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Transportation Carbon Emissions from a Perspective of Sustainable Development in Major Cities of Yangtze River Delta, China

Jialin Liu 1,2,*, Yi Zhu 1,3, Qun Zhang 1,3, Fangyan Cheng 3, Xi Hu 4,5,6,*, Xinhong Cui 1, Lang Zhang 1 and Zhenglin Sun 7,*

1 Key Laboratory of National Forestry and Grassland Administration on Ecological Landscaping of Challenging Urban Sites, Shanghai Engineering Research Center of Landscaping on Challenging Urban Sites, Shanghai Academy of Landscape Architecture Science and Planning, Shanghai 200232, China; zhuyi0816@163.com (Y.Z.); zq_208@hotmail.com (Q.Z.); kysxinhongcui@163.com (X.C.); zhanglang2018@hotmail.com (L.Z.)
2 Harvard China Project, Harvard John A. Paulson School of Engineering and Applied Sciences, Cambridge, MA 02138, USA; jialinliu@seas.harvard.edu
3 Coastal Ecosystems Research Station of the Yangtze River Estuary, Ministry of Education Key Laboratory for Biodiversity Science and Ecological Engineering, Institute of Biodiversity Science, School of Life Sciences, Fudan University, Shanghai 200433, China; fangyan_cheng@fudan.edu.cn
4 Labor and Worklife Program, Harvard Law School, Harvard University, Cambridge, MA 02138, USA; xhu@law.harvard.edu
5 Environmental Change Institute, University of Oxford, Oxford OX1 3QY, UK
6 National Bureau of Economic Research, 1050 Massachusetts Ave., Cambridge, MA 02138, USA
7 School of Economics, Northeastern University at Qinhuangdao, Qinhuangdao 066004, China
* Correspondence: sunzhenglin@neuq.edu.cn; Tel.: +86-335-839-6077

Abstract: Since the late 1990s, the Yangtze River Delta (YRD) has experienced profound growth in economic scales and urban size. However, it is still unclear how much energy is consumed from both fossil fuel and electricity usage for transportation sectors (TCO2). We take 10 sampled cities in the YRD as examples and examine their city-level sustainable levels from 1990 to 2018. Then, we observed that SHSN (Shanghai, Suzhou, Nanjing) are in leading positions, followed by WCN (Wuxi, Changzhou, Ningbo) and NXH (Nantong, Xuzhou, Hefei). We found that the cumulative TCO2 in SHSN from 1990 to 2018 is the highest among groups, which is mainly due to the earlier industrialization in history. In 2018, SHSN had the highest TCO2 (623.9 × 10^4 t), WCN was 311.9 × 10^4 t, and NXH was 166.4 × 10^4 t. TCO2 per capita in SHSN reached its minimal (≈0.12 t) in 2018 among 29 years, while WCN and NXH shared the same levels (≈0.07 t). This could be attributed to the dense population and a series of low carbon policies announced in SHSN and WCN. NXH is still in the stage of high demands on economic-centered development. The primary source for TCO2 in the YRD is fossil fuels. The TCO2 contributed by transportation electricity usage is continually increasing, especially after 2010. This phenomenon represents that electricity can be a significant part of the YRD’s transportation sectors’ energy consumption shortly. A complex estimation model uncovers the complexity between the economy, environment, and carbon emissions in the YRD, which indicated that the decrease of TCO2 in YRD could not be regulated solely by economic or environmental interventions. This study highlighted the urgency for socio-economic adjustments from carbonized to decarbonized structures in the YRD.

Keywords: transportation; CO2 emission; green productivity; sustainability; megacities

1. Introduction

The control and mitigation of CO2 emissions are among the most pressing global environmental challenges [1]. CO2 emission in the transport sector has attracted significant attention from policymakers in both transport and climate change fields because of its...
share in the overall emissions and continuous growth [2]. According to the International Energy Agency [3], 6.57 billion tons of global CO\textsubscript{2} was generated due to oil consumption in the transport sector in 2010, accounting for 22% of total fossil fuel-related CO\textsubscript{2} emission, which is 50% higher than the 4.39 billion tons of CO\textsubscript{2} emission generated from the transport sector in 1990. In addition, transportation emissions are often associated with high energy consumption and air pollution in the urban environment. For instance, oil consumption and CO\textsubscript{2} emission in transportation account for approximately 50% and 25% of global totals, respectively [4]. Consequently, it is critical to evaluate the total CO\textsubscript{2} emissions from the transport sector so that regional to global CO\textsubscript{2} emission mitigation can be appropriately adjusted.

China is now the world’s leading contributor to CO\textsubscript{2} emissions [5,6]. Much of this is attributed to the rapid growth of the transportation sector, which is partly driven by China’s e-business booms. From the late 1990s to the early 2010s, China’s freight turnover increased by 11% annually, and passenger turnover increased by 14% annually (National Bureau of Statistics, 1998–2013). These rapid changes in China’s transport sector are closely associated with increasing energy consumption and CO\textsubscript{2} emissions [7]. China’s energy consumption from the transport sector reached 474.35 million tons of CO\textsubscript{2} emission in 2010 [8]. It was also predicted that China’s transport sector’s greenhouse gas emissions would likely double by 2020 [9]. Therefore, appropriate CO\textsubscript{2} emission evaluation for China’s transport sector should be conducted so that we can keep China’s sustainable development on track in the coming decades.

In order to respond to such a challenge in the background of fast transportation growth, this study will set the scene in the largest national world-class city clusters, the Yangtze River Delta (YRD). In 2018, the YRD accounted for approximately 28% of the country’s gross domestic product and was comparable to Germany’s economic size. However, CO\textsubscript{2} emissions from the transport sector in the YRD have not been explicitly studied [7]. Therefore, we think the investigations of transportation-related CO\textsubscript{2} emission in this vital region will be instructive and informative for furthering nation-wide studies and policymaking.

1.1. Yangtze River Delta: The Forefront of National Energy, Environmental, and Economic Developments

In addition to Shanghai, the YRD region is also made up of Jiangsu, Zhejiang, and Anhui. The YRD is China’s most prosperous region per capita, and it is responsible for 1/3 of China’s imports and exports, according to The Shanghai Statistical Yearbook and China Statistical Yearbook. In the last 30 years, the YRD has played a significant role in China’s recent economic advances, having transformed into a world-class city cluster and boasted its strategic significance in the country’s modernization and further opening up [10]. In December 2019, the Communist Party of China Central Committee and the State Council jointly issued an outline of a plan to integrate the regional development of the YRD. Tasks specified in the outline include establishing a coordinated, innovative industry system, enhancing infrastructure connectivity, strengthening environmental protection, advancing public services, and building the Shanghai free trade zone. The document detailed a high level of sustainable development goals to be achieved by 2025.

As the pioneer region in China, YRD’s gross domestic product rose from 200 billion USD in 2000 to 3 trillion USD in 2018. However, there still seem to be many unsustainable factors in its total development, and prosperity may have been at the expense of enormous energy consumption. According to statistical data, the average annual growth rate of energy consumption reached 21.7% from 2000 to 2018. The similarity between GDP and annual growth of energy consumption shows a significant fact that the economic growth could remain strong in the future for the YRD; the government should not only focus on pursuing economic gains but also consider improving energy conservation and environmental quality. The case of the transportation industry in the YRD further proves this. Driven by the fast national development of domestic e-commerce (Wei et al., 2019), the transportation industry is experiencing rapid change and development in the YRD. From 2000 to 2018, the transportation industry’s energy consumption grew at an average annual
rate of 19.1% (reports from China Electricity Power Yearbook). Therefore, further research on recognizing the complicated relationships among economic growth, energy consumption, and environmental pollution in the transportation industry will be entirely meaningful and instructive for future policy goals.

1.2. Methods of Quantifying Sustainable Developments

Quite a few indicators have been proposed and introduced for evaluating city-level productivity and ecological sustainability development. Among them, GDP and ecological footprints are the most common index and model. For instance, the per capita GDP of the YRD is higher than that of the eastern, central, western, and northeastern regions, and the per capita GDP has been on the rise, with steady economic development and higher than the national average [11]. The YRD exhibits a high level of collaborative economic development and plays a crucial role in China’s Belt and Road Initiative regarding its economic linkages and dependence on rapid urban agglomeration and population concentration in recent decades (Ibid). Previous studies had mostly concentrated on the relationship between urbanization and ecosystem services at the regional level [12]. A stronger case would show how ecosystem-service alterations determine regional land-use change, water contamination, air pollution, and energy use [13]. However, each of the widely used indicators would be biased for multiple reasons. For instance, there is usually a trade-off between higher GDP and reduced ecological services. In contrast, overemphasis on the ecological footprint will overlook the level of regional economic development. In this case, a comprehensive indicator that accounts for economic, environmental, and energy aspects is recommended to assess the region’s whole level of development [14].

A previous study applied a Malmquist–Luenberger (M–L) productivity index to calculate city productivity growth or green productivity growth by incorporating economic, environmental, and energy factors [15]. However, the index of its conventional formats is derived from a contemporaneous production possibility set that may face spurious technical regress problems. To overcome this weakness, we will adopt the global M–L productivity index as an alternative [14]. The modified index has been widely used to measure productivity growth in recent years, given specific energy and environment constraints. For example, Ananda and Hampf applied the index [16], which included greenhouse gas emissions, to evaluate productivity in the Australian urban water sector and found that the conventional indicator significantly overstated sustainable developments. Fan et al. applied the M–L index to measure and decompose the CO2 emission performance of 32 industrial subsectors in Shanghai over 1994–2011 [17]. Wang and Shen used the M–L index to calculate China’s industrial productivity by considering environmental factors and examining the nonlinear relationship between environmental regulation and environmental productivity and found a rapid, sustainable development in the Chinese industry [18].

1.3. Transportation-Related CO2 Emissions and the Associated Knowledge Gaps

Although many studies quantify and predict transportation-based CO2 emissions, they can be narrow in scope and might not account for interactions with other associated sectors such as electricity, the environment, or society. From national and regional perspectives, Cai et al. calculated CO2 emissions in the transport sector by accounting and using a new set of fuel consumption data from the transport sector [2]. Zhang and Nian investigated CO2 emissions in China’s transport sector by employing a stochastic impact by regression on population, affluence, and technology model and using provincial panel data [19]. Zhou et al. studied the transport sector’s CO2 emissions performance throughout China’s 30 administrative regions by using undesirable output-oriented data envelopment analysis models with different returns of scales [20]. From the specific transport mode perspective, Yan and Crookes analyzed the future trends of energy demand and greenhouse emissions in China’s road transport sector and assessed the possible reduction measures [21]. Wang et al. calculated the CO2 and pollutant emissions of passenger cars in China from 2000 to 2005.
and projected the future trends under three scenarios [22]. Hao et al. discussed how CO₂ emissions increased more in regions with less public transport [9]. Tian et al. examined different regions’ freight turnover and energy consumption by various transport modes and compared the regional greenhouse gas emissions from different freight transport modes [23]. Geng et al. examined the co-benefits of the urban public transport sector by analyzing the cost-effectiveness and environmental benefits of various vehicles [24].

Generally, carbon emission estimation in the existing literature only considers fossil fuels, and few studies consider electricity as a carbon calculation source [25]. From an ecological perspective, transportation considerations with electricity instead of fossil fuels are becoming increasingly common [26]. This study is innovative because CO₂ emission estimation covers two sources: fuel and electricity consumption. Briefly, calculating CO₂ emissions from fuel involves estimating the product of fuel consumption amounts and the relevant emission coefficients. While taking the electricity into account is necessary because there was an explosion of electric vehicles after the year 2014 when the government encouraged and subsidized the electric vehicles industry [26], it is not clear whether the electricity from battery-powered vehicles is clean or not. According to the China Electricity Power Yearbook (2018), national electricity is generated primarily by thermal (fossil fuel) power (60%), followed by hydraulic (19%), solar (9%), wind (10%), and nuclear (2%). So, the electricity still indirectly produces considerable CO₂ emissions. Furthermore, data regarding electricity consumption are prepared and estimated according to the official energy and electricity statistical yearbook.

Prior research has explained the correlation between CO₂ emission in the transport sector and growing environmental degradation in different countries. Meng and Han concluded that road transportation enhances CO₂ emission in Tunisia [27]. We notice that the previous analysis was performed in a one-to-one context, explicitly analyzing the impact of economic conditions or environmental changes on carbon emissions related to energy consumption. This previous analysis deviates from the real-world scenario and ignores that economic conditions and environmental changes are coupled factors that simultaneously affect energy consumption. Therefore, a model or method that can perform the complex scenario analysis is optimal [14]. Among various complexity analysis tools, the dynamic panel estimation model is highly relevant. The advantages of the dynamic common correlated effects outweigh both mean group and pooled mean group estimators. In a common word, the method has the power to explain the complexity of energy consumption, environmental regulation, and economic interventions in our cases. Specifically, it estimates both homogeneous and heterogeneous parameters and allows for endogenous regressors, computes the cross-sectional dependence test, corrects small sample time series bias, and ultimately yields a compelling correlated result between dependent and independent variables.

2. Materials and Methods

2.1. Research Frameworks and Data Acquisitions

The YRD covering a total area of approximately 210,700 km². It encompasses Shanghai Municipality, Jiangsu Province, Zhejiang Province, and Anhui Province, with over 40 prefecture-level cities. In 2018, the total population was over 200 million. As the engine of China’s economic development, the region has experienced an unprecedented rate of rapid urbanization, which dramatically altered the landscape and detrimentally affected the area’s ecological conditions [28]. From 1990 to 2018, the YRD’s urbanization rate doubled [10].

This study consists of three parts (Figure 1). First, we propose a uniformed index to evaluate the sustainable development potential of the 10 representative cities in YRD. Secondly, we estimate the patterns of transportation-related CO₂ emissions from these cities based on raw data sources from different official statistical yearbooks. Thirdly, we analyze various regulations of economic and environmental policies on TCO₂. Overall, this study has three significant contributions: (a) We apply the M–L index to calculate
and evaluate the sustainable levels for top-10 cities in the YRD; (b) We apply a modified algorithm to analyze CO$_2$ emission from different energy sources, including fossil fuels and electricity; (c) We introduce dynamic panel estimation to analyze the correlated impacts of economic and environmental factors on energy consumption in the YRD. This study aims to provide quantitative evaluations for policymakers to decide pathways of realizing the long-term sustainable development in the transport sectors of the YRD.

![Figure 1. Research framework, data acquisitions, and fundamental algorithms.](image)

To accomplish this study, we focused on 10 cities in the YRD rather than the entire region, including Nanjing, Suzhou, Wuxi, Nantong, Changzhou, Xuzhou, Hangzhou, and Ningbo—firstly, because their statistics data are accessible and retrievable, and secondly, because they are very representative cities for the YRD in aspects of energy usages, environmental management, and economic developments. This study’s data were primarily derived from two sources, China Energy Statistical Yearbooks and China Statistical Yearbooks. The end-use energy consumption data from the transport sector in each province comes from the China Energy Statistical Yearbook’s provincial energy balance table published by the National Bureau of Statistics. To better facilitate the study, we also take into account a series of published data, open-resources, and protocols, including “timetable of vehicle emission standards in China” [22], “CO$_2$ emission factor of various energy sources” [7], “energy consumption in China’s transport sector 2000–2010” [4], “methods for quantifications of green productivity growth for major Chinese urban agglomerations” [29], “carbon emission caused by various fuels consumption in transportation in Jiangsu” [26], “impervious surface maps in Shanghai” [12], and “a framework for linking environmental regulation and economic growth” [11].

### 2.2. City Sustainability Determination

The Global M–L algorithm (Figure 2a) is applied to assess city sustainability from three perspectives [15]: the economy, environment, and energy (Figure 2b). The algorithm considers a panel of $k = 1, \ldots, K$ cities and $t = 1, \ldots, T$ time periods, for city $k$ at time period $t$, the inputs and outputs set can be assumed as $(x^{k,t}, y^{k,t}, b^{k,t})$, where the production technology can produce $M$ desirable outputs, $y = (y_1, y_2, \ldots, y_M) \in \mathbb{R}^M_+$, and $J$ undesirable outputs, $b = (b_1, b_2, \ldots, b_J) \in \mathbb{R}^J_+$, by using $N$ inputs, $x = (x_1, x_2, \ldots, x_N) \in \mathbb{R}^N_+$. The measurement of productivity has traditionally focused on measuring firms or industries’ marketable outputs relative to paid factors of production. Undesirable outputs are often produced.
we define a global benchmark technology as

\[ p^t(x^t) = \{ (y', b^t) : x^t \text{ can produce } (y', b^t) \}. \quad (1) \]

To incorporate undesirable outputs, we adopted a variable of directional distance functions formulated as:

\[ D_0(x, y, b, g) = \max \{ \beta : (y, b) + \beta g \in P(x) \}. \quad (2) \]

where \( \beta = (y, b) \) is a direction vector, and it denotes the value of the directional distance functions. Taking the direction vector, \( g \), as the weight, the directional distance functions seek more desirable output and fewer that are undesirable. Then, we express the M–L algorithm index developed as:

\[ ML^t(x^t, y', b', x^{t+1}, y^{t+1}, b^{t+1}) = \frac{1 + D^t(x^t, y', b')}{1 + D^t(x^{t+1}, y^{t+1}, b^{t+1})}, \quad (3) \]

where the M–L algorithm measures the sustainability of cities between periods \( t \) and \( t + 1 \). Note we canceled a default protocol of normalization so that the larger the index, the higher the sustainability in the sampled city. For instance, representing the larger economic concentration, with less energy consumption, and fewer pollutant emissions (mainly \( \text{CO}_2 \)).

However, we have noted that the M–L algorithm’s geometric mean form has a weakness in that it is not circular or transitive and that a linear programming infeasibility arises in measuring the cross-period directional distance functions. To overcome this limitation, we define a global benchmark technology as \( P^G = P^1 \cup P^2 \cup P^3 \cup P^T \). As depicted in Figure 2a, \( P^G \) envelopes the contemporaneous benchmark technologies, this shows that the directional distance function may also be computed using linear programming. Based on this model framework, we apply the global Malmquist city productivity levels as follows:

\[ CPI^{L,t+1}(x^t, y', b', y^{t+1}) = \frac{D^G(x^{t+1}, y^{t+1})}{D^G(x^t, y')} \]. \quad (4) \]

However, M–L does not consider undesirable outputs, such as pollution emissions. We defined a global directional distance function on the global technology set \( P^G \) incorporating the undesirable outputs as follows:

\[ D^G(x, y, b) = \max \{ \beta : (y + \beta y, b - \beta b) \in P^G(x) \}. \quad (5) \]

Then, we express the city productivity index (CP-Index) as:

\[ CPI^{L,t+1}(x^t, y', b', x^{t+1}, y^{t+1}, b^{t+1}) = \frac{1 + D^G(x^t, y', b')}{1 + D^G(x^{t+1}, y^{t+1}, b^{t+1})}. \quad (6) \]

We use the city sustainable index (CPI) to measure cities’ sustainability based on the global production possibility set between periods \( t \) and \( t + 1 \). Mathematically, CPI can be expressed into two major components:
\[ \text{CPI}^{t+1}(x^t, y^t, b^t, x^{t+1}, y^{t+1}, b^{t+1}) = \frac{1 + D_C(x^t, y^t, b^t)}{1 + D_C(x^{t+1}, y^{t+1}, b^{t+1})}, \]

\[ \times \left[ \frac{(1 + D_C(x^t, y^t, b^t)) / (1 + D_C(x^{t+1}, y^{t+1}, b^{t+1}))}{(1 + D_C(x^{t+1}, y^{t+1}, b^{t+1})) / (1 + D_C(x^{t+1}, y^{t+1}, b^{t+1}))} \right]^{TE^{t+1}} = \frac{BPC^{t+1}}{BPC^{t+1}^*}, \]

\[ = EC^{t+1} \times BPC^{t+1}. \]  

where \( TE^t \) is the green technical efficiency at period \( t \) and \( EC^{t+1} \) is the green efficiency change between two time periods. The latter captures the catch-up effect whereby cities approach the efficiency frontiers more closely and catch up with the relatively progressive cities, such that there is a green efficiency improvement (deterioration) when its value is greater (smaller) than one. The measure \( BPC^{t+1} \) denotes the best-practice gap between a contemporaneous technology frontier and a global technology frontier, along the ray from the observation at period \( t \) in the direction \( (y^t, b^t) \). Hence, in calculating the green technical change during two periods, \( BPC^{t+1} \) denotes the best-practice gap change during these same two periods, reflecting how close a contemporaneous technology frontier shifts toward the global technology frontier in the direction of more desirable outputs and fewer pollutant emissions, whereby a value of \( BPC^{t+1} \) greater (or smaller) than one indicates green technical progress (or regress).

As shown through Figure 2b, we adopted three economic proxies that thoroughly quantified each studied city’s economic trends and population baselines. This method can avoid using gross domestic production (GDP) as a single measure of the city and region. Equations for estimating Economic strength (ES), Economic agglomeration (EA), and Employment (E) are given below:

\[ ES = 50 \left( \frac{\ln(GDP) - \ln(\alpha)}{\ln(\beta) - \ln(\alpha)} + \frac{\ln(ETPR) - \ln(\chi)}{\ln(\delta) - \ln(\chi)} \right). \]  

\[ EA = 100 \left( 1 - \left| \frac{GDP}{\text{Area}} - X \right| \right), \quad X = 8.57. \]  

\[ E = 100 \left( 1 - \left( \frac{\sqrt{UR}}{\sqrt{\theta}} - \frac{\sqrt{T}}{\sqrt{\gamma}} \right) \right). \]

where \( ETPR \) is the number of employees divided by the numbers of the residential population. The area represents the administrative area of the studied city. Since the surveyed unemployment rate (UR) in China is not specific to the city level, the registered unemployment rate is used in this ranking. In this study, \( \alpha = 714.64, \beta = 108,818.96, \gamma = 0.37, \theta = 0.28, \) and \( \gamma = 0.01. \)

2.3. Transportation-Related CO2 Emission (TCO2)

In this section, we describe a comprehensive algorithm that considers different sources of CO2 emission in China’s transportation sector. The system is based on fossil fuel and electricity consumption and then converts it to the CO2 emission equivalent. Under this estimation method, time series CO2 emission occurs as the service is provided, and a debit occurs when carbon is released (again by burning fossil fuels and consuming electricity). Aggregating CO2 emissions can calculate CO2 emissions from different energy sources as Equation (11):

\[ C^T_j = \sum_i E^T_i \times EF_i \times CV_i \times k. \]

where \( C^T_j \) denotes the total carbon emission from fuels consumption in T year \((10^4 \text{ t})\); \( E^T_i \) is the total amount of energy consumption based on the \( i \)-th fuel in T year \((10^4 \text{ t} \text{ or } 10^8 \text{ m}^3)\); \( EF_i \) is the carbon emission standard factor of the \( i \)-th fuel (KgC GJ\(^{-1}\)); \( CV_i \) is the calorific value of energy (Kcal Kg\(^{-1}\) or Kcal m\(^{-2}\) in China, which can be directly found in the
yearbook; and $k$ here denotes the constant conversion fraction between different units of energy ($4.19 \times 10^{-6}$ GJ Kcal$^{-1}$).

Figure 2. (a): Fundamental of the Malmquist–Luenberger algorithm. (b): Driven input and output variables for the $M$–$L$ algorithm.

In addition to the carbon emission from fuel consumption above, electric power emission should also be considered for a comprehensive calculation. There is no direct access to data on how much carbon emission comes from electricity consumption, since the electricity generation in China is mainly from thermal power plants. Therefore, we adopted an approximate estimation method as the following formula [26]. In this study, we argued that the TCO$_2$ from electricity consumptions (production) come mainly from electric carriers, including high-speed train, subway, electric cars, and electric bicycles.

\[
C^T_e = C^T_{f} + C^T_{e}, = \sum E^T_{i} \times EF_{i} \times CV_{i} \times k + C^T_{e} = E^T_{tra} \times \frac{E^T_{th}}{E^T} \times \frac{C^T_{eth}}{E^T_{th}}.
\]

where $C^T_e$ denotes the estimation value of carbon emission from electricity in $T$ year ($10^4$ t); $E^T_{tra}$ is the amount of electricity used in transportation in $T$ year ($10^8$ Kwh); $E^T$ is the total electricity generation in sampled cities of YRD in $T$ year ($10^8$ Kwh); $E^T_{th}$ denotes the total electricity generation from thermal power in $T$ year ($10^8$ Kwh); and $C^T_{eth}$ is the carbon emission estimated from thermal power in $T$ year. This formula can also be understood easily as the term $E^T_{th}/E^T$, referring to the percentage of thermal power in the whole generated power, and the term $C^T_{eth}/E^T_{th}$ referring to the carbon emission produced by per thermal power.

With the preparation above, it is easy to calculate the carbon emission in the transportation sectors. Table 1 outlined the CO$_2$ emission factor of various energy sources adopted by previous studies [7,26]. The formula is expressed as:

\[
C^T = C^T_{f} + C^T_{e}, = \sum E^T_{i} \times EF_{i} \times CV_{i} \times k + C^T_{e} = E^T_{tra} \times \frac{E^T_{th}}{E^T} \times \frac{C^T_{eth}}{E^T_{th}}.
\]
Table 1. CO$_2$ emission factor of various energy sources. Note that the oxidation rate adopted in this study follows the default value recommended by China’s National Development and Reform Commission. Note that PCC = Potential carbon content (kg C GJ$^{-1}$), OR = Oxidation rate (%), LCV = Low calorific value (KJ m$^{-3}$), CEF = CO$_2$ emission factor (t CO$_2$ ton$^{-1}$).

| Fuel Types     | PCC   | OR | LCV      | CEF      |
|----------------|-------|----|----------|----------|
| Raw coal       | 26.4  | 98 | 20,908   | 1.98     |
| Clean coal     | 25.4  | 98 | 26,344   | 2.41     |
| Washed coal    | 25.4  | 98 | 10,454   | 0.96     |
| Briquettes     | 33.6  | 90 | 17,584   | 1.95     |
| Coke           | 29.5  | 93 | 28,435   | 2.86     |
| Crude oil      | 20.1  | 98 | 41,816   | 3.02     |
| Gasoline       | 18.9  | 98 | 43,070   | 2.93     |
| Kerosene       | 19.6  | 98 | 43,070   | 3.03     |
| Diesel         | 20.2  | 98 | 42,652   | 3.1      |
| Fuel oil       | 21.1  | 98 | 41,816   | 3.17     |
| LPG            | 17.2  | 98 | 50,179   | 3.1      |
| Natural gas    | 15.3  | 99 | 38,931   | 2.16     |
| Petroleum      | 20    | 98 | 35,168   | 2.53     |
| LNG            | 15.3  | 100| 51,498   | 2.89     |

2.4. Quantifying Economic and Environmental Regulations on TCO$_2$

We adopted the panel data estimation techniques, which account for heterogeneous coefficients across different city clusters (grouped by the CPI mentioned above) within one region, cross-sectional dependence, and dynamic correlated effects—a requirement for most socio-economic, consumption, and pollution models (Ditzen, 2018). Specifically, we applied a panel fixed-effects regression model with a modified Wald test to ascertain whether estimated coefficients are homogeneous or heterogeneous. The modified Wald test examines the GroupWise heteroscedasticity in the fixed-effects model, which assumes homoscedasticity but is often violated due to specific error variances of cross-sectional units [14]. Significantly, the modified Wald test statistic accommodates panel settings with unequal distribution of observations across cross-sectional units [14].

Herein, the dynamic panel estimation is for accounting for the heterogeneous effect of economic and environmental variables (represented by economic productivity proxy and pollution; e.g., clustered CPI) on energy consumption (represented by CO$_2$ emission in the transportation sector). The novel dynamic common correlated effects technique is essential for panel data with large cross-sectional units and periods, which is a situation evident in this study, 10 cities and 19 years (1990–2018).

The advantages of the dynamic common correlated effects outweigh both mean group and pooled mean group estimators. Apart from the dynamic typical correlated effects specification, first, it estimates both homogeneous and heterogeneous parameters and allows for endogenous regressors. Second, it computes the cross-sectional dependence test and corrects small sample time series bias. Third, it accommodates both balanced and unbalanced panel data setting. The econometric model for dynamic panel estimation that controls for heterogeneity can be expressed as:

$$y_{i,t} = \beta_0i + \beta_1y_{i,t-1} + \beta_2x_{i,t} + \beta_3i_{i,t-1} + \alpha_{i,t},$$

where the response variable $y$ of the cross-sectional units $i$ in periods $t$ is regressed on the control variables $x_{i,t}$, assumed to be strictly exogenous, resulting in the estimated heterogeneous coefficients $\beta$’s—randomly distributed around common mean errors $\alpha_{i,t}$ with unobserved common $f_{i}$ and heterogeneous factor $\gamma_{i}$ loadings.

The dynamic common correlated effect is the empirical specification of Equation (15) but without lagged independent variable expressed as:

$$y_{i,t} = \beta_0i + \beta_1y_{i,t-1} + \beta_2x_{i,t} + \sum\delta z_{i,s} + \alpha_{i,t}, s = t, \ldots, t - pT.$$ 

(15)
where the number of lags indicates that the cross-sectional means $z$ are incorporated in the dynamic panel data estimation model to achieve consistency.

3. Results and Analysis

3.1. Determined Sustainable Levels in the YRD

We showed the averaged $CPI$ (of 1990–2018) of the 10 representative cities in the YRD region (Table 2). This post $M$–$L$ processing depicted these cities’ fundamental sustainable levels rather than a more direct comparison between their economic developments and environmental achievements. Shanghai, without exception, is the most developed city in the region. Jiangsu Province has six cities in the list (Nanjing, Suzhou, Wuxi, Nantong, Changzhou, and Xuzhou), followed by Zhejiang Province, which has two cities involved (Hangzhou and Ningbo), while Anhui Province has only one city (the capital Hefei). The degree of urban and regional development in the YRD still has many challenges. For example, economic vitality that has been achieved in the region also induced environmental degradation, which calls for more sustainable development. Unbalanced regional growth occurs in Zhejiang and Anhui provinces relatively underdeveloped compared to Shanghai [7,17,26].

Table 2. Normalized city productivity index ($CPI$) of 10 sampled cities in Yangtze River Delta (YRD) from 1990 to 2018. $CPI$, estimated by $M$–$L$ algorithm, is an indicator for city sustainable development levels as described in the methodology. $¶¶$ indicates the initial level of $CPI$, $§§$ indicates the most current level of $CPI$. $\Delta$ is the changing rate from 1990 to 2018, numbers in parentheses are the annual increase from 1990 to 2018.

| Cities   | $Index_{1990-1999}$ | $Index_{2000-2009}$ | $Index_{2010-2015}$ | $Index_{2016-2018}$ | $¶¶$ Index$_{1990}$ | $§§$ Index$_{2018}$ | $\Delta$ (%) |
|----------|----------------------|----------------------|----------------------|----------------------|----------------------|----------------------|--------------|
| Shanghai | 0.396                | 0.454                | 0.512                | 0.59                 | 0.221                | 0.720                | 216.7 (5.4)  |
| Hangzhou | 0.299                | 0.379                | 0.489                | 0.587                | 0.192                | 0.639                | 217.2 (5.3)  |
| Suzhou   | 0.222                | 0.282                | 0.501                | 0.589                | 0.157                | 0.635                | 304.5 (7.6)  |
| Nanjing  | 0.332                | 0.37                 | 0.462                | 0.553                | 0.202                | 0.630                | 196.0 (4.9)  |
| Wuxi     | 0.199                | 0.253                | 0.492                | 0.592                | 0.132                | 0.603                | 377.3 (9.4)  |
| Changzhou| 0.183                | 0.243                | 0.467                | 0.561                | 0.128                | 0.598                | 411.0 (10.3) |
| Ningbo   | 0.192                | 0.291                | 0.492                | 0.551                | 0.131                | 0.594                | 353.4 (8.8)  |
| Nantong  | 0.175                | 0.222                | 0.442                | 0.543                | 0.107                | 0.578                | 440.2 (11.0) |
| Xuzhou   | 0.273                | 0.302                | 0.443                | 0.506                | 0.168                | 0.559                | 232.7 (5.8)  |
| Hefei    | 0.151                | 0.201                | 0.403                | 0.509                | 0.117                | 0.521                | 437.1 (10.9) |

In 1990, a decade after China first announced its reform and opening policies, Shanghai’s $CPI$ was approximately 10–15 years ahead of the other cities in the YRD region. Provincial capital cities, such as Nanjing and Hangzhou, also maintained relatively high development levels, except for Hefei, the capital city of Anhui province. In addition, as an important national transportation hub, Xuzhou also had a relatively high $CPI$. In an approximately 20-year period, the $CPI$ of the YRD region increased by 319% on average. Gaps in economy and energy across cities are narrowing down in 2018. However, other cities in the YRD are not likely to match Shanghai in the economy or environment because of its advantage as the region’s primary economic center and entire China.

Then, we applied the random forest algorithm to classify the 10 representative cities into three major groups. Figure 3a highlighted the programming logic. Random forest is an ensemble learning method for classification that operates by constructing a multitude of decision trees at training time and outputting the class’s mode. Among many other machine learning algorithms, the random forest is an effective method for regression. Compared to other machine learning methods, the random forest is useful to handle multi-dimensional data and multicollinearity and it is less sensitive to noise and the overfitting problem. Then, we input the same data as $CPI$ calculation, including economic, environmental, and energy variables listed in Figure 2b. The city clusters are determined by the range of the normalized random forest major-voted eigenvalues (Figure 3b). The first cluster has eigenvalues between 0 and 0.25, the second cluster ranges from 0.25 to 0.5, and the third cluster is higher than 0.5. Subsequently, the leading group (Figure 3c), also the third
cluster, contains Shanghai, Hangzhou, Suzhou, and Nanjing (hereafter named as SHSN). The second group involves Wuxi, Changzhou, and Ningbo (WCN). The last group, also the first cluster, consists of Nantong, Xuzhou, and Hefei (NXH).

**Figure 3.** Panel (a): Schema on using the random forest algorithm to classify the 10 sampled cities into three major city clusters. Panel (b): Regression between majority vote (normalized eigenvalues) of all predicted classes and averaged three input variables’ eigenvalues all predicted classes. Iteration \(n\) is set to 500, and underlying statistics showed in the panel’s top left (b). Panel (c): visualization of categorized results.

Statistics of random forest show that economic situations are less influential on the classification since the YRD is the most developed and affluent region in China [1]. However, environmental variables were weighted more in the results, which indicated that these 10 representative cities in the YRD still confront severe environmental issues for sustainable development. Most importantly, the YRD posed an imbalance of energy consumption across these 10 cities. This is further manifested in the transportation-related \(\text{CO}_2\) emissions that were also different across three groups. Furthermore, the differences in environment and energy might be the biggest obstacle to the ultimate integration of the YRD. For example, the more developed city group (e.g., SHSN) should not transfer its pollution or carbon-intensive industries to other city groups (e.g., WCN and NXH) in terms of achieving their own sustainable goals. In the studied period, the SHSN achieved a stable growth trend of green productivity. However, for both the WCN and the NXH, the cumulative CPI index fell in 2011. The most likely reason is that the global financial crisis and domestic economic downturn accounted for a major shock to these two labor-intensive city clusters. To stabilize urban employment and productivity, the production of energy or pollution-intensive sectors in these two clusters may need to remain at this level or even expand. However, urban growth in the SHSN consists of more technology-dependent cities and is less affected than the other two.

3.2. \(\text{TCO}_2\) in the Three City Clusters of the YRD

As shown in Figure 4, energy consumption and their leading carbon emissions in the YRD showed rapid increases after 2000. In the recent five years (2013–2018), the \(\text{TCO}_2\)
from SHSN, WCN, and NXH shows significant variation. The magnitudes of TCO\textsubscript{2} of the three city clusters are consistent with the city hierarchy. SHSN had the highest 2018 TCO\textsubscript{2} among the group \((623.9 \times 10^4 \text{ t})\), followed by WCN \((311.9 \times 10^4 \text{ t})\), while NXH had the least \((166.4 \times 10^4 \text{ t})\). The per capita TCO\textsubscript{2} from WCN and NXH of 2018 shared similar levels \((\approx 0.07 \text{ t})\). This could be attributed to the implementation of low-carbon development policies in WCN, which has led to emission control and energy restructuring. NXH is still in high demand for economic development, which results in significant energy consumption and higher TCO\textsubscript{2} emissions. However, the per capita consumption reached its minimum in SHSN by 2018 \((\approx 0.12 \text{ t})\), which is likely because of the population density and a series of low-carbon development policies.

![Figure 4. Variations of time-series trends of C\textsubscript{T} (fuel CO\textsubscript{2} emission) and C\textsubscript{T} (total CO\textsubscript{2} emission) with of C\textsubscript{E} (electricity CO\textsubscript{2} emission) in three representative city clusters of YRD.](image)

In addition, oils make up most of the fuel consumption compared with coal and gas. Moreover, the trend of oil consumption was gradually increasing, which is an inherent characteristic of the transportation industry. Among different types of oils, gasoline and diesel play the most significant role, accounting for an average of 77% of the carbon emission. Increasing trends of these two fuels without signs of slowing indicates that road transport will continue as the primary mode of transportation in future years. Kerosene fuel, an indicator for aviation and shipping situations, showed an apparent increasing trend since 2007 in the YRD (2002 for SHSN, 2005 for WCN, and 2008 for NXH). As for other fuels as a whole (e.g., coal and gas), consumption plunged while natural gas steeply increased after 2009 in the YRD (2007 for SHSN, 2009 for WCN, and 2011 for NXH), which gives evidence that the energy structure in the YRD is under adjustment. For instance, the overall increasing trend of the TCO\textsubscript{2} between 2012 and 2018 \((\approx 6\% \text{ yr}^{-1})\) is slower than that between 1990 and 2011 \((\approx 10\% \text{ yr}^{-1})\) due to more restrictions and higher standards of air pollution policy announced by the Chinese government in 2011 (Table 3).

Further, we observed that carbon emissions caused by fossil fuel consumption increased continuously from 1990 to 2018 (Table 3). Carbon emission from electricity usage steadily increased, which indicated that electricity power gradually becomes a significant component in the total energy consumption of TCO\textsubscript{2} in all three city clusters of the YRD (but the order remains the same: SHSN > WCN > NXH). This is not surprising, since China is the largest electric vehicle market and consumed more than double the number of electric vehicles than the U.S. did in 2016 [2,26]. China’s central government mandated that 11% of all cars sold in the market ought to be electric by 2020. Some good policies were announced, including the government tax exemption for the purchase of electric vehicles. An electric vehicle license plate’s application time is much shorter and less complicated than for traditional vehicles in Beijing and Shanghai. It can be expected that by 2030, electricity will account for more than 70% of the energy consumption in the transportation sectors of YRD [25]. However, it should be emphasized that the high consumption rate of electricity can only represent a potential energy greenness (low-carbon degree), because China’s current electricity is mostly delivered by thermal power plant but less from other clean energy sources (e.g., solar, wind, nuclear, etc.).
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Table 3. TCO₂ from fuels and electricity in SHSN (Shanghai, Suzhou, Nanjing), WCN (Wuxi, Changzhou, Ningbo), and NXH (Nantong, Xuzhou, Hefei). Note that units of C are in 10⁸ t, and E in 10⁸ Kwh. Cₜ is the estimation value of carbon emission from electricity in T year (10⁸ t); Eₜ is the amount of electricity used in transportation in T year (10⁸ Kwh); E₈ is the total electricity generation in sampled cities of YRD in T year (10⁸ Kwh); Cₜ is the carbon emission estimated from thermal power in T year.

| City Cluster | Year | Cₜ | Eₜ | E₈ | Cₜ | Cₜ | Cₜ |
|--------------|------|----|----|----|----|----|----|
| SHSN         | 1990 | 79.63 | 3.93 | 397.13 | 396.91 | 1130.94 | 11.18 | 90.82 |
|              | 1991 | 87.51 | 4.31 | 436.41 | 436.16 | 1242.79 | 12.29 | 99.80 |
|              | 1992 | 96.16 | 4.74 | 479.57 | 479.30 | 1365.70 | 13.50 | 109.67 |
|              | 1993 | 105.67 | 5.21 | 527.00 | 526.70 | 1500.77 | 14.84 | 120.51 |
|              | 1994 | 116.13 | 5.72 | 579.12 | 578.80 | 1649.20 | 16.31 | 132.43 |
|              | 1995 | 127.61 | 6.29 | 636.40 | 636.04 | 1812.30 | 17.92 | 145.53 |
|              | 1996 | 145.94 | 6.56 | 681.18 | 680.75 | 2469.93 | 18.59 | 164.52 |
|              | 1997 | 137.81 | 7.29 | 699.06 | 698.58 | 1931.49 | 20.14 | 157.96 |
|              | 1998 | 157.90 | 7.43 | 702.96 | 702.30 | 1963.06 | 20.74 | 178.63 |
|              | 1999 | 173.05 | 7.62 | 761.03 | 760.74 | 2101.37 | 21.05 | 194.09 |
|              | 2000 | 171.25 | 8.65 | 875.30 | 874.67 | 2375.81 | 23.62 | 194.69 |
|              | 2001 | 224.78 | 10.03 | 957.08 | 936.56 | 2501.22 | 26.76 | 251.55 |
|              | 2012 | 262.14 | 11.23 | 1051.88 | 1050.44 | 2776.58 | 29.65 | 291.79 |
|              | 2013 | 347.22 | 13.37 | 1203.09 | 1199.49 | 3135.97 | 34.86 | 358.02 |
|              | 2014 | 428.58 | 15.78 | 1475.11 | 1471.91 | 3758.65 | 40.20 | 468.79 |
|              | 2015 | 442.03 | 14.81 | 1908.00 | 1902.86 | 4853.44 | 37.52 | 479.55 |
|              | 2016 | 470.41 | 15.21 | 2282.40 | 2261.70 | 5336.31 | 35.56 | 505.87 |
|              | 2017 | 514.50 | 17.55 | 2542.50 | 2438.10 | 5394.61 | 37.23 | 551.75 |
|              | 2018 | 581.79 | 20.60 | 2598.30 | 2461.50 | 5312.99 | 42.13 | 623.91 |
| WCN          | 1990 | 39.82 | 1.96 | 198.57 | 198.45 | 565.47 | 5.59 | 45.41 |
|              | 1991 | 43.75 | 2.16 | 218.21 | 218.08 | 621.39 | 6.14 | 49.90 |
|              | 1992 | 48.08 | 2.37 | 239.79 | 239.65 | 682.85 | 6.75 | 54.83 |
|              | 1993 | 52.84 | 2.60 | 263.50 | 263.35 | 750.38 | 7.42 | 60.26 |
|              | 1994 | 58.06 | 2.86 | 289.56 | 289.40 | 824.60 | 8.15 | 66.22 |
|              | 1995 | 63.81 | 3.15 | 318.20 | 318.02 | 906.19 | 8.96 | 72.77 |
|              | 1996 | 72.97 | 3.28 | 340.59 | 340.38 | 1234.97 | 9.29 | 82.26 |
|              | 1997 | 68.90 | 3.65 | 349.53 | 349.29 | 965.75 | 10.07 | 78.98 |
|              | 1998 | 78.95 | 3.71 | 351.48 | 351.15 | 981.53 | 10.37 | 89.32 |
| NXH          | 1990 | 86.53 | 3.81 | 380.52 | 380.37 | 1050.68 | 10.53 | 97.05 |
|              | 1991 | 85.63 | 4.32 | 437.65 | 437.33 | 1185.93 | 11.81 | 97.34 |
|              | 1992 | 112.39 | 5.01 | 468.54 | 468.28 | 1250.61 | 13.38 | 125.78 |
|              | 1993 | 131.07 | 5.62 | 525.94 | 525.22 | 1388.29 | 14.82 | 145.89 |
|              | 1994 | 173.61 | 6.69 | 601.55 | 599.75 | 1567.98 | 17.43 | 191.04 |
|              | 1995 | 214.29 | 7.89 | 737.55 | 735.95 | 1879.34 | 20.10 | 234.40 |
|              | 1996 | 221.01 | 7.40 | 954.00 | 951.43 | 2417.72 | 18.76 | 239.77 |
|              | 1997 | 235.21 | 7.61 | 1141.20 | 1130.85 | 2668.16 | 17.78 | 252.99 |
|              | 1998 | 257.25 | 8.78 | 1271.25 | 1219.05 | 2697.30 | 18.62 | 275.87 |
|              | 1999 | 290.89 | 10.30 | 1299.15 | 1230.75 | 2656.49 | 21.06 | 311.92 |

Note: C is the carbon emission estimated from thermal power in T year (10⁸ t); Eₜ is the amount of electricity used in transportation in T year (10⁸ Kwh); E₈ is the total electricity generation in sampled cities of YRD in T year (10⁸ Kwh); Cₜ is the carbon emission estimated from thermal power in T year.
3.3. The Complexity between Energy Consumption, Environmental Regulations, and Economic Intervention in YRD

Significant progress has been made toward mitigating transportation emissions in the YRD as well as across the country. Given the transboundary effect of CO2 emissions, it is alarming that some previous studies have excluded the actions and inactions of economic and environmental policies that escalate emissions. We examined the heterogeneous contribution of immediate and underlying drivers of the economy and environment on TCO2 in the three city clusters of the YRD for the period spanning 1990–2018 (Table 4). Figure 5 depicts the descriptive mean distribution of dynamic panel correlations of economy and environment on TCO2 in the three city clusters of the YRD. Results outline that the SHSN and WCN city clusters contribute to carbon emissions in the YRD due to their more vital tied correlation values (Table 4). ECNTCO2 (economic interventions vs. TCO2) is on the rise from 1990 to 2019 in the NXH, and NXH’s ENVITCO2 (environmental regulations vs. TCO2) is on a reducing trend after 2010. Meanwhile, both SHSN and WCN exhibited similar trends that ECNTCO2 was higher than ENVITCO2 from 1990 to 2010 and then turned to a comparable level after 2010. These comparisons demonstrate the spatial–temporal heterogeneity of TCO2 regulations in the YRD and further enrich the body of knowledge. The integrated economic intervention and environmental policy approach can be the leading solution to control transportation pollution in both developing and developed regions.

The method we deployed, the dynamic panel estimation technique, functions by accounting for cross-sectional dependence, heterogeneous parameters across city clusters, and dynamic correlated effects—which is a constraint for socio-economic, consumption, and pollution-based models. Therefore, the model can represent the economic dynamic and environmental-related aggregate indicators in a carbon emission function. The empirical results demonstrate that the overarching effect of the immediate increase in economic development and energy utilization stimulates TCO2 emissions in all three city clusters. Environmental sustainability, which closely links urbanization, urban economic growth, and urban energy consumption, is found to escalate the emission level and regional pollution. The complexity between the economy, environment, and carbon emissions revealed the urgency for socio-economic adjustment from carbonized to decarbonized structures. The complex interaction highlights the diversification of the energy mix by including clean and renewable energy sources, fossil fuel-switching, and modern technologies such as carbon capture and storage to improve energy efficiency and decline TCO2 intensities [5].

Table 4. Panel dynamic common correlated effects. ECNTCO2 referred to economic interventions vs. TCO2. ENVITCO2 referred to environmental regulations vs. TCO2. * indicates statistically significant differences (p < 0.05).

| Category | 1990–1999 | 2000–2009 | 2010–2018 |
|----------|-----------|-----------|-----------|
|          | SHSN  | WCN  | NXH  | SHSN  | WCN  | NXH  | SHSN  | WCN  | NXH  |
| Correlations (0, 1) |     |     |     |     |     |     |     |     |     |
| ECNTCO2 | 0.75  | 0.63 | 0.65 | 0.81 | 0.72 | 0.64 | 0.86 | 0.76 | 0.78 |
| ENVITCO2 | 0.73  | 0.64 | 0.49 | 0.82 | 0.69 | 0.51 | 0.81 | 0.65 | 0.62 |
| CONS    | −8.84 | 1.44 | −3.21 | −3.14 | 2.20 | 1.27 | 3.98 | 0.34 | −5.17 |
| Diagnostics |     |     |     |     |     |     |     |     |     |
| Prob > F | 0.00 * | 0.00 * | 0.00 * | 0.00 * | 0.00 * | 0.00 * | 0.00 * | 0.00 * | 0.00 * |
| R²      | 0.58  | 0.47 | 0.62 | 0.66 | 0.49 | 0.57 | 0.80 | 0.74 | 0.69 |
| Root MSE | 0.07  | 0.09 | 0.12 | 0.12 | 0.11 | 0.27 | 0.09 | 0.17 | 0.22 |
| CD Statistic | −0.28 | −0.88 | −0.67 | −0.32 | −0.75 | −0.55 | −0.17 | −0.85 | −0.93 |
| p-value | 0.15  | 0.26 | 0.51 | 0.45 | 0.29 | 0.38 | 0.60 | 0.26 | 0.77 |
Figure 5. Investigations of dynamic panel correlations of (a) economic interventions vs. TCO$_{2}$ and (b) environmental regulations vs. TCO$_{2}$ in three representative city clusters of the YRD with a time interval of $\approx$10 years (referenced to Table 4).

3.4. Research Implications

As a long-term hot topic in social studies, regional collaborative development needs multidisciplinary perspectives and multi-scalar methods. Regional collaborative development can also be analyzed from the perspectives of infrastructure, ecology, and environmental sciences [4,5]. Developing countries such as China must achieve collaborative development of the economy, society, environment, and infrastructure. It is worth exploring how to evaluate the collaborative development ability of regional infrastructure and ecological environments. Therefore, it is necessary to conduct some comparative research based on some typical cases and methodological examination on using and integrating the different methods. Regional collaborative development is critical in regional sustainability. The collaborative development ability across cities is based on economic development and connections with other regions, which directly determines the degree of collaborative development within a region [7,8].

Several policy recommendations have been raised to build a low-carbon transportation system at the regional level [18]. China’s transport sector has experienced fast development since the late 1990s, resulting in the increasing consumption of fossil fuels and corresponding CO$_{2}$ emission. From both energy conservation and CO$_{2}$ emission reduction perspectives, China’s rapid development in the transport sector deserves more attention to raise appropriate mitigation policies. This requires an in-depth study on uncovering the features and driving forces of CO$_{2}$ emission growth from the transport sector at regional and provincial levels due to China’s imbalanced regional development. Multiple measures
related to the improvement of energy intensity, energy structure, public awareness, and transport modes are proposed and should be adopted. However, since CO₂ emission features and driving forces from the transport sector in different cities are significantly different, mitigation measures should be diversified [11,13]. Local to provincial governments need to select the most appropriate mitigation measures by considering their local energy endowment, energy structure, technology levels, and financial ability. However, regional collaboration is always essential and should be encouraged to promote the best practices, technologies, and vehicles [22,26].

4. Conclusions

The study is of significance in promoting a higher level of regional sustainable development. Regional sustainable development is a complex issue that tests the effectiveness of government policy interventions and examines the resilience of the regional economy and the region’s carrying capacity of the eco-environment. Regulating the energy structure and reducing transportation-related carbon emissions may be an effective measure to achieve YRD’s long-term carbon-neutral development. The integrated approach of economic and environmental interventions should be implemented to control transportation pollutions and conserve associated energy consumption. We concluded our findings as follows:

(1) Sustainable urban development within the YRD is still imbalanced. Shanghai and Jiangsu’s development level are at the forefront of the YRD, but southern Zhejiang and Anhui are relatively underdeveloped. From 1990 to 2018, YRD’s city productivity increased significantly (319% represented by the city sustainable index). Gaps in the economy and energy across cities are narrowing down since 2018. However, Shanghai’s leading position is far ahead from being caught by its followers, which is mainly attributed to its role as the regional and national economical center. More importantly, Random Forest analysis revealed that the top-10 cities in the YRD still confront severe environmental issues for the ultimate goals of sustainable development. As suggested by this automated algorithm, we presented three city clusters that should group in their sustainable development goals, which are SHSN (Shanghai, Hangzhou, Suzhou, Nanjing), WCN (Wuxi, Changzhou, and Ningbo), and NXH (Nantong, Xuzhou, and Hefei). Cross-city collaboration is essential for promoting the best practices and technologies in all aspects of local energy endowment, energy structure, technology level, and financial ability.

(2) Different city clusters represent various scenarios of energy consumptions, which glance at relationships between urban development and carbon emissions. For instance, the WCN cluster is in the early stage of low-carbon development (311.9 10^4 t and ≈0.07 t per capita), which in turn has led to emission control and energy restructuring, while NXH is in the phase of high demands focused solely on economic development (166 10^4 t but still 0.07 t per capita), which certainly result in significant energy consumption and the higher emission once the population increased. In the YRD, carbon emission from electricity use is continually increasing in recent years (e.g., ≈13% in 1990 to ≈47% in 2018), especially after 2010, when China’s central government announced a series of reform policies. It is observed that electricity will account for a significant part (presumably 70%) of the total transportation energy consumption in the YRD before 2040.

(3) The complexity between energy consumption, environmental regulation, and economic intervention revealed the urgency for socio-economic adjustment from carbonized to decarbonized structures in the YRD. The reduction of carbon emission cannot be determined only by economic policies. An integrated approach to economic and environmental interventions should be the leading solution to control transportation pollutions and lower the associated energy consumption.

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