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Original Article

## Socio-Economic Drivers of Agroforestry Practices in Kaiti Watershed, Makueni County, Kenya

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*Deforestation,  
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Farm Tree Density,  
Tree Species Diversity,  
Socio-Economic  
Factors,  
Kaiti Watershed.*

Forests and trees are essential resources for sustainable provision of goods and services. However, trees have not only been depleted in reserved forests but also on agricultural lands. Several measures have been formulated to improve forest cover in Kenya and one of such strategies is agroforestry. This study aimed to examine agroforestry practices, tree density on farms and determine the relationship between socio-economic characteristics of households and tree density on farms in Kaiti watershed, Makueni County, Kenya. Quadrats were used to determine tree density and tree species diversity on farms while questionnaires were used to record socio-economic characteristics of households. Data files were prepared in the Microsoft Excel and SPSS version 20 software where descriptive and inferential statistics were used. The study found 8 agroforestry practices. The results of One-Way ANOVA for both Shannon Diversity Index and Simpsons' Index of Diversity showed significant difference in species diversity in Kaiti watershed with p-value of 0.00023 and 0.00012, respectively. The mean of tree density was 104.5 trees per acre where 54% of farms had less than 40 trees per acre while 46% of farms had more than 40 trees per acre. Further, the study found significant relationship between socio-economic characteristics of households and tree density on farms. Household income was the most significant with p-value of 0.000. The study recommends sensitization of farmers about importance of trees and suitable tree species for growing in arid and semi-arid areas. Further, supply of certified seedlings close to farmers and at affordable prices would improve tree species diversity and tree density on farms. There is also need for private land ownership for households to promote sense of ownership of trees.

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## INTRODUCTION

Forests occupy 31% land on Earth's surface (FAO, 2020) and provide essential benefits to both people and the planet. They are source of food, medicine, fuel to many people across the globe and habitat to wildlife (FAO, 2018). Further, the forest sector employs many people across the world. According to Lippe et al. (2022), the forest industry employed 33 million people worldwide between 2017 and 2019. Despite their abundant benefits, forests face destruction and degradation by humans (Seymour, 2020).

Globally, 178 million hectares of forest were destroyed between 1990 and 2020 (FAO, 2020). However, global forest net loss reduced significantly over the three decades because of decline in forest reduction in certain nations and increase in others. Between 1990 and 2000, there was a 7.8-million-hectare annual net loss of forests worldwide; between 2000 and 2010, this decreased to 5.2 million hectares annually, and between 2010 and 2020, it further decreased to 4.7 million hectares annually (FAO, 2020).

Forests in Africa occupy 26% of the continental land, with the majority of them being in Tanzania, Zambia, Angola, and the Democratic Republic of the Congo (Igini, 2022). Deforestation is rampant in Africa with 3 million hectares of forests lost annually (Mwanjela, 2018), endangering human livelihoods and eliciting extinction of wildlife due to habitat loss. The primary reason behind deforestation in Africa is agricultural expansion. In West Africa, the main causes of deforestation are cultivation of cocoa in Côte d'Ivoire, Ghana, Nigeria, and Cameroon as well as production of palm oil in Cameroon (Igini, 2022). Cocoa is produced to a tune of three million tons per year

which requires enormous land. Between 2001 and 2014, Côte d'Ivoire lost one quarter and Ghana 10% of its forests to cocoa production (Higonnet et al., 2017).

Kenya has seen significant forest losses at its water towers due to deforestation. Between 2000 and 2010, the predicted annual loss of forests at the water towers was 5,000 hectares (Ministry of Environment and Mineral Resources Kenya, 2018). Further, National Forest Resources Assessment in 2021 reported the rate of deforestation in Kenya at 50,000 hectares per year causing over 1.9 billion loss to the economy (Kenya Forest Service, 2022). The national forest cover is approximated at 8.8% of the total land which is less than the globally recognized minimum of 10% for forests (Kenya Forest Service, 2022; Ministry of Environment and Forestry, 2020). The consequences of deforestation are dire with decline in forest products and services, loss of biodiversity and climate change (Lemenih & Kassa, 2014).

The population of Kenya has increased from approximately 7 million people in 1962 to 47.5 million in 2019 (Kenya National Bureau of Statistics, 2019; Tengnas, 1994). The growth has led to higher demand for forest products and more land for food production. Trees have not only been lost in reserved forests but also on agricultural lands. For instance, the dry woodlands in Ewaso North which mainly serve as grazing lands, are exploited for wood energy in form of charcoal which is then supplied to towns such as Meru and Isiolo (Government of Kenya, 2013). The country, therefore, requires intensifying agroforestry as a means to restore trees lost and improve forest cover.

Several strategies have been developed to improve forest cover in Kenya (Ministry of Environment and Forestry, 2019). One of such strategies is implementation of Agriculture (Farm Forestry) Rules, 2009. The rules require farm owners to set up at least 10% of the land under agroforestry. The Sessional Paper No. 1 of 2007 on Forest Policy, the National Climate Change Action Plan 2018 to 2022 and Forests Act 2005 also support scaling up of agroforestry (Government of Kenya, 2021; Kenya Forestry Research Institute, 2013). For instance, the National Climate Change Action Plan 2018 to 2022 aimed at increasing agroforestry on agricultural lands by 200,000 acres.

Adoption of agroforestry practices such as home gardens, boundary planting and fodder banks have been evident at grass-roots level. However, there is inadequate data on tree cover and adoption rates of agroforestry practices for the various agro-climatic zones in Kenya (FAO, 2016; Yila, 2016).

Kenya's Makueni County has 803,470 hectares, of which 43,988.25 hectares are covered by forest representing 5.38% of the total area covered by forests (Kenya Forest Service, 2022). In the County, there has been evidence of upstream catchment degradation (Population Action International, 2012). According to Ndavi et al. (2016), Kaiti watershed in Makueni County is degraded as a result of poor land practices, deforestation, poverty, and growing population.

Existing literature on agroforestry studies focus on factors affecting agroforestry adoption (Magugu et al., 2018; Mukundente et al., 2020; Mwase et al., 2015; Obeng & Weber, 2014) and benefits and challenges in agroforestry (Kiyani et al., 2017; Mugure et al., 2013; Wanjira & Muriuki, 2021). However, research on tree density on agricultural farms is inadequate and estimates on agroforestry extent is not well accounted for. Research on the precise extent of agroforestry in Kenya and worldwide has been inexhaustive (Zomer et al., 2014). Further, the measurement, reporting and verification of agroforestry is poorly developed (Rosenstock et al., 2019). Therefore, this study aimed to provide

data on agroforestry practices and fill the research gap on tree density on farms and relationship between socio-economic characteristics of households and tree density on farms in Kaiti watershed, Makueni County, Kenya. The research objectives were: (i) To assess agroforestry practices and tree species diversity across locations in Kaiti watershed (ii) To evaluate tree density on farms of households in Kaiti watershed (iii) To examine socio-economic characteristics of households in Kaiti watershed and (iv) To determine the relationship between socio-economic characteristics of households and tree density on farms in Kaiti watershed. The null hypotheses of the study were (i) There is no significant difference in species diversity across locations in Kaiti watershed and (ii) There is no relationship between sex of household head, age of household head, level of education, household size, household age composition, land tenure, household income, farm size, secondary occupation, years of farming experience and tree density on farms in Kaiti watershed.

## RESEARCH METHODOLOGY

### Research Design

Experimental research design was adopted for this study because it best handles the issues outlined in the objectives. It examines cause-effect relationships of set of circumstances. Through this design, one is able to observe how the independent variable affects the dependent variable (Bhattacharjee, 2019).

### Description of the Study Area

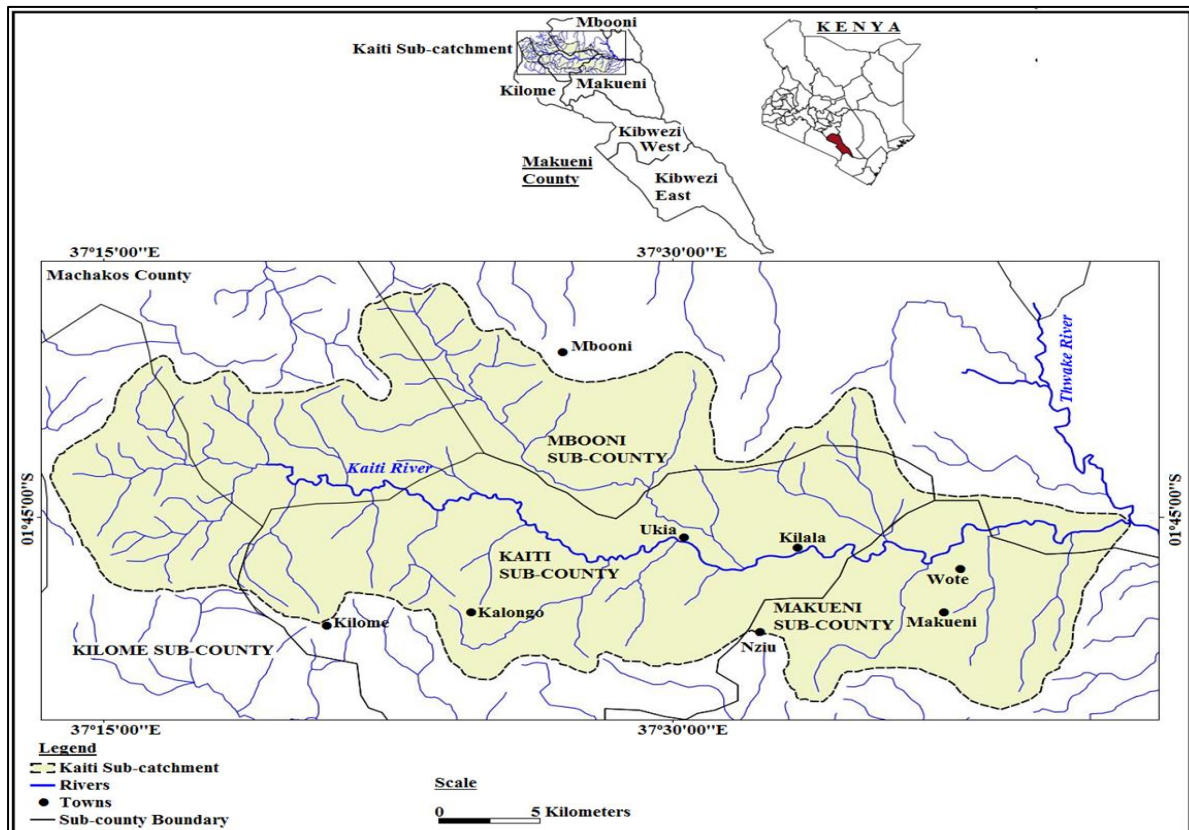
The research was carried out in Kaiti Watershed in Makueni County as shown in figure 1. Kaiti Watershed is found between 10° 38' South and 10° 51' South and 37°14' East and 37°41' East and covers an area of 723.864 km<sup>2</sup>. The watershed stretches from Machakos Town, Kilome, Kaiti, Mbooni and Makueni sub-counties and has a population of approximately 276,692 people (KNBS, 2019).

Kaiti watershed topography features highlands including Mbooni, Makongo, Kilungu, and Nthangu hills. Kaiti River is the main river and

provides water for the watershed along with its tributaries which originate from the hills. There are two distinct rain seasons in Kaiti watershed: the long rains, which run from October to December, and the short rains, which run from

March to May. The highlands experience rainfall of 800 mm to 1200 mm per year while the lower regions of the watershed receive rainfall of less than 500 mm per year (Ndavi et al., 2016).

**Figure 1: Map of Kaiti watershed**



**Source:** Kenya Bureau of Statistics, Topographic sheets for Nairobi (SA-37-5) and Kitui (SA-37-6), Survey of Kenya.

Agriculture is the primary land use practice in the watershed as shown in the land use map of Kaiti watershed in figure 2. Grasslands and croplands cover 37,061 and 25,391 hectares, respectively. While forests, woodlands and built-up areas cover 3,290, 2,799 and 1,481 hectares, respectively. Crops grown include bananas, maize, green grams, beans, sorghum, millet, cow peas, peas, sweet potatoes and vegetables. Maize is the staple food for most households in the watershed. Livestock farming is also carried out in Kaiti watershed. The livestock activities include dairy and beef cattle farming, poultry and bee keeping (Government of Makueni County, 2018).

**Sample size and Sampling techniques**

*Target population and Sample Size*

The target population were households and there are 71,005 households in Kaiti watershed. The Yamane (1967) formula was used to determine the sample size for households shown in equation 1 (Singh and Masuku, 2014):

$$n = \frac{N}{1+N(e)^2} \tag{1}$$

The sample size is denoted by n, N is the total number of households within the watershed, and e is the margin of error. Equation 2 illustrates how the formula was used to get a sample size of 100 where N is 71005 and margin of error is 10%

$$n = \frac{71005}{1+71005(0.1)^2} \quad [2]$$

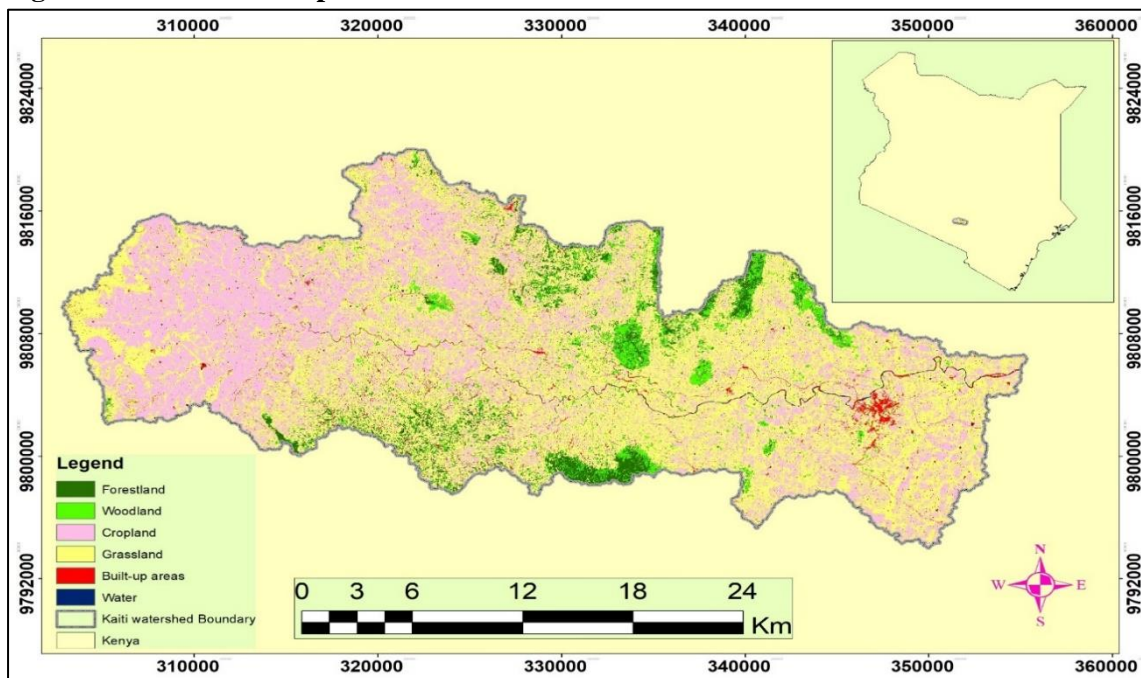
n = 99.86 approximately 100.

**Sampling Techniques**

Cluster, purposive, proportional, and simple random sampling techniques were employed in the study. Due to the extensive size of Kaiti watershed, cluster sampling was used to divide the area into clusters which are the administrative sub-counties in the watershed. Machakos Town, Kaiti, and Makueni sub-counties were sampled. In each sub-county, locations were purposively

selected. In Machakos Town Sub-County, two locations were selected, Lubwa and Kola, because they fall largely in Kaiti watershed. Six locations were selected in Kaiti Sub-County, they include Kee, Kithembe, Kikoko, Iuani, Ukia, and Kilala. In Makueni Sub-County, Wote and Nziu locations were selected. Since the ten locations have uneven household population, the sample size of 100 households was proportionally distributed across the ten locations to ensure unprejudiced distribution of the sample size. Households from each location were then randomly selected using simple random sampling.

**Figure 2: Land cover map of Kaiti watershed**



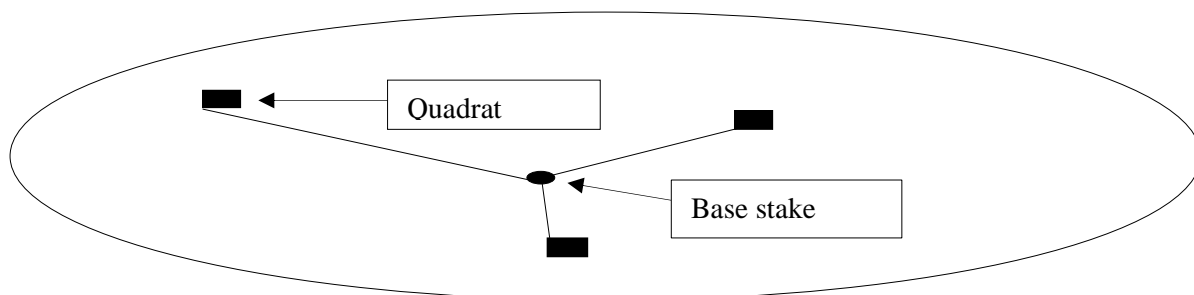
Source: System for Earth Observation Data Access, Processing and Analysis for Land Monitoring

**Data Collection**

On the selected farmer’s field, two points were randomly selected and base stakes hammered onto

the points. From each of the selected point, as shown in *Figure 3* quadrat locations were randomly selected in any direction from the point.

**Figure 3: Quadrats of 20 m x 20 m radiating from a central base stake**



Source: Adopted from Barker (2001)

The distance of quadrats from the selected point was set apart for independence. The tip of a radiating line represented the location of a corner of a quadrat (Barker, 2001). Five quadrats measuring 20 m × 20 m were laid out. Tree density on farms was determined by dividing the total number of trees in the five quadrats by the entire area of the farm (Barker, 2001; Baxter, 2014). The total area of the farms was determined using GPS Fields Area Measure Tool installed on smart phone.

Agroforestry practices, tree species and the number of each species were observed and recorded on field sheets. Species diversity of the study area was determined using data on types of tree species and the abundance of each species (Supriatna, 2018). Further, questionnaires on socio-economic characteristics of households were administered to farmers.

### Data Analysis

Data files were prepared and analysed in Microsoft Excel software and SPSS software version 20. In Microsoft Excel software, Simpson's Index of Diversity, Shannon diversity index, Shannon's evenness, single-factor analysis of variance, Tukey's Honest Significant Difference (HSD) test, and descriptive statistics were done, while in SPSS software, descriptive statistics, normality and regression tests were carried out. The independent variables in this study were the households' socio-economic characteristics while the dependent variable was households' tree density.

Data on agroforestry practices were analysed using frequencies in SPSS while tree species diversity for the study area was calculated using Simpson's Index of Diversity, Shannon Diversity Index and Shannon's evenness in Microsoft Excel. Further, One-Way ANOVA was employed to determine whether the mean species diversity varied throughout the study area. Thereafter, Tukey's Honest Significant Difference (HSD) test ascertained where major differences in species diversity occurred across the study area.

Tree density on farms and socio-economic characteristics of households were analysed using SPSS's mean, frequencies, standard deviation, and range functions and the relationship between households' socio-economic characteristics and farm tree density was analysed using multiple linear regression. Normality test on the dependent variable was done before the multiple linear regression was run.

## RESULTS AND DISCUSSION

### Types of Agroforestry Practices in Kaiti Watershed

The agroforestry systems observed were agrisilviculture and agrisilvopastoral with frequencies of 53% and 47%, respectively. The major land use practices were crop farming and livestock keeping. Crops grown were maize, beans, peas, green grams, sweet potatoes, arrow roots, cassava, bananas, and paw paws. The livestock reared included; poultry, cows, goats, sheep, and donkeys. The findings on agroforestry systems in Kaiti watershed align with the findings of Jordan et al. (2016) who observed that 77% of households in Mumbuni and Ndovoini sub-locations in Makueni County, Kenya practiced agrisilviculture while 36% of households practiced agrosilvopastoral system.

The agroforestry practices observed in Kaiti watershed were multi-purpose trees on croplands, orchards, trees on pastures, windbreaks, woodlots, trees in soil conservation and reclamation, home gardens, and apiculture. Multi-purpose trees on croplands, orchards, trees on rangelands, windbreaks, and woodlots were common practice with frequencies of 59%, 55%, 47%, 41%, and 26%, respectively. While home gardens, trees on soil-conservation structures, and reclamation and apiculture were least practiced with frequencies of 14%, 15%, and 2%, respectively. The diversity of agroforestry practices in Kaiti watershed are in line with Wanjira and Muriuki (2021) and Tengnas (1994) who found that agroforestry practices in Kenya are diverse throughout the country with no agroforestry practice tied to a certain region.

Tree species found in orchards were *Citrus sinensis* and *Mangifera indica*. On pasture lands, the tree species found included *Terminalia brownii*, *Banalite aegyptica*, *Acacia senegal*, *Acacia nilotica*, *Acacia mellifera*, *Acacia tortilis*, *Commiphora baluensis*, *Euphorbia tirucalli*, *Combretum collinum*, *Combretum molle*, *Lannea schweinfurthii*, and *Dalbergia melanoxylon*. These species provided fuelwood, construction material and animal feed. Similarly, Endale et al. (2017); Houerou and Hoste (1977) and Stepler and Nair (1987) found *Banalite aegyptica*, *Acacia* and *Commiphora* species as common species found on pastoral lands of Somalia, northern Kenya and Tanzania, Ethiopia, Botswana, and Namibia.

*Grevillea robusta* was the common species in windbreaks. Other tree species used in windbreaks were *Jacaranda mimosifolia* and *Senna siamea*. The windbreaks in Kaiti watershed were used to demarcate boundaries, reduce the force of wind, control soil erosion and also to improve landscape aesthetics. In woodlots, the common tree species found were *Eucalyptus*, *Cypripedium* species and *Grevillea robusta*.

### Tree Species Diversity in Kaiti Watershed

Fifty-two tree species were identified with *Citrus sinensis*, *Citrus limon*, *Persea americana*, *Eucalyptus*, *Mangifera indica*, *Croton megalocarpus*, *Grevillea robusta*, and *Acacia nilotica* being most frequent. The finding that 52 tree species thrive in Kaiti watershed is similar to findings by (Harvey et al., 2005; Kumari & Kansuntisukmongkol, 2009; Nair & Kumar, 2006; Ndolo et al., 2016; Sonwa et al., 2007) that diverse tree species grow in different regions. Harvey et al. (2005) found 161 tree species in Costa Rica and Nicaragua while Nair and Kumar (2006) found 27 tree species in home gardens in Sri Lanka and 602 tree species in West Java. Kumari and Kansuntisukmongkol (2009) on their study on plant diversity in home gardens in Sri Lanka found 289 tree species while in cocoa agroforests of South Cameroon. Sonwa et al. (2007) found 206 species. In Machakos County, Kenya, Ndolo et al. (2016) found 102 species

consisting of 42 exotic species and 60 native species.

The average number of trees per farm in Kaiti watershed was 382 with range of 9 to 2642. Tree species richness range was 2 to 28 with a mean of 6.86. The mean of Shannon diversity index and Shannon's evenness were 1.32 and 0.72, respectively and ranged from 0.34 to 2.08 and 0.21 to 0.99, respectively. While Simpson's Index of Diversity average was 0.66 and ranged from 0.14 to 0.88. Among the 10 locations surveyed, Kee location had the highest species diversity of 1.61 of Shannon index and value of 0.77 of Simpson's Index of Diversity while Nziu location had least species diversity of 1.0 of Shannon Index and value of 0.53 of Simpson's Index of Diversity.

The results of One-Way ANOVA for both Shannon Diversity Index and Simpson's Index of Diversity showed significant difference in species diversity across all locations in Kaiti watershed with p-values of 0.00023 and 0.00012, respectively, thus rejecting the null hypothesis that there is no significant difference in species diversity across locations in Kaiti watershed. The Tukey test results of Shannon Diversity Index showed the differences in species diversity between locations: Wote and Kee, Nziu and Iuani, Nziu and Ukia, Nziu and Lumbwa were significant with p-values of 0.0306, 0.022, 0.044, and 0.0379, respectively. The difference between Nziu and Kee was most significant with p-value of 0.001.

The significant diversity difference between Kee and Nziu locations can be attributed to their contrasting climate conditions and socio-economic factors. Kee location covers 53.5 km<sup>2</sup> and has a population density of 274 people per square kilometre (KNBS, 2019). It is semi-arid experiencing annual rainfall of between 250 mm and 500 mm. Livestock keeping is the main land use activity and indigenous species such as *Acacia* species are commonly found on agricultural lands. On the other hand, Nziu location covers 39.6 square kilometres (KNBS, 2019) with a population of 198 people per square kilometre. The area is sub-humid with annual precipitation of

between 500 to 800 mm. The favourable climatic conditions allow crop farming and large-scale orange and mango farming. *Grevillea robusta* are commonly used as windbreaks. The higher farm land disturbance in Nziu location may contribute to the low species diversity compared to Kee location. Sharma (2023) in their study on variation of species in tropical dryland of Northern India asserted that as land disturbance increases, species diversity declines.

Similarly, Ndolo et al. (2016) in their study on socio-economic factors influencing tree species diversity in Machakos County in Kenya found that the humid region in the County had lower tree species richness and diversity. They attributed this to intense agriculture carried out by farmers in the humid region where little land was left uncultivated. Farmers also majored on planting non-indigenous tree species that grow at a quicker rate. Additionally, the study found that households headed by women and farm size positively influenced tree species diversity.

### **Tree Density on Farms in Kaiti Watershed**

This study found the mean tree density in Kaiti watershed was 104.5 trees per acre with a range of 7 to 1323 trees per acre. Forty six percent of surveyed farms had more than 40 trees per acre while 54 percent had less than 40 trees per acre. Tengnas (1994) opined that a population of 40 trees per acre is appropriate on croplands if crops grown are light demanding. This population is equivalent to a spacing distance of 10 m by 10 m or a narrow spacing of 5 m within the rows and wider distance of 20 m between the rows. High tree densities on rangelands affect grass production, therefore, tree spacing of 10 m by 10 m and 15 m by 15 m is recommended for small trees and large trees, respectively. Further, Lerberghe (2017) stated that tree densities of 20 to 40 trees per acre in arable lands are profitable.

The finding on tree density in Kaiti watershed is similar to findings by other studies (Akpalu et al., 2019; Baul et al., 2013; Endale et al., 2017; Jordan et al., 2016; Madrigal-gonzález et al., 2023) that tree density on farms vary from region to region. Baul et al. (2013) in their study on

agrobiodiversity in Nepal found peak tree density of 226 trees per hectare on farms less than 0.25 hectares and lowest tree density of 165 trees per hectare on farms between 0.26 to 0.5 hectares. In Ethiopia's semi-arid East Shewa region, tree density range was 55 trees per hectare to 100 trees per hectare (Endale et al., 2017). Further, Akpalu et al. (2019) in their study in Upper East Ghana found the average tree densities in three districts namely Garu-Tempene, Bawku West and Kassena Nankana West as 18.5, 18.4 and 25.9 trees per hectare, respectively. Jordan et al. (2016), in their study on agroforestry in Makueni County in Kenya found that average tree density in Mumbuni was 40 trees per acre while in Ndovoini, mean tree density was 9 trees per acre.

### **Socio-Economic Characteristics of Households in Kaiti Watershed**

The socio-economic characteristics of households examined were sex, age and education of household heads, family size, household age composition, household income, farm size, land tenure, secondary occupation and years of farming experience. The study found that 64% of households were headed by men and 36% by women. Forty four percent of household heads were aged between 36 to 50 years followed by farmers aged between 51 to 65 years (31%) while 13% were aged between 18 to 35 years and 12% were aged above 65 years.

Forty three percent of household heads had attained secondary school education, 29% had tertiary while 28% had primary education. The findings of this study also showed that 47.34% of households had family members aged between 18 and 60 years. Thirty six percent of households had children aged between 0 and 17 years while 16.91% of households had older people aged above 60 years. The average household size was 6, and the range of sizes was 1 to 19. Majority of households (72%) had family size of 4 to 7 people while household sizes of 1 to 3 and 8 to 19 made up 14% each.

In this study, 34% of households had monthly income of less than KES 5,000 and 31% had monthly income between KES 5,000 and 10,000,



these were categorized as low-income households. Eleven percent and 8% of households had monthly income of KES 10,001 to 25,000 and 25,001 to 50,000, respectively and were categorized as medium income households. Sixteen percent of households had monthly income above KES 50,000 and were categorized as high-income households.

Seventy three percent of farmers were engaged in off-farm employment where the income from their farms supplemented earnings received from off-farm employment while 27% of farmers were solely involved in their own farms' activities. The study also found 84% of households had farm sizes between 1 and 5 acres, 15% had more than five acres while 1% had less than one acre. Further, 53% of households were settled on communal lands, 43% had private land ownership, and 4% rented land for agriculture for a certain period of time. Majority of farmers in Kaiti watershed had rich farming experience where 82% of farmers had farming experience of more than 5 years. Fourteen percent had experience of one to five years and 4% had less than one year in farming.

**Relationship between socio-economic characteristics of households and tree density on farms in Kaiti watershed**

The regression equation produced a good fit of R<sup>2</sup> 0.39 and adjusted R<sup>2</sup> of 0.35, and indicated that household income, land tenure, household farm size, sex of household head, secondary occupation, and household composition of people aged 18 to 60 years were good predictors of tree density on farms with F value of 9.75 and P value of 0.000. Therefore, rejecting the null hypothesis that there is no relationship between sex, age, and level of education of household head, household age composition, farm size, household income, land tenure, secondary occupation, years of farming experience, and tree density on farms.

Using stepwise regression, household income, land tenure, household farm size, sex of household head, secondary occupation, and household age composition (18 to 60 years) had significant influence on tree density on farms. While the following predictor variables; age of household head, level of education, years of farming experience, household size, and household age composition (0 to 17 years and above 60) were found to be not statistically significant as shown table 1.

**Table 1: Linear regression of independent variables (socio-economic characteristics of households) on the dependent variable (tree density on farms)**

Tree Density	Coefficient	T-test	P-value
<b>Socio-economic characteristics</b>			
Constant		3.757	0.000**
Household income	.451	4.601	0.000**
Land tenure	.256	-2.877	0.005**
Farm size (acres)	.223	-2.471	0.015**
Sex of household head	.201	-2.371	0.020**
Secondary occupation	.231	2.526	0.013**
Household composition - 18 to 60 years	.183	2.160	0.033**
Age of household head	-.048	-.546	0.586
Level of education	-.101	-.744	0.459
Household composition – 0 to 17 years	.002	.017	0.986
Household composition – above 60 years	-.123	-1.349	0.181
Household size	.005	.052	0.959
Years of farming experience	.141	1.545	0.126

Household income positively influenced tree density on farms at a P-value of 0.000. This implies a farm's tree density increases with

household income. This finding is in agreement with that of Nyamweya (2017), who in their study in Nakuru, Kenya found a strong correlation

between household income and agroforestry practice. Land tenure had negative coefficient and statistically significant P-value of 0.005. This study result agrees with findings of Mugure et al. (2013) who found that private land ownership greatly influenced adoption of agroforestry practices and Simmons et al. (2002) who found that with secure land tenure, planting of trees increased 15.4 times in the Brazilian Amazon.

Study results showed farm size was statistically significant with P-value of 0.015 and had a negative coefficient meaning that larger farm size does not guarantee high tree density. This finding agrees with Baul et al. (2013) who in their study in Pokhara Khola watershed in Nepal found that tree density was highest at 226 trees per hectare on farms less than 0.25 hectares and lowest at 165 trees per hectare on farms sized between 0.26 to 0.5 hectares. However, Mugure et al. (2013) and Mukundente et al. (2020) found size of farm positively influenced tree planting on farms at significance level of 5%, meaning that tree density is higher on larger farms.

Sex of household head positively influenced tree density and was statistically significant. This implied that farms headed by men were more likely than those headed by women to have a greater number of trees. This result is comparable to that of Kiptot and Franzel (2012) who found that, on average, households led by men had 1,666 trees, while homes headed by women had 840 trees in their study on gender and agroforestry in Africa. Further, in Central Kenya, Oeba et al. (2012) found that homes headed by men had a higher likelihood of maintaining more trees than homes led by women. However, Keil et al. (2005) found that tree density was equally the same in both male and female headed households, however, households headed by women engaged in agroforestry practice at a lesser extent.

With a p-value of 0.013, secondary occupation was statistically significant and had a favourable impact on tree density. Tree density was found to be higher among farmers who worked off the farm than in those who solely earned income on the farm. This is consistent with Oeba et al. (2012)

who found that farmers who had full time off-farm jobs had a 50% increased likelihood of planting and maintaining trees on their farms than farmers dedicated only on their farms.

Household size positively influenced tree density on farms but was not statistically significant. Household size and composition corresponds to the availability of labour in a household. This finding implied that large size households were more likely to take up agroforestry than smaller size households and is in agreement Ayuya et al. (2012) and Mukundente et al. (2020) who found that adoption of agroforestry practices was positively influenced by farmers' household sizes.

Households with children aged 0 to 17 years positively influenced tree density while households composed of older people aged above 60 years negatively influenced tree density. Both categories of household composition were not statistically significant. However, household composition of people aged 18 to 60 years positively influenced tree density on farms and was statistically significant with p-value of 0.033. Household members in this age category are energetic and can provide labour needed in tree planting and management.

Age of household head and level of education negatively influenced tree density on farms and was not statistically significant. This meant that older household heads above 60 years were less likely to engage in tree planting and farmers with higher education most likely concentrated on better off-farm jobs and had shorter time engaged in agricultural and agroforestry practices. This aligns with the findings of Matthews et al. (1993); Mukundente et al. (2020) and Place et al. (2004) who conducted studies in Ontario, Rwanda, and Kenya, respectively, and reported that education levels and age of household heads did not influence adoption of agroforestry practices.

Years of farming experience positively influenced tree density but was not statistically significant. Farmers with higher farming experience had settled on their farms for a longer period than those with lower farming experience and they

most likely had high tree density. Mukundente et al. (2020) also found that years of farming experience positively influenced agroforestry adoption but was not statistically significant.

## CONCLUSION

Agroforestry particularly tree density on farms as observed in this study, is affected by socio-economic factors. Agroforestry not only has environmental benefits, but also social and economic advantages to farmers. Adoption of agroforestry practices also has potential to improve tree and forest cover in Kenya and help in achievement of Sustainable Development Goals: 1, 2, 6, 13, and 16 which call for eradication of poverty, hunger, and availability of water to everyone, mitigation of climate change and protection of terrestrial ecosystems, respectively. Therefore, agroforestry support in terms of sensitization about agroforestry laws, importance of agroforestry and agricultural extension services by government and non-governmental organizations need to be intensified. Further, structures that promote agroforestry such as good roads, water resources and ready market for tree products need to be improved.

## Recommendations

Based on the study's findings, there is need for sensitization about importance of trees, various agroforestry practices, suitable tree species and regulations regarding agroforestry. Farmers' education on importance of trees and trees species suitable in arid and semi-arid areas would increase tree density, species richness and diversity on farms in Kaiti watershed. In addition, supply of certified seeds and seedlings close to farmers and at affordable prices would also improve tree density on farms. Further, there is need for private land ownership by households to promote sense of ownership of trees.

## REFERENCES

- Akpalu, S. E., Adeyiga, G. K., & Amooh, M. K. (2019). Population Density and Diversity of Trees on Farmlands in Three Districts of the Upper East Region of Ghana: Implications for Food Security and Ecosystem Population Density and Diversity of Trees on Farmlands in Three Districts of the Upper East Region. <https://doi.org/10.9734/bpi/npacs/v1>
- Ayuya, O. I., Kenneth, W. S., & Eric, G. O. (2012). Multinomial logit analysis of small-scale farmers' choice of organic soil management practices in Bungoma County, Kenya. *Current Research Journal of Social Sciences* 4, 4(4), 314–322.
- Barker, P. (2001). A Technical Manual for Vegetation Monitoring. *Water*, 80. [https://dpiwwe.tas.gov.au/Documents/Manual\\_screen.pdf](https://dpiwwe.tas.gov.au/Documents/Manual_screen.pdf)
- Baul, T. K., Tiwari, K. R., & McDonald, M. A. (2013). Exploring Agrobiodiversity on Farm: A Case from Middle – Hills of Nepal Exploring Agrobiodiversity on Farm: A Case from Middle – Hills of Nepal, (May 2014). <https://doi.org/10.1007/s11842-012-9234-y>
- Baxter, J. (2014). Vegetation Sampling Using the Quadrat Method. *Department of Biological Sciences*, 1– 3. [https://www.csus.edu/indiv/b/baxterj/bio\\_221b/vegetation\\_sampling\\_quadrat.pdf](https://www.csus.edu/indiv/b/baxterj/bio_221b/vegetation_sampling_quadrat.pdf)
- Bhattacharjee, A. (2019). Chapter 10 Experimental Research | Research Methods for the Social Sciences. *Research Methods for the Social Sciences*. <https://courses.lumenlearning.com/suny-hccc-research-methods/chapter/chapter-10-experimental-research/>
- Endale, Y., Derero, A., Argaw, M., & Muthuri, C. (2017). Farmland tree species diversity and spatial distribution pattern in semi-arid East Shewa, Ethiopia. *Forests, Trees and Livelihoods*, 8028, 1– 16. <https://doi.org/10.1080/14728028.2016.1266971>
- FAO. (2016). Trees, forests and land use in drylands. *Forest Ecology and Management* (Vol. 158). [www.fao.org/publications](http://www.fao.org/publications)
- FAO. (2018). The State of the World's Forests 2018 - Forests Pathways to sustainable

- development. Rome. <https://www.fao.org/3/I9535EN/i9535en.pdf>
- FAO. (2020). Global Forest Resources Assessment 2020 - Key Findings. <https://doi.org/10.1163/157180808X353939>
- Government of Kenya. (2013). Analysis of drivers and underlying causes of forest cover change in the various forest types of Kenya. Ministry of Forestry and Wildlife. Nairobi, Kenya. <https://www.fao.org/forestry/energy/catalogue/search/detail/en/c/1307571/>
- Government of Kenya. (2021). National Climate Change Action Plan: Second Implementation Status Report for the FY2019/2020. Nairobi, Kenya.
- Government of Makueni County. (2018). Makueni County Integrated Development Plan (Cidp) 2018- 22, 1– 59. [https://roggkenya.org/wp-content/uploads/Makueni\\_CIDP\\_2018-2022\\_County-Integrated-Development-Plan.pdf](https://roggkenya.org/wp-content/uploads/Makueni_CIDP_2018-2022_County-Integrated-Development-Plan.pdf)
- Harvey, C. A., Villanueva, C., Villacís, J., Chacón, M., Muñoz, D., López, M., Sinclair, F. L. (2005). Contribution of live fences to the ecological integrity of agricultural landscapes. *Agriculture, Ecosystems and Environment*, 111(1–4), 200–230. <https://doi.org/10.1016/j.agee.2005.06.011>
- Higonnet, E., Bellantonio, M., & Hurowitz, G. (2017). Chocolate's dark secret - How the Cocoa Industry Destroys National Parks, 1–24. [http://www.mightyearth.org/wp-content/uploads/2017/09/chocolates\\_dark\\_secret\\_english\\_web.pdf](http://www.mightyearth.org/wp-content/uploads/2017/09/chocolates_dark_secret_english_web.pdf)
- Houerou, H. N. Le, & Hoste, C. H. (1977). Rangeland Production and Annual Rainfall Relations in the Mediterranean Basin and in the African Sahelo-Sudanian Zone. *Journal of Range Management*, 30(3), 181. <https://doi.org/10.2307/3897463>
- Igini, M. (2022). Deforestation in Africa: Causes, Effects, and Solutions. <https://earth.org/deforestation-in-africa/>
- Jordan, C. G., Mudavadi, M. W., Keino, D. K., & Samuel, K. A. (2016). Assessment of agroforestry in the semi-arid lands of Kenya. *International Journal of Agricultural Extension and Rural Development*, 3(4), 174–183.
- Keil, A., Zeller, M., & Franzel, S. (2005). Improved tree fallows in smallholder maize production in Zambia: Do initial testers adopt the technology? *Agroforestry Systems*, 64(3), 225–236. <https://doi.org/10.1007/s10457-004-2410-0>
- Kenya Forest Service. (2022). National Forest Resources Assessment Report 2021 Kenya. <https://www.kenyanews.go.ke/kenya-surpasses-10-tree-cover-assessment-report-2021-says/>
- Kenya Forestry Research Institute. (2013). *Kenya Forestry Research Institute Strategic Plan 2013-2018* (Vol. 00). <http://www.library.arizona.edu/sites/default/files/users/blakisto/strategic-plan-2013.pdf>
- Kenya National Bureau of Statistics (KNBS). (2019). *2019 Kenya Population and Housing Census Volume I: Population By County and Sub-County* (Vol. I). <http://www.knbs.or.ke>
- Kiptot, E., & Franzel, S. (2012). Gender and agroforestry in Africa: A review of women's participation. *Agroforestry Systems*, 84(1), 35–58. <https://doi.org/10.1007/s10457-011-9419-y>
- Kiyani, P., Andoh, J., Lee, Y., & Lee, D. (2017). Benefits and challenges of agroforestry adoption: a case of Musebeya sector, Nyamagabe District in southern province of Rwanda. *Forest Science and Technology*, 13(4), 174–180. <https://doi.org/10.1080/21580103.2017.1392367>
- Kumari, M. A. S., & Kansuntisukmongkol, K. (2009). Plant Diversity in Home Gardens and Its Contribution to Household Economy in Suburban Areas in Sri Lanka. *Environment and Natural Resources 12 Journal*, 7(2), 12–30.

- Lemenih, M., & Kassa, H. (2014). Re-greening Ethiopia: History, challenges and lessons. *Forests*, 5(8), 1896–1909. <https://doi.org/10.3390/f5081896>
- Lerberghe, P. van. (2017). *Planning an agroforestry project*. [www.agforward.eu](http://www.agforward.eu)
- Lippe, R.S., Schweinle, J., Cui, S., Gurbuzer, Y., Katajamäki, W., Villarreal-Fuentes, M. & Walter, S. (2022). Contribution of the forest sector to total employment in national economies- Estimating the number of people employed in the forest sector. *Rome and Geneva, FAO and ILO*. <https://doi.org/10.4060/cc2438en>
- Madrigal-gonzález, J., Calatayud, J., Ballesteros-cánovas, J. A., Escudero, A., Cayuela, L., Marqués, L., ... Espinosa, C. I. (2023). Global patterns of tree density are contingent upon local determinants in the world's natural forests. *Communications Biology*, 6–11. <https://doi.org/10.1038/s42003-023-04419-8>
- Magugu, J. W., Feng, S., Huang, Q., & Ototo, G. O. (2018). Socio-economic factors affecting agro-forestry technology adoption in Nyando, Kenya. *Journal of Water and Land Development*, 39(1), 83–91. <https://doi.org/10.2478/jwld-2018-0062>
- Matthews, S., Pease, S. M., Gordon, A. M., & Williams, P. A. (1993). Landowner perceptions and the adoption of agroforestry practices in southern Ontario, Canada. *Agroforestry Systems*, 21(2), 159–168. <https://doi.org/10.1007/BF00705227>
- Ministry of Environment and Forestry. (2019). *National Strategy For Achieving and Maintaining over 10 % Tree Cover by 2022*. <https://watertowers.go.ke/download/national-strategy-for-achieving-and-maintaining-over-10-percent-tree-cover-by-2022/>
- Ministry of Environment and Forestry. (2020). The National Forest Reference Level for REDD+ Implementation, (August), 1–102. [https://redd.unfccc.int/files/kenya\\_national\\_rl\\_report-\\_august\\_2020.pdf](https://redd.unfccc.int/files/kenya_national_rl_report-_august_2020.pdf)
- Ministry of Environment and Mineral Resources Kenya. (2018). Taskforce Report on Forest Resources Management and Logging Activities in Kenya, (April). <http://www.environment.go.ke/wp-content/uploads/2018/08/Forest-Report.pdf>
- Mugure, A., Oino, P. G., & Sorre, B. (2013). Land Ownership and its Impact on Adoption of Agroforestry Practices among Rural Households in Kenya: A Case of Busia County. *International Journal of Innovation and Applied Studies*, 4(3), 552–559. <http://www.issr-journals.org/ijias/abstract.php?article=IJIAS-13-215-08>
- Mukundente, L., Ndunda, E., & Gathuru, G. (2020). Socio-economic and institutional factors affecting smallholders farmers to adopt agroforestry practices in southern province of Rwanda. *International Journal of Agricultural Science and Food Technology*, 6(1), 068–074. <https://doi.org/10.17352/2455-815x.000057>
- Mwanjela, G. (2018). Why is it critical to restore Africa's degraded landscapes? A glimpse of WWF's efforts and vision. <https://medium.com/wwftogetherpossible/why-is-it-critical-to-restore-africas-degraded-landscapes-a-glimpse-of-wwf-s-efforts-and-vision-b251369d1eef>
- Mwase, W., Sefasi, A., Njoloma, J., Nyoka, B. I., Manduwa, D., & Nyaika, J. (2015). Factors Affecting Adoption of Agroforestry and Evergreen Agriculture in Southern Africa. *Environment and Natural Resources Research*, 5(2), 148–157. <https://doi.org/10.5539/enrr.v5n2p148>
- Kumar, B.M., Nair, P.K.R. (2006). Introduction. In: Kumar, B.M., Nair, P.K.R. (eds) *Tropical Homegardens*. Advances in Agroforestry, vol 3. Springer, Dordrecht. [https://doi.org/10.1007/978-1-4020-4948-4\\_1](https://doi.org/10.1007/978-1-4020-4948-4_1)
- Ndavi, K., Kioko, K., & Patrick, K. (2016). Household Livelihood Strategies and Socio-

- Economic Conditions Influencing Watershed Degradation in Kaiti Sub-watershed, Makueni County, Kenya. *Journal of Scientific Research and Reports*, 12(2), 1–13. <https://doi.org/10.9734/jsrr/2016/28412>
- Ndolo, M. C., Dharani, N., & Kehlenbeck, K. (2016). Socioeconomic and biophysical Factors affecting tree richness and diversity in Machakos County, Eastern Kenya. *International Journal of Plant, Animal and Environmental Sciences*, (3).
- Nyamweya, J. (2017). *Analysis of Socio-Economic factors that affect agroforestry adoption among smallholders in Temiyotta location, Nakuru County*. University of Nairobi. Retrieved from <http://erepository.uonbi.ac.ke/handle/11295/102242>
- Obeng, E. A., & Weber, M. (2014). Social-Economic Factors Affecting Agroforestry Adoption by Smallholder Farmers In Ghana. *Ghana J. Forestry*, Vol. 30 (1(November), 43 – 60.
- Oeba, V. O., Otor, S. C. J., Kung'u, J. B., & Muchiri, M. N. (2012). Modelling Determinants of Tree Planting and Retention on Farm for Improvement of Forest Cover in Central Kenya. *ISRN Forestry*, 2012, 1–14. <https://doi.org/10.5402/2012/867249>
- Place, F., Franzel, S., Noordin, Q., & Jama, B. (2004). *Improved Fallows in Kenya: History, Farmer Practice, and Impacts*. EPTD Discussion Paper No. 115. Washington D.C, USA: International Food Policy Research Institute.
- Population Action International. (2012). *Population Dynamics, Environment and Sustainable Development in Makueni County*. <https://pai.org/resources/>
- Rosenstock, T. S., Wilkes, A., Jallo, C., Namoi, N., Bulusu, M., Suber, M., ... Wollenberg, E. (2019). Making trees count: Measurement and reporting of agroforestry in UNFCCC national communications of non-Annex I countries. *Agriculture, Ecosystems and Environment*, 284(April), 106569. <https://doi.org/10.1016/j.agee.2019.106569>
- Seymour, F. (2020). Is Destruction the Inevitable Fate of Our Forests? Retrieved from <https://www.wri.org/insights/destruction-inevitable-fate-our-forests>
- Sharma, A., Patel, S. K., & Singh, G. S. (2023). Variation in Species Composition, Structural Diversity, and Regeneration Along Disturbances in Tropical Dry Forest of Northern India. *Journal of Asia-Pacific Biodiversity*, 16(1), 83–95. <https://doi.org/10.1016/j.japb.2022.11.004>
- Simmons, C. S., Walker, R. T., & Wood, C. H. (2002). Tree planting by small producers in the tropics: A comparative study of Brazil and Panama. *Agroforestry Systems*, 56, 89–105. <https://doi.org/10.1023/A>
- Singh, A., & Masuku, M. (2014). Sampling Techniques & Determination of Sample Size in Applied Statistics Research: an Overview. *Ijcem.Co.Uk*, II(11), 1–22. Retrieved from <http://ijcem.co.uk/wp-content/uploads/2014/11/21131.pdf>
- Sonwa, D. J., Nkongmeneck, B. A., Weise, S. F., Tchatat, M., Adesina, A. A., & Janssens, M. J. J. (2007). Diversity of plants in cocoa agroforests in the humid forest zone of Southern Cameroon. *Biodiversity and Conservation*, 16(8), 2385–2400. <https://doi.org/10.1007/s10531-007-9187-1>
- Steppler, H. A., & Nair, P. K. R. (Eds.). (1987). *Agroforestry; a decade of development*. Nairobi, Kenya: ICRAF. [https://doi.org/10.1016/0378-1127\(89\)90092-3](https://doi.org/10.1016/0378-1127(89)90092-3)
- Supriatna, J. (2018). Biodiversity Indexes: Value and Evaluation Purposes. *E3S Web of Conferences*, 48, 1–4. <https://doi.org/10.1051/e3sconf/20184801001>

Tengnas, B. (1994). *Agroforestry extension manual for Kenya*. Nairobi, Kenya: World Agroforestry Centre.

Wanjira, E., & Muriuki, J. (2021). Review of the Status of Agroforestry Practices in Kenya . Background study for preparation of Kenya National Agroforestry Strategy (2020-2030). World Agroforestry. <https://doi.org/10.13140/RG.2.2.35739.59681>

Yila, O. (2016). A Scoping Study To Document the Agroforestry Technologies / Practices / Systems, and Their Characterisation Release, Adoption and Use By Farmers in Kenya.

Zomer, R., Trabucco A, Coe, R., Place, F., van Noordwijk, M., & Xu, J. . (2014). Trees on farms: an update and reanalysis of agroforestry's global extent and socio-ecological characteristics. Working Paper 179. Bogor, Indonesia: World Agroforestry Centre (ICRAF) Southeast Asia Regional Program, (February), 54. <http://www.worldagroforestry.org/downloads/publications/PDFs/WP14064.PDF>