International Journal of
Geo-Information

MDPI

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Annual and Seasonal Dynamics of CO_2 Emissions in Major Cities of China (2019–2022)

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Abstract: To control the growth of CO_2 emissions and achieve the goal of carbon peaking, this study carried out a detailed spatio-temporal analysis of carbon emissions in major cities of China on a city-wide and seasonal scale, used carbon emissions as an indicator to explore the impact of COVID-19 on human activities, and thereby studied the urban resilience of different cities. Our research re-vealed that (i) the seasonal patterns of CO2 emissions in major cities of China could be divided into four types: Long High, Summer High, Winter High, and Fluctuations, which was highly related to the power and industrial sectors. (ii) The annual trends, which were strongly affected by the pan-demic, could be divided into four types: Little Impact, First Impact, Second Impact, and Both Impact. (iii) The recovery speed of CO2 emissions reflected urban resilience. Cities with higher levels of de-velopment had a stronger resistance to the pandemic, but a slower recovery speed. Studying the changes in CO2 emissions and their causes can help to make timely policy adjustments during the economic recovery period after the end of the pandemic, provide more references to urban resilience construction, and provide experience for future responses to large-scale emergencies.

Keywords: CO_2 emissions; time series decomposition; annual dynamics; seasonal dynamics; urban resilience; social emergencies (COVID-19)

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Citation: Zhao, Y.; Feng, Y.; Du, M.; Fraedrich, K. Annual and Seasonal Dynamics of CO_2 Emissions in Major Cities of China (2019–2022). *ISPRS Int. J. Geo-Inf.* **2024**, *13*, 181. https://doi.org/10.3390/ijgi13060181

Academic Editors: Jingzhe Wang, Yangyi Wu, Yinghui Zhang, Ivan Lizaga, Zipeng Zhang and Wolfgang Kainz

Received: 20 March 2024
Revised: 23 May 2024
Accepted: 27 May 2024
Published: 29 May 2024

1. Introduction

Global warming is broadly agreed to be mainly caused by human activity, and is currently an important issue facing sustainable human development [1]. Evidence shows that the heat-trapping gases released by burning fossil fuels, referred to as greenhouse gases, are responsible for causing global warming [2], which is related to multiple sectors such as power, industry, transportation, and residential consumption [3]. Thus, greenhouse gas emissions (GHG), such as carbon dioxide (CO_2), are critical for understanding and addressing the climate crisis [4]. In this context, many countries have set clear targets to reduce their CO_2 emissions in order to face the challenges of climate change. China promises to peak carbon by 2030 and achieve carbon neutrality by 2060 [5]. Correspondingly, despite facing many difficulties, China is taking a series of measures to achieve this goal, making a positive contribution to promoting global governance in response to climate change. These measures include developing and widely promoting low-carbon technologies; developing a new energy industry to promote energy transformation; and implementing comprehensive low-carbon policies and laws [6–8]. So far, CO_2 emissions per unit of energy consumption, energy consumption per unit of gross domestic product (GDP), and CO_2 emissions per unit of GDP all present downward trends in China, but China is yet to reach its peak in CO_2 emissions per capita, which is the key factor of CO_2 emission measurements [9]. Therefore, accurately characterizing the dynamics of CO_2 emissions (before the carbon peak is attained as a turning point) is critical for China to formulate and implement corresponding policies in order to fulfill its commitment of reducing CO_2 emissions.

At present, China's total CO_2 emissions rank first in the world, but their growth rate is constantly decreasing and has been effectively controlled. In addition, China's CO_2 emissions are unevenly distributed in space, with significant differences among different sectors [10]. According to studies in recent years, there was an initial dip in CO_2 emissions due to the COVID-19 pandemic, followed by varying degrees of rebounds [11]. Studying the dynamics of CO_2 emissions can observe the impact of the COVID-19 pandemic on human socio-economic activities and reveal patterns of urban resilience occurring during the pandemic period (2019–2022). Urban resilience is the capacity of a city to rebound from major and minor disasters [12], which shows whether a city can cope with risks or events and is an important goal in SDG 11 (making cities and human settlements inclusive, safe, resilient, and sustainable). According to the recovery of CO_2 emissions, we can adjust the relevant policies in the post-pandemic period in a timely manner and study the laws of urban resilience through the recovery rate of CO_2 emissions. This can also provide experience for dealing with disturbances in the future and improve the adaptability of cities to risks [13].

As the world's current major economic power and emitter of CO_2, there are abundant CO_2 emissions studies focusing on China [14]. However, due to the lack of high-spatiotemporal-accuracy CO_2 emission data, studies of CO_2 dynamics are mostly analyzed on an annual basis [15], lacking a high temporal accuracy. Moreover, most studies choose the whole country or certain provinces as their research object, but less focus on the urban scale [16], which lacks fine-scale conclusions for the guidance of emission reduction. Furthermore, the contribution of each CO_2 emission sector is worth considering, but the specific classification of various CO_2 emission sources is needed now [17]. According to relevant research, the influencing factors of CO_2 emissions are mainly divided into three categories: technology, scale, and structure, which are also the main ideas involved in implementing CO_2 reduction policies [18–20]. In recent years, some studies have noticed the impact of seasonal changes on carbon emissions [21], which provides new possible methods for emission reduction, but there is a lack of more extensive and detailed research. The development of CO_2 emission datasets brings new possibilities for finer-scale studies. Fine temporal–spatial CO_2 emission management becomes the inevitable trend, keeping the goals of carbon peak and carbon neutrality. More precision in terms of the accuracy of timing allows us to grasp the dynamic changes occurring due to the impact of major social events on human activities in a more timely and accurate manner. The precise spatial scale allows us to focus on typical research areas. In addition, detailed sources of CO_2 emissions make it easier for us to study the causes of CO_2 emission changes.

In order to summarize the patterns of CO_2 emission changes occurring during the pandemic period and provide new ideas for the implementation of future emission reduction policies, this study separated the seasonal and annual trends of CO_2 emissions by time series decomposition. Taking COVID-19 from 2019 to 2022 as an example, we analyzed the relationship between the impact of major social events and changes in CO_2 emissions, as well as the relationship between seasons and CO_2 emissions during this period, which is lacking in previous relevant studies. This study fills the gap in related research by conducting more refined studies (urban and monthly scales), comparing and analyzing CO_2 emissions from different sectors and cities, and studying the seasonal trends of CO_2 emissions. In addition, we studied the recovery rates of CO_2 emissions in different cities after COVID-19 (2019.1–2022.12) and analyzed their patterns.

2. Data and Methods

This study contains three major steps (Figure 1): (1) Data collection and the preprocession of CO_2 emissions and relevant variables. (2) Time series decomposition of CO_2 emission trends into annual and seasonal patterns, and then an analysis of both patterns by types and causes. (3) Evaluation of urban resilience during the COVID-19 pandemic based on the annual patterns of CO_2 emissions. The following sub-sections detail the data and main methods.

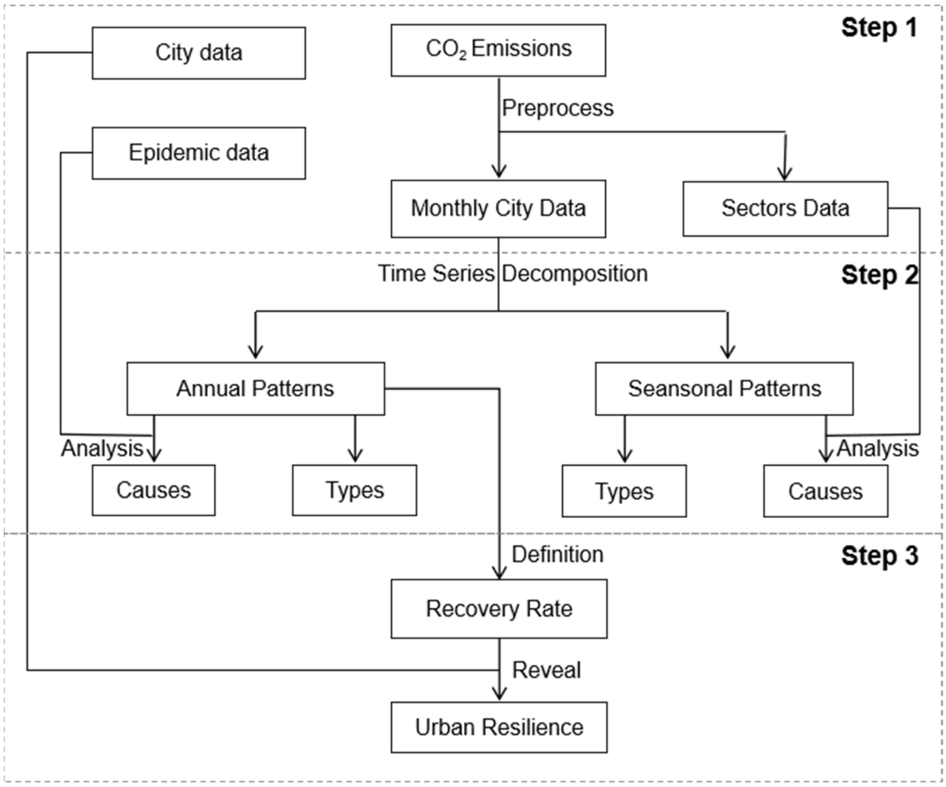

Figure 1. The process in this study.

2.1. Raw Data Collection and Pre-Procession

Thirty-one major cities in China with intensive human activities were selected as the research areas to be analyzed, which have high carbon footprints and become the main locations for controlling CO_2 emissions. The research period lasted from January 2019 to December 2022, which includes the period from the outbreak to the end of the pandemic.

The raw data for this article came from Global gRidded dAily CO_2 Emissions Dataset (GRACED) [22–25], which provides near-real-time global gridded daily CO_2 emissions data from fossil fuel and cement production with a global spatial resolution of 0.1° by 0.1° and a temporal resolution of 1 day, and the measure in kilograms of CO_2 per hour (kgC/h). The data satisfy the demand for high-quality, high-precision, and near-real-time data on CO_2 emissions to support global emissions monitoring across various spatial scales.

We calculated the monthly CO_2 emission data for provincial capital cities in China. For each city, we obtained the total CO_2 emission data, as well as specific CO_2 emission data for each of the four sectors: Power, Industry, Residential, and Ground Transportation. GRACED also provided CO_2 emission data from three sectors: International Aviation, International Shipping, and Domestic Aviation, which were not studied in detail in this work, due to their small contributions and their very low or even zero CO_2 emissions. A data summary is provided in Table 1 to provide readers with a general understanding of the data.

Table 1. Summary of total CO_2 emissions data for the studied cities (unit: kgC/h).

Year	2019	2020	2021	2022
Max	13,005,368	12,957,019	13,696,092	12,686,413
Min	71,630	73,133	77,953	71,983
Mean	2,255,063	2,333,183	2,470,084	2,413,396
STDEV	2,297,401	2,331,765	2,438,838	2,279,562

Other relevant data, such as population and gross domestic product (GDP). etc., were obtained from the China Statistical Yearbook to serve as a reference for exploring the causes of CO_2 emission changes in the subsequent experiments [26].

2.2. Time Series Decomposition of CO_2 Emissions Trend

A time series Y_t with seasonal factors can be decomposed into the following three components: (1) a trend component (T_t) representing long-term changes; (2) a seasonal component (S_t) which reveals periodic changes over time; and (3) an error component (E_t) as a mutation caused by errors [27]. Thus, Y_t can be decomposed by an additive model.

$$Y_t = T_t + S_t + E_t \tag{1}$$

This seasonal trend decomposition based on LOESS (STL) is a time series data analysis method, which makes the curve smoother and employs locally weighted regression models to decompose a time series into trend, seasonal, and remaining contributions. STL consists of an inner and an outer loop; the inner loop calculates the trend and seasonal components and the outer loop provides the robustness weights for the next inner loop. The process of STL is shown in Figure 2.

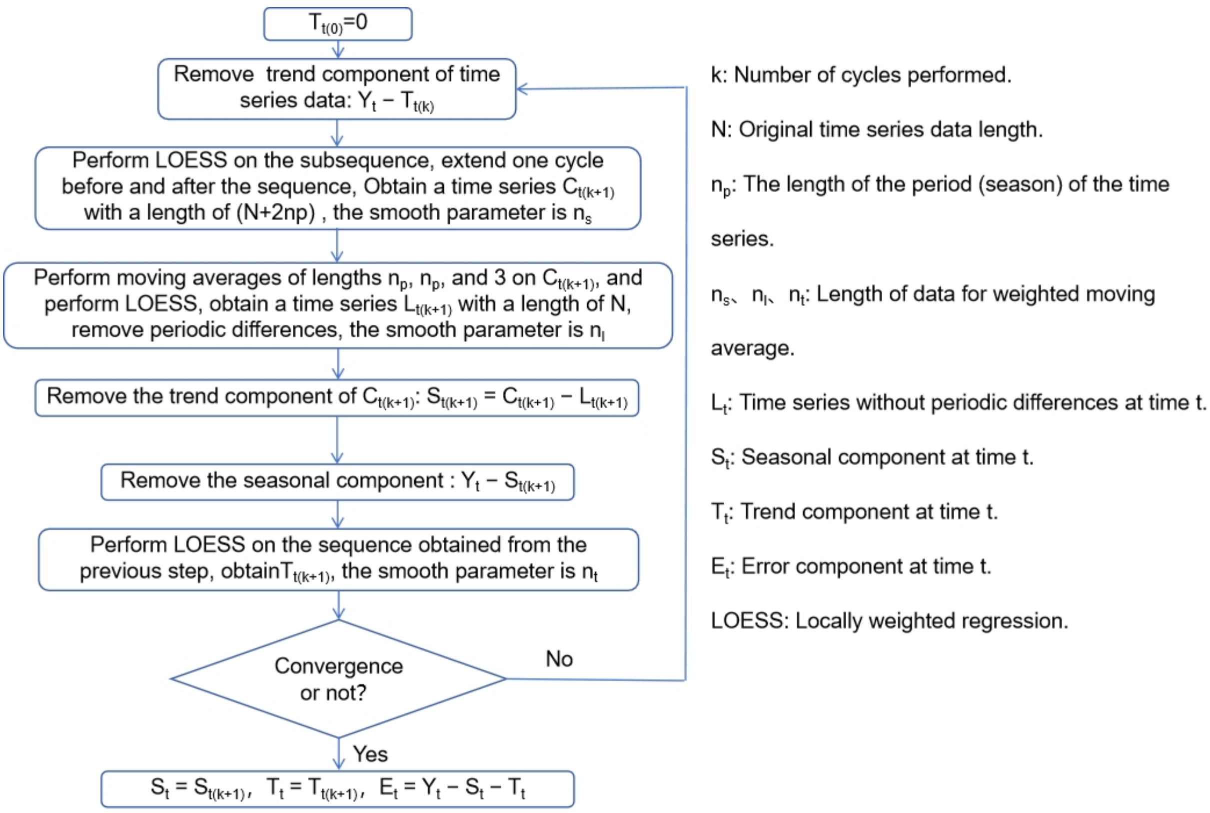

Figure 2. The process of STL.

STL is a simple and easy-to-use method for obtaining robust trend and seasonal components, and has a better applicability for complex long-term time series. The advantages of STL is that it can identify seasonal components changing over time, it is responsive to nonlinear trends, and it is robust in the presence of outliers [28]. The STL procedure was developed and implemented in the R software (version 4.2.1), and decomposed the CO_2 emissions into seasonal and annual patterns. Further, we analyzed the types and causes of the seasonal and annual patterns from the perspectives of CO_2 emission sectors and urban development, respectively.

2.3. Evaluation of Urban Resilience

A city is a huge artificial ecosystem in the sense that we can deal with the city problem as an ecological entity. We found that when cities were facing the impact of the pandemic, their human activity levels reflected in CO_2 emissions exhibited different fluctuations, which were related to their different levels of development. In this study, we used the per capita GDP of 2019 to represent the development levels of different cities during normal periods. Some cities, which revealed strong resistance to external influences and quickly recovered after being affected, we identified as urban resilient. Due to the fact that CO_2 emissions levels can reflect the strength of human activity levels, the recovery rate of CO_2 emissions can reflect the recovery rate of human activity levels, thereby reflecting the resistance of different cities (Equation (2)). Note that, in order to quantitatively compare cities with different levels of CO_2 emissions, their variations in CO_2 emission levels were measured by the ratio of the increase in CO_2 emissions to the initial value per time interval of the recovery period,

$$V = \frac{\frac{\Delta E}{E_0}}{T_{end} - T_{star}} \tag{2}$$

with the recovery rate of CO_2 emissions V, the total increase in CO_2 emissions during the recovery period is represented by ΔE. E_0 is the initial value of CO_2 emissions (the average CO_2 emissions in the first half of 2019, which represents the normal CO_2 emissions without experiencing the pandemic); T_{star} denotes the time when CO_2 emissions begin to show a long-term upward trend; and T_{end} defines the time when CO_2 emissions do not show an upward trend or the monthly increase is very small. Furthermore, we used per capita GDP as an indicator to represent the development level of the city to investigate the relationship between the development level of the city and its own recovery rate, and then reveal the patterns of urban resilience.

3. Results

We decomposed the CO_2 emission variation patterns into seasonal and annual variations by STL, and then classified and summarized the results. In Section 3.1, we discuss the seasonal patterns of total CO_2 emissions and further investigate the seasonal patterns of the four specific CO_2 emission sectors, power, industry, residential, and others. As the power and industry sectors were the main sources of CO_2 emissions, we focused on their discussion. In Section 3.2, we analyze the annual patterns of total CO_2 emissions divided into four types. Then, we choose a city as an example for more detailed analysis. In Section 3.3, we calculate the recovery rate of the city and plot it.

3.1. Seasonal Patterns of CO_2 Emissions

The seasonal patterns of the total CO_2 emissions in major cities in China can be generally classified into the following four categories in Figure 3. The number on the vertical axes in Figure 3 represents the proportion of seasonal components of CO_2 emissions relative to the initial value. The distribution of these patterns is shown in Figure 4. More detailed data can be found in Table 2. Power and Industry, respectively, represent the proportion of CO_2 emissions from the power sector and industry sector in the total CO_2 emissions. Type represents the classification of the seasonal components of CO_2 emissions in cities. No data represents missing relevant raw data.

Long-term High: CO_2 emissions have a low peak around February and a high to medium level during other time periods, such as Shanghai.

Summer High: CO_2 emissions have a high peak during summer and a low level during other time periods, such as Beijing.

Winter High: CO_2 emissions have a high peak during winter and a low level during other time periods, such as Guangzhou.

Fluctuations: CO_2 emissions fluctuate frequently throughout the year, such as Hohhot.

Considering the sectors of CO_2 emissions, we found that CO_2 emissions from the same sector in different cities had similar patterns. The power sector peaked in summer, in winter, or both, and often fluctuated in the other months. For the industry sector, all cities' CO_2 emissions revealed a low peak around February, and most of them stayed at a high level in the other months. Note that all cities' CO_2 emissions from the residential sector showed the same pattern: peaking around January and remaining at low levels at all other times. Due to the significant impact of the pandemic on CO_2 emissions from the transportation sector, the data could not be decomposed into a trend component and seasonal component. But we can find patterns by observing the original data in Figure 5: during the pandemic, there were two time periods (January to October 2021 and March to December 2022) during which CO_2 emissions were at very low levels, while CO_2 emissions fluctuated greatly at other times. The other sectors were not studied in detail, due to their small contributions and the very low or even zero CO_2 emissions.

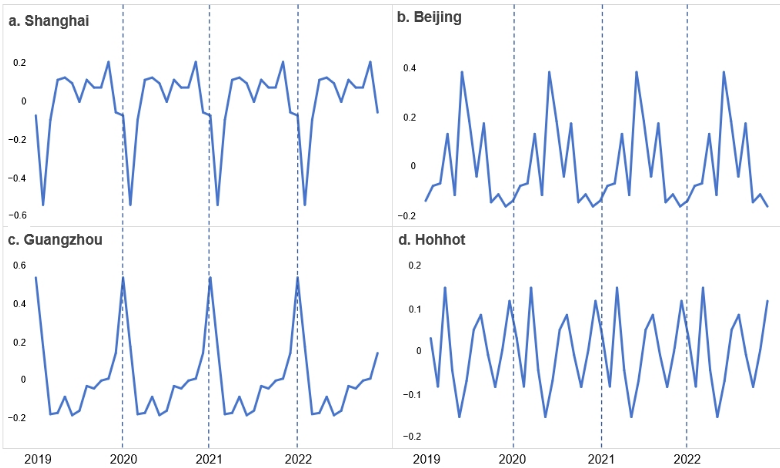

Figure 3. Seasonal patterns of CO_2 emissions in cities: (**a**) Shanghai, (**b**) Beijing, (**c**) Guangzhou, and (**d**) Hohhot.

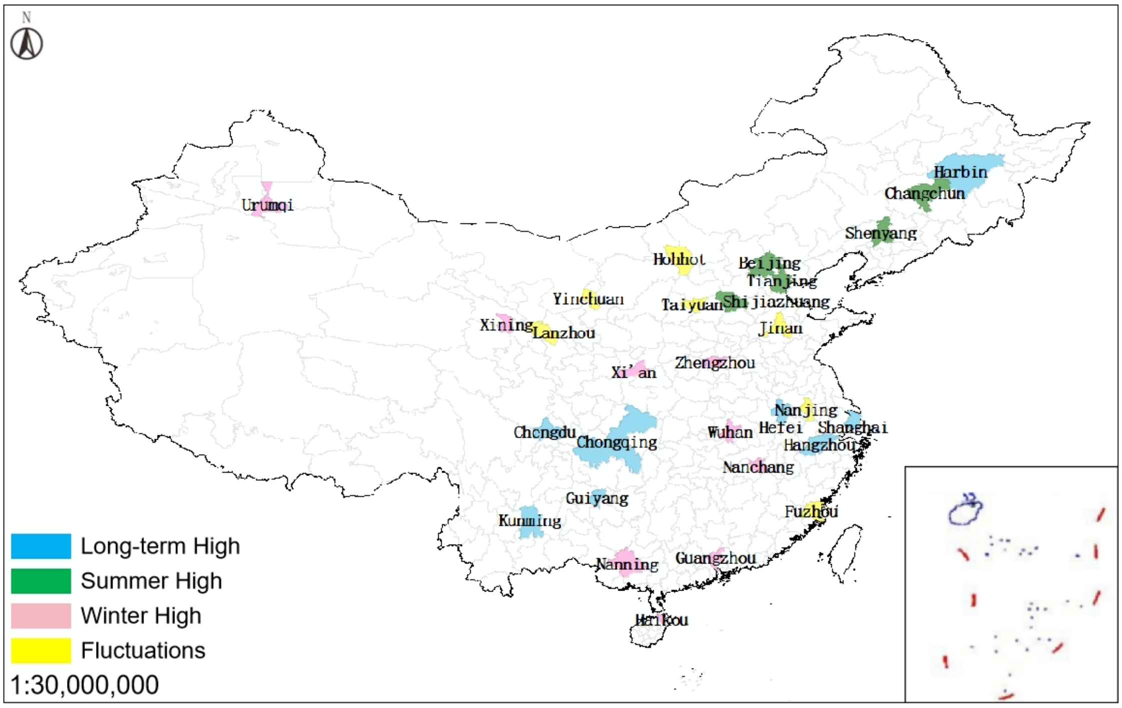

Figure 4. Major cities analyzed in this study and their seasonal patterns.

Table 2. The composition and seasonal classification of CO_2 emissions in cities.

City	Power/%	Industry/%	Type
Chengdu	11.04	69.58	Long-term High
Guiyang	39.74	36.79	
Hangzhou	11.05	65.63	
Hefei	36.07	48.58	
Kunming	18.86	57.83	
Shanghai	8.36	83.53	
Chongqing	37.02	41.87	
Nanjing	31.32	56.47	
Harbin	-	-	
Beijing	17.98	60.2	Summer High
Shenyang	26.4	57.03	
Changchun	69.38	14.65	
Tianjing	55.11	24.19	
Shijiazhuang	63.91	25.33	
Guangzhou	40.58	34.15	Winter High
Haikou	72.29	13.53	
Nanchang	58.97	26.73	
Nanning	30.34	53.59	
Urumqi	40.97	38.19	
Wuhan	27.15	62.87	
Xi'an	41.99	31.99	
Zhengzhou	58.28	28.99	
Xining	-	-	
Lhasa	10.31	28.96	
Changsha	28.83	45.89	
Taiyuan	67.06	22.25	Fluctuations
Hohhot	79.97	11.11	
Lanzhou	59.74	24.84	
Jinan	63.59	23.46	
Yinchuan	86.51	7.74	
Fuzhou	58.23	28.04	
Mean	43.14	38.76	
Max	86.51	83.52	
Min	8.36	7.74	
SD	22.40	19.52	

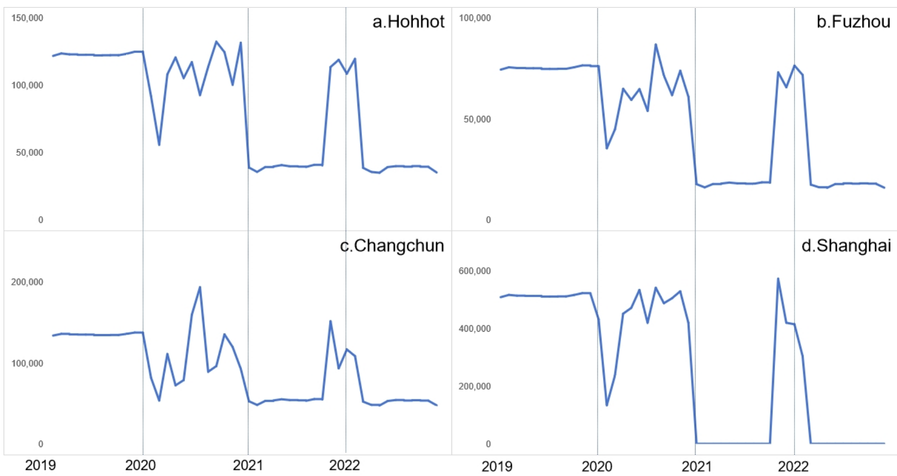

Figure 5. Line charts of CO_2 emissions in the transportation sector of (**a**) Hohhot, (**b**) Fuzou, (**c**) Changcun, and (**d**) Shanghai.

3.2. Annual Patterns of CO_2 Emissions

In our study, city CO_2 emissions showed an upward trend most of the time. However, almost all cities fluctuated during specific time periods, which coincided highly with the outbreaks of the pandemic. Based on these specific fluctuations, we divided the annual patterns of total CO_2 emissions into the following four types in Figure 6. First and Second represent the time of the first and second outbreaks of the pandemic.

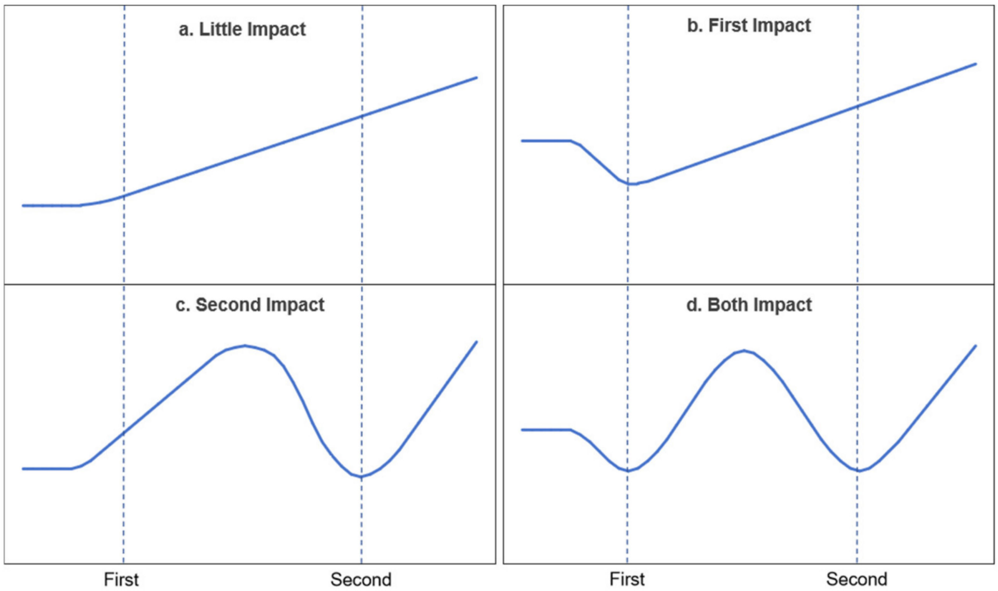

Figure 6. Conceptual charts of the four trend patterns of CO_2 emissions: (**a**) Little Impact, (**b**) First Impact, (**c**) Second Impact, and (**d**) Both Impacts.

Little Impact: CO_2 emissions showed a stable upward trend or little change, such as in Hohhot.

First Impact: CO_2 emissions showed a low peak in early 2020, followed by a slow upward trend, such as in Fuzhou.

Second Impact: CO_2 emissions showed a low peak at the end of 2021, such as in Beijing.

Both Impacts: CO_2 emissions showed low peaks in early 2020 and at the end of 2021, such as in Changchun.

For each type, we selected a typical city to display the STL results (Figure 7). The number on the vertical axes in Figure 7 represents the proportion of seasonal components of CO_2 emissions relative to the initial value. To more specifically describe the relationship between the impact of the pandemic and the changes in CO_2 emissions, we selected Changchun as an example. During the period from January 2020 to April 2020, Changchun City had a cumulative increase of 49 new infected individuals, which led to the implementation of strict control measures and a reduction in human activities, so, accordingly, CO_2 emissions decreased during this period. For a long time afterwards, there were no new infections and CO_2 emissions increased during this period. At the beginning of 2022, there was a large number of new infections, while CO_2 emissions decreased again at the same time. Due to China's implementation of the policy of liberalization at the end of the pandemic, this subsequent part was not within the scope of this study. It can be seen that the CO_2 emissions of Changchun significantly decreased during the two time periods of sudden increases in the number of infected individuals, since the levels of human activities were significantly affected by the pandemic at those times. Almost all cities showed a similar pattern: when the impact of the pandemic was severe or aggravated, CO_2 emissions decreased, and vice versa, when the impact was mild, CO_2 emissions rose.

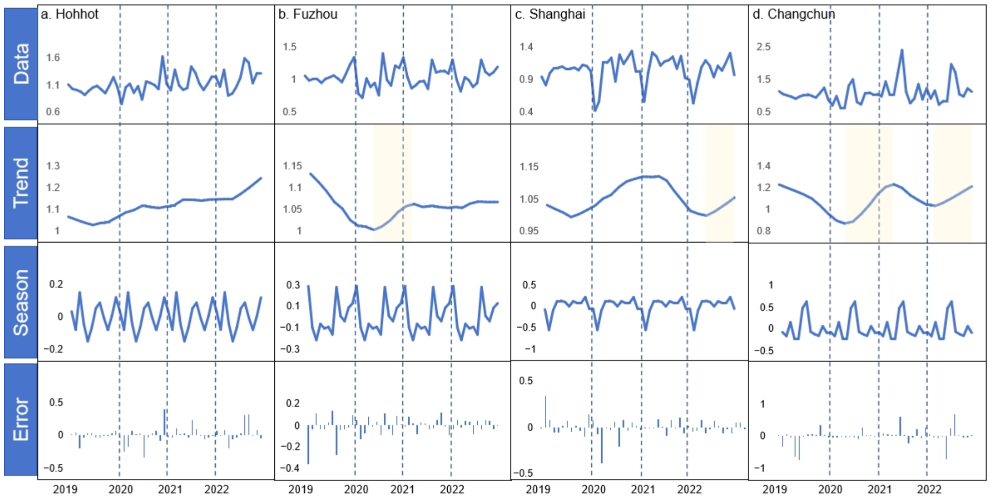

Figure 7. Seasonal trend decomposition result of total CO_2 emissions in (**a**) Hohhot, (**b**) Fuzhou, (**c**) Shanghai, and (**d**) Changchun. (The shaded areas represent that the city was in a period of recovery.)

3.3. Urban Resilience

We calculated the rates of increase in CO_2 emissions in cities and indicated which post-pandemic recovery rate they belonged to; the results are presented in Table 3. The Recovery Speed I and Recovery Speed II represent the recovery speeds of CO_2 emissions in cities after experiencing the impact of the first and the second outbreak of the pandemic. Recovery Value I and Recovery Value II represent the proportion of CO_2 emissions increasing relative to the initial value after experiencing the impacts of the first and second pandemic outbreaks. No data means that the city did not experience a decrease in CO_2 emissions due to the pandemic during this period, or it did not recover until the end of the research period. Then, we plot the calculation results in Figure 8. Blue means the recovery rate after the first outbreak of the pandemic, while red means the second.

Table 3. The recovery rate of CO_2 emissions in cities and other data.

City	Per Capita GDP /$\times 10^4$ Yuan	Recovery Speed I	Recovery Speed II	Recovery Value I	Recovery Value II
Fuzhou	13.53	0.54%	-	9.62%	-
Hefei	12.12	1.17%	-	7.5%	-
Jinan	12.31	1.66%	-	18.6%	-
Lhasa	8.68	1.15%	-	−0.72%	-
Nanchang	10.48	1.00%	-	−1.78%	-
Nanning	5.82	1.21%	-	18.76%	-
Tianjing	11.37	1.07%	-	14.39%	-
Urumqi	9.08	2.02%	-	1.57%	-
Wuhan	13.53	0.98%	-	15.24%	-
Xi'an	8.37	0.75%	-	3.52%	-
Xining	6.26	1.89%	-	−0.65%	-
Changsha	13.07	0.47%	-	8.27%	-
Nanjing	17.45	-	1.43%	-	6.25%
Shanghai	17.54	-	0.78%	-	3.72%
Beijing	18.75	-	1.71%	-	14.49%
Shijiazhuang	5.78	-	1.22%	-	12.5%
Taiyuan	9.56	-	1.37%	-	9.79%
Shenyang	7.97	2.31%	0.85%	13.71%	5.37%
Changchun	7.83	2.54%	1.70%	3.39%	1.75%
Harbin	5.07	1.69%	1.36%	5.01%	14.43%
Zhengzhou	10.01	1.66%	1.09%	10.93%	9.19%
Kunming	8.51	0.98%	0.51%	7.57%	6.12%
Guangzhou	15.04	1.10%	0.89%	−1.68%	1.19%
Hangzhou	14.99	0.51%	0.47%	1.27%	−2.06%
Chengdu	9.46	0.62%	0.48%	8.08%	8.45%
Hohhot	8.98	-	-	-	-
Guiyang	7.79	-	-	-	-
Haikou	7.1	-	-	-	-
Lanzhou	7.38	-	-	-	-
Yinchuan	7.88	-	-	-	-
Chongqing	8.75	-	-	-	-

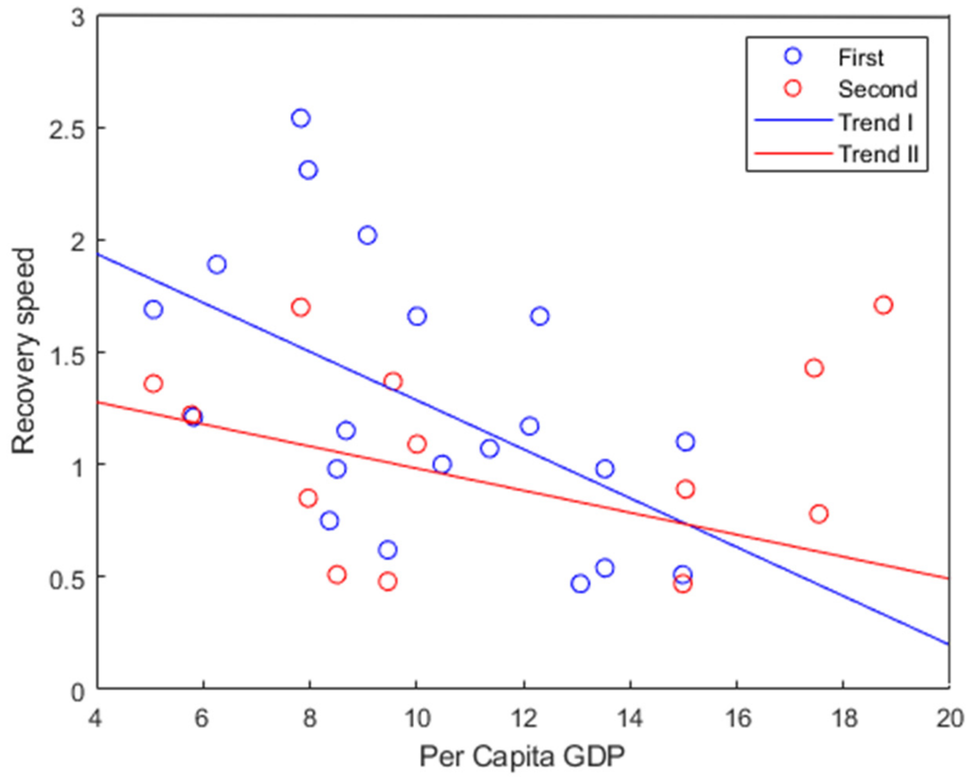

Figure 8. Scatter plot of urban per capita GDP and recovery rate of CO_2 emissions.

4. Discussion

4.1. Seasonal Patterns and the Causes

The data sources used in this study, which provide the CO_2 emissions, include many sources (such as industrial electricity and building electricity). For the power sector, about half of the cities saw seasonal fluctuations in CO_2 emissions, while the others peaked only during summer or winter. In most cities, the CO_2 emissions from the industry sector were at high levels throughout the year, but lower peaks were experienced during the Spring Festival (traditional Chinese festival during which many companies, factories, enterprises, and schools give employees and students a long holiday). However, different from the industry sector, due to the impact of the pandemic, most people choose to celebrate the Spring Festival at home, resulting in an increase in CO_2 emissions from the residential sector during this period. As for CO_2 emissions from the transportation sector, due to the uncertainty of people's travel willingness during the pandemic and other possible factors, various transportation modes, such as express delivery, saw fluctuation. When implementing travel restriction policies, it will drop to a very low or even close to zero level.

For all cities in this study, the CO_2 emissions of the power and industrial sectors accounted for at least 75% of the total CO_2 emissions; that is, these two sectors are the main contributors to changes in the total CO_2 emissions. In general, cities with the industry sector as their main source of CO_2 emissions reveal more obvious seasonal patterns of CO_2 emissions, while cities with the power sector dominating as the main source of CO_2 emissions are more prone to fluctuations in their seasonal CO_2 emission patterns. In addition, we also found that most cities with similar seasonal patterns in their CO_2 emissions are geographically clustered (see Figure 3). As for the residential and transportation sectors, both have undergone significant changes at certain times, but CO_2 emissions from the industrial and electricity sectors have not shown significant fluctuations during these times. This indicates that emissions reduction in the power and industrial sectors is important for achieving carbon peaking, while low-carbon transportation and residential energy saving cannot make sufficient contributions to this. Although seasonal components account for a relatively small proportion of CO_2 emissions, they are more prone to significant changes in the short-term time scale. Therefore, in order to observe the changes in CO_2 emissions more accurately, it is necessary to remove seasonal effects. This way, we can grasp the rising and falling trends of CO_2 emissions in a timely and accurate way, which is conducive to a fast-responding policy to achieve carbon peaking.

4.2. Resilience of Annual Patterns in CO_2 Emissions

The impact of the pandemic on cities varied in degree and duration, and thus on human activities, which could be reflected through the changes in the CO_2 emission trends. At the same time, different cities had varying levels of resistance and resilience to the impact of the pandemic. We compared the changes in the number of infected individuals and the annual patterns in CO_2 emissions during the pandemic period, and obtained the relationship between the two:

(i) When the impact of the pandemic did not exceed the city's resistance to the pandemic, CO_2 emissions showed an upward trend associated with the normal development of the economy and the acceleration of various production activities.

(ii) When the impact of the pandemic exceeded the city's resistance, CO_2 emissions rapidly decreased in the short-term time scale and then rose after the impact ended.

During the pandemic, the period when urban CO_2 emissions suddenly decreased is similar to the period when the number of infected people in the city suddenly increased significantly (which also indicates that the impact of the pandemic is increasing). This result indicates that it is feasible to measure the impact of large-scale emergencies on cities through real-time observations of changes in CO_2 emissions. When a city is affected by large-scale emergencies, we can react in a timely manner and respond accordingly. It can be seen that cities with a higher per capita GDP have a lower recovery rate. In fact, a higher level of development means that the internal structure of the city is more complex, which means that a small amount of impact can not only lead to the paralysis of the urban system, but also to a more difficult recovery after destruction.

In this sense, urban resilience means "resistance", "quick transformation", and "rapid recovery". But from the results, most cities have been more or less affected by the pandemic, indicating that the current construction of urban resilience is insufficient. Therefore, the construction of urban resilience is important and should consider different levels of urban development. The improvement in urban resilience can reduce the impact of large-scale emergencies such as COVID-19, and accelerate the recovery rate of cities after the city is affected. In addition, our study found that the CO_2 emission levels of most cities after the recovery period had exceeded the initial levels, with some even approaching a 20% increase. For cities affected by two outbreaks, we found that the recovery rate of CO_2 emissions had an unreasonably high value after the first impact ended. In addition, comparing the two trend lines in Figure 8, we found that the recovery rate of CO_2 emissions after the first impact of the pandemic was faster than the second. This means that the rising rate of CO_2 emissions during the period was not under control, which may be due to the lack of experience in responding to the pandemic. This also indicates that there are still many risks that need to be carefully addressed during the urban recovery period. Achieving a fast recovery speed of cities after disasters is important, but ensuring that recovery is not too excessive is also highly important. How to achieve these goals is what we need to focus on in the future.

5. Conclusions

The impact of the pandemic on human activities is analyzed accurately and in more detail, thereby studying the urban resilience of different cities. This included the seasonal and annual patterns of CO_2 emissions by STL, and urban resilience by calculating and comparing the recovery rates of CO_2 emissions in different cities.

Seasonal trends can be classified into four types, mainly generated by the power and industrial sectors, which are also the focus of emission reduction. The seasonal portion of CO_2 emissions generally does not exceed 15% overall, but can change significantly in the short term, which means that we must consider it when observing the short-term trend of CO_2 emissions. When facing large-scale emergencies such as the pandemic, we need to consider the seasonal trends of human activities when evaluating the short-term impacts of the event. In addition, due to the significant differences in seasonal patterns between different seasons, implementing emission reduction policies tailored to the seasons can achieve better results. Due to the fact that cities with the same seasonal pattern are not geographically dispersed, it is feasible to implement this differentiated policy nationwide. However, this study still has the following limitations: (1) It is difficult to explain seasonal trends related to the power sector due to the lack of more detailed classifications from the raw data. (2) There is no analysis of urban resistance to compare with urban resilience (existing research indicates an inverse relationship between the two). (3) Due to the significant impact of the pandemic on the transportation sector, time series decomposition cannot be performed.

The annual trend can also be classified into four types, which are related to the impact of the pandemic. During the pandemic, CO_2 emissions in many cities rose or recovered with normal economic development, and rapidly decreased if severely affected by the pandemic. Many cities are experiencing economic development or recovery, but uncontrolled CO_2 emissions are detrimental to achieving the goal of carbon peaking. In our study, most cities had already exceeded their initial CO_2 emission levels after rebounding. Especially after the end of the first pandemic outbreak, the rebound rate in some cities showed abnormally high values, and their CO_2 emissions eventually exceeded the initial value. When facing large-scale emergencies, apart from the degree of impact, we also need to consider factors such as urban development, economy, and population, etc., which can reflect the strength of the city's resistance to such events and play an important role in the achievement of SDG 11. During the recovery period after the impact of the event, we also need to achieve economic recovery while preventing excessive rebounds in CO_2 emissions. Especially in recent years, when SDG11 and the carbon peak target date are approaching, it is crucial to control the growth rate of CO_2 emissions and even achieve a reduction. In future research, we can construct an urban resilience evaluation system based on CO_2 emissions to achieve the goals of urban health assessment, sustainable development, and carbon peaking.

Author Contributions: Conceptualization, Yue Zhao; Software, Yue Zhao; Validation, Klaus Fraedrich; Investigation, Yue Zhao; Data curation, Yue Zhao; Writing-original draft, Yue Zhao; Writing-review & editing, Yuning Feng and Klaus Fraedrich; Supervision, Yuning Feng and Mingyi Du; Project administration, Mingyi Du. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by: National Natural Science Foundation of China: 41930650; Youth Research and Innovation Project—Young teachers research ability enhancement program: X23002.

Data Availability Statement: Raw data were generated at https://carbonmonitor-graced.com/ (accessed on 19 March 2024). Derived data supporting the findings of this study are available from the corresponding author Y.F. on request.

Conflicts of Interest: All authors have no conflicts of interest. On behalf of all authors, the corresponding author states that there is no conflict of interest.

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