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Impact of the Management Scale on the Technical Efficiency of Forest Vegetation Carbon Sequestration: A Case Study of State-Owned Forestry Enterprises in Northeast China

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Abstract: Improving the technical efficiency of forest vegetation carbon sequestration is an effective way to accelerate the pace and reduce the cost of carbon neutrality in China. Therefore, it is particularly important to explore the technical efficiency, influencing factors, and optimization paths of forest vegetation carbon sequestration. This work uses a 21-year panel data set (2000–2020) of 87 state-owned forestry enterprises (SOFEs) in Northeast China and combines geographic information system (GIS) and remote sensing (RS) technology. First, stochastic frontier analysis (SFA) was used to quantitatively analyze the technical efficiency of forest vegetation carbon sequestration in different SOFEs during different periods. Then, the individual fixed-effects model was used to examine the factors influencing technical efficiency under the control of climate factors. Finally, the panel threshold model was used to determine the impact of different management scales on the technical efficiency of forest vegetation carbon sequestration. The main results were as follows: technological progress can effectively reduce forestry investment and improve the technical efficiency of forest vegetation carbon sequestration production. There was technological progress in forest vegetation carbon sequestration production during the study period, but the rate of technological progress showed a decreasing trend. Forest management scale, total output value, employee wages, precipitation, and sun duration had a significant positive impact, whereas wood production had a significant negative impact on the technical efficiency of carbon sequestration. The impact of different management scales on the technical efficiency of carbon sequestration is highly heterogeneous. The study established an analytical framework for researching the technical efficiency and optimization of forest vegetation carbon sequestration, providing a theoretical and practical basis for forest management.

Keywords: forest vegetation carbon sequestration; technical efficiency; management scale; SFA; panel threshold model; GIS; RS

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1. Introduction

The Paris Agreement to the United Nations Framework Convention on Climate Change requires governments to commit to keeping the global temperature rise below 2 °C and to work to limit it to 1.5 °C [1]. In November 2021, the 26th United Nations Climate Change Conference presented the full details for fulfilling the Paris Agreement. They set the goal of achieving net-zero global emissions by mid-century and holding the temperature rise to within 1.5 °C. Society often wants to achieve this goal by mitigating climate change at the lowest cost [2]. Nature-based policies are one of the most cost-effective ways to increase carbon sequestration while providing major socioeconomic benefits [3]. Among terrestrial vegetation types, the forest carbon pool accounts for 70–80% of global carbon storage and has a large carbon offset potential and a long-lasting storage effect [4–6].

Therefore, measuring and exploring the technical efficiency of forest vegetation carbon sequestration and its driving factors will help to objectively evaluate the cost of increasing carbon sequestration and improve its efficiency.

The 87 state-owned forestry enterprises (SOFEs) located in northern China serve as important natural barriers. They have important strategic significance for maintaining regional ecological balance and national food security and ensuring the harmonious development of the local economy and society [7]. The carbon storage of these SOFEs is 124,631.42 tons, but the arbor forest area per hectare is similar to the national average level of natural forests—less than 50%—and less than 1/3 of the world average level [8]. The productivity of forestland in SOFEs has not been fully developed, and the growth potential of forest carbon storage is very large, which plays a crucial role in achieving the carbon neutrality goal. Additionally, SOFEs are faced with conflicts between ecological and economic benefits due to the advancement of the reform of state-owned forest areas [9–11]. The production efficiency of forest vegetation carbon sequestration is mainly related to the input of capital, labor, and land. From the perspective of land resources, China's current forest cover rate is 23.06% [12]. Due to limited land resources, it is estimated that the upper forest cover limit in the country is approximately 26%. Given the limited land, to fully exploit the productive potential of forestland, SOFEs mainly improve the forest growth environment and reduce dieback caused by external disturbance through forest management [13]. Simultaneously, the carbon storage of forests can be increased by increasing forest area and improving stand quality. China's forest resource inventory is conducted every five years, and these data have high accuracy regarding forest structure, forest accumulation, and carbon storage. However, the data are not from consecutive years, and the measurement efficiency of forest vegetation carbon sequestration is greatly limited. Additionally, there may be uncertainties in the efficiency model results for cross-sectional data. Therefore, we use the annual net primary productivity (NPP) data obtained from remote sensing to calculate the forest vegetation carbon sequestration within the study area to ensure the continuity and objectivity of measurements of forest vegetation carbon sequestration production efficiency.

The main methods for calculating efficiency are the Olley and Pakes (OP), Levinsohn and Petrin (LP), generalized method of moments (GMM), and fixed-effects (FE) methods at the micro level and two methods, data envelopment analysis (DEA) and stochastic frontier analysis (SFA), at the macro level [14,15]. Since the SOFEs we studied differ from microenterprises, they belong to the macro-scope. Therefore, we only considered DEA and SFA. The main deficiency of the DEA method is that it cannot consider the influence of environmental factors and random error terms on efficiency. Additionally, DEA is more sensitive to outliers [16]. However, forest vegetation carbon sequestration production is a complex process. Furthermore, forest growth is greatly affected by meteorological conditions, forest fires, and national financial investment, and abnormal values will inevitably appear [17]. Additionally, the DEA method treats all deviations from the leading edge as inefficiencies, which may overestimate inefficiencies. Compared with DEA, the SFA method considers the influence of random factors and avoids the large measurement error that may be caused by outliers. SFA works by separating the error term and the efficiency loss term. This makes the estimation result more accurate. Moreover, SFA has a clear setting for the form of the production function, taking into account other random factors beyond the control of the producer that may lead to deviations from the frontier. Additionally, SFA can distinguish the influence of various factors on inefficiency. Therefore, for the research question of this work, the SFA method was chosen over the DEA method.

Most researchers focus on the spatiotemporal evolution of forest vegetation carbon sequestration, urbanization and rural depopulation, land use change, forestry engineering evaluation, potential prediction, carbon pricing, and other influencing factors [18–21]. The measurement of forest vegetation carbon sequestration efficiency mostly adopts research methods such as DEA and slack-based measure–data envelopment analysis (SBM-DEA) [22]. In addition to general socioeconomic factors, forest vegetation carbon sequestration efficiency is affected by regional topographical conditions, climatic conditions, and management scale [23]. In particular, due to differences in development, geographical location, and historical background, SOFEs exhibit significant differences in forest management scale. Due to differences in scale, the effect of large-scale forestry management is considerably higher [24]. Therefore, the forest vegetation carbon sequestration efficiency should be higher in areas with larger forest management scales than in those with smaller scales. The technical efficiency of forest vegetation carbon sequestration is the ratio of the actual output of the decision unit to the optimal output when the given factor inputs are optimally allocated [25]. In reality, it is difficult to achieve the frontier level of the production function due to the influence of stochastic noise and technical inefficiency factors. Therefore, we generally use the ratio of the expectation of output in the sample to the expectation of the stochastic frontier to express technical efficiency. Hence, exploring the factors influencing the technical efficiency of forest vegetation carbon sequestration and evaluating the impact of different management scales on technical efficiency will help improve the management system of SOFEs and provide a basis for sustainable forestry development.

In summary, this work takes the 87 SOFEs in Northeast China as the research object. First, the carbon sequestration and related meteorological data of the 87 SOFEs were obtained at the grid scale using geographic information system (GIS) and remote sensing (RS) technologies. Second, based on the SFA method, the technical efficiency of forest vegetation carbon sequestration was calculated, and the corresponding heterogeneity among different forest industry groups was further analyzed. Next, the land use transfer and spatiotemporal evolution pattern of forest vegetation carbon sequestration in the study area from 2000–2020 were explored. Combined with socioeconomic and meteorological factors, the factors influencing forest vegetation carbon sequestration technical efficiency and the impact of different forest management scales on it were then analyzed. Finally, we discuss how to improve the technical efficiency of forest vegetation carbon sequestration. This study created a research framework for examining forest vegetation carbon sequestration efficiency and optimization paths and promoting forest vegetation carbon sequestration efficiency research from phenomenological analysis to mechanistic analysis. Additionally, this work provides a theoretical and practical basis for enacting high-quality forest management in SOFEs and promoting carbon neutrality by 2060 from the perspective of economic efficiency.

2. Study Area, Data, and Methods

2.1. Study Area

The 87 SOFEs under study are located in China's Heilongjiang Province, Jilin Province, and the eastern part of the Inner Mongolia Autonomous Region, with a total operating area of 327,900 km^2 (Figure 1). They extend from the edge of the Hulunbuir Grassland in the west to the northernmost end of the Mohe River in the north, to Wanda Mountain on the banks of the Ussuri River in the east, and to the Yalu River on the border of China and Korea in the south, between geographic coordinates 119°36′26″~134°05′00″E, 41°37′00″~53°33′25″N. The total operating area of key state-owned forest areas is 106,800 km^2 in Inner Mongolia, 36,600 km^2 in Jilin Province, 101,000 km^2 in Heilongjiang, and 83,500 km^2 in the Great Khingan Mountains in Heilongjiang. The 87 SOFEs belong to the Inner Mongolia Forest Industry Group, Jilin Forest Industry Group, Changbai Mountain Forest Industry Group, Longjiang Forest Industry Group, Great Khingan Forestry Group, and Yichun Forest Industry Group [8]. In 2020, the total forestry output value of the SOFEs was CNY 49,171,810 thousand, of which primary and tertiary industries accounted for 48.02% and 37.54%, respectively [26].

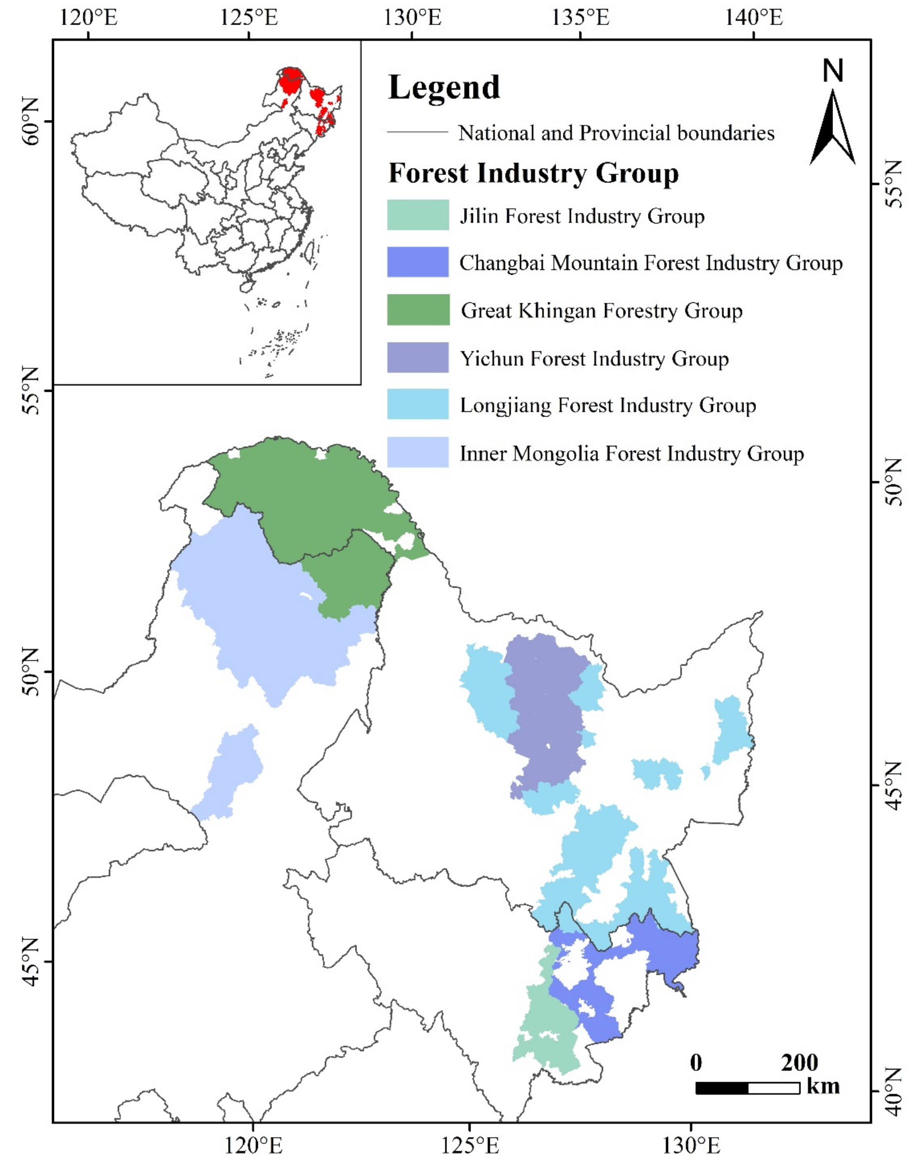

Figure 1. Study area.

2.2. Variable Selection

(1) Output variable. To study the technical efficiency of forest vegetation carbon sequestration and its influencing factors, we chose carbon sequestration as the output of forest management. Most scholars calculate forest vegetation carbon sequestration based on forest inventory volume per unit area or using tree growth models. At large scales, carbon sequestration is calculated using the InVEST model based on land use change and fixed parameters [27]. Although the forest inventory data are very accurate, there are temporal discontinuities. Most of the public data are based on provinces, so it is impossible to quantify the carbon sequestration of each SOFE. The InVEST model calculation considers changes in forest quantity rather than quality. According to previous studies, NPP can accurately characterize the amount of organic matter accumulated via plant photosynthesis per unit time, i.e., the part remaining after deducting autotrophic respiration (AR) from the total organic matter (gross primary productivity, GPP) fixed by plant photosynthesis [28,29]. To obtain the carbon sequestration in consecutive years at the grid scale, this study measures the carbon sequestration level of each forestry enterprise based on the NPP of the vegetation.

(2) Input variables. The initial production function considers the input of capital, labor, and land [30]. According to the theory of forest management, afforestation, renewal, and tending, preventing diseases, insect pests, forest fires, and other events requires considerable capital and labor input [31,32]. Therefore, we take forest management investment (invest), the average annual number of employees (staff), and the area of afforestation, regeneration, and tending (area) as input variables. It should be noted that the total forest area during the study period is not used as an input variable in this study.

(3) Variables (socioeconomic factors) affecting the technical efficiency of forest vegetation carbon sequestration. ① The existence of the scale effect leads to large-scale forest management having a higher efficiency. To quantify and examine the impact of different management scales on the technical efficiency of forest vegetation carbon sequestration, we included the management scale as a threshold variable in the model (scale). ② There should be a positive relationship between SOFE employee wages and the technical efficiency of forest vegetation carbon sequestration, and thus employee wages should be considered as an indicator [33]. ③ A higher wood yield of SOFEs corresponds to a greater reduction in forest living stock and carbon sequestration, which may have a negative impact on the technical efficiency of forest vegetation carbon sequestration [11]. Therefore, the timber yield (timber) is incorporated into the model. ④ In addition to a small amount of tree harvesting, forest maintenance measures such as thinning will also promote the development of related downstream enterprises such as wood products. Additionally, forest health care and forest parks will increase tourism revenue and promote development of the tertiary industry. Therefore, the impact of the total output value (tov) of enterprises on the technical efficiency of carbon sequestration should be examined in the model. Most studies add the square term of total output value to the model when considering environmental output and economic development, indicating that the relationship between the level of economic development and the ecological environment follows the path of the environmental Kuznets curve (EKC) [34–36]. However, unlike other studies, the SOFE primary and tertiary industries account for a relatively high proportion of the total output value. Moreover, the economic development of forest industry enterprises mainly depends on the increase in forest area and the improvement in forest quality. Therefore, this study does not consider the squared term of the total output value when constructing the model.

(4) Variables affecting the technical efficiency of forest vegetation carbon sequestration (meteorological factors). The meteorological factors affecting forest biomass mainly include precipitation, air temperature, wind speed, sun duration, and relative humidity [37,38]. ① Precipitation directly affects forest growth by affecting soil moisture. Within a certain range of precipitation, higher temperatures result in longer growing seasons [39]. In winter, due to the low temperatures and frozen soil in the study area, the forest enters a dormant period. Therefore, we input the total precipitation (per) from March to November and the average temperature (temp) from March to November into the model. ② Increased wind speed causes internode shortening and a reduction in leaf area and the total number of stems of afforestation trees, which eventually leads to the dwarfing of trees [40]. Sunshine is a necessary condition for plants to perform photosynthesis and can slow the rate of leaf senescence by delaying the accumulation of abscisic acid. Relative humidity is related to soil water evapotranspiration and plant transpiration. Therefore, we incorporated the year-round sun duration, average wind speed, and relative humidity into the model.

2.3. Data Sources and Processing

The sampling period of this study is from 2000–2020, the sampling unit is the SOFE, and the data type is panel data. The spatial reference for the spatial data is the World Geodetic System 1984 (WGS-84) projected coordinate system, with 108°E as the central meridian and the Universal Transverse Mercator as the projection. The main variable data sources and processing procedures were as follows.

(1) The NPP data are the basis for calculating the carbon sequestration of each SOFE and were obtained from the National Aeronautics and Space Administration (https:

//www.nasa.gov/, accessed on 5 July 2021). The data product number is MOD17A3HGF, with a spatial resolution of 500 m and a temporal resolution of one year. First, we used MRT software and ArcGIS 10.7 software to stitch, crop, and project the data and remove outliers. Then, through the chemical equation of green vegetation photosynthesis ($6CO_2 + 6H_2O \rightarrow C_6H_{12}O_6 + 6O_2$), it is calculated that every 1 kg of dry matter produced by vegetation can fix 1.63 kg of CO_2. Moreover, given that the carbon content of dry matter accounts for approximately 45% of the total NPP, the formula for calculating carbon sequestration in this study is $W_{CO2} = NPP/0.45 \times 1.63$. From this, we calculated the carbon sequestration of each forestry enterprise on the grid scale in g/m^2. Finally, using boundary maps for the 87 SOFEs, ArcGIS 10.7 was used to extract the year-on-year carbon summaries of each SOFE from 2000–2020.

(2) Land use data: Land use data were obtained from data published in the Earth System Science Data journal. The data range is 1985–2020, with a spatial resolution of 30 m. The data set is based on 335,709 Landsat images on the Google Earth Engine (GEE) platform. Using the land use classification results obtained by the random forest classifier, the overall accuracy reached 79.31% [41].

(3) Input and socioeconomic data: ① The data on forestry investment, number of on-the-job employees, employee wage, total output value of SOFEs, and business scale (forest management area/number of on-the-job employees) were obtained from the 2000–2020 the China Forestry and Grassland Statistical Yearbook. ② The administrative boundary data for each province in Figure 1 were obtained from the National Catalogue Service for Geographic Information of China (http://www.webmap.cn, accessed on 1 July 2021).

(4) Meteorological data: ① The average temperature and precipitation data from March to November of 2000 to 2020 and the basic wind speed, sun duration, and relative humidity data from 2000 to 2015 of each forestry enterprise were obtained from the Loess Plateau Science Data Center, National Earth System Science Data Sharing Infrastructure, National Science & Technology Infrastructure of China (http://loess.geodata.cn, accessed on 3 April 2022). ② The wind speed, sun duration, and relative humidity data from 2016 to 2020 are based on multiyear site data obtained from the website of the China Meteorological Administration (http://data.cma.cn/, accessed on 8 April 2022). Then, with the help of ArcGIS 10.7 software, we used kriging to interpolate and extract the regional mean. The spatial resolution of all meteorological data is 1 km.

Because some of the variables take the value of 0 in individual years, to facilitate the logarithmic treatment of the data in the SFA model and subsequent regression models, the samples that take a value of 0 are treated as $ln(x+1)$ in this paper. A summary of each variable and descriptive statistical analysis are shown in Table 1.

Table 1. Variable design and descriptive statistics.

Variable	Code	Unit	Mean	Std. Dev.	Min	Max
carbon sequestration	cs	ton	6,682,722	3,759,808	940,180.40	19,800,000
forest management investment	invest	CNY 10 thousand	11,385.36	10,041.77	0.00	86,843
average number of employees	staff	1 person	4532.67	2303.96	684	21,466
afforestation and tending area	area	hectare	27,048.88	65,630.72	2.00	993,682
forest management scale	scale	hectares/1 person	101.50	113.44	13.37	984.12
total output value of SOFEs	tov	CNY 10 thousand	52,694.56	47,981.64	0.00	354,364
employee wage	wage	CNY 1 thousand	70,805.75	49,372.39	2391	320,001
total production of timber	timber	m^3	76,802.86	80,246.53	0.00	499,461
forest management and protection area	manage	hectare	233,898.80	229,644.10	0.00	1,337,997
precipitation	per	0.1 mm	5785.37	1339.32	2991.92	10,986.26
temperature	temp	0.1 °C	73.16	23.36	16.99	111.63
wind speed	wind	0.1 m/s	26.06	9.07	15.76	101.67
year-round sun duration	sun	hour	2438.38	220.95	1973.72	3130.38
relative humidity	humidity	%	66.96	2.87	54	76.27

2.4. Research Methods

2.4.1. Kernel Density Estimation

Kernel density estimation is a nonparametric estimation method. Its main role is to estimate unknown density functions. The continuous density curve can describe the distribution of random variables and perform interval estimation. Compared with traditional histograms, kernel density estimation has good statistical properties. It replaces the histogram with a continuous density curve, and the estimation result is smoother. Additionally, the kernel density estimation process does not add any assumptions to the data distribution and studies only the characteristics of the data distribution based on the data samples themselves. Therefore, the authenticity and accuracy of its estimation results are high.

Let the density function of the random variable be $f(x)$, and there are n independent and identically distributed observations for the random variable X. In this study, n is 87, representing the number of SOFEs in Northeast China. The observed values are represented by $X_1,\ X_2, \ldots, X_n$, so the specific expression form of the kernel density estimation function is Equation (1):

$$f(x) = \frac{1}{nh}\sum_{i=1}^{n} K\left(\frac{x_i - x}{h}\right) \tag{1}$$

In Equation (1), n is the number of study areas, which is 87; h is the window width (bandwidth); $K(\cdot)$ is a random kernel function, which is a smooth function or a weighting function; and the convergence rate of the kernel density estimator is $\sqrt{nh}$.

2.4.2. Land Use Change Transition Matrix

One important way to increase forest vegetation carbon sequestration is to increase forest area [42]. This is achieved mainly through artificial afforestation, aerial seeding afforestation, closure of mountains (sand) for afforestation, restoration of degraded forests, and artificial renewal. However, the expansion of urbanization, the expansion of cultivated land, natural disasters in forests, and inadequate forest management and protection reduce the forest area. Therefore, we used a land-use transition matrix to identify transitions in forest areas. We superimposed and analyzed the 2000 and 2020 land use type maps in ArcGIS and identified the land use types at the beginning and end of the period with the rows and columns of the matrix, respectively. This mathematical model can be expressed as Equation (2):

$$\mathrm{S}_{ij} = \begin{bmatrix} S_{11} & S_{12} & \cdots & S_{1n} \\ S_{21} & S_{22} & \ldots & S_{2n} \\ \vdots & \vdots & & \vdots \\ S_{n1} & S_{n2} & \ldots & S_{nn} \end{bmatrix} \tag{2}$$

In Equation (2), the sum of the elements in each row represents the total area of the land type at the beginning of the period, and the addition of the off-diagonal elements of the row represents the total area of the land type reduction during the period. The sum of the data in each column represents the total area of the land category at the end of the period, and the sum of the off-diagonal elements of this column represents the total growing area of the land category at the end of the period. The diagonal elements of the matrix represent the number of land use types that did not change at the beginning and end of the period. The off-diagonal elements of the matrix represent the number of transitions from each beginning type to the ending type.

2.4.3. Stochastic Frontier Analysis Model

The specific forms of the frontier production function mainly include the Cobb Douglas (C-D) production function, the frontier production function (FPF), the constant elasticity of substitution production function (CES), the variable elasticity of substitution production function (VES) and the trans-log production function (TLP). Compared with other production functions, the factor output elasticity of the TLP not only reflects the substitution effect and interaction between input factors but also reflects the impact of time changes. Therefore, differences in the technological progress of different inputs can be decomposed. Furthermore, TLP relaxes the strict assumption of technical neutrality and effectively avoids the deviation caused by the misconfiguration of functions. Therefore, this study selects the TLP and performs maximum likelihood estimations. The model setting form is Equation (3):

$$\begin{aligned} lny_{it} = {} & \beta_0 + \beta_K lnK_{it} + \beta_L lnL_{it} + \beta_N lnN_{it} + \beta_t t + \beta_{KK}\ln(K)_{it}^2 + \beta_{LL}\ln(L)_{it}^2 \\ & + \beta_{NN}\ln(N)_{it}^2 + \beta_{KL}(lnK_{it})(lnL_{it}) + \beta_{KN}(lnK_{it})(lnN_{it}) \\ & + \beta_{LN}(lnL_{it})(lnN_{it}) + \beta_{Kt}(lnK_{it})t + \beta_{Lt}(lnL_{it}) + \beta_{Nt}(lnN_{it}) \\ & + \beta_{tt}t^2 + v_{it} - u_{it} \end{aligned} \tag{3}$$

In Equation (3), y_{it} represents the forest vegetation carbon sequestration of the i-th SOFE in the t-th year; $K,\ L,\ and\ N$ represent the capital input of forest management, labor input (annual average number of employees at each SOFE), and afforestation and tending area input, respectively; t is the time trend term; β is the parameter to be estimated; v_{it} is the random error term representing uncontrollable factors such as statistical error and random fluctuation with a distribution of $v_{it} \sim N\left(0, \sigma_v^2\right)$; and u_{it} is the technical inefficiency term, i.e., the efficiency loss from the optimal frontier. We assume that u_{it} obeys the $u_{it} \sim N^+\left(m_{it}, \sigma_{it}^2\right)$ distribution. Therefore, the production technology efficiency of forest vegetation carbon sequestration can be expressed by Equation (4):

$$te_{it} = exp(-u_{it}) \tag{4}$$

2.4.4. Panel Threshold Model

The threshold effect means that when a parameter reaches a certain critical value, it will cause another parameter to change in direction or quantity. The threshold regression model can determine the critical value that leads to a structural mutation in forest vegetation carbon sequestration technical efficiency [43]. Moreover, the model's structural changes are determined by its endogeneity, which avoids the statistical bias and estimation bias caused by the subjective judgment of the critical value. This study uses a panel threshold model and then adopts the bootstrap method to estimate the threshold value γ and its significance. The basic model is set as Equation (5):

$$\begin{aligned} te_{it} = {} & \beta_1 lnscale'_{it} I(scale_{it} \le \gamma) + \beta_2 lnscale'_{it} I(\gamma < scale_{it}) + \beta_3 lngov_{it} \\ & + \beta_4 lnsalary_{it} + \beta_5 lntimber_{it} + \beta_6 lnafforest_{it} \\ & + \beta_7 lnafforest_{it}^2 + \beta_8 lnper_{it} + \beta_9 lntemp_{it} + \beta_{10} lnwind_{it} \\ & + \beta_{11} lnsun_{it} + \beta_{12} lnhumidity_{it} + \varepsilon_{it} \end{aligned} \tag{5}$$

In Equation (5), γ is the threshold value to be estimated; $I(\cdot)$ is an indicative function, which satisfies the requirements in parentheses and takes the value 1, and takes the value 0 otherwise; and β_1 to β_{12} are the coefficients to be estimated for the model. The corresponding meanings of the other variables are shown in Table 1. The model assumes the existence of a single threshold. If there is a double threshold in the model test result, the model is expressed as Equation (6):

$$\begin{aligned} te_{it} = {} & \beta_1 lnscale'_{it} I(scale_{it} \le \gamma_1) + \beta_2 lnscale'_{it} I(\gamma_1 < scale_{it} \le \gamma_2) \\ & + \beta_3 lnscale'_{it} I(\gamma_2 < scale_{it}) + \beta_4 lngov_{it} + \beta_5 lnsalary_{it} \\ & + \beta_6 lntimber_{it} + \beta_7 lnafforest_{it} + \beta_8 lnafforest_{it}^2 \\ & + \beta_9 lnper_{it} + \beta_{10} lntemp_{it} + \beta_{11} lnwind_{it} + \beta_{12} lnsun_{it} \\ & + \beta_{13} lnhumidity_{it} + \varepsilon_{it} \end{aligned} \tag{6}$$

In Equation (6), γ_1 and γ_2 are the threshold values to be estimated; $\gamma_1 < \gamma_2$; $I(\cdot)$ is an indicative function, which satisfies the requirements in parentheses and takes the value 1, and takes the value 0 otherwise; and β_1 to β_{13} are the coefficients to be estimated for the model. The corresponding meanings of the other variables are shown in Table 1.

3. Analysis of Land Use Change and Carbon Sequestration Spatiotemporal Evolution

3.1. Analysis of Land Use Change

To examine the land use change of SOFEs during the study period, this study uses the land use data of 2000 and 2020. Combined with the function of the raster calculator in ArcGIS 10.7, the land use transfer results for the seven land types were calculated (Table 2).

Table 2. Land use change matrix from 2000 to 2020.

Land Type	Cropland (km^2)	Forest (km^2)	Grassland (km^2)	Water (km^2)	Barren (km^2)	Impervious Land (km^2)	Wetland (km^2)
Cropland	14,409.68	2546.15	499.32	65.27	0.33	368.83	0.02
Forest	4920.80	284,505.00	294.70	10.27	0.07	176.03	0.00
Grassland	768.82	3526.36	2327.35	2.12	0.97	65.17	0.09
Water	12.72	48.32	1.58	601.50	0.16	31.53	0.01
Barren	0.10	0.13	0.12	0.20	0.34	0.67	0.00
Impervious land	1.48	0.58	0.21	20.33	0.10	933.84	0.00
Wetland	91.49	25.59	7.45	1.64	0.00	0.42	96.19

According to the analysis in Table 2, during 2000–2020, the total areas of cultivated land, forestland, grassland, water, barren land, impervious land, and wetland converted from other land types were 5795.41 km^2, 6147.13 km^2, 803.38 km^2, 99.83 km^2, 1.63 km^2, 642.65 km^2, and 0.12 km^2, respectively. Among them, the area converted from other land types to forestland was the largest (6147.13 km^2).

During the study period, the total reduced areas of cultivated land, woodland, grassland, water, barren land, impervious land, and wetland were 3479.92 km^2, 5401.87 km^2, 4363.53 km^2, 94.32 km^2, 1.22 km^2, 22.7 km^2, and 126.59 km^2, respectively. Among them, the total area of forestland reduction was the largest (5401.87 km^2).

3.2. Analysis of the Spatiotemporal Evolution of Carbon Sequestration

3.2.1. Analysis of Temporal Changes in Carbon Sequestration

To investigate the temporal evolution of carbon sequestration in the 87 SOFEs during the study period, we used the processed carbon sequestration raster data for regional statistics. Combined with ArcGIS 10.7, the annual carbon summarization of the study samples was calculated and plotted, as shown in Figure 2.

Temporally, the aggregate carbon stock amount of the SOFEs showed an overall upward trend from 2000–2020, with a total growth rate of approximately 22.17%. It increased from 496.66 million tons in 2000 to 606.79 million tons in 2020. The aggregate carbon amount reached the maximum value of approximately 655.53 million tons in 2018. The average value was 581.40 million tons, but the overall fluctuation was large.

The main reasons for the increase in forest vegetation carbon sequestration are as follows: from 1998–2018, the effect of comprehensive elimination of the commercial logging of timber gradually emerged. During this period, the forest area increased by 2.342 million hectares, showing a steady growth trend. From the perspective of forest stock, from 1998–2008, the forest stock increased by 229 million cubic meters, and from 2008 to 2018, the forest stock increased by another 657 million cubic meters, an increase of 27.95%. From the perspective of age group structure, the proportion of middle-aged forest and near-mature forest increased by 15.53% and 7.80%, respectively, and the forest structure was significantly improved.

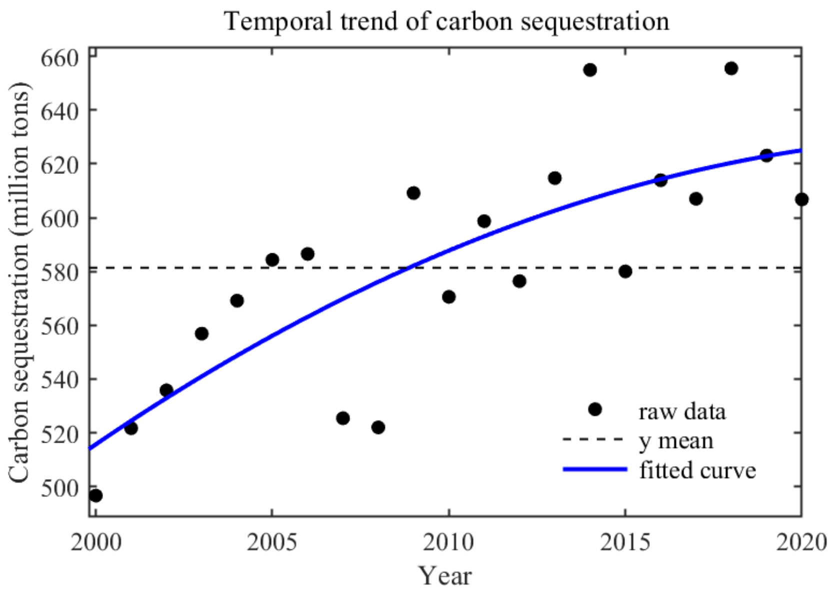

Figure 2. Temporal trends of carbon sequestration.

3.2.2. Carbon Sequestration Kernel Density Estimation

To observe the evolution of carbon sequestration in each SOFE during the study period, we used MATLAB software to draw the estimation results of the three-dimensional spatial kernel density from 2000–2020, as shown in Figure 3.

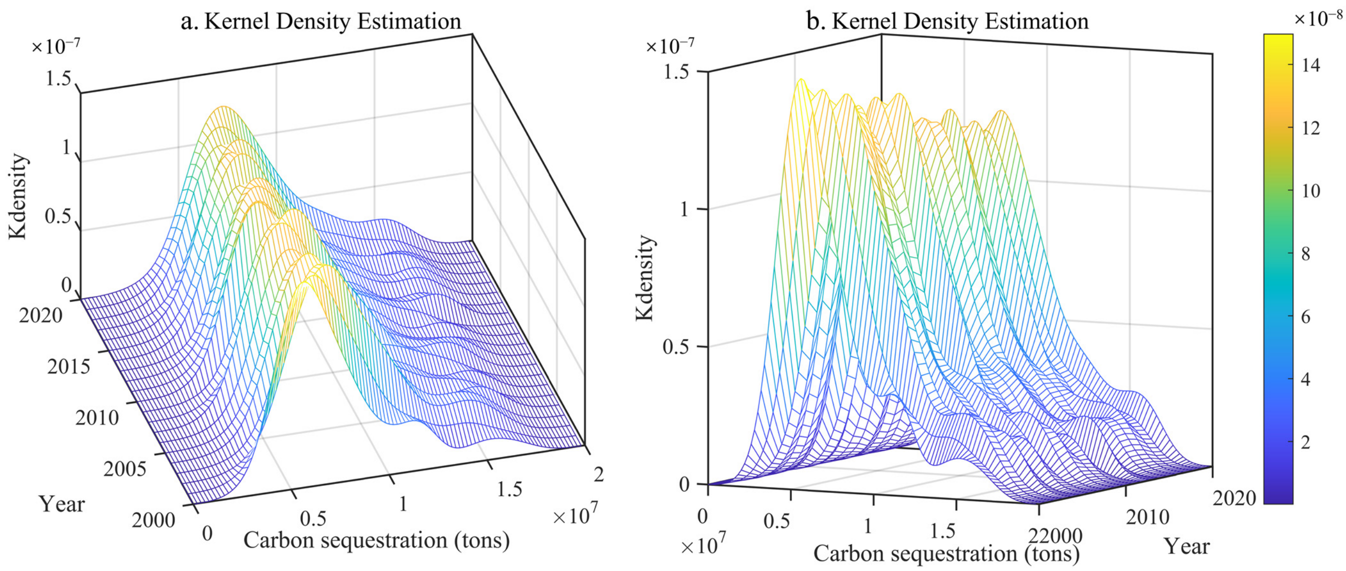

Figure 3. Kernel density estimates of forest vegetation carbon sequestration.

Figure 3 shows that, overall, from 2000–2020, the nuclear density curve continued to move to the right with time, indicating that the carbon sequestration of each SOFE increased significantly during the study period. From the perspective of skewness, the nuclear density curves of forest vegetation carbon sequestration for all SOFEs showed a right tailing phenomenon during the study period. From the perspective of kurtosis, the peaks of the nuclear density curves of forest vegetation carbon sequestration generally decreased with fluctuations in time, indicating that the differences in the carbon sequestration among the SOFE were increasing.

3.2.3. Analysis of Spatial Changes in Carbon Sequestration

To visualize the spatial changes in carbon sequestration, we first drew the spatial distribution maps of carbon sequestration for the 87 SOFEs in 2000 and 2020. Next, using 21 periods of data from 2000–2020, combined with the map algebra function in ArcGIS 10.7, the carbon sequestration growth rate was calculated at the grid scale. Through reclassification, the corresponding proportions and occupied areas of the change trends at all levels were calculated, as shown in Table 3.

Table 3. Annual growth rate and corresponding area of carbon sequestration.

Changing Trend	2000–2010		2010–2020	
	Annual Rate of Change	Proportion (%)	Annual Rate of Change	Proportion (%)
Obviously Worse	−0.099–−0.020	0.12	−0.099–−0.020	0.38
Slightly Worse	−0.019–0.000	2.44	−0.019−0.000	17.54
Basically Stable	0.001−0.020	41.23	0.001−0.020	55.76
Slightly Better	0.021−0.040	38.31	0.021−0.040	25.36
Obviously Better	0.041−0.894	17.89	0.041−0.890	0.95

From the perspective of carbon sequestration per unit area, the SOFE forest vegetation carbon sequestration showed an overall increasing trend from 2000–2020, and the distribution of "blue" areas increased significantly, as shown in Figure 4a,b. Judging from the average annual growth rate of carbon sequestration at the grid scale, the annual growth rate of carbon sequestration in 2000–2010 was generally higher than that in 2010–2020. Both periods showed an "overall increase but decrease in small areas" in carbon sequestration (Figure 4c,d). From 2000–2010, the area with an average annual carbon sequestration growth rate between 0.001 and 0.020 was the largest, accounting for 41.23%. This was followed by areas with growth rates between 0.021–0.040 and 0.041–0.897, accounting for 38.31% and 17.89%, respectively. This indicates that from 2000–2010, the total proportion of areas with positive growth in carbon sequestration reached 97.43%. The negative average annual growth rate was divided into two levels, −0.099 to −0.020 and −0.019 to 0.000; the corresponding area proportions were 0.12% and 2.44%, respectively. From 2010 to 2020, the area with an average annual growth rate of carbon sequestration between 0.001 and 0.020 was the largest, accounting for 55.76%, an increase of 14.53% from 2000–2010. This was followed by the proportions of the areas with growth rates between 0.021–0.040 and 0.041–0.890, which were 25.36% and 0.95%, respectively. This indicates that the total proportion of areas with positive growth in carbon sequestration from 2010 to 2020 reached 82.07%, a decrease of 15.36% from 2000–2010. For the average annual growth rates of −0.099–−0.020 and −0.019–0.000, the area proportions were 0.38% and 17.54%, respectively. The results show that the average annual growth rate of carbon sequestration slowed from 2010–2020 and showed negative growth in SOFEs in jurisdictions such as Huzhongju and Xinlin.

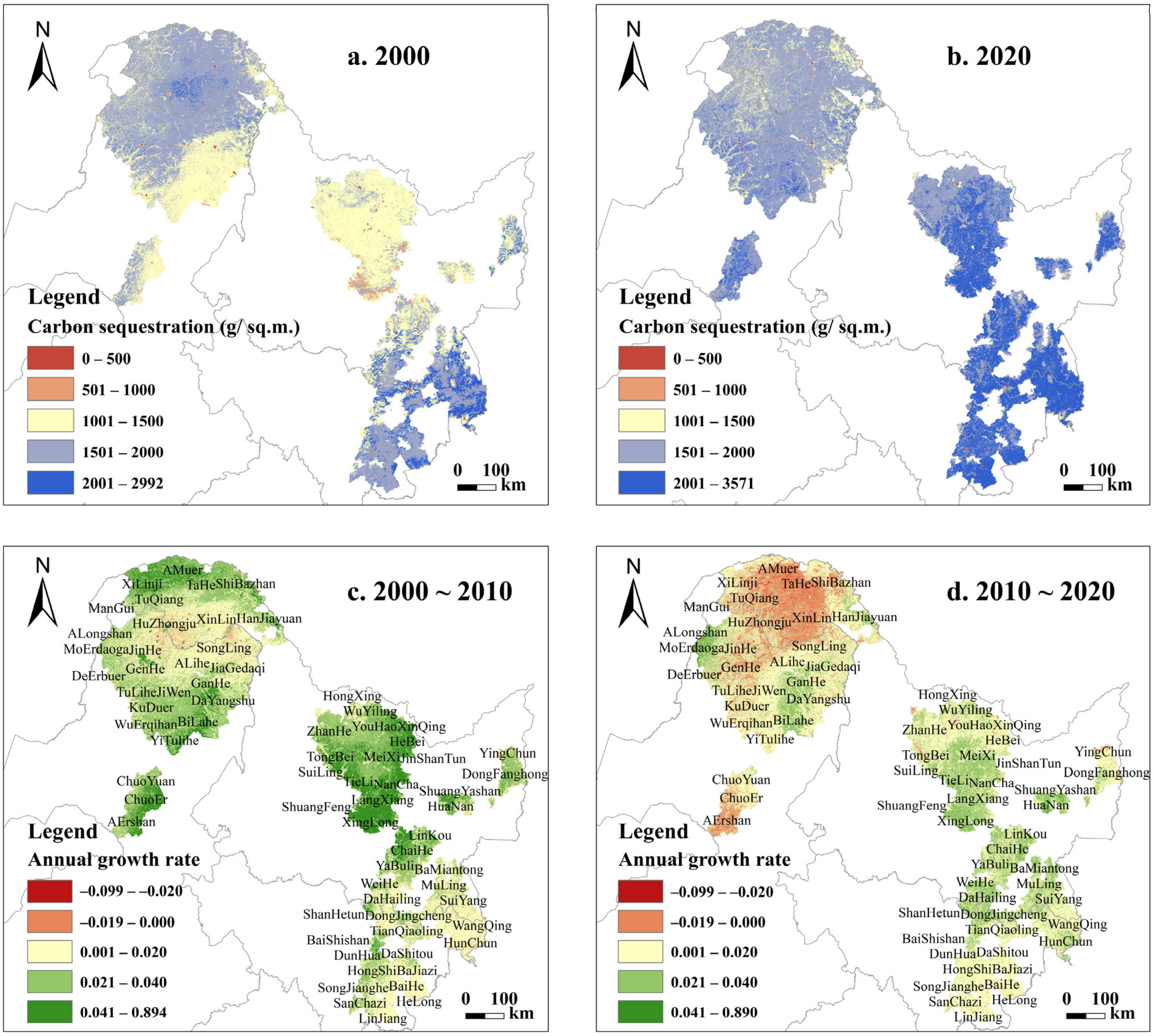

Figure 4. Map of spatial change in carbon sequestration growth rate. (**a**) Carbon sequestration in 2000; (**b**) Carbon sequestration in 2020; (**c**) Annual growth rate from 2000 to 2010; (**d**) Annual growth rate from 2010 to 2020. (**c**,**d**) show the names of the SOFEs.

4. Results Analysis

4.1. Technical Efficiency of Forest Vegetation Carbon Sequestration

In this work, Stata 16 software was used to estimate the maximum likelihood of the model defined by Equation (1). The model results are shown in Table 4. Most of the parameters in the model are statistically significant. Among them, δ_u and δ_v are statistically significant at the 1% level. This shows that there are technical inefficiencies in producing forest vegetation carbon sequestration and that the stochastic frontier model is effective.

Table 4. SFA model results.

Variable	Coef.	Std. Err.	*p*	Variable	Coef.	Std. Err.	*p*
lninvest	−2.4316 ***	0.3016	0.0000	lnstaff*t	−0.0517 ***	0.0070	0.0000
lnstaff	−3.0656 ***	0.5765	0.0000	lnafforest*t	0.0252 ***	0.0050	0.0000
lnafforest	−0.7674 ***	0.2134	0.0000	t^2	−0.0037 ***	0.0009	0.0000
$lninvest^2$	−0.0234	0.0244	0.3370	_cons	41.7678 ***	2.8347	0.0000
$lnstaff^2$	0.0040	0.0408	0.9210	usigmas			
$lnafforest^2$	0.0047	0.0034	0.1710	t	−0.0926 *	0.0550	0.0920
lninvest*lnstaff	0.3339 ***	0.0434	0.0000	_cons	−1.3528 ***	0.3801	0.0000
lninvest*lnafforest	−0.0004	0.0245	0.9880	vsigmas			
lnstaff*lnafforest	0.0614 **	0.0271	0.0240	_cons	−1.4914 ***	0.0974	0.0000
lninvest*t	0.0264 ***	0.0089	0.0030	obs		1827	

Note: ***, ** and * indicate significance at the levels of 1%, 5%, and 10%, respectively.

We analyzed the sign and significance of the coefficients of each variable from the translog production function. The coefficient of the first-order term 'forestry capital investment' is significantly negative, the coefficient of the quadratic term is not significant, and the coefficient of the interaction term with time is significantly positive. This shows that over time, technological progress can effectively reduce forestry capital investment and improve the technical efficiency of forest vegetation carbon sequestration. The coefficient of the first-order term 'labor input' (number of employees) and the coefficient of the interaction term with time are significantly negative, and the coefficient of the quadratic term is insignificant. This shows that technological changes causing increases in forest vegetation carbon sequestration have resulted in a continuous reduction in labor input. The coefficient of the first-order term 'afforestation and tending area input' is significantly negative, the coefficient of the second-order term is not significant, and the coefficient of the interaction term with time is significantly positive. This shows that technological progress can promote the quality improvement of afforestation and tending.

Both the linear and quadratic coefficients of the time trend variables are significantly negative. This shows technological progress in forest vegetation carbon sequestration during the sample period, but the rate of technological progress shows a decreasing trend. From the interaction term, the coefficients of forestry capital investment and labor input, labor input and afforestation, and tending area input are all significantly positive. This shows that there is complementarity between the above two groups of variables.

4.2. Technical Efficiency Change and Heterogeneity Analysis

This work estimated the technical production efficiency of forest vegetation carbon sequestration in the study area from 2000–2020 based on Equation (3), as shown in Figure 5. From 2000–2020, the technical efficiency of forest vegetation carbon sequestration in the 87 SOFEs showed an overall increasing trend, with an average value of 0.78. The technical efficiency value increased from 0.67 in 2000 to 0.86 in 2020, and the technical efficiency increased by 28.36% compared with 2000.

From the perspective of the six forest industry groups to which the SOFEs belong, the technical efficiency of each forest industry group is on the rise. The gap in technical efficiency is narrowing over time. In 2000, the technical efficiency of forest vegetation carbon sequestration of the different forest industry groups was quite variable, with a range of 0.24 between the maximum and minimum values. In 2020, the technical efficiency of all forest industry groups was basically the same, and the difference between the maximum and minimum values was only 0.06. This phenomenon is consistent with the β-convergence theory. Among them, the technical efficiencies of forest vegetation carbon sequestration for the Great Khingan Forestry Group and the Inner Mongolia Forest Industry Group were significantly higher than average, with mean values of 0.85 and 0.81, respectively. The technical efficiencies of the Longjiang Forest Industry Group and Changbai Mountain Forest Industry Group remained at the average level. The average of the two forestry industry groups was approximately 0.78. The technical efficiencies of the Jilin Forest Industry Group and Yichun Forest Industry Group were lower than the average level, and the average of the two forest industry groups was approximately 0.73.

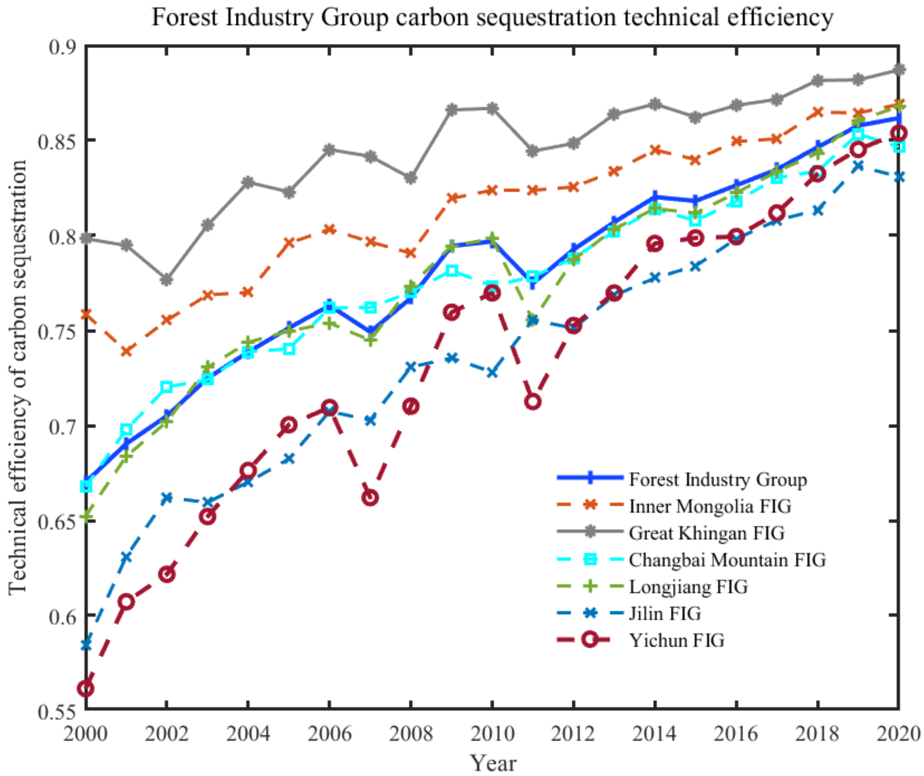

Figure 5. Temporal trend in forest vegetation carbon sequestration technical efficiency of forest industry groups.

Specifically, from 2000–2020, the technical efficiency value of Yichun Forest Industry Group increased from 0.56 to 0.85, an increase of 52.03% compared with 2000, which was the largest increase. The technical efficiency of carbon sequestration for the Jilin Forest Industry Group increased from 0.58 to 0.83, an increase of 42.25%, second only to that of the Yichun Forest Industry Group. This was followed by the carbon sequestration technical efficiency of the Longjiang Forest Industry Group, which increased by 33.07% from 0.65 to 0.87. The carbon sequestration technical efficiency of the Changbai Mountain Forest Industry Group increased from 0.67 to 0.85, an increase of 26.78%. The carbon sequestration technical efficiency of the Inner Mongolia Forest Industry Group increased from 0.76 to 0.87, an increase of 14.54%. Lastly, the carbon sequestration technical efficiency of the Great Khingan Forestry Group increased from 0.80 to 0.89, an increase of 11.12%, which was the smallest increase.

4.3. Impact of Management Scale on the Technical Efficiency of Forest Vegetation Carbon Sequestration

4.3.1. Threshold Effect Test Results

In this work, the number of thresholds was selected according to the results of the threshold effect test. According to Table 5, the F-statistic and the corresponding P value indicate that the management scale has a threshold effect on the technical efficiency of forest vegetation carbon sequestration output. The F-statistic of the single-threshold model and the double-threshold model were 197.85 and 105.32, respectively, and both passed the 1% significance level test. The confidence interval for a single threshold is [23.1136, 23.4472], and the confidence intervals for a double threshold are [23.0075, 23.4472] and [35.2174, 36.3699]. Based on the above analysis, it is concluded that the double-threshold model should be selected for the study. When the corresponding likelihood ratio statistic LR is 0, the estimated threshold parameters are 23.2777 and 35.9804, respectively.

Table 5. Test results of the threshold effect.

Threshold Type	Threshold Level	F Value	*p*-Value	BS Times	Threshold	Confidence Interval
Single threshold	(pfgc1)	197.85 ***	0.0000	300	23.2777	[23.1136, 23.4472]
Double threshold	(pfgc1)	105.32 ***	0.0000	300	23.2777	[23.0075, 23.4472]
	(pfgc2)			300	35.9804	[35.2174, 36.3699]

Note: *** indicates significance at the significance level of 1%; the *p*-value and critical value are obtained by repeated sampling 300 times using the Bootstrap method.

4.3.2. Analysis of the Threshold Effect of Management Scale

The study used Stata 16 software to perform regression and examine the factors influencing forest vegetation carbon sequestration technical efficiency and the threshold effect of management scale in 87 SOFEs in Northeast China. The specific results are shown in Table 6.

Table 6. Analysis of factors influencing carbon sequestration technical efficiency and the threshold effect of management scale.

Variable	Model (1)		Model (2)		Model (3)	
	Coef.	Std.Err	Coef.	Std.Err	Coef.	Std.Err
lnscale	0.0474 ***	0.0073				
lnscale (scale < 23.2777)			−0.0102 **	0.0043	−0.0096 **	0.0044
lnscale (23.2777 < scale < 35.9804)			0.0078 **	0.0039	0.0084 **	0.0039
lnscale (35.9804 < scale)			0.0175 ***	0.0033	0.0180 ***	0.0033
lnmanage					−0.0002	0.0002
lntov	0.0192 ***	0.0033	0.0190 ***	0.0013	0.0190 ***	0.0013
lnwage	0.0258 ***	0.0033	0.0284 ***	0.0021	0.0287 ***	0.0021
lntimber	−0.0018 ***	0.0004	−0.0017 ***	0.0002	−0.0017 ***	0.0002
lnafforest	0.0128 ***	0.0047	0.0111 ***	0.0028	0.0116 ***	0.0029
$lnafforest^2$	−0.0011 ***	0.0003	−0.0009 ***	0.0002	−0.0009 ***	0.0002
lnper	0.0397 ***	0.0062	0.0451 ***	0.0052	0.0433 ***	0.0054
lntemp	−0.0265 ***	0.0055	−0.0234 **	0.0095	−0.0224 **	0.0096
lnwind	0.0116 ***	0.0024	0.0108 ***	0.0035	0.0106 ***	0.0035
lnsun	0.0668 ***	0.0110	0.0831 ***	0.0111	0.0750 ***	0.0131
lnhumidity	−0.0100	0.0301	−0.0388	0.0237	−0.0366	0.0238
R-sq (overall)	0.7249		0.7159		0.7165	
_cons	−0.6588 ***	0.2193	−0.6107 ***	0.1493	−0.5503 ***	0.1576

Note: *** and ** indicate significance at the levels of 1% and 5%, respectively.

(1) The factors affecting the technical efficiency of forest vegetation carbon sequestration were explored using a fixed-effect model (1). The results showed that the scale of forest management had a significant positive impact on the technical efficiency of carbon sequestration ($p < 0.01$), and the coefficient value was 0.0474. This indicates that for every 1% increase in business scale, the technical efficiency of carbon sequestration increases by 0.0474. The total output value of the SOFEs had a significant positive impact on the technical efficiency of carbon sequestration ($p < 0.01$), and the coefficient value was 0.0192. This indicates that for every 1% increase in the total output value of the SOFEs, the technical efficiency of the carbon sequestration increases by 0.0192. This increase is because, after the ban on logging in natural forests, the sources of the total output value in SOFEs are mostly based on the primary and tertiary industries, which directly or indirectly enhance forest management and improve the technical efficiency of carbon sequestration. Employee wages had a significant positive impact on the technical efficiency of carbon sequestration

($p < 0.01$), and the coefficient value was 0.0258. This indicates that for every 1% increase in employee wages, the technical efficiency of carbon sequestration increases by 0.0258. This shows that increasing the employee wages of various SOFEs will have a better incentive effect. Wood yield had a significant negative effect on carbon sequestration technical efficiency ($p < 0.01$), with a coefficient value of −0.0018. This shows that for every 1% increase in wood production, the technical efficiency of carbon sequestration decreases by 0.0018. This is mainly due to a reduction in the stock of standing trees in forests that have been cleared for afforestation. Among the key environmental control variables, precipitation from March–November and annual sun duration had a significant positive impact on carbon sequestration technical efficiency ($p < 0.01$), with coefficient values of 0.0397 and 0.0668, respectively. For every 1% increase in precipitation and sun duration, the technical efficiency of carbon sequestration increases by 0.0397 and 0.0668, respectively. The R^2 of the model (1) is 0.7249, and the goodness of fit is high. Moreover, the statistical significance and economic significance of the model results are good. This result agrees with the forest growth principle and theoretical expectation, which demonstrates the reliability of the model's logic and results.

The regression results of the panel fixed-effect model indicate that the scale of operation has a significant linear impact on the technical efficiency of carbon sequestration. However, due to the scale effect, the impact of forest management scale may differ over different scale ranges. That is, there may be a nonlinear relationship between the two variables.

(2) The impact of different forest management scales on the technical efficiency of carbon sequestration was estimated using model (2). According to the panel double-threshold model, different forest management scales significantly affect the technical efficiency of carbon sequestration ($p < 0.01$), but there is strong heterogeneity. From the results of model (2), it can be seen that the large-scale management effect of forestry is better. When the management scale value (total forest management area of each SOFE/annual average number of employees) was less than 23.2777, the management scale had a significant negative impact on the technical efficiency of carbon sequestration ($p < 0.05$), and the coefficient value was −0.0102. For every 1% increase in the forest management scale in this range, the technical efficiency of carbon sequestration decreases by 0.0102. This indicates staff redundancy, and forest management has not yet reached a certain scale, which is not conducive to improving technical efficiency. When the forest management scale is greater than 23.2777 and less than 35.9804, the forest management scale has a significant positive impact on the technical efficiency of carbon sequestration ($p < 0.05$), and its coefficient value is 0.0078. For every 1% increase in forest management scale, the technical efficiency of carbon sequestration increases by 0.0078. When the forest management scale is greater than 35.9804, the forest management scale has a significant positive impact on the technical efficiency of carbon sequestration ($p < 0.01$), and the coefficient value is 0.0175. For every 1% increase in forest management scale, the technical efficiency of carbon sequestration increases by 0.0175. This means that when the forest management scale is greater than 23.2777, increasing the forest management scale has a significant positive impact on technical efficiency, but the coefficient value of the 35.9804 threshold value is 124.36% higher than that of the 23.2777 threshold value. The regression results of the other control variables are basically consistent with the direction and coefficient of the model (1).

Figure 6 shows the estimation results corresponding to the threshold values of 23.2777 and 35.9804. The lowest point of the LR statistic is the corresponding true threshold value, and the dotted line represents the critical value of 7.35. Since the critical value of 7.35 is larger than the two threshold values, it can be considered that the above threshold values are real and effective.

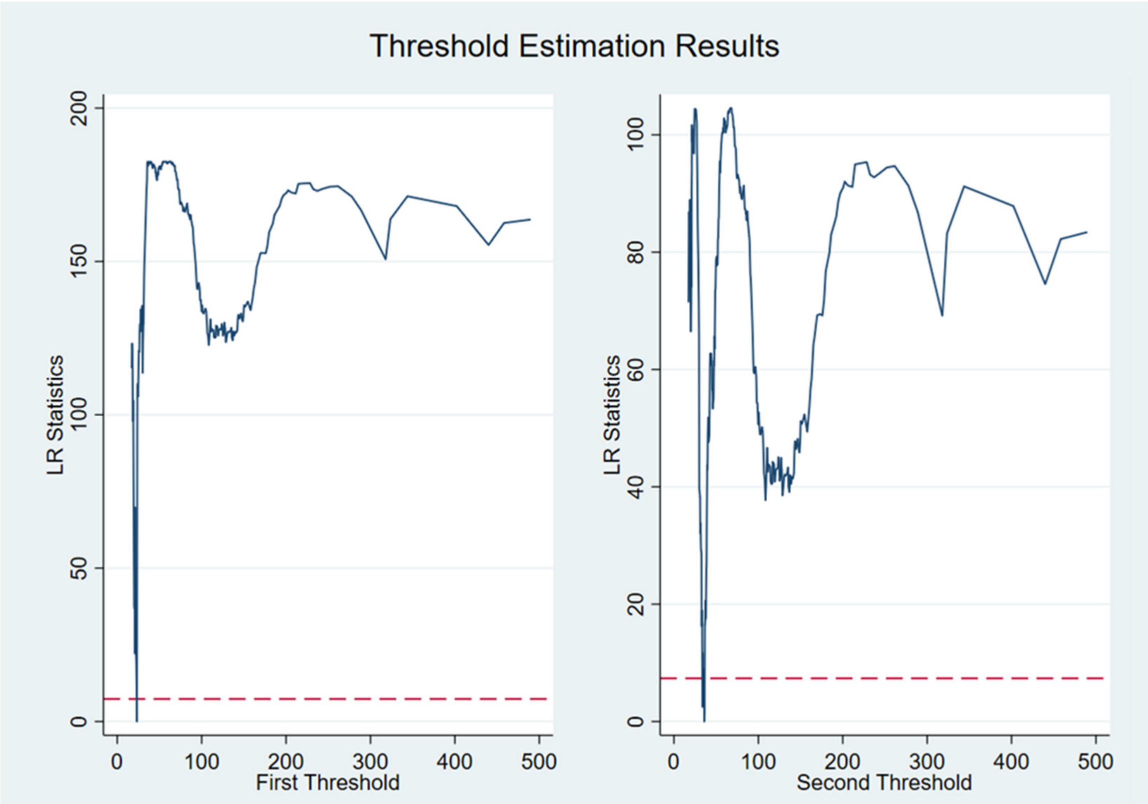

Figure 6. Double-threshold estimation results.

(3) Robustness test. To confirm the robustness of the above results, we used the method of increasing the forest management and protection area as a control variable for robustness testing. However, the regression result for this variable was not statistically significant. However, it can be seen from the model (3) that the regression results of other variables are basically consistent with the directions and coefficients of models (1) and (2), and the scale effect remained significant.

5. Discussion

In the context of carbon neutrality in 2060, China faces a high cost of increasing carbon sequestration. Measuring the technical efficiency of forest vegetation carbon sequestration and its influencing factors helps to identify existing problems and the potential for future increases in carbon sequestration. In this study, using SOFEs in Northeast China as an example and accounting for resource endowment to the greatest possible extent, an evaluation system of forest vegetation carbon sequestration technical efficiency and its influencing factors was constructed. From the perspective of forest management scale, the system provides specific solutions for improving the technical efficiency of forest vegetation carbon sequestration.

First, most research on forest vegetation carbon sequestration concerns the value of its ecosystem services and focuses on the accuracy of measurements and calculations [44]. Examples include the processing and use of remote sensing imagery [45,46], using NPP to calculate carbon sequestration [28], measuring carbon sequestration potential in specific social and natural contexts [47], and the role of carbon sequestration in improving soil productivity, air and water quality, and biodiversity conservation [48]. These studies provide a very strong theoretical database for our research. However, this part of the research is mainly limited to remote sensing and ecological fields and is less integrated with economic models. Moreover, many studies have linked forest vegetation carbon sequestration to climate change, using economic models to measure the risk of forest management [49]. This work also provides a reasonable basis for including natural meteorological factors in our models. Additionally, in terms of the cost-effectiveness of forest vegetation carbon sequestration, there have been many high-quality studies that have explored forest vegetation carbon sequestration from land, social, and capital perspectives and have combined forest management with carbon sequestration effects [50–52]. However, there are few regional studies on SOFEs in China, and there is a further lack of investigation on the scale effect of forest management. Regarding modeling carbon sequestration efficiency, some scholars use DEA models that combine distance functions to represent multiple output and input variables [53,54]. Some studies have also used this method in combination with time series to evaluate the ecoefficiency of complex forestry [55]. However, the noise in the process of carbon sequestration production cannot be avoided, and the results of such a study may have strong limitations. There is room for synthesizing previous studies concerning the topic explored in this paper.

Our research deepens previous studies on forest vegetation carbon sequestration production efficiency, model setting, variable selection, and efficiency optimization. This study differs from previous studies in the following primary ways: (1) Use of remote sensing data and ArcGIS software to quantify large-scale and long-term carbon sequestration at the raster scale. This was combined with an econometric model to base decisions on the heterogeneity of regional natural conditions; (2) Visualization of the spatiotemporal changes in land use and carbon sequestration of the 87 SOFEs, which is convenient for the comparison and analysis of the individual enterprises; (3) Use of the SFA method. First, the inefficiency term that affects the forest vegetation carbon sequestration efficiency is separated from the stochastic disturbance factors. Second, the technical efficiency of forest vegetation carbon sequestration for each SOFE and the relationships between each input element were obtained. Third, the variation and heterogeneity of the technical efficiency of the SOFEs during the study period were analyzed. This helps identify the overall changes and individual gaps in the efficiency of carbon sequestration technology among forest industry groups; (4) Taking the forest management scale as the threshold variable, the nonlinear relationship between the management scale and the technical efficiency of forest vegetation carbon sequestration is depicted. Additionally, the most important meteorological factors affecting forest vegetation carbon sequestration were incorporated into the measurement model to explore the factors affecting the technical efficiency of forest vegetation carbon sequestration. This fully verified the impact of different management scales on the technical efficiency of forest vegetation carbon sequestration.

The research significance and contribution of this study lie mainly in the analysis of the spatial characteristics of SOFE forest vegetation carbon sequestration and land use changes in Northeast China in the form of data and measurement models to facilitate scientific research. Using the SFA method and input-output data to measure the technical efficiency of carbon sequestration helps to control the cost of carbon sequestration and improve efficiency from an economic perspective. The key natural meteorological factors that affect the effects of forest management are incorporated into the measurement system of factors influencing technical efficiency, which can better control the spatial heterogeneity of natural resource endowments. From the perspective of management scale, the nonlinear relationship between the two is studied in depth to provide a theoretical basis and practical path for improving the technical efficiency of forest vegetation carbon sequestration in SOFEs. Additionally, this will help promote the high-quality and sustainable development of state-owned forests and aid China in achieving carbon neutrality by 2060.

Examining the evolutionary trend of forest vegetation carbon sequestration in SOFEs, our results show the same trend as most studies [56,57]. Following the implementation of a series of forestry ecological projects in China, an overall increase in the level of forest vegetation carbon sequestration is manifested on a large scale. Regarding forest management objectives, society's demands on forest management are becoming more diverse [58]. In the context of carbon neutrality, we aim to investigate ways to optimize the efficiency of forest vegetation carbon sequestration technologies. Therefore, we measured the factors influencing technical efficiency, including management scale, total output value of the forest industry, employee wages, and timber production, and included natural meteorological factors in the model. Our study differs from forest management, which prioritizes and quantifies demand for ecosystem services by measuring carbon sequestration efficiency as an objective [59]. Previous research methods have not yet incorporated nonlinear models into the study of the effect of management scale on the technical efficiency of carbon sequestration, which can easily lead to waste of human capital and inefficiency in forest management. In this paper, the technical efficiency interval of carbon sequestration by management scale shows a scale effect, and technical efficiency increases with the increase of management scale. This may differ from the results obtained in temperate and boreal forest areas in Europe, where authors have used a forest growth model to simulate the relation between increasing management intensity and reducing the carbon sequestration capacity of forests [60]. Of course, we can also improve the technical efficiency of carbon sequestration, for example, through incentive programs [61].

However, it is difficult to show the economic benefits of some investments in forest management measures, such as salvage logging and some subsequent management steps in the short term. Therefore, we are planning the use of funds in such a way that simply reducing investments may lead to significant carbon losses in the future. Therefore, state-owned forestry groups, as well as SOFEs, should use investments more effectively to achieve specific forest management objectives according to the conditions of their own forest stands.

Additionally, the technical efficiency of SOFE forest vegetation carbon sequestration is also affected by internal supervision and management methods, staff quality, government policies, and the forest tourism market [62]. Improving the technical efficiency of forest vegetation carbon sequestration still faces many difficulties in practice, and we will continue to explore and improve them in the future. Furthermore, the development of the digital economy has impacted the traditional management methods of various industries. The digital economy has the characteristics of decreasing marginal cost but increasing marginal benefit. All forest industry groups should develop the digital forestry economy and effectively promote the reform of forest management methods.

Our study also has limitations. From the perspective of forest tenure, our research focuses only on state-owned forests. Among the forestland area in China, state-owned forestland comprises 130.8145 million hectares, accounting for 40.41% of the total forestland area, and collective forestland comprises 192.871 million hectares, accounting for 59.59%. Due to the different forms of forest tenure, the technical efficiency of forest vegetation carbon sequestration between state-owned and collective forests may differ. In collective forestland, it is unclear whether the expansion of the forest management scale can improve the technical efficiency of carbon sequestration. However, for the initial stand level and the growth cycle of the stand, forest vegetation carbon sequestration may depend at some level on the stand condition and age or may have unknown pathways throughout the rotation period. Therefore, there may be a time constraint in the model setting for the 21-year data set for forest management and carbon stock resilience. This may possibly invalidate the study results over a long period. Using the SFA model, we have also not considered the spatial spillover effects of input and output variables, which may lead us to overestimate the technical efficiency of forest vegetation carbon sequestration. We will further explore technical efficiency after spatial correction in future research.

In the future, we can study the differences and reasons for the technical efficiency of collective forests and state-owned forests. There is still plenty of room for research and exploration of the differences between the two. There are great challenges in quantifying, assessing, and improving the productivity of forest vegetation carbon sequestration by region. Research in this area will help form a differentiated theoretical basis for forest management to support sustainable forestry practices in state-owned and collective forests, reduce the cost of forest vegetation carbon sequestration, and promote the process of carbon neutrality in China.

6. Conclusions

Improving the technical efficiency of forest vegetation carbon sequestration is an effective way to promote the pace and reduce the cost of carbon neutrality in China. This study used a 21-year panel data set of 87 SOFEs in Northeast China as an example and mainly used the stochastic frontier model and the panel threshold model to analyze and improve the technical efficiency of forest vegetation carbon sequestration. The main research conclusions are as follows:

(1) During the period from 2000–2020, the overall carbon aggregation of SOFEs showed an upward trend, with a total growth rate of approximately 22.17%, but the overall fluctuation was relatively large. From the perspective of spatial changes, the growth rate of carbon sequestration shows a phenomenon of "increase overall and decrease in small areas". The nuclear density curve of the forest vegetation carbon sequestration also shows that the carbon sequestration of each SOFE increases significantly;

(2) The results of the stochastic frontier model show that over time, technological progress can effectively reduce forestry capital investment and improve the technical efficiency of forest vegetation carbon sequestration. Moreover, technological changes in forest vegetation carbon sequestration have led to a continuous reduction in labor input. Furthermore, technological progress can improve the quality of afforestation and tending. Additionally, there was technological progress in forest vegetation carbon sequestration during the study period, but the rate of technological progress showed a decreasing trend. From the perspective of the six forest industry groups, the technical efficiency of each forest industry group is on the rise, and the gap in technical efficiency is narrowing over time;

(3) Employee wages, total output value of SOFEs, forest management scale, precipitation from March–November, and annual sun duration have a significant positive impact on the technical efficiency of carbon sequestration. Wood yield has a significant negative impact on carbon sequestration technical efficiency. Different forest management scales significantly affect carbon sequestration technical efficiency, but there is strong heterogeneity. The threshold values of the model are 23.2777 and 35.9804, respectively, indicating that the efficiency of large-scale forestry management is relatively high and there is a scale effect in forest management.

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