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Research of Carbon Emission Reduction Potentials in the Yellow River Basin, Based on Cluster Analysis and the Logarithmic Mean Divisia Index (LMDI) Method

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Abstract: China has implemented many green transition policies to reach its carbon peak target, some of which do not consider the actual carbon reduction pressures that localities can afford, thus lowering the living standards of residents and economic growth, which makes the green transition process unsustainable. The Yellow River Basin plays an important role in China’s energy, food, manufacturing, and ecological sectors. Thus, the design of green transition policies in the region needs to be modest and efficient. Based on the data of 100 prefecture-level cities in the Yellow River Basin from 2006 to 2017, this paper uses the K-means clustering to divide the carbon reduction potential of cities into four types. Most cities’ carbon reduction potentials are low or medium, unsuitable for adopting a rapid green transition. Based on the logarithmic mean Divisia index (LMDI) decomposition results and the carbon reduction potential, we designed different carbon-control pathways: Shandong and Henan should focus on increasing investment in green technology, especially oxy-combustion technology; Gansu, Ningxia, and Qinghai could partially offset carbon emissions through land use, land-use change and forestry (LULUCF) activities; Sichuan and Inner Mongolia should increase their energy-use efficiency; Shaanxi and Shanxi could use green finance to complete the upgrading of local industries. The above emission-reduction strategies can be actively pursued in cities with high emission reduction potential and should be implemented with caution in cities with low emission reduction potential. This paper provides a new and cost-effective perspective on carbon emission control in the Yellow River Basin.

Keywords: Yellow River; carbon emission reduction potential; cluster analysis

1. Introduction

Continued climate warming has caused irreversible damage to the global ecological, social, and economic environment. The locking effect of the current high-carbon growth path further continues the future warming trend, which is a challenge to global sustainable development [1]. As the world’s largest carbon emitter, the carbon emission dynamics of each province collectively influence the changes in China’s carbon emissions. China has developed different carbon reduction programs for different regions, but these programs do not adequately assess the maximum carbon reduction pressure that the different regions can withstand, making some policies counterproductive. Some cities may face emission reduction mandates that exceed their emission reduction potential, forcing them to reduce carbon emissions by reducing people’s well-being and the speed of economic development. For example, in 2017, some governments disallowed coal and charcoal for heating, which led to many poor residents enduring the cold winter without heating.

The nine provinces located in the Yellow River Basin (Shandong, Henan, Shanxi, Inner Mongolia, Ningxia, Shaanxi, Sichuan, Gansu, and Qinghai) face the challenges of resource depletion and ecological degradation [2]. On 8 October 2021, the Chinese
government promulgated the Outline of the Plan for Ecological Protection and High-Quality Development of the Yellow River Basin. This plan makes this region the focal point for carbon control and green transformation. The Yellow River Basin plays an essential role in China’s food security and energy security, so the design of green transition policies in the region needs to be modest and efficient.

It is a traditional practice to delineate strategic regions based on geographical features and set related policies in China, such as the plan to build the Yangtze River Economic Belt (YREB) and the Bohai Economic Circle. Theoretical and practical studies on the Yangtze River Economic Belt have provided valuable experiences for carbon emission control in the Yellow River Basin [3]. Chen et al. [4] researched the relationship between tourism, carbon dioxide (CO2) emissions, and economic growth in the Yangtze River Delta (YRD) of China. Tang [5] used the technique for order performance by similarity to ideal solution (TOPSIS) and an “obstacle factor diagnosis method” to measure the reduction capacity of each province of the YREB. In recent years, the gap in carbon emission intensity between the Yellow River Basin and the Yangtze River Basin has been increasing [6]. To achieve the overall control of carbon emissions in China, the issue of carbon control in the Yellow River Basin deserves more attention.

Carbon emissions are influenced by many factors, such as socioeconomic factors, technological advances, policies, and culture [7]. Some literature classifies cities based on the characteristics of various factors and designs carbon reduction pathways [8]. The current widely used classification method is cluster analysis based on machine learning algorithms. Creutzig et al. [9] analyzed the urban attributes of energy utilization using a classification tree model based on 274 cities and three global datasets. Hu et al. [10] applied the K-means clustering algorithm and evolution tree model to analyze 144 countries’ carbon emissions characteristics. Currently, there is a research gap in the clustering analysis of the emission reduction potential of cities in the Yellow River Basin.

Summarizing the characteristics of regional carbon emissions is necessary to accurately explore and identify the drivers of carbon emissions. Researchers used the impact model of population, affluence, and technology (IPAT) or stochastic impacts by regression on population, affluence, and technology (STIRPAT) model as a path for quantitative regression analysis [11–13]. However, those two methods have limitations in analyzing the driving factors for carbon emission. Thus, many researchers chose the structural decomposition analysis (SDA) methods [14–16] and the index decomposition analysis (IDA) methods [17–20] to analyze the issue of driving factors. In the IDA approaches, the logarithmic mean Divisia index (LMDI) method eliminates residuals and zero values to ensure accuracy in meeting factor reversibility [21] and has been widely used for energy demand or to analyze drivers of emission changes.

Based on previous research, this paper chooses to combine K-means clustering and LMDI decomposition methods to propose corresponding carbon control strategies for the characteristics of the Yellow River Basin with significant regional differences. The specific research framework is shown in Figure 1.

Previous studies discussed the decomposition of carbon emission factors and the design of emission reduction pathways in the Yellow River basin without considering each prefecture-level city’s actual carbon reduction potential. This paper attempts to cluster the carbon emission reduction potential of cities and combine the carbon emission drivers of each province to design a more cost-effective CO2 reduction plan in the Yellow River Basin. Moreover, this paper innovatively adds the vegetation carbon sequestration capacity to reflect the dynamic changes in land use, land-use change, and forestry (LULUCF), which can measure the carbon peak and carbon-neutral pressure of each city more comprehensively.
2. Materials and Methods

2.1. Study Area and Data Source

The Yellow River originates from the Qinghai–Tibet Plateau and enters the sea in Shandong Province, spanning 5400 km. Although scholars have different determinations of the scope in the study of the Yellow River Basin [22], according to the planning scope of the Outline of the Plan for Ecological Protection and High-Quality Development of the Yellow River Basin, promulgated by the State Council of China, the mainstream believes that the Yellow River Basin contains nine provinces: Qinghai, Sichuan, Gansu, Ningxia, Inner Mongolia, Shanxi, Shaanxi, Henan, and Shandong.

The study area of this paper follows the above definition. After excluding the ten autonomous cities that lacked the necessary data (Gannan Tibetan Autonomous Prefecture, Linxia Hui Autonomous Prefecture in Gansu Province, Aba Tibetan Qiang Autonomous Prefecture in Sichuan Province, Haibei Tibetan Autonomous Prefecture in Qinghai Province, Huangnan Tibetan Autonomous Prefecture, Hainan Tibetan Autonomous Prefecture, Guoluo Tibetan Autonomous Prefecture, Yushu Tibetan Autonomous Prefecture, Haixi Mongolian and Tibetan Autonomous Prefecture, and Alxa League in Inner Mongolia), the study area of this paper contains 100 prefecture-level cities in the Yellow River basin.

Following the method of [23], we used county-level carbon emission and vegetation carbon sequestration data derived from the combined analysis of satellite images and nighttime lights to construct municipal-level carbon-related data [24]. The socioeconomic data are mainly from the China City Statistical Yearbook.

As for total carbon emissions in LMDI analysis, we use the carbon emission coefficient method to calculate the amount of carbon emission considering the availability of data. This method has been widely used in carbon emission calculation [25], as Equation (1) shows:

$$ C_i = \sum_{j=1}^{n} E_{ij} \times K_j $$

where $C_i$ means the total energy consumption carbon emission of the industrial sector $i$; $E_{ij}$ is the amount of fuel type $j$ that was consumed by the industrial sector $i$; and $K_j$ is the carbon emission coefficient of energy type $j$. The carbon emission coefficient for each energy type is shown in Table 1.

According to Figure 2, even within the same province, carbon emissions’ spatial and temporal characteristics vary considerably among cities. Therefore, it is necessary to make a separate measurement of the carbon reduction potential of each city in this region.
Table 1. Carbon emission coefficient of each energy.

| Category         | Fuel Name           | Carbon Emission Coefficient (kg CO₂/kg, m³) |
|------------------|---------------------|---------------------------------------------|
| Coal fuel        | Raw coal            | 1.977897                                   |
|                  | Clean coal          | 2.818808                                   |
|                  | Other coal washing  | 0.79114                                    |
|                  | Briquette           | 1.977897                                   |
|                  | Coke                | 3.042545                                   |
|                  | Coke oven gas       | 0.742634                                   |
|                  | Other gas           | 0.232079                                   |
|                  | Other coking products | 3.069733                               |
| Petroleum fuel   | Crude oil           | 3.065113                                   |
|                  | Petrol              | 2.984751                                   |
|                  | Kerosene            | 3.096733                                   |
|                  | Diesel              | 3.160513                                   |
|                  | Fuel oil            | 3.236558                                   |
|                  | Liquefied petroleum gas | 3.166295                           |
|                  | Refinery dry gas    | 3.375832                                   |
|                  | Other petroleum products | 3.236558                           |
| Natural gas      | Natural gas         | 2.184029                                   |
|                  | Charcoal            | 3.304000                                   |
| Biofuels         | Biogasoline/Biodiesel | 1.911600                               |

Data source: 1998–2018 China Energy Statistical Yearbook, IPCC Guidelines National Greenhouse Gas Inventories.

Figure 2. Distribution of energy-related carbon emissions in the Yellow River Basin.

2.2. K-Means Clustering and Indicators Choice

Clustering is a technical approach to data mining and is widely used in region classification. There are many different branches of cluster analysis algorithms, including hierarchical clustering, fuzzy clustering, systematic clustering, and K-means clustering. Cluster analysis can be used in an unsupervised state to obtain an optimal division according to the similarity or distance of sample characteristics (maximum similarity of samples within groups and high heterogeneity of samples between groups). K-means clustering is a method of vector quantization, originally from signal processing, that aims to partition n observations into k clusters in which each observation belongs to the cluster with the nearest mean (cluster centers or cluster centroid), serving as a prototype of the cluster [26]. K-means clustering minimizes within-cluster variances (squared Euclidean distances).

In this paper, we standardized all clusters to build a sample collection X = {x₁, x₂, ⋯ , xₙ}. Then, K sample points were randomly selected as the initial clustering centers, and then the distance from each sample to the class center was calculated, and each sample was
assigned to the nearest central class, which constitutes the initial clustering result. Again, the mean value of the samples in each class was calculated as the new class center, and the above steps were repeated until convergence. In this paper, we used Euclidean distance squared \( d(x_i, x_j) \) to represent the distance or similarity between samples.

\[
d(x_i, x_j) = \sum_{k=1}^{m} (x_{ki} - x_{kj})^2 = \sum_{k=1}^{m} \| x_{ki} - x_{kj} \|^2 \tag{2}
\]

\[
\text{WCSS} = \sum_{l=1}^{k} \sum_{C(i)=l} \| x_i - x_l \|^2 \tag{3}
\]

The convergence condition or evaluation index of the clustering algorithm is the sum of the distances between the samples and the centers of the classes they belong to. In Equation (2), the sum of the distances is the average within-cluster sum of squares (WCSS). The smaller this index is, the greater the similarity between similar classes and the better the clustering effect, see Equation (3). The degree of distortion decreases as the category increases, and if the degree of distortion is greatly reduced when a critical point is reached, it decreases slowly afterward. This critical point can be considered the point with better clustering performance, and its image resembles an elbow, so it is named the elbow method.

The elbow method can determine the optimal number of groups based on the sum of squares of deviations under different group numbers [27]. Therefore, using this method to determine the number of clusters could improve the objectivity of the classification [23].

In the process of constructing the carbon emission reduction potential indicator system, relevant factors affecting carbon emissions and the trend of peak achievement should be included. In this paper, three static indicators and three dynamic indicators are selected to cluster 100 cities in the Yellow River Basin. Static indicators are selected based on the results of previous studies to reflect the cross-sectional characteristics of carbon emissions in different types of cities. Dynamic indicators can observe the trend characteristics of carbon emission peaks of different cities. Details of these six indicators are shown in Table 2.

### Table 2. Clustering indicators.

| Type          | Indicators                  | Specific Data                          | Reference Year |
|--------------|-----------------------------|----------------------------------------|----------------|
| Static       | development level           | GDP per capita                         | 2017           |
|              | industrial structure        | the share of the output value of the   |                |
|              | carbon emissions level      | secondary industry carbon emissions    |                |
|              |                             | per capita.                            |                |
| Dynamic      | GDP growth                  | the average change rate of GDP         | 2006–2017      |
|              | carbon emission growth      | the average change rate of carbon      | 2006–2017      |
|              | carbon sequestration growth | the average change rate of carbon      | 2006–2017      |
|              |                             | sequestration                          |                |

Compared with existing studies, we add carbon sequestration growth as a dynamic indicator to reflect land use, land-use change, and forestry (LULUCF) activities. As the carbon sequestration capacity of surface vegetation increases, the carbon emission allowable margin in the carbon budget will also rise, which will reduce the difficulty of carbon emission control [28]. Therefore, the analysis of the carbon reduction potential of each city in this paper will be more accurate.

### 2.3. Carbon Decoupling Method

Carbon decoupling is the indicator to measure the transition to a green economy. The carbon decoupling status of cities in the Yellow River Basin affects the prospect of carbon reduction in each city. Measuring the carbon decoupling status of cities can help to set carbon peaking schedules and develop carbon reduction policies. The Organisation for
Economic Co-operation and Development (OECD) method [29] and the Tapio method [30] are mainstream methods for measuring the degree of carbon decoupling.

OECD [31] introduced decoupling analysis to study the relationship between environmental pressure and economic development. The OECD decoupling calculation is as Equation (4):

\[ \gamma = 1 - \frac{EP_t}{EP_0} \frac{DF_t}{DF_0} \]  

In Equation (4), EP represents environmental pressures and DF means economic driving force; 0 and t are the base year and the target year, respectively. On the left side, \( \gamma \) means the decoupling indicator, whose value has two situations: if \( \gamma \) is smaller than 0, there is no decoupling. If \( \gamma \) is greater than 0, the degree of decoupling increases as \( \gamma \) gets closer to 1. The OECD decoupling model is easy to understand. However, there are two drawbacks to this model. First, the result of this model is sensitive to the change in benchmark years, which makes results unstable. Second, \( \gamma \) only contains two states in this model: decoupling and no decoupling. Thus, subtle changes in variables are not reflected in the results and may cause less accurate results.

Tapio [30] introduced another model to measure the degree of decoupling. Taipo decoupling uses elasticity instead of absolute value, increasing the sensitivity to variables’ changes.

\[ \gamma_{TC} = \frac{\Delta TC}{\Delta GDP/GDP_0} = \frac{\left( TC_t - TC_0 \right)}{TC_0} \frac{\left( GDP_t - GDP_0 \right)}{GDP_0} \]  

In Equation (5), \( \Delta TC \) means the change in total carbon emissions and \( \Delta GDP \) means the economy’s growth rate. Year 0 is the base year; year t is the target year. There are three categories and eight subcategories to describe decoupling states (Table 3).

| Decoupling Status         | \( \Delta TC \) | \( \Delta GDP \) | \( \gamma_{TC} \) |
|---------------------------|-----------------|-----------------|-------------------|
| Decoupling                |                 |                 |                   |
| Strong decoupling (SD)    | <0              | >0              | \( \gamma_{TC} < 0 \) |
| Weak decoupling (WD)      | >0              | >0              | 0 < \( \gamma_{TC} < 0.8 \) |
| Recessive decoupling (RD) | <0              | <0              | \( \gamma_{TC} > 1.2 \) |
| Coupling                  |                 |                 |                   |
| Expansive coupling (EC)   | >0              | >0              | 0.8 < \( \gamma_{TC} < 1.2 \) |
| Recessive coupling (RC)   | <0              | <0              | 0.8 < \( \gamma_{TC} < 1.2 \) |
| Negative decoupling       |                 |                 |                   |
| Weak negative decoupling (WND) | <0          | <0              | 0 < \( \gamma_{TC} < 0.8 \) |
| Expansive negative decoupling (END) | >0          | >0              | \( \gamma_{TC} > 1.2 \) |
| Strong negative decoupling (SND) | >0          | <0              | \( \gamma_{TC} < 0 \) |

2.4. LMDI Decomposition Method

From the perspective of policymakers, it is important to identify the main drivers of carbon emissions growth and develop targeted policies. In the field of energy and environment, decomposition methods can effectively analyze the characteristics and drivers of carbon emission changes. Currently, there are two main analysis methods, the SDA approach and IDA approach. The implementation of SDA requires the support of the input-output model, which is more than IDA. Ang proposed the LMDI method [21,32], which improves the implementation of IDA and systematically and comprehensively considers the availability of data in the decomposition process and is widely used in the research of carbon emission decomposition.

Based on [32], changes in carbon emission were decomposed into five factors, which are industrial activity (\( \Delta C_{act} \)), sectoral energy intensity (\( \Delta C_{int} \)), sectoral energy mix (\( \Delta C_{mix} \)), industry activity mix (\( \Delta C_{str} \)), and CO\(_2\) emission factors (\( \Delta C_{emf} \)), as Equation (6) shows:

\[ \Delta C_{tot} = C^T - C^0 = \Delta C_{act} + \Delta C_{str} + \Delta C_{int} + \Delta C_{mix} + \Delta C_{emf} \]
\[ \Delta C_{\text{act}} = \sum_{ij} \frac{C_{Tij} - C_{0ij}}{\ln C_{Tij} - \ln C_{0ij}} \ln \left( \frac{\text{GDP}_T}{\text{GDP}} \right) \]
\[ \Delta C_{\text{str}} = \sum_{ij} \frac{C_{Tij} - C_{0ij}}{\ln C_{Tij} - \ln C_{0ij}} \ln \left( \frac{\text{IS}_T}{\text{IS}_i} \right) \]
\[ \Delta C_{\text{int}} = \sum_{ij} \frac{C_{Tij} - C_{0ij}}{\ln C_{Tij} - \ln C_{0ij}} \ln \left( \frac{\text{IT}_i}{\text{IT}_i} \right) \]
\[ \Delta C_{\text{mix}} = \sum_{ij} \frac{C_{Tij} - C_{0ij}}{\ln C_{Tij} - \ln C_{0ij}} \ln \left( \frac{\text{EM}_T}{\text{EM}_i} \right) \]
\[ \Delta C_{\text{emf}} = \sum_{ij} \frac{C_{Tij} - C_{0ij}}{\ln C_{Tij} - \ln C_{0ij}} \ln \left( \frac{\text{UT}_i}{\text{UT}_i} \right) \]

where \( C \) is the total carbon emissions and \( C_{ij} \) is the CO\(_2\) emissions made by using fuel type \( j \) in the industrial sector \( i \). \( E_{ij} \) is the amount of fuel type \( j \) that was consumed by industrial sector \( i \), \( E_i = \Sigma_j E_{ij} \); GDP\(_T\) is the total industrial activity level, and we use GDP to reflect this variable. IS\(_T^i\) is GDP of industrial sector \( i \) as a share of total GDP in year \( T \), IS\(_i^T = \frac{\text{GDP}_i}{\text{GDP}_T} \), and I\(_i^T = \frac{E_i}{\text{GDP}_i} \). EM\(_T^i\) represents the fuel-mix variable in year \( T \), we set M\(_{ij}^T = \frac{E_{ij}}{E_j} \). U\(_T^i\) is the CO\(_2\) emissions factor, we set U\(_{ij} = \frac{C_{ij}}{E_{ij}} \).

3. Results
3.1. Results of Clustering

Using the elbow method based on Python 3.7.6, according to Figure 3, the decline in WCSS becomes significantly smaller when the number of types is greater than 4. Thus, we set the number of clusters as 4.

![Figure 3. Elbow method result.](image)

Based on K-means clustering results, we divided the carbon reduction potential of 100 cities in the Yellow River Basin into four types, as follows. Table 4 shows the index range of different types of cities. Table S1 reports the detailed results of the clustering.
Table 4. The index range of different types of cities.

| Indicator                      | 1. Transition City | 2. Mature City | 3. Declining City | 4. Resource-Dependent City |
|--------------------------------|-------------------|----------------|------------------|----------------------------|
| X1: Carbon emission growth    | 2.65% (−2.9~−6%) | 3.34% (1.2~6.1%) | 3.36% (0.4~9%) | 2.75% (0.9~4.6%) |
| X2: Carbon sequestration growth | 1.49% (−10~23%) | 7.96% (−5.70~28.7%) | −2.61% (−14.31~26.80%) | 15.75% (1.80~29.71%) |
| X3: GDP growth                | 5.56% (−9.61~11.12%) | 5.60% (−19.3~12.7%) | 6.45% (−25.7~11.9%) | 2.65% (0.80~14.50%) |
| X4: Secondary industry value-added ratio | 49.30% (34.5~64.9%) | 48.27% (27.9~65.1%) | 44.34% (20.5~63%) | 59.20% (55.7~62.7%) |
| X5: GDP per capita (Yuan)     | 57485.7 (46,130~78,368) | 100310.8 (81,660~132,253) | 33064.2 (11,693~44,086) | 187570.5 (167,978~207,163) |
| X6: Carbon emission per capita (ton/person) | 10.18 (1.80~31.50) | 19.75 (6.20~60.30) | 6.34 (1.21~25.50) | 43.20 (21.50~64.92) |

The first type is the transition city with middle carbon reduction potential (Group 1 in Figure 4). The main characteristics of this type are the low level of economic development and the high dependence on the secondary industry, with the proportion of secondary industry output exceeding 49%. A total of 33 cities of this type have slow growth in carbon emissions and are transitioning from industry-driven cities to service-driven cities. Since the growth rate of carbon sequestration in transition cities is slow, if the transition is not successful, the carbon control and economic growth will face serious challenges. The typical city of this type is Taiyuan, the capital of Shanxi Province, which relied on local coal resources to drive the rapid development of energy-intensive industries before 2013. However, after the coal resources were depleted, the share of its output value of the secondary industry dropped from 51.2% in 2007 to 38% in 2017.

The second type is the mature city with high carbon reduction potential (Group 2 in Figure 4). There are 14 such cities in the Yellow River Basin. Cities of this type have larger populations and higher development levels. Most of them are provincial capitals, such as Jinan, Chengdu, Zhengzhou, and Hohhot, or mature industrial cities, such as Qingdao and Baotou. The average GDP per capita in mature cities is 1.75 times higher than that in transition cities and 3 times higher than that in declining cities. It is worth noting that the average growth rate of this type of city in carbon sequestration (7.96%) is higher than the growth rate of their carbon emissions (3.34%).

The third type is the declining city with low carbon reduction potential (Group 3 in Figure 4). There are 51 such cities in the Yellow River Basin, accounting for 50% of all cities in this area. This type performed the worst on the indicator of GDP per capita and experienced urban contraction and population loss over the past few decades. Given the lagging transformation of traditional industries, such cities have experienced a shrinkage in the size of their industries, and the share of secondary industry output is the lowest. In addition, this type has a high growth rate of carbon emissions, but the per capita carbon emission is the lowest among the four types of cities, only 6.34 tC. Declining cities contribute more than 50% to carbon sequestration in the region. Some studies thought the shrinkage of the local, urban, built-up area would bring the rise of natural green space area [9,23].

The fourth type is the resource-dependent city with low carbon reduction potential (Group 4 in Figure 4). There are only two cities belonging to this type, and they are both bases for domestic energy supply. Erdos is rich in coal resources, while Dongying has China’s second-largest oil industry base. The industrial structure of this type is dominated by secondary industries, accounting for 59.20% of the total. These cities’ per capita carbon emissions are much higher than the regional average (43.20 tons per capita), and the growth of carbon emissions is fast. Moreover, the growth rate of carbon sequestration of this type is high-speed, reaching 15.75%, but their GDP growth is the lowest of the four types.
According to Figure 5, the distribution pattern of cities’ carbon reduction potential is not based on provinces. In the downstream area of the Yellow River, most of the cities are mature and transitional cities. In the upper and middle reaches of the Yellow River, most cities are declining cities. In the middle reaches of the Yellow River, at the junction of Inner Mongolia, Shaanxi, and Shanxi provinces, there is an agglomeration of the mature city and the transition city. The southern part of Shaanxi Province and the northern part of Sichuan Province are mainly covered by declining cities.

3.2. Results of Decoupling

According to Table 5, the performance of carbon decoupling differs among different types of cities, with the highest proportion of weakly decoupled cities in the mature city (85.71%), indicating that cities of this type have the most promising prospects for achieving carbon peaking. The strong negative decoupling is the most dangerous one among the various decoupling states. The declining city has three cities in the strong negative decoupling state: Datong in Shanxi Province, Ziyang in Sichuan Province, and Qingyang in Gansu Province. In addition, among the transition cities, there are two cities in strong negative decoupling: Yan’an in Shaanxi Province and Jinchang in Gansu Province. These cities are located in the western region, so it is more difficult to reach the carbon peak in the western region than in the eastern and central regions. The number of cities in the strong decoupling state is 0 in the Yellow River Basin and 15 in the Yangtze River Basin. In that case, the pressure and challenge in reducing carbon emissions in the Yellow River Basin are much greater than in the Yangtze River Basin [25].
Figure 5. Spatial characteristics of clusters.

Table 5. Carbon decoupling status of different types.

| City Type          | Decoupling Status | Number of Cities | City Type          | Decoupling Status | Number of Cities |
|--------------------|-------------------|------------------|--------------------|-------------------|------------------|
| 1. Transition city | EC                | 4                | 2. Mature city     | END               | 0                |
|                    | END               | 3                |                    | SND               | 1                |
|                    | SND               | 2                |                    | WD                | 12               |
| 2. Mature city     |                   |                  |                    |                   |                  |
| 3. Declining city  | EC                | 4                | 4. Resource-dependent city | END         | 0                |
|                    | END               | 2                |                    | SND               | 1                |
|                    | SND               | 3                |                    | WD                | 1                |
|                    | WD                | 42               |                    |                   |                  |

3.3. Results of LMDI Decomposition

After decomposing all provinces’ carbon emission driving factors between 2006 and 2016, we found that six provinces showed significant increases in carbon emissions, namely Gansu Province, Inner Mongolia, Ningxia, Qinghai, Shaanxi, and Sichuan. Figure 6 shows the driving factors of the increase in carbon emissions.

Gansu is the province with the most considerable increase in carbon emissions among the provinces in the Yellow River Basin. According to the results of LMDI decomposition, the growth of carbon emissions in Gansu mainly comes from the growth of industrial activities (61.68%) and the change in energy intensity (38.32%). One cost of China’s rapid economic development over the past 20 years is the increase in carbon emissions, and the LMDI results show that the main driver for Inner Mongolia, Ningxia, Shaanxi, Qinghai, and Sichuan is the rise in local production capacity. It is worth noting that the optimization of energy use efficiency in Inner Mongolia, Ningxia, Shaanxi, and Sichuan has effectively curbed the growth of carbon emissions.
4. Discussion and Policy Suggestions

In the empirical part of this paper, K-means cluster analysis was used to classify the carbon emission reduction potential of 100 cities in the Yellow River Basin into four categories. Furthermore, this paper also measures the carbon decoupling status of different cities and explores the drivers of carbon emissions in each province at the provincial level using LMDI. We propose policy suggestions for carbon peaking and carbon neutrality based on empirical results from three perspectives.

4.1. Suggestion for Carbon Peaking Schedule Setting

The more the decoupling states are strong decoupling states, the earlier the time of carbon peaking will be. The more expansive connections and expansive negative decoupling, the later the time of carbon peaking will be. The corresponding carbon peaking schedule can be set according to the carbon decoupling characteristics of different cities.

For transition cities, the schedule for carbon peaking should be set in 2027–2030, because such cities have the highest number of negative decoupling states. In the transformation process of such cities, attention should be paid to guiding the industrial structure to low-carbon strategic emerging industries, such as high-end equipment manufacturing, new materials, and modern service industries. For mature cities, the timepoint for carbon peaking should be set in 2025. This type of city has sufficient capital to support the low-carbon transformation of its industrial structure. The timeline for carbon peaking for declining cities should be set at 2030. These cities have the lowest per capita carbon emissions, face the challenges of deindustrialization and job losses, and, worse, have negative growth in carbon sequestration. Most cities in this category do not have sufficient funds to increase carbon sequestration, and existing industries have difficulty making the low-carbon transition. For resource-dependent cities, the schedule for carbon peaking should be set in 2030. This type of city relies on resource extraction and processing industries with high energy consumption and low production value and faces severe challenges in the low-carbon
transformation of energy supply. In that case, it needs to improve the level of resource conservation and comprehensive utilization.

4.2. Suggestions for Carbon Control by Province

Provincial governments lead the strategy for China’s green transition. This part will develop four main carbon control strategies based on the results of the LMDI analysis and the carbon reduction potential of cities under each province.

4.2.1. Shandong and Henan: Increasing Investment in Green Technology

Both Shandong and Henan are in the lower reaches of the Yellow River and have similar industrial structures, carbon emission types, and energy structures. Henan has 11 low-potential cities and should prevent imposing excessive pressure on the low-potential cities, which could cause the degradation of existing local industries. Compared with Henan, Shandong has more medium-potential cities, making its green transformation progress faster (Figure S1 shows the carbon reduction potential of these two provinces). The carbon control pathways for both provinces are divided into the production side and consumption side.

On the production side, it is necessary for them to increase R&D investment to promote the development of oxy-combustion technology. Oxy-combustion technology focuses on improving combustion efficiency by separating nitrogen from oxygen in the air, and it is a branch of carbon capture and storage (CCS) technology. Oxy-combustion technology is applicable to the steel industry, chemical industry, and construction materials industries, which are the pillar industries of Shandong and Henan. In 2020, Shandong accounted for 45% of China’s plate steel production and 50% of China’s tire production and had the sixth-largest construction industry output; Henan has the biggest alumina, and electrolytic aluminum industry in China, and its production of methanol is the first all over the country. Therefore, the industrial structure of the two provinces is well suited for the development of oxy-combustion technology. In addition, fostering alternative industries, such as the electric vehicle and power battery industries, will bring new growth points to the economy in the future.

On the consumption side, despite the excellent infrastructure in both provinces, there are not enough charging posts to encourage local people to buy electric vehicles to save energy and reduce emissions. According to the China Electric Vehicle Charging Infrastructure Promotion Alliance (EVCIPA), in September 2021, Shandong’s number of public charging posts was 55,058 and 38,727 in Henan, far behind Beijing’s 93,604 and Guangdong’s 160,961. They should increase the coverage of charging posts and increase the proportion of electric vehicles on the road.

4.2.2. Gansu, Ningxia, and Qinghai: Land Use, Land Use Change, and Forestry (LULUCF)

Gansu, Ningxia, and Qinghai have the worst economic base in the Yellow River Basin, with low population density. The primary city type in those three provinces is declining cities. Thus, industrial activity and CO2 emission intensity are expected to decline. Based on the ecological environment and economic foundation of the three provinces, the three provinces can choose to strengthen the role of LULUCF in balancing the carbon budget and then have a beneficial impact on the national carbon neutrality goal (Figure S2 shows the carbon reduction potential of these three provinces).

Human activities impact terrestrial sinks through land use, land-use change, and forestry (LULUCF) activities, such as tree plantations. Carbon mitigation can be achieved through activities in the LULUCF sector that increase the removals of greenhouse gases (GHGs) from the atmosphere or decrease emissions by halting the loss of carbon stocks. The ability of soil to absorb carbon dioxide varies greatly depending on land cover and utilization. Forests are considered to have the most carbon sinks, followed by grasslands and wetlands, and construction land is the least. Due to the decrease in tropical forests,
there was 1.99 ± 0.13 PgC year$^{-1}$ carbon loss in 2015–2019, which means the atmosphere has been subjected to such a large amount of additional carbon [33].

Gansu, Ningxia, and Qinghai are severely affected by desertification. To slow down desertification, China has been planting forests in the northern regions for a long time. Of all the plantation plans in the Yellow River Basin, the Three-North Shelterbelt Program (TNSP) is the largest [34]. According to [35], in carbon-poor soils, planting new trees increases soil organic carbon density. However, the new forest will reduce organic carbon density if the soil is already saturated with carbon. In that case, blindly increasing the density of trees may be counterproductive. In addition, high-density afforestation can lead to a decline in groundwater resources, affecting the growth of other species of plants and reducing ecological diversity. It is vital to choose the appropriate planting density in the local area.

In the arid areas of the Yellow River Basin, plantation programs should focus more on improving tree survival than on increasing planted density. For example, big data can be used to analyze the climate and use the wind direction of the desert to plant trees under the windward slope of a flowing dune, using the wind to blow the sand from the upper part of the dune to the leeward slope and fill in the bottom of the dune to make the area flatter and help plants grow. By the time the wind direction changes, the previously planted plants will already be able to withstand the wind and sand.

4.2.3. Sichuan and Inner Mongolia: Improving Energy Efficiency and Optimizing the Energy Mix

Sichuan and Inner Mongolia need to improve energy use efficiency as soon as possible. Based on the decomposition results of LMDI, inefficient energy use is the primary driver of the increase in carbon emissions. These two provinces only have two mature cities. Moreover, declining cities with low abatement potential make up the vast majority of the two provinces (Figure S3 shows the carbon reduction potential of these two provinces).

For Sichuan, because most of its cities are declining cities with low potential, it is suggested to abolish and merge some of them so that the merged new prefectural governments can effectively reduce local protection and market segmentation. Such a merger could also reduce resource mismatch and improve the local energy mix and energy use efficiency. Inner Mongolia is the province with the most outgoing power in China and generates the most power from coal and wind power. The share of clean energy in the energy supply should be increased, and the traditional power grid should be intelligently upgraded. Moreover, Inner Mongolia needs to upgrade energy efficiency in transition cities such as Hulunbuir, Tongliao, and Bayanur to boost their green transformation.

4.2.4. Shaanxi and Shanxi: Seeking Green Financial Support and Upgrading the Industrial Structure

Both Shaanxi and Shanxi are provinces in the middle reaches of the Yellow River, and the main driver of the increase in carbon emissions in both provinces is the increase in production activities. Besides, the upgrading effect of their industrial structure is not significant, and the existing industrial structure needs to be upgraded. The green transformation in the region needs financial support from green finance [36]. For example, the payment platform Alipay has launched an online game project called “Ant Forest” that allows the public to plant real trees by using Alipay to pay for public transportation [37]. Many provinces in the Yellow River Basin have been funded by this green technology project, enhancing local vegetation cover and biodiversity, and relieving local financial pressure, allowing local governments to have more budget to achieve green transformation and upgrading industries.

It is worth noting that only Yulin in Shaanxi Province has high potential for carbon emission reduction in these two provinces, while most of the cities have low potential. Therefore, it is necessary to accelerate the industrial upgrading process of cities with middle potential, such as Ankang, Xi’an, and Taiyuan (Figure S4 shows the carbon reduction potential of these two provinces).
4.3. Suggestions for Intra-Regional Cross-Provincial Cooperation

This paper provides a new collaborative platform for environmental management in the Yellow River Basin. According to cluster analysis results, cities of the same type have similar carbon emission patterns, industrial structure characteristics, and vegetation carbon sequestration capacity. Therefore, in addition to the traditional inter-provincial cooperation model, cities with the same carbon emission reduction potential can establish a practical cooperation platform to integrate resources and elements, bring comparative advantages, and improve each party’s development quality and green production capacity. The establishment of such a platform can reduce a large number of decision-making costs and accelerate the green transformation of the whole region.

5. Conclusions

Studying the carbon emission reduction potential of the Yellow River Basin, identifying the drivers of carbon emissions, and formulating low-carbon transition policies are the basis for China to fulfill its commitment to carbon neutrality. According to the elbow method result, the 100 prefecture-level cities were divided into four categories based on their carbon reduction potential: 33 transition cities, 14 feature cities, 51 declining cities, and 2 resource-dependent cities. In terms of spatial distribution, the number of material cities in the lower reaches is much more than that in the upper reaches, and the main city types in the upper reaches are transition cities and declining cities. Near the provincial capitals and industrial centers of some midstream provinces, there are also gatherings of the mature city and transition city. Cities with high carbon reduction potential can take on a larger share of carbon reduction and can be used as pilot cities for green transition policies. Low-potential cities need to focus on monitoring whether green transition policies will seriously harm local economic development and the welfare of their residents.

Regarding the proportion of cities in the state of decoupling, from large to small, the order is resource-dependent city, mature city, declining city, and transition city. Combining decoupling states and the performance of the clustering index, we suggest setting different carbon peak schedules for cities with different emission reduction potentials to reduce the pressure of green transformation on the local economy. For transition cities, the schedule for carbon peaking should be during 2027–2030. For mature cities, the peak of carbon emissions should be reached by 2025. For declining cities, they can accomplish this mission before the final timepoint of 2030 to reduce the impact on the fragile local economy. For resource-dependent cities, we suggest that they complete carbon peaking before 2030.

Cities in the upper, middle, and lower reaches of the Yellow River differ in terms of economic development, industrial structure, and energy structure. Therefore, it is not appropriate to adopt a one-size-fits-all carbon-reduction measure. Based on the LMDI decomposition results of each province and the carbon emission reduction potential of the cities under its jurisdiction, we designed four carbon-control strategies. On the one hand, these policies correspond to each province’s main carbon emission drivers and can effectively control carbon emissions; on the other hand, these policies can take into account the carbon emission reduction potential of each region and reduce the resistance to implementation. For example, for less developed provinces with less potential, such as Gansu, Ningxia, and Qinghai, we suggest focusing on LULUCF to make the local carbon budget more balanced.

This paper eliminated some prefecture-level administrative regions due to a severe lack of data. Most of those regions are remote minority settlements with weak industry and traditional agriculture. There are vast grasslands, forests, and deserts. Thus, we may underestimate the vegetation carbon sequestration capacity of the Yellow River Basin. In addition, the level of urbanization in the Yellow River Basin is relatively low, and people in rural areas tend to collect biofuels such as charcoal to reduce heating costs. However, this part of emissions is not included in China’s energy statistics. In that case, the carbon emission level of the Yellow River Basin may be underestimated. With the improvement of
statistical data, we can expand the study sample and extend the study period to improve the study’s accuracy in future studies.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/su14095284/s1, Table S1: Results of clustering results, Figure S1: Cities’ carbon reduction potential (Shandong and Henan), Figure S2: Cities’ carbon reduction potential (Gansu, Ningxia, and Qinghai), Figure S3: Cities’ carbon reduction potential (Inner Mongolia and Sichuan), Figure S4: Cities’ carbon reduction potential (Shanxi and Shaanxi).

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