African Journal of
Agricultural and Resource Economics
Volume 20, Number 3 (2025), pp 220–238

Influence of dissemination pathways on the adoption of circular economy practices among coconut farmers in Kilifi County, Kenya: A duration analysis approach

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Received: June 2025
Published: September 2025

DOI: https://doi.org/10.53936/afjare.2025.20(3).13

Abstract

The underutilisation of coconut and its by-products imply poor livelihoods and, ultimately food insecurity for farmers growing coconut. Sustainable practices like a circular economy (CE) need to be promoted for uptake by the farmers to achieve sustainable development through better utilisation of coconuts and their by-products. Various stakeholders have disseminated the technology through different pathways that have different uptake-enhancement capabilities. Furthermore, previous studies have focused on modelling technology adoption as a static, discrete choice, and therefore fail to consider the timing of the adoption. Using a discrete-time duration model, this study sought to determine how different dissemination pathways influence farmers' time of adoption of CE practices in Kilifi County in Kenya. A multistage sampling technique was used to sample 384 farmers from the county. Semi-structured questionnaires from a household survey were used to collect primary data. The data was analysed using a parametric (Weibull) functional form to specify time to adoption from the date a farmer was first aware of the technology. The findings indicate positive duration dependence and a positive rate of change in the adoption process. The media, specifically radio and television, had a positive effect on the speed of adoption. Other variables that accelerated adoption were access to credit, frequency of interaction with other value chain actors and farmers' perceptions *on the importance of CE. Frequency of interaction with friends and family on coconut farming and farmer field schools (FFS) as a dissemination pathway had delaying effects on the adoption process. The findings suggest that strategies for promoting faster adoption should focus on providing information about new technologies through the media (particularly radio and television).*

Key words: circular economy (CE), dissemination pathways, adoption, duration model, Kilifi County

1. Introduction

Coconut (*Cocos nucifera*) is an important food and cash crop in Kenya. According to the Agriculture and Food Authority – Nuts and Oil Crops Directorate ([AFA-NOCD] 2020), coconuts contribute over 1.5% of the agricultural GDP and 0.4% of the national GDP. The sub-sector supports more than 80% of coastal households (about 2.4 million people) who derive their livelihood directly or indirectly from coconut and its by-products (Mwachofi 2016; Oyoo 2021; Adoyo 2022). Despite its relevance, the crop remains strongly underutilised and underdeveloped, receiving little research and policy attention. It is estimated that the subsector generates around KES 3.2 billion against a potential of KES 13 billion annually (AFA-NOCD 2020). Therefore, the country is denied much-needed agro-based revenue that would be critical to achieving Kenya's Vision 2030. This underutilisation has been attributed largely to low value addition and processing opportunities due to low technological development and adoption (Mwachofi 2016; Oyoo 2021; Adoyo 2022).

Given the persistent poor livelihoods of coconut farmers, coupled with predictions on climate change in the future, circular economy (CE) practices are touted as potential and efficient solutions to sustain economic development and environmental sustainability. CE is a regenerative system in which resource input, waste, emissions and energy leakage are minimised by slowing, closing and narrowing material and energy loops (Geissdoerfer *et al*. 2017; Schroeder *et al*. 2019). CE practices involve the utilisation and reuse of coconuts and their by-products with the aim of earning higher value from the waste generated. The various waste and by-products generated in the coconut value chain entail, but are not limited to, shells, husks and copra meal. These waste and by-products can be utilised from a circular economy perspective to produce technical materials such as mats, cocopeat and compost, briquettes and activated charcoal, coconut flour and livestock feed (Kaur *et al*. 2019; Obeng *et al*. 2020; Da Silva *et al*. 2021; Munib 2021; De Side *et al*. 2022).

In Kenya, as in many other developing countries, the uptake of agricultural technologies and practices such as the circular economy (CE) at the farm level has remained slow and modest, despite various stakeholder efforts to promote their adoption in Africa (Mwangi & Kariuki 2015). Therefore, various studies have tried to examine factors that condition farmers' adoption behaviour so as to design and implement effective policies that could stimulate the adoption of new agricultural practices. Empirical studies have documented that a low adoption rate of technology among farmers is a result of technical, socioeconomic, market, environmental and institutional factors (Muriithi *et al*. 2018; Khataza *et al*. 2019; Nyang'au *et al*. 2021; Musafiri *et al*. 2022). However, these studies have modelled technology adoption as a static, discrete choice and therefore fail to consider the timing of the adoption event. They also do not explicitly address the effect of explanatory variables on the time-path of adoption, which is an important attribute of the adoption process (Burton *et al*. 2003; Abdulai & Huffman 2005). Therefore, the use of a static discrete-choice modelling framework, such as logit and probit models, are inadequate in explaining the dynamic process of technology adoption, as they fail to explain why some farmers adopt earlier than others and why others dis-adopt.

The potential benefits of CE, as in the case of any other new technology, can be realised by farmers if there is timely adoption (Batz *et al*. 2003; Murage *et al*. 2011; Beyene & Kassie 2015; Liu *et al*.

2018). According to Hazell and Anderson (1984), an increase in production in the early years of adoption have a significant impact on the rate of return on capital investment compared to increases in later years. For some technologies, their widespread adoption when new is likely to put downward pressure on product prices and upward pressure on the prices of inputs purchased. Therefore, farmers who adopt technology early are likely to enjoy the full benefits (Murage *et al*. 2011).

To enhance the adoption of new technologies like CE, stakeholders often use diverse dissemination pathways to provide farmers with information about innovations. These dissemination pathways include public meetings (barazas), radio/television, farmer field schools (FFSs), field days (FDs), fellow farmers (FFs) and farmer teachers (FTs) (Murage *et al*. 2011; Simtowe *et al*. 2019). The use of these pathways plays a crucial role in shaping farmers' awareness, perceptions and eventual adoption of new technologies. Kolady *et al*. (2021) argues that access to information through effective dissemination pathways does not only facilitate faster adoption, but also enables appropriate and continued use. Such information sources do not only revise farmers' perceptions about the profit-effectiveness of new innovations, but also influence the replicative effect on productivity enhancement among target and non-target farmers (Lohr & Salomonsson 2000; Chatzimichael *et al*. 2014). Indeed, Nyambo and Ligate (2013) established that weakness associated with information flows in a system are likely to inhibit the uptake and wide use of validated technologies, even where good incentive structures are in place. Therefore, widespread use of information alone may not be effective in speeding up technology adoption without the associated incentives embedded in a particular pathway.

Research on dissemination pathways for scaling agricultural technologies has gained significant attention in recent years (Murage *et al*. 2012; Simtowe *et al*. 2019; Waaswa *et al*. 2021). However, the effectiveness of specific pathways in accelerating adoption remains unclear, particularly in the context of circular economy (CE) practices. While Murage *et al*. (2011) provide a strong methodological foundation by analysing the impact of dissemination pathways on push-pull technology adoption in maize farming, their study did not address CE adoption in the coconut value chain. Therefore, this study aims to contribute to the limited literature on the effectiveness of the different pathways in order to identify the most promising information sources that would enhance faster technology adoption. The results generated will inform relevant policy makers and extension agents on the most effective dissemination pathways to fortify and speed up technology dissemination for better targeting of resources in an optimal dissemination strategy.

2. Materials and methods

2.1 Study area and sampling design

The study was conducted in Kilifi County, which lies between latitude 2º and 4º South and longitude 39º 40 East, and covers an area of approximately 12 370 km^2 (Kenya National Bureau of Statistics [KNBS] 2013). The county borders Kwale County to the southwest, Taita Taveta County to the west, Tana River County to the north, Mombasa County to the south, and the Indian Ocean to the east. The county is made up of 35 wards and seven sub-counties, namely Kilifi South, Kilifi North, Ganze, Malindi, Magarini, Kaloleni and Rabai (Republic of Kenya 2013), as displayed in Figure 1. Kilifi County is among the six counties in the coastal region of Kenya.

The area receives a bimodal rainfall pattern, with the average annual precipitation ranging from 300 mm in the hinterland to 1 300 mm in the coastal belt. Evaporation in the county ranges from 1 800 mm along the coastal strip to 2 200 mm in the Nyika plateau in the hinterland (Ogega *et al*. 2020). All parts of the county experience prolonged dry spells from January to March. It lies at an altitude of 100 m to 340 m metres above sea level. Some of the main crops farmed in Kilifi County include mangoes, citrus, cashew nuts, cassava and coconuts. Livestock rearing is also a major economic activity in most parts of the county. Livestock kept include goats, sheep, cattle and poultry. The county has good climatic conditions, and the majority of the population is involved in agriculture, with 55% of land area being used for this purpose. Agriculture plays an important role in the county, offering income to support livelihoods and improve food security. Kilifi County is the highest coconut-producing county in Kenya by volume, and second in acreage. The area under coconut production in the county is 35 494 ha, producing 40 510 MT of nuts (AFA-NOCD 2020). Coconut trees produce nuts throughout the year and are one of the most important food security crops in Kilifi County (Kenya Agricultural & Livestock Research Organization [KALRO] 2022). Despite being a high coconut-producing area, food insecurity and poverty continue to devour the majority of the population, where 62% of the population living below the poverty line (Mwachofi 2016), which is higher than national average of 45.9% (Atsiaya *et al*. 2023).

The high poverty levels can be attributed mainly to the underutilisation of coconut and its by-products. Thus, innovative enhancement of the adoption of CE practices for better coconut and by-product utilisation is an impetus for poverty alleviation in the county. Kilifi County has embraced circular economy (CE) practices to enhance sustainability in coconut farming. These include using coconut waste (husks for briquettes, shells for crafts) and practising organic farming by composting coconut husks to improve soil fertility (Muriuki *et al*. 2024). Key promoters include AFA-NOCD, KALRO and the Kilifi County Government, and private firms like Kentaste (AFA-NOCD 2020). Despite growing adoption, challenges such as low awareness and funding constraints persist (Adoyo 2022). The status of CE adoption remains limited but evolving, with increasing interest from a number of stakeholders, although more research, investment and policy support are needed to scale up solutions and improve livelihoods.

The study was guided by a cross-sectional research design. The target population was coconut farmers in Kilifi County. The study used a multistage sampling technique to select the appropriate sample size. In the first stage, Kilifi County was selected purposively because it is the highest coconut-producing county in Kenya. In the second stage, three out of seven sub-counties (Kaloleni, Malindi and Rabai) were purposively selected since they are the main coconut-producing areas in the county. In the third stage, four wards were randomly selected and, in the fourth and last stage, a random sample of 384 farmers was selected from the wards through a simple random sampling technique proportionate to the population size per ward. Table 1 shows the distribution of the sample size among the four wards in the county.

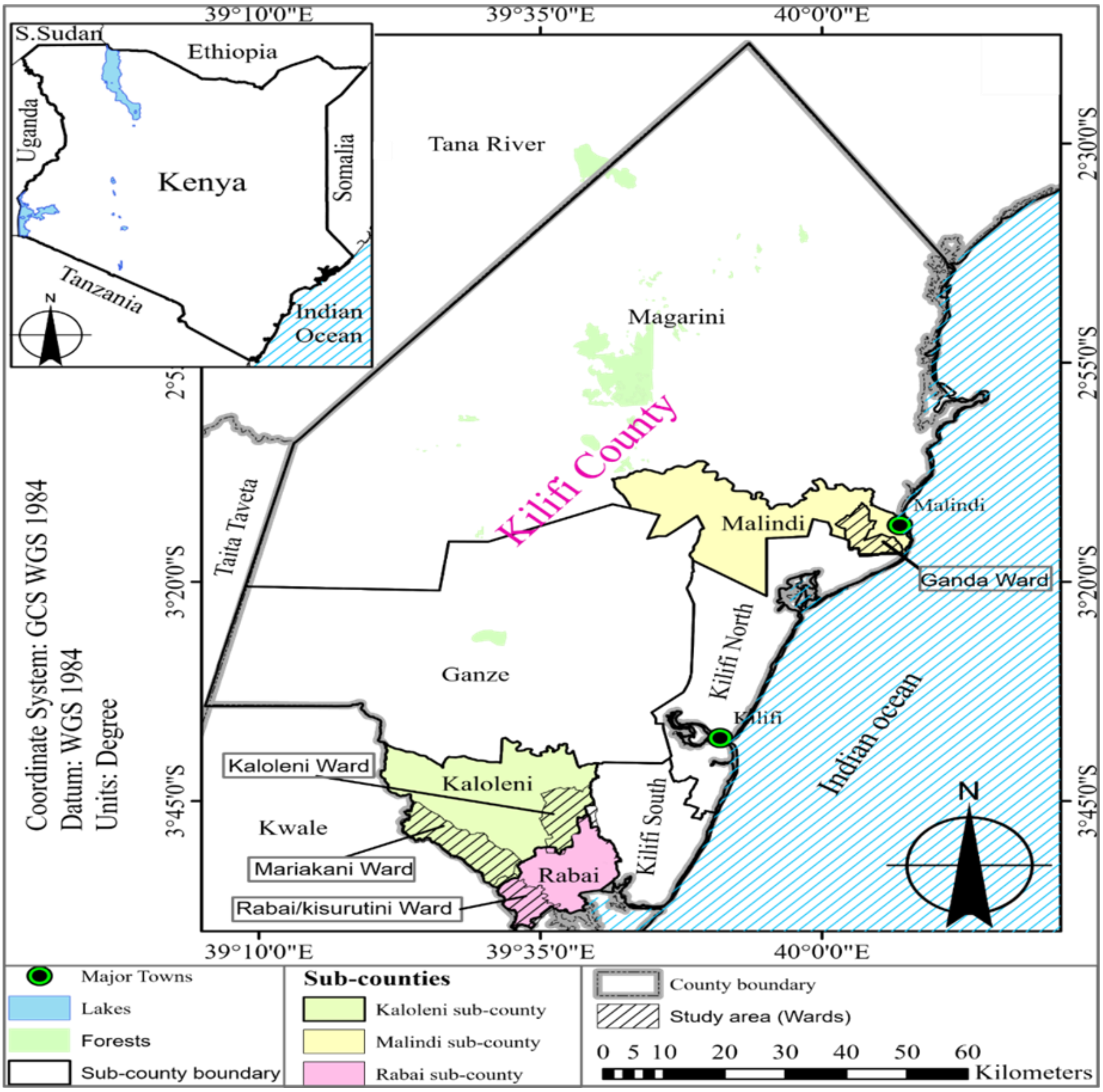

Figure 1: Map of Kilifi County

Since the exact population size of coconut farmers in Kilifi County is known with certainty, the desired sample size was derived from the approach of Yamane (1967), as shown in Equation (1). According to AFA-NOCD (2020), the actual number of coconut farmers in Kilifi County was 47 561. The sample size was calculated at a 95% confidence level, where "*e*" was 0.05

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

where n is the sample size, N is the population size, and "*e*" is the level of precision. Equating smallholder farmers' population size, which is 47 561 farmers, and the level of precision, namely 0.05, then the sample size for the study had to be 384 coconut farmers, as shown in Equation (2).

$$n = \frac{47561}{1+47561(0.051)^2} = 384 \text{ coconut farmers} \tag{2}$$

Hence, a sample of 384 coconut farmers participated in the study. The sample was distributed across the four selected wards, proportionate to the population size per ward.

The study collected primary data from coconut farmers using a semi-structured questionnaire administered by duly trained enumerators. The questionnaire covered socioeconomic and institutional factors, and the types of dissemination pathways used to access information on CE practices. The questionnaire design was done in the mobile-based KoboCollect data collection platform. In preparing the enumerators to administer the questionnaire, two days training was conducted so that they could familiarise themselves with the questionnaire, which was administered using smartphones. Before data collection, a pilot study was conducted to ascertain the feasibility of the digitised data collection tool. Connelly (2008) recommends that a pilot study sample should be done by at least 10% of the total sample size. Therefore, a pilot study was conducted in Watamu and Matsangoni wards in Kilifi North sub-county among 39 randomly selected coconut farmers. The results from the pilot study were used to refine and improve the questionnaire. Data collection was done in an offline-online mode. This meant that data was collected offline, but internet connectivity was needed only when sending the completed questionnaires to the Kobo Toolbox server. The data was collected by a team of five enumerators in June and July 2023. Upon completion of the survey, data was exported to STATA software for cleaning and analysis. Econometrics and descriptive analyses were used to analyse the obtained data. The study adhered to ethical principles, including voluntary participation, informed consent and confidentiality, and was granted ethics approval by the National Commission for Science, Technology, and Innovation (NACOSTI) to ensure compliance with research integrity standards.

Table 1: Sample size and distribution

Wards	Population	Proportion to size	Sample
Mariakani	43 199	0.24	94
Kaloleni	56 026	0.32	122
Ganda	32 562	0.19	72
Rabai	43 144	0.25	96
TOTAL	174 931	1	384

2.2 Empirical strategy

The dependent variable for the study was time lag preceding adoption. Famers' socioeconomic, institutional characteristics and the type of dissemination pathway used to acquire information were the independent variables. Some of the independent variables vary with time (age, coconut produced, prices) and others that are time-invariant (geographical location, gender, dissemination pathways used). Therefore, to model the influence of various dissemination pathways and other covariates on the time lag preceding the adoption of CE practices, duration analysis was employed. This is because the response variable is the time until an event of interest occurs, which in our case is the adoption of CE practices.

Duration analysis is a statistical method that originated from biomedical and statistical engineering, and studies the expected time an individual spends in one state before transitioning to another (Burton *et al*. 2003; Dadi *et al*. 2004). This modelling has recently gained popularity in agricultural economics to explain factors affecting the time lags for new agricultural technology to be adopted by a farmer (Burton *et al*. 2003; Dadi *et al*. 2004; Ahsanuzzaman 2015; Beyene & Kassie 2015; Ngango & Hong 2021; Kaur *et al*. 2023). For the present study, duration time was defined as the period from when a farmer first learnt about or became aware of CE practices to the time he/she adopted this technology. This variable was measured as the date at which the innovation was first made available, or the date at which the respondent started farming, whichever is latest, until the time the farmer adopted the technology, as proposed by Burton *et al*. (2003). A farmer has two states – adoption and non-adoption – hence the model was to determine the influence of dissemination pathways on the time to transition between the two states. In other words, duration was measured as the time it took for an individual farmer to move awareness to the adoption stage (Kour *et al*. 2023). For the farmers who had not adopted CE practices by the end of the study period, their duration was right-censored at the time of data collection, indicating that, for these farmers, the process is ongoing.

To establish the framework, let the length of adoption time be denoted by a non-negative continuous random variable, T, such that $T \geq 0$. As noted by Beyene and Kassie (2015), probability theory plays a fundamental role in duration analysis. Rather than explicitly focusing on the length of time of a spell, one can consider the probability that the spell will end in the next short time interval, given that it has lasted to that period (Burton *et al*. 2003). The probability that a farmer adopts CE (if he/she had not adopted before), at time t, is defined by a conditional distribution function, as follows:

$$F(t) \text{ as: } F(t) = \Pr(T \leq t) \quad (3)$$

Thus, if T is a non-negative continuous random variable representing the duration of stay in a given state in the case of adoption, the time a farmer waits before adopting, or the probability of an individual not adopting until or beyond time t, is given by the survival function, $\{S(t)\}$, as

$$S(t) = 1 - F(t) = Pr\,(T \geq t) \quad (4)$$

To explore the relationship between explanatory variables to the timing of adoption, a hazard rate, $h(t)$, was specified. This is the instantaneous rate of adoption obtained by taking the average of the duration of stay in the non-adoption state over a short time interval, Δt. The hazard rate is formally given as:

$$h(t) = \lim_{\Delta t \to 0} \frac{\Pr(t \leq T < t + \Delta t \mid T \geq t)}{\Delta t}, \quad (5)$$

where $h(t)$, the hazard rate, is the probability that farmer i adopts circularity innovations at time $T + \Delta$, conditional on him/her not having adopted at time t, and Δ is short interval of time.

According to Ngango and Hong (2021), duration analysis can be conducted by way of three fundamental approaches: non-parametric, semi-parametric, and parametric. The non-parametric approach includes the Kaplan-Meier (KM) and log-rank test. It does not make assumptions about the probability distribution of survival time, unlike the parametric approach. The Kaplan-Meier (KM) survival estimate is the most commonly used in the non-parametric approach for its simplicity (Abebe & Bekele 2015). Its function is expressed as follows:

$$S_{KM}(t) = \prod_{t_j < t} \frac{n(t_j) - d(t_j)}{n(t_j)}, \quad (6)$$

where t represents time, n is the number of subjects at risk of failure, and d represents the number of failures.

The most popular way of specifying a hazard function (Equation (5)) in empirical modelling (i.e., semi-parametric and parametric models) is by way of the proportional hazard models proposed by Cox (Dadi *et al*. 2004). Its function form is expressed as:

$$h(t \mid X_i) = h_0(t)\exp(\beta X_i), \tag{7}$$

where β is a vector of parameters to be estimated, and $h_0(t)$ represents the baseline hazard, which is solely a function of time and is independent of the covariates, (X). Furthermore, exp (βX_i) is the relative hazard that depends on the covariates, (X), which may influence the speed of adoption, and β is a vector of parameters to be estimated. According to Alcon *et al*. (2011), the exponential specifications of the PH model guarantee that the hazard function, h, is non-negative, as required by definition, without imposing restrictions on the parameter.

Several parametric specifications for the hazard function have been suggested for duration analysis (Beyene & Kassie 2015; Ngango & Hong 2021). The most widely used functional forms in empirical studies include the Weibull, exponential, log-logistic, lognormal, generalised gamma and Gompertz. The Weibull model can accommodate both increasing and decreasing hazard functions, while the exponential distribution has a constant hazard function, which suggests that the conditional probability of an event is independent of the duration of time (Burton *et al*. 2003; Dadi *et al*. 2004).

The hazard function is estimated by the maximum likelihood procedure. Here, the illustration of the likelihood function accounts for both farmers adopting within the study period (i.e., completed spells) and farmers not adopting the technology by the end of the study period (i.e., censored spells). Thus, following Burton *et al*. (2003), the log-likelihood function is defined as:

$$Ln\ L(\theta) = \sum_{i=1}^{n} c_i lnf(t_i, \theta) + \sum_{i=1}^{n} (1 - C_i) \ln S(t_i, \theta), \tag{8}$$

where n is the sample size and θ denotes the parameter to be estimated, $lnf(t_i, \theta)$ represents the likelihood contribution for completed spells, while the survival function, $\ln S(t_i, \theta)$, represents the likelihood for the censored individual, i, not to adopt the technology by the end of the study period.

The socio-economic, institutional and dissemination pathways used as explanatory variables were adopted from previous, related studies in developing countries (Murage *et al*. 2012; Kinyangi 2014; Beyene & Kassie 2015; Wanyama *et al*. 2016; Simtowe *et al*. 2019; Worku 2019; Kimathi *et al*. 2021; Mogaka *et al*. 2021; Njenga *et al*. 2021; Fadeyi *et al*. 2022; Wairimu *et al*. 2022). These variables include age, sex, education level, land size, farming experience, group membership, social capital, household size, off-farm employment and access to credit. The dissemination pathways include public barazas (public meetings), radio, farmer field schools (FFSs), field days (FDs) or open day demonstrations, farmer teachers/trainers (FTs) and fellow farmers (FF) (farmer-to-farmer extension), as presented in Table 2.

Table 2: Description of variables to be used in duration analysis model

Variable	Description of the variables	Measurement	Hypothesised sign
Dependent variable			
Duration	Number of years from the date of first hearing to the date of adoption		
Independent variables			
Socioeconomic factors			
Gender	Gender of household head	Dummy (1 = male; 0 = female)	+/-
Age	Age of household head (years) at time of adoption	Discrete	+/-
Educ	Level of formal education of household head	Categorical	+
H/h size	Number of people residing in the household	Discrete	+/-
Landcoco	Land allocated to coconut farming	Continuous	+
Off-farm	If the household head participated in any off-farm employment	Dummy (1 = yes, 0 = no)	+/-
Institutional factors			
Crdtacess	Availability of credit services	Dummy (1 = yes, 0 = no)	+
Famfreq	Frequency of interaction with members of family in the ward on CE practices	Continuous	+
ActorFreq	Frequency of interaction with other value chain actors	Continuous	+
Dissemination pathway			
FFS	Farmer has attended farmer field school	Dummy (1 = yes, 0 = no)	+
FDs	Farmer has attended field days	Dummy (1 = yes, 0 = no)	
FT	Farmer has been trained by farmer teachers	Dummy (1 = yes, 0 = no)	+
FF	Farmer has been trained by fellow farmers	Dummy (1 = yes, 0 = no)	+
Radio/ television	Farmer has received information on CE from radio/television	Dummy variable (1 = yes, 0 = no)	+
Baraza	Farmer attended baraza related to circular economy	Dummy (1 = yes, 0 = no)	+

3. Results and discussion

3.1 Descriptive results

Table 3 presents the results of the descriptive analysis of the key variables describing farmers' and farm characteristics. To find significant differences between adopters and non-adopter, a t-test was employed for continuous and chi-square statistics (χ^2) for the categorical variables. Among 384 household farmers, 74.74% had adopted at least one circular economy practice, while 25.26% had not adopted any CE practices in the reference period. The average time to adoption of CE practices was 14.5 years. This implies quite a lengthy lag time, indicating generally slow uptake and implementation of CE practices among farmers after their initial access to information.

The results reveal that adopters of circular economy (CE) practices in coconut farming had an average age of 51 years, while non-adopters averaged 54 years. This suggests that younger farmers may be more inclined to adopt innovative and sustainable farming practices. The households had seven members on average, suggesting that the majority of the households were an extended type of family system. In contradiction of the findings, Kenya's population census of 2019 indicated an average household size of five persons in Kilifi County and a national average of 3.9 persons (KNBS 2019).

The study found that adopters of circular economy (CE) practices in coconut farming had an average of 19 years of experience, while non-adopters averaged 22 years, with the t-test revealing a significant difference between the two groups. This suggests that less experienced farmers may be more open to adopting innovative and sustainable farming practices. This agrees with the findings of Finizola e Silva *et al*. (2024), who found that less experienced farmers are often more receptive to adopting new agricultural technologies and methods.

Table 3 shows that 58% of household heads were male and 42% were female, reflecting the patriarchal system in coastal Kenya, where men have greater access to resources and land rights. Njenga *et al*. (2021) similarly found that men are the primary decision-makers in family leadership, influencing key household and economic decisions, while women often play supportive roles. The study also found that 64.6% of household heads owned their coconut farms with title deeds, while 35.4% did not possess a title deed. The chi-square results show a 1% level of significance, indicating that adopters were more likely to have legal land ownership than non-adopters. This shows the association between land ownership status and the adoption of CE practices.

Table 3: Summary statistics of key variables between adopters and non-adopters

Continuous variables		**Adopters**	**Non-adopters**	**Pooled**	**t-test**
Time to adoption		14.5	–		
Age (years)		51.47	53.96	52	1.35*
Household size (number)		7.11	6.85	7.05	-0.64
Total land owned (acres)		2.89	2.17	2.26	0.41
Total land under coconut (acres)		1.44	1.10	1.35	-1.53
Experience in coconut farming (years)		18.99	22.47	21.59	2.6***
Categorical variables	**Category**	**Non-adopters**	**Adopters**	**Pooled sample**	**Chi^2**
Gender	Female	35.1	44.2	41.93	
	Male	64.9	55.8	58.07	
Education	No school	21.65	30.66	28.39	9.16
	Primary school complete	17.53	24.04	22.40	
	Primary school incomplete	25.77	21.95	22.92	
Land ownership	Own without title deed	49.48	30.66	35.42	11.23***
	Own with title deed	50.52	69.34	64.58	

Note: * and *** indicate significance at the 10% and 1% level, respectively

Table 4 shows the distribution of the dissemination pathways in the study area. At least 22.9% of the sampled farmers received information about CE practices for the first time from radio/television. Farmer networks, including information shared between fellow farmers and through organised farmer groups, collectively reached 34.4% of respondents in this study. The results indicate that 11.7% of the sampled farmers received information on CE practices via farmer teachers. Moreover, 17.2% of the sampled farmers received information about CE practices for the first time from field days and farmer field schools. The results also indicated that 13.8% of the sampled farmers source information concerning CE practices from baraza.

Table 4: Farmers' stated first sources of information about CE practices

Pathway	Percentage of farmers per ward, and overall				
	Overall	Ganda	Kaloleni	Mariakani	Rabai
Field days	8.1	4.11	11.48	10.64	4.21
Fellow farmers	19.0	21.92	13.93	23.40	18.95
Radio/television	22.9	26.03	22.13	23.40	21.05
Baraza	13.8	8.22	16.39	12.77	15.79
Farmer field schools	9.1	9.59	11.48	7.45	7.37
Farmer teachers	11.7	9.59	13.93	5.32	16.84
Farmer group	15.4	20.55	10.66	17.02	15.79

3.2 Non-parametric results

According to Ngango and Hong (2021), a non-parametric approach in duration analysis examines the probability of survival times for all observations in the sample, without considering the effect of explanatory variables. The Kaplan-Meier estimate is employed when the dataset contains censored observations. Figure 2 presents the Kaplan-Meier survivor function for adoption, that is the proportion of farmers who had not adopted (surviving) the technology at the time of the survey. Initially, all cases enter the graph at time t = 0, where the value of survival probability is one, since all farmers are non-adopters at this stage. The value of the function decreased rapidly in the first 20 years, implying that, during these years, many farmers were able to adopt the technology. However, after the 20 years, it decreased at a sluggish rate. The survival probability seems to continue to fall, implying that the uptake of CE practices is still ongoing.

Although the non-parametric approach is advantageous, since it does not require assumptions about the underlying probability distribution of survival times, it does not explicitly model the effects of the explanatory variables (Burton *et al*. 2003; Dadi *et al*. 2004). Therefore, a parametric duration was employed to assess the influence of dissemination pathways on the time taken by farmers in Kilifi County to adopt coconut circular economy innovations.

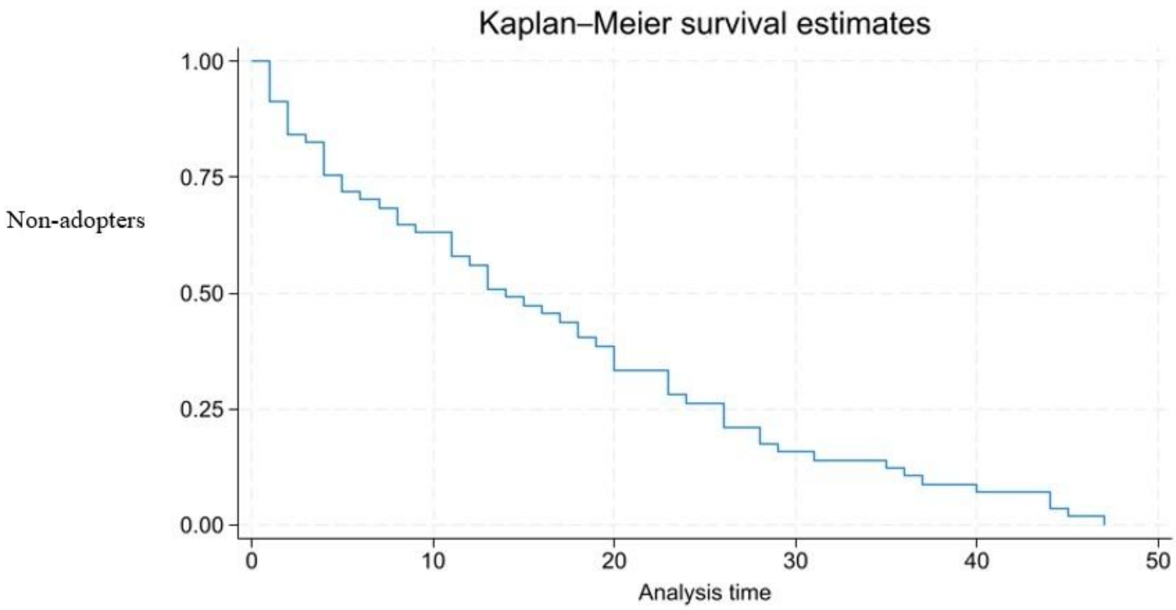

Figure 1: Kaplan-Meier survivor function

3.3 Parametric results

Before conducting the survival analysis, diagnostic tests were performed to assess the fit of the models, specifically the exponential and Weibull proportional hazards models. As noted by Ngango and Hong (2021), the Akaike information criterion (AIC) and Bayesian information criterion (BIC) are usually used as measures of goodness of fit. They were used to select the model that best fits the data. In other words, these criteria balance the complexity of a model against how well it fits the data, with lower values indicating a better fit. The AIC and BIC for both models are displayed in Table 5.

Table 5: AIC and BIC results for exponential and Weibull proportional hazards models

Model	N	(null)	(model)	Df	AIC	BIC
Exponential	348	-179.1747	-144.3877	17	322.7754	386.9955
Weibull	348	-178.0701	-113.2193	18	262.4386	330.4363

The results established that the Weibull proportional hazards model had the lowest values of AIC (262.44) and BIC (330.44) compared to the values of the exponential model. According to Beyene and Kassie (2015), the distribution with the least AIC and BIC bests fits the data. Therefore, the Weibull PH model best fits the data. More importantly, by using the Weibull distribution approach, more reliable and accurate estimates were obtained of the influence of dissemination pathways on the time it took farmers in Kilifi Country to adopt innovations of the coconut circular economy (Lemessa 2017).

The results for the Weibull hazard function are presented in Table 6. The table provides a comprehensive overview of the hazard ratios, along with their respective standard errors and z-values for different variables. According to Beyene and Kassie (2015), a hazard ratio greater than one suggests that an explanatory variable has a positive impact. In other words, it implies that the variable hastens the conditional probability of adoption. A hazard ratio of less than one implies that a covariate has a negative effect on adoption speed, while a unit hazard suggests that an explanatory variable has no impact on the adoption speed.

In a Weibull distribution function, p is the shape parameter, capturing the monotonic time dependency of the phenomenon at hand. In this study, the shape parameter, p (3.046), in Table 6 is greater than one, implying positive duration dependence. Therefore, the probability of the adoption of circular economy innovations among farmers increases over time. Further, Murage *et al*. (2011) note that the parameter, "ln_p", measures the rate of change in the adoption process. The estimated results show a positive "ln_p" (1.114) and that it was highly significant ($p < 0.001$), implying that there was a positive rate of change over time. The log-likelihood values indicate Prob > chi^2 = 0.0000, indicate that the explanatory power of the duration model had a strong effect.

The results show that several variables have statistically significant effects on the hazard of adopting CE practices. Notably, variables such as access to credit, frequency of interaction with other value chain actors, farmers' perceptions of the importance of CE, and the information pathway, namely media such as radio and TV, were significant. These all had a hazard ratio of greater than one, implying that these variables accelerated the conditional probability of CE adoption, given their reference variable. On other hand, the frequency of interaction with friends and family on coconut farming, and dissemination pathways such as FFS, were also significant, but with a hazard ratio of less than one, implying that it took a longer time before adoption. All the other variables included in the model were not significant.

Table 6: Weibull proportional hazard models: Results for influence of dissemination pathway on time to adopting coconut circular economy innovations

Variable	Hazard ratio	Standard error	Z value
Socio-economic factors			
Age of the household head	0.99	0.01	-0.81
Sex of the household head	0.76	0.24	-0.85
Education level of the household head	1.09	0.11	0.9
Household size	1.01	0.04	0.27
Participation in off farm employment	1.10	0.33	0.32
Farmers perception on importance of CE	1.56*	0.41	1.7
Institutional factors			
Frequency of interaction with other value chain actors	1.06*	0.03	1.92
Land under coconut	0.93	0.11	-0.59
Credit access	3.43***	1.56	2.71
Frequency of interaction with friends and family on coconut farming	0.99*	0.01	-1.7
Dissemination pathways			
Baraza	0.87	0.27	-0.44
Farmer field schools	0.41*	0.22	-1.68
Field days (FDs)	1.29	0.39	0.85
Radio and television	2.95**	1.27	2.51
Lead farmers	0.89	0.29	-0.35
Cons	0.000222***	0.01	-6.29
/ln_p	1.11***	0.11	9.58
P	3.05	0.354	
1/p	0.33	0.05	
Number of observations	348		
Number of failures	57		
LR $chi^2(16)$	129.70		
Prob > chi^2	0.000		

Note: *, ** and *** indicate significance at the 10%, 5% and 1% level, respectively

For all the dissemination pathways considered, only two pathways, namely farmer field schools (FFSs) and radio and television, were found to significantly influence the speed of CE adoption (Table 6). However, these two pathways had contrasting effects on adoption. Farmer field schools were found to slow the adoption rate, as indicated by a hazard ratio of 0.41, which is less than one and statistically significant at the $p < 0.05$ level. This suggests that farmers who acquired information through FFS were less likely to adopt CE practices, indicating a delay in adoption. The findings are consistent with Murage *et al*. (2011), who found that FFS led to a delay in the uptake of push-pull technology (PPT) in Western Kenya because of the intensive learning process and the need for repeated farmer interactions before adoption. In contrast, radio and television had a coefficient of 2.95, which is greater than one and statistically significant at the $p < 0.01$ level. This suggests that farmers exposed to CE information through the mass media were more likely to adopt the practices quickly. This finding aligns with the work of Nazli and Smale (2016), who found that radio programmes effectively disseminate information, leading to the increased adoption of these agricultural innovations. This can be attributed to the broad reach, accessibility and repeated exposure provided by mass media, making it one of the most effective tools for disseminating agricultural innovations. These results imply that intensive, structured learning approaches such as FFS may slow down adoption, whereas mass media can accelerate it by providing quick, widespread access to information.

Farmers' perceptions of the importance of CE had a hazard ratio greater than one (1.568) and was statistically significant ($p < 0.05$). This indicates that farmers who perceived CE as important were more likely to adopt CE practices at a faster rate compared to those who did not perceive CE as important. This finding implies that farmers who place a higher priority on the importance of conservation practices are quicker to implement them in their own fields. This aligns with the theory of planned behaviour, which states that attitudes shape intentions, which in turn drives adoption decisions (Ajzen 2020). Therefore, when farmers perceive environmental practices as more personally beneficial, worthwhile and effective, they form stronger intentions to utilise them, hastening the adoption process. This study's findings are similar to those of Meijer *et al*. (2015), who found that farmers with positive perceptions of the importance of sustainability had a significantly positive relationship with adoption rates. Therefore, agricultural policies and programmes boosting awareness of the importance of adoption can widen implementation by increasing the speed of adoption.

Credit access had a hazard ratio of 3.432, which is greater than one, and was statistically significant at the $p < 0.01$ level. This indicates that farmers with access to credit are more likely to adopt CE practices at a faster rate compared to those without access to credit. A plausible explanation is that credit access enables farmers to acquire the required capital to mechanise coconut production as well as purchase complementary inputs. Furthermore, with access to affordable credit, farmers likely feel more empowered to try new revenue streams from underutilised waste resources that require some upfront costs before generating returns. As such, credit unlocks the working capital required to take on any risks, as well as to overcome short-term losses. This finding is in line with those of Ngango and Hong (2021), who found access to credit results in faster adoption of both fertilisers and improved maize varieties. The findings imply that improving access to credit for farmers can significantly accelerate the adoption of circular economy (CE) practices in coconut production by providing the necessary capital for investment in technology and sustainable practices.

Surprisingly, with respect to social networks, the frequency of interactions with family members and friends on coconut farming had an unexpected hazard ratio of 0.993, which is less than one and statistically significant at $p < 0.05$. This implies that, as the number of times a farmer interacts with family and friends on issues concerning coconut farming increases, they were likely to adopt CE practices slightly later than those with a lower number of interactions. The results align with the hypothesis of Di Falco and Bulte (2011), namely that social networks may hinder the adoption of technology. One possible explanation is that strong norms within tightly-knit social circles may create peer pressure that reinforces existing practices and makes farmers hesitant to adopt new approaches until they become more widespread. As such, when social connections are dominated by those with similar cultural backgrounds and experiences, it can limit exposure to diverse viewpoints and openness toward adopting new agricultural technologies and practices such as CE. The results are in line with the findings of Beyene and Kassie (2015), who found that the number of relatives that the household can rely on in times of critical need is negatively related to the speed of adoption of the technology.

The frequency of interaction with other value chain actors had a hazard ratio of 1.063, which is greater than one and statistically significant at $p < 0.05$. This indicates that farmers who frequently interact with other value chain actors, such as processors, traders and input suppliers, are more likely to adopt CE practices at a faster rate compared to those with fewer interactions. These findings are in line innovation diffusion theory (Rogers 2003), which posits that a broader network bridging farmers to external information sources exposes them to new ideas and technologies, making adoption more likely. As noted by Abdulai and Huffman (2014), embedding farmers within wider social systems beyond just community ties provides exposure to new agricultural innovations and persuasion to shift entrenched techniques. This is even more so given the low level of extension services in many rural areas, specifically Kilifi County. Therefore, farmers' interactions with other value chain actors may supplement the information they have, thereby facilitating the quicker adoption of CE. The positive effect of value chain actor engagement on adoption here reinforces conclusions regarding the pivotal role played by bridging social capital with external partners in the diffusion of agricultural innovation, technology transfer and sustainable intensification.

In the context of the duration analysis presented in Table 6, the term ‘failures’ refers to farmers who adopted circular economy (CE) practices during the study period. This aligns with the standard definition in survival analysis, where a failure represents the occurrence of the event of interest. While the descriptive statistics show that 74.74% of farmers adopted at least one CE practice, only 57 farmers were considered ‘failures’ in the model because they adopted during the study period, with the remaining farmers being right-censored. Right-censoring refers to farmers who had not yet adopted CE practices at the time of data collection, and their duration was considered incomplete.

4. Conclusions and recommendations

The timely adoption of CE by coconut farmers in coastal Kenya means improved livelihoods and increased food security through the utilisation of coconuts and their by-products. Using duration analysis, this study examined the effect of dissemination pathways on technology adoption in order to inform on the dissemination pathway that promoted faster technology dissemination and adoption. The findings indicate that the use of mass media is the quickest way to spread technology information, since it has a low cost, reaches large audiences, and does not require high literacy levels to understand key messages. The use of FFS concurrently was found to slow the spreading of information, and therefore led to the delayed adoption of CE practices due to the time required to train farmers. To accelerate CE adoption while maintaining the benefits of farmer field schools (FFSs), it therefore is necessary to integrate mass media, decentralised peer-led training and shorter, more intensive training modules. All these can enhance information dissemination and reduce delays. Policy insights derived from this study suggest that strategies of promoting a faster adoption rate of intensive agricultural practices should focus on teaching and providing relevant information through the media, with radio and television in particular. This may imply that, in the development of a dissemination strategy, radio and television must be considered if speedy adoption and diffusion of a technology is to be achieved. However, for information-intensive innovations, other dissemination pathways that promote learning by doing should be used.

5. Limitations and further considerations

This study has several limitations that should be acknowledged. First, the data collected was self-reported by the farmers, particularly regarding the timing of their awareness and adoption of CE practices. As such, the study may be subject to recall bias, where farmers may not accurately remember or report the exact timing of these events, and social desirability bias, where farmers may overstate their adoption of CE practices to align with socially acceptable norms. These biases may affect the accuracy of the estimated duration of time between awareness and adoption, which could influence the study’s conclusions.

In addition, while the study employs the Weibull proportional hazards model, which assumes that the effects of explanatory variables on the likelihood of adoption remain consistent over time, the proportional hazards assumption was not formally tested. Future research could benefit from testing this assumption, such as using Schoenfeld residuals, to confirm that the model’s findings are valid.

Acknowledgements

This paper is part of an ongoing master of science in the Collaborative Masters in Applied and Agricultural Economics programme undertaken by the corresponding author. The authors wish to thank the African Economic Research Consortium, for its support through Egerton University. The study benefited from funding from the African Economic Research Consortium (AERC) (an AERC thesis grant). The data used in this study comes from the household survey conducted in Kilifi County, Kenya in the year 2023 and is available on request

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