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The Relationship Between Socio-economic Factors and Different Energy Options for Household Use in the Municipality of Zomba

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ABSTRACT

Over-dependence on wood-fuel as a source of household energy is a major cause of deforestation and other environmental problems in Malawi. To investigate factors that affect choices between different energy options in the Municipality of Zomba, a survey was conducted using a structured questionnaire. Respondents (160) were selected through stratified (by housing density area) systematic sampling with random starting points. Multiple and multinomial logistic regression were used to identify which of the factors: housing density area, household income, sex, marital status, and education level of household head were significant in predicting energy choices.

Education and income levels were found to be significant predictors of a household using firewood for each of cooking and water heating. Similarly, housing density area, education and income were predictive of the probability of using electricity for cooking and lighting. In each case, as education and income levels increased, the likelihood of using electricity and not using firewood increased. Likewise, those in low housing density areas tended to be more likely to use electricity for cooking and lighting. These findings emphasize the importance of enhancing poverty alleviation programmes to achieve improved standards of living, both in terms of education and income, as part of the strategy for combating deforestation.

1 INTRODUCTION

The main sources of energy for domestic use in Malawi are wood-fuel (firewood and charcoal), electricity, and paraffin. Other less widely used sources include coal, solar energy, candles and gas. Firewood and charcoal are the principal urban fuels for cooking and heating, making up over 90% of the total urban households' energy requirements. Electricity and paraffin together account for less than 10% (Arpaillange, 1996). According to the Lake Chilwa Wetland State of the Environment Report (Malawi Government, 2000a),the national per capita wood usage is estimated at 388 kg annually. It is estimated that the urban area of Zomba alone consumes 37,000m^3 of wood-fuel a year with per capita consumption of 0.67m^3, and that only 7% of the total land area of the district is forested, mainly by pine plantation which occupies 6,352 hectares. Over-dependence on wood-fuel contributes to deforestation, which is estimated at 2.8% nationally per annum resulting in a national loss of 2 million ha of forest in the past 23 years (Malawi Government, 2000b).

Since the early 1980's a number of studies and surveys have been carried out on household energy options in Malawi. Most of these studies focussed on production, transportation, expenditure, marketing and pricing. Two of these studies (Energy Studies Unit, 1984) and Arpaillange (1996) focussed specifically on urban energy use. Both studies investigated the association between price, size of city, type of housing (permanent or temporary), and income groups on one hand and energy used on the other. Each factor was considered separately using frequency cross-tabulations. These studies found that energy choices were mainly in-

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Table 1: Sampling details

Strata	Popn size (N_i)	Sample size (n_i)	Interval	1st random number
Low density	520	40	13	3
Medium density	345	40	9	7
High density permanent	1046	40	26	2
High density traditional	9093	40	227	4
Total	11004	160		

fluenced by size of city, type of housing and income. Although the studies were planned to employ 3-stage sampling, this random selection procedure was not followed. For instance, during the 1st stage, towns were selected arbitrarily. Similarly, in the 2nd stage, enumeration areas were selected based on the advice of planning authorities rather than scientific theory. The estimates were not based on the sampling design employed, which rendered the results unreliable. The univariate approach to analysis ignored associations between the various factors considered. This rendered the results less sensitive to detect and quantify the relative influence of each of the factors considered.

In addition to price, housing type, and income, the current study also investigated the effect, if any, of sex, marital status and education level of household head on energy choices. Sex was included because of the possibility that there are gender imbalances regarding participation in most economic activities in Malawi. Similarly, marital status was included in order to be able to see whether there are any differences due to marital status. Education was added because of the belief that it is critical for informed decision making, especially regarding adoption of new technologies or change of attitudes or practices. The study is therefore an extension and improvement on past studies.

The overall objective of the study was to examine the relationship between socio-economic factors and different energy options for household use in the Municipality of Zomba. Specifically, socioeconomic factors influencing choice of a particular energy source were identified, and best fitting models on energy choices were built and selected.

2 MATERIALS AND METHODS

2.1 Data collection

A survey was conducted among heads of households in the Municipality of Zomba in 2000, using a questionnaire concerning socio-economic factors and energy sources used. An urban setting was chosen for the study because of the availability of different household energy options in urban areas. This consideration made it possible to investigate how socio-economic factors relate to different energy choices. The target population was households within the Municipality of Zomba.[1] Sampling was stratified by housing density area. Households in commercial, industrial, institutional and aforestation areas were excluded due to difficulties in categorising them according to housing density area.

Stratified systematic sampling was employed to obtain a representative sample of households from each type of housing density area. Maps that were used by the National Statistical Office for the 1998 Population and Housing Census (updated in May 2000 for the Demographic and Health Survey) and the land use map for the Municipality of Zomba (Malawi Government, 1989) were used to produce the sampling frame. Each household, in the study population, was assigned a serial number on the map. A sample of 40 households within each density area (stratum) was selected using systematic sampling with random starting points selected using the Excel `RANDBETWEEN` function. This sampling design was used to obtain sufficient representation of minority groups in the population such as "university educated". Only then would it be possible to detect differences due to these groups. In all, a sample of 160 households was selected. Manda (2001) provides more details regarding the sampling mechanism and questionnaire used. Table 1 gives the sampling details based on Casley and Kumar (1992).

The variables collected in the questionnaire survey included: energy sources used for cooking, water heating and lighting at least once a week; housing density area; sex; marital status; level of education of household head; household income, type of employment, and household composition.

[1] The municipality has four housing density areas: low density, medium density, high density permanent, and high density traditional.

Table 2: Explanatory variables, categories and codes.

Housing density area (X_1)	Sex (X_2)	Marital status (X_3)	Code	Education level (X_4)	Income group (X_5)
	Female (15)	Other (23)	0		
High - traditional	Male (145)	Married (137)	1	Illiterate (6)	Below K300 (2)
High - permanent			2	Standards 1-3 (6)	K300 - K799 (7)
Medium			3	Standards 4-5 (4)	K800 - K1,299 (8)
Low			4	Standards 6-8 (26)	K1,300 - K1,999 (13)
			5	Secondary (73)	K2,000 - K2,999 (25)
			6	University (45)	K3,000 - K4,999 (39)
			7		K5,000 - K6,999 (20)
			8		K7,000 - K10,000 (14)
			9		Above K10,000 (32)

Note that numbers in brackets within the body of this table indicate the sampled number in the category

2.2 Data analysis

All statistical analyses were performed using SPSS and Microsoft Excel computer software.

2.3 Logistic regression models

The main aim of statistical modeling is to achieve a reduction in complexity or produce a simple theoretical pattern to substitute for the ragged data (McCullagh and Nelder, 1983). Simplicity represented by parsimony of parameters is also a desirable feature of a model; parameters that are not needed are excluded. A parsimonious model that is substantially correct gives better predictions than one that includes unnecessary extra parameters (Hosmer and Lemeshow, 1989) and (Agresti, 1996). A good fitting model has several benefits. Firstly, the structural form of the model describes the patterns of association and interaction. Secondly the estimated model parameters indicate the strength and importance of the effects. The signs of these estimates signify the directions of the relationships. In addition, the model's predicted values smooth the data and provide improved estimates of the mean of the response distribution. Such models can also simultaneously analyse the effects of several explanatory variables. In contrast to significance testing, the model-building paradigm is more informative because it focuses on estimating parameters that describe the effects (Agresti, 1996).

Model types differ, depending on the distribution of the response variable. When the outcome of the response variable is binary, such as success or failure, the binomial distribution is often applicable. Where trials have three or more such outcomes multinomial distributions are used. The binomial distribution is a special case of a multinomial distribution, with only two possible outcomes for each trial (Agresti, 1996).

Logistic regression models are used to analyze data with binary, ordinal or nominal response variables. The explanatory variables (or predictors) can be quantitative, qualitative or both types. When logistic regression models are generalized to allow for several response categories they become multicategory (polytomous) logistic regression models. Logistic regression (or logit) models resemble regression models for continuous response variables but they involve binomial or multinomial distributions for response variables rather than normal distributions (Agresti, 1996). They predict the probability of a selected response (instead of predicting the value of the response).

2.4 Notation and forms of models

Following Agresti (1996)'s notation, let Y denote a binary response variable, taking values coded as 0 and 1 and X denote an explanatory variable. These variables are coded as indicated in Table 2. Let $\pi(x)$ denote the probability of response category 1 when X takes the value x. Then $\pi(x)/(1-\pi(x))$ is known as the odds of the response and the log of this odds (the log odds) is also known as the logit (function). The simple logistic regression model relating $\Pr(Y=1)$ to X can then be expressed in two equivalent ways:

$$\pi(x) = \frac{\exp(\alpha+\beta x)}{1+\exp(\alpha+\beta x)}$$

or

$$\operatorname{logit}\pi(x) = \ln\frac{\pi(x)}{1-\pi(x)} = \alpha+\beta x$$

where α is a constant and β denotes the rate of increase or decrease (slope) of the logit against X. Thus if the fitted model is logit $\pi(x) = -1 + 0.5x$ then $\pi(0) = 0.27$, $\pi(1) = 0.38$, $\pi(2) = 0.50$, $\pi(3) = 0.62$, $\pi(4) = 0.73$, $\pi(5) = 0.82$ and $\pi(6) = 0.98$.

In multiple regression models, the fitted value of the response variable is a function of the values of one or more predictor (X) variables. Inferences for model parameters help to evaluate which explanatory variables affect the response, while controlling effects of possible confounding variables. If there are k predictors for a binary response Y, denoted by $X_1, X_2, \ldots, X_k$, the logit model in multiple logistic regression takes the form:

$$\operatorname{logit} \pi(x) = \ln \frac{\pi(x)}{1-\pi(x)} = \alpha + \beta_1 x_1 + \cdots + \beta_k x_k$$

where the parameter β_i refers to the effect of X_i on the log odds, controlling for the other X's.

Multinomial logit models are used for discrete-choice modelling of subject's choice from one of several response options. The multinomial logistic regression is synonymous with the polytomous, or multicategory, logistic regression. For a multinomial response variable, a reference category is selected and indexed by j (Agresti, 1990).

When the last category is the reference, the logit model is given by:

$$\ln\left(\frac{\pi_j}{\pi_J}\right) = \alpha_j + \beta_j x \qquad j = 1, 2, \ldots. J-1$$

where x is the predictor, J is both the reference category and the number of categories of the nominal response variable; β_j and β_J are parameters used to describe response probabilities for response categories j and J.

2.5 Model specification

Multiple logistic regression models were fitted for eight outcome variables, namely the probabilities of using: firewood for cooking (π_{fc}), charcoal for cooking (π_{cc}), electricity for cooking (π_{ec}), firewood for water heating (π_{fh}), charcoal for water heating (π_{ch}), electricity for water heating (π_{eh}), paraffin for lighting (π_{pl}) and electricity for lighting (π_{el}). At household level each one of these response variables had two categories: *use* (at least once a week) and *do not use*. Respondents could choose multiple energy sources for each purpose, though most of them only chose one. No distinction was made between sole and joint use of fuels. The probabilities of using paraffin for cooking and for water heating were not considered due to rare usage.

Table 2 lists the five explanatory variables considered, and indicates the categories assigned to each of the codes used. In each case, the categories were treated as equally spaced in the analyses performed. Thus for example, the difference between *illiterate* and *standards 1-3* was assumed to be equal to that between *secondary* and *university* education.

For each response **res** considered, the maximal multiple logistic regression model used was:

$$\operatorname{logit} \pi_{\mathbf{res}} = \ln \frac{\pi_{\mathbf{res}}}{1-\pi_{\mathbf{res}}} = \alpha + \beta_1 x_1 + \cdots + \beta_5 x_5$$

where $\pi_{\mathbf{res}}$ denotes the response variable, α is a constant and the β_i's denote the rate of increase or decrease (slope) of the curves of the logit against X_i, i.e. β_i refers to the effect of X_i on the log odds of the probability of the response, controlling for the other X's.

For multinomial logistic regression, the explanatory variables were those used in multiple logistic regression, above. However, only one response variable (i.e. energy source for cooking) was considered. The variable had three levels: wood-fuel only (1), combinations of wood-fuel and electricity (2) and electricity only (3). The last category i.e. electricity only was the reference. Although the response variable for water heating has the same categories as cooking, multinomial logistic regression was not applied for water heating because the combination category had only five counts.

2.6 Model fitting and selection

For each outcome variable models were fitted using the backward stepwise likelihood ratio method in SPSS. Initially all 5 explanatory variables were entered into the model together and were tested for removal one by one until no more variables satisfied the removal criterion. The removal of the variable from the model was based on the significance of the change in the log-likelihood (SPSS Corporation Inc., 1998). The models identified at each step of the procedure were candidate models.

To achieve more accurate model selection the corrected Akaike's Information Criterion (AIC_c) was used. This is a more precise 2^{nd} order Taylor series approximation than Akaike's Information Criterion (AIC). This was calculated for each model in the selection procedure and the model with the smallest AIC_c was selected since the smaller the AIC_c, the better the model fit to the data (Chatfield, 1995). It was used because it provides more satisfactory conclusions than ei-

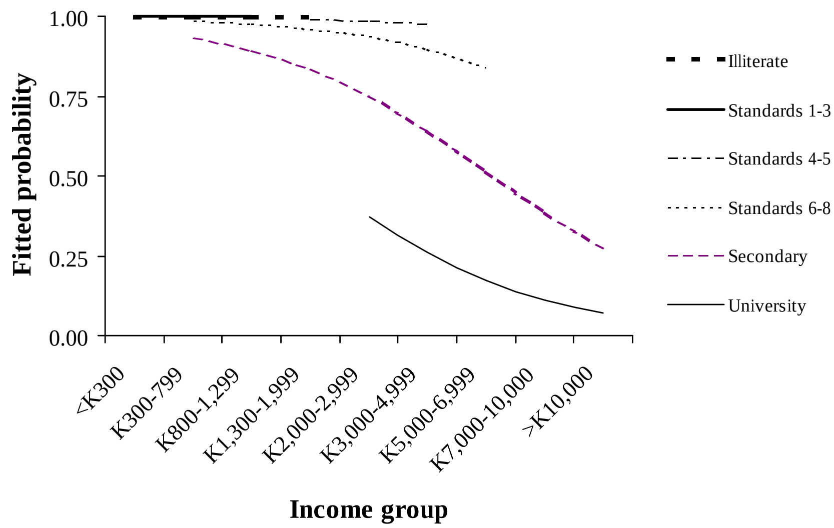

Figure 1: Fitted probabilities of using firewood for cooking by income group and education level for the selected model

Table 3: Model estimates for energy sources used for cooking

Variable	Firewood			Charcoal			Electricity		
	β	S.E.	exp(β)	β	S.E.	exp(β)	β	S.E.	exp(β)
Housing density area				-0.53	0.22	0.59	0.55	0.24	1.73
Education	-1.62	0.41	0.20	0.66	0.28	1.93	1.96	0.50	7.11
Income	-0.52	0.15	0.59				0.38	0.16	1.46
Sex									
Marital status									
Constant	11.80	2.09		-3.40	1.25		-13.87	2.51	

ther classical testing or Bayes Information Criterion (BIC) for small samples (Lindsey, 1999).

The AIC_c is an information-theoretic measurement of error defined as:

$$AIC_c = AIC + \frac{2k(k+1)}{n-k-1}$$

where $AIC = -2\log\ \text{likelihood} + 2k$, $k =$ number of parameters in the model, including the constant and $n =$ sample size. AIC_c was chosen rather than the stepwise and best subsets selection method used by SPSS for the following reasons (Burnham and Anderson, 1998):

(i) The statistics used in stepwise and best subsets selection methods address the wrong question: Does the model differ from the null model? The right research question being, How well does the model fit the reality, represented by the data?

(ii) Specious covariates are commonly entered as significant because of compounded Type I error effects.

(iii) You cannot assess the uncertainty of your selected model and of competing models.

3 RESULTS AND DISCUSSION

We report results of main effects multiple and multinomial logistic regression models and their interpretation. Some of these results are also included among those reported in Manda et al. (2001). For each response variable (energy source and use) the parameter estimates of the selected model are tabulated with their standard errors and the corresponding odds (exp(β)). When a variable was not selected using the AIC_c, no estimate is tabulated.

3.1 Energy sources for cooking

The main energy sources used for cooking are firewood, charcoal and electricity. Table 3 summarises the models selected for each of these energy sources. For cooking, education was found to be a significant predictor for all three fuels, while

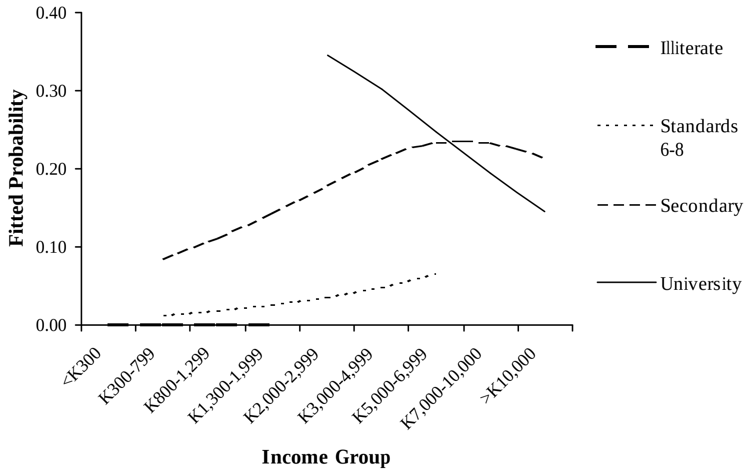

Figure 2: Fitted probability of using a combination of wood-fuel and electricity for cooking by income group and education level

income was significant for both firewood and electricity and housing density area was significant for both charcoal and electricity.

For each unit increment in education category and in income category, the odds ratios for using firewood rather than any other fuel type are estimated to be 0.20 and 0.59 respectively, i.e. the odds ratios reduce by 80% and 41% respectively. Figure 1 illustrates how the predicted probability of using firewood varies with education and income. This model estimates that almost all households with income below K5,000.00 whose heads did not proceed further than Standard 5 use firewood for cooking. By contrast when income exceeds K10,000.00 and University education was reached only 10% use firewood.

The odds of using charcoal rather than any other fuel type reduces as housing density area improves, but increases as education increases. For each unit increment in housing density area, the estimated odds ratio is 0.59, i.e. the odds almost halves. For each unit increment in education category, the estimated odds ratio is 1.93, i.e. the odds almost doubles. The association with housing density area may be due to people tending to use the energy source commonly used in their place of residence.

The estimated odds of using electricity rather than any other fuel type increases as the status of housing density area, education level and income group each improves. The odds ratios are 1.73, 7.11 and 1.46 (i.e. increases of 73%, 611% and 46%) respectively. Thus although there are pair-wise associations among these three predictors each is useful in predicting the probability of using electricity for cooking. (See Manda et al. (2001) for a graphical presentation of this model).

Table 4: Multinomial model estimates for main energy sources used for cooking

Category	Variable	β	S.E.	exp(β)
Wood-fuel	Education	-2.67	0.60	0.07
	Income	-0.70	0.19	0.50
	Constant	18.76	3.20	
Wood-fuel/ electricity combination	Education	-0.79	0.51	0.46
	Income	-0.37	0.19	0.69
	Constant	6.33	2.75	

Table 4 summarises the model selected, using multinomial logistic regression. This model yields similar results to the multiple logistic regression model for use of firewood for cooking. The model shows that the odds of choice of wood-fuel (instead of electricity) reduce as education and income each increase. For each unit increment in education and income the odds reduce by 93% and 50% respectively. In addition, the model shows that the odds of choice of wood-fuel and electricity combinations (instead of electricity) reduce as education and income each increases. For unit increments in education and income, the estimated odds reduce by 54% and 31% respectively.

The estimated probabilities of using wood-fuel (firewood and charcoal) obtained from multinomial logistic regression are similar to those presented for firewood only in Figure 1. This reflects the fact that firewood is a more popular fuel than charcoal.

Figure 2 illustrates how the estimated probabilities of using combinations of wood-fuel and electricity vary with income and education. It in-

Table 5: Model estimates for energy sources used for water heating

Variable	Firewood			Charcoal			Electricity		
	β	S.E.	exp(β)	β	S.E.	exp(β)	β	S.E.	exp(β)
Housing density area				-0.93	0.31	0.40			
Education	-2.26	0.48	0.10	1.35	0.47	3.85			
Income	-0.31	0.15	0.73				0.58	0.16	1.78
Sex	1.83	1.00	6.21						
Marital status							-0.99	0.64	0.37
Constant	12.41	2.43		-6.71	2.17		-12.37	2.38	

dicates that in income categories up to and including K800 to K1,299 and secondary education category almost 10% use combinations of wood-fuel and electricity for cooking. For those with secondary education the peak estimated proportion using the combination is 25% at incomes of K7,000 to K10,000. Among those with University education the proportion decreases with increasing income.

3.2 Energy sources for water heating

The main energy sources used for water heating are firewood, charcoal and electricity. Table 5 summarises the models selected for each of these energy sources. For water heating, as for cooking, education was found to be a significant predictor in the leading model for all three fuels, while income was again significant for both firewood and electricity and housing density area was only significant for charcoal. These associations are similar to those found for cooking. Sex was also significant for use of firewood and marital status for use of electricity.

The odds of using firewood is lower for female headed than male headed households, and it reduces as education and income each increases. The estimated odds ratio for using firewood, for male compared with female-headed households, is 6.2. For unit increases in education and income categories, the estimated odds ratios reduce by 90% and 27% respectively.

The odds of using charcoal rather than any other fuel type reduces as housing density area increases, and increases as education increases. For unit increases in housing density area and education, the estimated odds ratios are 0.40 and 3.85 respectively. These associations are similar to those found for use of charcoal for cooking.

For a change from a household headed by an unmarried person to a married person, the odds of using electricity reduce by 63%. For unit increases in education and income category, the estimated odds ratios are 5.17 and 1.78 respectively. The associations with education and income are similar to those found for firewood for cooking. However here marital status is found to be more relevant than housing density area.

3.3 Energy sources for lighting

The main energy sources used for lighting are paraffin and electricity. Table 6 summarises the model selected for each of these energy sources.

Housing density area, education and income are significant predictors of a household using paraffin for lighting. The odds of using paraffin rather than any other fuel type reduces as housing density area, education and income each increases. For unit increments in housing density area, education category and income category, the estimated odds are approximately halved (the estimated odds ratios are: 0.41, 0.45 and 0.50 respectively).

Since only two energy sources are used, with almost no overlap, the probability of using electricity is approximately equal to the probability of not using paraffin. (See Manda et al. (2001) for a graphical presentation of this model). The same predictors are selected, with each approximately doubling the odds of use (the estimated odds ratios are: 2.41, 2.14 and 1.73 respectively).

4 CONCLUSIONS AND RECOMMENDATIONS

The study demonstrates that univariate analysis of the data is not sufficient to explain all the variation in the data. Multiple logistic regression has revealed that a single socio-economic factor is not adequate to predict choice of each energy source. Specifically, results of the study show, for instance, that regardless of their income levels, households with a more educated head are less likely to use firewood for cooking. Similarly, regardless of their income levels, households with a more educated head and in a lower housing density area are more likely to use electricity for cooking and lighting. Also, in spite of the household head's education level, relatively richer households are less likely to use firewood for cooking and more likely to use

Table 6: Model estimates for energy sources used for lighting

Variable	Paraffin			Electricity		
	β	S.E.	exp(β)	β	S.E.	exp(β)
Housing density area	-0.89	0.29	0.41	0.88	0.27	2.41
Education	-0.80	0.34	0.45	0.76	0.32	2.14
Income	-0.69	0.20	0.50	0.55	0.18	1.73
Sex						
Marital status						
Constant	8.7	1.67		-7.83	1.5	

electricity as an energy source. Thus, improvements in education, income levels and housing density areas each reduce the likelihood of households using wood-fuel.

This study was conducted in only one location within Malawi. Zomba municipality has some unique characteristics within Malawi. There is no manufacturing industry and Chancellor College is a major employer. Within low density housing areas there is more homogeneity of occupation than in the cities of Malawi. The extent to which the models fitted are applicable to other locations is unclear. In many rural areas electricity is not an available option. Thus the models identified in this work do not apply to such areas. Further research is necessary to confirm the magnitude of influence of some of the identified variables in other types of locations in Malawi.

Dependence on wood-fuel is mainly prevalent in least developed countries like Malawi where there is extensive poverty and illiteracy. Those with least income and least education are more dependent on wood-fuel. For this dependence to reduce there is need of enhancing poverty alleviation programmes in order to achieve improved standards of living. Therefore, improvements in income and education should be considered part and parcel of the strategy for combating deforestation.

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