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Production efficiency of loblolly pine stands under roundwood and carbon price risks

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Abstract

This study examines the efficiency of loblolly pine (*Pinus taeda* L.) production under roundwood and carbon price risks. The data are generated from the biophysical–economic optimization model, consisting of the loblolly pine growth and yield model in Georgia, United States, combined with a stochastic economic model. The model incorporates the timber and carbon price risk parameters and generates the optimal biomass volumes and the associated harvest profits for 56 scenarios given different silvicultural treatments and price risks. Timber production efficiencies under each scenario are evaluated using the data envelopment analysis. This study also assesses potential economic losses due to inefficient forest production. The result shows that forest landowners with lower risk tolerance have a higher profit foregone. Inefficient forest management could cause up to $319/ha and $405/ha of potential economic losses under herbicide and fertilizer treatment scenarios, respectively. As timber-related price risks can influence forest landowners' decisions, the findings of this study incorporating different risks would help forestry professionals and policymakers to establish a more realistic and greater degree of accuracy in the forest productivity evaluation.

Key words: loblolly pine, carbon, data envelopment analysis, stochastic modeling, price risk

1. Introduction

Assessing forest productivity has received considerable attention in light of carbon sequestration and storage in recent years (Olschewski and Benítez 2010; Susaeta et al. 2014; Gren and Zeleke 2016). With increasing concern about climate change and its impacts, policymakers and forestry practitioners have been seeking ways to improve overall forest productivity to sequester more atmospheric carbon and mitigate the effects of climate change (Susaeta et al. 2014).

Forest carbon enhancement has been viewed as a low-cost approach to mitigate climate change but needs efficient policy design to be implemented (Gren and Zeleke 2016;Fuller and Dwivedi 2021). Given the growing interest in carbon markets, decision-makers and land managers need to know how much carbon is held in the landscape and how the storage and sequestration transfer to actual payments (Conte et al. 2011). Nevertheless, the variability of the carbon price undoubtedly makes the implementation and participation in the voluntary carbon markets more challenging. Moreover, prices for forestry-based carbon offsets have been lower than other carbon offset projects (Conte and Kotchen 2010). Thus, it is vital to assess forest productivity, considering carbon sequestration credit and related price uncertainty.

Another concern in evaluating forest productivity is the impact of price uncertainties[1] on roundwood (i.e., unprocessed wood) production. It is crucial to consider this impact because the variation in roundwood prices will influence forest landowners' decisions (Forboseh et al. 1996; Susaeta and Gong 2019). The theory of demand and supply implies a positive relationship between the prices of products at different stages of manufacturing (Zhou and Buongiorno 2005). Therefore, lumber (i.e., processed wood) and roundwood prices should be correlated (Busby and Binkley 2021; Fu 2023). Because if lumber demand increases, then the roundwood demand should also increase to meet lumber production, leading to higher roundwood prices (Tian and Stottlemyer 2018). Nevertheless, in practice, the roundwood price is usually correlated with lumber price but with exceptions, as determined by several factors under a typical supply and demand situation. For instance, the lumber demand is influenced by the demand for home-building, renovation, and interest rates (Lambert 2022). For the lumber supply, factors

[1] Throughout this paper, 'uncertain' refers to the situation under which the parameter distribution information is unknown by a decision-maker; and the term 'risk' refers to the situation under which the parameter distribution information is known to a decision-maker (Park and Shapira, 2017).

like tariffs (Song et al. 2011; Buongiorno 2018), export tax (Lin and Zhang 2017), import regulation (Zhang 2006; Buongiorno and Johnston 2018), carbon sequestration credits (Olschewski and Benítez 2010; Straka 2010), extreme weather events (e.g., wildfires, mudslides, etc.), sawmill capacity, and lumber shipment can have significant impacts on the level of lumber supply (Lambert 2021). The supply and demand factors constantly vary, which in turn leads to variable lumber and roundwood prices, which leave forest landowners/operators' profits and roundwood production efficiencies in a highly uncertain circumstance.

Pine plantations in the southern United States are among the most intensively managed forests in the world. Their productivity has tripled over the past 50 years due to the application of modern, intensive, integrated, and site-specific silvicultural pine plantation management practices (Fox et al. 2007; Zhao et al. 2016). Among different pine species, loblolly pine (*Pinus taeda* L.) is particularly important as it is the most productive commercial tree species in the southern United States (Shephard et al. 2021). Oswalt et al. (2019) reported that loblolly pine in the region contributes the largest amount of biomass for a single species at 1.8 billion tonnes of aboveground live-tree biomass (AGB), representing 20% of southern biomass and 8% of the US's AGB. Because of the vital role of loblolly pines in the economy and environment in the region, assessing its productivity is of interest in light of emerging carbon markets and the presence of uncertain carbon and roundwood prices.

Several existing studies apply data envelopment analysis (DEA) for measuring production efficiency. It is a nonparametric approach and has been widely used to evaluate efficiencies in banking and insurance (Banker et al. 2010; Nur and Gunay 2014; Segovia-Gonzalez et al. 2017), supply chain management (Ross and Droge 2002), and petroleum distribution system design (Ross and Droge 2004). Existing forestry studies also have applied the DEA approach to evaluate productivity in timber production (Kao et al. 1993; Korkmaz 2011*b*; Susaeta et al. 2016; Shahi and Dia 2019; Młynarski et al. 2021; Shephard et al. 2021), logistics and transportation of timber (Marinescu et al. 2005), and the operation of wood processing facilities (Upadhyay et al. 2012). Among DEA-related timber production studies, most of them applied the Charnes–Cooper–Rhodes (CCR) model (Salehirad and Sowlati 2011; Upadhyay et al. 2012) and Banker–Charnes–Cooper model (Kao and Yang 1992; Korkmaz 2011*a*; Salehirad and Sowlati 2011; Młynarski et al. 2021). The efficiency scores derived from DEA are easy to compare across different analysis scenarios, but they are also less intuitive when researchers interpret the implications of the efficiency scores. Therefore, the slack-based DEA has been applied to assess the monetary loss of inefficiency (Susaeta et al. 2016; Shephard et al. 2021). In addition, studies have shown the importance of accounting for price risk in forest management (Alvarez and Koskela 2006, 2007; Ning and Sun 2019; Ekholm 2020). Nevertheless, to date, much less is known about the monetary loss of inefficient roundwood production, considering roundwood and carbon price risks in the context of different silvicultural practices and risk preferences of the forest landowners.

This study fills these research gaps by evaluating the efficiency of loblolly pine production under roundwood and carbon price risks using the slack-based DEA modeling approach. The study area is the Piedmont and Upper Coastal Plain region in Georgia, United States. The biophysical–economic model, which consists of the loblolly pine growth and yield model (Harrison and Borders 1996) and stochastic economic optimization model (Huang et al. 2022), is used to generate biomass volumes, and resulting profits incorporate the effect of timber and carbon price risks. In addition, this study considers silvicultural practices (e.g., applications of herbicides and fertilizers, rotation ages) and different risk tolerance levels for roundwood and carbon prices. The biophysical–economic model generates biomass volumes and harvesting profits under 56 silvicultural treatment scenarios. Then, the forest productivity in each scenario is assessed with the generated output data from the biophysical–economic model using the DEA method.

The remaining part of the paper proceeds as follows: first, the data-generating process from the biophysical–economic model and considered scenarios are introduced; second, the DEA methodology and efficiency measures are described; next, the results of the biophysical–economic model and productivity efficiency assessment from the DEA model are presented; lastly, the paper concludes with a discussion of the effect of silvicultural treatments and price risks on forest productivity and related implications.

2. Data generating process: stochastic biophysical–economic model

i. Design modeling scenarios: this study creates 56 scenarios, which consider the application of herbicide and fertilizer and risk tolerance parameters (α) from Olson and Wu (2017). There are two risk tolerance parameters considered, roundwood price risk and carbon price risk. Therefore, scenarios are further broken down into (1) considering roundwood price risk without including carbon price, (2) considering carbon price risk without considering the roundwood price risk, and (3) considering both roundwood and carbon price risks. The above three subscenarios include deterministic ($\alpha = 0.5$) and stochastic cases ($\alpha = 0.8,\ 0.9,\ 0.95$, and 0.99). The optimal rotation length, which is the stand age generating the maximum net present value (NPV) in step iv, is used for each silvicultural treatment scenario. Please see Table 1 for all scenarios' attributes and their associated levels.
ii. Process the stumpage and carbon prices: the original roundwood price data are from TimberMart-South (2021) and are reported in nominal \$/ton. We first convert them to \$/tonne at the 2012 price level using a GDP implicit price deflator (Federal Reserve Bank 2021). Then, we calculate the mean price of each roundwood product (i.e., sawtimber, chip-n-saw, and pulpwood) and their covariance using historical data from 2012 to 2020. This duration is chosen because the earliest available complete carbon price data from the US carbon market is 2012. Since the California cap-and-trade program is the first

Table 1. Scenario attributes and associated levels.

Scenario	Herbicide	Fertilizer	Risk factor ($\alpha_{\text{roundwood}}$)*	Risk factor (α_{carbon})*
1	x	x	0.5	x
2	x	x	0.8	x
3	x	x	0.9	x
4	x	x	0.95	x
5	x	x	0.99	x
6	x	x	0.5	0.5
7	x	x	0.5	0.8
8	x	x	0.5	0.9
9	x	x	0.5	0.95
10	x	x	0.5	0.99
11	x	x	0.8	0.8
12	x	x	0.9	0.9
13	x	x	0.95	0.95
14	x	x	0.99	0.99
15	o	x	0.5	x
16	o	x	0.8	x
17	o	x	0.9	x
18	o	x	0.95	x
19	o	x	0.99	x
20	o	x	0.5	0.5
21	o	x	0.5	0.8
22	o	x	0.5	0.9
23	o	x	0.5	0.95
24	o	x	0.5	0.99
25	o	x	0.8	0.8
26	o	x	0.9	0.9
27	o	x	0.95	0.95
28	o	x	0.99	0.99
29	x	o	0.5	x
30	x	o	0.8	x
31	x	o	0.9	x
32	x	o	0.95	x
33	x	o	0.99	x
34	x	o	0.5	0.5
35	x	o	0.5	0.8
36	x	o	0.5	0.9
37	x	o	0.5	0.95
38	x	o	0.5	0.99
39	x	o	0.8	0.8
40	x	o	0.9	0.9
41	x	o	0.95	0.95
42	x	o	0.99	0.99
43	o	o	0.5	x
44	o	o	0.8	x
45	o	o	0.9	x
46	o	o	0.95	x
47	o	o	0.99	x
48	o	o	0.5	0.5
49	o	o	0.5	0.8
50	o	o	0.5	0.9
51	o	o	0.5	0.95
52	o	o	0.5	0.99
53	o	o	0.8	0.8
54	o	o	0.9	0.9
55	o	o	0.95	0.95
56	o	o	0.99	0.99

Note: "x" denotes "not included" in a corresponding scenario, and "o" denotes "included". *The level of risk tolerance follows Olson and Wu (2017). When $\alpha = 0.5$, it indicates a forest landowner is risk neutral. The higher the value of α, the lower the risk tolerance.

multisector cap-and-trade program in North America, its auction settlement carbon prices (Energy Information Administration 2022) are used in this study. We converted the original California carbon price from nominal \$/tonne of carbon dioxide to \$/tonne of carbon at the 2012 price level using the same GDP implicit price deflator (Federal Reserve Bank 2021).

iii. Formulate the biophysical model: the loblolly pine growth and yield model reported by Harrison and Borders (1996) in Piedmont and Upper Coastal Plain for Georgia, United States, is used. The model consists of one objective function and seven loblolly pine growth and yield constraint functions, including dominant height function, survival function, basal area function, whole stand yield function, and three merchantable stem volume functions for three roundwood products (i.e., sawtimber, chip-n-saw, and pulpwood). The site index at the base age of 25 years is assumed to be 75 ft (i.e., 23 m). The model includes parameters that can reflect the 56 scenarios mentioned in step i.

iv. Formulation of the stochastic biophysical–economic models: we incorporate the mean price and covariance for each roundwood product (step ii) with the biophysical model (step iii) and develop the biophysical–economic model. The objective function of the biophysical–economic model takes the following form:

$$\text{(1)} \quad \max_{y} \pi = (1+r)^{-t} \times \left(\sum_{w} \bar{p}_w y_{w,t} - Z_\alpha \sum_{wi \le w} \sum_{w} \sqrt{y_{w,t} \cdot \sigma_{w,wi} \cdot y_{wi,t}} \right) - c^{\mathrm{c}} - c^{\mathrm{p}} - c^{\mathrm{s}} - c^{\mathrm{z}} \cdot N \cdot (1+r)^{-8} - c^{\mathrm{h}}$$

where π refers to NPV of annual harvesting profit (in US \$/ha); r is the real discount rate[2] (set to 4% in this study); $\bar{p}_w$ is a price vector of the past 9 year (2012–2020) average prices for revenue source w, including three types of merchantable roundwood products and carbon; $y_{w,t}$ is a vector of volumes for each revenue source w (i.e., three types of merchantable roundwood products and carbon)

[2] The assumed discount rate in our study is based on a range of 3%–7% commonly applied in social discounting of environmental investments (Office of Management and Budget, 2003).

at stand age t from the biophysical model (step iii); and Z_α represents the one-tailed normal quantile at $1 - \alpha$ level confidence and acts as a risk discount factor, implying the risk preference related to variations of roundwood and carbon prices. $\sigma_{w,wi}$ is an element of 4×4 variance–covariance matrix for three types of roundwood prices and carbon price. For the purpose of retrieving elements in the variance–covariance matrix, wi is an alias for w. Costs (in US \$/ha) incurred by the forest landowner consist of five types: c^c is the chemical site preparation cost, c^p and c^s refer to respective planting and seedling costs, c^h is the herbicide cost after planting, and c^z is the fertilization cost. Nitrogen fertilizer application (N), in accordance with regional practice, is assumed to take place in Year 8, and therefore fertilization cost is discounted at Year 8. The default amount for elemental nitrogen fertilization usage is 140 kg/ha.

The expected annual profit determined by the level of assurance of a positive profit can be mathematically expressed as

$$P\left[E\left(\pi\right) \geq 0\right] \geq a \tag{2}$$

where candidate α values are 0.5, 0.8, 0.9, 0.95, and 0.99, following Olson and Wu (2017). Varying α from 0.5, 0.8, 0.9, 0.95, and 0.99 indicates that a probability of having a positive annual harvesting profit is greater than 0.5, 0.8, 0.9, 0.95, and 0.99, respectively. When $\alpha = 0.95$, it implies that the decision-maker could only tolerate a 5% chance of losing money. When α is 0.5, $Z_{0.5}$ implies a forest landowner is risk-neutral, and there is a fifty–fifty chance that the expected profit is positive (i.e., $Z_{0.5} = 0$). Namely, if α is 0.5, the resulting objective function is deterministic, for which no assurance of positive profit is specified.

v. Undertake the biophysical–economic modeling: this biophysical–economic optimization model solves the dynamic optimization modeling given the 56 scenarios in General Algebraic Modeling System (GAMS). Namely, the value of survival trees and stem volumes at a later year is determined by their value at an earlier year. After running the model, the maximum NPV, the optimal rotation age, and associated stand stem volumes are retrieved.

vi. Assess the loblolly pine production efficiency: the productivity in each scenario is evaluated using the DEA method with the resulting output (i.e., maximum NPV) and corresponding input factors from step iv. Summary statistics for all generating DEA input and output factors by silvicultural treatment groups are presented in Table 2. The DEA model is conducted using the *Benchmark* R package (Bogetoft and Otto 2020).

3. Productivity assessment: DEA model

This study applies the DEA modeling method to evaluate forest productivity under different silvicultural treatments and levels of risk tolerance for the roundwood and carbon price risks. The term decision-making unit (DMU) refers to each scenario, which is evaluated in terms of its efficiency in converting inputs into outputs. Three efficiency measures are estimated in this study: technical efficiency (TE), cost efficiency (CE or Farrell efficiency), and allocative efficiency (AE). TE is attained by any DMU if and only if none of its inputs or outputs can be improved without worsening some of its other inputs or outputs (Cooper et al. 2011*a*). However, TE does not require input price information. Despite its requirement of minimal information and minimal assumptions, TE is still fundamental because other types of efficiency need TE to be attained before other efficiencies can be achieved (Cooper et al. 2011*a*). To extend the analysis to consider input prices in the production efficiency evaluation, CE is estimated. Finally, once TE and CE are estimated, AE, which assumes both technical and cost feasibilities, can be obtained by calculating the ratio of CE to TE.

Having defined the efficiency measures used in the study, the above three efficiency measures are assessed under the constant returns to scale (CRS). TE for each scenario can be calculated using the CRS model, also known as the CCR model (Charnes et al. 1978), which assumes that a proportional increase in all the inputs results in the same proportional increase in the output. Its input-oriented form can be expressed as follows:

$$\max_{\mu,\nu} \sum_{r=1}^{s} \mu_r y_{r0} \tag{3}$$

s. t.

$$\sum_{r=1}^{s} \mu_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} \leq 0 \tag{4}$$

$$\sum_{i=1}^{m} v_i x_{i0} = 1 \tag{5}$$

$$x_{ij}, y_{rj}, v_i, \mu_r \geq 0, \forall i, r, j$$

where y_{rj} denotes the amount of output factor r for DMU j and x_{ij} denotes input factor i for DMU j. y_{r0} and x_{i0} denote the amount of output r and input i for the reference DMU. The output factor is the NPV of forest operation profits from the biophysical–economic model, which consists of profits from harvesting sawtimber, pulpwood, chip-n-saw, and carbon sequestration credit. Six input factors considered in this study include the application of herbicide, fertilizer, rotation year, dominant height, planting density, and basal area. v_i and μ_r are the variables determined by solving the mathematical programming formulation.

The CE is yielded by solving the following mathematical programming formulation (Cooper et al. 2011*b*):

$$\min_{\mu,\nu} \sum_{i=1}^{m} c_i x_{ij} \tag{6}$$

s. t.

$$\sum_{j=1}^{J} z_j x_{ij} \leq x_{ij} \tag{7}$$

$$\sum_{j=1}^{J} z_j y_{rj} \geq y_{r0} \tag{8}$$

Table 2. Summary statistics of data envelopment analysis (DEA) input and output factors generated from the stochastic biophysical–economic model.

Variable	Samples	Mean	Std. Dev.	Min	Pct. 25	Pct. 75	Max
Group: No-treatment							
Optimal rotation length (years)	14	36	4	31	32	37	45
Dominant height (m)	14	29	2	26	27	30	33
Planting density (trees/ha)	14	759	75	598	728	835	859
Planting basal area (sq. m/ha)	14	154	5	147	149	156	164
Optimal NPV (2012 US$/ha)	14	3586	1561	1270	1862	4899	5322
Group: Herbicide							
Optimal rotation length (years)	14	39	17	22	31	38	94
Dominant height (m)	14	30	6	22	27	30	48
Planting density (trees/ha)	14	761	186	323	714	853	1,119
Planting basal area (sq. m/ha)	14	157	13	133	152	159	193
Optimal NPV (2012 US$/ha)	14	3945	2052	738	1996	5855	6417
Group: Fertilizer							
Optimal rotation length (years)	14	37	13	30	30	36	79
Dominant height (m)	14	29	5	26	26	29	44
Planting density (trees/ha)	14	772	145	360	758	884	884
Planting basal area (sq. m/ha)	14	203	14	193	193	204	245
Optimal NPV (2012 US$/ha)	14	6374	2993	1425	3834	9210	10 077
Group: Herbicide + Fertilizer							
Optimal rotation length (years)	14	35	13	27	28	34	79
Dominant height (m)	14	29	5	25	26	29	44
Planting density (trees/ha)	14	812	159	360	795	931	966
Planting basal area (sq. m/ha)	14	201	13	189	192	202	241
Optimal NPV (2012 US$/ha)	14	6535	3124	1388	3891	9500	10425

$$(9) \qquad L \leq \sum_{j=1}^{J} z_j \leq U$$
$$z_j, x_{ij} \geq 0, \forall j = 1, \ldots, J, \forall i = 1, \ldots, m$$

where the objective of this optimization formulation is to choose the x_{ij} and z_j values to minimize the total cost of satisfying the output and input constraints. c_i denotes the unit cost of input factor i. The input costs include herbicide cost, fertilizer cost, cost of tree density per plot, and planting basal area cost. The herbicide cost is $141.12/ha (Paudel and Dwivedi 2021) and the cost of elemental nitrogen fertilizer is $0.54/kg (Paudel and Dwivedi 2021). The application of 57 kg of elemental nitrogen is assumed. The cost of tree density per plot uses hand planting costs of $0.114 per loblolly pine seedling from Dooley and Barlow (2013). The planting basal area cost uses the site preparation cost of $415.45/ha (Dooley and Barlow 2013). The sources of input cost data are documented in Table 3.

4. Result

4.1. Biomass yields and optimal profits from the stochastic biophysical–economic model

Figure 1 shows the biomass yields by timber products under different stand ages and silvicultural treatments. Pulpwood biomass reaches the maximum yield earlier than chip-n-saw and sawtimber. Specifically, when no treatment is applied, pulpwood reaches the maximum yield in the 16th year, chip-n-saw is in the 28th year, and sawtimber's yield continues to increase as the stand age increases. When the fertilizer treatment is applied, pulpwood and chip-n-saw reach their maximum yields in the 14th and 22nd years, respectively. Note that there is not necessarily a linear relationship between biomass volume and the age of trees. Figure 2 shows the optimal rotation ages resulting in the maximum profits under different silvicultural treatments. When the forest landowners consider the carbon payment, the lower risk tolerance (i.e., higher α) forest landowners are, and the longer optimal rotation length they tend to have. All those optimal rotation ages are also included in the DEA analysis as one of the input factors.

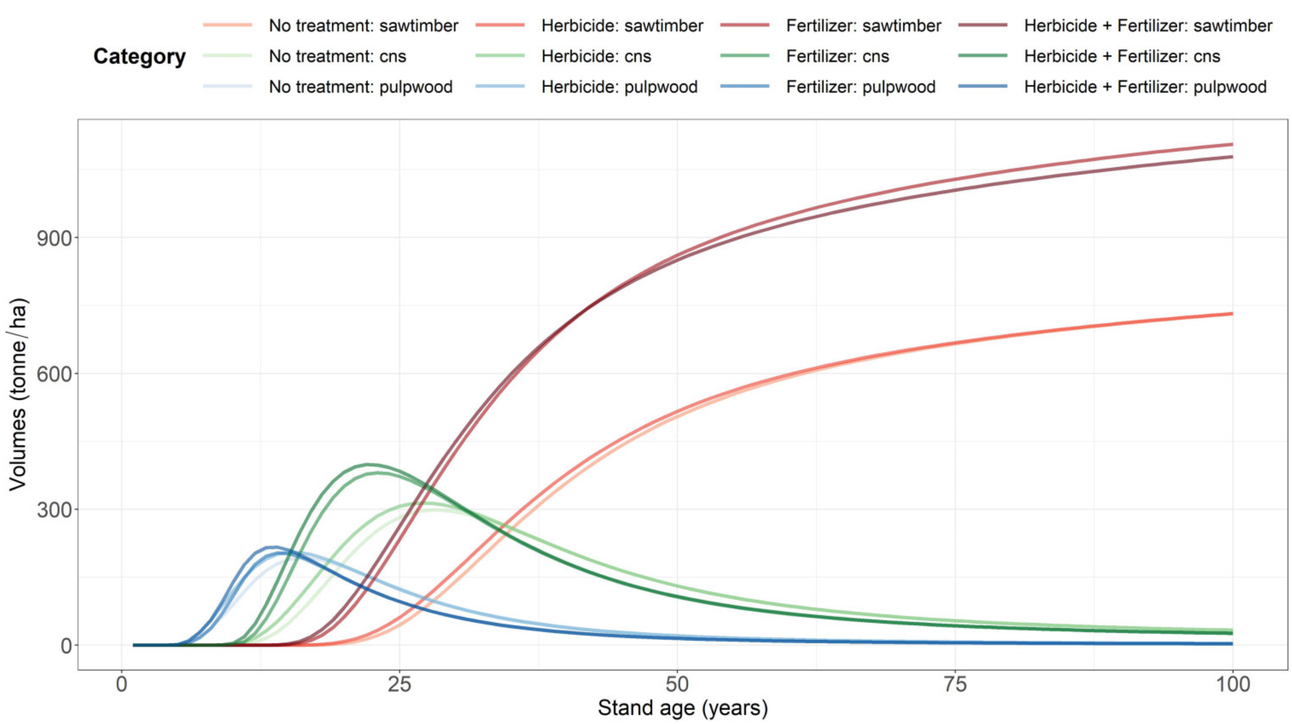
The maximum profits under different silvicultural treatments and risk factors are identified from the stochastic biophysical–economic model (Fig. 3). Scenarios without including the carbon price have a relatively lower NPV because the carbon payment income is excluded in those scenarios. In addition, without considering any price risk factors, the NPV is higher under the combination of applying herbicide and fertilizer (Scenario 48), followed by fertilizer treatment (Scenario 34), herbicide treatment (Scenario 20), and no-treatment (Scenario 6).

Regarding the effect of risk tolerance on the NPV, a risk-neutral forest landowner ($\alpha = 0.5$) has a higher NPV than

Table 3. Price parameters used for cost efficiency (CE) DEA modeling.

Price parameters	Values (standard deviation)	Sources
Herbicide cost	$141.12/ha	Table 4 in Paudel and Dwivedi (2021)
Fertilizer cost	$0.54/kg of elemental nitrogen	Table 4 in Paudel and Dwivedi (2021)
Hand planting costs	$0.114 per seedling	Table 2 in Dooley and Barlow (2013)
Site preparation cost	$415.45/ha	Table 1 in Dooley and Barlow (2013)
Stumpage price (2012 US$/metric tonne)		
Sawtimber	22 (1.9)	TimberMart-South (2021)
Chip-n-saw	15 (1.1)	TimberMart-South (2021)
Pulpwood	9.6 (0.9)	TimberMart-South (2021)
Carbon price (2012 US$/metric tonne)	46 (6.6)	Energy Information Administration (2022)

Fig. 1. Biomass yields by timber products under different treatments.



risk-averse ones (i.e., = 0.8, 0.9, 0.95, and 0.99). This result reflects the fact that low risk tolerance leads to low returns. Not considering roundwood price risk tends to yield higher NPVs within each silvicultural treatment scenario (i.e., green bars). On the other hand, considering both roundwood and carbon price risks results in lower NPVs (i.e., red bars) due to the reduction in NPVs caused by more risk discount factors.

4.2. Overall efficiency scores from the DEA model

Figure 4 shows efficiency scores for CE, TE, and AE, respectively. Each subpanel in Fig. 4 consists of 56 cells, showing the combination of four silvicultural treatments with the corresponding optimal rotation ages and 14 price risk cases (Table 1). Scores range from 0 (inefficient) to 1 (efficient).

To compare the effect of silvicultural treatments on CE scores, given a price risk case (i.e., at the *y*-axis in each subpanel), scenarios involving fertilizers tend to have a higher CE than other scenarios (darker yellow and darker purple).

Regarding the effect of price risks on CE scores, given a silvicultural treatment case (i.e., at the *x*-axis in each subpanel), the lower the risk tolerance (i.e., higher α), the lower the CE score is. Furthermore, scenarios without the carbon price have lower efficient scores because those scenarios have lower NPV due to the exclusion of the carbon payment.

For the TE (i.e., the middle panel in Fig. 4), the overall pattern is similar to CE, but some scenarios are higher in TE than in CE. For instance, given a price risk case (i.e., at the *y*-axis in each subpanel), "no-treatment" scenarios in TE are higher than CE because TE solely considers input quantities and does not consider the input costs. Similar patterns also appear in other treatment scenarios.

The AE result, which consists of both CE and TE, is shown in the right panel in Fig. 4. The scenarios involving fertilizers tend to have a higher AE. In addition, the lower risk tolerance (i.e., higher α) a scenario has, the lower is the AE score.

Fig. 2. Optimal rotation ages under different treatments and risk conditions. **Note:** α denotes the risk tolerance level. When $\alpha = 0.5$, the forest landowner is risk neutral. When $\alpha = 0.8$, 0.9, 0.95, and 0.99, implying the forest landowner could only tolerate only a 20%, 10%, 5%, and 1% chance of losing money, respectively. The numbers in the parentheses denote the associated level of risk tolerance. Two price risks considered in the biophysical model are roundwood price risk and carbon price risk.

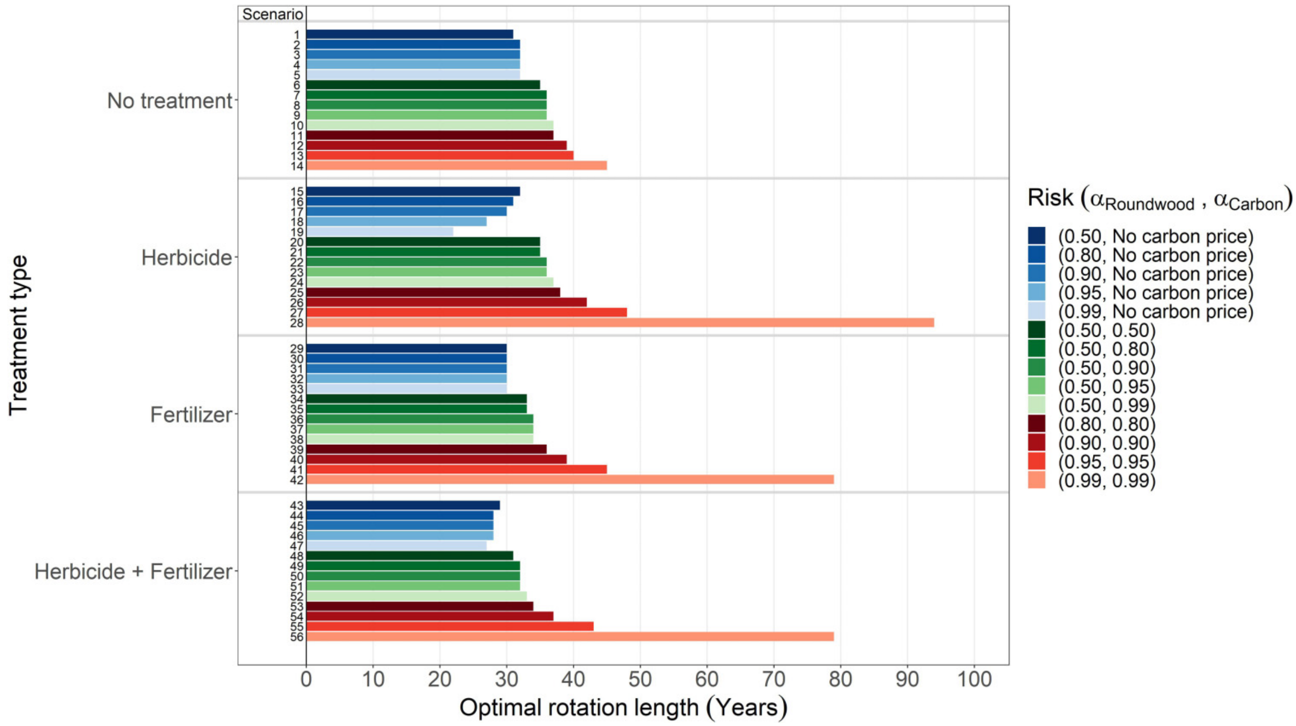


Fig. 3. Profits under different treatments and risk conditions. **Note:** α denotes the risk tolerance level. When $\alpha = 0.5$, the forest landowner is risk neutral. When $\alpha = 0.8$, 0.9, 0.95, and 0.99, implying the forest landowner could only tolerate only a 20%, 10%, 5%, and 1% chance of losing money, respectively. The numbers in the parentheses denote the associated level of risk tolerance. Two price risks considered in the biophysical model are roundwood price risk and carbon price risk.

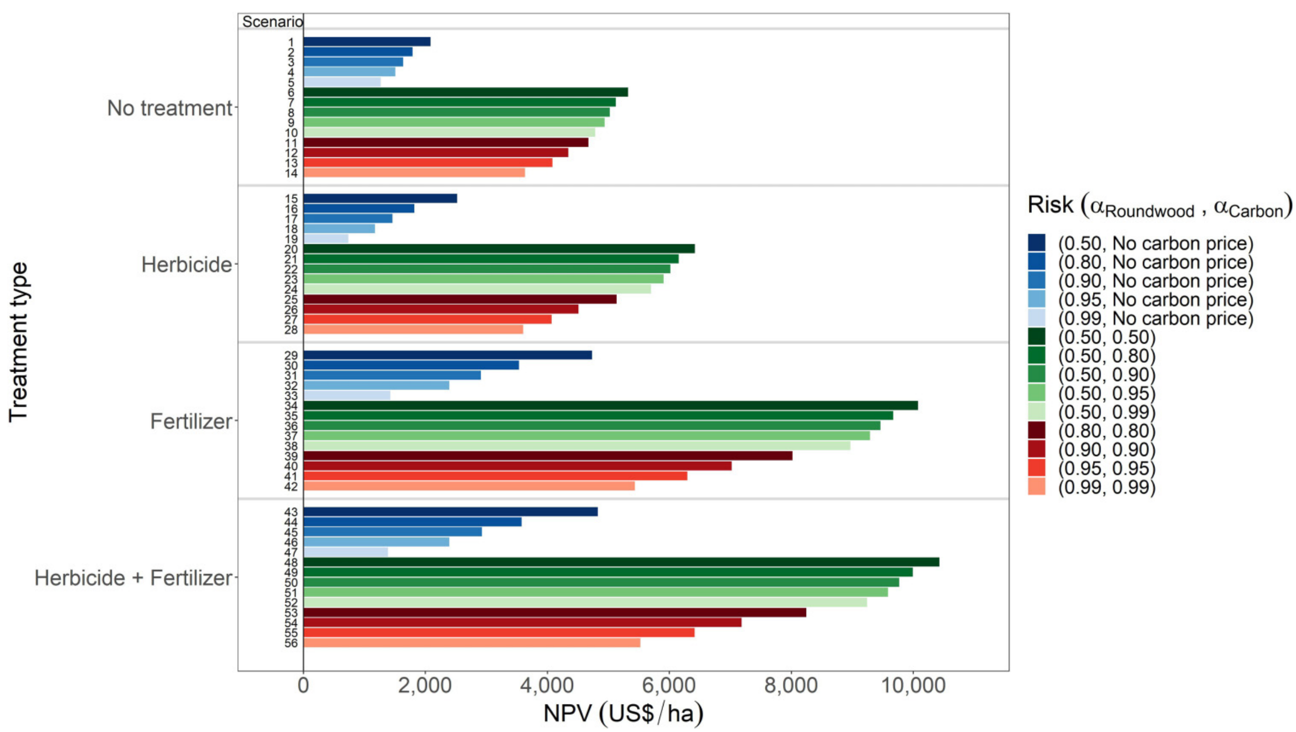
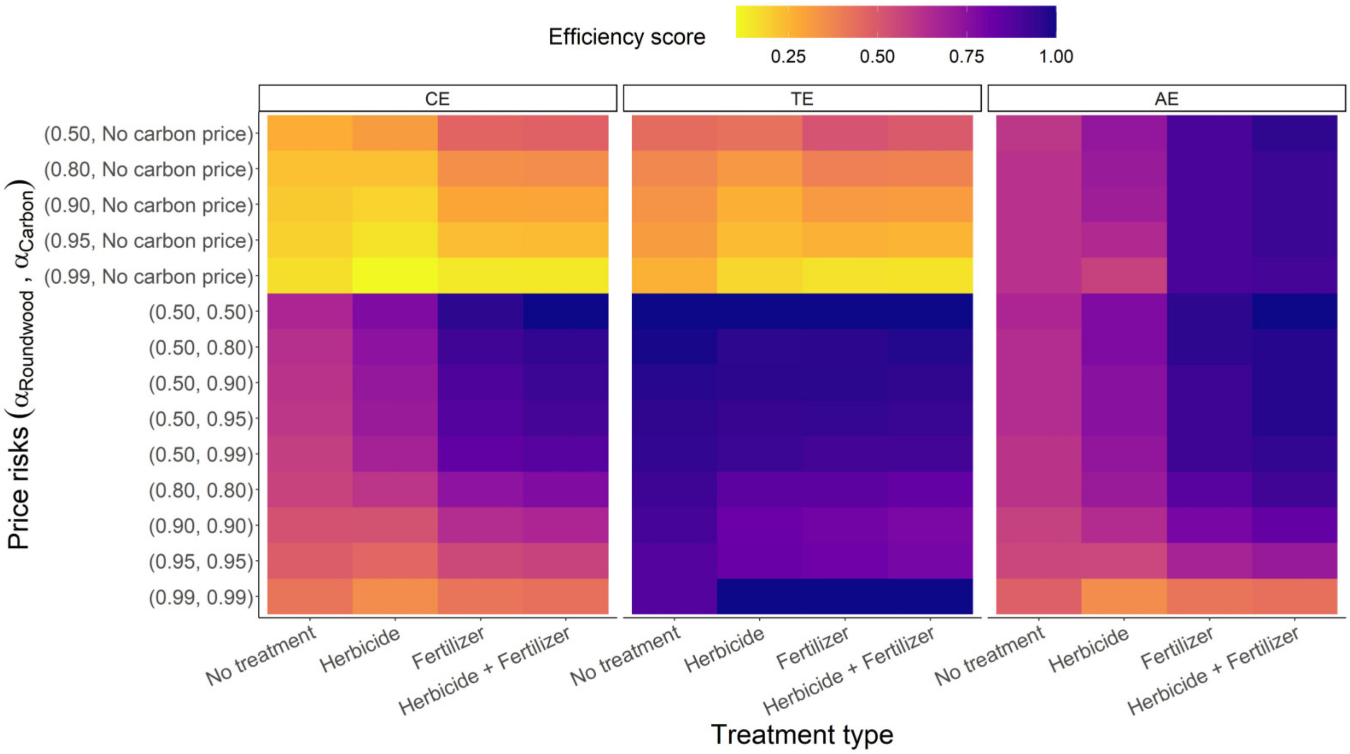


Fig. 4. Efficiency scores under different treatments and risk conditions. **Note:** CE, TE, and AE denote cost efficiency, technical efficiency, and allocative efficiency, respectively.



4.3. Potential profit losses due to inefficiencies

Inefficient production can lead to potential profit losses. This section demonstrates the profit forgone derived from the difference between a profit with and without inefficiency. Figure 5 illustrates the profit forgone in each scenario for CE, TE, and AE measures.

The effect of silvicultural treatments on profits forgone derived from CE is shown in the left panel in Fig. 5. Given a price risk case (i.e., at the *y*-axis in each subpanel), scenarios involving fertilizers have a lower profit forgone than other scenarios, except for (0.99, no carbon price) and (0.99, 0.99). This result reflects that the potential improvement for the CE score is determined by the trade-off between the adverse effect of increasing input costs and its corresponding preferable effect of increasing biomass volume.

With respect to the effect of price risks on profits foregone from CE scores, given a silvicultural treatment case (i.e., at the *x*-axis in the left panel), scenarios with lower risk tolerance (i.e., higher α) have a higher profit foregone, particularly for scenarios with the roundwood price risk. Specifically, inefficient forest production could cause \$0–\$219/ha of potential economic losses when price risk factors are not considered. With considering price risk factors at the 99% level, inefficient forest production leads to \$356–\$414/ha of potential economic losses.

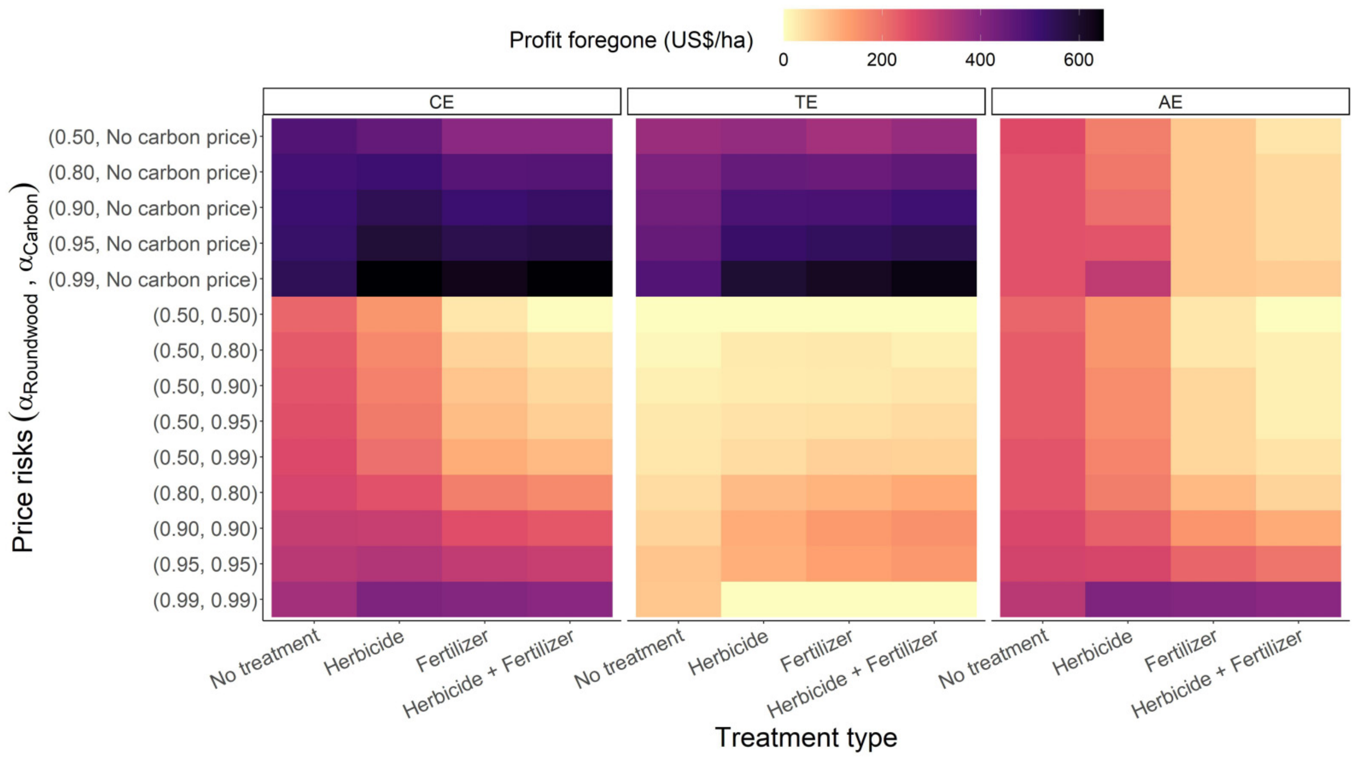
In the case of profits foregone derived from TE (middle panel in Fig. 5), overall, profits foregone for TE are similar to CE when the carbon price is not included. TE has lower profits forgone than CE in other cases due to the exclusion of input costs for the TE measure. Specifically, inefficient forest production has no potential economic losses derived from TE when price risk factors are not considered. Considering price risk factors at the 99% level, TE-inefficient forest production leads to \$0–\$76/ha of potential economic losses.

For profits foregone derived from AE, which considers both CE and TE metrics, are shown in the right panel in Fig. 5. Profits foregone for AE are lower when the fertilizer is applied, except for the price risk case of (0.99, 0.99). In addition, when both roundwood and carbon price risks are considered, profits forgone are higher, reflecting the fact that price risks induce higher economic losses due to the adverse risk preference discounting.

5. Discussions

Existing forestry management literature has noted the importance of evaluating optimal forest management under various risks and uncertainty using distinct methods, such as NPV metrics derived from slack-based DEA models (Susaeta et al. 2016; Shephard et al. 2021), generalized Faustmann model (Faustmann 1995; Zhang 2001;Rakotoarison and Loisel 2017; Chang 2018), real option analysis (Gjolberg and Guttormsen 2002; Duku-Kaakyire and Nanang 2004; Sauter et al. 2016), Hartman (Hartman 1976; Touza et al. 2008), and reducing emissions from deforestation and forest degradation models (REDD) (Pana and Gheyssens 2016;Chesney et al. 2017). Empirical studies using the above methods provide different ranges of forest values. For instance, Susaeta et al. (2016) evaluated the impact of climate change on loblolly pine production and found that, under a mild climate change scenario,

Fig. 5. Profit foregone under different treatments and risk conditions. **Note:** CE, TE, and AE denote cost efficiency, technical efficiency, and allocative efficiency, respectively.



profits forgone are expected to range from $0 to $294/ha, and the estimates of the maximum profits forgone are larger under more severe climate change scenarios. Shephard et al. (2021) showed that longer rotation ages tend to have higher profits forgone under different treatments, and their estimated profits forgone range from $0/ha to approximately $6,000/ha. Rakotoarison and Loisel (2017) applied the Faustmann approach and found that the effect of storms on the values of forest investment varies from −$918 to $6326/ha. Duku-Kaakyire and Nanang (2004) applied the real option approach, which relaxes deferral and reversibility assumptions from the conventional NPV or Faustmann methods, to evaluate forest management. Their result shows that the values of forest investment projects with real options range from $143 to $2329/ha, which is higher than those without real options. Table 4 summarizes estimated forest values from the related studies.

The effect of price risk preferences on roundwood production efficiencies and associated economic losses induced by inefficiencies is not yet clear in the DEA forestry literature. This study estimates the economic losses induced by inefficient forest production under different risk preferences and silvicultural treatment scenarios. Figure 5 shows that estimated profits forgone derived from AE, varying by different risk tolerance levels, range from $219 to $319/ha under the no-treatment scenarios, from $145 to $319/ha under the herbicide scenarios, from $31 to $405/ha under the fertilizer scenarios, and from $0 to $393/ha under the combination of herbicide and fertilizer scenarios. Due to the inclusion of the risk discount factor in this study, the estimated profits forgone are relatively smaller than Shephard et al. (2021), which doesn't consider the risk preferences.

Figure 5 also shows how risk preferences affect potential economic losses from inefficient forest production. The result indicates that scenarios with a lower risk tolerance (i.e., higher α) have a higher profit forgone. This outcome implies that risk-averse foresters have a stronger risk-discounting preference, reflecting the higher profit forgone. The implication of this result is that price risk-averse forest landowners tend to lead to inefficient roundwood production because the volatility of price changes discounts risk-averse forest landowners' profits more. Combing this finding with the optimal rotation length reported in Fig. 2, risk-averse forest landowners also tend to have a longer rotation length. This result is aligned with Pukkala and Kellomäki (2012), suggesting that timber price risk (i.e., increasing timber price volatility) tends to increase the rotation length because a longer rotation length can produce a more diverse and profitable stand structure. Another implication of these findings is adopting strategies to reduce uncertainty and assure potential income from forest investment. Some studies have shown that introducing a REDD scheme could reduce uncertainty (Chesney et al. 2017; Ji and Ranjan 2019). Pana and Gheyssens (2016) showed that relative price volatility significantly impacts a risk-averse investment decision-maker. In that case, risk-averse forest landowners could adopt the strategy giving the smallest cash flow variability, which REDD schemes can incentivize.

Table 4. Forest value comparison with forestry literature.

Authors (year)	Method	Estimated forest value (value per ha)
This study	Slack-based DEA model	Profit forgone by treatments: – No-treatment [\$219, \$319] – Herbicide [\$145, \$414] – Fertilizer [\$31, \$405] – Herbicide + Fertilizer [\$0, \$393]
Susaeta et al. (2016)	Slack-based DEA model	Profit forgone [\$0, \$294]
Shephard et al. (2021)	Slack-based DEA model	Profit forgone by thinning: – [∼ \$2000, ∼ \$6000] with fertilizer/drought treatment – [∼ \$500, ∼ \$4,200] with drought treatment – [∼ \$2000, ∼ \$4200] with/fertilizer treatment – [\$0, ∼ \$1000] with non-thinning
Rakotoarison and Loisel (2017)	Faustmann model	[\$275, \$6326] without storm risk
		[−\$918, \$3909] with storm risk
Duku-Kaakyire and Nanang (2004)	Real option analysis	[\$143, \$2329]

6. Conclusions

Numerous studies have investigated the efficiency of roundwood production, but very little was found in the DEA forestry literature (Susaeta et al. 2016; Shephard et al. 2021) on considering the effect of price uncertainty on roundwood production efficiency in terms of economic losses due to inefficiencies in given different risk preferences. This study fills the literature gap by incorporating roundwood and carbon price risks in the DEA modeling framework with varying efficiency measures and calculating forgone economic losses due to inefficiencies for loblolly pine production in Georgia, United States. The data are generated from the biophysical model, which consists of the loblolly pine growth and yield model of Piedmont and Upper Coastal Plain in Georgia (Harrison and Borders 1996). The loblolly pine growth and yield data are further incorporated with price risk factors in the stochastic economic optimization model (Huang et al. 2022) to obtain optimal harvest profits considering the effect of roundwood and carbon price risks. Finally, the optimal profits and associated biomass volumes for 56 scenarios given in different silvicultural treatments and price risks are evaluated using the DEA method.

For the CE result, scenarios involving fertilizers tend to have a higher CE. Moreover, a higher risk tolerance (i.e., lower α) also tends to lead to a higher CE score. With respect to TE, the overall pattern is similar to CE. The main difference is that TE scores under "no-treatment" scenarios are higher than scenarios with applying any treatments. The result of AE, which considers both CE and TE, shows that the scenarios involving fertilizers tend to have a higher AE, and scenarios with higher rotation age are more efficient.

Potential economic losses due to inefficient forest production were assessed in this study. The result indicates that scenarios with silvicultural treatment have a high profit forgone than no-treatment scenarios because the adverse effect of increasing input costs outweighs the effect of correspondingly increasing biomass volume. Finally, scenarios with higher risk tolerance (i.e., lower α) also have lower profits foregone. Overall, profits foregone for TE are relatively higher than CE.

This study extends existing DEA studies in forest management by investigating the efficiency of loblolly pine production and quantifying the economic losses of inefficient forest management considering stochastic roundwood and carbon prices. The findings of this study will be of interest to forest practitioners and related policymakers as the roundwood-related price risks can influence forest landowners' decisions (Forboseh et al. 1996; Susaeta and Gong 2019). Due to the increasing threat induced by climate change, the forest sector plays a critical role in mitigating carbon emissions. More information on assessing future forest production efficiency by incorporating different risks would help us establish a more realistic and greater degree of accuracy in the forest productivity evaluation. Incorporating the uncertainty of El Niño–Southern Oscillation or decadal climate variation (Fan et al. 2017; Wang et al. 2021) in forest productivity evaluation could be usefully explored in further research. A further study could also assess the effects of climate change adaptation strategies (Susaeta et al. 2014) on forest productivity. In addition, this study assesses forest production efficiency and monetary losses of inefficiency with different risk tolerance levels. The forest investment value metric (i.e., NPV) is chosen at a given stage of stand development, due to its advantage of generalization, instead of the land expectation value (LEV) (Faustmann 1995; Heshmatol Vaezin et al. 2009; Chang 2013), which is the NPV of an infinite series of identical, even-aged forest rotations, starting from bare land. Using the LEV could identify optimal even-aged management regimes for forest stands, corresponding maximum financial returns, and the value of bare land from the beginning of an even-aged forest rotation. Further research using the LEV with the slack-based DEA and similar risk analytic approach could shed more light on different perspectives of forest and forestland valuation.

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Data availability

Data generated or analyzed during this study are available from the corresponding author upon reasonable request.

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Competing interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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