Profit-efficiency analysis of forest ecosystem services in the southeastern US

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Abstract

Technical, allocative, and profit efficiency of longleaf pine (*Pinus palustris.* Mill) forests in the southeastern United States, producing ecosystem services such as timber, tree biodiversity, water, and carbon sequestration, were estimated. This study employed a non-parametric two-stage approach involving data envelopment analysis (DEA) and robust linear regression. Utilizing data from the Forest Inventory and Analysis (FIA) program spanning 1977-2015 and covering 2,282 forest plots, most longleaf pine forest plots were technically and profit inefficient in ecosystem service production. The inefficiency in profit appeared more attributable to allocative rather than technical inefficiency. Furthermore, the impact of various exogenous variables on inefficiency scores was assessed through robust linear regression. The findings suggested that forest disturbances under private ownership could reduce technical inefficiency. Surprisingly, contrary to stochastic frontier analysis (SFA) results, the robust regression model, considering geographical factors, disturbance, ownership, management, and time in the presence of outliers/influential observations, indicated that disturbances often increased technical inefficiency. Therefore, forest

management strategies aiming to mimic or replicate the effects of forest disturbances might compromise the efficiency of ecosystem service provision.

Keywords: data envelopment analysis; efficiency; ecosystem services; longleaf pine; disturbance; ownership

1. Introduction

The southeastern forests of the United States (US) play a critical role in the nation's economy. These forests occupy 87 million hectares and provide around 66% of the timber harvested in the US (Oswalt et al., 2019), and support more than 1 million jobs throughout the supply chain (Abt, 2013). They can sequester around 25% of the annual carbon emissions (Han et al., 2007) and generate 34% of the water production in the southern US (Lockaby et al., 2013). Furthermore, they are expected to generate around \$14 (through water, carbon and habitat services) for every \$1 in timber value (Escobedo and Tilmisina, 2012).

In the southeastern US, temperature levels and precipitation are expected to increase throughout the century, with mean annual temperatures possibly increasing over 2°C and precipitation over 10% compared to the 1986-2005 average (Hicke et al.,2021), and with these changes the production of some ecosystem services will be at risk. Elevated temperatures are projected to lead to a decrease in water supply, subsequently exerting a negative impact on forest growth (Lockaby et al., 2013). Climate change is expected to cause changes in the geographic distribution of several species of wildlife and plants, influencing seasonal movement, recruitment, and mortality (Trani Griep and Manley, 2012). Furthermore, climate change can exacerbate the frequency and intensity of natural disturbances such as wildfires, pest outbreaks, and windstorms, threatening the sustainability of forestlands and creating ecological change such as the structure of the ecosystem (e.g., changes in species composition, heightened tree mortality, and diminished forest productivity), economic losses, and socioeconomic challenges (Lecina-Diaz et al., 2021).

Sustainable forest management is considered a critical strategy to safeguard ecosystem services (Mori et al., 2017). Adaptive management strategies such as forest conversion, changes in rotation age, or thinning regimes are feasible options to conserve and preserve ecosystem services and alleviate climate change impacts on forests (Hanewinkel et al., 2013). Active forest management allows managers and landowners to consider several frequently competing objectives (Uhde et al., 2015). This implies that certain forest management practices can increase the production or availability of one or a bundle of ecosystem services, but they can simultaneously harm the provision or availability of other ecosystem services (Kolo et al., 2020; Schwaiger et al., 2019). Mori and Kitagawa (2014), however, claim that sustainable forest management can provide a win-win solution to address trade-offs between ecosystem services and timber production.

The efficient allocation of forest resources (e.g., timber, nontimber forest products, and other ecosystem services) by considering different management objectives has been thoroughly analyzed since the early 1960s, particularly from an optimization perspective (Kaya et al., 2016). Improving the allocation of forest resources by formulating a resource efficiency policy mix, i.e., a rational collection of instruments, across several governance levels, aimed at encouraging the effective and sustainable use of resources in production and consumption systems– is critical to promoting the sustainable use of forest resources in production and consumption (Wilts and O’Brien, 2019). With the growing societal demand for ecosystem services, it is imperative to determine, to the best possible extent, the best management practices that ensure an efficient allocation of such services.

Non-parametric approaches developed to estimate production efficiency such as data envelopment analysis (DEA, Charnes et al., 1978) have been applied to evaluate natural resource allocation (Gutiérrez and Lozano, 2022; Masuda, 2016; Whittaker et al., 2015). DEA is a mathematical optimization method that determines the production technology frontier, identifies those production units that perform efficiently, and allows comparison of each unit's performance relative to the identified efficient units (Cooper et al., 2006). DEA is a data-driven methodology that only requires the observed input and output data, i.e., the amounts of resources consumed by each unit and the amounts of products it produced. From the data, the production possibility set (also known as the DEA technology) is determined. This production possibility set contains all the operating points that are deemed feasible, i.e., the possible combinations of outputs can be produced given the existing inputs. An operating point is said to be inefficient if there exists a feasible operating point that can produce the same amount (or more) of outputs consuming less resources, or if it can produce more outputs consuming the same amount (or less) of inputs. The efficiency score of an operating point measures these potential input and output improvements. If no improvements are feasible then the observed operating point is technically[1] efficient.

In addition to the technical efficiency, and provided that data on the unit costs and prices of the different inputs and outputs are known, the profit efficiency of any observation can also be determined. Profit efficiency can be defined as the ratio of the profit associated with the observed operating point to the maximum profit that can be attained considering the

[1] The term technical refers to the DEA technology, i.e., the production possibility set, which implicitly defines what is technically possible in terms of what can be produced with any given amount of resources. Mathematically, the non-dominated subset of the production possibility set is the efficient frontier and contains all the technical efficient operating points.

whole production possibility set. For example, an 80% profit efficiency means that the profit generated by the observed operating point is 80% of that of the maximum profit operating point. The difference between profit efficiency and technical efficiency is called allocative efficiency[2].

The main objective of our paper is to determine, using DEA, the profit and technical efficiency of longleaf pine (*Pinus palustris*. Mill) forest ecosystems in the production of ecosystem services, in the southeastern United States. We specifically examine carbon sequestration, water production, tree species richness, and timber production. The present study contributes to the scientific literature on the provision of forest ecosystem services by using a weighted additive DEA model and decomposing profit efficiency into technical and allocative efficiency, and as a secondary step in our model, by analyzing the statistical significance of the factors that impact efficiency. Furthermore, the study sheds light on forest management practices that can improve the provision of forest ecosystem services from an efficiency perspective in the region.

We have selected longleaf pine – using plot-level Forest Inventory and Analysis (FIA) data from the USDA Forest Service (US Department of Agriculture Forest Service, 2021)– due to the relevance of this forest species in the provision of ecosystem services in the Southeastern United States. Longleaf pine is the core of the North American Coastal Plain,

[2] It is possible, indeed common in practice, that an observed operating point is technically efficient but not profitably efficient. In that case, although it is not possible for the corresponding production unit to increase its outputs without increasing its inputs also (i.e., technical efficiency), it is nonetheless possible to increase its profit by allocating inputs and outputs differently (i.e., allocative inefficient). Therefore, a profitably efficient observation needs to be both technically and allocatively efficient.

the World's 36th Biodiversity Hotspot (Noss, 2016). Furthermore, longleaf pine forests sequester more carbon and are home to higher levels of wildlife compared to other southern pines such as loblolly pine (Kirkman et al., 2013; Samuelson et al., 2014).

2. Literature review

Efficiency analysis in the forest sector generally involves two quantitative methods: the parametric stochastic frontier analysis (SFA)[3] and the non-parametric data envelopment analysis (DEA). SFA was proposed about the same time as DEA (Aigner et al., 1977) and its main strength is the stochastic treatment of the deviations from the frontier– deviations which are decomposed into a non-negative inefficiency term and a random noise term. However, SFA has not been as widely used as DEA. The reasons for this may be that, as indicated by Olesen and Petersen (2016), the restrictive assumptions generally employed in SFA on the functional form and the distribution characteristics of the inefficiency term, may in some cases, involve an unacceptable functional structure of the stochastic frontier that will potentially violate the purpose of the efficiency analysis. In spite of the deterministic

[3] Although SFA has been traditionally considered a parametric approach, non-parametric versions of SFA have been developed to handle multiple inputs and outputs, thereby avoiding endogeneity problems (Simar and Wilson, 2022). Non-parametric SFA also helps tackle issues related to the assumptions of the parametric functional form and the stochastic specifications of the error component (Kumbhakar et al., 2007).

character of DEA–all deviations from the frontier are attributed to inefficiency, ignoring the presence of noise in the data–its non-parametric nature as well as its ability to include multiple outputs become major arguments that justify its use for efficiency analysis as proposed in this analysis.

Salehirad and Sowlati (2005), Sowlati (2005), Gutiérrez and Lozano (2022), and Strange (2021), provided a comparative literature review of SFA and DEA studies in forestry from 1991 to December 2020. The reader is referred to those articles for an in-depth review of forest efficiency studies up to 2020. This literature review demonstrates that DEA has been used in most forestry efficiency related studies. This is likely due to its lack of a specific functional form a priori based on probabilistic distribution, its ability to integrate multiple inputs, outputs, and production technologies using a simple mathematical programming approach, and its ability to handle different types of variables (e.g., non-discretionary variables, undesirable outputs, dual role factors), even in the presence of uncertainty). The vast majority of studies have focused particularly on the wood-based products industry, followed by forest management analyses, while only a small number of studies are dedicated to forest operations (Aalmo et al., 2021; Obi and Visser, 2017a, 2017b, 2018, 2020).

Since December 2020, several efficiency-based studies have been published on forest management and primary forest products. For example, Chen and Yao (2021) explored the forestry ecological efficiency using the Malmquist productivity index[4] and the super

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[4] The Malmquist productivity index (Färe et al., 1994) is a method to gauge the productivity change of a production unit between two periods and it can be decomposed into an efficiency change term and a technology change term, i.e., from one period to the next, the unit may have increased or decreased its efficiency and the efficient frontier of one period may have shifted reflecting progress or regress in the corresponding DEA technology.

efficiency SBM model[5] in 31 Chinese provinces from 2014 to 2018. They found spatial differentiation between regions, highlighting efficiency improvements in the southern coastal regions. From the perspective of the wood industry, Banaś et al. (2021) and Krišt'áková et al. (2021) used input-oriented[6] (timber production) and output-oriented (lumber and wood panels) DEA models in Poland (1990-2019) and Bulgaria versus Slovakia (8 enterprises, 2014-2018), respectively. Susaeta and Rossato (2021) analyzed the efficiency of the Brazilian pulp and paper industry (8 enterprises, 2016) in the production of pulp and bioelectricity using an output-oriented radial[7] model. They adjusted the efficiency score using a synthetic indicator, and a truncated linear regression model was conducted to examine the effects of external and related industry factors on the adjusted efficiency score. Lundmark et al. (2021) evaluated improvements in forest bioenergy production efficiency of Sweden's harvesting products (20 counties, 2008-2014), combining a network DEA model (i.e., the production units consist of different subprocesses, each of which has its own inputs and outputs, and

[5] The super efficiency SBM model (Tone, 2002) is a non-oriented DEA model – a model that tries to simultaneously reduce inputs and increase outputs as opposed to input-oriented or output-oriented– that allows to rank the technical efficient units by assigning them efficiency scores that can be larger than one–hence the term super-efficiency.

[6] While non-oriented approaches aim at simultaneously reducing inputs and increasing outputs, input-oriented models prioritize input reduction over output increase. Similarly, output-oriented models prioritize output increase over input reduction.

[7] An output-oriented DEA model uses a radial metric if it expands the outputs uniformly, i.e., increasing all outputs by the same multiplicative factor. Similarly, an input-oriented DEA model uses a radial metric if it contracts the inputs uniformly, i.e., reducing all inputs by the same multiplicative factor (Cooper et al., 2006).

there exist also intermediate products produced and consumed within the system) to estimate harvesting volumes and a partial equilibrium forest sector model to estimate price effects. They found that inefficiencies in forest management translate into higher prices of forest products and a reduction in other ecosystems services.

DEA has also been applied to new areas of interest by, for example, assessing the performance of tourist forests (Li et al., 2021) and of forest ecosystems (Mizuta et al., 2022; Pukkala, 2016; Shepard et al., 2021; Toma et al., 2020). However, few DEA studies have addressed the efficiency of pine forests in the provision of ecosystem services. In the case of the southeastern US, Susaeta et al. (2016a) analyzed the efficiency of loblolly pine forests in the provision of timber, sequestered carbon, and tree species richness under changing climatic conditions. Susaeta et al. (2016b) extended this previous analysis by decomposing efficiency into allocative and profit efficiency. Mizuta et al. (2021) measured the efficiency of soil carbon sequestration in various land uses, including pinelands. Shepard et al. (2021) analyzed the economic and technical efficiency of loblolly pine in timber production considering different levels of fertilization and evidence of drought in Oklahoma. Mizuta et al. (2022) assessed the efficiency in above net primary productivity of loblolly pine in the region.

In this study, the DEA analysis presents a new perspective on the efficiency of forest-based ecosystem services production that distinguishes it from previous studies by Susaeta et al. (2016a, 2016b) in several ways. Notably, our analysis incorporates water supply as an essential ecosystem service provided by forests. Additionally, we broaden the scope of our efficiency analysis beyond Florida to encompass multiple states in the southeastern US. Furthermore, we conduct a parametric analysis to examine the factors that impact both technical and profit efficiency in the production of ecosystem services. By adopting a more comprehensive approach and accounting for multiple determinants of efficiency, the current study provides a deeper understanding of the intricate dynamics involved in forest-based ecosystem services production.

3. Proposed methodology and data

The decision-making unit (DMU) is the basic unit of analysis in DEA. Each DMU requires the same inputs to generate the same outputs. DEA uses the input and output variables to assess the efficiency in each DMU. Both inputs and outputs are viewed as either discretionary (i.e., they can be affected by management decisions) or non-discretionary (i.e., they cannot be affected by management decisions). We propose to assess the efficiency in the production of forest ecosystem services using a two-stage approach. In the first stage, we conduct DEA using FIA outputs and inputs from the FIA program to estimate the technical and profit inefficiency of forests in the provision of forest ecosystem services. In the second stage, we use exogenous variables also from the FIA program to identify the factors that affect the technical inefficiency.

3.1. Stage 1: Efficiency assessment

In this analysis, the DMU is the longleaf pine plot surveyed by the Forest Inventory and Analysis database (US Department of Agriculture Forest Service, 2021). Each forest plot consists of four 7.3-meter radius subplot (0.015 ha) on which trees > 13.0 in diameter are measured (Burrill et al., 2021). This database contains information on 2,282 forest plots (61% and 39% under private and public ownership, respectively) located in the states of Alabama (AL), Florida (FL), Georgia (GA), Mississippi (MS), North Carolina (NC), and South Carolina (SC) and covers a period from 1977 to 2015 (Figure 1).

Insert Figure 1 here

Following the Common International Classification for Ecosystem Services (CICES V5.1) framework (Haines-Young and Potschin-Young, 2018), we assume that each forest plot produces biotic and abiotic provisioning outputs (timber production and water production), and biotic and abiotic regulating and maintaining outputs (tree biodiversity and carbon sequestration). These forest ecosystem services play a critical role in the region. Southern forests provide a net volume of growing stock of around 4 billion cubic meters (Oswalt et al., 2019). State and private forests annually contribute to approximately 32% of the total southern surface water supply serving around 19 million people; national forests contribute to around 3.4% of the total surface water supply serving around 19 million people (Caldwell et al., 2014) In terms of tree biodiversity, southern forests are home to more than more than 12 forest types, with the most representative being loblolly-shortleaf pine and oak-hickory. Annuals timber removals of these forest types are approximately 97 and 66 million of cubic meters, respectively (Oswalt et al., 2019). Southern forests contain about 12.3 billion tons of carbon, which represent around 30% of the nation's carbon stock (Huggett et al., 2013; Johnsen et al., 2014)

With the exception of water production, all the other outputs were obtained from the FIA program, and under the following assumptions (Burrill et al., 2021): we consider the merchantable volume of timber with a minimum 10.2 cm top diameter for timber production; we consider the total carbon stored belowground and aboveground divided by the age of the forest plot to estimate carbon sequestration, and; we use tree species richness- the number of different tree species in a given area (forest plot)- as a proxy for tree biodiversity. Tree biodiversity is a wide-ranging concept encompassing the biological diversity of trees, and can span various dimensions such as genetic, functional, and landscape diversity. Quantifying these diverse forms of biodiversity at a larger scale can often be challenging (Costanza et al., 2007). We acknowledge that this metric only represents once facet of biodiversity. However, tree species richness is widely employed as an indicator of tree biodiversity and is thought to favor forest productivity and carbon storage (Gamfeldt et al., 2013; Jeffries et al., 2010), and also water flow regulation (Bremer and Farley, 2010).The water supply for each forest plot was obtained using the relationship between water supply and the leaf area index (*LAI*, procured from the FIA program) developed by McLaughlin et al. (2013):

$$Water=[1-(0.06LAI+0.54)]P \quad (1)$$

where P is the mean annual precipitation.

We consider the following inputs variables that are thought to impact the production of outputs: site productivity, tree density, forest plot age, total annual precipitation, and average annual minimum and maximum temperatures. Site productivity reflects the potential growth of the forest, and it is determined by soil quality and climatic conditions (Landsberg and Sands, 2011). High productivity sites can increase the use of water by forest therefore reducing the water supply (Sun et al., 2015). Tree density, which reflects the number of trees per hectare, is expected to favor tree biomass but it might lead to more consumption of water (Sun et al., 2015). All the input variables, except for the climatic variables, were obtained from the FIA program (Burrill et al., 2021). Historical annual precipitation and average annual temperatures for each forest plot were measured at the time of FIA observation, i.e., in the year when the forest plot was recorded. These measurements were obtained from the Multivariate Adaptive Constructed Analogs (MACA) that contains the global climate model's dataset to obtain estimates of temperatures and precipitation (Abatzoglou and Brown, 2012). Table 1 lists all the discretionary and nondiscretionary inputs and outputs in this study, as well as some summary statistics of these variables.

Table 1 here

The Global Moran's I statistic and the Geary's C statistic for spatial autocorrelation are statistically significant for all inputs and outputs (Table 1), with the exception of Geary's C statistic for carbon sequestration. This indicates a positive spatial autocorrelation between input/output values for the tested plots; that is the spatial distribution of high and/or low values in the dataset is more spatially clustered than would be expected if the underlying spatial processes were random.

The proposed DEA approach consists of using two DEA models: one to assess the technical inefficiency (TI) of each DMU, and the other to assess its profit inefficiency (PI). The TI DEA model is based on the Slacks-based inefficiency (SBI) approach of Fukuyama and Weber (2009) and maximizes a weighted sum of the input and output slacks[8]. The PI DEA model uses input unit costs and output unit prices, projecting each DMU onto its corresponding profit maximizing operation point. The PI decomposition proposed by Cooper et al. (2011) is used to relate PI and TI, deriving the corresponding residual allocative inefficiency (AI)[9].

3.1.1 Technical inefficiency (TI)

Let

j=1,2,...,n index on forest plots

[8] The input and output slacks are the amounts that the inputs and outputs can be reduced and increased, respectively. They therefore represent the potential efficiency improvements along the different dimensions.

[9] The allocative inefficiency is computed as the difference between PI and TI and represents the amount of profit inefficiency that is not due to technical inefficiency, but to a misallocation of the inputs consumed and the outputs produced.

$PRECIP_j$ Total Annual Precipitation for DMU j

$PROD_j$ Site productivity for DMU j

$MINTEMP_j$ Average annual minimum temperature for DMU j

$MAXTEMP_j$ Average annual maximum temperature for DMU j

$PLOTAGE_j$ Plot age of DMU j

$TREE_j$ Tree density of DMU j

$RICH_j$ Tree richness of DMU j

$TIMBER_j$ Timber Production of DMU j

$CARBON_j$ Carbon sequestered by DMU j

$WATER_j$ Water supply from DMU j

0 Index of the DMU whose efficiency is assessed

$(g_{TREE}, g_{TIMBER}, g_{CARBON}, g_{WATER})$ Directional vector (used for normalizing slacks)

<u>Variables</u>

$(\lambda_1, \lambda_2, ..., \lambda_n)$ Intensity variables used to compute the convex linear combination of the observed DMUs

$slack_{TREE}$ Potential improvement in Tree density of DMU 0

$slack_{TIMBER}$ Potential improvement in Timber Production of DMU 0

$slack_{CARBON}$ Potential improvement in Carbon sequestered by DMU 0

$slack_{WATER}$ Potential improvement in Water supply from DMU 0

TI_0 Technical inefficiency score of DMU 0

The following Variable Returns to Scale (VRS) SBI model is proposed:

$$TI_0 = Max \quad \frac{1}{4} \cdot \left(\frac{slack_{TREE}}{g_{TREE}} + \frac{slack_{TIMBER}}{g_{TIMBER}} + \frac{slack_{CARBON}}{g_{CARBON}} + \frac{slack_{WATER}}{g_{WATER}} \right) \tag{2}$$

Subject to

$$\sum_{j=1}^{n} \lambda_j PRECIP_j \leq PRECIP_0 \tag{3a}$$

$$\sum_{j=1}^{n} \lambda_j SITEPROD_j \leq SITEPROD_0 \tag{3b}$$

$$\sum_{j=1}^{n} \lambda_j MINTEMP_j \leq MINTEMP_0 \tag{3c}$$

$$\sum_{j=1}^{n} \lambda_j MAXTEMP_j \leq MAXTEMP_0 \tag{3d}$$

$$\sum_{j=1}^{n} \lambda_j PLOTAGE_j \leq PLOTAGE_0 \tag{3e}$$

$$\sum_{j=1}^{n} \lambda_j TREE_j = TREE_0 - slack_{TREE} \tag{3f}$$

$$\sum_{j=1}^{n} \lambda_j RICH_j \geq RICH_0 \tag{3g}$$

$$\sum_{j=1}^{n} \lambda_j TIMBER_j = TIMBER_0 + slack_{TIMBER} \tag{3h}$$

$$\sum_{j=1}^{n} \lambda_j CARBON_j = CARBON_0 + slack_{CARBON} \tag{3i}$$

$$\sum_{j=1}^{n} \lambda_j WATER_j = WATER_0 + slack_{WATER} \tag{3j}$$

$$\sum_{j=1}^{n} \lambda_j = 1 \tag{3k}$$

$$\lambda_j \geq 0 \ \forall j \qquad slack_{TREE}, slack_{TIMBER}, slack_{CARBON}, slack_{WATER} \geq 0 \tag{3l}$$

It should be noted that the components of the directional vector g that are used in the objective function (2) to normalize the slack variables (and make them dimensionless) implicitly weigh those slacks. In that sense, their respective values can reflect the preference and priorities of the corresponding stakeholders. Like all DEA models, the above TI model projects DMU 0 onto a dominating target operating point, one that consumes fewer resources and generates more outputs. The objective function maximizes the sum of these potential enhancements, referred to as 'slacks' in DEA terminology. These input and output slacks are normalized using the directional vector components. The target operating point is calculated as a convex linear combination of the observed DMUs, with the coefficients of the linear combination λ_j serving as non-negative variables. The resulting target operating point is inherently technically efficient, implying no further improvements are possible. In fact, if DMU 0 itself were technically efficient, no improvements would be attainable, and the DMU would project onto itself. Note that the non-discretionary variables are handled as per Banker and Morey (1986)[10].

3.1.1 Profit inefficiency (PI)

The maximum profit DEA model is similar to the TI model above just substituting the objective function (2) by

$$\begin{aligned}\pi_0 = Max \quad & p_{TIMBER} \cdot TIMBER + p_{CARBON} \cdot CARBON + p_{WATER} \cdot WATER \\ & - q_{TREE} \cdot TREE\end{aligned} \tag{4}$$

and also substituting these other constraints

$$TREE = \sum_{j=1}^{n} \lambda_j TREE_j \tag{5a}$$

$$TIMBER = \sum_{j=1}^{n} \lambda_j TIMBER_j \tag{5b}$$

$$CARBON = \sum_{j=1}^{n} \lambda_j CARBON_j \tag{5c}$$

$$WATER = \sum_{j=1}^{n} \lambda_j WATER_j \tag{5d}$$

[10] Since they are outside management's control, non-discretionary variables cannot be treated as discretionary ones. Thus, they do not have an associated slack variable and they appear neither in the objective function of the technical inefficiency model nor in the objective function of the profit maximization model.

where $p_{TIMBER}, p_{CARBON}, p_{WATER}$ are the unit price of the three discretionary outputs, q_{TREE} is the unit price of the only discretionary input, π_0 is the maximum profit that DMU 0 could obtain, provided it operates as indicated by the optimal value of the variables *TREE*, *TIMBER*, *CARBON* and *WATER*.

The PI model described above calculates a target operating point that maximizes profit, determined using input and output prices. Just like in the TI model, this target operating point is computed as a convex linear combination of observed DMUs, ensuring technical efficiency. Unlike the TI model, it is not a requirement for the target operating point to dominate DMU 0. Interestingly, the technically efficient target derived from the TI model is feasible in the PI model, though not necessarily optimal. The corresponding profit might not be the maximum achievable.

Following Cooper et al. (2011), the PI of DMU 0 can be computed as

$$PI_0 = \frac{\pi_0 - \left(p_{TIMBER} \cdot TIMBER_0 + p_{CARBON} \cdot CARBON_0 + p_{WATER} \cdot WATER_0 - q_{TREE} \cdot TREE_0\right)}{4 \cdot min\left\{q_{TREE} \cdot g_{TREE}, p_{TIMBER} \cdot g_{TIMBER}, p_{CARBON} \cdot g_{CARBON}, p_{WATER} \cdot g_{WATER}\right\}} \qquad (6)$$

and can be expressed as

$$PI_0 = TI_0 + AI_0 \qquad (7)$$

where the residual term AI_0 represents the Allocative Inefficiency of DMU 0, i.e., the part of the profit inefficiency that is not due to technical inefficiency but to an inadequate input and output mix that does not respond to the input and output prices faced by the DMU.

In order to estimate PI, we assumed a value of \$28 per m^3 of timber (Timber Mart South, 2022). For carbon sequestration, we used a value of \$18 per metric ton of carbon (Forest Trends' Ecosystem Marketplace, 2021). In the case of water yield, we used the cost of pumping groundwater for the upper Floridian aquifer, \$0.07 per mm, as a proxy for the price of water (Florida Department of Environmental Protection 2015). A unit price for species richness was ruled out since this variable is a non-discretionary output.

The input costs were calculated as the management costs of growing longleaf pine trees. Management costs ($ per ha) were calculated as a function of the silvicultural treatments performed on each single plot. The silvicultural treatments defined in the FIA program were absence of management, site preparation ($324 per ha), artificial regeneration ($166 per ha), natural regeneration ($83 per ha), and fertilizer application ($311 per ha) (Maggard, 2021). Only one of the silvicultural treatments described above was carried out for each plot, and these treatments occurred at the time the plots were recorded. Furthermore, we calculated the cost of establishing trees at age zero for each plot– a proxy for the present planting/regeneration costs–by assuming a value of $0.13 per tree (Maggard, 2021), considering an annual mortality rate of 5% and the age of the plot.

3.2. Stage 2: Robust multiple linear regression analysis

The second stage carries out a regression analysis of those inefficiency scores with the objective of identifying exogenous variables that have an effect on the inefficiency of the DMU. As such, our objective is to determine which external factors are significantly related to the average TI of longleaf pine forest ecosystems; specifically, those that are considered as descriptive measures of the relative performance plots in the sample.

Additionally, two non-parametric statistical significance hypothesis tests were conducted. First, the one-sample Wilcoxon signed-rank test (Gibbon, 1971) was employed to compare the average technical inefficiency versus allocative inefficiency across several exogenous variables. Second, a pairwise multiple-comparison Dunn's test (Dunn, 1964) was utilized, with corrections made using the Benjamini-Hochberg multiple-comparison adjustment (Benjamini and Hochberg, 1995), to identify similarities among exogenous variables.

Because the TI scores do not take values in the unit interval and TI scores naturally contain outliers and high leverage points, this robust approach, even when the observations deviate from the assumptions of the model, is appropriate to increase the reliability and accuracy of statistical modeling (Maronna et al., 2006). The specification of the multiple linear regression model is as follows:

$$TI_j = \beta_0 + \sum_{k=1}^{5} \beta_k STATE_{jk} + \sum_{l=6}^{10} \beta_l MANAGEMENT_{jl} + \beta_{11} OWNERSHIP_j + \beta_{12} DISTURB_j + \beta_{13} ZTIME_j + u_j,\ \ j=1, \ldots n \tag{8}$$

where STATE represents the location of the forest plots in the different states, MANAGEMENT reflects the evidence of the following types of management per forest plot: cutting, site preparation, artificial regeneration, natural regeneration, fertilizer application, and absence of management; OWNERSHIP represents if the forest plot is under private or public ownership; DISTURB reflects whether the plot shows any level of damage cause by disturbances such as wildfires, storms, floods, drought, diseases, insects or animals, and; ZTIME is a standardized continuous variable that represents the time of the FIA observation associated to the forest plot. β represents the coefficients to be estimated and u is the error associated with each forest plot. Table 1 shows the summary statistics of the variables employed in this model. The multiple linear regression analysis is performed using R code (Maechler et al., 2022), using an extension of the maximum likelihood method (M-estimation), which is robust to the presence of outliers and feasible with both continuous and categorical exogenous variables. Finally, in addition to the present DEA study, we also employ stochastic frontier analysis to determine technical and profit efficiency (SFA, Section A.1 and A.2, Appendix A), providing a complementary perspective on our findings.

4. Results

4.1. Efficiency assessment

Most of the forest plots were not efficient in the production of ecosystem services. In the case of TI, we can see that the majority of the forest plots were in the range of 1.90-3.81, with the exception of those plots located in western FL and south AL-MS, which showed higher TI values (3.81-5.71)[11] (Figure 2). Since the component of the directional vector g used for normalizing the input and output slacks corresponds to the average of the observed values, this means that for most forest plots, the total enhancement in the provision of timber, water, carbon sequestration, and tree density could amount to 190-381% of the average plot. Opposite results were found when using SFA, with an average of only 3.3% of the production of ecosystem services lost to due to technical inefficiency (Table B.1, Appendix B)

Insert Figure 2

In general, longleaf pine plots were more technically inefficient in private ownership, with an absence of disturbances and with evidence of natural regeneration (Figure 3). However, from an allocative perspective, plots in public ownership, with presence of disturbances and with evidence of cutting, were more inefficient (Figure 3). From a profitability perspective, the majority of the longleaf plots were highly inefficient, within the PI range of 19.36-29.04, except for some plots located predominantly in GA, SC and NC, which showed lower PI estimates (Figure 2). The relatively high values of PI obtained, much higher than the corresponding TI values, indicated, according to equation (7), that there is

[11] Note that while the absolute value of the TI scores depends on the specific values of the components of the directional vector (which function as normalization coefficients), their labelling as low or high above is qualitive (subjective) and based on their relative values.

significant profit inefficiency and that it mainly has an allocative character more than a technical origin. SFA estimates supported these findings, indicating that forest plots are highly inefficient in terms of profitability. The estimated SFA profit inefficiency was 1.48 (148%) suggesting that most of the profit inefficiency is due to allocative reasons (Table B.2, Appendix B).

There is evidence that medians of TI (private versus public), AI (private versus public), TI (presence of disturbance-absence of disturbance), AI (presence of disturbance-absence of disturbance), AI (management- absence of management) distributions were statistically different at the 0.001 significance level (Wilcoxon signed-rank test, Figure 3). However, non-differences were shown between management practices with respect to AI. Significant TI differences were observed between "cutting" and each other practices, between "nothing" and "site preparation"/"natural regeneration"/ "artificial regeneration" and between "fertilization" and "site preparation". Significant differences were not detected between the rest of other pairs of management practices (Table 2).

Insert Figure 3 and Insert Table 2

It can be noted that a non-homogeneous pattern arose between states across the management, ownership, and disturbance variables, namely, a right-skewed TI distribution (Fig. 4a-4c), a left-skewed PI distribution (Fig. 5a-5c), and right-skewed and left-skewed AI distribution (Fig. 6a-6c)[12]. Therefore, extreme values far from the median values occurred.

[12] While all these activities are indeed conducted under private ownership (see Fig. 4d), the level of management, in relative terms, appears to be relatively low. Around 34% of the private forest plots demonstrated evidence of forest management. Notably, cutting stands out as the primary activity, accounting for 24% of the forest plots, followed by fertilization

Considerable disparities were evident among the different groups of variables. The state of NC and the treatment with artificial regeneration were the subgroups with low levels of TI/PI values, and where the dispersion of AI was observed.

At the state level, the TI values of all levels of ownership, management, and disturbance were non-homogeneous with the exception of SC (ownership), FL and NC (management), and GA and MS (disturbance). Approximately 75% of forest plots located in AL and MS in private ownership showed a TI value lower than 4.0 (Figure 4a). With the exception of FL, forest plots with evidence of disturbances were technically less inefficient in providing ecosystem services than those without evidence of disturbance (e.g., wildfires, storms, floods, drought, diseases, insects, animals) (Figure 4c). TI between management and ownership variables behaved similarly when cutting was used as treatment by public and private ownership (Figure 4d). Furthermore, TI appeared to be higher in publicly owned plots with evidence of site preparation.

In the case of PI, different patterns also emerged in ownership/management/disturbance by state identifying upper and lower extreme points (Figure 5a, 5b, 5c). NC and SC, however, are states where the extreme values were located in the upper tail of the distributions. The pattern discrepancy was even sharper when the plots showed evidence of natural regeneration, other preparation, and site preparation (Figure 5e) and in the case of ownership (Figure 5f) for all levels of disturbance. Most of the plots showed a PI value greater than 25.0 in the presence of disturbance, with the exception of NC (Figure 5c). Furthermore, disturbances also generated higher levels of PI only in forest plots located

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(3.8%) and artificial regeneration (2.4%). Conversely, site preparation and natural regeneration are scarcely observed under private ownership.

in AL and GA. From an economic perspective, compared to public ownership, roughly 75% of privately owned longleaf plots were less inefficient in the absence of forest management and with evidence of natural regeneration, fertilizer application, and site preparation (Figure 5d). Furthermore, compared to public ownership, natural regeneration, fertilizer application, and site preparation decreased PI levels of PI in privately-owned forest plots.

Insert Figure 4, Figure 5 and Figure 6

4.2. Regression analysis

The global precision of the estimated model is evaluated by calculating the adjusted R^2 and the standard error statistics, indicating a good fit to the proposed model (Table 3). The most important predictor of TI in the provision of ecosystem services was the geographical location of the plots. The estimates of the coefficients were significantly positive in all states with respect to the baseline (SC) indicating that the plots located in SC have lower TI scores, i.e., they are more efficient from a technical point of view. Furthermore, we found that those states farther from SC were technically more inefficient in the production of ecosystem services. For example, the average TI value of the plots in MS was twice higher than the average TI value in SC, which was the largest effect in TI. Furthermore, the smallest difference is observed in NC with an average TI 0.47 higher than that of SC. The negative signs of coefficient of SFA model suggest that forest plots in FL, GA and NC show to be more efficient in the provision of ecosystem services than those located in SC (Table B.1, Appendix B).

The estimate of land ownership revealed that, on average, the TI under private forest ownership is 0.71 higher than under public forest ownership. In addition, the positive coefficient effect of the disturbance variable indicated that forest plots with damage tend to be more inefficient in the provision of ecosystem services. The SFA approach revealed that private forest plots were more inefficient in providing ecosystem services compared to those under public ownership, as indicated by the positive sign of ownership. Conversely, forest plots that have been damaged were less inefficient in the provision of ecosystem services, as implied by the negative sign of disturbance (Table B.1, Appendix B).

Only natural regeneration and the use of other types of management prescriptions such as fertilizers are significant in the model of TI, in both cases increasing the inefficiency in the provision of ecosystem services in longleaf pine plots compared to the absence of forest management. In the case of the SFA, natural regeneration along with artificial regeneration and site preparation also increased inefficiency (Table B.1, Appendix B). The time predictor indicates that the provision of ecosystem services has become more inefficient over time.

Insert Table 3

5. Discussion

The present DEA findings showed that most of the longleaf pine forest plots were technically inefficient in providing ecosystem services. Susaeta et al. (2016a) used a standard output-oriented DEA model to maximize ecosystem services and found similar results for loblolly pine in the region. Their study indicated that approximately 66% of loblolly pine plots were inefficient in providing timber, tree species richness, and carbon sequestration. Our results indicated that the provision of forest ecosystem services could be increased to a larger extent, reflecting a five-fold increase in inefficiency compared to that of loblolly pine. Given the dissimilarity with the SFA findings–most of the forest plots are technically efficient– the present results suggests that careful consideration of the choice of technique is critical while conducting efficiency analyses. As such, the interpretation of our findings should be done with a certain a degree of caution considering the difference in the methods and their underlying assumptions[13].

Similar to Susaeta et al. (2016b), who employed an additive DEA model that allows simultaneous maximization of outputs and minimization of inputs, our results also indicated that profit inefficiency was mainly attributed to allocative components. This finding was also supported by the SFA results. This suggests that by minimizing costs, profit efficiency in the provision of ecosystem services could be improved. Minimizing costs can be achieved in longleaf pine forest systems by using minimum management interventions such as weed control and the use of prescribed fires (Jose et al., 2007).

Our findings suggested the inefficiency of forest plots in the production of ecosystem services did not follow a consistent pattern per geographical location, evidence of management, and presence of disturbances. This is in line with the complexity and multifunctionality of forests on spatial and time scales, which influence production and trade-offs between ecosystem services (Coffin et al., 2021).

Examining the DEA inefficiency scores, disturbances reduced the technical inefficiency of longleaf pine plots in the provision of ecosystem services. In the regression analysis, however, which in this respect performs a more reliable assessment since it considers the effects of other exogenous variables, the disturbance contributed to the increase in technical inefficiency. On the other hand, SFA findings suggested the opposite. From an

[13] It is common to observe a lack of consistency between DEA and SFA results, even when using the same variables and data, as noted by Jacobs et al. (2009). The main reasons for these differences are attributed to how the techniques establish and shape the efficiency frontier, and to how the techniques determine the distance of individual observations from the frontier (Jacobs et al., 2009).

empirical perspective, although disturbances may result in forest cover loss, compromising the ability of forests to provide ecosystem services (Sanchez et al., 2021), other studies have shown that disturbances could benefit some ecosystem services such as species diversity (Thom and Seidl, 2016).

Given the above comments and considering different management objectives, forest landowners could adopt certain management practices that can, to some extent, keep a balanced or improve the efficiency in the provision of ecosystem services. Managing disturbance regimes (salvage logging and prescribed burning) at a low cost, e.g., with a low or medium frequency, might benefit biodiversity and have a limited impact on carbon storage (Thom and Seidl, 2015). Landowners could also mimic disturbances to favor biodiversity by creating canopy gaps (Kern et al., 2014). The choice of rotation period (Loisel, 2014) and the adoption of harvesting patterns to disturbance risk (Byrne and Mitchell, 2013) are viable strategies to avoid disturbance-related losses and balance disturbance risk and economic benefits regarding timber production.

From a technical perspective, privately owned longleaf pine forest plots were more inefficient than publicly owned longleaf pine forest plots in the provision of ecosystem services. Potential reasons for these findings could be that private property imposes challenges to the provision of ecosystem services, such as legal property rights (Miksa et al., 2020), and the historical lack of interest from forest landowners in conserving ecosystems services (Davidson, 2014). However, from an allocative perspective, we found the opposite. Typically, public ownership is thought to be less efficient due to unbalanced political resource allocation reflected by a lack of resource capacity of forest management agencies, such as budgetary and personnel constraints (Deacon, 1999; Repetto and Gillis, 1998). Despite this advantage of private management, the provision of ecosystem services might be lost considering the dynamics of forest ownership. Thus, financial incentives and conservation easements are critical to retain private forest ownership and maintain environmental benefits (Siry et al., 2010). This is particularly relevant for longleaf pine, whose establishment–more than 80% annual establishment by area–occurs mainly on private land (America's Longleaf, 2020).

Natural regeneration showed a decline in the efficiency of ecosystem services. Although natural regeneration has been considered a cost-effective mechanism (Chazdon and Uriarte, 2016), longleaf pine forests often require site preparation for their successful establishment and provision of environmental benefits, specifically in those sites with a history of fire exclusion and heavy competition from woody plants (Brockway et al., 2006).

6. Conclusions

We utilized FIA data to employ DEA to determine the technical, allocative, and profit efficiency in longleaf pine forest plots in tree species richness, water, carbon sequestration, and the production of timber. Our findings indicated that the longleaf pine forest plots were technically and profitably inefficient in the production of ecosystem services. Profit inefficiency was mainly caused by allocative factors. Furthermore, DEA results indicated that the presence of forest disturbances and private ownership resulted in a decrease in technical efficiency in the provision of ecosystem services. However, given the implications of forest disturbances for technical inefficiency according to the regression results and the different landowners' goals, forest management interventions that aim to mimic or mitigate the effects of forest disturbances should ensure a sound provision of ecosystem services. Additionally, from an allocative perspective, public-owned longleaf pine plots were more inefficient when providing ecosystem services, compared to privately owned longleaf pine plots.

The current research can be extended in several ways. Although we selected a specific area of study due to the ecological significance of longleaf pine forests in the southeastern

US, our analysis could be replicated in other areas in the US, and also in the world. Furthermore, it would be interesting to carry out a SFA study to compare it with the results obtained in our analysis. The combined use of DEA and parametric approaches analysis could provide more fruitful management implications for the restoration of longleaf pine forests in the region. We have assumed in our analysis the same weight for the different outputs. As such, the results from this study correspond to a specific selection of the directional vector, one that could be labelled as neutral. It would be interesting, however, to approach the problem from the point of view of the different stakeholders, appropriately modifying the directional vector (outputs with different weights) to reflect their preferences and comparing the targets computed in each case. The use of different types of proxies for biodiversity or indicators of wildlife could provide more insight to determine feasible management prescriptions that ensure a sustainable flow of ecosystem services. The use of spatial analysis to determine the level of relationships in the production of ecosystem services between longleaf pine forests located in different geographical locations is also a subject of further research.

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References

Aalmo, G.O., Kerstens, P.J., Belbo, H., Bogetoft, P., Talbot, B., Strange, N., 2021. Efficiency drivers in harvesting operations in mixed Boreal stands: a Norwegian case study. Int. J. For. Eng. 32, 74–86.

Abatzoglou, J., Brown, T., 2012. A comparison of statistical downscaling methods suited for wildfire applications. Int. J. Climatol. 32, 772 – 780.

Abt, K., 2013. Employment and Income trends and projections for forest-based sectors in the U.S. South, in: Wear, D.N., Greis, J. (Eds.), The Southern Forest Futures Project: Technical Report. U.S. Department of Agriculture Forest Service, General Technical Report SRS-178. Asheville, NC, pp. 293–308.

Aigner, D.J., Lovell, C.A.K., Schmidt, P. 1977. Formulation and estimation of stochastic frontier production function models. J. Econ., 6, 21–37.

America's Longleaf Restoration Initiative, 2020. 2020 Range wide accomplishment report. https://americaslongleaf.org/media/zelc21dp/2020-alri-accomplishment-report-final.pdf.

Banaś, J., Utnik-Banaś, K., Zi, S., Janeczko, K., 2021. Assessing the technical efficiency of timber production during the transition from a production-oriented management model to a multifunctional one: a case from Poland 1990–2019. Forests 12, 1287.

Banker, R.D., Morey, R., 1986. Efficiency analysis for exogenously fixed inputs and outputs, Oper. Res. 34, 513–521.

Benjamini, Y, Hochberg, Y., 1995. Controlling the false discovery rate: a practical and powerful approach to multiple testing. J. R. Statist Soc. Series B (Methodological), 57, 289-300.

Bremer, L., Farley K., 2010. Does plantation forestry restore biodiversity or create green desert? A synthesis of the effects of land-use transitions on plant species richness. Biodivers. Conserv. 19, 3893–3915.

Brockway, D.G., Outcalt, K.W., Boyer, W.D., 2006. Longleaf pine regeneration ecology and methods, in: Jose, S., Jokela, E.J., Miller, D.L. (Eds.), The Longleaf Pine Ecosystem: Ecology, Silviculture, and Restoration. Springer, New York, pp. 95–133.

Burrill, E., DiTommaso, A., Turner, J., Pugh, S., Christensen, G., Perry, C., Conkling, B., 2021. The Forest inventory and analysis database: database description and user guide for phase 2 (version 9.01). USDA For. Serv. Report. Available at https://www.fia.fs.usda.gov/library/database-documentation/current/ver90/FIADB%20User%20Guide%20P2_9-0-1_final.pdf

Byrne, K. E., Mitchell, S. J., 2013. Testing of WindFIRM/ForestGALES_BC: a hybrid-mechanistic model for predicting windthrow in partially harvested stands. Forestry 86, 185–199.

Caldwell, P., Muldoo, C., Ford-Miniat, C., Cohen, E., Krieger, S., McNulty, S., Bolstad, P., 2014. Quantifying the role of National Forest System lands in providing surface drinking water supply for the southern United States. U.S. Forest Service General Technical Report SRS-197, Asheville, NC, 145 p.

Charnes, A., Cooper, W.W., Rhodes, E., 1978. Measuring the efficiency of decision making units. Eur. J. Oper. Res. 2, 429–444.

Charnes, A., Cooper, W., Lewin, A.Y., Seiford, L.M., 1994. Data Envelopment Analysis: Theory, Methodology and Application. Kluwer, Boston.

Chazdon, R. L., Uriarte. M., 2016. Natural regeneration in the context of large-scale forest and landscape restoration in the tropics. Biotropica 48, 709–715.

Chen, S., Yao, S., 2021. Evaluation of forestry ecological efficiency: a spatiotemporal empirical study based on China's provinces. *Forests* 12, 142.

Coffin, A., Sclater, V., Swain, H., Ponce-Campos, G., Seymour, L., 2021. Ecosystem services in working lands of the Southeastern USA. Front. Sustain. Food Syst. 5, https://doi.org/10.3389/fsufs.2021.541590.

Cooper, W.W., Seiford, L.M., Tone, K., 2006. Introduction to Data Envelopment Analysis and its uses with DEA-Solver Software and References. Springer, New York.

Cooper, W.W., Pastor, J.T., Aparicio, J., Borras, F., 2011. Decomposing profit inefficiency in EA through the weighted additive model. Eur. J. Oper. Res. 212, 411–416.

Costanza, R., Fischer, B., Mulder, K., Liu, S., Cristopher, T., 2007. Biodiversity and ecosystem services: A multi-scale empirical study of the relationship between species richness and net primary production. Econ. Ecol. 61, 478–491.

Davison, M., 2014. Rights to ecosystem services. Environ. Values 23, 465–483.

Deacon, R., 1999. Deforestation and ownership: evidence from historical accounts and contemporary data. Land Econ. 77, 341–35.

Dunn, O. J. ,1964. Multiple comparisons using rank sums. Technometrics 6, 241–252.

Escobedo, F.J., Timilsina, N., 2012. Final report: stewardship ecosystem services survey project. University of Florida, Gainesville, FL. https://www.sfrc.ufl.edu/cfeor/docs/EcosystemServices.FloridaStewardshipReport.Jul2012.pdf.

Färe, R, Grosskopf S, Lovell, C.A.K., 1994. Production Frontiers. Cambridge University Press.

Florida Department of Environmental Protection, 2015. Report on expansion of beneficial use of reclaimed water, stormwater and excess surface water (Senate Bill 536). Florida Department of Environmental Protection Office of Water Policy. Tallahassee, FL. https://floridadep.gov/sites/default/files/SB536%20Final%20Report.pdf.

Forest Trends' Ecosystem Marketplace, 2021. State of Voluntary Carbon Markets 2021. Installment 1: Market in motion. https://www.forest-trends.org/publications/state-of-the-voluntary-carbon-markets-2021.

Fukuyama, H., Weber, W.L., 2009. A directional slacks-based measure of technical inefficiency. Socio-Econ. Plan. Sci. 43, 274–287.

Gamfeldt, L., Snäll, T., Bagchi, R., Jonsson, M., Gustafsson, L., Kjellander, P., Ruiz-Jaen, M.C., Fröberg, M., Stendahl, J., Philipson, C.D., Mikusiński, G., Andersson, E., Westerlund, B., Andrén, H., Moberg, F., Moen, J., Bengtsson, J., 2013. Higher levels of multiple ecosystem services are found in forests with more tree species. Nat. Commun. 4 (1340)

Gibbon, D., 1971). Non Parametric Statistics. McGraw Hill, New York.

Gutiérrez, E., Lozano, S., 2022. Cross-country comparison of the efficiency of the European forest sector and second stage DEA approach. Ann. Oper. Res. 314, 471–496.

Haines-Young, R., Potschin-Young, M., 2018. Revision of the common international classification for ecosystem services (CICES V5. 1): a policy brief. One Ecosyst. 3, e27108.

Han, F.X., Plodinec, M.J., Su, Y., Monts, D.L., Li, Z., 2007. Terrestrial carbon pools in the southeast and south-central United States. Clim. Change 84, 191–202.

Hanewinkel, M., Culmann, D., Schelhaas, M. J., Nabuurs, G. J., Zimmermann, N.E., 2013. Climate change may cause severe loss in the economic value of European forest land. Nat. Clim. Change 3, 203–207.

Hicke, J.A., Lucatello, S., Mortsch, L.D., Dawson, J., Domínguez Aguilar, M., Enquist, C., Gilmore, E., Gutzler, D., Harper, S., Holsman, K., Jewett, E., Kohler, T., Miller, K., 2022. North America, in: Pörtner, H., Roberts, D., Tignor, M., Poloczanska, E., Mintenbeck, K., Alegría, A., Craig, M., Langsdorf, S., Löschke, S., Möller, V., Okem, A., Rama, B. (Eds.), Climate Change 2022: Impacts, Adaptation, and Vulnerability. Contribution of Working Group II to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change, Cambridge University Press, NY.

Hugget, R., Wear, D., Li, H., Coulston, J., Liu, s., 2013. Forecasts of Forest Conditions, in: Wear, D.N., Greis, J. (Eds.), The Southern Forest Futures Project: Technical Report. U.S. Department of Agriculture Forest Service, General Technical Report SRS-178. Asheville, NC, pp. 73–101.

Jacobs, R., Smith, P., Street, A., 2009. A Comparison of SFA and DEA, in: Measuring Efficiency in Health Care: Analytic Techniques and Health Policy. Cambridge University Press, pp. 151–166.

Jeffries, S., Wentworth, H., Lee, A., 2010. Long-term effects of establishment practices on plant communities across successive rotations in a loblolly pine (Pinus taeda) plantation. For. Ecol. Manag. 260, 1549–1556.

Johnsen, K., Keyser, T., Butnor, J., Gonzalez-Benecke, C., Kaczmarek, D., Maier, C., McCarthy, H., Sun, G., 2014. Productivity and carbon sequestration of forests in the southern United States, in: Vose, J., Klepzing, D. (Eds.): Climate change adaption and mitigation management options: a guide for natural resource managers in southern forest ecosystems, CRC Press-Taylor and Francis Group, pp. 193–258.

Jose, S., Jokela, E.J., Miller, D.L., 2007. The Longleaf Pine Ecosystem: Ecology, Silviculture, and Restoration. Springer, New York.

Kaya, A., Bettinger, P., Boston, K., Akbulut, R., Ucar, Z., Siry, J., Merry, K., Cieszewski, C., 2016. Optimisation in forest management. Curr. For. Rep. 2, 1–17.

Kern, C. C., Montgomery, R. A., Reich, P. B., Strong, T. F., 2014. Harvest-created canopy gaps increase species and functional trait diversity of the forest ground-layer community. For. Sci. 60, 335–344.

Kirkman, L.K., Barnett, A., Williams, B.W., Hiers, J.K., Pokswinski, S.M., Mitchell, R.J., 2013. A dynamic reference model: a framework for assessing biodiversity restoration goals in a fire- dependent ecosystem. Ecol. Appl. 23, 1574–1587.

Kolo, H., Kindu, M., Knoke, T., 2020. Optimizing forest management for timber production, carbon sequestration and groundwater recharge. Ecosyst. Serv. 44, 101147.

Krišt'áková, S., Neykov, N., Antov, P., Sedliaˇciková, M., Reh, R., Halalisan, A-F., Hajdúchová, I., 2021. Efficiency of wood-processing enterprises-evaluation based on DEA and MPI: a comparison between Slovakia and Bulgaria for the period 2014–2018. Forests 12, 1026.

Kumbhakar, S., Park, B., Simar, L., Tsionas, E., 2007. Nonparametric stochastic frontiers: a local maximum likelihood approach. J. Econom. 137, 1–27.

Landsberg, J., Sands, P., 2011. Physiological Ecology of Forest Production. American Press, London.

Lecina-Diaz, J., Martinez-Villata, J., Alvarez, A., Banque, M., Birkmann, J., Feldmeyer, D., Vayreda, J., Retana, J., 2021. Characterizing forest vulnerability and risk to climate-change hazards. Front. Ecol. Environ. 19, 126–133.

Li, B., Ma, X., Chen, K., 2021. Eco-efficiency measurement and spatial–temporal evolution of forest tourism. Arab. J. Geosci. 14, 568.

Lockaby, G., Nagy, C., Vose, J., Ford, C., Sun, G., Mcnulty, S.G., Caldwell, P. V., Cohen, E., Moore Myers, J., 2013. Forests and Water, in: Wear, D.N., Greis, J. (Eds.), The Southern

Forest Futures Project: Technical Report. U.S. Department of Agriculture Forest Service, General Technical Report SRS-178. Asheville, NC, pp. 309–339.
Loisel, P., 2014. Impact of storm risk on Faustmann rotation. For. Pol. Econ. 38, 191–198.
Lundmark, R., Lundgren, T., Olofsson, E., Zhou, W., 2021. Meeting challenges in forestry: improving performance and competitiveness. Forests 12, 208.
Maechler M., Rousseeuw P., Croux C., Todorov V., Ruckstuhl A., Salibian-Barrera M., Verbeke T., Koller M., Conceicao E.L., di Palma, M.A., 2022. Robustbase: Basic Robust Statistics. R package version 0.95-0. http://robustbase.r-forge.r-project.org/.
Maggard, A., 2021. Costs and trends of southern forestry practices, 2020. The Alabama Cooperative Extension System. https://www.aces.edu/wp-content/uploads/2021/12/FOR-2115_CostsandTrendsofSouthernForestryPractices2020_121021L-G.pdf.
Maronna, R.A., Douglas Martin, R., Yohai, V.J., 2006. Robust Statistics: Theory and Methods. John Wiley & Sons, NY.
Masuda, K., 2016. Measuring eco-efficiency of wheat production in Japan: a combined application of life cycle assessment and data envelopment analysis. J. Clean. Prod. 125, 373–381.
McLaughlin, D.L., Kaplan, D.A., Cohen, M.J., 2013. Managing forests for increased regional water yield in the southeastern U.S. Coastal Plain. J. Am. Water Resour. Assoc. 49, 953–965.
Miksa, K., Kalinauskas, M., Inacio, M., Gomes, E., Pereira, P., 2020. Ecosystem services and legal protection of private property. Problem or solution? Geogr. Sustain. 1, 173–180.
Mizuta, K., Grunwald, S., Phillips, M.A., Moss, C.B., Bacon, A.R., Cropper, W.P., 2021. Sensitivity assessment of metafrontier data envelopment analysis for soil carbon sequestration efficiency. Ecol. Indic. 125, 107602.
Mizuta, K., Grunwald, S., Bacon, A.R., Cropper, W.P., Phillips, M.A., Moss, C.B., Gonzalez-Benecke, C.A., Markewitz, D., Clingensmith, C.M, Xiong, X., 2022. Holistic aboveground ecological productivity efficiency modeling using data envelopment analysis in the southeastern U.S. Sci. Total Environ. 824, 153802.
Mori, A.S., Kitagawa, R., 2014. Retention forestry as a major paradigm for safeguarding forest biodiversity in productive landscapes: a global meta-analysis. Biol. Conserv. 175, 65–73.
Mori, A.S, Lertzman, K., Gustafsson, L., 2017. Biodiversity and ecosystem services in forest ecosystems: a research agenda for applied forest ecology. J. Appl. Ecol. 54, 12–27.

Noss, R.F., 2016. Announcing the World's 36th biodiversity hotspot: The North American Coastal Plain. https://www.cepf.net/stories/announcing-worlds-36th-biodiversity-hotspot-north-american-coastal-plain.

Obi, O.F., Visser R., 2017a. Influence of the operating environment on the technical efficiency of forest harvesting operations. Int. J. For. Eng. 28, 140–147.

Obi, O.F., Visser R., 2017b. Operational efficiency analysis of New Zealand timber harvesting contractors using data envelopment analysis. Int. J. For. Eng. 28, 85–93.

Obi, O.F., Visser, R., 2018. Including exogenous factors in the evaluation of harvesting crew technical efficiency using a multi-step data envelopment analysis procedure. Croat. Int. J. For. Eng. 39, 153–162.

Obi, O.K, Visser, R., 2020. Estimating the influence of extraction method and processing location on forest harvesting efficiency - a categorical DEA Approach. Eur. J. Oper. Res. 6, 60–67.

Olesen, O.B., Petersen, N.C., 2016. Stochastic data envelopment analysis — A review. Eur. J. Oper. Res. 251, 2–21

Oswalt, S.N., Smith, W.B., Miles, P.D., Pugh, S. A., 2019. Forest Resources of the United States, 2019: A technical document supporting the Forest Service 2020 update of the RPA Assessment. U.S. Department of Agriculture, Forest Service, Gen. Tech. Rep. WO-97. Washington DC, 223 p.

Pukkala, T., 2016. Which type of forest management provides most ecosystem services? For. Ecosyst. 3, 9.

Repetto, R., Gillis, M., 1988. Public Policies and the Misuse of Forest Resources. Cambridge University Press, New York.

Salehirad, N., Sowlati, T., 2005. Performance analysis of primary wood producers in British Columbia using data envelopment analysis. Can. J. For. Res. 35, 285–294.

Schwaiger, F., Poschenrieder, W., Biber, P., Pretzch, H., 2019. Ecosystem service trade-offs for adaptive forest management. Ecosyst. Serv. 39, 100993.

Samuelson, L.J., Stokes, T.A., Butnor, J.R., Johnsen, K., Gonzalez-Benecke, C.A., Anderson, P., Jackson, J., Ferrari, L., Martin, T.A., Cropper, W.P., 2014. Ecosystem carbon stocks in Pinus palustris Mill, Forests. Can. J. For. Res. 44, 476–486.

Sanchez, J., Marcos-Martinez, R., Srivastava, L., Soonsawad, N., 2011. Valuing the impacts of forest disturbances on ecosystem services: An examination of recreation and climate regulation services in U.S. national forests. Trees, Forests and People 5, 100123.

Shepard, N., Joshi O., Susaeta, A., Will, R., 2021. A stand level application of efficiency analysis to understand efficacy of fertilization and thinning with drought in a loblolly pine plantation. For. Ecol. Manag. 482, 118855.

Simar, L., Wilson, P., 2022. Nonparametric, stochastic frontier models with multiple inputs and outputs. J. Bus. Econ. Stat. https://doi.org/10.1080/07350015.2022.2110882.

Siminsky, A., Zambiazi, D., dos Santos, K., Fantini, A., 2021. Dynamics of natural regeneration: implications for landscape restoration in the Atlantic Forest, Brazil. Front. For. Glob. Change 4, 576908.

Siry, J., Cubbage, F., Newman, D., Izlar, R., 2010. Forest ownership and management outcomes in the U.S., in global context. Int. For. Rev. 12, 3848.

Sowlati, T., 2005. Efficiency studies in forestry using data envelopment analysis. For. Prod. 55, 49–57.

Strange, N., Bogetoft, P., Aalmo, G.O., Talbot, B., Holt, A.H., Astrup, R., 2021. Applications of DEA and SFA in benchmarking studies in forestry: state-of-the-art and future directions, Int. J. For. Eng. 32, 87–96.

Susaeta, A., Adams, D.C., Carter, D.R., Dwivedi, P., 2016a. Climate change and ecosystem services output efficiency in southern loblolly pine forests. Environ. Manag. 58, 417–430.

Susaeta, A., Adams, D.C., Carter, D.R., Gonzalez-Benecke, C., Dwivedi, P., 2016b. Technical, allocative, and total profit efficiency of loblolly pine forests under changing climatic conditions. For. Pol. Econ. 72, 106–114.

Susaeta, A., Rossato, F.G., 2021. Efficiency of pulp and paper industry in the production of pulp and bioelectricity in Brazil, For. Pol. Econ. 128, 102484.

Thom, D., Seidl, R., 2016. Natural disturbance impacts on ecosystem services and biodiversity in temperate and boreal forests. Biol. Rev. 760–781.

Timber Mart South, 2022. Timber Mart South market newsletter: annual stumpage prices. University of Georgia Warnell School of Forestry and Natural Resources, Center for Forest Business, and Frank W. Norris Foundation, Athens, GA.

Toma, P., Miglietta P.P., Morrone, D., Porrini, D., 2020. Environmental risks and efficiency performances: The vulnerability of Italian forestry firms, Corp. Soc. Responsib. Environ. Manag, 27, 2793–2803.

Tone, K., 2002. A slacks-based measure of super-efficiency in data envelopment analysis. Eur. J. Oper. Res. 143, 32–41.

Trani Griep, M., Collins, B., 2013. Wildlife and forest communities, in: Wear, D.N., Greis, J. (Eds.), The Southern Forest Futures Project: Technical Report. U.S. Department of

Agriculture Forest Service, General Technical Report SRS-178. Asheville, NC, pp. 341–396.
Uhde, B., Hahn, W., Griess, V., Knoke, T., 2015. Hybrid MCDA methods to integrate multiple ecosystem services in forest management planning: a critical review. Environ. Manag. 56, 373–388.
U.S. Department of Agriculture Forest Service, 2021. Forest Inventory and Analysis National Program. https://www.fia.fs.fed.us/tools-data/index.php.
Whittaker, G., Barnhart, B., Fare, R., Grosskopf, S., 2015. Application of index number theory to the construction of a water quality index: Aggregated nutrient loadings related to the areal extent of hypoxia in the northern Gulf of Mexico. Ecol. Indic. 49, 162–168.
Wilts, H., O'Brien, M., 2019. A policy mix for resource efficiency in the EU: key instruments, challenges and research needs. Ecol. Econ. 155, 59–69.

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Table 1. Summary and statistics of variables employed in the two-stage analysis.

Variable (units)	Mean	Max	Min	Std. Dev.	Global Moran's I statistic (Z_I-score)[c]	Local Geary's C statistic (Z_C-score)[c]
First-stage DEA: inputs and outputs						
Inputs						
Total annual precipitation (mm)[a]	1425.2	2971.5	772.0	281.3	0.12 (27.1)***	0.89 (6.9)***
Site productivity (m3/ha/yr)[a]	4.2	14.0	0.5	1.8	0.10 (21.2)***	0.85 (10.1)***
Average annual minimum temperature (ºC)[a]	13.1	18.6	7.6	1.9	0.33 (69.5)***	0.54 (41.5)***
Average annual maximum temperature (ºC)[a]	26.0	31.0	19.7	1.7	0.34 (72.8)***	0.49 (40.8)***
Plot age (years)[a]	44.2	113.0	1.0	22.8	0.05 (11.8)***	0.96 (3.7)***
Tree density (trees/ha)[b]	633.6	6167.0	4.7	736.3	0.06 (13.9)***	0.94 (2.0)**
Outputs						
Timber production (m^3/ha)[b]	76.0	470.4	0.1	66.7	0.07 (16.1)***	0.95 (2.1)**
Carbon sequestered (C ton/ha/year)[b]	6.7	168.0	0.5	11.0	0.01 (2.6)***	1.01 (-0.2)
Water yield (ton)[b]	5381.1	12531.7	945.2	1,310.9	0.10 (22.3)***	0.91 (5.9)***
Richness (1-10 level)[ae]	2.2	10.0	1.0	0.98[d]	Richness frequency 1 [36%]; 2 [33%]; 3 [16%]; 4 [7%]; 5 [4%]; 6 [2%]; 7 [1%]; 8 [0.3%]; 9 [0.2%]; 10.0 [0.04%)	
Second-stage multiple linear regression: exogenous variables						
OWNERSHIP (1=private; 0=public)	0.69	1	0			
DISTURB (1=disturbance; 0=no disturbance)	0.41	1	0			
STATE						
AL (Alabama)	0.13	1	0			
FL (Florida)	35.8	1	0			

GA (Georgia)	19.2	1	0
MS (Mississippi)	7.5	1	0
NC (North Carolina)	6.7	1	0
SC (South Carolina)	17.6	1	0
MANAGEMENT			
cutting	0.223	1	0
site preparation	0.007	1	0
natural regeneration	0.018	1	0
fertilization	0.048	1	0
no management	0.706	1	0

[a] Non-discretionary; [b] Discretionary; [c] Standard deviation calculated under the assumption of randomization; [d] Index of qualitative variation; [e] The number of different forest species per forest plot ranges from 1 to 10; *** significant at the 0.001 significance level; ** significant at the 0.01 significance level; values between parenthesis represent standard errors.

Table 2. Dunn's statistic (with Benjamini-Hochberg correction for p-values).

	Art. Reg	Cutting	Fert	Nat.reg	Nothing
Cutting	-3.09***	-	-	-	-
Fert	1.98	2.98***	-	-	-
Nat.Reg	-0.6	3.67***	1.91	-	-
Nothing	-2.34***	4.59***	-0.82	-2.53***	-
Site Prep	0.06	3.69***	2.37**	0.75	2.83***

*** significant at the 0.001 significance level; ** significant at the 0.01 significance level.

Table 3. Robust regression results of technical inefficiency.

Variable	Coeff. Estimate (Std. Error)	t-value
AL	1.78 (0.08)	20.83***
FL	1.15 (0.05)	20.38***
GA	1.06 (0.08)	13.27***
MS	2.00 (0.10)	19.14***
NC	0.47 (0.10)	4.38***
OWNERSHIP	0.70 (0.05)	13.36***
DISTURB	0.14 (0.05)	2.64**
Cutting	0.02 (0.06)	0.32
Site Prep.	-0.30 (0.34)	-0.90
Art. Reg	-0.17 (0.38)	-0.45
Nat. Reg	0.50 (0.24)	2.04*
Fertilizer application	0.38 (0.12)	3.05**
ZTIME[b]	0.09 (0.12)	3.29**
Adjusted R^2 = 0.64	Robust RSE[a] =1.26	

Number of observations: 2282; *** significant at the 0.001 significance level; ** significant at the 0.01 significance level; * significant at the 0.05 significance level; [a] Residual Standard Error; [b]ZTIME is a standardized variable and represents the time of the FIA observation associated to the forest plot.

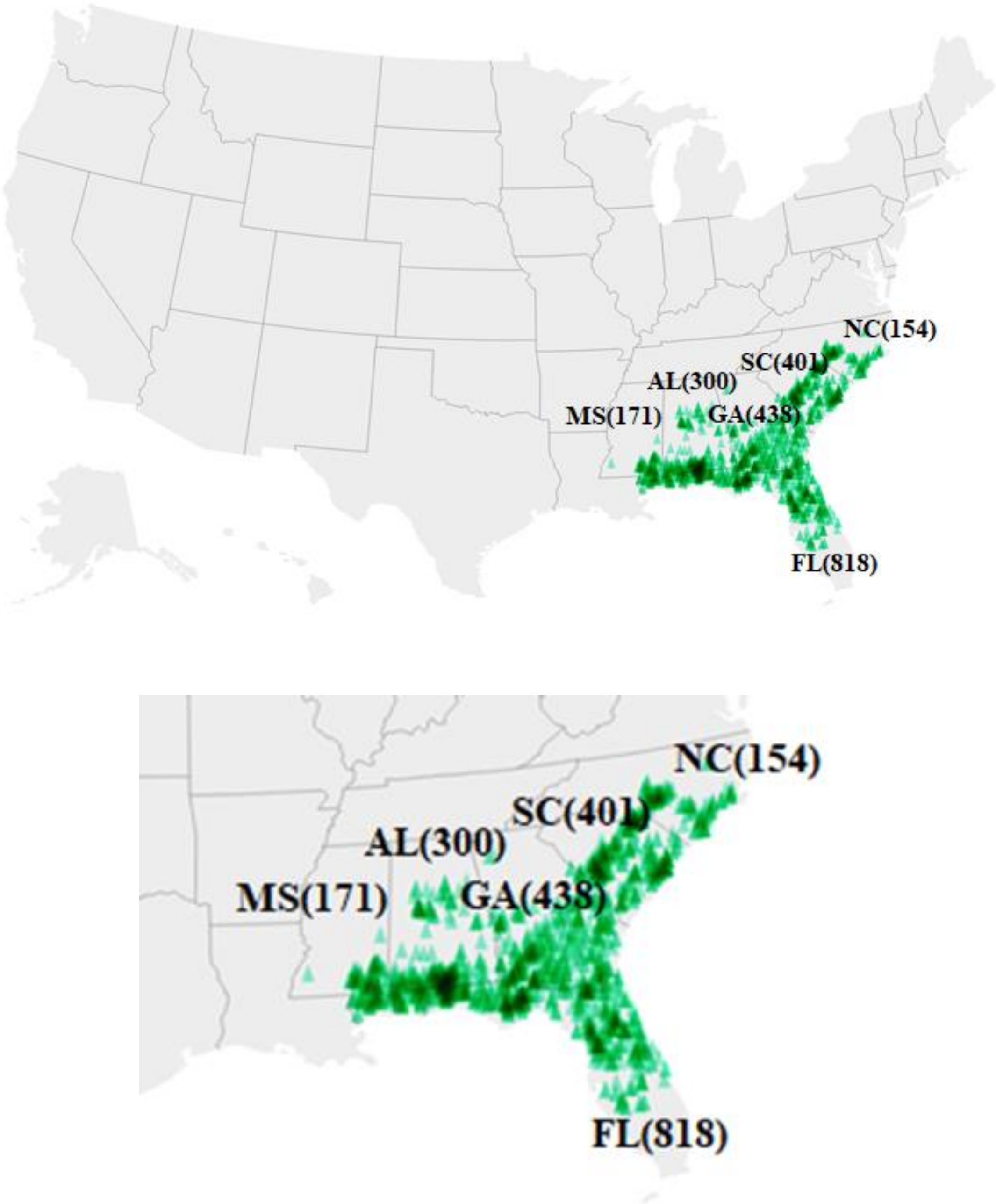

Fig. 1. Location of the forest plots ▲ in the southeastern US (numbers between parenthesis represent the number of forest plots per state).

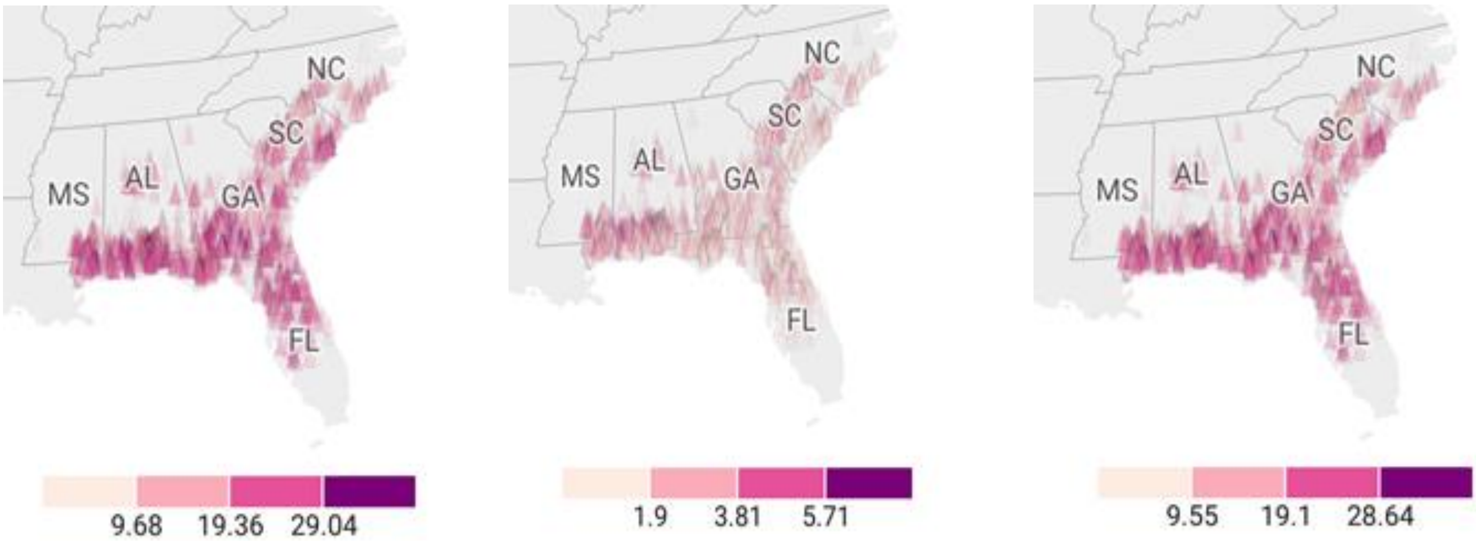

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Fig. 2. Profit, technical and allocative inefficiencies of longleaf pine plots Δ.

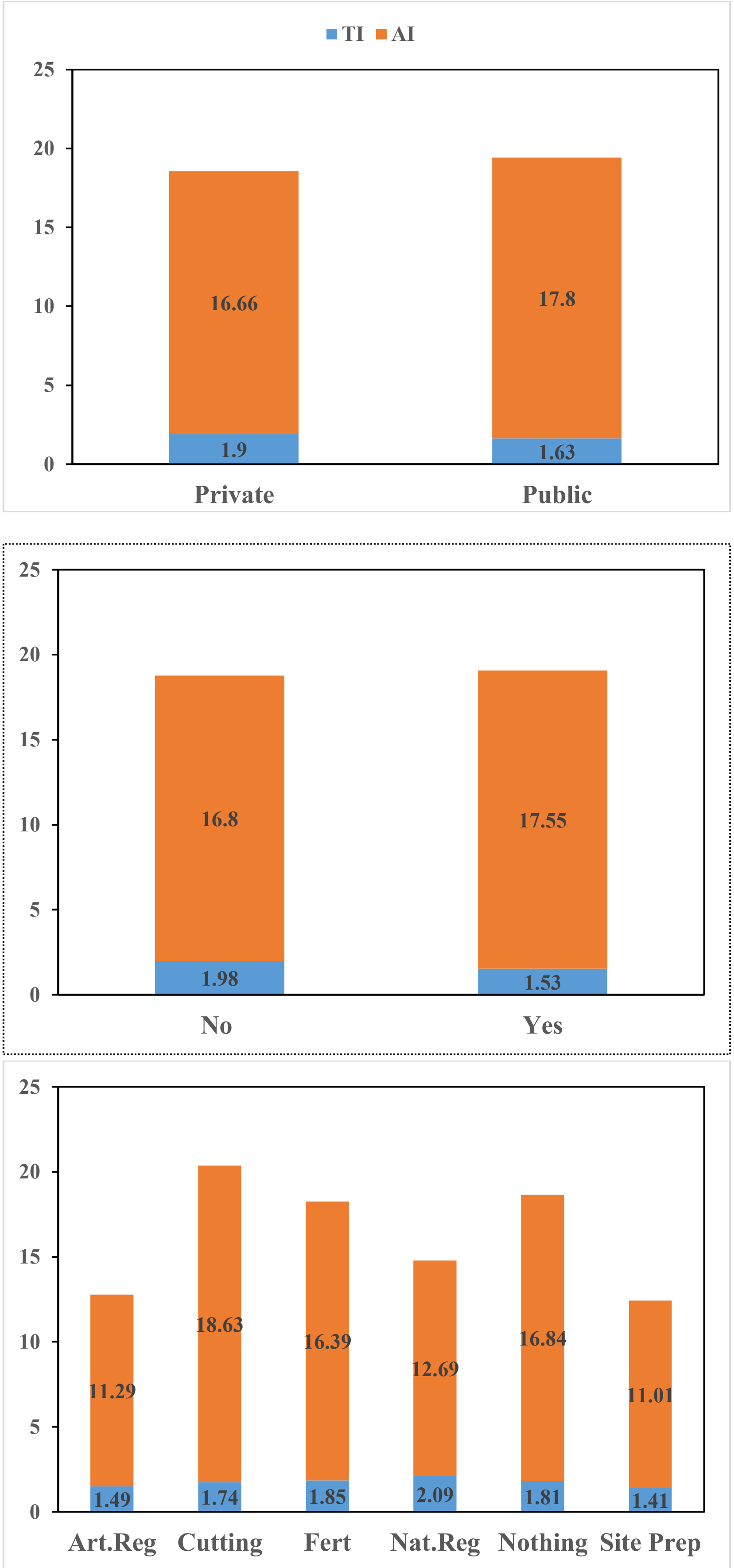

Fig. 3. Average technical inefficiency/allocative inefficiency per ownership group, disturbance group and management group (Wilcoxon statistic-one sided: Ownership-TI= 4151642***; Ownership-AI= 5089232 ***; Disturbance-TI= 4413899***; Disturbance-AI= 5100958***; Kruskal-Wallis statistic: Management-TI= 7.51; Management-AI=45.98***). Significant at 0.001 significance level (***).

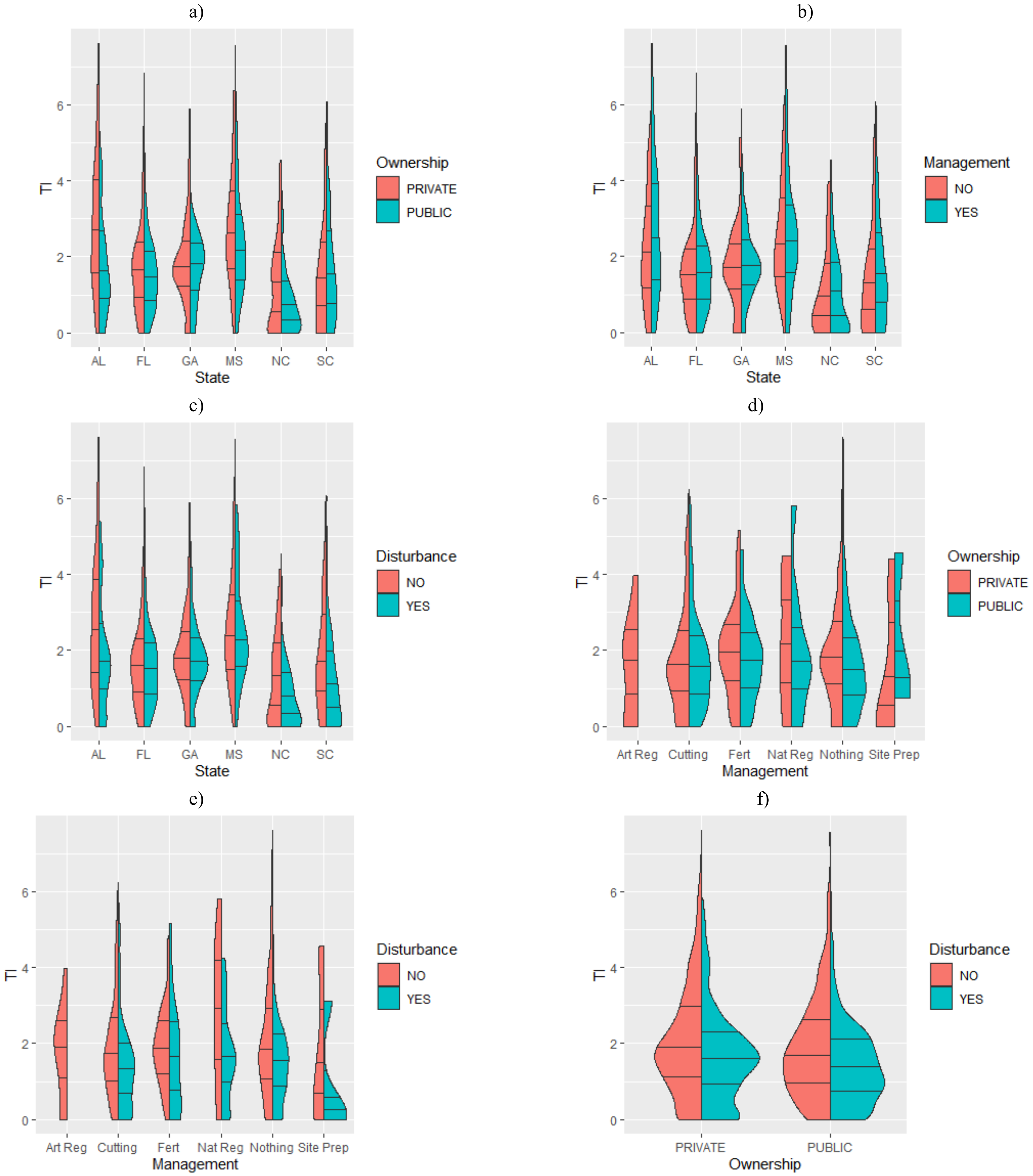

Fig. 4. Violin plot (combination of boxplot and density trace) of technical inefficiency grouped into different exogenous variables (state, ownership, management and disturbance). Horizontal lines represent first quartile, second quartile and third quartile of the dataset.

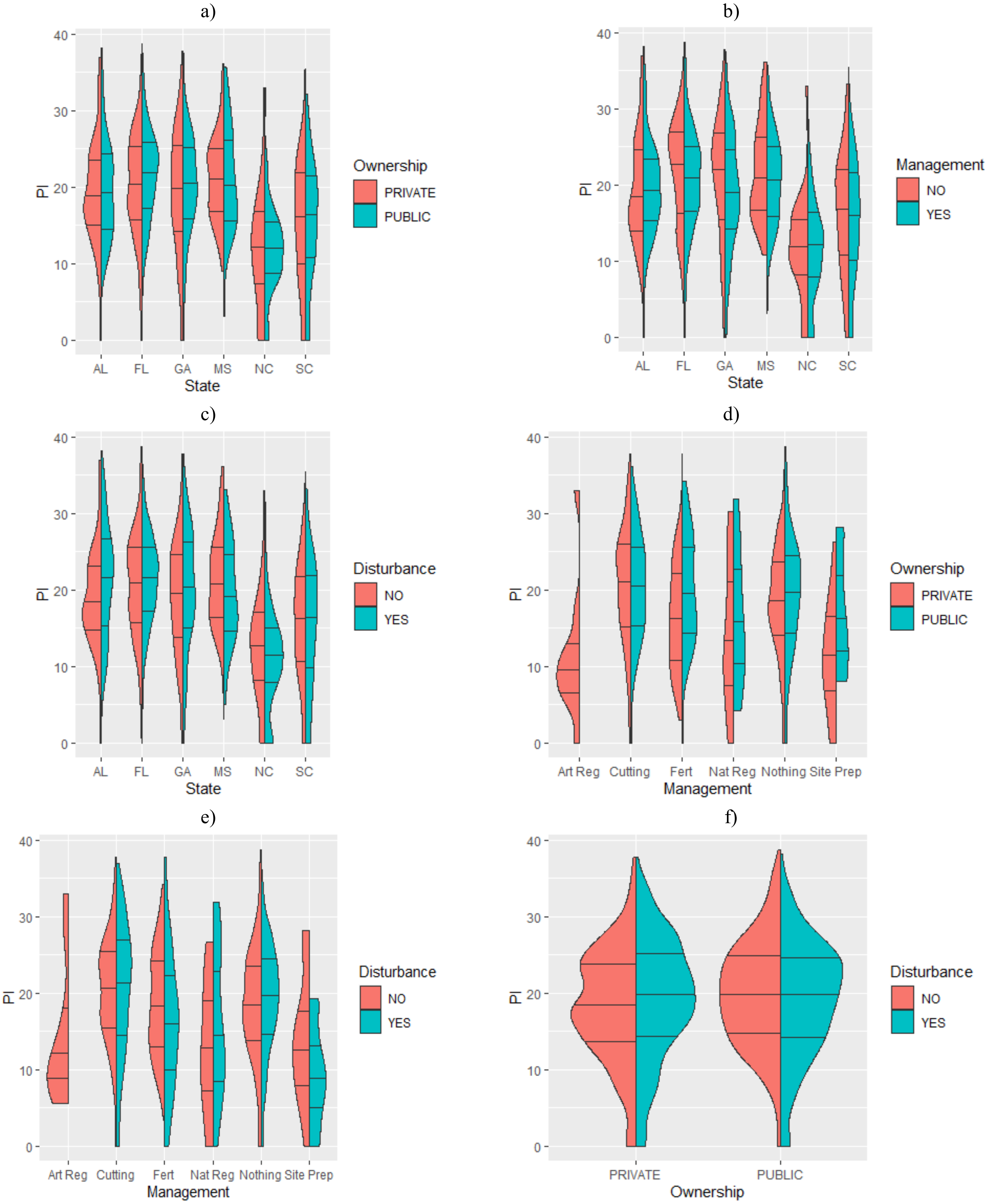

Fig. 5. Violin plot (combination of boxplot and density trace) of profit inefficiency grouped into different exogenous variables (state, ownership, management and disturbance). Horizontal line represent first quartile, second quartile and third quartile of the dataset.

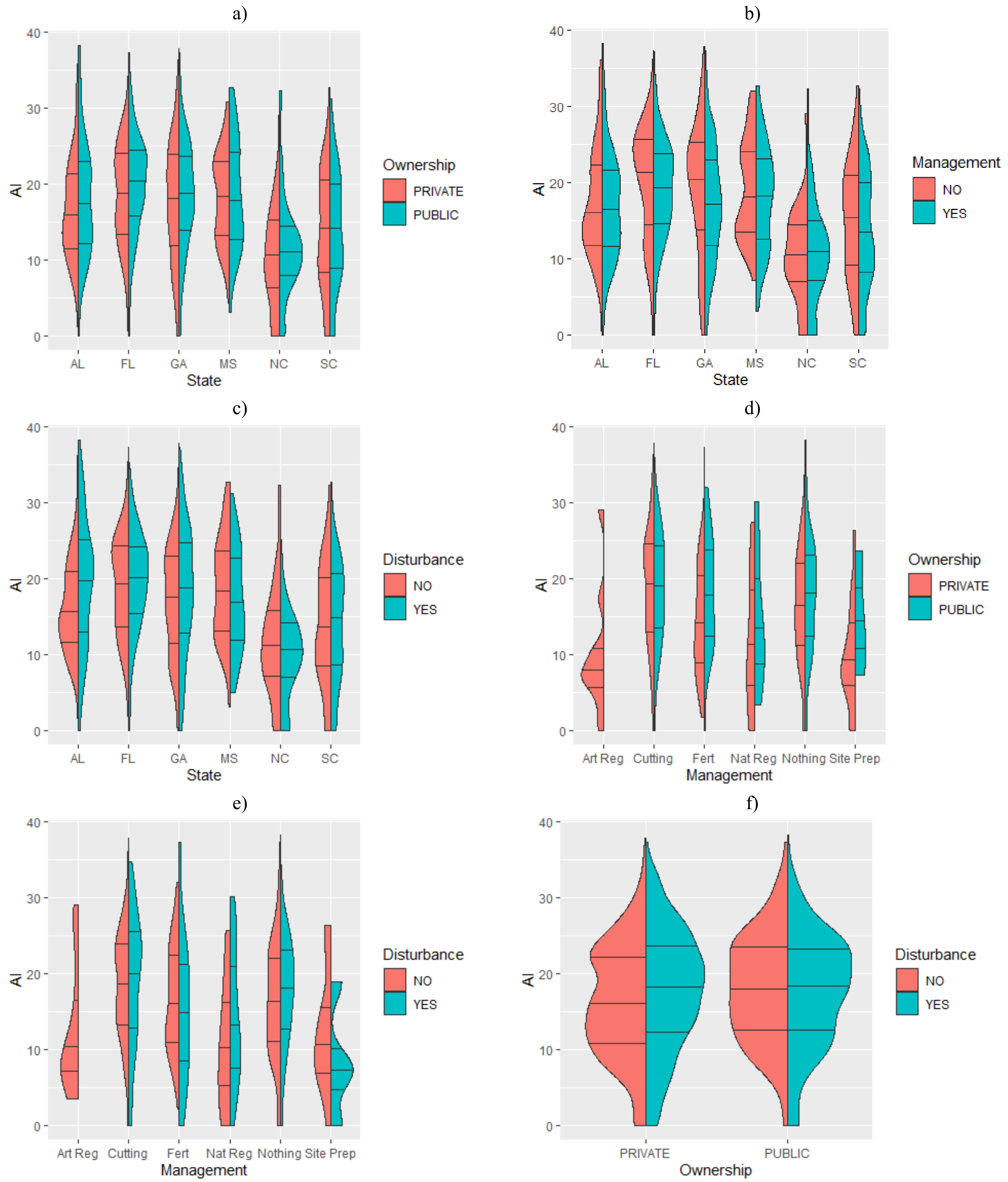

Fig. 6. Violin plot (combination of boxplot and density trace) of allocative inefficiency grouped into different exogenous variables (state, ownership, management and disturbance). Horizontal lines represent the first quartile, second quartile and third quartile of the dataset.