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A Configurational Analysis of Green Development in Forestry Enterprises Based on the Technology–Organization–Environment (TOE) Framework

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Abstract: The construction of ecological civilization is intrinsically connected to green development. The green development of forestry enterprises serves as a key approach to achieving this goal. The research purpose of this paper is to explore the realization path of green development of forestry enterprises. First, an improved CRITIC (Criteria Importance Through Intercriteria Correlation)–entropy weight method was used to construct a reasonable input-output indicator system. Next, a three-stage data envelopment analysis (DEA) model was employed to evaluate the comprehensive technical efficiency of green development across 33 forestry enterprises in China, using panel data from 2017 to 2022. Finally, the study explored various configurational pathways for achieving green development by integrating the Technology–Organization–Environment (TOE) framework with dynamic qualitative comparative analysis (QCA). The findings reveal that green development in forestry enterprises is shaped by the interplay of multiple factors. Four distinct configurations were identified as instrumental in driving high green development. These configurations could be classified into two categories: the environment–organization synergistic development model and the technology–organization dual-driven model. This study provides empirical insights into the complex configurational relationships underlying green development in forestry enterprises, offering valuable guidance for optimizing development strategies.

Keywords: green development; forestry enterprises; improved CRITIC–entropy weight method; three-stage DEA; TOE framework; dynamic QCA; configurational analysis

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1. Introduction

Development has been a central theme throughout human history. However, the associated challenges of resource depletion, environmental degradation, and ecological imbalance are increasingly hindering sustainable societal progress. Economic growth and ecological protection must go hand in hand. Promoting green development is not only a practical response to China's reform and opening-up in the new era, but also aligns with global trends. Forestry represents the largest green economy globally and plays a critical role in advancing green development. Within this sector, forestry enterprises serve as the

primary drivers of green development, and their progress is crucial for building China's socialist ecological civilization.

The concept of green development remains theoretically contested in academic discourse, with interpretations diverging significantly between domestic and international contexts. Internationally, scholarly works lack a unified expression of "green development", often focusing on related constructs such as sustainable development [1], the Green New Deal [2], and green growth [3]. Synthesizing the common ground of related concepts, the main research point is how to obtain a win–win situation for both economic growth and environmental protection. This notion aligns closely with several internationally recognized concepts. For instance, green development is a key pathway to achieving the United Nations Sustainable Development Goals (SDGs), and is particularly closely linked to goals related to clean energy, climate action, and terrestrial ecology. It also resonates with the principles of the circular economy (CE), which emphasizes how societies can maximize resource efficiency while minimizing waste. In addition, the relationship between green development and environmental, social, and governance (ESG) is mutually reinforcing. Both concepts emphasize the imperative of integrating environmental protection, social responsibility, and robust governance structures throughout the development process to achieve sustainable equilibrium across economic, social, and environmental dimensions. In contrast, Chinese scholars have developed a unique philosophical framework for green development, emphasizing the dialectical relationship between human society and natural ecosystems. This perspective is grounded in the traditional Chinese philosophy of Tianren Heyi (the oneness of nature and humanity), which highlights the organic interdependence between nature and human society. Research on green development has encompassed a diverse range of industries and geographical regions. Geographically, studies have analyzed green development patterns in different countries [4], provinces within nations [5], and urban levels [6]. Industrially, the scope of research has covered manufacturing [7], agriculture [8], aquaculture [9], and more. Additionally, there has been growing academic interest in the green development of enterprises [10,11]. Methodologically, data envelopment analysis (DEA) has emerged as a robust analytical tool. For instance, Yu has used a non-radial DEA model to assess the green development efficiency of industrial parks in China [12]. Lubsanova et al. used the DEA method to analyze the eco-efficiency of socio-economic development in the Russian North Asian regions [13]. Sadri et al. used the network data envelopment analysis to evaluate the performance of 11 Iranian ports in two stages of greenness and intelligence over 4 years [14]. Additionally, some scholars have combined QCA with the TOE framework in enterprise development research. They have examined the roles of technological, organizational, and environmental factors in driving digital innovation in firms [15], as well as the complex synergistic effects of multiple factors on digital transformation performance [16].

In summary, the existing literature has predominantly concentrated on green development at the national or industry level, leaving enterprise-level green development under-researched. This gap is particularly pronounced in studies of forestry enterprises. Although DEA has been widely adopted for efficiency measurement and offers valuable methodological support for this research, few studies have integrated DEA with dynamic QCA to examine enterprise green development from a configurational perspective. This study contributes in two key aspects: First, it shifts the analytical focus from macro-level (national/industry) analyses to the micro-level by investigating forestry enterprises. Second, methodologically, it chooses the three-stage DEA to measure the comprehensive technical efficiency of green development in China's forestry enterprises. Additionally, dynamic QCA is used to trace the temporal evolution of configurations, aiming to identify the conditional combinations that shape the green development pathways of forestry enterprises

through a configurational lens. Therefore, the research objective of this paper is to construct a framework of influencing factors for the green development of forestry enterprises and examine the configurational combinations of these factors within the framework to identify pathways for enhancing their green development levels. Building on the research objective, this study formulated two key research questions: (1) Is the green development of forestry enterprises driven by a combination of multiple conditions, or can it be achieved through a single factor? (2) Are there distinct configurations of influencing factors that lead to high-level green development in forestry enterprises?

The structure of the remainder of this paper is as follows: Section 2 conducts a literature review. Section 3 introduces the research subjects, data sources, and research methodologies. Section 4 provides a detailed explanation of the construction process of the indicator system for this study, which includes the development of input and output indicators for the three-stage DEA, the selection of environmental variables, and the choice of causal variables for the dynamic QCA phase. Section 5 outlines the empirical process, presenting a comprehensive display of the results obtained from the three-stage DEA and dynamic QCA and analyzing them accordingly. Section 6 is the discussion section. Section 7 summarizes the results of the study, provides recommendations, and offers an outlook for future research.

2. Literature Review

2.1. Corporate Development Efficiency Assessment Based on Three-Stage DEA

In their seminal work introducing the concept of "efficiency evaluation", Farrell persistently emphasized its critical importance. He specifically asserted that measuring industrial production efficiency holds substantial value for both the economic theorist and the policy maker [17]. Parallel to this perspective, corporate efficiency evaluation constitutes a vital component of enterprise development. Given the inherent complexity of corporate production and operational processes, the adoption of multi-indicator efficiency assessment proves particularly appropriate. Data envelopment analysis (DEA) has emerged as the predominant methodology in corporate efficiency evaluation, with the successful implementation of the three-stage DEA model at the enterprise level empirically validating its scientific robustness and broad applicability. The subsequent paragraph systematically synthesizes existing research applications of the three-stage DEA methodology in efficiency analysis.

Existing studies have indicated that the three-stage DEA methodology plays an important role in both traditional areas and emerging industries. In power sector reform, Zhao et al. stripped environmental variables such as GDP (gross domestic product) per capita and the proportion of the second industry added value in GDP to accurately assess the real operational efficiency of the provincial electricity grid enterprises of China [18]. Mehrotra and Agarwal investigated the impact of investments made in information technology on firm performance using a three-stage DEA [19]. Torres-Pruñonosa et al. carried out a three-stage data envelopment analysis to analyze the social and economic efficiency of Spanish financial institutions [20]. Moreover, other studies have examined pharmaceutical companies [21], logistics companies [22], hospitals [23,24], and others. Collectively, these application cases demonstrate that the three-stage DEA method significantly enhances the objectivity of efficiency evaluations, establishing itself as a valuable analytical tool in contemporary enterprise efficiency research.

2.2. Research on Enterprise Development Pathways Using the TOE Framework and Dynamic QCA

The TOE framework is an integrated analytical model designed to analyze the various factors influencing an enterprise's adoption decisions. It consists of three key dimensions—technology, organization, and environment—which are not independent but rather interdependent and interconnected. Currently, the TOE framework is widely applied across multiple disciplines, especially in the field of business management, and the application of the TOE framework is more and more significant. Based on the TOE framework, some researchers examined the factors influencing small-medium enterprises' adoption of blockchain for operations and supply chain management [25,26]. Similarly, Abed utilized the TOE framework to analyze small–medium enterprises' adoption of social commerce, highlighting different emphases across its three dimensions: the technology dimension focused on preserved usefulness and security concerns, the organizational dimension emphasized top management support and organizational readiness, and the environmental dimension addressed consumer pressure and trading partner pressure [27]. Furthermore, Maroufkhani et al. demonstrated the importance of the most influential elements (technical, organizational, and environmental) of big data analytics for enterprises [28]. Therefore, applying the TOE framework to the study of the green development of forestry enterprises is well-founded. The rationale is as follows: First, extensive research has demonstrated that the TOE framework is a widely adopted and well-established theoretical model, making it a mature and practical research tool with strong interpretability. Second, the uniqueness of the TOE framework lies in its ability to integrate multiple factors into a systematic analysis. While traditional research often focuses on a single factor, the TOE framework constructs a three-dimensional interactive analysis that better captures the complexity of corporate behavior in dynamic environments. Given the multifaceted nature of the factors influencing the green development of forestry enterprises, relying solely on a single-factor analysis would be overly simplistic. A comprehensive application of the TOE framework ensures a more scientific and rigorous approach. Third, the three dimensions of the TOE framework—technology, organization, and environment—provide a well-structured foundation for enterprise development analysis, enabling a systematic examination of relevant influencing factors.

Configuration theory originated from the study of complex social phenomena, particularly the examination of substitution and complementary effects among different factors [29]. It emphasizes a comprehensive analysis of how configurational relationships influence outcomes. Without doubt, isolating single factors is insufficient for addressing complex enterprise-level problems [30]. In this context, the advantages of the configurational perspective, rooted in systems thinking, become evident. QCA is a widely used method for configurational analysis [31,32], with dynamic QCA enabling panel data analysis and gaining increasing adoption. Liu and Kim applied a combined approach of dynamic QCA and MATLAB 9.12 to explore pathways for green innovation and the high-quality development of influential regional enterprises [33]. Song et al. utilized dynamic fsQCA (fuzzy-set qualitative comparative analysis) to examine the driving pathways that enhance enterprise digital innovation intention and digital innovation performance under the influence of multiple factor combinations [15]. Additionally, some scholars employed dynamic QCA to analyze the complex causal mechanisms and configurations underlying green regional development, driven by digital innovation ecosystems from both temporal and spatial perspectives [34].

The green development of forestry enterprises is a complex process influenced by numerous factors; for example, variations in regional development levels, enterprise sizes, and times all exert varying degrees of impact on green development. While it is essential

to examine all potential influencing factors, research constraints necessitate a selective approach. To incorporate as many multidimensional factors as possible, we constructed a TOE framework. Drawing on the existing literature on enterprise development, we recognized that achieving a high level of green development in forestry enterprises is unlikely to be driven by a single factor alone. Therefore, we integrated the dynamic QCA methodology and adopted a configurational perspective to explore this issue comprehensively. We proposed the following two research hypotheses:

- Hypothesis 1: The realization of green development in forestry enterprises results from the combined effects of multiple conditions rather than a single factor.
- Hypothesis 2: There are different configurations of condition variables for achieving high-level green development in forestry enterprises.

3. Materials and Methods

This chapter is structured into two main sections. Section 3.1 introduces the research subjects and the data sources utilized in this study. Section 3.2 elaborates on the primary research methodologies employed, encompassing Section 3.2.1, which presents the improved CRITIC–entropy weight method; Section 3.2.2, which details the three-stage DEA method; and Section 3.2.3, which elucidates the dynamic QCA approach.

3.1. Research Objects and Data Sources

3.1.1. Research Objects

From a narrow perspective, forestry enterprises are traditionally defined as entities primarily engaged in silvicultural and timber production activities. In a broader sense, the business scope of forestry enterprises is more diverse, such as silviculture, the processing and trade of forest products, and forest tourism. With the ongoing evolution of modern forestry industries toward greater complexity and diversification, the forest industrial system gradually contained timber processing, sub-forest economic activities (e.g., non-timber forest products), and forest ecosystem services such as ecotourism and wellness programs. This study explains forestry enterprises within this expanded framework, defining them as organizations that directly or indirectly utilize forest resources to produce, process, or provide services related to forest products. The forest product underpinning this definition includes diverse categories, including raw logs, simply processed timber, further processed materials, waste paper and recyclable wooden products, refined lignocellulosic biomass, and forest ecosystem services, among others. By adopting this comprehensive definition, this study broadens the scope of forestry enterprises beyond the traditional boundaries to encompass industries such as the paper industry and the furniture manufacturing industry.

3.1.2. Data Sources

First of all, the study period was set between 2017 and 2022. Listed firms with significant missing data and those designated as ST (Special Treatment), *ST (Special Treatment with Asterisk), and PT (Particular Transfer) were excluded from the sample. After a rigorous selection process, 33 eligible listed companies were retained, as detailed in Table 1. Primary data sources included the China Stock Market and Accounting Research Database (CSMAR), Chinese Research Data Services Platform (CNRDS), corporate annual reports, and China National Statistical Yearbooks. For the remaining samples with only a few missing values, we applied linear interpolation to impute the missing data. Specifically, we constructed a straight line between two known data points (x_0, y_0) and (x_1, y_1), and used it to estimate the missing y values corresponding to x values within the interval [x_0, x_1]. The three-stage DEA was conducted using DEAP 2.1 and Frontier 4.1 software, while dynamic QCA was performed in RStudio (R version 4.4.2).

Table 1. Sample of forestry enterprises used in this study.

Name	Stock Code	Location (City, Province)
Shandong Chenming Paper Holdings Limited	000488	Weifang, Shandong
Zhongfu Straits (Pingtan) Development Company Limited	000592	Fuzhou, Fujian
Mcc Meili Cloud Computing Industry Investment Co., Ltd.	000815	Zhongwei, Ningxia
Guangxi Yuegui Guangye Holdings Co., Ltd.	000833	Guigang, Guangxi
Dare Power Dekor Home Co., Ltd.	000910	Zhenjiang, Jiangsu
Zhejiang Kan Specialities Material Co., Ltd.	002012	Lishui, Zhejiang
Dehua Tb New Decoration Material Co., Ltd.	002043	Huzhou, Zhejiang
Zhejiang Jingxing Paper Joint Stock Co., Ltd.	002067	Jiaxing, Zhejiang
Shandong Sun Paper Co., Ltd.	002078	Jining, Shandong
Xiamen Hexing Packaging Printing Co., Ltd.	002228	Xiamen, Fujian
Mys Group Co., Ltd.	002303	Shenzhen, Guangdong
Gem Co., Ltd.	002340	Shenzhen, Guangdong
Zhejiang Fuchunjiang Environmental Thermoelectric Co., Ltd.	002479	Hangzhou, Zhejiang
C&S Paper Co., Ltd.	002511	Zhongshan, Guangdong
Qifeng New Material Co., Ltd.	002521	Zibo, Shandong
Shanghai Shunho New Materials Technology Co., Ltd.	002565	Shanghai
Suofeiya Home Collection Co. Ltd.	002572	Guangzhou, Guangdong
Der Future Science And Technology Holding Group Co., Ltd.	002631	Suzhou, Jiangsu
Shenzhen Yuto Packaging Technology Co., Ltd.	002831	Shenzhen, Guangdong
Guangzhou Devotion Thermal Technology Co., Ltd.	300335	Guangzhou, Guangdong
Kangxin New Materials Co., Ltd.	600076	Weifang, Shandong
Fujian Qingshan Paper Industry Co., Ltd.	600103	Fuzhou, Fujian
Jilin Quanyangquan Co., Ltd.	600189	Changchun, Jilin
Shandong Huatai Paper Industry Shareholding Co., Ltd.	600308	Dongying, Shandong
Mudanjiang Hengfeng Paper Co., Ltd.	600356	Mudanjiang, Heilongjiang
Guangdong Guanhao High-Tech Co., Ltd.	600433	Zhanjiang, Guangdong
Shanying International Holdings Co., Ltd.	600567	Ma'anshan, Anhui
Yueyang Forest & Paper Co., Ltd.	600963	Yueyang, Hunan
Guangxi Fenglin Wood Industry Group Co., Ltd.	601996	Nanning, Guangxi
Shanghai Xintonglian Packing Co., Ltd.	603022	Shanghai
Jason Furniture (Hangzhou) Co., Ltd.	603816	Hangzhou, Zhejiang
Qu Mei Home Furnishings Group Co., Ltd.	603818	Beijing
Guangzhou Holike Creative Home Co., Ltd.	603898	Guangzhou, Guangdong

3.2. Research Methods

A hybrid methodological framework integrating three-stage DEA, the improved CRITIC–entropy weight method, and dynamic QCA is adopted. The analytical framework is presented in Figure 1.

3.2.1. Improved CRITIC–Entropy Weight Method

Part 1: Normalization of Indicators

A min-max normalization approach with a shifting adjustment (adding 0.001) is employed to standardize both positive and negative indicators, as detailed in Equations (1) and (2). Additionally, neutral indicators are handled using the procedure outlined in Equation (3).

- Positive indicators:

$$x'_{ij} = \frac{x_{ij} - x_{min}}{x_{max} - x_{min}} + 0.001 \quad (1)$$

- Negative indicators:

$$x'_{ij} = \frac{x_{max} - x_{ij}}{x_{max} - x_{min}} + 0.001 \quad (2)$$

where x_{ij} represents the actual value of the j-th indicator for sample i, x_{ij}' is the normalized value, and x_{max} and x_{min} denote the maximum and minimum values of the j-th indicator across all samples.

- Neutral indicators:

$$x_{ij}' = 1 - \frac{\max(x_{ij} - a_j, b_j - x_{ij})}{\max(x_{max} - a_j, b_j - x_{min})} + 0.001 \quad (3)$$

where the interval $[a_j, b_j]$ indicates the appropriate range for the j-th indicator.

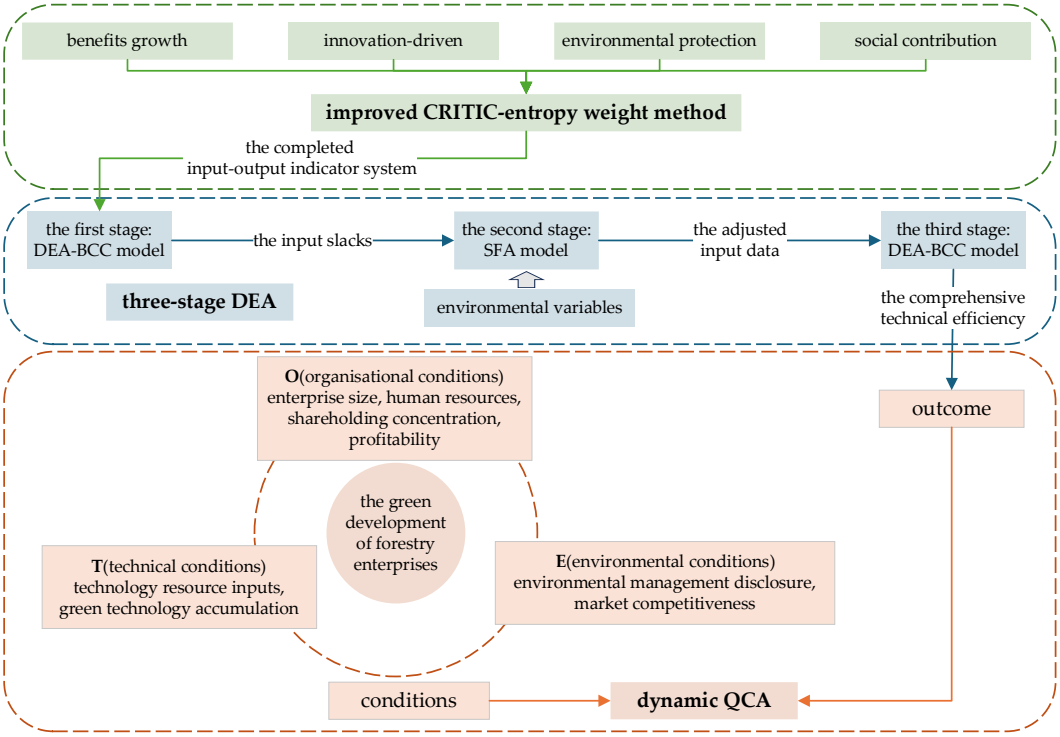


Figure 1. Schematic diagram of the key process.

Part 2: Improved CRITIC–Entropy Weight Method

To develop an appropriate input–output framework within a complex indicator system and provide a solid foundation for the three-stage DEA, it is essential to assign weights to indicators. This study proposes an improved weighting method that effectively integrates two classic objective weighting techniques: the CRITIC method and the entropy weight method. The CRITIC approach determines weights by assessing both the contrast intensity and the conflict degree among indicators, whereas the entropy weight method calculates weights based on information entropy theory [35]. Building on these foundations, this study implements an improved CRITIC method with two key modifications: substituting the standard deviation with the coefficient of variation, and using absolute values for correlation coefficients. The computational framework, detailed in Equations (4)–(8), incorporates parameters such as c (information quantity), e (information entropy), w (indicator weight), σ (standard deviation), and r_{ij} (correlation coefficient).

- The improved CRITIC method:

$$c_j = \frac{\sigma_j}{\overline{x}_j} * \sum_{i=1}^{m} (1 - |r_{ij}|) \quad (4)$$

$$w_1 = \frac{c_j}{\sum_{j=1}^{n} c_j} \quad (5)$$

- The entropy weight method:

$$e_j = -\frac{1}{\ln m} * \sum_{i=1}^{m} \left(\frac{x_{ij}}{\sum_{i=1}^{m} x_{ij}} * \ln \left(\frac{x_{ij}}{\sum_{i=1}^{m} x_{ij}} \right) \right) \tag{6}$$

$$w_2 = \frac{1 - e_j}{\sum_{j=1}^{n} (1 - e_j)} \tag{7}$$

- The portfolio weight:

$$w_j = \beta w_1 + (1 - \beta) * w_2 \tag{8}$$

where the weighting coefficient β is set to 0.5 [36]. This assignment ensures both methodologies receive equal importance, achieving a balanced integration of the two approaches.

3.2.2. Three-Stage DEA Model

Data envelopment analysis (DEA) is a nonparametric efficiency evaluation method based on linear programming, offering significant advantages in assessing the relative efficiency of decision-making units (DMUs) with multiple inputs and outputs. However, the traditional DEA framework does not account for the influence of environmental factors and random disturbances on efficiency measurements. To overcome this limitation, Fried et al. introduced a three-stage DEA model that integrates stochastic frontier analysis (SFA) [37]. This approach consists of the following three stages:

1. The first stage: the traditional DEA model

The DEA model is fundamentally classified based on returns-to-scale assumptions, consisting of the CCR model under constant returns to scale (CRS) and the BCC model, which accounts for variable returns to scale (VRS). Given this study's focus on assessing corporate green development levels, the input-oriented BCC framework is particularly suitable. Originally proposed by Banker, Charnes, and Cooper (1984), the BCC model decomposes comprehensive technical efficiency into pure technical efficiency and scale efficiency [38]. The mathematical formulation of the input-oriented BCC model is given as follows [39,40]:

$$\min \left[\theta - \varepsilon \left(\widehat{e}^{T} S^{-} + e^{T} S^{+} \right) \right]$$
$$\text{s.t.} \begin{cases} \sum_{j=1}^{n} X_j \lambda_j + S^{-} = \theta X_0 \\ \sum_{j=1}^{n} Y_j \lambda_j - S^{+} = Y_0 \\ \sum_{j=1}^{n} \lambda_j = 1 \\ \lambda_j, S^{-}, S^{+} \geq 0 \end{cases} \tag{9}$$

where n denotes the total number of DMUs, while the variables X and Y correspond to the input and output indicators, respectively. The slack variables S^{-} and S^{+} quantify input excesses and output shortfalls, respectively. Moreover, the comprehensive technical efficiency score θ ranges between 0 and 1, with values closer to 1 indicating higher levels of efficiency. Additionally, λ represents the weight coefficient for input and output indicators, while ε is a minimal positive number (typically set to 10^{-6}) ensuring the model's feasibility.

2. The second stage: SFA model

In the first stage, the comprehensive technical efficiency is affected by the environmental factors and random disturbances. To obtain a more accurate efficiency, in the SFA

model, the slack variables are decomposed into three components: environmental effects, statistical noise, and managerial inefficiency. The SFA model is as follows:

$$S_{ni} = f(Z_i; \beta_n) + \nu_{ni} + \mu_{ni}; i = 1, 2, \ldots, I; n = 1, 2, \ldots, N \quad (10)$$

where S_{ni} represents the slack variable for the n-th input of the i-th DMU, while $f(Z_i; \beta_n)$ captures the effect of environmental factors on input redundancy. Here, Z_i denotes the environmental variable, and β_n is its corresponding coefficient. The term $v_{ni} + u_{ni}$ represents the mixed error, which consists of two components: the random disturbance term v_{ni}, which accounts for stochastic influences on input redundancy, and the managerial inefficiency term u_{ni}, which reflects the impact of managerial factors on input slack.

The equation for separating the managerial inefficiency item is as follows:

$$E(\mu | \varepsilon) = \sigma * \left[\frac{\varnothing\left(\lambda \frac{\varepsilon}{\sigma}\right)}{\Phi\left(\frac{\lambda \varepsilon}{\sigma}\right)} \right] + \frac{\lambda \varepsilon}{\sigma} \quad (11)$$

where $\sigma* = \frac{\sigma_\mu + \sigma_\nu}{\sigma}$, $\sigma = \sqrt{\sigma_\mu^2 + \sigma_\nu^2}$, and $\lambda = \frac{\sigma_\mu}{\sigma_\nu}$.

The formula for separating the random disturbance term is as follows:

$$E(\nu | \varepsilon) = S_{ni} - f(Z_i; \beta_n) - E(\mu | \varepsilon) \quad (12)$$

Finally, the values of the original input variables are adjusted as follows:

$$X_{ni}^A = X_{ni} + \left[\max\left(f(Z_i; \hat{\beta}_n)\right) - f(Z_i; \hat{\beta}_n)\right] + \left[\max(\nu_{ni}) - \nu_{ni}\right]; i = 1, 2, \ldots, I; n = 1, 2, \ldots, N \quad (13)$$

where X_{ni}^A represents the adjusted input, while X_{ni} denotes the original input before adjustment. The term $\left[\max\left(f(Z_i; \hat{\beta}_n)\right) - f(Z_i; \hat{\beta}_n)\right]$ accounts for the correction of external environmental factors, while $[\max(v_{ni}) - v_{ni}]$ adjusts the random errors of all DMUs to the same level, ensuring that each DMU operates under identical external conditions.

3. The third stage: the adjusted DEA model

The third stage reintroduces the SFA-adjusted input data into the BCC model for recalibration. This adjustment generates a refined measure outcome of comprehensive technical efficiency, which demonstrates notable accuracy improvements compared to the initial DEA-BCC evaluation. Ultimately, the comprehensive technical efficiency obtained in the third stage can serve as the outcome variable for subsequent dynamic QCA, ensuring a robust analytical foundation for downstream procedures.

3.2.3. Dynamic QCA

Rooted in Boolean algebra and set theory, qualitative comparative analysis (QCA) is widely utilized to examine causal conditions and their configurations that give rise to the same outcomes [41]. However, the green development of forestry enterprises is a dynamic, multi-stakeholder process. Traditional QCA, based solely on cross-sectional data, restricts the exploration of spatiotemporal configuration evolution. To address this limitation, this study adopts a dynamic QCA to combine panel data with QCA, facilitating the analysis of temporal dimensions. By dividing consistency into inter-group, intra-group, and overall dimensions, dynamic QCA departs from the traditional QCA paradigm and offers a more detailed representation of consistency variations over time and case dimensions [42].

4. Development of the Indicator System

4.1. The Input–Output Indicator Framework

Constructing a reasonable input–output index system is essential for accurately measuring efficiency. But as of right now, there is currently no universally accepted index system for assessing enterprise green development. To address this gap, we employed CiteSpace 6.2.R1 to analyze paper data retrieved from the Web of Science, a leading global academic citation database that provides interdisciplinary literature retrieval services. First and foremost, we set the search formula in the Web of Science Core Library as TS = ("green development" OR "sustainable development") AND TS = (corporation* OR firm* OR enterprise*), and then set the date range as 2015–2024 and the document type as article. This process yielded a total of 4932 valid papers, which then ended up with 4930 valid articles after removing duplicates. Based on this dataset, we used CiteSpace to generate the keyword co-occurrence map shown in Figure 2. As illustrated in the figure, terms such as firm performance and financial performance were closely linked to economic benefits, while innovation and green innovation were strongly associated with innovation driven. Keywords like environmental regulation and sustainability highlighted environmental sustainability, whereas corporate social responsibility and social responsibility emphasized the role of corporate social responsibility. Building on these insights and drawing from recent influential studies on green development, we proposed a comprehensive green development indicator system for forestry enterprises. This system encompassed four key dimensions: benefit growth, innovation-driven development, environmental protection, and social contribution, as detailed in Table 2.

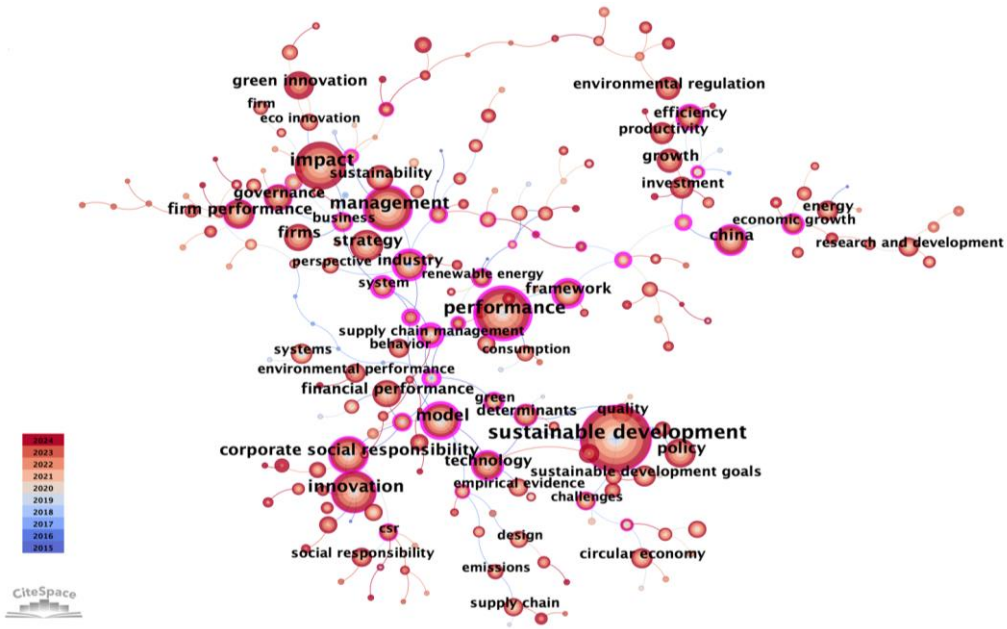


Figure 2. Co-occurrence network diagram of green development keywords. Each node represents a keyword whose size is related to its frequency. The thickness of the lines between the nodes represents the strength of co-occurrence between the keywords.

Next, the indicator weights were calculated using the improved CRITIC–entropy weight method. Following the principle of diversity in indicator selection, one indicator was chosen from each category at the same level. Consequently, the final input indicators included total asset turnover ratio (A2), the number of highly educated personnel (B4), environmental investment (C3), and the number of employees (D2). The output indicators consisted of the total asset growth rate (A9) and the number of patents obtained (B6). Figure 3 illustrates the selection process for the input indicators.

Table 2. Green development indicator system for forestry enterprises.

Target Layer	Criteria Layer	Index Layer	Nature of Indicators
Benefit growth	Operating ability	Current assets turnover ratio (A1)	+
		Total assets turnover ratio (A2)	+
	Solvency	Current ratio (A3)	±
		Quick ratio (A4)	±
	Profitability	Return on assets (A5)	+
		Return on total assets (A6)	+
		Operating profit margin (A7)	+
	Growth capacity	Growth rate of prime business income (A8)	+
		Total asset growth rate (A9)	+
Innovation-driven development	Innovation inputs	Research and development (R&D) expenditure intensity (B1)	+
		Number of innovative personnel (B2)	+
		Proportion of innovative personnel (B3)	+
		Number of highly educated personnel (B4)	+
		Proportion of highly educated personnel (B5)	+
	Innovation outputs	Number of patents obtained (B6)	+
Environmental protection	Green production	Energy intensity (per 10,000 Yuan revenue) (C1)	−
		Energy consumption per capita (C2)	−
	Green governance	Environmental investment (C3)	+
Social contribution	Employee rights	Growth rate of employee compensation payable (D1)	+
		Number of employees (D2)	+
		Average employee compensation (D3)	+
		Growth rate of average employee compensation (D4)	+

Note: + represents the positive indicator, − represents the negative indicator, and ± represents the neutral indicator.

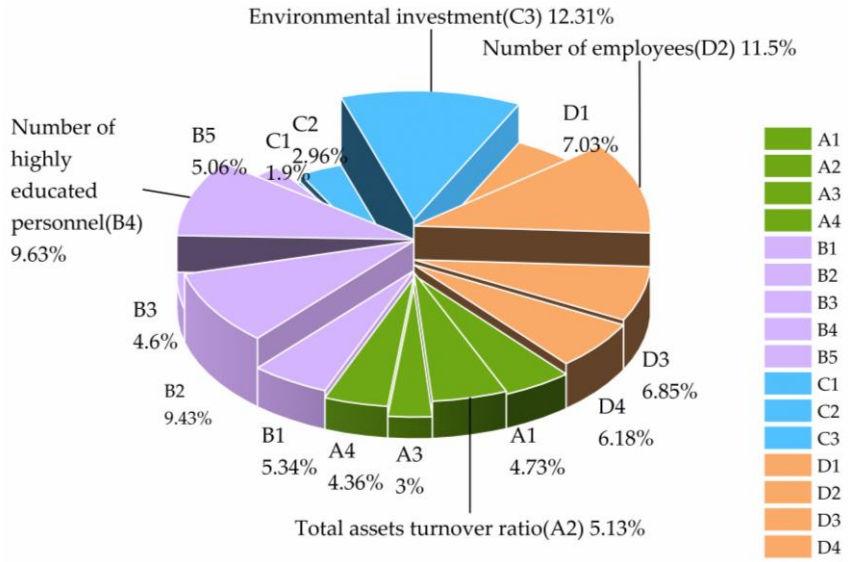


Figure 3. Pie chart of input indicator weights. The four colors represent the input indicators for each of the four dimensions: green represents benefit growth, purple denotes innovation-driven development, blue signifies environmental protection, and orange corresponds to social contribution. The indicators with the highest weights under each dimension are marked with separate callout lines.

4.2. Environmental Variables

The three-stage DEA methodology offers significant advantages over traditional DEA, particularly in its second stage, where SFA is applied using selected environmental variables. For this study, three environmental variables were incorporated: regional GDP (gross

domestic product) per capita, enterprise age, and government investment. Further details can be found in Table 3.

Table 3. Environmental variables to be used in SFA regression analyses.

Target Layer	Criteria Layer	Index Layer	Description of Indicators
Environmental variables	Regional development	Regional GDP per capita (E1)	GDP per capita in the province where the enterprise is located
	Time in business	Enterprise age (E2)	Years since establishment
	Government support	Government investment (E3)	Government grants received by the enterprise during the year

4.3. Dynamic QCA Causal Variables

The TOE framework originated as a theoretical construct to explain the multidimensional impacts of technological, organizational, and environmental factors on corporate technological innovation. This integrative analytical framework overcomes the limitations of one-dimensional analyses by emphasizing synergistic interactions across dimensions. As its scope of application expands, the TOE framework has been increasingly applied in diverse fields, including public libraries and high-quality corporate development research. Drawing on the TOE framework, this study systematically identified and selected eight antecedent variables and employed three-stage DEA-derived comprehensive technical efficiency as the outcome variable, thereby establishing an analytical framework.

1. Technological conditions:

- Investment in technical resources. Technology is a critical factor for enterprises to maintain a competitive edge in the market. Investment in research and development (R&D) serves as the foundation for enterprises to innovate processes and improve product quality, thereby reflecting their innovation capacity.
- Accumulation of green technology. A higher number of green patents not only demonstrates an enterprise's strength and achievements in sustainable development but also highlights its proactive behavior to address environmental challenges.

2. Organizational conditions:

- Firm size. Large enterprises generally excel in resource acquisition and allocation, while small enterprises benefit from greater flexibility.
- Human resources. Highly educated personnel typically possess strong learning abilities and open-mindedness, enabling enterprises to navigate complex and dynamic market environments and adapt to evolving technologies.
- Equity concentration. Appropriate equity concentration ensures that decision-making bodies can make accurate strategic decisions while mitigating the risks of excessive concentration or overly dispersed equity.
- Profit-making capability. Strong profit-making capability directly reflects a company's sound financial performance and provides essential funding to support its strategic initiatives.

3. Environmental conditions:

- Environmental management disclosure. This is a reflection of the company's environmental transparency and helps build trust among stakeholders. Environmental disclosure positively impacts firm value, as evidenced by data from the environmental management disclosure tables of listed companies [43].
- Market competitiveness. The market competitiveness of a company affects its strategic decisions as well as the effectiveness of the company's strategic implementation, and we measure this indicator with the Lerner index [44].

However, it is essential to clarify the fundamental distinction between the environmental conditions examined in this section and the environmental variables used in the three-stage DEA. Within the three-stage DEA methodology, environmental variables were introduced to control for and mitigate the impact of uncontrollable external factors, such as government investment, regional economic disparities, and firm age. This approach aimed to isolate a more precise measure of comprehensive technical efficiency, thereby providing a clearer reflection of corporate performance. In contrast, the environmental factors considered within the TOE framework, as applied in the dynamic QCA, represented elements that firms could actively perceive and strategically adapt to. By integrating variables such as corporate environmental management disclosures and market competitiveness, this study explored how diverse configurations of technological, organizational, and environmental factors collectively drove corporate green development. These variables were not merely external constraints but were instead dynamic conditions that firms could influence through targeted strategies. Detailed definitions and operationalizations of these variables are systematically outlined in Table 4.

Table 4. Definition table of conditions and outcome variables in the dynamic QCA.

Type	Variables	Indicators	Explanations
Conditions	Technical conditions	Investment in technical resources (X1)	The proportion of R&D investment in operating revenue
		Accumulation of green technology (X2)	Number of green patent grants
	Organizational conditions	Firm size (X3)	Logarithm of total asset scale
		Human resources (X4)	Proportion of highly educated employees
		Equity concentration (X5)	Shareholding ratio of the largest shareholder
		Profit-making capability (X6)	Return on equity
	Environmental conditions	Environmental management disclosure (X7)	The environmental management disclosure of listed Companies in the CSMAR database
		Market competitiveness (X8)	Lerner Index: proportion of the remaining part (excluding operating costs, selling expenses and administrative expenses) in operating revenue
Outcome	Green development	Comprehensive technical efficiency (Y)	The comprehensive technical efficiency obtained from the third stage DEA-BCC

5. Results

5.1. Three-Stage DEA Results

5.1.1. The First Stage: DEA-BCC

As shown in Table 5, comprehensive technical efficiency experienced a significant decline, dropping from 0.667 in 2017 to 0.245 in 2022. This downward trend was primarily driven by a substantial reduction in scale efficiency, which decreased from 0.839 to 0.321 over the same period. Moreover, by 2022, 31 firms were operating under diminishing returns to scale. Therefore, in the next stage of analysis, it is necessary to examine whether external environmental factors contributed to these observed changes.

Table 5. Results of the first stage DEA-BCC model.

Year	Comprehensive Technical Efficiency	Pure Technical Efficiency	Scale Efficiency	IRS	-	DRS
2017	0.667	0.754	0.839	17	13	3
2018	0.639	0.700	0.864	17	13	3
2019	0.580	0.624	0.913	10	10	13
2020	0.598	0.673	0.883	14	8	11
2021	0.479	0.548	0.837	9	7	17
2022	0.245	0.712	0.321	0	2	31

5.1.2. The Second Stage: SFA

As demonstrated in Table 6, the results of the second-stage SFA regression indicated a relatively high log-likelihood function value, suggesting a robust goodness of fit for the model. Additionally, both σ^2 and γ were statistically significant, with most γ values approaching 1. Furthermore, the LR test results were statistically significant at the 0.01 level, reinforcing the validity of the model. These findings collectively underscored the importance of controlling for environmental variables and random noise in the analysis, confirming the significance of this phase of our research.

Table 6. Results of the second stage SFA regression analysis.

	A2	B4	C3	D2
Constant term	0.35	0.49	0.17	0.80
E1	0.04	0.028	−0.03	0.05
E2	0.35	−0.21	0.10	−0.46
E3	−0.02	0.00	0.24	0.08
σ^2	0.21 ***	0.11 ***	0.05 ***	0.23 ***
	(3.59)	(3.67)	(4.02)	(3.60)
γ	0.96 ***	0.93***	0.43 ***	0.96 ***
	(70.77)	(44.94)	(2.63)	(76.56)
Log likelihood function	121.61	154.84	52.22	122.43
LR test of the one-sided error	143.34 ***	80.49 ***	11.54 ***	139.28 ***

Note: *** represents the significance levels of 1%, and the results in parentheses are the t-statistics of the estimated coefficients.

5.1.3. The Third Stage: DEA-BCC

Figure 4 illustrates the comparative trends of comprehensive technical efficiencies derived from the first and third phases of the three-stage DEA analysis. A marked divergence between these trends clearly indicated the substantial influence of external environmental factors on DEA methodology applications. The heatmap presented in Figure 5 visualizes individual enterprises' comprehensive technical efficiency variations. The predominance of blue regions in 2020 reflects superior green development efficiency levels across numerous enterprises, which was followed by a moderate efficiency decline in 2021. Subsequently, 2022 witnessed a notable recovery, with multiple enterprises achieving restored efficiency levels. Particularly noteworthy were the consistently outstanding performances of Gem Co., Ltd. (stock code: 002340, location: Shenzhen, Guangdong, China) and Jason Furniture (Hangzhou) Co., Ltd. (stock code: 603816, location: Hangzhou, Zhejiang, China), whose sustained high efficiency levels demonstrated operational excellence. Overall, the three-stage DEA framework yields more precise and reliable comprehensive technical efficiency measurements.

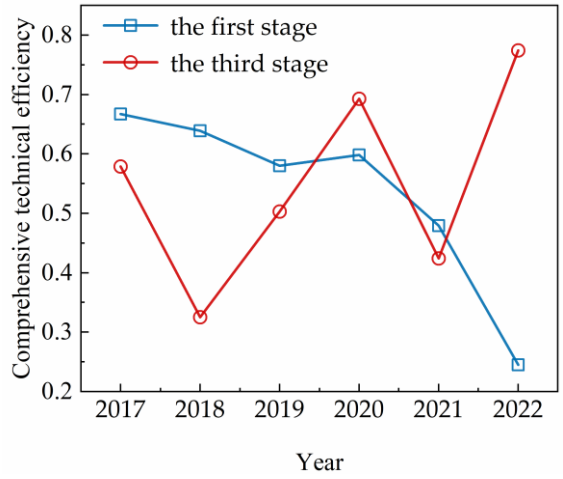


Figure 4. Comparison of trends in comprehensive technical efficiency changes between the first stage and the third stage.

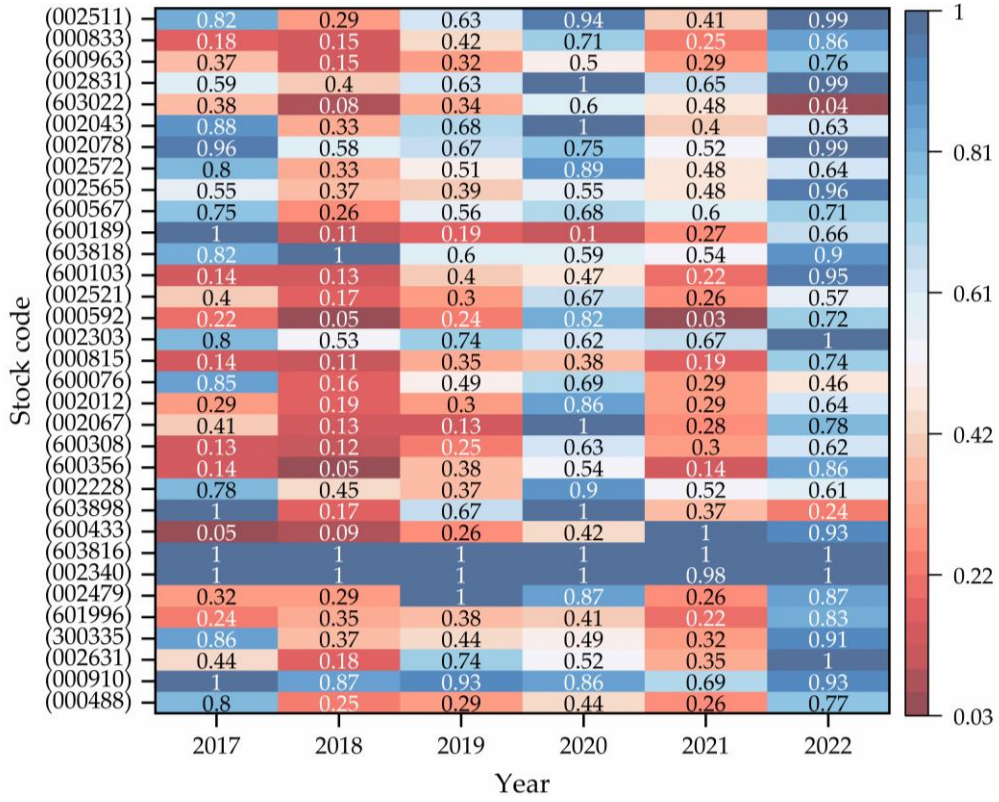


Figure 5. Heat map of the comprehensive technical efficiency in the third stage. The vertical coordinate is the stock code of the 33 firms, and the comprehensive technical efficiency is labeled in the grid.

5.2. Analysis of Configuration Path

5.2.1. Calibration of Variables

This study employed the direct calibration method to transform raw data into fuzzy sets, with values standardized on a scale from 0 to 1 [45]. To ensure comprehensive case retention while maintaining analytical rigor, a calibration threshold of 0.501 was implemented instead of the conventional 0.5 [46]. Based on the available studies, the 95%, 50%, and 5% quantiles were used as three qualitative anchors for complete affiliation, crossover, and complete disaffiliation [47,48]. The results of this calibration process are systematically presented in Table 7.

Table 7. Calibration of variables.

Variables	Fuzzy Calibration		
	Complete Affiliation	Crossover	Complete Disaffiliation
X1	4.782	2.394	0.723
X2	88.200	4.000	0.000
X3	24.515	22.491	21.519
X4	21.065	13.504	6.705
X5	52.982	28.900	11.283
X6	21.587	6.439	−3.565
X7	8.000	3.000	0.000
X8	20.426	11.390	1.381
Y	1.000	0.528	0.117

5.2.2. Analysis of Necessary Conditions

In panel data analysis, consistency and coverage are key indicators for assessing the sufficiency relationship between condition variables and outcome variables. Conventionally, a condition is called "necessary" or "almost always necessary" if the consistency score exceeds the threshold of 0.9 [49]. When the inter-group consistency gap is less than 0.2, the aggregated consistency accuracy is high and can be directly used as a basis for judgment [50]. As shown in Table 8, the aggregated consistency level of each condition was below 0.9, failing to meet the threshold for determining necessary conditions. It is therefore crucial to identify instances where the inter-group consistency distance exceeded 0.2. A total of 13 such cases are summarized in Table 9, where no inter-group consistency exceeded 0.9. In conclusion, no single factor could be identified as a necessary condition for either high or non-high green development levels in forestry enterprises. Furthermore, cases numbered 3, 10, and 13 in Table 9 warranted further analysis. The trend in the level of inter-group consistency for these three cases visually demonstrated a fluctuating upward trend in the necessity of firm size, profit-making capability, and market competitiveness, representing a significant time effect, as shown in Figure 6.

Table 8. Analysis of necessary conditions.

Conditions	Y				~Y			
	CON	COV	CON′	COV′	CON	COV	CON′	COV′
X1	0.645	0.652	0.119	0.456	0.601	0.605	0.263	0.492
~X1	0.610	0.605	0.141	0.504	0.654	0.647	0.082	0.462
X2	0.543	0.695	0.141	0.601	0.489	0.624	0.293	0.619
~X2	0.706	0.581	0.128	0.372	0.761	0.624	0.137	0.366
X3	0.685	0.723	0.186	0.432	0.529	0.556	0.226	0.564
~X3	0.580	0.553	0.086	0.474	0.737	0.700	0.125	0.384
X4	0.611	0.629	0.232	0.480	0.603	0.617	0.257	0.510
~X4	0.628	0.613	0.232	0.462	0.637	0.620	0.116	0.462
X5	0.632	0.660	0.220	0.498	0.584	0.607	0.205	0.498
~X5	0.624	0.601	0.116	0.492	0.673	0.646	0.125	0.438
X6	0.715	0.703	0.244	0.300	0.584	0.572	0.116	0.402
~X6	0.565	0.577	0.260	0.456	0.697	0.709	0.192	0.324
X7	0.619	0.641	0.217	0.492	0.601	0.620	0.128	0.480
~X7	0.633	0.614	0.196	0.468	0.652	0.631	0.199	0.432
X8	0.671	0.659	0.238	0.342	0.606	0.593	0.168	0.444
~X8	0.586	0.599	0.226	0.444	0.651	0.664	0.189	0.426

Note: CON represents the aggregated consistency, COV denotes the aggregated coverage, CON′ indicates the inter-group consistency distance, and COV′ signifies the intra-group consistency distance.

Table 9. Causal combinations with inter-group consistency distances greater than 0.2.

No.	Case	Index	2017	2018	2019	2020	2021	2022
1	X1/~Y	Inter-group consistency	0.545	0.450	0.612	0.729	0.646	0.875
		Inter-group coverage	0.545	0.831	0.737	0.459	0.783	0.349
2	X2/~Y	Inter-group consistency	0.380	0.359	0.490	0.705	0.573	0.593
		Inter-group coverage	0.584	0.842	0.731	0.529	0.836	0.291
3	X3/~Y	Inter-group consistency	0.417	0.457	0.550	0.605	0.567	0.725
		Inter-group coverage	0.494	0.782	0.663	0.395	0.711	0.314
4	X4/Y	Inter-group consistency	0.423	0.570	0.636	0.544	0.749	0.739
		Inter-group coverage	0.605	0.349	0.601	0.771	0.446	0.892
5	X4/~Y	Inter-group consistency	0.513	0.446	0.602	0.815	0.688	0.763
		Inter-group coverage	0.636	0.849	0.733	0.559	0.788	0.270
6	~X4/Y	Inter-group consistency	0.745	0.754	0.718	0.689	0.645	0.395
		Inter-group coverage	0.639	0.304	0.583	0.885	0.518	0.850
7	X5/Y	Inter-group consistency	0.636	0.816	0.800	0.582	0.715	0.485
		Inter-group coverage	0.655	0.390	0.696	0.851	0.544	0.858
8	X5/~Y	Inter-group consistency	0.606	0.538	0.552	0.664	0.529	0.821
		Inter-group coverage	0.541	0.799	0.619	0.469	0.774	0.425
9	X6/Y	Inter-group consistency	0.896	0.845	0.857	0.676	0.797	0.466
		Inter-group coverage	0.777	0.369	0.717	0.944	0.585	0.881
10	~X6/Y	Inter-group consistency	0.327	0.566	0.527	0.599	0.671	0.675
		Inter-group coverage	0.460	0.311	0.483	0.780	0.430	0.883
11	X7/Y	Inter-group consistency	0.408	0.720	0.651	0.588	0.727	0.694
		Inter-group coverage	0.628	0.353	0.576	0.841	0.473	0.952
12	X8/Y	Inter-group consistency	0.800	0.820	0.807	0.661	0.746	0.433
		Inter-group coverage	0.806	0.351	0.641	0.839	0.507	0.892
13	~X8/Y	Inter-group consistency	0.415	0.524	0.534	0.576	0.720	0.701
		Inter-group coverage	0.475	0.295	0.520	0.829	0.496	0.868

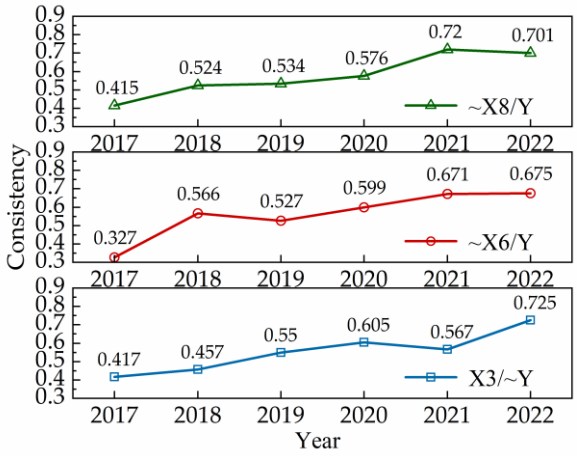


Figure 6. Changes in the level of inter-group consistency for the three causal scenarios.

5.2.3. Sufficiency Analysis of Conditional Configuration

To maintain analytical rigor and in reference to other studies, particular thresholds were defined throughout the truth table construction: the consistency threshold was set at 0.85, the minimum case threshold at 1, and the Proportional Reduction in Inconsistency (PRI) consistency threshold at 0.65 [33,50,51]. Additionally, no consistent conclusion was reached between the existing conditions and high or non-high green development, making it difficult to conduct a clear counterfactual analysis. Therefore, no directional assumptions were imposed on the antecedent conditions. In the final result analysis, the intermediate solution serves as the primary reference, while the simple solution provides supplementary insights [45]. Table 10 reveals the results of the configuration analysis for

the four conditional implementations of high green development, with each column representing one possible conditional configuration. The overall consistency of 0.861 exceeded the 0.75 threshold, indicating strong explanatory power of the identified condition combinations for the outcome variable. Additionally, the overall coverage of 0.393 met the QCA requirement for secondary data studies (coverage > 0.3). The adjustment distance between intra-group and inter-group values for the individual configuration was smaller than 0.2, suggesting that the four configuration paths could be considered sufficient conditions for high-level green development [52]. According to their respective characteristics, these four configurations could be divided into two types, H1 and H2, with the first three characteristics belonging to type H1. Moreover, typical cases for each of the four configurations are detailed in Table 11.

Table 10. Results of the configuration analysis.

Case	H1a	H1b	H1c	H2
Investment in technical resources	●	●	●	⊗
Accumulation of green technology	⊗		●	⊗
Firm size		•	•	•
Human resources	⊗	⊗	●	•
Equity concentration	●	●	⊗	●
Profit-making capability	●	●	●	●
Environmental management disclosure	⊗	⊗	•	⊗
Market competitiveness	•	•	⊗	●
Consistency	0.882	0.903	0.899	0.876
PRI	0.657	0.701	0.680	0.664
Original coverage	0.266	0.247	0.187	0.219
Unique coverage	0.034	0.006	0.053	0.052
Inter-group consistency distance	0.168	0.147	0.122	0.122
Intra-group consistency distance	0.174	0.156	0.102	0.174
Overall consistency		0.861		
Overall PRI		0.700		
Overall coverage		0.393		

Note: ● indicates the core condition is present, • represents the peripheral condition is present, ⊗ signifies the core condition is missing, and ⊗ denotes the peripheral condition is missing. A blank space indicates irrelevant to the outcome.

Table 11. Typical cases of configuration correspondence.

Configurations	Typical Cases
H1a	Qu Mei Home Furnishings Group Co., Ltd. (2017), Guangzhou Holike Creative Home Co., Ltd. (2017, 2020), Mys Group Co., Ltd. (2017, 2018, 2019), Shenzhen Yuto Packaging Technology Co., Ltd. (2017)
H1b	Mys Group Co., Ltd. (2017, 2018, 2019), Shenzhen Yuto Packaging Technology Co., Ltd. (2017, 2020, 2021)
H1c	Shanying International Holdings Co., Ltd. (2021), Yueyang Forest & Paper Co., Ltd. (2022)
H2	Jason Furniture (Hangzhou) Co., Ltd. (2017, 2018, 2019)

Type I: Technology–Organization Dual-Driven Model. This category encompassed the first three configurations. Configuration H1a demonstrated that high levels of green development could be achieved with high investment in technological resources, high equity concentration, and strong profit-making capability as core conditions, even with low human resource levels and limited environmental management disclosure. Additionally, low

green technology accumulation and high market competitiveness functioned as peripheral conditions. In contrast, Configuration H1b indicated that green technology accumulation had a minimal impact, while firm size became a peripheral condition. These two pathways suggested that strong profit-making ability and R&D investment could compensate for the limitations of human resources. Configuration H1c was also driven by technology and organization, sharing high technological resource investment and high profitability as core conditions with the other two configurations. However, unlike the previous configurations, H1c highlighted that under low market competitiveness and low equity concentration, firms required additional factors—such as human resource investment, green technology reserves, and transparency in environmental management—to achieve green development.

Type II: Environment–Organization Synergistic Development Model. Configuration H2 demonstrated that forestry enterprises could achieve high-level green development with low technological resource investment, low green technology accumulation, high equity concentration, high profitability, low environmental management disclosure, and high market competitiveness as core conditions, supplemented by high firm size and high human resource levels as peripheral conditions. The original coverage of this pathway was 21.9%, with a unique coverage of 5.2%, significantly higher than that of Configurations H1a and H1b. A representative example of Configuration H2 was the Jason Furniture (Hangzhou) Co., Ltd. This company vigorously implemented equity incentive plans, successfully attracting and retaining a large number of outstanding talents. In 2019, the company's revenue exceeded 10 billion yuan for the first time, reflecting its optimistic profitability and strong market competitiveness. Additionally, from 2017 to 2019, the largest shareholder of this company held more than 45% of the shares. The relatively concentrated equity structure enables the company's management to make decisions more efficiently, facilitating the implementation of corporate strategies and serving as an effective guarantee for achieving green development.

From a broader perspective, the unique coverage of four configurations remained relatively low, suggesting that forestry enterprises were not heavily reliant on any single pathway to achieve high-level green development. Instead, a certain degree of substitutability existed among these configurations. Notably, Configurations H1a and H1b shared identical core conditions. In comparison with Configuration H2, it became evident that under conditions of higher equity concentration and strong profit-making capability, high technological resource investment and strong market competitiveness exhibited a substitution effect in driving the green development of forestry enterprises. These findings suggest that forestry enterprises have multiple viable development pathways. Depending on their resource endowments and competitive environments, firms can adopt flexible and diversified strategies to achieve green development.

1. Inter-Group Results

An examination of the inter-group consistency distance revealed that all values fell below the 0.2 threshold, indicating no significant time effect. However, a temporal analysis still provided valuable insights. As shown in Figure 7, the consistency of the four configurations declined simultaneously in both 2018 and 2021. This fluctuation suggested that these changes cannot simply be attributed to benign deviations. The year 2018 marked the beginning of promoting high-quality development in China and was a critical period for deepening supply-side structural reforms and strengthening environmental policies. Enterprises needed time to adapt to these policy shifts. Additionally, the Sino–US trade dispute in 2018 affected numerous businesses, disrupting their development to some extent. In 2021, Carbon Peak and Carbon Neutrality Goals were formally integrated into China's national strategic framework. While this policy provided a clear direction for green development, it also imposed significant short-term transformation pressures on

enterprises. Furthermore, the downturn in China's real estate sector in 2021 had ripple effects on upstream and downstream industries, affecting forestry enterprises as well. The resurgence of COVID-19 during this period further exacerbated operational challenges for businesses. As a result, the explanatory power of normal antecedent conditions inevitably declined during these phases. Nonetheless, since the inter-group consistency distance remained below 0.2, it still retained reasonable explanatory power.

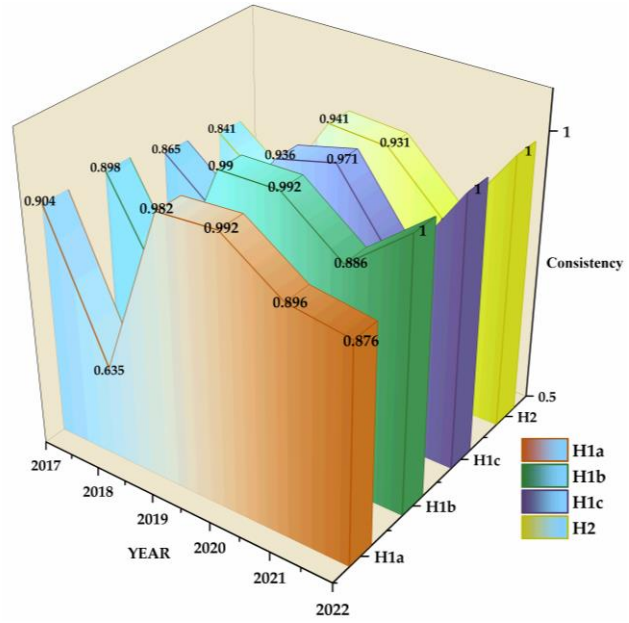


Figure 7. Inter-group consistency changes between groups.

2. Intra-Group Results

Similarly, an analysis of the intra-group consistency distance revealed that four configurations remained below the 0.2 threshold, indicating no significant differences among cases. Our findings showed that most firms exhibited intra-group consistency levels above 0.75, with 11 firms achieving a perfect consistency score of 1.0 across four configurations. This suggested that these firms could achieve high levels of green development through any of the four pathways. Next, we conducted a further exploration from the spatial dimension. Since most of the sample firms were located in the eastern region, we categorized them into two groups: the eastern and other regions. The results are shown in Table 12. The coverage of Configurations H1a and H1b was slightly higher in the eastern region, though the difference was not substantial. Compared to other regions, the eastern region exhibited a higher level of economic development, stronger corporate growth efficiency, and greater market competitiveness. These core conditions enabled firms in this region to more effectively achieve green development. Meanwhile, the coverage of Configurations H1c and H2 in other regions stood at 0.338 and 0.323, respectively. Representative firms in Configuration H1c included Shanying International Holdings Co., Ltd. (location: Ma'anshan, Anhui, China) and Yueyang Forest & Paper Co., Ltd. (location: Yueyang, Hunan, China). Notably, Shanying International Holdings Co., Ltd. accumulated 54 green patents in 2021—nearly three times the average—while its other indicators, except for equity concentration and market competitiveness, were slightly above the mean.

Table 12. Mean value of regional coverage.

Region	H1a	H1b	H1c	H2
Eastern regions	0.280	0.242	0.171	0.190
Other regions	0.218	0.218	0.338	0.323

5.2.4. Robustness Test

To ensure the robustness of our findings, we conducted three robustness tests. First, we raised the original consistency threshold from 0.85 to 0.9. Second, we increased the minimum case frequency requirement from 1 to 2. Third, we adjusted the PRI consistency threshold from 0.65 to 0.69. The results remained stable across all modifications, with no changes in the subset relationships of the fuzzy sets. These findings confirmed the stability of our configurational analysis, reinforcing the reliability of our conclusions.

6. Discussion

Most existing green development evaluation index systems are designed at the regional level [53,54] or industrial level [55], or are linked to the broader concept of sustainable development [56]. Drawing on the relevant literature on green development, this study identified high-frequency terms in green development research and constructed an enterprise-level green development index system. This system comprised four key dimensions: benefit growth, innovation-driven development, environmental protection, and social contribution. Through the three-stage DEA model, a more accurate measurement of the comprehensive technical efficiency of green development in forestry enterprises was obtained. The mean value of comprehensive technical efficiency in the first stage showed a year-on-year decline, which appeared evidently unreasonable. In contrast, the results from the third stage of the DEA indicated that the mean value of comprehensive technical efficiency reached its highest level in 2022, making it a more reasonable representation than the first-stage results. Notably, the comprehensive technical efficiency of Gem Co., Ltd. and Jason Furniture (Hangzhou) Co., Ltd. almost reached the level of effective DEA from 2017 to 2022, suggesting that these two enterprises have made significant achievements in advancing their green development.

The core focus of this study was to explore the green development pathways of forestry enterprises by integrating the TOE framework with dynamic QCA. Using the TOE framework, we identified eight antecedent conditions across the technological, organizational, and environmental dimensions as key influencing factors of the green development of forestry enterprises. This framework could provide a comprehensive and systematic approach to selecting antecedent conditions. Furthermore, by structuring the antecedent conditions through the TOE framework, we established a solid foundation for the QCA analysis, enabling a more robust identification of configurational pathways that drive green development. This approach not only considered the individual factors influencing corporate green development but also examined the interactions among these factors. In doing so, it facilitated the application of configuration theory and the dynamic QCA methodology in the context of forestry enterprises' green development and enhanced the explanatory power of our findings. By analyzing 33 publicly listed Chinese forestry enterprises, this study identified multiple driving pathways for achieving green development.

In Section 2.2, two research hypotheses were proposed regarding the influencing factors and development pathways of enterprise green development. The necessary condition analysis in Section 5.2.2 demonstrated that the aggregated consistency score across individual conditions was below 0.9. Additionally, an analysis of cases with inter-group consistency distance >0.2 showed that absence of inter-group consistency exceeding 0.9. These systematic findings empirically substantiated that a single influencing factor cannot

independently drive forestry enterprises to achieve green development, thereby confirming Hypothesis 1. Since no single factor can independently achieve the desired goal, further analysis must focus on factor configurations, necessitating the validation of Hypothesis 2. As evidenced in Section 5.2.3, four distinct enterprise configurations demonstrated capacity for superior green development performance, thereby empirically supporting Hypothesis 2. These four pathways could be categorized into two types: the environment–organization synergistic development type and the technology–organization dual-driven model, which showed that the organizational conditions within the enterprise were essential in both paths. In particular, the profit-making capability among the organizational conditions appeared in all four paths. This consistent presence highlights the necessity of maintaining a certain level of profitability to support the implementation of an enterprise's strategic plan, which is crucial for achieving both green development and long-term growth.

By focusing on forestry enterprises in China, this study provides industry-specific insights into green development. While this sector-specific approach enhances the applicability of our findings within the forestry industry, caution should be exercised when extending the conclusions to other industries, as sectoral differences in regulatory environments, technological adoption, and operational strategies may influence green development pathways.

7. Conclusions

7.1. Research Conclusions

This study examined data from 33 listed forestry companies spanning the years 2017 to 2022. Based on a systematic review of 4930 articles from the Web of Science, we developed a green development index system for forestry enterprises. To construct a robust input–output indicator system, we employed the improved CRITIC–entropy weight method. Finally, by integrating the three-stage DEA model with dynamic QCA, we identified the key pathways that drove green development in forestry enterprises. The main findings of this study were as follows:

1. Analysis of Necessary Conditions.

The consistency level of the firm size, the capability of profit-making, and market competitiveness exhibited a fluctuating upward trend from 2017 to 2022. However, no single factor alone was sufficient to drive high-level green development in enterprises.

2. Sufficiency Analysis of Conditional Configuration.

Four distinct configurations enabled forestry enterprises to achieve high levels of green development. Based on their characteristics, these configurations were classified into two types: technology–organization dual-driven and environment–organization synergistic development. The analysis revealed that profit-making capability served as a core condition in all four configurations, playing a crucial role in driving green development. Moreover, under constant conditions, technological resource investment and market competitiveness exhibited a certain degree of substitutability.

3. Dimensional analysis of space–time.

An examination of inter-group consistency distance did not reveal a significant time effect. However, a more detailed temporal analysis indicated a collective decline in 2018 and 2021, likely driven by policy shifts and changes in market conditions affecting the green development of forestry enterprises. Regarding intra-group results, the eastern region exhibited slightly higher coverage for Configurations H1a (0.28) and H1b (0.24) compared to the other two configurations. In contrast, other regions demonstrated greater coverage in Configurations H1c and H2. Enterprises should leverage their respective

resource endowments and market conditions, adopting specific strategies to achieve green development.

Theoretically, while academic research on green development is extensive, studies at the enterprise level remain relatively limited and are often descriptive in nature. Empirical research on enterprise-level green development predominantly relies on regression analysis to examine linear relationships between independent factors and outcomes. However, such approaches fail to comprehensively consider influencing factors and overlook the interconnections and alignment among them. Given the complexity of green development in forestry enterprises, adopting a configurational perspective is both reasonable and necessary to understand how multiple factors interact to drive green development. This study validates the explanatory power of the TOE framework in forestry enterprise green development research. Furthermore, it moves beyond traditional single-factor-driven analyses by leveraging dynamic QCA to explore the multifactor synergistic pathways that foster green development in forestry enterprises.

From a practical perspective, the industrial structure of Chinese forestry enterprises has been gradually optimized in recent years. However, many challenges remain. Green development places greater responsibility on these enterprises, making its analysis essential in the current era. Exploring green development pathways helps enterprises understand their own progress and provides valuable insights for future research. Based on the study's findings, targeted recommendations can support enterprises in seizing development opportunities. This not only benefits individual companies but also contributes to the overall growth of the industry.

7.2. Suggestions

1. To achieve green development, enterprises must strengthen their market position and enhance economic efficiency, as financial resources are crucial for this transition. Profitability emerged as a core condition across all four configurations, suggesting that enterprises maintaining a certain level of profitability are better positioned to succeed in green development. For instance, they can cultivate a green brand image, reinforce green supply chain management, enhance product value added, and improve both market competitiveness and financial performance. These strategic measures can transform green development into a sustainable competitive advantage for enterprises.
2. Enterprises must deepen their commitment to technological research and innovation. Technological resource investment emerged as a core condition in the first three configurations, underscoring technology's pivotal role in driving green development. However, firms should adopt a strategic approach to avoid the so-called "R&D trap." It is essential to precisely define research priorities, ensuring that R&D investments align with existing technological capabilities, organizational structure, and market conditions. Furthermore, fostering industry–academia collaboration and facilitating the adoption of green technologies can accelerate technological advancement and enhance firms' green innovation capacity.
3. Enterprises must fully capitalize on their scale advantages to optimize resource allocation and promote sustainable growth. A crucial first step is to conduct a comprehensive internal assessment, allowing firms to strategically leverage their size and market position. For example, selectively recruiting specialized talent can help cultivate a workforce that not only possesses a deep understanding of green development principles but also demonstrates strong implementation capabilities. Beyond human capital, equity ownership structure plays a pivotal role in shaping decision-making dynamics and long-term strategic orientation—particularly in green development,

which demands a forward-looking and sustained commitment. To address this, enterprises should refine their equity structures to align with their strategic objectives, ensuring both flexibility and long-term focus. Furthermore, establishing dedicated green development committees can serve as a transformative measure, enhancing decision-making efficiency and ensuring the effective execution of green development strategies.

7.3. Limitations and Prospects

Despite the comprehensive analysis of green development in forestry enterprises presented in this study, certain limitations remain. First, this study primarily focused on eight conditional variables, potentially overlooking the influence of other factors on the green development of forestry enterprises. Second, due to constraints in data availability and time, the sample selection was largely limited to enterprises in the eastern region. Future research could expand the scope by incorporating forestry enterprises from other regions and potentially extending the analysis to forestry enterprises worldwide. Moreover, as green development pathways evolve over time in response to changing environmental and economic conditions, research in this field should be viewed as an ongoing and long-term endeavor.

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