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The Impact of Climate Change on China's Forestry Efficiency and Total Factor Productivity Change

Wasi Ul Hassan Shah [1], Gang Hao [2], Hong Yan [1], Yuting Lu [1] and Rizwana Yasmeen [3,*]

[1] School of Management, Zhejiang Shuren University, Hangzhou 310015, China; wasi450@yahoo.com (W.U.H.S.); yanhong@zjsru.edu.cn (H.Y.); 202001013209@stu.zjsru.edu.cn (Y.L.)
[2] Department of Management Sciences, City University of Hong Kong, Hong Kong 999077, China; msghao@city.edu.hk
[3] School of Economics and Management, Panzhihua University, Panzhihua 617000, China
* Correspondence: rizwana_239@yahoo.com; Tel.: +86-199-8238-9397

Abstract: The objective of this study is to examine the impact of climate change on forestry efficiency (FRE) and total factor productivity change (TFPC) in 31 provinces of China for a study period of 2001–2020. Additionally, the study aims to evaluate the success level of governmental initiatives used to mitigate climate change. Using the DEA-SBM, this study estimates the forestry efficiency for 31 Chinese provinces and seven regions. Results indicate that the average forestry efficiency score obtained is 0.7155. After considering climatic factors, the efficiency level is 0.5412. East China demonstrates the highest average efficiency with a value of 0.9247, while the lowest score of 0.2473 is observed in Northwest China. Heilongjiang, Anhui, Yunnan, and Tibet exhibit the highest efficiency scores. Mongolia, Heilongjiang, Sichuan, Hebei, and Hunan are the five provinces most affected by climate change. This study's findings indicate that the average total factor forestry productivity (TFPC) is 1.0480, representing an increase of 4.80%. The primary determinant for change is technology change (TC), which surpasses efficiency change (EC). Including climate variables reduces total factor productivity change (TFPC) to 1.0205, mainly driven by a decrease in TC. The region of South China exhibits the highest total factor productivity change (TFPC) with a value of 1.087, whereas both Northeast China and Central China observe falls below 1 in TFPC. The Mann–Whitney U test provides evidence of statistically significant disparities in forestry efficiency and TFPC scores when estimated with and without incorporating climate factors. Kruskal–Wallis found a statistically significant difference in FRE and TFPC among seven regions.

Keywords: climate change; forestry efficiency; total factor productivity change; Chinese provinces; DEA

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1. Introduction

The significance of forest resources is of utmost importance in terms of both economic and environmental aspects. From an economic standpoint, forests serve as a valuable resource for producing timber and wood products, essential for supporting various industries such as building and paper manufacturing [1]. This utilization of forests not only generates significant capital but also contributes to generating employment opportunities. In addition, forests play a crucial role in providing non-timber goods, including fruits, nuts, and medicinal plants. These resources serve as a means of generating revenue for local populations and make significant contributions to regional economies [2,3]. Furthermore, forests possess a strong attraction for tourism and recreational purposes, drawing in individuals seeking activities like hiking and camping. Consequently, this influx of tourists stimulates local economies by generating heightened tourism and commercial revenue [4].

When viewed through an environmental lens, forests serve as crucial reservoirs of biodiversity, providing sanctuary to a diverse array of plant and animal species while conserving distinct and imperiled ecosystems [5]. Forests play a crucial role in climate regulation by serving as significant carbon sinks, thereby minimizing the adverse effects of global warming. Forests have a crucial role in enhancing air quality through their capacity to absorb pollutants and emit oxygen [6]. Additionally, they contribute to preserving water quality by acting as natural filters and mitigating soil erosion. They function as effective deterrents against soil erosion, playing a crucial role in maintaining the stability of landscapes [7,8]. Additionally, they serve as protective shields for vital wildlife habitats and watersheds. In addition to their ecological significance, forests provide opportunities for recreational activities, physical exercise, and stress reduction, thus enhancing mental well-being. Forest resources are of utmost importance for advancing economic growth and conserving our natural surroundings, serving as a crucial component in the pursuit of sustainable development and the overall welfare of our global ecosystem [9,10].

Enhancing efficiency and productivity in the forestry sector is crucial for ensuring environmental sustainability and economic prosperity. These actions directly influence the sustainable utilization of forest resources, preserving biodiversity, carbon sequestration, and timber availability, all while stimulating economic expansion [11]. Furthermore, by fostering technological and practical innovation and preserving ecosystem services, these initiatives ensure a sustainable ecological balance between long-term economic benefits and ecological health. Forestry productivity and efficiency are pivotal in generating economic and environmental advantages; therefore, their improvement is crucial for ensuring a sustainable future [12,13].

Climate change profoundly impacts forestry efficiency and total factor productivity, substantially affecting the sector's inputs and outputs. The changing patterns of precipitation and increasing temperatures harm the growth conditions of numerous tree species, requiring modifications to be made to planting and harvesting methods [14,15]. Furthermore, raised temperatures contribute to a heightened incidence of parasites and diseases, necessitating additional resources for their control, thereby diminishing overall efficiency. Water scarcity, frequently caused by changes in precipitation patterns, requires careful water management and irrigation system investments to sustain crop yields [16]. As a result of climate change-induced increases in the frequency and severity of forest fires, not only are timber and resources required for fire prevention and control significantly depleted, but inputs and outputs are also adversely affected [17].

Moreover, vulnerable to compromising the quality of timber are fluctuations in temperature and growing conditions, which may result in diminished economic efficacy. From a favorable perspective, climate change has generated increased attention toward carbon sequestration in forests, which has created prospects for generating revenue from the carbon market [18]. Given the obstacles mentioned above, it is critical to maintain or improve forestry efficiency and productivity by implementing sustainable forest management practices, climate-resilient tree species, and investments in monitoring and research to adapt to and mitigate the effects of climate change [19,20].

China possesses a substantial portion of the global forest resources inside its vast and varied terrain. China plays a significant role in world forestry because its extensive forests span several climatic zones, including temperate, subtropical, and tropical regions [21,22]. The forested regions within the country offer essential ecosystem services and facilitate a flourishing timber sector, contribute to the sustenance of rural communities, and play a pivotal role in carbon sequestration [23]. Acknowledging the diverse significance of these resources, the Chinese government has implemented significant efforts to increase the expansion of forest cover, optimize forestry efficiency, and promote growth in total factor productivity [24–26].

China has initiated ambitious afforestation and reforestation efforts to address the escalating environmental concerns and the rising timber demands. The primary objective of these programs is to enhance the extent of forested regions by implementing various strategies, such as tree planting initiatives, restoration of deteriorated forests, and adopting sustainable forest management practices [27,28]. These efforts have not only resulted in an expansion of forest areas but have also led to enhancements in the overall quality and ecological well-being of these forest ecosystems. Furthermore, the Chinese government has significantly emphasized improving forestry efficiency and increasing total factor production [29]. This encompasses using advanced forest management technologies, enhancing the efficient utilization of resources, and optimizing the value chains within the forestry sector. China aims to optimize the productivity of its forest resources and mitigate environmental consequences by leveraging technical progress, mechanization, and scientific investigation [30].

Nevertheless, the forestry sector in China is confronted with a substantial problem due to the consequences of climate change. The stability of China's forests is endangered by changes in temperature and precipitation patterns, heightened occurrences of pest infestations, and a rise in the frequency of forest fires [31]. The issues mentioned above directly impact the efficiency of forestry operations and the overall productivity of the factors involved. This is primarily due to the escalation of expenses associated with resource management and the consequential decline in the quality and amount of timber produced [32].

The Chinese government has implemented a comprehensive strategy to address the adverse effects of climate change on its forestry sector. It includes adopting climate-resilient tree species, improving monitoring and early warning systems for pest plagues and forest fires, and promoting sustainable forest management practices that effectively reconcile economic interests with ecological protection [33]. In addition, China has been actively involved in afforestation and reforestation initiatives, which function as carbon reduction and make significant contributions to global climate change mitigation efforts [34,35]. Although China has a significant advancement in these efforts to remove the impact of climate change on forestry resources utilization efficiency and total factor productivity growth, this mission's success level is still undiscovered and worth investigating. Therefore, this study contributes to the existing literature in several ways. In the first stage, it employs data envelopment analysis (DEA-SBM) on a set of inputs and outputs to estimate the forestry efficiency of 31 Chinese provinces over the well-strength period of 20 years (2001–2020). It explores the efficiency level of different Chinese provinces and regions in forest resource utilization over the study period. In the second stage, the study incorporates the climate factor in input variables to gauge the impact of climate change on forestry efficiency. This investigation illustrates the decline in forestry efficiency caused by climate change and advises of different implications for decision-making authorities. Thirdly, the research uses the Malmquist productivity index to gauge the total factor productivity change in forest resource utilization for 31 Chinese provinces and regions. It investigates the growth or decline in total factor productivity of forest resources and further explores the determinant of productivity change (efficiency of technology). Moreover, climate change's impact on total factor productivity change is also explored through input incorporating climate factors. Further climate impact on forestry TFPC for seven different Chinese regions (see Figure 1) is also gauged to show the regional impact of climate factors. Finally, the Mann–Whitney U and Kruskal–Wallis tests investigate the significant statistical differences in forestry efficiency and total factor productivity scores among the results estimated with and without climate factor incorporation and different Chinese regions. The rest of this study is arranged as follows: A comprehensive literature review is explained in Section 2. Section 3 illustrates the methodology employed in this study. Section 4 presents the results and Section 5 presents the discussion. The conclusions of this study are presented in Section 6.

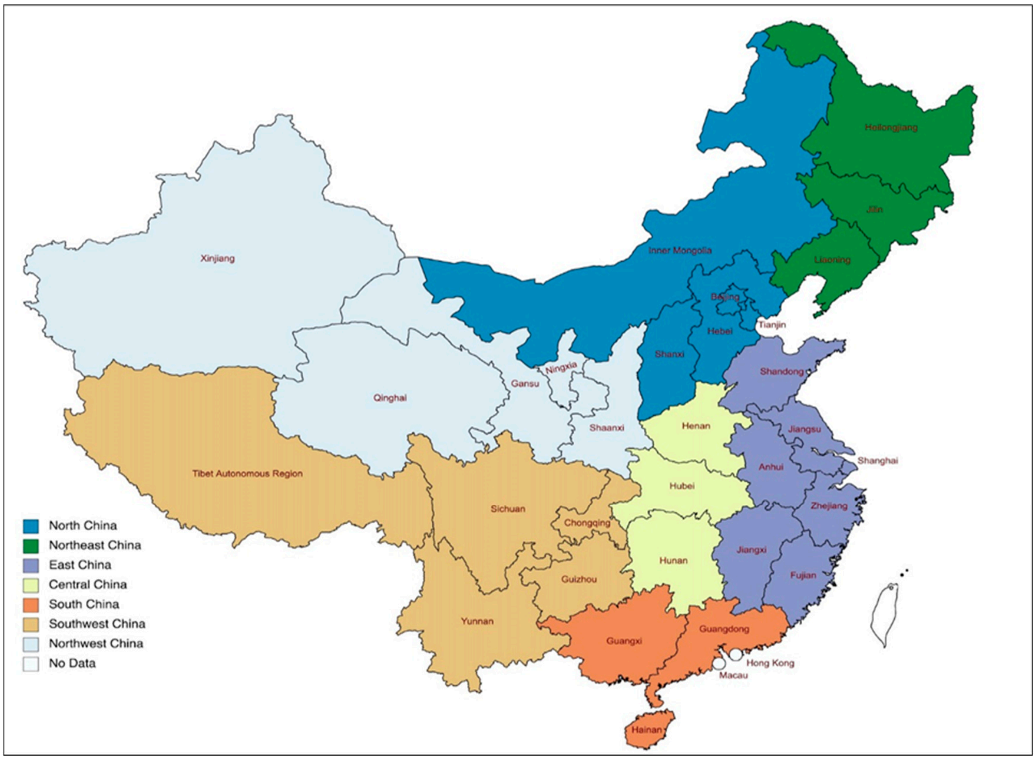

Figure 1. Forest regions in China. Different colors indicate the different forest regions in China.

2. Literature Review

Measuring efficiency in managing forestry resources is an important part of sustainable forest management because it helps make the best use of resources while causing the least environmental damage. The Data Envelopment Analysis (DEA) method helps check how well forestry operations and resource allocation work. The research on using DEA to measure how efficiently timber resources are used is a constantly changing field, with new studies and methods being formed in recent studies [36–38].

Liu et al. [36] examined the non-linear effects of forestry input factors and production efficiency on economic growth, emphasizing worker pay. They found significant double threshold effects in 40 Heilongjiang forestry bureaus using a panel threshold regression model. Forestry capital investment and production efficiency boosted growth, with labor pay mediating 69.88% of the effect. Labor compensation also moderated forestry capital input and labor input positively and negatively. Labor remuneration mediates and moderates forestry dynamics, which were shown to be non-linear. Anouze et al. [39] aimed to evaluate the effectiveness of banks in dynamic settings through the use of a three-stage DEA framework. The approach incorporates a random forest ensemble technique to identify crucial environmental variables and acknowledge their impact on DEA efficiency ratings. A regression analysis examines the relationship and ability to forecast bank performances of these factors. The study conducted a test on the framework using 110 banks in the Middle East and North African countries from 2014 to 2016. It found that the country in which the banks operated was a critical element that influenced their efficiency. The overall mean efficiency maintains consistently at approximately 87%. The findings enhance comprehension of the influence of environmental factors on bank efficiency, with the paper concluding by acknowledging its limits and suggesting potential areas for future research. Moreover, numerous research studies employed DEA to evaluate forestry efficiency and total factor productivity growth in different regions around the globe [40–42].

The Forest Production Efficiency (FPE) metric was presented in the research by Collalti et al. [43]. It evaluated the utilization of assimilated carbon to produce biomass or net primary production. The research extensively examines FPE about climate and age, uncovering an unforeseen positive correlation with temperature. Results illustrated enhanced forest production efficiency modeling in response to climate change. Using the DEA-SBM model, Wei and Shen [44] investigated the efficiency of forest carbon sinks in 30 Chinese provinces from 2005 to 2018. The findings indicated that the average annual forest carbon sink efficacy in China could be enhanced by 0.29. Urbanization, natural deforestation, precipitation (with a positive correlation), and temperature (with a negative correlation), with regional variations, are influential factors. Enhancing human capital, adapting strategies to local conditions, and optimizing the structure of the forestry industry are all policy recommendations that contribute to more efficient forest carbon sink management. Some research studies examined the impact of climate factors on forestry resources [45–47].

Research studies proved that regulating the carbon and water cycles and mitigating climate change and forests are essential. Schulze et al. [48] examined the differences between forests that are managed sustainably and those that are not managed, specifically about their ability to mitigate climate change. This research challenged the conventional methods used to measure carbon storage. Unrecorded firewood harvesting in managed forests in Germany makes a considerable contribution to energy substitution. The study suggested implementing a carbon dioxide tax that acknowledges the positive impact of forest management on the environment.

Reyer et al. [49] examined the dynamic relationship between disturbances and forest productivity in the context of the effects of climate change. They emphasized the importance of considering these factors collectively, as disruptions have the potential to either intensify or alleviate changes in productivity caused by climate change. These impacts are projected across seven European forest case studies using cutting-edge forest models, revealing the intricate interplay between climate change, disturbances, and forest productivity. The results emphasize the need for a comprehensive strategy in comprehending and preparing for the effects of climate change on forest ecosystems. Numerous studies gauged the impact of climate change on forest growth or productivity [50–53]. However, the impact of climate change on forest resource efficiency and total factor productivity has not been explored.

3. Methodology

Data Envelopment Analysis (DEA) is a widely employed mathematical technique that leverages linear programming to assess the efficiency of similar Decision-Making Units (DMUs) [47,48]. The conventional DEA model, introduced by Charnes et al. in 1978 [54], assumes a constant return to scale (CSR). Building on this foundation, Banker et al., in 1984 [55], adapted the model to incorporate a variable return to scale (VSR). In a preliminary exploration by Tone in 2001 [56], the Slack-based Measure (SBM) model was introduced. Subsequently, Karou Tone [57] devised a method for ranking the most efficient DMUs. The choice of DEA-SBM for evaluating the efficiency of forestry resources is due to its ability to assess systems with multiple inputs and outputs. More specifically, it compares forestry units (provinces) based on inputs such as forest area and investment and outputs like forestry output value, timber output, and forest storage. DEA-SBM employs the efficiency frontier as a metric to gauge unit performance. Notably, DEA-SBM is well-suited for situations where establishing a specific functional form for the production frontier is challenging, setting it apart from Stochastic Frontier Analysis (SFA). In contrast to SFA, which gauges inefficiency by comparing it to a predefined form, DEA-SBM's non-parametric approach offers flexibility when evaluating the efficiency of China's diverse forest resources.

3.1. DEA-SBM Model

The Slacks-Based Measure (SBM) provides an alternative approach to assess efficiency in Data Envelopment Analysis (DEA) from a non-radial standpoint. Its primary benefit is the direct assessment of excess inputs and insufficient outputs. When gauging efficiency, SBM takes into account slack, representing the difference between inputs and outputs at the production frontier. This methodology operates based on the following principles:

Suppose we have a study with n Decision-Making Units (DMUs) called "Provinces". M input indicators and s output indicators characterize each DMU. Let B_j, represent the j-th DMU, where j ranges: $j = 1, 2, \ldots, n$, $[x_{ij}]$ represents the $m \times 1$ input indicators of DMU B_j, with i ranging from 1 to m, $[y_{rj}]$ represents the $s \times 1$ output indicators of DMU B_j, with r ranging from 1 to s. The relative efficiency value of the DMU j_0-th DMUs is denoted as h_{j0}. Now, let us discuss how the output-focused SBM-DEA model with variable returns to scale operates:

$$\text{Min } h_{j0} = \theta$$

$$\text{s.t}\begin{cases} \sum_{j=1}^{n} \lambda_j x_{ij} \leq \theta x_{ij0}, i = 1, \ldots, m \\ \sum_{j=1}^{n} \lambda_j y_{rj} \geq y_{ij}, r = 1, \ldots, s \\ \sum_{j=1}^{n} \lambda_j = 1, \lambda_j \geq 0, j = 1, \ldots., n \end{cases}$$

The efficiency value at the j-th position is denoted as θ, and it is associated with a nonnegative vector λ_j. A Decision-Making Unit (DMU) is regarded as efficient only when θ is equal to 1, signifying that it is operating efficiently. In cases where θ deviates from 1, it indicates that the DMU is inefficient and has potential for enhancement.

3.2. DEA-Malmquist Productivity Index

Malmquist productivity indices offer a valuable instrument for a Decision-Making Unit (DMU) to monitor enhancements in efficiency over time. To harness this index effectively, it presupposes the presence of a production function that faithfully reflects the contemporary technological landscape. DEA models are employed to identify the position of this production function's threshold precisely. The variation in output between periods t and t+1 characterizes a particular DMU, denoted as (DMU_0) [58].

$$M_0 = \frac{D_0^{t+1}\left(x_0^{t+1}, y_0^{t+1}\right)}{D_0^t\left(x_0^t y_0^t\right)} \left[\frac{D_0^t\left(x_0^{t+1}, y_0^{t+1}\right)}{D_0^t\left(x_0^t, y_0^t\right)} \frac{D_0^{t+1}\left(x_0^{t+1}, y_0^{t+1}\right)}{D_0^{t+1}\left(x_0^t y_0^t\right)} \right]^{1/2} \quad (4)$$

where:

- $D_0^t\left(x_0^t, y_0^t\right)$ shows the TE estimation of the DMU_0 for period t;
- $D_0^{t+1}\left(x_0^{t+1}, y_0^{t+1}\right)$ illustrates the TE estimation for period t + 1;
- $D_0^t\left(x_0^{t+1}, y_0^{t+1}\right)$ specifies the variation in TE from time t to t + 1;
- $D_0^{t+1}\left(x_0^t, y_0^t\right)$ represents the technical efficiency of a specific DMU_0. This efficiency is computed by replacing its data from period t with the corresponding data from period t + 1.

The first part of Equation (4), excluding the parentheses, represents the change in the technical efficiency of DMU_0 between time t and t + 1. The period within the square brackets demonstrates the progress in technology for the same DMU. If the index value surpasses 1, it indicates that DMU_0 achieved higher output during the second period than in the first. Two hypotheses can be proposed to explain this significant increase in output. Firstly, it is possible that DMU_0 adopted cutting-edge methods, thereby improving its efficiency.

3.3. Mann–Whitney U and Kruskal–Wallis Tests

When comparing two independent groups, the Mann–Whitney U test is a nonparametric statistical method that does not depend on assumptions about the data distribution. It determines whether the values of the two groups differ substantially by comparing and ranking the data. It finds application in numerous disciplines and is beneficial when dealing with small sample sizes or non-normally distributed data. Unlike the Mann–Whitney U test, which is designed for comparing two independent groups and does not assume a normal distribution of data, the Kruskal–Wallis test examines whether the medians of multiple groups are comparable. It achieves this by ranking all the data values together and then determining if these ranked values exhibit significant differences across the groups [59]. When the Kruskal–Wallis test detects a statistically significant difference, it suggests that at least one group differs concerning the variable under investigation. This test is precious when dealing with ordinal or continuous data that do not meet the assumptions of parametric tests like analysis of variance (ANOVA). The Kruskal–Wallis test is commonly used in social sciences, healthcare, and environmental studies to compare groups when the data does not follow a normal distribution.

In our investigations, the Mann–Whitney U test is employed to identify statistically significant differences in the FRE and TFPC scores when assessed with and without considering climate factors. Additionally, the Kruskal–Wallis test is utilized to determine statistically significant differences among FRE and TFP changes across various Chinese regions. The hypotheses for this test are outlined as follows:

H_{01}. *The FRE scores are the same with and without climate factors.*

H_{02}. *The TFP change scores are the same with and without climate factors.*

H_{03}. *The FRE is the same in seven different Chinese regions.*

H_{04}. *The TFP change is the same in seven different Chinese regions.*

3.4. Variables Selection and Data Collection

The selection of inputs and outputs when estimating DEA efficiency is of great importance because choosing the wrong variables can result in inaccurate and biased estimations [60,61]. Many previous research studies have used a variety of input and output combinations to evaluate the efficiency of forest resources, as demonstrated by [62]. In alignment with this prior research, we have employed six distinct inputs and outputs to gauge Forest Resource Efficiency (FRE), as detailed in Table 1. Forest area is the total land area designated for forestry production, indicating investments in natural resource ecology. Investment tracks the accumulation of capital investments made since the beginning of the year, contributing to inputs related to reforestation. Employees represent the number of personnel at the end of the year, serving as an indicator of investments in human resources. Forestry output value reflects the resulting economic benefits. Timber output encompasses the generation of social benefits. Forest storage encompasses the ecological benefits generated. The specific names and units of these variables are provided in Table 1, and the data were sourced from China's Forestry and Grassland Statistical Yearbook. Further, the climate inputs include the measurement of temperature, expressed in degrees Celsius, which is an essential parameter when evaluating the impact that it has on forestry operations. Gaining insight into the effects of temperature fluctuations on forest growth and health is beneficial. Precipitation, which is measured in millimeters, is an additional crucial input that indicates the quantity of precipitation received by forests. Precipitation, whether adequate or inadequate, can substantially impact the growth and sustainability of forests.

Table 1. Inputs and outputs used to estimate the forestry efficiency.

No.	Inputs	Unit
1	Forest area	10,000 hectares
2	Investment	10 thousand Yuan
3	Employees	10 thousand persons
4	Temperature	°C
5	Precipitation	millimeter
6	Shortwave Radiation	W/m^2
	Outputs	
4	Forestry output value	100 million yuan
5	Timber output	10,000 cubic meters
6	Forest storage	10,000 cubic meters

Furthermore, quantified in Watts per square meter, shortwave radiation offers significant insights into the solar energy input pertinent to the forestry field. This input provides insight into the accessibility of sunlight, a critical factor influencing photosynthesis and the overall dynamics of forest ecosystems. The data for climate factors are collected from the China Environmental Statistical Yearbook. Table 2 represents the regional distribution of Chinese provinces.

Table 2. Forest regional distribution of Chinese provinces.

Region	Province	Region	Province
Northeast China	Heilongjiang	Central China	Henan
Northeast China	Jilin	Central China	Hubei
Northeast China	Liaoning	Central China	Hunan
North China	Beijing	South China	Guangdong
North China	Tianjin	South China	Guangxi
North China	Hebei	South China	Hainan
North China	Shanxi	Southwest China	Guizhou
North China	Inner Mongolia	Southwest China	Yunnan
East China	Shanghai	Southwest China	Chongqing
East China	Jiangsu	Southwest China	Sichuan
East China	Zhejiang	Southwest China	Tibet
East China	Anhui	Northwest China	Shaanxi
East China	Fujian	Northwest China	Gansu
East China	Jiangxi	Northwest China	Qinghai
East China	Shandong	Northwest China	Ningxia
		Northwest China	Xinjiang

3.5. Winsorize Technique

Our methodology incorporated the Winsorize technique, which Dixon initially proposed in 1960 [63], in order to reduce the impact of outliers within our dataset. We implemented predetermined percentile thresholds for each variable in order to eliminate the impact of outliers on the outcomes of our Data Envelopment Analysis (DEA). This methodology strives for equilibrium by recognizing exceptional values while guaranteeing that their influence is managed. The application of winsorizing improves the dependability and strength of our analysis, thereby bolstering the integrity of our research findings and facilitating a more stable depiction of the data.

4. Results

The study used Max-DEA for estimation. The following three Sections 4.1–4.3 illustrate the forestry efficiency, total factor productivity change, and statistical significance results.

4.1. Forestry Efficiency in Chinese Provinces

By employing the SBM-DEA on the inputs and outputs discussed in Table 1, we estimate the forestry efficiency of Chinese provinces for the study period of 2001–2020. Table 3 presents the efficiency scores of Chinese provinces each year. Further, it also distinguishes the efficiency scores estimated with and without climate factors. Results indicate that the average forestry efficiency score of Chinese provinces is 0.7155. After including the climate-influencing variables in the input bundle, the forestry efficiency score FRE was observeded to be 0.5412; this scenario shows us that climate change has negatively impacted the Chinese provinces' forestry efficiency. In essence, it indicates that climate factors have contributed to a reduction in the efficiency of forest resource utilization.

Table 3. Average forestry efficiency of Chinese provinces (2001–2020).

Years	Without Climate Factor	With Climate Factor
2001	0.6979	0.4901
2002	0.7577	0.4901
2003	0.7203	0.5664
2004	0.7102	0.5156
2005	0.6807	0.4899
2006	0.6861	0.4705
2007	0.6920	0.4924
2008	0.6919	0.4612
2009	0.7352	0.5579
2010	0.7622	0.5520
2011	0.6769	0.5160
2012	0.5546	0.4906
2013	0.7225	0.5830
2014	0.7371	0.5943
2015	0.7836	0.6140
2016	0.7001	0.6000
2017	0.7152	0.5753
2018	0.7624	0.5899
2019	0.7622	0.5890
2020	0.7603	0.5856
Avg. 2001–2020	0.7155	0.5412

Table 4 presents the mean forestry efficiency scores of all 31 Chinese provinces and seven regions. It further distinguishes the scores estimated with and without climate factors and gauges the climate impact on forestry efficiency change. Results illustrate that East China's mean efficiency scores (without climate factors) are the highest among all seven regions, with an efficiency score of 0.9247. South China ranked second with an efficiency score of 0.9101. At the same time, Northeast China ranked third with an average efficiency score of 0.8729. Northwest China was to be the lowest performer, with a mean efficiency score of 0.2473. Heilongjiang, Anhui, Yunnan, and Tibet are the most efficient in forestry efficiency, in terms of mean score of efficiency. These results indicate that the regions mentioned above and provinces optimized the forestry resources and utilized best operational practices to increase their forestry efficiency. This illustrates that these regions and provinces reduce the inputs of labor, forest resources, and government spending to maximize forestry output. Qinghai Ningxia and Gansu were the lowest performers in forestry resource utilization.

Table 4. Forestry efficiency evaluation in 31 and 7 regions (2001–2020).

Region	Province	Without Climate	With Climate	Change%
Northeast China	Heilongjiang	1.0000	0.3281	−67.19
	Jilin	0.9629	0.7889	−18.07
	Liaoning	0.6558	0.4059	−38.11
	Mean	**0.8729**	**0.5076**	**−41.85**
North China	Beijing	0.5523	0.4709	−14.74
	Tianjin	0.4890	0.6443	+31.76
	Hebei	0.5916	0.2926	−50.54
	Shanxi	0.3962	0.2493	−37.08
	Inner Mongolia	0.9377	0.2264	−75.86
	Mean	**0.5933**	**0.3767**	**−36.51**
East China	Shanghai	0.9569	0.9635	+0.69
	Jiangsu	0.8956	0.8131	−9.21
	Zhejiang	0.9025	0.8519	−5.61
	Anhui	1.0000	1.0000	0
	Fujian	0.9881	0.9705	−1.78
	Jiangxi	0.8078	0.5309	−34.28
	Shandong	0.9224	0.6712	−27.23
	Mean	**0.9247**	**0.8287**	**−10.38**
Central China	Henan	0.8010	0.4864	−39.28
	Hubei	0.4547	0.3620	−20.39
	Hunan	0.9399	0.5267	−43.96
	Mean	**0.7319**	**0.4584**	**−37.37**
South China	Guangdong	0.8667	0.8436	−2.67
	Guangxi	0.9470	0.8256	−12.82
	Hainan	0.9167	0.9462	+3.22
	Mean	**0.9101**	**0.8718**	**−4.21**
Southwest China	Guizhou	0.4983	0.3581	−28.14
	Yunnan	1.0000	0.5730	−42.7
	Chongqing	0.4735	0.4007	−15.37
	Sichuan	0.9864	0.4341	−55.99
	Tibet	1.0000	1.0000	0
	Mean	**0.7916**	**0.5532**	**−30.12**
Northwest China	Shaanxi	0.3629	0.2112	−41.8
	Gansu	0.2476	0.1540	−37.8
	Qinghai	0.0759	0.0679	−10.54
	Ningxia	0.1740	0.1575	−9.48
	Xinjiang	0.3759	0.2224	−40.84
	Mean	**0.2473**	**0.1626**	**−34.25**

Note: Mean values show the average of the region's provinces.

In the second scenario, the climate inputs were incorporated to gauge the impact of climate change on forestry efficiency. Results indicate that the forestry efficiency of Northeast China was most significantly affected by climate change. Central China also receives diverse climate change effects on its efficiency scores. North China is the third most affected region by climate change and its forestry efficiency. South China, East China, and Southwest China are the least affected regions by climate change for forestry resources utilization.

Further illustrating each province's climate impact on forestry efficiency, we found that Inner Mongolia, Heilongjiang, Sichuan, Hebei, and Hunan are China's top five most climate-affected provinces in terms of forestry efficiency. The forestry efficiency decline in Yunnan, Shaanxi, Xinjiang, Henan, Liaoning, Gansu, Shanxi, Jiangxi, Guizhou, Shandong, Hubei, Jilin, and Chongqing was recorded between 15 and 43 percent, showing a moderate effect of climate change. The climate effect on the forestry efficiency of Beijing, Guangxi, Qinghai, Ningxia, Jiangsu, Zhejiang, Guangdong, Fujian, Anhui, and Tibet was at a low level between 0 and 15 percent. This illustrates that these provinces were least affected by climate change regarding forestry resource utilization. Study results show that Tianjin, Hainan, and Shanghai's forestry efficiency is positively affected by climate change as these provinces grow in forestry efficiency with an average of 31.76, 3.22, and 0.69 percent.

4.2. Total Factor Productivity Change

By employing the DEA-Malmquist model on data collected from 31 Chinese provinces, this study evaluates changes in forestry productivity from 2001 to 2020 (Table 5). As a result, it facilitates the calculation of variation in total factor productivity (TFP) and the value of its decomposition. The two components that comprise total factor productivity change (TFPCH) are technical efficiency change (EC) and technical change (TC). An index value exceeding 1 indicates a level of growth in the current year concerning the previous year. Conversely, an index value falling below 1 indicates a decline in the level of that year in comparison to the previous year. The results show that the average total factor productivity change (TFPC) is 1.0480. This demonstrates the growth of 4.80 percent in total factor forestry productivity over the study period. By decomposing the total factor productivity change, we found that technology change (TC) is the primary determinant of productivity growth instead of technical efficiency change (EC); TC = 1.0403 is more significant than EC =1.0074. This further illustrates that TC witnessed 4.03 percent growth, and EC gained 0.74 percent over the study period. After incorporating the climate factor in the production function, we found that forestry's total factor productivity value is 1.0205. However, it still grows by 2.05 percent over the study period. In this case, efficiency change is the main decider of productivity growth as TC = 1.0049 < EC =1.0155. The total factor forestry growth was at its highest point in the years 2018–2019 (1.1614), 2001–2002 (1.1467), and 2017–2018 (1.1327). Similarly, the total factor forestry growth was at the lowest level in the years 2014–2015(0.8929), 2009–2010 (0.9591), and 2015–2016 (0.9626), respectively. In most of the years, the efficiency decline is the main culprit in the deterioration of TFPC. In contrast, after climate factor incorporation, the TFPC of Chinese provinces was highest in the years 2018–2019 (1.152), 2005–2006 (1.144), and 2017–2018 (1.119). While TFPC in 2014–2015(0.7619), 2013–2014 (0.7841), and 2003–2004(0.897) was at its lowest level.

Figure 2 indicates the difference in forestry total factor productivity change after incorporating climate factors. Figure 3 further indicates the climate factor's impact on EC and TC.

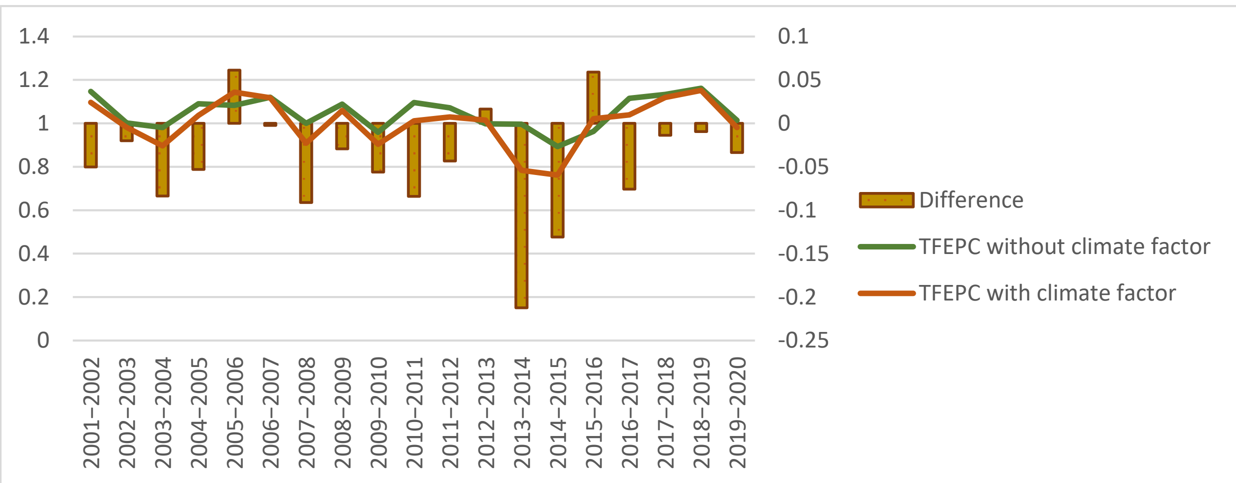

Figure 2. Climate impact on total factor productivity change.

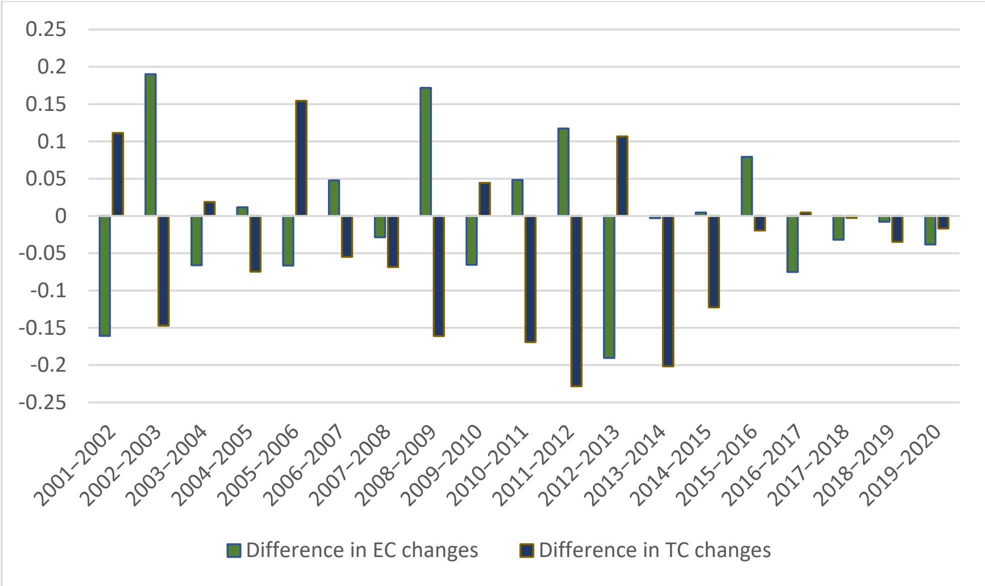

Figure 3. Climate impact on EC and TC.

Table 5. Total factor productivity change, efficiency change, and technology change with and without climate factors for 31 Chinese provinces (2001–2020).

	Without Climate			**With Climate**		
Years	**TFPC**	**EC**	**TC**	**TFPC**	**EC**	**TC**
2001–2002	1.1467	1.1343	1.0197	1.0965	0.9736	1.1309
2002–2003	1.0018	0.9765	1.0246	0.9818	1.1668	0.8774
2003–2004	0.9807	0.9533	1.0365	0.8970	0.8873	1.0552
2004–2005	1.0901	0.9421	1.1676	1.0370	0.9538	1.0929
2005–2006	1.0827	0.9999	1.0826	1.1440	0.9332	1.2369
2006–2007	1.1201	0.9991	1.1214	1.1178	1.0468	1.0665
2007–2008	1.0001	0.9933	1.0064	0.9091	0.9648	0.9379
2008–2009	1.0888	1.0444	1.0418	1.0595	1.2160	0.8808
2009–2010	0.9591	1.0683	0.8982	0.9032	1.0029	0.9424
2010–2011	1.0957	0.8808	1.2629	1.0118	0.9291	1.0937
2011–2012	1.0724	0.8697	1.2797	1.0291	0.9870	1.0513
2012–2013	0.9980	1.3246	0.7913	1.0145	1.1341	0.8979
2013–2014	0.9963	1.0435	0.9593	0.7841	1.0408	0.7578
2014–2015	0.8929	1.0787	0.8332	0.7619	1.0834	0.7105
2015–2016	0.9626	0.8897	1.0898	1.0216	0.9689	1.0704
2016–2017	1.1154	1.0336	1.0803	1.0395	0.9583	1.0850
2017–2018	1.1327	1.0631	1.0905	1.1190	1.0312	1.0879
2018–2019	1.1614	1.0277	1.1678	1.1520	1.0199	1.1330
2019–2020	1.0138	1.0340	1.0014	0.9802	0.9959	0.9847
Avg.	1.0480	1.0074	1.0403	1.0205	1.0155	1.0049

Note: Avg. shows the average values by years for climate and without climate models.

Table 6 presents the TFPC in seven different forest regions of China. Results indicate that TFPC is at its highest level in South China, with an average value of 1.087, indicating 8.7 growth over the study period. North China (1.0607) and Southwest China (1.0547) ranked second and third among all seven regions. Northwest China region had the lowest TFPC with an average score of 1.0065. Moreover, the TFPC in all seven regions grew as their scores exceeded 1. Decomposing the TFPC into TC and EC, study results found that in all regions, TC is the primary determinant of the TFPC of forestry. This study incorporates the climate factors and gauges the TFPC of all seven regions to measure the impact of climate change on TFPC in different regions. Results show that the TFPC of Northeast

China, Central China, Southwest China, and Northwest China declined to less than 1. This illustrates the deterioration in TFPC in these regions due to the climate factor.

Table 6. TFPC, EC, and TC in seven different regions of China.

	Without Climate			With Climate		
	TFPC	**EC**	**TC**	**TFPC**	**EC**	**TC**
Northeast China	1.0471	1.0112	1.0627	0.9717	1.0071	0.9898
North China	1.0607	1.0159	1.0679	1.0177	1.0111	1.0227
East China	1.0471	1.0218	1.0459	1.0239	1.0122	1.0198
Central China	1.0488	1.0061	1.0592	0.9850	1.0024	0.9971
South China	1.0870	1.0262	1.0728	1.0658	1.0180	1.0527
Southwest China	1.0547	1.0333	1.0356	0.9963	1.0534	0.9725
Northwest China	1.0065	1.0106	1.0270	0.9584	0.9978	0.9838

Moreover, the TFPC in North China, East China, and South China also declined due to climate factors; however, it did not decline below 1. Figure 4 indicates the TFPC, EC, and TC decline of all seven regions after incorporating the climate factor. However, a slight growth of EC was witnessed in the South China region. The main culprit in the deterioration of TFPC was TC, which declined due to the climate factors included in the production function. Figure 5 further displays the difference between all seven regions' gauged TFPC, EC, and TC with and without climate factors.

Table 7 presents the TFPC, EC, and TC in 31 Chinese provinces. Results indicate that the average forestry TFPC without climate factor was at its highest level in Guangxi (1.1596), Liaoning (1.1512), and Chongqing (1.151). This indicates that Guangxi witnessed a 15.96% growth in total factor productivity in forestry. Similarly, Liaoning observed 15.12 percent, and Chongqing observed 15.11 percent growth. Further results found that the primary determinant of TFPC in all three provinces was found to be technology change as efficiency change is less for all three DMUS (1.0358 < 1.1228) (1.0451 < 1.1492) (1.1052 < 1.1112).

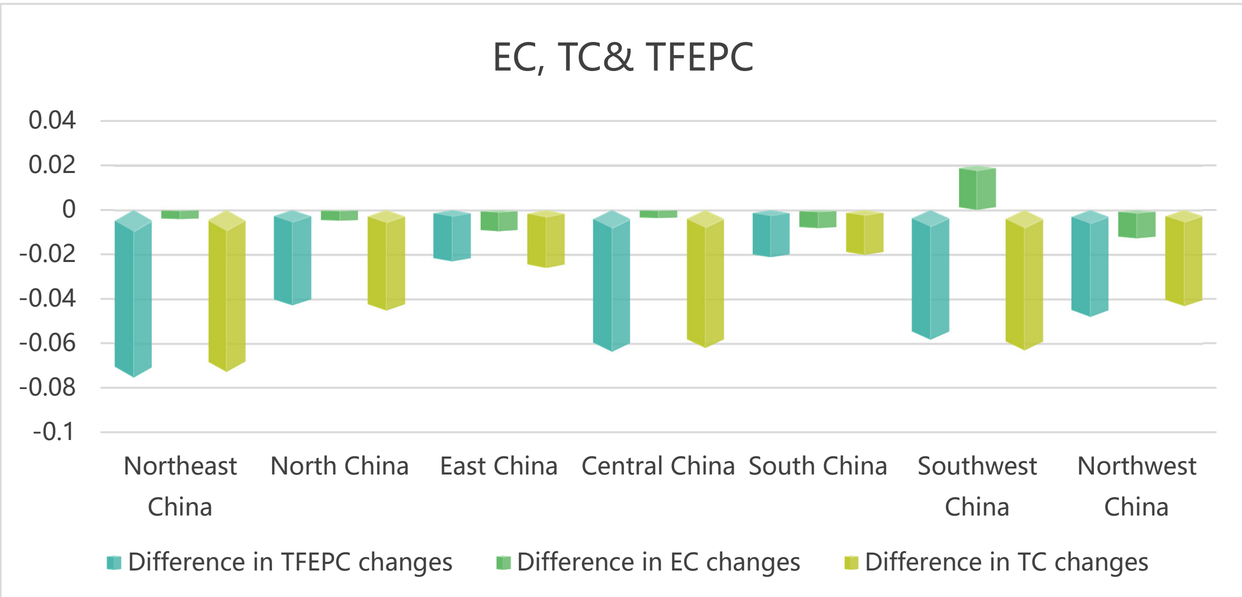

Figure 4. Differences in TFPC, EC, and TC due to climate factor incorporation.

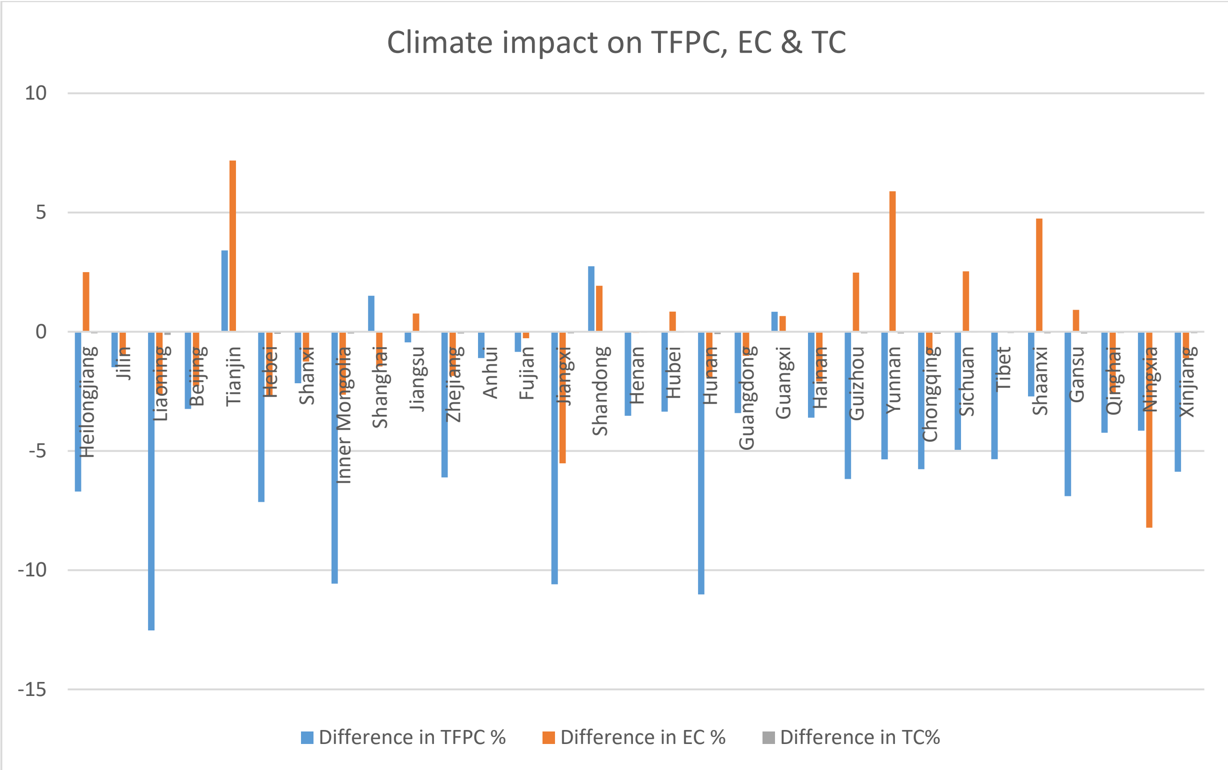

Figure 5. Climate impact on TFPC, EC, and TC.

Further, Zhejiang, Guizhou, Hunan, Shandong, Shanxi, Jiangxi, Guangdong, Inner Mongolia, Beijing, Hubei, Yunnan, Anhui, Sichuan, Gansu, Hainan, Fujian, Jiangsu, Shaanxi, Xinjiang, Henan, and Heilongjiang also witnessed growth in total factor productivity change as their TFPC score is over one. In most provinces, TC is the primary reason for productivity growth. It indicates that these provinces efficiently utilized their forest resources for optimum output and witnessed growth. Moreover, they also received an incline in their technology and efficiency over the study period. However, in Qinghai, Tianjin, Shanghai, Ningxia, Jilin, and Tibet, the TFPC declined over the study period as their scores were less than 1. The culprit of deterioration in TFPC is both efficiency and technology decline.

After the inclusion of climate factors in the production function, we found that Guangxi (1.1693), Shandong (1.1199), and Chongqing (1.0847) are the top 3 performers in terms of TFPC level. Shanxi, Guangdong, Hebei, Zhejiang, Guizhou, Tianjin, Anhui, Beijing, Jiangsu, Shanghai, Hubei, Liaoning, and Fujian grew in TFPC as their average values were over 1. Shaanxi, Hainan, Hunan, Yunnan, Jiangxi, Jilin, Sichuan, Henan, Qinghai, Xinjiang, Ningxia, Gansu, Inner Mongolia, Heilongjiang, and Tibet deteriorated their TFPC after the inclusion of climate factors. This demonstrates that the TFPC of more than half of Chinese provinces declined due to climate factors. This indicates a diverse effect of climate change on forestry total factor productivity.

Moreover, the climate also deteriorated the TC and impacted the decline of TFPC in Chinese provinces. Therefore, this advocates that limiting the climate factor could increase the TC, ultimately boosting the TFPC in China's forestry sector.

The level of difference due to climate factors on TFPC, EC, and TC of Chinese provinces is essential as it gives an overview of the diverse regional impact of climate change and suggests a path for the central government to focus on specific provinces or regions. We found that Liaoning, Hunan, and Jiangxi were the most affected provinces as their TFPC declined (see Figure 5). However, the TFPC of Guangxi, Shanghai, Shandong, and Tianjin obtained positive effects from climate change. Ningxia, Jiangxi, and Hebei were found to be the top diverse impacts of climate on EC.

Table 7. TFPC, EC, and TC in 31 different provinces of China.

		Without Climate			With Climate		
		TFPC	**EC**	**TC**	**TFPC**	**EC**	**TC**
Northeast China	Heilongjiang	1.0031	1.0000	1.0031	0.9359	1.0250	0.9410
	Jilin	0.9870	0.9885	1.0358	0.9723	0.9786	1.0279
	Liaoning	1.1512	1.0451	1.1492	1.0070	1.0177	1.0006
North China	Beijing	1.0472	0.9867	1.0719	1.0133	0.9643	1.0521
	Tianjin	0.9966	0.9357	1.0689	1.0306	1.0029	1.0451
	Hebei	1.1175	1.0775	1.1053	1.0377	1.0487	1.0112
	Shanxi	1.0884	1.0571	1.0570	1.0649	1.0439	1.0448
	Inner Mongolia	1.0536	1.0226	1.0365	0.9423	0.9956	0.9601
East China	Shanghai	0.9938	1.0148	0.9822	1.0088	1.0000	1.0088
	Jiangsu	1.0140	1.0224	1.0207	1.0095	1.0302	0.9936
	Zhejiang	1.1015	1.0417	1.1193	1.0342	1.0224	1.0357
	Anhui	1.0265	1.0000	1.0265	1.0152	1.0000	1.0152
	Fujian	1.0156	1.0039	1.0191	1.0070	1.0012	1.0067
	Jiangxi	1.0880	1.0473	1.0652	0.9728	0.9895	0.9988
	Shandong	1.0900	1.0222	1.0883	1.1199	1.0419	1.0794
Central China	Henan	1.0046	0.9697	1.0570	0.9692	0.9693	1.0212
	Hubei	1.0431	1.0274	1.0235	1.0081	1.0361	0.9829
	Hunan	1.0986	1.0212	1.0971	0.9776	1.0018	0.9872
South China	Guangdong	1.0851	1.0413	1.0557	1.0481	1.0308	1.0377
	Guangxi	1.1596	1.0358	1.1228	1.1693	1.0426	1.1190
	Hainan	1.0164	1.0013	1.0401	0.9798	0.9805	1.0014
Southwest China	Guizhou	1.0992	1.0559	1.0479	1.0313	1.0821	0.9810
	Yunnan	1.0321	1.0000	1.0321	0.9769	1.0589	0.9571
	Chongqing	1.1510	1.1052	1.1112	1.0847	1.0949	1.0157
	Sichuan	1.0218	1.0054	1.0176	0.9712	1.0309	0.9911
	Tibet	0.9692	1.0000	0.9692	0.9174	1.0000	0.9174
Northwest China	Shaanxi	1.0132	1.0007	1.0321	0.9857	1.0482	0.9654
	Gansu	1.0168	1.0104	1.0323	0.9467	1.0197	0.9640
	Qinghai	0.9967	1.0124	1.0216	0.9545	0.9860	0.9672
	Ningxia	0.9930	1.0113	1.0286	0.9518	0.9282	1.0590
	Xinjiang	1.0127	1.0184	1.0204	0.9533	1.0071	0.9632

4.3. Statistical Significant Difference

Sections 4.1 and 4.2 found that forestry's FRE and total factor productivity change is heterogeneous with and without climate factors. Similarly, the results indicate that average FRE and TFPC differ for seven Chinese forest regions. However, whether these results significantly differ is a question of great concern. This research applied the Mann–Whitney U and Kruskal–Wallis tests to investigate this scenario. The first hypothesis states that the FRE scores are the same with and without climate factors. Table 8 and Figure A1 indicate that the sig level of the first hypothesis is 0.001, which is less than 0.05; therefore, we reject the hypothesis that FRE scores are the same with and without climate factors. This result indicates that climate significantly impacts forestry resource utilization efficiency.

Similarly, the sig level of the second hypothesis is 0.004, below 0.05. Thus, this study rejects the hypothesis stating that "the TFP change scores are same with and without climate factor." It proves that TFPC is significantly different with and without climate factors. Climate factors have diverse effects on TFPC in forestry. The third and fourth hypotheses claim that the FRE and TFPC in forestry are the same for seven regions. The significance levels of 0.009 and 0.003 indicate that these are less than 0.05; therefore, this study concludes that FRE and TFPC significantly differ in seven different Chinese forest regions.

Table 8. Statistically significant test results.

Hypothesis Test Summary				
	Null Hypothesis	**Test**	**Sig.**	**Decision**
1	The FRE scores are the same with and without climate factors.	Independent-Samples Mann–Whitney U Test	0.001	Reject the null hypothesis.
2	The TFP change scores are the same with and without climate factors.		0.004	Reject the null hypothesis
3	The FRE is the same in seven different Chinese regions.	Independent-Samples Kruskal–Wallis Test	0.009	Reject the null hypothesis
4	The TFP change is the same in seven different Chinese regions.		0.003	Reject the null hypothesis

Asymptotic significances are displayed. The significance level is 0.050.

5. Discussion

An analysis of forestry efficiency in different Chinese regions provides significant insights into the influence of climate change on the exploitation of resources. The recorded mean forestry efficiency score was 0.7155. After including the climate factors, the average forestry efficiency score was 0.5412, highlighting the substantial impact of climate change on the forestry sector of China. This decline is a concrete obstacle to the effective usage of forest resources, highlighting the difficulties caused by changing climate conditions. The findings suggest that the forestry sector in China is experiencing negative impacts due to climate change. The decline in efficiency scores observed when including climate factors implies that the practical usage of forest resources is hindered by changing climate conditions, including extreme weather events, altered precipitation patterns, and temperature changes. These results are aligned with the past forestry research [64].

The regional analysis presented in Table 4 reveals a detailed and complex distribution of efficiency scores among provinces and regions. East China has exceptional performance with the greatest efficiency scores, whereas Northwest China severely falls behind. Provinces such as Heilongjiang, Anhui, Yunnan, and Tibet have admirable efficiency, which can be attributed to their efficient resource utilization and implementation of best operational methods. In contrast, the provinces of Qinghai, Ningxia, and Gansu face challenges in effectively utilizing their forestry resources, highlighting the urgent requirement for customized policies. The findings are consistent with the current body of research that highlights the harmful impacts of climate change on the forestry sector. The decrease in efficiency scores reflects reservations regarding severe climate impact, modified precipitation patterns, and temperature changes. It highlights the importance of implementing adaptive strategies and resilient practices to reduce the effects of climate change on the efficiency of forestry. Studies have suggested several measures to improve forestry efficiency and lessen climate change's impact on different places. Heilongjiang, Anhui, Yunnan, and Tibet have optimized resource use, adopted the best operational techniques, and reduced input costs, teaching others. Forest management in climate-affected areas should include selecting resilient tree species, monitoring methods, and biodiversity. Effective forestry management requires early warning systems, government backing, research, and capacity building. These measures can boost forestry efficiency and help regions adjust to climate change, ensuring sustainable forest management [65].

The analysis of total factor productivity change (TFPC) investigates the dynamic characteristics of forestry productivity over the research period. The computed mean total factor productivity change (TFPC) of 1.0480 indicates a total growth rate of 4.80%, primarily driven by technological change (TC). The decomposition of TFPC underscores the importance of technological advancements in comparison to efficiency enhancements. It indicates that when climate impact is taken into account, there is a decline in TFPC to 1.0205. Efficiency change (EC) plays a crucial role in determining productivity growth in this setting, surpassing the significance of technological advancements. The fluctuations in TFPC recorded across many years demonstrate the temporal variability of forestry productivity. Numerous research studies also found technological advancement as a key factor in forestry productivity growth (Ref.). Further, the diverse effects of climate change on forestry growth are proved in previous research studies, making a strong background for this study's results [66,67]. These results indicate that climate factors significantly impact the TC instead of EC. However, after 2012–2013, the diverse effects of climate change on both TC and EC gradually decreased. This indicates that government efforts to decrease the climate effect on total factor productivity, efficiency, and technological advancement have started working with time. It further demonstrates the efficiency and technological progress to boost the total factor productivity of forestry resources in China over the study period.

The regional analysis presented a clear understanding of the varied influence of climate conditions on TFPC. The South China region demonstrates resilience by exhibiting the highest total factor productivity change (TFPC). In contrast, the Northeast China and Central China regions see drops below 1, showing a decline in productivity attributed to climate-related issues. The examination particular to each province highlights the diverse impacts, as Guangxi, Shandong, and Chongqing demonstrate a positive increase in total factor productivity change (TFPC) despite the influence of climate factors. The combination of these findings highlights the complex interaction between climate change and the productivity of forestry. The decrease in total factor productivity change following the integration of climate factors requires a reassessment of approaches to enhance efficiency and technological advancement. Moreover, the varied effects reported in different locations and provinces necessitate targeted interventions to improve resilience and flexibility. Studies highlight the importance of TFPC (Timber, Forest, and Paper Products Company) for forestry needs technology change of efficiency, sustainability, and worker safety. Optimizing operations, promoting sustainable forest management, and reducing hazards benefits the industry and environment [68,69]. Our study results are aligned with numerous research studies that witnessed the diverse impact of climate change on forestry productivity [70–72]. This scenario illustrates that benchmarking the efficient DMUs in these provinces could increase their TFPC by increasing their TC and EC. Numerous research studies highlighted the importance of technological development and efficiency incline to increase the TFPC level [73–75].

Several research studies investigate the impact of climate change on forestry productivity and suggest policy recommendations to boost technological advancement to increase the TFPC [76–78]. Climate change dramatically impacts the total factor productivity, EC, and TC of forestry in many Chinese provinces. Cultivating climate-resilient tree species, adaptive forest management, climate monitoring, sustainable land use, research and innovation, and international cooperation are some measures to counteract these consequences [79]. Statistically significant differences among the FRE and TFPC for different regions and with and without climate change are evident from the results of Section 4.3. Numerous research studies advocate for the impact of climate change on forestry efficiency and productivity and further differences in efficiency and productivity levels in different regions [80–82].

6. Conclusions

In the last two decades, the Chinese government has employed numerous strategies to minimize the impact of climate change on forestry efficiency and total factor productivity. However, the level of success in this mission to mitigate the climate impact on forestry efficiency and TFPC is still undiscovered and needs comprehensive investigation. To this end, this research employed different estimation methods to investigate the climate impact on FRE and TFPC. This study employed data envelopment analysis (DEA-SBM) on a set of inputs and outputs to estimate the forestry efficiency of 31 Chinese provinces over the well-strength period of 20 years (2001–2020). It explores the efficiency level of different Chinese provinces and regions in forest resource utilization over the study period. Afterwards, the study incorporates the climate factor in input variables to gauge the impact of climate change on forestry efficiency. This investigation illustrates the decline in forestry efficiency caused by climate change. Thirdly, the research uses the Malmquist productivity index to gauge the total factor productivity change in forest resource utilization for 31 Chinese provinces and regions. It investigates the growth or decline in total factor productivity of forest resources and further explores the determinant of productivity change (efficiency of technology).

Moreover, climate change's impact on total factor productivity change is also explored through input incorporating climate factors. Further climate impact on forestry TFPC for seven different Chinese regions is also gauged to show the regional impact of climate factors. Finally, the Mann–Whitney U and Kruskal–Wallis tests investigate the significant statistical differences in forestry efficiency and total factor productivity scores among the results estimated with and without climate factor incorporation and different Chinese regions.

Results revealed that the average forestry efficiency score in Chinese provinces is 0.7155. However, when climate-influencing variables are considered, the forestry efficiency scores significantly decrease to an average of 0.5412, highlighting the negative impact of climate change on forestry efficiency. Regionally, East China demonstrates the highest mean efficiency score (0.9247), followed by South China (0.9101), while Northwest China performs the lowest with a mean efficiency score of 0.2473. In the presence of climate factors, Northeast China experiences the most significant decline in forestry efficiency, emphasizing the adverse impact of climate change on different regions. Heilongjiang, Anhui, Yunnan, and Tibet are the most efficient in forestry efficiency. Inner Mongolia, Heilongjiang, Sichuan, Hebei, and Hunan are China's top 5 most climate-affected provinces regarding forestry efficiency. Studies suggested several ways to enhance forestry efficiency and minimize the effect of climate on forestry production. It is imperative to adopt a comprehensive and multidimensional strategy to optimize forestry efficiency and mitigate the detrimental impacts of climate change. Using sustainable forest management strategies, such as selective logging and replanting, plays a pivotal role in maximizing the efficient utilization of resources. Utilizing technological tools, such as Geographic Information Systems (GIS) and remote sensing, can facilitate the acquisition of up-to-date information, enhancing the quality of decision-making processes. Ensuring sustainability necessitates implementing several crucial measures, including cultivating tree species that are tolerant to climate variations, active engagement of local populations in forest management practices, and the seamless integration of land use planning with forestry initiatives. The use of erosion control and water management strategies is crucial in addressing the issues of soil erosion and water scarcity. To effectively mitigate the risks posed by wildfires and climate-related difficulties, adopting proactive fire control tactics and climate-adaptive policies is imperative. Continuous research, monitoring, and international collaboration facilitate informed decision-making and foster standard solutions. By implementing these strategies, there is potential to enhance the efficiency of forestry practices and mitigate the adverse effects of climate change on forest ecosystems.

This study reveals an average total factor productivity change (TFPC) of 1.0480, indicating a 4.80% growth in total forestry productivity. Technology change (TC) emerges as the primary driver of productivity growth, with TC (1.0403) exceeding efficiency change (EC) (1.0074). Incorporating climate factors leads to a decline in forestry total factor productivity (1.0205), primarily influenced by a decrease in TC. The impact of climate change on TFPC is evident, with varying effects across different regions and years. South China exhibits the highest TFPC (1.087), while Northeast China and Central China experience declines below 1. The further analysis highlights the top five provinces most affected by climate change regarding forestry efficiency: Inner Mongolia, Heilongjiang, Sichuan, Hebei, and Hunan. These provinces witness substantial declines ranging from 43.96% to 75.86%. The Mann–Whitney U and Kruskal–Wallis tests investigated the significance of the results. The findings reject the hypotheses that forestry efficiency scores and total factor productivity change remain the same with and without climate factors, emphasizing the significant impact of climate change on forestry resource utilization efficiency. Additionally, this study concludes that forestry efficiency and total factor productivity change vary significantly across the seven Chinese forest regions.

This study's findings have significant policy consequences for the forest authority in China. The rapid implementation of climate-resilient measures is essential due to the significant adverse effects of climate change on forestry efficiency and total factor productivity change. Customizing these measures following regional disparities is imperative, mainly focusing on regions such as Northeast China that experience substantial impacts. The prioritization of the adoption of innovative technologies and practices should be emphasized by forest authorities, recognizing the significant role that technology change plays in driving productivity increase. Provinces identified as being particularly vulnerable to climate change, including Inner Mongolia, Heilongjiang, Sichuan, Hebei, and Hunan, necessitate targeted initiatives to enhance their ability for adaptation and resilience. Establishing robust monitoring and evaluation systems is crucial to evaluate the efficacy of mitigation measures and to change policies in response to evolving climate circumstances. Incorporating international cooperation, integrating climate issues into preexisting policies, and cultivating public knowledge and engagement are integral elements of a holistic approach. This study emphasizes the importance of adaptive forest planning that can effectively respond to dynamic climate circumstances. It also highlights the need for effective cooperation between appropriate government agencies, research institutions, and non-governmental organizations to meet the diverse difficulties mentioned in this study.

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

Appendix A

Table A1. Effect of climate change in TFPC, EC, and TC.

Effect of Climate Change			
Years	**TFEPC**	**EC**	**TC**
2001–2002	−0.0502	−0.1607	0.1112
2002–2003	−0.0200	0.1903	−0.1472
2003–2004	−0.0837	−0.0660	0.0188
2004–2005	−0.0531	0.0117	−0.0747
2005–2006	0.0613	−0.0667	0.1542
2006–2007	−0.0023	0.0476	−0.0548
2007–2008	−0.0910	−0.0285	−0.0684
2008–2009	−0.0293	0.1716	−0.1610
2009–2010	−0.0559	−0.0654	0.0443
2010–2011	−0.0840	0.0484	−0.1692
2011–2012	−0.0433	0.1174	−0.2284
2012–2013	0.0165	−0.1905	−0.1066
2013–2014	−0.2123	−0.0028	−0.2016
2014–2015	−0.1310	0.0047	−0.1228
2015–2016	0.0590	0.0792	−0.0194
2016–2017	−0.0759	−0.0752	0.0047
2017–2018	−0.0137	−0.0320	−0.0026
2018–2019	−0.0095	−0.0079	−0.0348
2019–2020	−0.0336	−0.0381	−0.0167

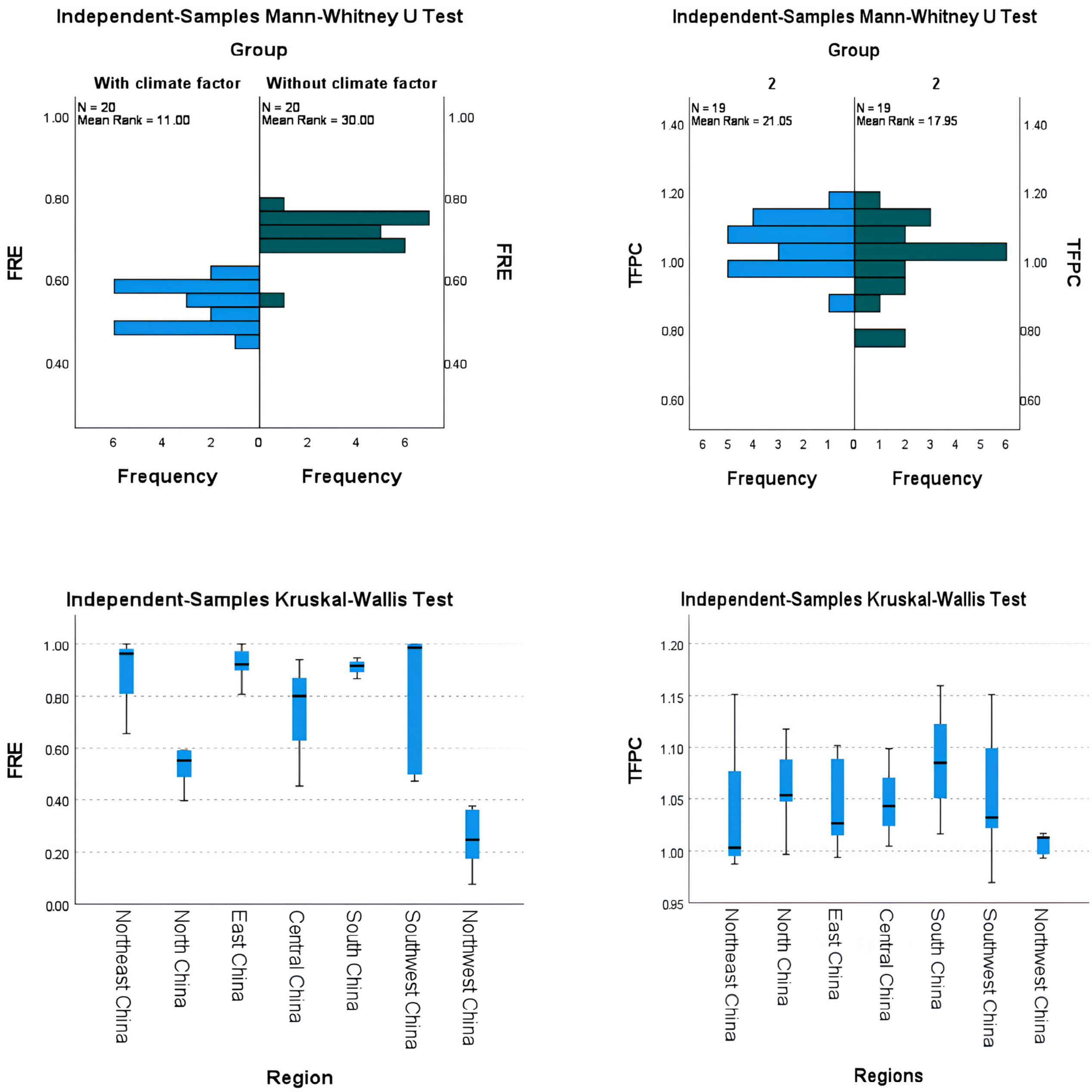

Figure A1. The distribution of Average FRE, TFPC with and without climate factors and in seven different Chinese forest regions.

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