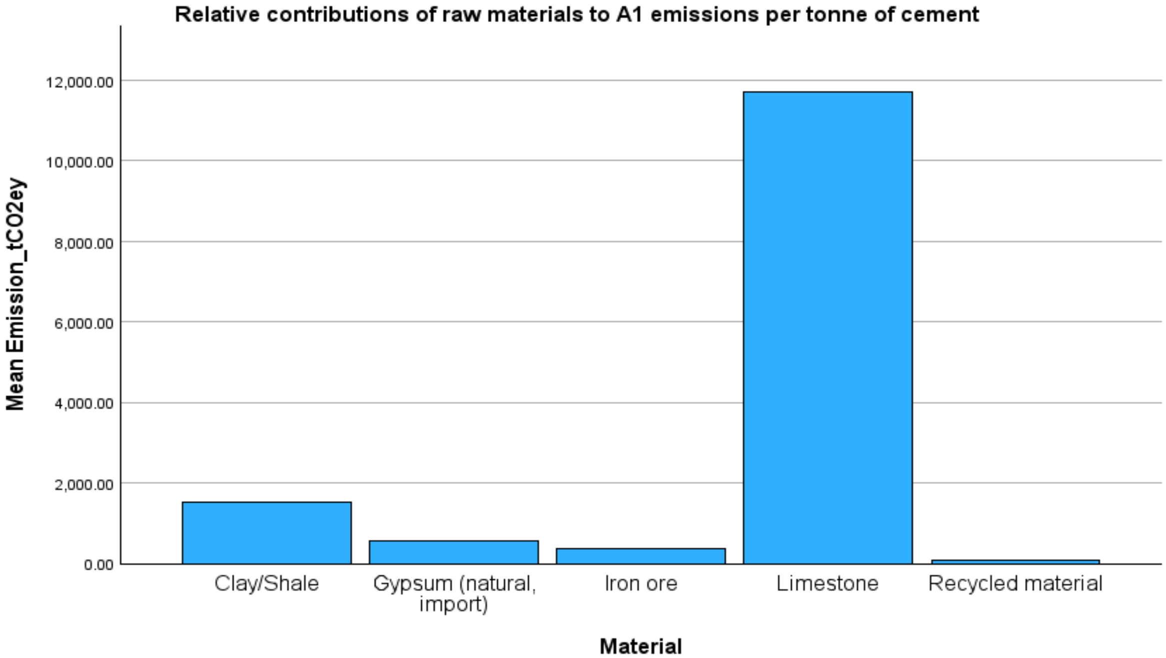

Figure 9. Relative contributions of raw materials (limestone, clay or shale, iron ore, gypsum, recycled material) to A1 emissions per tonne of OPC cement (kg CO_2e per t). Limestone dominates by mass share; iron ore and gypsum contribute disproportionately on a per-unit-mass basis.

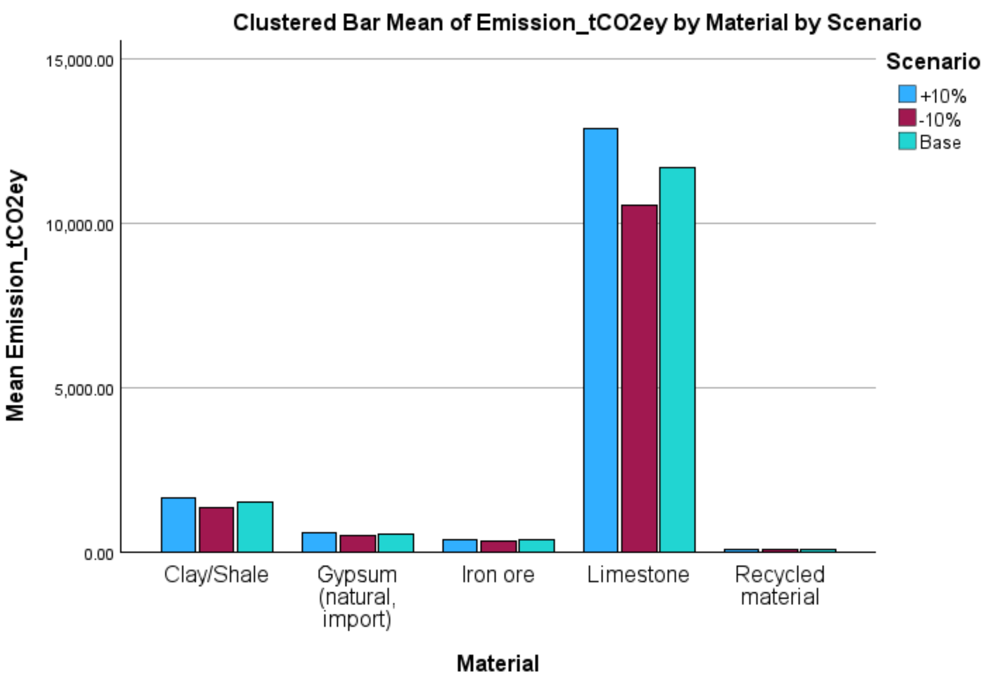

Figure 10. Clustered bar chart of mean emission factors for each raw-material input (kg CO_2e per kg of material). Error bars indicate within-stream variability across baseline and ±10% scenarios.

4.4.5 Statistical Modelling of Transportation-Related Emissions

The following log–log specification quantifies inbound transport (A2) emissions; the regression confirms proportional scaling between tonnage, distance, and emission factor for both road and sea freight.

Transport of raw materials contributed only approximately 1.7 kg CO2e per tonne of cement, representing less than 0.3% of total A1–A3 emissions. This reflects a combination of local trucking for limestone and clay, and shipping plus short-haul trucking for imported gypsum and iron ore. SPSS regression (Table 8) confirmed the deterministic relationship between transport activity (tonne-kilometres) and emissions, reproducing published emission factors with $R^2 = 1.000$. Scenario testing (±10%) showed negligible variation (less than 0.05%) in overall embodied carbon, underscoring the marginal role of transport in Qatar, where most quarries are proximate and imports are efficiently shipped (Figures 11 and 12). Although transport is structurally important in life-cycle models, its current contribution in the Qatari cement sector is trivial. Maintaining disaggregated models for road and sea freight remains valuable, however, because future sourcing changes such as increased imports of supplementary cementitious materials could elevate its significance.

Table 8. SPSS regression coefficients for transportation (road and sea, log–log specification).

Mode	Specification	Predictor	Coefficient (B)	Sig. (p)	Interpretation
Road	Log–log (multiplicative)	Constant	−6.908	—	Unit conversion (ln 0.001)
Road	Log–log (multiplicative)	ln(Tonnage)	1.000	<0.001	Proportional effect
Road	Log–log (multiplicative)	ln(Distance)	1.000	<0.001	Proportional effect
Road	Log–log (multiplicative)	ln(EF)	1.000	<0.001	Proportional effect
Road	Through-origin (slope)	tonne·km	0.068	<0.001	Equals EF (kg CO_2 per t·km)
Sea	Log–log (multiplicative)	Constant	−6.908	—	Unit conversion (ln 0.001)
Sea	Log–log (multiplicative)	ln(Tonnage)	1.000	<0.001	Proportional effect
Sea	Log–log (multiplicative)	ln(Distance)	1.000	<0.001	Proportional effect
Sea	Log–log (multiplicative)	ln(EF)	1.000	<0.001	Proportional effect

Sea	Through-origin (slope)	tonne·km	0.0035	<0.001	Equals EF (kg CO_2 per t·km)

$$\ln(CO_2\_transport) = -6.908 + \ln(Tonnage) + \ln(Distance) + \ln(EF)$$

where *CO_2_transport* is the annual transport CO_2 emissions (tonnes CO_2 per year); Tonnage is the mass transported (tonnes); Distance is the transport distance (km); EF is the mode-specific emission factor (kg CO_2 per t·km; truck = 0.068, ship = 0.0035; DEFRA and IPCC). Equivalent linear form: *CO_2_transport* = Tonnage × Distance × EF × 0.001.

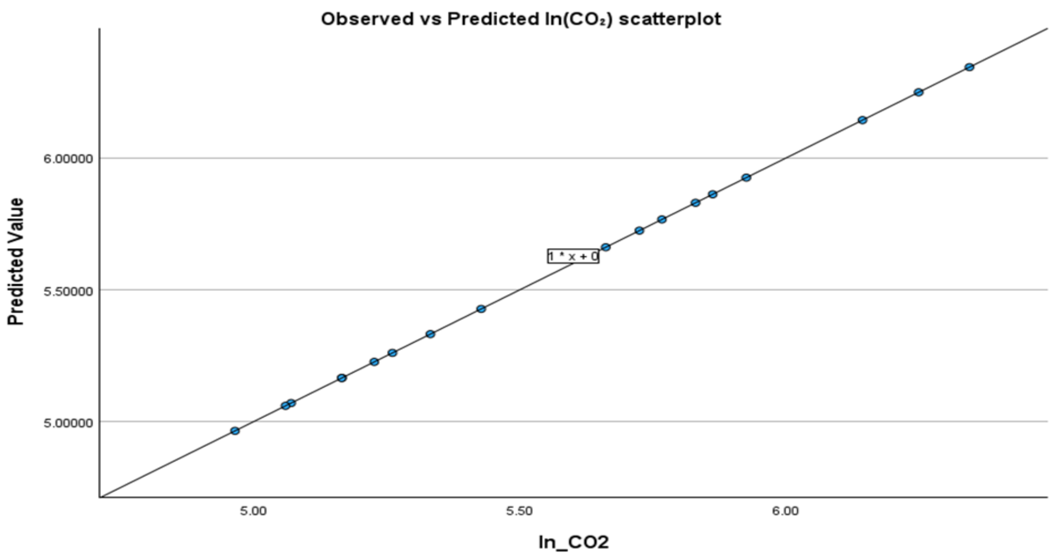

Figure 11. Observed with SPSS-predicted ln(CO_2) emissions for inbound transport across baseline and ±10% scenarios. Points lie on the 1:1 identity line, confirming exact proportionality ($R^2 = 1.000$) of transport CO_2 to tonne-kilometres and EF.

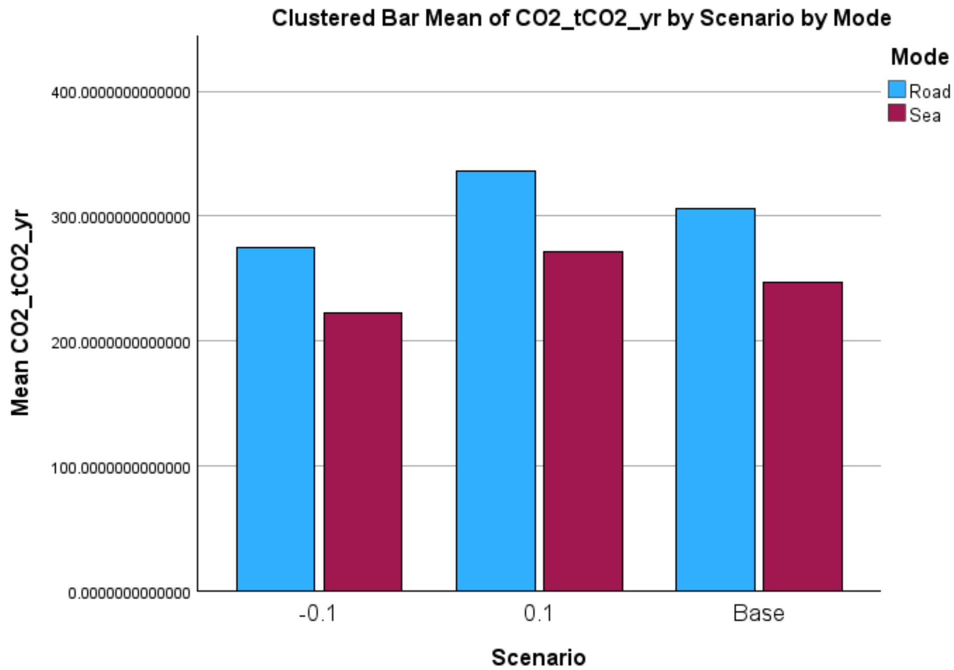

Figure 12. Emission contributions from road (truck) with sea (ship) freight modes for inbound raw-material transport (kg CO_2e per tonne of cement). Sea freight dominates total tonne-km but, with EF ≈ 0.0035 kg CO_2 per t·km versus 0.068 for road, contributes a smaller absolute share than its volume would suggest.

4.4.6 Summary of Governing Equations and Comprehensive A1–A3 Equation

The summary of all governing equations derived above is shown in Table 9.

Table 9. Summary of governing equations used in the Results section: fuel, raw material, transport, electricity, and calcination models.

Emission type	Equation	Key variables	Notes
Fuel combustion	CO_2_fuel = Fuel × NCV × EF × 0.001	Fuel; NCV; EF	Log–log identity; intercept ln(0.001) converts MJ to GJ.
Raw material extraction	Emissions_A1 = 1.000·QE + 0.067·D_IronOre	QE (Q × EF); D_IronOre dummy	R^2 = 1.000; iron ore adds adjustment.
Transportation	CO_2_transport = Tonnage × Distance × EF × 0.001	Tonnage; Distance; EF	Log–log identity; DEFRA and IPCC factors.
Electricity	CO_2_electricity = Electricity × EF	Electricity (kWh); EF = 0.431 kg CO_2 per kWh	Identity with R^2 = 1.000.

Calcination (process CO_2)	CO_2_process = −762,675.449 + 7,464.286·CaO% + 62,400.253·MgO% + 0.291·CKD_t/yr + 7,691.200·FracOrigCKD + 3,460.994·FracCalcCKD + 0.542·Clinker_t/yr	CaO%; MgO%; CKD; FracOrigCKD; FracCalcCKD; Clinker	Multiple regression; R^2 = 0.939.

Integrating the SPSS-based sub-models and deterministic calculations, the total embodied carbon for cement production (A1–A3) is represented by the following comprehensive equation:

$$EC(A1\text{–}A3) = [\Sigma(m_i \times EF_i) + 0.067 \cdot D\_IronOre] + [\Sigma(TKm_j \times EF_j\text{^}A2 \times 10^{-3})] + \{-762{,}675.449 + 7{,}464.286(CaO\%) + 62{,}400.253(MgO\%) + 0.291(CKD\_yr) + 7{,}691.200(f\_orig) + 3{,}460.994(f\_calc) + 0.542(Clinker\_yr)\} / P\_cem{,}yr + (F\_MJ \times EF\_fuel \times 10^{-3}) + (E\_kWh \times EF\_grid)$$

where m_i is the mass of raw material *i* per tonne of cement (kg per t); EF_i is the emission factor for material *i* (kg CO_2e per kg); D_IronOre is the dummy (1 = iron ore used; 0 = not used); TKm_j is the tonne-kilometres for route *j* (t·km per t); $EF_j^{\wedge A2}$ is the transport EF for mode *j* (kg CO_2e per t·km); CaO% and MgO% are clinker chemistry parameters; CKD_yr is non-recycled CKD per year (t per year); f_orig and f_calc are the original carbonate and calcined fractions in CKD (dimensionless); Clinker_yr is the annual clinker production (t per year); P_cem,yr is the annual cement output (t per year); F_MJ is the kiln fuel energy per tonne of cement (MJ per t); EF_fuel is the fuel emission factor (kg CO_2e per GJ); E_kWh is the purchased electricity (kWh per t); and EF_grid is the grid emission factor (kg CO_2e per kWh).

4.5 Framework Summary: Three Integrated Components

The framework developed in this study comprises three integrated components: (i) a structured primary data-collection protocol aligned with WBCSD and ISO standards; (ii) governing emission equations (Table 9) that combine deterministic process balances with SPSS regression; and (iii) a sensitivity-tested scenario-analysis capability that enables what-if projections for clinker ratio, fuel type, and grid intensity. Together these components constitute a reproducible decision-support architecture that supports cradle-to-gate carbon assessment in data-scarce industrial contexts. The complete architecture is summarised in Figure 13.

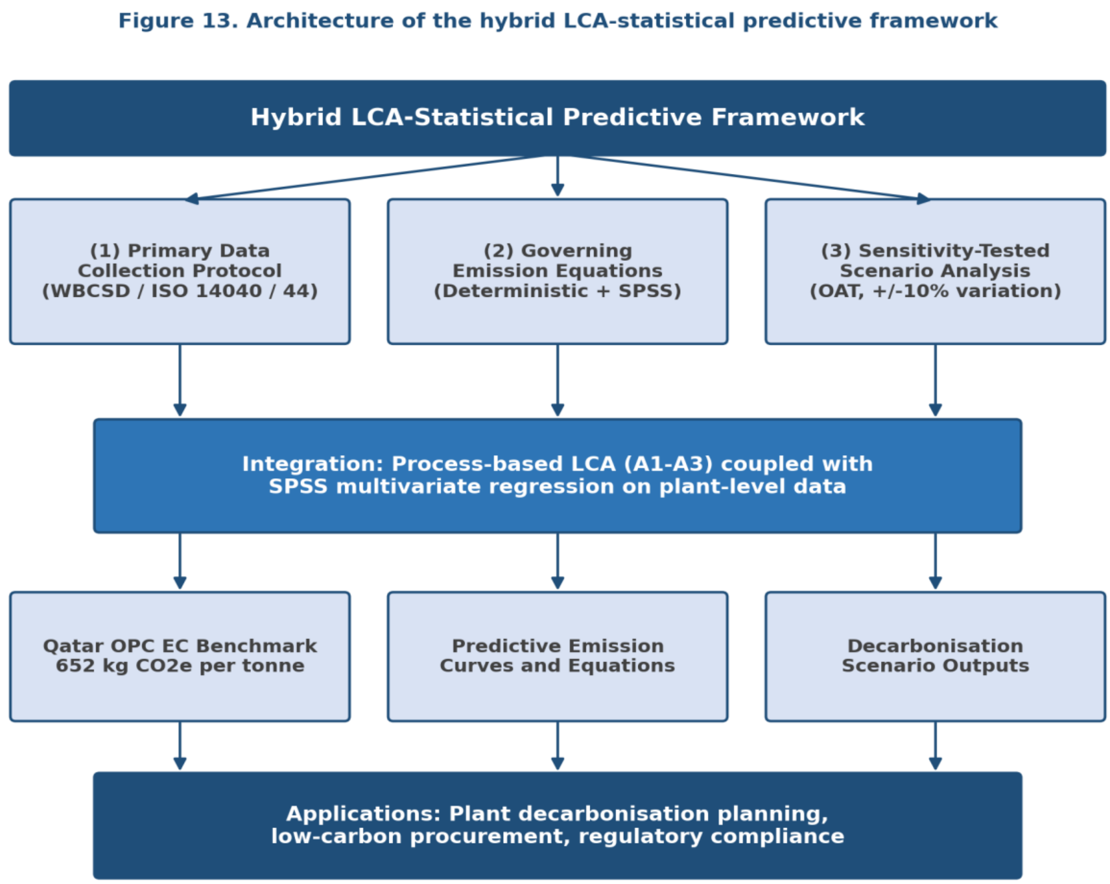

Figure 13. Architecture of the hybrid LCA and statistical predictive framework, showing the three integrated components, their coupling through process-based LCA and SPSS multivariate regression, and the resulting outputs used for plant decarbonisation planning, low-carbon procurement, and regulatory compliance.

4.6 Model Transferability and Regional Recalibration

The governing equations (Table 9) consist of two conceptually distinct components. The first is the structural (transferable) form, namely the algebraic architecture of each equation representing a universally applicable physical or statistical relationship. The calcination regression's structure (multivariate linear regression on CaO%, MgO%, CKD fractions, and clinker volume) is applicable to any OPC plant following IPCC and WBCSD Tier 3 protocols; only the coefficients require recalibration using local kiln-chemistry data. Similarly, the fuel, electricity, and transport equations retain their structural form for any facility globally.

The second component is case-study-specific parameter values, which reflect Qatar's conditions and must be replaced when applying the framework elsewhere: (a) the electricity grid factor (0.431 kg CO2 per kWh) reflects Qatar's gas-based grid and should be replaced with the national or regional grid factor for other deployments; (b) the calcination regression coefficients (for example, 7,464.286 for CaO%) were estimated from Qatar plant data and should be recalibrated via OLS regression on multi-year data from the target facility; (c) the transport emission factors (DEFRA and IPCC) are transferable structurally, but transport distances and sourcing routes are site-specific and must be updated; and (d) the small A2 contribution in Qatar (approximately 2.5%) reflects short local quarrying distances and efficient port logistics, a share that may be substantially larger in other regional contexts.

Users of this framework should retain the structural equations while systematically replacing all case-study-specific parameter values with locally verified inputs, following the primary data-collection and SPSS regression-calibration protocol described in Section 3.2.

4.7 Discussion

The findings of this study directly address the three objectives set out in the introduction: to establish a Qatar-specific benchmark for embodied carbon in cement production, to identify the key process parameters influencing carbon intensity, and to develop a predictive and transferable framework by integrating process-based LCA with statistical modelling.

The analysis responds to clear gaps identified in the literature review. Earlier studies (De Wolf, Pomponi and Moncaster, 2017; Röck et al., 2020) emphasised that while global inventories of cement-related CO2 emissions are well established, regional and process-level datasets remain scarce, particularly for Gulf countries. As highlighted by Biswas et al. (2017) and Al-Nuaimi, Banawi and Al-Ghamdi (2019), most Gulf LCAs have relied on generic European datasets (ICE, ecoinvent), often misrepresenting local energy sources and supply routes. The present research bridges this gap by using primary operational data from a cement plant in Qatar, complemented with secondary EPD and protocol sources to generate a context-specific yet globally comparable dataset.

The primary result, 652 kg CO2e per tonne of OPC (A1–A3), sits within the lower-mid range of international OPC values when the clinker ratio is high (approximately 95%) but the kiln fuel is natural gas and electricity intensity is moderate. Calcination (approximately 525 kg per t cement) dominates, followed by fuel (approximately 81 kg per t), electricity (approximately 30 kg per t), and combined A1 and A2 (approximately 16 kg per t). This hierarchy is consistent with the stoichiometric dominance of process emissions and with datasets for efficient gas-fired kilns (Barcelo et al., 2014; Hottle and Bare, 2022; Scrivener, John and Gartner, 2018). Plants with coal or petcoke fuel or carbon-intensive grids report higher fuel and electricity shares, pushing totals toward approximately 700 to 900 kg per t (Hottle and Bare, 2022).

The WBCSD and IPCC stoichiometric method typically yields approximately 510 to 530 kg CO2 per tonne of clinker at approximately 65% CaO, before conversion to per-cement values based on clinker factor (WBCSD/CSI, 2011). With a 95%-clinker cement, calcination alone near 500 to 560 kg per tonne of cement is expected, which is precisely where the result lands. The fuel (gas) and electricity components (approximately 81 and 30 kg per tonne) are lower than for coal-dominant plants and are consistent with a gas-fuelled region and the grid factor used here. In short, 652 kg per tonne for gas-fired, high-clinker OPC in Qatar aligns with the lower half of global OPC ranges, largely because gas has a lower EF than solid fossil fuels (Hottle and Bare, 2022; Scrivener, John and Gartner, 2018).

Gulf concrete EPD analyses highlight the leverage of cement content and clinker factor, and the role of marine imports for gypsum and iron ore, generally a secondary but non-negligible contribution (Biswas et al., 2017). The A2 result (approximately 1.7 kg per tonne of cement) is modest given short local truck and bulk-shipping efficiencies, reinforcing that process, fuel, and electricity are the levers for Qatar's OPC.

The chemistry-based (CaO and MgO) accounting with explicit CKD and bypass treatment reproduces the decomposition of OPC embodied carbon while quantifying it under Qatar-specific boundary conditions. The integration of SPSS modelling extends conventional LCA by offering predictive relations between GWP and operational parameters. These relations bridge deterministic process balances with statistical scenario analysis. The resulting decision curves support procurement and policy applications.

For plants and ready-mix producers, the results prioritise (in roughly decreasing order of effect) clinker reduction; fuel decarbonisation through higher-biogenic alternative fuels and waste-derived fuels with robust accounting; and grid decarbonisation or electrification of grinding via renewable power purchase agreements. Scenario curves derived from the regressions can support performance-based specifications for cementitious materials by function, preserving strength and durability while lowering clinker (Habert and Roussel, 2009; Scrivener, John and Gartner, 2018).

For Qatar's standards, Global Sustainability Assessment System (GSAS) and EPD adoption, and public procurement, a Qatar-anchored EF of 652 kg per tonne for OPC at 95% clinker, together with component breakdowns, supplies decision-ready inputs for material passports, database curation, and targets (for example, incentive tiers for low-clinker cements and encouragement of LC^3 pilots). The study also underlines the importance of regionalised A2 defaults and transparent use of the WBCSD and Global Cement and Concrete Association (GCCA) cement CO2 protocol to ensure comparability across plants. Some global datasets report lower OPC factors when clinker ratios are below 75 to 85% (for example CEM II or CEM III, or concretes with high SCM content) or where the grid is cleaner; conversely, higher values arise with coal or petcoke kilns or older lines (Hottle and Bare, 2022; Barcelo et al., 2014). The value should therefore be interpreted as a plant- and mix-specific OPC baseline, not an upper bound for all cements in Qatar. While transport is modest here, route disruptions or longer hauls can raise A2 (Al-Nuaimi, Banawi and Al-Ghamdi, 2019); maintaining live, auditable transport factors in the national database is advisable.

These relations are formalised in Table 9, notably the calcination regression on clinker, CaO, and MgO (R^2 ≈ 0.94), and the log–log identities for electricity, fuel, and transport, all with slopes ≈ 1.000 and $R^2 = 1.000$, which together provide decision-ready curves for scenario testing.

Beyond validating known emission hierarchies, the study extends existing knowledge by coupling deterministic LCA outputs with SPSS regression-based predictive models. The strong model fit ($R^2 > 0.9$) and statistically significant coefficients verify that clinker ratio, clinker chemistry, and energy intensity can be represented through predictive equations, transforming conventional LCAs into quantitative decision-support tools. This approach directly answers the methodological limitations raised in earlier reviews that LCAs often lack reproducibility and predictive insight (Habert and Roussel, 2009; Tait and Cheung, 2016; Chen *et al.*, 2025).

The present study consolidates empirical observations and statistical validation to propose a universal, predictive framework for embodied-carbon assessment in cement production. By integrating stoichiometric modelling, sensitivity testing, and regression analysis, it provides both process transparency and scenario flexibility, supporting global decarbonisation strategies while delivering region-specific benchmarks.

5. Conclusions

This research developed a universal and predictive framework for assessing the embodied carbon of cement production through the integration of process-based LCA and statistical modelling, validated using data from a cement plant in Qatar as a representative case. The approach directly addressed three objectives: to establish a regional benchmark, to identify the most influential process parameters, and to develop a predictive framework that can be adapted globally. The first objective, developing a robust regional benchmark, was achieved through detailed cradle-to-gate quantification (modules A1–A3) using primary plant-level data. The resulting embodied carbon intensity of 652 kg CO_2e per tonne of OPC provides the first comprehensive, Qatar-specific benchmark and contributes to filling a significant regional data gap. This benchmark complements and refines existing international references (WBCSD/CSI, 2011; Hottle and Bare, 2022; Röck *et al.*, 2020) and can serve as a reference point for regional embodied-carbon databases and policy frameworks.

The second objective, identifying influential parameters, was realised through structured sensitivity analysis and regression modelling. The results confirmed the clinker-to-cement ratio and CaO content as the dominant levers influencing total emissions, producing up to approximately 9.5% variation under ±10% changes. These findings reaffirm global evidence that process chemistry and clinker substitution are the most effective mitigation pathways (Scrivener, John and Gartner, 2018; Habert *et al.*, 2020). Energy-related parameters such as fuel and electricity had secondary influence, while transport and raw-material extraction were negligible in the Qatari context, reflecting the efficiency of localised supply chains and natural-gas-based production.

The third objective, establishing a predictive and transferable framework, was fulfilled through the integration of LCA results with SPSS-based statistical modelling, yielding robust predictive equations ($R^2 > 0.9$). These models enhance transparency, reproducibility, and scalability, enabling what-if scenario analyses for variations in clinker ratio, fuel switching, and grid decarbonisation. The hybrid LCA and statistical framework therefore advances conventional assessment methods by transforming deterministic LCA results into dynamic predictive tools capable of guiding both industrial decisions and policy interventions.

From a practical standpoint, the findings highlight that deep decarbonisation of cement production, both in Qatar and globally, cannot be achieved through efficiency improvements alone. Instead, it requires substantial reductions in clinker intensity, substitution with low-carbon binders, adoption of alternative or biogenic fuels, and progressive grid decarbonisation. The proposed framework offers a structured pathway for quantifying and comparing these strategies across diverse production contexts, aligning local practices with international net-zero objectives.

Beyond its immediate methodological contribution, this study has broader implications for research and practice. For the research community, the explicit separation of emission components requiring statistical treatment (calcination, which is chemistry-dependent and inter-annually variable) from those suited to deterministic computation (fuel, electricity, transport) provides a generalisable modelling template applicable to other high-emission industrial processes; the strong goodness-of-fit ($R^2 > 0.9$) validates that a multi-year dataset from a single facility, when anchored in stoichiometric first principles, is sufficient to produce robust predictive models, addressing documented gaps in Gulf and Middle Eastern embodied-carbon literature. For the cement industry, the framework provides a what-if decision-support tool that enables plant operators to quantify the carbon consequences of operational changes such as clinker-ratio reduction, fuel switching, or grid decarbonisation before capital investment, and offers contractors, developers, and specifiers a verified, Qatar-anchored input of 652 kg CO2e per tonne of OPC for project-level embodied-carbon calculations, replacing generic European database values that systematically misrepresent Qatar's gas-based energy mix and supply chains.

At the societal and policy level, the establishment of Qatar's first plant-level OPC embodied-carbon benchmark supports evidence-based environmental regulation and procurement policy aligned with Qatar National Vision 2030 sustainability commitments. By quantifying specific mitigation levers and their relative magnitudes, the study provides the numerical foundations needed to design performance-based procurement thresholds, incentive tiers for low-clinker cements, and regional environmental benchmarks consistent with international standards (ISO 14040/44; EN 15804+A2). Incorporation of this benchmark into Qatar's GSAS and EPD programme infrastructure would enable consistent, verifiable material-carbon accounting across the built environment and amplify the global impact of the framework by enabling other emerging markets to develop process-level emission factors rather than relying on misaligned generic values from European or North American industrial contexts.

Limitations

The cradle-to-gate (A1–A3) system boundary, while appropriate for manufacturer-level EC assessment and consistent with EN 15804+A2, excludes downstream stages (A4 to C) relevant to whole-life building-carbon assessments, and project-level LCA practitioners using this benchmark should supplement it with site-specific A4 transport data; the impact of this boundary on total life-cycle emissions is mitigated by the fact that cement's dominant carbon contribution occurs within A1–A3 (more than 97% of cradle-to-gate EC in this study), and the A4 exclusion ensures direct comparability with published OPC EPDs. The study is also based on data from a single cement facility, which, while representative of large-scale OPC production in Qatar and the wider Gulf region, means that the benchmark and regression coefficients reflect one plant's specific kiln technology, fuel mix, and raw-material chemistry; the regression model was further developed within an OPC-only operational envelope, so extrapolation to SCM-inclusive cement formulations should be conducted with caution and validated with additional plant data. Finally, primary-data confidentiality restrictions preclude full public disclosure of production volumes and facility-specific parameters; however, the governing equations and their structural forms are fully disclosed in Table 9, enabling methodological replication. Future work can extend the framework to multi-plant and multi-year datasets, integrate machine-learning techniques for continuous refinement, and explore alternative emission scenarios including LC^3, alternative fuels, and CCUS.

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Data Availability

The datasets generated and analysed during the current study are available from the corresponding author on reasonable request. Due to confidentiality agreements with the industrial partner, primary plant data cannot be publicly shared, but summary statistics and regression models are provided within the article.

Competing Interests

The authors declare that there are no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Ethical Approval

Ethical approval for this research was granted by the Liverpool John Moores University Research Ethics Committee (Approval Ref: 25/CIV/001). All data collection and analysis were conducted in accordance with the approved ethical guidelines. The study did not involve human participants, and all industrial data were handled in accordance with institutional ethical requirements and confidentiality agreements.

Supplementary Material

The full data-collection questionnaire used to obtain primary plant inputs is provided as a supplementary document accompanying this article. The questionnaire covers raw-material inputs, fuel and electricity data, clinker production and CKD management, and inbound transport, and can be reapplied to other facilities for framework replication.

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