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Modeling farmer's adoption of on-farm technologies

BY

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DECLARATION

DECLARATION BY THE CANDIDATE

I Alice M. Nyathoko, hereby declare that this project is my original work and has not been presented for a degree in any other University.

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DEDICATION

To my late grandmother for her tender love and care.

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Abstract

Soil fertility degradation has been a major issue attributed to poor crop yield among many small-scale holders in various parts of Kenya and other nations in developing countries. Adoption of new technologies to improve farm yields have continously been advocated by agricultural researches. This study provide an empirical analysis on farmer, farm-level and service characteristics that influence farmers' adoption behavior of new on-farm (agro forestry) technologies. The data was collected in three locations of Malindi district: namely Ganda, Goshi and Jirole. A sample of 69 households was randomly selected from all households (farmers) for assessment of adoption of the new on-farm technologies. Chi-square tests were used to determine the levels of association between the above characteristics that influence adoption of on-farm technologies and the rate of adoption. Logistic regression model was as well used to identity the characteristics that significantly influence adoption of technologies in the three locations. Out of the respondents, 33% were classified as "adopters" while the rest, 67% were "non-adopters" households. The factors that were found to significantly influence adoption were group membership, location and food situation. Households that were activen in local community groups or associations, and have sufficient food supply were more likely to adopt new on-farm technologies.

Factors that were found not to significantly influence adoption of on-farm technologies are age of household head, head of household, labour used in the farm, occupation of the household head, house type that the farmer lives in, credit facilities size of the farm, and education level of the household head.

Contents

Chapter 1

Introduction

1.1 Background and introduction

Agriculture is the backbone of Kenyan's economy. Changing technologies are nothing new to agriculture. Plows, selective breeding, artificial insemination, vaccines, antibiotics, computers all of these are good examples of commonly used technologies in agriculture. Sometimes new ideas never take hold and sometimes-old technology is replaced. The market generally sorts out which technologies offer a competitive advantage and which do not. No technology is appropriate for every farm. The issue for any single farmer is whether to adopt a new technology on his own farm or not. In a world where rapidly growing populations are putting greater demands on our available arable lands and our environment, improved agricultural technologies are critical for our future.

Agro forestry is a farming system that integrates crops and /or livestock with trees and shrubs. The resulting biological interactions provide multiple benefits, including diversified income sources, increased biological production, better water quality and improved habitat for both humans and wildlife. Farmers adopt agro forestry for two main reasons. They want to increase their economic stability and to improve the management of natural resources under their care. A well-managed agro forestry system might produce firewood, biomass, feedstock, pine straw mulch, fodder for grazing animals and other traditional forestry products. At the same time, the trees are sheltering livestock from wind or sun, providing wildlife habitat, controlling soil erosion, and in the case of most leguminous species fixing nitrogen to improve soil fertility.

The people of Malindi(the study area) practice agro forestry and some of the technologies that they have been exposed to by KARI and KEFRI include boundary planting, hedgerow intercropping, woodlots, the nursery establishments, beekeeping, vegetable nursery and research plot. The main products from the forests are trees, which are put into different uses. The most important use of forest products is as a source of energy in form of fuel wood. The forests also provide the people with building poles and timber for furniture and boat making. The exploitation of the forests is therefore controlled due to the high demand for wood fuel and timber. Currently, there is a high demand on Casuarina, which is used as building roofing poles in the beach hotels. As a result of this demand, most farmers have developed their own forest plantations to generate income.

1.1.1 Problem statement

To safeguard the forests from destruction, farmers are being encouraged to practice agro forestry. In an effort to disseminate information on agro forestry and provide the necessary tree seedlings to the farmers the forestry department has established eight forest stations in the district. They include Gede and Jirole forest stations. The department is also encouraging the establishment of private nurseries throughout the district. A considerable amount of work on farm forestry/agro forestry has been done in the area but very little is known on the adoption of these technologies. Farmers are known to constantly change their management strategies based on their own experiences, those of their neighbours, resource availability, natural conditions and marketing trends. The study therefore aims looking at the feasibility, acceptability and economic viability of the technologies that the farmers in Ganda, Goshi and Jirole in Malindi District were exposed to in 1993.

1.1.2 Aims and objectives of the study

The main aim of this study is to find out the major factors that influence the adoption of farm forestry technologies in Ganda, Goshi and Jirole locations of Malindi District in Kenya. The specific objectives of this study are;

1. To model the factors that influences the adoption of farm forestry technologies in Ganda, Goshi and Jirole locations.

2. To examine the major factors that hinders the adoption of new technologies among the farmers in the study area.

1.1.3 Research hypothesis

There are several factors that are suspected to influence the choice of on-farm technologies. These factors will be tested for association to the adoption of technology. They are broadly divided into farmer, farm-level and service characteristics. Specifically, the factors are gender, age, household type, occupation, education level, labour, food situation, credit facilities, group membership, location and the size of the farm.

1.1.4 Significance of the study

Adoption is not a passive unreflective act at the end of a line of communication; rather adoption is a deliberate decision by an individual. Farmers have a strong desire to hand the farm on to their children. The belief of the continuity of the farm makes improvement of the farm worthwhile, far beyond economically rational levels. The land degradation problems of today were largely caused by the adoption of practices actively promoted by extension in the past. Agro forestry is frequently invoked as a solution to problems of land and water degradation as well as an answer to shortages of food, fuel wood, cash income, animal fodder and building materials in sub-Saharan Africa. Soil fertility degradation has been a major issue attributed to poor crop yield among many small-scale holders in various parts of Kenya and other nations in developing countries.

This study attempted to provide an empirical explanation as to which farmer, farm-level factors and service characteristics are associated with farmers' adoption behavior of new soil fertility replenishment technologies in Malindi District located in the Kenyan Coast. The findings can then be used to advice farmers on the best technology to adopt in order for them to accrue maximum gain and guide investors and decision makers to choose the type of technology to invest in.

Chapter 2

LITERATURE REVIEW

A number of studies have been done in relation to adoption of on-farm technologies. From studies conducted in many different parts of the world, it comes out clearly that there is a lot of concern on the adoption of different on-farm technologies by the farmers. Most of the studies have used a logit model to achieve their objectives. This is because in all cases, the response variable is whether to adopt or not to adopt. This implies that for a binary variable, the most appropriate method of analysis is by using the logit model.

A micro-economic analysis of adoption of contour hedgerows by upland farmers in the Philippines was conducted by Lapar et al(1999) to identify the factors that determine adoption. The empirical results show that adoption depends on several farm and farmer characteristics and relative importance of these factors differ a cross sites. The high cost of establishment, maintenance and the loss of land to hedgerows are considered to be the major constraints to adoption by non-adopters.

Njuki et al (2004) used a multiple linear regression to study male versus female labour in an agro forestry system in the central highlands of Kenya. He concluded that female labour was significantly higher than male labour in all crops. Women contribute 67% of the labour used in cash crops, which composed 78% of the total female labour on crops.

Sureshwaran et al (1996) used a logit model for evaluating farmer participation in soil conservation programs; sloping technology on upland farms in the Philippines. The results suggest that government assistance; land size, age, land intensity and tenure have a significant impact on the adoption decision.

Ayuk Elias (1997) used a logit model to study the adoption of agro forestry technology. He used the case of live hedges in the central plateau of Burkina Faso. The results indicate that water availability and the profitability of the technology itself enhance the probability of adopting live hedges.

Adesina and Chianu (2002) used econometric logit models to come up with the determinants of farmers' adoption and adoption of alley farming technology in Nigeria. The results show that farmer characteristics that influenced adoption included the gender of the farmer, contact with extension agents, years of experience with agro forestry and tenancy status in the village. Human capital variables were significant in explaining farmers' decisions to adopt and modify the technology.

Ramji et al (2002) used a logistic regression analysis to model adoption of agro forestry in the hills Nepal. The results showed that male membership in local Ngos' female education level, livestock population, and farmers positive perception towards agro forestry have significant positive effects on adoption of agro forestry.

Lapar and Simeon (2004) looked at factors affecting adoption of dual-purpose forages in the Philippine uplands. The study used an econometric approach and concluded that farmers who are more educated have higher income, and have access to credit are more likely to adopt the dual-purpose forages.

Gockowski and Ndoumbe (2004) modeled the adoption of intensive monocrop horticulture in Southern Cameroon. A logit model of monocrop adoption indicated that the size of the land holding per household had a negative effect on adoption, congruent with population driven technical change and that increases in unit transportation cost significantly decreased the probability of adoption.

A logistic analysis of the factors that determine the decision of smallholder farmers to intercrop was done by Iqbal et al (2006) taking the case study of rubber-tea intercropping in Sri-Lanka. Factors that significantly influence the decision to intercrop tea with rubber are level of income, source of income and availability of land considered suitable for tea cultivation.

Hans et al (2006) modeled determinants of income-earning strategies and adoption of conservation practices in hillside communities in rural Honduras. A multinomial logit models is used to explain the choice of income earning strategy that includes biophysical, economic, social and institutional variables.

Chapter 3

METHODOLOGY

3.1 Data collection and sampling design

Researchers working at the Kenya Forestry Research Institute in the year 2005 collected the data used in this study. This was done in Malindi District in the Kenyan coast. Malindi district has four major topographical features. First is a narrow belt, which forms the coastal plain and varies in width from 3km to 20km. The coastal plain lies below 30m above sea level with a few prominent peaks on the western boundary including hills like Mwembetungu and Mambrui old sand dunes. Across this plain run several creeks and the estuaries of river Sabaki resulting in excellent marine and estuarine swamps. These swamps are endowed with mangrove forests and presents great potential for marine culture. This zone is composed of marine and deltaic sediments, including coral limestone, marble, clay stones and other alluvial deposits that support agriculture.

A baseline questionnaire was administered to the farmers. The questionnaire was in three sections; the first section characterized the farmers by giving a background of the farmers. The second section Characterized the household and farm resources while the third section Looked at the type of technologies being practiced by farmers, the use, management, benefits, modifications, problems, possible solutions, discontinuations and reasons for it.Farmers involved in the survey were chosen randomly. The sample also included farmers who had not used any on-farm technology at all and those who did not have market gardens. The sample selection was random and was based on the number of farmers who were using the technologies. The people who filled the questionnaires correctly were 69. This constitutes the data used in this study.

Farmers were randomly sampled, approximately 1/3 of all who were using the technologies. Not less than 50 households or farmers were selected from each of the three locations covered. Therefore approximately 69 farmers were interviewed. Before any data entry, all the filled questionnaire forms were examined thoroughly to determine farmers who had continuously used the new on-farm technologies and were classified as "adopters" and farmers who were not using the new on-farm technologies called "non-adopters'. The data collected was coded and captured in SPSS (Statistical Package for Social Science) Version 11.0 computer software.

Descriptive statistics in form of cross tabulation tables, frequency tables and figures will be used in analyzing farmer, farm-level and service Characteristics for the adopters and non-adopters. Determination of relationships between explanatory variables and adoption, which is the dependent variable, will be carried out using the binary logistic model.

3.2 The logistic regression model

The decision to adopt a technology or not is a binary decision (Ayuk, 1997). It can be represented as a qualitative variable whose range is actually limited. This variable is limited because it can only take on two values; 1 or 0 (adopt or not adopt). Adoption decisions can be analyzed with binary choice models (Makrus, 1993).

Different models have been proposed in the econometric literature for estimating binary choice models; the linear probability, logit, and probit models. Feder et al (1982) provide a useful survey of empirical studies of adoption using these types of model. There are a number of well-known drawbacks associated with the use of the linear probability model: predicted probabilities can be greater than one, the disturbance terms suffer from heteroscedascity (equal variance) and their distributions are non-normal (Judge et al 1985; Capps and Kramer, 1985). The logit and probit models overcome these problems since both are based on a cumulative distribution function. They use monotonic transformations to guarantee that predictions lie in the unit interval. Since it has been shown (Capps and Kramer, 1985) that neither of the models has any advantage over other, the logit model is chosen because of its simplicity and computational ease.

3.2.1 The linear logistic model

Suppose that we have n binomial observations of the form $\frac{y_i}{n_i}$, $i = 1, ..., n$ where $E(y_i) = n_i p_i$ and p_i is the probability of success corresponding to the i^{th} observation. The linear logistic model relating p_i to k explanatory variables $x_{1i}, x_{2i}, ..., x_{ki}$ associated with the observation is

$$logit\ (p_i) = \beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + ... + \beta_k x_{ki} \tag{3.1}$$

Where $logit\ (p_i) = ln\ (\frac{p_i}{1-p_i})$ is the logarithmic transformation of the probability of success. Let

$$\sum_{j=0}^{k} \beta_j x_{ji} = \beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + ... + \beta_k x_{ki} = z_i \tag{3.2}$$

Equation 3.1 becomes the same as

$$\frac{p_i}{1-p_i} = e^{z_i} \rightarrow p_i = (1-p_i)e^{z_i} \rightarrow p_i = \frac{e^{z_i}}{1+e^{z_i}} \tag{3.3}$$

The linear logistic model is a member of the generalized linear models. The link function relating p to the linear component of the model is the logistic function.

3.2.2 Fitting the linear logistic model to binomial data

In order to fit a linear logistic model to a given set of data, the unknown parameters have first to be estimated. These parameters are estimated using the method of maximum likelihood. The likelihood function is given by

$$L = \prod_{i=1}^{n} \binom{n_i}{y_i} p_i^{y_i} (1-p_i)^{n_i-y_i} \qquad (3.4)$$

The log-likelihood function is given by

$$\begin{aligned} ln\ L &= \sum_{i=1}^{n} [ln \binom{n_i}{y_i} + y_i\ ln\ p_i + (n_i - y_i)\ ln\ (1-p_i)] \\ &= \sum_{i=1}^{n} [ln \binom{n_i}{y_i} + y_i\ ln\ (\frac{p_i}{1-p_i}) + n_i\ ln\ (1-p_i)] \\ &= \sum_{i=1}^{n} [ln \binom{n_i}{y_i} + y_i\ n_i - n_i\ ln\ (1+e^{z_i})] \end{aligned}$$

Where $z_i = \sum_{j=0}^{k} \beta_j\ x_{ji}$. The derivative of the log-likelihood function with respect to the $k+1$ unknown β parameters is

$$\frac{\partial lnL}{\partial \beta_j} = \sum_{i=1}^{n} y_i\ x_{ji} - \sum_{i=1}^{n} n_i\ x_{ji} \frac{e^{z_i}}{1+e^{z_i}}, \quad j = 0, 1, ..., k \qquad (3.5)$$

3.2.3 Goodness of fit of a linear logistic model

This is an attempt to check the extent to which the fitted values of the response variable under the model compare with the observed values.

Assessing the goodness of fit is done by comparing the current model of interest (whose maximum likelihood shall be denoted by L_c) with an alternative baseline model termed as the Full or Saturated model (whose maximum likelihood is denoted by L_f). The full model is not useful in its own rights, since it does not provide a simpler summary of the data than the individual observations themselves. However, by comparing L_c) With L_f, the extent to which the current model adequately represents the data can be judged.

A comparison between L_c and L_f can be made on the basis of the deviance statistic which is given by

$$D = -2\ ln\ \frac{L_c}{L_f} = -2\ [ln\ L_c - ln\ L_f] \qquad (3.6)$$

This statistic measures the extent to which the current model deviates from the full model. Large values of D are encountered when L_c is similar to L_f , indicating that the current model is a good one.

In modeling n binomial observations, where p_i is the true success probability corresponding to the i^{th} observation , $\frac{y_i}{n_i}$, $i = 1, ..., n$ the likelihood function is

$$L = \prod_{i=1}^{n} \binom{n_i}{y_i} p_i^{y_i} (1 - p_i)^{n_i - y_i} \tag{3.7}$$

On fitting a linear logistic model with $(k+1)$ unknown parameters $\beta_0, \beta_1, ..., \beta_k$, fitted values $\hat{p}_i$ are obtained, where

$$logit\ \hat{p}_i = \beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + ... + \beta_k x_{ki} \tag{3.8}$$

From equation (3.2), the maximum log-likelihood function under this model is given by

$$ln\ \hat{L}_c = \sum_{i=1}^{n} [ln\binom{n_i}{y_i} + y_i\ ln\hat{p}_i + (n_i - y_i)\ ln(1 - \hat{p}_i)] \tag{3.9}$$

Under the fitted model, the fitted probabilities will be the same as the observed proportion $p_i^* = \frac{y_i}{n_i}$, $i = 1, ..., n$ and so the maximum log-likelihood function for the full model is given by

$$\begin{aligned} \ln\ L_f &= n \sum_{i=1}^{n} \left[ln \binom{n_i}{y_i} + y_i \ \ln p_i^* + (n_i - y_i) \ \ln(1 - p_i^*) \right] \\ D &= -2 \left[\ln\ \hat{L}_c - \ln\ \hat{L}_f \right] \\ &= -2 \sum_{i=1}^{n} \left[\ln\ \frac{p_i^*}{\hat{p}_i} + (n_i - y_i)\ \ln\ \left(\frac{1 - p_i^*)}{1 - \hat{p}_i} \right) \right] \end{aligned}$$

3.3 Model adaptation

Applying the model to the study we start by using equation (3.1);

$$p_i = \frac{e^{z_i}}{1 + e^{z_i}} \tag{3.10}$$

p_i Is probability of the household with i^{th} attributes likely to adopt technology.

$E\ (y_i) + p_i = 1$ Given

$y_i = 1$ if the individual household adopts the on-farm technology and

$y_i = 0$ if the individual household, does not adopt the on-farm technology.

And therefore, for an individual farmer;

$$n_i = \ ln\ (\frac{p_i}{1 - p_i}) = \beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + ... + \beta_{11} x_{11i} \tag{3.11}$$

$x_i,\ i = 1, 2, ..., 11$ That represents a vector of characteristics or attributes associated with the individual. The regression model is linearized as follows

$$ln\ (\frac{p_i}{1 - p_i}) = \beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + ... + \beta_{11} x_{11i} \tag{3.12}$$

The dependent variable is the natural log of the probability of adopting p divided by the probability of not adopting it $1 - p$. β_0 is the intercept term, and $\beta_1 x_{1i} + \beta_2 x_{2i} + ... + \beta_1$ are the coefficients associated with each explanatory variable $x_1, x_2, ..., x_1 1$.

This model adaptation of the logistic regression is based on the hypothesis that a farmer's decision to adopt or reject new technology at any time is influenced by the combined effect of hypothesized farmer, farm-level and service characteristic factors.The main assumptions of this model are:

(1) The farmer is faced with a choice etween two alternatives. That is adopt or not adopt new on-farm technologies.

(2) The choice the farmer makes will depend on his or her attributes or characteristics.

(3) The farmer is considered to either have adopted or not adopted.

(4) No consideration is given to the length of time the farmer has used the technologies since if the farmer is not entirely aware about the technologies, then it cannot be assumed that he/she has used the technologies.

These factors are:

Gender of the household head(HH2type) which is **1** if a male and **0** if a female. Gender is introduced in the model to capture gender influence on adoption of technology.

Age of the farmer(Agehh). It is hypothesized that age is positively related to the decision to adopt a technology. Older farmers are likely to have more experience in the use of technology. It is categorized into five levels.

The house the farmer lives in(Mhsetyp). It is characterized into two levels and it portrays the farmer's capability to finance the use of technology in terms of capital requirement

Occupation of the household head(Ocupation). It is in two levels. It is hypothesized that farmers who are self employed and are doing business will have a high level of adoption. This is because they have the technical knowledge and even capital to facilitate use of these technologies. Again, it is hypothesized that farmers who are not full time farmers may be negatively related to technology adoption as the land user may not have time to spend on the gardening activity.

Education level of the farmer(Leveedu). It represents the number of years of education attained by the household head. It is hypothesized that with more years of formal education, the household head being the main decision maker, is more likely to adopt the use of on-farm technology. Educated farmers may have a better understanding of theenvironmental benefits and other merits of using on-farm technologies. It is in two levels.

labour used in the farm(Labfar). It is in three levels. It is assumed that the bigger the size of active full-time working persons in the household, the easier it is for the various activities needed in the farm. This implies therefore, that this household will least likely adopt new technology.

Food situation(Foodsit), which is either sufficient or deficient. It is hypothesized that the food situation in a household will positively influence the decision to adopt on-farm technology.

Farmer's access to credit facilities(Credfac). It is positively related to adoption of technology because again, the capacity of the farmer to finance his or her operational costs will be important in determining rate of adoption.

Group membership(Groupmem) which tell us whether the farmer is a member of any group. It is categorized in to two and it is hypothesized that group membership is negatively related to adoption of on-farm technology.

Size of the farm the farmer lives in(Sizefarm) which is in two levels where some farmers have more then six acres and others have less than six acres. It is hypothesized that farmers who have more pieces of land are likely to adapt more than those who have less.

Location(Location). There are three locations and it is hypothesized that the level of adoption is the same in Ganda, Goshi and Jilore locations.

On this basis, the model estimated in this study is:

$$\begin{aligned} \boldsymbol{Ey_i} &= \beta_0 + \beta_1 \; \boldsymbol{HH2type} + \beta_2 \; \boldsymbol{Agehh} + \beta_3 \; \boldsymbol{Mhsetyp} \\ &+ \beta_4 \; \boldsymbol{Ocupation} + \beta_5 \; \boldsymbol{Leveedu} + \beta_6 \; \boldsymbol{Labfar} + \beta_7 \; \boldsymbol{Foodsit} \\ &+ \beta_8 \; \boldsymbol{Credfac} + \beta_9 \; \boldsymbol{Groupmem} + \beta_1 0 \; \boldsymbol{Sizefarm} + \beta_{11} \; \boldsymbol{Location} \end{aligned}$$

3.4 Hypothesis testing

Tests for significance of coefficients of predictor variables in the fitted model is based on the deviance statistic, which is the square of the t-statistic and is distributed as the chi-square. The deviance statistic is used to assess the goodness of the fit or appropriateness of regression models fitted by the method of maximum likelihood. It is good to note that the greater the deviance, the worse the fit of the model.

The significance of the variables $\boldsymbol{x_1, x_2, ..., x_{11}}$, in explaining the outcome variable is based on the hypotheses below.

Null hypothesis,

$\boldsymbol{H_0 : \beta_1 = \beta_2 = \beta_{11}}$

Meaning that the model explains the choice of adoption of on-farm technologies more without a set of predictor variables.

Alternative hypothesis

$\boldsymbol{H_0}$: Not all the other $\boldsymbol{\beta_j's}$ is zero in $\boldsymbol{H_0}$ given $\boldsymbol{j = 1, 2, ..., 11}$. This is based on equation (3.1).

Chapter 4

RESULTS AND DISCUSSION

This is the frequencies, figures, cross-tabulattions and logistic regression analysis used in analysing adoption of on-farm technologies.

4.1 Descriptives

a) *Agroforestry technologies and their percentage distribution*

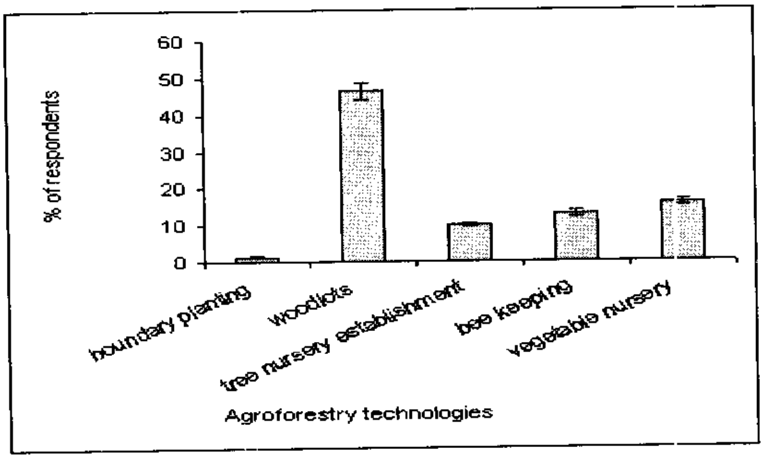

Figure 1: Showing level of adoption according to technology

The most popular type of on-farm technology from the above results is woodlots 46.4% and vegetable nurseries 15.9% while the least popular is boundary planting 1.4% .

(b)*Percentages of the respondents*

Majority of the respondents are in Goshi 40.6% location, Jilore 33.3% location and 26 % in Ganda location.

(c) *Gender of the household head*

Most of the adopters households are headed by men in the three locations, 100% for Goshi and Jilore and 91.7% for Ganda. Only 8.3% of the households in Ganda are headed by women.

(d)*Age of the household head*

Majority of the adopters (66.7%) are aged between 31-50-years in the three locations. The least number of adopters is in the age bracket of 61 years and above.

Table 4.1: Adoption level (%) according to age class

Age	% of adoption
20-30	14.3
31-40	38.1
41-50	28.6
51-60	9.5
61+	9.5

(e)*House type the farmer lives in*

Most of the adopters in Ganda (75%), Goshi (66.7%) and Jirole (80%) live in grass-thatched semi-permanent houses while, 25 %, 33.3% and 20% respectively live in permanent iron-roofed houses.

(f)*Occupation of the household head*

Majority of the adopters here are part-time farmers, 58.2% in Ganda, 100% in Goshi and 66.7% in Jirole location. The rest are full time farmers.

(g)*Education level of household head*

A big percentage of the adopters had gone to school up to primary level while only a few of them had post-primary education. The table below shows this.

Table 4.2: Percentage of adoption by education level

	Education level	
Location	Primary	Post-primary
Ganda	100	-
Goshi	83.3	16.7
Jirole	50	50

(h)*Labour used in the farm*

Most of the adapters use own labour, 50% in Ganda and Goshi, and 20% in Jirole location.Hired labour is common in Goshi (50%) and Jirole (60%). Both own and hired labour is practiced in Ganda (41.7%) and in Jirole (20%).

(i)*Food situation*

Majority of the adapters in Ganda (100%) and Jirole (60%) locations lack sufficient food for their families' consumptions. All farmers in Goshi and 40% in Jirole have enough food for consumption.

(j)*Access to credit facilities*

All adopters in Jirole and 58.3% in Ganda have no access to credit facilities while 100%

in Goshi and 41.7% in Ganda have access to the same.

(k) *Group membership*

Majority of the adapters from the table below are strong active members to various local community groups while a small number of the adapters did not associate themselves with any group.

Table 4.3: percentages of adoption by group membership

	Group membership	
Location	None-no membership	Strong-active membership
Ganda	25	75
Goshi	-	100
Jirole	20	80

(l) *The size of the farm*

Most of the adopters have less than six acres of land, 75% in Ganda, and 80% in Jirole while the rest have more than six acres.

(m) *Time farmer started to use agro forestry technology*

Most of the adopters started using on-farm technologies from the year 2002, 58.3% in Ganda and 100% in Goshi while the others started using before the year 20002.

(n) *Benefits of agroforestry technologies*

The most important benefit of the agroforestry technologies according to the adapters is income generation (26.1%). The other benefits are

(i)Source of knowledge (7.2%).

(ii)Source of timber (5.8%).

(iii)Source of fuel wood (4.3%).

(iv)Source of fodder (1.4%).

(v)Boundary marking (1.4%).

(vi)Honey for home consumption (1.4%).

(vii)Increase in food crops for home consumption (1.4%).

(viii)Windbreaks (1.4%).

(o)*Problems that hinder practice of agro forestry technologies*

The most serious problem in the three locations is lack of market of the farm produce (15.9%). The other problems are drought (11.6%), diseases/pests (11.6%), takes a lot of space that could be used for crops competition with crops (4.3%), destruction by livestock (2.9%), lack of capital (2.9%), lack of knowledge (2.9%), no follow-up by the project (2.9%), and lack of machinery (tractor/ bicycle) (1.4%).

4.1.1 Cross tabulations

The results for descriptive analysis (Table 4.4) show that there is an association (from the P-value of the chi-square test) between some of the household characteristics namely labour used in the farm, occupation of the household head, group membership and location; and adoption of on-farm technologies, whereas there is no association between age of household head, head of household, food situation, house type that the farmer lives in, credit facilities, size of the farm, education level of the household head and adoption of on-farm technology at 10% level of significance. These results are shown in Table 4.4.

A χ^2 association of labour and the head of the household shows that there is a very strong association ($\boldsymbol{P = 0.000}$) between the two and adoption of on-farm technologies. Own labour comes from both men and women with men cotributing 67.7% and women 83.3%. This agrees with the work of Njuki et al (2004) who used a multiple linear regression to study male versus female labour in an agro forestry system in the central highlands of Kenya. He concluded that female labour was significantly higher than male labour in all crops. Women contribute 67% of the labour used in cash crops, which composed 78% of the total female labour on crops.

Again there is a very high association ($P = 0.001$) between type of agroforestry technologies and benefits of these technologies. The technologies with high benefits are woodlots and vegetable nursery and these benefits are income generation and source of knowledge while associating types of agroforestry with problems that hinders agroforestry, we find that ther is a very high association ($P = 0.002$) between the two and adoption of on-farm technologies. Woodlots contributes a lot of income but again competes for soil nutrients with crops and uses a lot of space while, vegetable nursery gives income but lacks market and is attacked by diseases/pests.

4.1.2 Logistic regression

The adapted model estimated for adoption of technology (Table 4.5.) explains 89.3% of the total variation in the sample. The model predicted at least 88.2% of the cases correctly for adopters as adopters, and 89.3% non-adopters as non-adopters. Group membership, location and food situation significantly influence adoption of on-farm technologies at 5% and 10% probability level of significance. While on the other hand, age of household head, head of household, labour used in the farm, occupation of the household head, house type that the farmer lives in, credit facilities, size of the farm, education level of the household head do not significantly influence adoption of on-farm technologies at 5% and 10% probability level of significance.

On assessing the likelihood of adopting from the model using the odds ratio, the odds of adoption on-farm technology indicate that farmers who are aged 41-50 years are 8 times more likely to adopt on- farm technologies as compared to those who are 61 or more years old while those who are aged between 51-60 years are 90 times more likely to adopt compared to those who are 61 or more years old. On the other hand, those who use own labour have a 34% higher chance of adopting on-farm technologies compared to those who use both hired and own labour. Household heads who have primary school education have 3% higher chance of adopting on-farm technologies relative to those who went beyond primary school.

Those farmers who have access to credit facilities have 11% higher chances of adopting on-farm technology than those who are not getting the credit facilities. Those farmers who live in grass-thatched semi-permanent houses have 9% higher chance of adopting as compared to those who live in iron-roofed permanent houses. The farmers who are none-no group members are 154 times more likely to adopt on-farm technologies as compared to those who are strong-active group members, while those who have farm sizes less than six acres are 28 times more likely to adopt compared to those who have more than six acres of land. Finally, adapters in Goshi location are 3 times more likely to adopt on-farm technologies compared to those who live in Jirole location. However, the level of adoption is higher in Ganda location again, compared to the level of adoption in Jirole location. These results are clearly shown by table 4.5.

4.2 Discussion

The log-likelihood ratio statistic is used to test whether slope coefficients are equal to zero, that is, whether x is irrelevant in the determination of $E(y_i)$. The statistic in this study is 26.015 with 16 degrees of freedom indicating that the amount of variation explained in the model is different from zero. Nagelkerke R squared and the percentages of correctly classified responses based on the model are goodness-of-fit measures. The R squared in this model is 0.755, meaning that the model explains 76% of the variability in adoption of on-farm technologies. Secondly, the model correctly classified 56 of the 69 responses yielding a correct classification rate of 89.3%.

Influence of the explanatory variables on adoption indicates that group membership(none-no membership), food situation and location(Ganda) significantly influence adoption of on-farm technologies while, age of household head, type of house the farmer lives, access to credit, size of farm, education of household head, labour used in the farm, occupation of the household head, and the the head of the household do not significantly influence adoption of on-farm technologies.

The results agrees with Ramji et al (2002) who used a logistic regression analysis to model adoption of agro forestry in the hills of Nepal and the results showed that male membership in local NGO's, female education level, livestock population, and farmers positive perception towards agro forestry have significant positive effects on adoption of agro forestry. On the other hand, the results differs from the findings of Akinwumi and Jonas (2002) who used econometric logit models to come up with the determinants of farmers' adoption and adoption of alley farming technology in Nigeria. The results showed that farmer characteristics that influenced adoption included the gender of the farmer, contact with extension agents, years of experience with agro forestry and tenancy status in the village. Human capital variables were significant in explaining farmers' decisions to adopt and modify the technology.

The likely explanation for farmers who are strong- active members in the local community groups having a higher probability of adopting on-farm technologies is that they will be able to exchange ideas and labour force. We noted earlier that majority of the adopters use own labour. This may be positively related to exchange of labour among the local group members. This reduces the cost of farming and encourages farmers to use on-farm technologies. Again, the exchange of labour translates into farmers influence in the use of on-farm technologies. Associating group membership to food situation, it comes out clearly that, households that are strong active group members have sufficient food supply while most of the members who do not belong to the local groups suffer from food deficiency. It is noted that households in Goshi location have a 100% strong active group membership and a 100% sufficient food supply. It again shows clearly that group membership means availability of labour, exchange of on-farm technologies, influence in use of technologies and hence sufficient food supplies. It transcends very well in the three locations. When farmers' occupation is only in his or her own farm, means that he or she will have enough time to take care of on-farm technologies. This is because the farmer expects to get enough resources from the farm. These resources are in terms of food, firewood, fodder for the animals, manure, milk other farm produces for his subsistence needs and for commercial purposes.

Access to credit facilities helps the farmer to buy farm inputs like seeds, seedlings, bicycles and pays for labour when neccessary. Grass thatched semi-permanent roofed houses depicts the economic status of the farmers and it shows that majority of them are poor. They are using the new on-farm technologies because they want to improve their economic status. Majority of them have got no other occupation and thus spend most of their time in the farms. They have small pieces of lands whose soil fertilities must be improved through use of new on-farm technologies to enhance their produce. These farmers are primary school graduates and thus their only way of improving their economic status is by improving their farming systems. They rely on the credit facilities and hence these services should be enhanced for their sake. It comes out clearly that majority of these farmers are old(41-60 years) and are aware of the benefits of the new on-farm technologies.

However, some of the results were highly inflated like age at 51-60 years level, group membership and size of the farm indicating that further analysis needs to be done on the residuals.

Table 4.4: Descriptive statistics results of adopters and non-adopters

Characteristic/factors	Adopters (N=23)	Non-adopters (N=46)	χ^2
Age of household head			0.848
20-30 years	14.3%	10.9%	
31-40 years	38.1%	30.4%	
41-50 years	28.6%	26.1%	
51-60 years	9.5%	17.4%	
61+ years	9.5%	15.2%	
Head of the household			0.249
Male-headed	95.7%	87.0%	
Female-headed	4.3%	13.0%	
Food situation			0.162
Deficient	68.2%	52.2%	
Sufficient	31.8%	47.8%	
Labour used in the farm			0.005
Own labour	43.5%	82.2%	
Hired labour	30.4%	8.9%	
Both hired and own	26.1%	8.9%	
Occupation of the household head			0.052
Full-time farmer	28.6%	53.3%	
Part time farmer	71.4%	46.7%	
House type that the farmer lives in			0.453
Grass-thatched semi-permanent	73.9%	78.3%	
Permanent iron roofed	26.1%	21.7%	
Group membership			0.001
Nono-no membership	17.4%	57.8%	
Strong-active membership	82.6%	42.2%	
Credit facilities			0.584
Available	47.4%	46.5%	
Not available	52.6%	53.5%	
The size of the farm			0.130
Less than six acres	56.5%	73.3%	
More than six acres	43.5%	26.7%	
Education level of household head			0.153
Primary	86.4%	71.7%	
Post primary	3.6%	28.3%	
Location			0.002
Ganda	52.2%	13.0%	
Goshi	26.1%	47.8%	
Jirole	21.7%	39.1%	

Table 4.5: Logit regression results of farmer, farm-level and service characteristics influencing adoption of on-farm technology.

Characteristics	Sig.	Exp (B)	90.0%C.I.forEXP(B)	
			Lower	Upper
Age of household head	.515			
20-30 years (1)	.628	.024	.000	7849.232
31-40 years (2)	.314	.094	.002	4.463
41-50 years (3)	.413	7.985	.123	520.211
51-60 years (4)	.258	90.366	.129	63126.584
61+ years (REF)	-	-	-	-
Head of the household				
Male-headed (1)	.692	.049	.000	13629.975
Female-headed (ref)		-	-	-
Food situation				
Deficient (1)	.107	.009	.000	1.095
Sufficient (ref)	-	-	-	-
Labour used in the farm	.149			
Own labour(1)	.893	.760	.026	21.879
Hired labour(2)	.138	.000	.000	2.436
Both hired and own (ref)	-	-	-	-
Occupation of the household head				
Full-time farmer(1)	.988	1.026	.064	16.463
Part time farmer(ref)	-	-	-	-
Type of house the farmer lives in				
Grass-thatched semi-permanent	.221	.099	.004	2.209
Permanent iron-roofed	-	-	-	-
Group membership				
None-no membership (1)	.020	154.082	4.419	5372.544
Strong-active membership (ref)	-	-	-	-
Access to credit facilities				
Available (1)	.271	.110	.004	2.966
Not available (ref)	-	-	-	-
The size of the farm				
Less than six acres (1)	.193	28.165	.413	1921.084
More than six acres (ref)	-	-	-	-
Education level of the household head				
Primary (1)	.166	.032	.001	1.896
Post-primary (ref)	-	-	-	-
Location	.158			
Ganda (1)	.081	.006	.000	.739
Goshi (2)	.624	3.287	.061	177.715
Jirole (REF)	-	-	-	-

Chapter 5

CONCLUSION AND RECCOMENDATIONS

5.1 Conclusion

Out of the 69 households surveyed, 33.3% were classified as adapters, while 66.7% were non-adapters. The factors found to significantly influence adoption in this study are , group membership, food situation, and the location significantly influence adoption of on-farm technologies while age of household head, labour used in the farm, occupation of the household head,the size of the farm,education level of the household head, access to credit facilities, the type of house the farmer lives in, and the head of the household were found not to significantly influence adoption of on-farm technologies. The study found that farmers' problems in the three locations are lack of market of the farm produce, drought, diseases/pests, agro forestry technologies takes a lot of space that could be used for other crops, pose competition with other crops, destruction by livestock, lack of capital, lack of knowledge, lack of machinery (tractor/ bicycle), and no follow-up by the project.

5.2 Limitations of the study

(1) The design of the questionnaire was not in line with what it was supposed to measure.

(2) Some of the results were highly inflated and thus requires further analysis on the residuals.

(3) Sample size was not sufficient in most of the categorical variable lendering the power of the test ineffective in declaying the significance differences like in the case of age of the household, group membership and size of the farm.

5.3 Areas of further research

(1) Further modeling can be done on errors of the measurement variables.

(2) The same study can be done with a multinomial logistic analysis to capture adoption.

5.4 Reccomendations

(1) Adoption of the new on-farm technologies could be enhanced through targeting farmers who do not have enough food supply and are not members of the local community groups. The highest proportion of these groups are found in Ganda location.

(2) Farmers should be educated by the agricultural extension officers and foresters, on the importance of the local community groupings.

(3) There is need to research on other technologies that can benefit farmers more and have less or no problems.

(4) Farmers should be educated on the type of trees to plant together with other crops and will not cause drought, disease/pests, will not use a lot of space and will add nutrients to the soil.

(5) The researchers should visit the farmers frequently, provide them with the best tree seedlings and show them how to plant, how to take care of the trees and even look for sponsors to issue farmers with capital, farm equipment and machinery.

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Appendix

Map of Kilifi

KILIFI DISTRICT ADMINISTRATIVE BOUNDARIES