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Farm Plot Level Determinants of the Number of Sustainable Agricultural Intensification Practices Adopted in a Maize-Legume Cropping System in Kenya.

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Abstract.

Using data from 513 households, we apply an ordered probit to model importance of social-economic, household and plot characteristics in determining the number of sustainable agricultural intensification (SAI) practices adopted by smallholder farmers in Kenya. We find that the number of technology adopted depends on a range of socio-economic, household and plot characteristics including: labour use intensity, family income, plot tenure, land size and contact frequency with extension service providers significantly determine adoption. These results can help in packaging SAI practices for enhanced uptake by smallholder farmers especially in the presence of declining soil fertility and high commercial input costs.

Keywords: Adoption, Sustainable agricultural intensification practices, Smallholders, Farm plots, Kenya

JEL codes: O13, Q12, Q15, Q16

1. Introduction

African smallholder farmers still face several challenges including, access to information and uptake of new technologies through effective dissemination pathways that are crucial in optimizing the adoption process especially of 'knowledge- based' innovations (Padel 2001). However, limited effort has been given to the factors that impede or aid in the adoption of Sustainable Agricultural Intensification (SAI) practices as a package, hence the need to explore factors that facilitate or impede farmers' adoption behavior. Naturally, farmers are rational and would always want to earn as much as possible from their farms. If adopting a given number of technologies would provide an assurance of maximizing their output, they would definitely go for that. For this to be realized, There is need to control for technology interdependence and simultaneous adoption in complex farming systems to avoid underestimating or overestimating the influence of various factors on the technology choices (Wu and Babcock, 1998).

With the low adoption rate of SAI practices still experienced in developing countries Kenya being not an exception, substantial efforts have been put by national and international organizations to encourage farmers to invest in them (Kassie et al., 2009; Wollni et al., 2010). A study by Hailemariam *et al* ., (2012) on adoption of multiple sustainable agricultural practices in rural Ethiopia showed that the probability and extent of adoption of SAPs are influenced by several factors: a household's trust in government support, credit constraints, spouse education, rainfall and plot-level disturbances, household wealth, social capital and networks, labor availability, plot and market access.

Earlier researchers including (Tey and Brindal 2012: Kassie et al., 2009) have shown that, common factors that influence the adoption of SAI practices can be categorized as: socio-economic factors, institutional factors, informational factors, agro-ecological factors, psychological factors, and the perceived attributes of SAI practices. Knowledge of farmers' preferences for uptake of various SAI technologies is vital in evaluating the effectiveness in the adoption pathways. Though some researchers believe that this body of research may have reached its edge in contributing to a refined understanding, particularly in respect to the voluntary uptake of SAPs (Knowler and Bradshaw 2007), common managerial factors include those related to human capital: gender, age, education levels, ethnicity, and experience are also important.

While trying to make decision concerning the number of technologies to use on their plots small scale farmers are faced with a myriad of challenges. This therefor calls for a need to redesign favorable policies that could motivate adoption of these SAI practices and in the long run increase agricultural productivity. This chapter determines a better understanding of the relative importance of social-economic, household and plot characteristics including (farmers' education level, age, gender, farmers' main occupation, membership to groups, frequency to extension services, sub plot tenure and area, Soil fertility and farmers' income) in shaping the probability and the number of SAI practices adopted.

2. Model specification and empirical analysis

Several adoption studies in the past have widely used dichotomous choice data models such as Logit and probit in trying to determine probability of adoption and its determinants such as socioeconomic, household and plot characteristics (Kim *et al*., 2005: Isgin *et al*., 2008 and Sharma *et al*., 2009). This is due to the fact that they allow for a more detailed analysis of farmers' adoption decisions on a single technology (Burton et al. 1999) and Zhou et al. (2008). Currently there is need for adoption of SAI technologies as a package hence the need of analyzing using count data model. This methodology is useful in cases where farmers have a variety of interrelated technologies to choose from. An ordered probit model was then used to estimate the factors that determine the use of one or more practices. Given the assertion that over time there are more than just two identified groups (adopters and non-adopters), it is possible to have a more refined distinction of adopters. Based on the number of SAI technologies that a farmer uses on each plot, we have farmers using one, two or more technologies. Since there are multiple choices and particular interest lies in the individual effects of explanatory variables on each outcome. The ordered probit model recognizes unequal differences between ordinal categories in the dependent variables. That is given a unit change in explanatory variable the model captures the qualitative differences between different categories of number of SAI used, hence accounting for the categorical nature of dependent variables as well as its ordinal nature. Having the measure of technology adopted as number across plots, we treat the number of SAPs adopted by farmers as an ordinal variable and use it as dependent variable measuring determinants of adoption (Wollni *et al.,* 2010). The model is then specified as;

$$Y^* = \beta' X + \varepsilon \tag{1}$$

where Y* is the dependent variable (number of technologies) taking the values (1, 2, 3, 4 and 5), β' is a vector of parameters to be estimated, X is a vector of explanatory variables, and ε is the error term which is assumed to be normally distributed with zero mean and unit variance. The number (Y) of observed technologies used are related to the underlying latent variable Y* through threshold μ_n where n = 1… 5. The probability that any given technology Y is used is given by:

$$prob(Y=n)=\varphi(\mu_n-\beta' X)-(\mu_{n-1}\beta' X). \quad \forall n=1,.......,5$$

(2)

The ordered probit estimation will give the thresholds with μ and parameters β. The threshold μ show the range of normal distribution associated with the specific values of the response variables. The remaining parameters, β, represent the effect of changes in explanatory variables on the underlying scale. A measure of goodness of fit is obtained by:

$$\rho^2 = 1\left[\ln L_h / \ln L_0\right] \tag{3}$$

Where $\ln L_h$ is the log likelihood and $\ln L_0$ is log likelihood computed at zero. Although ρ^2 cannot equal to one, a value close to one shows a very good fit. The study hypothesize that the use of one or more SAI technology in a specific plot is influenced by a number of socioeconomic and plot characteristics, used in this study as the explanatory variables.

3. Study Area and Data.

The data used in this study was obtained from a farm household survey in Kenya carried between October–November 2013. The sample size was determined using the proportionate to size sampling approach which generated a sample of five hundred and thirty six households. Data was collected in western and eastern regions of Kenya. Five counties were purposively selected, based on agro ecological zones (high altitude-eastern and lower altitude-western). This was based on their maize-legume production potential. A multi stage sampling was then employed to select lower levels sampling clusters: divisions, locations, sub-locations and villages.

Using a structured questionnaire, the responds households were interviewed by researchers from Adoption Pathways Project and CIMMYT. Several household, social economic, plot and village characteristics variables were considered This include input and output market access, household composition, the age, gender and education level attained by a household head, asset ownership, various sources of income, participation in credit markets, membership of formal and informal organizations, labour use, participation and frequency of contact with extension personnel, cropping pattern, crop production, plot slop, land tenure, soil fertility, land size, access to credit and sub plot distance from home.

4. Results and discussions

4.1. Descriptive results

Table 1 shows description of variables that were used with choice of explanatory variables based on literature review findings. A description of these variables is discussed, with specific mean and standard deviation.

Gender (gender of household head) is used as a dummy variable with 1 to represent male and 0 to represent female. It has been argued that women have less access to critical farm resources (land, labor, and cash) and are generally discriminated against in terms of access to external inputs and information. It is postulated that male farmers are more likely to adopt new technologies because they are more endowed with resources compared to their female counterparts.

Aghh (age of household head) is used as continuous variable with the assumption that older farmers are likely to adopt new technology due to their experience or reject all together while younger farmers may be less risk averse. Age means more exposure to production technologies and greater accumulation of physical and social capital. However, age can also be associated with loss of energy as well as being more risk averse. Hence it is expected that age may positively or negatively affect adoption of SAI technologies.

Educlevel (educational Level) is a continuous variable measured in terms of number of years a farmer was in school. Households with more education may have greater access to non-farm income and thus be more able to purchase inputs. Educated farmers may also be more aware of the benefits of modern technologies and may have a greater ability to learn new information hence easily adopt new technologies. Likewise educated households may be less likely to invest in labor-intensive technologies and practices, since they may be able to earn higher returns from their other sources of income. It is expected that education would increase the chances of a farmer accessing information and also enhancing the farmer’s chance to adopt SAI technologies.

The variabl*e HHsize* (number of persons in a household) is a continuous variable measured in terms of number of persons living together. Family size may be associated with labour. So that large families may have adequate labour that would enhance adoption of SAI technologies. Larger household could also translate to more income if members of that spesific households are engauged in activities that could earn them more income to enable them adopt SAI technologies.

The variable *Farmsize* **(**farm size in acres) is a continuous variable measured in acres. Land is an indicator of wealth, thus it is hypothesized that increase in size would positively influence adoption. In addition it is expected that the small pieces of land would promote farmers to practice mixed farming in order to meet their household food demand. Farm size is therefor expected to positively or negatively influence adoption of SAI technologies.

TAssetvalue (total value of assets) is a continuous variable measured in terms of Kenya Shillings (KES). It is expected that farmers with high asset value are likely to adopt a multiple of SAI technologies since they are more endowed.Farmers with higher asset value can easily meet their production cost hence adopt more SAI technologies.

Frequentcontact (frequency of contact with extension personnel) is a continuous variable measured in terms of number of contacts in days/year that a farmer has with the service providers such as ministry of Agriculture personnel. Agricultural extension agents are mandated to deliver and implement agricultural-related services and goods to farmers. Agricultural inputs and supply of credit are delivered to rural farmers through government's local extension argent. This affects the return from technology adoption and affects adoption of technologies Farmers who have more contacts with extension agents tend to get more information and are likely to adopt more of SAI technologies.

The variable *Crdacc* (if farmer needed credit) is measured as a dummy. In this study it is expected that those smallholder farmers who do not need credit would be in a better position to take up new technology because they have ready money that they can use to purchase farm inputs and other services when need arises. Hence, this will increase their chances of adopting SAI technologies in maize legume farming.

Grpmbr (membership to an organization) is a variable measured as a dummy. Group membership is a form of social network expected to affect technology adoption. Farmers involved in informal and or formal organizations would be in a better position, compared to other farmer's in terms of access to information and possibly market access. With inadequate information sources and imperfect markets and transactions costs, social networks are expected to facilitate the exchange of information, this increases farmers' bargaining power, helping farmers earn higher returns when marketing their products. Thus it is hypothesized that membership to an organization would positively influence uptake of SAI technologies.

The variable *Occupation* **(**main occupation of household head) is a categorical variable showing various activities that farmers are involved in to earn their livelihood. Main occupation of the household head is likely to influence the level of income thereby positively or negatively influencing the number of technologies that a famer can adopt. This is likely to enhance the incomes of the farmers. This may enable the farmers to purchase inputs. As a result occupation is expected to positively or negatively influence use of SAI practices.

Distmkt (distance to the market) is a continuous variable measured in terms of walking distance to the market in minutes. The distance to markets can influence farmers' decision making in various ways. Better access to the market can influence the use of output and input markets, and the availability of information. It is expected that farmers living near the market would easily access market for their farm produce hence readily practice maize-legume farming. Therefor distance to the market would positively or negatively influence uptake of SAI technologies.

The variable *Plottenure* (tenure of farmer's plot) is a categorical variable showing if the plot is owned by a farmer, if it's borrowed or rented. Security of land proprietorship has a substantial effect on the agricultural performance of farmers. Better tenure security raises the likelihood that farmers will capture the proceeds from their investments. Since land is a scarce resource is assumed that farmers who don't own land have to spend extra cash to rent land, hence reducing their income and in the long run are unable to adopt a multiple of SAI technologies.

Soilfertility (how fertile the plot is) is used as a categorical variable showing how fertile the plot is. For instant farmers whose plots are very fertile are likely to use less of inorganic fertilizer and animal manure compared to plots with good soil fertility. Soil fertility can positively or negatively influnce uptake of SAI practices.

4.2. Econometric Results

Table 2 presents coefficient estimates and marginal effects of the ordered probit model, for the various factors influencing farmers' preferences for the number Sustainable Agricultural Intensification (SAI) practices used. The estimated thresholds or cut-off points (μ) indicates the range of normal distribution associated with the specific values of the response variable and satisfy the conditions $\mu_1 < \mu_2 < \mu_3$ implying that the categories are ordered (Knight et al.

2005).The first cut-off point (Y =1 for ‘use of one technology’) was used as reference for comparison purposes.

For the decisions concerning adoption of SAI practices the pooled results showed land size had a negative influence on the number of SAI technologies that a farmers uses. Though farmers’ age and sex did not significantly influence the number of SAI practices adopted, they had a positive impact on adoption decision. In this study farmers education level has a significant and positive effect on the level of SAI use. Primary occupation has a significant and negative impact on the number of SAI used

Though sex of plot decision maker, sub plot distance and soil fertility had a positive impact on the number of SAI technologies used, this was not significant. The number of contact with extension personnel had a positive and significant influence to the number of SAI technologies used. Likewise group membership and access to credit did not significantly influence the number of SAI technologies adopted

Farmers’ level of income positively influence the number of SAI technologies that were adopted by the farmers. Income also plays a significant role in uptake of these technologies since most small-scale farmers are poor and so they find the cost of some of these technologies such as use of fertilizer and improved seed to be costly. Similarly sub plot tenure had no significant impact on the number of technologies that farmers use

Marginal effects were also estimated in order to understand the link between the dependent and independent variables, since the interpretation of coefficients in ordered probit alone are not very informative. Hence, the marginal effects (partial derivatives) which denote the probabilities of the number of SAI practices that farmers’ adopt ranked from one to six. This would therefor show the impact of a change in an explanatory variable on the predicted probabilities.

Though the impact of the variable *Gender* (gender of household head) on the number of technologies adopted was not significant it had a positive marginal effect in the adoption of more than three technologies. Male Headed Households (MHHs) use more than three technologies on their plots implying that male farmers are economically stable in terms of resources compared to their female counterparts. The result also agrees well with findings by World Bank, (2007) which revealed that women’s have a lower average earnings compared to men, less access to remunerative jobs, and productive resources such as land and capital, contribute to the economic vulnerability of Female-Headed Households (FHHs).

Credit availability has a positive impact on use of less than three SAI technologies while it reduces the probability of using four, five and six technologies on a given plot by a margin of 2.7%, 6% and 1% respectively. This confirms the fact that adoption of some of the SAI technologies such as minimum tillage has very high initial costs, yet access to credit is a major challenge to most small scale farmers. This is in line with other studies which revealed that credit constraints was found to affect adoption, particularly when initial investment costs are high (e.g. purchase of cover crop seeds, herbicides, sprayers), given the evidence that the benefits of Conservation Agriculture (CA) effects are usually realized after around 4years (Hobbs *et al.*, 2008: Blanco and Lal, 2008;)

The hypothesis that farmers are more likely to adopt more SAI technologies and do so more intensively if they own more of their plots was confirmed. The variable land tenure negatively influenced adoption of less than three technologies and positively influenced the use of more than three technologies on a single plot. Land ownership increases the margin of using four, five and six technologies by 17.6%, 1.1% and 2.2% respectively. Tenure rights and tenure security can affect adoption decisions in multiple ways. With substantial cost expenditures and benefits to conservation agriculture deemed to delay, tenure insecurity will reduce farmers' incentives to adopt (Arslan *et al.,* 2009).

Membership of group (*Grpmember)* had a negative impact on adoption of less than three technologies and otherwise on the adoption of more than three technologies. The probability of using four, five and six technologies on a single plot reduces by 1.9%, 1.1% and 2.3% respectively if one is not a member of any group. This is perhaps because farmers who belong to organized groups are expected to benefit from the established social capital that is likely to enhance information and knowledge sharing. This implies that such farmers would desire to get information from colleagues with whom they interact.

Distance to the market (*Distarmakt*) is often related to accessibility to information and other services. The coefficient for this variable had a negative influence on use of less than three technologies and has a positive impact on adoption of more than three technologies on a given plot. Farmers who easily access their farms have margins of 1.2%, 0.7% and 1.5% respective probabilities of adopting four, five and six technologies. This implies that distance increases the cost of transaction that the farmers incur while delivering their products to the market as well as when they acquire inputs from the market.

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Farmers' education level significantly influence dis adoption of three technologies and adoption of five technologies with a margin of 43.3% and 2.6% respectively. Likewise education level was found to increase the use of more than three technologies in a single plot. This suggests that educated farmers can easily acquire knowledge regarding the use of several SAI practices. A similar result is noted by Murage *et al* (2011) who found that educated farmers are more flexible in acquisition of information sources and would often consult depending on the prevailing circumstances to meet their information needs.

With the variable *Aghh* (age of household head) not significant in this study, older farmers were seen to adopt more SAI technologies compared to young farmers. An increase in age would lead to adopting four, five and six technologies by 5.4%, 0.3% and 0.7% respectively. Older farmers are considered to have enough expertise through own experience compared to the young ones and therefore more likely to adopt new farming methods without consulting external information sources. Likewise as age increase farmers are likely to be endowed with resources accrued from continued savings for a long period. Hence they are able to meet higher cost associated with use of SAI practices more so at initial.

Access to labour was found to increase the probability of using more than three technologies on a single plot, though this was only significant for the use of five technologies with a margin of 14.8%. Most of the SAI practices are labour intensive. This finding imply that since most of the SAI practices considered in this study are labour intensive, use of more technology would call for more labour. Hence labor is more often assigned to effective production activities. This conforms to a study by Mussue *et al.*, (2001) which revealed that labour was a significant factor affecting the proportion of land allocated to improved wheat.

Female plot decision makers adopt less than three technologies on a single plot as compared to their male counter parts, with a margin of adopting four, five and six technologies of 2.6%, 4.9% and 5.9% respectively. A similar pattern emerges with respect to soil fertility for farmers who perceived their plots to be fertile. Low soil fertility increased the probability of adopting four, five and six technologies by margins of 20.2%, 1.3% and 0.3% respectively

The frequency of contact between farmers and extension officers significantly influence dis adoption of three technologies and adoption of five technologies with a margin of 31.1% and

24.7% respectively. Low farmers income reduces the probability of adopting four, five and six technologies by margins of 18.2%, 15.9% and 0.6% respectively. This result is consistent with the positive effect of wealth on the chance of adoption of SAPs

5. Conclusion and implications

The role of social economic, household and plot characteristics in shaping adoption process has been of interest in the recent past. This study generally contributes to the literature on agricultural technology adoption and specifically on determinants of number of SAI practices used in Kenya. It examined how various social-economic, household and plot characteristics aid in shaping the probability and the number of SAI practices adopted.

There was a robust relationship between labour required and the number of SAI practices used as well as the primary occupation of the smallholder farmers. This study indicates that size of land that farmers own and their education level plays a vital role in determining the number of SAI practices used. Likewise famers' Income was also key in determining the number of technology they would use on their plots. Another key and robust finding is the frequency of contact between extension officers and farmers that positively affects the number of SAI technologies used. Generally socio-economic and plot characteristics such as: slop of sub plot, gender of household head, soil fertility, sub plot tenure, access to credit and distance to the sub plot Soil had a less clear role in determining the number of SAI practices used on a given plot.

Consequently to ensure that farmers adopt more SAI practices on a given plot, frequent contact with extension officers is paramount. Since SAI practices are labor-intensive, labor plays a key role in farm management. Larger household size means greater availability of labor. The relationship between labour required and the number of SAI practices used implies that policies that will make micro-credit from government and nongovernmental agencies accessible to these farmers will go a long way in addressing their resource use. These would help farmers to purchase critical inputs and paying for hired labour. This can be achieved through the enactment and enforcement of requisite legal framework whose aim will be to facilitate farmers" access to cheaper credit facilities to finance SAI technology uptake". In addition, farmers should be encouraged to mobilize their savings through the establishment of SACCOs and the strengthening of community based lending systems that would improve their bargaining power. The significant relationship between land and the number of SAI practices used implies that policies aimed promoting SAI practices are likely to expand the area under maize and legumes a development that will improve the household food security status and soil health as well.

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8. Appendices

Table 1. Model variable definition and summary statistics.

Variable	Variable Description	Means	Standard deviation
Gender	Gender (1= Male, 0 = Female)	0.46	0.50
Aghh	Age of household in years	50.76	14.71
Educlevel	Education level, years in school	7.74	6.76
HHsize	Household size in number	5.81	2.71
Farmsize	Farm size acres	0.71	1.56
Frequentcontact	Extension contact,(Number of days/ year)	1.34	1.96
Crdacc	If farmer needed credit (1= Yes. 0=No)	0.06	0.23
Grpmbr	Group membership (1= Yes. 0=No)	0.47	0.49
Occupation	Occupation of the household head (1 = Agriculture self, 2 = Non-agriculture self, 3 = Salaried, 4= Retired)	1.56	1.49
Plotdist	Walking distance from home to plot	7.15	16.08
Income	Total household income per month	113,178	159,578
Soilfertility	Soil fertility (1=Good, 2=Medium, 3=Poor)	1.92	0.60
Plottenure	Plot ownership (1 = Owned, 2 = Rented in, 3 =Rented out, 4=Borrowed,)	1.19	0.64

Note: 1 KES was equivalent to 80 US dollar at the time of survey.

Source: Survey data, 2013

Table2. Coefficient estimates, marginal effects and predicted probabilities of the ordered probit model

Variables	Marginal effects					
Land size (10^{-2})	0.064(0.082)	0.077(0.091)	0.208(0.012)	-0.002(0.004)	-0.154(0.010) *	-0.003(0.002)
Gender	-0.194(0.407)	-0.232(0.453)	-0.062(0.095)	0.076(0.017)	0.046(0.072)	0.009(0.015)
Age of HH (10^{-2})	-0.014(0.021)	-0.017(0.024)	-0.046(0.004)	0.054(0.001)	0.003(0.003)	0.007(0.007)
Education level	-0.105(0.130)	-0.127(0.146)	-0.433(0.016) **	0.040(0.007)	0.026 (0.012) **	0 .006(0.003)
Occupation (10^{-2})	0.039(0.486)	0.477(0.532)	0.129(0.052) **	-0.015(0.028)	-0.096(0.039) ***	-0.019(0.013)
Labour (10^{-2})	-0.006(0.772)	-0.731(0.854)	-0.198(0.095) **	0.023(0.043)	0.148(0.073) **	0.030(0.021)
Sex plot decision maker (10^{-2})	-0.121(0.228)	-0.145(0.271)	-0.039(0.059)	0.046(0.011)	0.029(0.044)	0.059(0.009)
Sub plot distance	-0.308(0.006)	-0.004(0.007)	-0.101(0.002)	0.012(0.002)	0.007(0.001)	0.015(0.003)
Soil fertility(10^{-2})	-0.053(0.259)	-0.064(0.305)	-0.172(0.081)	0.202(0.010)	0.013(0.060)	0.003(0.012)
Plot slope(10^{-2})	-0.250(0.361)	-0.302(0.416)	-0.082(0.071)	0.096(0.019)	0.061(0.053)	0.012(0.013)
Extension contact	-0.124(1.289)	-0.125(1.353)	-0.311 (0.089) ***	-0.052(0.063)	0.247(0.077) ***	0.065(0.039)
Group membership (10^{-2})	0.047(0.306)	0.057(0.365)	0.016(0.096)	-0.019(0.013)	-0.011(0.070)	-0.023(0.014)
Credit access(10^{-2})	0.340(1.656)	0.441(1.694)	0.094(0.279)	-0.027(0.125)	-0.060 (0.157)	-0.010(0.024)
Income	0.138(0.546)	0.251(0.129)	0.234(0.132) **	-0.182(0.191)	-0.159(0.671) **	-0.067(0.075)
Plot tenure (10^{-2})	-0.044(0.251)	0.054(0.305)	-0.015(0.081)	0.176(0.017)	0.011(0.061)	0.022(0.012)
Predicted Probabilities						
Prob(Y=1|X)			0.003			
Prob(Y=2|X)			0.004			
Prob(Y=3|X)			0.254			
Prob(Y=4|X)			0.527			
Prob(Y=5|X)			0.185			
Prob(Y=6|X)			0.021			
Number of observations			67			
LR chi2(15)			28.47			
Prob > chi2			0.0188			
Pseudo R2			0.1533			
Log likelihood			78.629			

Note: ***, ** and * denote significance at 1%, 5% and 10% confidence level. Standard errors are in parenthesis.

Source: Survey data, 2013

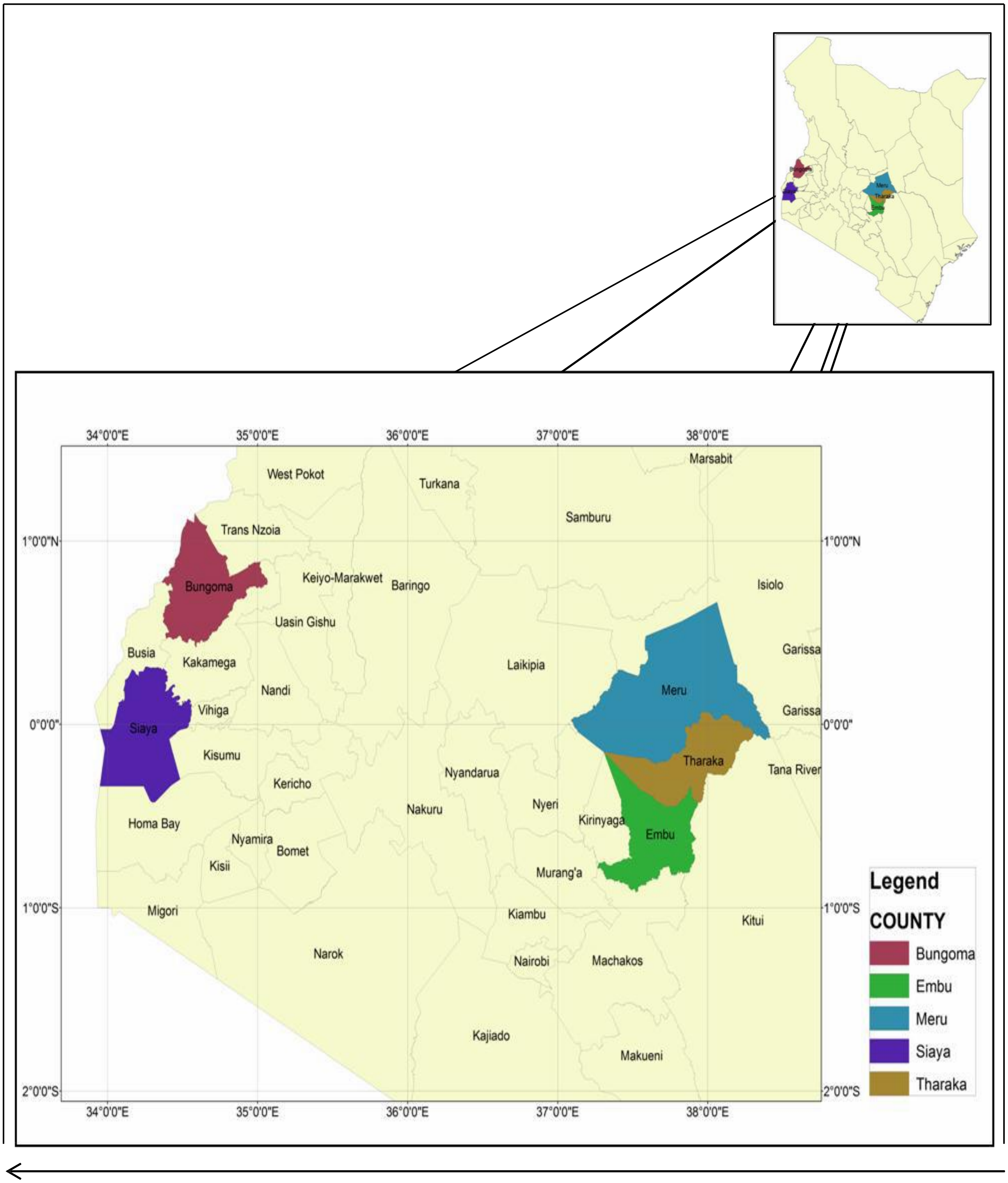

Figure 1: Map of study area.
Source: Virtual Kenya and Google Earth Pro. 2014.