Article

Land Zoning Management to Achieve Carbon Neutrality: A Case Study of the Beijing–Tianjin–Hebei Urban Agglomeration, China

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Abstract: Land use/cover change (LUCC) has been identified as a crucial driver of changes in the spatiotemporal distribution of carbon dioxide (CO2) emissions. However, few studies have proposed land use optimization to identify key zones for launching ecological engineering projects. Adopting multi-source data and spatial analysis, we estimate the impact of LUCC on CO2 emissions and ecological support capacity. Importantly, the spatial evolution and inequality of carbon sources and sinks are evaluated. The results suggest that (1) the growth of urban areas due to urbanization has exceeded 5293 km2 over the last 18 years and that the number of closed forest areas increased by 1444 km2 while decreases of 16,418, 9437, and 1250 km2 were observed in the water body, cropland, and grassland land-use types, respectively; (2) CO2 levels rose dramatically in the Beijing–Tianjin–Hebei urban agglomeration, increasing from 8.7 × 107 tCO2 in 2000 to 26 × 107 tCO2 in 2018; (3) there is increasing inequality in the emission levels among cities; and (4) the spatial differences in the carbon sink and ecological support capacity are huge. Our findings have the potential to improve the government’s understanding of how to take action to optimize land-use types and how to launch engineering projects in key zones to achieve carbon peak and carbon neutrality, as well as to provide a new perspective for studies on the controls and mitigation of CO2 emissions.

Keywords: land use planning; CO2 emissions; Gini coefficient; ecological engineering; spatial analysis

1. Introduction

There has been a surge of interest in the science of climate change, with greenhouse gas emissions serving as the primary focus for understanding the Earth’s response to climate change. Anthropogenic greenhouse gas emissions, particularly carbon dioxide (CO2) emissions, have been major contributors to climate change since the mid-twentieth century [1]. CO2 accumulation is caused by a variety of factors, with CO2 emissions induced by land use/cover change (LUCC) accounting for one-third of the global anthropogenic carbon emissions and influencing the carbon source and sink patterns in a given region [2]. In addition to direct emissions from the land, indirect emissions from human societies that are caused by the combustion of fossil fuels have become a significant source of increasing atmospheric CO2 concentrations and spatiotemporal changes in the terrestrial surface layer [3–5].

There is a correlation between CO2 emissions and land use/cover. Previous studies have revealed interactions between land use and CO2 emissions, with various land-use types resulting in a disparity in CO2 emissions [6–8]. People are actively looking for ways to improve CO2 emission reduction schemes, such as by regulating and supervising land uses and adjusting the intensity of land development [9]. The appropriate transformation of land use types and the optimization of land use modes contribute to lower CO2 emissions and lower CO2 concentrations in the atmosphere [10]. Ecological engineering, which modifies the abundance of closed forest, other forest, grassland, and wetland land-use
types, improves regional carbon sink [11], whereas urbanization increases CO₂ emissions. However, few studies have proposed land use optimization to identify the key zones in which ecological engineering can be implemented [12].

CO₂ emissions are estimated by adopting a combination of bottom–up inventories and top–down measurements [13,14]. Bottom–up inventories are derived from global and regional integrated statistics from various data systems and databases [15–17]. Different statistical methods, energy consumption, and carbon emissions data are adopted in various inventories, resulting in uncertainty in inventory-based estimates [18]. In addition to quantifying the uncertainties of inventories from various sources, it is critical for carbon emission calculations to combine sampling analysis with the continuous monitoring of emissions and to update emission data in a timely manner to reduce time errors [19]. Combining bottom–up inventories and top–down measurements improves the precision of CO₂ emission estimates [20].

Analyzing the effect and interaction between the land use mode and carbon emissions as well as identifying key zones for ecological engineering are critical key steps for the development of low-carbon land-use systems and a low-carbon economy. Therefore, this study aims to quantify the impact of LUCC on CO₂ emissions. We used finely classified land use/cover change (LUCC) types, which allowed us to evaluate the variation in CO₂ emissions and the interaction between LUCC and emissions. Our research focuses on the spatial variation in CO₂ emissions and absorption in the Beijing–Tianjin–Hebei agglomeration (BTH) at the regional and city levels. The characteristics of carbon source and sink inequality are also identified. Finally, we propose a zoning solution for the BTH that is based on the spatial divergence in the carbon sources and sinks.

2. Literature Review

There are difficulties in balancing the development of productive social forces and in protecting the natural environment [21]. The land use category conversion and land management mode can lead to spatio-temporal changes in vegetation and soil carbon storage [22–24]. Meanwhile, scholars have analyzed the effects of carbon emissions on land-use types. With reference to direct computing methods or the energy consumption analysis method, based on the land-use modes in the IPCC’s list of greenhouse gases, the emission coefficients of CO₂ for different land-use types have been calculated, and carbon inequality has been revealed for different space scales and for different land-use types [25,26]. However, long-term localized high-resolution spatiotemporal patterns of CO₂ emissions in China have not been realized yet, so more efforts are needed [2].

There has been a large body of literature recognizing that it is important to optimize land use to achieve carbon neutrality. LUCC has a significant influence on the variation in carbon storage and sequestration, while land zoning management for carbon storage conservation is positive for carbon neutrality [27]. Considering that cities have become a hotspot of CO₂ emissions, it is essential to implement city-level emission mitigation strategies [28]. At the city level, CO₂ emission policies can be integrated with urban planning policies [12]. On the other hand, reducing emissions in rural areas should also not be neglected. When identifying ecological engineering zones, it is more beneficial for environmental sustainability to consider urban–rural land use in an integrated manner [29,30]. Beyond the city level, studies related to China should place more focus on urban agglomerations, as urban agglomerations have become the main urbanization pattern [31].

3. Methodology and Materials

3.1. Study Area

The BTH (36°05′–42°40′ N, 113°27′–119°50′ E) is located on the coastal plain of northeast China (Figure 1). It borders the Bohai Sea to the east, Inner Mongolia and Liaoning to the north, Shanxi to the west, and Henan to the south. The BTH is the central hub of the Bohai Rim. Its development indicates major progress in promoting China’s regional development system, and it has become the largest and most dynamic region in northern
China. It is a world-class city agglomeration, with the capital as its core. The BTH is made up of 13 cities in the Beijing, Tianjin, and Hebei Provinces. The region has a land area of 218,000 km$^2$ and a permanent population of 112.7 million people (2018). The BTH’s urban–rural economy has seen rapid development in recent years. Urbanization has facilitated population growth and the expansion of construction land, while population growth has also resulted in increased resource consumption. The government’s focus has shifted to the coordinated development of ecological construction (referring to increasing the forest, grassland, and water body land types) and urbanization [32].

Figure 1. Geographic distribution of the terrain and cities in Beijing–Tianjin–Hebei area.

3.2. CO$_2$ Emissions Estimation Models

3.2.1. Direct Emissions

Anthropogenic CO$_2$ emissions induced by LUCC include both direct and indirect emissions. Direct emissions from cropland, forest, grassland, water bodies, and other land types are all examples of land-based direct emissions. CO$_2$ emissions from urban and rural areas are attributed to indirect emissions caused by the combustion of fossil fuels. In this study, direct emissions are estimated by employing the emissions coefficient, as shown in Equation (1):
\[ E_d = \sum E_i = \sum T_i \times \mu_i \]  

where \( E_d \) indicates the direct emissions, \( E_i \) is the CO\(_2\) emissions contributed by land-use type \( i \), \( T_i \) denotes the area of land-use type \( i \), and \( \mu_i \) is the carbon emission coefficient.

Ecological engineering (forest, grassland, water body), cropland, and other land types are generally recognized as carbon sinks, whereas rural and urban areas are carbon sources. To distinguish between carbon sources and sinks, we use positive numbers to represent carbon sources and negative numbers to represent carbon sinks. The annual carbon emission coefficients were calculated using previous studies and by considering the characteristics of the study area (Table 1). Emission coefficients vary from region to region due to geographical location, latitude and longitude, and climatic conditions. We further analyzed the uncertainty of the carbon emission coefficient in the discussion below.

Table 1. Carbon emission coefficients of various land-use types.

| Land Use Types | Coefficient (tCO\(_2\)/km\(^2\)) | Reference | Coefficient in This Study (tCO\(_2\)/km\(^2\)) |
|----------------|----------------------------------|-----------|---------------------------------------------|
| Cropland       | (39, 46)                         | Lin et al., 2021 [6]; Quijano et al., 2017 [33];  | 42                                           |
| Closed forest  | (−90, −58)                       | Lai et al., 2016 [34]; Chen et al., 2020 [35];   | −84                                          |
| Other forest   | (−52, −1)                        | Zhao et al., 2021 [36]; Cui et al., 2019 [37]; Zhou et al., 2018 [38];  | −41                                          |
| Grassland      | (−18, −0.2)                      | Raihan et al., 2022 [39]; Zhao et al., 2020 [2]; Cui et al., 2019 [37]; | −14                                          |
| Water body     | (−5, −1)                         | Xia et al., 2021 [40]; Yang et al., 2020 [41]; Cui et al., 2019 [37]; | −3                                           |
| Other land     | (−8, 1)                          | Cao and Yuan, 2019 [10]; Wang et al., 2011 [42]; | −5                                           |

Annual LUCC maps with 1 km resolutions were obtained from the Resource and Environment Science and Data Center (http://www.resdc.cn/; accessed on 11 December 2021) and cover the period from 2000 to 2018. The original data was obtained from Landsat TM observations, and, after artificial visual interpretations, all of the land-use types were classified into 25 classes. Given that our study focuses on a region comprising 13 cities, covering approximately 220,000 km\(^2\), high-resolution images are appropriate for accurately identifying LUCC. To meet the scope of this study, we divided the 25 land use classes into 8 broad categories: cropland, closed forest, other forest, grassland, water body, urban area, rural area, and other land. Urban area includes urban built-up areas, including the concentrated and contiguous part of urban areas and the urban construction land scattered in suburban areas that are closely connected to the main city and that have nearly perfect municipal public facilities. Rural area refers to rural settlements that contain land for rural public utilities and public facilities as well as land for rural residences.

### 3.2.2. Indirect Emissions

The indirect CO\(_2\) emissions occurring in urban and rural areas were derived from the Open-Data Inventory for Anthropogenic Carbon Dioxide (ODIAC), developed by National Institute for Environmental Studies in Japan [19]. Gridded indirect CO\(_2\) emissions are provided at 1 km resolution and were estimated by combining power plant distribution and nightlight remote sensing images. Compared to similar datasets, the ODIAC is based on an integrated model that accounts for the statistics of energy materials using CO\(_2\) and net CO\(_2\) emissions resulting from burning fossil fuels. Furthermore, the ODIAC considers indirect CO\(_2\) emissions that are closely related to human factors, such as settlements and transportation, and characterized by the nightlight and energy use described by power plants. This accounting method is adopted on both provincial and urban scales and has low uncertainties (meaning higher precision), making it suitable for our study.
3.3. Exploratory Spatial Data Analysis

This study used exploratory spatial data analysis (ESDA) to describe the CO$_2$ emission characteristics in the BTH to help us to better understand the spatiotemporal variation patterns. Global and local spatial autocorrelation are two ESDA measures:

$$I = \frac{n \sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{(\sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij}) \sum_{i=1}^{n} (x_i - \bar{x})^2}$$

$$I_i = \frac{n(x_i - \bar{x}) \sum_{j=1}^{n} w_{ij}(x_j - \bar{x})}{\sum_{i=1}^{n} (x_i - \bar{x})^2}$$

where $I$ denotes Moran’s $I$, $I_i$ is the local Moran’s $I$, $n$ is the number of cities, $w_{ij}$ indicates the spatial weight matrix, $x_i$ and $x_j$ are the CO$_2$ emissions of city $i$ and $j$, and $\bar{x}$ denotes the mean of CO$_2$ emissions.

3.4. Ecological Support Coefficient

We introduced an ecological support coefficient (ESC) to evaluate the carbon sink capacity of a region. ESC denotes the quotient of the proportion of carbon absorption in a region to the proportion of carbon emissions in that region to all regions. Mathematically, the ESC can be calculated by the following calculation:

$$ESC = \frac{C_{Ai}}{C_A} \div \frac{C_{Ei}}{C_E}$$

where $C_{Ai}$ and $C_A$ indicate the carbon absorption of city $i$ and all cities, respectively; $C_{Ei}$ and $C_E$ represent the carbon emissions of city $i$ and all cities. For a city, $ESC > 1$ represents how the carbon sink contribution is more significant than that of the contribution of carbon emissions. However, $ESC < 1$ indicates that the carbon sink contribution is less than that of carbon emissions.

3.5. Spatial Differentiation of CO$_2$ Emissions Measurement

Measuring the spatial variations in CO$_2$ emissions lays the foundations for identifying the coordination of carbon emissions among cities in the region. The Gini coefficient has been widely used to evaluate the variations in different income groups, and it performs admirably when measuring variability. In this study, we used the Gini coefficient to estimate the difference between 13 cities in the BTH. The traditional Gini coefficient is calculated as follows:

$$G = \sum_{i=1}^{n} D_i Y_i + 2 \sum_{i=1}^{n} D_i (1 - T_i) - 1$$

where $G$ denotes the Gini coefficient, $D_i$ is the proportion of the population in group $i$, $Y_i$ refers to the proportion of the income in group $i$, and $T_i$ represents the cumulative proportion of group $i$. In this study, we replaced income and population with CO$_2$ emissions and areas, respectively, to measure the spatial differentiation in CO$_2$ emissions in the BTH.

4. Results and Discussion

4.1. Land Use/Cover Changes from 2000 to 2018

The LUCC of the BTH varied notably from 2000 to 2018, as shown in Figure 2. Urban areas increased, and other types of areas decreased. The growth of urban areas caused by urbanization exceeded 5293 km$^2$ over the course of 18 years, while a 16,418 km$^2$, 9437 km$^2$, ...
and 1250 km² decrease was observed in the water body, cropland, and grassland land-use areas, respectively. However, great progress was observed in ecological construction, with grain plots returning to forests being witnessed. The area of closed forests increased to 44,790 km² in 2018 from 43,346 km² in 2000, an increase of 1444 km². We grouped eight land-use/cover categories into three purposes to further analyze the trade-off between ecological construction and urbanization. The closed forest, other forest, grassland, and water body types were grouped into the ecological purpose category; urban area was grouped into the urbanization purpose category; and cropland, rural area, and other land were grouped into the other purpose category. The water body land type experienced a decrease in the center of the BTH over the last 18 years, while a wide region comprising the other forest type appeared southwest of the BTH. Furthermore, other land types located northeast and north of the BTH decreased significantly. However, the total area of other land types has increased from 2000 to 2018 due to the growth of other land types in the eastern coastal regions of the BTH.

Among the 13 cities located in the BTH, big cities expanded more rapidly (Figure 3). As municipalities, Beijing and Tianjin saw the most significant increase in the urban area land type. Furthermore, from 2000 to 2018, the provincial capital of Hebei, Shijiazhuang, experienced rapid growth. The other ten cities experienced an increase in the urban area land type but at different rates. This implies that cities expanded into urban areas as the urban area land type grew. The expansion of urban areas as well as urbanization was bound to occupy other land-use/cover types, and cropland bore the brunt of the increase in city scale. Aside from the decrease in the water body land type as a result of water resource consumption, the decrease in cropland was the most remarkable. Despite the expansion of rural areas, cities were the primary driving force, and city expansion has been far more widespread than rural expansion.

Cropland was the most common type of land-use/cover type in almost all of the cities in the BTH, with the exception of Beijing and Chengde, which had the closed forest type as the most common type. The proportion of land types varied significantly across the 13 cities. This significant disparity was able to be determined when analyzing the closed forest type. Chengde, for example, had a much higher proportion of closed forests, while Beijing and Qinhuangdao also had a high proportion of closed forests. The proportion of closed forests in Baoding and Zhangjiakou, on the other hand, was relatively low. The proportion of closed forests was very low in Tianjin, Handan, Cangzhou, Langfang, and Hengshui.
Figure 3. LUCC of 13 cities located in Beijing–Tianjin–Hebei from 2000 to 2018.

There were prominent LUCC changes in all cities. The urban area of Beijing expanded by 695 km$^2$ from 2000 to 2018. As for the ecological land types, the proportion of the closed forest type increased by 347 km$^2$, the proportion of the other forest type decreased by 233 km$^2$, and the grassland and water body land types decreased by 83 km$^2$ and 24 km$^2$, respectively. The total area of ecological land decreased by 341 km$^2$ in total, which was less than the increase in the closed forest land type. Therefore, the amount of ecological
land in Beijing increased from 2000 to 2018 from a global perspective. In Tianjin, the urban area has increased by 244 km$^2$ over the past 18 years. The proportion of closed forest increased by 125 km$^2$, and the proportion of other forests decreased by 121 km$^2$, while grassland increased by 81 km$^2$ and the water body land type decreased by 343 km$^2$. The area dedicated to the water body land type in Tianjin declined dramatically. There was an increase of 1299 km$^2$ in Shijiazhuang, while the amount of ecological land increased by 118 km$^2$. Specifically, the proportion of closed forests increased by 4 km$^2$, the proportion of other forests increased by 260 km$^2$, while the amount of grassland decreased by 531 km$^2$ and the water body land type expanded by 384 km$^2$. The variations in the grassland and water body land types were obvious.

In the BTH, land use/cover was closely related to terrain (Figure 4). The primary land cover types in mountainous regions were forest and grassland, with a large number of croplands being distributed in plain regions. Cities on the plains grew faster than those in mountainous regions. Remarkable variations in land types were observed around bodies of water rather than in plains or mountains. The loss of other forests and grassland did not imply that ecological construction had stalled. On the contrary, the expansion of closed forests annexed the two land cover types, suggesting that ecological construction in the BTH was a huge success.

4.2. Spatiotemporal Variations of Regional CO$_2$ Emissions in BTH

Figure 5 shows the changes in the CO$_2$ emissions in the BTH. The total and net emissions rose dramatically between 2000 and 2018, which was primarily due to an increase in indirect emissions. Overall, indirect emissions have increased dramatically in the BTH, increasing from $8.7 \times 10^7$ tCO$_2$ in 2000 to $26 \times 10^7$ tCO$_2$ in 2018. Over the course of 18 years, total emissions increased by $18 \times 10^7$ tCO$_2$. On the contrary, reductions in cropland resulted in a decrease ($0.4 \times 10^7$ tCO$_2$) in direct emissions. Despite the fact that the areas of the water body, other forest, and grassland land types decreased, the increase in the closed forest land type from 2000 to 2018 resulted in the growth of carbon sinks in the BTH. In 2005 and 2010, indirect emissions totaled $14.5 \times 10^7$ and $22.5 \times 10^7$ tCO$_2$, respectively. The average annual growth rate of 8.35% from 2000 to 2005 was the highest, but it has steadily declined since then. Between 2005 and 2010, the average annual growth rate in the amount of indirect emissions was 6.89%, a 1.46% decrease from the previous five years. However, between 2010 and 2018, this rate fell to 2.29%. These intriguing findings can be explained by variations in the development patterns in the BTH. In the early twenty-first century, the Chinese government and the public had little awareness of ecology, and the pursuit of rapid development resulted in the development of a high-emission pattern [43]. Furthermore, a large number of people migrated from counties to cities, and rapid urbanization increased CO$_2$ emissions [44]. However, this unsustainable development pattern had a number of negative ecological, social, and economic consequences. As a result, more and more cities and regions have chosen sustainable development [45], and the rate of indirect emission growth has slowed.

Despite the variation observed from 2000 to 2005, as shown in Figure 6, the spatial pattern of the indirect emission clusters in the BTH varied slightly between 2005 and 2018. High–high indicates that the emissions in this region are high in the region itself as well as in the rest of the surrounding area. Low–low indicates that the emissions in this region are low, as are the emissions in the surrounding areas. High–low indicates that the emissions in this region are high but that the emissions in the surrounding areas are low. Low–high indicates that the emissions in this region are low but that emissions in surrounding regions are high. There were noticeable changes in the BTH from 2000 to 2005, but the trends in the different clusters were disparate. For example, the changes in the two largest clusters in Beijing and Tianjin were extremely large, whereas the changes in smaller clusters were minor. Furthermore, we observed significant variations in the southeast region of the BTH, with a large number of low–low clusters emerging. This was directly related to the changes
in indirect emissions. From 2005 to 2018, the low–low clusters in the southeast of the BTH continued to expand, while the clusters in other regions shrunk.

Figure 4. The LUCC in Beijing–Tianjin–Hebei from 2000 to 2018.
The cities with the greatest increases in CO$_2$ were Beijing, Tangshan, and Shijiazhuang, while Chengde was the city releasing the least CO$_2$. In 2018, although Beijing and Tianjin also had the most CO$_2$ emissions, the CO$_2$ emissions of Tangshan grew rapidly and reached $2.25 \times 10^7$ tCO$_2$, exceeding that of Shijiazhuang. Chengde was still the city with the least CO$_2$ emissions, with emissions at $0.57 \times 10^7$ tCO$_2$. It is an interesting finding that the cities with high CO$_2$ emissions emitted CO$_2$ more quickly. This could be attributed to the LUCC of these cities. The cities with high CO$_2$ emissions comprised a large proportion of the urban area land type, meaning these cities expanded more easily and rapidly.

From 2010 to 2018, all of the CO$_2$ emissions of the 13 cities located in the BTH increased (Figure 8). The cities with the greatest increases in CO$_2$ emissions were Beijing and Tianjin, showing increases of $4.80 \times 10^7$ and $4.02 \times 10^7$ tCO$_2$, respectively. Tangshan was next, with CO$_2$ emissions increasing by $1.61 \times 10^7$ tCO$_2$ over the past 18 years. The CO$_2$ emissions of Shijiazhuang have grown to $1.37 \times 10^7$ tCO$_2$. We also noted an increase of $0.9 \times 10^7$ tCO$_2$ in the CO$_2$ emissions in Handan, Baoding, and Zhangjiakou. However, there were several cities whose CO$_2$ emissions only increased slightly from 2000 to 2018. For example, the CO$_2$ emissions of Hengshui and Chengde grew by $0.45 \times 10^7$ and $0.41 \times 10^7$ tCO$_2$ during the last 18 years, respectively. Furthermore, the CO$_2$ emissions of Langfang increased by $0.80 \times 10^7$ tCO$_2$. Compared to other cities, the increase in CO$_2$ emissions in Beijing and Tianjin was enormous and approximately three times higher than the emission increase in Tangshan, which had the third-largest increase in CO$_2$ emissions.

### 4.3. Spatial Variation of Carbon Emissions and Absorption in BTH

According to the results of the above analysis, there are significant differences in the carbon emissions among cities in the BTH. We calculated the Gini coefficients for carbon emissions and carbon absorption in the BTH from 2000 to 2018 to assess spatial variation (Table 2). The Gini coefficient ranged from 0 to 1, with a lower value indicating a narrower variation. The various ranges represented have different meanings. In general, when the Gini coefficient is less than 0.3, it indicates that the differences between cities are minor. A value of 0.3–0.4 indicates that the differences are barely coordinated, 0.4–0.6 indicates that the differences are uncoordinated, and values greater than 0.6 indicate a significant gap between cities. According to the Gini coefficient, the emissions among cities in the BTH were
barely coordinated in terms of spatial differences in 2000, but the Gini coefficient showed an increasing trend year after year. The Gini coefficient increased to 0.4353 in 2010 from 0.3616 in 2000. However, the Gini coefficient grew at a slower rate, only increasing by 0.0017 between 2010 and 2018. This is consistent with the trend in the transformation of the total regional carbon emissions. Compared to carbon emissions, the Gini coefficient of carbon absorption in the BTH has remained stable over the last 18 years, albeit at an incongruous interval. Combined with the LUCC results, the cities in the north and west (with large amounts of forest and grassland) have higher carbon sinks, whereas other regions, which are in plain areas and that have a higher proportion of cropland and construction land, have low carbon absorption.

Figure 6. Spatial cluster maps for indirect emissions in Beijing–Tianjin–Hebei from 2000 to 2018 (High–High: high-value clusters; Low–Low: low-value clusters; Low–High/High–Low: there is a distribution of both high-value and low-value clusters).
There was a great amount of variation among the total emissions of different cities (Figure 7). In 2000, the top three cities emitting the most CO2 emissions were Beijing, Tianjin, and Shijiazhuang, while Chengde was the city releasing the least CO2. In 2018, although Beijing and Tianjin also had the most CO2 emissions, the CO2 emissions of Tangshan grew rapidly and reached 2.25 × 10^7 tCO2, exceeding that of Shijiazhuang. Chengde was still the city with the least CO2 emissions, with emissions at 0.57 × 10^7 tCO2. It is an interesting finding that the cities with high CO2 emissions emitted CO2 more quickly. This could be attributed to the LUCC of these cities. The cities with high CO2 emissions comprised a large proportion of the urban area land type, meaning these cities expanded more easily and rapidly.

Figure 7. Variations in the CO2 emissions of 13 cities located in Beijing–Tianjin–Hebei from 2000 to 2018.

From 2010 to 2018, all of the CO2 emissions of the 13 cities located in the BTH increased (Figure 8). The cities with the greatest increases in CO2 emissions were Beijing and Tianjin, showing increases of 4.80 × 10^7 and 4.02 × 10^7 tCO2, respectively. Tangshan was next, with CO2 emissions increasing by 1.61 × 10^7 tCO2 over the past 18 years. The CO2 emissions of Shijiazhuang have grown to 1.37 × 10^7 tCO2. We also noted an increase of 0.9 × 10^7 tCO2 in the CO2 emissions in Handan, Baoding, and Zhangjiakou. However, there were several cities whose CO2 emissions only increased slightly from 2000 to 2018. For example, the CO2 emissions of Hengshui and Chengde grew by 0.45 × 10^7 and 0.41 × 10^7 tCO2 during the last 18 years, respectively. Furthermore, the CO2 emissions of Langfang increased by 0.80 × 10^7 tCO2. Compared to other cities, the increase in CO2 emissions in Beijing and Tianjin was enormous and approximately three times higher than the emission increase in Tangshan, which had the third-largest increase in CO2 emissions.

Figure 8. Spatiotemporal evolution of CO2 emissions in Beijing–Tianjin–Hebei from 2000 to 2018.

4.3. Spatial Variation of Carbon Emissions and Absorption in BTH

According to the results of the above analysis, there are significant differences in the carbon emissions among cities in the BTH. We calculated the Gini coefficients for carbon emissions and carbon absorption in the BTH from 2000 to 2018 to assess spatial variation (Table 2). The Gini coefficient ranged from 0 to 1, with a lower value indicating a narrower variation. The various ranges represented have different meanings. In general, when the Gini coefficient is less than 0.3, it indicates that the differences between cities are minor. A value of 0.3–0.4 indicates that the differences are barely coordinated, 0.4–0.6 indicates that the differences are uncoordinated, and values greater than 0.6 indicate a significant gap between cities. According to the Gini coefficient, the emissions among cities in the BTH were barely coordinated in terms of spatial differences in 2000, but the Gini coefficient showed an increasing trend year after year. The Gini coefficient increased to 0.4353 in 2010 from 0.3616 in 2000. However, the Gini coefficient grew at a slower rate, only increasing by 0.0017 between 2010 and 2018. This is consistent with the trend in the transformation of the total regional carbon emissions. Compared to carbon emissions, the Gini coefficient of carbon absorption in the BTH has remained stable over the last 18 years, albeit at an incongruous interval. Combined with the LUCC results, the cities in the north and west (with large amounts of forest and grassland) have higher carbon sinks, whereas other regions, which are in plain areas and that have a higher proportion of cropland and construction land, have low carbon absorption.
Table 2. The variation in the Gini coefficients.

| Year | Gini Coefficient (Emissions) | Gini Coefficient (Absorption) |
|------|-------------------------------|------------------------------|
| 2000 | 0.3616                        | 0.4210                       |
| 2005 | 0.4127                        | 0.4218                       |
| 2010 | 0.4353                        | 0.4129                       |
| 2018 | 0.4370                        | 0.4107                       |

ESC is a great tool for evaluating the carbon sink capacity of cities, laying the groundwork for identifying ecological engineering zones. There are significant spatial differences in the ESC in the BTH, but the ESC in each city remained stable between 2000 and 2018 (Figure 9). Chengde and Zhangjiakou, both of which are located in the northwest, have ESC values greater than 2. Given the large area of forest and grassland, this suggests that the two cities have a high carbon sink capacity. Qinhuangdao and Baoding are also relatively strong carbon sinks and have an ESC value greater than 1. Beijing and Shijiazhuang have ESCs that are greater than 0.5 but less than 1, indicating that these cities have some carbon sink capacity. Despite the fact that Xingtai’s ESC was less than 0.5 in 2000 and 2005, the carbon sink capacity increased after 2010. The ESCs of other cities are less than 0.5, indicating that the proportion of CO\(_2\) emissions is significantly greater than that of carbon sequestration. As a result, it is critical to improving their carbon emission efficiency.

Figure 9. Spatiotemporal evolution of the ecological support coefficient in Beijing–Tianjin–Hebei from 2000 to 2018.
4.4. Land Use Optimization

The analysis of the spatial variation in the CO$_2$ emissions and ESCs reveals significant differences among the 13 cities in the BTH. To achieve the goal of carbon neutrality and carbon peaking, the 13 cities in the BTH were divided into different zones based on the characteristics of their carbon sources and sinks so that appropriate carbon reduction measures could be implemented for different zones. We established principles for land-use optimization based on city development and the ESCs, laying the groundwork for carbon reduction and ecological engineering (Table 3). Despite large spatial differences between carbon sources and sinks within cities, the zoning scheme proposed in this study can still serve as a policy reference for future city development. On the basis of the carbon emissions and ESCs in 2018, we divided the 13 cities located in the BTH into three zones: carbon sink zones, emission control zones, and low-carbon development zones (Figure 10).

Table 3. Land-use optimization zoning.

| Zone Types                        | Zoning Principles                                      |
|-----------------------------------|--------------------------------------------------------|
| Carbon sink zone                  | ESC > 1 & total carbon emissions < 2 $\times$ 10$^7$ tCO$_2$ |
| Emissions control zone            | 0.5 < ESC < 1 & total carbon emissions > 2 $\times$ 10$^7$ tCO$_2$ |
| Low carbon development zone       | ESC < 0.5                                               |

Figure 10. Land-use optimization zoning in Beijing–Tianjin–Hebei.
Carbon sink zone: This zone has a low level of carbon emissions and a high ESC. It includes four cities: Baoding, Zhangjiakou, Chengde, and Qinhuangdao. This zone contains a significant amount of forest and grassland. The presence of a high carbon sink capacity indicates that this zone has a strong ecological foundation. Furthermore, this zone makes a significant contribution to the BTH carbon sink. There is limited land for urban construction, whereas there is a vast amount of mountainous land. As a result, this zone is appropriate for launching ecological engineering projects.

Emission control zone: This zone has a high level of emissions but some carbon sink capacity. Beijing and Shijiazhuang are classified in this zone. Although there are vast mountainous areas, there are also significant proportions of cropland and land that is suitable for urban construction. Therefore, there are obstacles to implementing ecological engineering construction in this area. Due to the developed economic level, industries in this zone are clustered, so low-carbon production industries are relevant to reducing carbon emissions in this zone. Furthermore, this zone should focus on protecting the environment and controlling carbon emissions, adjusting the energy consumption structure, increasing investments in science and technology, and improving the energy utilization rate.

Low carbon development zone: Because of the high proportion of cropland in this zone, it is unsuitable for ecological engineering. The government should strive to improve carbon emission efficiency while lowering carbon emissions. Industries such as high-tech, new material, and new energy industries can gradually transition to low-carbon industries, highlighting the benefits of the service industry. Driving the economic and industrial restructuring of the surrounding areas as well as improving the economic benefits of carbon emissions is also something that can be achieved in this land type.

5. Discussion

LUC leads to significant changes in carbon sinks and carbon sources, and increases in urban areas influence not only the carbon emissions but also the carbon sinks that are within terrestrial vegetation. Forests and grassland have large CO₂-absorbing capacity via photosynthesis. Decreasing forest and grassland areas results in a larger amount of carbon emissions. On the contrary, ecological engineering, which increases forest and grassland areas, will lead to remarkable carbon sink capabilities. However, we must recognize the reality that it is not possible to implement ecological projects in all areas. For cities with a large proportion of arable land and urban construction land, increasing the areas of forests and grassland means reducing cropland and urban areas. This is clearly not in line with existing Chinese policy [46]. Taking action to optimize land-use types and implement engineering in key zones is a vital way to overcome the current dilemma. This research analyzed the spatial evolution and inequality of carbon sources and sinks in the BTH by adopting land use and remote sensing data and developing a land-use optimization plan to mitigate BTH emissions.

However, there are uncertainties in this study. Due to the differences in geographical location, latitude and longitude, and climatic conditions, there is a huge gap in the land-use carbon emission coefficients for various regions. In fact, it is difficult to determine the special coefficients of every city in the BTH. This study adopted the same coefficient to estimate the carbon emission levels of different cities in the region, following the lead of previous studies [6,34,42]. This method resulted in uncertainty because we were unable to identify the differences among cities. Furthermore, seasonal variations and long-term changes (such as decadal scale) in carbon emissions were not considered. We assessed carbon emissions and carbon sequestration on an annual basis and did not identify their changes over the course of the year. It will be interesting to employ an approach to identify the dynamic nature of the emissions and uptake rates. These uncertainties and limitations highlight the direction of future work.
6. Conclusions

Our study develops a land-use optimization zoning framework for cities based on spatial divergences in carbon sources and sinks and provides evidence to help us to better understand the contribution of LUCC to climate change. LUCC has a significant impact on CO$_2$ emissions. Given that urbanization has resulted in an increased population concentration in cities, the expansion of urban areas as a result of urbanization has increased the indirect emissions caused by human activities. The effects of ecological engineering, on the other hand, were diametrically opposed. The expansion of forests, grassland, and water bodies was beneficial to the region’s carbon sink capabilities. Furthermore, there was a strong relationship between indirect emissions and urban areas. Large cities had higher indirect emissions because they consumed more fossil energy, produced more cement, and flared more gas. Carbon inequalities between cities were discovered during the city-level analysis. The bigger cities had higher CO$_2$ emissions, and the increased CO$_2$ emissions in the bigger cities were several times those of smaller cities.

Our findings will help to increase the government’s understanding of the importance of taking active steps to develop ecological engineering plans and reach a carbon peak. In order to reduce CO$_2$ emissions, it is necessary to consider the future development patterns of cities. Launching land-use optimization zoning is critical for improving regional carbon sinks and avoiding unsustainable development paths with high emission levels. It is necessary to pursue clean energy usage rather than fossil fuels, and green development patterns must be encouraged in high-emission zones.

This study has provided new knowledge on the drivers, factors, and mitigation of CO$_2$ emissions and developed a land-use optimization zoning scheme based on the carbon source and sink characteristics of cities. In the context of many countries promising to achieve carbon peak and carbon neutrality, our findings lay the groundwork for future work in other regions and on larger scales.

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References

1. IPCC 2021 Climate Change 2021: The Physical Science Basis; Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change; Cambridge University Press: Cambridge, Cambridgeshire, UK, in press.
2. Zhao, J.; Cohen, J.B.; Chen, Y.; Cui, W.; Cao, Q.; Yang, T.; Li, G. High-resolution spatiotemporal patterns of China’s FFCO$_2$ emissions under the impact of LUCC from 2000 to 2015. Environ. Res. Lett. 2020, 15, 44007. [CrossRef]
3. Park, H.-C. Fossil fuel use and CO$_2$ emissions in Korea: NEAT approach. Resour. Conserv. Recycl. 2005, 45, 295–309. [CrossRef]
4. Han, P.; Zeng, N.; Oda, T.; Lin, X.; Crippa, M.; Guan, D.; Janssens-Maenhout, G.; Ma, X.; Liu, Z.; Shan, Y.; et al. Evaluating China’s fossil-fuel CO$_2$ emissions from a comprehensive dataset of nine inventories. Atmos. Chem. Phys. 2020, 20, 11371–11385. [CrossRef]
5. Jiang, S.; Deng, X.; Liu, G.; Zhang, F. Climate change-induced economic impact assessment by parameterizing spatially heterogeneous CO$_2$ distribution. Technol. Forecast. Soc. Change. 2021, 167, 120668. [CrossRef]
6. Lin, Q.; Zhang, L.; Qiu, B.; Zhao, Y.; Wei, C. Spatiotemporal Analysis of Land Use Patterns on Carbon Emissions in China. Land 2021, 10, 141. [CrossRef]
7. Rosan, T.M.; Goldewijk, K.K.; Ganzenmüller, R.; O'Sullivan, M.; Pongratz, J.; Mercado, L.M.; Aragao, L.E.O.C.; Heinrich, V.; Von Randow, C.; Wiltshire, A.; et al. A multi-data assessment of land use and land cover emissions from Brazil during 2000–2019. *Environ. Res. Lett.* **2021**, *16*, 74004. [CrossRef]

8. Si, R.; Aziz, N.; Raza, A. Short and long-run causal effects of agriculture, forestry, and other land use on greenhouse gas emissions: Evidence from China using VECM approach. *Environ. Sci. Pollut. Res.* **2021**, 28, 64419–64430. [CrossRef]

9. Dong, N.; Liu, Z.; Luo, M.; Fang, C.; Lin, H. The Effects of Anthropogenic Land Use Changes on Climate in China Driven by Global Socioeconomic and Emission Scenarios. *Earth’s Future* **2019**, 7, 784–804. [CrossRef]

10. Cao, W.; Yuan, X. Region-county characteristic of spatial-temporal evolution and influencing factor on land use-related CO\(_2\) emissions in Chongqing of China, 1997–2015. *J. Clean. Prod.* **2019**, 231, 619–632. [CrossRef]

11. Deng, C.; Liu, J.; Nie, X.; Li, Z.; Liu, Y.; Xiao, H.; Hu, X.; Wang, L.; Zhang, Y.; Zhang, G.; et al. How trade-offs between ecological construction and urbanization expansion affect ecosystem services. *Ecol. Indic.* **2021**, 122, 107253. [CrossRef]

12. Hurlimann, A.; Moosavi, S.; Browne, G.R. Urban planning policy must do more to integrate climate change adaptation and mitigation actions. *Land Use Policy* **2021**, *101*, 105188. [CrossRef]

13. Chuai, X.; Huang, X.; Wang, W.; Zhao, R.; Zhang, M.; Wu, C. Land use, total carbon emissions change and low carbon land management in Coastal Jiangsu, China. *J. Clean. Prod.* **2015**, 103, 77–86. [CrossRef]

14. Hakkarainen, J.; Ialongo, I.; Tamminen, J. Direct space-based observations of anthropogenic CO\(_2\) emission areas from OCO-2. *Geophys. Res. Lett.* **2016**, 43, 11400–11406. [CrossRef]

15. Reuter, M.; Buchwitz, M.; Hilboll, A.; Richter, A.; Schneising, O.; Hilker, M.; Heymann, J.; Bovensmann, H.; Burrows, J.P. Decreasing emissions of NOx relative to CO\(_2\) in East Asia inferred from satellite observations. *Nat. Geosci.* **2014**, 7, 792–795. [CrossRef]

16. Park, C.; Schade, G.W. Anthropogenic and Biogenic Features of Long-Term Measured CO\(_2\) Flux in North Downtown Houston, Texas. *J. Environ. Qual.* **2016**, 45, 253–265. [CrossRef] [PubMed]

17. Li, M.; Klimont, Z.; Zhang, Q.; Martin, R.V.; Zheng, B.; Heyes, C.; Cofala, J.; Zhang, Y.; He, K. Comparison and evaluation of anthropogenic emissions of SO\(_2\) and NOx over China. *Atmos. Chem. Phys.* **2018**, 18, 3433–3456. [CrossRef]

18. Shen, L.; Sun, Y. Review on carbon emissions, energy consumption and low-carbon economy in China from a perspective of global climate change. *J. Geogr. Sci.* **2016**, 26, 855–870. [CrossRef]

19. Oda, T.; Maksyutov, S.; Andres, R.J. The Open-source Data Inventory for Anthropogenic CO\(_2\) version 2016 (ODIAC2016): A global monthly fossil fuel CO\(_2\) gridded emissions data product for tracer transport simulations and surface flux inversions. *Earth Syst. Data* **2018**, 10, 87–107. [CrossRef]

20. Shan, Y.; Huang, Q.; Guan, D.; Hubacek, K. China CO\(_2\) emission accounts 2016–2017. *Sci. Data* **2020**, 7, 54. [CrossRef]

21. Jain, P.; Jain, P. Are the Sustainable Goals really Sustainable? A policy perspective. *Sustain. Dev.* **2020**, 28, 1642–1651. [CrossRef]

22. Knauer, J.; Zaehe, S.; De Kauwe, M.G.; Bahar, N.H.A.; Evans, J.R.; Medlyn, B.E.; Reichstein, M.; Werner, C. Effects of mesophyll conductance on vegetation responses to elevated CO\(_2\) concentrations in a land surface model. *Glob. Change. Biol.* **2019**, 25, 1820–1838. [CrossRef] [PubMed]

23. Li, Z.; Tang, D.; Han, M.; Bethel, B.J. Comprehensive Evaluation of Regional Sustainable Development Based on Data Envelopment Analysis. *Sustainability* **2018**, 10, 3897. [CrossRef]

24. Yang, S.; Sheng, D.; Adamowski, J.; Gong, Y.; Zhang, J.; Cao, J. Effect of Land Use Change on Soil Carbon Storage over the Last 40 Years in the Shi Yang River Basin, China. *Land* **2018**, 7, 11. [CrossRef]

25. Gao, L.; Wen, X.; Gao, T.; Wang, Y.; Shen, L. Spatiotemporal Variability of Carbon Flux from Different Land Use and Land Cover Changes: A Case Study in Hubei Province, China. *Energies* **2014**, 7, 2298–2316. [CrossRef]

26. Göpel, J.; Schüngel, J.; Schaldach, R.; Meurer, K.; Jungkunst, H.F.; Franko, U.; Boy, J.; Strey, R.; Strey, S.; Guggenberger, G.; et al. Future land use and land cover in Southern Amazonia and resulting greenhouse gas emissions from agricultural soils. *Reg. Environ. Chang.* **2018**, 18, 129–142. [CrossRef]

27. Cai, W.; Peng, W. Exploring Spatiotemporal Variation of Carbon Storage Driven by Land Use Policy in the Yangtze River Delta Region. *Land* **2021**, 10, 1120. [CrossRef]

28. Ghosh, S.; Dinda, S.; Das Chatterjee, N.; Dutta, S.; Bera, D. Spatial-explicit carbon emission-sequestration balance estimation and evaluation of emission susceptible zones in an Eastern Himalayan city using Pressure-Sensitivity-Resilience framework: An approach towards achieving low carbon cities. *J. Clean. Prod.* **2022**, 336, 130417. [CrossRef]

29. Penazzi, S.; Accorsi, R.; Manzini, R. Planning low carbon urban-rural ecosystems: An integrated transport land-use model. *J. Clean. Prod.* **2019**, 235, 96–111. [CrossRef]

30. Stokes, D. *Zoning for Climate Change*; (SSRN Scholarly Paper No. ID 3810940); Social Science Research Network: Rochester, NY, USA, 2021. [CrossRef]

31. Ravetz, J.; Neuvonen, A.; Mäntyalo, R. The new normative: Synergistic scenario planning for carbon-neutral cities and regions. *Reg. Stud.* **2021**, 55, 150–163. [CrossRef]

32. Peng, C.; Li, B.; Nan, B. An analysis framework for the ecological security of urban agglomeration: A case study of the Beijing-Tianjin-Hebei urban agglomeration. *J. Clean. Prod.* **2021**, 315, 128111. [CrossRef]

33. Quijano, L.; Van Oost, K.; Nadeu, E.; Gaspar, L.; Navas, A. Modelling the Effect of Land Management Changes on Soil Organic Carbon Stocks in a Mediterranean Cultivated Field. *Land Degrad. Dev.* **2017**, 28, 515–523. [CrossRef]
34. Lai, L.; Huang, X.; Yang, H.; Chuai, X.; Zhang, M.; Zhong, T.; Chen, Z.; Chen, Y.; Wang, X.; Thompson, J.R. Carbon emissions from land-use change and management in China between 1990 and 2010. Sci. Adv. 2016, 2, e1601063. [CrossRef] [PubMed]
35. Chen, Y.; Lu, H.; Li, J.; Xia, J. Effects of land use cover change on carbon emissions and ecosystem services in Chengyu urban agglomeration, China. Stoch. Environ. Res. Risk Assess. 2020, 34, 1197–1215. [CrossRef]
36. Zhao, Y.; Ma, S.; Fan, J.; Cai, Y. Examining the Effects of Land Use on Carbon Emissions: Evidence from Pearl River Delta. Int. J. Environ. Res. Public Health 2021, 18, 3623. [CrossRef]
37. Cui, X.; Wei, X.; Liu, W.; Zhang, F.; Li, Z. Spatial and temporal analysis of carbon sources and sinks through land use/cover changes in the Beijing-Tianjin-Hebei urban agglomeration region. Phys. Chem. Earth Parts A/B/C 2019, 110, 61–70. [CrossRef]
38. Zhou, D.; Tian, Y.; Jiang, G. Spatio-temporal investigation of the interactive relationship between urbanization and ecosystem services: Case study of the Jingjinji urban agglomeration, China. Ecol. Indic. 2018, 95, 152–164. [CrossRef]
39. Raihan, A.; Begum, R.A.; Nizam, M.; Said, M.; Pereira, J.J. Dynamic impacts of energy use, agricultural land expansion, and deforestation on CO₂ emissions in Malaysia. Environ. Ecol. Stat. 2022, 1–31. [CrossRef]
40. Xia, Q.; Li, L.; Dong, J.; Zhang, B. Reduction Effect and Mechanism Analysis of Carbon Trading Policy on Carbon Emissions from Land Use. Sustainability 2021, 13, 9558. [CrossRef]
41. Yang, B.; Chen, X.; Wang, Z.; Li, W.; Zhang, C.; Yao, X. Analyzing land use structure efficiency with carbon emissions: A case study in the Middle Reaches of the Yangtze River, China. J. Clean. Prod. 2020, 274, 123076. [CrossRef]
42. Wang, F.; Wang, B.; Liu, C.-Q.; Wang, Y.; Guan, J.; Liu, X.; Yu, Y. Carbon dioxide emission from surface water in cascade reservoirs–river system on the Maotiao River, southwest of China. Atmos. Environ. 2011, 45, 3827–3834. [CrossRef]
43. Xiong, L.; Yu, C.; De Jong, M.; Wang, F.; Cheng, B. Economic Transformation in the Beijing-Tianjin-Hebei Region: Is It Undergoing the Environmental Kuznets Curve? Sustainability 2017, 9, 869. [CrossRef]
44. Zhou, T.; Jiang, G.; Zhang, R.; Zheng, Q.; Ma, W.; Zhao, Q.; Li, Y. Addressing the rural in situ urbanization (RISU) in the Beijing–Tianjin–Hebei region: Spatio-temporal pattern and driving mechanism. Cities 2018, 75, 59–71. [CrossRef]
45. Liao, M.L.; Chen, Y.; Wang, Y.J.; Lin, M.S. Study on the coupling and coordination degree of high-quality economic development and ecological environment in Beijing-Tianjin-Hebei region. Appl. Ecol. Environ. Res. 2019, 17, 11069–11083. [CrossRef]
46. Zhou, Y.; Li, X.; Liu, Y. Cultivated land protection and rational use in China. Land Use Policy 2021, 106, 105454. [CrossRef]