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LMDI and STIRPAT Analysis of Carbon Emissions in the Chengdu-Chongqing Region: An Industrial Advancement Perspective

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Abstract

This study investigates the driving factors of carbon emissions in the Chengdu-Chongqing urban agglomeration, a key economic region in western China, using the LMDI decomposition method and the STIRPAT model. The results reveal that energy structure optimization and energy consumption intensity reduction are the primary drivers of carbon emission reductions, highlighting the importance of clean energy adoption and improvements in energy efficiency. In contrast, economic growth and secondary industry expansion are the dominant contributors to carbon emission increases, reflecting the energy-intensive nature of industrial activities and the strong coupling between economic development and energy consumption. The tertiary industry exhibits a dual role, with its expansion reducing emissions in regions with higher levels of green transformation but increasing emissions in areas dominated by traditional service sectors. Industrial advancement (or industrial structural upgrading) emerges as a critical strategy for mitigating emissions, while population size has a relatively small direct impact, though urbanization amplifies emissions in high-density areas.

This study contributes methodologically by integrating the LMDI and STIRPAT approaches, providing a robust framework for analyzing carbon emission drivers. Empirically, it highlights significant regional heterogeneity in emission drivers across counties and districts, offering valuable insights for targeted low-carbon development strategies. The findings underscore the need to accelerate clean energy adoption, enhance energy efficiency, promote green industrial transformation, and optimize urbanization patterns. These results provide a scientific basis for formulating policies to achieve carbon neutrality and sustainable development in the Chengdu-Chongqing urban agglomeration.

Keywords: Carbon Emissions, LMDI and STIRPAT Models, Industrial Advancement, Chengdu-Chongqing Region

1. Introduction

1.1 Research Background

Global climate change has become one of the most pressing challenges of the 21st century, drawing significant attention from the international community. The increasing severity of climate-related impacts has underscored the urgency of implementing effective global strategies to mitigate greenhouse gas emissions, with reducing carbon dioxide (CO_2) emissions being a central focus for achieving sustainable development. As one of the largest carbon-emitting nations and the world's largest developing country, China plays a pivotal role in addressing global climate challenges.

China has made substantial commitments to global climate governance. In 2015, the country submitted its "Enhanced Actions on Climate Change - Intended Nationally Determined Contributions (INDCs)" to the United Nations Framework Convention on Climate Change (UNFCCC). This document outlined specific goals, including peaking carbon emissions by around 2030, reducing CO_2 emissions per unit of GDP by 60–65% relative to 2005 levels, increasing the share of non-fossil energy in primary energy consumption to 20%, and expanding forest stock volume by 4.5 billion cubic meters compared to 2005. These commitments reflect China's active participation in global sustainability efforts.

In 2020, China further reinforced its climate ambitions by announcing its "Dual Carbon" goals, which aim to achieve peak carbon emissions before 2030 and carbon neutrality by 2060. These targets provide a strategic framework for transitioning toward a low-carbon economy, emphasizing energy conservation, emission reduction, and ecological transformation. However, achieving these goals requires a nuanced understanding of the drivers of carbon emissions, particularly at the regional level, where economic and industrial characteristics vary significantly.

The Chengdu-Chongqing region, located in southwestern China, has emerged as a critical economic hub characterized by rapid development and urbanization. As one of the most advanced urban clusters in the country, the region plays a strategic role in national initiatives such as the Belt and Road Initiative and the Yangtze River Economic Belt. However, its rapid economic growth has been accompanied by rising carbon emissions, posing significant challenges to balancing environmental sustainability with economic development. This highlights the urgent need for effective carbon reduction policies tailored to the region's unique characteristics.

1.2 Significance of the Study

The problem of rising carbon emissions in the Chengdu-Chongqing region deserves new research due to its unique economic and industrial landscape. While industrial upgrading is widely recognized as a pathway for harmonizing economic growth and environmental sustainability, the mechanisms through which structural transformation impacts carbon emissions remain underexplored.

The Chengdu-Chongqing region serves as a crucial case study for understanding these dynamics. As a major economic engine in southwestern China, the region represents a microcosm of the challenges facing rapidly urbanizing and industrializing areas across the country. Rising emissions in this region highlight the tension between economic expansion and environmental sustainability, emphasizing the urgency of identifying effective strategies to reduce carbon intensity while maintaining economic growth.

This research addresses the need to explore the interaction between industrial structural advancement and carbon emissions, particularly in regions with diverse development levels. By examining the Chengdu-Chongqing region, the study aims to provide actionable insights for designing region-specific carbon reduction strategies that align with China’s broader sustainability goals.

1.3 Relevant Research

Industrial advancement, energy consumption, and technological progress are critical factors influencing carbon emissions, and their interactions have been extensively studied using various analytical frameworks. This section synthesizes the relevant literature on industrial structural upgrading, the application of the LMDI decomposition method, and the STIRPAT model, highlighting their contributions to understanding carbon emission dynamics and identifying gaps for further exploration.

Industrial structural upgrading is widely regarded as a key pathway for achieving economic growth while reducing environmental impacts. Theoretical studies suggest that transitioning from resource- and labor-intensive industries to capital- and technology-intensive sectors optimizes resource allocation, enhances energy efficiency, and promotes technological innovation, thereby reducing carbon emissions per unit of economic output (Zhou Lin et al., 1987). Empirical research has demonstrated that while industrialization initially increases energy consumption and emissions, the adoption of cleaner technologies and less energy-intensive industries can mitigate emissions over time. For instance, in the Chengdu-Chongqing region, the uneven pace of industrial transformation across sub-regions has resulted in varying emission patterns, underscoring the importance of understanding regional characteristics to devise effective low-carbon strategies (Niu Zhensheng et al., 2024).

The Logarithmic Mean Division Index (LMDI) decomposition method has been widely applied to analyze the driving factors of carbon emissions due to its adaptability and ability to quantify the contributions of various factors, such as energy structure, energy intensity, and economic activity. Studies in China have revealed that economic growth is the primary driver of carbon emissions, while improvements in energy intensity have played a critical role in mitigating emission increases (Guo Chaoxian et al., 2010). Globally, similar findings have been reported, with research in the United States highlighting the importance of structural improvements in energy generation and consumption for reducing emissions (Ferdinand et al., 2010). Despite its widespread application, the use of the LMDI method to analyze regional disparities in emission drivers remains limited. Applying this approach to the Chengdu-Chongqing region can provide valuable insights into the contributions of industrial, economic, and energy-related factors to carbon emissions.

The STIRPAT model (Stochastic Impacts by Regression on Population, Affluence, and Technology) extends the classical IPAT framework by incorporating stochastic variations and nonlinear relationships, making it a flexible tool for analyzing the drivers of carbon emissions. Studies using the STIRPAT model have highlighted the significant roles of population growth, economic affluence, and technological progress in driving emissions (Wang Xiaoting & Gao Jixi, 2009). Advanced versions of the model have incorporated geographic and temporal effects, enabling more detailed analyses of spatial variations in emission drivers (Zhang Huilin, 2019). Additionally, the STIRPAT model has been used to assess emission mitigation pathways, such as predicting carbon peaking timelines in regions like the Yangtze River Economic Belt (Tian Ze et al., 2021). However, integrating the STIRPAT model with complementary methods, such as the LMDI decomposition approach, remains underexplored. Combining these methods can yield more robust insights into the demographic, economic, and technological factors influencing carbon emissions in the Chengdu-Chongqing region.

1.4 Research Design

To address the issue of rising carbon emissions in the Chengdu-Chongqing region and explore the role of industrial structural advancement in mitigating these emissions, this study adopts a dual analytical framework that integrates the Logarithmic Mean Division Index (LMDI) decomposition method and the STIRPAT model (Stochastic Impacts by Regression on Population, Affluence, and Technology). This approach provides a comprehensive means of analyzing the factors driving carbon emissions and their interactions with industrial structural dynamics.

The LMDI decomposition method is employed to quantify the contributions of key factors—such as industrial structure, energy intensity, and economic activity—to changes in carbon emissions. This method is particularly well-suited for identifying the specific drivers of emissions and their relative importance over time. By applying the LMDI method to the Chengdu-Chongqing region, the study captures the dynamic interplay between economic growth, energy consumption, and carbon emissions, offering insights into how industrial transformation influences emission trends.

The STIRPAT model complements the LMDI analysis by examining the effects of demographic, technological, and consumption-related variables on carbon emissions. This model allows for the inclusion of stochastic variations and nonlinear relationships, making it effective for analyzing the complex interactions between population growth, economic affluence, and technological progress. By incorporating regional data, the STIRPAT model provides a broader perspective on how socioeconomic and technological factors shape emission patterns across the Chengdu-Chongqing region.

The integration of these two methods ensures a robust and multidimensional analysis of the drivers of carbon emissions. While the LMDI method focuses on decomposing and quantifying the contributions of specific factors, the STIRPAT model provides a more holistic understanding of the broader socioeconomic and technological influences. Together, these methods enable the study to evaluate the mechanisms through which industrial structural advancement impacts carbon emissions and to identify actionable insights for policy development.

This research design is tailored to address the unique characteristics of the Chengdu-Chongqing region, where rapid economic growth and industrial transformation have created significant challenges for balancing environmental sustainability with development goals. By combining theoretical perspectives with empirical analysis, the study provides a rigorous framework for understanding and addressing the drivers of carbon emissions in this critical economic hub.

2. Method

This study integrates multiple analytical frameworks and datasets to investigate the spatial and temporal dynamics of energy consumption and carbon emissions in the Chengdu-Chongqing region. The frameworks include the Logarithmic Mean Division Index (LMDI) decomposition method and the Stochastic Impacts by Regression on Population, Affluence, and Technology (STIRPAT) model. Furthermore, high-resolution energy consumption data were estimated using nighttime light data in combination with existing statistical yearbooks and carbon emission datasets.

2.1 Study Area: Chengdu-Chongqing Region

The Chengdu-Chongqing region, located in southwestern China, is characterized by its dual role as both a major economic center and a key national ecological barrier. Covering an area of approximately 185,000 square kilometers, the region includes Sichuan Province and Chongqing Municipality, with a combined population exceeding 100 million. Rapid industrialization and urbanization have driven significant economic growth in the region, solidifying its position as a crucial hub in China's Western Development Strategy and Belt and Road Initiative. However, this expansion has also led to high energy consumption and associated carbon emissions, posing challenges for sustainable development and environmental protection.

The Chengdu-Chongqing region exhibits marked spatial and economic heterogeneity. Chengdu and Chongqing serve as the urban cores driving regional development, while surrounding cities and counties have varied economic models, ranging from agriculture-based economies to industrial manufacturing hubs. These variations provide a unique opportunity to explore localized drivers of energy consumption and carbon emissions, which are critical for implementing effective carbon reduction policies tailored to the region's diverse conditions. This study focuses on the region's carbon emission dynamics with the aim of providing actionable insights to inform "Dual Carbon" objectives.

2.2 LMDI Decomposition Framework

Appropriate identification of research participants is critical to the science and practice of psychology, particularly for generalizing the findings, making comparisons across replications, and using the evidence in research syntheses and secondary data analyses. If humans participated in the study, report the eligibility and exclusion criteria, including any restrictions based on demographic characteristics.

The LMDI decomposition method, derived from the Kaya identity, is employed to analyze the driving forces behind energy-related carbon emissions in the Chengdu-Chongqing region. The Kaya identity expresses carbon emissions (C) as a product of four factors—energy consumption (E) per unit of carbon emissions, energy intensity (E/Y), economic intensity per capita (Y/P), and population (P)—as follows:

$$C = \frac{C}{E} \times \frac{E}{Y} \times \frac{Y}{P} \times P \tag{1}$$

To better quantify the contributions of specific socioeconomic and industrial factors to carbon emission changes, this framework is expanded into seven components: 1) energy structure intensity (ES, the carbon emissions per unit of energy consumption), 2) energy consumption intensity (EI, energy consumption per unit GDP), 3) tertiary industry share (A, the reciprocal of tertiary industry as a share of GDP), 4) industrial upgrading (B, the ratio of tertiary to secondary industry output), 5) secondary industry share (Γ, secondary industry as a share of GDP), 6) per capita GDP (PGDP), and 7) population size (P):

$$CO2 = \frac{CO2}{E} \times \frac{E}{GDP} \times \frac{GDP}{iii} \times \frac{iii}{ii} \times \frac{ii}{GDP} \times \frac{GDP}{POP} \times POP \tag{2}$$

The additive LMDI decomposition method is applied in this study, whereby changes in carbon emissions between the baseline year (2000) and year t are represented as:

$$\Delta C = \mathrm{C_t} - \mathrm{C_0} = \Delta ES + \Delta EI + \Delta \mathrm{A} + \Delta \mathrm{B} + \Delta \Gamma + \Delta PGDP + \Delta P \tag{3}$$

The contribution of each factor is calculated using logarithmic weights, ensuring a consistent and robust decomposition. This approach allows for a clear quantification of the distinct roles of energy structure, industrial composition, population growth, and economic development in driving changes in carbon emissions.

2.3 STIRPAT Model Framework

Describe the procedures for selecting participants, including (a) the sampling method, if a systematic sampling plan was used; (b) the percentage of the sample approached that participated; and (c) the number of participants who selected themselves into the sample. Describe the settings and locations in which the data were collected as well as any agreements and payments made to participants, agreements with the institutional review board, ethical standards met, and safety monitoring procedures.

To further analyze the relationship between socioeconomic factors and carbon emissions, the STIRPAT model is employed. The STIRPAT model, an extension of the IPAT framework, introduces stochastic flexibility and allows for nonlinear relationships between variables. It is particularly useful for regional and urban studies, where heterogeneity in population, affluence, and technology levels can significantly influence environmental impacts. The general form of the STIRPAT model is as follows:

$$I_i = \alpha \times P_i^{\theta} \times A_i^{\beta} \times T_i^{\delta} \times e_i \tag{4}$$

In this expression, I_i represents environmental impact (carbon emissions), P_i represents population size, $A_i$represents affluence (GDP per capita), and T_i refers to technology level or energy intensity, while α, θ, θ, and δ are parameters capturing the respective elasticities. e_i is a stochastic error term.

To align the STIRPAT model with the LMDI framework, this study extends the basic model by incorporating additional factors, including energy structure (ES), energy consumption intensity (EI), tertiary industry share (A), industrial upgrading (B), secondary industry share (Γ), per capita GDP (PGDP), and population size (P). The extended model is expressed as:

$$C_i = a \times ES_i^s \times EI_i^i \times A_i^{\alpha} \times B_i^{\beta} \times \Gamma_i^{\gamma} \times PGDP_i^g \times P_i^p \times e_i \tag{5}$$

Log-linearization is applied for regression analysis:

$$\ln(C_i) = \ln a + s\ln(ES_i) + i\ln(EI_i) + \alpha\ln(A_i) + \beta\ln(B_i) + \gamma\ln(\Gamma_i) + g\ln(PGDP_i) + p\ln(P_i) + \ln(e_i) \quad (6)$$

This extended STIRPAT model captures nuanced elasticities and regional variability, enabling a comprehensive investigation of the socio-economic drivers of carbon emissions in the Chengdu-Chongqing region.

2.4 Data Sources and Processing

This study integrates multiple datasets to analyze energy consumption and carbon emissions in the Chengdu-Chongqing region. The data sources include statistical yearbooks, nighttime light data, and gridded carbon emission datasets, which together provide a comprehensive foundation for the analysis.

Population, GDP, and industrial structure data at the provincial and municipal levels were obtained from the Chongqing Statistical Yearbook, Sichuan Statistical Yearbook, and the China Energy Statistical Yearbook. These datasets provide detailed information on socio-economic indicators, which are essential for the LMDI decomposition and STIRPAT model analyses. Nighttime light data, sourced from the Harvard Dataverse, were derived from the NPP-VIIRS dataset, which offers high-resolution annual composite images of nighttime light intensity. These data have been widely validated for their ability to reflect human activity and energy consumption. Carbon emission data were obtained from the ODIAC database, which provides gridded CO_2 emission data based on fossil fuel consumption and industrial processes. Together, these datasets enable a detailed investigation of the spatiotemporal dynamics of energy consumption and carbon emissions in the Chengdu-Chongqing region.

2.4.1 Energy Consumption Estimation Using Nighttime Light Data

Along with the description of subjects, give the mended size of the sample and number of individuals meant to be in each condition if separate conditions were used. State whether the achieved sample differed in known ways from the target population. Conclusions and interpretations should not go beyond what the sample would warrant.

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To estimate energy consumption at the municipal and county levels, this study employed a regression-based approach that combines nighttime light data with provincial energy consumption statistics. Previous studies have demonstrated that nighttime light intensity is strongly correlated with regional energy consumption, making it a reliable proxy for estimating energy use at finer spatial scales (Wu et al., 2014). Building on this foundation, this study developed a regression model to downscale provincial energy consumption data to the municipal level.

Three types of regression relationships—exponential, linear, and logarithmic—were tested to determine the optimal model. The results indicated that the no-intercept linear model provided the best fit. This finding is consistent with the conclusions of Wu et al. (2014), who also observed that nighttime light data exhibit a strong linear relationship with energy consumption at the municipal level. The no-intercept model was chosen for both theoretical and practical reasons. Theoretically, when nighttime light intensity (DN) is zero, energy consumption (E) should also be zero, as areas without light emissions are unlikely to consume energy. Including an intercept term would contradict this assumption and could introduce bias into the results. Practically, the inclusion of an intercept term was found to reduce the explanatory power of the model, further supporting the decision to adopt a no-intercept approach. The final model is expressed as:

$$E = kDN \quad (7)$$

where E represents total energy consumption, k is the regression coefficient, and DN is the sum of raster pixel values (digital numbers) from the nighttime light data. Using this model, regression analyses were conducted for the years 2000 to 2022. The regression coefficients (k) and goodness-of-fit values (R^2) for each year are presented in Table 1:

Table 1. Regression Results of NTL and Provincial Energy Consumption (2000–2022)

Year	k	R^2
2000	0.014367	0.885096
2001	0.014812	0.889596
2002	0.015051	0.905128
2003	0.015456	0.904927
2004	0.017507	0.919346
2005	0.020492	0.938136
2006	0.019539	0.930637
2007	0.020816	0.93114
2008	0.021119	0.926368
2009	0.023801	0.92552
2010	0.020922	0.93329
2011	0.021649	0.918082
2012	0.022025	0.930916
2013	0.020819	0.942159
2014	0.021087	0.936215
2015	0.021238	0.933707
2016	0.022177	0.92918
2017	0.016454	0.94757
2018	0.016525	0.94621
2019	0.015223	0.942477
2020	0.016649	0.942512
2021	0.015755	0.948487
2022	0.010425	0.937906

As shown in Table 1, the regression results demonstrate high accuracy across all years, with R^2 values consistently above 0.85. These results confirm the robustness of the no-intercept linear model and its suitability for estimating energy consumption at the municipal level. By integrating nighttime light data with provincial energy statistics, this approach addresses the limitations of traditional energy statistics, which often lack spatial resolution, and provides high-resolution energy consumption estimates for the Chengdu-Chongqing region.

The estimated energy consumption data serve as the foundation for the subsequent LMDI decomposition and STIRPAT model analyses. This high-resolution dataset not only supports the investigation of carbon emission drivers but also offers new insights into the spatiotemporal distribution of energy consumption in the region.

3. Results

3.1 Results of the LMDI Decomposition Analysis

The LMDI decomposition analysis provides a detailed quantitative assessment of the factors influencing carbon emissions in the Chengdu-Chongqing urban agglomeration from 2000 to 2022. The analysis decomposes carbon emission changes into seven driving factors: energy structure intensity (ΔES), energy consumption intensity (ΔEI), tertiary industry scale effect (ΔA), industrial upgrading effect (ΔB), secondary industry scale effect (ΔΓ), economic effect (ΔPGDP), and population scale effect (ΔP). Each factor in formula (3) is calculated as:

$$\Delta ES = W \ln \frac{ES^t}{ES^0},$$

$$\Delta EI = W \ln \frac{EI^t}{EI^0},$$

$$\Delta A = W \ln \frac{A^t}{A^0},$$

$$\Delta B = W \ln \frac{B^t}{B^0},$$

$$\Delta \Gamma = W \ln \frac{\Gamma^t}{\Gamma^0},$$

$\Delta PGDP = W \ln \frac{PGDP^t}{PGDP^0}$,

$\Delta P = W \ln \frac{P^t}{P^0}$,

where W is defined as:

$W = \frac{C^t - C^0}{\ln C^t - \ln C^0}$;

to facilitate interpretation, the contribution rates of each factor to carbon emission changes are calculated as:

$\theta_{ES} = \frac{\Delta ES}{\Delta C} \times 100\%$,

$\theta_{EI} = \frac{\Delta EI}{\Delta C} \times 100\%$,

$\theta_{A} = \frac{\Delta A}{\Delta C} \times 100\%$,

$\theta_{B} = \frac{\Delta B}{\Delta C} \times 100\%$,

$\theta_{\Gamma} = \frac{\Delta \Gamma}{\Delta C} \times 100\%$,

$\theta_{PGDP} = \frac{\Delta PGDP}{\Delta C} \times 100\%$,

$\theta_{P} = \frac{\Delta P}{\Delta C} \times 100\%$.

The results of the LMDI decomposition analysis are summarized in Table 1, which presents the contribution rates of each factor from 2001 to 2022. The findings reveal that energy structure optimization (ΔES), energy consumption intensity reduction (ΔEI), and industrial upgrading (ΔB) are the primary contributors to carbon emission reductions, while economic growth (ΔPGDP) and the expansion of the secondary industry (ΔΓ) are the main drivers of carbon emission increases. Population scale effects (ΔP) and tertiary industry scale effects (ΔA) have relatively minor impacts.

Table 2. LMDI Result

Year	ES	EI	A	B	Γ	PGDP	p
2001	-507%	205%	-64%	-26%	90%	387%	15%
2002	-55%	57%	-9%	-13%	22%	94%	3%
2003	-18%	33%	-3%	-18%	21%	89%	-4%
2004	-44%	37%	0%	-27%	27%	122%	-15%
2005	-34%	34%	4%	-32%	28%	109%	-10%
2006	-26%	22%	6%	-38%	33%	112%	-8%
2007	-23%	9%	8%	-44%	36%	120%	-7%
2008	-13%	-6%	9%	-46%	37%	125%	-6%
2009	-27%	-2%	11%	-50%	39%	133%	-5%
2010	-23%	-7%	14%	-54%	40%	135%	-5%
2011	-11%	-21%	15%	-56%	41%	137%	-5%
2012	-15%	-25%	16%	-58%	42%	144%	-4%
2013	-23%	-23%	16%	-59%	43%	149%	-4%
2014	-37%	-17%	16%	-60%	43%	157%	-3%
2015	-41%	-22%	16%	-60%	44%	166%	-2%
2016	-53%	-19%	15%	-59%	44%	174%	-2%
2017	-42%	-35%	14%	-58%	44%	177%	-1%

2018	-46%	-31%	13%	-55%	42%	177%	0%
2019	-42%	-36%	12%	-53%	41%	178%	0%
2020	-36%	-41%	12%	-52%	40%	176%	2%
2021	-34%	-44%	11%	-49%	38%	176%	2%
2022	-51%	-30%	12%	-51%	39%	179%	2%

3.1.1 Analysis of Factors Influencing Carbon Emissions

To better understand the driving forces behind carbon emissions in the Chengdu-Chongqing urban agglomeration, this section provides a detailed analysis of the contribution rates of various factors. By examining the roles of energy structure, energy consumption intensity, industrial and economic effects, and population dynamics, we can identify both the progress made and the challenges that remain in achieving carbon reduction goals. The following subsections discuss each factor in detail.

Energy structure (ΔES) optimization consistently exhibited a negative contribution to carbon emissions, with an average contribution rate of -36% over the study period. This finding highlights the significant role of clean energy adoption, such as hydropower and renewable energy, in mitigating emissions. Notably, in 2001, the contribution rate reached -507%, reflecting the initial phase of clean energy adoption. However, the effectiveness of energy structure optimization has fluctuated over time, with a decline in its impact during certain years, such as 2020 (-36%) and 2022 (-51%). These results suggest that while progress has been made, further efforts are needed to accelerate the transition to clean energy.

The contribution rate of energy consumption intensity (ΔEI) to carbon emissions demonstrates a clear temporal pattern. In the early years (before 2007), energy consumption intensity had a positive contribution, indicating that low energy efficiency exacerbated carbon emissions. For example, in 2001, the contribution rate was 205%. However, with advancements in energy-saving technologies and improvements in energy utilization efficiency, the contribution rate turned negative after 2007, reaching -44% in 2021. This shift underscores the growing importance of technological innovation and energy efficiency improvements in reducing emissions.

The tertiary industry scale effect (ΔA) generally exhibited a positive contribution to carbon emissions, with an average contribution rate of 12%. This finding suggests that while the tertiary industry is characterized by low-carbon attributes, its rapid expansion has increased energy demand and emissions. For instance, in 2010, the contribution rate was 14%, but it decreased to 12% in 2022. These results highlight the need for further green transformation of the tertiary industry to maximize its potential for emission reductions.

Industrial upgrading (ΔB) consistently contributed to emission reductions, with an average contribution rate of -51%. This result demonstrates the effectiveness of transitioning from energy-intensive industries to high-tech and service-oriented sectors in mitigating carbon emissions. The impact of industrial upgrading was particularly significant in the early years, such as 2010 (-54%) and 2015 (-60%), reflecting the initial stages of structural optimization. However, its contribution has slightly weakened in recent years, indicating that additional efforts are needed to sustain the momentum of industrial upgrading.

The secondary industry scale effect (ΔΓ) was a significant positive driver of carbon emissions, with an average contribution rate of 40%. The expansion of energy-intensive industries has led to increased energy consumption and emissions, particularly during the mid-study period (e.g., 2010, 2015). This finding underscores the ongoing reliance of the Chengdu-Chongqing urban agglomeration on industrial activities and highlights the need for green industrial transformation to curb emissions from this sector.

Economic growth (ΔPGDP) emerged as the largest positive contributor to carbon emissions, with an average contribution rate of 135%. This finding reflects the strong coupling between economic development and energy consumption in the region. For example, in 2022, the contribution rate of economic growth was 179%, highlighting the region's reliance on carbon-intensive activities to drive economic expansion. These results emphasize the importance of decoupling economic growth from carbon emissions through the development of low-carbon technologies and sustainable economic models.

The population scale effect (ΔP) had a relatively small positive contribution to carbon emissions, with an average contribution rate of 2%. Although population growth increases energy demand and emissions, its impact is moderated by urbanization and improved living standards. For instance, in 2022, the contribution rate was 2%, indicating that population growth has not been a major driver of carbon emissions in the Chengdu-Chongqing urban agglomeration.

3.1.2 Comparison with Existing Studies

The findings of this study align with those of Fu Junyue (2023), Chen Feng et al. (2022), and Liu Maohui et al. (2023) regarding the effects of energy structure, energy consumption, and economic growth. All studies highlight the suppressive effect of clean energy adoption on carbon emissions, the temporal variability of energy consumption intensity contributions, and the dominant role of economic growth as a driver of emissions. However, this study diverges from Liu Maohui et al. (2023) regarding the role of the tertiary industry. While Liu's study found a significant contribution of the tertiary industry to emission reductions in Tianjin, the results here suggest a limited impact in the Chengdu-Chongqing urban agglomeration. This discrepancy may be attributed to the relatively lower development level of the tertiary industry in the Chengdu-Chongqing region, indicating significant potential for further optimization.

3.2 Results of the STIRPAT Model Analysis

Analysis of data and the reporting of the results of those analyses are fundamental aspects of the conduct of research. Accurate, unbiased, complete, and insightful reporting of the analytic treatment of data (be it quantitative or qualitative) must be a component of all research reports. Researchers in the field of psychology use numerous approaches to the analysis of data, and no one approach is uniformly preferred as long as the method is appropriate to the research questions being asked and the nature of the data collected. The methods used must support their analytic burdens, including robustness to violations of the assumptions that underlie them, and they must provide clear, unequivocal insights into the data.

To further explore the driving factors of carbon emissions in the Chengdu-Chongqing urban agglomeration, this study employs the STIRPAT model, which decomposes carbon emissions into multiple influencing factors, including energy structure, energy consumption intensity, tertiary industry scale effect, industrial upgrading, secondary industry scale effect, per capita GDP, and population size. The STIRPAT model is expressed as follows:

$$\ln(C_i) = \ln a + s\ln(ES_i) + i\ln(EI_i) + \alpha\ln(A_i) + \beta\ln(B_i) + \gamma\ln(\Gamma_i) + g\ln(PGDP_i) + p\ln(P_i) + \ln(e_i) \quad (6)$$

The carbon emissions of region i, denoted as C_i, are influenced by several key factors. The share of clean energy in the energy mix, represented by ES_i, reflects the impact of energy structure optimization on carbon emissions, with the coefficient s quantifying this effect. Energy consumption intensity, denoted as EI_i, captures the role of energy efficiency improvements, with the coefficient i measuring its contribution to emission reductions. Additionally, the tertiary industry scale effect and industrial upgrading are represented by A_i and B_i, respectively, with their corresponding coefficients α and β indicating the extent to which these factors contribute to emissions. The secondary industry scale effect, represented by Γ_i, reflects the impact of industrial expansion on emissions, with the coefficient γ quantifying this relationship. Economic development, measured by per capita GDP ($PGDP_i$), is another critical factor, with the coefficient g capturing its influence on emissions. Finally, population size, represented by P_i, highlights the impact of population growth on emissions, with the coefficient p measuring this effect. The error term, denoted as $\ln(e_i)$, accounts for any unexplained variation in the model.

3.2.1 Model Estimation and Data Processing

To address multicollinearity among the explanatory variables, this study adopts the Partial Least Squares (PLS) regression method, which ensures the robustness and reliability of the model results. The data used in the analysis are derived from statistical yearbooks, energy consumption data, and carbon emission accounting results for each county and district within the Chengdu-Chongqing urban agglomeration.

The PLS regression results indicate that the model has a high explanatory power, with the R^2 values for most counties and districts exceeding 0.8. This suggests that the model can effectively explain the variation in carbon emissions across the region. The regression results for key factors are summarized in Table 3.

Table 3. STIRPAT Result

City	R^2	ES	EI	A	B	Γ	PGDP	P
Wanzhou District	0.92	-0.50	-0.13	37313.46	-143325.23	49324.53	3.50	-0.63
Fengdu County	0.78	0.13	0.00	36181.48	-45430.51	62689.48	0.79	-0.07
Leshan City	0.89	-0.43	-0.18	44581.27	-468987.76	632952.53	6.32	-0.98
Jiulongpo District	0.86	-0.14	-0.43	-1550153.47	-2225681.58	4570938.12	5.39	0.36
Yunyang County	0.86	0.06	0.01	-83976.81	-53868.64	51948.08	1.06	-0.13
Neijiang City	0.95	-0.12	-0.55	243162.20	-935186.60	1033552.46	6.85	-0.33
Beibei District	0.88	0.25	-0.11	50536.88	-201829.96	345000.81	1.08	0.27

Nanchong City	0.96	-0.69	-0.27	94825.42	-342846.75	911709.95	16.97	-0.13
Nan'an District	0.79	0.47	-0.07	41676.61	-364647.95	444217.91	1.70	0.15
Nanchuan District	0.98	-0.10	-0.09	-50195.05	-259134.77	229544.92	0.69	0.02
Hechuan District	0.95	-0.36	-1.65	-601015.70	-852443.97	1668862.16	9.08	-0.35
Dianjiang County	0.81	0.17	0.04	32815.92	-61867.31	68560.49	0.73	-0.27
Dadukou District	0.84	-0.08	-0.08	28053.28	-226474.06	-15149.67	0.96	0.24
Dazu District	0.96	-0.16	-0.15	27076.01	-135613.38	274571.46	1.10	-0.03
Yibin City	0.98	-0.50	0.16	475734.88	-1660692.37	2151094.44	18.80	-0.64
Banan District	0.73	-0.08	-0.02	26035.14	-320504.90	279757.88	0.85	0.07
Guang'an City	0.96	-0.49	-0.33	286081.77	-874535.92	950762.19	18.33	-0.20
Kaizhou District	0.96	-0.13	-0.09	64398.01	-183568.93	293553.68	3.40	-0.38
Deyang City	0.98	1.60	-0.60	521029.65	-1305078.33	1826491.94	8.41	-1.20
Zhong County	0.65	0.05	0.05	1189.79	-14754.97	28587.19	0.31	-0.23
Chengdu City	0.98	2.23	-4.09	5825152.99	-7029958.58	14215679.4	54.76	0.23
Liangping District	0.78	0.07	-0.02	48321.09	-42760.70	65868.64	0.79	-0.03
Yongchuan District	0.94	-0.54	-0.04	168479.96	-289100.67	706555.38	2.14	-0.17
Jiangbei District	0.93	0.35	-0.20	-207030.92	289086.83	-592899.66	1.95	0.39
Jiangjin District	0.96	-0.16	-2.22	345849.18	-745976.13	1611605.93	7.06	-1.17
Shapingba District	0.78	0.27	-0.01	2697.49	-272725.50	687317.89	4.31	0.49
Luzhou City	0.95	-0.39	-0.49	242844.45	-495257.48	844706.90	10.18	-0.40
Fuling District	0.91	-0.22	-0.27	78477.52	-366964.45	470569.38	1.62	-0.17
Yuzhong District	0.95	0.02	-0.40	-888056.73	5997.16	-524552.18	0.31	0.47
Yubei District	0.86	0.42	-0.26	15710.96	-448377.21	414577.31	23.32	0.38
Tongnan District	0.94	-0.02	-0.01	-5468.43	-27623.68	89551.21	0.57	-0.12
Bishan District	0.95	-0.26	-0.01	25841.49	-357253.69	348128.99	0.89	-0.07
Meishan City	0.95	-0.74	-0.43	19996.48	-216775.17	487631.65	8.14	-0.05
Qijiang District	0.95	-0.15	-1.56	2111554.87	-1363500.12	2561157.37	9.44	0.13
Mianyang City	0.93	-0.95	-1.64	807199.83	-1346504.84	2593245.92	22.69	-0.34
Zigong City	0.96	-0.51	-0.44	98582.43	-248615.39	332789.20	2.89	-0.08
Rongchang District	0.86	-0.03	-0.08	47879.81	-96579.38	163688.50	0.87	-0.26
Ziyang City	0.97	-0.13	0.15	110121.74	-180025.43	219206.29	0.75	-0.03
Dazhou City	0.97	-0.73	-0.06	63641.63	-714134.73	685085.82	19.64	-0.33
Suining City	0.94	0.22	0.14	227676.77	-465429.79	520386.01	2.85	-0.19
Tongliang District	0.96	-0.11	-0.01	33314.70	-111587.78	147611.02	0.47	-0.09
Changshou District	0.85	-0.06	-0.20	154584.77	-355029.77	530443.78	1.59	0.18
Ya'an City	0.96	0.08	0.23	150150.64	-773434.94	630130.21	3.29	-0.53
Qianjiang District	0.83	-0.04	0.00	7239.64	-63401.52	72300.91	0.86	-0.21

3.2.2 Analysis of Carbon Emission Drivers

In studies reporting the results of experimental manipulations or interventions, clarify whether the analysis was by intent-ta-treat. That is, were all participants assigned to conditions included in the data analysis regardless of whether they actually received the intervention, or were only participants who completed the intervention satisfactorily included? Give a rationale for the choice.

The analysis reveals significant regional variations in the factors influencing carbon emissions within the Chengdu-Chongqing urban agglomeration. Each factor demonstrates unique impacts across different regions, reflecting the diverse economic, industrial, and energy characteristics of the area.

Energy structure (s) optimization generally exhibits a negative impact on carbon emissions, indicating that an increased share of clean energy effectively reduces emissions. For example, in Chengdu and Deyang, the coefficients for energy structure are 2.23 and 1.60, respectively, highlighting the significant role of clean energy adoption in these regions. However, in some districts, such as Jiulongpo and Yibin, the coefficients are relatively small or even slightly positive, suggesting that the promotion of clean energy in these areas is insufficient. Overall, energy structure optimization is an important driver of emission reductions, but its effectiveness varies across regions.

Energy consumption intensity (i) has a predominantly negative impact on carbon emissions, reflecting the significant role of energy efficiency improvements in emission reductions. For instance, in Chengdu, the coefficient is -4.09, indicating that technological advancements and energy-saving measures have effectively reduced emissions. However, in certain regions, such as Yibin, the coefficient is slightly positive (0.16), suggesting that energy efficiency improvements have not yet been fully realized. These results highlight the need to further enhance energy efficiency, particularly in regions with high energy consumption intensity.

The tertiary industry scale effect (α) has a mixed impact on carbon emissions, with significant regional variations. In Chengdu, the coefficient is 5825152.99, indicating that the expansion of the tertiary industry contributes to emission reductions. In contrast, in Jiulongpo, the coefficient is -1550153.47, suggesting that the tertiary industry expansion has led to increased emissions, possibly due to insufficient green transformation. These findings underscore the dual role of the tertiary industry in carbon emissions and the need to promote its green development.

Industrial upgrading (β) consistently exhibits a negative impact on carbon emissions, demonstrating its critical role in emission reductions. For example, in Chengdu and Deyang, the coefficients are -7029958.58 and -1305078.33, respectively, indicating that the transition to high-tech and service-oriented industries has significantly reduced emissions. However, in some regions, such as Jiulongpo, the impact of industrial upgrading is less pronounced, highlighting the need to further optimize industrial structures in these areas.

The secondary industry scale effect (γ) is a major positive driver of carbon emissions, reflecting the high energy consumption associated with industrial activities. For instance, in Chengdu, the coefficient is 14215679.40, indicating that the expansion of the secondary industry is a significant contributor to emissions. These results emphasize the importance of promoting green industrial transformation to reduce emissions from this sector.

Economic growth (g) is the largest positive driver of carbon emissions across all regions, with coefficients ranging from 5.39 in Jiulongpo to 54.76 in Chengdu. These results highlight the strong coupling between economic development and carbon emissions in the Chengdu-Chongqing urban agglomeration. Decoupling economic growth from carbon emissions remains a critical challenge for the region.

The impact of population size (p) on carbon emissions is relatively small and varies across regions. For example, in Chengdu, the coefficient is 0.23, indicating a modest positive impact, while in Deyang, the coefficient is -1.20, suggesting a slight negative impact. These findings suggest that population growth has a limited direct impact on emissions, but its influence may increase with urbanization.

3.2.3 Comparison with Existing Studies

The findings of this study are consistent with those of Wang Juntao (2023) in terms of the positive impact of economic growth and the negative impact of energy consumption intensity on carbon emissions. However, this study diverges in the analysis of population size, where most counties exhibit a negative or negligible impact, while Wang's study found a positive impact at the provincial level. This discrepancy may be attributed to differences in spatial scales and population aggregation, as regions with higher population densities (e.g., Chengdu) tend to have a more pronounced impact on emissions.

3.3 Integrated Discussion of Findings

The results of the LMDI decomposition analysis and the STIRPAT model provide complementary insights into the driving factors of carbon emissions in the Chengdu-Chongqing urban agglomeration. By integrating the findings from both methods, several key patterns and implications emerge.

Energy structure optimization and energy consumption intensity reduction are highlighted as critical drivers of emission reductions. The LMDI results show that energy structure consistently contributes negatively to emissions, with an average contribution rate of -36%, while energy consumption intensity also exhibits a significant negative impact, particularly in recent years. Similarly, the STIRPAT model confirms that clean energy adoption and improvements in energy efficiency are effective in reducing emissions, as evidenced by the negative coefficients for energy structure and energy intensity in most regions. However, regional disparities, such as in Yibin and Jiulongpo, suggest that further efforts are needed to enhance clean energy adoption and energy efficiency in these areas.

Industrial and economic factors play contrasting roles in carbon emissions. The expansion of the secondary industry and economic growth are identified as the primary drivers of emission increases in the LMDI analysis, with average contribution rates of 40% and 135%, respectively. These findings are corroborated by the STIRPAT model, where the coefficients for secondary industry scale and economic growth are predominantly positive and significant. For example, in Chengdu and Mianyang, the secondary industry scale effect is a major contributor to emissions, reflecting the energy-intensive nature of industrial activities in these regions. This underscores the urgent need for green industrial transformation to decouple industrial growth from carbon emissions.

The tertiary industry demonstrates a dual role in carbon emissions, with mixed impacts across regions. The LMDI results indicate a modest positive contribution to emissions, while the STIRPAT model reveals significant regional variations. In regions such as Chengdu, the tertiary industry contributes to emission reductions due to its higher degree of green transformation, whereas in other areas, such as Jiulongpo, tertiary industry expansion has led to increased emissions. These findings highlight the need to promote green development of the tertiary industry across the region.

Industrial upgrading consistently contributes to emission reductions, as shown in both analyses. The LMDI results indicate an average contribution rate of -51%, while the STIRPAT model further confirms the importance of transitioning to high-tech and service-oriented industries. For instance, in Chengdu and Deyang, industrial upgrading has significantly reduced emissions. However, its limited impact in some regions, such as Jiulongpo, suggests that further efforts are needed to optimize industrial structures.

Population scale has a relatively small impact on carbon emissions. The LMDI analysis shows an average contribution rate of 2%, while the STIRPAT model indicates coefficients close to zero or slightly negative in most regions. However, in high-density areas such as Chengdu, population growth and urbanization amplify emissions, highlighting the importance of optimizing urbanization patterns and promoting low-carbon urban development.

Significant regional disparities in carbon emission drivers are evident in both analyses. For example, Chengdu and Mianyang exhibit strong positive contributions from economic growth and secondary industry expansion, while regions such as Jiulongpo and Yibin show weaker impacts from energy structure optimization and industrial upgrading. These differences emphasize the need for tailored low-carbon development strategies that consider regional characteristics and priorities.

In summary, the integrated findings underscore the importance of energy structure optimization, energy efficiency improvements, industrial upgrading, and green transformation of the tertiary industry in reducing carbon emissions. At the same time, the challenges posed by economic growth, secondary industry expansion, and urbanization require targeted interventions to achieve sustainable development in the Chengdu-Chongqing urban agglomeration.

4. Discussion

4.1 Summary

This study examines the driving factors of carbon emissions in the Chengdu-Chongqing urban agglomeration using the LMDI decomposition method and the STIRPAT model. The results reveal that energy structure optimization and energy consumption intensity reduction are the most significant drivers of emission reductions, with clean energy adoption and energy efficiency improvements playing a critical role. In contrast, economic growth and secondary industry expansion are the primary contributors to emission increases, reflecting the energy-intensive nature of industrial activities and the strong coupling between economic development and carbon emissions. The tertiary industry shows a dual role, reducing emissions in regions with advanced green transformation, such as Chengdu, but increasing emissions in areas dominated by traditional service sectors, such as Jiulongpo. Regional disparities in the effectiveness of these factors highlight the need for tailored low-carbon strategies.

To achieve low-carbon development in the Chengdu-Chongqing urban agglomeration, policymakers should focus on accelerating clean energy adoption and improving energy efficiency, particularly in regions like Yibin and Jiulongpo where progress is limited. Promoting green industrial transformation, especially in industrial hubs such as Chengdu and Mianyang, is essential to decouple economic growth and secondary industry expansion from carbon emissions. Efforts should also target the green development of the tertiary industry by encouraging low-carbon practices in traditional service sectors. Additionally, optimizing urbanization patterns through compact city planning and improved public transportation can help mitigate emissions in high-density areas. Tailored strategies and strengthened regional coordination are crucial to addressing disparities and ensuring balanced low-carbon development across the region.

4.2 Contributions and Limitations

This study contributes to the understanding of carbon emissions and low-carbon development by integrating the LMDI decomposition method and the STIRPAT model, offering a comprehensive analysis of the driving factors of carbon emissions from both additive and multiplicative perspectives. It provides detailed, region-specific insights into the Chengdu-Chongqing urban agglomeration, highlighting significant regional heterogeneity and offering practical guidance for policymakers to develop targeted low-carbon strategies.

However, the study has several limitations. It relies on statistical yearbooks and carbon accounting data, which may lack precision and timeliness, and provides a static analysis, without capturing temporal changes in emission drivers. Future research could address these gaps by incorporating real-time data, dynamic models, and sector-specific analyses, while also exploring the role of individual behaviors and social factors in carbon emissions.

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