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Environmental Degradation and Its Implications for Forestry Resource Efficiency and Total Factor Forestry Productivity in China

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Abstract

Environmental costs (carbon emissions) have come with China's economic rise, and its forestry sector now faces difficulties in maintaining both its profit and the health of its ecosystems. This study assesses the impact of carbon emissions on forestry efficiency and total factor productivity (TFFP) in China's 31 provinces between 2001 and 2021. Using the data envelopment analysis (DEA) model through the slack-based measure (SBM framework) and Malmquist–Luenberger index (MLI), we examine the efficiency and productivity growth of forestry, both with and without accounting for carbon emissions. The study reveals that when carbon emissions are not taken into account, traditional measures of productivity tend to overstate both efficiency and total factor forestry productivity (TFFP) growth, resulting in an average of 7.7 percent higher efficiency and 1.6 percent of additional TFFP growth per year. If we compare the regions, coast provinces with stricter technical regulations have improved efficiency in usage, but places like Tibet and Qinghai, with more vulnerable ecosystems, endure harsher consequences. Regardless of incorporating bad output into the TFFP estimation, China's growth in forestry productivity primarily depends on efficiency change (EC) rather than technological change (TC).

Keywords: forestry efficiency; Chinese provinces; carbon emissions; environmental degradation

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1. Introduction

Improving living conditions requires economic growth; however, it also significantly increases environmental damage and greenhouse gas emissions. The reliance on fossil fuels for energy, industrial activities, and urban growth exacerbates climate change, which in turn raises global temperatures, causes extreme weather events, and harms ecosystems [1]. Traffic emissions and industrial operations degrade air quality, hence creating significant health risks, including respiratory and cardiovascular diseases [2]. Industrial waste and agricultural chemicals harm water supplies, thus causing pollution, depletion, and environmental disruptions [3]. Furthermore, large-scale deforestation for farming and infrastructure purposes reduces the Earth's ability to store carbon dioxide, thereby aggravating ecological damage and endangering biodiversity [4]. Often caused by inappropriate land practices, soil erosion and desertification threaten food security and agricultural production [5].

One of the primary causes of environmental degradation is deforestation, which significantly exacerbates climate change, biodiversity loss, and ecological instability. Forests naturally store carbon dioxide, thereby helping to regulate the climate. However, large-scale deforestation increases greenhouse gas levels, exacerbating global warming and contributing to extreme weather events [6]. Moreover, deforestation compromises the hydrological cycle by reducing soil moisture retention, hence amplifying drought and desertification. Compromising food security depletes soil nutrients, causes erosion, and reduces agricultural production. The destruction of forest ecosystems displaces many species, resulting in habitat loss and reduced biodiversity [7]. Furthermore, by filtering toxins and producing oxygen, trees play a crucial role in air purification; thus, their loss compromises the quality of the air [8]. The loss of forest cover increases the likelihood of deforestation, which in turn increases the probability of natural disasters, such as landslides and floods, in many parts of the world [9]. Regional hydrology is seriously disrupted because of deforestation, increasing the vulnerability to climate change. Deforestation has the same effect of decreasing evapotranspiration and rainfall recycling, which deepens continental droughts and dries out the groundwater supply during dry times [10]. At the same time, reduced root systems and more soil organic matter led to more flood danger due to the increase in surface runoff that creates destructive sedimentation and floods downstream. This twin hydrological imbalance of increasing the rates of drought at the same time as causing the severity of floods is an illustration of how human-induced forest degradation is increasing climate risks [11].

Reconciling economic development with environmental sustainability depends on maximizing forestry resource efficiency and raising total factor forestry productivity (TFFP). Efficient resource management ensures the prudent use of non-timber resources and wood, thereby minimizing waste [12]. Enhancing TFFP through innovative technologies, sustainable forestry practices, and efficient regulations enhances production while preserving biodiversity and increasing carbon sequestration [13]. It also promotes long-term economic stability by guaranteeing resource availability, creating jobs, and supporting forest-related businesses [14]. Utilizing techniques such as precision forestry, circular bioeconomy frameworks, and reforestation projects can enhance output while preserving environmental integrity, thereby ensuring a sustainable future for forests and the economy [15]. In addition to deforestation, forestry practices themselves are also developing different threats to the environment. Unsustainable logging operations lead to soil compaction and erosion, poor water quality in watersheds, as a result of sediment runoff, and the breaking of important wildlife habitats [16]. Although monoculture plantations may enhance the timber, they are likely to lower the resilience of biodiversity and predispose it to invasive pests and diseases [17]. Also, when there is a problem of mismanagement, natural fire regimes may also be distorted, resulting in either an unnaturally intense wildfire or an absence of a fire that must occur to promote the regeneration of some types of ecosystems [18]. These problems aggravate the more general problems of climate and biodiversity losses with a very high urgency in seeking forestry practices that are active and aim at reducing degradation of the ecosystem and sustaining productivity [19].

Over the last forty years, China's rapid industrial expansion has led to significant environmental problems, including severe air pollution, deforestation, water contamination, and increased greenhouse gas emissions. The air quality of major cities was harmed by their significant dependence on coal and extensive industrial activities [20]. To reduce emissions, the government implemented programs, including the Blue Sky Defence Plan and the Air

Pollution Action Plan, increased funding for renewable energy, and pledged to achieve carbon neutrality by 2060 [21,22]. Furthermore, programs such as carbon trading systems, afforestation projects, and strengthened water protection laws have been implemented to reduce environmental damage and promote sustainable development [23,24]. However, data shows that pollution has been on the rise in China in the last few years [25].

By initiating large-scale planting projects, such as the "Green Great Wall", and emphasizing sustainable forest management, China has significantly expanded its forest cover [26]. To enhance forestry efficiency and productivity, the government has utilized modern technology, including satellite monitoring. Simultaneously, it has backed green financing, motivating companies to implement environmentally friendly policies and fund forest rehabilitation [27]. China is not only combating pollution but also ensuring its forests flourish through regulations that encourage carbon trading and financial incentives, ultimately benefiting both the nation's ecology and economy in the long run.

Numerous research studies explore the forestry efficiency level and total factor forestry productivity growth in China through secondary data analysis [28–31]. However, the level of success in enhancing forestry efficiency and promoting productivity growth with minimal environmental degradation in China remains unexplored, highlighting an academic research gap that needs further investigation. Therefore, this study has contributed several ways to the existing forestry literature. First, this research employed the data envelopment analysis (DEA) SBM model to assess the forestry efficiency of China's 31 mainland provinces and municipalities, exploring the effectiveness of government policies on forestry during the study period of 2001–2021. In the second stage, research incorporates carbon emissions into the inputs-outputs bundle of the efficiency estimation process to explore the impact of environmental degradation on forestry efficiency in different provinces. The difference in efficiency scores with and without the inclusion of bad output will explore the diverse effect level of carbon emissions on forestry efficiency over the study period. Thirdly, the research employed the Malmquist–Luenberger index (MLI) to gauge total factor forestry productivity growth, both with and without considering bad output (carbon emissions), thereby assessing the level of variance in productivity scores across Chinese mainland provinces over the study period. It further examines the factors influencing total factor forestry productivity change in forestry, including efficiency changes and technological changes. The rest of the study is organized as follows: The methodology is illustrated in Section 2. Section 3 explicates the method of variable selection and data collection. Results and Discussion are illustrated in Section 4, while Section 5 of the manuscript describes the study's conclusion.

2. Methodology

Data envelopment analysis (DEA) is a nonlinear programming technique extensively used to gauge homogeneous decision-making units' efficiency and productivity change (DMUS). Conventional DEA models are used to estimate technical efficiency and pure technical efficiency with scale effect [32,33]. Later, the SBM model was developed to gauge the efficiency of different units [34]. This study used the SBM model, which can incorporate the undesirable output during the estimation process.

2.1. DEA SBM with Undesirable Outputs

Let's consider a scenario with *n* decision-making units (DMUS), where each DMU utilises three types of factors:

1. Inputs $x \in R^m$: Resources consumed in the production process;
2. Good outputs $y^g \in R^{s_1}$: Desirable products or services generated;
3. Bad outputs $y^b \in R^{s_2}$: Undesirable byproducts (e.g., pollution, waste).

These factors can be organized into three matrices representing all DMUs:

- Input matrix: $= [x_1, \cdots, x_n] \in R^{m \times n}$;
- Good output matrix: $Y^g = \left[y_1^g, \cdots, y_n^g\right] \in R^{s_1 \times n}$;
- Bad output matrix: $Y^b = \left[y_1^b, \cdots, y_n^b\right] \in R^{s_2 \times n}$.

We make the following assumptions about these matrices:

- All input values are positive (X > 0);
- All good outputs are positive ($Y^g > 0$);
- All bad outputs are positive ($Y^b > 0$).

The production possibility set (P) represents all feasible combinations of inputs and outputs that the DMUs can achieve. This set captures the technological relationships between the inputs used, the desirable outputs produced, and the unavoidable undesirable outputs generated in the production process. This formulation provides the foundation for analyzing efficiency while explicitly accounting for both the beneficial outputs and the environmentally harmful byproducts of production activities. The positive values assumption ensures that all DMUs consume inputs and produce both types of outputs, making the efficiency evaluation meaningful and practically relevant.

$$P = \left\{\left(x, y^g, y^b\right) \mid x \geq X\lambda, y^g \leq Y^g\lambda, y^b \geq Y^b\lambda, \lambda \geq 0\right\} \tag{1}$$

The vector $\lambda \in R^n$ represents the intensity weights assigned to each DMU in constructing the production frontier. This formulation assumes constant returns to scale (CRS), where all production activities can be scaled proportionally. Alternative returns to scale scenarios will be examined later in Section 4. The SBM model is fundamentally flexible and can incorporate CRS, VRS (variable returns to scale), or other returns-to-scale assumptions via constraints on the intensity vector.

Definition 1. (Efficient DMU with Undesirable Outputs).

A decision-making unit DMU $U_o\left(x_o, y_o^g, y_o^b\right)$ *is considered efficient when:*

No alternative production combination $\left(x, y^g, y^b\right)$ *exists within the production possibility set P that can achieve:*

Equal or fewer inputs ($x \leq x_0$) $x_o \geq x$;
Equal or more good outputs $y_o^g \leq y^g$;
Equal or fewer bad outputs $y_o^g \leq y^g$.
At least one of these inequalities is strictly better (either strictly less input, strictly more good output, or strictly less bad output).

Building on this efficiency definition, we adapt Tone's (2004) [34] *slack-based measure (SBM) model to properly account for undesirable outputs in our evaluation framework. This modification ensures our efficiency measurement simultaneously considers input minimization, desirable output maximization, and undesirable output minimization.*

$$[\text{SBM}]\rho^* = \min \frac{1 - \frac{1}{m}\sum_{i=1}^{m} \frac{s_i^-}{x_{io}}}{1 + \frac{1}{s_1+s_2}\left(\sum_{r=1}^{s_1} \frac{s_y^g}{y_{ro}^q} + \sum_{r=1}^{s_2} \frac{s_r^b}{y_{ro}^b}\right)} \tag{2}$$

subject to

$$x_o = X\lambda + s^- \tag{3}$$

$$y_o^g = Y^g\lambda - s^g \tag{4}$$

$$y_o^b = Y^b\lambda + s^b \tag{5}$$

$$s^- \geq 0, s^g \geq 0, s^b \geq 0, \lambda \geq 0.$$

The model incorporates three types of slack variables that measure inefficiencies:

- *Input slacks* $s^- \in R^m$*: Represent excess amounts of inputs being used;*
- *Good output slacks* $s^b \in R^{s_2}$*: Capture shortfalls in desirable outputs;*
- *Bad output slacks* $s^b \in R^{s_2}$*: Reflect excesses in undesirable outputs.*

The efficiency score ρ^* *is determined by an objective function that exhibits these key properties:*

1. *Strictly decreases as any input excess* (s^-) *or bad output excess* (s^b) *increases;*
2. *Strictly decreases as any good output shortfall* (s^g) *increases;*
3. *Bounded between* 0 *and* 1 $(0 < \rho^* \leq 1)$*, where 1 represents full efficiency.*

When we solve this optimization problem, we obtain an optimal solution consisting of:

- λ^**: Optimal intensity weights for DMU* $s\left(\lambda^*, s^{-*}, s^{g^*}, s^{b^*}\right)$*;*
- s^{-*}*: Optimal input slack values;*
- s^{g^*}*: Optimal good output slack values;*
- s^{b^*}*: Optimal bad output slack values.*

This solution provides a comprehensive evaluation of the DMU's performance by simultaneously considering:

- *How much input reduction is possible;*
- *How much good output could be expanded;*
- *How much bad output could be reduced;*

While maintaining the production possibility constraints.

2.2. Malmquist–Luenberger Index (MLI)

While traditional DEA models effectively measure technical efficiency at a specific point in time, they cannot capture productivity changes over different periods. Researchers have developed dynamic productivity measures to address this limitation and developed the Malmquist productivity index [35]. Chung et al. [36] enhanced the conventional Malmquist productivity index by developing the Malmquist–Luenberger index (MLI), which accounts for undesirable outputs through directional distance functions and enables a more comprehensive assessment of productivity in environmentally sensitive contexts.

The MLI decomposes productivity changes into two meaningful components:

Efficiency Change (EC): measures how well DMUS improves its managerial practices and resource utilization.

Technological Change (TC): captures shifts in the production frontier due to innovation or technological progress.

The MLI calculation between period t and t + 1 can be expressed mathematically as in Equation (6). This formulation enables analysts to distinguish whether productivity improvements stem from better utilization of existing technologies (EC) or technological advancements (TC), providing valuable insights for policy and management decisions.

$$ML^{t+1} = \left\{ \frac{\left[1 + \vec{D}_0^t\left(x^t, y^t, b^*; y^t, -b^t\right)\right]}{\left[1 + \vec{D}_0^t\left(x^{t+1}, y^{+1}, b^{t+1}; y^{t+1}, -b^{t+1}\right)\right]} \times \frac{\left[1 + \vec{D}_0^{t+1}\left(x^t, y^t, b^t; y^t, -b^t\right)\right]}{\left[1 + \vec{D}_0^{t+1}\left(x^{t+1}, y^{+1}, b^{t+1}; y^{t+1}, -b^{s+1}\right)\right]} \right\}^{1/2} \quad (6)$$

$$EC^{x+1} = \frac{1 + \vec{D}_0^t\left(x^t, y^t, b'; y^t, -b^2\right)}{1 + \vec{D}_0^{t+1}\left(x^{t+1}, y^{t+1}, b^{+1}; y^{k+1}, -b^{t+1}\right)}$$

$$TC^{4+1} = \left\{ \frac{\left[1 + \vec{D}_0^{t+1}(x^t, y^t, b^t, y^t, -b^t)\right]}{\left[1 + \vec{D}_0^{t}(x^t, y', b^t; y^t, -b')\right]} \times \frac{\left[1 + \vec{D}_0^{t+1}(x^{t+1}, y^{t+1}, b'^{+1}; y^{t+1}, -b^{t+1})\right]}{\left[1 + \vec{D}_0'(x^{t+1}, y^{t+1}, b^{t+1}; y^{t+1}, -b^{++1})\right]} \right\} \tag{7}$$

The model incorporates three fundamental components:

x: Input quantities;
y: Desirable outputs;
b: Undesirable outputs (environmental byproducts).

We evaluate productivity changes using distance functions calculated for consecutive time periods (t and t + 1). The distance function $\vec{D}_0^t(x^2, y^r, b^r; y^t, -b^t)$ measures efficiency relative to period t's technology, while $\vec{D}_0^{t+1}(x^{s+1}, y^{t+1}, b^{t+1}; y^{t+1}, -b^{t+1})$ assesses performance against period $t+1$'s technological frontier (see Equation (7)).

The cross-period comparisons include:

$\vec{D}_0^t(x^{s+1}, y^{s+1}, b^{t+1}; y^{s+1}, -b^{t+1})$: $t+1$ period performance evaluated against t period technology;
$\vec{D}_0^{t+1}(x^t, y^t, b^t; y^t, -b^t)$: t period performance evaluated against t + 1 technology.

Interpretation Guidelines:

Malmquist–Luenberger index (MLI):

- MLI > 1: Improvement in total factor productivity;
- MLI = 1: Stable productivity;
- MLI < 1: Productivity decline.

Efficiency Change (EC):

- EC > 1: Enhanced operational efficiency;
- EC = 1: Unchanged efficiency;
- EC < 1: Efficiency deterioration.

Technological Change (TC):

- TC > 1: Technological progress;
- TC = 1: Static technology;
- TC < 1: Technological regression.

This framework enables a comprehensive assessment of productivity dynamics by separating efficiency improvements from technological advancements while accounting for desirable and undesirable outputs. The directional vectors (y^t, $-b^t$) emphasize the simultaneous maximization of good outputs and minimization of bad outputs in the productivity measurement.

3. Variable Selection and Data Collection

In the estimation process of DEA evaluation, if variables are not chosen carefully, the results may be biased, the model may be less able to distinguish among alternatives, and it may also violate DEA rules. However, selecting suitable variables helps the model perform better, evaluate data more precisely, maintain good discrimination and remain consistent with the structure of the production process. Researchers argue that when statistical analysis, expert advice and reading literature are used well, variable selection is improved for strong and thorough efficiency checks [37,38]. Therefore, in this study, the inputs and outputs employed to evaluate the forestry efficiency and productivity change are selected from previous research studies that repeatedly used these variables in their research [31,39–41]. Table 1 describes the inputs and outputs that estimate this forestry efficiency and productivity change. Carbon emissions (undesirable outputs) are directly attributable to provincial forestry activities. The data for 31 mainland Chinese provinces were collected from China's Forestry, Grassland Statistical Yearbook and China Energy Statistical Yearbook. The MAXDEA Ultra 9.0 was used for efficiency and productivity evaluation.

Table 1. List of inputs and outputs used to gauge the efficiency and productivity change.

Inputs		Unit
Forest area		10,000 hectares
Investment		10,000 yuan
Employees		10,000 persons
	Outputs	
Forestry output value		100,000,000 yuan
Timber output		10,000 m^3
Forest stock volume		10,000 m^3
	Bad Output	
Carbon emissions		1,000,000 t

4. Results and Discussion

Research on forestry efficiency (FE) both with and without carbon emissions (bad output, BO) provides significant information about China's forestry sector from 2001 to 2021. According to Table 2, forestry efficiency scores decreased significantly when carbon emissions were included, with mean FE scores dropping by 7.7%, from 0.7655 to 0.7064. This decline clearly shows how the harm done to the environment significantly impacts forestry efficiency, especially when clearance escalates during years with fast industrial development, as seen in 2007 and 2013. The results support popular views that provinces in these years used more coal and were more industrialised compared to earlier times. At the same time, the data shows concerted efforts for change in recent years. Scores of FE came close to and in some years surpassed scores that id not have BO adjustments. This result suggests that the improvements in sustainability made by China, such as the Blue Sky Defence Plan and tree-growing efforts, are lowering forestry's environmental impact. Figure 1 shows this trend by showing a U-shaped growth in FE without BO and an improved trajectory for FE with BO since 2020, suggesting that the eventual gains from carbon neutrality efforts are tangible.

The annual variation of FE, presented in Figure 2, adds evidence to our first conclusions. FE declined continuously from 2001 to 2016, and its sharpest decline of −0.081 occurred during the year when industrial emissions were highest. Nevertheless, the situation flipped sharply after 2016, showing an improvement by the end of 2020 (+0.0032). After the country's 2015 Revised Environmental Protection Law was passed and carbon trading pilots were launched, the performance improved, and emissions declined. The results show that certain regions differ in the use and outcomes of these policies. The main reason for the surge in efficiency after 2020 can be attributed to areas like Guangdong and Zhejiang, whose emissions regulations are stricter and have access to the most advanced technology. Alternatively, other provinces such as Inner Mongolia often do not advance in technology and efficiency quickly since they follow old methods and policies. Since such variations exist, acting differently in each area is crucial to support fair progress everywhere. The report shows that environmental degradation has slowed forestry efficiency, but the latest efforts in policy have helped reduce these effects. After adopting BO in 2019, there was an overlap of FE scores from economic and environmental viewpoints, which suggests that environmental protection can still be possible with monetary gains. Even so, unequal development for regions and the evidence of past problems mean we must keep investing in green energy and ensure strong regulations to reach longer-term sustainability. There are numerous research studies that have investigated how carbon emissions adversely impact on forestry output and altimetry, reducing the efficiency of forests output [42,43].

Table 2. Forestry efficiency of Chinese provinces with and without carbon emissions.

Year	FE Without BO	FE with BO	Change in FE
2001	0.7464	0.693	−0.0534
2002	0.7101	0.6538	−0.0563
2003	0.7864	0.7441	−0.0423
2004	0.7356	0.6644	−0.0712
2005	0.7099	0.6354	−0.0745
2006	0.6905	0.6153	−0.0752
2007	0.7124	0.6314	−0.081
2008	0.6812	0.6035	−0.0777
2009	0.7779	0.7086	−0.0693
2010	0.772	0.6958	−0.0762
2011	0.736	0.6599	−0.0761
2012	0.7106	0.6538	−0.0568
2013	0.803	0.7221	−0.0809
2014	0.8143	0.7363	−0.078
2015	0.834	0.7837	−0.0503
2016	0.82	0.7409	−0.0791
2017	0.7953	0.7219	−0.0734
2018	0.8099	0.7559	−0.054
2019	0.809	0.789	−0.02
2020	0.8056	0.8088	0.0032
2021	0.8146	0.8164	0.0018
Mean	0.7655	0.7064	−0.0591

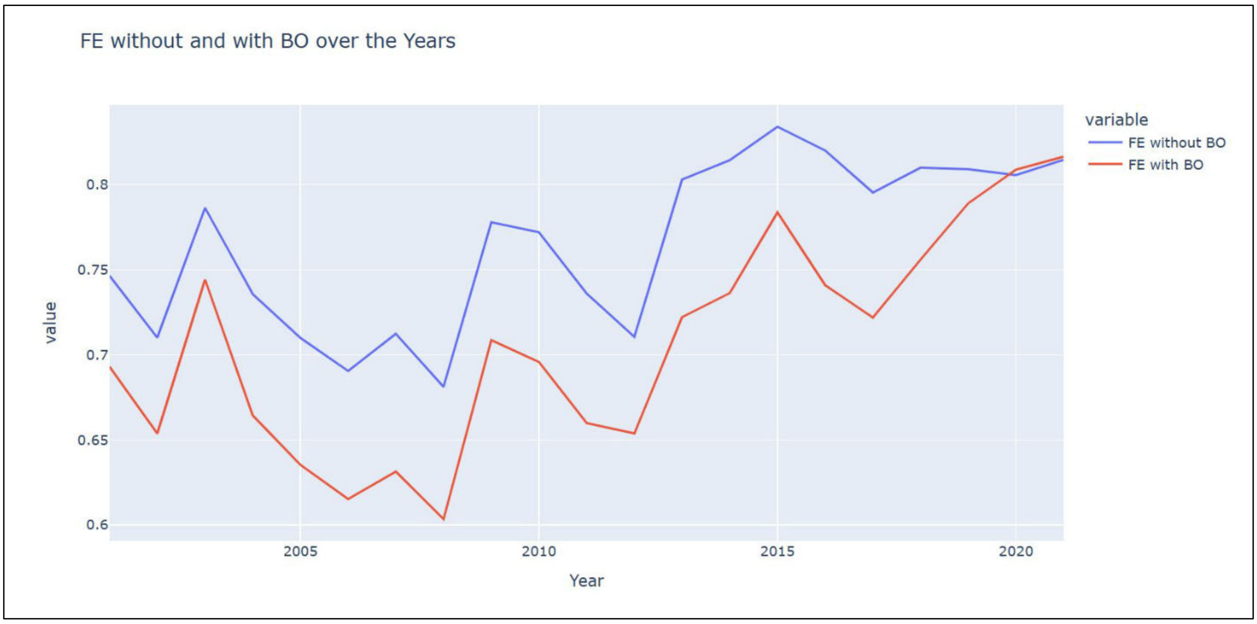

Figure 1. Forestry efficiency level with and without bad output (2001–2021).

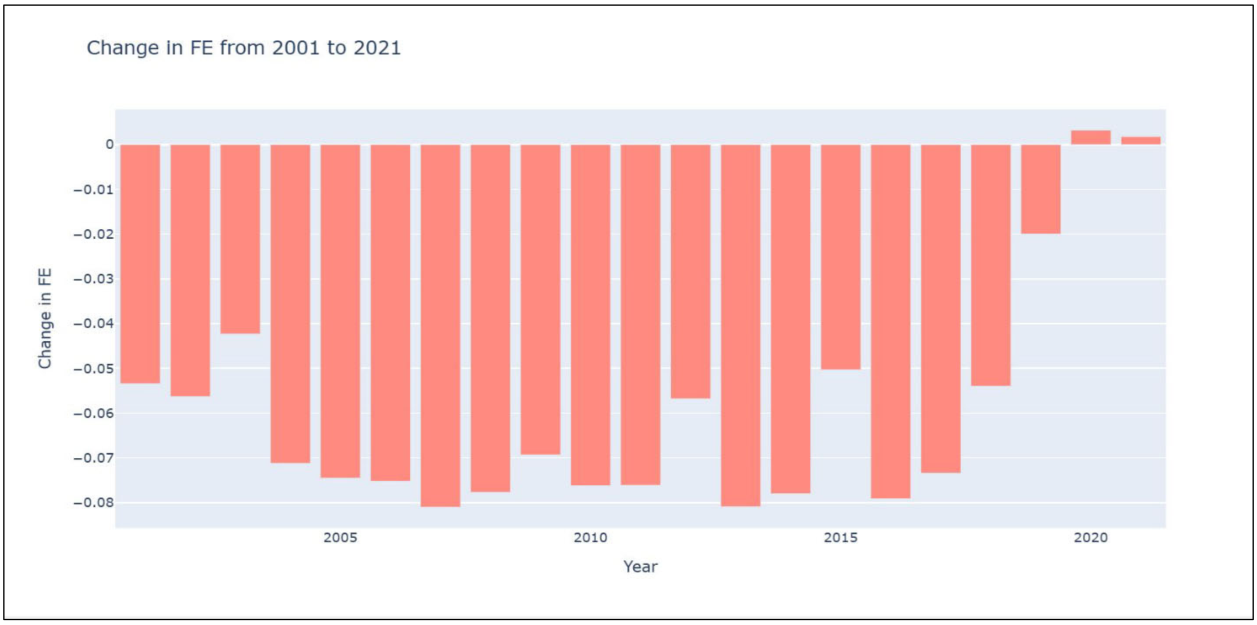

Figure 2. Change in the forestry efficiency level with and without bad output (2001–2021).

Considering and excluding carbon emissions, the FE analysis at the provincial level found that Chinese forestry sector performance varies considerably across regions. Table 3 and Figures 3 and 4 show that if accounting for carbon emissions is considered, the production of forest output often becomes less efficient in most provinces, suggesting significant environmental costs. However, the impacts are very different in different areas due to China's wide range of natural and economic backgrounds. Even though Anhui, Fujian, Hainan and Tibet emit vast amounts of greenhouse gases, they still score perfect efficiency (FE = 1) in sustainable forest management. These areas likely benefit from good natural conditions and strong conservation procedures. The most significant efficiency declines can be seen in western and northern provinces, in places like Qinghai (−0.7911), Gansu (−0.7072), Ningxia (−0.7041) and Inner Mongolia (−0.6334). In these regions, balancing production and emissions control may be tough because of the need for energy-rich irrigation methods, which are affected by water shortages. By contrast, provinces along the developed coast in Guangdong, Shanghai, and Jiangsu have much smaller efficiency gaps, indicating that their advanced equipment and rules make it easier to protect the environment. Shandong province is a noteworthy case, as it achieves greater efficiency in dealing with emissions, which might mean better control of these releases. Numerous research studies explore the impact of forest revenues on economic, social and environmental benefits and endorse our results [44,45].

These results guide how China should continue building a sustainable forestry sector. Because provinces have uneven environmental results, western areas require extra investment and technology to meet their goals. The decent results of some provinces point to the need to spread the most effective forest management practices to other areas. The strong coastal results suggest that technology from these provinces can be applied to inland regions. The findings explain how regional coordination and ecological efforts matter in China, pointing out that specifically targeting interventions in western China can help China reach its national carbon neutrality target. Future rules should aim to improve the observation of emissions, support energy-saving approaches, set up regional carbon markets and use environmental rules adapted to every region's capability. The results from province-based assessments guide efforts to reach China's 2060 carbon neutrality objectives in forestry.

Table 3. Forestry efficiency of Chinese provinces with and without carbon emissions.

Province	FE Without BO	FE with BO	Change
Anhui	1	1	0
Beijing	0.6872	0.6329	−0.3671
Chongqing	0.557	0.5695	−0.4305
Fujian	1	1	0
Gansu	0.3728	0.2928	−0.7072
Guangdong	1.0715	0.9915	−0.0085
Guangxi	1.057	0.9739	−0.0261
Guizhou	0.5818	0.5054	−0.4946
Hainan	1	1	0
Hebei	0.5251	0.4451	−0.5549
Heilongjiang	0.536	0.471	−0.529
Henan	0.7216	0.6416	−0.3584
Hubei	0.5834	0.5034	−0.4966
Hunan	0.7363	0.6795	−0.3205
Inner Mongolia	0.4461	0.3666	−0.6334
Jiangsu	1	0.962	−0.038
Jiangxi	0.7118	0.6692	−0.3308
Jilin	1.0036	0.9166	−0.0834
Liaoning	0.6285	0.5485	−0.4515
Ningxia	0.3758	0.2959	−0.7041
Qinghai	0.2889	0.2089	−0.7911
Shaanxi	0.4351	0.3551	−0.6449
Shandong	0.8241	0.8322	−0.1678
Shanghai	1	0.993	−0.007
Shanxi	0.4704	0.3904	−0.6096
Sichuan	0.5998	0.5791	−0.4209
Tianjin	0.8856	0.8056	−0.1944
Tibet	1	1	0
Xinjiang	0.4422	0.3622	−0.6378
Yunnan	0.9848	0.7148	−0.2852
Zhejiang	0.9706	0.8906	−0.1094

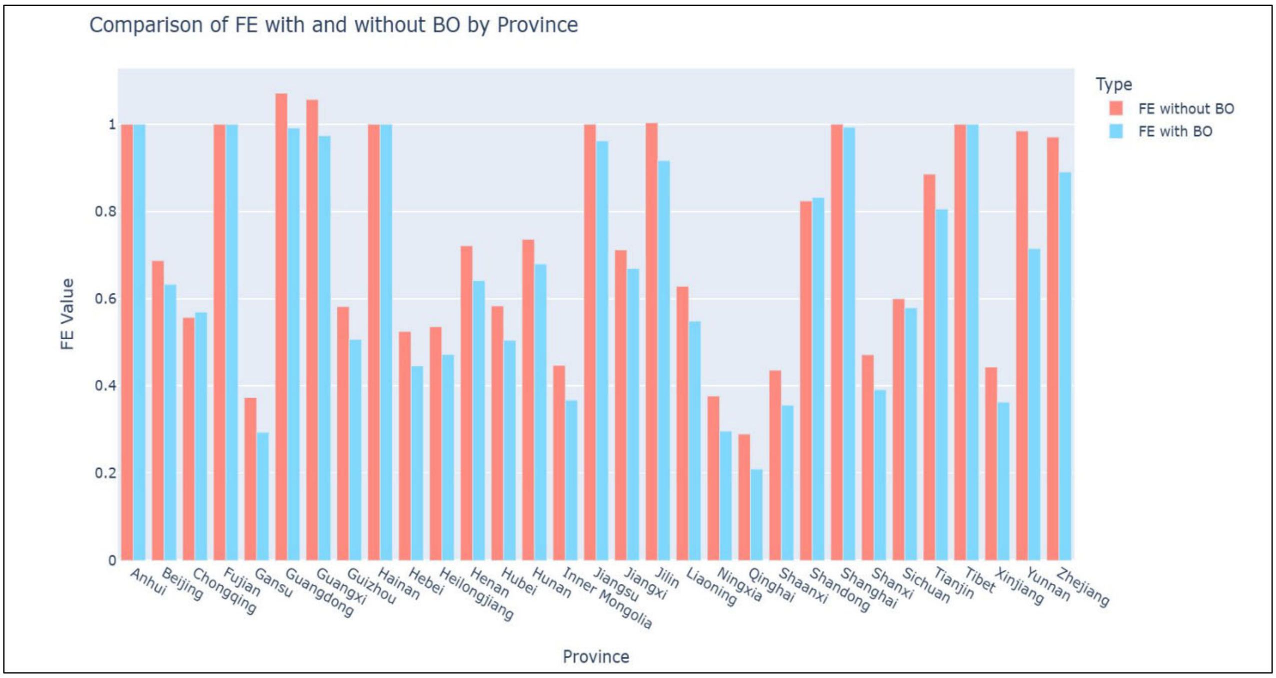

Figure 3. FE of Chinese provinces with and without bad output.

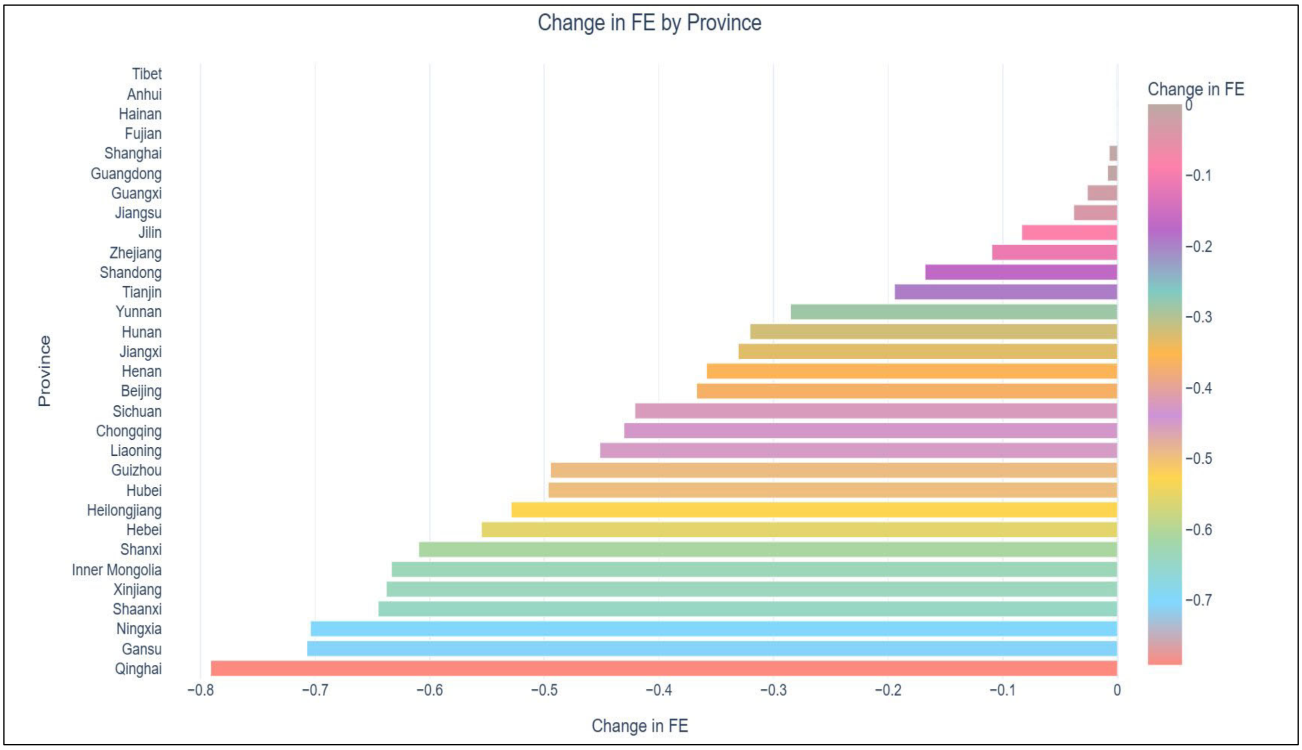

Figure 4. Change in the forestry efficiency in Chinese provinces.

Using the MLI, researchers gain an essential understanding of China's growth in forestry productivity when factors such as the environment are included (Table 4 and Figure 5). For 2001–2021, the productivity growth measured by MLI without bad outputs (BO) was 9.45%, rising to 7.85% when carbon emissions were included. Thus, environmental costs caused productivity growth to decrease by 1.6 percentage points yearly. This shows that traditional productivity assessment can misrepresent real performance, since it does not consider the role of the environment. Productivity growth breaks down into some unique patterns. Improvements in using resources through efficiency change (EC) showed an average increase of 11.46% for non-PRISM and 11.02% for PRISM data. However, differences between with and without BO were greater regarding technological change (TC), at 9.14% versus 7.46%. It demonstrates about 1.68 percent of the overall growth, which shows that it does not include enough attention to environmental costs. The 1.6 percent annual MLI gap, that is, the traditional measures overestimate the growth of productivity by 17.5 percent, entails material policy implications. The high-gap provinces (e.g., Qinghai, Gansu) are now allocated decarbonization funds specifically, whereas the low-gap regions (e.g., Guangdong, Zhejiang) can make use of the carbon markets. This instead uses > 3.8 B/year of forestry investments in regions with high emissions and reveals the power of environmental accounting in terms of resource allocation. Researchers have strongly recommended technological advancements in forest protection and development [46,47].

Yearly changes often uncover some essential patterns. Productivity growth rose substantially during the early 2000s (19.36% without BO, 13.32% with BO in 2001–2002), perhaps due to the first reforms and extra spending. During 2013–2015, both measures (MLI with and without BO) show negative productivity growth (−11.17% in 2014) against China's slow economy and industrial transformation. It is clear that there has been a recovery following 2015, and in 2017–2018 (MLI with BO: 21.77%), the company showed substantial progress, proving it had adapted well to the new regulations. The difference in MLI between regions that do and do not use BO has steadily reduced since 2001–2002, which shows that thinking about the environment is more often included in improving productivity. This is probably the result of China's collective efforts in environmental protection and sectoral technology. The results suggest essential steps for policy creation. In the first place, they underline China's efforts to increase innovation and efficiency in forest management. Furthermore, they show that actions to protect the environment are generally consistent with improving productivity. Third, they explain that productive growth cannot be overestimated if we start to include environmental factors in the assessment. Based on the study, China's forestry sector should maintain efforts to adopt eco-friendly technologies and enhance forest management to achieve success in eco-friendly production.

Table 4. MLI, EC and TC with and without bad output in Chinese provinces 2001–2021.

Year	MLI Without BO	MLI with BO	EC Without BO	EC with BO	TC Without BO	TC with BO
2001–2002	1.1865	1.1332	1.0891	1.0636	1.2209	1.1601
2002–2003	1.0718	1.0342	1.2623	1.2568	0.9674	0.9398
2003–2004	0.987	0.9787	0.9548	0.9773	1.1452	1.1683
2004–2005	1.127	1.099	1.0546	1.0438	1.1829	1.1439
2005–2006	1.234	1.2355	1.0205	1.0232	1.3269	1.3308
2006–2007	1.2078	1.1991	1.1262	1.1368	1.1565	1.1605
2007–2008	0.9991	0.9852	1.0594	1.0548	1.0279	1.0092
2008–2009	1.1615	1.114	1.3229	1.3196	0.9639	0.9264
2009–2010	0.9932	0.9763	1.0791	1.0929	1.0324	1.0301
2010–2011	1.1018	1.0797	1.0184	1.0191	1.1837	1.1617
2011–2012	1.1191	1.1124	1.1136	1.0952	1.1233	1.1012
2012–2013	1.1045	1.075	1.2277	1.2451	0.9817	0.9605
2013–2014	0.8741	0.8883	1.1358	1.1308	0.8478	0.8585
2014–2015	0.8519	0.8518	1.2013	1.1734	0.8005	0.7772
2015–2016	1.1116	1.0997	1.0331	1.0589	1.1604	1.1792
2016–2017	1.1295	1.1424	1.0589	1.0483	1.175	1.1756
2017–2018	1.209	1.2177	1.1555	1.1212	1.1779	1.1632
2018–2019	1.242	1.2036	1.1324	1.1099	1.223	1.1608
2019–2020	1.0702	1.0453	1.1042	1.0859	1.0747	1.0357
2020–2021	1.1076	1.0995	1.143	1.1461	1.0564	1.0486
Average	1.0945	1.0785	1.1146	1.1102	1.0914	1.0746

Figure 5. MLI with and without bad output from 2001 to 2021.

A review of productivity in the Chinese forestry sector between 2001 and 2021 points to significant differences between the usual measures and those incorporating environmental factors (see Table 5 and Figure 6). The MLI indicates a regular yearly decrease of 2.9 percentage points in the measured productivity shown by the Malmquist index, proving that regular assessments of sector performance are exaggerated. In the early 2000s, the environmental adjustment led to a 6.63 percentage point overestimation of productivity growth, reflecting China's rapid growth during its industrialization period. The difference got smaller over time and fell to 2.11 percentage points in 2020–2021, possibly indicating that environmental concerns and productivity grew together. Looking at the productivity change in detail helps us see important patterns. Environmental ECs consistently lowered average energy use by −1.74 percentage points each year, but these effects were the strongest when regulations were at their highest levels (2014–2015 and 2017–2018). In other words, first, following the new environmental requirements increased the efficiency costs of the provinces. Twice as much TC was revised, with an average annual decline of 2.98 percentage points. There were the largest differences between 2001 and 2002 (7.38 percentage points) and 2018 and 2019 (7.52 percentage points), meaning that much of the progress claimed in technology leads to significant problems for the environment. These results are aligned with the previous research studies that concluded that excluding the environmental degradation from the production function of efficiency estimation overestimates the efficiency and productivity in different countries and regions [48,49]

Table 5. MI, EC and TC over the study period.

Year	Change in MLI	Change in EC	Change in TC
2001–2002	−0.0663	−0.0385	−0.0738
2002–2003	−0.0506	−0.0185	−0.0406
2003–2004	−0.0213	0.0095	0.0101
2004–2005	−0.041	−0.0238	−0.052
2005–2006	−0.0115	−0.0103	−0.0091
2006–2007	−0.0217	−0.0024	−0.009
2007–2008	−0.0269	−0.0176	−0.0317
2008−2009	−0.0605	−0.0163	−0.0505
2009–2010	−0.0299	0.0008	−0.0153
2010–2011	−0.0351	−0.0123	−0.035
2011–2012	−0.0197	−0.0314	−0.0351
2012–2013	−0.0425	0.0044	−0.0342
2013–2014	0.0012	−0.018	−0.0023
2014–2015	−0.0131	−0.0409	−0.0363
2015–2016	−0.0249	0.0128	0.0058
2016–2017	-1×10^{-4}	−0.0236	−0.0124
2017–2018	−0.0043	−0.0473	−0.0277
2018–2019	–0.0514	–0.0355	–0.0752
2019–2020	–0.0379	–0.0313	–0.052
2020–2021	–0.0211	–0.0099	–0.0208
Average	–0.029	–0.0174	–0.0298

How these gaps have changed over time highlights essential information about China's forestry development. The results show that in the early 2000s, the most significant divergence was found because the sector was mainly concerned with production rather than the environment. Although wide gaps still exist, the slow shrinkage shows that sustainability is integrated into productivity development. Because of these findings, investing heavily in green technologies and using adjusted productivity measures to properly judge a country's performance is essential. The study shows that while some progress has been made in the forestry sector, serious obstacles stand in the way of achieving completely environmentally responsible growth.

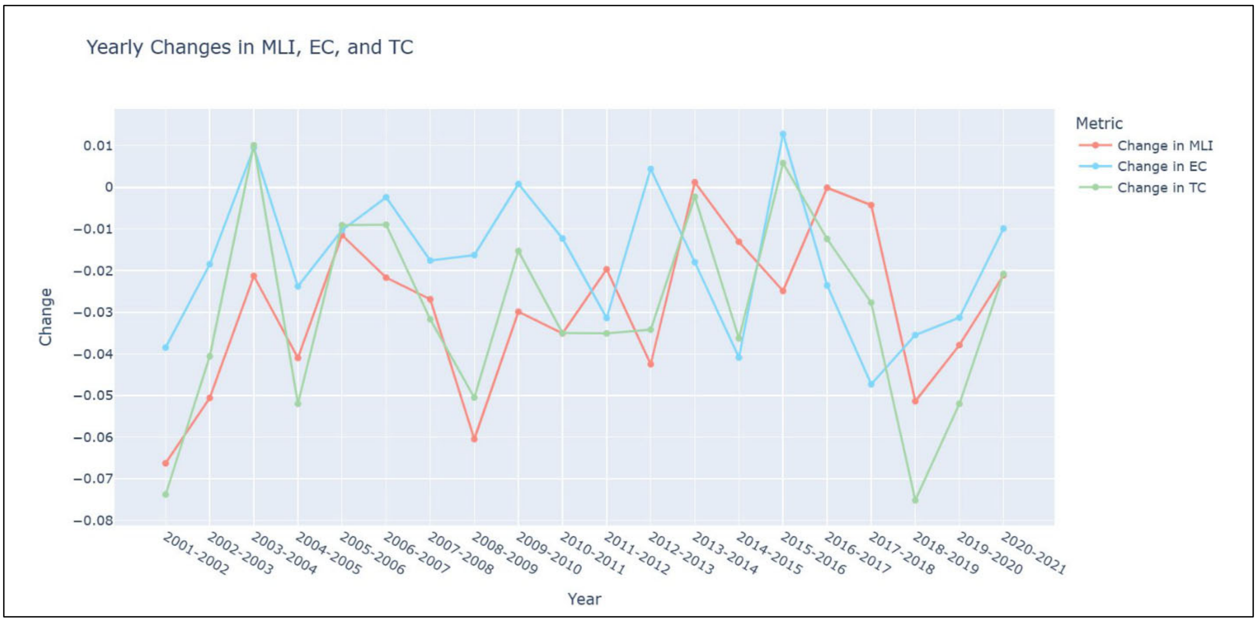

Figure 6. Change in MLI, EC and TC.

The regional investigation of productivity shifts in China's forestry sector found significant differences in carbon emissions across regions (Table 6). Even though all provinces had lower measured productivity growth when considering environmental factors, the change in productivity was much greater in some areas due to their unique growth styles and kinds of challenges. Some main trends are visible when we examine the data region by region. The differences between the two approaches to productivity were moderate in coastal provinces such as Guangdong, Jiangsu and Zhejiang. It follows that more advanced areas with stricter environmental rules have had greater success tying productivity gains to protecting the environment. The results in Fujian (−0.0754) differ significantly from those of other coastal provinces and require additional study to understand the reasons. Meanwhile, western and northern provinces performed in a broader range of ways. Levels of productivity stand far below emissions in Guangxi (−0.1026), Shandong (−0.0971) and Jilin (−0.0653), meaning that these regions struggle to balance the two. At first sight, these provinces obtain excellent results from forestry or energy sectors, though they put tremendous strain on their environment. The province of Tibet (−0.1384) shows the most significant adjustment, probably because high-altitude environments in Tibet are more sensitive to changes from forestry.

In several provinces, the annualized and quarterly growth numbers did not differ much. Gansu, Guizhou, Qinghai and Henan showed similar changes in forestry productivity, even when leaving out environmental costs. This could mean that their operations are more sustainable than others or involve little environmental pollution. There are economically undeveloped areas in this group, as well as those that protect essential parts of the environment. The findings impact the way ecological policies in the region are made. Since provinces have very different performance gaps, a standard solution to sustainable forestry development would not be suitable. In Guangxi and Shandong, where the environmental impacts of economic growth are the highest, more effort may be necessary to lower these costs. Still, Gansu and Guizhou could help to show the way by copying their approach. The results focus on how certain places, such as Tibet, need distinctive environmental safety measures because the usual productivity indicators do not reflect reality in those locations.

Table 6. Change in MLI in the Chinese forestry sector.

Province	MLI Without BO	MLI with BO	Change in MLI
Anhui	1.1344	1.1327	−0.0017
Beijing	1.1343	1.1309	−0.0034
Chongqing	1.2059	1.2	−0.0059
Fujian	1.1267	1.0513	−0.0754
Gansu	1.0748	1.0738	−0.001
Guangdong	1.1659	1.1522	−0.0137
Guangxi	1.2858	1.1832	−0.1026
Guizhou	1.1504	1.1499	−0.0005
Hainan	1.088	1.08	−0.008
Hebei	1.1569	1.1539	−0.003
Heilongjiang	1.0594	1.0226	−0.0368
Henan	1.0918	1.0908	−0.001
Hubei	1.1295	1.1285	−0.001
Hunan	1.0994	1.0971	−0.0023
Inner Mongolia	1.0662	1.0654	−0.0008
Jiangsu	1.1577	1.1413	−0.0164
Jiangxi	1.0948	1.0632	−0.0316
Jilin	1.0938	1.0285	−0.0653
Liaoning	1.1383	1.1283	−0.01
Ningxia	1.1086	1.0948	−0.0138
Qinghai	1.1008	1.1004	−0.0004
Shaanxi	1.1081	1.1071	−0.001
Shandong	1.332	1.2349	−0.0971
Shanghai	1.1123	1.0875	−0.0248
Shanxi	1.1857	1.1837	−0.002
Sichuan	1.093	1.0861	−0.0069
Tianjin	1.1575	1.1375	−0.02
Tibet	1.0401	0.9017	−0.1384
Xinjiang	1.0787	1.0687	−0.01
Yunnan	1.0984	1.0878	−0.0106
Zhejiang	1.1477	1.1464	−0.0013

These variations between provinces are most likely a result of several factors working together. (i) Forestry operations using different technological levels; (ii) Differences in how regulations are applied and in environmental rules; (iii) The kind of forest and the ecological conditions in each place; (iv) Different industries and steps of value adding. This study points out that tailoring policies for different regions is essential for Chinese forestry development, primarily as the country aims to become carbon neutral. A future approach should acknowledge how countries are differently situated, with eastern provinces, which have achieved faster development, assisting western regions by providing technology while taking more action against pollution early on.

It is clear from the provincial analysis that ecological factors distinctly influence the measured improvements for different parts of the Chinese forestry sector (Table 7). Most provinces made steady efficiency gains, apart from those reported using environmental accounting, and the results refer to notable regional differences in the development process. Guangdong, Hebei and Zhejiang, as coastal provinces, displayed about the same and moderate decrease in efficiency gains relative to carbon emissions each year, indicating they all follow a similar approach to reaching operational excellence and environmental standards. In comparison, several inland regions showed greater offsets, as Beijing experienced the most negative shift in efficiency (−0.0486), since ensuring eco–friendliness in the capital is a big challenge with economic growth. Extraordinarily, several provinces became more efficient while still conserving the environment, shown by identity in their EC scores between accounting methods for all six of Anhui, Hubei, Jiangsu, Qinghai, Shaanxi and Tibet. These situations prove that improving operations and protecting the environment is possible. In contrast, Jiangxi and Sichuan recorded negative efficiencies after environmental factors were included, suggesting that much of their increased efficiency came at the harm to the environment. Inner Mongolia (+0.0006) and Shanghai (+0.0041) improved unexpectedly because their approaches help the environment while making the economy more efficient.

Table 7. Change in EC in the Chinese forestry sector.

Province	EC Without BO	EC with BO	Change in EC
Anhui	1.12	1.12	0
Beijing	1.1504	1.1018	−0.0486
Chongqing	1.2127	1.2102	−0.0025
Fujian	1.1238	1.1212	−0.0026
Gansu	1.1429	1.1329	−0.01
Guangdong	1.1493	1.1393	−0.01
Guangxi	1.1812	1.1605	−0.0207
Guizhou	1.2019	1.1986	−0.0033
Hainan	1.12	1.1012	−0.0188
Hebei	1.1672	1.1572	−0.01
Heilongjiang	1.1699	1.1439	−0.026
Henan	1.0921	1.0821	−0.01
Hubei	1.1551	1.1551	0
Hunan	1.1226	1.1219	−0.0007
Inner Mongolia	1.1159	1.1165	0.0006
Jiangsu	1.1487	1.1487	0
Jiangxi	1.2029	1.1402	−0.0627
Jilin	1.1063	1.0998	−0.0065
Liaoning	1.1392	1.1382	−0.001
Ningxia	1.0985	1.0888	−0.0097
Qinghai	1.1303	1.1303	0
Shaanxi	1.1672	1.1672	0
Shandong	1.1621	1.1598	−0.0023
Shanghai	1.1374	1.1415	0.0041
Shanxi	1.1767	1.1667	−0.01
Sichuan	1.1758	1.1495	−0.0263
Tianjin	1.1538	1.1438	−0.01
Tibet	1.12	1.12	0
Xinjiang	1.1298	1.1295	−0.0003
Yunnan	1.12	1.1159	−0.0041
Zhejiang	1.1515	1.1415	−0.01

These results affect the formulation of regional forestry policies in China. Such wide differences in tradeoffs between saving the environment and using resources show that generic approaches to sustainable forestry will not fit all provinces. The significant differences between Beijing and Jiangxi highlight the need for extra help from policies. At the same time, equally good standards in Jiangsu and Anhui could teach us how to achieve environmental and efficiency objectives together. The results suggest that obtaining further insights into regions with efficiency improvements and no environmental costs would support China's efforts to transition toward sustainable forestry development.

A review of TC across the forestry sector in China shows clear regional differences in the impact of environmental factors on progress (Table 8). Guangdong, Jiangsu and Zhejiang, all coastal provinces, show almost no difference between their conventional and environmentally adjusted TC measures, implying that they have introduced environmental considerations into their technology more successfully. What stands out is that Fujian's

−0.0757 change means that developed regions still struggle with sustainability in their innovation systems. A bigger problem is the huge differences seen in the west and north, particularly Guangxi's −0.0962 gap, Jilin's −0.0636 gap and Tibet's −0.1384 gap, since these regions' development has mainly used energy–consuming, environmentally harmful processes. Overall, advanced areas appear to do better at matching technology and environmental success despite occasional issues, while environmentally weak places find it difficult to grow environmentally friendly industries. Two success stories, Anhui and Zhejiang, whose progress in clean energy and pollution levels has closely followed one another, give useful examples for how to achieve progress in technology without harming nature. The results suggest that China's forestry sector needs regional policies for innovation to deal with its various sustainability challenges. These results are empirically specific to China, but the degree to which internalizing carbon costs comes at huge costs in efficiency (average decline of 7.7 percent) has a general lesson on the challenge of achieving efficiency in the natural resource sector. The post-2020-recovery has proven that economically and environmentally oriented aims may be reconciled by special policies, a precedent that can be brought to emerging economies that are forced to go through analogical transitions. We offer an approach to replication to evaluate the sustainability of forestry in other geographies, especially in the Global South, where development and decarbonization are challenging issues.

Table 8. Change in TC in the Chinese forestry sector.

Province	TC Without BO	TC with BO	Change in TC
Anhui	1.1344	1.1327	−0.0017
Beijing	1.1685	1.1339	−0.0346
Chongqing	1.1384	1.1372	−0.0012
Fujian	1.1265	1.0508	−0.0757
Gansu	1.096	1.086	−0.01
Guangdong	1.1559	1.1423	−0.0136
Guangxi	1.233	1.1368	−0.0962
Guizhou	1.1019	1.0983	−0.0036
Hainan	1.1086	1.08	−0.0286
Hebei	1.1409	1.1309	−0.01
Heilongjiang	1.0641	1.0334	−0.0307
Henan	1.1501	1.1401	−0.01
Hubei	1.1137	1.1037	−0.01
Hunan	1.1083	1.0998	−0.0085
Inner Mongolia	1.0824	1.0708	−0.0116
Jiangsu	1.1242	1.1127	−0.0115
Jiangxi	1.0894	1.0326	−0.0568
Jilin	1.1465	1.0829	−0.0636
Liaoning	1.1208	1.1205	−0.0003
Ningxia	1.1737	1.1562	−0.0175
Qinghai	1.0892	1.078	−0.0112
Shaanxi	1.0874	1.0774	−0.01
Shandong	1.2136	1.2053	−0.0083
Shanghai	1.1048	1.0853	−0.0195
Shanxi	1.1596	1.1576	−0.002
Sichuan	1.1118	1.0991	−0.0127
Tianjin	1.142	1.122	−0.02
Tibet	1.0401	0.9017	−0.1384
Xinjiang	1.0853	1.0753	−0.01
Yunnan	1.1372	1.0795	−0.0577
Zhejiang	1.1489	1.1477	−0.0012

5. Conclusions and Policy Implications

This study examines how China can reconcile the expansion of the forestry industry with environmental protection, addressing a global challenge of striking a balance between economic growth and ecological conservation. Our results show that using traditional productivity indicators overstates results because they ignore environmental damage, reducing the measured efficiency of forestry by 7.7% and shrinking the annual productivity growth rate by 1.6 percentage points. The systematic overestimation in the performance of forestry is brought about by consideration of conventional metrics that do not reflect the cost of opportunity of the environment. When the carbon consequences are added, the calculations of productivity give provincial credits for maximizing timber and economic production without subtracting commensurate environmental degradation to put a forged efficiency premium on it. An example of this would be that one province that utilizes coal to cut down forests may seem to have a more efficient exploitation and harvest than the province that has sustainable harvesting but both have the same levels of timber. Our findings measure this distortion: the 7.7 percent efficiency gap and the 1.6 percent overstatement of annual productivity is the concealed environmental liability of the forestry business. The research highlights significant differences between regions, with Guangdong and Jiangsu aligning their interests due to better technology and stricter regulations, whereas Qinghai and Tibet exhibit greater environmental damage. The findings reveal that traditional development is focused more on production than on caring for the environment, which can endanger delicate ecosystems.

The analysis has yielded several significant policy recommendations for achieving carbon neutrality by 2060. Forestry performance measurements at all levels should first include aspects of the environment, evaluated using the Malmquist–Luenberger index to ensure accuracy. Developed eastern regions must pass on green technologies to inland parts, and those that are ecologically vulnerable depend on approaches that focus on preserving nature. Moving forward, introducing new carbon trading and green financing systems can help encourage sustainability efforts, and we can learn from model efforts like the “Green Great Wall” initiative. Furthermore, close satellite monitoring and stricter rules will be vital, especially in the most vulnerable areas. High-technological coastal provinces (e.g., Guangdong, Jiangsu) can focus on the forest carbon trading and AI-aided satellite monitoring to utilize the available infrastructure to ensure real-time compliance. Using green finance, which includes conservation performance payments, ecologically vulnerable areas (Qinghai, Tibet) must be set up with green livelihoods (non-timber based) with proper land-use zoning. The implementation should be phased as follows: (1) Short-term (2025–2027): Introduce Forest carbon markets in 3 eastern provinces with the help of the MLI–adjusted metrics; (2) Medium-term (2028–2030): Integrate the satellite alerts with the provincial enforcement systems; (3) * Long-term (post–2030): Scale successful models (e.g., Green Great Wall incentives) to the national level. This multi–level plan will concentrate traditional, tech-heavy instruments in areas where they are possible to allow carbon–neutrality by 2060.

The results are significant for countries facing comparable environmental challenges. While China’s economy can prosper while maintaining a healthy environment, it first needs to reform its outdated ways of thinking about growth. The study shows that, as economic resources, forests are essential, but they are also crucial for climate control and biodiversity conservation. Additional research will enhance the current study by examining whether sustainability measures remain effective over time and by exploring new options to assess the environmental impact of policies. As climate goals are being set internationally, this research demonstrates how forestry can benefit both humans and the environment.

This research suggests that the way forestry productivity is measured and managed in China should be reconsidered. We have found that it is essential to use metrics that report carbon and other ecological consequences, rather than relying on simplified output-only indicators that fail to demonstrate the extent to which we are harming the environment. Based on the needs of each province, provincial governments must advance technology in coastal regions while conserving ecologically sensitive areas and providing new income opportunities. Market mechanisms should be further developed by establishing forest-focused provincial carbon trading systems and incentives for low-emission technologies. Using satellite monitoring and artificial intelligence to track activities, the government can identify unsustainable actions in real time and impose fines on violators in at-risk areas. We should include green financing projects that support sustainable forest use and greening initiatives, inspired by practical projects such as the Green Great Wall. Most importantly, our findings demonstrate that clear connections between forestry rules and broader climate and biodiversity action plans are necessary to protect nature as China strives to achieve its goal of carbon neutrality. These recommendations would help China's forestry sector demonstrate to the world that balancing economic growth with environmental protection is possible and that conserving resources benefits both people and nature. In future research, this methodology should be used cross-nationally, including the regions in the Global South where the forestry-development tensions are similar, to find the solutions that can be scaled to solve the climate problems in the sector with more recent data. In this study, carbon emission was considered the main bad output associated with the environment; however, future research ought to consider energy efficiency outputs (e.g., energy input divided by the amount of timber output) in order to determine substitutability between capital and labor and energy. In addition, future studies might utilize the stochastic frontier analysis (SFA) to estimate such elasticities or consider the dynamic interactions between the carbon efficiency, energy efficiency and biodiversity conservation utilizing multi-output models.

This research has various shortcomings. First, it is empirically specific to China and hence does not represent a practicable universal extrapolation to other governments of governance, although the methodological scheme has transfer incentives. Second, aggregation at the provincial level may provide an alluring cover of sub-regional diverse forestry practices and environmental changes. Lastly, in our environmental accounting, carbon is the most privileged dimension, leaving aside other environmental aspects (e.g., biodiversity destruction, soil erosion) that might supplement further evaluation of efficiency. The latter should be examined in the future by cross-national comparisons, smaller-scale analysis, and multi-indicator environmental accounting.

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References

1. Hunjra, A.I.; Bouri, E.; Azam, M.; Azam, R.I.; Dai, J. Economic Growth and Environmental Sustainability in Developing Economies. *Res. Int. Bus. Financ.* **2024**, *70*, 102341. [CrossRef]
2. Khreis, H.; Nieuwenhuijsen, M.J.; Zietsman, J.; Ramani, T. Traffic-Related Air Pollution: Emissions, Human Exposures, and Health: An Introduction. In *Traffic-Related Air Pollution*; Elsevier: Amsterdam, The Netherlands, 2020; ISBN 9780128181225.

3. Elumalai, P.; Gao, X.; Parthipan, P.; Luo, J.; Cui, J. Agrochemical Pollution: A Serious Threat to Environmental Health. *Curr. Opin. Environ. Sci. Health* **2025**, *43*, 100597. [CrossRef]
4. Tanveer, A.; Song, H.; Faheem, M.; Daud, A. Caring for the Environment. How Do Deforestation, Agricultural Land, and Urbanization Degrade the Environment? Fresh Insight through the ARDL Approach. *Environ. Dev. Sustain.* **2024**, *27*, 11527–11562. [CrossRef]
5. Pacheco, F.A.L.; Sanches Fernandes, L.F.; Valle Junior, R.F.; Valera, C.A.; Pissarra, T.C.T. Land Degradation: Multiple Environmental Consequences and Routes to Neutrality. *Curr. Opin. Environ. Sci. Health* **2018**, *5*, 79–86. [CrossRef]
6. Hurteau, M.D. The Role of Forests in the Carbon Cycle and in Climate Change. In *Climate Change: Observed Impacts on Planet Earth, Third Edition*; Elsevier: Amsterdam, The Netherlands, 2021; ISBN 9780128215753.
7. Hou, Y.; Wei, X.; Zhang, M.; Creed, I.F.; McNulty, S.G.; Ferraz, S.F.B. A Global Synthesis of Hydrological Sensitivities to Deforestation and Forestation. *For. Ecol. Manag.* **2023**, *529*, 120718. [CrossRef]
8. Yu, X.; Cheng, X.; Dong, J.; Yang, Z.; Xu, D.; Peng, J. Trees' Cooling Amplified the Effect of Air Purification in Shanxi. *Appl. Geogr.* **2025**, *177*, 103569. [CrossRef]
9. Zhang, J.; Qu, X.; Huang, Y.; Tan, M.; Xu, K. Assessing the Potential of Species Loss Caused by Deforestation in a Mature Subtropical Broadleaf Forest in Central China. *Trees For. People* **2024**, *18*, 100673. [CrossRef]
10. Rohde, M.M. Floods and Droughts Are Intensifying Globally. *Nat. Water* **2023**, *1*, 226–227. [CrossRef]
11. Deng, L.; Peng, C.; Kim, D.G.; Li, J.; Liu, Y.; Hai, X.; Liu, Q.; Huang, C.; Shangguan, Z.; Kuzyakov, Y. Drought Effects on Soil Carbon and Nitrogen Dynamics in Global Natural Ecosystems. *Earth Sci. Rev.* **2021**, *214*, 103501. [CrossRef]
12. Jin, M.; Chen, N.; Wang, S.; Cao, F. Does Forestry Industry Integration Promote Total Factor Productivity of Forestry Industry? Evidence from China. *J. Clean. Prod.* **2023**, *415*, 137767. [CrossRef]
13. Wang, G.G.; Lu, D.; Gao, T. Climate–Smart Forestry: An AI-Enabled Sustainable Forest Management Solution for Climate Change Adaptation and Mitigation. *J. For. Res.* **2025**, *36*, 7. [CrossRef]
14. Jie, H.; Khan, I.; Alharthi, M.; Zafar, M.W.; Saeed, A. Sustainable Energy Policy, Socio-Economic Development, and Ecological Footprint: The Economic Significance of Natural Resources, Population Growth, and Industrial Development. *Util. Policy* **2023**, *81*, 101490. [CrossRef]
15. D'Amato, D.; Korhonen, J. Integrating the Green Economy, Circular Economy and Bioeconomy in a Strategic Sustainability Framework. *Ecol. Econ.* **2021**, *188*, 107143. [CrossRef]
16. Fatima, S.; Abbas, S.; Rebi, A.; Ying, Z. Sustainable Forestry and Environmental Impacts: Assessing the Economic, Environmental, and Social Benefits of Adopting Sustainable Agricultural Practices. *Ecol. Front.* **2024**, *44*, 1119–1127. [CrossRef]
17. Liu, C.L.C.; Kuchma, O.; Krutovsky, K.V. Mixed-Species versus Monocultures in Plantation Forestry: Development, Benefits, Ecosystem Services and Perspectives for the Future. *Glob. Ecol. Conserv.* **2018**, *115*, e00419. [CrossRef]
18. Cochrane, M.A.; Bowman, D.M.J.S. Manage Fire Regimes, Not Fires. *Nat. Geosci.* **2021**, *14*, 455–457. [CrossRef]
19. Pörtner, H.O.; Scholes, R.J.; Arneth, A.; Barnes, D.K.A.; Burrows, M.T.; Diamond, S.E.; Duarte, C.M.; Kiessling, W.; Leadley, P.; Managi, S.; et al. Overcoming the Coupled Climate and Biodiversity Crises and Their Societal Impacts. *Science* **2023**, *380*, eabl4881. [CrossRef] [PubMed]
20. Xie, Z. China's Historical Evolution of Environmental Protection along with the Forty Years' Reform and Opening-Up. *Environ. Sci. Ecotechnol.* **2020**, *1*, 100001. [CrossRef]
21. Jiang, X.; Li, G.; Fu, W. Government Environmental Governance, Structural Adjustment and Air Quality: A Quasi-Natural Experiment Based on the Three-Year Action Plan to Win the Blue Sky Defense War. *J. Environ. Manag.* **2021**, *277*, 111470. [CrossRef] [PubMed]
22. Yu, Y.; Dai, C.; Wei, Y.; Ren, H.; Zhou, J. Air Pollution Prevention and Control Action Plan Substantially Reduced PM2.5 Concentration in China. *Energy Econ.* **2022**, *113*, 106206. [CrossRef]
23. Li, X.; Ning, Z.; Yang, H. A Review of the Relationship between China's Key Forestry Ecology Projects and Carbon Market under Carbon Neutrality. *Trees For. People* **2022**, *9*, 100311. [CrossRef]
24. Wu, W.; Nel, W.; Ji, J.; Chen, J. Prospects for the Potential Carbon Sink Effects of Afforestation to Enhance Weathering in China. *J. Asian Earth Sci.* **2024**, *276*, 106370. [CrossRef]
25. Zhang, R.; Zhu, S.; Zhang, Z.; Zhang, H.; Tian, C.; Wang, S.; Wang, P.; Zhang, H. Long-Term Variations of Air Pollutants and Public Exposure in China during 2000–2020. *Sci. Total Environ.* **2024**, *930*, 172606. [CrossRef] [PubMed]
26. Veste, M.; Gao, J.; Sun, B.; Breckle, S.-W. The Green Great Wall-Combating Desertification in China. *Geogr. Rundsch. Int. Ed.* **2006**, *2*, 14–20.
27. Meng, G.; Wu, S.; Yu, Y. Forestry Policy Effectiveness and Performance Evaluation in China–Quantitative Study Based on Policy Texts 1998–2020. *For. Policy Econo.* **2025**, *170*, 103367. [CrossRef]
28. Chen, Y.; Ma, L.; Miao, J.; Hui, X. Does Chinese Forestry Eco-Efficiency Converge? A Three-Stage DEA-Malmquist Approach. *Eur. J. For. Res.* **2023**, *142*, 1259–1277. [CrossRef]

29. Lin, Y.; Chen, W.; Liu, J. Research on the Temporal and Spatial Distribution and Influencing Factors of Forestry Output Efficiency in China. *Sustainability* **2021**, *13*, 4687. [CrossRef]
30. Li, L.; Hao, T.; Chi, T. Evaluation on China's Forestry Resources Efficiency Based on Big Data. *J. Clean. Prod.* **2017**, *142*, 513–523. [CrossRef]
31. Shah, W.U.H.; Hao, G.; Yan, H.; Shen, J.; Yasmeen, R. Forestry Resource Efficiency, Total Factor Productivity Change, and Regional Technological Heterogeneity in China. *Forests* **2024**, *15*, 152. [CrossRef]
32. Banker, R.D.; Charnes, A.; Cooper, W.W. Some Models for Estimating Technical and Scale Inefficiencies in Data Envelopment Analysis. *Manag. Sci.* **1984**, *30*, 1078–1092. [CrossRef]
33. Charnes, A.; Cooper, W.W.; Rhodes, E. Measuring the Efficiency of Decision Making Units. *Eur. J. Oper. Res.* **1978**, *2*, 429–444. [CrossRef]
34. Tone, K. *Dealing with Undesirable Outputs in DEA: A Slacks-Based Measure (SBM) Approach*; National Graduate Institute for Policy Studies (GRIPS): Minato, Japan, 2004.
35. Färe, R.; Grosskopf, S. Estimation of Returns to Scale Using Data Envelopment Analysis: A Comment. *Eur. J. Oper. Res.* **1994**, *79*, 379–382. [CrossRef]
36. Chung, Y.H.; Färe, R.; Grosskopf, S. Productivity and Undesirable Outputs: A Directional Distance Function Approach. *J. Environ. Manag.* **1997**, *51*, 229–240. [CrossRef]
37. Edirisinghe, N.C.P.; Zhang, X. Input/Output Selection in DEA under Expert Information, with Application to Financial Markets. *Eur. J. Oper. Res.* **2010**, *207*, 1669–1678. [CrossRef]
38. Peykani, P.; Seyed Esmaeili, F.S.; Mirmozaffari, M.; Jabbarzadeh, A.; Khamechian, M. Input/Output Variables Selection in Data Envelopment Analysis: A Shannon Entropy Approach. *Mach. Learn. Knowl. Extr.* **2022**, *4*, 688–699. [CrossRef]
39. Dong, B.; Chen, L.; Zhang, Y.; Xie, B. How Does Green Credit Supply Enhance the Efficiency of Forestry Ecological Development? Taking the Perspective of Ecological Total Factor Productivity. *J. Clean. Prod.* **2025**, *488*, 144643. [CrossRef]
40. Lozano, S.; Gutiérrez, E.; Susaeta, A. Forest Efficiency Assessment and Prediction Using Dynamic DEA and Machine Learning. *For. Policy Econ.* **2025**, *173*, 103461. [CrossRef]
41. Shah, W.U.H.; Hao, G.; Yan, H.; Lu, Y.; Yasmeen, R. The Impact of Climate Change on China's Forestry Efficiency and Total Factor Productivity Change. *Forests* **2023**, *12*, 2464. [CrossRef]
42. Kauffman, J.B.; Adame, M.F.; Adinugroho, W.C.; Anshari, G.; Basuki, I.; Donato, D.; Gangga, A.; Murdiyarso, D.; Ritonga, R.P.; Warren, M.; et al. Total Ecosystem Carbon Stocks of Tropical Peat Forests and Greenhouse Gas Emissions from Their Disturbance. *For. Ecol. Manag.* **2025**, *593*, 122840. [CrossRef]
43. Ellis, E.A.; Montero, S.A.; Hernández Gómez, I.U.; Romero Montero, J.A.; Ellis, P.W.; Rodríguez-Ward, D.; Blanco Reyes, P.; Putz, F.E. Reduced-Impact Logging Practices Reduce Forest Disturbance and Carbon Emissions in Community Managed Forests on the Yucatán Peninsula, Mexico. *For. Ecol. Manag.* **2019**, *437*, 396–410. [CrossRef]
44. Whiteman, A.; Wickramasinghe, A.; Piña, L. Global Trends in Forest Ownership, Public Income and Expenditure on Forestry and Forestry Employment. *For. Ecol. Manag.* **2015**, *352*, 99–108. [CrossRef]
45. Lee, T.H.; Liou, Y.Y.; Chang, H.H. Forest Diversity and the Distribution of Farm Revenue–Empirical Evidence from Forest Farms in Taiwan. *For. Policy Econ.* **2025**, *171*, 103411. [CrossRef]
46. Wu, L.; Zhang, Z. Impact and Threshold Effect of Internet Technology Upgrade on Forestry Green Total Factor Productivity: Evidence from China. *J. Clean. Prod.* **2020**, *271*, 122657. [CrossRef]
47. Lewis Hood, K.; Gabrys, J. Keeping Time with Digital Technologies: From Real-Time Environments to Forest Futurisms. *Environ. Plan. D Soc. Space* **2024**, *42*, 254–274. [CrossRef]
48. Shah, W.U.H.; Hao, G.; Yan, H.; Zhu, N.; Yasmeen, R.; Dincă, G. Role of Renewable, Non-Renewable Energy Consumption and Carbon Emission in Energy Efficiency and Productivity Change: Evidence from G20 Economies. *Geosci. Front.* **2023**, *15*, 101631. [CrossRef]
49. Zhou, P.; Ang, B.W.; Poh, K.L. A Survey of Data Envelopment Analysis in Energy and Environmental Studies. *Eur. J. Oper. Res.* **2008**, *189*, 1–18. [CrossRef]