Evaluation of Forestry Ecological Efficiency: A Spatiotemporal Empirical Study Based on China’s Provinces

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Abstract: Forests play a very important role in carbon dioxide emissions and climate change, and the development of China’s forestry is of great significance to our citizens. However, it is an arduous task for us to improve forestry output at a high and good level while taking environmental factors into account. In this paper, the non-expected super-efficiency SBM (slacks-based measure) model was used to measure the forestry ecological efficiency (FEE) of 31 provinces in China from 2004 to 2018, and the spatial and temporal evolution of FEE in different regions of China was analysed by using spatial econometric method. Tobit regression and random forest algorithm were selected to analyze the influence on FEE. The results showed that, firstly, the average annual increase of the national total factor productivity change of China’s forestry was 1.2%, and that the average annual increase of the national total factor productivity change in the eastern region was lower than that in the central and western regions. Secondly, the distribution of China’s FEE of the northeast and the south was higher, and FEE of China’s middle regions was relatively lower in 2004, but then the FEE in Northeast China has decreased, and the FEE has increased gradually from north to south in 2018. The agglomeration of high-tech industries in most regions of China had obvious positive spatial correlation characteristics in 2018. Thirdly, there was a negative correlation between forestry fixed assets investment and FEE, environmental regulation was an important factor affecting the ecological efficiency of forestry in China, and the level of economic development and industrial structure also had a certain impact on FEE.

Keywords: forestry ecological efficiency; spatial distribution; super-efficiency SBM; spatiotemporal difference; influencing factors

1. Introduction

Forestry is not only an important foundation of China’s national economy, but also which is an important part of public welfare undertakings. The ownership of the whole people and collective is the main form in terms of ownership of forests in china, ownership by the whole people refers to state-owned forestry accounting for more than 70% of the total forest area in China, including state-owned forestry enterprises and state-owned forest farms. China’s forestry industrial structure and output value have been constantly optimized and improved in recent years. Specifically, China’s forest coverage rate has increased from 18.2% in 2004 to 23% in 2018, and the total forestry output value has increased from 93.65 billion yuan in 2000 to 575.57 billion yuan in 2019. The growth rate of forestry was more than five times, and it has a continuous upward trend. Although the output value of forestry has increased rapidly, the quality and cost of growth were easily ignored by this simple quantity of growth, and people have had to face the ecological imbalance, energy crisis, environmental pollution, and other negative problems. Since the 19th National Congress of the Communist Party of China, the State Council and the people’s government have focused on forestry development sustainably.

FEE is to measure the quantity and quality of forestry products under the premise of minimizing environmental pollution and resource consumption [1]. At present, more
and more scholars have turned to forestry efficiency. Some scholars used data envelop analysis (DEA) model to calculate the efficiency value generally. Zhang et al. [2] used two-stage DEA to analyze the data of 30 provinces in China and found that the ecological efficiency gradually decreased from the east to the west, and the eastern coastal areas had high economic efficiency but low environmental efficiency. Wang [3] used the model to calculate the efficiency of China’s green economy and found that the green efficiency value of developed regions, such as Shanghai, Beijing, and Tianjin, was at a high level, and the relationship between environmental regulation and green economic efficiency was inverted “U”. Lin and Ge [4] adopted the three-stage DEA model to adjust regional forest carbon by introducing economic and environmental factors. Chen et al. [5] studied the effective number of DEA efficiency provinces increased from 2003 to 2017, however, which still was lower than half of all provinces. The efficiency value of most provinces increased evidently in the southern forest area while the efficiency value of the northern forest area decreased. In addition, some scholars used spatial econometric method to analyze the efficiency problem. Chen et al. [6] analyzed the impact of technological innovation on urban ecological efficiency by using the spatial Durbin model. They found that 273 prefecture level cities in China showed strong spatial heterogeneity, and higher innovation ability can greatly improve urban ecological efficiency. Ren et al. [7] adopted the s-ebm mixed distance model of bad output to find that the positive spatial autocorrelation of ecological efficiency in China has gradually increased, and gradually decreased from relatively developed areas to developing areas. Zheng et al. [8] concluded the externalities brought by industrial agglomeration would promote the ecological efficiency of forestry industry in econometric model regression.

There were also some scholars evaluated the forestry industry. Xiong [9] used the stochastic frontier analysis method to find that the forestry production efficiency of the six northwest provinces was in a state of decline from 2005 to 2015, and the spatial differences of the forestry production efficiency of the provinces were gradually reduced, Moreover, the collective forest right reform had a negative impact to forest right reform. Yang et al. [10] calculated the total factor productivity of state-owned key forestry enterprises in northeast, southwest and northwest regions by using Malmquist index. They found that the average growth rate of total factor productivity in Northwest China was higher than that in northeast and southwest of China. China’s western development has made more and more contributions to the economic development of the western region.

Foreign scholars have also made good achievements in forestry research. One of the most frequently used models to measure forestry efficiency was DEA through the study of foreign literature. Viitala and Hanninen [11] studied the efficiency of regional forestry committees funded by 19 countries. They found that there were great differences in the efficiency of the Forestry Commission, and the investment saving potential was about 20%. Sporocic et al. [12] evaluated the efficiency of the basic organizational unit of forest office in Croatia by using DEA, they studied that DEA was a powerful multi criteria decision-making tool, and it played a significant part in forest management assessment. Similarly, Sowlati [13] proved that DEA had a good applicability in forestry efficiency measurement in his study. Toma et al. [14] adopted a nonparametric method to evaluate the efficiency performance of Italian forestry companies, which was stratified according to the environmental risk measurement. They found that the input and output oriented efficiency performance is higher for forestry companies belonging to medium and high environmental risk categories in Italy. However, forestry companies facing low environmental risks have shown greater progress in improving efficiency.

In this context, this paper attempts to measure the total factor productivity of forestry from 2004 to 2018 to study the dynamic changes of forestry production. The super-efficiency SBM model is used to measure the ecological efficiency of forestry in three periods in recent years to reveal the distribution characteristics and evolution law of FEE in different periods in China. In addition, the internal relationship between various factors and FEE was
analyzed in the study. These results provide a reference framework for macro policy making to coordinate the development of forestry.

2. Materials and Methods

2.1. Indicator Description and Data Sources

The input elements of FEE should at least include land, labor and capital [15], this paper calculates the ecological efficiency of forestry from the perspective of green production. The aim is to achieve the maximum forestry output at the cost of less resource reduction and environmental pollution. Considering the characteristics of forestry industry and the availability of data, the area of forestry land is used as the index of land production factors, the number of employees in the forestry system at the end of each year is taken as the labor factor, and capital element is the annual fixed asset investment. These elements are the three basic input elements of forestry industry investment. In addition, energy investment is another input element and it’s index is obtained by calculating the proportion of forestry output value to industrial output value and industrial energy investment. These indicators can be seen from Table 1.

Table 1. Input and output indicators for measuring forestry ecological efficiency.

| The Index Type       | Level Indicators              | The Secondary Indicators                      | Unit            |
|----------------------|-------------------------------|-----------------------------------------------|-----------------|
| Input                | Land                          | The forest area                               | Ten thousand km²|
|                      | Labor                         | The number of employees in the forestry system at the end of each year | People          |
|                      | Capital                       | Fixed asset investment                         | Ten thousand Yuan|
|                      | Energy                        | Forest energy investment                       | Hundred million Yuan|
| Desirable output     | Economic benefit              | Total output value of forestry                | Hundred million Yuan|
|                      | Direct benefit                | Timber felling                                | Ten thousand cubic meters|
| Undesirable output   | Wastewater pollution          | Forestry wastewater discharge                  | Ten thousand cubic meters|
|                      | Air pollution                 | Waste gas emission                            | Ten thousand ton |

The expected output includes total output value of forestry and timber felling, and the non-expected output mainly include forestry wastewater discharge and waste gas emission [1]. The data are calculated from the ratio of forestry output value to total output value and the discharge amount of gas and wastewater.

Based on the existing research results [16–20], this paper enriched and perfected the influencing factors of FEE. The specific indicators were as follows: EDL was the level of economic development by per capita GDP. IEC was the investment in forestry ecological construction, which was specifically expressed by the investment in forestry fixed assets [21]. ERL was used to represent environmental regulation level, the investment in wastewater treatment and the investment in waste gas treatment were selected, and then entropy method was used to calculate the two weights, as a result, the environmental regulation level of each region can be calculated. The industrial structure was represented by ISL, and it was expressed by calculating the proportion of regional output value of forestry to total forest output value. FRE was used to express resource endowment, and forest resource coverage was used to reflect it. The dependent variable was forestry ecological efficiency, which was expressed by FEE.

The all indicators are from China Statistical Yearbook, China Forestry Statistical Yearbook, China Energy Statistical Yearbook and China Environment Statistical Yearbook, the missing data are estimated by simple linear extrapolation method.

2.2. Malmquist Index

Malmquist productivity index model was first proposed by Malmquist in 1953 [22], and then Fare et al. [23] redefined it as a multi-stage dynamic production efficiency evaluation method guided by production efficiency. Malmquist is a total factor productivity index based on panel data, it evaluates the efficiency of input and output on the basis of distance
function. This model gives the distance function from two different angles of input and output, input vector can reduce the level of production frontier and evaluate the efficiency of production technology [24]. The change rate of technical efficiency can be divided into scale efficiency change rate and pure technical efficiency change rate, the change index of scale efficiency represents the change of forestry production level, and the pure technical efficiency change index only represents the change of allocation and utilization level of forestry production factor resources [25]. If the change rate of technical efficiency is more than 1, it means that the forestry production efficiency has improved in the period from \( t \) to \( t+1 \). If the change rate of technical efficiency is less than 1, it means that the forestry production efficiency has decreased in this period; if the change rate of technical efficiency is equal to 1, it means that the forestry production efficiency has not changed in this period. When the returns to scale remain unchanged, the Malmquist productivity index formula in the period from \( t \) to \( t+1 \) can be written as follows as in Equation (1).

\[
M_{t+1} = \left[ \frac{D^t(x_t^{t+1}, y_t^{t+1})}{D^t(x_t^t, y_t^t)} \times \frac{D^{t+1}(x_t^{t+1}, y_t^{t+1})}{D^{t+1}(x_t^{t}, y_t^{t})} \right]^{\frac{1}{2}}
\]  

(1)

In Equation (1), \( D^t(x_t^t, y_t^t) \) represents the technical efficiency level of the current period; \( D^t(x_t^{t+1}, y_t^{t+1}) \) represents the technical efficiency level of phase \( t+1 \) with the technology of phase \( t \); \( D^{t+1}(x_t^t, y_t^t) \) represents the technical efficiency level of phase \( t \) with the technology of phase \( t+1 \); \( D^{t+1}(x_t^{t+1}, y_t^{t+1}) \) represents the technical efficiency level of phase \( t+1 \) with the technology of phase \( t+1 \).

### 2.3. SBM Model

Slacks-based measure (SBM) model is one of the DEA models which was first proposed by Tone [26]. The DEA methods are mainly applied to traditional models, such as constant return to scale (CCR) model and variable return to scale (BBC) models [27], and the output of these models is mostly based on the expected output without considering the problem of unexpected output. The SBM model can take the unexpected output into account, and it has two measurement methods including radial and non-radial [28]. SBM model not only has the characteristics of the traditional CCR model, but also has higher accuracy in the case of multiple inputs. Because the model takes both slack input and slack output into account, so it is more effective to evaluate the actual efficiency level [29].

Decision making unit (DMU) is an operational entity that can transform certain input into corresponding output [30]. Some DMU may be calculated relatively effective in SBM model, that means the efficiency value of these DMU is 1. Therefore, it is impossible to compare the production efficiency of these effective DMU. Therefore, this paper combines super efficiency with SBM model, that is super efficiency SBM model [31]. The efficiency value of the effective DMU can be calculated more than 1 in this model, and the gap between the efficiency values measured by this model is larger, so it is better to compare the efficiency values of each DMU [32]. Therefore, this paper uses the super efficiency SBM model to calculate and analyze the FEE of 31 provinces in China.

### 2.4. Moran’s I Index

This paper analyzes the FEE of 31 provinces and cities in China from 2004 to 2018 by using spatial econometrics, the spatial autocorrelation of FEE is studied to find out the specific distribution law of FEE in China. Generally speaking, Moran’s I index is used to judge the existence of spatial correlation. Moran’s I can be divided into global Moran’s I and local Moran’s I, global Moran’s I is used to test global spatial correlation, while local Moran’s I is used to measure local spatial correlation [33]. The expression for Moran’s I is as follows:
In Equation (2), $y_i$ and $y_j$ represent the observed values of $i$ and $j$ areas respectively, $N$ is the number of spatial units, which is the mean value of FEE in each region, and $W_{ij}$ is the spatial weight matrix. If the province $i$ and $j$ is adjacent, then $W_{ij} = 1$; if not, then $W_{ij} = 0$. The range of Moran’s I index is between $[-1, +1]$. If Moran’s I value is significantly greater than 0, it means that there is a spatial positive correlation; if Moran’s I value is significantly less than 0, then there is a negative correlation. If Moran’s I value is equal to 0, it is spatial uncorrelated [34].

Local spatial autocorrelation is used to determine whether a certain attribute value of each space has spatial correlation locally. The local Moran’s I index is presented below in Equation (3):

$$
Moran's\ I_i = \frac{N \sum_{i=1}^{N} \sum_{j=1}^{N} W_{ij} (y_i - \overline{y})(y_j - \overline{y})}{(\sum_{i=1}^{N} \sum_{j=1}^{N} W_{ij}) \sum_{i=1}^{N} (y_i - \overline{y})^2}, \quad (i \neq j)
$$

In Equation (3), if Moran’s I is positive, it means that there is similar spatial agglomeration around the regional unit; if Moran’s I is negative, it means that there is spatial agglomeration with non-similar values around the regional unit. The higher the Moran’s I index is, the higher the degree of closeness is [35]. The biggest drawback of global Moran’s I is that it can’t analyze the spatial agglomeration characteristics between local areas, however, local Moran’s I just makes up for this vacancy. It can reflect greatly whether there is spatial dependence between a certain area and its surrounding areas [36]. Therefore, this paper uses the local Moran’s I index to analyze the local spatial correlation of China’s FEE. The results of local Moran’s I can be divided the local spatial characteristics into four types: the first quadrant is the high-high (H-H) aggregation area, which means that the level of FEE in this region and its adjacent areas is high, and the spatial correlation is high-level area. The second quadrant is the low-high (L-H) aggregation area, which means that the ecological efficiency of forestry in this region is low, but the adjacent areas are high, so the spatial correlation is in the development stage. The third quadrant is the low-low (L-L) aggregation area, which means that the ecological efficiency of forestry in this region and its adjacent areas is low. Therefore, the spatial correlation is low efficiency area. The fourth quadrant is the high-low (H-L) cluster area, which means that the ecological efficiency of forestry in this region is higher than that of adjacent areas, and the spatial performance is spillover effect [37]. Generally, H-H type and L-L type mean that there is positive spatial correlation between regions, while L-H type and H-L type indicate that there is spatial negative correlation between regions.

2.5. Tobit Regression

Tobit model is a model in which dependent variables satisfy certain constraints. Tobit model includes two kinds of models: discrete dependent variable model and restricted dependent variable model [38]. The restricted dependent variable is the case that the dependent variable is restricted in practice [39]. In this case, the sample data obtained from a subset of the population may not fully reflect the population. The basic definition model of Tobit model is Equation (5).

$$
\begin{align*}
\{ & FEE, if \ FEE > 0 \\
& 0, if \ FEE \leq 0
\end{align*}
$$
The value of FEE in this paper is such a dependent variable, and the review regression model of the restricted dependent variable model is used for regression analysis. The econometric model is shown in Equation (6).

\[
FEE = \beta_0 + \beta_1 \text{EDL} + \beta_2 \text{IEC} + \beta_3 \text{ERL} + \beta_4 \text{ISL} + \beta_5 \text{FRE} + \epsilon
\]  

(6)

In Equation (6), \(\beta_0\) is the intercept term, \(\beta_1, \beta_2, \beta_3, \beta_4, \beta_5\) are the independent variable coefficients of the parameter to be estimated, and \(\epsilon\) is the random interference term. EDL was the level of economic development by per capita GDP, IEC was expressed by the investment in forestry fixed assets, ERL represents environmental regulation level, ISL means the industrial structure, FRE was used to express resource endowment level. The dependent variable FEE represents forestry ecological efficiency.

2.6. Random Forest

Generally, ensemble learning is a method that combines multiple learners to improve the performance of solving a problem. In the 1980s, Breiman et al. [40] came up with a classification tree algorithm after a long time of research. The data can be classified precisely through this classification tree. Later, Breiman combined the classification trees previously into random forest [41], that is taking the decision tree as the basis, the learner uses bagging to do simple voting on the classified objects based on decision tree, so it is a classifier combined with decision tree based on learners as an algorithm in ensemble learning [42]. In order to make the effect of processing data better, the individual learner’s discrimination effect should not be too bad. Random forest is random in the selection of attributes, and then select an optimal attribute to divide these samples. The principle of random forest is as follows: k samples are extracted from the sample set D (bootstrap is put back for sampling) for training, and then the k decision trees are combined into random forests, so that these decision trees can judge the classification results of each sample separately [43]. If there are many voting results of a certain classification, it will be divided into this category first.

Random forest algorithm has many excellent characteristics in application. Generally speaking, random forest has high prediction accuracy in dealing with classification and regression problems [44]. When the data are missing or unbalanced, the random forest algorithm has good adaptability and the effect is not bad. When we increase the number of learners, the prediction error in random forest will gradually decrease and finally converge to a certain level [45]. Moreover, it can judge the importance of thousands of explanatory variables, it performs well on the data set, and when multiple randomness is introduced, it will not easily lead to over-fitting [46]. In addition, random forest is usually used to deal with classification problems, but it can also be used to deal with regression problems [47]. In general, linear regression model analysis in this study, there are explanatory variables and explained variables. In random forest regression model, each factor can be regarded as explanatory variable. In this paper, EDL, IEC, ERL, ISL, and FRE are used as the explanatory variables, and FEE is the explanatory variable.

In random forest model, the importance of variables is evaluated by IncMSE and IncNodePurity. The IncMSE index is actually the abbreviation of increase in MSE, it represents the increasement of mean square error (MSE). When variable in the sample is assigned arbitrarily, if the variable is very important, the prediction error would increase. Therefore, the greater the value of IncMSE is, the more important it is [47]. IncNodePurity index is the abbreviation of increase in node purity. It refers to the error value of leaf nodes. In dealing with regression problems, the increase of node purity is equivalent to the decrease of Gini index, and the larger the IncNodePurity value is, the more important the factor is [48], which these variables should be focused on.
3. Results

3.1. Analysis of Total Factor Productivity of China’s Forestry

In this paper, Malmquist productivity index model is used to measure the total factor productivity change (TFPC) of China’s provincial forestry production in 14 periods from 2004 to 2018. In order to better analyze the regional characteristics of TFPC in China, China is divided into three regions according to the National Bureau of Statistics. The eastern region includes 12 provinces, municipalities and autonomous regions, including Beijing, Tianjin, Hebei, Liaoning, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, Guangxi, and Hainan while the central region includes Shanxi, Inner Mongolia, Jilin, Heilongjiang, Anhui, Jiangxi, Henan, Hubei, and Hunan, and the western region includes Chongqing, Sichuan, Guizhou, Yunnan, Tibet, Shaanxi, Gansu, Ningxia, Qinghai, and Xinjiang.

According to Table 2, the average growth rate of Malmquist index of TFPC from 2004 to 2018 was 1.012, and the average growth values of ecological efficiency in eastern, central and western regions were 0.994, 1.011 and 1.038, which showed that the average TFPC in the western region was greater than that of the eastern and central regions. However, the overall trend was not stable enough, and the fluctuation was obvious. Noticeably, the TFPC of China, the east and the central regions from 2008 to 2009 reached the lowest point, which were 0.845, 0.783, and 0.834, that showed the TFPC in this year has been greatly decreased compared with the previous period, and the forestry industry has suffered a huge strike. However, the TFPC of China’s forestry showed a fluctuating growth trend from 2012 to 2018, and the values were all greater than 1, which indicated that forestry ecology was developing in a benign direction. In the western region during 2012–2013, the TFPC of west forestry reached the maximum value during 2015–2016, but then began to decline. Generally speaking, China’s forestry TFPC was in an upward trend and the fluctuation range of TFPC in the eastern and western regions was greater than that in the central region.

Table 2. Total factor productivity change (TFPC) of forestry in China from 2004 to 2018.

| Time         | All  | East | Central | West |
|--------------|------|------|---------|------|
| 2004–2005    | 0.942| 0.926| 0.927   | 0.986|
| 2005–2006    | 1.058| 1.066| 1.045   | 1.020|
| 2006–2007    | 1.042| 1.099| 1.055   | 0.925|
| 2007–2008    | 1.011| 0.962| 1.052   | 1.007|
| 2008–2009    | 0.845| 0.783| 0.834   | 0.952|
| 2009–2010    | 1.033| 1.010| 1.044   | 0.957|
| 2010–2011    | 0.941| 0.857| 0.910   | 1.117|
| 2011–2012    | 0.983| 0.980| 1.042   | 0.988|
| 2012–2013    | 1.078| 1.075| 1.090   | 1.111|
| 2013–2014    | 1.039| 1.035| 1.067   | 1.064|
| 2014–2015    | 1.026| 1.021| 0.996   | 1.054|
| 2015–2016    | 1.050| 0.997| 0.988   | 1.265|
| 2016–2017    | 1.056| 1.040| 1.046   | 1.148|
| 2017–2018    | 1.090| 1.124| 1.088   | 0.997|
| Average      | 1.012| 0.994| 1.011   | 1.038|

3.2. Analysis of China’s FEE

3.2.1. Descriptive Analysis of China’s FEE

There is the static evaluation of FEE of 31 provinces and cities in China in 2004, 2011 and 2018. Which was measured in super efficiency SBM model with DEA-SOLVER Pro 5.0 software. The FEE value and ranking of each region were shown in the Table 3 below:
### Table 3. Forestry ecological efficiency values of 31 provinces and cities in China in 2004, 2011 and 2018.

| Region          | 2004 FEE | Rank | 2011 FEE | Rank | 2018 FEE | Rank |
|-----------------|----------|------|----------|------|----------|------|
| Beijing         | 1.000    | 17   | 1.000    | 14   | 1.123    | 9    |
| Tianjin         | 5.105    | 1    | 1.649    | 3    | 1.669    | 3    |
| Hebei           | 0.112    | 26   | 0.072    | 25   | 0.103    | 23   |
| Shanxi          | 0.030    | 31   | 0.013    | 29   | 0.041    | 27   |
| InnerMongolia   | 1.427    | 6    | 0.135    | 23   | 0.048    | 26   |
| Liaoning        | 0.302    | 21   | 0.195    | 21   | 0.293    | 18   |
| Jilin           | 1.089    | 11   | 1.059    | 11   | 0.129    | 22   |
| Heilongjiang    | 1.056    | 12   | 0.235    | 19   | 0.102    | 24   |
| Shanghai        | 3.489    | 2    | 1.647    | 4    | 1.587    | 4    |
| Jiangsu         | 1.045    | 13   | 1.001    | 13   | 1.014    | 14   |
| Zhejiang        | 1.243    | 7    | 0.306    | 18   | 0.380    | 17   |
| Anhui           | 1.132    | 8    | 1.194    | 6    | 1.158    | 8    |
| Fujian          | 1.443    | 5    | 1.097    | 10   | 1.162    | 7    |
| Jiangxi         | 1.127    | 9    | 1.001    | 12   | 1.016    | 13   |
| Shandong        | 0.248    | 22   | 0.402    | 15   | 0.455    | 16   |
| Henan           | 1.018    | 16   | 0.325    | 16   | 0.265    | 19   |
| Hubei           | 0.203    | 24   | 0.311    | 17   | 0.249    | 20   |
| Hunan           | 1.039    | 14   | 1.182    | 8    | 1.027    | 11   |
| Guangdong       | 0.520    | 20   | 1.190    | 7    | 1.300    | 5    |
| Guangxi         | 1.031    | 15   | 1.540    | 5    | 1.721    | 2    |
| Hainan          | 3.458    | 4    | 4.219    | 2    | 3.651    | 1    |
| Chongqing       | 0.068    | 29   | 0.094    | 24   | 1.021    | 12   |
| Sichuan         | 0.126    | 25   | 0.155    | 22   | 0.224    | 21   |
| Guizhou         | 0.225    | 23   | 0.204    | 20   | 1.042    | 10   |
| Yunnan          | 1.102    | 10   | 1.164    | 9    | 1.209    | 6    |
| Tibet           | 3.484    | 3    | 6.555    | 1    | 0.996    | 15   |
| Shaanxi         | 0.088    | 28   | 0.050    | 27   | 0.011    | 28   |
| Gansu           | 0.031    | 30   | 0.013    | 28   | 0.007    | 29   |
| Qinghai         | 0.999    | 18   | 0.010    | 30   | 0.003    | 31   |
| Ningxia         | 0.999    | 19   | 0.001    | 31   | 0.006    | 30   |
| Xinjiang        | 0.100    | 27   | 0.055    | 26   | 0.064    | 25   |

In terms of year, the highest value of FEE in 2004 was Tianjin, and the value was 5.105. The ecological efficiency of forestry in Shanghai and Tibet came next, the values were 3.489 and 3.484. The three regions of the lowest FEE were Chongqing, Gansu and Shanxi. The values were 0.068, 0.031, and 0.030, it can be seen that the gap of FEE in different regions was very large in 2004. Tianjin was ranked first in forestry ecology in 2004 has fallen behind to the third place in 2011, and the FEE ranking of Tibet and Hainan Province has increased, their values were 6.555 and 4.219 respectively. The three regions of the lowest FEE were Shanxi, Qinghai and Ningxia. In 2018, the FEE of Hainan province has risen to the first place, and the Guangxi with the rapid increase of FEE was ranked second. The regions of the lowest FEE were Shaanxi, Gansu, Ningxia, and Qinghai.

In terms of region, Tianjin, Shanghai and Hainan were the areas with high level of FEE. The FEE of Tibet ranked third in 2004 and first in 2011, but the FEE has been far lower than other regions in 2018, and its ranking was behind 15. Hebei, Shanxi, Shaanxi, Gansu, Ningxia were at the bottom of the list in the three periods. The regions in the middle level of forest ecological efficiency in the three periods included Liaoning, Jilin, Heilongjiang, Jiangsu, Shandong, Henan, Hubei, Hunan, Sichuan, Guizhou, etc. The areas where the relative efficiency of forestry ecology has been greatly improved included Beijing, Guangdong, Chongqing, and so on.

3.2.2. Spatial Distribution Analysis of China’s FEE

In order to study the spatial characteristics of FEE in China, this paper made a spatial analysis of the above ecological efficiency values of forestry industry in 2004, 2011, and 2018 by using ArcGIS software. The spatial distribution is presented in Figures 1–3.
In Figure 1, China’s FEE of the northeast and the south was higher, and FEE of China’s middle regions was relatively lower. The FEE of Shanghai and Tianjin ranked top in the east region, the reason was that forestry area and forestry practitioners had no serious redundancy. Moreover, the total forestry output value of Shanghai reached 13.14 trillion yuan, the timber output of Tianjin was about 40 thousand cubic meters. The FEE in Tibet was the highest, because the emissions of waste gas and wastewater in Tibet were the lowest in the whole country, and there was also no redundancy of forestry practitioners. Therefore, the FEE in this region was relatively high. The high forestry efficiency of Hainan province was related to the low energy investment and the high output value of forestry. The central regions of low ecological efficiency were Hubei, Hunan, Shaanxi, and Hebei, because there was redundancy in various input elements including forestry planting area, energy input, emissions of waste gas and wastewater.

Figure 1. Distribution of forestry ecological efficiency (FEE) in China in 2004.

Figure 2. Distribution of forestry ecological efficiency (FEE) in China in 2011.
Hebei, because there was redundancy in various input elements including forestry planting, energy input, emissions of waste gas and wastewater. Moreover, the input output ratio of forestry production was 1.6 in Beijing, and the remaining input redundancy was not high. Therefore, the forestry efficiency in Beijing was relatively low. Tianjin and Hainan had low forestry efficiency due to the low input output ratio of forestry production, which was 1.3, and the low energy input per unit output of forestry. The central regions of low ecological efficiency were Hubei, Hunan, Shaanxi, and Hainan province was related to the low energy investment and the high output value of forestry. The central regions of low ecological efficiency were Hubei, Hunan, Shaanxi, and Hainan province was related to the low energy investment and the high output value of forestry. The central regions of low ecological efficiency were Hubei, Hunan, Shaanxi, and Hainan province was related to the low energy investment and the high output value of forestry. The central regions of low ecological efficiency were Hubei, Hunan, Shaanxi, and Hainan province was related to the low energy investment and the high output value of forestry. The central regions of low ecological efficiency were Hubei, Hunan, Shaanxi, and Hainan province was related to the low energy investment and the high output value of forestry. The central regions of low ecological efficiency were Hubei, Hunan, Shaanxi, and Hainan province was related to the low energy investment and the high output value of forestry. The central regions of low ecological efficiency were Hubei, Hunan, Shaanxi, and Hainan province was related to the low energy investment and the high output value of forestry. 

As can be seen from Figure 3, China’s FEE was basically higher in the south in 2018. In Figure 2, the spatial differentiation feature of FEE in China was high in southeast and south but low in northwest except Tibet. Compared with 2004, the ecological efficiency of forestry in Northwest China remained unchanged except Qinghai. The low value of FEE in Qinghai was mainly due to the increase of input from various factors and the output has not increased significantly, which led to the decrease of FEE. The ranking of FEE in Tibet, Shanghai, Tianjin, and Hainan remained unchanged, all of which ranked at the top. As can be seen from Figure 3, China’s FEE was basically higher in the south in 2018. It was worth noting that Tibet, which has been greatly reduced due to the reduction of timber production. Because of the decrease of timber output and the increase of forestry fixed assets investment in the three northeast provinces, the forestry production efficiency was relatively reduced. Shanghai, Tianjin, and Hainan still maintained a leading position in terms of FEE.

3.2.3. Characteristics of Spatial Scatter of FEE in China

Moran’s I scatter plot is an important tool to analyze local spatial correlation. The Figure 4 showed the local Moran’s I scatter diagram of China’s FEE agglomeration in 2018.

![Figure 3: Distribution of forestry ecological efficiency (FEE) in China in 2018.](image1)

![Figure 4: Moran’s I scatter chart of provincial forestry ecological efficiency (FEE) cluster in 2018.](image2)
The result showed Moran’s I index of ecological efficiency of China’s 31 provinces was 0.222, which indicated that the ecological efficiency of 31 provinces in China had a significant positive autocorrelation in spatial distribution, and most regions were distributed in the H-H cluster area and the L-L cluster area.

As depicted in Figure 5, the H-H cluster area of China’s FEE in 2018 included Hainan, Guangxi, Guangdong, Yunnan, Fujian, Guizhou, Hunan, Anhui, Jiangsu, Jiangxi, and Shanghai. These provinces were mostly located in the southern coastal areas with a more developed development level, and the areas had reasonable industrial layout and structure level, superior location advantages, and more advanced environmental protection concepts. So, the ecological efficiency has been continuously improved, which had a great radiation and diffusion effect on the surrounding areas.

The L-H cluster area included Zhejiang, Henan, Hubei, and Xinjiang. These four regions were relatively scattered with the obvious location character of being diffused, the ecological efficiency was greatly improved, and the speed of improvement was fast.

The L-L cluster area included the economically underdeveloped northwest and northeast provinces in 2018, including Gansu, Heilongjiang, Qinghai, Ningxia, Jilin, Liaoning, Inner Mongolia, Shaanxi, Shanxi, Shandong, and Sichuan. We found that L-L cluster area was also the agglomeration area with low FEE by looking at Figures 3 and 5. The northwest was rich in resources, however, the traditional forestry cultivation mode and the environmental pollution brought by forestry investment made the ecological efficiency of forestry in these areas became the state of L-L agglomeration. These factors made it difficult to change the state of L-L concentration in a short time.

The H-L cluster area mainly included Tianjin and Beijing, Tibet, Chongqing and Hebei. Beijing and Tianjin have made remarkable achievements in social and economic development as the regions with high openness in the north, and they have a high level of FEE in 2018. However, due to the lack of effective regional cooperation mechanism and incomplete industrial chain layout with surrounding areas, there was no effective radiation and driving effect on the surrounding areas, which resulted in the phenomenon that the ecological efficiency of the regions was high and the adjacent areas’ ecological efficiency was low.

It can be seen that more than 70% of the regions were distributed in the first and third quadrants, and only less than 30% of the provinces were distributed in the second and
fourth quadrants. This showed that most of China’s high-tech industrial agglomeration in 2018 had obvious positive spatial correlation characteristics, and a few provinces and cities had a negative spatial autocorrelation.

3.3. Analysis of Influencing Factors

Traditional forestry only considered the output of forestry in the process of production, but it was unreasonable that the influence of resources, economy, environment and other factors was ignored. In order to study the improvement of ecological efficiency in forestry, it was necessary to study the factors affecting the ecological efficiency of forestry.

3.3.1. Analysis of Tobit Regression

In this paper, the influencing factors of FEE of 31 regions were discussed. There were 465 samples and the FEE value was calculated by the super efficiency SBM model from 2004 to 2018. The result is shown in Figure 6.

![Figure 6. Comparison of regional forestry ecological efficiency (FEE) in China from 2004 to 2018.](image)

It can be seen that the fitting results of this model was good in Table 4, and the correlation was significant at the level of \( p = 0.05 \), which indicated that EDL, IEC, ERL, ISL and FRE affected the FEE to a certain extent. The detailed analysis of each factor was as follows:

| Variable | Intercept | EDL  | IEC  | ERL  | ISL  | FRE  |
|----------|-----------|------|------|------|------|------|
| Coefficient | \(-6.695 \times 10^{-3}\) | \(2.197 \times 10^{-2} \, ***\) | \(-3.253 \times 10^{-4} \, **\) | \(2.146 \times 10^{-5} \, ***\) | \(6.399 \times 10^{0} \, ***\) | \(3.967 \times 10^{-3} \, ***\) |

Note: ** and *** denote statistical significance at the 5% and 1% levels, respectively.

The result showed that the economic development level was positively correlated with the FEE. The higher the level of economic development was, the higher the value of forestry ecological performance was. With the expansion of economic scale and the improvement of people’s income level, people had higher demand for forestry production efficiency. Therefore, speeding up economic development was an important factor to improve the ecological efficiency of forestry.

There was a negative correlation between the investment in forestry ecological construction and the FEE value. This showed that the higher the investment in forestry ecological construction was, the lower the value of FEE was. It was true that forestry ecological construction investment has provided impetus for the growth of forestry industry, but redundancy of forestry ecological construction investment in forestry production would
reduce the FEE, ecological construction would also increase the environmental burden. When the pollution exceeded the carrying capacity of the environment, environmental pollution would inevitably affect the improvement of forestry ecological productivity and economic development. Therefore, the coefficient of investment in forestry ecological construction was negative.

The relationship between environmental regulation factors and forestry ecology was very significant. The FEE calculated in this paper took the environmental pollution factors into account. The purpose of environmental regulation was to reduce the unexpected output such as wastewater and waste gas, because reducing the pollution caused by forestry production can improve the ecological efficiency of forestry. Therefore, the local governments should increase the investment in environmental governance to improve the ecological efficiency of forestry.

There was a strong positive correlation between the industrial structure and the ecological efficiency of forestry, and the correlation coefficient was as high as 6.399, indicating that the industrial structure of forestry had a positive impact on improving the ecological efficiency of forestry. Therefore, on the one hand, the government accelerated the upgrading of industrial structure and vigorously developed the forest industry.

The correlation coefficient between FRE and FEE was $3.967 \times 10^{-3}$. Generally speaking, the better the resource endowment was, the higher the FEE was. However, the resource endowment cannot be changed in a short time.

3.3.2. Importance Analysis of Factors

There was an analysis of the importance of factors affecting forestry ecological efficiency by using random forest. The importance of factors can be ranked by IncMSE and IncNodePurity, and the results are shown in Figure 7 and Table 5.

![Figure 7. Scatter diagram of IncMSE and IncNodePurity.](image)

**Table 5. Analysis results of IncMSE and IncNodePurity.**

|       | EDL | IEC | ERL | ISL | FRE |
|-------|-----|-----|-----|-----|-----|
| %IncMSE | 47.837 | 53.186 | 46.328 | 51.520 | 33.890 |
| IncNodePurity | 9.442 | 12.972 | 12.413 | 11.270 | 5.969 |

It can be concluded that IEC had the highest value in both IncMSE and IncNodePurity, which indicated that the variable had an important impact on FEE. Then, ERL and ISL came next. It can be seen that these two factors were a little important in affecting the ecological efficiency of forestry. In contrast, FRE was the lowest important factor among these indicators, and the values of IncMSE and IncNodePurity were 33.89 and 5.969, which showed that forestry resource endowment was not particularly significant to FEE.
4. Discussion

The result of the Malmquist index of China’s forestry efficiency only was 1.012, which reflected the growth rate of China’s forestry total factor is slow, the result is in accordance with the study by Liu and Li [49]. However, the TFPC of China’s forestry from 2008 to 2009 reached the lowest value in recent years. Due to severe low temperature, rain, snow and freezing disaster occurred in southern China at the beginning of 2008, and Wenchuan earthquake occurred in May at the same year. What’s worse was that the international financial crisis continued to spread in the second half of the year, the forest product market and export fluctuated significantly, and the TFPC of the whole region of China reduced greatly.

The results of this paper also reflected China’s FEE was basically higher in the south and lower in the northwest in recent years. The result was roughly the same as Luo et al.’s study [50]. Similarly, the H-H cluster area of China’s FEE in 2018 was in the south, which the L-L cluster area included northwest regions. It was not conducive to the sustainable development of forestry in northwest regions.

Our results also indicated that there was a negative correlation between the investment in forestry ecological construction and the FEE value. This is because the redundancy of investment in forestry fixed assets would also increase the environmental burden. On the other hand, the increase of forestry fixed assets would lead to the increase of tax, and the increase of tax can lead to the decrease of forestry efficiency. This conclusion was based on study of Ghebremichael and Potter-Witter verify [51], because they confirmed tax incentives did stimulate capital formation and total factor productivity growth. So, it was conducive to adjust the fixed assets of forestry in Northwest China. What’s more, IEC was the most important factor in random forest regression, so more attention should be paid on investment in forestry ecological construction.

This paper results suggested the governments should promote the regional coordinated development of forestry industry. The results indicated that the ecological efficiency of forestry development was different in all regions, and the eastern and southern FEE was high, therefore, the advanced technology, experience and capital of the eastern region to the central and western regions were the focus of investment consideration. At the same time, the rich forestry resources in the northwest can be put into the forestry construction in the south, only in this way can it greatly promoted the optimization of the forestry industry in the whole region of China. Of course, the local government needed to innovate forestry science and technology means and improved the forestry management system.

From the analysis of the factors of forestry ecological efficiency, EDL was a moderating important factor. However, in the study of Ester and Sebastian [52], GDP was a vital factor to the efficiency of the forest sector. The reasons for the different conclusions the 28 EU/EFTA countries taken as a subject, and GDP played an important role in international efficiency evaluation. It was also shown in the above results that ERL was other important factors affecting the ecological efficiency of forestry. The result was in accord with study of Chand et al. [53] that forest product benefits and environmental benefits were complementary to each other. Forestry enterprises need to strengthen the research on clean production technology, such as clean energy development, waste recycling, wastewater, and waste gas treatment technology in the production process, as governments need to improve the environmental management level of forestry industry and meet the requirements of forestry ecological security construction.

In terms of the study of input and output efficiency between different regions, some scholars used conventional DEA, which likely lead to the situation that the calculated value of many units is 1, and the efficiency value of some units has little difference, so it is not better to compare the efficiency values of different regions. This result is the same as study of some scholars [32,54–61]. In contrast, the super efficiency SBM used in this paper can solve this problem well, which is also an advantage of efficiency comparison in this paper. However, there are also some shortcomings in this paper, the regional characteristics of FEE are very obvious, which is affected by regional climate, topography, water source,
and other factors, and these factors are not taken into account in this paper. In the later analysis of influencing factors of FEE, although reading a lot of relevant literature, some factors affecting FEE are not taken into account because the data are restricted, such as the implementation of forestry industry policies by local governments, the willingness of farmers for forest production, and the application of new forestry technology. These contents will be considered in the next step of forestry production efficiency research.

5. Conclusions

Based on selected forests industry statistics from 31 Chinese provinces in China, the methods of super-efficiency SBM model and Malmquist productivity index to measure forestry efficiency has been applied in this paper from the static and dynamic angles. Then, to better study the distribution and evolution of FEE in China, this paper made a spatial analysis of the above ecological efficiency values of forestry industry by using ArcGIS software. Last, tobit regression and random forest were applied to explore the driving factors for FEE, and the conclusions were as follows.

From dynamic angles, China’s forestry productivity change was in an upward trend from 2004 to 2018. The utmost average growth rate of TFPC from 2004 to 2018 is western regions, the TFPC of all Chinese regions from 2008 to 2009 decreased significantly. From static angles, Tianjin, Shanghai, and Hainan were the areas with high level of FEE and Hebei, Xinjiang, Gansu, and Shaanxi were the areas with high levels of FEE in these three periods.

The result of spatial analysis showed that China’s FEE of the northeast and the south was basically higher, which FEE of China’s middle regions was relatively lower in 2004. However, as time went on, the distribution of FEE gradually appeared higher in the south and lower in the north. The H-H cluster appeared in south regions of China, these areas were economically developed and possessed high-tech industries. The regions of the L-L cluster area appeared the northeast and most of the northwest, which was consistent with the lower distribution FEE.

Through the factor analysis of forestry ecological efficiency, there was a negative correlation between forestry fixed assets investment and FEE, but it was the most important factor to affect FEE. ERL and ISL were slightly important factors affecting FEE and they had a positive correlation with FEE.

Author Contributions: Conceptualization, S.C. and S.Y.; methodology, S.C.; software, S.C.; validation, S.C. and S.Y.; formal analysis, S.C. and S.Y.; investigation, S.C.; sources, S.C. and S.Y.; data curation, S.C.; writing—original draft preparation, S.C.; writing—review and editing, S.C. and S.Y.; visualization, S.C.; supervision, S.Y. project administration, S.Y. funding acquisition, S.Y. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the National Natural Science Foundation of China, grant number 71473195, 71773091; Special Fund for Scientific Research of Forestry Commonwealth Industry, grant number 201504424.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The data presented in this study are available in article.

Acknowledgments: I sincerely thank my tutor for the guidance of my thesis. I am also grateful to the students in Center of Resource economy and Environmental Management Research for their help to me.

Conflicts of Interest: The authors declare no conflict of interest.
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