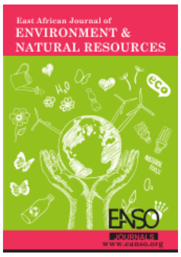

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Original Article

Role of Household's Tree Population, Socio-economic and Behavioural Determinants on Carbon Footprint Mitigation and Carbon Credit Balance in East Ugenya Ward, Kenya

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ABSTRACT

Scope 1 harmful emissions are directly linked to high levels of industrialization; Scope 2 and 3 carbon footprints are locally oriented and indirectly associated with household activities and behavioural alignment. East Ugenya Ward is perceived as the leader in firewood consumption, with the socioeconomically marginalized population in Siaya County resorting to this mode of fuel usage. Conversely, how the mentioned factors relate to both carbon footprints and credits is concluded with no concrete local and global resolution. The effort to reverse households' carbon emissions through green energy campaigns has proved less operative due to little understanding of carbon-related working concepts and socio-economic hardships. This study analyses the role of household Tree population. It assesses the role of socio-economic and behavioural determinants in relation to carbon footprints and potential credits that can arise through sound environmental management within local community initiatives. Three hundred eighty-four household heads were interrogated. A descriptive cross-sectional research design and simple random sampling were found to be functional. Databases were Questionnaires, field research, measurement, photography, Focused Group Discussions, observation, key informants, and enumeration. Carbon Footprint Calculator (C.F.C.) and (V.C.S.)-Verra were used to assess the household's emissions and potential credits. The spatial scale for tree population count was 20 m x 20 m quadrat. The tree-based biomass was translated using a conventional carbon sink conversion (Tons of Co2 Equivalent- tCo2eq). Data analysis involved the use of SPSS. The potential net carbon offset was (M = 0.334, SD = 0.006) tCo2eq per household. The Multinomial Logistic Regression model X2 (8, N= 384) = 24.69, Nagelkerke R2=.56, p <. 001, Strongly proved that the belief that Carbon Credit is profitable had a significant statistical association with Carbon Footprint Mitigation. The multiple linear coefficients of determination proved that 67.6%, F (381) = 69.51, p = .031, R2 = .676 of change in Carbon Footprints and 72.1%, F (381) = 72.58, p = .026, R2 =.721 of the variation in Net Carbon Credits, was attributable to combined variation in Tree population, Mean household age, and mean average monthly income. Both the Carbon Footprint and Carbon credit are affected. Therefore, local sensitization is needed to achieve knowledge and understanding of favourable emission budgets and profitable carbon trade.

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INTRODUCTION

Carbon emission is considered non-catastrophic if its net footprints are equivalent to its net credit, and disproportion in the balance may indicate a malfunction in the atmosphere (Billings et al., 1993). The qualitative justification for the relationship between carbon footprints and carbon credits is readily available for local to global studies. Conversely, scanty literature is presented on the quantity's aspects (Kassouri and Altıntaş, 2020). All households are known to emit and offset carbon. Nonetheless, an attempt to understand the balance between carbon footprints and credit attracts mixed scientific reactions (Sobrino and Monzon, 2014). The available literature addresses the carbon issue as though it is universally common knowledge with little regard for scholarly hardships faced by the developing world (Ottelin et al., 2019). The scale for carbon footprint conversion and assessment also assumes the ideal material acquisition and distribution of the modern-day developed society with a low level of consideration for the realities in rural Africa and other developing societies (Wiedenhofer et al., 2018).

Moreover, even if such studies are performed, global organizations and other external agencies command the knowledge, leaving out detailed local experience and input (Patel et al., 2022). Equatorial Africa has been the main source of carbon credit in the carbon trade because the region commands more intact forest cover (Mensah, 2014). With Africa taking on a negative trajectory of forest cover depletion while the industrialized world maintains the carbon emission above the cap, there is a crucial need to speed up research that may reverse the carbon footprints from the global high (Mohammed et al., 2015).

The mentioned studies are important because they show the direction the world will plunge if carbon emission is uncontrolled. Most of the problems and solutions cited were globally scaled, apart from Mensah (2014), who proposed the inclusion of individual rural-based households in carbon footprint mitigation in Africa more so at the local scale. The parameters for assessing the household's carbon emission and credit were unspecified. The role of tree cover in biogenic carbon sequestration was dealt with, even so, the quantitative influence of the household's tree population on carbon credit and footprint. As the trend had been, the unfavourable balance of trade in the international carbon business was again recurring because of inadequate knowledge and information at the grassroots. The leadership in

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sub-Saharan Africa is already agitating for economic fairness in the lucrative carbon sector.

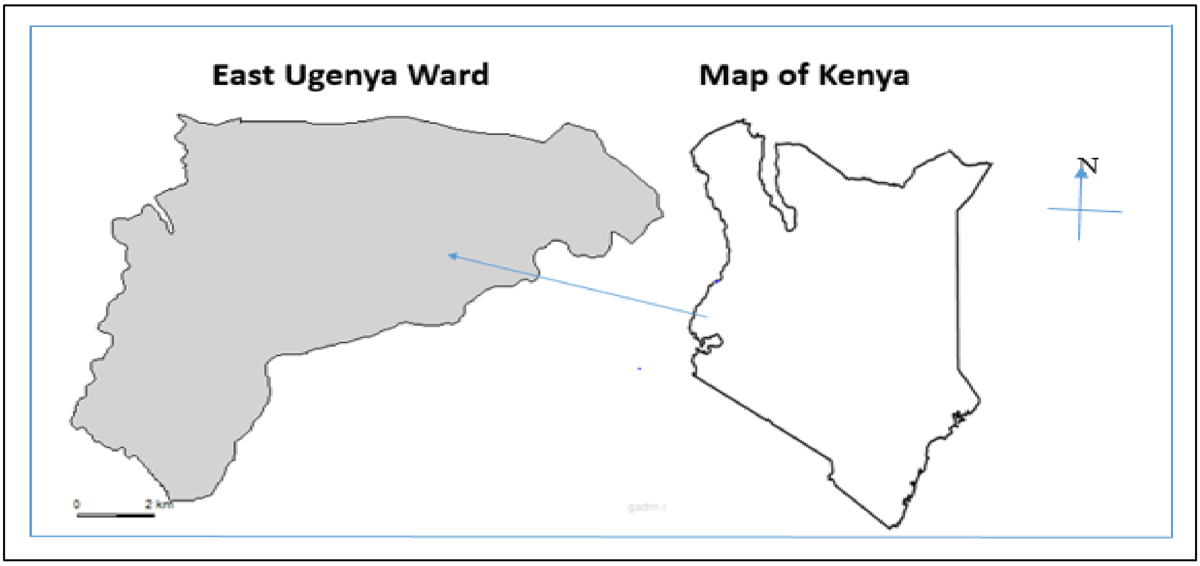
Conversely, unlike other forms of international trade, the carbon sector is more sensitive because, with it, there is a delicate balance including an unlimited economy of scale, fair bargains, Green House Gas (G.H.G) emissions, Global warming, Climate change adaptability through resilient livelihoods, Nature conservation, and effective coping strategies. This is an opportunity to compare the local carbon footprints and credits to national and global averages. Perhaps a parametric analysis of how the forest cover at the household's level, socio-economic, and behavioural determinants operate may assist in understanding the local carbon footprint and credit dynamics, which are the basic foundations for local carbon trade initiatives.

MATERIALS AND METHODS

Study Area

A descriptive cross-sectional research. The East Ugenya Ward (See *Figure 1*) is a village situated in the Ugenya sub-county (Oduor et al., 2022). The locality is considered among the socioeconomically marginalized in Siaya County. The incidences of unauthorized tree harvesting are common in the region because many households are engaged in charcoal burning and brick baking (Musafiri et al., 2022). It is known for bicycle transport among commuting high school students, a habit that contributes positively to offsetting carbon emissions (Oluoch et al., 2020). The majority of the youths are employed in the motorcycle transport industry, which entirely relies on fossil fuels, which is associated with rising carbon footprints on a global scale (Owino et al., 2020). To fit the scale, only aged 10 years or more were enumerated. The number of trees counted was modelled per acre, and the class interval created was then matched with the corresponding tCo^2eq in the scale (Ondiek et al., 2020). Wood fuel is the main source of household energy in East Ugenya Ward. The households of the mentioned Ward were among the first to embrace farm forestry in a bid to mitigate tree cover loss (Oloo et al., 2013). The population was 30,258 persons as of 2019. Using Fisher's formula, a sample of 384 household heads was randomly selected, and questionnaires were administered (Singh & Masuku, 2014).

Figure 1: A Map displaying the location and sketch of the study area



Source: adapted and modified from Oduo et al. (2022)

Data was collected in early December 2022; interviews, focused group discussions, and observation were used to collect primary data on the socio-economics, behavioural, and demographic tendencies of the households. Journals formed the bulk of secondary sources of data. A descriptive cross-sectional survey design was used. One Focused Group Discussion per

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sub-set carefully chosen by simple random sampling was engaged. At least eight to twelve persons per group, as commended by Singh and Masuku (2014), contributed to the dialogue. The outline was discussed in advance with the local administration and the group of the particular local organization. At least a single chief's baraza per sub-location, Outdoor Catering Units during local functions and Gender groupings (*Chamas*) were involved. Questions displayed on the interview schedule were deliberated, and notes were taken for data strengthening. Key informants were interviewed on varied dates they included timber yard owners and solar energy professionals. The consultation schedule comprised questions which needed expertise. The interviewers delivered the study with a technical understanding and inputs in specific subject areas (Singh & Masuku, 2014).

The method was essential in the research because it clarified some preconceived insights and inferences. It gave the researchers an opportunity to gauge the respondents' own perspectives on the issue. It gave relevance in uncovering the ideas or issues which were initially considered insignificant in the research and decision formulation. The flexibility to dig deeper into the subject matter that arose in the discussion made the researchers understand both the accomplished and the unaccomplished study needs (Singh & Masuku, 2014).

Key informants comprised Geography teachers, Forest department officials, Traders dealing with emission-free products, Kenya power officials, and former senior employees of Solar Africa. The Carbon Footprint Calculator (C.F.C.) was used to determine the amount of Carbon emission per household (Lin, 2017). The calculator is a mobile application where household heads' qualitative attributes are fed in, and by the end, it automatically generates a household's carbon footprint. Both the Verified Carbon Standards (V.C.S.)- Verra scale and C.F.C. calculator were useful because they eased and hastened the frequency of complex data collection, conversion, and analysis (Spilker & Nugent, 2022). The econometric formula for calculating net profit was substituted and applied to simplify the calculation of net carbon credit at the household level. Both the qualitative and quantitative data were organized into suitable output layouts. Both Microsoft Excel and SPSS version 22 were applied in quantitative data analysis. Therefore, the multiple linear coefficients of determination (R^2) were the relevant statistical model for measuring the predictors' collective influence on the dependent variable. The research aimed to verify whether the kind of carbon footprint mitigation chosen was predictable from the belief that carbon credit is profitable and a person's income. The kind of carbon footprint mitigation the participants last participated in was recorded as Tree planting, Education/Sensitization, and Adoption of Green innovations. The presence of the binary independent variables called for Multinomial Logistic Regression (Yan et al., 2019). The model is appropriate for assessing the maximum possible binary effect of the latent variables, such as beliefs, emotions, and feelings, on the output variable (Opeyo, 2018).

$$(Gross\ Carbon\ Credit - Carbon\ Footprint) = Net\ Carbon\ Credit \quad (1)$$

Therefore, the percentage (%) of net carbon credit is expressed as;

$$\boldsymbol{Net\ Carbon\ Credit}\ (\%) = \frac{\boldsymbol{Gross\ Carbon\ Credit - Carbon\ Footprint}}{\boldsymbol{Gross\ Carbon\ Credit}} \times \mathbf{100} \quad (2)$$

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RESULTS AND DISCUSSION

The majority of the households (60%) had at least basic education, while 40% of the respondents had attained higher levels of education. More people migrate to the urban sector after successfully graduating from high school (*Table 1*). Formal employment is directly linked to higher education (Eini-Zinab et al., 2021). The rural informal sector has been thriving labour mainly drawn from people with basic levels of education (Hailemariam et al., 2020). Provided that formal urban employment is highly competitive, people with basic education frequently opt to remain in rural areas to embark on farming and other less education-oriented economic practices (Eshton & Katima, 2015).

At least 10% of them were undecided when it comes to offsetting carbon emissions. This was probably because knowledge and understanding of Greenhouse Gas emission is currently low in sub-Saharan Africa (Shao et al., 2022). A substantive 50% of the interviewed households were unwilling to offset their carbon footprints. Local cultural conservation plays a vital role in the adoption of modernity (Song et al., 2020). Rural households in Africa tend to practice the traditional ways of energy use and natural resource conservation (Yang et al., 2022). Nevertheless, 40% of the respondents portrayed the urge to reduce emissions. Through observation, the material indicators were used to assess the level and use of green technology per household, as proposed by (Nam and Jin, 2021). Provided with opportunity and economic power, 80% of the sampled population could upgrade to emission-free technologies. The remaining 20% blamed inadequate technical know-how, which they feared could hinder them from operating the modern green innovations. One of them said:

> *I yearned for higher education because, after successful completion, I imagined I would get a good-paying job. My dream came to pass. My first car was small, as you can see in this photo; later, God blessed me and acquired the big car parked over there. I have heard about tree planting for nature conservation, but how trees and carbon emissions relate is a new idea to me and probably to many others around here* (Oyengo Owiro (not real name), local timber yard owner).

Table 1: Data on the distribution of social and behavioural determinants

	Frequency	Per cent
Basic Education	230	60.0
Higher Education	154	40.0
Undecided to offset carbon emission	38	10.0
Unwilling to offset carbon emission	192	50.0
Willing to offset carbon emission	154	40.0
Unwilling to upgrade to Emission-free technologies	77	20.0
Willing to upgrade to Emission-free technologies	307	80.0

A total of 4,823 trees, as shown in *Table 2*, were counted (M = 12.56, SD = 5.656) trees/household, which translated to about 0.724 tCo^2eq of household’s gross carbon emission sequestration per annum. Biogenic carbon sinks are the common components of carbon offset in the developing world (Mensah, 2014). Old age (about 55 years) was a common scenario among household heads. Retirement was the major driver in urban-rural migration that caused an influx of aged people back into the village (Moser & Kleinhückelkotten, 2018). By conversion, an ordinary household lived on an average of USD 105.85 a month. At Least a net carbon credit of (M = 0.334, SD = 0.006) tCo^2eq per household was potentially available for trade. If the households maintained a status quo, at an average of USD 60/ tCo^2eq based on the Verra scale, each household could earn an average of USD 20.04 of carbon profit per annum. Compared to the national Carbon footprint per capita at 0.34 tCo^2eq per household (Mogaka et al., 2021), this was 14.7% more on a national scale. However, in relation to the global 2017 emission per capita of 4.8

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tCo^2eq/person, the Ward was likely operating at 1,130.76% lower on a global scale. Therefore, the household's carbon sequestration rate was 46.13% above the average local emission rate.

Table 2: Frequencies and Distribution of the Main Variables

	Tree Count/20 m x 20 m Quadrats	Mean household age (years)	Mean average Income/month	carbon footprints (tCo^2eq)	Potential Gross Credit tCo^2eq)	Potential net carbon credit (tCo^2eq)
N	384	384	384	384	384	384
Mean	12.56	54.84	15566.41	0.390	0.724	0.334
StD	5.656	17.026	9633.026	0.028	0.15	0.006
Sum	4,823		5,977,500	149.76	278.02	128.26

A multinomial logistic regression (*Table 3*) was executed to generate a model of the association between the predictor variables and the household's carbon footprint mitigation approaches. The fit between the model having only the intercept and data significantly upgraded with an accumulation of the forecaster variables, X^2 (8, N= 384) = 24.69, Nagelkerke R^2=.56, p <. 001

Table 3: Model Fitting Criteria and Likelihood Ratio Tests for Carbon Footprint Mitigation

Model 1	-2 Log Likelihood	Chi-Square	df	Sig.	Pseudo R-Square (Negelkerke)	N
Intercept Only	1153.966					
Final	24.692	1129.274	8	.0007	.56	384

As shown in *Table 4*, the belief that the mean average monthly income influences carbon footprint mitigation was statistically insignificant in the multinomial logistic regression analysis (*p* = .102). Conversely, the model further revealed that the household's belief in Carbon Credit Profitability was statistically significant (P =.036), the most likely decision to mitigate Carbon footprints.

Table 4: The selected Predictors in Carbon Footprint Mitigation

Effect	-2 Log Likelihood of Reduced Model	Chi-Square	df	Sig.
Intercept	58.326a	.000	0	.
Mean Average Monthly Income (Ksh. ,000)	62.893	4.567	2	.102
Carbon Credit is Profitable	59.404	1.077	6	.036

With the on-farm Tree Planting being treated as a reference category in the multinomial logistic parametric analysis, the sole coefficient ("B" column), which has a statistical significance (table 5), is the second group of coefficients is [Carbon Credit is Profitable = Agree] (p = .021) which is a latent variable signifying the contrast between "strongly disagree and strongly agree" to Carbon Credit is Profitable. The sign is negative (-1.94), showing that if the respondent strongly agreed in comparison to strongly disagree that Carbon Credit is Profitable, then they are more likely to be involved in education and public sensitization as a form of mitigating carbon footprints than being involved in on-farm tree planting. It is, therefore, most likely that the local households are involved in education and sensitization as a form of carbon footprint mitigation rather than in the on-farm tree planting if they strongly agree rather than strongly disagree with the statement that carbon credit is profitable.

> *In our group, as women, we collect funds for table banking and the money is circulated weekly per individual member. Our aim is to*

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get rid of kerosene lamps from our homes because they produce little light and a lot of smoke. Children find it difficult to study at night with such lamps. All of us here hate the use of firewood; it irritates our eyes and is difficult to use in wet weather. We buy solar products on a Must Pay Daily to Use (MPDU) Mobile Loan Subscription (M.L.S.) that runs from 3 months to a year. The products serve us well. As you might have observed, many homesteads are off the main electricity grid, but we are unbothered; we charge phones, watch TV, pump water, and light our homes. We missed a few luxury items like a fridge, electric-powered iron box, and cooker. Ok, on tree planting, we cannot really say much; it is a long story, and it depends on one's family background, religion, culture, and traditions; in short, men understand matters to do with trees better than we, so you should consult with them (In own words of Betty Omoga (not real names), the treasurer of Ujwang'a rice out-growers self-help group).

Table 5: Parameter Estimates for the Multinomial Logistics Regression in Carbon Footprint Mitigation

Carbon Footprint Mitigation		B	Sig.	Exp(B)	Lower Bound	Upper Bound
Adaptation of Green innovation	Intercept	271	.86			
	Mean Average Monthly Income (Ksh. ,000)	-.022	.56	.978	.910	1.053
	[Carbon Credits Profitable=Agree]	-.641	.49	.527	.084	3.293
	[Carbon Credits Profitable=Disagree]	-.096	.92	.909	.155	5.340
	[Carbon Credits Profitable=Strongly agree]	-.330	.73	.719	.113	4.554
	[Carbon Credits Profitable=Strongly disagree]	0b	.	.	.	.
Education and Public sensitization	Intercept	.117	.94			
	Mean Average Monthly Income (Ksh. ,000)	-.146	.081	.864	.733	1.018
	[Carbon Credits Profitable=Agree]	-1.94	.021	.186	.062	.672
	[Carbon Credits Profitable=Disagree]	-.511	.75	.600	.026	.924
	[Carbon Credits Profitable=Strongly agree]	.315	.82	1.370	.086	.852
	[Carbon Credits Profitable=Strongly disagree]	0b	.	.	.	.

The reference category is On-farm Tree Planting.

Plate 1: Ground close-up photo depicting an inefficient wood fuel stove compared to locally assembled solar cookers.

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Table 6: Multiple Linear Coefficients of Determinations

Model	R Square	Adjusted R Square	F	Sig	df
Carbon footprints	.678	.676	69.51	.031	381
Carbon Credits	.723	.721	72.58	.026	381

Predictors: (Constant), Mean average Income/month, Tree Count/20 m x 20 m Quadrats, and the Mean household age(years)

The outcome of multiple linear coefficients of determination (table 6) showed that 72.1%, F (381) = 72.58, p = .026, R^2 =.721 of the variance in the potential carbon credit from the tree-based resources could significantly be justified by the joint change in the values of the predictors. Again, the model proved that a significant 67.6%, F (381) = 69.51, p = .031, R^2 = .676 of the variation in carbon footprints was attributed to a collective variability in the predictors. Finally, the joint change in tree population, Monthly income, and household age could explain a significant 67.2% change in the potential net carbon credit in East Ugenya Sub-County.

Rural households enjoy enormous benefits from trees (Halkos & Tsirivis, 2023). The unharvested tree stands act as net biogenic carbon sinks, thereby assisting households in offsetting emissions (Yan et al., 2017). It is worth noting that for a profitable carbon trade, the locals needed more trees (Basu, 2009). As depicted in plate 1 the carbon emissions came from unrefined use of biomass fuel (Coelho Junior et al., 2019). Electricity and other sources of green energy were either expensive or inadequately available to most locals (Mostafa, 2016). With forest land reducing in size, there is an urgent need to educate households on modern ways of raising carbon credits (Hu et al., 2023). Aged people are generally conservative and deceptive to change (Kragt et al. 2016). This is because the aged lack the impetus to learn new operational manuals (Li et al., 2019). Individuals earning more are likely to conserve natural resources relatively longer (Cacho et al., 2008). On the other hand, poverty is linked to the massive exploitation of natural resources and ecosystem services, which may spell doom to carbon sequestration prospects (Shen et al., 2022). The change in ideological perspective, such as the shift from bicycle riding to motorcycle, may bring speed and efficiency. However, the carbon emission rates remain compromised (Wang et al., 2022). Because of the weak policies and the institutional frameworks, the efforts of the external agencies to promote zero carbon emission at the local scale are likely diluted (Abbas et al., 2021).

Table 7: Multiple linear coefficients and Individual Predictors

Model		B	Std. Error	Beta	T	Sig.
net carbon credit	(Constant)	-.004	.0003		-0.038	.072
	Tree Count/20 m x 20 m Quadrats	.320	.002	.267	18.101	.018
	Mean household age(years)	.078	.003	.858	23.932	.048
	Mean average Income/month	-1.141	.000	.478	-12.149	.033
carbon footprints	(Constant)	.016	.005		.047	.081
	Tree Count/20 m x 20 m Quadrats	-.055	.0011	-.903	-29.479	.0004
	Mean household age(years)	-.023	.002	.314	-9.457	.034
	Mean average Income/month	2.041	.000	.251	9.880	.022

The predictors were further individually examined to determine their influence on Carbon Credit and footprints (*Table 7*). The household's tree count was positive and significant to carbon credit (t = 18.10, p =.018); households that maintained more trees per acre of land were most likely to offset a significant amount of carbon emission. Trees are known to sequester significant carbon emissions (Moser & Kleinhückelkotten, 2018). Mean household age was similarly found statistically significant and positively related to carbon credits (t = -12.149, p = .033); in other

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words, as people aged, they seemed less likely to contribute significantly to emissions. Old people are conservative and actively unaggressive in their daily operations (Mogaka et al., 2021). On the contrary, the average mean monthly income showed a statistically significant negative trend with the potentiality in net carbon credits ($t = -23.932$, $p = .048$). As the income bracket appreciated, the carbon offset prospects likely dwindled. This kind of outcome appeared both controversial and contradictory to a number of the previous studies. For instance, Wei et al. (2017), Nielsen et al. (2021), Zhang et al. (2021), and Yang and Usman (2021) all agreed that improved income and better living standards were good indicators for good carbon emission offsets. In Africa, as people earn more, most resort to living large by acquiring, for example, bigger fossil fuel-guzzling vehicles, which emit more carbon-related fumes (Okoko et al., 2017).

The household's tree population was statistically significant and negatively associated with carbon footprints ($t = -29.479$, $p < .001$). Maintaining more trees on the farm likely reversed the carbon emissions locally. The amount of plant biomass inversely influences the amount of carbon emission in the atmosphere (Li et al., 2021). Similarly, the emission was likely to decrease significantly with a unit increase in household age ($t = -9.457$, $p = .034$). Older household heads lived alone or with a few extended family members who cared for them (Jone & Kammen,2011). Smaller household sizes are known for low emission levels (Liddle, 2014).

> *The entire time I worked for a solar company, I noted low income favoured the sales of most solar products. People with reputable financial ability opted to connect to the electricity grid, some invested in generators. The solar products fit the pocket of a common household. It is also worth realizing that old people preferred basic essential items like a small radio set and lighting systems. Young men took the game further; they bought bigger T.V.s, inverters, amplifiers, and relatively bigger music systems. I understand well the role of trees in our society. We rolled out the solar technology to help curtail the use of fossil biomass fuel and to conserve forests* (Veratim words of Dennis Otis, a former employee of Solar Africa now engaged with Sun King Solar product distribution).

CONCLUSIONS

Carbon credit and emission are new concepts in Ugenya East Ward. The majority of the respondents, though engaged in carbon-related practices, are unaware as to whether they are offsetting or emitting more carbon. Cheapness, efficiency, and ease of availability are the overriding factors in adopting a green innovation. The main reason for tree planting is commercial conversion. When provided with monetary and nonmonetary incentives, most of the respondents are willing to sustain trees on the farms for longer. Education plays a role in Promoting natural resource conservation; even so, there is a need for elaborating on the carbon emission concept. Apart from socio-economic factors, there is a need to address the role of a household's forest quality, cultural orientation, and Psychosocial dynamics in relation to carbon footprint and credit. The local indigenous green innovation should technically be improved through a fair partnership with external agencies. Being equatorially zoned, Cheap solar cooking innovations per household could be the best appropriate in meeting the carbon zero initiative. Because the local emission per capita is slightly above the national scale, there is a need to pay more attention to reversing the Carbon footprints at the local scale. Given the potentiality of net Carbon Credit availability, local households should be brought on board to benefit from the lucrative Carbon Trade.

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