Private forest owners harvesting behaviour and technical efficiency: effects of other income sources

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ABSTRACT

In Norway, as in many other European countries, income from forestry has become marginal to owners' household economies and most employment is now undertaken off the property. Also, many forest owners have focused increasingly on other productions on the propery, such as providing recreational services and cottage building. Income from these new activities has become an important part of the total household income.

It is a challenge in all kinds of production to find the optimal way converting inputs into outputs, i.e. to be technically efficient. The financial dependency of income from forestry differs between part- and full-time forest owners. Since the two groups have different livelihood strategies, it is plausible that full-time forest owners have more professional forest management policies.

We base our study of forest management efficiency on a cross-section of 3,249 active (i.e. harvesting) forest owners extracted from the 2004 Sample Survey of Agriculture and Forestry. Employing a stochastic production frontier analysis we evaluate efficiency impacts of important factors like property and owner characteristics, outfield-related and agricultural activities, off-property incomes and geographical location.

The results show that many forest owners are technically inefficient. Therefore, there are significant opportunities for improving their performances. The study indicates that off-property income has negative impact on technical efficiency, the inefficiency arising with increasing share of household incomes from outfield activities, and properties in central areas are less efficient than those in remote areas. One policy implication of these results is that there is probably a significant potential efficiency gain from allowing small inefficient woodlots to merge into larger units of forestry production. Also, supporting means to forest management plans may improve efficiency.

INTRODUCTION

The forest ownership in Norway has been in transition the past few decades. Forestry income has become more marginal to owners' household economies and most employment is now undertaken off the property. In addition, owners have focused increasingly on other productions on the properties, for example cottage building and providing recreational services. Incomes from such productions have gained importance relative to revenues from timber harvesting, and non-production management objectives have become more important to many owners. Previous studies of nonindustrial forest owners (NIPF) have found forest owners' harvesting decisions to be influenced by such non-timber production activities (e.g. outfield activities, amenities) on the properties, e.g. Kuuluvainen et al. (1996), as well as off-property (wage) income, e.g. Løyland et al. (1995) and Tahvonen and Salo (1999). Increased focus on other production strategies is found not only in Norway and other Nordic countries but also in the rest of Europe as well as in the USA (Amacher et al. 2003).

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An important question to address is how these abovementioned changes influence the performance of the forest owners as timber suppliers and forest managers. The objective of this study is to examine technical efficiency (performance) in harvesting of active forest owners in Norway, and how this is affected by owner and ownership characteristics.

Performance can be measured in several ways. One, which is applied here, is to analyse the production frontier, which defines the relationships between inputs and outputs. Considering the forest owners' timber supplies as output, and relating this to inputs in form of labour, forest area cut and capital, the performance (or productivity improvements) can be achieved in (at least) two ways: One can either improve the state of new technology by, e.g. inventing new logging equipment or forest road construction, which is commonly referred to as technological change and is represented by an upward shift of the production frontier. Alternatively, one can implement various procedures, such as extension and advisory services (Leffler and Rucker 1991), to ensure that forest owners use the existing technology more efficient given the feasible technology (e.g. Coelli et al. 2005). Forest owners can either operate on the frontier if they are technically efficient or beneath the frontier if they are technically inefficient. Analysis of technical efficiency has two further components. The first one is to estimate the efficiency. Many studies end there. It is, however, often more interesting to associate variation in technical efficiency with variation in exogenous variables characterising the environment in which production occurs (Kumbhakar and Knox Lovell 2000). In other words, what environmental factors (e.g. human capital (experience, age of the decision maker, education), off-property employment, other activities at the property) contribute to reduce, and what contribute to increase, the degree of technical inefficiency. This can, besides providing information on where potential sources of inefficiency originate, also suggest policies that may be implemented (or eliminated) to enhance overall efficiency levels. Both nonparametric (e.g. data envelopment analysis) and parametric (e.g. econometric) approaches can be used to analyse efficiency performance (e.g. Coelli et al. 2005 for an overview). In general, parametric approaches are more demanding with regard to data. On the other hand they take variation of data into account. This study is based on a rich data set of Norwegian forest owners, which makes it possible to estimate a feasible functional form representing the owners' technology. Therefore a parametric approach is taken in this study.

In the forest production and harvesting literature, there are few econometric studies of efficiency. Carter and Cubbage (1995) measured technical efficiency in the Southern U.S. pulpwood harvesting industry by estimating a stochastic frontier production function. The estimated efficiency scores were then regressed against exogenous variables in a second-stage[1], to analyse exogenous factors influence on efficiency. A study of the technical efficiency of Polish state timber production and management policies following the transition to more competitive market (Siry and Newman 2001), provided evidence that efficiency are improved by the privatization of forest operators. A stochastic Cobb-Douglas frontier production function was estimated, but, due to lack of data, the sources of technical efficiency were not investigated. Recently, Misra and Kant (2005) have investigated efficiency and shadow prices of economic, biological, and social outputs of village-level organizations of joint forest management in Gujarat, India. A nonparametric multi-output distance function framework was used.[2]

1 *There are several serious econometric problems with this two-stage formulation, e.g. Kumbhakar and Knox Lovell (2000: 262-266).*

2 *The frontier technique and efficiency analyses have also to some extent been used within forestry analyses, but on other aspects than harvesting and forest production. Munn and Palmquist (1997) estimated hedonic price equations for a timber stumpage market using parametric stochastic frontier estimation procedures. Yin (2000) measured the productive efficiency of global bleached softwood kraft pulp producers using both stochastic frontier analysis and data environmental analysis. Technical efficiency evaluation of logging contractors using nonparametric analysis (LeBel and Stuart 1998) and impact of environmental regulation on the profitability and efficiency of paper mills using distance function within the nonparametric approach (e.g. Färe et al. 1993; Chung et al. 1997) are other applied examples.*

In this study we apply the model by Kumbhakar et al. (1991) that estimates the parameters of a stochastic frontier and inefficiency model simultaneously for cross-sectional data.[3] We have used cross-sectional data of 3,249 active (i.e. harvesting) forest owners, extracted from the 2004 Sample Survey of Norwegian Agriculture and Forestry. Hypotheses investigated are:

1. A high share of forest owners with off-property income will cause high level of technical inefficiency in timber production, and large differences between financial dependency on forestry income cause large differences in technical efficiency level between the forest owners;
2. An increasing share of total household income on-property from other sources than forestry income will decrease the technical efficiency of timber production;
3. Since there are generally more (attractive) alternatives for use of human capital in peri-urban than in rural areas, due to a larger market for high educated labour, focus on the property resources is larger in rural areas, leading to a higher level of technical efficiency.

The rest of the paper is organized as follows. First, the stochastic frontier production function model with inefficiency effects is outlined, and our applied estimation technique is described. Second, the data set of the 2004 Sample Survey of Norwegian Agriculture and Forestry is presented. Third, the empirical results are presented. Finally, a discussion and some concluding comments are provided.

MODEL

We consider a stochastic frontier production function model for cross-section data:

$$(1) \quad \ln y_i = \phi + \mathbf{x}'_i \boldsymbol{\alpha} + v_i - u_i$$

where y_i denotes the timber supply in m^3 of the ith (i=1,...,N) forest property, ϕ is the intercept, $\mathbf{x}'_i$ is a vector of inputs at forest property i, α a vector of slope coefficients, and $v_i \sim N(0,\sigma^2_v)$ is a random error term. The technical inefficiency effect, u_i, is assumed to be a function of a set of explanatory variables, $\mathbf{z}_i$, and of an unknown vector of coefficients, $\boldsymbol{\delta}$. In this study we follow Kumbhakar et al. (1991) specifying the technical inefficiency effects in the ith property as:

$$(2) \quad u_i = z'_i\delta + w$$

where the random variable vector **w** is defined by the truncation of the normal distribution with zero mean and variance σ^2_u, such that the point of truncation is $-z'_i\delta$, i.e. $w \geq -z'_i\delta$. This assumption is consistent with u_i being a non-negative truncation of the $N^+(z'_i\delta, s^2_u)$-distribution. If $z'_i\delta$ is only a constant term (i.e. the first z-variable has value one and all the coefficients of the other z-variables are zero) one obtains the truncated-normal inefficiency model proposed by Stevenson (1980). The half-normal distribution inefficiency model pioneered by Aigner et al. (1977) is obtained when all elements of the δ-vector (including the intercept) are equal to zero.

Within this framework the values of the unknown parameters in (1) and (2), $\alpha, \delta, \sigma^2_v$ and σ^2_u, are obtained simultaneously using maximum-likelihood estimation. The estimates are calculated using the computer program FRONTIER 4.1 (Coelli, 1996). This program uses the reparameterizations $\sigma^2 = \sigma^2_v + \sigma^2_u$ and $\gamma = \sigma^2_u/\sigma^2$ which have advantages during estimation because the value of γ must lie between zero and one. If γ is not significantly different from zero, the variance of the inefficiency effects is zero, and the model reduces to a mean response function in which the inefficiency variables enter directly.

For the prediction of technical inefficiency effects, it is common to use an output-oriented measure defined as the ratio of observed output to the corresponding stochastic frontier output:

$$(3) \quad TE_i = \frac{\exp(\phi + \mathbf{x}'_i \hat{\boldsymbol{\alpha}} + v_i - u_i)}{\exp(\phi + \mathbf{x}'_i \hat{\boldsymbol{\alpha}} + v_i)} = \exp(-u_i)$$

This expression relies upon that the value of the unobservable u_i being predicted, which is achieved

[3] *Battese and Coelli (1995) extended the model by Kumbhakar et al. (1991) to estimate the inefficiency effects in a stochastic production function for panel data.*

by deriving the expression for the conditional expectation of exp($-u_i$), conditioned on the observed value of (v_i - u_i).

For the deterministic component of equation (1) a flexible translog functional form with three input variables was employed:

$$(4)\quad x_i = \left[\ln x_{1i}, \ln x_{2i}, \ln x_{3i}, 0.5(\ln x_{1i})^2, \ln x_{1i} \ln x_{2i}, \ln x_{1i} \ln x_{3i}, 0.5(\ln x_{2i})^2, \ln x_{2i} \ln x_{3i}, 0.5(\ln x_{3i})^2\right]'$$

The input variables are labour input (x_1), forest area cut (x_2), and capital (x_3). The error component in (2) which captures the effects of technical efficiency has a systematic component ($z'_i\delta$) associated with following exogenous variables:

z_1 = age of the forest owner (yrs)
z_2 = income from outfield related productions (NOK)
z_3 = income from agriculture (NOK)
z_4 = wage income (NOK)
z_5 = debt (NOK)
z_6 = dummy variable for managing plan, 1 = plan, 0 = no plan
z_7 = dummy variable for education, 1 = Master degree or higher education, 0 = else
z_8 = dummy variable for centrality, 1 = properties close to urban areas, 0 = else

Age of the forest owner, dummy variable for management plan and dummy variable for education intend to represent the human capital influence on technical efficiency. The other income source variables, debt and location of the property are socioeconomic attributes that may influence the forest properties level of technical efficiency.

Prior to estimation output and input variables were scaled to have unit means, such that the first-order coefficients in the model can be interpreted as elasticities of output evaluated at input means.

DATA

We have applied individual cross-sectional data of 3,249 active (i.e. that harvest) forest owners extracted from the 2004 Sample Survey of Agriculture and Forestry, compiled by Statistics Norway. These data include results from a postal survey that are linked to data from the tax register, the harvesting register, and from the agricultural register (which reports each farmer's support payments including stocking and cropping details). All data represent the year 2003. It should be noted that the sample consists of forest properties that on average are somewhat larger than the whole population of forest properties in Norway. Thus the sample is biased against larger properties, which in turn may have implication for the generalization of our findings.

The output variable (y) consists of annual timber sales from the forest. The labour variable (x_1) was calculated as the sum of hours worked by contractors and hours worked by the owner, his family or hired labour in 2003, the latter calculated as contractor equivalent hours, i.e. the amount of hours a contractor would have used to cut and haul the specific amount of timber. The data set gave no information of hours worked by contractors, so these were estimated as the total costs in NOK involved with contractor work divided by 1925 NOK/hour. The latter is an estimate of costs pr. hour of contractors given as the sum of 1175 NOK/hour for harvester and 750 NOK/hour for forwarder (Eid and Hoen 2005).

The hectares forest area cut variable (x_2) expresses the area of various types of final fellings in 2003. The capital input variable (x_3) is an expression of capital claim, or the shadow price of increment, from the forest. It was calculated as the value of the maximum sustainable yield (MSY) from the property, where the MSY denotes the quantity and the price was calculated as the mean (value divided with quantity) from harvesting in 2003. Using mean price also adjusts for the timber quality of the property, which varies significantly. For a few properties there was no information of value or quantity from timber sales. We chose to replace missing values with the mean value of the sample.

Table 1 gives some descriptive statistics of the data. Cf. Statistics Norway (2004) for a closer description of the data and the sampling.

RESULTS

The maximum-likelihood estimates of the parameters in the translog stochastic frontier production function (equation 1), given

TABLE 1: Descriptive statistics.

Variable	Label	Mean	SD	Min	Max
Output variable					
Harvesting level, m^3	y	997.4	2,621.2	2.0	46,068.0
Input variables					
Labour input, hours	x_1	58.0	141.2	0.1	2,632.5
Forest area cut, ha	x_2	6.0	14.8	0.01	229.0
Capital value of maximum sustainable yield, NOK*	x_3	313,740	821,481	1,476	16,186,055
"Efficiency variables"					
Age of the forest owner, yrs	z_1	51.9	11.8	16.0	95.0
Income from outfield related productions, NOK 1,000*	z_2	71.0	467.0	0.0	11,814.0
Income from agriculture, NOK 1,000*	z_3	54.2	125.9	0.0	2,488.4
Wage income, NOK 1,000*	z_4	240.3	269.2	0.0	2,183.1
Debt, NOK 1,000,000*	z_5	1.3	5.3	0.0	132.0
Management plan, 1 = plan, 0 = else	z_6	0.69	0.46	0.00	1.00
Education, 1 = Master degree or higher education, 0 = else	z_7	0.24	0.43	0.00	1.00
Centrality, 1 = properties in central municipalities, 0 = else	z_8	0.38	0.48	0.00	1.00

* 1 NOK = € 0.125 (2003)

specification for the technical inefficiency effects, defined by equation (2), are presented in Table 2. Before we discuss these parameters further, various null hypotheses will be tested and discussed.

Model tests

The null hypotheses are tested using the generalised likelihood-ratio (LR) test, reported in Table 3. To conduct test involving the γ parameter, the LR has mixed Chi-square distribution. Critical values for X^2_J are taken from Kodde and Palm (1986).

The first hypothesis, H_0: $\gamma=0$, which specifies that the forest owners are fully technical efficient or that the mean production function is adequate, is strongly rejected by the data. The second hypothesis, H_0: $\alpha_{jk} = 0$, $j \leq k = 1,...,3$, that Cobb-Douglas frontier is an adequate representation for the forest owners, is also rejected. The null hypotheses, that the explanatory variables (H_0 : $\sigma l = 0$, $l = 1,...,8$) and that the intercept and the explanatory variables (H_0:$\sigma l = 0$, $l = 0,...,8$) in the model for technical inefficiency effects have zero coefficients, are also rejected by the data. Given the specification of the full model as done in equation (1) and (2), the preferred model is thus the stochastic frontier translog production function with model for technical inefficiency. The parameters for this model are reported in Table 2, and they are discussed more thoroughly below.

Input elasticities and scale economies

As shown in Table 2, elasticities with respect to labour, forest area cut, and capital input are all statistically significantly different from zero, and all three have the expected positive sign. From a theoretical standpoint positive signs are also

TABLE 2: Maximum-likelihood estimates.

Variable	Label	Coefficient	t-test
Stochastic frontier			
Constant	ϕ	0.103	22.611
Labour	α_1	0.908	131.734
Forest area cut	α_2	0.075	12.653
Capital input	α_3	0.055	10.389
(Labour)^2	α_{11}	-0.044	-8.227
Labour Area cut	α_{12}	0.034	8.453
Labour Capital	α_{13}	-0.008	-1.463
(Area cut)^2	α_{22}	-0.033	-5.201
Area cut capital	α_{23}	0.007	1.312
(Capital)^2	α_{33}	0.012	2.104
Inefficiency model*			
Constant	δ_0	-5.197	-6.522
Age of forest owner	δ_1	0.017	5.161
Income, outfield related productions	δ_2	0.0002	5.188
Income, agriculture	δ_3	-0.001	-6.379
Wage income	δ_4	0.0004	7.066
Debt	δ_5	-0.012	-5.594
Management plan, 1 = yes	δ_6	-0.517	-7.520
Education, 1 = Master or higher	δ_7	0.478	5.487
Centrality, 1 = yes	δ_8	0.169	4.346
Variance parameters			
	σ^2_u	0.558	7.726
	γ	0.965	198.264
Log-Likelihood function			
		963.71	

* A negative sign on the coefficients indicates positive impact on efficiency.

TABLE 3: Generalised likelihood-ratio tests of hypothesis of the flexible stochastic frontier translog production function specified in equation (1) and (2).

Null hypothesis	Log-likelihood	LR statistic	$X^2_{0.95}$ -value	Decision
Given flexible model	963.71			
$H_0 : \gamma = 0$	839.44	248.55	16.27	Reject H0
$H_0 : \alpha_{jk} = 0, j \leq k = 1,...,3$	929.34	68.74	12.59	Reject H0
$H_0 : \delta_l = 0, l = 0,...,8$	889.13	149.17	16.92	Reject H0
$H_0 : \delta_l = 0, l = 1,...,8$	955.45	16.52	15.50	Reject H0

required to maintain the monotonicity property. Labour has the largest magnitude. It is more than 10 times as large as the elasticities with respect to forest area cut and capital input. It is as expected that harvesting level depends strongly on labour used in harvesting.

Scale economies are computed as the sum of all input elasticities. On average, the scale-elasticity is equal to 1.04, indicating the production function exhibits increasing return to scale. Or, with other words, the results implies that, on average, the forest owner operate a forest property (or more specifically the harvests) that are too small.

Technical efficiency

The average technical efficiency for the sample, estimated with the full flexible model is equal to 0.90. For the average forest owner, the harvesting level could have been 10% higher in the investigated year 2003, without requiring more input. However, behind the mean trends there can be a huge variation between the properties, as illustrated in the histogram in Figure 1. Almost 5% of the forest owners have a technical efficiency level less than 0.75. These have a huge potential for improvements. On the other hand, about 10% of the forest owners are almost technical efficient, with a technical efficiency score 0.95 or higher.

Factors that explain technical efficiency level

In order to examine more closely the reasons for variations in efficiency score in the sample, we refer to the lower part of Table 2. The age coefficient is positive, which indicates that the younger forest owners were more technically efficient than the older ones. The positive estimate of the dummy for education indicates that highly educated forest owners were less technical efficient in timber production than the lower educated ones. Debt was significant negative, indicating that technical efficiency increases with debt level. As expected, forest management plans contributed to increase technical efficiency. Properties typically rurally located had a higher efficiency level than properties located close to urban areas.

Off-property wage income and income from on-property outfield activities led to decreased technical efficiency, while properties combining forestry and agriculture (i.e. properties where income from agriculture is high) had a higher technical efficiency.

CONCLUDING REMARKS

In the introduction we put forward a set of hypotheses regarding efficiency. Our first hypothesis related to the potential inefficiency that may arise from off-property income sources may be confirmed: Wage income (off-property) was found to have a significant impact on technical efficiency. This result probably relates to both the different livelihood strategies chosen by wage-earners compared to self-employed owners, the fact that forest income accounts for a lower share of total household income for wage-earners and that this group has less time available for efficient production planning. This result is also comparable to Løyland et al. (1995) who found that work outside the property were likely to have a negative impact on forest activities.

The second hypothesis regarding the potential inefficiency arising from increasing share of household incomes from sources other than forestry may also be confirmed when we look at the impact from other outfield activities. Causes for this could be that "pure" foresters have larger focus on profitable forestry, while the more diversified foresters maximize utility, where forestry is only

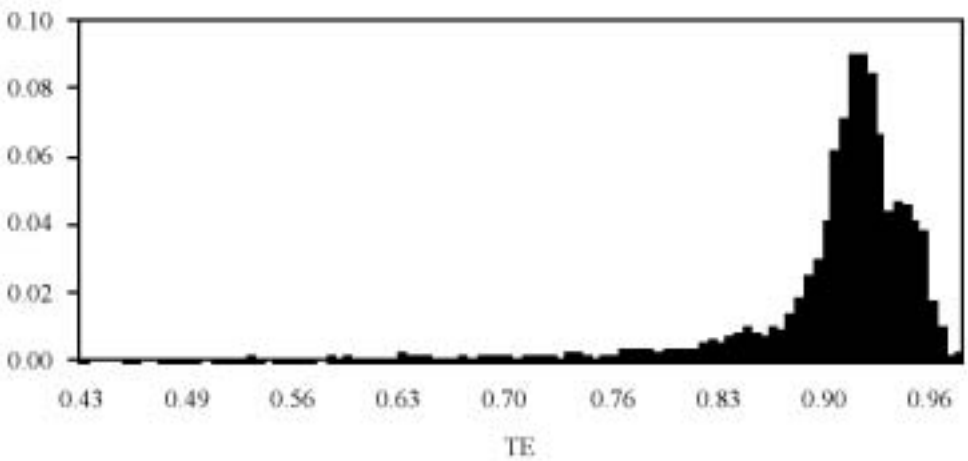

FIGURE 1: Histogram of technical efficiency (TE) for the sample.

on out of many utility-increasing activities. Full-time foresters will often also have better information about the forest resources, and then possibility for better forestry management and adaptation. We also found agricultural income (on-property) to impact positively. An explanation for this is that agriculture is more separated from forestry production regarding the area used than other on-property productions. Thus, there are few conflicts related to the joint maximisation of forestry and agricultural production.

Our third hypothesis regarding larger focus on the property resources in rural areas is also confirmed. The sign and magnitude of the centrality dummy clearly indicate that properties in central areas are less efficient than those in remote areas. To a certain extent this is comparable to Størdal et al. (2004) who found that remote regions experienced relatively higher harvesting levels in "boom" periods, which may be a consequence of owners in these regions putting more weight on utilisation of their forest resources.

We found a noticeable share of the properties technically inefficient. Though, one has to keep in mind that some of the findings of "inefficiency" may be due to owners taking other concerns in forest management into account. For example, shelter wood cutting in urban (or nearby) areas occur in order to reduce the potential conflict level that may occur between commercial and multiple use forestry (Størdal et al. 2004). Still, such behaviour may also have a commercial explanation: If a forest owner is also engaged in other outfield businesses such as tourism or providing recreational services, a more extensive (and thus may less "technical efficient") forest management may be beneficial from a commercial point of view. Thus, such "inefficiency" may be a result from optimising a portfolio of different activities at a specific property. This may explain the negative impact of income from other outfield activities for technical efficiency. On the other hand, there are truly elements of profit-maximising behaviour in our findings. This relates to the positive impact of debt and agricultural income for efficiency, as well as the benefits from forest management plans, probably due to increased information of the property's resources.

The finding of increasing returns to scale is not surprising given the relative rigid system for property sales in Norway. Previous studies (e.g. Aanesland and Holm 2000) have pointed at the potential gains of releasing some of the constraints for merging the small non-industrial woodlots in Norway.

There are a number of limitations of the analysis worth mentioning. First, cross-sectional data used to study harvesting behaviour, and the effects other income sources have on the level of technical efficiency between input use and harvesting level, relate to one single year – 2003. Thus, preceding or planned harvesting behaviour could not be accounted for. Further, the frontier approach used in this study decomposes deviations from the frontier into inefficiency and noise. Ignoring variation in output caused by uncontrollable factors, often called production risk, means that input elasticity and technical efficiency estimates can be over-estimated and misleading. To reduce these problems, some studies have included both inefficiency and production risk aspects (e.g. Battese et al. 1997, Kumbhakar 2002, O'Donnell and Griffiths 2006), where deviations from the production frontier are decomposed into inefficiency, risk, and noise. Inclusion of production risk aspects on the problems evaluated in this study is left for future research. So is the examination of overall forest property profiles based on efficiency rankings of the forest properties, i.e. how the key property characteristics differ when related to how efficient the properties are (e.g. Kompas and Che 2006).

The policy implication from this study is that there is probably a significant potential efficiency gain from allowing small inefficient woodlots to merge into larger units of forestry production. As real prices for timber drops there is an incentive for owners, especially in urban areas, to take off-property work, or to explore other resources at the property. Both are found to impact efficiency negatively. Releasing some of the constraints that are put on property sales may be a well-targeted mean in order to improve the forest management, and increase forestry income. Also supporting means in order to improve information about property resources through forest management plans may improve efficiency.

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