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# Analysis of the Efficiency of Forest Carbon Sinks and Its Influencing Factors—Evidence from China

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**Abstract:** The study of the input–output efficiency and influencing factors of forest carbon sinks is beneficial for the realization of the rational allocation of forest carbon sink resources. Based on the DEA-SBM model, the efficiency of forest carbon sinks is measured and analyzed in 30 provinces (cities) of China from 2005 to 2018; the influencing factors of forest carbon sink efficiency are constructed from the three perspectives of pressure subsystem, state subsystem, and response subsystem with the help of the PSR model and regression analysis is conducted using the FGLS model so that the results of the study can provide a basis for formulating a regionally differentiated forest carbon sink system. The empirical results show that the average annual forest carbon sink efficiency in China is only 0.29, and there is much room for improvement. The level of urbanization, the degree of natural damage to forests, precipitation, and the proportion of financial support for forestry are positively correlated with forest carbon sink efficiency, while temperature is negatively correlated with forest sink efficiency. Additionally, different influencing factors have regional heterogeneity on forest carbon sink efficiency. Based on the above findings, we propose the following policy recommendations: formulate forest carbon sink strategies according to local conditions, adjust and optimize the forestry industry structure at the right time, minimize the intervention in forest ecosystems, improve the supervision mechanism of special forestry funds, improve the level of forestry human capital, and accelerate the transformation of scientific and technological achievements.

**Keywords:** forest carbon sink efficiency; influencing factors; DEA-SBM model; FGLS model



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## 1. Introduction

On 22 September 2020, Secretary Xi Jinping proposed for the first time at the United Nations General Assembly that China should strive to peak its carbon dioxide emissions by 2030 and strive to achieve carbon neutrality by 2060 [1]. Achieving the "double carbon" goal requires an integrated approach to reducing carbon emissions and increasing carbon sinks. However, with the advancement of emission reduction, the marginal cost of carbon emission reduction is rapidly increasing, and the cost advantage of carbon sinks is becoming more and more prominent. Carbon sinks are actions, activities, or mechanisms that fix and absorb carbon dioxide in the air. It can be divided into engineering carbon sinks and ecosystem carbon sinks. In terms of engineering carbon sinks, carbon capture and sequestration and other engineering carbon sinks have been largely planned or shelved in the near future due to huge investment costs, and there is no possibility of industrialization yet. Carbon sequestration by ecosystem carbon sinks is safer, more stable, and more efficient than artificial physical methods [2]. In terms of sink pathways, marine ecosystems and terrestrial ecosystems are the main carbon pools [3]. Although marine ecosystems have good prospects for carbon sequestration, the academic community lacks sufficient understanding of the storage, rate, process mechanism, and function of marine carbon sinks and has not yet established a specific observation and evaluation system, which makes it difficult to achieve "measurable, reportable and verifiable" results [4]. In contrast, terrestrial ecosystems are easier to measure and have greater potential to increase sinks compared to marine carbon sinks. Among them, forests, as the main part of terrestrial ecosystems, account for about two-thirds of the annual carbon sequestration of the whole ecosystem and have an irreplaceable role in regulating climate [5]. A large number of studies have shown that China's forests have great potential to increase carbon sinks [6–8]. With China's economy shifting from high-growth to high-quality development, improving quality and efficiency has become the main theme of economic work. In this process, forest carbon sinks to improve quality and efficiency will become a central issue for the in-depth study of forestry construction and a major practical issue facing the development of regional forest carbon sinks.

There is a lack of articles on the efficiency of forest carbon sinks that focus on the measurement of forest carbon sinks and the analysis of their influencing factors. On the whole, China's forest carbon sink potential is huge, but the level of forest carbon sink efficiency is not known. In fact, under the premise of resource scarcity, it is obvious that forest carbon sink efficiency, which is measured by including input factors and forest carbon sinks into the forest carbon sink assessment framework, is a more accurate measure of the forest carbon sink level than considering only forest carbon sink output. At the same time, economic, social, and natural factors influence the input–output levels of forest carbon sinks, but the specific effects are rarely conclusive. Hence, what are the key factors that affect the efficiency of forest carbon sinks? The empirical study of the influencing factors of forest carbon sink efficiency is beneficial to deepening the understanding of forest carbon sink efficiency, which can better influence the formulation of the development policies of forest carbon sinks in China and the region.

Through an empirical study on the measurement of forest carbon sink efficiency in China and its influencing factors, this paper attempts to answer the following three questions: First, what is the level of efficiency of forest carbon sinks in China and its different regions? Second, what are the key factors affecting the efficiency of carbon sinks? Third, how do we explore differentiated improvement paths based on regional heterogeneity?

## 2. Literature Review

This paper is devoted to the study of forest carbon sink efficiency and the analysis of its influencing factors. The relevant literature can be reviewed in the following aspects.

The first is the literature on the assessment of forest carbon sinks. Most of the articles express the level of forest carbon sinks by calculating the total carbon sequestered by forests in a certain area [9]. Li Qi [10] measured the total carbon stock of the eighth inventory of China's tree forests as 6135.68 Tg and proposed that China's forests have great carbon sink potential. Wu Guoxun [11] used the biomass conversion factor method and the average biomass method to measure the forest carbon sink in Jiangxi Province and calculated that the forest carbon stock in Jiangxi Province increased from 81.38 to 188.52 Tg during the period 1998–2011. Considering the function of soil carbon stock in forests, Xu Enyin et al. [12] used a continuous function of the biomass conversion factor to measure forest carbon stock in three major forest areas in China. It was found that both the transformation of the forest phase and the increase of forest area contributed to the increase of forest carbon stock. In fact, forest carbon sink is an incremental concept; that is, it is the change of forest carbon stock per unit time [13]. Obviously, the assessment of forest carbon sinks should focus more on the incremental part of forest carbon sequestration, which emphasizes the role of human factors on forest carbon sinks and can accelerate the achievement of carbon neutrality goals.

The second is the literature on the efficiency of forest carbon sinks. The literature on forest carbon sink efficiency and its influencing factors is relatively scarce. Long Fei et al. [14] measured forest carbon sink efficiency in Hangzhou City using the number of different types of forest land use as input indicators and the total amount of forest carbon sequestration as output indicators and found that the carbon sink efficiency varied widely among counties and cities; there was a certain negative correlation between its spatial distribution and economic development. Xue Longfei et al. [15] selected capital, labor, and land as input indicators and total forestry output values and forest carbon sink values as output indicators to construct the input–output indicators of forestry carbon sequestration efficiency in four major forest regions in China from 1988 to 2013. On this basis, they analyzed the driving forces and convergence of forestry carbon sequestration efficiency. Qi Lin and Zhou Xiaolin [16] constructed input–output indicators with forest area, total wages of state-owned economic units in the forestry system, total investment in forestry capital construction, forest stock, and tree forest carbon storage and used a non-radial DEA model to assess the forest carbon sequestration efficiency of forestry inputs from 1950 to 2013. All the above literature adopted the traditional DEA model to measure efficiency, and the output of the constructed input–output index system is the total amount of forest carbon sequestered but not the forest carbon sink. In contrast, Lin Boqiang et al. [17] used the SBM model to measure the efficiency of forest carbon sinks, in which the difference between forest carbon stocks in adjacent years is used as an output indicator to measure the ecological development of forests. It can be found that there are few articles that measure the efficiency of forest carbon sinks accurately from the input–output perspective, and there is a lack of articles that empirically analyze its influencing factors.

Although few articles have been published on the efficiency of forest carbon sinks, studies on efficiency in other fields can also provide implications for this paper. Some scholars have constructed an indicator system according to the framework of total factors to measure efficiency and empirically analyze its influencing factors. For example, Ma Linyan et al. [18] measured the ecological efficiency of arable land use in China using land, labor, and materials as input indicators, grain yield and agricultural output value as desired output indicators, and carbon emissions during arable land production as non-desired output indicators. On this basis, the authors selected the influencing factors, such as GDP per capita and disaster area, for empirical analysis. Wen Gaohui et al. [19] measured the ecological efficiency of arable land use in the Dongting Lake Plain, explored its influencing factors, and found that there were significant spatial differences in the ecological efficiency of arable land use, while urbanization and regional scientific and technological inputs had significant positive effects on it.

Finally, there is literature on the factors affecting forest carbon sinks. Factors affecting forest carbon sinks mainly include the natural environment. Fire, pests, and diseases that occur in nature can damage mature forests or forests in the growing season, resulting in the partial or total reversal of the stored carbon and changes in total forest carbon stocks [20]. In addition, climate change is an important factor affecting the difference in forest carbon sinks between regions [21]. Johnston et al. [22] found that timber harvesting, wood products consumption, and forest area were determinants. Chong Xu et al. [23] identified GDP and urbanization level as positive drivers of forest carbon sinks. Daigneault and Favero [24] found that population growth, economic development, land use policy, and technological change are important potential drivers of forest carbon sinks.

In summary, most of the previous literature has focused on the assessment of forest carbon sinks, but little has been done to measure the relative value of forest carbon sinks, i.e., the efficiency of forest carbon sinks, and there is a lack of quantitative analysis of the factors influencing the efficiency of forest carbon sinks. Therefore, this paper attempts to extend the above literature in the following ways: (1) measuring forest carbon sink efficiency in 30 provinces (cities) across China using labor, land, and capital as input indicators and applying non-radial and non-angle DEA-SBM to measure forest carbon sink efficiency more accurately in each province from 2005 to 2018; (2) dividing 30 provinces (cities) into regions (east, central, west, and northeast) and conducting comparative analysis between regions; (3) constructing a system of indicators affecting forest carbon sink efficiency with the help of the PSR model, selecting an econometric model for econometric testing, and then providing policy suggestions for the regional enhancement of forest carbon sink efficiency.

# 3. Methods and Data

## *3.1. Research Methodology*

### 3.1.1. Forest Carbon Sink Estimation Methods

The forest carbon sink in this paper is the difference between the total forest carbon sequestration of adjacent years. Based on the carbon sink accounting formula of the 2006 IPCC Guidelines for National Greenhouse Gas Inventories, the total carbon sequestration of the entire forest ecosystem is estimated, taking into account the carbon stock of living forest biomass (including above-ground and below-ground parts of biomass) and the carbon stock of dead wood [17]. The calculation formula is as follows:

$$C = A \times V \times BEF \times D \times (1+R) \times (1+RDW) \times CF \tag{1}$$

A is the remaining land area in the same land use category (unit: ha); V is the volume of timber storage (unit: $m^3$ /ha); A × V is the total forest stock. The data on total forest stock were obtained from the China Forestry Statistical Yearbook. BEF is the biomass expansion factor, D is the basic wood density, and R is the ratio of below-ground biomass to above-ground biomass, RDW is the "dead–live ratio" of dead wood dry weight to live biomass; CF is the dry matter carbon fraction. The data of other parameters were calculated by Lin Boqiang et al. [17], and the parameter values are shown in Table 1.

**Table 1.** Parameter values in the carbon sink estimation equation.

| Parameters | Parameter Value |
|---|---|
| BEF | 1.3539 |
| D | 0.43 |
| R | 0.3789 |
| CF | 0.47 |
| RDW | 0.1727 |

### 3.1.2. DEA-SBM Model for Measuring the Efficiency of Forest Carbon Sinks

Forest carbon sink efficiency is an indicator to evaluate the level of forest carbon sinks in a region based on the consideration of forestry system inputs and carbon sink outputs. The DEA model is widely used for efficiency measurement, which is a systematic analysis method for the evaluation of the relative efficiency between factor inputs and outputs. Its measurement models can be divided into four categories: (1) radial and angular; (2) radial and non-angular; (3) non-radial and angular; (4) non-radial and non-angular. "Radial" means that the input ratio or output ratio changes in the same proportion to be effective, while "angular" means from the input perspective or output perspective [25]. Traditional DEA models are the CCR model and the BCC model (the CCR model is for constant scale payoffs and the BCC model for variable scale payoffs), which are mostly radial or angular and do not take into account input or output slackness [26]. Later, Tone Kaoru proposed a non-radial and non-angular DEA-SBM model that puts the slack variables directly into the objective function to solve the slackness problem and, thus, improve measurement accuracy [27]. The calculation equation is:

$$\begin{aligned} &\min \rho = \left(1 - 1/m\sum_{i=1}^{m}\frac{S^-{}_i}{x_{ik}}\right) / \left(1 + 1/q\sum_{r=1}^{q}\frac{S^+{}_i}{y_{rk}}\right) \\ &\text{s. t. } x_k = X\lambda + s^- \\ &y_k = Y\lambda - s^+ \\ &s^- \geq 0,\ s^+ \geq 0,\ \lambda \geq 0 \end{aligned} \tag{2}$$

where ρ is the value of forest carbon sink efficiency; $x_{ik}$ is the forestry input index of the ith of region k (i = 1, 2,..., m); $y_{rk}$ is the forestry input index of the rth of region k (i = 1, 2,..., q); s denotes the slack variables of inputs and outputs; λ is the linear programming weight vector. The objective function ρ takes values from 0 to 1. When $\rho = 1$, it is valid, and when $\rho < 1$, it means that the evaluation unit is invalid and there is room for improvement and optimization.

### *3.2. Indicator Construction*

Forest carbon sink efficiency is essentially about getting the maximum forest carbon sink output with the least amount of forest resources possible. According to the Cobb–Douglas production function, the input factors include labor, land, and capital, and this paper uses these factors as input indicators. Among the input variables, capital is measured by the complete annual investment in forestry fixed assets, labor is measured by the number of forestry employees at the end of the year, and land is measured by forest area. For output variables, forest carbon sinks are used as output indicators.

### *3.3. Data Sources and Description*

This paper takes 30 provinces (cities) in China (excluding Tibet and Hong Kong, Macao, and Taiwan) from 2005 to 2018 as the research sample. The data on the labor force, forest area, capital, and forest stock in the forestry system were obtained from the China Forestry Statistical Yearbook. Among them, capital input indicators were measured by the perpetual inventory method and deflated using 2005 as the base period. Since forest inventory data are inventoried every five years, the values of forest area and forest stock for 2004–2008, 2009–2013, and 2014–2018 remained unchanged. Regarding the missing data during the inventory interval, this paper refers to Tian Jie's [28] data processing method and uses linear interpolation to supplement our study. Other data were obtained from the China Forestry Statistical Yearbook, the China Statistical Yearbook, and regional meteorological observation data.

## **4. Measurement of Regional Forest Sink Efficiency in China**

### *4.1. Parameter Selection for the Forest Carbon Sink Efficiency Model*

Considering that different conditions may cause different measurement results, this paper conducts a comprehensive measurement comparison analysis based on the scale payoff variability qualification. From constant returns to scale (CRS) to general returns to scale (GRS) to variable returns to scale (VRS), the qualifying conditions are relaxed in order to set:

$$\begin{aligned} & \mathrm{L} \leq \mathrm{e}\lambda \leq \mathrm{U} \\ & \mathrm{e} = (1, \ldots, 1) \end{aligned} \tag{3}$$

λ is the weight matrix in Equation (2) above. L and U are the lower and upper bounds of scale payoffs, respectively. When both are 1, it indicates that the model is scale payoff invariant; when $L = 0$ and $U = 1$, the scale payoff decreases; when $L = 1$ and $U = \infty$, the scale payoff increases; when $L = 0.8$ and $U = 1.2$, the model is at the general scale payoff.

DEA-SOLVER PRO was used to measure and analyze forest carbon sink efficiency under the three scenarios of CRS, GRS, and VRS. The average value of forest carbon sink efficiency by year was calculated, and the basic situation is shown in Figure 1.

From the average forest carbon sink efficiency by year in the country, the average forest carbon sink efficiency increases sequentially under the three qualifying conditions. Overall, all three are in a slow, decreasing trend that can be specifically divided into three stages: decreasing from 2005 to 2013, increasing from 2014 to 2015, and decreasing from 2016 to 2018. Meanwhile, it can be seen from Figure 1 that although the evolution trend of the average forest carbon sink efficiency under the three qualifying conditions is basically the same, the degree of consistency of the trend under GRS and VRS is relatively higher in comparison. Combining this result with the different conditions of forestry development in each province (city), the more general measurements under the GRS were chosen as the basis of the analysis in this paper. Under the qualification of GRS, the average value of forest carbon sink efficiency in 30 provinces (cities) was 0.468 in 2005; it reached 0.392 in 2013, rose to 0.438 in 2015, and then showed a slow, decreasing trend to 0.427 in 2018.

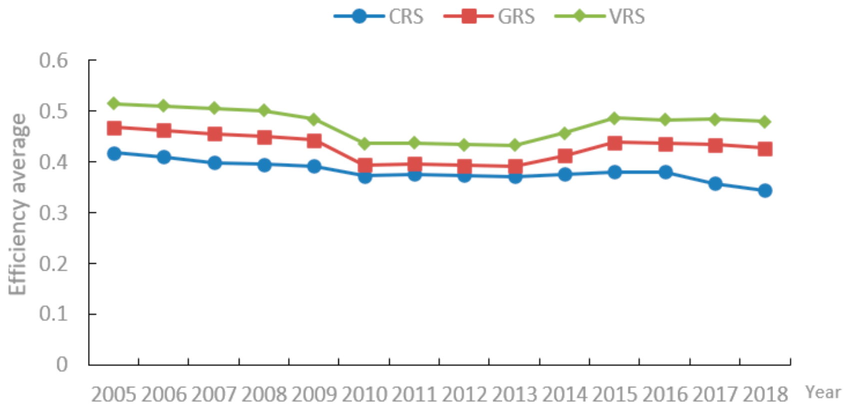


**Figure 1.** Average trend of forest carbon sink efficiency in China, 2005–2018.

### *4.2. Analysis of Regional Differences in the Efficiency of Forest Carbon Sinks*

Table 2 shows the efficiency of forest carbon sinks in China from 2005 to 2018, calculated based on the SBM model. To examine the provincial differences in forest carbon sink efficiency using the average values of forest carbon sink efficiency in each province from 2005 to 2018, the 30 provinces (cities) are generally divided into five echelons: the first echelon includes Yunnan, Chongqing, and Zhejiang (0.8 or more), the second echelon includes Tianjin, Fujian, and Shanghai (0.7–0.8), the third echelon includes Jiangsu, Henan, and Guizhou (0.5–0.7), the fourth echelon includes Sichuan, Anhui, Guangdong, Guangxi, Jiangxi, Hainan, Hubei, and Heilongjiang (0.4~0.5), and the fifth echelon includes Inner Mongolia, Beijing, Jilin, Ningxia, Shandong, Shanxi, Xinjiang, Hebei, Hunan, Gansu, Liaoning, Shaanxi, and Qinghai (below 0.4). According to the average value of forest carbon sink efficiency of each echelon, the first and second echelon, the third echelon, and the fourth and fifth echelon can be regarded as high-, medium-, and low-efficiency groups, respectively. It is worth noting that, according to the calculation results of the carbon sink estimation formula, Heilongjiang Province, Sichuan Province, Inner Mongolia Autonomous Region, and Jilin Province ranked at the top in terms of total forest carbon sequestration, but their forest carbon sink efficiency was at a low level. The possible reason is that although these regions are rich in resource endowments, the level of forestry technology development is slow, the degree of forestry mechanization is low, and the forestry economic development model is relatively crude. In contrast, the regional forest carbon sink efficiency in the provinces represented by Zhejiang, Fujian, Tianjin, Shanghai, Chongqing, and Yunnan is at a high level, and the effect of forest carbon sinks is obvious. In particular, the forest carbon sink efficiency of Zhejiang Province has always been 1 in this period, and the input–output ratio has reached the optimal state, which reflects the leading role of Zhejiang Province in forest construction. Most provinces, however, lack efficiency in forest carbon sinks and have more room for continuous improvement.

In order to examine the efficiency differences between regions on a larger scale, this paper divides the 30 provinces (cities) into the eastern region, central region, western region, and northeastern region based on resource endowment, economic development, and climatic conditions. The eastern region includes the 10 provinces (cities) of Zhejiang, Hebei, Tianjin, Beijing, Shandong, Jiangsu, Shanghai, Fujian, Guangdong, and Hainan; the central region includes the 6 provinces of Shanxi, Anhui, Jiangxi, Hubei, Hunan, and Henan; the western region includes the 11 provinces of Sichuan, Chongqing, Inner Mongolia, Guizhou, Yunnan, Shaanxi, Guangxi, Gansu, Xinjiang, Ningxia, and Qinghai; and the northeast region includes the 3 provinces of Heilongjiang, Jilin, and Liaoning. The results are shown in Table 2. It can be found that the average value of forest carbon sink efficiency in China is 0.29, which means there is more room for improvement. Comparing the average values of forest carbon sink efficiency in different regions, we can find that the eastern region has the highest forest carbon sink efficiency, with an average value of 0.53, followed by the central and western regions, with an average value of 0.39; the northeastern region has the lowest forest carbon sink efficiency, with an average value of 0.31.

**Table 2.** Regional forest carbon sink efficiency in China by province, 2005 to 2018.

| | 2005 | 2006 | 2007 | 2008 | 2009 | 2010 | 2011 | 2012 | 2013 | 2014 | 2015 | 2016 | 2017 | 2018 | Average Value |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Beijing | 0.12 | 0.08 | 0.08 | 0.08 | 0.08 | 0.22 | 0.23 | 0.23 | 0.23 | 0.22 | 0.26 | 0.25 | 0.24 | 0.23 | 0.18 |
| Tianjin | 0.62 | 0.63 | 0.64 | 0.65 | 0.66 | 0.90 | 0.90 | 0.90 | 0.89 | 0.89 | 0.70 | 0.69 | 0.68 | 0.68 | 0.75 |
| Hebei | 0.21 | 0.21 | 0.19 | 0.18 | 0.18 | 0.21 | 0.22 | 0.22 | 0.23 | 0.23 | 0.14 | 0.14 | 0.14 | 0.14 | 0.19 |
| Shanghai | 0.87 | 0.84 | 0.79 | 0.77 | 0.74 | 0.71 | 0.70 | 0.70 | 0.71 | 0.71 | 1.00 | 1.00 | 0.88 | 0.87 | 0.80 |
| Shandong | 0.57 | 0.56 | 0.55 | 0.56 | 0.57 | 0.42 | 0.42 | 0.42 | 0.43 | 0.43 | 0.04 | 0.05 | 0.05 | 0.05 | 0.37 |
| Jiangsu | 0.37 | 0.36 | 0.36 | 0.33 | 0.34 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 0.11 | 0.11 | 0.11 | 0.10 | 0.51 |
| Zhejiang | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 |
| Guangdong | 0.19 | 0.19 | 0.19 | 0.19 | 0.20 | 0.36 | 0.39 | 0.41 | 0.41 | 0.42 | 0.94 | 0.95 | 0.94 | 0.94 | 0.48 |
| Fujian | 0.29 | 0.30 | 0.30 | 0.31 | 0.32 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 0.94 | 0.95 | 0.95 | 0.94 | 0.73 |
| Hainan | 0.03 | 0.03 | 0.03 | 0.03 | 0.03 | 0.49 | 0.49 | 0.46 | 0.47 | 0.47 | 1.00 | 1.00 | 1.00 | 1.00 | 0.47 |
| Jiangxi | 0.71 | 0.69 | 0.65 | 0.62 | 0.59 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.48 | 0.50 | 0.49 | 0.48 | 0.41 |
| Anhui | 0.59 | 0.59 | 0.58 | 0.59 | 0.60 | 0.56 | 0.55 | 0.54 | 0.52 | 0.51 | 0.26 | 0.25 | 0.24 | 0.25 | 0.47 |
| Shanxi | 0.32 | 0.32 | 0.31 | 0.31 | 0.31 | 0.26 | 0.25 | 0.24 | 0.23 | 0.23 | 0.22 | 0.22 | 0.22 | 0.21 | 0.26 |
| Hubei | 0.63 | 0.61 | 0.58 | 0.56 | 0.54 | 0.51 | 0.52 | 0.51 | 0.49 | 0.48 | 0.35 | 0.33 | 0.33 | 0.32 | 0.48 |
| Hunan | 0.54 | 0.54 | 0.54 | 0.54 | 0.54 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.25 | 0.25 | 0.25 | 0.23 | 0.26 |
| Henan | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 0.44 | 0.44 | 0.44 | 0.44 | 0.43 | 0.20 | 0.20 | 0.20 | 0.20 | 0.57 |
| Guangxi | 0.75 | 0.70 | 0.69 | 0.62 | 0.58 | 0.15 | 0.15 | 0.14 | 0.14 | 0.14 | 0.54 | 0.54 | 0.54 | 0.57 | 0.45 |
| Shanxi | 0.21 | 0.21 | 0.20 | 0.20 | 0.20 | 0.33 | 0.32 | 0.31 | 0.31 | 0.30 | 0.30 | 0.30 | 0.30 | 0.29 | 0.27 |
| Gansu | 0.28 | 0.26 | 0.24 | 0.22 | 0.21 | 0.15 | 0.15 | 0.14 | 0.14 | 0.14 | 0.16 | 0.16 | 0.16 | 0.15 | 0.18 |
| Ningxia | 0.15 | 0.15 | 0.15 | 0.15 | 0.15 | 0.13 | 0.13 | 0.12 | 0.12 | 0.12 | 0.07 | 0.06 | 0.06 | 0.06 | 0.12 |
| Xinjiang | 0.28 | 0.27 | 0.25 | 0.24 | 0.23 | 0.32 | 0.32 | 0.32 | 0.32 | 0.32 | 0.35 | 0.35 | 0.37 | 0.34 | 0.31 |
| Qinghai | 0.06 | 0.06 | 0.06 | 0.07 | 0.06 | 0.07 | 0.06 | 0.07 | 0.07 | 0.07 | 0.06 | 0.04 | 0.04 | 0.04 | 0.06 |
| Yunnan | 0.97 | 0.97 | 0.96 | 0.97 | 0.96 | 0.52 | 0.53 | 0.53 | 0.54 | 0.54 | 0.97 | 0.97 | 0.95 | 0.94 | 0.81 |
| Sichuan | 0.45 | 0.44 | 0.44 | 0.44 | 0.44 | 0.23 | 0.23 | 0.24 | 0.25 | 0.24 | 0.57 | 0.57 | 0.56 | 0.55 | 0.40 |
| Guizhou | 1.00 | 0.99 | 0.98 | 0.98 | 1.00 | 0.39 | 0.41 | 0.41 | 0.41 | 0.40 | 0.52 | 0.52 | 0.53 | 0.48 | 0.64 |
| Chongqi | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 0.57 | 0.57 | 0.56 | 0.56 | 0.57 | 1.00 | 1.00 | 1.00 | 1.00 | 0.85 |
| Inner Mongolia | 0.18 | 0.18 | 0.17 | 0.18 | 0.18 | 0.21 | 0.22 | 0.22 | 0.19 | 0.18 | 0.34 | 0.34 | 0.35 | 0.35 | 0.23 |
| Liaoning | 0.29 | 0.28 | 0.28 | 0.28 | 0.27 | 0.35 | 0.36 | 0.36 | 0.35 | 0.36 | 0.24 | 0.22 | 0.22 | 0.21 | 0.29 |
| Jilin | 0.16 | 0.16 | 0.16 | 0.17 | 0.17 | 0.30 | 0.31 | 0.31 | 0.30 | 0.29 | 0.22 | 0.23 | 0.23 | 0.22 | 0.23 |
| Heilongjiang | 0.60 | 0.59 | 0.57 | 0.57 | 0.43 | 0.21 | 0.20 | 0.20 | 0.19 | 0.44 | 0.44 | 0.43 | 0.44 | 0.42 | 0.41 |
| National | 0.31 | 0.30 | 0.30 | 0.30 | 0.26 | 0.27 | 0.27 | 0.27 | 0.26 | 0.32 | 0.31 | 0.30 | 0.31 | 0.30 | 0.29 |
| East | 0.46 | 0.46 | 0.45 | 0.44 | 0.44 | 0.58 | 0.58 | 0.58 | 0.58 | 0.58 | 0.57 | 0.57 | 0.56 | 0.56 | 0.53 |
| Central | 0.62 | 0.62 | 0.61 | 0.60 | 0.60 | 0.30 | 0.30 | 0.30 | 0.29 | 0.29 | 0.26 | 0.25 | 0.25 | 0.24 | 0.39 |
| West | 0.48 | 0.48 | 0.47 | 0.46 | 0.46 | 0.28 | 0.28 | 0.28 | 0.28 | 0.27 | 0.44 | 0.44 | 0.44 | 0.43 | 0.39 |
| Northeast | 0.35 | 0.35 | 0.34 | 0.34 | 0.29 | 0.28 | 0.29 | 0.29 | 0.28 | 0.36 | 0.30 | 0.29 | 0.29 | 0.28 | 0.31 |

By looking at Figure 2, we can also find that the forest carbon sink efficiency is basically below 0.4 in all years nationwide, and overall, the forest carbon sink efficiency in China is low. This means that there is much room for saving and improving the efficiency of China's forest carbon sinks. From the trend of forest carbon sink efficiency, the turning point generally occurred around 2010 and 2015, which may be related to the national forest resources continuous inventory system, which is applied every 5 years. If we analyze the situation from a large regional perspective, forest carbon sink efficiency in the eastern region is on the rise, rising sharply to 0.58 in 2010, mainly because the forest carbon sink efficiency in eastern regions such as Fujian and Hainan has increased significantly since 2010. The efficiency values in the central region have been well above the national average but have fallen to near-average levels since 2010. The reason lies in the high proportion of non-state-owned economic afforestation in the central region, which makes it difficult to consolidate the achievements of afforestation, coupled with frequent forest disasters; hence, the efficiency value has decreased. Additionally, the efficiency of forest carbon sinks in the western region shows a "U" curve during the period 2005–2018, i.e., the efficiency of forest sinks increasingly declined in 2010 but rapidly increased in 2015. The reason is that in 2009, more than fifty percent of the country's investment was in the west; however, the western region is larger, and, hence, it led to a low level of unit investment and a decline in efficiency values. Subsequently, supported by national policy, the pace of ecological management accelerated, and the efficiency value increased. The trend of forest carbon sink efficiency change in northeast China is consistent with the whole country. Additionally, there is no significant fluctuation in general. This result does not differ much from Lv Jiehua's [29] calculation since all the frameworks adopted are based on full elements. Although Lv Jiehua calculated the green total factor productivity of China's forestry based on an input–output index that was slightly different from that in this paper, the calculated results show that the efficiency of ecological output in China's forestry production process is not high. In addition, Lv Jiehua's results indicated that the high-efficiency areas of forestry production are concentrated in the central–eastern region and that low-efficiency areas are concentrated in the western and northeastern regions. Table 3 shows the distribution of members of each high- and low-efficiency group in the eastern, central, western, and northeastern regions. Overall, the eastern region has a clear advantage in both the level of economic development and the level of forest carbon sink efficiency, with provinces such as Zhejiang maintaining a high level of forest carbon sink efficiency. Only from the average level of forest carbon sink efficiency is the forest carbon sink efficiency in the western region stronger than that in the central region and the northeastern region overall, with the individual provinces of Yunnan and Chongqing at high-efficiency levels.

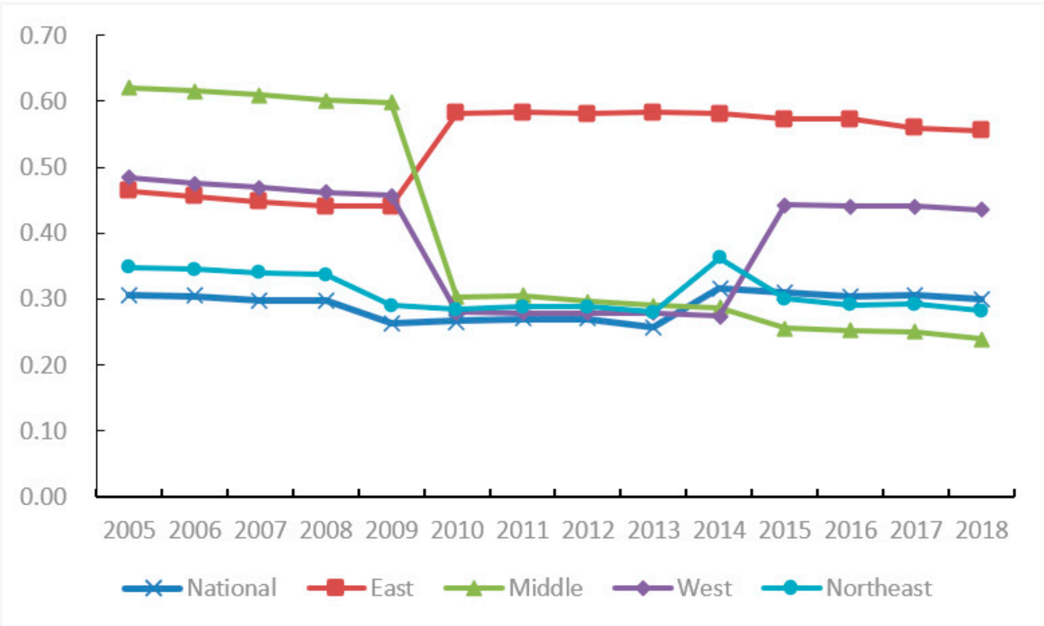


**Figure 2.** Trends in the efficiency of forest carbon sinks in different regions of China, 2005–2018.

**Table 3.** Grouping of forest carbon sink efficiency in the major regions of China.

| Region | High-Efficiency Group | Medium-Efficiency Group | Low-Efficiency Group |
| --- | --- | --- | --- |
| East | Tianjin, Shanghai, Zhejiang, Fujian | Jiangsu | Beijing, Hebei, Shandong, Guangdong, Hainan |
| Middle | | Henan | Jiangxi, Anhui, Shanxi, Hubei, Hunan |
| West | Yunnan, Chongqing | Guizhou | Guangxi, Shaanxi, Gansu, Ningxia, Xinjiang, Qinghai, Sichuan, Inner Mongolia |
| Northeast | | | Liaoning, Jilin, Heilongjiang |

## 5. Analysis of Factors Influencing the Efficiency of Forest Carbon Sinks in Each Region

### *5.1. Variable Selection*

Based on the above results, it is clear that the efficiency of forest carbon sinks in China is not high and that there are regional differences; hence, what are the main factors that lead to this? For further analysis, this paper explores the factors influencing the differences in the efficiency of forest carbon sinks with the framework system of the PSR model (Pressure–State–Response model) (Table 4). The model constructs an indicator system from pressure, state, and response, integrating natural and human factors, and the specific variables are selected as follows:

**Table 4.** Regression equation indicator system of factors influencing the efficiency of forest carbon sink.

| Variable Type | | Indicator Composition | Indicator Description | Indicator Code (Unit) |
| --- | --- | --- | --- | --- |
| Explained variables | | Integrated efficiency value | DEA measurement of integrated efficiency values | TE |
| Explanatory variables | Pressure subsystem (P) | Economic development level | Total real GDP/total population (expressed in constant 2005 prices) | X1 (Yuan/person) |
| | | Level of urbanization | Proportion of urban population to total population in a given region | X2 |
| | | Forestry industry development level | Forestry primary industry total output value of forest-related industries | X3 |
| | State Subsystem (S) | Forest natural disasters Degree of disaster | Incidence of forest disasters | X4 |
| | | Precipitation | | X5 |
| | | Temperatures | | X6 |
| | Response Subsystem (R) | Forestry science and technology level | Ratio of middle and senior technical staff in a provincial district forestry station to the number of permanent employees in a provincial district forestry station | X7 |
| | | The rate of forest disaster prevention and control | Forest disaster prevention and management ratio | X8 |
| | | Investment in scientific research | R&D investment intensity | X9 |
| | | The proportion of financial support for forestry | Financial expenditure on agriculture, forestry, and water affairs/total local financial expenditure | X10 |

P is the pressure subsystem, characterizing the pressure of human social activities on the forest system. The level of economic development, the level of urbanization, and the level of forestry industry development are selected to represent. The level of economic development directly determines the input capacity of forestry construction in the region. In theoretical analysis, an increase in the level of economic development leads to the optimization of external factors such as forestry technology, thus increasing the efficiency of forest carbon sinks. Additionally, urbanization was first considered as the process of transferring rural populations to urban populations, and then it was pointed out that urbanization is not only the urbanization of populations but also the urbanization of lifestyle, economic activities, and geographical factors [30]. The mechanism of the impact of urbanization on forest carbon sinks is manifested in two aspects: first, as the rural population decreases, people reduce their dependence on forests and reduce deforestation; second, as their lifestyles change, people's demand for ecologically valuable products subsequently increases and they pay more attention to forest resource conservation. Therefore, it is presumed that accelerating urbanization can help to improve the efficiency of forest carbon sinks. In the long run, the level of forestry development and the efficiency of forest carbon sinks have a mutually reinforcing effect. The primary sector of forestry reflects the cultivation of forests, and this paper argues that the higher the proportion of the primary sector of forestry, the higher the efficiency of forest carbon sinks.

S is the state subsystem, characterizing the environmental conditions and environmental changes presented by the forest system in a specific time period. The amount of precipitation, temperature, and degree of forest natural disaster damage are selected to represent this subsystem. Precipitation and temperature are important factors that affect forest carbon sequestration. Forest carbon sequestration increases with increasing precipitation and decreases with increasing temperature [31]. It can be seen that precipitation has a positive effect on forest carbon sink efficiency and temperature has a negative effect on forest carbon sink efficiency. Forest natural disasters are disasters caused by the destruction of forest ecosystems due to human activities. Forest natural disasters in China mainly include pests and diseases as well as activities, and the frequent occurrence of these disasters leads to the instability of forestry ecosystems, which reduces forest carbon sinks, so it can be presumed that this variable has a negative impact on forest carbon sink efficiency.

R is the response subsystem, which represents actions that humans or society will take to mitigate or prevent the negative impact of human production activities on the environment. The level of forestry science and technology, the forest disaster prevention rate, the investment in scientific research, and the proportion of financial support to forestry are selected to represent this subsystem. The level of forestry science and technology is an important factor that affects the efficiency of forest carbon sinks. Areas with high efficiency of forest carbon sinks are rich in science and technology resources, which are more likely to attract talents and promote forestry technology promotion and innovation. In contrast, areas with low efficiency of forest carbon sinks are relatively backward in forestry production methods; it is difficult to match a large number of forestry science and technology talents with the development of the forestry industry, which may slow down or even hinder the improvement of forest carbon sink efficiency. It is speculated that there is a difference in the influence of forestry science and technology levels on the efficiency of forest carbon sinks in different regions. The rate of forest disaster prevention and control reflects the human management of forest disasters, and this is a positive indicator. Scientific research investment represents the level of scientific and technological progress in a region, and, generally speaking, the higher the level of scientific and technological investment, the more obvious the effect of forest carbon sinks. Additionally, the proportion of financial support to forestry indicates the strength of government forestry support, which is crucial for weak forestry areas. It will effectively improve the level and efficiency of forest carbon sinks.

*5.2. Research Methodology*

The estimation methods for panel data are aggregated least squares, fixed effects models, and random effects models. For this purpose, the F-test, the Breusch–Pagan LM test, and the Huasman test were performed on the models. Since this paper uses short panel data with short time and more than one region and the differences between regions are large, the Modified Wald test for between-group heteroskedasticity and within-group autocorrelation and the Pesaran test for between-group contemporaneous correlation were conducted. The results show the existence of between-group heteroskedasticity and a within-group contemporaneous correlation. Therefore, the feasible generalized least squares (FGLS) method was chosen in this paper, and GDP per capita, precipitation, and temperature were logarithmically processed and introduced into the model in order to maintain the smoothness of the data. The model is set as follows:

$$\begin{aligned} TE_{i,t} = C + \beta_1 \ln X1_{i,t} + \beta_2 X2_{i,t} + \beta_3 X3_{i,t} + \beta_4 X4_{i,t} + \beta_5 \ln X5_{i,t} + \\ \beta_6 \ln X6_{i,t} + \beta_7 X7_{i,t} + \beta_8 X8_{i,t} + \beta_9 X9_{i,t} + \mu_{i,t} \end{aligned} \quad (4)$$

where $TE_{i,t}$ is the explanatory variable, indicating the forest sink efficiency of province (city) i in period t; $\ln X1_{i,t}$, $X2_{i,t}$, $X3_{i,t}$, $X4_{i,t}$, $\ln X5_{i,t}$, $\ln X6_{i,t}$, $X7_{i,t}$, $X8_{i,t}$, $X9_{i,t}$ are explanatory variables corresponding to the value of each influencing province (city) i in year t; $\mu_{i,t}$ is the random error term.

*5.3. Results and Analysis*

Table 5 gives the estimates of the explanatory variables obtained from the regression of Equation (4) for each of the 30 provinces (municipalities) in the country and for each of the four regions.

In the pressure subsystem (P), some regions corroborate that the increase in GDP per capita is beneficial to promoting forest carbon sink efficiency. The results show that GDP per capita does not have a significant and small coefficient on forest carbon sink efficiency in the nationwide regression; however, the regressions for the four regions show completely different conclusions: The change of GDP per capita in the eastern and northeastern regions had a positive impact on the efficiency of forest carbon sinks, indicating that the forestry development level in these two regions is at a high level, which has a positive radiation and driving effect on forest carbon sinks and is conducive to improving the efficiency of forest carbon sinks; the economic development level in the central and western regions shows a significant negative correlation to forest carbon sinks, revealing that the development level of the forestry industry in this region is not high and that forestry production is still dominated by crude management, which is facing a severe test in forest carbon sinks. This is consistent with the findings of Zhang H. et al. [32] regarding the large disparity in the impact of GDP per capita on carbon sinks across Chinese counties. In addition, for every 1% increase in urbanization level, the efficiency of forest carbon sinks will increase by about 0.12%. Du Zhili et al. [17] concluded that when the proportion of urbanized populations is high, the increase in urban populations will reduce deforestation and thus increase forest carbon stock density. In the regressions of the four regions, the regression results of the western region are opposite to those of the eastern and central regions, where the urbanization level has a negative impact on forest carbon sinks. This may be attributed to the fact that human capital accumulation and technological progress in the eastern and central regions are conducive to the improvement of forest carbon sink efficiency, while the accelerated urbanization in the western region is not conducive to the agglomeration effect of the forestry industry. The level of forestry industry development has a significant negative effect on forest sink efficiency, but it is worth noting that the level of forestry industry development in the central and northeastern regions has a significant positive effect on forest carbon sink efficiency, especially since the correlation coefficient is larger in the northeastern region, which may be related to the forestry industry structure; the northeastern region has a good industrial structure [33], and this advantage promotes the forest carbon sink efficiency in this region. In contrast, although the eastern region has a good industrial structure, its main advantage is in the tertiary industry; the efficiency improvement brought by the restructuring of the primary forestry industry is offset by the growth of the tertiary forestry industry; hence, in the eastern region, the increase in the total forest-related output value of the primary industry has an inverse effect on the efficiency of forest carbon sinks.

**Table 5.** FGLS regression results.

| | **Explanation Variables** | **China** | **Eastern Region** | **Central Region** | **Western Region** | **Northeast Region** |
|---|---|---|---|---|---|---|
| Pressure subsystem (P) | lnX1 | 0.000591<br>(0.15) | 0.0359 ***<br>(8.87) | −0.0485 ***<br>(−3014.70) | −0.0000443 ***<br>(−3.95) | 0.0695 ***<br>(7.47) |
| | X2 | 0.121 ***<br>(4.68) | 0.377 ***<br>(12.62) | 0.0807 ***<br>(753.61) | −0.169 ***<br>(724.96) | −0.224<br>(−1.04) |
| | X3 | −0.0301 ***<br>(−4.83) | −0.00650<br>(−1.96) | 0.0742 ***<br>(809.22) | −0.0161 ***<br>(−748.88) | 1.110 ***<br>(11.82) |
| State Subsystem (S) | X4 | 0.0434 *<br>(2.29) | 0.0459 ***<br>(3.35) | 0.0458 ***<br>(274.66) | 0.0450 ***<br>(664.36) | −1.334 ***<br>(−3.98) |
| | lnX5 | 0.00421 ***<br>(3.58) | 0.000747<br>(0.75) | 0.00197 ***<br>(278.28) | 0.00865 ***<br>(548.14) | −0.0730 ***<br>(−9.55) |
| | lnX6 | −0.0340 ***<br>(−4.73) | 0.0976 ***<br>(9.79) | 0.0593 ***<br>(1110.51) | 0.0197 ***<br>(712.63) | −0.117 ***<br>(−6.54) |
| Response Subsystem (R) | X7 | 0.0150<br>(1.64) | 0.0218 **<br>(2.60) | 0.0921 ***<br>(1469.03) | 0.00197 ***<br>(18.79) | −0.121<br>(−1.13) |
| | X8 | 0.00128<br>(0.57) | −0.0113 ***<br>(−5.06) | −0.00287 ***<br>(−316.34) | 0.00333 ***<br>(110.88) | 0.0719 ***<br>(6.06) |
| | X9 | −0.392<br>(−1.77) | −1.266 ***<br>(−5.03) | −0.748 ***<br>(−548.25) | −0.0643 ***<br>(−15.24) | −10.35 ***<br>(−7.29) |
| | X10 | 0.000580 **<br>(2.80) | 0.000387 **<br>(3.00) | −0.00394 ***<br>(−683.20) | −0.000109 ***<br>(−245.74) | 0.00810 ***<br>(14.64) |
| | _cons | 0.501 ***<br>(11.10) | −0.160 ***<br>(−3.37) | 0.592 ***<br>(2837.13) | 0.212 ***<br>(2099.79) | 0.279 *<br>(2.02) |
| | N | 420 | 140 | 98 | 140 | 42 |

Note: Regression coefficients are accompanied by z-values in parentheses below the regression coefficients, and superscripts ***, ** and * denote 1%, 5% and 10% statistical significance respectively.

In the state subsystem (S), more interesting phenomena can be found in the regression coefficients of the degree of forest natural disaster exposure of the different regions. Nationally, the regression coefficients of forest natural disaster extent and forest carbon sink efficiency are significantly and positively correlated, breaking the preconceptions. Kerong Zhang et al. [34] pointed out that while natural disasters often destroy forests, they also stimulate governments to take temporary remedial measures, which, in turn, increase forest resources. Looking at different samples, the regression coefficients of forest natural disaster extent in the east, central and western regions are consistent with the overall result and are significantly positively correlated, while the northeast region shows a significant negative correlation, indicating that the extent of forest natural disasters is not necessarily harmful to forest ecosystems. The effects of precipitation and temperature on forest carbon sink efficiency verified the previous analysis that precipitation can promote forest carbon sink efficiency, while the opposite is true for temperature. However, the precipitation coefficient is significantly negative in northeast China, which may be related to the limitation of forest growth when precipitation exceeds a certain range. In recent years, the frequent floods in northeast China have seriously hindered the improvement of forest carbon sink efficiency levels in the region. In addition, the increase in temperature in the northeastern region leads to the loss of forest carbon sink efficiency, while the increase in temperature in the eastern, central, and western regions promotes forest carbon sink efficiency, which this paper suggests may be related to the different sensitivities of different vegetation types to the temperature between regions.

In the response subsystem R, each influencing factor has less significant or even no significant effects on forest carbon sink efficiency at the national scale. In contrast, the regression results of the regional samples show that each factor in the response subsystem has an effect on the efficiency of forest carbon sinks in different regions. Table 5 shows that the level of forestry technology has a significant positive impact on the efficiency of forest carbon sinks in the east, central and western regions, while the level of forestry technology in the northeast region failed to significantly improve the efficiency of forest sinks. The reason may be that the eastern, central, and western regions with relatively high forest carbon sink efficiency have high levels of forestry human capital and strong abilities in forestry technology popularization and application, which promote the improvement of forest carbon sequestration efficiency. In addition, investment in scientific research has a significant negative effect on the efficiency of forest carbon sinks in different regions. This may be due to the weak innovation capacity of China's industry, academia, and research institutes, which cannot drive forestry science and technology innovation; a large number of scientific research results have not been transformed into actual productivity of forest carbon sinks. This result is consistent with the conclusion of Wu Yuanzheng et al. [35], who stated that the intensity of investment in research funding failed to increase forestry ecosafety efficiency. In addition, the proportion of financial support to forestry is significantly positively correlated in the national regression, indicating that, on the whole, the proportion of local financial expenditure on the forestry industry can enhance the efficiency of forest carbon sinks. This indicates that the more local attention to the forestry industry, the higher the efficiency of forest carbon sinks. However, the increase in the proportion of fiscal forest support in the central and western regions failed to effectively improve the efficiency of forest carbon sequestration; this may be related to the fact that the forestry funds in these regions were not directly invested in forestry production [36].

### *5.4. Robustness Tests*

In this paper, robustness tests were conducted by replacing the explanatory variables in the following manner. From the previous section, it is clear that forest carbon sink efficiency under the VRS condition and forest carbon sink efficiency under the GRS condition have the same trend; thus, forest carbon sink efficiency under the VRS condition was chosen to replace the forest carbon sink efficiency under the GRS condition as the explanatory variable for robustness testing. The final results are shown in Table 6. This result shows that the direction and significance of the coefficients of variables X3, X4, lnX5, lnX6, and X10 remained consistent with the previous paper, confirming that the above findings are generally reliable and robust.

**Table 6.** Robustness tests.

| Explanatory Variables | The Efficiency of Forest Carbon Sink Selected in This Paper | Alternative Forest Carbon Sink Efficiency |
|---|---|---|
| lnX1 | 0.000591<br>(0.15) | −0.00704 **<br>(−2.72) |
| X2 | 0.121 ***<br>(4.68) | −0.0325<br>(−1.43) |
| X3 | −0.0301 ***<br>(−4.83) | −0.0472 ***<br>(−8.07) |
| X4 | 0.0434 *<br>(2.29) | 0.0162 *<br>(2.04) |
| lnX5 | 0.00421 ***<br>(3.58) | 0.00591 ***<br>(3.61) |
| lnX6 | −0.0340 ***<br>(−4.73) | −0.0223 ***<br>(−4.60) |
| X7 | 0.0150<br>(1.64) | −0.0203 *<br>(−2.52) |
| X8 | 0.00128<br>(0.57) | −0.00213<br>(−1.80) |
| X9 | −0.392<br>(−1.77) | 0.00105 ***<br>(5.84) |
| X10 | 0.000580 **<br>(2.80) | 0.00105 ***<br>(5.84) |
| _cons | 0.501 ***<br>(11.10) | 0.639 ***<br>(26.46) |
| N | 420 | 420 |

Note: Regression coefficients are accompanied by z-values in parentheses below the regression coefficients, and superscripts ***, ** and * denote 1%, 5% and 10% statistical significance respectively.

## 6. Conclusions and Discussion

In this paper, a forest carbon sink input–output indicator was constructed using the DEA-SBM model, and the forest carbon sink efficiencies of each province (city) and four regions in China were calculated using data from 2005 to 2018. On this basis, the influencing factors that may affect the efficiency of forest carbon sinks were constructed with the help of the PSR model for econometric testing, and several main conclusions were drawn.

First, the traditional DEA model cannot accurately measure the efficiency of forest carbon sinks. In this paper, we measured it using a non-radial and non-angular SBM model and compared the values under different scale payoffs. The forest carbon sink efficiency under GRS conditions was chosen as a relatively accurate value.

Second, the efficiency of China's forest carbon sink has more room for improvement. The average value of China's forest carbon sink efficiency during the sample period was only 0.29, which is 71% less than the frontier value; there is great potential for improving the forest carbon sink efficiency. In addition, except for Zhejiang, the efficiency of forest carbon sinks remains at the level of 1, and there is room for improvement in all other provinces. This is due to the fact that Zhejiang Province always takes the forestry industry as an important part of developing forestry construction, thus promoting the development of highly efficient forest carbon sinks. Other provinces can learn from Zhejiang's experience in increasing forest carbon sinks.

Third, the spatial distribution pattern of forest carbon sink efficiency is "eastern region>central and western region > northeastern region", with significant spatial disparity. The formation of this spatial difference pattern is closely related to economic development and natural resource endowment. The relatively superior economic base of the eastern region provides financial support for the high-quality development of forest carbon sinks, and the advanced technology level provides technical support for forest protection; hence, the overall efficiency shows a leading level. The central and western regions are in the middle level of forest sink efficiency because the western region is rich in forest resources, although the ecological environment is more fragile. The central region has neither the economic and technological advantages of the eastern region nor the better forest resource endowment of the western region; hence, its forest sink efficiency is not high.

Fourth, different influencing factors have different relationships with the efficiency of forest carbon sinks. The level of urbanization, the degree of natural damage to forests, precipitation, and the proportion of financial support to forests show a positive relationship with forest sink efficiency, implying that forest carbon sink efficiency will increase when the urbanization rate increases, the degree of natural damage to forests and precipitation increases moderately, and the proportion of financial support to forests increases; At the same time, there is a negative relationship between temperature and forest carbon sink efficiency, indicating that an increase in temperature is not conducive to forest carbon sink efficiency.

Fifth, there is regional heterogeneity in the efficiency of forest carbon sinks from different influencing factors. Broadly speaking, the eastern, central, western, and northeastern regions are influenced by social conditions, natural factors, and systems of human activities. Except for the level of investment in scientific research, which has the same direction of effect on forest carbon sink efficiency in different regions, the other factors do not have the same direction of effect on forest carbon sink efficiency. This indicates that regional characteristics affect forest carbon sink efficiency, i.e., forest carbon sink efficiency is related to regional developments and forestry development levels. High-quality development of forest carbon sinks should be made from both a global perspective and the development characteristics of each region, taking into account each region's advantages and formulating strategies according to local conditions. The eastern region should continue to play on its own advantages and take the lead. The central region should strengthen cooperation with the western region, learn from the advanced technology of the eastern region, and give full play to the role of a bridge between the "top" and "bottom" regions. The western region should strengthen ecological restoration to improve the quality and stability of forest systems on the basis of maintaining the advantages of forest resources.

Based on the above findings, the following policy insights can be derived. The government should: formulate forest carbon sink strategies according to the dominant factors affecting the efficiency of forest carbon sinks in each region; adjust and optimize the forestry industry structure at the right time and change crude forestry operation modes; minimize intervention in the forest ecosystem on the basis of respecting the objective laws of forest growth; increase the financial support for forestry in regions with low efficiencies of forest carbon sinks; improve the supervision mechanism of special forestry funds; improve the level of forestry human capital and attach importance to the cultivation of forest resources; strengthen forestry science and technology innovation and accelerate the transformation of scientific and technological achievements.

It should be pointed out that there are deficiencies in this study: first, the constructed input–output index of forest carbon sink efficiency is not comprehensive enough. The input index only considers land, capital, and labor force, and the calculation result is relatively rough. The index system needs to be further improved. Secondly, it is one-sided to select 10 influencing factors from the PSR model. In addition, only the degree and direction of the influencing factors of forest carbon sequestration efficiency were explored, and the domestic mechanism of these factors was not very in-depth. These factors will be the direction of continuous optimization research in the future.

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