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The Impact of Technological Dynamics and Fiscal Decentralization on Forest Resource Efficiency in China: The Mediating Role of Digital Economy

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

1 School of Economics and Management, Panzhihua University, Panzhihua 617000, China; rizwana_239@yahoo.com
2 Department of Management Sciences, City University of Hong Kong, Hong Kong 999077, China; msghao@city.edu.hk
3 School of Management, Zhejiang Shuren University, Hangzhou 310015, China
* Correspondence: wasi450@yahoo.com

Abstract: This study explores the multi-dimensional relationships between technology, fiscal decentralization, and forest resource efficiency, and the pivotal role played by the digital economy as a mediator in 2002–2020. First, this study evaluates the Chinese provinces' forest resource efficiency using multi-dimensional inputs and outputs of forest sectors. Further, we use two sorts of technology: high-technology expenditure and forest technology education. Fiscal decentralization in terms of local government expenditure on forest resources makes the study innovative and richer in analysis. A SBM-DEA analysis showed that the Anhui, Beijing, Jiangsu, Shanghai, and Zhejiang provinces have the highest efficiency scores, implying very efficient forest resource management. Subsequently, the robust econometric estimator Driscoll and Kraay is applied. The study's findings disclose that both dimensions of technology increase the Chinese provinces' forest resource efficiency through technological expenditure and forest technology education. Fiscal decentralization towards forest resource management expenditure increases the efficiency of forests. Urbanization and economic development reduce the efficiency of forests. The digital economy can effectively help to improve the efficiency of forest resources. The presence of moderating effects reveals that the influence of the digital economy on forest resource efficiency is positive when it is coupled with economic development, fiscal decentralization, technology, and urbanization.

Keywords: forests resource efficiency; high-technology expenditure; forest technology education; fiscal decentralization; digital economy

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1. Introduction

Indeed, forest resources are of immense significance as an essential component of natural resources for the maintenance of ecological stability and for the well-being of the planet [1]. They offer not only timber and non-timber forest products, but also play a crucial role in protecting soil and water resources, maintaining biodiversity, reducing the effects of natural disasters, regulating climate, enabling recreational activities, promoting pollination, and managing pests and diseases [2–5]. Hence, the conservation and efficient administration of forest resources is of utmost importance to the balance and well-being of both the environment and human society. Moreover, ensuring efficient forest resource utilization, known as forest resource efficiency, becomes essential to maintain a wide range of ecological, economic, and social advantages in the long run without exhausting these resources [6,7]. Further, forest resource efficiency refers to the smart and sustainable utilization of forest resources, striking a balance between extracting goods and services while preserving the forest ecosystem's health and resilience. Forest resource efficiency seeks to maximize the beneficial outcomes of resource utilization while minimizing any negative consequences through integrating technology, research, and community engagement. Unfortunately, maintaining forest resource efficiency is challenging due to economic expansion and infrastructure development, which leads to deforestation and territory destruction. The conversion of land for housing, industry, and transportation leads to a decrease in forest cover, emphasizing the urgent need to tackle these issues to maintain the efficiency of forest resources.

Over the past three centuries, commencing with the advent of the Industrial Revolution in Britain during the 1760s and the subsequent global population expansion, there has been an imbalance between the rate of natural resource consumption and the rate at which these resources are replenished [8]. Moreover, since the advent of the Industrial Revolution, the primary feature of production technology has transitioned from manual labor to capital-intensive methods [9]. This change has resulted in an unprecedented surge in energy use. The growing dependence on capital-intensive technology and the rapid increase in energy consumption have exerted further strain on diverse natural resources, such as forests and the environment. This disparity has contributed to apprehensions over sustainability and the imperative for more effective and accountable resource management strategies to safeguard the welfare of both current and future generations.

According to the United Nations Convention to Combat Desertification (UNCCD), the rate of deforestation experienced a significant increase of 20% in 2021 [10]. According to the World Bank, deforestation and forest degradation have raised forest sector losses from 42 USD billion to 88 USD billion annually. As a result, there has been a growing concern about the tremendous importance of forest biotopes globally. Recognizing the urgent need for action, Sustainable Development Goals (SDGs) have become pivotal in shaping current environmental policies [11,12]. Furthermore, the Sustainable Development Goals (SDGs) offer a comprehensive structure for tackling environmental issues. Moreover, the SDGs provide a comprehensive framework for addressing environmental challenges beyond forests, emphasizing the interconnected goals of clean water, climate action, life below water, and life on land. This integrative approach ensures that environmental measures go beyond individual difficulties, fostering a harmonious and enduring solution to global challenges. The 2015 Paris Agreement and the laws related to Nationally Determined Contributions (NDC), particularly in countries such as China, emphasize the dedication to sustainable forest management as a crucial component of wider initiatives to tackle climate change and biodiversity decline.

After that, China emerged as a proactive participant in strategically managing its forest resources. Since 2015, the Chinese government has incorporated within its NDC the commitment to augment its forest stock volume by around 4.5 billion cubic meters by 2030, compared to the level observed in 2005 [13]. Additionally, the government aims to strengthen systems and capabilities to mitigate climate change risks in forest management. Furthermore, the Chinese government has implemented comprehensive domestic forest protection programs. Among the most extensive initiatives, the Natural Forest Conservation Program encompasses the implementation of large-scale afforestation efforts, the enlargement of forest reserves, and the prohibition of logging activities within primary forest areas [14]. Between the years 1998 and 2018, the central government allocated a total expenditure of over 475 billion RMB, which is equivalent to approximately $72 billion, to the program.

China possesses an extensive landmass that is marked by broad forest coverage, encompassing a diverse range of forestry indicators and a wealth of substantial data. China is home to approximately 211 million hectares (Mha) of tree cover, making it the fifth country with the most trees in the world [15]. However, the forest coverage in China has grown significantly, from 8.6% in 1949 to 23.04% by the end of 2020. This notable expansion may be attributed to reforestation initiatives implemented during the 1950s and 1970s. These programs were specifically designed to address the adverse effects of soil erosion by planting around 28 million hectares and 27 million hectares of trees, respectively. Yet, China's forest resources are currently facing unprecedented challenges [16]. According to

Global Forest Watch, the total area of primary forest in China has declined by 4.4% from 2002 to 2020. Further, according to data published by the State Forestry Administration, China's forest coverage rate is notably lower than the global average of 31 percent, and the per-capita forest area in China is only a fourth of the global average (Liu et al., 2023) [17].

During the APEC Economic Leaders' Meeting in 2009, China committed to a double increase in both forest area and storage, pledging this to the international community. For that reason, China has formulated several national forestry programs with the aim of facilitating the advancement of ecological forestry and forestry practices that cater to the well-being of the populace. Figure 1 shows the forest area of the sample province (2002–2020). Inner Mongolia, Heilongjiang, Yunan, and Sichuan have the largest forest area. Shanghai, Tianjin, Beijing, and Ningxia have the lowest forest resources (area-wise). Figure 2 shows the growth of forests in the province over the year. Despite the challenges, China's forest resources are increasing in some provinces. However, there might not be enough significant efforts to preserve and maintain these resources.

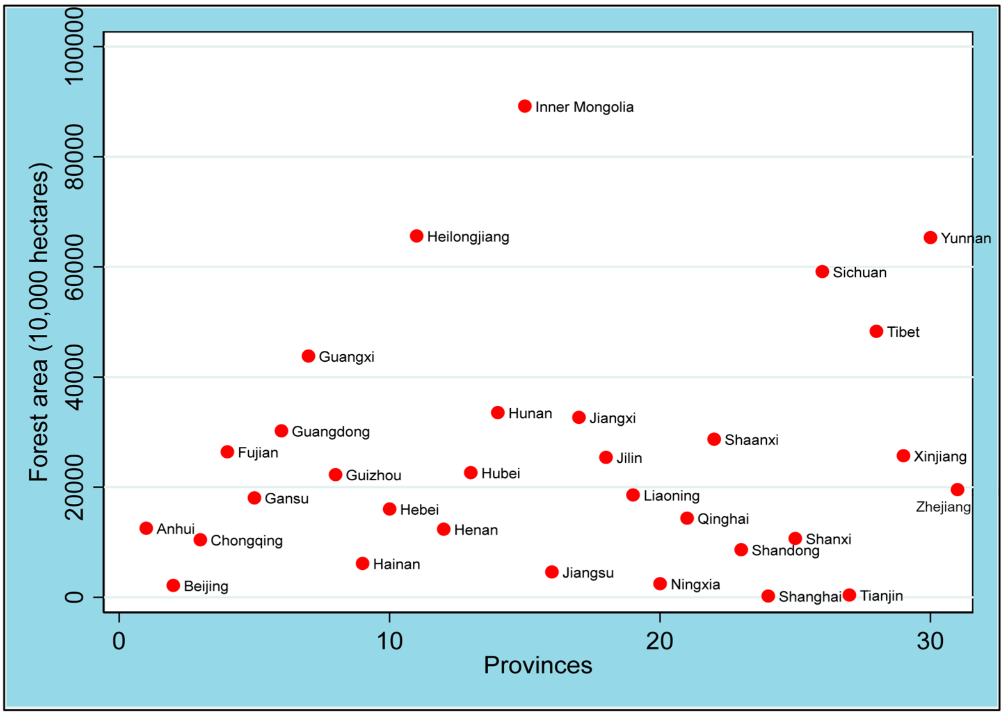

Figure 1. Forest area over (2002–2020) of Chinese provinces. Provinces are shown at horizontal axis.

Therefore, the study aims to find China's forest resource efficiency and the most influential factors that can increase China's forest utilization efficiency. Nonetheless, a multitude of factors drive the efficient utilization of forest resources.

However, technological developments are regarded as a key driver of increased efficiency in resource allocation [18]. High technology has the potential to enhance forest resource efficiency significantly, as it can enable advanced tools like remote sensing, geographic information systems (GIS), and satellite imagery to provide real-time data on forest health, monitoring, and management [19,20]. According to Gavilanes Montoya (2023) [21], technology enables forest managers to make well-informed decisions on the allocation of resources, detection of wildfires, and control of pests, thus enhancing the overall health of the forest. It highlights the importance of technology education in enhancing forest resource efficiency. The inclusion of technology education is vital to adequately educate the workforce with the necessary abilities to utilize modern technologies proficiently. Training programs and educational activities have the potential to enhance the skills of foresters and conservationists in utilizing advanced technological instruments, hence facilitating the promotion of sustainable forest management, conservation efforts, and the optimization of resources [22,23]. However, it is essential to have accurate and up-to-date data on the growth and productivity of forests to make informed decisions about their management and conservation.

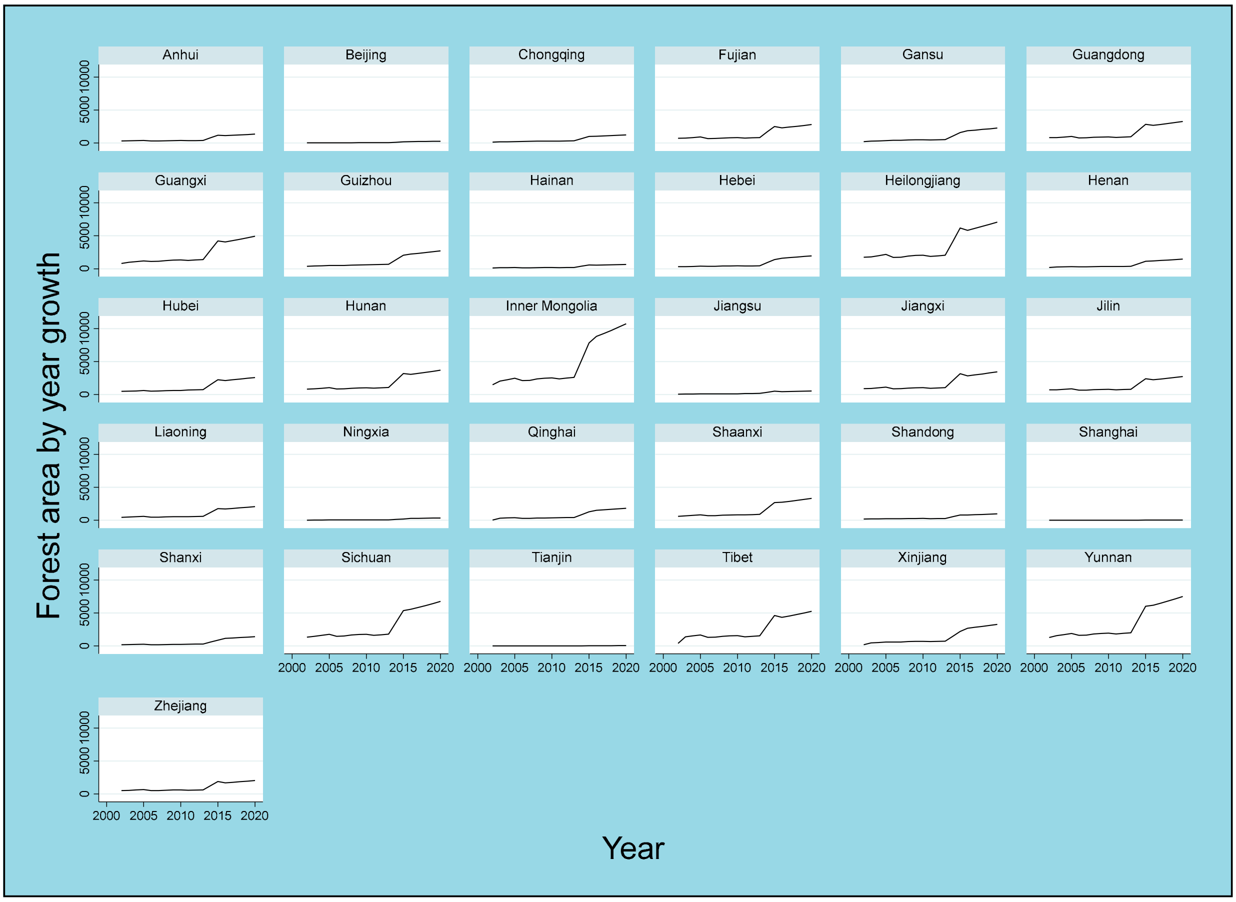

Figure 2. Trend of forests in the province over the years 2002–2020.

Additionally, digitalization is the most powerful instrument because it extends the range and timescale of remote sensing beyond what is possible with other observation techniques. Moreover, the digital platform facilitates a wide range of advanced functionalities, including but not limited to big data analysis and storage, online computing, shared user platforms, timber tracking, certification, monitoring, artificial intelligence, machine learning, and digital twin replication [24,25]. The features are of utmost importance in the improvement of forest resource management, the facilitation of data-driven decision-making, and the promotion of sustainable practices.

However, under fiscal decentralization, the government can facilitate the adoption of advanced tools and systems for forest management. Fiscal decentralization can improve the management of forest resources by giving local authorities more control and incentives to manage their forests sustainably [26]. Local governments can allocate their resources to invest in technologies such as remote sensing, GIS, and data analytics, which aid in real-time monitoring, inventory management, and conservation efforts [27]. Local governments invest in technology, education, and infrastructure that can enhance forest resource efficiency. By linking technology with forest resource efficiency, fiscal decentralization can enable local communities to harness the power of data-driven approaches, promoting sustainable forest management practices and ensuring the long-term vitality of forest resources [28,29].

To this end, the primary objective of this empirical study is to evaluate the influential role of technology, fiscal decentralization, and the digital economy on China's forest resource efficiency. Precisely, the contribution of this study to the growing body of knowledge is as follows. Firstly, the study started to estimate the forest resource efficiency of China province using SBM-Data Envelopment Analysis (2002–2020). The subsequent array of contributions of the study is as follows: First, the study incorporates the two features of technology, such as high technology expenditure and forest technology-related education, to provide a foundation for evidence-based policy decisions to foster sustainable development of forest resources in China's Provinces. Second, the study used the local government expenditure on forests to approximate the fiscal decentralization impact on forest resource efficiency. Third, the study used the effects of digital economy development on forest resource efficiency. Additionally, we expand the digital economy's role in moderating the influence of economic development, urbanization expansion effect, fiscal decentralization, and technology towards forest resources efficiency. Fourth, the study controls the investment spillover effect to shape forest resource efficiency, making this study more comprehensive on the subject.

2. Discussion of Former Literature

Forests offer a diverse array of functions and advantages to society [30]. Scholars have conducted research in diverse domains related to forest resources, examining their influencing factors from various perspectives and approaches. However, our research gives top priority to the most relevant literature to formulate a hypothesis that is simultaneously plausible and well-grounded in the current body of knowledge and aligns with the research context and goals.

2.1. Technology and Forest Resources Efficiency

The utilization of technology not only serves to mitigate deforestation but also facilitates the process of restoring previously removed forested areas. Li et al. (2017) [19] examined China's forestry resources and proposed that enhancing investment in technologies plays a crucial role in enhancing the efficiency of forestry resources. They also emphasized the importance of improving operational and managerial practices by relevant administrative departments to enhance the utilization of technology. Cheng et al. (2010) [20] analyze the characteristics of flows of "primarily wood and wood byproducts" during China's critical early economic development (from 1953 to 2000). They recognize the importance of increasing research and development (R&D) endeavors to generate innovative technologies that have the potential to optimize the utilization of forest resources.

Further, technological endeavors ensure the sustainable growth and longevity of forest resources, hence safeguarding their availability for future generations. Wei and Shen (2022) [31] assessed the efficiency of forests as carbon sinks. Based on the study findings that emphasize the forestry industry structure optimization through the transformation of scientific and technological advancements, green technologies are important for managing natural resources resource [32]. The government must prioritize the development of human capital and the use of technological advancements to enhance efficiency in sustainable forestry practices [33–35]. Thus, we can hypothesize the following hypotheses.

Hypothesis 1 (H1). *Can high technological development enhance forest resource efficiency in Chinese provinces?*

Hypothesis 2 (H2). *Simultaneously, can technology education be a source of increasing forest resource efficiency?*

2.2. Fiscal Decentralization and Forest Resource Efficiency

Fiscal decentralization is widely acknowledged as a fundamental approach to enhance the overall efficacy and efficiency of governance by granting local governments financial autonomy [36]. They raised the importance of natural resources and fiscal decentralization in the context of the environment. Xu et al. (2020) [37] researched the implementation of decentralization reforms in collective forestry in China. The analysis is conducted by utilizing government documents and secondary literature that focus on the concepts of democratic decentralization and environmental governance. Tebkew and Atinkut (2022) [26] examined the effects of forest decentralization on forest management in East Africa. The study's findings emphasize the need for well-defined roles and authorities if forests are to be managed sustainably. This requires clearly outlining the roles, responsibilities, and privileges of each stakeholder involved in the process. According to Oldekop et al. (2019) [38], decentralized forest management can enhance sustainable forest use. Studying fiscal policy in the Indonesian forestry sector, the researchers discovered legislation pertaining to local government authority and forest protection that was deemed improper and exhibited contradicting elements. Hu et al. (2023) [28] raise the importance of fiscal decentralization to strengthen the natural resources markets. By reviewing the existing body of literature, the following hypothesis can be developed.

Hypothesis 3 (H3). *Can fiscal decentralization matter to increase China's forest resource efficiency?*

2.3. Digital Economy and Forest Resource Efficiency

Chen et al. (2023) [39] investigate the diverse impact of the digital economy on forestry green total factor productivity and its specific manifestation. A noteworthy inverted U-shaped correlation was discovered between the digital economy and total factor productivity in the forestry green sector. This correlation initially stimulates production but eventually hinders it. The digital economy has a striking positive spatial spillover effect on the total factor productivity of forestry green. Similarly, the study conducted by Chen et al. (2023) [40] showed that the digital economy has a substantial impact on enhancing total factor productivity in forestry, particularly in terms of promoting green practices. The researchers confirmed the validity of this conclusion through rigorous robustness testing and careful consideration of endogeneity. The implementation of digitalization in forestry education has the potential to enhance the effectiveness of human capital within forest sector organizations, consequently influencing the efficiency of forest resource utilization in Russia [22]. The advent of the internet has brought about a significant shift in consumer shopping behavior, leading to the emergence and subsequent growth of e-commerce. The practice of online purchasing frequently results in a decreased utilization of packing materials compared to conventional brick-and-mortar retail, hence contributing to a decline in the need for paper and cardboard. Watanabe et al. (2018) [41] examine the progression of the forest-based bioeconomy enabled by digital solutions and explore the potential for transformative corporate innovation within the digital economy, notwithstanding challenges related to the natural environment and geographical constraints.

Nitoslawski et al. (2021) [42] investigate the incorporation of innovative digital technologies in the field of forest management, with a particular focus on the widespread use of remote sensing and machine learning techniques for monitoring, planning, and data analysis. Additionally, it sheds light on the emerging applications of virtual and augmented environments, as well as automated workflows. The findings of this study offer valuable insights into how these technologies can be utilized to tackle the uncertainties posed by environmental and technological factors in forest ecosystems. According to Singh et al. (2022) [43], internet-based technologies offer the capability to obtain up-to-date information on the condition of forests, hence enhancing the effectiveness of resource allocation and initiatives aimed at conserving forest ecosystems. Morkovina et al. (2020) [44] examine the significance of digital technology within Russia's forestry sector. They said that the establishment of such a platform would enhance the efficiency of forest management, promote greater transparency in the dissemination of information regarding regional forest resources, and streamline communication processes. Artificial Intelligence systems can offer a technical edge in the conservation and rehabilitation of biodiversity through the implementation of sustainable forest management practices [45]. Thus, the following hypothesis development in the domain of digital development on forest resource efficiency is rational.

Hypothesis 4 (H4). *Does the digital economy increase forest resource efficiency in Chinese provinces?*

2.4. Research Gap

The literature reveals that previous studies have mostly focused on the assessment of total factor productivity and efficiency of forest resource management. However, insufficient attention has been given to the factors that influence the efficiency of forest resources. There is a significant research gap, especially in the domain of technology, including several aspects of technology, about enhancing the efficiency of forest resource utilization. A key component of forest resource management is the involvement of governmental entities. The significance of local government involvement in forest resource management cannot be ignored since it serves an essential role in organizing and enhancing the efficiency of a nation's forest resources.

Moreover, despite a few studies, the current body of literature lacks a comprehensive examination of the relationship between the digital economy and the efficiency of forest resource utilization. The continuous gap in the field of technology, fiscal decentralization (specifically the role of local government), and the digital economy are primarily attributed to the little attention given to this pertinent subject matter. Therefore, this study aims to fill this research gap by examining the significance of high-tech expenditure, forest-related technical education, local government expenditure on forests (fiscal decentralization), and the digital economy in relation to forest resource efficiency in Chinese provinces. Moreover, the objective of this study is to conduct a comprehensive analysis of the moderating influence of the digital economy through GDP, technology, urbanization, and fiscal denaturalization on increasing forest resource efficiency in an updated econometric framework.

3. Variable, Data, and Methodology

3.1. Data and Variables

This study employed a sample of thirty-one (31) provinces (See Table A1 in Appendix A) for the panel study over the time (2002–2020). The determination of a period is contingent upon the availability of data. Table 1 presents a full summary of the variables together with their respective descriptive statistics. Figures 3 and 4, which are the key figures in this study, offer a graphic representation of the dependent and independent variables for the year 2020. The observed variance in values indicates that the provinces of China reflect fluctuating levels of efficiency in managing forest resources, which can be attributed to the differences in the amount and nature of their forest resources as well as their respective contributions to the overall output value. Furthermore, there is variation observed among the provinces in terms of the digital economy, technological spending, technology education, forest investment, local government expenditure, and urbanization across different regions. The correlation between the dependent and independent variables is given in Figure 5.

Table 1. Descriptive statistics and data measurement.

Variable	Measurement	Mean	Std.	Min	Max
FRE	Inputs: (i) Forest area (10,000 hectares), (ii) Investment (10 thousand Yuan), (iii) Employees (10 thousand persons). Output: Forestry output value (100 million yuan).	0.4140311	0.3130816	0.0112	1
GDP	GDP per Capita (yuan)	38,037.18	27,576.64	3257	164,889.5
Tech1	High-tech expenditures on scientific research activities (Thousand yuan)	3.61×10^7	6.38×10^7	97,634	5.15×10^8
Tech2	Investment in Technology Education (Forest) 10 thousand yuan	2675.41	5301.768	1	57,360
FiscalD	Local Government Expenditure on Forest (10 thousand yuan)	4,331,433	2,875,321	229,619	1.34×10^7
invst	Completed Investment in Forest (10 thousand yuan)	807,442.2	1,285,912	3492	1.09×10^7
UN	Urban Population% of total population	52.23012	15.42139	20.85	90.26

Table 1. *Cont.*

Variable	Measurement	Mean	Std.	Min	Max
DigEco	Internet User (10,000 persons)	1833.297	2143.533	3.19	14,251.39
Moderation1		8.41×10^7	1.42×10^8	34,110.51	1.11×10^9
Moderation2		8.06×10^9	1.46×10^{10}	4.59×10^9	1.00×10^{11}
Moderation3		8.01×10^{10}	3.13×10^{11}	3.02×10^{10}	4.51×10^{12}
Moderation4		3,720,246	5.07×10^7	6.98×10^8	5.31×10^8
Moderation5		103,549.9	133,797.7	154.546	989,902.3

Note: Moderation1 (Digital economy × GDP), Moderation2 (Digital economy × FisD), Moderation3 (Digital economy × Tech1), Moderation4 (Digital economy × Tech2), Moderation5 (Digital economy × UN).

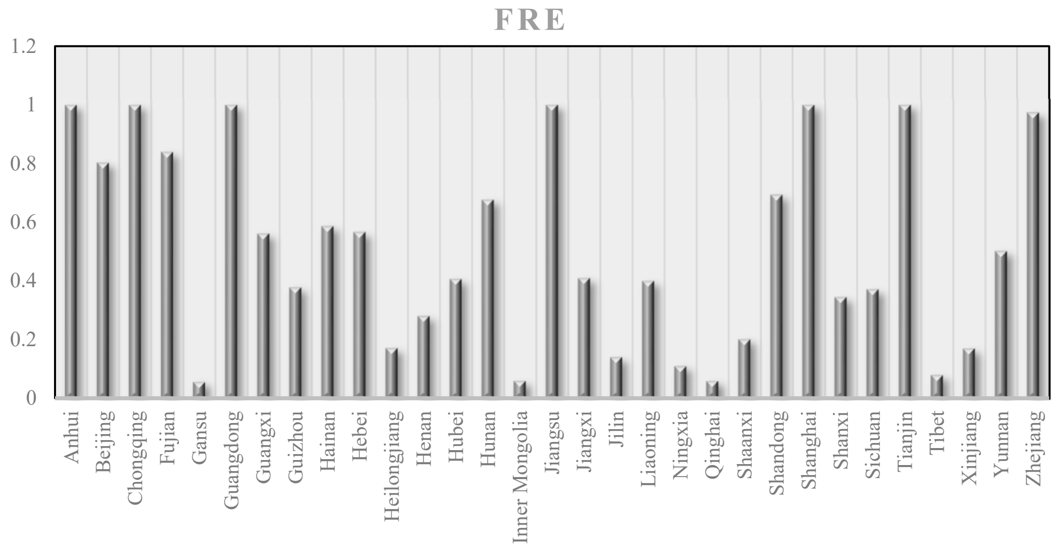

Figure 3. Forest resource efficiency in 2020.

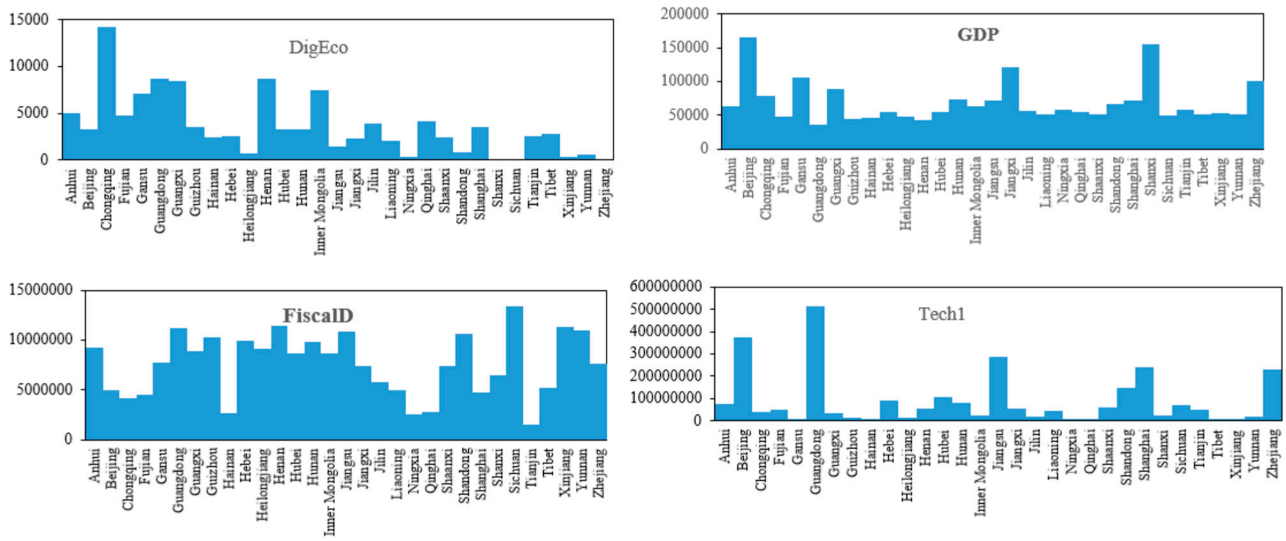

Figure 4. *Cont.*

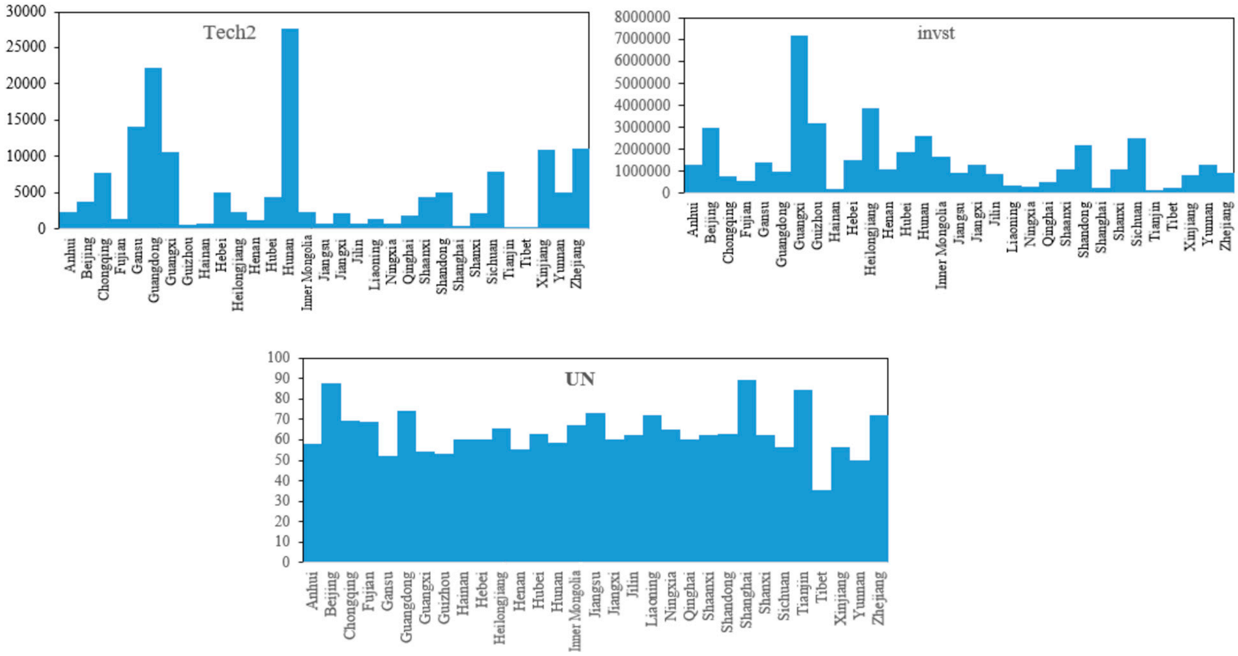

Figure 4. Independent variables trend in the 2020 year.

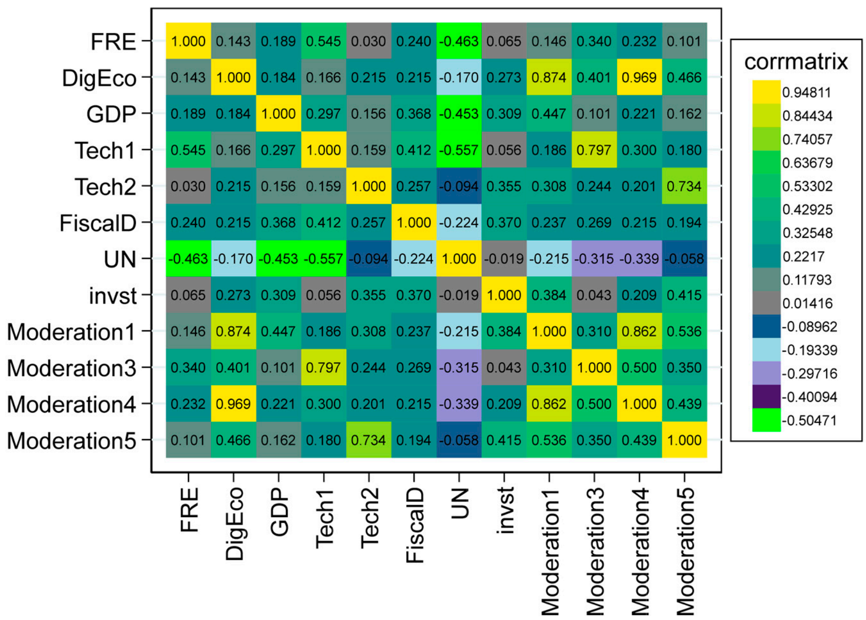

Figure 5. Heat map of correlation. Different color shows the Corr matrix values between variables.

3.2. Variables Description

3.2.1. Dependent Variable (Forest Resource Efficiency (FRE))

This study uses the "Forest Resource Efficiency" measured by Data Envelopment Analysis. It incorporates various components, including inputs such as forest area, investment, and employees. Furthermore, it incorporates the forestry output value as output. This technique is consistent with prior research conducted by (Neykov et al., 2021; Lu et al., 2021) [46,47]. For details see Table 1. However, the meticulous choice of forest resource efficiency inputs and outputs is particularly important [48]. It is crucial to choose these variables appropriately, as an incorrect selection might result in estimation outcomes that are both erroneous and biased [49]. A variety of research studies have utilized different combinations of inputs and outputs to evaluate the effectiveness of forest resources [50,51].

Accordingly, in accordance with prior scholarly investigations, we have employed four discrete inputs and outputs to assess forest resource efficiency, as outlined in Table 1. The term "forest area" refers to a broad expanse of land that is specifically designated for forestry production, hence indicating the allocation of resources towards the management and utilization of natural ecological assets. The concept of investment pertains to the accumulation of capital investments made during the current year, which play a significant role in supporting the many inputs required for reforestation efforts. The term "employees" refers to the number of individuals employed by an organization at the conclusion of a given year. This metric serves as a valuable indicator of the level of investment made in human resources. The value of forestry output represents the economic benefits that are generated as a result. The data utilized in this study was obtained from the China Forestry and Grassland Statistical Yearbook and National Bureau of Statistics.

3.2.2. Major Independent Variables

As given in Table 1, the study used two technology indicators (Technology1, Technology2) to measure technology impact. Technology1 impact is measured with high technology expenditure. Technology2 impact is measured through forest technology education. These parameters can influence the production capacity [52] and capabilities of forest resource management and, thereby, efficiency. Further, the government can attract investment to improve the sustainable management and utilization of their forest resources in terms of afforestation, management of forest activities, and forest certification and monitoring [53]. Therefore, the local government expenditure on forests is used to measure fiscal decentralization. We live in a digital era; most monitoring and management are done through digital devices. Therefore, the digital economy's indirect and (moderation impact) is measured through internet users.

3.2.3. Control Variables

In line with Ullah et al. (2021) [54], we adopted GDP per capita for economic development levels in provinces. Additionally, this analysis incorporated investment in forest areas and urbanization as controlled variables derived from prior research to mitigate potential biases due to omitted variables. Consequently, the variable is incorporated into the study following [55,56].

3.2.4. Moderation Variables

The study included the digital economy as a moderating component, along with essential variables such as fiscal decentralization and technology, and two important control variables (GDP, and urbanization). The purpose of this comprehensive approach was to clarify the intricate linkages and potential moderating impacts of the digital economy on the correlations between these factors. The research aimed to gain a comprehensive understanding of the intricate dynamics involved in sustainable forest management and environmental conservation.

3.3. Empirical Modelling

Following a comprehensive analysis of the data and the measurements of the various variables, the study established an empirical notation subject to additional examination in subsequent parts. Hence, by considering forest resource efficiency as a dependent variable, this study conducted an empirical analysis to examine the relationship between technology, fiscal decentralization, investment, economic development, urbanization, the digital economy, and forest resource efficiency. The practical form of the baseline model is as follows:

$$FRE_{it} = f(GDP_{it}, FiscalD_{it},\ Tech1_{it}, UN_{it},\ Tech2_{it},\ invst_{it}) \tag{1}$$

FRE is the forest resource efficiency of the Chinese province. $Tech1$, $Tech2$, are the essential detriment of technological impact measurement, which is determined by expenditure on high technology and forest technology education. $FiscalD$ is fiscal decentralization measured with local government expenditure. $Invst$ is an investment in the forest, GDP is economic development, UN is the urbanization measured with the urban population of Chinese provinces.

Following the above base line model, the study regressed four regressions. At first, the study focusses on fiscal decentralization and $Tech1$ with control parameters. In subsequent regression, the study incorporated $Tech2$ instead of $Tech1$. For strength, we incorporated $Tech2$ and $Tech2$ in the third regression with the investment control variable.

In the following equations, we expand the study by incorporating the moderation effect of the digital economy with technology, fiscal decentralization, and urbanization.

$$FRE_{it} = f(\ DigEco_{it},\ GDP_{it}, FiscalD_{it},\ Tech1_{it}, UN_{it},\ Tech2_{it},\ invst_{it}) \quad (2)$$

$$FRE_{it} = f(\ DigEco_{it},\ GDP_{it}, FiscalD_{it},\ Tech1_{it}, UN_{it},\ Tech2_{it},\ invst_{it}, Moderation_{it}) \quad (3)$$

where, $DigEco$ is the digital economy measured by internet users. $Moderation$ are the interaction terms of $DigEco \times (GDP,\ FiscalD,\ Tech1,\ Tech2,\ UN)$ evaluating the role of the digital economy in managing forest resource efficiency through technology, fiscal decentralization, controlling urban population and economic development.

4. Empirical Methods

The current study utilizes econometric approaches that are deemed most suitable for the dataset at hand. For econometric analysis, we used Stata version 17. The investigation was initiated by analyzing cross-sectional dependence heterogeneity in slopes, conducting unit root analysis, and determining co-integration. In conclusion, the long-run parameters and causal dimensions of the modeled variables were estimated. Figure 6 presents the econometric steps that we used for study estimation.

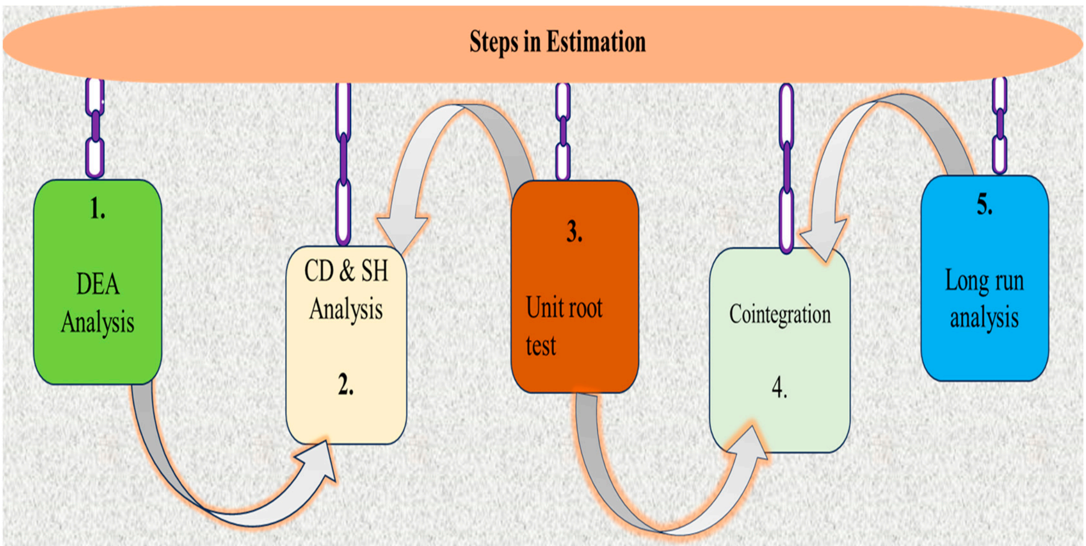

Figure 6. Estimation road map.

4.1. Super SBM Data Envelopment Analysis for Forest Resource Efficiency

The Slacks-Based Measure (SBM) represents a non-radial approach to assessing DEA (Data Envelopment Analysis) efficiency [57]. Its primary strength lies in its capacity to assess excess inputs and insufficient outputs directly. When determining efficiency, it takes into consideration the slack, which represents the difference between inputs and outputs at the production frontier. This method operates based on the following principles:

Suppose we have a study with n Decision-Making Units (DMUs) referred to as "Provinces". Each DMU is characterized by m input indicators and s output indicators.

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 DMU's is denoted as h_{j0}. Now, let us discuss how the output-focused SBM-DEA model with variable returns to scale operates:

$$Min\ h_{j0} = \theta$$
$$s.t \begin{cases} \sum_{j=1}^{n} \lambda_j x_{ij} \leq \theta x_{ij0}, i = 1, \ldots, m \\ \sum_{j=1}^{n} \lambda_j y_{rj} \geq y_{ij}, r = 1, \ldots, s \\ \sum_{j=1}^{n} \lambda_j = 1, \lambda_j \geq 0, j = 1, \ldots, n \end{cases} \tag{4}$$

The efficiency value at the j-th position is represented as θ, where λ_j is a non-negative vector. A DMU is considered efficient if and only if θ equals 1, indicating that it is operating at maximum efficiency. If θ is not equal to 1, it means the DMU is inefficient and has room for improvement.

4.2. Econometric Methodology Path

The initiation of econometric analysis can be traced back to the development of the cross-sectional dependence test. The phenomenon of modernization and economic integration has led to the recognition that policy adjustments implemented in one country might have spillover effects on other ones. Yasmeen et al. (2023) [58] underscored the significance of including these dynamics in the estimation of panel datasets, as neglecting them can lead to biases in the obtained results. Hence, the matter of addressing cross-sectional dependence in panel datasets has become a significant focal point in modern econometrics. A range of tests can be utilized within the empirical framework to assess the presence or absence of cross-sectional dependence (CD).

However, the diagnostic evaluations proposed by Pesaran (2004, 2015) [59,60] are preferred in this case. The CD test verifies the absence of cross-sectional dependence as a null hypothesis. The rejection of the null hypothesis demonstrates the presence of cross-sectional dependency in the data. The CD test's equation can be stated in the following way.

$$CD = \sqrt{\frac{2T}{N(N-1)}} \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \partial_{ij} \rightarrow N(0,1) \tag{5}$$

∂_{ij} is explained in Equation (7).

$$\partial_{ij} = \frac{\sum_{t=1}^{T} \in_{it} \in_{jt}}{\left(\sqrt{\sum_{t=1}^{T} \in^2{}_{it}}\right)\sqrt{\sum_{t=1}^{T} \in^2{}_{jt}}} \tag{6}$$

Next, we extend our research to examine the variability of the slope coefficient across different provinces. The heterogeneity of slope coefficients across provinces could stem from variations in forest resources and the rate of technological advancements, as discussed in a previous study. This study examines the homogeneity of slopes for the variables of interest using the Pesaran and Yamagata (2008) [61] method. This method is based on two statistics: delta Δ and adjusted delta Δ. In the following, this study applied the distinct second-generation panel unit root CIPS test proposed by Pesaran (2007) [62]. The CIPS' specification:

$$CIPS(N, T_m) = \frac{\sum_{i=1}^{N} t_i(N, T_m)}{N} \tag{7}$$

This test is efficient compared to Phillip Perron, Levin, Lin, and Chu. Additionally, Westerlund's (2005) [63] co-integration tests, which are more suitable for CD problems and provide efficient results free from residual dynamics, are applied.

4.3. Driscoll and Kraay (1998)

In the case of CD, the application of Driscoll and Kraay (1998) [64] is more efficient for long-run analysis [65]. In their seminal work, Driscoll and Kraay put out a methodological framework aimed at effectively tackling the challenges provided by heteroscedasticity and autocorrelation in the context of regression analysis. This methodology employed by the researchers entails the utilization of ordinary least squares (OLS) to estimate a regression model. Subsequently, residuals are computed, and standard errors are adjusted to rectify the influence of heteroscedasticity and autocorrelation. The utilization of robust standard errors, which are computed using a specific formula, enhances the dependability of inference and hypothesis testing when the basic linear regression assumptions are violated. Further, it is suitable for panel data and offers a significant instrument for researchers aiming to obtain more precise parameter estimations and dependable statistical inferences when dealing with correlated and heteroscedastic residuals [66].

5. Discussion of the Findings

5.1. Forest Resource Efficiency Findings

Figure 7 shows "forest resource efficiency values" for China's provinces from 2002 to 2020. Forest Resource Efficiency (FRE) is a measure that quantifies the effectiveness of a province in using its forest resources. A higher FRE number indicates a higher level of efficiency. Anhui, Beijing, Jiangsu, Shanghai, and Zhejiang provinces have continuously exhibited high Forest Resource Efficiency levels throughout the years, indicating efficient utilization of their forest resources. Conversely, provinces such as Tibet and Xinjiang demonstrate fluctuating and relatively lower forest resource efficiency scores, suggesting possible difficulties or differences in their management of forest resources. The evaluation highlights that diverse approaches might be utilized in the efficient use of forest resources in different provinces of China during the past twenty years. This demonstrates the intricate collaboration between economic, environmental, and regional issues.

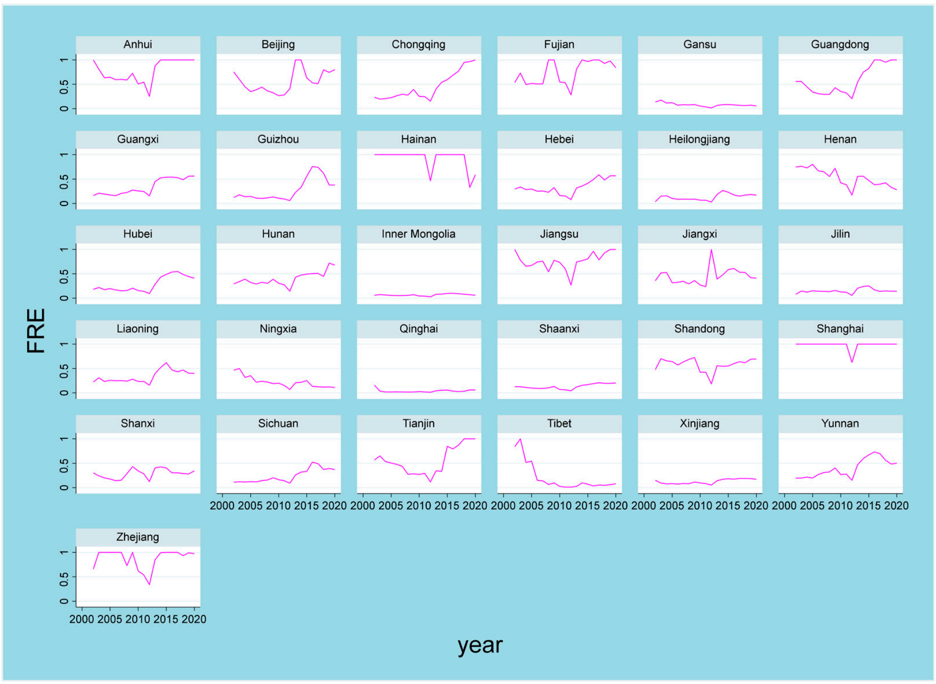

Figure 7. Forest resource efficiency of Chinese provinces (2002–2020).

Figure 8 illustrates the average forest resource efficiency across the provinces of China by the Years (2002–2020). A year-wise period reflects a dynamic pattern in the management of forest resources. In 2002, the FRE started at 0.4009 and experienced a gradual increase over the following years. In 2016, there was a noteworthy increase, reaching a maximum value of 0.5163. This suggests a period of heightened efficiency or possibly strategic interventions in forest management during that year. From 2017 to 2018, FRE maintained a consistent range, remaining close to 0.51. In both 2019 and 2020, there was a slight decrease in FRE, with values of 0.4931 and 0.4956, respectively. The slight reduction raises questions about the possible impact of environmental, economic, or policy variables on the use of forest resources during this time. The data presented indicate that there was an overall improvement in the management of forest resources across China's provinces during the sample period but with some variations in efficiency levels.

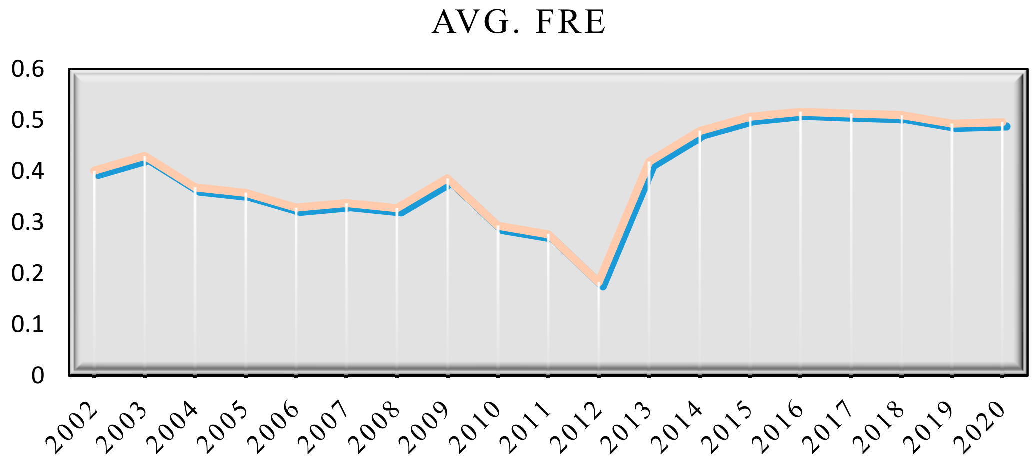

Figure 8. Average forest resource by year (2002–2020). Color lines shows the average forest resource efficiency.

5.2. Primary Econometric Findings

The former statistical data of the study parameters led to econometric analysis starting from the cross-dependence test. The results of the CD are given in Table 2 and show that all parameters are cross-sectional, as the prob values are zero (0.000). It indicates that provinces are correlated and can influence each other through their policy decision.

Furthermore, Table 3 presents the results of the panel analysis regarding the homogeneity of slopes in relation to forest resource efficiency, technology, fiscal decentralization, and the digital economy models. The delta (Δ) for Base line-Model1 was computed as 3.052, with a corresponding *p*-value of 0.002. The adjusted delta (Adj Δ) was found to be 5.328, with a *p*-value of 0.000. These results conclusively reject the null and suggest that there are significant discrepancies in the slopes, indicating varied associations among the panels. In the instance of Base line-Model2, the delta (Δ) and adjusted delta (Adj Δ) were 2.219 and 4.605, respectively. Both values were associated with *p*-values of 0.026 and 0.000. Once again, the null is rejected, providing further evidence that the slope coefficients are not consistent. This highlights the significance of acknowledging contextual variances, as the connections between the variables demonstrate significant variety.

These findings highlight the complex characteristics of the models that were studied, emphasizing the importance of considering varied slopes when analyzing the dynamics of forest resource efficiency, technology, fiscal decentralization, and the digital economy across several panels. Owing to CD's existence, the adoption of CIPS unit root tests is appropriate for the determination of the order of integration among the concerned variables [67]. The CIPS test is conducted at the level and first difference with the trend and for the exclusive trend. The results are presented in Table 4. Based on the findings of the CIPS test, it is observed that the variables reveal a mixed order of integration. However, it is worth noting that all variables approach a stationary position after undertaking first-order differencing.

After knowing the stationarity properties, we performed the Westerlund co-integration (2005), which was robust in the CD case [68]. The findings are described in Table 5. This test co-integrates the estimated models based on some panels and all panels' statistics. The results show a strong co-integration among the models' indicators, and the probability of estimating statistics is highly significant.

Table 2. Cross-sectional Dependence (CD) (2004–2015).

Variable	CD-Test	*p*-Value	Average Joint T	Mean ρ	Mean abs (ρ)
FRE	36.733	0.000	19.00	0.39	0.49
GDP	92.433	0.000	19.00	0.98	0.98
DigEco	28.512	0.000	19.00	0.3	0.44
FiscalD	92.153	0.000	19.00	0.98	0.98
Tech1	71.276	0.000	19.00	0.76	0.76
UN	77.659	0.000	19.00	0.83	0.87
Tech2	20.937	0.000	19.00	0.22	0.54
invst	81.676	0.000	19.00	0.87	0.87
Moderation1	56.352	0.000	19.00	0.60	0.60
Moderation2	60.351	0.000	19.00	0.71	0.71
Moderation3	56.332	0.000	19.00	0.62	0.63
Moderation5	47.284	0.000	19.00	0.53	0.62
Moderation4	34.356	0.000	19.00	0.37	0.44

Notes: Under the null hypothesis of cross-section independence, CD~N(0, 1) *p*-values close to zero indicate data are correlated across panel groups.

Table 3. Testing for slope heterogeneity (Pesaran, Yamagata 2008 [61]).

Models	Δ (Delta)	Pr	Adj (Δ)	Pr
Base line-Model1	3.052	0.002	5.328	0.000
Base line-Model2	2.219	0.026	4.605	0.000

Table 4. Panel CIPS unit root.

Variable(s)	CIPS—Level		CIPS—First Difference	
	Trend—Exclusive	Trend—Inclusive	Trend—Exclusive	Trend—Inclusive
FRE	−2.415 **	−3.352 ***	−4.686 ***	−4.644 ***
GDP	−1.455	−2.705	−3.555 ***	−3.836 ***
DigEco	−3.818 ***	−3.709 ***	−4.775 ***	−5.020 ***
FiscalD	−1.628	−1.864	−2.985 **	−3.998 ***
Tech1	−3.021 ***	−3.751 ***	−3.299 ***	−3.563 ***
UN	−2.040	−1.940	−3.144 ***	−3.566 ***
Tech2	−1.200	−1.777	−3.392 ***	−3.973 ***
invst	−2.915 *	−3.192 ***	−4.738 ***	−4.876 ***
Moderation1	−2.608 ***	−3.711 ***	−4.532 ***	−4.766 ***
Moderation2	−2.662 ***	−3.317 ***	−4.007 ***	−4.260 ***
Moderation3	−3.562 ***	−4.072 ***	−5.028 ***	−4.944 ***
Moderation4	−0.698	−1.271	−2.825 *	−3.586 ***
Moderation5	−3.441 ***	−3.862 ***	−4.598 ***	−4.803 ***

Note: significance level *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 5. Co-integration Westerlund (2005).

Models	Panels (Specification)	Statistic	p-Value
Baseline-Model1	Some Panels	−3.3032	0.0005
	All Panels	−2.3656	0.0090
Baseline-Model2	Some Panels	−1.3729	0.0849
	All Panels	−1.6671	0.0478

In preliminary tests, we find two important findings: cross-dependence and co-integration among the panels. However, these are not enough for long-run findings; rather, they lead us to analyze the long-run relationships between the variables for each model by using appropriate methods. Therefore, in the next section, we estimated the study's model for the comprehensive analysis of forest efficiency, technology, fiscal decentralization, and digital economy with Driscoll and Kraay. This method is effective and reliable in the case of cross-dependence.

5.3. Long-Run Findings

5.3.1. Fiscal Decentralization, Technology Findings

For long-run parameters, we applied the Driscoll and Kraay, which is robust in cross-dependence cases. Table 6 provides a regression model that investigates the correlation between forest resource efficiency and many factors, including technology, fiscal decentralization, GDP, urban population (as urbanization), and investment. The main objective is to find the impact of technology, fiscal decentralization, and the impact of the digital economy. Thus, the first part of the regression focuses on technology and fiscal decentralization for forest resource efficiency.

Table 6. Forest resources efficiency and fiscal decentralization, technology.

	Fiscal Decentralization, Technology Impact Model			
Variables	**FRE**	**FRE**	**FRE**	**FRE**
GDP	−0.0589 **	−0.0484 **	−0.0442 *	−0.0247 ***
	(0.0255)	(0.0179)	(0.0245)	(0.00758)
FiscalD	0.113 ***	0.0255 ***	0.0367 *	0.0400
	(0.0368)	(0.00824)	(0.0183)	(0.0305)
Tech1	0.133 ***		0.120 ***	0.141 ***
	(0.0122)		(0.0147)	(0.0138)
UN	−0.0221 **	−0.453 ***	−0.0804 **	−0.124 ***
	(0.00870)	(0.0534)	(0.0381)	(0.0396)
Tech2		0.0385 ***	0.0155 **	0.00361 **
		(0.00971)	(0.00675)	(0.00131)
invst				0.0993 ***
				(0.0174)
Constant	−43.86 **	−45.71 ***	−52.90 ***	−49.10 ***
	(16.86)	(8.574)	(16.91)	(14.89)
Number of groups	31	31	31	31

Note: Standard errors in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

The outcomes are shown for four distinct classifications, each characterized by different combinations of these independent variables. In the first column, we include the two main independents, "fiscal decentralization and technology1", with control variables (GDP, and

UN). In the second column, we estimate the impact of technology2 on forest resource efficiency. In the third column, we estimate the technology impact for FRE for more comprehensive findings of both technology and fiscal decentralization. In the fourth column, we include the investment as a control variable for the robustness analysis of the earlier three regressions.

In the first column, it is observed that GDP has a statistically significant negative impact on forest resource efficiency. This implies that for every 1 percent rise in GDP, there is an average drop of (−0.0589, −0.0484, −0.0442, −0.0247) percent, respectively, in forest resource efficiency. Overall, findings suggested that the presence of a negative coefficient for GDP in all models suggests a negative correlation between economic development and forest resource efficiency. These results show that when a region experiences economic development, there may be an increased pressure on forest resources due to higher demand for land, raw materials, and infrastructure development [69]. The extraction or disturbance of forest resources might result in a decrease in the efficiency of resource utilization. Prochazka et al. (2023) [70] conducted research on understanding the socio-economic causes of deforestation from a global perspective. This study highlights the necessity of implementing sustainable forest management practices and policies that effectively address the adverse environmental consequences associated with economic expansion. Furthermore, the results can be verified with (Chang, 2017) [71].

Fiscal decentralization has a statistically significant positive impact (in the first three columns) on forest resource efficiency, suggesting that a 1% higher government expenditure is associated with improved forest resource efficiency (0.113, 0.0255, 0.0367) percent, respectively. The presence of a positive coefficient in the context of fiscal decentralization underscores the significance of government investment in enhancing the efficiency of forest resources. This finding implies that there is a positive relationship between higher government spending in forest resource management, specifically in conservation programs, replanting projects, monitoring and enforcement, and efficiency. From an economic perspective, it may be inferred that strategically focused public investments in the forestry sector have the potential to enhance resource management and efficiency [20,26].

The evaluation of the influence of technology is conducted in two distinct manners. The implementation of Tech1, characterized by substantial investments in advanced technology, is found to have a notable and favorable impact on the efficiency of forest resource management. The data suggests that a marginal increase of 1% in high technology expenditure in China's provinces would result in a corresponding gain of (0.133, 0.120, and 0.141), respectively, in forest resource efficiency. The presence of a positive coefficient for technology1 highlights the economic importance of embracing sophisticated technological advancements within the forestry sector [72–75]. The co-efficient impact of Tech2 (0.0385, 0.0155, 0.00361) is also statistically significant, showing that technology education matters to improve forest resource efficiency. There is a positive correlation between the level of investment in high technology for forest management and the attainment of greater forest resource efficiency in various regions. It highlights the advantages of technological progress, namely in the areas of remote sensing, data analytics, and precision forestry, in enhancing the efficient distribution of resources and minimizing inefficiencies, resulting in enhanced economic and ecological results. Nevertheless, the presence of small coefficients implies that educational endeavors should prioritize technology knowledge or adoption as the key catalyst for enhancing forest resource management. The results can be verified by (Mushkarova et al., 2020) [22].

The presence of a positive coefficient in column 4 suggests that an increase in investment in forest-related activities has the potential to enhance forest resource efficiency by (0.0993) percent. Investments of this nature encompass activities such as reforestation, the adoption of sustainable harvesting practices, and the protection of forest ecosystems. From an economic standpoint, this outcome underscores the significance of forest-related activities, such as wood production and ecotourism, in terms of their capacity to generate financial gains. These investments can enhance general economic prosperity while simultaneously upholding the efficient utilization of resources [76].

The negative coefficient of urbanization implies that the expansion of the urban population can have detrimental impacts on the efficiency of forest resources [77]. This suggests that a 1% increase in urbanization will result in a decline in forest resource efficiency by approximately (−0.0221, −0.453, −0.0804, −0.124) percent, respectively. The expansion of metropolitan areas typically exerts heightened strain on adjacent forests in terms of land development and resource utilization, resulting in a potential decrease in overall efficiency (Liu 2019) [78]. From an economic standpoint, this situation underscores the inherent trade-off between the progress of urban growth and the preservation of forests, underscoring the significance of urban planning that considers the principles of environmental sustainability.

Robustness for the main independent variables (fiscal decentralization and technology) findings can be endorsed by Figures 9–11. The graphs show the positive relationship between high technology expenditure, technology education, and fiscal decentralization with forest resource efficiency. It implies that technology and local government expenditure can enhance forest resource efficiency. Further, investing in technology and research can result in the development and implementation of cutting-edge technologies and methods that maximize the potential of resources in forest environments. Augmenting the financial outlay of local governments towards conservation programs and initiatives might directly increase the efficiency of forest resources.

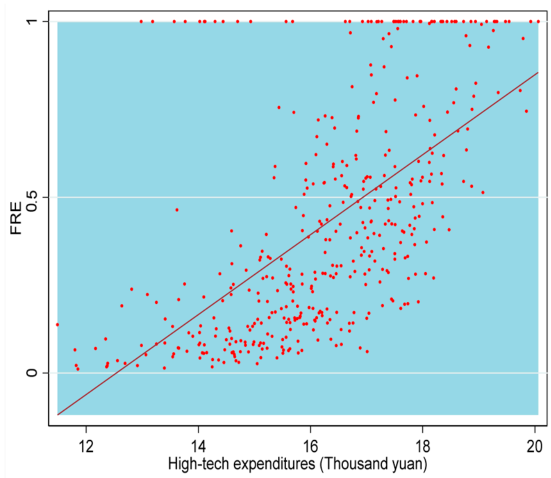

Figure 9. High technology impact on forest resources efficiency.

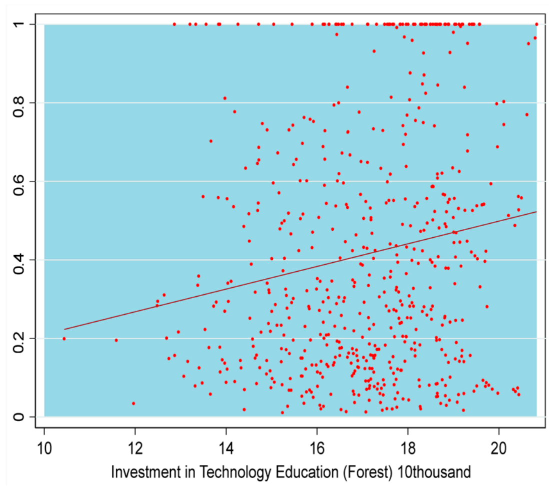

Figure 10. Technology education impact on forest resources efficiency.

Figure 11. Fiscal decentralization impact on forest resources efficiency.

5.3.2. Digital Economy's Moderation Impact Findings

Today, digital technology plays an increasingly important role in virtually every industry [79]. Thus, we expand the analysis of the study to the digital economy's role in forest resource management, thereby increasing forest resource efficiency. Thus, we used the internet as a proxy for the digital economy since digitalization implies a greater reliance on the internet. Further justification for using the internet as a proxy is based on the interconnected nature of the digital economy, where internet-based technologies have a crucial role. The level of internet technology adoption is a measure of a region's digitization, including the economic activity, communication channels, and technological breakthroughs. Consequently, scholars sometimes use internet technology as a proxy to evaluate the influence and impact of the digital economy on many phenomena, such as forest resource efficiency in this case.

Considering this, in the first column, we evaluate the direct impact of the digital economy on forest resource efficiency. Later, we used five moderations to analyze the moderation (indirect) role of the digital economy with GDP, fiscal decentralization, and technology on forest resource efficiency. The findings are presented in Table 7. The findings indicate that a 1% rise in the digital economy by using the internet will lead to a 0.0218 percentage point rise in forest resource efficiency. A considerable and positive coefficient for the digital economy shows that places with a more extensive presence of the digital economy tend to display greater levels of forest resource efficiency. Information technology and data-driven decision-making have been crucial in achieving this result in forest management and resource allocation [80,81]. Figure 12 endorsed the positive relationships between the digital economy and forest resource efficiency.

In columns 2 to 6, the digital economy is used as a moderation variable with GDP, fiscal decentralization, technology1, technology2, and urbanization. The coefficient of 0.0154 (Moderation1) exhibits a positive and statistically significant relationship, indicating that the influence of the digital economy on forest resources is amplified in provinces with a higher Gross Domestic Product. That is because the positive impact of a thriving online economy on forest resource efficiency is more in proportion to the Gross Domestic Product.

This could be because a growing digital economy is likely to spur technical innovation and breakthroughs, which, when added to a healthy GDP, can result in better forest resource management that is both effective and environmentally friendly. The positive and statistically significant coefficient of 0.0104 in column 3 indicates that the digital economy has a higher beneficial influence on FRE in regions with greater fiscal decentralization. When combined with a thriving digital economy, fiscal decentralization can lead to more effective and adaptable resource management. This is especially true in the case of forest management.

Table 7. Forest resources efficiency and moderation of digital economy.

	Moderation of the Digital Economy Model					
Variables	**FRE**	**FRE**	**FRE**	**FRE**	**FRE**	**FRE**
DigEco	0.0218 ***					
	(0.00397)					
GDP	−0.141 *	−0.104 ***	−0.0807 ***	−0.0370 *	−0.0941 **	−0.0396 **
	(0.0693)	(0.0171)	(0.00891)	(0.0181)	(0.0446)	(0.0169)
FiscalD	0.0531 **	0.348 ***	0.0683 ***	0.0241 ***	0.114 ***	0.668 ***
	(0.0226)	(0.0980)	(0.0214)	(0.00791)	(0.0325)	(0.177)
Tech1	0.133 ***	0.141 ***	0.108 ***	0.111 ***	0.130 ***	0.0756 **
	(0.0132)	(0.0141)	(0.00978)	(0.0124)	(0.0103)	(0.0336)
UN	−0.117 **	−0.442 ***	−0.818 ***	−0.126 ***	−0.474 ***	−0.868 ***
	(0.0416)	(0.0692)	(0.197)	(0.0396)	(0.0661)	(0.177)
Tech2	0.00172	0.00526	0.00103	0.0162	0.000693	0.00258
	(0.00478)	(0.00505)	(0.00892)	(0.0250)	(0.00687)	(0.00260)
invst	0.0950 ***	0.0896 ***	0.0151 **	0.0461 ***	0.0956 ***	0.0693 ***
	(0.0153)	(0.0199)	(0.00673)	(0.0143)	(0.0149)	(0.0190)
Moderation1		0.0154 ***				
		(0.00450)				
Moderation2			0.0104 **			
			(0.00400)			
Moderation3				0.0671 ***		
				(0.0173)		
Moderation4					0.0163 **	
					(0.00584)	
Moderation5						0.0728 ***
						(0.00397)
Constant	−45.23 ***	−47.91 ***	−42.41 **	−24.55 **	−19.91	−37.63 ***
	(15.51)	(15.51)	(17.99)	(9.199)	(14.66)	(11.28)
Number of groups	31	31	31	31	31	31

Note: Standard errors in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Within the fourth column, the interaction analysis reveals a statistically significant positive coefficient of 0.0671, indicating that the impact of the digital economy on FRE is amplified in regions characterized by greater levels of high-technology expenditure. The synergy between a robust digital economy and smart technology can foster novel strategies in forest management, encompassing remote sensing, data analysis, and digital platforms for monitoring and optimizing resource utilization. The impact of technology2 with digitalization (0.0163) is positive, indicating that education combined with digital is also effective in improving forest resource efficiency.

In the sixth column, the coefficient for urbanization, which was previously negative, has now become positive with a value of 0.0728. The coefficient that is positive and significant suggests that the impact of the digital economy on FRE is improved, showing a more pronounced influence of the digital economy in urbanized areas. Urbanization exhibits enhanced connectivity to digital infrastructure and technological resources. Further, the justification can be as digital technologies enable better resource management, monitoring, and sustainability. Digital technologies can improve resource utilization and conservation in urban areas with increasing resource demands. The digital economy may moderate the negative effects of urbanization on forest resources by promoting innovative, technology-driven environmental conservation and sustainable resource use.

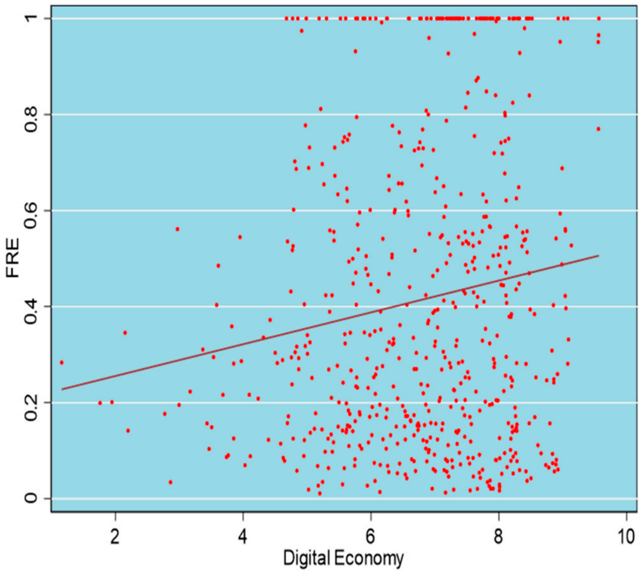

Figure 12. Digital economy impact on forest resources efficiency.

This advantageous circumstance enables the cultivation of a flourishing digital economy, which, in turn, facilitates the emergence of innovative approaches to forest resource management within urban settings. Consequently, these advancements contribute to heightened operational effectiveness and efficiency.

The effects of fiscal centralization and technology on forest resource efficiency exhibit similarities to those previously discussed. The impact of fiscal decentralization reveals a positive correlation between the degree of fiscal resource control held by local governments and enhanced efficiency in managing forest resources. Enhanced fiscal autonomy provides local authorities with the opportunity to customize forest management methods according to their distinct needs and goals, hence potentially improving operational effectiveness. The parallel and beneficial effects of technology improvements indicate that high-tech businesses have the potential to enhance forest management practices in terms of sustainability and efficiency. Nevertheless, urbanization is not advantageous as it results in urban expansion, leading to alterations in land use that can have detrimental impacts on the management of forest resources and the effectiveness of conservation initiatives. Nonetheless, it has been determined that investment continues to be advantageous, indicating that rising levels of investment in the forest industry can result in enhanced management strategies, sustainable utilization of resources, and heightened efficiency.

The study's overarching conclusions highlight the significance of government investment, technology uptake, and the implementation of well-balanced policies in enhancing forest resource efficiency. Additionally, the authors highlight the complexities associated with urbanization and the potential economic benefits that can be derived from adopting sustainable forest management practices. Moreover, the analysis of moderation effects demonstrates that the influence of the digital economy on the efficiency of forest resource utilization is magnified when a robust gross domestic product, fiscal decentralization, advanced technology, and urbanization accompany it. This emphasizes the importance of considering the wider economic and technological framework to promote more effective and sustainable practices in forest management.

6. Conclusions

This research offers an original perspective on the role of technology, fiscal decentralization, and digital economy in improving China's forest resource efficiency. Therefore, this study selected the thirty-one (31) provinces of China for (2002–2020). This study used a systematic road map for analysis. First, we focus on the key aspects related to forest resource inputs and outputs that are most pertinent to our analysis. Subsequently, we employ SBM-Data Envelopment Analysis to assess the efficiency of China's forest resources. In the next stage, we follow a proper econometric series: cross-sectional dependence, slop heterogeneity, order of integration, and co-integration, including checks for correlation. Following this, we proceed to conduct an in-depth examination of long-term analysis by Driscoll and Kraay estimators. This study uses two sorts of technology: high-technology expenditure and technology (forest) education. Further, fiscal decentralization (local government expenditure) on forest resources makes the study more innovative and richer in analysis. This research also emphasizes the moderating role of the digital economy in forest resource management and efficiency enhancement.

The study's significant findings disclose that both dimensions of technology increase the Chinese provinces' forest resource efficiency through technological expenditure and forest technology education. Further, fiscal decentralization is positive for improving forest resource efficiency. However, urbanization and economic development reduce the efficiency of forests. The digital economy can effectively help improve forest resource efficiency. Furthermore, the presence of moderating effects reveals that the influence of the digital economy on the efficiency of forest resources is greatly enhanced when it is coupled with a strong Gross Domestic Product, fiscal decentralization, modern technology, and urbanization. This emphasizes the significance of considering the wider economic and technological framework to advance more efficient and enduring forest management practices. Consequently, the study's findings have substantial implications on the topic.

Technology and Forest Resource Efficiency: China has the potential to achieve its forest resource objectives by implementing increased forest management practices, supported by the utilization of novel technology and the promotion of advanced technical education. To improve resource allocation and ecological sustainability, policymakers should promote investments in high-tech solutions and technical education, such as remote sensing, data analytics, and precision forestry. Improved financial and ecological outcomes are possible because of technological developments in forest management.

Fiscal decentralization and Forest Resource Efficiency: The governmental allocation of resources towards the management of forest resources is important to improve efficiency. It is urged that governments contemplate augmenting their expenditures on forest-related endeavors, encompassing conservation initiatives, reforestation actions, and the oversight and implementation of regulatory measures. Targeted public investments in the forestry sector have the potential to yield improved outcomes in resource management and conservation, thereby generating positive impacts on both the economy and the environment.

Digital Economy and Forest Resource Efficiency: A digital economy's impact on forest resource efficiency implies that a robust digitalized economy has the potential to enhance the effectiveness of forest management and the distribution of resources. Policymakers must deliberate upon the implementation of policies that facilitate the expansion of digitalization, particularly in metropolitan regions, with the aim of cultivating inventive strategies for the management of forest resources. The utilization of digital technologies and data-driven decision-making has the potential to improve the efficiency of resource allocation significantly.

Urbanization and Forest Resource Efficiency: China has a vast population as well as a growing economy. Since the demand for land and resources increases as populations grow, urbanization reduces the effectiveness of forest management. Sustainability concepts should be incorporated into urban planning to balance urban expansion and forest protection, making economic growth consistent with ecological conservation.

Limitations and Future Research

Although this research offers significant insights, it is crucial to recognize its limitations. The study's conclusions are derived from the data that is currently accessible and the approaches that have been used, both of which may have inherent limitations. Future research should further investigate advanced technological solutions and pedagogical initiatives that have the highest efficacy in improving China's forest resource efficiency. Furthermore, examining the intricate relationship between the digital economy and other influential factors could provide a detailed comprehension of its moderating impacts.

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Data Availability Statement: Data was collected from China forestry and Grassland statical year book. Data is freely available at: https://www.forestry.gov.cn (accessed on 10 October 2023) and National Bureau of Statistics China.

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

Appendix A

Table A1. Provinces.

Anhui	Heilongjiang	Qinghai	Zhejiang
Beijing	Henan	Shaanxi	
Chongqing	Hubei	Shandong	
Fujian	Hunan	Shanghai	
Gansu	Inner Mongolia	Shanxi	
Guangdong	Jiangsu	Sichuan	
Guangxi	Jiangxi	Tianjin	
Guizhou	Jilin	Tibet	
Hainan	Liaoning	Xinjiang	
Hebei	Ningxia	Yunnan	

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