East African Journal of Forestry & Agroforestry
eajfa.eanso.org
Volume 8, Issue 1, 2025
Print ISSN: 2707-4315 | Online ISSN: 2707-4323
Title DOI: https://doi.org/10.37284/2707-4323

EAST AFRICAN NATURE & SCIENCE ORGANIZATION

Original Article

Determinants of Tree Growers' Preferences for Forest Insurance in Mufindi District, Tanzania

Riziki Habakuki. Nyange[1], Gerald Claudius Monela[1] & Beatus John Temu[1]*

[1] Sokoine University of Agriculture, P. O. Box 3011, Morogoro, Tanzania.
[*] Author for Correspondence ORCID ID; https://orcid.org/0009-0009-2233-4128; Email: rizikinyange9@gmail.com

Article DOI: https://doi.org/10.37284/eajfa.8.1.3497

Date Published:

18 August 2025

Keywords:

Forest insurance, Tree growers, Binary logistic model, Forest fire, Pest and diseases, Tanzania.

ABSTRACT

Private tree growers play a key role in sustainable wood supply and rural livelihoods, but face high vulnerability to natural disasters, fire, pests, and diseases. These hazards threaten incomes, market access, and forest productivity, yet research and policies addressing their specific risk management needs remain little known, creating a critical gap in enhancing their resilience and sustainability. This study analyses the factors influencing the decision of the tree growers to purchase forest insurance. One hundred twenty tree growers were sampled in four villages using a multistage sampling technique. Results show that 76.7% of the respondents were willing to pay for forest insurance on an annual premium payment basis. A binary logistic regression was used to analyse factors influencing willingness to pay for forest insurance. Results showed the extent of exposure to modern education, experience in tree planting, total income, and size of the forest significantly (Omnibus test value for model fitness 45.7659, p-value=0.000). Also, the multinomial logit model was used to analyse factors influencing the choice of insurance type, and results show that sex, income, experience in tree growing, previous occurrence of fire, tree species planted, and location of the farm have statistical significance. These insights also inform extension service agents and other forest stakeholders on how to tailor sensitisation and training programs. By focusing on the factors that most influence adoption, extension efforts can better address knowledge gaps, highlight the economic value of insurance, and build trust in the policy, ultimately increasing uptake among tree growers

APA CITATION

Nyange, R. H., Monela, G. C. & Temu, B. J. (2025). Determinants of Tree Growers' Preferences for Forest Insurance in Mufindi District, Tanzania. *East African Journal of Forestry and Agroforestry*, *8*(1), 390-405. https://doi.org/10.37284/eajfa.8.1.3497

CHICAGO CITATION

Nyange, Riziki Habakuki, Gerald Claudius Monela and Beatus John Temu. 2025. "Determinants of Tree Growers' Preferences for Forest Insurance in Mufindi District, Tanzania" *East African Journal of Forestry and Agroforestry* 8 (1), 390-405. https://doi.org/10.37284/eajfa.8.1.3497.

HARVARD CITATION

Nyange, R. H., Monela, G. C. & Temu, B. J. (2025), "Determinants of Tree Growers' Preferences for Forest Insurance in Mufindi District, Tanzania", *East African Journal of Forestry and Agroforestry*, 8(1), pp. 390-405. doi: 10.37284/eajfa.8.1.3497.

Article DOI: https://doi.org/10.37284/eajfa.8.1.3497

IEEE CITATION

R. H., Nyange, G. C., Monela & B. J., Temu "Determinants of Tree Growers' Preferences for Forest Insurance in Mufindi District, Tanzania", *EAJFA*, vol. 8, no. 1, pp. 390-405, Aug. 2025.

MLA CITATION

Nyange, Riziki Habakuki, Gerald Claudius Monela & Beatus John Temu. "Determinants of Tree Growers' Preferences for Forest Insurance in Mufindi District, Tanzania". *East African Journal of Forestry and Agroforestry*, Vol. 8, no. 1, Aug. 2025, pp. 390-405, doi:10.37284/eajfa.8.1.3497

INTRODUCTION

Private tree growers reduce pressure on natural forests by supplying wood resources and providing livelihood opportunities for communities involved in production (Flanagan *et al.,* 2020; Nambiar, 2021; Temu *et al.,* 2024). Natural disasters, fire, pests, diseases and other environmental hazards can severely impact the earnings and livelihoods of tree growers globally (Ofoegbu *et al.,* 2017; Abbass *et al.,* 2022; Etherton *et al.,* 2024; Mgoo *et al.,* 2024). Despite these risks, forest insurance uptake among tree growers was relatively lower, particularly in the global south (Mensah *et al.,* 2021). Globally, the area of forest plantations was reported to increase at a rate of 4.5 million hectares per year (Abbass *et al.*, 2022). Asia and South America account for more new plantations than the other regions (Payn *et al.,* 2015; Cubbage *et al.,* 2020). Forest resources serve as the primary source of livelihood for forest-adjacent communities by acting as one of the major sources of income, medicine, and food (Cubbage *et al.,* 2020). The objectives of establishing private forest plantations include ensuring a sustainable yield of wood material due to the increasing forest demand for export and local consumption and mitigation measures to climate change (Nambiar, 2021; Mwinyimkuu *et al.,* 2022). Most of the forest plantations were dominated by exotic tree species due to their rapid growth and high production within a shorter period (Zhou *et al.*, 2020; Farooq *et al.,* 2021). These exotic species are considered highly susceptible to fire, pests and disease damage (Meyer *et al.*, 2021). Natural hazards continue to increase, which affects the production of forestland in the world (Zhang and Stenger, 2014). Globally, between the years 2001 and 2019, fire cleared on average 67 million hectares of forest per year, insects affected 85 million hectares of forests and 12.5 million forests were affected by various diseases (Stanturf and Mansourian, 2020). Due to serious problems such as fire, disease, and pests in forest plantations, some private tree growers in various parts of the world have addressed these risks by introducing forest insurance to safeguard investments against natural hazards (Sauter et al., 2016 and Kimambo et al., 2020). Plantation forestry in Tanzania started during German rule in the early 1990s(Petro and Madoffe, 2011; Mgina and Wawa, 2021). The major tree species in these plantations are Eucalyptus 22.4% of all planted area, followed by Pinus (20.5%), Hevea (7.1%), Acacia (4.3%) and *Tectona grandis* (2.6%) (Mwambusi *et al.,* 2021). Tree growers mostly face hazards such as forest fires, diseases and pests (Kaganzi *et al.*, 2021). Although tree growers face substantial risks, measures to mitigate these threats and protect investments remain inadequate. Limited information on solutions such as forest insurance, coupled with scarce research on factors influencing growers' preferences and willingness to pay, hinders the development of effective products. This study addresses this gap by examining tree growers' preferences and identifying key determinants of willingness to pay, providing insights for designing tailored insurance schemes that enhance resilience and sustainability in the forestry sector.'

METHODOLOGY

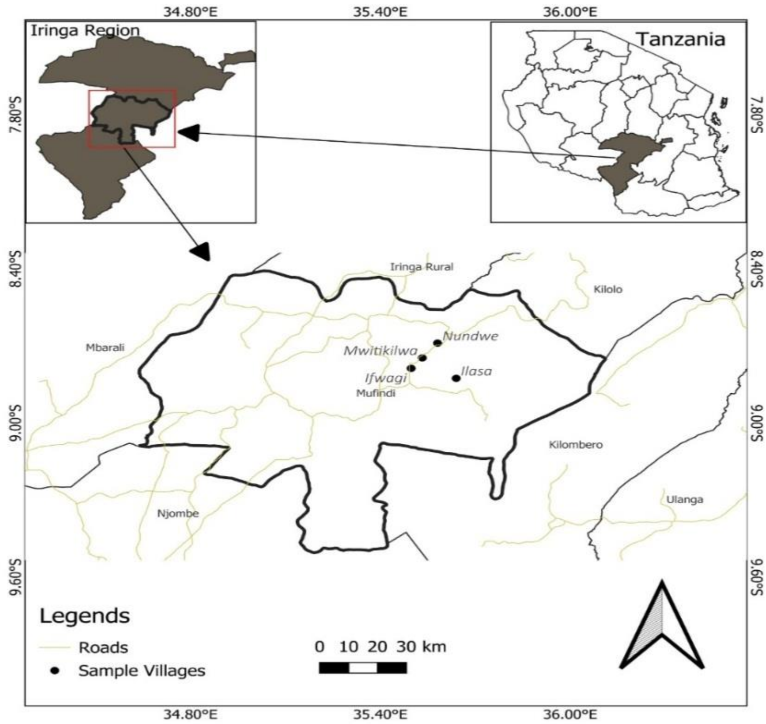
Descriptions of the Study Area

The study was conducted in Mufindi district, one of seven districts of Iringa region in Tanzania (8°-9°S; 30°-36°E). The district lies 800 to 2200 meters above sea level (m.a.s.l k.) with an average annual temperature of 17.1℃. It experiences a well-distributed rainfall ranging from 950 to 1,600 mm yr, 263 kha of tree cover and the main commercial crops are tea and forest plantations

Article DOI: https://doi.org/10.37284/eajfa.8.1.3497

(Lusambo *et al.,* 2021). It covers 712,200 ha and is divided into 5 Divisions, 30 Wards, 125 Villages and 608 Hamlets (Mwambusi *et al.,* 2021). The total human population was 288,996, with a 41.66/km² population density and a 1.6% annual population change from 2012 - 2022. The area is a centre for forestry and different tree planting programs (Komu, 2020). For instance, the largest state forest plantation, Sao Hill Forest Plantation (SHFP occupies a large part of this district (Kifyasi, 2021). Mufindi district experiences the problem of forest fires and disease, especially during the dry season (Mgina and Wawa, 2021; Petro and Madoffe, 2011). The main tree species which are planted in Mufindi district are *Pines patula* and Eucalyptus species (Mwakasungula and Mombo, 2025).

Figure 1: A Map of the Study Area



Research Design

This study employed a cross-sectional research design

It was cross–sectional because collection was done only once in the study area; the results may not reflect changes over time, which limits the ability to identify trends or seasonal variations (Archibald *et al.,* 2015).

Sampling Design and Data Collection

A multistage sampling technique was employed. In the first stage, a purposive sampling approach was used to select the Mufindi District in the Southern Highlands of Tanzania, objectively due to the large number of tree growers observed. In the second stage, the purposive sampling technique was applied to select 4 Villages: Mwitikilwa, Ifwagi, Ilasa, and Nundwe. Proportional random sampling was then used to select households per village to be included in the study. In the third stage, a simple random technique was applied to select the required households in each village, ensuring each household had an equal chance of being selected (Karupu *et al*., 2021). A list of tree growers was obtained in the villages, which are registered and unregistered in the TTGA.

The study area has a population of 2728 households, according to the census of 2022, and the study employs (Singh Masuku, 2014) for sample size determination.

Article DOI: https://doi.org/10.37284/eajfa.8.1.3497

$n = \frac{N}{1+Ne^2}$ Whereby;

$N = Total\ popultion\ size\ and\ e = Margin\ of\ error\ or\ allawable\ erro(10\%)$.

$n = \frac{2728}{1+2728(0.1^2)}$ n =97

The formula minimises sampling error and bias as it draws a representative sample from the target population (Suleiman *et al.,* 2017). The generated sample size was 97 households. The sample size generated aligns with the central limit theorem states that a sample size ≥ 30 is enough for a standard deviation and can provide enough results; however, for this study, 120 households were used, which was greater than the 97 minimum sample size required. Therefore, the sample size selected is appropriate and was employed for the statistical analysis. A list of all households (tree growers) was acquired from the village's office in a registered book according to the census of 2022. The sample size population from different villages were selected (Table 1) with the proportion of the study population similar to (Kothari, 2004). The observational unit was the household independent of his/her gender status, who is 18 or more years old.

Table 1: Sampling Frame and Sampling Size

S/N	Village	Sampling frame	Proportion	Sample size
1	Ifwagi	682	682/2728*120	30
2	Mwitikilwa	644	644/2728*120	28
3	Ilasa	784	784/2728*120	35
4	Nundwe	618	618/2728*120	27
	Total	2728		120

Data Sources and Methods Collections

The study utilised primary data, which are qualitative and quantitative data collected from households which are tree growers. Household surveys, questionnaires and field observations were employed in data collection. The survey questionnaire tools were composed of both open- and closed-ended types to collect reliable data about the demographic and social characteristics of the tree growers, the willingness to pay for the forest insurance, the type of tree species planted, the size of the forests, threats affecting the forest, knowledge on insurance, perceptions and attitudes in forest insurance. Factors influencing willingness to pay for the forest insurance and factors influencing choices of the forest insurance type and questionnaires were administered by researchers and trained enumerators.

Methods of Data Analysis

Data collected through questionnaires were analysed using descriptive and inferential statistics, along with a multinomial logit model as well as a binary logistic model. Qualitative categorical types of data were analysed using percentages and frequency distributions and quantitative continuous data were analysed using means and standard deviations. Qualitative data were analysed through thematic analysis. Data analysis was conducted using SPSS version 26 (Statistical Package for Social Science).

Factors Influencing Tree Growers' Willingness to Participate in Forest Insurance

Binary logistic regression was employed to analyse the factors that influence tree growers' WTP for forest insurance at a 5% significance level in SPSS software version 26 under the following assumptions: the observations must be independent, there is no perfect multicollinearity among independent variables, and continuous predictors are linearly related to the transformed version of the outcome. Binary logistic regression was used because the dependent variable was dummy-coded (0,1) and the independent variable was categorical, continuous and a mixture of categorical and continuous (Güneri and Durmuş, 2020). The relationship between dependent and independent variables is modelled through the logit function, which is the natural log of the odds

Article DOI: https://doi.org/10.37284/eajfa.8.1.3497

of the dependent variable occurring, as shown below;

$$\ln\left(\frac{p}{1-p}\right) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 \dots\dots\dots\dots\dots\dots\dots\dots\dots + \beta_n X_n$$

$Where\ by\ ln\ (p) = Probability\ of\ the\ dependent\ variable\ (if\ y = 1)$
$= 1\ and\ \ln(1-p)\ is\ the\ probabilityof\ depedent\ variable\ \ (if\ Y = 0)$

$Intercept\ \beta_0 = odd\ function\ when\ all\ preditor\ are\ zero$

$\beta_1, \beta_2, \beta_3 and\ \beta_n = coefficient\ of\ explanatory\ variable$

$X_1, X_2, X_3 and x_n\ independent\ variable\ (Social\ characteristics\ and\ Forest\ variable\ as\ shown\ in\ table$

The Random Utility Maximization (RUM) for the Logit Model

Consider a scenario where there are two states of the words, denoted as z^0(initial state) and z^1 (improved state). An individual is aware of their preferences and expresses them through a utility function $u\ (x, z)$, where x represents income and z is the state of the world. As researchers, we can only partially observe these preferences, observe $V\ (x, z) = u\ (x, z) + \varepsilon$, where ε is an error term that accounts for unobserved factors affecting utility. To analyse decision-making under this framework, we can ask an individual to pay an amount A to prevent the forest plantation from unplanned disasters z^1 the response - whether they are willing to pay or not provides insight into their utility-maximising behaviour. Specifically, if they answer “yes”, we interpret it as a utility-maximising choice in line with the interpretation of random utility theory (Simon *et al.,* 2023). When an individual responds “no” to paying A, this implies that the utility they derive from the improved state, less the payment, is not enough to outweigh the utility of the status quo.

Mathematically, this is expressed as:

$u(z^1, m-A) + \varepsilon_1, \leq u(z^0, m-A) + \varepsilon_0$

Conversely, a “yes” response implies that the utility from the improved state exceeds that of the initial state:

$u(z^1, m-A) + \varepsilon_1, \geq u(z^0, m-A) + \varepsilon_0$

By simplifying this, we get the inequality:

$u(z^1, m-A) - u(z^0, m-A) \geq \varepsilon_0 - \varepsilon_1$Letting $\triangle\, u(\bullet) = u(z^1, m-A) - u(z^0, m-A)$ we can further write:

$$\triangle\, u(\bullet) \geq \varepsilon$$

Thus, the probability that the individual says” yes” can be written as:

$\Pr(\text{”yes”}) = \Pr(\varepsilon \leq \triangle\, u(\bullet)) = F\varepsilon(\triangle\, u(\bullet))$

Here, $F\varepsilon$ represents the cumulative distribution function (CDF) of the error term ε.

Willingness to Pay

An individual will accept the payment A for the improved state only if they are willing to pay (WTP) is greater than or equal to A. This condition can be expressed as:

$$\begin{aligned} Pr(\text{”yes”}) &= Pr(W\,TP \geq A) \\ &= 1 - G_{WTP}\,(A) \\ &= F\varepsilon(\triangle\, u(\bullet)) \end{aligned}$$

Where $GW\,T\,P$ are the cumulative distribution function of WTP. This formulation gives us the basis for analysing the probability of a positive response based on A and the underlying utility differences. G_{WTP}

Welfare Measures

To calculate welfare measures such as expected willingness to pay (E (WTP)), below expressions were used.

Article DOI: https://doi.org/10.37284/eajfa.8.1.3497

$$E(WTP) = \int_0^\infty (1 - G_{WTP}(A)dA - \int_{-\infty}^0 G_{WTP}(A)dA$$

This equation integrates over the distribution of WTP, accounting for both positive and negative values. Importantly, we allow for the possibility of negative WTP, which reflects situations where individuals might have negative utility for the improvement.

Consider a simple utility function of the form:

$$u(z,m) = \alpha^i + \beta m, i = 0, 1$$

The difference in utility between the two states is given by:

$$\triangle u(\bullet) = \alpha^1 - \alpha^0 - \beta A = \alpha - \beta A$$

Assume that the error term follows a logistic distribution with CDF:

$$F(x) = \frac{1}{1 + \exp(-x)}$$

The probability of a response "yes" respons1 e then becomes

$$F_\varepsilon(\triangle u(\bullet)) = \frac{1}{1 + \exp(-\alpha + \beta A)}$$

Expected Willingness to Pay

Recalling the formula for expected willingness to pay, we now have:

$$E(WTP) = \int_0^\infty \frac{1}{1 + \exp(-\alpha + \beta A} dA - \int_{-\infty}^0 \frac{1}{1 + \exp(-\alpha - \beta A)} dA$$

The median willingness to pay occurs where the probability is 0.5, which implies

$$Median = \frac{\alpha}{\beta}$$

In this model, α represents the marginal utility of improving the statez, while β represents the marginal utility of income. Thus, the ratio α/β gives us a utility-theoretic interpretation of expected WTP. This result holds under the assumption that the utility function is quasi-linear and G_{WTP} is defined over the entire real line.

Factors Influencing the Choice of the Forest Insurance Types

The multinomial logit model (MLM) was adopted in examining factors influencing the choice of insurance type in SPSS Vision 26. MLM was used because the dependent variable contains more than two choices. When we have a dependent variable more than two, the appropriate econometric model would be either MLM or multinomial probit regression model (Washington *et al.,* 2020). In this study, we employ MLM to analyse the factors influencing tree growers' choices of the forest insurance type because the multinomial probit regression model was rarely used due to the complexity of solving multiple integrations related to multivariate normal distribution (Mubarik & Naghavi, 2020). The data consists of 120 tree growers who face four choices coded 1,2,3 and 4 which include no insurance, fire, pest and disease and combined insurance respectively, no insurance was used as the reference category, based on the utility theory tree growers will choose an alternative with high satisfaction based on their risk appetite and risk management preference (Liao *et al.,* 2023).

Hence, let

$$Yij = 1, if\ the\ individual\ i\ chooses\ alternative\ j\ (j = 1,2,3\ and\ in\ 4\ in\ the\ present\ case\ )$$
$$= 0, otherwise$$

Let$P = \Pr(Y_{ij} = 1)$.....................................(1)

Therefore, P_{i1}, P_{i2}, P_{i3} and P_{i4} represent the probabilities that individual i chooses alternative 1, 2,3 or 4, which present no forest insurance, fire, disease and pest, combined insurance respectively. The sum of the probability was one, as shown in equation one

$$p_{i1} + p_{i2} + p_{i3} + p_{i4} = 1 \ldots\ldots\ldots\ldots\ldots\ldots\ldots.\ldots\ldots\ldots\ldots\ldots (2)$$

Article DOI: https://doi.org/10.37284/eajfa.8.1.3497

The general equation for the multinomial logit model

$$P_{ij} = \frac{e^{\alpha_j + \beta_j X_j}}{\sum_{j=1}^{4} e^{\alpha_j + \beta_j X_j}} \text{.............................} (3)$$

The intercept j and slope coefficient can vary from choice to choice, which means tree growers who do not want forest insurance would attach different weights compared to the tree growers who want fire, disease, and pest or combined insurance. Also, tree growers who want fire insurance would attach a different weight than tree growers who prefer pest and disease or combined insurance, causing the slope of each category to vary. Eight slope coefficients would be estimated, and they differ from choice to choice. In this model, we have four probabilities, and each probability cannot be estimated independently. However, the coefficient value for the reference category is zero. When the first category (no forest insurance) is selected as α=0 and β=0, we obtained the following estimate of four probabilities.

$$P_{i1} = \frac{1}{1 + e^{\alpha_2 + \beta_2 x_i} + e^{\alpha_3 + \beta_3 x_i} + e^{\alpha_4 + \beta_4 x_i}} \dots\dots\dots (4)$$

$$P_{i2} = \frac{e^{\alpha_2 + \beta_2 X_i}}{1 + e^{\alpha_2 + \beta_2 x_i} + e^{\alpha_3 + \beta_3 x_i} + e^{\alpha_4 + \beta_4 x_i}} \dots\dots\dots (5)$$

$$P_{i3} = \frac{e^{\alpha_3 + \beta_3 X_i}}{1 + e^{\alpha_2 + \beta_2 x_i} + e^{\alpha_3 + \beta_3 x_i} + e^{\alpha_4 + \beta_4 x_i}} \dots\dots\dots (6)$$

$$P_{i4} = \frac{e^{\alpha_4 + \beta_4 X_i}}{1 + e^{\alpha_2 + \beta_2 x_i} + e^{\alpha_3 + \beta_3 x_i} + e^{\alpha_4 + \beta_4 x_i}} \dots\dots\dots (7)$$

Adding all four probabilities (equations four to seven) will give a value of one because of mutually exclusive choices, so in this model, we have four mutually exclusive choices. One of the assumptions of MLM is the independence of irrelevance assumption (IAA), which is not violated because the choice was made independent of other alternatives (Mensah *et al.,* 2021).

RESULTS

Social Economic Characteristics

The study included a total of 120 respondents, of whom 75.8% were male and 24.2% were female. The average age of the households was 47 years. Respondents had varying educational backgrounds: 54.2% had attained primary education, 21.7% had completed secondary education, 12.4% had attained higher education (college or university), and 11.7% had no formal education. The average experience in tree planting was 19 years, and the average annual income was USD 2,049.34 (TZS 5,334,333) based on an exchange rate of 1 USD = TZS 2,607.27. In terms of farm size, 83.3% of respondents owned farms smaller than 4 ha, 15.8% had farms between 4 ha and 10 ha, and 0.9% had farms larger than 10 ha (see Table 2).

Article DOI: https://doi.org/10.37284/eajfa.8.1.3497

Table 2: Socio-economic Characteristics of the Respondents

Variable	Mean	Std. Deviation	Frequency (N)	Percentage (%)
Age	47 years	9.532		
Gender				
Male			91	75.8
Female			29	24.2
Education				
No formal education			14	11.7
Primary			65	54.2.
Secondary			26	21.7
Colleges/universities			15	12.4
Income	TZS 5 343 333.33	3 303 976.045		
Experience in tree planting	19 years			
Size of the farm				
Less than 4Ha			100	83.3
Between 4Ha to10Ha			19	15.8
Above 10Ha			1	0.9

Source: *(Nyange, 2025)*

Table 3 indicates that 76.7% of respondents were willing to pay for forest insurance, while 23.3% were not. Preference for insurance type was highest for fire insurance (42.0%), followed by combined insurance (28.2%) and pest and disease insurance (6.5%). Most respondents preferred annual payments (89.2%), with smaller proportions opting for semi-annual (4.2%), quarterly (5.0%), or more than once-a-year payments (1.6%).

Table 3: Willingness to Pay, Type of Forest Insurance and Insurance Time Premium

Category	Frequency	Percent (%)
WTP for Forest Insurance		
No	28	23.3
Yes	92	76.7
Type of forest insurance		
Fire insurance	52	42.0
Pest and Disease insurance	9	6.5
Combined insurance	31	28.2
No insurance	28	23.3
Insurance time premium (year)		
Annual	107	89.2
Quarter	6	5
Semi-annual	5	4.2
More than Annual	2	1.6

Factors Influencing Willingness to Pay for Forest Insurance

Table 4 indicates that out of the twelve variables entered into the model, only four had a significant relationship with the dependent variable, namely, years spent in school, total income, size of the forest, and experience in tree planting. The Omnibus Test of Model Coefficients and the Hosmer and Lemeshow Test were employed to assess the model's goodness of fit. The Omnibus Test of Model Coefficients revealed that the overall model fit statistic for the regression model

Article DOI: https://doi.org/10.37284/eajfa.8.1.3497

was 45.765, with a corresponding p-value of 0.000, which is less than 0.05. Furthermore, the Hosmer and Lemeshow Test yielded a value of 0.967, which is greater than 0.05, confirming that the model demonstrated a good fit.

Table 4: Factors Influencing Willingness to Pay for Forest Insurance

Variables	B	S.E.	Wald	Df	Sig.	Exp(B)	95% C.I.for EXP(B)	
							Lower	Upper
Age	-0.01	0.048	0.015	1	0.903	0.994	0.905	1.092
Sex	-0.77	0.804	0.918	1	0.338	0.463	0.096	2.237
Years spent in school	0.373	0.145	6.607	1	0.01**	1.452	1.093	1.929
Total income	0.000	0	12.232	1	0.000***	1.000	1.000	1.000
Size of the forest	0.979	0.329	8.857	1	0.003**	2.661	1.397	5.068
Experience in tree planting	-0.14	0.055	6.398	1	0.011**	0.869	0.78	0.969
Previous fire	-0.92	0.948	0.939	1	0.332	0.399	0.062	2.558
Disease and pest	-1.29	1.064	1.47	1	0.225	0.275	0.034	2.216
Type of tree species planted	0.161	0.903	0.032	1	0.859	1.174	0.200	6.896
Type of land ownership	1.306	1.033	1.596	1	0.206	3.690	0.487	27.957
Stand age	21.24	6010.379	0.000	1	0.997	1.679E+09	0.000	0.000
Location of the farm	-1.52	0.989	2.366	1	0.124	0.219	0.031	1.518
Constant	3.81	2.901	1.725	1	0.189	45.141		

Note: *** indicates significance at 1% level, ** indicates significance at 5% level, *indicates significance at 10% level.

Preference for Forest Insurance Type

Table 5 presents the significant factors influencing the choice of insurance type. Prior to model estimation, multicollinearity among the hypothesised explanatory variables was assessed using variance inflation factors (for continuous variables) and contingency coefficients (for discrete variables). The results indicated no serious multicollinearity issues, as tolerance values were less than one and the sum of tolerances for dummy and continuous variables was also below one. The validity of the independence of irrelevant alternatives (IIA) assumption was tested using the Hausman test, and no violations were detected. Significant factors affecting the choice of insurance type included sex, income of tree growers, experience in tree planting, previous occurrence of fire, tree species planted, and farm location.

Table 5: Factors Influencing Choice of Forest Insurance Types

Variable	Forest insurance types								
	Fire insurance			Pest and disease insurance			Combined insurance		
	B	P-Value	EX (B)	B	P-Value	EX (B)	B	P-Value	EX (B)
Intercept	-0.87	0.842		-0.112	0.983		-2.44	0.601	
Age	-0.043	0.474	0.958	-0.06	0.408*	0.939	0.004	0.947	1.000
Sex	-2.482	0.059*	0.084	-2.497	0.111	0.082	-3.02	0.03**	0.05
Years in school	0.227	0.262	1.255	0.206	0.36	1.229	0.229	0.274	1.26
Total income	0.000	0.03**	1.000	0.000	0.049*	1.000	0.000	0.054*	1.000
Size of the forest	0.52	0.107	1.682	0.449	0.19	1.567	0.435	0.189	1.55
Experience	-0.097	0.097*	0.907	-0.11	0.087*	0.893	-0.13	0.046**	0.88
Previous fire	5.943	0.001**	381.1	5.514	0.005***	248.1	5.834	0.002***	342
Disease and pest	2.966	0.179	19.42	1.964	0.428	7.128	4.346	0.049**	77.2
Tree species planted	-2.174	0.043*	0.114	-3.40	0.032**	0.033	-2.82	0.02**	0.06
Land ownership	0.757	0.61	2.132	1.184	0.498	3.269	0.13	0.932	1.14
stand age	0.513	0.74	1.671	0.978	0.583	2.66	1.203	0.451	3.33
Farm location	-2.504	0.04**	0.082	3.729	0.025**	0.024	-1.64	0.191	0.19

Article DOI: https://doi.org/10.37284/eajfa.8.1.3497

Variable	Forest insurance types								
	Fire insurance			Pest and disease insurance			Combined insurance		
	B	P-Value	EX (B)	B	P-Value	EX (B)	B	P-Value	EX (B)
Reference category	No forest insurance								
Dependent variable	Preference of the insurance type								
Number of observations	120								
-2log likelihood model Fitting:	Intercept only 299.008, Final 183.480								
LR chi-square test:	115.578								
Degree of freedom:	36								
Significance:	0.000***								
Pseudo R2:	0.674								

Note: *** indicates significance at 1%, ** indicates significance at 5% and * indicates significance at 10%.

DISCUSSIONS

Table 2 shows that 75.8% of tree growers were male, indicating a male-dominated ownership structure in woodlot farming. This suggests that men were the primary decision-makers in managing forest plantations and addressing associated threats. Previous studies attribute this trend to gendered divisions of labour and the physical demands of tree growing (Akanle & Nwaobiala, 2020; Dinkelman & Ngai, 2022). Phiri et al. (2022) highlight the need for gender mainstreaming policies to enhance female participation in tree growing within African contexts.

In the Mufindi district, both youths and elders are actively engaging in tree growing as the main business activity. Results suggest the mean age of the respondents was 52 years, which is reproductive age, and they are active in tree growing due to their experience in business, and they want to invest more to generate more income for the future. Similarly, (Alemayehu and Melka, 2022) observed that investment in tree growing was influenced by age because older age and young households are less productive and generate lower income. This study revealed that education plays an interesting role as a determinant of activity income because households with higher education invest more since they are aware of the investment. Similarly, (Yassine and Bakass, 2022) found that education and employment play a role in a youth's poverty alleviation. The average annual income of the tree growers was USD 2049.34 (TZS 5343 333). These findings complement observations by Sauter *et al.* (2016), who found the average income of tree growers was US$1956 (TZS 4,850,000) per year.

Table 4 shows that the size of the forest has a significant positive influence on the willingness to pay for forest insurance. This indicates that increasing the size of the forest by one unit would raise tree growers' willingness to participate in forest insurance by a factor of 2.66661, assuming all other factors remain constant. The results were consistent with the findings of Qin *et al*. (2016), who reported that as forest size increases, the demand for forest insurance also rises. Additionally, the number of years spent in school significantly positively influenced willingness to pay in forest insurance, with each additional year of education increasing tree growers' desire to purchase forest insurance by a factor of 1.452, assuming other factors remained constant. These findings align with those of Falola *et al.* (2013) and Ajiboye *et al.* (2018), who observed that the education level of households positively influenced the purchase of agriculture insurance.

Income was found to be statistically significant, with an odds ratio close to one, which means that variations in the income of tree growers have little to no practical effect on their willingness to pay for forest insurance. This suggests that, regardless of income differences, tree growers are generally willing to participate in forest insurance, possibly due to shared perceptions of its benefits or risk mitigation. This finding aligns with Fonta et al. (2018), who reported that household income

Article DOI: https://doi.org/10.37284/eajfa.8.1.3497

positively influences decisions to participate in forest insurance. However, it contrasts with Islam et al. (2021), who found a negative relationship between income and willingness to purchase agricultural insurance. The discrepancy may be attributed to differences in sample size and methodological approaches between the studies.

Experience in tree planting was found to have a statistically significant negative effect on the willingness to pay (WTP) for forest insurance. Specifically, each additional year of experience decreased the odds of WTP by a factor of 0.869, holding other factors constant. This indicates that more experienced tree growers may feel more confident in their ability to manage and mitigate risks in their forests, thereby reducing their perceived need for insurance. These findings are consistent with Mensah et al. (2021) and Islam et al. (2021), who also reported a negative relationship between tree planting experience and WTP for forest insurance. However, they contrast with Ajiboye et al. (2018), who found that forest size positively influenced WTP. The discrepancy may be due to differences in sample size (154 respondents in Ajiboye et al.) and the analytical methods used, as this study employed binary logistic regression, whereas Ajiboye et al. used logistic regression.

Table 5 indicates that previous occurrences of fire were the strongest predictor influencing tree growers' choice of insurance type, exhibiting the highest odds ratios across all categories. Specifically, each additional fire occurrence increased the likelihood of selecting fire insurance by a factor of 381.1, followed by a factor of 342 for combined insurance and 248.1 for pest and disease insurance, holding all other factors constant. These findings suggest that fire is perceived as the most significant threat to forest investments, leading tree growers to prefer fire insurance as a means to mitigate potential financial losses from forest fires. This result aligns with Mensah et al. (2021), who similarly reported that fire occurrence significantly influences tree growers' decisions to purchase forest insurance.

Previous occurrences of fire were the strongest predictor influencing tree growers' choice of insurance type, exhibiting the highest odds ratios across all categories. Specifically, each additional fire occurrence increased the likelihood of selecting fire insurance by a factor of 381.1, followed by a factor of 342 for combined insurance and 248.1 for pest and disease insurance, holding all other factors constant. These findings suggest that fire is perceived as the most significant threat to forest investments, leading tree growers to prefer fire insurance as a means to mitigate potential financial losses from forest fires. This result aligns with Mensah et al. (2021), who similarly reported that fire occurrence significantly influences tree growers' decisions to purchase forest insurance.

Experience in tree planting was found to have a statistically significant negative effect on the likelihood of purchasing all types of forest insurance, as indicated by odds ratios less than one. Specifically, each additional year of experience reduced the probability of opting for fire insurance by a factor of 0.907, pest and disease insurance by 0.893, and combined insurance by 0.880, assuming other factors remained constant. This negative relationship suggests that more experienced tree growers are less likely to purchase forest insurance, likely because they possess the skills and knowledge necessary to manage and mitigate risks such as fire, pests, and diseases without relying on insurance. Over time, these growers may have developed effective preventive measures and strategies, increasing their confidence in protecting their investments independently. These findings are consistent with Mensah et al. (2021), who also reported a negative association between tree planting experience and willingness to purchase forest insurance. However, Brunette and Couture (2023) presented a contrasting perspective, finding that greater experience positively influenced the choice of insurance types, suggesting that experienced growers may also perceive insurance as a valuable complementary risk management tool. The divergence in findings may be attributed to

Article DOI: https://doi.org/10.37284/eajfa.8.1.3497

differences in methodological approaches used to assess factors influencing forest insurance adoption.

The income of tree growers has no significant impact on their preference for forest insurance types, with an odds ratio of 1, suggesting that changes in income do not affect the likelihood of choosing a particular insurance type when other factors are held constant. This indicates that the decision to select a specific forest insurance type is more influenced by threats faced by the forest rather than by the grower's income. These findings differ from previous studies by Sauter *et al.* (2016); Attipoe and Adams (2024) due to different sample sizes and methodology, which reported that an increase in tree growers' income led to a higher probability of selecting a preferred insurance type.

Tree species planted have a statistically negative influence, preference on all types of forest insurance. The statistically negative influence of tree species on forest insurance preference is likely driven by the perception that certain species are naturally more resilient to risks like fire, pests or diseases. This perception reduces the necessity for insurance coverage. The specific reductions in the likelihood by 0.114 for fire insurance, 0.06 for combined insurance, and 0.032 for disease and pest insurance suggest that growers adjust their risk management strategies according to the species they plant. This was similar to Davies (2019), who reported that farmers and growers often make risk management decisions based on their perception of risk and cost-benefit analysis. If they feel that the species they are growing and less at risk, they might forego insurance altogether.

The location of the tree farm has a negative statistically significant in influence on the preference of forest insurance type. Changes in the location of farmland decrease the probability of fire insurance by 0.82 and 0.024 for disease and pest insurance. This shows that some of the forest plantations are located near government plantations, where all risks of fire occurrence were considered, which lowers the preference for fire, disease, and pest insurance. This differs from the result reported by Sacchelli et al. (2018), who found that the location of the forest does not influence the choice of insurance type. Still, the location influences the valuation of the forest.

CONCLUSIONS AND RECOMMENDATIONS

The study examines the factors influencing the willingness to pay (WTP) for forest insurance among tree growers. The findings reveal that WTP is significantly influenced by a range of social, economic and environmental factors; key determinants include income level, education, and previous occurrence of fire. Preference for forest insurance type shows that stakeholders favour insurance schemes that are affordable, easy to understand and offer comprehensive coverage tailored to local risks; simpler, flexible plans are more attractive, especially to smallholder forest owners. The study recommends the following.

- To boost willingness to pay for forest insurance, awareness campaigns and education should be prioritised. Promoting premiums and building trust in insurers are essential, and tailored insurance products can address diverse local needs. Public-private partnerships can enhance accessibility and long-term sustainability.
- Policymakers and insurance providers should collaborate to design inclusive and accessible schemes, taking into account socioeconomic and demographic factors influencing growers' choices, to ensure the products are both relevant and sustainable.

REFERENCES

Abbass, K., Qasim, M. Z., Song, H., Murshed, M., Mahmood, H., & Younis, I. (2022). A review of the global climate change impacts, adaptation, and sustainable mitigation measures. *Environmental Science and Pollution Research*, *29*(28), 42539–42559.

Ajiboye, B. O., Adeyonu, A. G., Faseyi, S. A., & Isitor, S. U. (2018). Factors Influencing Farmers' Choice of Agricultural Insurance on

Article DOI: https://doi.org/10.37284/eajfa.8.1.3497

Arable Crop Production in Kwara State, Nigeria. *Nigerian Journal of Agricultural Economics*, *8*(1), 89–100.

Akanle, O., & Nwaobiala, U. R. (2020). Changing but fragile: Female breadwinning and family stability in Nigeria. *Journal of Asian and African Studies*, *55*(3), 398–411.

Alemayehu, A., & Melka, Y. (2022). Small-scale eucalyptus cultivation and its socioeconomic impacts in Ethiopia: A review of practices and conditions. *Trees, Forests and People*, *8*, 100269.

Attipoe, S. G., & Adams, A. (2024). Influential factors shaping cocoa farmers' crop insurance participation and coverage amount in Ghana. *Cogent Food & Agriculture*, *10*(1), 2417830.

Brunette, M., & Couture, S. (2023). Forest Insurance for Natural Events: An Overview by Economists. *Forests*, *14*(2), 289.

Cubbage, F., Kanieski, B., Rubilar, R., Bussoni, A., Olmos, V. M., Balmelli, G., Mac Donagh, P., Lord, R., Hernández, C., & Zhang, P. (2020). Global timber investments, 2005 to 2017. *Forest Policy and Economics*, *112*, 102082.

Davies, S. A. (2019). *Applying financial risk approaches to the challenge of assessing natural disturbance risks to forests*.

Dinkelman, T., & Ngai, L. R. (2022). Time use and gender in Africa in times of structural transformation. *Journal of Economic Perspectives*, *36*(1), 57–80.

Etherton, B. A., Choudhury, R. A., Alcalá Briseño, R. I., Mouafo-Tchinda, R. A., Plex Sulá, A. I., Choudhury, M., Adhikari, A., Lei, S. L., Kraisitudomsook, N., & Buritica, J. R. (2024). Disaster plant pathology: Smart solutions for threats to global plant health from natural and human-driven disasters. *Phytopathology®*, *114*(5), 855–868.

Falola, A., Ayinde, O. E., & Agboola, B. O. (2013). Willingness to take agricultural insurance by cocoa farmers in Nigeria. *International Journal of Food and Agricultural Economics (IJFAEC)*, *1*(1), 97–107.

Farooq, T. H., Shakoor, A., Wu, X., Li, Y., Rashid, M. H. U., Zhang, X., Gilani, M. M., Kumar, U., Chen, X., & Yan, W. (2021). *Perspectives of plantation forests in the sustainable forest development of China*.

Flanagan, A. C., Midgley, S. J., & Stevens, P. R. (2020). Smallholder tree-farmers and forest certification in Southeast Asia: alternative approaches to deliver more benefits to growers. *Australian Forestry*, *83*(2), 52–65.

Güneri, Ö. İ., & Durmuş, B. (2020). Dependent dummy variable models: An application of logit, probit and tobit models on survey data. *International Journal of Computational and Experimental Science and Engineering*, *6*(1), 63–74.

Islam, D. Il, Rahman, A., Sarker, M. S. R., Luo, J., & Liang, H. (2021). Factors affecting farmers' willingness to adopt crop insurance to manage disaster risk: evidence from Bangladesh. *International Food and Agribusiness Management Review*, *24*(3), 463–479.

Kaganzi, K. R., Cuni-Sanchez, A., Mcharazo, F., Martin, E. H., Marchant, R. A., & Thorn, J. P. R. (2021). Local perceptions of climate change and adaptation responses from two mountain regions in Tanzania. *Land*, *10*(10), 999.

Karupu, R. M., Mbeyale, G. E., & Lusambo, L. P. (2021). Forest resources perceived importance and dependency in Masida community forest, Zambezi region, Namibia. *Tanzania Journal of Forestry and Nature Conservation*, *90*(2), 18–26.

Kifyasi, A. A. (2021). Exploitation Paradox: Sao-Hill Forest Plantation and the Indigenous Community Livelihoods in Mufindi, Tanzania, 1970s to 2010. *Tanzania Zamani*, *13*(2), 147–180.

Kimambo, N. E., L'roe, J., Naughton-Treves, L., & Radeloff, V. C. (2020). The role of smallholder woodlots in global restoration pledges–Lessons from Tanzania. *Forest Policy and Economics*, *115*, 102144.

Komu, S. C. S. (2020). The Prevalence of HIV/AIDS in Mufindi District–Iringa Region. *International Journal of Academic Research*, *2*(3), 185–194.

Kothari, C. R. (2004). *Research methodology: Methods and techniques*. New Age International.

Liao, H., He, Y., Wu, X., Wu, Z., & Bausys, R. (2023). Reimagining multi-criterion decision making by data-driven methods based on machine learning: A literature review. *Information Fusion*, 101970.

Lusambo, L. P., Midtgaard, F., & Nyamoga, G. (2021). Effects of participatory forest management on livelihoods of communities adjacent to forests in redd+ pilot areas of Mufindi, Iringa Rural and Mbozi districts, Tanzania. *Tanzania Journal of Forestry and Nature Conservation*, *90*(3), 104–116.

Madoffe, P. R. and. (2011). Status of pine wooly aphid in Sao Hill forest plantation. In *Journal of Entomology*.

Masara, C., & Dube, L. (2017). Socio-economic factors influencing uptake of agriculture insurance by smallholder maize farmers in Goromonzi district of Zimbabwe. *Journal of Agricultural Economics and Rural Development*, *3*(1), 160–166.

Mensah, N. O., Twintoh, J. J., Amrago, E. C., Donkor, A., & Anang, S. A. (2021). Forestry insurance preference among tree growers in the Ashanti Region of Ghana: a tobit and multi-nomial regression approach. *Managerial Finance*.

Meyer, S. E., Callaham, M. A., Stewart, J. E., & Warren, S. D. (2021). Invasive species response to natural and anthropogenic disturbance. *Invasive Species in Forests and Rangelands of the United States: A Comprehensive Science Synthesis for the United States Forest Sector*, 85–110.

Mgina, M., & Wawa, A. (2021). Assessment of wildfires in Tanzania forest plantations: A case of Sao Hill in Mufindi District. *Huria: Journal of the Open University of Tanzania*, *27*(2).

Mgoo, O. S., Temu, B. J., Mwambusi, J. N., & Chamshama, S. A. O. (2024). Forest Management Optimization Scenarios for Climatic and Economic Benefits Generated from Tectona grandis Plantation in Muheza, Tanzania. *Tanzania Journal of Science*, *50*(3), 483–495.

Mubarik, M. S., & Naghavi, N. (2020). Human capital, green energy, and technological innovations: Firm-level analysis. *Econometrics of Green Energy Handbook: Economic and Technological Development*, 151–164.

Mwakasungula, K., & Mombo, F. (2025). Cost effectiveness and financial implications to smallholder tree growers in Mufindi district Tanzania. *Trees, Forests and People*, *20*, 100809.

Mwambusi, J. N., Kapp, G., & Chamshama, S. A. O. (2021). The silviculture of woodlots of smallholder forest producers in Mufindi District, Tanzania: knowledge and treatments. *Tanzania Journal of Forestry and Nature Conservation*, *90*(3), 40–61.

Mwinyimkuu, R. S., Temu, B. J., Makindara, J. R., & Abdallah, J. M. (2022). Sawnwood value chain analysis in Ulanga District and Morogoro Municipality, Tanzania. *International Forestry Review*, *24*(2), 208–224.

Nambiar, E. K. S. (2021a). Small forest growers in tropical landscapes should be embraced as partners for Green-growth: Increase wood supply, restore land, reduce poverty, and mitigate climate change. *Trees, Forests and People*, *6*, 100154.

Article DOI: https://doi.org/10.37284/eajfa.8.1.3497

Nambiar, E. K. S. (2021b). Strengthening Vietnam's forestry sectors and rural development: Higher productivity, value, and access to fairer markets are needed to support small forest growers. *Trees, Forests and People*, *3*, 100052.

Norton, M., van Sprundel, G.-J., Turvey, C. G., & Meuwissen, M. P. M. (2016). Applying weather index insurance to agricultural pest and disease risks. *International Journal of Pest Management*, *62*(3), 195–204.

Nyange, R., Monela, G., & Temu, B. (2025). Willingness to Pay and Factors Influencing the Amount of Forestry Insurance by Tree Growers in Mufindi, Tanzania. *East African Journal of Interdisciplinary Studies*, *8*(1), 1-12.

Ofoegbu, C., Chirwa, P., Francis, J., & Babalola, F. (2017). Assessing vulnerability of rural communities to climate change: A review of implications for forest-based livelihoods in South Africa. *International Journal of Climate Change Strategies and Management*, *9*(03), 374–386.

Payn, T., Carnus, J.-M., Freer-Smith, P., Kimberley, M., Kollert, W., Liu, S., Orazio, C., Rodriguez, L., Silva, L. N., & Wingfield, M. J. (2015). Changes in planted forests and future global implications. *Forest Ecology and Management*, *352*, 57–67.

Petro, R., & Madoffe, S. S. (2011). Status of Pine Woolly Aphid (Pineus boerneri) in Sao-Hill forest plantation, Tanzania. *Journal of Entomology*, *8*(5), 468–475.

Phiri, A. T., Toure, H. M. A. C., Kipkogei, O., Traore, R., Afokpe, P. M. K., & Lamore, A. A. (2022). A review of gender inclusivity in agriculture and natural resources management under the changing climate in sub-Saharan Africa. *Cogent Social Sciences*, *8*(1), 2024674.

Qin, T., Gu, X., Tian, Z., Pan, H., Deng, J., & Wan, L. (2016). An empirical analysis of the factors influencing farmer demand for forest insurance: Based on surveys from Lin'an County in Zhejiang Province of China. *Journal of Forest Economics*, *24*, 37–51.

Sacchelli, S., Cipollaro, M., & Fabbrizzi, S. (2018). A GIS-based model for multiscale forest insurance analysis: The Italian case study. *Forest Policy and Economics*, *92*, 106–118.

Sauter, P. A., Möllmann, T. B., Anastassiadis, F., Mußhoff, O., & Möhring, B. (2016). To insure or not to insure? Analysis of foresters' willingness-to-pay for fire and storm insurance. *Forest Policy and Economics*, *73*, 78–89. https://doi.org/10.1016/j.forpol.2016.08.005.

Simon, S. M., Glaum, P., & Valdovinos, F. S. (2023). Interpreting random forest analysis of ecological models to move from prediction to explanation. *Scientific Reports*, *13*(1), 3881.

Singh, A. S., & Masuku, M. B. (2014). Sampling techniques & determination of sample size in applied statistics research: An overview. *International Journal of Economics, Commerce and Management*, *2*(11), 1–22.

Stanturf, J. A., & Mansourian, S. (2020). Forest landscape restoration: state of play. *Royal Society Open Science*, *7*(12), 201218.

Suleiman, M. S., Wasonga, V. O., Mbau, J. S., Suleiman, A., & Elhadi, Y. A. (2017). Non-timber forest products and their contribution to households income around Falgore Game Reserve in Kano, Nigeria. *Ecological Processes*, *6*, 1–14.

Temu, B. J., Monela, G. C., Darr, D., Abdallah, J. M., & Pretzsch, J. (2024). Forest sector contribution to the National Economy: Example wood products value chains originating from Iringa region, Tanzania. *Forest Policy and Economics*, *164*, 103246.

Washington, S., Karlaftis, M. G., Mannering, F., & Anastasopoulos, P. (2020). *Statistical and econometric methods for transportation data analysis*. Chapman and Hall/CRC.

Article DOI: https://doi.org/10.37284/eajfa.8.1.3497

Yassine, A., & Bakass, F. (2022). Do education and employment play a role in youth's poverty alleviation? Evidence from Morocco. *Sustainability*, *14*(18), 11750.

Zhang, D., & Stenger, A. (2014). Timber insurance: perspectives from a legal case and a preliminary review of practices throughout the world. *New Zealand Journal of Forestry Science*, *44*(1), 1–7.

Zhou, X., Zhu, H., Wen, Y., Goodale, U. M., Zhu, Y., Yu, S., Li, C., & Li, X. (2020). Intensive management and declines in soil nutrients lead to serious exotic plant invasion in Eucalyptus plantations under successive short-rotation regimes. *Land Degradation & Development*, *31*(3), 297–310.

