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# Understanding forest land conversion for agriculture in a developing country context: An application of the theory of planned behaviour among a cohort of Nigerian farmers

Fausat Motunrayo Ibrahim<sup>1</sup>  $\boxtimes$ , Benson Osikabor<sup>2</sup>, Bolanle Tawakalitu Olatunji<sup>3</sup>, Grace Oluwatobi Ogunwale<sup>1</sup>

#### **ABSTRACT**

Natural and forest-rich ecosystems are determinants of environmental sustainability, which are threatened by forest land conversion for agricultural purposes, especially in less-developed contexts. Moreover, human behaviour is central to achieving the much desired ecologically balanced environment. Hence, a partly novel model informed by the theory of planned behaviour was used in the examination of forest land conversion for agricultural purposes.

The study design was a cross-sectional survey targeted at a group of farmers of southwestern Nigeria. Data were collected using a structured questionnaire among 320 randomly selected crop farmers. Independent samples *t* test and one-way analysis of variance (ANOVA) were used to test the significance of difference in respondents' forest conversion behaviour across subgroups of gender and age/education, respectively. Stepwise multiple linear regression was used to identify the determinants of forest conversion behaviour.

Results showed that 87.8% of respondents had ever engaged in forest conversion. Gender and education had no significant effect on forest conversion behaviour (p > 0.05), but age did (p < 0.05). Attitude was the best determinant ( $\beta = 0.289$ , r = 0.510,  $R^2 = 0.260$ , p < 0.001), subjective norm was better ( $\beta = 0.257$ , r = 0.496,  $R^2 = 0.055$ , p < 0.001), while perceived behavioural control was good ( $\beta = 0.131$ , r = 0.398, p < 0.001,  $R^2 = 0.012$ , p < 0.005). The three variables correlated with intention by a degree of 57.2% (multiple R = 0.572), while they explained 32.7% of the variance in intention ( $R^2 = 0.327$ ). Intention was also found to be a significant determinant of behaviour ( $\beta = 0.222$ , r = 0.222,  $R^2 = 0.049$ , p < 0.001).

Middle age predisposes to, whereas younger and older age protects against greater extent of forest conversion. The partly novel model derived from the theory of planned behaviour proves the likely viability of the pursuit of socio-psychologically predicated interventions to enthrone forest conservation.



<sup>&</sup>lt;sup>1</sup> Forestry Research Institute of Nigeria, Federal College of Forestry, Ibadan, Department of Agricultural Extension and Management, Ibadan, Oyo State, Nigeria, phone: +2348055822100, e-mail: fausatibrahim@gmail.com, ORCID ID: https://orcid.org/0000-0002-2264-1891

<sup>&</sup>lt;sup>2</sup> Forestry Research Institute of Nigeria, Federal College of Forest Resource Management, Sakpoba, Department of Agricultural Extension and Management, Sakpoba, Edo State, Nigeria

<sup>&</sup>lt;sup>3</sup> Forestry Research Institute of Nigeria, Department of Forest Economics and Extension, Ibadan, Oyo State, Nigeria

#### **K**EY WORDS

attitude, behaviour, forest conversion behaviour, intention, perceived behavioural control, subjective norm, theory of planned behaviour

#### Introduction

The global and Africa's loss of forest area was 4.74 and 3.94 million hectares between 2010 and 2020, respectively, placing Africa on top of the list on account of this loss across the world regions in the decade (FAO and UNEP 2020). Africa is losing its forest area progressively, whereas this loss is regressing globally (Ibid). Using datasets captured with the use of satellite images of the Landsat TM/ETM+, Arowolo and Deng (2018) reported that forest land decreased and increased by 30.1% and 19.5%, respectively, in Nigeria between 2000 and 2010, leading to a loss of 10.6% of forest land in the decade. Arowolo and Deng (2018) further reported that cultivated land reduced by 18.1% and increased by 34.2% between 2000 and 2010 in Nigeria, making the increased cultivated land to be 16.1% in the decade. Forest loss is on account of several factors, but boosting agricultural production is a major motive of decimating forests, which results in the loss of biodiversity (Badamasi et al. 2018; Fasona et al. 2020; Miyamoto 2020; FAO and UNEP 2020). Agricultural expansion is solely responsible for 70-80% of forest loss in Africa (Olorunfemi et al. 2021). This underscores the significance of forest land conversion for the purpose of agricultural expansion.

The importance of agricultural land area/use must not be underemphasised. It serves as the base of providing food, fibre, fodder and other necessities. It boosts livelihood opportunities and occupies 40% of the land cover (Hasan et al. 2020), making agricultural land a prime land use type. Especially in least developing countries like Nigeria, increasing human population puts the agricultural enterprise under pressure to expand (Olorunfemi et al. 2021). Nigeria is classified as the second of the nine countries that will account for 50% of the global population growth by 2050 (United Nations Population Division 2017). 'The demand for food is resulting in inappropriate agricultural practices that drive large-scale conversion of forests to agricultural production' (FAO and UNEP 2020). Hence, forest land areas are

continuously converted. As opposed to the situation in Southeast Asia where agriculture for export drives land conversion, subsistence agriculture for the local market motivates this conversion in Africa (Doggart 2020).

Converting natural forest system to agricultural land impedes the capacity of the ecosystem to function, thereby hindering sustainability of the ecosystem (Buytaert et al. 2014; Fagerholm et al. 2016; Turner et al. 2016; Tolessa et al. 2017; Fu et al. 2017). Converting land for agriculture is a variant of deforestation because deforestation is essentially the transformation of forest land to non-forest land (Fasona et al. 2020; Doggart 2020). Forest degradation hampers biodiversity (Duraiappah et al. 2005; FAO and UNEP 2020; Fasona et al. 2020), and therefore weakens the adaptableness of the ecosystem (Corral-Verdugo 2009). More specifically, the functioning of forests as carbon sinks is negatively affected when lands are converted for agricultural use. Aside from energy use, forest land conversion is the largest contributor to CO<sub>2</sub> and other greenhouse gas emissions in Nigeria, considering that 60% of total emissions were on account of this conversion (Fasona et al. 2020). Greenhouse gas emissions herald into rising temperature and climate change (Olorunfemi et al. 2021). Reducing these emissions is central to mitigating climate change. Climate change is probably the greatest global environmental threat of our time, making international accords to resolve to mitigate the same by halting the global CO<sub>2</sub> emissions to net zero by 2050 (Ayompe et al. 2021). One-third of the greenhouse gas emission is on account of land use change cum agricultural activities in sub-Saharan Africa (Olorunfemi et al. 2021). The preservation of Africa's forests has been identified as a means of lightening the burden of climate change in the Reducing Emissions from Deforestation and Degradation (REDD) programmes (Olorunfemi et al. 2021).

Natural and forest-rich ecosystems optimally provide regulatory services that protect climate, prevent hazards such as landslides and wildfires, purify the atmosphere, preserve soil and detoxify water (Hasan et al. 2020). Farmers' forest land conversion for agricultural

purposes, therefore, represents a dilemma warranting systematic examination. As opposed to this conversion, farmers have the choice of sparing forest lands for conservation purposes and cultivating high-yielding varieties of seeds. They also have the choice to regard forest land conversion as an indispensable route to food production. Whether or not they accelerate forest conversion, farmers also have the choice of embracing agroforestry where food production and biodiversity could thrive in an integrated fashion (FAO and UNEP 2020). The point is that there are diverse courses of human action which have weighty implications on environmental health. This bares the relevance of models of human behaviour in understanding motivators of environmentally related actions. Natural resource disciplines are yet to optimally exploit the potentials of human behaviour models in understanding the dynamics of environmental resource use. Yet, man is in the anthropocene age, where actions in his ecological space have ushered in a new geological era (Lewis and Maslin 2015). Forest and environmental degradation are general samples of human behaviour. Effective conservation of environmental resources depends tremendously on human behaviour, thereby showcasing the huge relevance of human social research (St John et al. 2011; St John et al. 2013; Schultz 2011; Veríssimo 2013; Crandall et al. 2013; Nielsen et al. 2021; Travers et al. 2021; Chua et al. 2020; Häyrinen and Pynnönen 2020; Knapp et al. 2021; Cosyns et al. 2020; Crandall et al. 2018). It follows that human behaviour is central to achieving the much desired ecologically balanced environment. Hence, the employment of a prime human behaviour model, the theory of planned behaviour (TPB), in the examination of forest land conversion for agricultural purposes is called for.

The TPB is probably the most popular heuristic social science theory. It was developed by Ajzen and Fishbein (1980) and Ajzen (1985, 1991). The TPB is an extension of the theory of reasoned action which recognises individuals as rational beings and, therefore, upholds that they select their course of action after considering the favourability of the same (Ajzen 1985). According to the TPB, human behaviour is determined by behavioural intention. Intention is construed as the 'indicators of how hard people are willing to try... to perform the behavior' (Ajzen 1991). Intention to behave in a certain way is determined by a confluence of three factors – at-

titude, subjective norm and perceived behavioural control. 'Attitude is defined as an individual's favorable or unfavorable evaluation of the behavior; subjective norm refers to the perceived social pressure towards the behavior; and perceived behavioral control is the personal assessment of the feasibility of executing the behavior in a given context' (Yurieva et al. 2020). The TPB is very useful in creating behavioural interventions (Riebl et al. 2015). It has been employed in a wide variety of contexts, including the study of environmental behaviours (Yurieva et al. 2020). These environmental behaviours include farmers' tree planting (Zubair and Garforth 2006), water conservation (Lam 2006), usage of alternate transportation (Muñoz et al. 2016), recycling (Echegaray and Hansstein 2017), choice of tree species for reforestation (Osei et al. 2018), conservation of energy (Allen and Marquart-Pyatt 2018), reduction of flood risk (Allred and Gary 2019), low-carbon enhancement (Kaffashi and Shamsudin 2019), consumption of low carbon (Jiang et al. 2019) and agroforestry practices (Buyinza et al. 2020). In the context of this study, the implication of employing TPB is that forest conversion behaviour is determined by a partly novel construct – intention to convert forest land for agriculture. Further, this intention is collectively determined by three partly novel constructs - attitude towards converting forest land for agriculture, subjective norm of converting forest land for agriculture and perceived control of decision to convert forest land for agriculture. Therefore, the specific aims of this study included the prediction of forest conversion behaviour by the intention to convert forest. Another aim was the prediction of intention to convert by attitude towards, subjective norm of and perceived behavioural control of forest conversion. Analyses of items used in the measurement of variables were attempted, while the effects of gender, age and education on forest conversion behaviour were examined. These were accomplished among a group of Nigerian farmers.

#### **M**ETHODS

#### Study area

The study area was Afijio Local Government Area (LGA) of Oyo State, southwestern Nigeria. The coordinates of the headquarter of the LGA are 7°45'45" N 3°55'13" E. Nigeria is in West Africa. It is a developing

country in the sub-Saharan African region. Nigeria is the most populous black nation in the world. Its current population is about 201 million (United Nations Population Division 2019). Nigeria has become a democratic nation since 1999; its total land area is about 923,773 km², which constitutes roughly 14% of West Africa's total land area. Nigeria is divided into 36 states and the Federal Capital Territory (FCT). These states are clustered into six geopolitical zones. Nigeria is Africa's biggest economy (Peng and Poudineh 2019; Oludaisi et al. 2017), and it exerts some influence among its West African neighbours (Wright and Okolo 2018).

Oyo State belongs to the southwestern geopolitical zone, the region of the Yoruba ethnic group. Being the largest of the six states in the zone, it has the biggest land mass of about 29,000 km² (Fasona et al. 2020). According to Fasona et al. (2020), forests of Oyo state are mostly exploited. Such forests constituted 16% of the land area in 1986, which declined to 14.5% by 2006 and further declined grossly to 4% by 2016. Landscapes around Oyo State had long been described as transitioning from rainforest to savannah (Clayton 1958). The report of Fasona et al. (2020) further indicated that savanna woodland increased from 25% of landmass in 1986 to 47% by 2006, but reduced notably to 34% by 2016. Moreover, savanna grassland reduced drastically from 36% of the land area in 1986 to 3% by 2016.

Oyo State comprises 33 LGAs. The capital city of the state is Ibadan, which has five urban as well as six peri-urban LGAs. The other 22 LGAs are typically rural/semi-urban in character (Gbadegesin and Olorunfemi 2012). Afijio LGA constitutes one of the remaining 22 LGAs. The total land area of Afijio LGA is about 1.365 km² (Adeoye et al. 2020). The LGA comprises six districts, including Ilora/Oluwa-tedo, Akinmorin/Jobele, Iware, Imini, Awe and Fiditi. The last national population census of 2006 indicated that Afijio's population is 134,173 (National Population Commission 2007). The people of the area are notably farmers who mostly plant food crops like yams, maize and cassava as well as vegetables.

#### Study design

This work employed a cross-sectional survey design targeted at crop farmers in the study area. Therefore, a cohort of randomly selected crop farmers was studied at one specific point in time.

#### Sampling procedure

In order to determine sample size, the population of Afijio LGA, that is, 134,173 (National Population Commission 2007) was projected. The 2021 population at 2.6% growth rate was estimated using the formula below:

$$P = P_0 \times e^{rt} \tag{1}$$

where:

P – final population,

 $P_0$  – initial population,

e - exponential,

r – growth rate,

t – time interval (15 years).

The 2021 projected population was 198,171. This was assumed to be the total population (N) for the study, considering that agriculture is the dominant occupation of the study area. An adjusted variant of the Cochran formula below was used to evaluate the sample size:

$$n = \frac{Npqz^2}{e^2(N-1) + pqz^2}$$
 (2)

where:

n – the required sample size,

N – the population = 198,171,

p – the assumed proportion of the population which exhibits the attribute of interest, 50% = 0.5,

q-1-p,

z – obtained from 95% confidence on z table as 1.96,

e – the precision level (i.e. the margin of error) = 5.5% or 0.055.

The required sample size was 317. This was increased to 320. Half of the six districts in the LGA were randomly selected – Akinmorin/Jobele, Awe and Fiditi. The villages and communities that make up each district were identified and five of the same were selected. Hence, in Awe, Aba-Ogunremi, Aba-Bara, Aiyekale, Awe and Asipa were selected. Jagun, Aba-Ibadan, Jobele, Oniyanrin and Akinmorin were selected in Akinmorin/Jobele, while Agbaakin, Bello, Egbejoda, Adekunfe and Ijaiye were selected in Fiditi. Twenty-one copies of the study questionnaire were administered in each of the selected 15 communities, but five more copies were administered in Jobele.

Response categories Variable Operational definition Measurement and scoring Respondents' evaluation of the degree to Strongly Agree(4), Agree Attitude towards converting A 5-item authorwhich forest conversion is considered as (3), Disagree (2) and forest land for agriculture developed scale advantageous Strongly Disagree (1) Respondents' evaluation of the acceptability Subjective norm of converting A 4-item author-Totally true (3), fairly true of forest conversion within their forest land for agriculture developed scale (2) and not true at all (1) (respondents') social network Perceived control of decision Respondents' evaluation of their own A 3-item author-Totally true (3), fairly true to convert forest land for independent power to decide to convert developed scale (2) and not true at all (1) agriculture forest Intention to convert forest A 3-item author-Totally true (3), fairly true Respondents' resolve to convert forest land for agriculture developed scale (2) and not true at all (1) The extent to which respondents had ever A 5-item author-Forest conversion behaviour engaged in clearing out of vegetation of a Yes (1), no (0) developed index forest for agricultural purpose<sup>b</sup>

**Table 1.** Variables<sup>a</sup>, operational definitions, measurements and response categories

#### Study tool

The questionnaire was the instrument of data collection. A Yoruba version of the same was prepared in order to be able to communicate with respondents who are hardly fluent in English language. The study tool was administered through closed-ended, structured interview. Full (100%) response rate was achieved. Data were collected in April of 2021. Respondents' right to selfdetermination was greatly respected. They were treated with great reverence, and they consented to be involved in the study after basic details of the research were read to them in the language of their choice. Respondents appended their thumb print or signature on the informed consent form as a way of documenting the same. The variables of this study including how they were contextually defined and measured are presented in Table 1. The measures were found to be reliable considering the Cronbach's alpha values reported in Table 3.

#### General null hypotheses

H<sub>0</sub>1: There will be no significant prediction of intention to convert forest by attitude towards converting forest, subjective norm converting forest and perceived behavioural control of decision to convert forest.

H<sub>0</sub>2: There will be no significant prediction of forest conversion behaviour by intention to convert forest.

 $H_03$ : There will be no significant difference in the mean score of forest conversion behaviour across the subgroups of gender, age and education.

#### Analyses of data

Descriptive percentile analysis was used to assess distribution of data. Kolmogorov-Smirnov test (for normaley) was used to examine if distributions of all interval-level data did not deviate significantly from normal distributions. The distributions were normal (p > 0.05). The significance of difference in respondents' forest conversion behaviour across the subgroups of gender and age/education was tested using independent samples t test and one-way analysis of variance (ANOVA), respectively. Homogeneity of variance across these subgroups was tested with Levene's test. Post hoc test (least significant difference [LSD]) was used to isolate homogenous subgroups, while eta and eta<sup>2</sup> were the measures of effect size. Stepwise multiple linear regression (using multiple R,  $R^2$  and adjusted  $R^2$ ) was employed to examine the combined explanatory power of attitude, subjective norm and perceived behavioural control.  $R^2$ change, standardised B and zero-order correlation were used to examine the solo contribution of each covariate. Statistical Package for Social Sciences (version 24) was used to analyse data.

<sup>&</sup>lt;sup>a</sup>Gender is respondent's sex. Gender, age and education were assessed nominally.

<sup>&</sup>lt;sup>b</sup>Forest was defined to the respondents as any piece of land that had not been used for agriculture before.

#### **R**ESULTS

#### Sociodemographic profile of respondents

More respondents were male (61.9%), while female respondents constituted 38.1%. The mean  $\pm$  standard deviation (SD) of respondents' age was  $57.29 \pm 14.12$ (range = 19-85 years). Categorical data indicated that the distribution of respondents' age exhibit an inverted U shape, which reached a peak at the 46-60 years subgroup. About three of 10 and one of 10 respondents were aged between 61 and 75 years and 76 years and above, respectively. These indicate the ageing of the population of farmers in the study area, whereas Nigerian population structure is dominated by young people. Results further show that a sizeable proportion (14.7%) received no formal education. The proportion of those who had primary education and secondary education was 22.5% and 15.9%, respectively. Meanwhile, the highest educational qualification of 30.6%, 9.1% and 5.0% of respondents was post-secondary education, first-degree and postgraduate degree, respectively. The distribution of respondents' gender, age and education is shown in Table 2.

**Table 2.** Distribution of respondents' gender, age and education (N = 320)

Socio- -demographic characteristic	Subgroups	Fre- quency	Percentage
Gender	male	198	61.9
Gender	female	122	38.1
	16–30	13	4.1
	31–45	50	15.6
Age*	46–60	131	40.9
	61–75	95	29.7
	76 and above	31	9.7
	no formal education	47	14.7
	primary education	72	22.5
Highest	secondary education	51	15.9
educational	post-secondary education	98	30.6
qualification	B.Sc./HND	29	9.1
	postgraduate	16	5.0
	no response	7	2.2

<sup>\*</sup> The mean  $\pm$  SD of age was 57.29  $\pm$  14.12, minimum = 19, maximum = 85.

# Univariate analyses of items in the scales of attitude, subjective norm and perceived behavioural control and intention to convert forest land

The descriptive analyses in Table 3 indicate that respondents' responses to items in the scale of attitude were very similar. The mean score of the items ranged from 3.11 to 3.54, while the range of scores for each item was 1-4. These means-indicates that forest conversion for agricultural purposes was first seen as good, very useful and then seen as an activity to be promoted for food availability. Forest conversion was further construed as a positive development and as a responsible option. The mean scores of items in the scale of subjective norm ranged from 2.36 to 2.69; the minimum and maximum scores were the same throughout (1-3). The item analyses show that respondents perceive that their partners are the biggest supporters of forest land conversion, and then their fellow farmers, neighbours and the community where they live. The scores accorded the three items used in the measurement of perceived behavioural control were also similar. The mean values ranged from 2.22 to 2.52. Among the three intention-assessing items, the item that was specific about converting forest as long as respondents have the opportunity to do so attracted the greatest agreement, while the one asserting that respondents will clear forest soon attracted the lowest agreement. The summary of results obtained in the analyses of items used in variable measurement is presented in Table 3.

## Univariate analyses of items in the index of forest conversion behaviour

The univariate analyses of items in the index of forest conversion behaviour show that 87.8% of respondents concurred that they had ever engaged in forest conversion before. About six of every 10 (59.1%) also concurred that the converted forest land in order to have the plot they cultivated currently. More than seven of every 10 (71.3%) considered themselves to be 'good converters' of forests, while about four of 10 (38.8%) advocated for the conversion of forest land to boost agricultural productivity before. Majority of respondents (70.0%) also sought opportunities to covert forest land for agriculture. These distributions were skewed in favour of forest degradation. The mean  $\pm$  SD of forest conversion was  $3.34 \pm 1.14$  (minimum = 0, maximum = 5). If

**Table 3.** Item statistics and indicators of reliability of author-developed scales

Items of the author-developed scales	Mean ± SD	Minimum	Maximum	Cronbach's alpha				
Attitude towards converting forest land for agriculture								
Converting forest land for agriculture is a good activity	$3.54 \pm 0.63$	1	4					
Converting forest land for agricultural use is a positive development	$3.36 \pm 0.63$	1	4					
More forest land should be converted for agricultural use to promote food availability	$3.46 \pm 0.71$	1	4	0.836				
Converting forest land for agricultural use is a very useful activity	$3.48 \pm 0.73$	1	4					
Converting forest land for agricultural use is a responsible option	$3.11 \pm 0.87$	1	4					
Subjective norm of converting forest land for agriculture				•				
My partner (e.g. husband/wife/cohabitor) perceives the idea of converting forest land for agricultural use as good	$2.69 \pm 0.55$	1	3					
It is acceptable to my neighbour(s) to convert forest land for agricultural use	$2.39 \pm 0.62$	1	3	0.767				
My fellow farmers see the conversion of forest land for agricultural use as a good activity	$2.48 \pm 0.68$	1	3					
In the community where I live, converting forest land for agricultural use is acceptable to them	$2.36 \pm 0.70$	1	3					
Perceived control of decision to convert forest land for agricultur	e							
The decision to convert forest land for agricultural use is completely up to me	$2.52 \pm 0.60$	1	3					
I have complete control in deciding whether or not to convert forest land for agricultural use	$2.30 \pm 0.61$	1	3	0.790				
If I want to, I could convert forest land for agricultural use	$2.22 \pm 0.76$	1	3					
Intention to convert forest land for agriculture								
I will always clear forest land to expand the scope of my farming activities as long as I have the opportunity	$2.75 \pm 0.53$	1	3	0.622				
I have no reason not to clear forest land for agricultural purpose	$2.42 \pm 0.56$	1	3	0.632				
I am likely to clear forest land for agriculture soon	$2.37 \pm 0.72$	1	3					

the range of the distribution is arranged from lowest to highest (0, 1, 2, 3, 4 and 5), this mean is located above the mid score. The percentile analyses of responses to items in the index of forest conversion behaviour are shown in Table 4.

#### Gender, age, education and forest conversion behaviour

Forest conversion behaviour was slightly higher among male farmers (mean =  $3.41 \pm 1.19$ ) compared to their female counterparts ( $3.25 \pm 0.99$ ). However, these means were not significantly different (p > 0.05).

**Table 4.** Distribution of responses to items in the index of forest conversion behaviour

Items*		No	No response			
nem	frequency (%)					
Have you ever cleared forest in order to use it for agricultural purpose?	281 (87.8)	38 (11.9)	1 (0.3)			
Did you convert any forest to have the plot you currently cultivate?	189 (59.1)	129 (40.3)	2 (0.6)			
Will you consider yourself a good converter of forest for agricultural purpose?	228 (71.3)	85 (26.6)	7 (2.2)			
Have you ever advocated for the conversion of forest for agriculture as a way of boosting productivity?	124 (38.8)	188 (58.8)	8 (2.5)			
Do you seek opportunities to convert forest for agricultural purpose?	224 (70.0)	90 (28.1)	6 (1.9)			

<sup>\*</sup> Responses were scored 0 (no) and 1 (yes), with the total score ranging from 0 to 5. Mean ± SD forest conversion is 3.34 ± 1.14 (range = 0-5)...

Forest conversion behaviour yielded an inverted U-shaped distribution across the subgroups of age. The peak of this behaviour was recorded among those in the 46-60 years subgroup of age (mean  $\pm$  SD =  $3.52 \pm 1.15$ ), while the lowest exhibition of the behaviour was found among those in the 16-30 years subgroup of age (mean  $\pm$  SD = 2.38  $\pm$  1.33). Levene's test indicated homogeneity of variance across subgroups of age (p > 0.05), and one-way ANOVA indicated differences in these means (p < 0.05). Hence, age has a main effect on forest conversion behaviour. Eta was 0.226, while eta<sup>2</sup> was 0.051, indicating that 5.1% of the variance in forest conversion behaviour is explained by age. Post hoc test (LSD) indicated that the 16–30 years and the 76 years and above age subgroups were similar (p > 0.05), while other age subgroups were dissimilar from them (p < 0.05). Hence, the extreme age subgroups (16–30) years and 76 years and above) are significantly predisposed to lower extent of forest conversion behaviour, while the middling age categories (31-45, 46-60 and 61–75 years) are significantly predisposed to higher extent of forest conversion behaviour.

Respondents who had no formal education exhibited the lowest extent of forest conversion behaviour (mean  $\pm$  SD = 2.87  $\pm$  1.00), while those who had secondary education exhibited the highest extent of the same (mean  $\pm$  SD = 3.71  $\pm$  0.94). One-way ANOVA indicated that the differences in means across subgroups of education were significantly different (p < 0.05). However, the result of Levene's test threatens the validity of this significance because it did not indicate subgroup homogeneity (p < 0.05). Hence, it cannot be concluded that education has a significant effect on forest conversion behaviour. Meanwhile, the relationship between education and forest conversion behaviour was inverse (Pearson's r = -0.021, p > 0.05). The summary of results obtained in the analyses of the effects of gender, age and education on forest conversion behaviour is presented in Table 5.

### Prediction of intention and behaviour using the partly novel constructs of TPB

The multiple regression analysis shown in Table 6 indicates that attitude towards converting forest land for agriculture is a significant and best predictor of inten-

Tabl	e 5.	Effects	of gend	er, age and	lec	lucation	on	forest	conversion	be	haviour	
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Socio- demo-	Subgroups	Mean ± SD	Levene's test for homogeneity of variances		Independent samples <i>t</i> test		ANOVA		Eta	Eta <sup>2</sup>
-graphic variable			Levene's statistic	p value	T stati- stic	p value	F stati- stic	p value		
Gender	male	$3.41 \pm 1.19$	4.623	0.032	1.174	0.247	-	-		
Gender	female	$3.25 \pm 0.99$	4.023	0.032					_	_
	16–30	$2.38 \pm 1.33$		0.469	_	ı	4.001	0.004	0.226	
Age <sup>a,b</sup>	31–45	$3.39 \pm 1.22$	0.893							0.051
	46–60	$3.52 \pm 1.15$								
	61–75	$3.32 \pm 1.00$								
	76 and above	$2.96 \pm 1.03$								
	no formal education	$2.87 \pm 1.00$				-	4.133			_
	primary education	$3.55 \pm 1.14$						0.001		
Education <sup>c</sup>	secondary education	$3.71 \pm 0.94$	4.491	0.001						
Education	post-secondary education	$3.30 \pm 0.11$	4.491	0.001	_				_	
	first degree	$3.00 \pm 1.65$								
	postgraduate	$3.00 \pm 1.03$								

<sup>&</sup>lt;sup>a</sup> The influence of age on forest conversion behaviour deviates from linearity (p = 0.001). <sup>b</sup> Post hoc test (LSD) shows that the 16–30 years age subgroup is significantly different from the 31–45 years age subgroup (p = 0.005), the 46–60 years age subgroup (p = 0.001) and the 61–75 years age subgroup (p = 0.005). However, the 16–30 years age subgroup is not significantly different from the 76 years and above age subgroup (p = 0.124). <sup>c</sup> Pearson's p = 0.005 education and forest conversion behaviour is p = 0.001 (p = 0.717). LSD: least significant difference.

**Table 6.** Result of stepwise multiple linear regression analysis showing a model of significant predictors of intention to convert forest land for agriculture

Mo	del summ	ary	Change statistics								
multiple R	$R^2$	adjusted $R^2$	predictors	R <sup>2</sup> change	standardi- sed β	F statistic	p value (F change)	zero-order correlation	p value (zero-order correlation)		
		0.327 0.320	attitude	0.260	0.289	98.55	0.000	0.510	0.000		
0.572	0.572 0.327 0		subjective norm	0.055	0.257	22.28	0.000	0.496	0.000		
0.572	0.527		perceived control	0.012	0.131	5.02	0.026	0.398	0.000		

Dependent variable: intention to convert forest land for agriculture.

Table 7. Result of linear regression analysis showing prediction of forest land conversion behaviour by intention to convert forest land for agriculture

Model summary			Change statistics								
multiple R	$R^2$	adjusted R <sup>2</sup>	predictors	$R^2$ change	standard- ised β	F statistic	p value (F change)	zero-order correlation	p value (zero-order correlation)		
0.222	0.049	0.046	intention to convert forest land for agri- culture	0.049	0.222	14.50	0.000	0.222	0.000		

Dependent variable: forest land conversion behaviour.

tion to convert forest land for agriculture (standardised  $\beta = 0.289$ , p < 0.001). This attitude is also positively and significantly related to intention (r = 0.510, p < 0.001). Attitude also explained 26.0% of the variation in intention to convert ( $R^2 = 0.260$ , p < 0.001). For every 1 unit increase in attitude, there is 0.289 increase in intention to convert. Subjective norm of converting forest land for agriculture is a better predictor of intention (standardised  $\beta = 0.257$ , p < 0.001), correlates positively and significantly with intention (r = 0.496, p < 0.001) and explains 5.5% of the variation in intention to convert  $(R^2 = 0.055, p < 0.001)$ . For every 1 unit increase in subjective norm, there is 0.257 increase in intention to convert. Perceived control of decision to convert forest land for agriculture is a good predictor (standardised  $\beta = 0.131$ , p < 0.001), which correlates positively and significantly (r = 0.398, p < 0.001) and explains 1.2% of the variance intention to convert ( $R^2 = 0.012$ , p < 0.005). For every 1 unit increase in perceived control, there is 0.131 increase in intention.

The combination of attitude, subjective norm and perceived control correlates with intention by a degree of 57.2% (multiple R = 0.572) while explaining 32.7%

of the variance in intention ( $R^2 = 0.327$ ). The result of the multiple regression of the predictors of intention is shown in Table 6.

Intention to convert is a significant predictor of forest conversion behaviour (standardised  $\beta = 0.222$ , p < 0.001), which correlates positively and significantly with this behaviour (r = 0.222, p < 0.001) and also explains 4.9% of the variation in behaviour ( $R^2 = 0.049$ , p < 0.001). For every 1 unit increase in intention to act, there is 0.22 increase in forest conversion behaviour. Table 7 presents the summary of results obtained in the analysis of intention and behaviour.

#### **DISCUSSION**

The results of the univariate analyses of forest conversion behaviour are indications of the high extent of forest conversion among respondents in the study area. This is certainly contrary to the interest of optimal ecosystem functioning. Similar results were reported by Doggart et al. (2020) who conducted observations on 119 randomly selected plots from areas that have been

deforested in Tanzania. Doggart et al. (2020) reported that 89% of plots were cultivated as opposed to 69% and 35% of plots that were used for grazing and charcoal production, respectively. Doggart et al. (2020) asserted that agriculture was the major driver of deforestation in Tanzania because there is no clear governmental policy banning the conversion of forest land for agriculture beyond protecting selected areas. Tesfahunegn, Ayuk and Adiku (2020) also reported that 84.3% and 63.3% of their respondents opined that arable land expansion was responsible for the state of forest degradation in northern and eastern Ghana, respectively. The high level of forest conversion in the current study vindicates the findings of Fasona et al. (2020) who indicated that agriculture land area increased drastically from 21% in 1986 to 37% by 2016 in in Oyo state, Nigeria. Indeed, the trend of forest land conversion for agriculture in the study area is inimical to environmental sustainability.

The higher extent of forest conversion behaviour among male respondents is supported by Meijer et al. (2016), who also found that men held stronger unhealthy attitude towards falling forest trees when compared with women. The higher tendency of forest conversion among men is probably born out of unequal land tenure rights bestowed to men and women. Customary laws are typically in favour of land ownership on the part of men as opposed to women (Marin and Kuriakose 2017). This situation could also be born out of greater connectedness and protectiveness to the environment among women (Lau et al. 2021). However, the current study shows that the differential means between gender subgroups were not significantly different. The literature is scant with regard to determinants of forest conversion behaviour, but related studies support the current finding: Tesfahunegn, Ayuk and Adiku (2020) reported that gender was not a significant factor affecting farmers' perceived severity of forest degradation in selected communities of eastern and northern Ghana. Soe and Yeo-Chang (2019) similarly reported that gender was not a significant determinant of willingness to participate in forest conservation in a forest-dependent community of South-Central Myanmar.

The finding of extreme age subgroups (16–30 years and 76 years and above) rather than the middling age categories (31–45, 46–60 and 61–75 years) as being significantly predisposed to lowered extent of forest conversion behaviour is quite interesting. It indicates that

protectiveness of the forest space is a prerogative of younger and older persons, while middle-aged persons are significantly less protective. Tesfahunegn, Ayuk and Adiku (2020) similarly reported that age was a significant determinant of perceived severity of forest degradation among farmers in Ghana (p < 0.05). However, Soe and Yeo-Chang (2019) reported that age did not significantly influence willingness to participate in forest conservation (p > 0.05) in South-Central Myanmar. Ratsimbazafy et al. (2012) reported that older persons were more supportive and demonstrated greater confidence to participate in forest conservation in Madagascar, while Shan (2012) and Zhang et al. (2011) found that younger persons demonstrated greater willingness to participate in decision-making of urban green spaces and converting cultivated land to wetland in China, respectively. The literature is diversified with regard to the role of age in peoples' demonstration of forest protection.

Education had no significant effect on forest conversion behaviour. Soe and Yeo-Chang (2019) similarly found that education did not significantly influence willingness to participate in forest conservation. However, Tesfahunegn, Ayuk and Adiku (2020) asserted that education significantly affected perceived severity of forest degradation. The insignificantly inverse relationship between education and forest conversion indicates that increased education insignificantly predisposes to decreased forest conversion behaviour. This suggests the protectiveness of education against peoples' forest conversion behaviour.

Although the application of TPB in the examination of forest land conversion seems non-existent, other relevant studies have reported the performance of the constructs of TPB: Maleksaeidi and Keshavarz (2019) applied the TPB to study intention towards on-farm biodiversity conservation among 274 Iranian farmers. They found that the theory explained 53.4% of the variance in intention. Attitude towards biodiversity conservation was the best predictor ( $\beta = 0.59$ , p < 0.001), while subjective norm of biodiversity conservation was a better predictor ( $\beta = 0.40$ , p < 0.001). However, perceived behavioural control was not a statistically significant predictor. Empidi and Emang (2021) similarly engaged the TPB to explain behavioural intention of the public to take part in programmes aimed at protecting forested watershed areas in Cameron. They found that attitude  $(\beta = 0.432, p < 0.01)$  was the best predictor, while subjective norm was a better predictor ( $\beta = 0.190, p < 0.05$ ). However, perceived behavioural control was not a significant predictor ( $\beta = 0.087, p > 0.05$ ). The current findings are highly congruent with the reports of Maleksaeidi and Keshavarz (2019) as well as Empidi and Emang (2021) in terms of the relative strength of attitude, subjective norm and perceived behavioural control. Meanwhile, Deng et al. (2016) also used the TPB to examine ecological conservation behaviour among 1004 farmers of the Loess Plateau, China. Deng et al. (2016) reported that perceived behavioural control was the best predictor (standardised path coefficient = 0.50, p < 0.01), subjective norm was a better predictor (standardised path coefficient = 0.42, p < 0.01), while attitude was a good predictor (standardised path coefficient = 0.33, p < 0.01). In addition, behaviour was a positive determinant of intention (standardised path coefficient = 0.88, p < 0.01). In Uganda, Buyinza et al. (2020) examined the intention to adopt agroforestry among 400 famers and reported that attitude and perceived behavioural control were significant determinants of intention, but subjective norm was not. Contrary to the findings of Buyinza et al. (2020), Ofoegbu and Speranza (2017) found subjective norm to be the major determinant of intention to adopt sustainable forest use in South Africa. These indicate that perceived behavioural control and subjective norm are also strong determinants of intention depending on the context. Ajzen (1991) asserted that contexts and differential samples of behaviour affect the predictive ability of TPB constructs. The stronger the degree to which forest conversion is considered as advantageous (attitude), the more the acceptability of forest conversion in peoples' social network (subjective norm); the stronger the independent power to decide to convert forest (perceived behavioural control), the greater the resolve to convert forest (intention). The greater this resolve, the higher the extent to which people will engage in clearing out forest vegetation for agricultural purpose (behaviour).

#### **C**ONCLUSIONS

There is an intensive extent of forest land conversion for agriculture, which is a cog in the wheel of optimal ecosystem functioning in the study area. Gender and education are trivial sociodemographic variables in matters

of forest conversion. Meanwhile, middle age is predisposing to, whereas younger and older age is protective against greater extent of forest conversion. The more robust the attitude towards converting forest land for agriculture, subjective norm of converting forest land for agriculture and perceived control of decision to convert forest land for agriculture, the stronger the intention to convert forest land for agriculture. The stronger this intention, the higher the forest conversion behaviour. Socio-psychological variables of the TPB are apposite in instilling forest conservation. Socio-psychologically inspired interventions are, therefore, promising in ensuring that forests are handled with the consciousness of the need of future generations to fulfil their needs.

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