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Heca Journal of Applied Sciences

Vol. 3, No. 2, 2025

Top Global Concrete-Producing Countries: A Hierarchical Cluster Analysis of Concrete Production, CO_2 Emissions, and Economic Growth

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Article History

Received 14 June 2025
Revised 12 August 2025
Accepted 17 August 2025
Available Online 31 August 2025

Keywords:
Hierarchical cluster analysis
Environmental quality
Concrete production

Abstract

Concrete production plays a vital role in infrastructure and economic development, yet it remains one of the most significant sources of global CO_2 emissions. This study focuses on the top 10 concrete-producing countries, using variables such as concrete production (CP), carbon dioxide (CO_2) emissions, and gross domestic product (GDP) as a proxy for economic growth. Using hierarchical cluster analysis, we categorize the countries into three distinct groups based on the combined metrics. Cluster 1 includes developing and transitional economies such as India, Indonesia, Brazil, Egypt, Russia, Turkey, and Vietnam, which exhibit moderate levels of CP and GDP alongside relatively low CO_2 per capita. Cluster 2, represented by China and Saudi Arabia, demonstrates high levels of CP and CO_2, coupled with moderate to high GDP, reflecting intensive industrial activity and rapid development. Cluster 3, which includes only the United States, is characterized by high GDP, moderate CP, and persistently high CO_2, indicating a stable developed economy that maintains its prosperity through infrastructure upkeep rather than rapid growth. The findings reveal how these three indicators interact across different stages of development and emphasize the importance of tailored sustainability strategies.

1. Introduction

Concrete is the most widely used construction material in the world, playing a vital role in shaping modern infrastructure [1, 2]. Its widespread use in projects such as highways, bridges, residential buildings, and industrial complexes is due to its strength, durability, versatility, and cost-effectiveness [3, 4]. A key factor in concrete's dominance is its ability to be molded into various shapes when wet and its ability to harden and gain strength over time, making it suitable for both structural and aesthetic purposes [5–7].

The primary materials used in concrete, including cement, water, sand, and gravel, are abundant and relatively inexpensive, contributing to its global accessibility [3, 8–10]. Cement is the essential binding component that reacts with water through hydration, transforming the mixture into a solid and durable mass [11]. Cement production is central to concrete manufacturing, and any shifts in its supply, demand, or production capacity have a direct impact on global construction trends. Without cement, concrete would not exist. Given its foundational role, cement is crucial to infrastructure development and economic progress [12–15].

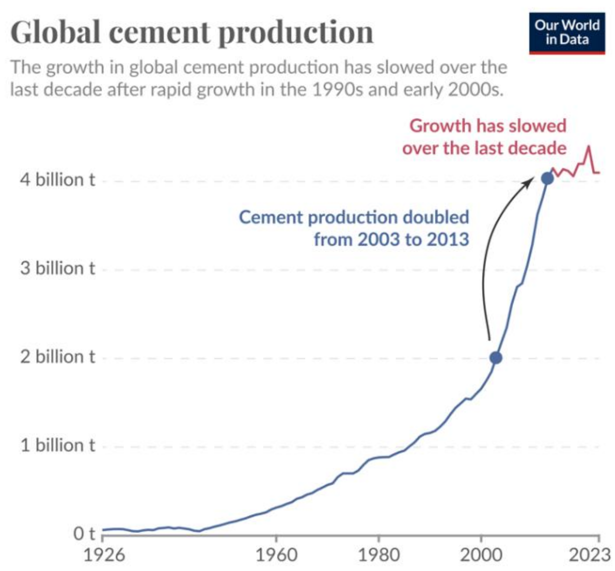

Figure 1. Global cement production. Source form OWID [16].

In recent decades, rapid urbanization and industrialization, particularly in developing countries, have led to a significant increase in concrete and cement production [17, 18]. Countries such as China, India, and the United States have emerged as leading producers, with China accounting for more than half of global cement output. As shown in Figure 1, global cement production surged during the 1980s, 1990s, and early 2000s. Output doubled from around 2 billion tonnes in 2003 to 4 billion tonnes by 2013. This growth was driven by infrastructure investments and rising housing demands, especially in fast-growing economies [16].

However, this upward trend has leveled off in the past decade, with global production stabilizing at approximately 4 billion tonnes annually. This plateau suggests possible market saturation in some regions, particularly in China, which appears to have reached its production limit.

According to the Global Cement Report, in 2021, concrete production was concentrated among the top 10 producing countries, which together accounted for nearly half of global output [19]. Figure 2 presents the top 10 countries with the highest concrete production in 2021, highlighting significant differences in production volumes. China led by a wide margin, producing an estimated 3.29 billion cubic meters, or 34 percent of global production. This dominance reflects China's extensive infrastructure projects and reliance on off-site mixing. The United States followed with 333 million cubic meters, representing 3.5 percent of global output, typical of a mature economy focused on maintaining existing infrastructure rather than expanding new developments. India ranked third with 219 million cubic meters, though its large population and continued use of on-site mixing reflect the characteristics of a developing construction sector. Indonesia produced 141 million cubic meters, with production expected to rise as the country develops its new national capital. Russia followed with 122 million cubic meters, driven by ongoing infrastructure and residential projects. Türkiye reported 119.7 million cubic meters, supported by a well-established ready-mix concrete industry. Egypt and Vietnam produced 102 million and 97.7 million cubic meters, respectively, both maintaining stable construction demand and benefiting from domestic cement supply. Brazil generated 87.3 million cubic meters, showing prior growth before signs of market cooling. Saudi Arabia rounded out the list with 63.5 million cubic meters, reflecting heavy investment in infrastructure as part of its Vision 2030 agenda [19].

To gain a clearer understanding of the topic, this study employs cluster analysis to classify the world's top ten concrete-producing countries. In addition to production volume, the analysis incorporates two other key variables: carbon dioxide (CO_2) emissions and economic growth, both of which are closely linked to patterns of concrete consumption.

The increase in global CO_2 emissions is one of the most serious environmental challenges facing the world today [20]. These emissions are a major driver of climate change, contributing to rising temperatures, shifting weather patterns, and long-term environmental degradation [21]. As CO_2 accumulates in the atmosphere, it traps heat and disrupts natural climate systems, leading to consequences such as sea level rise, increased frequency of extreme weather events, and threats to biodiversity [22–24]. The persistence of high emission levels reflects the heavy reliance on fossil fuels and carbon-intensive industrial activities in many countries [25].

Among these activities, the construction sector plays a particularly important role due to its reliance on concrete and cement [14, 17]. This focus on CO_2 emissions is necessary because the environmental impact of concrete production has become a growing global concern. The cement industry alone accounts for an estimated 7 to 8 percent of global CO_2 emissions [17, 26]. Cement, which is the key binding ingredient in concrete, generates large amounts of emissions primarily through the calcination of limestone, a process that releases carbon dioxide, as well as through the combustion of fossil fuels used in production [27, 28]. As global demand for concrete continues to rise, especially in rapidly developing countries, the need to reduce the environmental impact of construction becomes increasingly urgent [29, 30].

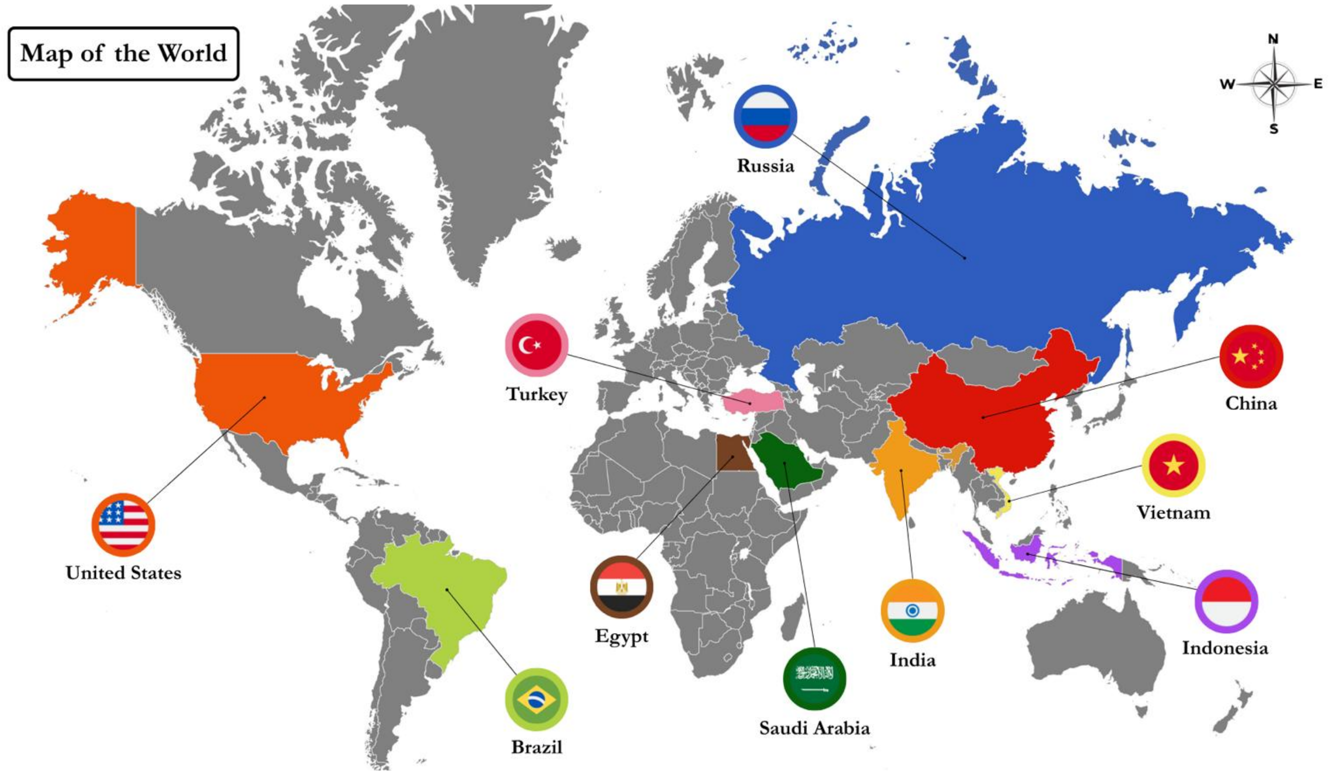

Figure 2. Top 10 countries with the highest concrete production in the world in 2021.

Responding to this challenge will require innovations in technology, the use of more sustainable materials, and the adoption of environmentally conscious construction practices [31].

Furthermore, shifting focus from CO_2 emissions to Gross Domestic Product (GDP), which serves as a proxy for economic growth, highlights its significant influence on infrastructure development and, consequently, concrete production [32]. As economies expand, both governments and private sectors typically invest in large-scale infrastructure projects such as roads, bridges, housing, and public facilities, all of which require substantial volumes of concrete [18, 33]. In developing countries, rapid economic growth is often accompanied by urbanization, population increases, and industrialization, leading to intensified construction activity to meet growing societal needs [34, 35]. This phase is characterized by the creation of essential infrastructure that supports further economic advancement. In contrast, mature economies with already established infrastructure tend to experience slower growth in new construction. Instead, economic development in these countries often shifts toward service industries and technology-driven sectors, which require less physical expansion. In such contexts, concrete use is more focused on the maintenance, renovation, and upgrading of existing structures rather than on new builds. As a result, the relationship between economic growth and material demand evolves over time, with higher-income countries typically experiencing a decline in material intensity per unit of economic output. Understanding this progression is key to identifying how infrastructure needs and environmental pressures align with different stages of national development.

Although cluster analysis has been widely used in sustainability, energy, and material-related studies, few have specifically explored the intersection of concrete production, CO_2 emissions, and economic performance at the international level. For instance, Kanzari et al. [36] clustered African countries based on energy and socio-economic indicators to examine the factors influencing their energy transition pathways. Noviandy et al. [37] applied cluster analysis to classify 34 Indonesian provinces using air quality index, electricity consumption, and GDP. Similarly, Idroes et al. [38] analyzed geothermal energy potential in Indonesia through provincial clustering. In the field of construction materials, Kılınçarslan et al. [39] employed both hierarchical and K-means clustering on normal-strength concrete mixtures, identifying three distinct clusters based on aggregate type and demonstrating the influence of material properties on concrete variability. While these studies highlight the versatility of cluster analysis across environmental, energy, and construction domains, none have applied this approach to examine global-level patterns among top concrete-producing countries. Addressing this gap, our study uses hierarchical clustering to group the top 10 producers based on per capita concrete production, CO_2 emissions, and GDP, offering new insights into the environmental and economic dimensions of global construction activity.

Hierarchical clustering was selected for this study due to its suitability for small datasets and its ability to reveal nested groupings without requiring the pre-specification of cluster numbers [40, 41]. Unlike methods such as k-means, which rely on random initialization and assume spherical clusters of equal variance, hierarchical clustering offers a deterministic process that produces a dendrogram, allowing for a more intuitive exploration of the data structure [42, 43]. This is particularly valuable in policy-oriented analyses, where understanding the relative similarities and dissimilarities between countries is as important as identifying the final groupings. The method also accommodates different linkage criteria and distance measures, providing flexibility in capturing complex relationships among the selected indicators: per capita concrete production, CO_2 emissions, and GDP. Overall, hierarchical clustering supports a transparent and interpretable classification process that aligns with the comparative goals of this cross-country analysis.

Prior to clustering, exploratory data analysis (EDA) was conducted to better understand the dataset's structure and distribution [44–46]. Descriptive statistics, including means, standard deviations, and range values, were computed for each variable, while a correlation matrix and various visualizations such as histograms with kernel density curves, scatter plots, and boxplots were used to explore relationships between variables and identify potential outliers [37, 47]. Following this, an agglomerative hierarchical clustering approach was implemented using Ward's linkage method and Euclidean distance as the dissimilarity metric. Ward's method, which minimizes the total within-cluster variance at each step, is particularly effective for producing compact and interpretable clusters. The clustering process was visualized through a dendrogram, which illustrated the nested structure of the groupings and guided the determination of an optimal number of clusters [48]. Although HCA does not test for causal relationships, it provides a robust framework for identifying natural groupings of countries with similar structural profiles [38, 43, 49].

This study employs hierarchical cluster analysis (HCA) to classify the top 10 concrete-producing countries based on three standardized indicators: per capita concrete production (CP), per capita CO_2 emissions (CO_2), and per capita gross domestic product (GDP), serving as a proxy for economic output. We use data from 2021, the most recent year with comprehensive and internationally comparable data available for all three indicators. By this time, most countries had resumed construction and industrial activities, making 2021 a representative period for assessing global patterns in concrete-related emissions and economic development. This provides a stable and informative snapshot for identifying how leading producers align or diverge in terms of environmental and economic performance. The resulting clusters reflect patterns associated with different stages of economic development, ranging from infrastructure-driven growth in emerging economies to lower material intensity and maintenance-focused construction in more advanced economies. This classification offers valuable insight into how construction activity, economic performance, and environmental pressures interact across varying national contexts.

2. Materials and Methods

2.1. Data

In this study, we use data from the year 2021 to examine patterns in concrete production, CO_2 emissions, and economic growth across the top producing countries. This year was selected because it provides the most recent and complete dataset available with internationally comparable statistics across all three indicators. By 2021, many economies had resumed infrastructure and industrial activity, making it a representative period for assessing current global trends in construction-driven emissions and development. Using 2021 data allows us to capture a more stable and informative snapshot of national performance, offering meaningful insights into how concrete production relates to environmental and economic outcomes in a post-disruption global context.

Concrete production data were sourced from Global Cement (GC), CO_2 emissions data were obtained from Our World in Data (OWID), and economic growth figures were drawn from the World Development Indicators (WDI). A summary of the dataset is presented in Table 1.

2.2. Methods

2.2.1 Exploratory Data Analysis

Exploratory Data Analysis (EDA) was conducted to develop an initial understanding of the dataset's structure, distribution, and inter-variable relationships [44, 45, 50]. The process began with calculating descriptive statistics, including the mean, standard deviation, minimum, and maximum for the three variables: CP, CO_2, and GDP. These metrics offered insights into the central tendency and variability of each variable [45].

Table 1. Synopsis of the variables.

Variable (symbol)	Description	Unit of Measurement	Data Source
Concrete Production (CP)	Total volume of concrete produced per individual, representing the intensity of infrastructure and construction activity on a per capita basis [29, 51].	Cubic meters per capita (m^3)	GC [19]
CO_2 Emissions (CO_2)	Amount of carbon dioxide released into the atmosphere per individual, serving as an indicator of environmental pressure from human and industrial activities [52].	Metric tons per capita	OWID [53]
Economic Growth (GDP)	Inflation-adjusted gross domestic product per individual, reflecting the average economic output and standard of living within a country [35].	Constant 2015 USD per capita	WDI [54]

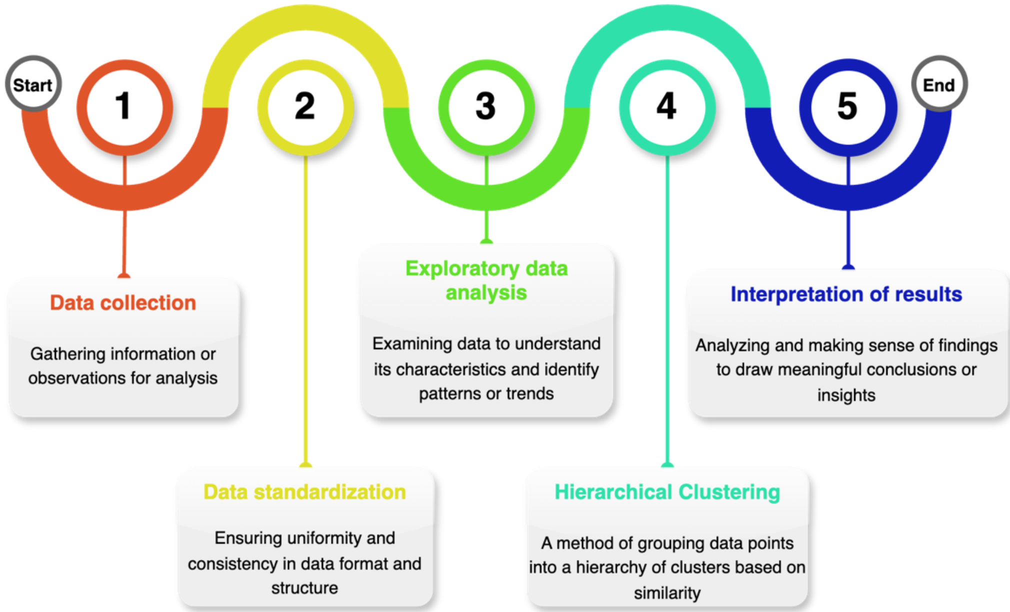

Figure 3. Workflow of the study.

To assess relationships between variables, a correlation matrix was created, highlighting the strength and direction of pairwise correlations. Visualizations complemented the statistical analysis: histograms with kernel density estimation curves illustrated the distributions, while scatter plots and boxplots were used to identify patterns and potential outliers [44].

2.2.2 Hierarchical Cluster Analysis

Hierarchical Cluster Analysis was employed to identify natural groupings within the dataset [49, 55]. An agglomerative approach was used, which begins with each observation as its own cluster and iteratively merges the most similar clusters until a single cluster remains. Specifically, Ward's linkage method was chosen, as it minimizes the total within-cluster variance at each step of the merging process [56].

Euclidean distance served as the dissimilarity metric to quantify the distance between observations [55–57]. This combination, agglomerative clustering with Ward's method and Euclidean distance is well-suited for capturing compact and spherical clusters. The resulting hierarchical structure was visualized using a dendrogram, which provided insight into the cluster formation process and helped determine the optimal number of clusters based on the height of the merges [58].

2.3. Workflow of the Study

The workflow of the study, illustrated in Figure 3, follows five structured stages. It starts with gathering relevant data, which is then standardized to maintain consistency and ensure reliable analysis. After standardization, an exploratory analysis is conducted to identify patterns and trends within the dataset. These insights inform the application of a hierarchical clustering algorithm, which groups similar data points into distinct clusters. The number of clusters is carefully adjusted to achieve optimal results. Finally, the clustering outcomes are interpreted to extract insights, support conclusions, and inform data-driven decision-making.

Table 2. Descriptive statistics of the data (percapita form).

Stat.	CP	CO_2	GDP
Count	10.0	10.0	10.0
Mean	1.06	0.000008	14350
Std. Dev.	0.70	0.000007	18272
Min.	0.15	0.000002	1965
25%	0.59	0.000002	3841
50%	0.95	0.000004	9590
75%	1.32	0.010890	12893
Max.	2.33	0.000023	62996.

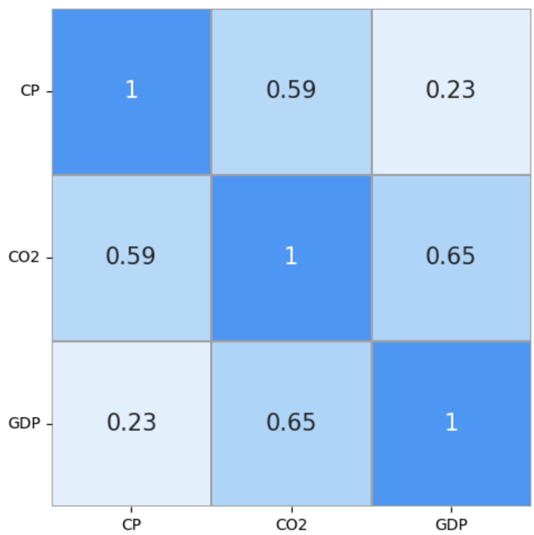

Figure 4. Correlation matrix.

3. Results and Discussion

3.1. Descriptive Statistics

The descriptive statistics of the dataset, as shown in Table 2, summarize the per capita values for concrete production (CP), CO_2 emissions, and GDP across ten countries. The average per capita concrete production is 1.06 metric units, with values ranging from a minimum of 0.15 to a maximum of 2.33, and a standard deviation of 0.70. Per capita CO_2 emissions average 0.000008, with a minimum of 0.000002, a maximum of 0.000023, and a standard deviation of 0.000007. GDP per capita has a mean of $14,350, ranging from $1,965 to $62,996, with a standard deviation of $18,272. These table reflect the variability in economic output, material use, and emissions among the countries studied.

3.2. EDA Results

The correlation matrix for the three variables is shown in Figure 4. The analysis reveals a moderate positive correlation between CP and CO_2 ($r = 0.59$), indicating that higher CP values are generally associated with increased CO_2 emissions. A slightly stronger correlation is observed between CO_2 and GDP ($r = 0.65$), suggesting that economic growth tends to be accompanied by rising emission levels. In contrast, the correlation between CP and GDP is relatively weak ($r = 0.23$), implying a less direct relationship between energy consumption and economic performance. These results highlight CO_2 emissions as a key connecting factor between CP and GDP, reinforcing the notion that economic activity often drives both energy demand and environmental impact.

Histograms overlaid with kernel density estimation curves for the variables CP, CO_2, and GDP are presented in Figure 5. These visualizations help illustrate the distribution of each variable. The CP distribution appears right-skewed, with most values concentrated below 1.5 and a few higher values extending the tail. CO_2 exhibits a similar right-skewed pattern, with the majority of values clustered near the lower end of the scale, indicating a few countries or observations with disproportionately high emissions. The GDP distribution is also heavily right-skewed, with most data points concentrated at the lower end and a long tail extending toward higher values, reflecting significant economic disparity among observations. These skewed distributions suggest potential benefits from data transformation if parametric modeling techniques are later applied.

Figure 6 shows scatter plots illustrating the pairwise relationships between CP, CO_2, and GDP. In the CP vs. CO_2 plot, a general upward trend is visible, supporting the moderate positive correlation previously observed, although the relationship is somewhat influenced by a few high-value points. The CP vs. GDP plot reveals a more dispersed pattern with weaker alignment, consistent with the relatively low correlation coefficient, suggesting that CP alone may not strongly predict GDP. The CO_2 vs. GDP plot displays a clearer positive trend, reinforcing the stronger correlation between these variables and indicating that higher economic output tends to align with increased emissions. Overall, these scatter plots visually affirm the findings of the correlation matrix and underscore the presence of a few influential data points that may affect statistical interpretations.

Box plots for the variables CP, CO_2, and GDP are presented in Figure 7. The CP and CO_2 variables both

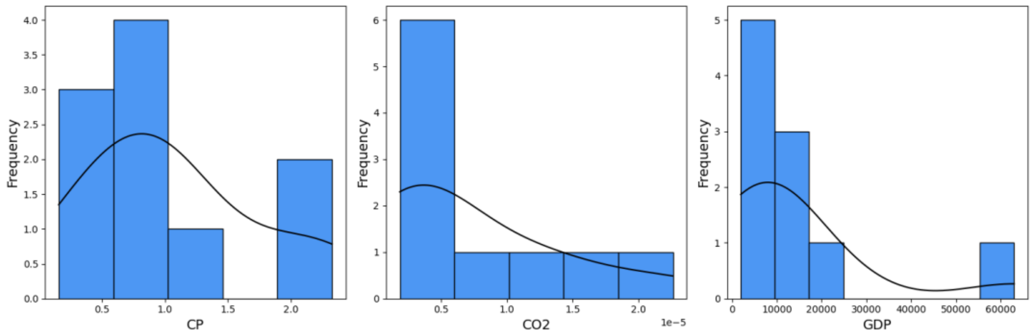

Figure 5. Histogram and kernel density estimation.

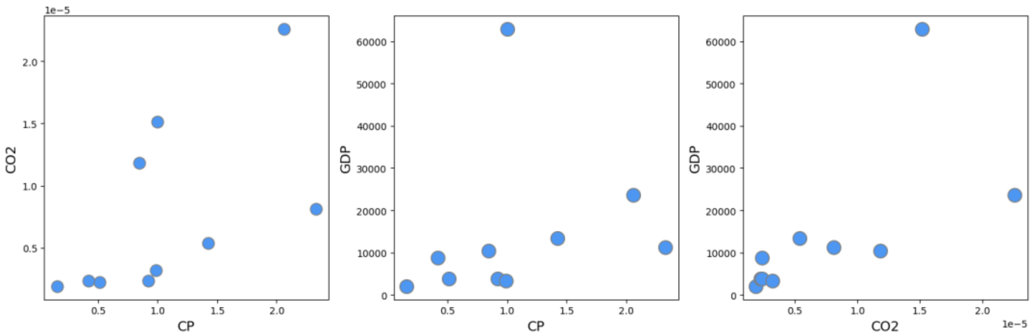

Figure 6. Scatter plots.

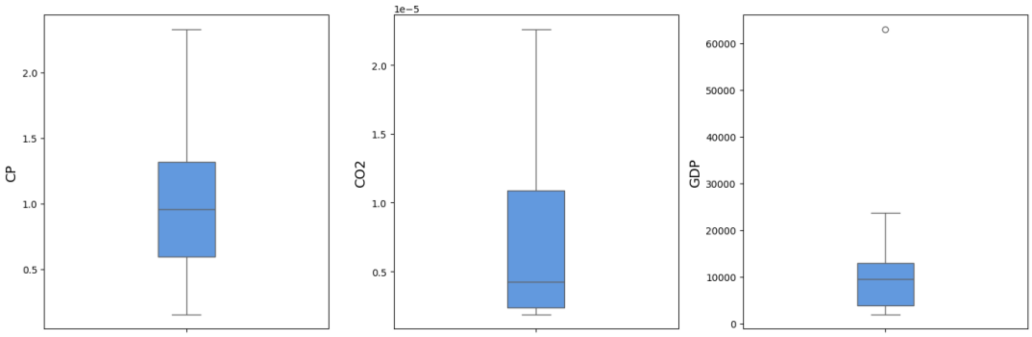

Figure 7. Box plots.

exhibit moderately symmetrical distributions without extreme outliers, although CO_2 shows a wider interquartile range, suggesting greater variability. In contrast, the GDP box plot reveals a strong right-skew with one visible outlier significantly above the upper whisker, indicating the presence of a high-income observation that deviates substantially from the rest of the data. The majority of GDP values are clustered in the lower range, consistent with the previously observed histogram and scatter plot patterns. These box plots reinforce earlier findings regarding distribution shape and outliers, especially for GDP, which may require normalization or transformation for further analysis.

3.3. Hierarchical Cluster Analysis Results

The dendrogram resulting from hierarchical clustering using Ward's method with Euclidean distance is shown in Figure 8. The diagram illustrates how countries are progressively merged based on their similarity across the variables CP, CO_2, and GDP. At a certain threshold, three distinct clusters emerge. The first cluster groups countries like India, Indonesia, Brazil, Russia, Türkiye, Egypt, and Vietnam, nations with relatively moderate values across the variables. The second cluster consists solely of the United States, which appears distinct due to its higher GDP and associated emissions. The third cluster includes China and Saudi Arabia, suggesting similar profiles likely driven by high CP and CO_2 values. The dendrogram clearly highlights structural groupings within the dataset, reflecting both economic scale and environmental impact.

To further validate and visualize the hierarchical clustering results, a two-dimensional plot using Principal

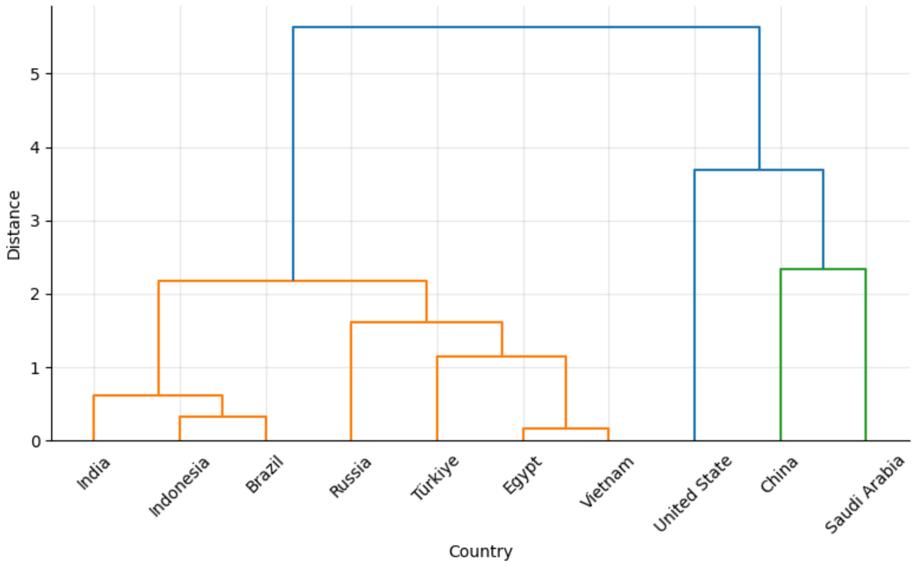

Figure 8. Dendrogram of hierarchical clustering.

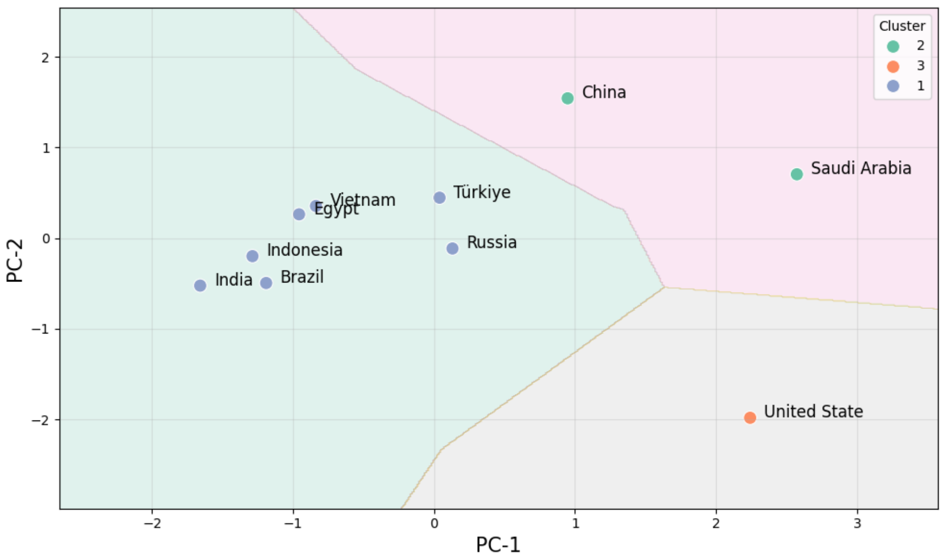

Figure 9. PCA plot showing countries clustered based on hierarchical clustering results.

Component Analysis (PCA) is presented in Figure 9. The plot reduces the dataset's dimensionality while preserving most of the variance, allowing for a clearer spatial representation of the country groupings. Each point represents a country, and the background regions indicate the boundaries of the identified clusters. The PCA plot confirms the three-cluster structure observed in the dendrogram. Cluster 1 includes countries like India, Indonesia, Brazil, Türkiye, and Egypt grouped closely in the lower-left quadrant, reflecting their similar economic and environmental profiles. Cluster 2 contains China and Saudi Arabia, which stands apart in the upper-right region, while the United States forms Cluster 3 in the bottom-right, indicating its distinct profile. This visualization reinforces the meaningful separation between clusters and supports the interpretation of divergent national profiles in terms of CP, CO_2, and GDP.

3.4. Discussion

The results of hierarchical cluster analysis are presented in Table 3 and visualized in Figure 10.

3.4.1. Cluster 1 (India, Indonesia, Brazil, Egypt, Russia, and Vietnam)

Cluster 1 comprises developing and transitional economies, including India, Indonesia, Brazil, Egypt, Russia, and Vietnam. These countries exhibit moderate to low levels of per capita concrete production, CO_2 emissions, and GDP, reflecting their ongoing industrialization and infrastructure development. Their modest CP values and relatively low emissions suggest

Table 3. The three-cluster groups resulting from hierarchical cluster analysis.

Cluster	Country
1	India, Indonesia, Brazil, Egypt, Russia, Turkey and Vietnam
2	China and Saudi Arabia
3	United States

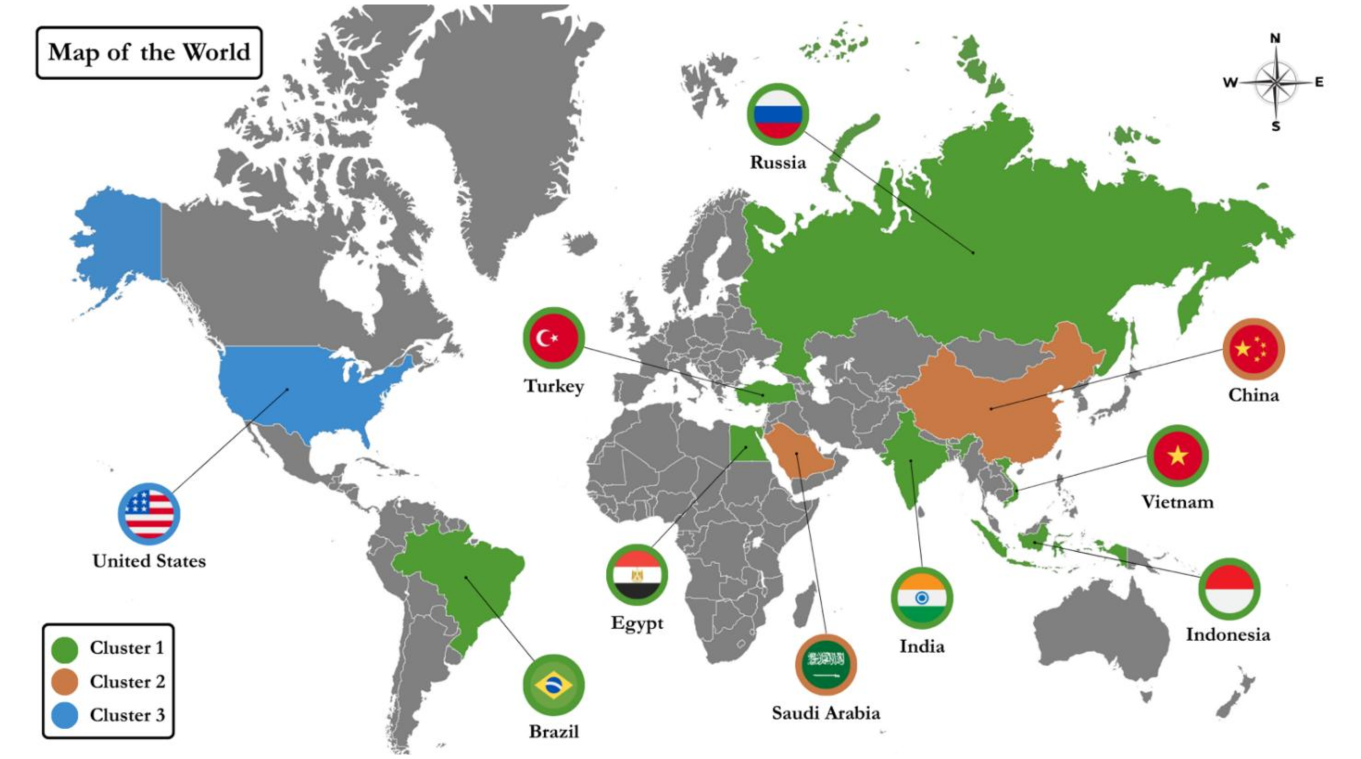

Figure 10. Thematic world map showing the geographic distribution of countries based on hierarchical clustering of per capita concrete production, CO_2 emissions, and GDP.

that construction activities are underway but have not yet reached the intensity observed in more advanced economies. While economic growth is steady, it still lags behind high-income nations, indicating potential for further development. The key challenge is to pursue this growth without repeating the carbon-intensive trajectories of earlier industrialized countries. This will require prioritizing sustainable construction, adopting energy-efficient technologies, and utilizing low-carbon building materials.

Their clustering highlights common structural challenges but also shared opportunities for proactive, climate-conscious development. With emissions still relatively low, these countries have a critical opportunity to integrate sustainability into infrastructure planning from the start. Unlike wealthier nations focused on retrofitting, they can leapfrog to cleaner systems by embracing green technologies early. Realizing this potential will depend on strong policy frameworks, international cooperation, and access to financing and innovation. How these countries develop in the coming years will significantly influence global progress toward low-carbon, inclusive growth.

3.4.2. Cluster 2 (China and Saudi Arabia)

Cluster 2 includes China and Saudi Arabia, both of which exhibit high levels of per capita concrete production and CO_2 emissions, along with moderate to high GDP per capita. Their grouping reflects a shared development trajectory marked by rapid urbanization and large-scale infrastructure investment. These activities have significantly driven resource consumption and environmental impact. Unlike countries in Cluster 1, which face financial and technological limitations, China and Saudi Arabia have the capacity to adopt cleaner construction methods and invest in green innovations. However, their continued reliance on emissions-intensive practices suggests that this potential is not yet fully realized.

As major players in the global economy and construction sector, both countries are at a critical juncture. They must decide whether to maintain current growth models or pivot toward more sustainable infrastructure strategies. The adoption of green concrete, carbon capture in cement production, and stronger regulatory frameworks could position them as leaders in climate-conscious development. Their decisions will have implications beyond their borders, shaping international standards and progress in low-carbon construction. The challenge lies in aligning long-term environmental objectives with short-term development goals, ensuring that economic advancement does not come at the cost of ecological stability.

3.4.3. Cluster 3 (United States)

Cluster 3 is represented solely by the United States, reflecting a mature, high-income economy with very high GDP per capita, high CO_2 emissions, and moderate levels of per capita concrete production. Unlike countries in the other clusters, the U.S. is focused not on rapid infrastructure expansion but on maintaining and modernizing aging systems. This indicates a stabilized development phase where economic prosperity is no longer directly tied to increasing material consumption, yet environmental impacts remain high due to ongoing reliance on fossil fuels and energy-intensive industries. As a global leader in innovation and finance, the United States is well-positioned to drive low-carbon infrastructure renewal through retrofitting, sustainable urban planning, and transportation upgrades. The main challenge lies not in resources, but in achieving the political commitment and structural reforms needed to enable such a transition.

The U.S.'s placement in a standalone cluster reinforces its distinct profile and the structural complexities faced by advanced economies. Its separation is not a methodological anomaly, but a meaningful reflection of a post-industrial nation grappling with persistent emissions from legacy infrastructure. The path to decarbonization requires more than technological solutions, it demands rethinking urban form, modernizing energy use in the built environment, and embedding climate goals into infrastructure policy. The U.S. exemplifies how decoupling economic growth from environmental degradation is possible, but only with sustained governance, strategic planning, and long-term political will.

4. Conclusions

This study used hierarchical cluster analysis to group the top 10 concrete-producing countries based on 2021 data for per capita concrete production, CO_2 emissions, and GDP. The analysis identified three distinct clusters, each representing different stages of development and environmental impact. Cluster 1, comprising India, Indonesia, Brazil, Egypt, Russia, and Vietnam, includes developing and transitional economies with moderate to low values across all indicators. These countries face the challenge of expanding infrastructure while avoiding the carbon-intensive development patterns of the past. Sustainable construction practices will be key to achieving growth without escalating emissions. Cluster 2 includes China and Saudi Arabia, which exhibit high levels of concrete use and CO_2 emissions. With strong financial and technological capacity, these countries have the potential to lead global efforts in green construction, but this will require a shift in priorities toward environmental responsibility. Cluster 3 is represented solely by the United States, a high-income nation with very high GDP per capita, moderate concrete use, and persistently high emissions. Its focus on infrastructure maintenance rather than expansion offers a unique opportunity to lead in low-carbon modernization, assuming sufficient political and institutional support.

This study is subject to several limitations. First, the analysis is limited to only ten countries, selected based on concrete production volume, which may exclude relevant emerging or mid-sized economies that are also undergoing significant construction-driven development. Second, the use of per capita indicators, while useful for standardization, may overlook absolute-scale impacts that are critical for global emissions accounting. Third, the study focuses on a single year (2021), which captures a snapshot in time but does not reflect temporal dynamics or trends. Future research could expand the sample size to include a broader set of countries and apply longitudinal clustering to track shifts over time. Integrating additional variables such as energy mix, construction sector policies, or technological innovation indicators could also provide a more comprehensive understanding of the drivers behind each cluster's environmental and economic behavior. Comparative case studies within clusters may further clarify how national contexts influence sustainable construction trajectories.

Author Contributions: Conceptualization, G.M.I. and I.S.H.; methodology, G.M.I. and I.S.H.; software, G.M.I. and I.S.H.; validation, G.M.I. and I.S.H.; formal analysis, G.M.I. and I.S.H.; investigation, G.M.I. and I.S.H.; resources, G.M.I. and I.S.H.; data curation, G.M.I. and I.S.H.; writing—original draft preparation, G.M.I. and I.S.H.; writing—review and editing, G.M.I.; visualization, G.M.I. and I.S.H.; supervision, I.S.H.; project administration, I.S.H.; All authors have read and agreed to the published version of the manuscript.

Funding: This study does not receive external funding.

Ethical Clearance: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The data used in this study is available upon request from the corresponding author.

Acknowledgments: The authors express their gratitude to their institutions and universities.

Conflicts of Interest: All the authors declare no conflicts of interest.

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