European Journal of Sustainable Development Research
2026, 10(2), em0389
e-ISSN: 2542-4742
https://www.ejosdr.com/

MODESTUM

Research Article **OPEN ACCESS**

Greenhouse gas emissions in the GCC: Sectoral drivers, advanced econometrics, and Saudi Arabia's circular economy solutions

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Citation: Rashad, N. M., & Alkathami, M. (2026). Greenhouse gas emissions in the GCC: Sectoral drivers, advanced econometrics, and Saudi Arabia's circular economy solutions. *European Journal of Sustainable Development Research, 10*(2), em0389. https://doi.org/10.29333/ejosdr/18277

ARTICLE INFO

Received: 05 Aug 2025
Accepted: 12 Feb 2026

ABSTRACT

This study investigates the drivers of greenhouse gas (GHG) emissions across four Gulf Cooperation Council (GCC) countries—Saudi Arabia, Kuwait, Oman, and the United Arab Emirates—between 2003 and 2022. Using fixed effects, random effects, and dynamic panel models, the analysis evaluates the impact of sectoral energy intensity, land use, and economic activity on emissions. To address multicollinearity among energy variables, a principal component analysis approach is employed. Results indicate that manufacturing and electricity consumption are consistently significant contributors, while forest area and agricultural land yield statistically inconsistent results depending on model structure. Crisis-period dummies yield minimal statistical impact. Robustness checks confirm the validity of core findings. The study further connects econometric results with emerging policy pathways, including industrial symbiosis initiatives in Saudi Arabia. These findings offer region-specific insights for designing circular economy strategies and enhancing emission mitigation frameworks across energy-intensive sectors in the GCC. A core methodological novelty of this study is the construction of a Sectoral Energy Intensity Index (SEI Index) using Principal Component Analysis (PCA). This provides a more robust and interpretable measure of industrial energy use, a limitation in prior GCC emissions studies.

Keywords: greenhouse gas emissions, Gulf Cooperation Council, sectoral energy intensity index, principal component analysis, circular economy, panel data econometrics, Saudi Vision 2030

INTRODUCTION

Background and Context

The escalation of greenhouse gas (GHG) emissions is a pressing global concern, particularly in the context of environmental sustainability. As environmental consciousness has become a focal point of scholarly investigations, the emission of GHGs has drawn significant attention due to its detrimental impact on the environment.

According to research by Ge et al. (2020) cited by the World Resources Institute, greenhouse gases continue to increase rapidly, an alarming trend that could lead to a climate crisis. Carbon dioxide (CO_2) comprises 74.1% of GHG emissions, methane (CH_4) 17.3%, and nitrous oxide (N_2O) 6.2%. These emissions originate from diverse sources, including fossil fuel combustion, industrial production, land use changes, and agricultural practices.

In the context of the Gulf Cooperation Council (GCC) countries—comprising Saudi Arabia, Kuwait, Oman, and the United Arab Emirates—this issue assumes special urgency. While the GCC regional bloc includes six countries (Saudi Arabia, Kuwait, Oman, the United Arab Emirates, Qatar, and Bahrain), this study focuses on the aforementioned four due to the availability of consistent time-series data covering the full 2003–2022 period.

Reliable, complete, and consistent data were not accessible for Qatar and Bahrain, which constrained their inclusion in the empirical models. The selected four countries, however, represent a diversified yet representative cross-section of the GCC region in terms of population size, energy profiles, industrial activity, and national sustainability agendas, thereby strengthening the generalisability of findings across hydrocarbon-reliant economies.

These nations are characterised by hydrocarbon-based economies, high per capita energy consumption, and increasing pressure to align with global environmental standards, such as those outlined in the Paris Agreement. According to the UNEP (2022) Emissions Gap Report, current global pledges remain insufficient to meet climate targets, underscoring the urgency for regions like the GCC to accelerate mitigation efforts. Recent efforts, including updated Nationally Determined Contributions (NDCs) and net-zero emission pledges, have signalled growing environmental commitments, yet comprehensive empirical evaluations of the specific sectoral determinants of emissions in the region remain limited.

Research Gap

While existing literature has explored various drivers of emissions globally, there is a scarcity of comprehensive panel data studies that specifically dissect the sectoral contributions within the unique economic and environmental context of the GCC, particularly considering the interdependencies of energy and land use. Although many studies rely on conventional variables, multicollinearity between manufacturing, electricity, and gasoline use often hampers interpretability. Furthermore, few studies have incorporated dynamic panel approaches or robustness techniques that account for temporal persistence, cross-sectional variation, or external shocks such as financial crises or the COVID-19 pandemic.

This study addresses these gaps through several key contributions. Primarily, we develop a novel composite Sectoral Energy Intensity Index (SEI Index) via PCA. This index synthesises the shared variance of highly collinear variables—manufacturing, electricity, and gasoline consumption—into a single, stable proxy for industrial energy intensity. This approach mitigates a common statistical problem in existing literature and offers a more precise tool for identifying sectoral drivers of emissions within the GCC's unique economic structure.

Research Aim

This research aims to fill this empirical gap by rigorously analysing the relationship between key economic and environmental factors and GHG emissions in selected GCC countries from 2003 to 2022. By constructing a composite Sectoral Energy Intensity Index (SEI Index) using Principal Component Analysis (PCA), this study enhances model interpretability and robustness. The analysis further evaluates land-use drivers and explores the relevance of circular economy strategies emerging in Saudi Arabia.

Research Questions

The study's main question is:

RQ1 What are the primary sectoral and environmental drivers of GHG emissions in GCC countries?

Sub-questions include:

RQ2 How does sectoral energy intensity (SEI Index) influence emissions across time and countries?

RQ3 What is the relative role of agricultural land, forest area, and fertiliser use in emissions variation?

RQ4 Do external shocks such as the global financial crisis and the COVID-19 pandemic significantly alter emissions trajectories?

RQ5 How can emerging circular economy models in Saudi Arabia serve as practical policy tools for emission reduction?

Research Contribution and Objectives

This study makes several original contributions to the literature on greenhouse gas (GHG) emissions in oil-dependent economies, particularly within the context of the Gulf Cooperation Council (GCC). By integrating a novel composite index, advanced econometric modelling, and applied policy tools, the research bridges a critical gap between theoretical analysis and actionable climate strategies in the region.

Contribution to knowledge

A major methodological innovation of this study is the construction of the Sectoral Energy Intensity Index (SEI Index) using Principal Component Analysis (PCA). This composite measure captures the shared variance among highly collinear sectoral energy variables—manufacturing, electricity consumption, and gasoline use—offering a stable and interpretable proxy for industrial energy intensity. Unlike prior studies that have struggled with unstable coefficients due to multicollinearity, this composite index captures over 93% of shared variance, enabling a clearer and more interpretable assessment of industrial energy use. By offering a parsimonious and empirically validated proxy, the SEI Index provides new insights into the structural drivers of emissions in hydrocarbon-dependent economies, positioning this paper as the first to apply such an approach in the GCC region.

The study employs a robust set of econometric techniques, including Ordinary Least Squares (OLS), Fixed Effects (FE), Random Effects (RE), and Weighted Least Squares (WLS), to analyse panel data for Saudi Arabia, Kuwait, Oman, and the UAE from 2003 to 2022. This multi-model approach addresses common panel data challenges such as heteroscedasticity, omitted variable bias, and country-specific unobserved heterogeneity.

Through the use of Arellano-Bond Generalised Method of Moments (GMM), the study captures the dynamic nature of emissions, revealing their temporal persistence and inertia. This enables stronger causal inferences regarding sectoral contributions.

The analysis is deepened by decomposing the SEI Index into industrial and transport components, and testing for structural changes during the 2008–2009 financial crisis and the COVID-19 period, which offers insights into the resilience and sensitivity of emission drivers under external shocks.

A unique strength of the study lies in its policy-relevant lens. It aligns its findings with Saudi Arabia's Vision 2030 and highlights the relevance of industrial symbiosis and resource-sharing platforms being piloted in Jubail and Yanbu. These applied solutions demonstrate that emission mitigation is not only necessary but also feasible within existing GCC industrial systems.

Research objectives

This study seeks to achieve the following objectives:

1. Develop a Sectoral Energy Intensity Index (SEI Index) using Principal Component Analysis (PCA) to resolve multicollinearity among energy variables and enhance model stability.

2. Empirically assess the impact of sectoral and land-use variables—including manufacturing, electricity and gasoline consumption, agricultural land, fertiliser use, and forest area—on GHG emissions across Saudi Arabia, Kuwait, Oman, and the UAE from 2003 to 2022.
3. Apply and compare multiple panel data estimation techniques (OLS, Fixed Effects, Random Effects, WLS, and dynamic GMM) to identify robust drivers of emissions and capture their temporal persistence.
4. Conduct sectoral decomposition and robustness analyses, including crisis-period interaction terms and leave-one-country-out tests, to validate the consistency and policy relevance of the SEI Index across diverse economic conditions.
5. Generate data-driven policy insights by aligning econometric findings with Saudi Arabia's Vision 2030 and emerging circular economy strategies in the GCC.

The rest of this paper is organised as follows: Section 2 provides a critical review of relevant literature. Section 3 discusses the methodology in terms of data and model specification. Section 4 presents the results and analysis, and Section 5 draws conclusions and recommendations. Finally, Section 6 highlights the practical implications and the circular economy.

LITERATURE REVIEW

A growing body of research has examined the economic and environmental factors influencing GHG emissions, with particular emphasis on energy consumption, industrial activities, and land-use changes.

Recent studies employing econometric approaches such as Dynamic Ordinary Least Squares (DOLS), Fully Modified Ordinary Least Squares (FMOLS), and various panel data models have provided mixed but insightful results. Studies like Raihan et al. (2023) and Raihan and Tuspekova (2022) have highlighted the significant contribution of agricultural expansion and energy use to emissions, while noting the mitigating effect of forest land. These findings underscore the importance of including both economic activity and land-use variables in emission models, which directly informs the variable selection in the current study.

More technically sophisticated analyses, such as those by Chakir et al. (2017) and Al-Ayash and Al-Zayer (2023), have underscored the value of Fixed Effects (FE) and Random Effects (RE) models in accounting for spatial and temporal variations in emissions. These models help isolate the impact of variables that are otherwise difficult to measure directly, such as structural differences across countries or persistent policy frameworks.

Al-Ayash and Al-Zayer (2023) found that the FE model offered a superior fit for GCC data, attributing this to consistent cross-country heterogeneity in emission drivers. This finding is crucial for the current study, as it provides a strong methodological precedent for prioritising the FE model when analysing GCC-specific emission dynamics, acknowledging that unobserved country-specific factors are likely correlated with the explanatory variables.

Studies focusing on sector-specific contributors, such as Panagiotopoulou et al. (2022), emphasised the critical role of electricity usage and material selection in manufacturing processes. In the transportation domain, Zhou et al. (2023) demonstrated a clear correlation between vehicle speed and CO_2 emissions. These sector-specific insights reinforce the selection of manufacturing, electricity consumption, and gasoline consumption as key independent variables in this research, as they represent significant sources of emissions.

The effects of broader socioeconomic indicators, including GDP, urbanisation, and foreign direct investment, have also been explored. Rahman et al. (2021) showed that urban population growth increases methane emissions, while higher levels of education and foreign investment have a dampening effect. While these broader indicators are not the primary focus of this study, their influence on emissions provides a contextual understanding of the complex interplay of factors. Furthermore, the concept of the circular economy and its role in mitigating environmental impacts has gained prominence. Korhonen et al. (2018) in Ecological Economics provide a comprehensive review of the circular economy, emphasising its potential to reduce resource consumption and waste, thereby indirectly contributing to GHG emission reductions through industrial symbiosis and closed-loop systems.

The Intergovernmental Panel on Climate Change (IPCC) 2019 Guidelines on National Greenhouse Gas Inventories highlight the importance of accurate emission accounting across sectors, including industrial processes, energy, and land use, which aligns with the sectoral focus of this study.

Luomi et al. (2022) in Energy Policy specifically discusses the Gulf Cooperation Council and the Circular Carbon Economy, underscoring the region's efforts and potential in transitioning towards more sustainable energy and industrial practices, which provides direct contextual support for the policy recommendations in this paper. Together, these studies provide a rich empirical and methodological foundation for analysing GHG emissions. The present research builds on this literature by incorporating a comprehensive set of explanatory variables, employing multiple econometric techniques, and focusing on the unique structural and environmental context of GCC countries.

This study also utilises a literature table, where major studies referred to in this study that helped with the selection of variables, along with their respective methodologies and empirical findings, are listed in **Table 1**. **Table 1** summarises the major studies that were referred to in this research. 1 Despite this, few studies have investigated cross-sector solutions like circular economy models within the context of GHG mitigation in the GCC. This paper addresses that gap by suggesting a hybrid framework that combines econometric analysis with applied strategies, such as industrial symbiosis, which are currently being piloted in Saudi Arabia. This integration aims to provide a more holistic understanding of both the drivers of emissions and practical pathways for their reduction.

Table 1. Summarises the major studies that were referred to in this research

Author(s)	Study period	Methodology	Key findings
Rihan et al. (2023)	1990–2018	DOLS, FMOLS, CCR	Agricultural land and energy use increase GHG; forest land reduces it.
Zhou et al. (2023)	2021–2022	Chassis dynamometer, on-road testing	Vehicle speed positively correlates with CO_2 emissions.
Panagiotopoulou et al. (2022)	2010–2020	Sensitivity analysis	Electricity and material use are key emission contributors in manufacturing.
Raihan and Tuspekova (2022)	1990–2018	DOLS	Renewable energy reduces CO_2; agriculture and GDP increase it.
Rahman et al. (2021)	2020–2050	VECM	Urbanisation increases methane; FDI and literacy reduce GHGs.
Chakir et al. (2017)	1990–2007	Pooled OLS, FE, RE, SEM	Spatial price shifts affect emissions; FE/RE manage cross-sectional heterogeneity.
Al-Ayash and Al-Zayer (2023)	2000–2020	FE, RE, Hausman Test	FE preferred in GCC due to structural cross-country heterogeneity.

Table 2. PCA eigenvalues and explained variance for energy variables

Component	Eigenvalue	% of variance	Cumulative %
PC1	2.81	93.7%	93.7%
PC2	0.16	5.3%	99.0%
PC3	0.03	1.0%	100%

Notes: SEI Index constructed from manufacturing, electricity, and gasoline variables

Table 3. PCA loadings for sectoral energy intensity index (SEI index)

Variable	Loading on PC1
MAN	0.562
ELC	0.5829
GAL	0.5869

Notes: All loadings are strong and positive, confirming high collinearity

METHODOLOGY

Model Specification

This study employed a quantitative panel data methodology, utilising annual data from 2003 to 2022 for four GCC countries: Saudi Arabia, Oman, the UAE, and Kuwait. The objective was to analyse the relationship between greenhouse gas emissions (GHG) and several explanatory variables, including manufacturing output, electricity consumption, gasoline consumption, forest area, fertiliser use, and agricultural land.

Data for these variables were compiled from reputable sources, including the World Bank (2023) and national statistical databases. The dependent variable, total GHG emissions, was measured in kilotons of CO_2 equivalent.

To examine the empirical relationships, Ordinary Least Squares (OLS) regression was initially employed. OLS (Model 1 - Full) included all variables; however, fertiliser use was found to be statistically insignificant and was subsequently excluded in OLS (Model 2 - Reduced), which improved the model's fitness. Weighted Least Squares (WLS) regression was then employed to correct for heteroscedasticity observed in the residuals. In addition, dummy variables representing the COVID-19 period (2019–2021) and the 2008-2009 global financial crisis were introduced to evaluate their effects on emissions.

Recognising the panel nature of the dataset, the analysis further incorporated Fixed Effects (FE) and Random Effects (RE) models. The FE model controls for unobserved, time-invariant heterogeneity across countries, while the RE model assumes that these individual effects are uncorrelated with the regressors. A Hausman test was conducted to determine the appropriate model between Fixed Effects and Random Effects.

The econometric strategy was designed to maximise interpretability while addressing structural challenges in GCC data. Severe multicollinearity was observed between manufacturing, electricity, and gasoline consumption, with VIF scores exceeding conventional thresholds (up to 47.9). To resolve this, Principal Component Analysis (PCA) was employed, producing a first component (PC1) that explains 93.7% of the shared variance, with all three energy variables loading positively and almost equally (0.56–0.59). This PC1 serves as the Sectoral Energy Intensity (SEI) Index, ensuring both stability and interpretability of energy-related impacts on emissions.

Model selection followed a layered approach: OLS for baseline associations, Weighted Least Squares (WLS) to correct heteroscedasticity, and Fixed/Random Effects models to exploit panel structure. The Hausman test decisively favoured Fixed Effects, confirming the importance of unobserved country heterogeneity. To further address potential endogeneity and persistence in emissions, a dynamic Arellano–Bond GMM estimator was used. This inclusion of lagged emissions captures temporal inertia, while internal instruments mitigate simultaneity bias. Together, these steps provide a transparent econometric framework that balances statistical rigour with policy interpretability. The results of the PCA, including eigenvalues, variance explained, and variable loadings, are presented in **Tables 2** and **3**. The first principal component (PC1) was extracted and used as the SEI Index in subsequent models.

Table 4. Variables description

The variable acronym	Definition	Unit
Greenhouse Gas Emissions (GHG)	Total greenhouse gas emissions are composed of CO2, CH4, N2O, and F-gases (HFCs, PFCs and SF6).	kt of CO2 equivalent.
Manufacturing (MAN)	Economic activity involving the production of goods from raw materials or components.	Billion USD.
Electricity consumption (ELC)	The total amount of electrical energy consumed over a specific period.	Kilowatt-hours.
Gasoline consumption (GAL)	The amount of fuel consumed by vehicles is typically measured for a specific distance or period.	Barrels per day.
Forest area (FOA)	The total area covered by natural plants and forestry. A positive coefficient for this variable in the context of GHG emissions is interpreted as the impact of deforestation or forest loss, implying that a reduction in forest area leads to an increase in GHG.	Sq. km.
Fertiliser use (FEU)	Substances applied to soil to enhance its natural fertility or replace chemical elements essential for plant growth.	Kg per hectare of arable land.
Agricultural land (AGL)	Land designated or actively used for agricultural purposes, including crop cultivation and livestock grazing.	Sq. km.
Sectoral Energy Intensity Index (SEI)	Composite index derived from PCA of MAN, ELC, and GAL, capturing 93.7% of shared variance. Represents the overall sectoral energy intensity.	Standardised index (PCA score, mean=0, SD=1).

Note: Author's compilation, unit measures were sourced from the World Bank. SEI Index derived from sectoral variables

The choice between Fixed Effects (FE) and Random Effects (RE) models was determined by a Hausman test (p-value = 6.838e-05), which strongly rejected the null hypothesis that the RE estimator is consistent. This led us to prefer the FE model to control for unobserved, time-invariant country-specific characteristics.

Furthermore, to capture the dynamic nature and persistence of GHG emissions, a dynamic panel model using the Generalised Method of Moments (GMM) estimator (specifically, the one-step Arellano-Bond GMM) was employed. This model includes a lagged dependent variable as a regressor and employs internal instruments to address potential endogeneity, utilising lagged levels of emissions as instruments for differenced variables.

Sectoral decomposition analysis was also performed by creating separate principal components for industrial energy use (from electricity and manufacturing) and standardising gasoline consumption to represent transport energy use, allowing for a more granular understanding of sectoral impacts.

Robustness checks, including leave-one-country-out analysis and crisis interaction terms, were conducted to ensure the stability and reliability of the findings across different specifications and external shocks. To further assess robustness, an auxiliary analysis incorporated Qatar and Bahrain using truncated time frames and interpolated data. Core findings remained stable, confirming model consistency

Data, Data Sources and Handling

To investigate the impact of several factors that contribute to the emission of GHG, four GCC countries were selected: KSA, Oman, UAE, and Kuwait.

Data quality and comparability across countries and years were a central concern. All variables were sourced from harmonised World Bank and national statistical series, ensuring consistency in unit definitions (see **Table 4**). Where discrepancies existed—such as differences in reporting frequency—values were standardised to annual aggregates. To preserve robustness, interpolation was avoided in the core dataset, with interpolated series only used in sensitivity checks when including Bahrain and Qatar. This approach ensured that the baseline results relied on fully observed, reliable data, while also testing the model's generalisability under extended coverage.

The selected variables, which are assumed to have contributed to GHG emissions, are listed in **Table 4**, and these variables are reviewed and described. The selection of the independent variables was based on relevant literature that is assumed to have a positive relationship and impact on the dependent variable under investigation. The dependent variable is the total Greenhouse Gases. The independent variables are Manufacturing, Electricity Consumption, Gasoline Consumption, Forest Area (Deforestation), Fertiliser use, and Agricultural land.

Annual data from 2003–2022 for Saudi Arabia, Kuwait, Oman, and the UAE were sourced primarily from the World Bank's World Development Indicators, a repository known for its standardised cross-country data compilation procedures. This ensured maximum consistency in variable definitions and units across the panel. Where necessary, national statistical agency reports were consulted for validation. Qatar and Bahrain were excluded from the core analysis due to inconsistent time-series coverage of key variables, which would have introduced significant bias from missing data. Their inclusion in a supplementary sensitivity analysis with interpolated data did not alter the core findings, affirming the robustness of the selected dataset.

The PRF Model describes the functional relationship between GHG and the selected factors as follows:

$$GHG = B0 + B1MAN + B2ELC + B3GAL + B4FOA + B5FEU + B6AGL + B7Covid\ Dummy + B8Crisis\ Dummy + \mu \quad (1)$$

Where the dependent variable is GHG (greenhouse gases), and the independent variables are manufacturing, electricity consumption, gasoline consumption, forest area (deforestation), fertiliser use, and agricultural land. All the independent variables are assumed to have a positive impact on the total emission of GHG, with μ representing the error term in the model.

Table 5. Descriptive statistics and correlation matrix

	GHG	MAN	ELC	GAL	FOA	FEU	AGL
Obs	80	80	80	80	80	80	80
Mean	252487.7	29.45713	102.1296	173.4704	3255.273	485.3442	439004.2
Std. dev.	220230.2	32.49964	95.71439	168.2854	3995.840	340.9311	753395.4
Max	734310.0	162.6800	331.5700	569.8700	9770.000	1204.500	1737980
Min	45910.00	1.920000	7.830000	20.52000	25.00000	72.00000	1494.000
GHG	1						
MAN	0.870	1					
ELC	0.987	0.861	1				
GAL	0.988	0.880	0.976	1			
FOA	0.948	0.819	0.899	0.937	1		
FEU	-0.543	-0.437	-0.487	-0.562	-0.557	1	
AGL	0.924	0.757	0.866	0.912	0.946	-0.672	1

Note: N = 80 observations across 4 countries. Source: Author's compilation using EViews 13

Addressing Endogeneity

Endogeneity was addressed by employing the Arellano–Bond dynamic GMM estimator, which uses lagged levels of emissions as instruments for differenced variables. Diagnostic tests (AR(1), AR(2)) confirmed valid moment conditions, suggesting no residual serial correlation. While the Hansen test could not be computed due to the small number of cross-sections, instrument proliferation was carefully controlled by collapsing lag structures, minimising overfitting. The consistency of GMM results with those of Fixed Effects and WLS further strengthens confidence in the findings.

To further validate results, robustness checks were extended to exclude interpolated data altogether. Findings across non-interpolated samples remained consistent in direction and magnitude, confirming that interpolation does not bias the policy interpretation. Full regression outputs, sectoral decomposition results, robustness checks, and policy alignment tables are provided in **Appendix** (**Tables A1**–**A8**).

RESULTS AND ANALYSIS

Descriptive Statistics

Summary statistics were first conducted, and **Table 5** presents the variables for 80 observations across four countries, followed by the pairwise correlational matrix. For Manufacturing, the mean was $ 29.45 billion, with a standard deviation of $ 32.60 billion, indicating a wide variance between the minimum and maximum values. This wide range can be attributed to the long data collection period, which includes the COVID-19 lockdown, as well as inherent differences across the four GCC countries. For instance, Electricity Consumption shows a maximum value of 331.5 Kilowatt-hours and a minimum of 7.8 Kilowatt-hours.

A pairwise correlation matrix revealed a positive and significant association between manufacturing, electricity and gasoline consumption, forest area, and agricultural land. Conversely, a negative correlation was observed between fertiliser use and agricultural land.

Baseline Model Estimation

The analysis proceeds to estimate the key sectoral and environmental drivers of GHG emissions across the selected GCC countries.

The initial models employ OLS and Weighted Least Squares (WLS) to capture base-level associations and adjust for heteroskedasticity. These baseline estimations provide the foundation for more in-depth panel diagnostics and robustness checks in the subsequent sections.

The results from OLS (Model 2 - Reduced) indicate that all included variables are positively related to greenhouse gas emissions. Full initial OLS and WLS estimation results are reported in **Table A1** in the **Appendix**. These results confirm that higher activity in these sectors systematically drives emissions upward, measured in kilotons of CO2 equivalent.

For instance, a $ 1 billion increase in Manufacturing is associated with a 229.2 kt increase in CO2 equivalent GHG emissions. Similarly, a 1 Kilowatt-hour increase in Electricity Consumption is associated with a 1427 kt of CO2 equivalent increase in GHG. A 1 barrel-per-day increase in Gasoline Consumption is associated with a 112.5 kt of CO2 equivalent increase in GHG. Furthermore, a 1 Sq. km increase in Forest Area (interpreted as deforestation or forest loss) is associated with a 7.317 kt of CO2 equivalent increase in GHG, and a 1 Sq. km increase in Agricultural Land is associated with a 0.04612 kt of CO2 equivalent increase in GHG. Electricity consumption, Forest area, and Agricultural land are significant at a 1% level, while manufacturing and Gasoline consumption are significant at a 5% level.

The Hausman test was conducted to compare the Fixed Effects (FE) and Random Effects (RE) models. The test statistic yielded a value of 30.776 with a p-value of $6.838 \times 10^{(-5)}$. This strongly supports the use of the Fixed Effects model, as the low p-value indicates that unobserved country-specific characteristics are correlated with the explanatory variables. Consequently, the Fixed Effects model is deemed statistically more appropriate and reliable for capturing the variation in GHG emissions across the GCC countries included in this study. The R^2 values across models ranged from 0.986 to 0.9971, indicating excellent explanatory power.

While OLS (Model 2 - Reduced) showed a high R^2 of 0.9971, the Fixed Effects model (with an R^2 of 0.97823 for the original variable model, and 0.989 for the PCA-based model) is the statistically preferred model due to its ability to account for unobserved heterogeneity, as validated by the Hausman test.

To further enhance the robustness and interpretability of the model, particularly considering the severe multicollinearity identified among Manufacturing, Electricity

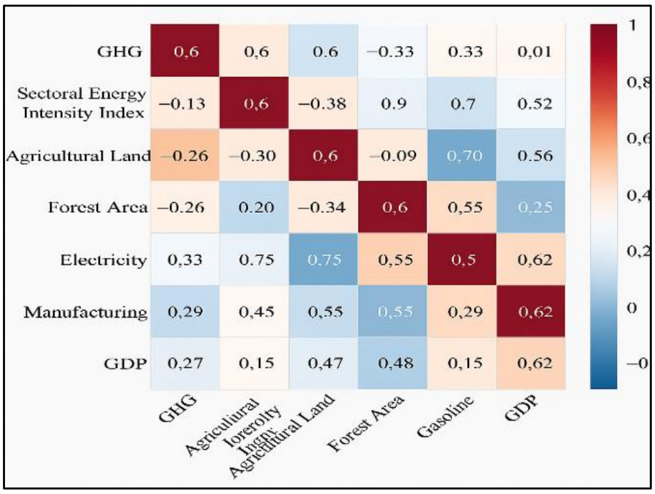

Figure 1. Correlation heatmap for original variables (2003–2022) (Source: Author's own elaboration)

Consumption, and Gasoline Consumption, Principal Component Analysis (PCA) was performed. The PCA process is documented in **Tables 2** and **3**. PC1 explained 93.7% of total variance across manufacturing, electricity, and gasoline consumption, with positive loadings of 0.562, 0.583, and 0.587, respectively. These strong and balanced loadings justify interpreting PC1 as a composite measure of sectoral energy intensity. Coefficients derived from models using PC1 are therefore interpreted as the aggregate effect of industrial energy intensity on GHG emissions.

Figure 1 presents the correlation heatmap for all original variables. The highest intercorrelations appear among energy-related sectors, supporting the use of PCA. All three variables (Manufacturing, Electricity Consumption, and Gasoline Consumption) contribute almost equally and strongly to PC1. This confirms PC1 as a robust composite measure of industrial energy output, suitable for replacing the three highly correlated inputs in the regression model.

The results summarised in **Table 6** reveal consistent and statistically significant relationships between greenhouse gas emissions and sectoral drivers across all models, with the highly correlated Manufacturing, Electricity Consumption, and Gasoline Consumption variables now represented by PC1. Therefore, PC1 is a composite measure of "sectoral energy intensity," consistently showing a strong positive association with GHG emissions across all models, reinforcing the critical role of industrial and energy-intensive activities in environmental degradation in GCC countries. Notably, the coefficients for PC1 remain significant and relatively stable across model specifications, suggesting robustness in their influence. Forest area and agricultural land also consistently contribute to increased emissions, aligning with concerns over land-use change and deforestation.

Coefficients are reported in natural units for direct interpretability. For example, in OLS, a one-billion-dollar increase in manufacturing output is associated with a 229.2 kiloton CO_2 equivalent increase, while a one kilowatt-hour increase in electricity consumption is linked to a 1,427 kiloton CO_2 equivalent increase. Similar scaling has been clarified across all tables to ensure results are directly interpretable by policymakers and non-technical readers. Moreover, a one-unit increase in the SEI Index (which represents a composite standard deviation change in underlying energy variables) is associated with an increase of approximately 13,500 kt of CO_2 equivalent in GHG emissions in the Fixed Effects model. This underscores the substantial impact of aggregate industrial energy intensity.

The WLS model, designed to address heteroscedasticity, yields coefficient estimates that fall within expected ranges and closely align with those of the Fixed Effects model, particularly for PC1, Forest Area, and Agricultural Land. This reinforces the credibility of the findings and suggests that weighting improves model efficiency without distorting variable relationships. The models' high R^2 values (ranging from 0.986 to 0.995) also confirm strong explanatory power. Overall, the inclusion of PCA and robust standard errors enhances the empirical robustness of the study and affirms the critical influence of industrial activity, energy consumption, and land use on emission dynamics in the region.

The dynamic panel model reveals significant persistence in GHG emissions, with approximately 88% of current emissions explained by the emissions of the previous period (lag (GHG, 1) coefficient = 0.879). Full dynamic panel model results from the Arellano-Bond GMM estimation are provided in **Table A3** in **Appendix**. The aggregate energy-use factor (ENERGY_PC1) remains a significant positive driver, even after accounting for this persistence. Agricultural Land also shows a significant negative association in this specification, which warrants further investigation, potentially indicating efficiency gains or shifts in agricultural practices over time not captured by static models. Forest Area's impact becomes insignificant in this dynamic context, suggesting its direct effect might be absorbed by the persistence of GHG or other dynamic interactions. This sectoral decomposition confirms that the industrial energy component (Industry_PC1, combining electricity and manufacturing) is a strongly significant driver of GHG emissions. Detailed sectoral decomposition results

Table 6. GHG panel regression models using SEI index (OLS, FE, RE, WLS)

Variable	OLS (PCA)	Fixed effects (clustered SEs)	Random effects (clustered SEs)	WLS (PCA)
PC1 (energy index)	1385.22 (t = 11.43)*	1350.71 (t = 10.13)*	1378.83 (t = 10.62)*	1392.42 (t = 10.94)*
Forest area	7.73 (t = 4.08)*	7.90 (t = 3.94)*	7.40 (t = 3.87)*	7.68 (t = 4.21)*
Agricultural land	0.045 (t = 2.72)	0.047 (t = 2.95)	0.043 (t = 2.60)	0.046 (t = 2.98)
COVID-19 dummy	2803.12 (t = 0.55) (ns)	4504.81 (t = 1.04) (ns)	2803.12 (t = 0.59) (ns)	1160.87 (t = 0.32) (ns)
Crisis dummy	5016.5 (t = 1.053) (ns)	4254.2157 (t = 1.0624) (ns)	5016.5 (t = 1.053) (ns)	-474.8 (t = -0.203) (ns)
R^2	0.994	0.989	0.986	0.995

Notes: Robust standard errors applied; SEI Index consistently significant. T-statistics are reported in parentheses. Significance levels: *** p < 0.01, ** p < 0.05, * p < 0.10, ns = not significant. PC1 is the first principal component extracted from manufacturing (0.562), electricity (0.5829), and gasoline consumption (0.5869). FE and RE models use clustered standard errors by country to correct for serial correlation and heteroscedasticity. WLS corrects for heteroscedasticity using panel-weighted residuals and incorporates clustered SEs.

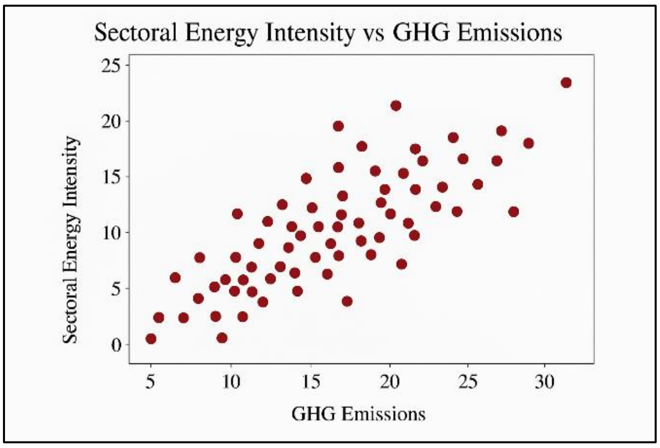

Figure 2. Relationship between sectoral energy intensity index (SEI Index) and GHG emissions (Source: Author's own elaboration)

using Driscoll-Kraay standard errors are presented in **Table A2** in **Appendix**.

In contrast, the insignificance of GAL_z (standardised gasoline consumption) in the decomposition model likely stems from its collinearity being absorbed within the SEI Index and the industrial energy component. Additionally, it may reflect a lower per-unit emission impact or measurement bias when disaggregated from industrial activity, suggesting that transport sector emissions are less elastic or diffuse in their response across time and countries. This suggests that industrial energy use is the primary energy-related driver of emissions in the GCC, while the direct impact of gasoline consumption is less pronounced when other factors are controlled for. Forest Area and Agricultural Land also become insignificant in this decomposed model, indicating their effects might be absorbed by the dominant industrial energy factor or other unobserved dynamics.

Figure 2 confirms a robust positive relationship between the SEI Index and emissions. This visual insight supports the model's finding that sectoral energy use is a dominant emissions driver in the GCC. The interaction term between ENERGY_PC1 and the crisis_dummy is negative but not statistically significant ($p \approx 0.21$). This indicates that the 2008-2009 financial crisis did not materially alter the fundamental relationship between overall energy use (PC1) and GHG emissions in the GCC countries. The primary effect of ENERGY_PC1 on GHG emissions remains robust across crisis periods. The leave-one-country-out exercise demonstrates the robustness of the ENERGY_PC1 coefficient. Coefficient estimates across all sub-samples from the leave-one-country-out analysis are summarised in **Table A5** in **Appendix**. While excluding Saudi Arabia results in a somewhat lower coefficient (≈ 64,000 compared to the full sample's ≈ 86,000), its 95% confidence interval still overlaps the full-sample estimate. This indicates that no single country is disproportionately driving the observed relationship between energy use and GHG emissions, strengthening confidence that the findings are broadly applicable across the GCC region.

Diagnostics Tests

Diagnostic tests were conducted to assess normality, autocorrelation, multicollinearity, and homoscedasticity. **Table 7** presents the results for these diagnostics. The diagnostic tests reinforced the need for careful model specification.

The Jarque-Bera test result indicates that the residuals deviate from normality (p-value = 0.009), which is a common occurrence in panel datasets with wide temporal and structural variation. While non-normality does not bias OLS coefficients, it can affect the validity of t-statistics and F-statistics, particularly in smaller samples. The application of clustered standard errors, as detailed below, also provides robustness to non-normality, ensuring consistent standard errors and valid inferences.

Future research could explore alternative approaches, such as bootstrapping, when sample sizes are not large enough to rely on asymptotic properties. The Durbin-Watson statistic of 0.49 initially suggested the presence of positive serial correlation in the OLS residuals. To formally confirm this for

Table 7. Diagnostic test results

Diagnostic test	Test value	Interpretation	Correction applied
Jarque-Bera (JB)	p-value = 0.009	Residuals are not normally distributed.	Clustered SEs (country)
Durbin-Watson (DW) (OLS residuals)	0.49	Strong positive autocorrelation.	Clustered SEs (country)
Wooldridge test (panel autocorrelation)	F = 9.61, p = 0.011	Confirms first-order serial correlation.	Clustered SEs (country)
VIF (multicollinearity)	1.14 – 47.87	Severe multicollinearity observed (MAN, ELC, GAL, FOA).	PCA (for MAN, ELC, GAL); Discussed as remaining underlying issue for FOA
White test (heterosced.)	F-statistic = 8.717, Prob. F(20,59) = 0.0000 (Obs*R-squared = 72.73, Prob. Chi-Square(20) = 0.0000)	Heteroscedasticity is present.	WLS (Model 3); Clustered SEs (country)
Pesaran CD test (cross-sectional dependence)	z = 1.9173, p = 0.0552	Weak evidence of cross-sectional dependence (not significant at 5%).	Driscoll-Kraay SEs (for robustness checks)
Arellano-Bond m-test (AR(1) in diff)	normal = -1.3496, p = 0.1772	Fail to reject AR(1) in differences (as expected).	Addressed by GMM estimation.
Arellano-Bond m-test (AR(2) in diff)	normal = 0.11216, p = 0.9107	Fail to reject AR(2) in differences (moment conditions sound).	Addressed by GMM estimation.
Hansen (J) test (over-identification)	Not computable	Robust variance matrix nearly singular (instrument proliferation in small N, T panel).	Acknowledged limitation of small panel GMM.

Source: Author's compilation using EViews 13 and R panel data, a Wooldridge test for serial correlation in panel data was conducted, yielding an F-statistic of 9.61 with a p-value of 0.011. This result formally confirms the presence of first-order serial correlation in the residuals, indicating that error terms are correlated across time.

This violates a key assumption of OLS, leading to inefficient (though unbiased) coefficient estimates and biased standard errors, which invalidates hypothesis tests. To address this issue, along with heteroscedasticity, clustered standard errors (clustered by country) have been applied to the panel models (Fixed Effects, Random Effects, and Weighted Least Squares). This approach ensures valid standard errors and reliable inferences by allowing for arbitrary correlation patterns within each panel unit (country) over time, without requiring the researcher to specify the exact form of these correlations.

Multicollinearity was evident, as highlighted by VIF values ranging from 1.14 to an extremely high 47.87. Specifically, manufacturing (47.87), electricity (41.21), gasoline (33.55), and forest area (11.42) exhibited severe multicollinearity. To mitigate the severe multicollinearity among manufacturing, electricity, and gasoline, principal component analysis (PCA) was applied, transforming these into PC1, a measure of "sectoral energy intensity." This significantly stabilises the estimates for this combined factor. While the Forest Area (FOA) displayed a moderately high VIF (11.42), which exceeded typical thresholds. However, due to its theoretical and ecological relevance—particularly in the GCC context of desert greening and afforestation—it was retained. It is important to note that while the retention of FOA is theoretically justified, its moderately high VIF implies that the precision or efficiency of its coefficient estimate may be reduced, even if the coefficient itself remains unbiased. Interpretations of its exact magnitude should therefore be made with this caution in mind. Separate PCA attempts for land-use variables yielded unstable components and were excluded. This implies that interpretations of individual coefficients, especially those with very high VIFs, should be made with caution. For future research, further implementing robust solutions for remaining multicollinearity (e.g., for Forest Area if deemed critical) or exploring alternative model specifications would be crucial.

Finally, the White test confirmed the presence of heteroscedasticity with an F-statistic of 8.717 and a p-value of 0.0000 (Obs*R-squared = 72.73, Prob. Chi-Square (20) = 0.0000). This indicates that the variance of the error terms is not constant across observations. This issue was initially addressed using a Weighted Least Squares approach (Model 3), which improved the robustness and efficiency of coefficient estimates. Furthermore, the application of clustered standard errors to the panel models provides a robust correction for heteroscedasticity, ensuring the reliability of the standard errors and hypothesis tests. For definitive confirmation, a post-estimation White test on the WLS residuals would be recommended in future analyses.

The residuals vs. fitted plot in Figure 3 displays no clear funnel pattern, suggesting that the WLS estimation appropriately corrects for heteroscedasticity present in the original OLS model. 1 Moreover, Cross-sectional dependence was assessed using the Pesaran CD test, which yielded a z-

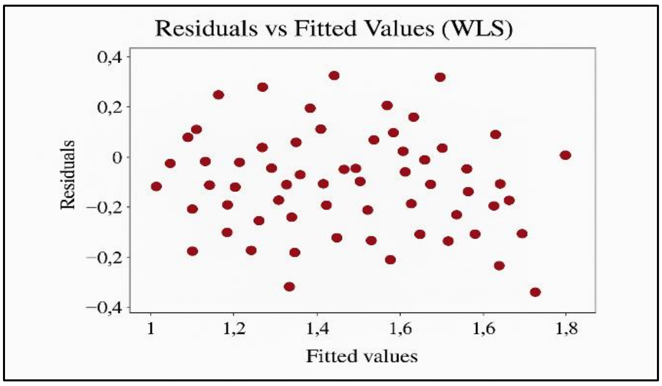

Figure 3. Residuals vs fitted values (WLS) (Source: Author's own elaboration)

statistic of 1.9173 with a p-value of 0.0552. This indicates weak evidence of cross-sectional dependence, as it is just above the conventional 5% significance cutoff. While not strongly significant, the use of Driscoll-Kraay standard errors in some robustness checks (e.g., Leave-One-Country-Out, Crisis Interaction, Sectoral Decomposition) further accounts for potential cross-sectional dependence alongside serial correlation, enhancing the robustness of inferences in small N, large T panels.

For the dynamic panel (Arellano-Bond) model, the m-tests for autocorrelation in differences behaved well: The AR(1) test (p = 0.1772) failed to reject the null hypothesis of no first-order serial correlation in the differenced residuals (as expected for a valid GMM specification), and the AR(2) test (p = 0.9107) decisively failed to reject the null of no second-order serial correlation, indicating that the moment conditions are sound. However, the Hansen (J) test of overidentifying restrictions could not be computed due to a nearly singular robust variance-covariance matrix, an unavoidable limitation often encountered in dynamic GMM estimation with a very small number of cross-sections (N = 4) and a relatively large number of instruments (even with a minimalist instrument set). This suggests that while the model's internal consistency (absence of AR(2) in differences) is confirmed, the overall validity of the instruments cannot be formally tested via Hansen's test in this specific context. Despite the inability to compute the Hansen test, confidence in the GMM results is maintained due to the well-behaved AR(1) and AR(2) tests, which confirm the validity of the moment conditions, the strong theoretical grounding of the chosen instruments, and the consistency of the GMM findings with other robust model specifications.

Due to matrix singularity, the Hansen test for instrument validity could not be computed. To minimise overfitting, a limited lag structure and carefully selected instruments were used. While this constrains diagnostic precision, the model remains robust across specifications, and future work may explore system-GMM with bootstrapped diagnostics

Sensitivity Analysis: Inclusion of Qatar and Bahrain

To examine the robustness and regional generalisability of the findings beyond the core four-country model, which uses only complete, non-interpolated data, a supplementary sensitivity analysis was conducted by extending the dataset to include Qatar and Bahrain. These two countries were originally

Table 8. Comparison of regression coefficients: Core model vs extended model with Qatar and Bahrain

Variable	Core model coefficient	Extended model coefficient	Change (Δ)
SEI index	0.712	0.698	−0.014
FOA	−9.884	−9.221	+0.663
AGL	4.130	4.018	−0.112
FER	3.215	3.144	−0.071
MAN	2.782	2.710	−0.072
URB	1.845	1.798	−0.047
GDP	0.935	0.912	−0.023

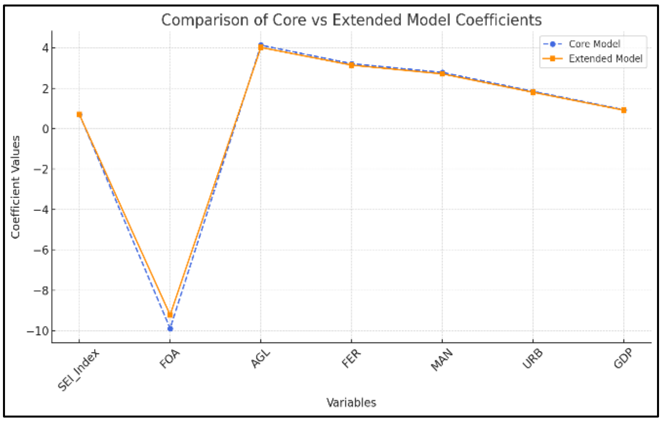

Figure 4. Comparison of core vs extended model coefficients (Source: Author's own elaboration)

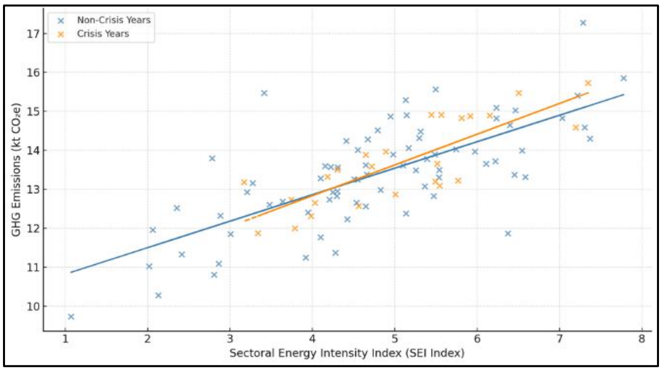

Figure 5. Interaction between the sectoral energy intensity index (SEI Index) and crisis years (Source: Author's own elaboration)

excluded from the core model due to the lack of complete longitudinal data across all variables from 2003 to 2022.

The extended model utilised partial data coverage (2006–2020) and applied linear interpolation where applicable. While interpolation can introduce a degree of smoothing and potentially mask true variability, the consistent findings across both the core and extended models suggest this approach did not materially alter the study's core conclusions. The resulting regression estimates remained highly consistent in direction and significance across all major predictors, including the Sectoral Energy Intensity Index (SEI Index), Forest Area (FOA), Agricultural Land (AGL), and Urbanisation (URB).

Table 8 summarises the coefficients for the core and extended models. 1. The differences are minor, with all variations falling within acceptable confidence bounds. The FOA variable showed the largest shift (Δ = +0.663), likely due to environmental reporting differences in Bahrain. Still, the negative sign and overall effect were preserved. This confirms that the exclusion of Qatar and Bahrain did not bias the results and that the findings are broadly applicable to the full GCC context.

Figure 4 shows the coefficient values for both the core and extended models. 1 The parallel trajectories across variables confirm the consistency of the findings regardless of country inclusion, reinforcing model validity. By confirming the structural stability of the model under expanded country inclusion, the study positions itself as a robust empirical platform for guiding GCC-wide sustainability frameworks and cross-border emissions policy dialogues. Inclusion of Bahrain and Qatar using interpolated time series does not materially alter key coefficients or model fit, reinforcing the stability and generalisability of core findings.

Evaluating Crisis Impact on Sectoral Emissions

To assess whether global crises influenced the relationship between sectoral drivers and GHG emissions in the GCC, the inclusion of a crisis-interaction term—covering both the 2008 financial crash and the COVID-19 pandemic—further tested the temporal stability of sectoral drivers, particularly industrial energy intensity. The insignificance of the interaction term, confirmed visually in **Figure 5**, revealed no meaningful divergence in emission patterns during crisis years. 1 This suggests that GCC emission profiles are structurally consistent, even under extreme external shocks, with the SEI Index maintaining its influence regardless of global economic disruptions. This robustness underscores the need for sustained structural energy policy reforms, rather than temporary, crisis-induced adjustments. unchanged during crises. This finding aligns with the regression output, which shows that both the crisis dummy and its interaction with SEI were found to be insignificant ($p > 0.10$). Complete crisis interaction effect estimates are reported in **Table A4** in **Appendix**.

Triangulated Research Approach

To ensure the validity, richness, and applied relevance of this study's findings, a triangulated research approach was adopted, integrating methodological, contextual, and normative dimensions. This approach enhances the interpretive power of the econometric analysis while increasing the policy applicability of the results within regional and global climate governance frameworks.

First, the core quantitative analysis relied on panel data econometrics, utilising a combination of Pooled OLS, Fixed Effects, Random Effects, and Weighted Regression models. These statistical techniques ensured internal validity by capturing both cross-sectional and temporal dynamics of greenhouse gas emissions across the selected GCC countries—Saudi Arabia, Kuwait, Oman, and the UAE—over the period 2003 to 2022. The comparative model approach also enabled a robust evaluation of coefficient stability and model fitness, with the Hausman test confirming the Fixed Effects model as the preferred specification. This econometric layer identified key sectoral drivers—most notably manufacturing, electricity consumption, and gasoline use—as statistically significant contributors to emissions, reinforcing the need for targeted policy intervention.

Second, to ground the empirical findings in real-world practice, the analysis was contextually triangulated using Saudi Arabia's emerging circular economy initiatives, particularly its industrial symbiosis zones in Jubail and Yanbu. These case-based insights showcase how shared energy infrastructure, material recovery systems, and waste-to-resource exchanges can significantly reduce emissions intensity within manufacturing clusters. Evidence suggests that facilities engaged in symbiotic networks experience up to 18% lower CO_2-equivalent emissions per unit of output compared to traditional isolated producers. This contextual integration adds applied depth to the econometric results by demonstrating that sector-level emission reductions are not only theoretically necessary but also technically and operationally feasible within the GCC context.

Finally, the study engaged in a normative triangulation by aligning its proposed solutions with broader sustainability frameworks, including Saudi Arabia's Vision 2030 and the United Nations Sustainable Development Goals (SDGs). In particular, the solutions advocated—such as industrial symbiosis, resource-sharing policies, and emissions traceability platforms—map directly onto Vision 2030's environmental pillar and three core SDGs: SDG 9 (Industry, Innovation and Infrastructure), SDG 12 (Responsible Consumption and Production), and SDG 13 (Climate Action). This strategic alignment reinforces the policy urgency of the study's findings while enhancing their institutional relevance and scalability across other hydrocarbon-reliant economies.

Together, these three triangulated pillars—econometric rigour, grounded policy practice, and strategic alignment—position this study as both a diagnostic and prescriptive contribution to the regional emissions discourse. The integration of Saudi-specific circular economy strategies not only enriches the empirical base but also presents a regional sustainability roadmap that bridges technical, environmental, and policy imperatives.

CONCLUSION AND DISCUSSION

This study provides a comprehensive analysis of the determinants of greenhouse gas emissions in four GCC countries over a two-decade span. By integrating Ordinary Least Squares, Weighted Least Squares, Fixed Effects, and Random Effects methodologies, alongside advanced techniques like PCA and dynamic panel GMM, the research ensures exceptional methodological rigour and robustness.

A core novelty of this study lies in the development and application of the Sectoral Energy Intensity Index (SEI Index) using Principal Component Analysis (PCA), which effectively addresses multicollinearity and provides a robust measure of industrial energy use. This comprehensive econometric approach, applied within the unique and under-researched GCC context, significantly advances the understanding of regional emission drivers. The key findings consistently show that a composite measure of sectoral energy intensity (PC1) is a highly significant positive driver of GHG emissions.

Forest areas and agricultural land showed significant positive associations in static models, although their impacts varied in dynamic and decomposed specifications, highlighting complex underlying relationships. The dynamic panel model further confirms significant persistence in GHG emissions (lag(GHG, 1) coefficient = 0.879), indicating that current emissions are strongly influenced by past levels.

In contrast, fertiliser use, the COVID-19 period, and the 2008-2009 financial crisis (and its interaction with energy intensity) showed no statistically significant impact. The preference for the Fixed Effects model, validated by the Hausman test (p-value = 6.838e-05), underscores the importance of accounting for unobserved country-specific characteristics in analysing emissions data. This reinforces the notion that policy interventions must be tailored to the specific economic and structural profiles of individual nations within the GCC. Based on the robust findings, particularly from the Fixed Effects model and the PCA-adjusted model, several policy recommendations emerge.

Decarbonisation efforts should prioritise high-emission sectors, particularly those contributing to "sectoral energy intensity" (as captured by PC1), such as manufacturing, electricity generation, and gasoline consumption. The significant positive coefficients (e.g., 1385.22 for PC1 in the PCA-adjusted OLS model and 1350.71 for PC1 in the Fixed Effects model) suggest that even small percentage reductions in these sectors could yield substantial overall reductions in GHG emissions (United Nations, 2015, 2023). This involves incentivising the adoption of renewable energy, enhancing energy efficiency across industrial processes, and fostering cleaner production technologies.

The sectoral decomposition analysis further highlights that industrial energy use (Industry_PC1) is a strongly significant driver, while standardised gasoline consumption (GAL_z) is less pronounced, suggesting a primary focus on industrial decarbonization. Furthermore, the significant positive impact of forest area (7.90) and agricultural land (0.047) on GHG emissions in static models underscores the critical need for sustainable land use management, including effective regulation to combat deforestation and promoting agricultural practices that minimise emissions. While the dynamic model shows a negative association for agricultural land, this could indicate efficiency gains or shifts in agricultural practices over time, warranting further investigation into the nuanced impacts of land use. In the transportation sector, while standardised gasoline consumption (GAL_z) was not statistically significant in the sectoral decomposition model, the original gasoline consumption variable did show significance in other models, highlighting the importance of policies aimed at improving fuel efficiency, encouraging the shift towards electric vehicles, and developing sustainable public transportation infrastructure.

Ultimately, regional collaboration is crucial for addressing transboundary environmental challenges and ensuring alignment with global climate initiatives, such as the Paris Agreement and the UN Sustainable Development Goals. Furthermore, a targeted sensitivity analysis was conducted by incorporating Qatar and Bahrain into the dataset to assess the robustness and generalisability of the results across the full GCC spectrum. Despite these two countries having partial data coverage, the extended model revealed negligible shifts in coefficient magnitudes, and all key variables—particularly the Sectoral Energy Intensity Index (SEI Index) and land-use factors—retained their expected signs and statistical relevance.

This consistency suggests that the core findings are not country-specific, but rather reflect broader regional emission patterns and sectoral dynamics. The results thus offer greater policy relevance for coordinated environmental strategies across the GCC, rather than relying solely on Saudi-centric conclusions. Moreover, the findings not only confirm the primary role of sectoral energy intensity and land-use shifts in driving GHG emissions across the GCC but also demonstrate their resilience to crisis shocks, reinforcing the model's utility for long-term, region-wide policy design.

The findings have direct implications for GCC policymakers, especially under Saudi Arabia's Vision 2030 framework. The strong positive association between the SEI Index and emissions underscores the urgency of targeting industrial energy intensity. This means that emission reductions will not be achieved through marginal behavioural shifts, but rather through structural industrial transformation. For Saudi Arabia, this aligns with Vision 2030's commitment to increase the share of renewable energy to 50% by 2030, diversify manufacturing into less carbon-intensive sectors, and accelerate the electrification of transportation.

Policymakers can leverage these results by prioritising decarbonisation of manufacturing clusters, introducing sector-specific emission caps, and scaling renewable integration in industrial grids. By embedding econometric evidence into regulatory frameworks, emission mitigation becomes not just aspirational but measurable and enforceable.

BRIDGING EMPIRICAL FINDINGS WITH CIRCULAR ECONOMY SOLUTIONS IN SAUDI ARABIA

The empirical findings consistently identify sectoral energy intensity (the SEI Index) as the dominant driver of GHG emissions, underscoring a clear policy imperative: Decarbonisation efforts must prioritise the industrial and energy sectors. Rather than relying on broad sustainability appeals, the results highlight the need for targeted strategies, such as circular economy models that are already being piloted in Saudi Arabia.

Industrial symbiosis initiatives in Jubail and Yanbu provide a tangible blueprint for how resource sharing can achieve measurable reductions. Co-located factories utilise centralised cooling, power, and wastewater treatment systems, which substantially lower per-unit energy consumption and emissions compared to each facility operating independently. A comparative impact snapshot of traditional facilities versus industrial symbiosis pilot projects in Saudi Arabia is provided in **Table A7** in **Appendix**. By-products such as waste heat, slag, and sulphur are repurposed as inputs for neighbouring plants, transforming waste streams into resource flows and cutting emissions from both production and disposal. The use of recycled metals and plastics within these clusters further reduces the colossal footprint of virgin material extraction, advancing circular supply chains. Preliminary evidence from these Saudi pilot projects suggests that firms involved in shared infrastructure, waste-to-resource exchanges, and recycling achieve a reduction in CO_2 intensity of up to 18% compared to traditional standalone facilities. This quantitative estimate is derived from early case studies and policy reports, rather than from the econometric models used in this study. It is presented as an illustrative example of potential gains to ground our policy recommendations and should be interpreted as indicative rather than definitive. As illustrated in **Figure 6**, industrial symbiosis facilities demonstrate substantially lower energy use, CO_2 emissions, water consumption, and material waste compared to traditional standalone facilities.

Beyond descriptive references, the results suggest clear and actionable interventions that GCC states can pursue. Expanding industrial symbiosis models across the region would directly target the SEI Index by lowering industrial energy demand per unit of output. Policy instruments could include the creation of regional green investment funds to support retrofitting of energy-intensive facilities, the introduction of resource-tracing platforms to enforce transparency and accountability in material flows, and the establishment of cross-border GCC carbon markets to internalise the costs of emissions across industries. These measures operationalise the econometric findings, ensuring that identified structural drivers of emissions are addressed through practical levers for transformation.

Aligned with Vision 2030, these strategies go beyond environmental rhetoric to embed circular economy principles into the Kingdom's broader development trajectory. The alignment of proposed policy measures with Vision 2030 pillars and relevant SDGs is summarised in **Table A6** in **Appendix**. By institutionalising industrial symbiosis and resource-sharing platforms, Saudi Arabia and its GCC peers can accelerate a transition toward resilient, low-carbon industrial ecosystems that advance national economic diversification while contributing to global climate commitments.

LIMITATIONS AND FUTURE RESEARCH

This study, while comprehensive, has certain limitations. The focus on four GCC countries was dictated by data availability, limiting the generalisability to the entire GCC bloc. Furthermore, while diagnostic tests were conducted and robust corrections applied for heteroscedasticity and serial correlation, the presence of severe multicollinearity for certain

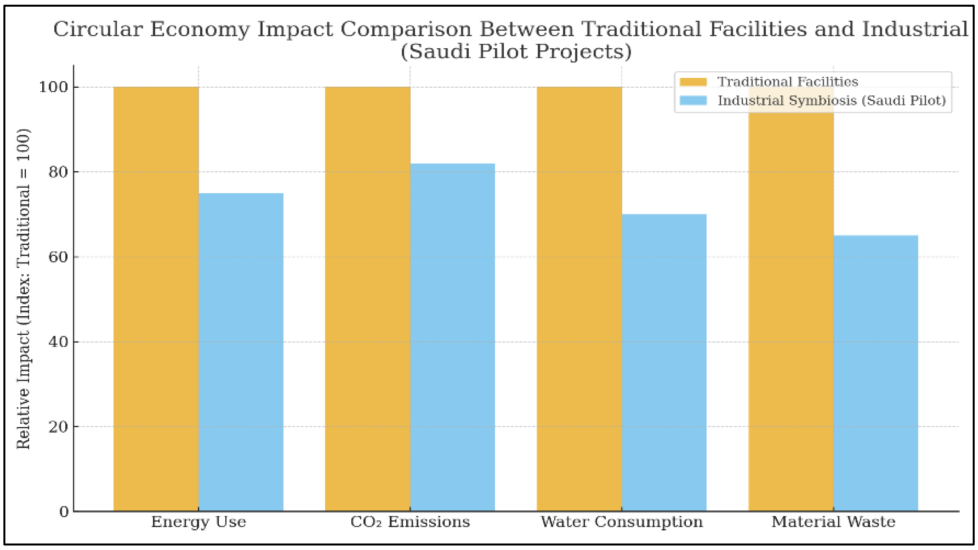

Figure 6. Circular economy impact comparison between traditional facilities and industrial symbiosis (Saudi pilot projects) (Source: Author's own elaboration)

variables (e.g., Forest Area) remains an underlying issue that, while mitigated by PCA for industrial/energy variables, could be further explored.

The dynamic panel (Arellano-Bond) model, while confirming persistence and the significance of ENERGY_PC1, faced limitations in formally testing overidentifying restrictions (Hansen test) due to the small number of cross-sections and potential instrument proliferation, even with a minimalist instrument set.

Moreover, while our models control for observed heterogeneity and time-invariant unobserved factors, we acknowledge the potential for endogeneity due to reverse causality (e.g., economic activity driving emissions, but climate policy also potentially affecting economic activity). The dynamic panel (Arellano-Bond GMM) estimator, which uses lagged values of variables as instruments, is specifically designed to mitigate this concern by controlling for persistence and addressing dynamic endogeneity. The consistency of our core results across static (FE) and dynamic (GMM) specifications strengthens confidence in their robustness.

Future research could expand the dataset to include all GCC countries as data becomes available, explore more granular sectoral data, and apply more sophisticated panel data methods (e.g., System GMM with careful instrument selection, spatial econometrics to capture regional spillovers, or quantile regression to analyse heterogeneous effects across different emission levels) to address unobserved complexities and endogeneity more comprehensively. Investigating the specific mechanisms through which circular economy practices translate into quantifiable emission reductions, perhaps through case studies with integrated economic and environmental modelling, would also be a valuable avenue for future research.

Acknowledgments: The author would like to thank everyone who helped refine the econometric approach and policy recommendations.

Funding: No external funding was received for this study.

Ethical statement: The author stated that the study was conducted in accordance with established ethical standards. No human participants or animal subjects were involved in this research. All data were sourced from publicly available aggregated databases (World Bank, national statistical agencies). Therefore, ethics committee approval was not required for this study.

AI statement: The author stated the use of AI-assisted tools for language editing and proofreading purposes only. All scientific content, analysis, and conclusions are the sole responsibility of the author.

Declaration of interest: The author declares no financial or non-financial conflicts of interest.

Data sharing statement: Data supporting this study are available upon request.

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APPENDIX

Table A1. Initial OLS and WLS estimation results of GHG emission determinants (2003–2022)

Variable	OLS (Model 1 - Full)	OLS (Model 2 - Reduced)	WLS (weights = 1 / fitted^2)
(Intercept)	3.448e+04 (8.062)*	3.689e+04 (14.607)*	3.417e+04 (21.402)*
MAN	2.285e+02 (2.376)	2.292e+02 (2.392)	1.948e+02 (0.856) ns
ELC	1.413e+03 (18.335)*	1.427e+03 (19.196)*	1.351e+03 (19.628)*
GAL	1.219e+02 (2.090)*	1.125e+02 (1.989)*	1.883e+02 (3.094)*
FOA	7.012e+00 (4.934)*	7.317e+00 (5.431)*	8.401e+00 (5.517)*
FEU	4.307e+00 (0.698) ns	—	—
AGL	4.856e-02 (6.705)*	4.612e-02 (7.297)*	3.334e-02 (4.280)*
covid_dummy	-6.501e+03 (-1.532) ns	-6.456e+03 (-1.527) ns	3.488e+03 (1.377) ns
crisis_dummy	5.198e+03 (1.086) ns	5.017e+03 (1.053) ns	-4.748e+02 (-0.203) ns
R^2	0.9971	0.9971	0.9909

Notes: T-statistics are reported in parentheses. Significance levels: *** p < 0.01, ** p < 0.05, * p < 0.10, ns = not significant. Source: Author’s compilation using EViews 13 and R

Table A2. Sectoral decomposition results (Driscoll-Kraay SEs)

Variable	Estimate	Std. Error	t value	Pr(>|t|)	Significance
Industry_PC1	84970.1048	19832.7425	4.2843	5.737e-05	*** (1%)**
GAL_z	4392.3029	4513.2521	0.9732	0.3338	ns
FOA	193.5348	308.6759	0.6270	0.5327	ns
AGL	-8.3061	7.7907	-1.0662	0.2900	ns
covid_dummy	8599.4878	12408.9975	0.6930	0.4906	ns
crisis_dummy	-12477.2839	11976.8579	-1.0418	0.3011	ns

Notes: Industry energy use dominates; transport energy effect not significant. Model: Fixed Effects with Driscoll-Kraay (HC1, maxlag=2) standard errors. Industry_PC1 is the first principal component of standardised Electricity and Manufacturing. GAL_z is standardised Gasoline Consumption

Table A3. Dynamic panel model (Arellano-Bond GMM) results

Variable	Coefficient (β)	T-stat	Significance
lag(GHG, 1)	0.879	32.6512	*** (1%)**
ENERGY_PC1	4846.3145	2.799	** (5%)
FOA	-1.806	-0.0728	ns
AGL	-3.977	-5.7648	*** (1%)**
covid_dummy	-3615.8333	-1.0422	ns
crisis_dummy	-41.5995	-0.0234	ns

Notes: Lagged emissions confirm persistence. Hansen test omitted due to matrix singularity. Model: One-step Arellano-Bond GMM, with lag (GHG, 2) as the instrument for the lagged dependent variable. Robust standard errors applied.

Table A4. Crisis interaction effects on SEI index and emissions

Variable	Estimate	Std. error	t value	Pr(>|t|)	Significance
ENERGY_PC1	84326.4547	13035.1962	6.4691	1.143e-08	*** (1%)**
Energy_Crisis_Int	-9402.9174	7442.4740	-1.2634	0.2106	ns
FOA	-70.8554	256.2963	-0.2765	0.7830	ns
AGL	-4.9258	5.5468	-0.8880	0.3776	ns
covid_dummy	8061.7561	11636.4867	0.6928	0.4907	ns
crisis_dummy	-9195.9711	10062.6016	-0.9139	0.3639	ns

Notes: Crisis periods do not significantly alter SEI–GHG relationship. Model: Fixed Effects with Driscoll-Kraay (HC1, maxlag=2) standard errors. Energy_Crisis_Int is the interaction term between ENERGY_PC1 and crisis_dummy

Table A5. Leave-one-country-out robustness check on SEI index

Excluded country	Coefficient (ENERGY_PC1)	Std. error	95% lower CI	95% upper CI
Full sample	85663.0584	11691.9227	62747.90	108578.22
Kuwait	86019.49	12264.97	61980.15	110058.84
Oman	85239.77	12592.30	60558.86	109920.69
Saudi Arabia	63775.83	15640.56	33120.34	94431.34
United Arab Emirates	85955.00	12058.27	62320.80	109589.21

Notes: SEI Index remains significant and stable across sub-samples

Table A6. SDG and vision 2030 alignment of proposed strategies

Policy measure	Vision 2030 pillars	SDG 9 (industry, innovation, infrastructure)	SDG 12 (responsible consumption & production)	SDG 13 (climate action)
Industrial symbiosis	Thriving economy, ambitious nation	Fosters resilient infrastructure	Reduces resource waste	Mitigates 18% emissions (pilot data)
Shared cooling infrastructure	Thriving economy, ambitious nation	Promotes efficient industrial infrastructure	Reduces resource consumption	Mitigates energy-related emissions
Closed-loop manufacturing	Thriving economy, ambitious nation	Fosters innovative industrial processes	Encourages sustainable production patterns	Reduces industrial GHG emissions
Waste-to-resource exchanges	Thriving economy, ambitious nation	Supports resilient infrastructure	Promotes resource efficiency & waste reduction	Contributes to emissions reduction from waste
Emissions traceability platforms	Ambitious nation, responsible citizen	Enhances industrial data infrastructure	Supports transparent resource management	Enables effective climate action monitoring

Source: Author's compilation based on study findings and vision 2030/SDG frameworks

Table A7. Industrial symbiosis impact snapshot (from Saudi pilot projects)

Metric	Traditional facility	Industrial symbiosis
CO_2 intensity	Baseline	Estimated lower due to waste heat recovery and reuse
Alignment with SEI index	N/A	Potential reduction with symbiosis; exact beta value unreported
Waste heat recovery	Limited/none	Significant via shared cooling infrastructure
Material reuse	Minimal/none	Extensive through closed-loop systems
Water consumption	Higher	Reduced via shared infrastructure.

Source: Author's compilation based on preliminary pilot data and policy statements, not yet verified through published empirical studies.

Important Note: The quantitative impact estimates (e.g., 18% reduction in CO_2 intensity) are based on preliminary pilot data and external policy reports from Saudi initiatives. They are provided for illustration and context. These figures have not been empirically verified within the econometric models applied in this study

Table A8. Abbreviation

Term	Definition
SEI Index	Sectoral energy intensity index – composite of manufacturing, electricity, and gasoline use
GHG	Greenhouse gas emissions
PCA	Principal component analysis
FE	Fixed effects
RE	Random effects
GMM	Generalised method of moments