

Research on Forestry Investment Efficiency in Jiangxi Province

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Abstract

This study assesses resource allocation in forestry investment in Jiangxi Province using annual data for 2012–2020. Input-oriented data envelopment analysis models under constant and variable returns to scale are used to estimate technical efficiency, pure technical efficiency, and scale efficiency. The inputs are fixed-asset investment and year-end employment; the outputs are afforestation area and forestry output value. Sensitivity is examined by changing the indicator specification and excluding the first observation. Mean technical efficiency is 0.6824. It declines between 2012 and 2014, rises continuously from 2015, and reaches the sample radial frontier in 2020. Mean pure technical efficiency and scale efficiency are 0.8639 and 0.7685, respectively. Scale efficiency is lower than pure technical efficiency in most years, suggesting that investment assessment should consider both scale alignment and resource utilization at a given scale. Model-based returns to scale are increasing during 2012–2019 and constant in 2020. Alternative specifications change some annual scores and rankings, whereas excluding 2012 leaves the remaining scores unchanged. The findings inform recommendations on investment performance management, technical services and labor allocation, financing terms aligned with project revenue cycles, and industrial coordination tailored to local conditions..

Keywords

Jiangxi Province; forestry investment efficiency; data envelopment analysis; pure technical efficiency; scale efficiency

1. Introduction

Forestry combines economic production with ecological protection, and returns often emerge after the initial investment. Investment expenditure and current output value therefore provide incomplete measures of resource allocation. Research on financing constraints, enterprise finance, financing platforms, financial support systems, and ecological product value realization has examined the supply of forestry finance[1–5]. Other studies have considered the output and profitability effects of investment and the relationships between investment, factor inputs, and economic growth[6–8]. Together, these studies establish the need to distinguish access to finance, economic returns, and input–output efficiency.

Regional studies using DEA and DEA–Tobit models have assessed forestry input–output efficiency in Hunan, Jiangxi, and Guangxi[9–13], providing a basis for distinguishing technical efficiency, pure technical efficiency, and scale efficiency. Related work addresses fiscal support and forest tenure reform[14], industrial development[15], investment risk[16,17], and investment opportunities[18]. However, differences in study periods, indicators, and reference sets prevent direct comparisons of absolute performance across regions.

Forestry investment is also shaped by environmental conditions, production cycles, and multiple output objectives. Studies of climate change and investment efficiency[19], losses from extreme weather[20], forest carbon accumulation[21], and community governance[22] address distinct environmental, ecological, and institutional dimensions that output value alone cannot represent. Research on efficiency and productivity[23], nonlinear relationships between inputs and economic growth[24], and multidimensional economic, ecological, and social outputs[25] further distinguishes these assessment objectives. Annual static efficiency, technical progress over time, and realized investment returns should therefore be interpreted separately.

This study examines annual forestry data for Jiangxi Province from 2012 to 2020. Forestry investment efficiency is defined here as relative resource allocation efficiency when financial investment and labor are used jointly. Input-oriented models under constant and variable returns to scale are used to examine annual technical efficiency and its decomposition into pure technical efficiency and scale efficiency. Alternative indicator specifications and sample exclusion assess the sensitivity of the estimates. The analysis provides a basis for discussing fund utilization, technical services, financing terms, and coordination across forestry activities, while keeping the interpretation of efficiency scores distinct from causal explanations.

2. Materials and Methods

2.1. Data and Indicator Selection

The analysis uses an existing compilation of annual forestry data for Jiangxi Province covering 2012–2020. Each year is treated as a decision-making unit (DMU), yielding nine observations. The compilation identifies the China Forestry Statistical Yearbook and the China Rural Statistical Yearbook as its main sources. Table 1 defines the indicators, and Table 2 reports the values used in the calculations.

Fixed-asset investment and year-end employment represent current financial and labor inputs, respectively. Afforestation area and forestry output value capture the extent of afforestation activity and monetary output. Fixed-asset investment is a flow rather than a measure of the capital stock, and afforestation area does not fully capture forest quality or ecological benefits. Area is measured in mu. The statistical coverage of inputs and outputs requires further verification. Accordingly, the estimates are interpreted as relative allocation performance within the selected indicator framework, rather than investment profitability or a comprehensive measure of economic and ecological performance.



Table 1. Input and output indicators.

Type	Indicator	Treatment	Interpretation and limitations
Input	Fixed-asset investment	Original values	Current investment flow, not capital stock; CNY 100 million
Input	Year-end employment	Original values	Persons; coverage relative to outputs requires verification
Output	Afforestation area	Original values	Area measure; mu
Output	Forestry output value	Original values	CNY 100 million; nominal values

Table 2. Annual data used in the analysis.

Year	Investment (CNY 100 million)	Employment (persons)	Afforestation area (mu)	Output value (CNY 100 million)
2012	28.54	65897	200778	1628.2
2013	4.17	60649	164521	2025.0
2014	2.99	57673	138645	2654.6
2015	3.99	56310	153368	3063.0
2016	10.55	50758	131973	3504.8
2017	4.11	42637	233694	4171.0
2018	5.01	46807	289650	4502.6
2019	2.47	45236	282407	5112.0
2020	2.35	46521	308143	5300.6

Note: Monetary values are in CNY 100 million; employment is measured in persons and afforestation area in mu (15 mu = 1 hectare). These values are reported to enable replication; their inclusion does not constitute independent verification of the underlying official statistics.

2.2. Model Specification and Efficiency Decomposition

Data envelopment analysis (DEA) constructs an empirical production frontier from observed input–output combinations. An input-oriented model measures the potential proportional reduction in inputs while maintaining at least the observed output levels. The Charnes–Cooper–Rhodes (CCR) model assumes constant returns to scale, whereas the Banker–Charnes–Cooper (BCC) model allows variable returns to scale [26,27]. Their combination distinguishes overall technical efficiency from its scale component. Because the observations represent different years, the estimates compare annual performance against a common reference set. The input-oriented BCC model is specified as follows:

$$\begin{aligned}
 \theta_{o,BCC}^* &= \min_{\theta, \lambda} \theta \\
 \text{s.t.} \quad &\begin{cases} \sum_{j=1}^n \lambda_j X_{ij} \leq \theta X_{io}, & i = 1, \dots, m, \\ \sum_{j=1}^n \lambda_j Y_{rj} \geq Y_{ro}, & r = 1, \dots, s, \\ \sum_{j=1}^n \lambda_j = 1, \\ \lambda_j \geq 0, & j = 1, \dots, n, \\ \theta \geq 0. \end{cases}
 \end{aligned} \tag{1}$$

Where o denotes the DMU being evaluated; j indexes the reference DMUs; n is the total number of

DMUs; $\mathbf{i}$ and $\mathbf{r}$ index the inputs and outputs, respectively; and $\mathbf{m}$ and $\mathbf{s}$ are the numbers of inputs and outputs. The quantities x_{ij} and y_{rj} denote input $\mathbf{i}$ and output $\mathbf{r}$ of DMU $\mathbf{j}$, respectively, while x_{io} and y_{ro} are the corresponding values for DMU $\mathbf{o}$. The nonnegative intensity variable λ_j represents the weight assigned to reference DMU $\mathbf{j}$, and $\boldsymbol{\lambda}$ is the vector of these weights. The variable θ is the radial input contraction factor, whose optimal value, $\theta_{o,BCC}^*$, measures pure technical efficiency; the superscript $*$ denotes an optimal solution. The convexity constraint $\sum_{j=1}^n \lambda_j = 1$ imposes variable returns to scale. Removing this constraint yields the CCR model. In the baseline specification, $n = 9$ and $m = s = 2$.

Both models use identical data, the same input orientation, and the same reference set. Let TE_o and PTE_o denote the CCR and BCC efficiency scores, respectively. Scale efficiency is calculated as:

$$SE_o = \frac{TE_o}{PTE_o},$$

$$TE_o = PTE_o \times SE_o \quad (2)$$

Where TE_o , PTE_o , and SE_o denote technical efficiency, pure technical efficiency, and scale efficiency for DMU $\mathbf{o}$. $\theta_{o,CCR}^*$ and $\theta_{o,BCC}^*$ are the optimal scores from the input-oriented CCR and BCC models, respectively. Scale efficiency is their ratio. This identity holds for individual DMUs; it does not generally hold for the arithmetic means of the three measures.

2.3. Data Preparation and Estimation

The values in Table 2 are used without logarithmic transformation, winsorization, or outlier replacement. To improve numerical scaling, each indicator is divided by its mean in the relevant sample. Positive rescaling of individual indicators leaves radial DEA scores unchanged and does not constitute price deflation. The monetary indicators remain in nominal terms. Table 2 and Appendix A provide the inputs and code needed to reproduce the estimates.

The linear programs are solved in Python using SciPy 1.17.0 and the HiGHS solver through `scipy.optimize.linprog`. All optimization problems terminate successfully. Checks on the baseline model confirm agreement between primal and dual objective values, invariance to positive changes in measurement units, and the identity $TE = PTE \times SE$. Means are calculated from unrounded annual scores, and reported values are rounded to four decimal places.

2.4. Robustness and Sensitivity Analysis

Five alternative specifications are examined: retaining only output value, retaining only afforestation area, excluding fixed-asset investment, excluding employment, and omitting the 2012 observation. The first four retain all nine years and assess changes in scores and rankings. The fifth tests whether the first observation affects the optimal scores of the remaining years. Comparisons use unrounded estimates; scores are treated as unchanged when their absolute difference does not exceed 10^{-7} . All tables report four decimal places.

Holding the other constraints and observations constant, removing an input or output constraint weakly expands the feasible set. The minimized efficiency score therefore cannot increase: $\theta_o(\text{reduced specification}) \leq \theta_o(\text{baseline})$. This property applies to both the CCR and BCC models used here, but it does not determine the direction of change in their ratio, SE. The analysis consequently focuses on which years are affected, the size



of the changes, and differences in rankings and model responses. A lower score after indicator removal is not, by itself, evidence of that indicator's economic contribution.

3. Results

3.1. Annual Technical Efficiency

Table 3. Annual efficiency estimates from the baseline model.

Year	TE	PTE	SE	Returns to scale
2012	0.4600	0.6470	0.7109	Increasing
2013	0.4095	0.7308	0.5604	Increasing
2014	0.4040	0.7993	0.5054	Increasing
2015	0.4774	0.7847	0.6084	Increasing
2016	0.6060	0.8400	0.7214	Increasing
2017	0.8586	1.0000	0.8586	Increasing
2018	0.9342	0.9733	0.9599	Increasing
2019	0.9918	1.0000	0.9918	Increasing
2020	1.0000	1.0000	1.0000	Constant
Mean	0.6824	0.8639	0.7685	—

Note: TE = technical efficiency; PTE = pure technical efficiency; SE = scale efficiency. Returns to scale are classified using the NIRS model.

Mean technical efficiency over 2012–2020 is 0.6824 (Table 3). Scores initially decline, from 0.4600 in 2012 to 0.4040 in 2014, before recovering to 0.4774 in 2015 and increasing in every subsequent year. Efficiency reaches 0.9918 in 2019 and 1 in 2020. The observations for 2012–2019 lie below the CCR radial frontier, whereas 2020 reaches it. Earlier observations thus show larger gaps from the sample frontier, with relative performance improving toward the end of the period. Describing the entire period as uniformly inefficient would obscure these annual differences.

Output growth does not consistently coincide with higher technical efficiency. Between 2012 and 2014, employment falls from 65,897 to 57,673 and output value rises from 1,628.2 to 2,654.6 in units of CNY 100 million, while afforestation area declines from 200,778 to 138,645 mu. Technical efficiency falls over the same interval. Between 2016 and 2017, employment decreases while both outputs increase, and efficiency rises from 0.6060 to 0.8586, the largest year-to-year gain in the sample. These patterns indicate that investment performance must be assessed through the joint input–output configuration rather than output value alone. They are descriptive associations and do not isolate the contribution of any individual indicator.

The score of 1 in 2020 indicates that no further proportional reduction in inputs is feasible within the estimated reference technology while maintaining the observed outputs. It does not imply that actual operations have no remaining scope for improvement. All years are evaluated against a common frontier, so higher scores in later years describe changes in relative position rather than identified technical progress. Since current investment and nominal output value enter an intertemporal comparison, price movements, production cycles, and statistical coverage must be considered when interpreting this pattern.

3.2. Pure Technical Efficiency and Scale Efficiency

Mean pure technical efficiency and scale efficiency are 0.8639 and 0.7685, respectively. Scale efficiency is below pure technical efficiency in every year from 2013 to 2019; both equal 1 in 2020, while the relationship is reversed in 2012. Within this decomposition, scale alignment is therefore relevant to understanding the gap from the CCR frontier in most years. The comparison does not establish that funds are wasted or that investment is insufficient. From 2012 to 2014, pure technical efficiency increases from 0.6470 to 0.7993, while scale efficiency falls from 0.7109 to 0.5054. Improved performance under variable returns to scale is thus accompanied by lower overall technical efficiency.

Pure technical efficiency equals 1 in both 2017 and 2019, whereas technical efficiency is 0.8586 and 0.9918, respectively. Although both observations reach the BCC radial frontier, they remain below the constant-returns frontier. In 2018, pure technical efficiency falls to 0.9733 from 1 in 2017, but scale efficiency rises from 0.8586 to 0.9599, and technical efficiency continues to increase. Reporting both components therefore provides a fuller account of annual performance. Pure technical efficiency should not, however, be interpreted as a direct, independent measure of managerial quality or technological capability.

3.3. Robustness and Indicator Sensitivity

Table 4. Mean efficiency under alternative specifications.

Specification	Inputs / outputs	n	TE	PTE	SE
Baseline	2 / 2	9	0.6824	0.8639	0.7685
Output value only	2 / 1	9	0.6324	0.8591	0.7032
Area only	2 / 1	9	0.6378	0.8639	0.7163
Without investment	1 / 2	9	0.6824	0.8511	0.7780
Without employment	1 / 2	9	0.4494	0.5818	0.7352
Excluding 2012	2 / 2	8	0.7102	0.8910	0.7757

Table 5. Annual technical efficiency under alternative indicator specifications.

Year	Baseline	Output value only	Area only	Without employment
2012	0.4600	0.2169	0.4600	0.0537
2013	0.4095	0.2930	0.4095	0.3009
2014	0.4040	0.4040	0.3629	0.3936
2015	0.4774	0.4774	0.4112	0.3403
2016	0.6060	0.6060	0.3925	0.1473
2017	0.8586	0.8586	0.8275	0.4499
2018	0.9342	0.8443	0.9342	0.4409
2019	0.9918	0.9918	0.9425	0.9176
2020	1.0000	1.0000	1.0000	1.0000

Mean technical efficiency is 0.6324 when output value is the sole output and 0.6378 when afforestation area is the sole output, respectively 0.0500 and 0.0446 below the baseline mean (Table 4). These similar means conceal different annual responses. With output value alone, efficiency falls from 0.4600 to 0.2169 in 2012, from 0.4095 to 0.2930 in 2013, and from 0.9342 to 0.8443 in 2018; other years are unchanged (Table 5). With area alone, the largest reduction occurs in 2016, from 0.6060 to 0.3925. Mean scores therefore provide only a



partial account of indicator sensitivity.

The changes also affect rankings. Under the output-value-only specification, the 2018 score of 0.8443 is below the 2017 score of 0.8586. Under the area-only specification, the 2016 score of 0.3925 is below the 2015 score of 0.4112. Both orderings differ from the baseline. Output value and afforestation area represent different dimensions of forestry activity, so these reversals must be interpreted in relation to the purpose of the assessment.

The two output specifications also affect the efficiency decomposition differently. When area is the sole output, annual pure technical efficiency scores are unchanged, and the differences in technical efficiency are reflected in the scale efficiency ratio. When output value is the sole output, pure technical efficiency changes only in 2018, falling from 0.9733 to 0.9305. The responses of the CCR and BCC models are therefore not identical. Because score reductions following constraint removal are a property of these models, the substantive comparison concerns the affected years, the magnitudes of change, and the resulting rankings.

Table 6. Annual pure technical efficiency with and without the investment input.

Year	Baseline BCC score	BCC score without investment
2012	0.6470	0.6470
2013	0.7308	0.7030
2014	0.7993	0.7393
2015	0.7847	0.7572
2016	0.8400	0.8400
2017	1.0000	1.0000
2018	0.9733	0.9733
2019	1.0000	1.0000
2020	1.0000	1.0000

Removing investment leaves every annual CCR score unchanged within the numerical tolerance. Under the current data and constant-returns assumption, including investment therefore does not alter the optimal technical efficiency score. The BCC model responds differently (Table 6): scores for 2013, 2014, and 2015 fall from 0.7308, 0.7993, and 0.7847 to 0.7030, 0.7393, and 0.7572, respectively; all other years are unchanged. The effect of including investment depends on model specification, and its lack of effect on the CCR scores cannot be generalized to all efficiency assessments.

Removing employment reduces mean technical efficiency to 0.4494, a decrease of 0.2330 from the baseline. The scores for 2012 and 2016 are 0.0537 and 0.1473, respectively. Investment in 2012 exceeds that in 2013, and investment in 2016 exceeds that in the adjacent years (Table 2). When investment is the only input, these relatively high expenditures coincide with low efficiency scores. This association does not identify an independent investment effect. Taken together, the input-removal exercises reveal different responses to the two inputs, but the score differences are not estimates of the economic contributions of capital and labor.

After excluding 2012, technical efficiency, pure technical efficiency, and scale efficiency for 2013–2020 remain unchanged. Mean technical efficiency rises from 0.6824 to 0.7102 because an observation below the original mean has been removed, rather than because efficiency in the remaining years has improved. Thus, inclusion of 2012 does not affect the optimal scores of the other observations. Since only the first year is

excluded, the exercise does not establish the influence of other observations on the frontier or robustness to arbitrary changes in sample composition.

4. Discussion

Technical efficiency in Jiangxi's forestry investment improves toward the end of the sample period, but pure technical efficiency and scale efficiency do not move together. Annual differences therefore need to be understood in terms of both resource utilization and scale alignment. The decomposition provides a more specific basis for discussing investment allocation than a single overall score. Nevertheless, efficiency is relative to the chosen reference set. The estimates cannot directly support provincial rankings across separate studies or attribute efficiency losses to technological deficiencies, excessive funding, or an imbalanced industrial structure.

Alternative outputs reverse some annual rankings: 2018 falls below 2017 when output value is used alone, while 2016 falls below 2015 when only afforestation area is retained. Economic output and afforestation activity thus provide different perspectives on investment performance. Indicators should be selected to reflect project objectives. Area alone cannot adequately represent forest quality or carbon accumulation, and output value does not capture community benefits or governance outcomes. Overall efficiency assessment should therefore be accompanied by separate evaluations of economic, ecological, and social objectives.

The input-removal exercises further demonstrate that efficiency scores depend on model specification. Excluding investment leaves CCR scores unchanged but alters BCC scores in some years; excluding employment substantially lowers technical efficiency. These results support considering financial and labor inputs together, but not ranking their actual economic contributions. Excluding 2012 leaves the remaining scores unchanged, providing evidence of stability only for that specific sample adjustment. Beyond these model-based comparisons, investment management should also consider how financing maturities and risk-sharing arrangements fit project revenue cycles. Forest establishment, resource protection, and processing operations have different financing needs, which should be reflected in both funding arrangements and performance assessment.

The analysis is limited to nine annual observations and does not describe variation within the province or across individual projects. The statistical coverage of inputs and outputs requires further verification, monetary values are not deflated, and current investment does not measure the capital stock or capture delayed output responses. A common frontier also does not distinguish technical change from changes in relative efficiency. These limitations constrain the interpretation of the estimates to the available data and model specification.

5. Conclusions and Policy Implications

5.1. Conclusions

For the available data and baseline specification, mean technical efficiency of forestry investment in Jiangxi Province over 2012–2020 is 0.6824. Scores decline initially, reach their minimum in 2014, and then rise con-



tinuously from 2015, with 2020 reaching the CCR radial frontier. Annual performance differs appreciably, demonstrating why output growth and changes in investment expenditure cannot substitute for an input–output efficiency assessment.

Mean pure technical efficiency and scale efficiency are 0.8639 and 0.7685, respectively. Scale efficiency is lower in most years, and the two components do not always change in the same direction. Investment assessment therefore needs to consider both scale alignment and resource utilization at a given scale. The non-increasing-returns model classifies 2012–2019 as exhibiting increasing returns to scale and 2020 as exhibiting constant returns. These classifications refer to the estimated sample technology and do not determine the direction or magnitude of an actual investment adjustment.

Indicator changes affect some annual scores and rankings, making the interpretation of efficiency conditional on assessment objectives and model specification. Removing investment leaves all CCR scores unchanged but affects BCC scores for 2013–2015. Removing employment lowers mean technical efficiency to 0.4494. Excluding 2012 does not alter the remaining annual estimates. These findings support interpreting aggregate scores alongside individual indicators; they do not justify ranking factor contributions from score differences or identifying industrial structure as the primary determinant of efficiency.

5.2. Policy Implications

Investment performance management should be organized around project objectives. Because technical efficiency and scale efficiency do not necessarily move together, funding assessments should record investment expenditure, construction progress, output targets, and subsequent operating performance. Afforestation, tending, and processing activities require distinct evaluation criteria. Where a project persistently falls short of comparable projects, its implementation stage, input mix, and supporting conditions should be examined before budgets or implementation plans are revised.

Technical services should be considered alongside labor allocation. Pure technical efficiency remains below the frontier in several years, and the estimates respond to removal of the employment indicator. Investment assessment should therefore consider labor organization as well as funding. Training and professional services can be tailored to nursery production, afforestation, tending, and pest monitoring, with their content linked to project tasks, equipment use, and operational quality. Their effectiveness should be assessed using records of quality, costs, and outputs before and after implementation. A decline in employment alone is not evidence of input savings or technical progress.

Financing arrangements should reflect the timing of project revenues. Expanding access to finance should be accompanied by closer alignment between financing maturities and cash flows. Projects with delayed returns, including forest establishment and protection, need identified sources of continuing maintenance funds and clear performance obligations. For revenue-generating projects, financing terms, repayment schedules, and risk-sharing arrangements should follow the expected revenue profile. Forest tenure-based finance and complementary insurance may be developed where rights are clear, fund use is traceable, and risks can be assessed, helping to reduce mismatches between financing terms and production cycles.

Industrial coordination should reflect local conditions rather than equate expansion with efficiency gains.

Wood and bamboo processing, oil-tea camellia production, forest-based understory activities, and forest tourism are possible areas for project appraisal, not uniform prescriptions based on provincial annual scores. Raw material availability, market demand, ecological capacity, and operating viability should be assessed before extending value chains or developing related services.

Statistical definitions should also be harmonized and performance assessed by activity. Financial and labor inputs should refer, as far as possible, to the same production coverage, current investment should be distinguished from output generated by existing assets, and monetary indicators should use comparable prices. Afforestation records should extend beyond area to include survival, subsequent stand retention, and maintenance. Commercial projects require information on costs, returns, and cash flows. Reporting aggregate efficiency alongside disaggregated outcomes and sensitivity results would make evaluation more useful for investment management than annual rankings alone.

Author Contributions

Dong Shaosheng developed the methodology and prepared the original draft. Tu Yuqing collected and analyzed the data and validated the results. Yuan Yuan conceptualized and supervised the study and reviewed and edited the manuscript.

Funding

This work was supported by Youth Project of Jiangxi Provincial University Humanities and Social Sciences Research (Grant No. JJ22229), the Science and Technology Research Project of Jiangxi Provincial Department of Education, the Jiangxi Provincial University Student Innovation and Entrepreneurship Training Program (Grant No. S202311319029), and the Innovation and Entrepreneurship Training Program of Nanchang Institute of Technology (Grant No. 2022059).

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