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RESEARCH

Efficiency analysis and CO_2 emission reduction strategies in the US forest sector: a data envelopment analysis approach

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Abstract

Industrial economic activities produce pollutants and environmentally sustainable production systems in forestry aim to minimize these undesirable outputs while maintaining high production and economic growth. In this contribution, we assume that in addition to plot-specific inputs and outputs, there are some contextual variables that may be exogenously fixed or may be under the control of the decision-makers. In this sense, we first propose a novel and practical approach to calculate environmental efficiency by reducing undesirable products. Then, we utilize an inverse data envelopment analysis (IDEA) model to effectively manage and reduce CO_2 emissions. In doing so, the applied models have been utilized to evaluate the efficiencies of 89 forest plots in the USA. Given our estimations in a real application to the forest plots, the study revealed that the average environmental efficiency score is nearly 0.75 (out of 1). However, there is potential for improvement by adjusting the impacts of contextual factors, which could raise the score to approximately 0.8. Furthermore, the analysis indicates a positive correlation between ownership and environmental efficiency, suggesting that increased ownership leads to higher environmental efficiency. Conversely, temperature exhibits a negative correlation with environmental efficiency. Finally, the results obtained from the IDEA indicate that in order to reduce undesirable outputs by a specific level of 5–10%, it is necessary to decrease other inputs and outputs. This is because, under the assumption of weak disposability, reducing the level of undesirable outputs requires a reduction in certain factors that influence production capacity. In other words, achieving the desired reduction in undesirable outputs inevitably involves diminishing certain aspects of the production process. As the major conclusion, the emergence of IDEA as a powerful tool for sensitivity analysis, along with its flexible nature, offers exciting opportunities for research and practical applications in various fields, including forestry activities. It has the potential to enhance overall environmental efficiency and enable better control over GHG emissions levels.

Keywords Forest plot efficiency · Greenhouse gas emissions (GHGs) · Inverse data envelopment analysis (IDEA) · Undesirable outputs

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Introduction

In recent years, the relationship between forests and sustainable development has undergone substantial progress (Linser and Lier 2020). Wood serves as a fundamental and valuable forest resource due to its renewable nature, recyclability, and sustainable characteristics. It has consistently demonstrated that wood holds several advantages over alternative materials, primarily in terms of its lower environmental impact (Janiszewska-Latterini and Pizzi (2023); Keshvardoost-chokami et al. (2023); Lukawski et al. (2023)).While the conservation and utilization of forest resources have long been crucial subjects in forest management, contemporary developments have brought forth novel dimensions to this discourse. The expansion of forest cover and the augmentation of forest productivity have assumed paramount importance as essential strategies for addressing climate change in the forthcoming 30–50 years. This recognition is shared by numerous countries and international organizations, who acknowledge the crucial role forests play in mitigating the adverse impacts of climate change. For instance, in the USA, forests play a crucial role in the overall carbon cycle and climate regulation. They act as carbon sinks, absorbing more CO_2 than they emit. The preservation and expansion of forests are therefore important strategies for mitigating climate change and minimizing CO_2 emissions (Walters et al. 2023). Hence, modeling undesirable output (CO_2 emissions, etc.) for various forest production systems has attracted considerable scholarly attention and is viewed as pivotal in safeguarding our planet's ecological balance and combating the adverse effects of climate change. To tackle this, one well-established managerial tool is data envelopment analysis (DEA) which was initially developed by Charnes et al. (1978) and has since been extended by other scholars in order to model undesirable output and measure environmental efficiency (Long et al. 2015). The analysis conducted by the DEA involves evaluating and comparing the environmental efficiency of a specific set of decision-making units (DMUs) based on their utilization of multiple inputs and corresponding outputs. For example, some studies have treated environmental factors as undesirable outputs, such as carbon emissions and waste generation (Seiford and Zhu 2002; Hua and Bian 2007; Zhou et al. 2014; Maghbouli et al. 2014), while others have considered them as inputs, such as energy consumption and water usage (Liu and Sharp 1999; Dyckhoff and Allen 2001; Hailu and Veeman 2001). However, the current methodology falls short in accurately representing the intricacies of the manufacturing process. To address this limitation, Färe et al. (1989) and Picazo-Tadeo et al. (2005) proposed an alternative approach that utilizes a directional distance function and incorporates a weak disposability assumption. In recent attempts, this methodology aims to expand the assessment of positive outputs while also contracting the evaluation of negative outputs (Fujii and Managi 2013; Huang et al. 2014; Tongying et al. 2017; Fan et al. 2017; Yu et al. 2018). In the field of forestry and its related activities, considerable research has been conducted to measure environmental efficiency (Obi and Visser (2018); Obi and Visser (2020); Obi et al. 2023). The predominant model used by scholars in this regard is the SBM-DEA model (Yang et al. 2011; Li et al. 2021; Zhang and Xu 2022). However, there is only one instance of applying a two-stage DEA model for measuring environmental efficiency. Specifically, Tan et al. (2023) employed the super-efficient DEA model to assess the forestry eco-efficiency (FECO) of 30 provinces and cities in China between 2008 and 2021. Additionally, the study utilized the Tobit model to examine the influencing factors on FECO, with the aim of gaining deeper insights into the level of sustainable development in forestry. However, DEA is traditionally recognized as a data-driven methodology that can give rise to issues related to homogeneity. For example, there might exist some contextual factors which impact on DMUs' environmental efficiency and steer forest managers toward an unfair comparison. Banker and Natarajan (2008)'s definition of contextual variables includes those variables that may be exogenously fixed as well as others that may be under the control of the DMU managers. Managers should therefore include two-stage efficiency measurements in their evaluation process; firstly, they should calculate environmental efficiency to assess DMUs' performance. Secondly, they need to separately adjust the effects of contextual factors by various regression models in order to obtain reliable results (Djordjević et al. 2023). In the context of DEA methodology, the inquiry recently revolved around ascertaining the maximum feasible augmentation in input allocation for a unit with the objective of augmenting its outputs by a specific magnitude, while simultaneously preserving its current efficiency levels should the unit persist with its operations (Zhang and Cui 2016). To close this theoretical gap, Inverse DEA (IDEA) is an analytical technique employed in post-DEA sensitivity analysis to address resource allocation problems. Its primary aim is to identify the optimal quantities of inputs and/or outputs for each DMU when subjected to perturbations in either inputs or outputs. Since Wei et al (2000) formulated the first instance of an inverse DEA model in 2000, the IDEA approach has garnered considerable attention and popularity in recent years, primarily due to its wide range of applications across various sectors. These sectors encompass business (Hosseininia and Saen 2020; Amin and Ibn-Boamah 2023), supply chain management (Kalantary and Saen 2019; Gharibi and Abdollahzadeh 2021; Moghaddas et al. 2022), education (Guijarro et al. 2020; Le et al. 2021), manufacturing, sustainable production (Hassanzadeh et al. 2018; Yousefi et al. 2021), energy, and environment (Ghiyasi 2019; Lim

2020; Orisaremi et al. 2022). In terms of environmental efficiency assessment, a groundbreaking inverse DEA model was developed with the objective of minimizing greenhouse gas (GHG) emissions across 23 oil companies situated in the USA and Canada (Wegener and Amin 2019). This innovative model provided valuable insights and strategies for effectively managing and reducing GHG emissions within the oil industry. In another recent investigation carried out by Emrouznejad et al. (2019), a unique approach so-called inverse DEA was utilized to allocate CO_2 emissions among specific sectors within the Chinese manufacturing industries. The research findings revealed three distinct stages in the process: reduction of total CO_2 emissions, allocation to two-digit industries, and subsequent allocation to various provinces. Nevertheless, there is only encompassing research conducted by He et al. (2022); the authors employed DEA to illustrate the efficiency of China's forest carbon sink. Additionally, a gray prediction model was utilized to estimate the alteration in the input indicator as China approaches peak carbon levels. Lastly, the inverse DEA model was applied to investigate the increase in forest carbon sink across various provinces within China.

In all the above-mentioned recent studies, the main goal is to determine the specific input and/or output adjustments necessary for the DMUs to attain a predefined efficiency target. Hence, the initial hypothesis of this practical research is to determine if the suggested methodology is capable of mitigating CO_2 emissions and how much the contextual factors can influence the results of this study.

To the best of our awareness, no study has been conducted to assess the environmental efficiency of the US forest sector using the two-stage DEA and simultaneously IDEA approaches, even though this sector holds immense importance for the region. This presents a unique opportunity to explore and uncover new insights into the environmental performance of the sector. To address this void, the novel contribution of this study is threefold:

- Evaluate environmental efficiency by incorporating the weak disposability assumption to effectively mitigate CO_2 emissions in the initial stage.
- Utilize a regression model as an intermediate analysis in the second stage to justify the impact of contextual factors.
- Minimize the levels of undesirable outputs, specifically CO_2 emissions, to the greatest extent possible within some predefined scenarios. Indeed, our developed IDEA model enables us to conduct a sensitivity analysis on the results of environmental efficiency and ultimately determine the optimal variations of the applied dataset.

The remaining sections of this practical research are outlined as follows: Sect. "Problem statement" describes the problem statement and research questions. Sect. "Methodology" provides a detailed description of the applied DEA, regression analysis, and IDEA modeling techniques. Sect. "An application to forest sector" applies the proposed procedure to a real dataset in the US forest sector. Sects. "Results", "Discussion", and "Concluding remarks" present the obtained results, discussion, and concluding remarks, respectively.

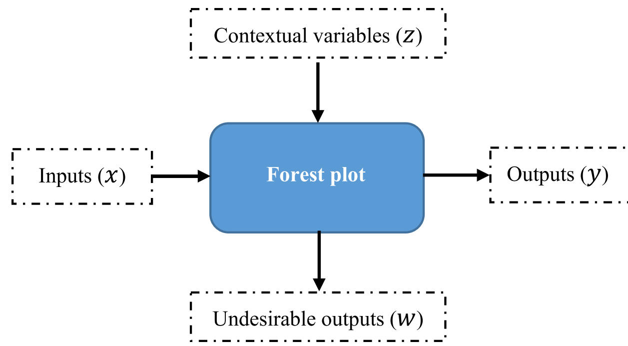

Fig. 1 A systemic view to a sample forest plot

Problem statement

Suppose there are J forest plots with each one using I inputs to generate R desirable outputs and K undesirable outputs. Moreover, we assume that in addition to these inputs and outputs, there are a finite number of contextual and explanatory variables that have significant impact on the performance of the plots. The work process in a sample forest plot is depicted in Fig. 1.

How do the contextual variables affect the technical efficiency of forest plots?

Consider a specific DMU_o : Suppose we are interested in reducing the level of undesirable outputs from w_o to $w_o - \varepsilon_o$, while preserving the current efficiency level. How much the level of desirable outputs and inputs of DMU_o should be reduced?

Methodology

Environmental efficiency assessment

Suppose there are J forest plots (each one as a DMU) to be evaluated and $x_j = \left(x_{1j}, \dots, x_{Ij}\right)^T \geq 0$, $y_j = \left(y_{1j}, \dots, y_{Rj}\right)^T \geq 0$ and $z_j = \left(w_{1j}, \dots, w_{Kj}\right)^T \geq 0$ are respectively, the input, desirable output, and undesirable output vectors of plot j. We assume that in addition to the plot-specific inputs and outputs, there are a finite number of contextual variables that have significant impact on the process. Suppose that $\left(z_{1j},\ldots,z_{Lj}\right)^T \geq 0$ denotes the vector of contextual variables. To achieve plot-specific efficiency, we use a two-stage procedure involving efficiency calculation in the first stage and removing the impact of contextual variables in the second stage. In this sense, in the first stage, we use the weak disposable model of Kuosmanen (2005) to calculate plot-wise environmental efficiency scores. Then, in the second stage, we use ordinary least squares (OLS) technique to remove the impact of contextual variables on the efficiency scores generated from the first stage.

To estimate the technical efficiency of plot εoε in the first stage, we use the following output-orientation model of Kuosmanen (2005):

$$\begin{aligned}
&\varphi_o^* = \min \varphi \\
&\text{s.t.} \\
&\sum_{j=1}^{J} \left(\lambda_j + \mu_j\right) x_{mj} \leq x_{mo}, m = 1,\ldots,M, \\
&\sum_{j=1}^{J} \lambda_j y_{rj} \geq \varphi y_{ro}, r = 1,\ldots,R, \\
&\sum_{j=1}^{J} \lambda_j w_{kj} = w_{ko}, k = 1,\ldots,K, \\
&\sum_{j=1}^{J} \left(\lambda_j + \mu_j\right) = 1, \\
&\lambda_j, \mu_j \geq 0, j = 1,\ldots,J.
\end{aligned} \tag{1}$$

Suppose φ_o^* is relative environmental efficiency of DMU_o. In order to remove the impact of contextual variables on efficiency scores, we use ordinary least squares method. The production frontier in technology set of model 1 is monotone increasing, piecewise linear and concave. Hence, as Banker and Natarajan (2008) stated, the regression of the calculated efficiency scores by Model (2) on the contextual variables using ordinary least squares provides good estimation of the parameters of contextual variables. In this sense, in order to refine efficiency scores, we will apply the following regression model in the second stage:

$$\text{Log}(\varphi_o^*) = \rho_0 + \rho_1 z_{1o} + \rho_2 z_{2o} + \cdots + \rho_L z_{Lo} + \beta \tag{2}$$

in which $\text{Log}(\varphi_o^*)$ is the logarithm of the environmental efficiency score of DMU_o obtained from model 2. In regression model (2), ρ_0 and β are, respectively, the intercept and error term. The coefficients $\rho_l : \ l = 1,\ldots,L$ can be positive or negative. The signs of ρ_l indicate that the $l-$th contextual variable has a direct or inverse impact on the environmental performance of DMU_o. Upon estimating the regression parameters using the least squares method, it becomes feasible to compute the residuals. The accurate environmental efficiency is therefore estimated as:

$$\overline{\varphi}_o^* = \varphi_o^* - \left[\text{Log}\left(\varphi_o^*\right) - \left(\rho_0 + \rho_1 z_{1o} + \rho_2 z_{2o} + \cdots + \rho_L z_{Lo} + \beta\right)\right]$$

An inverse DEA model

In this section, we discuss the problem of inverse DEA in two scenarios:

First, we examine the case that if we reduce undesirable outputs to a certain amount, how much should we reduce the inputs and the desirable outputs in order to maintain the level of environmental efficiency?

Second, we investigate that if we are interested in increasing the level of outputs to a certain amount, how much the inputs and undesirable outputs are increased while preserving the level of environmental efficiency?

In the first approach, the problem is: if DMU_o decreases its current level of undesirable outputs to $w_o - \pi$, how much should the inputs and desirable outputs be reduced to maintain the current efficiency level. We believe that reducing undesirable outputs requires reducing inputs and desirable outputs. In order to determine the optimal values of the changes in inputs and desirable outputs, we solve the following multi-objective linear programming problem model (3):

$$\begin{aligned}
&\text{Max}\delta_m : m = 1,\ldots,M \\
&\text{Min}\gamma_r : r = 1,\ldots,R \\
&\text{Min} \sum_{m=1}^{M} s_m \\
&\text{Min} \sum_{r=1}^{R} d_r \\
&\text{s.t.} \\
&\sum_{j=1}^{J} \left(\lambda_j + \mu_j\right) x_{mj} + s_m = \varphi_o^*(x_{mo} - \delta_m), m = 1,\ldots M, \\
&\sum_{j=1}^{J} \lambda_j y_{rj} - d_r = \left(y_{ro} - \gamma_r\right), r = 1,\ldots,R, \\
&\sum_{j=1}^{J} \lambda_j w_{kj} = w_{ko} - \pi_k, k = 1,\ldots,K, \\
&\sum_{j=1}^{J} \left(\lambda_j + \mu_j\right) = 1, \\
&\lambda_j \geq 0, j = 1,\ldots,J, \\
&s_m, d_r, \delta_m, \gamma_r \geq 0, \text{for all} m \text{and} r.
\end{aligned} \tag{3}$$

Clearly, the vector $(x_o - \delta, y_o - \gamma, w_o - \pi)^t$ belongs to $Pos(A)$, in which $A = [X, Y, W]^t$ and is the set of all nonnegative linear combinations of A. (Note that X, Y and W are matrixes of all inputs, desirable outputs and undesirable outputs, respectively.) This guarantees the feasibility of model (3).

In model 3, the r-th undesirable output is reduced by π_r and we are interested in determining the minimum values of reduction in desirable outputs and maximum values of reduction in inputs. It should be pointed out that π_r are user-defined values. Model 3 is a multi-objective linear programming model, and it is not easy to calculate an optimal solution to satisfy all objects. Suppose.

$\delta = \mathrm{Min}\{\delta_m : m = 1, \ldots, M\}$ and $\gamma = \mathrm{Max}\{\gamma_r : r = 1, \ldots, R\}$. Clearly, $\delta \le \delta_m$, for all $m = 1, \ldots, M$ and $\gamma \ge \gamma_r$, for all $r = 1, \ldots, R$. In order to derive a non-dominated solution, we can easily solve the following single-objective model:

$$
\begin{aligned}
&\mathrm{Max}\ \delta - \gamma - \sum_{m=1}^{M} s_m - \sum_{r=1}^{R} d_r \\
&\text{s.t.} \\
&\sum_{j=1}^{J} (\lambda_j + \mu_j) x_{mj} + s_m = x_{mo} - \delta_m, m = 1, \ldots M, \\
&\sum_{j=1}^{J} \lambda_j y_{rj} - d_r = \varphi_o^* (y_{ro} - \gamma_r), r = 1, \ldots, R, \\
&\sum_{j=1}^{J} \lambda_j w_{kj} = w_{ko} - \pi_k, k = 1, \ldots, K, \\
&\sum_{j=1}^{J} (\lambda_j + \mu_j) = 1, \\
&\delta \le \delta_m, \text{for all } m = 1, \ldots, M, \\
&\gamma \ge \gamma_r, \text{for all } r = 1, \ldots, R, \\
&\lambda_j \ge 0, j = 1, \ldots, J, \\
&s_m, d_r, \delta_m, \gamma_r \ge 0, \text{for all } m \text{ and } r.
\end{aligned}
\tag{4}
$$

Now suppose we are interested in increasing the level of desirable outputs from y_{ro} to $y_{ro} + \gamma_r$. The object is to determine the new optimal values for inputs and undesirable outputs, while preserving the level of environmental efficiency. To determine the optimal values of the changes in inputs and undesirable outputs, we solve the following linear programming problem:

$$
\begin{aligned}
&\mathrm{Min}\pi + \delta + \sum_{m=1}^{M} s_m + \sum_{r=1}^{R} d_r \\
&\text{s.t.} \\
&\sum_{j=1}^{J} (\lambda_j + \mu_j) x_{mj} + s_m = x_{mo} + \delta_m, m = 1, \ldots M, \\
&\sum_{j=1}^{J} \lambda_j y_{rj} - d_r = \varphi_o^* (y_{ro} + \gamma_r), r = 1, \ldots, R, \\
&\sum_{j=1}^{J} \lambda_j w_{kj} = w_{ko} + \pi_k, k = 1, \ldots, K, \\
&\delta \le \delta_m, \text{for all} m = 1, \ldots, M, \\
&\pi \le \pi_k, \text{for all} k = 1, \ldots, K, \\
&\sum_{j=1}^{J} (\lambda_j + \mu_j) = 1, \\
&\lambda_j \ge 0, j = 1, \ldots, J, \\
&s_m, d_r, \delta_m, \pi_k \ge 0, \text{for all } m, k \text{ and } r.
\end{aligned}
\tag{5}
$$

In model 5, $s_m, d_r, \delta, \delta_m, \pi, \pi_k, \lambda_j$ and μ_j are decision variables and γ_r is user-defined values. An important point to be noted is that model (5) may lead to infeasibility in some real cases. This is due to the fact that the user-defined values γ_r may be infeasible in practice. In this case, an interaction may be useful to achieve a feasible plan.

An application to forest sector

We now proceed to illustrate the practical application of our proposed approach by employing a dataset comprising 89 forest plots situated in the state of Oklahoma, USA. It should be noted that forest plots serve as the unit of observation for the forest inventory analysis (FIA) program. A standard plot typically comprises about four subplots, each with a radius of 7.3 m (equivalent to 0.015 hectares). Within each standard plot, trees with a diameter greater than 13 cm are measured. Additionally, within each subplot, a nested microplot with a 2.1-m radius (equivalent to 0.001 hectare) is utilized to measure trees with a diameter less than 13 cm (Burrill et al. 2021). This dataset, obtained from the FIA (USDA Forest Service 2023), encompasses detailed information regarding the ecosystem services generated by these forest plots in 2018.

In this application, we seek to estimate the environmental efficiency of the plots with emphasis on their ability to generate desirable outputs and reduce undesirable outputs. In this sense, we chose four desirable outputs, timber productions ($\boldsymbol{y}_1$), carbon sequestration ($\boldsymbol{y}_2$), water production ($\boldsymbol{y}_3$)

and tree richness (y_4), and one undesirable output, carbon emitted in the case of harvest (w_1). We also considered one input as site productivity (x_1). In addition to plot-specific input and outputs, we have also considered the following five contextual variables — age, damage, ownership, precipitation, and temperature — which are denoted by z_1-z_5, respectively. With the exception of the climatic variables, all input, outputs, and contextual variables were obtained from the FIA program. We used historical records of precipitation and temperatures in each forest plot and obtained from the WASSI model (Caldwell et al. 2019). Tables 1 and 2 show the descriptive variable of the dataset set. All units were taken to the hectare level, when applicable.

Results

Environmental efficiency analysis

First, the assessment of environmental efficiency in the US forest plots is initially conducted through the utilization of the conventional DEA model under weak disposability assumption (Model 1). The objective of this evaluation is to promote enhanced levels of desirable output. The outcomes of this approach are depicted in Table 3.

This analysis reveals that approximately 38% (34 out 0f 89) of forest plots are fully determined efficient (See Table 8 in Appendix A). This signifies that these fully efficient DMUs have optimized their desirable outputs while slightly reducing their input activity levels and keeping a constant undesirable output level, thereby attaining high efficiency and productivity (environmental efficiency = 1).

Table 1 The statistical description of the inputs and outputs data

Indicator	x_1 Site productivity (m^3/ha/yr)	y_1 Timber production (m^3/ha)	y_2 Carbon sequestration (ton/ha/yr)	y_3 Water production (ton/ha)	y_4 Tree richness	w_1 CO_2 emissions (ton/ha)
Min	0.5000	0.3952	0.0292	851.5867	1.0000	0.0011
Max	7.0500	283.3104	65.0599	9895.3650	9.0000	12.2137
Mean	1.4213	51.6868	7.7535	4054.9068	4.3258	1.2931
Std	1.3380	46.3529	10.9577	1475.4262	2.1835	2.2201
Median	0.5000	39.2249	3.7884	3909.1083	4.0000	0.3852

Table 2 The statistical description of the contextual variables

Indicator	z_1 Age (Years)	z_2 Damage* (1 = damage; 0 = no damage)	z_3 Ownership (1 = private; 0 = public)	z_4 Precipitation mm	z_5 Temperature °C
Min	3	0	0	737.2	12.958
Max	100	1	1	1762.2	17.358
Mean	56.7191	–	–	1164.0843	15.6970
Std	22.3322	–	–	196.6429	0.8519
Median	63	–	–	1160.6	15.642
Mode	–	1	1	–	–

*A forest plot is considered as damage if it displayed a tree mortality of 25% caused by biotic or abiotic agents (Burril et al. 2021)

Table 3 The statistical description of the EE and optimal inputs and outputs from model 1

Indicator	EE*	x_1	y_1	y_2	y_3	y_4	w_1
Min	1.0000	0.5000	0.3952	0.0292	851.5867	1.0000	0.0011
Max	3.8227	7.0500	283.3104	65.0599	9895.3650	9.0000	12.2137
Mean	1.3348	1.2288	65.1210	13.9515	5183.3285	5.5234	1.2931
Std	0.5192	1.1279	46.1214	12.6651	1482.3487	2.0524	2.2201
Median	1.0824	0.5000	62.5482	10.7932	4984.3600	6.0000	0.3852

*Environmental Efficiency score

Conversely, the remaining DMUs with inefficiency scores greater than one should improve their efficiency by following the improved input and output values determined by the efficient US forest sectors. In details, the statistical description of the projection points corresponding to inputs and outputs showed that the single input (Site productivity) needs to be reduced by 14%. Moreover, the outputs sawtimber and pulpwood productions, carbon sequestration, water production, and tree richness must be increased by 26, 79, 28, and 28%, respectively. However, as we should expect, the level of undesirable outputs, CO_2 emissions, remained unchanged. As we can see, the main source of inefficiency is related to carbon sequestration.

Calculating the impact of contextual variables

In the second step of our analysis, we first calculated the Pearson's correlation test to examine the relationship between the environmental efficiency of the forest plots and the contextual variables employed in this study. Specifically, we paired the logarithm of the environmental efficiency with each of the contextual variables to measure their correlation. The results are listed in Table 4. Prior to accounting for the influence of other contextual variables, we observed a positive correlation between the Log(φ) (Logarithm of environmental efficiency) and the contextual variables, including age, ownership, precipitation, and temperature. However, it is worth noting that the correlation becomes negative when considering the variable damage. The analysis revealed that the highest correlation value for Log(φ) is associated with precipitation. On the other hand, the lowest correlation is observed for the variable damage. This implies that while various types of damages (such as insect, disease, human, animal, fire, and weather-related damages) negatively impact plot efficiencies; however, none of the examined contextual variables showed statistically significant effects, according to the analysis conducted.

Now, the impact of contextual factors on the efficiency state of a plot is being measured. Our goal is to identify and minimize their impact so that we can calculate more accurate efficiency scores that are specific to each plot. Toward this end, we apply the regression model (2) during second phase and present the corresponding findings in Table 5. As the results show, ownership and temperature are statistically significant. Moreover, the temperature has inverse relationship with environmental efficiency, while ownership has direct relationship with efficiency.

The findings presented in Table 5 indicate that while there seems to be a correlation between the logarithm of environmental efficiency scores and variables such as age, damage, and precipitation, these relationships are not statistically significance. However, there is a direct significant relationship between ownership and the logarithm of environmental efficiency, indicating a notable association. More specifically, this finding suggests that private ownership has a favorable positive influence on environmental efficiency. Through our observations, we noted a negative significant relationship between the logarithm of environmental efficiency scores and temperature. This discovery indicates that as the temperature increases, there is a minor decline in efficiency levels across various plots. It should be noted that the R square value stands at approximately 0.26, indicating that the regression model encompasses over 26% of the observed data. Finally, after adjusting for contextual variables, we found that the average environmental efficiency of the plots is calculated to be 1.2428.

An inverse DEA analysis

In the last step, we apply our proposed IDEA model (5) on forest plots data. We design two scenarios to reduce the studied undesirable output: we first assume that we are interested in reducing the level of undesirable output (CO_2 emissions) by 5%. The optimal values of inputs and desirable outputs are calculated by model (5). The statistical description of the results is given in Table 6.

Our results indicated that if we want to reduce the level of undesirable outputs by 5%, we should reduce the levels of sawtimber and pulpwood production, carbon sequestration, water production, and tree richness by 2, 5, 0.3, and 7%, respectively. In this case, the site productivity should be reduced by 21%.

In the second scenario, aiming to reduce undesirable outputs by 10%, the findings from model (5) in Table 7 indicate that the levels of sawtimber and pulpwood, carbon

Table 4 Pearson correlation coefficients

	Log(φ)	Age	Damage	Ownership	Precipitation	Temperature
Log(φ)		0.2049	−0.0227	0.1162	0.4474	0.2221
Age			−0.0349	0.0377	0.0937	−0.0402
Damage				−0.1477	−0.0270	−0.1183
Ownership					0.0713	0.0897
Precipitation						0.5651
Temperature						

Table 5 Regression results

Regression statistics					
Multiple R					0.510613
R square					0.260725
Adjusted R square					0.216191
Standard error					0.119157
Observations					89
ANOVA					
	Df	SS	MS	F	Significance F
Regression	5	0.415618	0.083124	5.854446	0.000111
Residual	83	1.178464	0.014198		
Total	88	1.594082			
	Coefficients		Standard error	t Stat	*P* value
Intercept	−0.4737		0.2539	−1.8656	0.0656
Age	0.0011		0.0006	1.9786	0.0512
Damage	0.0008		0.0344	0.0220	0.9825
Ownership	0.0360		0.0425	0.8463	0.3998
Precipitation	0.0003		0.0001	3.9947	0.0001
Temperature	−0.0060		0.0184	−0.3243	0.7466

Table 6 The statistical description of the optimal inputs and outputs

Indicator	x_1	y_1	y_2	y_3	y_4
Min	0.5000	0.3754	0.0292	851.5867	0.7997
Max	6.7519	277.0955	63.0635	9585.8630	8.7553
Mean	1.1274	50.6851	7.3643	4045.4254	4.0361
Std	1.0670	45.5918	10.5710	1459.9453	2.0820
Median	0.5000	38.2966	3.5477	3908.9563	3.8464

Table 7 The statistical description of the optimal inputs and outputs

Indicator	x_1	y_1	y_2	y_3	y_4
Min	0.5000	0.3557	0.0292	851.5867	0.7980
Max	6.4539	270.8807	61.0672	9276.3610	8.5105
Mean	1.1084	50.0663	7.1656	4036.4464	3.9677
Std	1.0196	44.8709	10.1951	1445.2303	2.0242
Median	0.5000	38.2966	3.5221	3908.7777	3.8057

sequestration, water production, and tree richness must be reduced by 3, 8, 0.5, and 8%, respectively. Additionally, site productivity needs to be reduced by 22%.

Discussion

This study explored the applicability of DEA-based approaches to estimate environmental efficiency for the US forest plots, incorporating both undesirable output (CO_2 emissions) and contextual variables. Toward this end, an output-oriented DEA model was first implemented using weak disposability assumption to calculate plot-wise environmental efficiency scores. The results indicated that only 34 of forest plots were operating at high-efficiency levels while their total average environmental efficiency was quite high (0.75 out of 1) (Table 3 and Appendix A). However, the inherent characteristic of the implemented environmental DEA model results in the consistent preservation of the level of undesirable output (CO_2 emissions) for all inefficient forest plots. This is attributable to the implementation of a weak disposability strategy in which the model aims to proportionally adjust both desirable and undesirable output levels simultaneously based on environmental regulations. (Färe et al. 2007; Long et al. 2015). In practice, the process of mitigating undesirable outcomes like CO_2 emissions in forest logging activities involves incurring expenses related to proportional reduction or increased output. Consequently, operational costs emerge as a significant factor in this strategy (Palmer et al. 1995; Sueyoshi and Goto 2012). These costs impact the total operation costs or average operation cost by decreasing or increasing them, respectively, owing to reduced CO_2 emissions (Zadmirzaei et al. 2023). The outcomes also indicate the necessity of a 79% increase in carbon sequestration to offset the damages caused by CO_2 emissions, and there might be some exogenous/contextual factors which can easily impact on the levels of both desirable and undesirable outputs. Hence, the log of environmental efficiency ($\text{Log}(\varphi_o^*)$) was calculated in the second step in order to mitigate the effect of contextual factors on the previous obtained results. The findings of the OLS regression test showed that the logarithm of environmental efficiency exhibited a direct significant relationship with ownership and a negative significant relationship with temperature (Table 5). These findings are in line with some related research in the forest sector (Gutiérrez and Lozano 2022; Amirteimoori et al. 2023). Moreover, the residuals of the Log (φ_o^*) refer to the differences between the observed values and the predicted values based on the estimated regression model which provide a good measure of the studied DMUs' managerial ability (Banker and Park 2020). For instance, the coefficient of 0.0360 for the ownership variable demonstrates the significant and direct impact of private forest ownership on enhancing the environmental efficiency within this particular production system. Indeed, when forest plots are managed by private ownership, the environmental efficiency of forest management practices can vary depending on the individual goals and strategies of the private owners, leading to potential trade-offs between economic profitability and environmental sustainability (Feliciano et al. 2017). The temperature variable, characterized by a negative coefficient of -0.0060, holds significance in our analysis. This indicates that a unitary increase in temperature is associated with a $100\left(e^{-0.006}-1\right)=\%0.6$ decrease in the average environmental efficiency. Therefore, after adjusting these exogenous/contextual factors, the overall average environmental efficiency score significantly increases to 0.8 (on a scale of 1).

Lastly, to reduce/control the studied undesirable output (CO_2 emissions), an inverse DEA model was applied. The model incorporates two distinct scenarios, namely a 5% and 10% reduction in CO_2 emissions, to effectively analyze and determine optimal strategies. Although both scenarios exhibit a comparable pattern in reducing undesirable outputs, it is worth noting that the reduction of desired outputs and studied input was marginally more satisfactory in the scenario aiming to reduce CO_2 emissions to a level of 10% (Tables 6 and 7). In details, to achieve a 10% reduction in undesirable outputs, the research findings indicated that certain measures need to be taken. The study recommends decreasing the levels of sawtimber and pulpwood by 3 and 8%, respectively. Additionally, carbon sequestration should be reduced by 0.5%, while water production and tree richness should be decreased by 8%. Moreover, site productivity needs to be lowered by 22% to meet the desired target. While these practices may seem counterintuitive in terms of generating economic revenues, actions such as tree harvesting and the use of fertilization (as a means to increase site productivity) are expected to elevate carbon emissions. In light of achieving specific environmental standards, forest landowners/managers might consider reducing tree harvesting levels and minimizing the use of fertilizers to lower their carbon footprint. The use of fertilizers can also contribute to increased tree richness, and by managing tree richness, carbon emissions may be reduced. Furthermore, the quantity of water is inversely associated with the level of tree density (number of trees per hectare). Keeping trees unharvested can decrease water quantity but simultaneously reduce carbon emissions. These findings align with the recommended forest management strategies across various silvicultural practices as discussed in a recent study (Ameray et al. 2021). Therefore, the latest research findings provide compelling evidence that IDEA has the capacity to conduct sensitivity analysis, addressing the significant limitations of DEA models. In addition, the IDEA approach offers enhanced flexibility when compared to traditional DEA models. Given its proven effectiveness as an optimization technique, it presents an intriguing opportunity for further exploration and application in various production and service organizations, particularly in the realm of environmental efficiency measurement (Orisaremi et al. 2021). To elaborate further, the utilization of IDEA allows for the examination of how changes in inputs and outputs impact the efficiency scores obtained from the model. This sensitivity analysis is vital for understanding the robustness and reliability of the IDEA results, especially in complex and dynamic environments where nonlinear relationships exist between inputs and outputs, as well as where sustainable management of forest operations involves embracing a broader perspective that integrates carbon emissions, tree biodiversity, and a multitude of other vital parameters. By doing so, we can strive toward a holistic and harmonious approach that supports the ecological, social, and economic dimensions of sustainable forest management (Cooper and MacFarlane (2023); Latterini et al. (2023a and b), and Bowditch et al. (2023)). By incorporating this capability, IDEA addresses a key limitation of conventional DEA methods that often assume linearity, enabling researchers and practitioners to gain deeper insights into the underlying factors affecting efficiency (Emrouznejad 2023).

Concluding remarks

Mechanized forest logging operations have emerged as a significant source of air pollution, contributing to increased emissions of CO_2 and other greenhouse gases (GHGs) per unit of timber harvested. This poses challenges for implementing sustainable and economically viable practices, making it complex to strike a balance between efficient timber harvesting and minimizing carbon footprints in the pursuit of environmentally sustainable forest management. Consequently, incorporating considerations for environmental efficiency problems becomes essential as it encompasses enhancing efficiency and minimizing undesirable outputs. This serves as a valuable managerial tool in promoting environmentally sustainable harvesting practices that simultaneously enhance overall productivity and mitigate CO_2 emissions. Hence, the primary focus of this research lies in the formulation of DEA-based methodologies to evaluate the environmental efficiency of forest plots in the USA. These methodologies incorporate not only the measurement of undesirable outputs such as CO_2 emissions but also account for contextual variables, thereby providing a comprehensive assessment of environmental efficiency. To this end, the study implemented a two-stage DEA model to calculate plot-wise environmental efficiency scores. The average environmental efficiency was high (075), and the logarithm of environmental efficiency was used to account for contextual factors in the second stage. Ownership had a positive relationship with environmental efficiency, while temperature had a negative relationship. Adjusting for these factors increased the overall average environmental efficiency score (0.8). Finally, an Inverse DEA model was used to analyze strategies for controlling CO_2 emissions. It was found that reducing undesirable outputs required reducing other inputs and outputs, because naturally, to reduce the level of undesirable outputs under the weak disposability assumption, some influencing factors of production capacity must inevitably be reduced. These recommendations aimed to balance minimizing undesirable outputs with ecological functions. The specific magnitudes of reductions should be determined based on local conditions, ecological considerations, and sustainability goals.

This aspect is particularly noteworthy in cases where certain outputs, once produced, come at the expense of others. For instance, management practices that lead to higher rates of carbon sequestration and timber production, such as increased tree planting or regeneration, may potentially lead to a decrease in water yield. Examples of such practices include afforestation with fast-growing species and moderately intensive mechanical soil preparation. However, it is essential to acknowledge that certain policies in the USA, such as the conservation reserve program (CRP), have sought ways to promote carbon sequestration while also improving water yield. One approach employed by the CRP is the planting of softwood species (USDA 2015). Balancing these trade-offs between various ecosystem services remains a significant challenge for sustainable land management. Policy initiatives like the CRP provide valuable insights into potential solutions to address these trade-offs and advance more sustainable practices that optimize multiple environmental benefits.

In conclusion, the emergence of IDEA as a powerful tool for sensitivity analysis and its flexible nature present exciting opportunities for research and practical applications. Exploring the potential of this approach in various production and service organizations, particularly within the context of environmental efficiency measurement, holds promise for advancing our understanding of efficiency dynamics and informing decision-making processes. Continued investigation into the capabilities and limitations of IDEA will undoubtedly contribute to the advancement of performance evaluation methodologies and enhance organizational sustainability in an ever-changing world.

Appendix A

See Table 8.

Table 8 Environmental efficiency and optimal inputs and outputs

Forest plot number	EE	x_1	y_1	y_2	y_3	y_4	w_1
1	1	7.05	283.3104	18.6973	3973.142	9	8.2322
2	1.1156	2.05	130.1963	26.5806	4639.845	7.8091	3.2102
3	1.1185	1.6093	127.11	45.4682	4018.322	7.3116	3.5008
4	1	2.05	107.0759	4.1282	4820.603	8	1.9178
5	1	2.05	104.9498	28.27	851.5867	4	0.2412
6	1.0098	1.9247	100.3151	15.1108	4808.695	7.0689	0.4815
7	1	4.55	115.1426	1.7806	4097.833	7	12.2137
8	1.0473	0.5	95.7833	48.4574	4020.32	6.2838	2.9605
9	1	2.05	187.8212	1.3787	4342.512	5	1.4557
10	1.0824	2.05	90.4669	8.7082	5283.304	7.5767	1.0386
11	1	0.5	130.1425	54.0094	3078.912	8	1.4876
12	1.1548	2.05	88.8756	18.2603	4343.998	8.0839	0.9593
13	1	0.5	41.8059	11.7459	2490.615	3	0.0226
14	1.1683	2.05	85.7374	21.3456	4832.1	6.1394	6.8261
15	1	0.5	124.5342	28.0641	5600.75	4	0.9961
16	1.4946	0.5	94.822	38.8313	4233.285	7.4728	1.8823
17	1	2.05	99.697	0.0292	4854.765	3	0.3182
18	1.4997	1.6667	149.7103	11.205	5580.455	4.9627	1.5587
19	1.0139	0.5	60.6895	18.1693	7468.699	6.0836	0.8038
20	1.1562	2.05	107.6277	27.8042	4507.376	8.0934	3.7108
21	1.0264	2.05	139.7203	38.2647	3403.801	7.8433	4.6773
22	1.1732	1.0656	42.0396	8.1908	4739.961	7.0393	0.0522
23	1.4386	0.8144	63.0744	22.8092	7377.12	5.8434	1.5914
24	1.3513	0.7293	45.1796	22.9298	5688.558	4.1249	0.1668
25	1	0.5	98.2163	5.6982	3957.308	3	0.349
26	1.2503	0.5	37.0425	4.776	6180.011	6.2515	0.0911
27	1	4.55	75.8436	2.6645	6265.22	8	9.3987
28	1.2742	1.0846	40.8548	3.2792	6374.137	7.645	1.0005
29	1.4793	0.5	76.3369	5.3107	5897.932	3.6612	0.2661
30	1.055	0.5	77.792	12.4165	4813.071	3.548	0.3028
31	2.014	2.3306	85.4357	16.4357	4199.845	8.0561	0.5674
32	1.1297	2.05	86.8139	14.0826	4495.396	7.9076	0.7091
33	1.2948	0.5	75.4336	10.3937	6457.174	5.1792	0.4215
34	1.311	0.544	64.5809	21.6706	6802.536	6.5549	0.7245
35	1	0.5	14.4182	1.4365	5975.688	8	0.344
36	1	0.5	32.2003	19.6684	6662.855	4	0.0592
37	1	4.55	1.3306	0.2837	5525.678	6	0.0036
38	1	2.05	15.1442	3.7884	4984.36	7	0.0286
39	1	2.05	2.1744	2.2998	5639.238	1	0.0059
40	1	2.05	84.1166	8.2841	7481.955	6	0.2277
41	1.3346	1.2432	60.7838	15.7496	6266.281	6.6731	0.2275
42	1.3143	0.5	27.7898	1.8335	7437.361	6.5714	1.062
43	1	0.5	3.6015	4.719	3809.363	2	0.0034
44	1	0.5	109.8831	6.314	3277.748	5	0.5216
45	1	2.05	11.3682	24.4096	3476.872	1	0.031
46	2.4811	2.05	96.5939	11.4168	6765.373	5.5835	4.0701
47	1.7749	0.5	69.6204	10.6185	6908.923	5.3247	1.9817
48	1.3707	0.5	28.4946	14.8448	4713.201	2.7414	0.035
49	1.0691	0.5	19.9467	11.3527	3664.292	1.4314	0.0163
50	2.5222	0.5	69.6097	4.9475	4622.972	5.0444	0.2254

Table 8 (continued)

Forest plot number	EE	x_1	y_1	y_2	y_3	y_4	w_1
51	2.4323	0.5	44.8402	22.473	5864.394	4.8647	0.2395
52	1.7905	0.5	52.4664	24.9591	5132.588	7.162	2.1173
53	1.6896	0.5	67.334	24.3544	5873.685	5.5359	3.0112
54	1.0023	2.05	74.4284	15.4962	4309.046	8.0184	0.2679
55	1.304	0.5	72.3642	11.147	4533.225	6.5202	0.393
56	1	0.5	32.0822	5.5935	3770.133	7	0.0221
57	1.5797	0.5	74.6042	5.6588	6175.318	4.7392	0.3161
58	1.1938	0.5	8.684	1.6748	4481.193	2.9241	0.01
59	1.8798	2.05	91.8261	8.6463	6975.428	5.8293	0.3083
60	1	0.5	0.3952	2.0869	3527.362	1	0.0011
61	1.5987	0.5	46.644	14.2908	7066.951	6.3947	0.3852
62	1	2.05	73.6688	16.3012	4213.327	8	0.1116
63	1.2989	0.5	43.5315	10.7932	7378.971	6.4945	0.5115
64	1	0.5	43.4669	1.2005	7376.2	6	2.712
65	1	0.5	28.8972	3.3126	9895.365	5	0.0573
66	1	2.05	27.9137	18.2765	5674.48	1	0.0225
67	1	0.5	62.5482	65.0599	3260.412	6	5.3439
68	1	0.5	69.6502	4.5608	2957.727	7	0.2391
69	2.1381	0.5	48.6389	10.2119	6843.127	6.4143	0.3215
70	1.8712	0.5	87.069	21.8633	6178.367	5.6135	0.6888
71	1.0795	1.5972	125.3219	20.4114	5052.871	6.4768	0.9251
72	1	0.5	0.6193	0.2111	4074.198	1	0.0034
73	1	2.05	1.5095	0.3112	4056.812	4	7.744
74	1.0335	2.05	13.3871	2.9082	5017.375	4.134	0.0076
75	1.5791	0.8019	35.4803	10.0655	5644.306	3.4311	0.0362
76	2.1476	0.5	52.6179	17.8503	6650.015	6.4429	0.4609
77	1.4913	0.5	66.1441	5.7166	4550.475	4.4738	0.194
78	1	0.5	21.4553	2.0206	5897.482	8	0.2222
79	1.3249	0.5	32.1502	7.6436	5245.588	6.6247	0.1098
80	2.7019	0.5	33.3372	8.6541	8696.209	5.4038	0.9494
81	1	2.05	15.3311	3.688	5187.212	4	0.0084
82	3.8227	0.5	59.2616	29.2126	4585.359	7.6454	1.5893
83	2.5006	0.5	59.9248	10.878	8089.004	5.0011	0.8488
84	1	0.5	17.8888	9.9562	3160.72	1	0.0091
85	1	0.5	10.9116	0.2076	3694.667	4	0.0051
86	1.1429	0.5	53.3703	19.1323	5000.649	8	0.7289
87	1.0399	0.5	25.768	6.4066	3413.701	3.275	0.0155
88	2.6252	0.5	115.4716	32.0888	5303.912	5.2504	1.1438
89	2.0002	1.6038	23.5106	7.4254	4797.041	6.0005	0.0248

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Declarations

Competing interests The authors declare no competing interests.

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