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Determinants for adoption of nature-based income generating activities in Uluguru mountains, Tanzania

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A R T I C L E I N F O

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A B S T R A C T

Despite the wide recognition of the potential for Nature-based Income Generating Activities (NIGAs) to enhance livelihoods and nature conservation in fragile agro-ecologies of mountain areas, certain aspects that discourage or inspire their adoption remain poorly understood. We investigated the determinants for adoption of NIGAs in Uluguru Mountains using the Generalized Linear Binary Probit model. We also used the Multivariate Analysis of Variance (MANOVA) and Discriminant Function Analysis (DFA) to find out whether our pre-selected independent variables significantly influenced the adoption of NIGAs. We underscore the need to address gender-based disparities in access to land and financial resources through the establishment of tailor-made financing schemes to promote the adoption of NIGAs.

1. Introduction

Agroforestry, beekeeping and other Nature-based Income Generating Activities (NIGAs) are widely promoted as important strategies to achieve sustainable farming, especially in fragile agro-ecologies, such as mountain areas and highlands in the tropics. Owing to their climatic and topographic diversity, mountain areas are hotspots of biodiversity, providing habitats to many fauna and flora species, some of which being endemic to these areas [1–4]. The available information for example, shows that about half of the global endemic bird areas are in mountain regions, particularly in tropical forests [5]. The Mountain Agenda 2002 shows further that in 53 countries around the globe, mountain areas cover over 50% of the national area, and in 46 others between 25% and 50% [5]. The African continent has 11% of the world's mountains, and 20% of the continent's total surface is made up of mountains [6]. In East Africa, mountain areas cover about 23% of the total land area (in Kenya and Tanzania), and 19% in Uganda [7].

Despite their importance, mountain areas face socio-economic changes triggered by both internal and external factors, such as high population densities and land use changes making their natural ecosystems being vulnerable and easily destroyed [6–8]. Anthropogenic activities, including among others, the uphill expansion of agriculture and human settlements, and logging for timber and fuel wood threaten biodiversity in these areas [1,3,9]. This has consequently called for promotion of NIGAs in mountain areas to combat the loss of habitats for wild fauna and flora species as well as halt nature degradation while at the same time enhancing the income generation potential and welfare of smallholder farmers. In fact, there are many economic and environmental benefits of doing this, particularly in fragile agro-ecologies, such as, that of mountain areas. For example, the available evidence from areas bordering the Menagesha Suba State Forest in Ethiopia shows that income from beekeeping alone contributed up to about 17% of total household income for smallholder farmers [10]. In fact, it is not just honey from beekeeping and agroforestry products that provide income to these farmers. The NIGAs they practice also contribute enormously to safeguard nature or keep ecosystem services functional through crop pollination, provision of habitat to wildlife, restoration of water and nutrients to soils and pulling carbon out of the atmosphere, just to mention few [11].

In Tanzania, the Uluguru Mountains constitute one of the important mountain areas in East Africa hosting unique biodiversity of fauna and flora species, including a number of endemic bird species, mammals, reptiles and amphibians that are found nowhere in the world. Examples of these species include the Uluguru Bush shrike (*Malconotus alius*) and Loveridge's sunbird (*Nectarinia loveridge*); shrew mammal species, such as *Crocidura telfordi and Myosorex geata*; reptile species like *Lygodactylus williamsi, Cnemapsis barbouri, Scelotes Uluguruensis* (a skink), *Typhlops Uluguruensis* (a snake), *Prosymna ornatissima* (a snake) and *Geodipsas procterae* (a snake); as well as, the amphibian species such as *Nectophrynoides cryptus* (a toad), *Probreviceps Uluguruensis* (a micro-

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phylid frog), *Halophryne Uluguruensis* (microphylid frog), *Afrocaecilia Uluguruensis* (a caecilian) and *Scolecomrphus uluguruensis* (a caecilian) [9]. Endemism is also very high in the invertebrates, including 23 taxa of millipedes [ibid], and in plant species. The available information for example, indicates that about 108 species are identified as strict endemic plant species in Uluguru Mountains [12]. These species are under the danger of extinction if proper management strategies are not put in place. This recognition has attracted a particular attention of several programmes and initiatives, such as the Uluguru Mountains Agricultural Development Project (UMADEP) and the Uluguru Mountains Payment for Watershed Services Project (UMPWSP) to introduce and promote NIGAs. In fact, biodiversity conservation has emerged earlier as an important agenda in Tanzania since the county's independence in 1961 following the declaration of the Arusha Manifesto by the first President of Tanganyika, the Late Mwalimu Julius K. Nyerere who noted that:

> "The survival of our wildlife is a matter of grave concern to all of us in Africa. These wild creatures amid the wild places they inhabit are not only important as a source of wonder and inspiration, but are an integral part of our natural resources and our future livelihood and wellbeing. In accepting the trusteeship of our wildlife, we solemnly declare that we will do everything in our power to make sure that our children's grand-children will be able to enjoy this rich and precious inheritance …" [13].

To demonstrate this commitment, the United Republic of Tanzania signed the Convention of Biological Diversity (CBD) on 12th June 1992 and ratified it on 1st March 1996 [14]. The country also developed and begun to implement her first National Biodiversity Strategy and Action Plan (NBSAP) in 2001 as a requirement to Parties (Article 6 of the CBD). Other related actions have included the development and implementation of the Strategy on Urgent Actions on Land Degradation and Water Catchments (2006), the National Environmental and Action Plan (2013–2018) and the National Biodiversity Strategy and Action Plan (NBSAP) of 2015–2020. The overall objective of the latter (NBSAP) is "to reduce loss of biodiversity, promote the value of biodiversity and improve community livelihoods" [14]. In addition, a Management Plan for the Uluguru Mountains' Nature Reserve was developed which among other things, promotes the adoption of NIGAs such as, agroforestry, tree planting, and beekeeping, just to mention few [15].

Despite all these plan and actions, the rate of adoption of NIGAs in many of the countries mountain areas remains low [16,17]. Low adoption of Good Agricultural Practices (GAPs) is not unique to mountain areas of Tanzania. It is also reported for banana farmers of Chitwan in Nepal by Joshi et al. [18], and in the Upper Thukela situated at the foot of the Drakensberge in South Africa by Sterve [19]. A systematic review of factors influencing the adoption of packaged or bundled sustainable agricultural practices by Rajendran et al. [20] also indicates limited adoption of these practices in many other countries. As such, the low adoption of GAPs would imply existence of certain factors that discourage, or rather aspire some farmers to adopt these practices. Most importantly, is perhaps the fact that studies which focus on NIGAs are lacking. Most studies have investigated factors influence adoption of GAPs [see [21–26]] with little or no attention to NIGAs, especially in the context of mountain areas. Ochieng et al. [21] for example, evaluated the adoption of improved amaranth and GAPs in East Africa but they did not unpack the analysis into NIGAs and non-NIGAs components. In Ethiopia, studies by Asfaw et al., Tesfaye et al., and Teshome et al. [22–24] evaluated factors influencing the adoption of Soil and Water Conservation (SWC) practices, again with limited specification and analysis of NIGAs. A similar study was also conducted by Barungi et al. [25] who investigated factors that influenced the adoption of soil erosion control technologies along the slopes of Mountain Elgon in Eastern Uganda.

Where the NIGAs-focused analysis was attempted, such as, in the study by Kahimba et al. [26] who investigated the adoption and scaling-up of conservation agriculture in Arusha and Dodoma regions in Tanzania, the focus has been mainly on a single Nature-based Income Generating Activity (NIGA). It should be noted that, focusing entirely on a single NIGA can be misleading as it ignores the fact that farm sustainability issues are diverse, interconnected and complex. In fact, studies that assume the adoption of GAPs or NIGAs as mutually exclusive with little or no interdependence among the various influential factors are bound to be inaccurate and highly misleading because they assume that a farmer can only choose one income generating activity or practice to adopt on his/her single farming plot from several mutually exclusive (independent) options. The analysis based on this assumption ignores the possibility of GAPs and NIGAs to complement or substitute each other (i.e., the likelihood of having either positive or negative correlations respectively). This is imperative because some studies [27,28] have already observed that farmers can adopt more than one practice on an individual plot. In many cases, it is reasonable to unpack the GAPs/NIGAs and re-bundle the similar ones depending on the main objective of analysis (if economic growth or nature conservation or just striking a balance between the two). It is important to underline the fact that not all GAPs can optimize the contentious benefits of economic growth and nature conservation. For example, an initiative promoting the use of inorganic fertilizers and herbicides may increase crop yield but cause a huge cost on the environment if not properly handled.

It is also worth noting that different studies have used different economic models to evaluate factors influencing the adoption of GAPs and generally arising with different results and conclusions. Abdulai and Huffman [29], for example, have used the Endogenous Switching Regression Model to evaluate the adoption and impact of SWC technology in Africa. They identify the factors that affect farmers' decisions to adopt SWC technology as including farmers' education, capital and labor constraints, social networks and extension contacts, and soil conditions. Barungi et al. [25] and Asfaw and Neka [22] found the adoption of GAPs to be affected by socio-economic factors, like sex, age and education of head of household, household assets, income, size of land and livestock holdings, engagement in off-farm activities, as well as access to credits. Other studies found contact with extension agents [22,30] and perceptions of farmers regarding the farm characteristics and extent of environmental degradation [24] to be influencing the decision of farmers to adopt GAPs. In Nepal, Adhikari et al. [31] used the probit model to determine the extent of technology adoption between improved and local seed users in Arghakhanchi district of Nepal. They found that the extent of technology adoption was significantly higher for improved seed users than local seed users. The probability of adoption of improved seed for maize farming was found to be higher for those with access to extensive service. In this context, we define an extension agent as a public or non-state entity or individual whose main role is to set in motion a process of change after recognizing that the change is inevitable for the society, to arouse people to recognize and take an interest in their problems, to overcome these problems, to teach them how to do so, as well as, to persuade them to act on what is taught so that they ultimately achieve a transformation and egotism in their achievements. We dub the services provided by an extension agent as extension services.

In our study, we used a combination of Generalized Linear Binary Probit model/Multivariate Analysis of Variance (MANOVA) and Discriminant Function Analysis (DFA) to investigate the factors which determined the adoption of NIGAs in Uluguru Mountains and find out whether our pre-selected independent variables significantly influenced the adoption of NIGAs. We use cross-sectional data and information gathered between the end of 2019 and late 2020. Though basically based on a case study, the findings from this study are very useful for informing policy decisions. The novelty of our study derives from many aspects. Firstly, by focusing on mountain agro-ecologies, it provides some important lessons to inform policies and strategies to achieve the mutual goals of sustainable livelihoods and biodiversity conservation in mountain agro-ecologies. The study findings are relevant and will provide important implications for various change agents, including policymakers, governmental bodies, sponsorship or funding agencies, extension agents and non-governmental agencies. Secondly, through the identification of interlinked factors that consistently determine adoption of NIGAs, we hope that our study will serve as a significant knowledge base by provide information which can be used in either envisaging the reactions of potential adopters to NIGAs or to modify either the NIGAs themselves or the way in which they are introduced so as to be more harmonious with the motivational drivers of potential adaptors. Thirdly, our study recognises the reciprocal nature of the mutual objectives of ensuring sustainable livelihood and biodiversity conservation. Regarding this, we conducted a participatory ranking of all the NIGAs introduced in the study using the yardstick of their potential effects on both livelihoods and biodiversity conservation prior to the selection of NIGAs for further analysis. Fourthly, our study treated NIGAs as not necessarily mutually exclusive as farmers may implement more than one Nature-based Income Generating Activity (NIGA) simultaneously on a single plot, which is a common practice, at least in mountain areas where land resource is major limiting factor. We are, therefore, motivated to add to the knowledge base in these particular aspects.

In the next section, we start by presenting a theoretical framework that underpins our study (Section 2). We then present a brief description of the study area and methodology in Section 3. The study findings are presented and discussed in Section 4. We wind up our paper by presenting some concluding statements and policy implications from the study in Section 5.

2. Theoretical framework

The evaluation of factors influencing the adoption of NIGAs in our study borrowed from the expected utility maximization theory. The theory is broadly applied and discussed in the literature [32–41]. It is renowned as the best developed formal theory of rationality, which forms the core of neoclassical economics. The expected utility maximization theory postulates a utility function, which measures the degree to which an individual's aggregate goals are achieved as a result of their actions [37]. The theory considers the concept of satisfaction as synonymous with consumption utility in economic psychology [42]. The paper by Tan [39] provides a link between diffusion modeling and consumer diffusion research by examining the consumer's innovation adoption decision in a utility maximization context and proposes a choice model to aid in the prediction of innovation adoption. The model incorporates multi-attribute preference, risk, and information uncertainty in an individual level expected utility framework. Abadi-Ghadin & Pannell [38] also propose a model which includes the role of farmer's personal perceptions, managerial capacity and risk preferences over time in deciding to adopt. Their model represents the problem of adoption as a rational economic decision with the objective of profit maximization or expected utility maximization. They combine the perception expected profit with the farmer's perception of risks and their attitude to risk to define adoption as the result of maximizing expected utility of profit, which, according to Tversky & Kahneman [41], is the form of subjective expected utility theory. In Zambia, Umar [33] found that Conservation Agriculture (CA) smallholders did not aim to maximize profit but attempted to secure household consumption from their own production, before any other considerations in risky and uncertain environment. Thus, maximization of utility was the overriding goal for these smallholder farmers.

The main assumption of expected utility theory is that the farmer acts to maximize his level of utility. Since utility is hard to measure, profit is often used by researchers as merely a substitute for this concept [35]. When risk attitude is added to the analysis, then farmers are considered as maximizers of expected utility of profit, rather than the expected profit [38]. As such, if a NIGA has a higher expected utility of profit than the conventional practices, adoption will occur. It is also important to note that people do not necessarily engage in economically optimal decision-making, but instead they may wish to optimize social, intrinsic and/or expressive goals [36]. This is more in line with some findings from the psychological approach which suggest that, instead of maximizing expected utility of profit we can also borrow from Simon's [43] satisfactory theory. This viewpoint contemplates that the theory of innovation is more concerned with "satisfying" rather than "optimizing" as constructed by the classical theory of decision making.

Thus, we can argue that the expected utility maximization theory suggests that an individual farmer i will adopt a specific NIGA if the expected utility from practicing it, U^*_{ij} is greater than the expected utility from any other alternative practices,U_{ij}, i.e. $y^*_{ij} = U^*_{ij} - U_{ij} > 0$;where, y^*_{ij}, is the net benefit that the farmer can receive from practicing the jth activity. Farmers would therefore choose an activity or combination of practices for which they obtain the highest expected utility of profit, subject to the characteristics (or traits) of the practices [43–45]. Based on this theory, the factors influencing the adoption of NIGAs can be evaluated using the Multinomial Probit (MNP) model expressed in Eq. (1).

$$\cup_{ij} = \beta'_i X_{ij} + \varepsilon_{ij} \tag{1}$$

where; $\beta_i \approx N(b, \Sigma_\beta)$,$\varepsilon_i = (\varepsilon_{i1}, \dots \varepsilon_{ij})' \approx N(0, \varepsilon_\varepsilon)$. Thus the MNP model assumes a normal distribution for all unobserved components of utility.

It is important to note that Probit models basically apply the cumulative Gaussian normal distribution rather than the logistic function for calculating the probability of being in one category or not [45] represented in Eq. (2).

$$\begin{aligned} p_i &= \Phi\left(x_i\beta + \beta_0\right) \\ &= \int_{-\infty}^{x_1\beta+\beta_0} \phi(t)dt \end{aligned} \tag{2}$$

where the symbol Φ is simply the cumulative standard distribution, while the lower case symbol ϕ is the standard normal density function. The objective is to maximize the log-likelihood function. The partial derivatives come from the arithmetic relationship given in Eq. (3).

$$\frac{\partial p_i}{\partial x_{i,k}} = \phi\left(x_1\beta + \beta_0\right)\beta_k \tag{3}$$

It is important to use the maximum likelihood method to fit a set of statistical adoption models on sets of simulated data. The best relationships can be identified using the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) methods [46]. The AIC and BIC have the advantage of testing the significance of the difference between the functions of different model specifications. AIC evaluates how well a model fits the data it was generated from [ibid]. It is used to compare different possible models and determine which one is the best fit for the data. AIC is calculated from the number of predictor variables applied to build the model and the maximum likelihood estimate of the model (how well the model reproduces the data).

Suppose $\hat{\theta}$ is the value of the maximized log-likelihood objective function for a model with k parameters fit to T data points. The AIC for a given model is expressed as in Eq. (4).

$$-2\log L\left(\hat{\theta}\right) + 2k \tag{4}$$

According to AIC, the best-fit model is the one that explains the highest amount of disparity using the fewest possible independent variables. Lower AIC scores are better, and AIC punishes models that apply more parameters. So if two models explain the same amount of disparity, the one with fewer parameters will have a lower AIC score and will be the better-fit model. However, AIC lacks certain properties of asymptotic consistency [47,48].

The Bayesian Information Criterion (BIC) for a given model is expressed as in Eq. (5).

$$-2\log L\hat{\theta} + k\log(T) \tag{5}$$

Although BIC takes a similar form like AIC, it is generated within the Bayesian framework, reflecting sample size and having characteristics of asymptotic consistency. For reasonable sample sizes, BIC apply a larger punishment than AIC, thus other factors being equal it tends to choice modest models than does AIC. From a Bayesian view point this persuades the use of BIC [46].

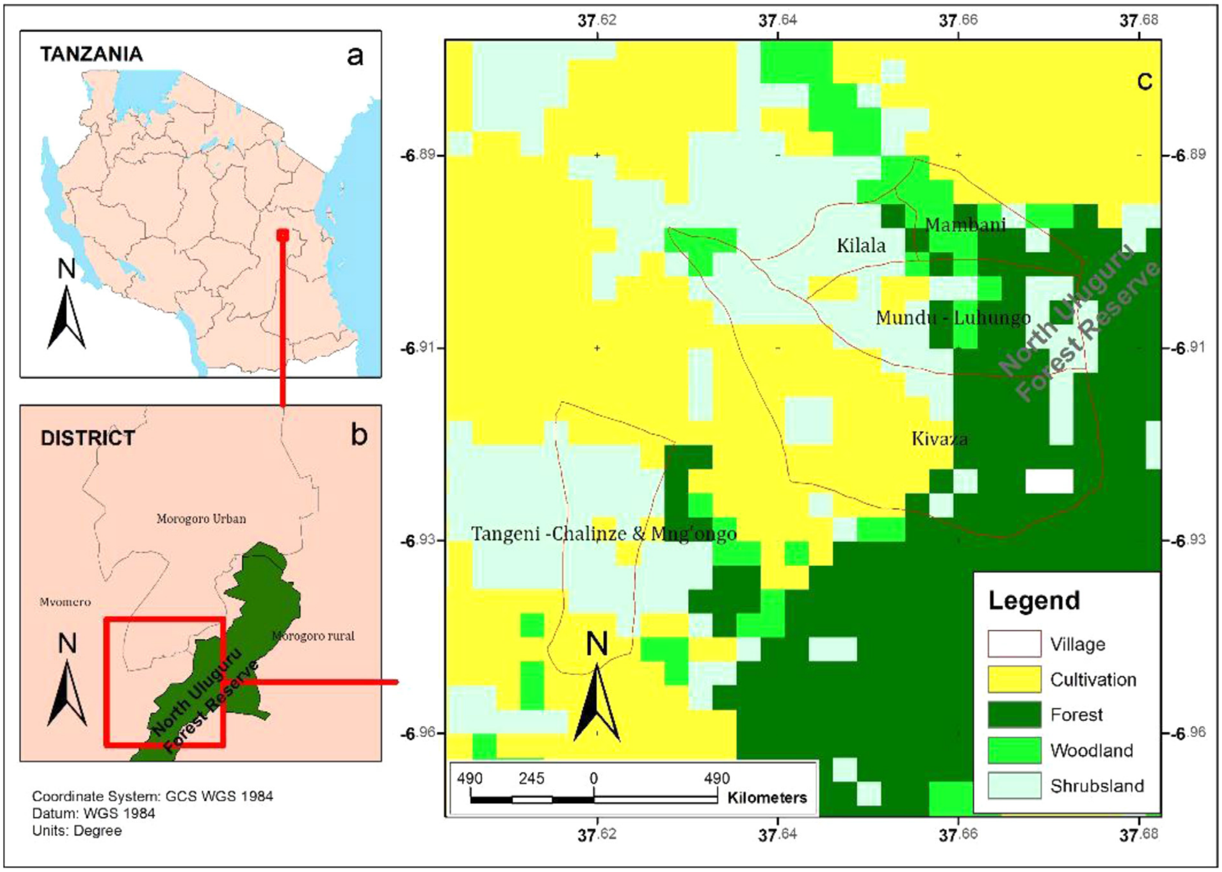

Fig. 1. Map showing the location of study sites and existing land uses.

Other criteria include the Finite Sample Corrected AIC (AICC) and the Consistent AIC (CAIC). AICC is the small-sample equivalent of AIC. It imposes an additional punishment for complex models, as compared to the BIC [46,49,50]. The AICC for a given model can be expressed as in Eq. (6).

$$AIC + \frac{2k(k+1)}{T-k-1} \tag{6}$$

The CAIC for a given model is given as in Eq. (7).

$$-2\log L\hat{\theta} + 2k(\log(T) + 1) = BIC + k \tag{7}$$

3. Study area and methodology

3.1. The study area

The study was conducted in fourteen hamlets located adjacent to the Uluguru Mountains (UMs) Nature Reserve (UMNR) in the wards of Mlimani and Luhungo (Morogoro Municipality), and Mzumbe (Mvomero district) in Tanzania. The UMs were selected as a case study area because of the challenge facing many mountain areas, notably the proliferation of anthropological activities in area which threaten biodiversity conservation [51–56]. There are different land uses in the study area (Fig. 1). Besides its importance as biodiversity hotspot and home to hundreds of species found nowhere else on earth, the area also serves as a water catchment and water source for populations living downstream in Morogoro rural and Municipality as well as in other areas such as the Dar es Salaam City. However, land degradation in this mountain area is reported as rampant caused by unsustainable economic activities [ibid].

3.2. Methodology

3.2.1. Sampling and data collection

We used the multi-stage sampling procedure to select the study hamlets and sample households. In the first stage, fourteen hamlets were selected purposely based on their participation in previous NIGA projects, notably the Uluguru Mountains Payment for Watershed Services Project (UMPWSP), which was funded by the Department for International Development Civil Society Challenge, and supported by the Royal Society for the Protection of Birds (RSPB) in partnership with the Wildlife Conservation Society of Tanzania (WCST). In the second stage, households were stratified into strata according to wealth ranks assigned by UMPWSP using the indicators of wealth presented in Table 1. The ranking exercise eventually resulted in five types of wealth groups namely “very rich”, “rich” “medium”, “poor” and “very poor”. The “very rich” and “rich” households were relatively a small group, covering only about 13% of the total households. They were food secure all year round and had a fairly secure livelihood base. The “medium” wealth class constituted about 35% of the households, with a smaller base of assets to draw on, but the majority of the households in this class were still food secure all year round. The “poor” and “very poor” households (combined together) made up more than half of the total households (52%). The third stage entailed the selection of sample households from each stratum using the proportionate probability sampling procedure. The distribution of sample size by hamlets is given in Table 2.

The study used both primary and secondary data. Prior to commencement of fieldwork, we hired six enumerators to assist us during data collection. These were specifically trained on how to administer questionnaires using other research tools (checklists and guidelines); how to avoid interview biases and use computer tablets (Kobo Collect) to create datasets. They were also reminded about the research ethics

Table 1
Indicators used in the wealth ranking exercise.

Indicator	Very rich	Rich	Medium	Poor	Very poor
Natural capital: Land owned	4 ha or more	3 ha	1–2 ha	0.4–0.9 ha	Less than 0.4 ha or do not own land at all
Financial capital: Livestock owned	Cattle: 5 or more, goats: 50–180, pigs: 10–20	goats: 20–50, pigs: 5–10	goats:3–20, pigs: 2–5	goats:1,2, pigs: 1,2, a few chickens	A few chickens only
Human capital: Labour	Hire labor	Hire labor seasonally	May hire labor seasonally	May sell labor	Selling labor
Human capital: Education	Primary level or above	Primary level	Primary level	Many have not been to school	Many have not been to school
Human capital: Health services	Can always pay for health services (Hospitals, Dispensary, Clinics, traditional healers)	Can pay for health service	Can afford to pay for services from Dispensaries and traditional healers	Can afford to pay for services from traditional healers /use traditional medicines	Cannot afford paying for health service (use traditional medicines)
Physical and financial capital: Other assets owned	Owns a house build using block or burnt blocks, connected with reliable electricity sources; good floors and walls; Possess other valuable assets such as Vehicles, Milling machine, Sewing machine, Refrigerator, Bicycles, TV, Radio, Water pump	Owns a house built using at least mud block and roofed using corrugated iron sheets; bicycle(s), radio, and TV	Owns a house built using mud block and roofed using corrugated iron sheets, can own a bicycle, radio and/or TV	Owns a house built using mud and poles, roofed using thatch grass, Few have radios	Owns a house built using mud and poles, roofed using thatch grass
Food security	Affords three meals per day for all days in a year	Affords three meals per day for most of days in a year	Affords three meals per day for at least six months in a year	Affords three meals per day for less than three months in a year	Cannot afford three meals per day
Proportion to total households	5%	8%	35%	40%	12%

Table 2
Distribution of sample size by study sites.

Study sites/hamlets	Households	Sample size*	%
Tangeni village (5 hamlets)	1030	66	32.8
Kilala	85	12	6.0
Mundu	145	15	7.5
Mambani	152	21	10.4
Kivaza	167	21	10.4
Mbete	22	9	4.5
Ruvuma	72	15	7.5
Choma	210	21	10.4
Kisosa	84	12	6.0
Tulo	42	9	4.5
TOTAL	**2009**	**201**	**100**

* The total sample size used in the final data analysis (after data cleaning) was 154 households.

they should comply with. The actual fieldwork started with a reconnaissance survey to get an overview and understanding of the study area and applicability of the questionnaire. During the reconnaissance survey the household questionnaire was pre-test to a small number of respondents before the actual fieldwork to check for their relevance to the study area and objectives. This was followed by the main survey which used different research tools and techniques, including structured questionnaires, and checklists for interviews with key informants (selected based on their involvement in NIGA initiatives) and Focus Group Discussions (FGDs).

The FGDs were attended by at least 10 participants per hamlet representing different socioeconomic groups that existed in the area, including the rich, poor, youth and women, men, abled and disabled people. In selecting the key informants for interview, the snowball technique was used. The technique is particularly suitable when the population of interest is hard to reach and compiling a list of the population poses difficulties for the researcher [57]. It begins with a convenience number of initial subject which serves as “seeds,” through which wave 1 subject is identified; wave 1 subject, in turn, identifies wave 2 subjects; and the number of interviewees consequently expands wave by wave-like a snowball growing in size as it rolls down a hill [58].

3.2.2. Data processing and analysis

Different NIGAs were identified using the household questionnaire, FGDs, KIIs, direct observation approaches, review of government and project document as well as office records and questionnaire survey. The analysis of adoption of NIGAs in this study adopted the Generalized Linear Model (GLM), which is a generality of the linear model, such as the multiple regression models. Like the linear model, GLM is concerned about the conditional mean of an outcome variable Y, usually denoted as μ. Like Logit, probit is a linear probability model for binary outcomes that allow one to elude the problems related to the linear probability model, such as non-constant error variance and the naive postulation of linearity in the parameters [59]. Logit and probit also serve as building blocks for more progressive regression models for other categorical outcomes [ibid]. Binary outcomes are dichotomous-dependent variables coded as 0 or 1 and nominal outcomes are dependent variables with three or more unordered categories.

The Multinomial Probit (MNP) model is a flexible model which permits random test variation and can embody any substitution pattern, avoiding the obstructive substitution pattern assumptions in other models [45]. In this study, the Multivariate Probit (MVP) model was preferred over other models because of its ability to allow the analysis of potential correlation between unobserved disturbances (error terms) and correlation between the adoption of each NIGA [60–62]. The means of two independent groups (adopters and non-adopters of NIGAs) were compared using the Independent Samples t Test (a parametric test), also known as the Uncorrelated Scores t Test or Unpaired t Test or unrelated t Test. The aim was to determine whether there is sufficient statistical evidence to justify that the associated population means are significantly different. Before running the Independent Samples t Test, we generated descriptive statistics and graphs to get an idea of what is expected from the test using the Explore procedure in IBM SPSS Statistics 26 software to obtain comparative boxplots for each predictor and NIGA. The Independent Samples t Test provided the group statistics, which offered basic information about the group comparison (i.e., NIGA adopters versus non-adopters), including the sample size (n), mean, standard deviation, and standard error for independent variables. In addition, the Independent Samples Test displays two types of results which are most relevant to this test, that is, the Levene’s Test for Equality of Variance and t-test for Equality of Means. The Levene's test is an alternative to Bartlett's test, which tests equality of variances between k sample populations [63]. However, the Bartlett's test is sensitive to departures from normality, and thus the Levene's test is preferred when the population samples are generally not normally distributed [63].

The null and alterative hypotheses of the Levene's test can be generally stated as follows;

H_0 :All of the k sample populations have equal variances

H_1 :$_{\text{At}}$ least one of the k sample population variances is not equal

The test statistic, W used in Levene's test is defined as in Eq. (9).

$$W = \frac{(N-k)\sum_{i=1}^{k} n_i \left(Z_i - Z\ldots\right)^2}{(k-1)\sum_{i=1}^{k}\sum_{j=1}^{n_i}\left(Z_{ij} - Z_i\right)^2} \tag{9}$$

where,

$k$is the number of groups

$n_i$is the number of samples belonging to the ith group

$N$is the total number of samples

$Y_{ij}$is the j-th observation from ith group and,

$$Z_i = \frac{1}{n_1}\sum_{j=1}^{n_i} Z_{ij}$$

$$Z\ldots = \frac{1}{N}\sum_{i=1}^{k}\sum_{j=1}^{n_i} Z_{ij}$$

are the mean of the calculated Z_{ij} for group I and mean of all Z_{ij}, respectively.

In Levene's Test,Z_{ij}can have one of the following three definitions:

$|Y_{ij} - \tilde{Y}_i|$, where$\tilde{Y}_i$is the median of the ith group

$|Y_{ij} - \bar{Y}_i|$, where$\bar{Y}_i$is the mean of the ith group

$|Y_{ij} - \bar{Y}_i'|$, where$\bar{Y}_i'$is the trimmed mean of the ith group

The null of Levene's test is rejected when p is less than the chosen significance level $\alpha = 0.05$, and can be concluded that the variance in the independent variable of interest for, say "adopters" is significantly different from that of "non-adopters." In this case, the values of "Equal variance not assumed" are used for the t-test (and corresponding confidence level) results. If this test gives insignificant values, that is, if the observation is $p > \alpha$ then the "Equal variances assumed" output would be used. The confidence interval (CI) output of the t - test complements the significance test results. Typically, if the CI for the mean difference contains 0, the results are not significant at the selected significant level. It is important to note that the Independent Samples t Test is suitable for a continuous dependent variable (i.e. interval or ratio level) and independent variables that are categorical (i.e. two or more groups). The test assumes a normal distribution (approximately) of the dependent variable for each group, as well as homogeneity of variances (i.e. variances nearly equal across groups and absence of outliers, just to mention few).

In our study, we used the maximum likelihood method to fit the set of statistical NIGA adoption models on the sets of simulated data. The best relationships were compared and selected using the Akaike information criterion (AIC); Bayesian information criterion (BIC) methods [46], and the Finite Sample Corrected AIC (AICC). In addition, we generated Q-Q plots and used them to test the assumption of normality. In this method, we plotted the observed value and expected value to check if the plotted values vary more from a straight line or not. Where they vary more from the straight line, then the data were considered to be not normally distributed, otherwise the data were considered to be normally distributed [64]. We also tested our dataset for heteroskedasticity (i.e. the state of systematic changes in the spread of residuals or the error term of the model). The presence of residual variance in a model would show that the scattering of the model is dependent on at least one independent variable [ibid]. Specifically, we tested heteroskedasticity using both graphical or visual (the P-P plot and histogram) and statistical tests (the Levene's and Breusch-Pagan tests). We then removed the variables with heteroskedasticity from our dataset before doing the final regression analysis using the robust standard method.

After data cleaning and removal of outliers, we correlated the independent variables to check for multicollinearity. For pairs of variables found to have correlation coefficient (r) of equal to or greater than 0.8 one or both variables were removed from the dataset [65]. The new dataset was retested by computing the Variance Inflating Factors (VIFs) and tolerances of independent variables. The VIF values were less than 1.5 and the tolerances greater than 0.1, which were not enough to overlay concerns about presence of multicollinearity. VIFs greater than 10 and tolerances less than 0.1 would imply the presence of muticollinearity problem [66].

We then applied the Multivariate Analysis of Variance (MANOVA) and Discriminant Function Analysis (DFA) to find out whether the independent variables significantly influenced the adoption of the four NIGAs (agroforestry, terraces/contour farming, soil/stone bunds and beekeeping). Specifically, we created syntax for MANOVA to uncover a meaningful underlying dependent variable which makes useful correlation amongst dependent variables and the effects of independent variables. The use of MANOVA instead of separate ANOVAs for each dependent variable is widely discussed in the literature [67–72]. By employing MANOVA, the analyst can obtain a more detailed description of the phenomenon under investigation and get a better opportunity of determining the overall impact of the treatment effect [67]. In addition, using MANOVA helps the analyst to control the overall alpha level at the desired level and increase the statistical power. Although it offers some useful advantages, MANOVA has a disadvantage of complicating the interpretation of results compared to ANOVA and losing the degree of freedom [ibid]. For that matter, if the hypotheses of interest are univariate in nature, it may be desirable to conduct separate ANOVAs. In the real world however, analysts often find that the response variables are correlated [67,73]. But it should be noted here that MANOVA gives same values as the GLM approach. In fact it is recommended to start with MANOVA first because it creates a liner equation upon which a variable which will maximally discriminate amongst the groups of independent variables is identified [67]. Without doing MANOVA some power of identifying influential factors is lost.

DFA is an extension of univariate regression analysis and ANOVA and it is similar to multiple regression analysis [74]. In the DFA, the canonical discriminant functions are defined as linear combinations that separate groups of observations, and the canonical variates are defined as linear combinations associated with canonical correlations between two sets of variables [75,76]. In standardized form, the coefficients in either type of canonical function provide information about the joint contribution of the variables to the canonical function. The standardized coefficients can be converted to correlations between the variables and the canonical function [ibid]. These correlations generally alter the interpretation of the canonical functions. For canonical discriminant functions, the standardized coefficients are compared with the correlations, with partial t and F tests, and with rotated coefficients [ibid]. The DFA output includes among others, the standardized discriminant function coefficients which show the relative contribution of each variable to the variates. The derived canonical variates summarize between-group variation and provide a simultaneous test describing which variables best account for group differences [ibid]. The canonical discriminant analysis (CDA) involves deriving the linear combinations (i.e., canonical functions) of the variables that will discriminate the best (i.e., maximize the variation) among the predefined groups [ibid].

4. Results and discussion

4.1. Normality testing

The results of normality tests using visualization (boxplots) helped to identify the outliers and remove them. As illustrated in Fig. 2 for selected independent variables (i.e. age of household head, household

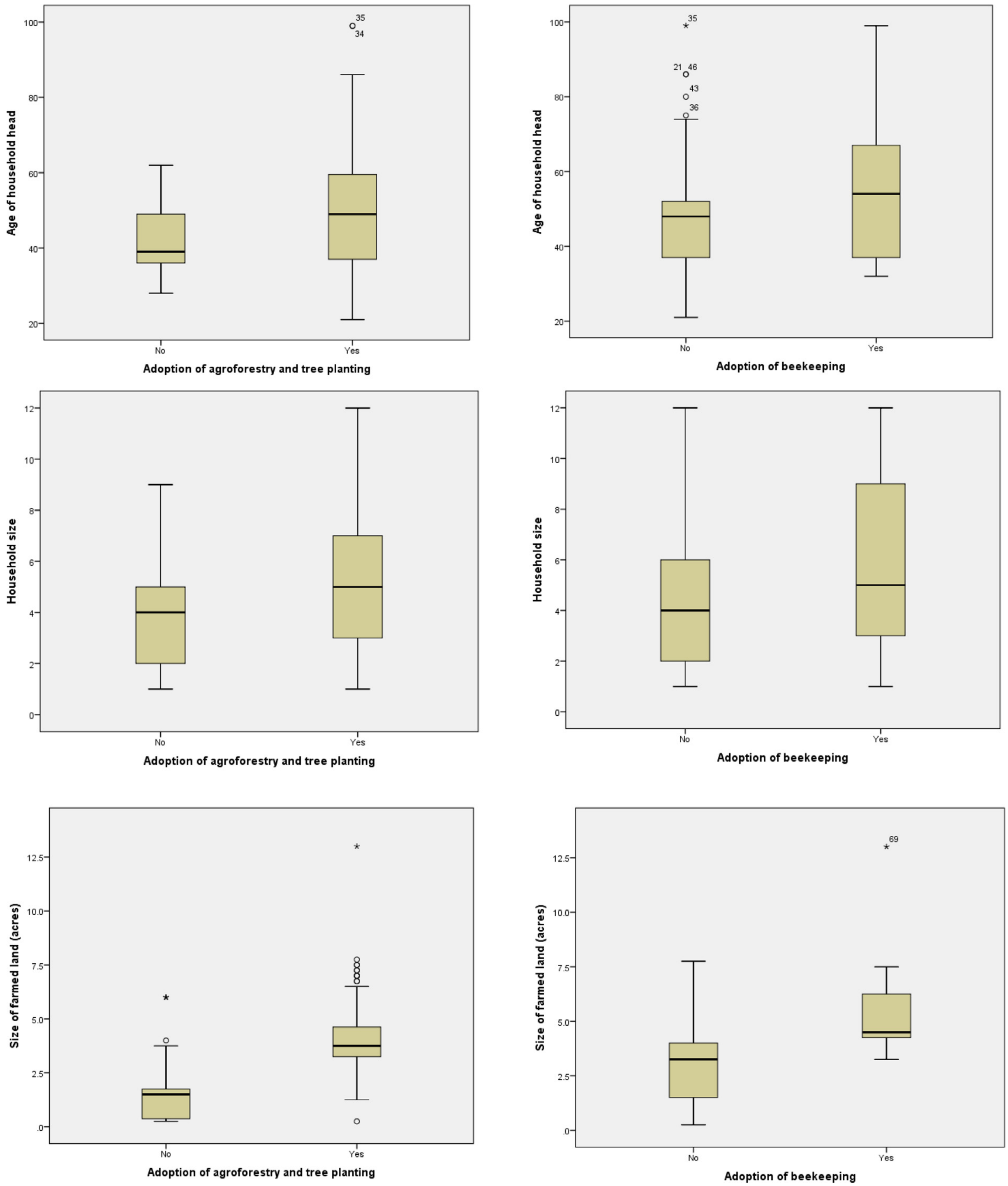

Fig. 2. Boxplots for selected predictor variables between adopters and non-adopters of agroforestry and beekeeping.

size, and size of farmland) and dependent variables (i.e. adoption of agroforestry and adoption of beekeeping), if the variances for adopters and non-adopters of NIGAs were equal, then the total length of the boxplots in this figure would be approximately similar for both groups. However, the boxplots show that, in many cases the observations for adopters of NIGAs were much greater than the spread of observations for non-adopters implying that the variances for these two groups were different. In Fig. 2, examples of outliers are presented as numbers marked by asterisks (e.g. observation number 35 and number 69). These observations together with other outliers were removed from the original dataset making the sample size to decline from 201 to 154 in the MANOVA, ANOVA and DFA.

The P-P plots and histogram of the square of standardized residual against continuous predictors (Fig. 3) also display some interesting visualizations. As expected, the results of an Independent *t* Test and Levene's Test yielded significant outputs for the predictors as shown in this figure. More discussion about the interpretation of the Levene's test statistics is presented in the next sub-section.

The results of test of goodness of fit for different NIGAs' models are presented in Table 3. The agroforestry model registered the best re-

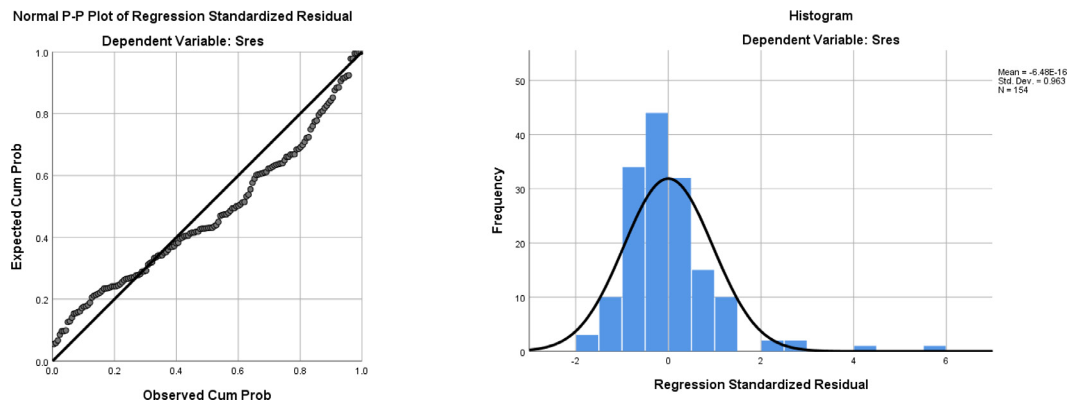

Fig. 3. P-P plot and histogram of the square of unstandardized residual against continuous predictor variables.

Table 3
Results of test of goodness of fit for different NIGAs ($N = 154$).

Criteria	Agroforestry	Terraces/Contours	Soil/stone bunds	Beekeeping
Deviance	0.000	192.264	53.355	45.830
Scaled Deviance	0.000	192.264	53.355	45.830
Pearson $\chi2$	0.000	155.019	73.571	99.547
Scaled Pearson $\chi2$	0.000	155.019	73.571	99.547
Log Likelihood^b	0.000	−96.132	−26.677	−22.915
AIC	24.000	216.264	77.355	69.830
AICC	26.213	218.477	79.567	72.043
BIC	60.443	252.708	113.798	106.273
CAIC	72.443	264.708	125.798	118.273

lationships (smallest values) for all model selection criteria (i.e., AIC, BIC, AICC, and CAIC). This is followed by beekeeping and soil and stone bunds models. The terraces and contour farming model yielded the largest AIC, BIC, AICC and CAIC values making it to rank the last amongst the four models tested for goodness of fit.

4.2. Results of MANOVA, ANOVA and DFA

One of the components of ANOVA output constitutes the Box's test statistics which are used to test the null hypothesis that the observed covariance matrices of the dependent variables are equal across groups. The Box's test statistics showed significant values (i.e. *Box's* $M = 57.235$, $F = 5.156$, $p = 0.000$). The p-value in this case was less than 0.05), hence, the covariance matrices were not equal (i.e. they were significantly different) and the assumption of equal covariance matrices was therefore violated. It is important to note that, if the matrices were equal (and therefore the assumption of homogeneity being satisfied) this statistic should be non-significant. However, since the group sizes in our study were equal, we ignored this test and applied the Pillais Trace, Wilk's Lambda, Hotelling's Trace and Roy's largest root, which test the statistical significance of the different effects of independent variables. These are used because they are robust to the violation of homogeneous covariance matrices.

Accordingly, we tested the interaction effect of four groups (i.e. sex of household head, farmland location, major source of working capital, and membership to Savings and Credit Cooperatives (SACCOS) and or Village Community Banking (VICOBA) to determine whether this effect is consistent across the four NIGAs (i.e. agroforestry, terraces/contour farming, soil/stone bunds, and beekeeping). It should be noted that the "interaction effect" determines whether the effect of our predetermined NIGAs is similar for the four groups or independent variables. The interaction effect in this case would be considered as statistically significant if the p-value is less than 0.05 (i.e. $p < 0.05$), otherwise, if $p > 0.05$ the interaction effect is considered as not statistically significant. We present the summary of interaction effect in Table 4.

The results in Table 4 indicate that the significant values of F-ratios which reach the criterion for significance at 0.05 level are the farmland location ($p = 0.004$) and major source of operating capital ($p = 0.000$). These two covariates show similar p-values for Pillai trace, Wilks' lambda, Hotelling's trace and Roy's largest root. Thus, we can conclude that there is a statistically significant interaction effect for these two groups. Stated differently, the effect of adopting NIGAs was not the same for farmland location and major sources of capital. These two independent variables do indeed differ in terms of effect on adoption of NIGAs. However, the nature of effect is still not clear from our multivariate test statistics for these independent variables as it does not clearly indicate the nature of effect (i.e. which groups differed from which). To determine the nature of the effect, reverting to our results of Levene's test of equality of error variance and DFA would be helpful. The results of Levene's test are presented in Table 5. It is important to note that, the Levene's test examines the null hypothesis that the error variance of the dependent variable is equal across groups (i.e. the assumption of homogeneity of variance) and the test should be non-significant for all dependent variables if this assumption has been met [77].

Our results of Levene's test show that, the assumption ($p > 0.05$) is met for only one dependent variable (adoption of terraces/contour farming), based on median as well as on median and with adjusted df ($p = 0.84$). Since the other three dependent variables do not meet the assumption of $p > 0.05$, the case for assuming that the multivariate test statistics are robust is then faded. As such, it becomes useful to carry out a univariate ANOVA to test for the between-subjects effects [77]. The statistics of univariate ANOVA for testing between-subjects effects are presented in Table 6.

The F-ratios for each univariate ANOVA and their significance values are listed in the columns labeled F and *Sig.*, respectively. It is important to note that these values are identical to those obtained in one-way ANOVA we conducted for each dependent variable independently. The values of p in test output indicate that there were significant differences between groups in terms of adoption of agroforestry for farmland location ($p = 0.003$), major source of capital ($p = 0.006$) and slightly for the

Table 4
Results of multivariate tests ($N = 154$).

Effect (a.)		Value	F	Hypothesis df	Error df	Sig.
Intercept	Pillai's Trace	0.612	54.365[b]	4.000	138.000	0.000
	Wilks' Lambda	0.388	54.365[b]	4.000	138.000	0.000
	Hotelling's Trace	1.576	54.365[b]	4.000	138.000	0.000
	Roy's Largest Root	1.576	54.365[b]	4.000	138.000	0.000
Sex	Pillai's Trace	0.034	1.199[b]	4.000	138.000	0.314
	Wilks' Lambda	0.966	1.199[b]	4.000	138.000	0.314
	Hotelling's Trace	0.035	1.199[b]	4.000	138.000	0.314
	Roy's Largest Root	0.035	1.199[b]	4.000	138.000	0.314
Land location	Pillai's Trace	0.104	4.016[b]	4.000	138.000	0.004
	Wilks' Lambda	0.896	4.016[b]	4.000	138.000	0.004
	Hotelling's Trace	0.116	4.016[b]	4.000	138.000	0.004
	Roy's Largest Root	0.116	4.016[b]	4.000	138.000	0.004
Major source of capital	Pillai's Trace	0.163	6.728[b]	4.000	138.000	0.000
	Wilks' Lambda	0.837	6.728[b]	4.000	138.000	0.000
	Hotelling's Trace	0.195	6.728[b]	4.000	138.000	0.000
	Roy's Largest Root	0.195	6.728[b]	4.000	138.000	0.000
Membership to SACCOS/VICOBA	Pillai's Trace	0.010	.339[b]	4.000	138.000	0.851
	Wilks' Lambda	0.990	.339[b]	4.000	138.000	0.851
	Hotelling's Trace	0.010	.339[b]	4.000	138.000	0.851
	Roy's Largest Root	0.010	.339[b]	4.000	138.000	0.851
Sex * Land location	Pillai's Trace	0.026	.928[b]	4.000	138.000	0.450
	Wilks' Lambda	0.974	.928[b]	4.000	138.000	0.450
	Hotelling's Trace	0.027	.928[b]	4.000	138.000	0.450
	Roy's Largest Root	0.027	.928[b]	4.000	138.000	0.450
Sex * Major source of capital	Pillai's Trace	0.059	2.165[b]	4.000	138.000	0.076
	Wilks' Lambda	0.941	2.165[b]	4.000	138.000	0.076
	Hotelling's Trace	0.063	2.165[b]	4.000	138.000	0.076
	Roy's Largest Root	0.063	2.165[b]	4.000	138.000	0.076
Sex * Membership to SACCOS/VICOBA	Pillai's Trace	0.010	.366[b]	4.000	138.000	0.833
	Wilks' Lambda	0.990	.366[b]	4.000	138.000	0.833
	Hotelling's Trace	0.011	.366[b]	4.000	138.000	0.833
	Roy's Largest Root	0.011	.366[b]	4.000	138.000	0.833
Land location * Capital	Pillai's Trace	0.046	1.649[b]	4.000	138.000	0.166
	Wilks' Lambda	0.954	1.649[b]	4.000	138.000	0.166
	Hotelling's Trace	0.048	1.649[b]	4.000	138.000	0.166
	Roy's Largest Root	0.048	1.649[b]	4.000	138.000	0.166
Land location * Membership to SACCOS/VICOBA	Pillai's Trace	0.006	.192[b]	4.000	138.000	0.942
	Wilks' Lambda	0.994	.192[b]	4.000	138.000	0.942
	Hotelling's Trace	0.006	.192[b]	4.000	138.000	0.942
	Roy's Largest Root	0.006	.192[b]	4.000	138.000	0.942
Capital * Membership to SACCOS/VICOBA	Pillai's Trace	0.029	1.026[b]	4.000	138.000	0.396
	Wilks' Lambda	0.971	1.026[b]	4.000	138.000	0.396
	Hotelling's Trace	0.030	1.026[b]	4.000	138.000	0.396
	Roy's Largest Root	0.030	1.026[b]	4.000	138.000	0.396
Sex * Capital * Membership to SACCOS/VICOBA	Pillai's Trace	0.013	.444[b]	4.000	138.000	0.777
	Wilks' Lambda	0.987	.444[b]	4.000	138.000	0.777
	Hotelling's Trace	0.013	.444[b]	4.000	138.000	0.777
	Roy's Largest Root	0.013	.444[b]	4.000	138.000	0.777
Land location * Major source of capital * Membership to SACCOS/VICOBA	Pillai's Trace	0.040	1.419[b]	4.000	138.000	0.231
	Wilks' Lambda	0.960	1.419[b]	4.000	138.000	0.231
	Hotelling's Trace	0.041	1.419[b]	4.000	138.000	0.231
	Roy's Largest Root	0.041	1.419[b]	4.000	138.000	0.231

a. Design: Intercept + Sex + Land_Locat + Capital + Membership + Sex * Land_Locat + Sex * Capital + Sex * Membership + Land_Locat * Capital + Land_Locat * Membership + Capital * Membership + Sex * Land_Locat * Capital + Sex * Land_Locat * Membership + Sex * Capital * Membership + Land_Locat * Capital * Membership + Sex * Land_Locat * Capital * Membership.
b. Exact statistic.

conjoined effect of farmland and major source of capita ($p = 0.051$). The output also shows significant differences between groups in the adoption of beekeeping for farmland location ($p = 0.005$). In addition, there were also significant differences between groups in the adoption of soil and stone bunds for major source of capital ($p = 0.000$) and for the conjoined interaction between sex of household head and major source of capital ($p = 0.007$). We can therefore argue that, respectively, these independent variables (groups) had a significant effect on the adoption of agroforestry, beekeeping as well as soil and stone bunds. However, we have to qualify this assertion further by using the results of DFA (Table 7) which show the initial statistics from the discriminant analysis (the Eigenvalues).

Procedurally, we tested the model as a whole and then removed variates one at a time to see whether what's left is significant. It should be restated here that the results of standardized canonical discriminant function coefficients tell us about the relative contribution of each variable to the variates. In DFA, the eigenvalues constitute an interesting part of the output. They are statistics of the matrix product of the inverse of the within-group sums-of-squares and cross-product matrix and the between-groups sums-of-squares and cross-product matrix [77]. The eigenvalues represent a linear combination of dependent variables that the analyst creates to establish the canonical variable, eigenvalues and the canonical correlation associated with it [ibid]. They are related to the canonical correlations and they describe how much discriminating ability a function possesses. The magnitudes of the eigenvalues are indicative of the functions' discriminating abilities [ibid]. Our results in Table 7 indicate different eigenvalues for the four independent variables we used in our analysis with farmland location having the largest eigen-

Table 5
Results of Levene's test of equality of error variances (N = 4).

		Levene Statistic	df1	df2	Sig.
Adoption of agroforestry	Based on Mean	52.912	11	141	0.000
	Based on Median	2.941	11	141	0.002
	Based on Median and with adjusted df	2.941	11	94.415	0.002
	Based on trimmed mean	44.102	11	141	0.000
Adoption of terraces/contour farming	Based on Mean	3.993	11	141	0.000
	Based on Median	0.574	11	141	0.848
	Based on Median and with adjusted df	0.574	11	135.856	0.848
	Based on trimmed mean	3.993	11	141	0.000
Adoption of soil and stone bunds	Based on Mean	11.763	11	141	0.000
	Based on Median	2.370	11	141	0.010
	Based on Median and with adjusted df	2.370	11	63.277	0.016
	Based on trimmed mean	9.710	11	141	0.000
Adoption of beekeeping	Based on Mean	8.698	11	141	0.000
	Based on Median	2.340	11	141	0.011
	Based on Median and with adjusted df	2.340	11	64.345	0.017
	Based on trimmed mean	7.517	11	141	0.000

Table 6
Results of univariate ANOVA for tests of between-subjects effects (N = 154).

Source		Type III SSs	df	Mean Square	F	Sig.
Corrected Model	Adoption of agroforestry and tree planting	8.177[a]	12	0.681	4.211	0.000
	Adoption of terraces and contour farming	2.170[b]	12	0.181	0.762	0.688
	Adoption of soil and stone bunds	2.842[c]	12	0.237	2.904	0.001
	Adoption of beekeeping	1.844[d]	12	0.154	2.154	0.017
Intercept	Adoption of agroforestry and tree planting	29.269	1	29.269	180.872	0.000
	Adoption of terraces and contour farming	6.968	1	6.968	29.359	0.000
	Adoption of soil and stone bunds	2.256	1	2.256	27.669	0.000
	Adoption of beekeeping	0.364	1	0.364	5.099	0.025
	Adoption of beekeeping	0.011	1	0.011	0.151	0.698
Farmland location	Adoption of agroforestry and tree planting	1.460	1	1.460	9.025	0.003
	Adoption of beekeeping	0.580	1	0.580	8.132	0.005
Source of capital	Adoption of agroforestry and tree planting	1.248	1	1.248	7.711	0.006
	Adoption of soil and stone bunds	1.513	1	1.513	18.557	0.000
Sex*Capital	Adoption of soil and stone bunds	0.600	1	0.600	7.362	0.007
Farmland location*Capital	Adoption of agroforestry and tree planting	0.629	1	0.629	3.890	0.051

[a] R Squared =0 0.264 (Adjusted R Squared = 0.201).
[b] R Squared = 0.061 (Adjusted R Squared = 0.019).
[c] R Squared = 0.198 (Adjusted R Squared = 0.130).
[d] R Squared = 0.155 (Adjusted R Squared = 0.083).

Table 7
Eigenvalues and canonical correlations.

Covariate	Eigenvalue	Canonical correlation	Canonical R^2
Sex of household head	0.09318	0.29196	0.085
Farmland location	0.29384	0.47656	0.227
Major source of capital	0.21032	0.41686	0.174
Membership to SACCOS/VICOBA	0.03176	0.17546	0.031

value (0.29384) and a squared partial canonical correlation of 22.7%. The major source of operating capital yielded an eigenvalue of 0.21032 and canonical R^2 of 17.4%. This implies that about 22.7% of the variability in canonical variables (the "super" dependent variables) was accounted for by farmland location and 14.4% by major source of working capital.

Another useful component of the DFA output is the multivariate F-test, the statistics of which are presented in Table 8. The results show that, with exception of membership to SACCOS and or VICOBA, there are some significant F-values for the other three functions (i.e. the sex of household head, farmland location and major source of capital). Note that, due to the absence of functions significant at level alpha (p = 0.05), the MANOVA did not report any canonical discriminant or correlation analysis for effect of membership to SACCOS and or VICOBA.

The results of discriminant function coefficients (Table 9) show further that the adoption of NIGAs in the study area differed amongst the four dependent variables on the three independent variables with the adoption of agroforestry carrying the highest weights based on sex of household head (0.67448) and farmland location (0.69308). Based on the major source of capital, the adoption of soil and stone bunds carries the highest score (0.74674). In absolute terms, the lowest standardized discriminant function coefficients are registered for sex of household head (0.23497) and farmland location (0.28080) in the case of the adoption of soil and stone bunds. For beekeeping the lowest discriminant function coefficients are observed for the major source of capital (0.02599).

Another way of interpreting this is to look at the correlation between the dependent and canonical variables or "super" variables created based on unstandardized coefficients (see Table 10). In fact, all our four dependent variables for adoption of NIGAs correlate with the canonical variables or super variables. The standardized canonical discriminant function coefficients were used to calculate the discriminant score for each case. The scores were calculated as products of standardized coefficients and the standardized variables. The magnitudes

Table 8
Results of multivariate *F*-Tests with (1, 152) DF (*N* = 154).

Variable	Hypothesis SS	Error SS	Hypothesis MS	Error MS	*F*	Sig of *F*
Sex of household head						
Adoption of agroforestry	1.75010	29.24341	1.75010	0.19239	9.09658	0.003
Adoption of terraces/contour farming	0.87365	34.76271	0.87365	0.22870	3.82004	0.052
Adoption of soil/stone bunds	0.10979	14.22787	0.10979	0.09360	1.17292	0.281
Adoption of beekeeping	0.15071	11.75188	0.15071	0.07732	1.94935	0.165
Farmland location						
Adoption of agroforestry	4.81391	26.179590	4.81391	0.17223	27.94983	0.000
Adoption of terraces/contour farming	0.43636	35.200000	0.43636	0.23158	1.88430	0.172
Adoption of soil/stone bunds	0.72134	13.616330	0.72134	0.08958	8.05232	0.005
Adoption of beekeeping	1.02913	10.873470	1.02913	0.07154	14.38616	0.000
Major source of capital						
Adoption of agroforestry	2.90480	28.08871	2.90480	0.18479	15.71910	0.000
Adoption of terraces/contour farming	0.15088	35.48548	0.15088	0.23346	0.64628	0.423
Adoption of soil/stone bunds	1.43282	12.90484	1.43282	0.08490	16.87655	0.000
Adoption of beekeeping	0.25206	11.65054	0.25206	0.07665	3.28853	0.072
Membership to SACCOS/VICOBA						
Adoption of agroforestry	0.51791	0.51791	0.51791	0.20050	2.58315	0.110
Adoption of terraces/contour farming	0.08640	0.0864	0.08640	0.23388	0.3694	0.544
Adoption of soil/stone bunds	0.20693	0.20693	0.20693	0.09297	2.22585	0.138
Adoption of beekeeping	0.06057	0.06057	0.06057	0.07791	0.77745	0.379

Table 9
Discriminant function coefficients (*N* = 154).

Variable	Raw	Standardized
Sex of household head		
Adoption of agroforestry	1.53771	0.67448
Adoption of terraces/contour farming	−1.20358	−0.57559
Adoption of soil/stone bunds	0.76799	0.23497
Adoption of beekeeping	0.90094	0.25051
Farmland location		
Adoption of agroforestry	1.67002	0.69308
Adoption of terraces/contour farming	−0.66277	−0.31894
Adoption of soil/stone bunds	0.93820	0.28080
Adoption of beekeeping	1.75885	0.47043
Major source of capital		
Adoption of agroforestry	1.33511	0.57393
Adoption of terraces/contour farming	−0.67919	−0.32817
Adoption of soil/stone bunds	2.5628	0.74674
Adoption of beekeeping	0.09388	0.02599

Table 10
Standardized discriminant coefficients and correlations between dependent and canonical variable (*N* = 154).

Variable	Coefficients	Correlations
Sex of household head		
Adoption of agroforestry	0.67448	0.80140
Adoption of terraces/contour farming	−0.57559	−0.51933
Adoption of soil/stone bunds	0.23497	0.28777
Adoption of beekeeping	0.25051	0.37098
Farmland location		
Adoption of agroforestry	0.69308	0.79107
Adoption of terraces/contour farming	−0.31894	−0.20540
Adoption of soil/stone bunds	0.2808	0.42461
Adoption of beekeeping	0.47043	0.56754
Major source of capital		
Adoption of agroforestry	0.57393	0.70121
Adoption of terraces/contour farming	−0.32817	−0.14218
Adoption of soil/stone bunds	0.74674	0.72657
Adoption of beekeeping	0.02599	0.32074

of the coefficients in Table 10 indicate how strongly the discriminating variables affected the score. The results indicate that the sex of household head registered the highest score in the adoption of agroforestry(r = 0.80140) whilst, farmland location scored the highest in adoption of agroforestry (r = 0.79107) and beekeeping (r = 0.56754). The major source of capital yielded the largest scores in the adoption of soil and stone bunds (r = 0.72657) and agroforestry (r = 0.770121).

We finally conducted a one-way ANOVA using the canonical or "super" variable to maximize discrimination between independent variables. In particular, we created a new variable namely "revised canonical variable" by flipping or switching the individual negative values into positive ones and vice versa, before running our model and the output is provided in Table 11. The mean squares were significantly largest for farmland location (8.965) and major source of working capital (6.367) accounting for the 7.4% and 5.3% of the variability in canonical or "super" variables respectively.

4.3. Summary and discussion of key findings

We summarize the key findings from our different analyses in the following three ways. Firstly, our study indicates significant effects on the adoption of NIGAs based on farmland location and major source of working capital. The test statistics generated from the Pillai's trace, for example, show significant statistics for farmland location, $V = 0.104$, $F(4, 138) = 4.016$, $p = 0.004$, and major source of capital, $V = 0.163$, $F(4, 138) = 6.728$, $p = 0.000$. As for Pillai's trace, the Wilks' lambda test statistics also indicate statistically significant interaction effect on adoption of NIGAs for farmland location, $F(4, 138) = 4.016$, $p = 0.004$; Wilks'$\lambda = 0.896$, and for major source of working capital, $F(4, 138) = 6.728$, $p = 0.000$; Wilks'$\lambda = 0.837$. Our separate univariate ANOVAs on the outcome variables also revealed significant effects of farmland location, $F(1, 8.965) = 11.210$, $p = 0.001$, and major source of capital, $F(1, 6.367) = 7.962$, $p = 0.005$. Secondly, our results of MANOVA, which was followed up with discriminant analysis revealed canonical R^2 of 22.7%, 17.4%, 8.5%, and 3.1% for farmland location, major source of capital, sex of household head, and membership to SACCOS or VICOBA, respectively. State differently, these results imply that 22.7% of the variability in canonical variables we generated from our four dependent variables (adoption of agroforestry, terraces/contour farming, soil/stone bunds, and beekeeping) was accounted for by farmland location. About 14.4% of the variability was accounted for by the major source of working capital. The remaining two independent variables, sex of household head and membership to SACCOS and or VICOBA, conjointly accounted for only 11.6% of the variance in canonical dependent variables. However, the results of our ANOVA for revised variables show that farmland location and major source of working capital accounted for relatively larger proportions of variability in the canonical or "super" variables, that is, 7.4% and 5.3% respectively.

Thirdly, our analysis show that the adoption of NIGAs in the study area were significantly differentiated by farmland location, λ= 0.773, $\chi^2(4) = 38.642$, $p = 0.000$, major source of capital, λ= 0.826,

Table 11
Tests of between-subjects effects for revised canonical variable as a dependent variable using univariate ANOVA (N = 154).

Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Corrected Model	53.400[a]	12	4.450	5.564	0.000	0.321
Intercept	46.769	1	46.769	58.480	0.000	0.293
Sex	0.989	1	0.989	1.236	0.268	0.009
Farmland location	8.965	1	8.965	11.210	0.001	0.074
Major source of capital	6.367	1	6.367	7.962	0.005	0.053
Membership to SACCOS/VICOBA	0.072	1	0.072	0.090	0.765	0.001
Sex * Farmland location	0.189	1	0.189	0.236	0.628	0.002
Sex * Major source of capital	0.223	1	0.223	0.279	0.598	0.002
Sex * Membership to SACCOS/VICOBA	0.077	1	0.077	0.097	0.757	0.001
Farmland location * Major source of capital	2.863	1	2.863	3.580	0.061	0.025
Farmland location * Membership to SACCOS/VICOBA	0.176	1	0.176	0.221	0.639	0.002
Capital * Membership to SACCOS/VICOBA	0.083	1	0.083	0.103	0.748	0.001
Sex * Capital * Membership to SACCOS/VICOBA	2.939E-05	1	2.939E-05	0.000	0.995	0.000
Farmland location * Major source of capital * Membership to SACCOS/VICOBA	0.755	1	0.755	0.944	0.333	0.007
Error	112.763	141	0.800			
Total	271.368	154				
Corrected Total	166.163	153				

[a] R Squared = 0.321 (Adjusted R Squared = 0.264).

$\chi^2(4)$ = 28.633, p = 0.000], and sex of household head, λ= 0.915, $\chi^2(4) = 13.364, p = 0.01$. However, the statistics of correlations between outcomes and the discriminant functions (the standardized canonical discriminant function coefficients), revealed that the adoption of agroforestry loaded more highly onto farmland location (r = 0.69308) and sex of household head (0.67448) than the other functions. The adoption of terraces and contour farming loaded more on the major source of capital (r = 0.69308) than the other functions. Therefore, we can argue that, the adoptive decision-making amongst smallholder farmers with regard to NIGAs in the study area was significantly tied to farmland location, major source of capital, and the sex of household head. Innately, it is also reasonable to affirm that these three factors were inter-related and conjointly affecting the capacity of individual farmers to adopt NIGAs.

The reasons for the relationships explained by our model coefficients can be several but one would intuitively expect the adoption of NIGAs to decrease with the distance from homestead to farmland because it becomes more demanding for smallholder farmers to mobilize resources, such as labor and time when the farmland is located far from homestead than when it is close to homestead. Similarly, the type of major source of capital for smallholder farming households determines the level of NIGA adoption. Farmers who rely solely on sale of own farm products and assets are less likely to adopt expensive NIGAs than their counterpart farmers who also access financial resources from other sources, such as, borrowing from SACCOS, VICOBA and other formal and informal financial institutions. In fact, most NIGAs are capital and labor-intensive making them too demanding for smallholder farmers to afford, especially in agro-ecologies of mountain areas where topographic limitations are rampant. Converging on these limitations, one would also argue that, the smallholder female-famers are less likely to adopt expensive NIGAs compared to their counterpart smallholder male-farmers. Thus, the disparities in sex/gender, farmland location, and type of major source of capital conjointly determine the level of NIGA adoption and hedging against risks and losses amongst smallholder farmers in the study area. As such, it is also important to note that any investment decision depends on how profitable it is perceived to be by the investor. The allocation of the available resources to invest in NIGAs is therefore rationally driven by the perception of smallholder farmers in study area as rational investors.

The role of these factors in influencing adoption of GAPs, NIGAs and Climate-Smart Agricultural (CSA) practices is generally widely acknowledged in the literature. In the King Cetshwayo District Municipality of South Africa, for example, the study by Abegunde et al. [78] revealed that the distance of farm to homestead was statistically significant but negatively correlated with the level of adopting Climate-Smart Agricultural (CSA) practices. They also found membership of an agricultural association or group (synonymous to membership to SACCOs and or VICOBA in our study), to be statistically significant and positively correlated with the level of adoption of these practices. Accordingly, they recommend that farmer associations or groups should be given adequate attention to facilitate CSA adoption as a means to mitigate climate change and enhance resilience. The research by Laosutsan [79], who evaluated factors influencing the adoption of GAPs and export decision amongst Thailand's vegetable farmers also, showed that location was the most influential factor in the adoption of GAPs by participating vegetable farmers. In line with the arguments of agricultural location theory, Lucas & Chhajed [80,81] and Laosutsan [79] recommend exporters and relevant government agencies to make GAP certification compulsory to effectively increase the GAP adoption rate among the Thai vegetable growers. In Sokoto State of Nigeria, the study byOjoko et al. [81] revealed that membership of a social group and access to credit were significant determinants of CSA adoption. In Ghana, the study by Akrofi-Atitianti at al. [82] who also investigated CSA adoption among cocoa farmers, found location of farms to be one of the most influential factors. In the Indo-Gangetic plains of India, Aryal et al. [83] who evaluated the factors influencing the adoption of CSA practices by farmers found that farmers' characteristics such as gender, as well as social and economic capital, were some of the key determinants of CSA adoption amongst the farmers. The literature underscores the need for addressing gender related disparity in the development and adoption of GAPs [84]. In this regard, Murray et al. [84] argue that the labor of many women smallholder farmers is constrained by the lack of access to labor–saving technologies and the rudimentary form of farm tools they use. They furthermore argues that for female smallholder farmers to become more climate change resilient, more serious attention should be directed to gender analysis to address the constraints facing these farmers in accessing basic agricultural technologies.

In a nutshell, our study contributes to enriching the adoption literature in three major ways. Firstly, our focus on ecologically fragile mountain areas to investigate the factors which determine adoption of NIGAs is not only timely but also urgent. As already mentioned, mountain areas are home to most endemic and endangered species, but are increasingly threatened by loss of biodiversity due to increasing human population and unsustainable anthropogenic activities. By focusing on these valuable agro-ecologies, we provide some important lessons to inform policies and strategies to achieve the mutual goals of achieving sustainable livelihoods and nature conservation in these areas. Secondly, as also already mentioned earlier, the rate of NIGA adoption in mountain areas is seemingly lower than expected by the promoters of NIGAs in these areas. As such, understanding the real causes of low adoption is even more important now than ever as human population densities and unsustainable anthropogenic activities are increasing at higher rates. Thirdly, our study uses different approaches, such as MANOVA, ANOVA, and DFA in an attempt to capture interconnected and complex relationship between dependent variables and independent variables and uncover a more meaningful underlying of relationships between the outcomes and causal factors. This is critical to get an understanding of how the different NIGAs complement or substitute each other. We attempt to achieve this by identifying the factor which maximally discriminated amongst the preselected determinants.

4.4. Limitations of the study

There are at least two important limitations of our study. Firstly, due to the diverse but interconnected and complex nature of mountain agro-ecologies, modeling of the factors which influence adoption of NIGAs in these areas can be cumbersome. For example, the statistics in our final stage of analysis (Table 11) show that our model was able to describe only 26.4% of all the causal-effect relationships, that is, the test statistics of between-subjects effects for our revised canonical variable show a multiple determination (R^2) of 26.4%. Actually, one may rate this value as still a weak goodness of fit for our model, understanding that R^2 measures the proportion of variation in the dependent variables that can be predicted from the preselected set of independent variables. When the regression equation fits the data well, R^2 will be large and vice versa.

Secondly, our model is based on cross-sectional instead of time series data. This can also be misleading unless the year under study precisely represents the long-term scenario of the phenomena under study. The use of time series data is preferred because it has the advantage of enabling natural ordering which makes it distinct from cross-sectional studies, in which there is no natural ordering of observations [85,86]. Most standard data analysis methods used in adoption studies, such as, ANOVA and OLS regression assume linear association between variables of interest. Time series analysis has an additional advantage of modeling both linear and nonlinear relationships between variables over time. In fact, nonlinear functions are reported to provide better approximation of the true relationship between adoption-related variables [84].

Despite these limitations our study still offers some very useful insights to inform agricultural policy reforms for balancing the existing trade-offs between economic gains and sustainable nature conservation in fragile agro-ecologies of mountain areas. The study identifies some of the key determinants of NIGA adoption upon which the policy reforms should focus on, notably, the issues related to access to land and financial resources. Equally important is the whole issue of combating inequality in access to land and financial resources between female and male farmers. We provide some key recommendations to address these issues in the next section.

5. Conclusion and policy recommendations

This study investigated the factors which influenced the adoption of introduced NIGAs in Uluguru Mountains, Tanzania using the Generalized Linear Binary Probit model/Multivariate Analysis of Variance (MANOVA), complemented by Discriminant Function Analysis (DFA). Different from most of the previous adoption research, our study considered and incorporated the fact that NIGAs are not necessarily mutually exclusive and that farmers may implement more than one NIGA simultaneously on a single plot.

The key findings in this study reveal that the variables of farmland location (whether close or far from homestead), major source of capital (whether sale of farm products and assets or other sources), and type of household based on the sex of household head (whether female or male –headed household) exert the most influence over smallholder farmers' decision to adopt NIGAs. Based on these findings, we recommend the government and non-state agencies promoting NIGA adoption in mountain areas to address the issue of gender inequality in access to land and financial resources. This should be supported by effective implementation of land laws and regulations that address gender inequality, and more generally the empowerment of female farmers. The latter (empowerment of female farmers) can be done in different ways, one of which being the establishment of tailor-made financing schemes, particularly targeted to address gender inequality and enhance livelihoods of smallholder farmers while at the same time conserving nature in mountains areas. In addition, public policies should recognize that gender gaps in separate dimensions complement and reinforce one another and therefore, have to be dealt with simultaneously. A naïve policy targeting a single gap in isolation is unlikely to have substantial achievement in the short run. Typically, inequalities in access to land and financial resources are not independent from each other. For example, if credit –constrained female-headed household face weak property rights, the household may also be unable to access certain markets, and may have mobility and time constraints, then the marginal return to capital may nevertheless be less for this household. We conclude that promising NIGA policy directions that would benefit smallholder farmers in mountain areas should establish a strong linkage between gender equality and pro-nature agendas.

Based on the limitations of our study as mentioned in the previous section, we also recommend further research to investigate the factors influencing NIGA adoption using time series data that facilitate the capacity to model and predict related processes. Time series analysis also has the capacity to enhance causal inference about the relationships between phenomena of interest. The ability to establish the temporal ordering of variables is desirable because it can greatly enhance researchers' ability to draw causal inference from their data.

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