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RESEARCH ARTICLE

The effect of carbon farming training on food security and development resilience in Northern Ghana

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ABSTRACT

Carbon farming has recently been advocated for as climate change and variability mitigation and/or adaptation strategy in global agriculture. In this study, we address an important research question of whether carbon farming training can improve household resilience capacity as well as food security by employing internationally standardized indicators. Household resilience capacity and its components are measured using the Food and Agriculture Organisation (FAO)'s resilience capacity index while the food security measures used include household and child food insecurity experience scale (FIES and CFIES), food consumption score (FCS) and household dietary diversity score (HDDS). We relied on doubly robust treatment effect estimators to account for potential selection bias and heterogeneity. We find that carbon farming training has no statistically significant effect on overall household resilience capacity. However, we find a large and statistically significant effect on key components of resilience (specifically, access to basic services, assets and social safety nets) and a marginal improvement in adaptive capacity. We also find statistically significant effect on FCS and HDDS but not for the other food security indicators (FIES and CFIES). Overall, the results suggest that agricultural training programs, particularly climate change adaptation capacity building initiatives, could improve important welfare measures in developing countries.

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1. Introduction

Carbon farming has been introduced in global agricultural system, particularly in Australia, North America and Europe since early 2000s. Recently, the farming practices associated with carbon farming have become a popular mechanism in climate change and variability frameworks of many developed countries. Carbon farming has been promoted internationally as a major innovation that could increase soil carbon sequestration leading to social, economic and environmental benefits (Kragt et al., 2012; Kragt et al., 2016; Lin et al., 2013; McDonald et al., 2021; Nyssens, 2021). Carbon farming has been defined by the European Environmental Bureau as 'the management of land-based greenhouse gas (GHG) fluxes, including carbon pools and flows in soils, materials and vegetation, with the purpose of reducing emissions and increasing carbon removal and storage' (see Nyssens, 2021, p. 5).

Despite its introduction about two decades ago, carbon farming is yet to receive the necessary attention in the agricultural system of developing countries, particularly in Sub-Saharan Africa (SSA). While carbon farming practices are similar to previous concepts on climate change and variability such as climate-smart agricultural (CSA) practices, their uniqueness lies in the use of land management practices to enhance carbon sequestration (Kragt et al., 2012; Kragt et al., 2016; Lin et al., 2013; McDonald et al., 2021; Nyssens, 2021). Five main components of carbon farming can be identified and these include maintaining and enhancing soil organic carbon (SOC) on mineral soils; livestock and manure management; agroforestry; managing peatlands; and nutrient management on croplands and grasslands (McDonald et al., 2021). Interestingly, the component of carbon farming receiving considerable attention in the literature is SOC due to recent global efforts (e.g. FAO's 'RECSOIL: Recarbonization of Global Soils') in improving soil health for the enhancement of farm performance and welfare (Amelung et al., 2020; FAO, 2019; Vanlauwe et al., 2015). Additionally, SOC is the most important indicator for soil fertility (FAO, 2021).

An important element of SOC is organic/conservation agriculture which among other things involves the application of biochar and compost to boost soil fertility (McDonald et al., 2021). Biochar is defined as a 'product of incomplete combustion (pyrolysis) of organic material' (Sparrevik et al., 2014). The study by Woolf et al. (2010) noted that 'biochar has a larger climate-change mitigation potential than combustion of the same sustainably procured biomass for bioenergy'. Unsurprisingly, the use of biochar in tropical soils has been identified as an important strategy to improve crop productivity through improvement in soil fertility and also to mitigate the adverse effects of climate change and variability (Borchard et al., 2014). Interestingly, the use of biochar and compost (i.e. organic products) has an additional advantage of having less adverse effect on soils and the environment compared to the

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use of inorganic materials which have a high likelihood of pollution and emissions of greenhouse gases (GHGs).

Consequently, biochar and compost application have been advocated internationally as one of the soil carbon mitigation strategies (Bach et al., 2016; Borchard et al., 2014; D'Hose et al., 2014; Gwenzi et al., 2015; Hernández et al., 2016; Ouédraogo et al., 2001; Woolf et al., 2010). Besides, anecdotal empirical evidence suggests that carbon farming practices can benefit farmers in terms of improvement in productivity, food security and development resilience. This has led to attempts by some researchers to understand the productivity and welfare impacts of soil carbon mitigation strategies (Badu et al., 2019; Borchard et al., 2014; Frimpong et al., 2021; Gross & Glaser, 2021; MacCarthy et al., 2020; Woolf et al., 2010). For example, a study by Jeffery et al. (2017) reported that the application of biochar has higher productivity gains for tropical soils compared to temperate soils. However, the empirical literature on the welfare effects of carbon farming in global agriculture is relatively new, and there is still debate on the potential benefits for the various components/categories (see for example, McDonald et al., 2021). Besides, few studies have been undertaken on the effects of soil carbon mitigation strategies (i.e. biochar and compost) on welfare in Sub-Saharan Africa. For example, Okyere and Kornher (2023) documented greater expenditure and poverty reduction due to carbon farming training. Specifically, Okyere and Kornher (2023) showed that carbon farming training allowed farm households to adopt organic fertilizer, and increased their perceptions of soil quality, maize productivity and returns on maize production. The farm households used the benefits from higher farm performance to increase expenses on food and other productive resources leading to significant poverty reduction (Okyere & Kornher, 2023).

This study is related to recent empirical evidence on the impact of agricultural capacity building initiatives (particularly, climate change adaptation strategies) on welfare in developing countries (see for example, Fafchamps et al., 2020; Kansanga et al., 2021; Lee & Gambiza, 2022; Martey et al., 2021; Mgendi et al., 2022; Zakaria et al., 2020). Interestingly, despite the considerable economic wellbeing improvement from carbon farming training programmes (for example, as reported in Okyere and Kornher (2023)), whether such intensive capacity building programmes could also help enhance key welfare outcomes such as food security and development resilience largely remain unanswered. Therefore, the key novelty of this study is that we examine the effect of climate change adaptation capacity building initiatives on important welfare outcomes beyond the farm performance, income and expenditure pathways using rigorous econometric approaches.

To the best of our knowledge, this is the first study that links climate change adaptation capacity building initiatives (particularly, carbon farming training) to household resilience. This study expects that the long-term carbon farming training will increase participation in farmer group activities leading to higher knowledge on resilience to climatic shocks, adoption of soil health practices, and increase in agricultural productivity and finally, resilience to food insecurity. We provide new evidence to the literature on carbon farming in SSA using newly collected data from three semi-arid regions of Northern Ghana. We analyse a 5-year (that is, 2015–2020) project undertaken with funding from United States Agency for International Development (USAID). This project provided biochar and compost preparation training to selected farmer groups in three districts in Northern Ghana using locally available agricultural by-products. Field experiments involving farmers and agricultural extension agents were undertaken in the respective project sites. Therefore, the project adopted a transdisciplinary approach in involving farmers in the design and execution of the field/plot experiments and the subsequent application of the biochar and compost on the farmer fields during 2019 and 2020 farming seasons (see also Okyere & Kornher, 2023).

We find that carbon farming training has a large and statistically significant effect on key components of resilience such as access to basic services, assets and social safety nets. We also find marginal improvement in adaptive capacity. In terms of food security, we find statistically significant effect on food consumption score (FCS) and household dietary diversity score (HDDS). However, we did not find statistical significance on other food security indicators such as household and child food insecurity experience scale (FIES and CFIES) and these results could be partly due to the 12 months' timeframe (instead of the past 24 hours, last 7 or 30 days) used in estimating the indicators by previous studies. However, our results are in consonance with similar works on the welfare effects of agricultural capacity building initiatives (Chesterman et al., 2019; Fafchamps et al., 2020; Martey et al., 2021; Okyere & Kornher, 2023).

These results have two main implications for the literature on the welfare effects of carbon farming. First, we show that a long-term training project on biochar and compost production in three regions of Northern Ghana did not only have positive effect on important food and nutrition security indicators and but also led to improvement in key components of development resilience. These results are interesting as they emerged from the use of internationally accepted and recently developed welfare indicators aside from the usual livelihood outcomes such as income, consumption and expenditure. This study therefore provides the first rigorous empirical evaluation of the prospect that carbon farming, particularly training on biochar and compost production, can lead to resilience to food insecurity, using locally designed project involving farmers, extension agents and researchers from academic institutions in a transdisciplinary framework in Northern Ghana. Second, this study provides new evidence in the broader literature related to the effect of climate change and variability adaptation strategies on development resilience. The results show that training on carbon farming techniques as a climate change mitigating strategy could have far reaching welfare effects in semi-arid areas beyond the impact on intermediary outcomes such as farm performance, income and consumption, which earlier studies such as Okyere and Kornher (2023) dealt with. The broad welfare impact of carbon farming training programme additionally suggests that promoting carbon farming training programmes in developing country contexts such as the study area of this paper can serve as an important avenue to address development issues enshrined in Sustainable Development Goals 1 and 2.

The rest of the study is structured as follows: Section 2 provides the study context, data source and the empirical strategy whilst Section 3 presents the results and discussion. Section 4 concludes the study by highlighting policy implications.

2. Context, data and estimation strategy

2.1. USAID-UG project

The project under study was designed and implemented with funding from USAID (for a more detailed description of the project, see Okyere and Kornher (2023)). Titled *USAID/UG Institutional Capacity Building for Agriculture Productivity Project* (hereinafter USAID-UG Project), this project involved working with selected farmer-based organizations (FBOs) and agricultural extension agents in Bawku municipal, Upper East region; Lawra municipal, Upper West region; and West Mamprusi municipal, North East region (see Figure 1 indicating the map of the project sites). The project districts were selected based on the cultivation of maize, rice and soyabeans (i.e. crops of interest). The 5-year project from 2015 to 2020 aimed at building the capacity of farmer groups and farmers to improve soil climate mitigation strategies in Northern Ghana, thereby improving agricultural productivity and welfare. The project uses readily available agricultural by-products which are not used for other activities in the preparation of biochar and compost. This is also expected to improve waste management in the selected communities.

The USAID-UG Project had four main components: *biochar and compost production*; *technical and business skills training; household waste sorting training; and biotechnology awareness programme*. However, the training on biochar and compost production component was the main project activity which has been vigorously undertaken in the study sites. The USAID-UG Project adopted a transdisciplinary approach to intensively promote the production of biochar and compost in the three selected districts in Northern Ghana among about 15 farmer groups. In each project district, farmers in their respective farmer groups were selected and trained on the production of biochar and compost using available local raw materials. The project also funded the construction of platforms and kilns to produce the biochar and compost. After the training, the farmer groups and also individual farm households have picked up the technology and implemented them by the continuous production and use of biochar and compost for their farming activities. The application of biochar and compost was demonstrated through field experiments and on-farm adaptive trials. Training on the various application rates of biochar and compost was undertaken together with the District Agricultural Extension Agents.

2.2. Data

The study received ethical approval from the Ethics Committee of Basic and Applied Sciences of the University of Ghana in

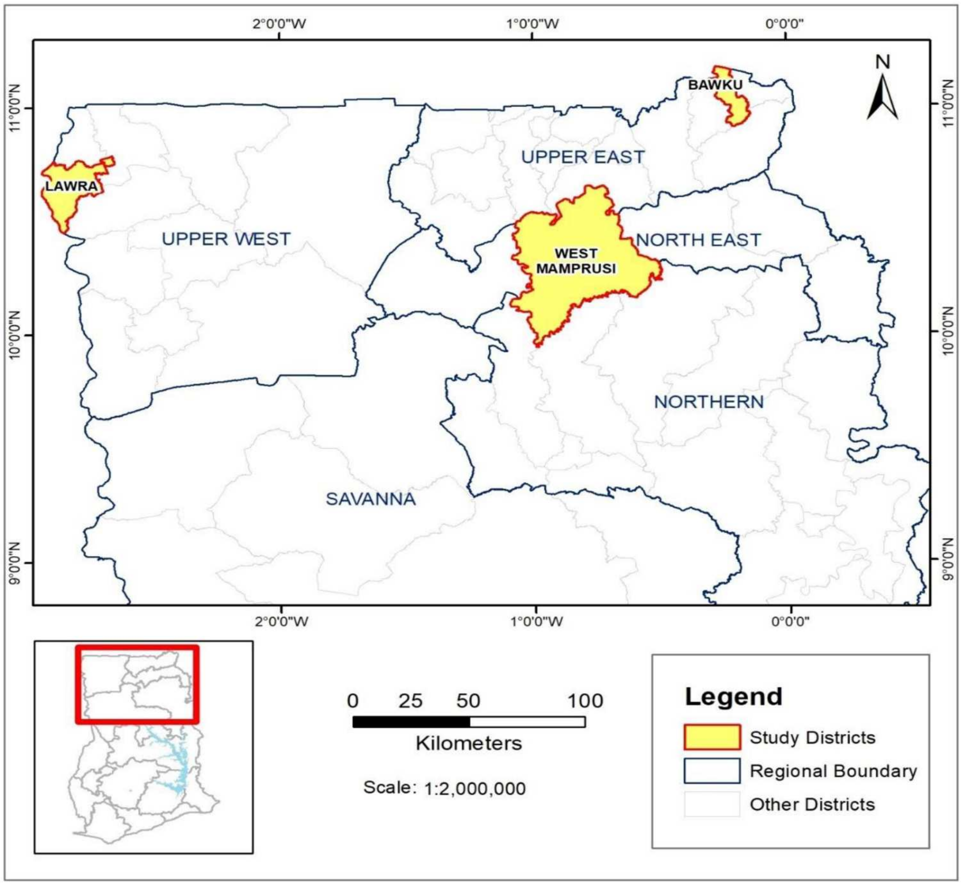

Figure 1. Map of the study sites. Source: Okyere and Kornher (2023).

December 2021. Between March and April 2022, we conducted farm household survey in three semi-arid regions located in Northern Ghana (refer to Okyere & Kornher, 2023 for details). The survey targeted farm households participating in the USAID-UG Project (including training on biochar and compost production component) in addition to non-participating farm households from neighbouring communities in the project sites. The survey enumerated 472 farm households across 38 communities in the three project sites. We employed a multi-stage sampling procedure and also relied on a sample frame from previous pilot surveys conducted in 2020 and 2021 to the select farm households. Based on information from the USAID-UG Project Secretariat and farmer group leaders, a total number of 137 farm households form the initial sample frame based on their participation in the pilot surveys. Furthermore, we proceeded to sample 335 farm households in the project districts who were not interviewed in the pilot surveys. The datasets employed for this study contain 192 farm households who have participated in the project activities, of which 165 farm households participated in the training on biochar and compost production component. Lastly, 280 farm households were classified in the comparison group who did not participate in the project activities. Highly skilled enumerators with tertiary education and knowledge in the local languages were employed to administer the computer-assisted personal interviews (CAPI) designed survey questionnaire using computer tablets. Household heads or spouses were interviewed during the survey due to their extensive knowledge on agricultural production activities, socio-economic characteristics and decision-making authority.

2.3. Estimation strategy

This study examines the effects of carbon farming training (specifically, training on biochar and compost production) on food security and development resilience of farm households in Northern Ghana. We estimate the effects of training on biochar and compost production by comparing welfare outcomes of farm households who participated in the training with the welfare outcomes of farm households that did not participate in the training. We employ a basic regression model, specified as follows:

$$Y_i = \beta + \alpha P_i + \pi X_i + \varepsilon_i \tag{1}$$

where Y_i represents the dependent variable which in this study context are the resilience capacity and food security outcomes for farm household i (see Section 2.4 for detailed discussion on the outcome variables), P_i is a binary treatment variable measured as 1 if farm household i participated in the training on biochar and compost production and 0 if otherwise, X_i is a vector of covariates including household head and household socio-economic characteristics and ε_i is the error term. We report both robust standard errors and clustered standard errors at the 38 communities for the econometric models.

Because participation in the training on biochar and compost production could be influenced by individual self-selection and farmer group leaders, and therefore not based on random assignment, estimating Equation (1) using standard econometric procedures (e.g. ordinary least squares (OLS)) could lead to upward biased results as participants and non-participants in the training on biochar and compost production may be systematically different based on observable and non-observable characteristics. Therefore, we employ doubly robust treatment effect estimators (i.e. inverse probability weighting regression adjustment (IPWRA) and treatment effects using Lasso (TELASSO)) to address the problem of selection bias and endogeneity. The doubly robust property of these estimators means that robust estimates are generated based on correct specification of either the treatment or outcome models (Cattaneo, 2010; Drukker, 2016; Imbens & Wooldridge, 2009). Interestingly, these treatment effect estimators, particularly the IPWRA have been employed by several studies to examine the effect of social, environmental and agricultural technologies on welfare in developing countries (Manda et al., 2018; Okyere, 2020; Okyere et al., 2022; Okyere & Ahene-Codjoe, 2022; Okyere & Kornher, 2023; Okyere & Usman, 2021; Tambo & Mockshell, 2018).

The IPWRA estimator works as follows: inverse probability weights are estimated from the probit regression of carbon farming training participation decisions. Relying on the estimated inverse probability weights, weighted OLS regression is used to generate the food security and development resilience outcomes for the probability of participation in the training on biochar and compost production. The differences in the average outcomes between participants and non-participants in the training on biochar and compost production generates estimates of the average food security and development resilience indexes of the carbon farming training participation decisions. Specifically, we estimate the average treatment effect on treated (ATET), which is specified as follows:

$$\text{ATET} = E(Y_{1i}|P_i = 1) - E(Y_{0i}|P_i = 1) \tag{2}$$

where $E(.)$ indicates the expectation operator, P_i is a binary variable indicating the participation status of farm household, Y_{1i} and Y_{0i} represent outcome of interest for farm households with participants and non-participants, respectively. Y_i in Equation (2) represents the same dependent variables (i.e. food security and development resilience indicators) as in Equation (1). Identification of the effect requires an overlap of the treatment probability densities for the training participants and the non-participants.

As robustness check, we employ TELASSO – a recently developed machine learning application which selects ‘relevant’ covariates in a regression specification to generate robust estimates (Chernozhukov et al., 2018; Koch et al., 2018). TELASSO also has the doubly robust property (see for example, Chernozhukov et al., 2018; Koch et al., 2018; StataCorp, 2021). TELASSO estimates the ATET from observational data using augmented inverse probability weighting (AIPW) method but unlike other treatment effects estimators in which the researcher determines which covariates are included, TELASSO uses the LASSO method to select from the potential control variables to be included in the model (StataCorp, 2021). Thus, it has the doubly robust property like IPWRA but also ensures that the most relevant covariates are used and this provides an additional robustness check on the model specification.

2.4. Outcome measures

This study employs the following outcome measures: resilience capacity index (RCI); household and child food insecurity experience scale (FIES and CFIES); food consumption score (FCS); and household dietary diversity score (HDDS). Therefore, we include internationally accepted and important welfare indicators used in the literature such as resilience to food insecurity by adopting FAO's Resilience Index Measurement and Analysis (RIMA) II module (FAO, 2020). The FAO's RIMA II module estimates the multidimensional resilience capacity index (RCI) (see also Otchere and Handa, 2022) by employing a principal component analysis (PCA) method.

We followed Otchere and Handa (2022) in estimating the RCI based on the FAO's RIMA II module (D'Errico et al., 2020; FAO, 2016; FAO, 2020). RIMA II module has been applied in different settings and proven to generate robust estimates of resilience. RIMA II approach generates the RCI which have both multiple predictors and outcomes (Otchere and Handa, 2022). The following components are estimated for the RCI: *(1) access to basic services (ABS); (2) ownership of assets (AST); (3) access to social safety nets (SSN); and (4) Household adaptive capacity (AC)*. We also undertake detailed analyses where we disentangle the indexes and estimate the effects on key components or pillars of the indexes. This was based on our expectation that the carbon farming training may be more related to some of the components or pillars of the indexes than others.

3. Results and discussion

3.1. Descriptive statistics

Table 1 reports descriptive statistics on the FAO's eight short questions that are used to estimate FIES score (refer to Tambo et al. (2021) and Obeng-Amoako et al. (2023) for food insecurity measurements). The results in Table 1 show a high prevalence of food insecurity among farm households in Northern Ghana in the 12 months preceding the survey. For instance, over 40% of farm households worried about not having enough food to eat, unable to eat healthy and nutritious diets, ate only few kinds of food, skip a meal when hungry, and ate less than thought should be eaten. Furthermore, about 40.5 and 20.3% were either moderately or severely food insecure, respectively. The FIES score was 3.02, signifying that most of the farm households in our sample faced moderate food insecurity in the past 12 months before the survey. Similar results are obtained for the CFIES using four short questions related to food availability and accessibility based on the 12 months' timeframe. The HDDS and FCS were estimated using 12 food groups consumed by the farm households in the past 7 days.

When comparing participating and non-participating farm households, the results show that participants were better off for each of the food insecurity indicators, except that for most of the indicators the differences were not statistically significant at the traditional confidence intervals. We, however, observe statistically significant differences between the training participants and non-participants with regards to HDDS (at 1% level of significance), the proportion of households that ran out of food (at 5% level of significance) as well as the proportion of households with a child skipping a meal (at 10% level of significance).

The RCI and its sub-components are also presented in Table 1, showing an average RCI score of 37.2. This result is similar to a baseline analysis found in Otchere and Handa (2022) for Malawi. The sub-component with highest score is access to basic services (ABS) (with a score of 49.5), followed by adaptive capacity (AC) (with a score of 38) and then social safety nets (SSN) (with a score of 22.7). Assets (AST) has the lowest score of 21.8. Table 1 further shows that the results are generally consistent with the previously reported results on the food security indicators where participating farm households have better scores compared to their non-participants counterparts. Table 1 shows that the training participants had higher scores on RCI and on each of its components than the non-participants. More importantly, the differences in the scores between the participants and non-participants are found to be highly statistically significant at the traditional confidence intervals, especially in the case of the components of RCI.

Table 1 further reports descriptive statistics on many household characteristics for both training participants and non-participants and shows no statistically significant difference between the two groups on many of the characteristics considered. It is important to note that for characteristics on which the groups differ statistically, the training participants recorded higher proportions or averages than the non-participants. These observed heterogeneities were directly controlled for in the treatment effects estimation by including them in the set of covariates used to generate the probability weights. These covariates were carefully selected based on literature (for example, Okyere & Kornher, 2023) as well as taking into account the variables used in estimating the resilience indexes and food security indicators.

The results from the descriptive statistics and t-test show that carbon farming training may have significant effect on household resilience capacity and food security (particularly household dietary diversity). The next subsection explores these effects using more robust analytical methods, specifically, the IPWRA and TELASSO estimators.

3.2. Econometric results and discussion

This section presents and discusses the results on the average treatment effects on the treated (ATET) of carbon farming training on the key outcome variables of interest, based on the econometric specification in Equation (2). The models for the various outcome variables relied on the same set of covariates, presented in Table 1. Based on these covariates, Figure 2 provides plots of the estimated densities of the probability of receiving the treatment as well as the probability of not receiving the treatment and helps to check whether the overlap assumption is violated. From Figure 2, both plots do not show too much probability mass near zero or one while

Table 1. Summary statistics and covariate balance test.

Indicators	Full sample (1)	Participant group (2)	Comparison group (3)	Differences (4) = (2)-(3)
Household food and nutrition security status in the past 12 months				
Household was worried about lacking adequate food to eat (dummy)	0.413 (0.493)	0.376 (0.486)	0.433 (0.496)	−0.057 (0.048)
Household was not able to eat healthy/nutritious diets (dummy)	0.453 (0.498)	0.406 (0.493)	0.479 (0.500)	−0.073 (0.048)
Household ate no more than a few variety of food (dummy)	0.492 (0.500)	0.479 (0.501)	0.498 (0.501)	−0.020 (0.048)
Household had to skip a meal (dummy)	0.432 (0.496)	0.400 (0.491)	0.450 (0.498)	−0.050 (0.048)
Household ate less than what should be adequate (dummy)	0.424 (0.495)	0.400 (0.491)	0.436 (0.497)	−0.036 (0.048)
Household ran out of food (dummy)	0.320 (0.467)	0.261 (0.440)	0.352 (0.478)	−0.091 (0.045)**
Household was hungry but did not eat (dummy)	0.305 (0.461)	0.285 (0.453)	0.316 (0.466)	−0.031 (0.045)
Household did not eat for a whole day (dummy)	0.176 (0.381)	0.176 (0.382)	0.176 (0.381)	−0.000 (0.037)
Household food insecurity experience scale (FIES) (0–8)	3.015 (3.012)	2.782 (2.944)	3.140 (3.045)	−0.358 (0.291)
Moderately food insecure (FIES> = 4; dummy)	0.405 (0.491)	0.370 (0.484)	0.423 (0.495)	−0.054 (0.047)
Severely food insecure (FIES> = 7; dummy)	0.203 (0.403)	0.176 (0.382)	0.218 (0.414)	−0.042 (0.039)
Household dietary diversity score (HDDS) (0–12)	7.826 (2.883)	8.309 (2.612)	7.567 (2.990)	0.742 (0.276)***
Child food security indicators in the past 12 months				
Child's food size was reduced (dummy)	0.322 (0.468)	0.279 (0.450)	0.345 (0.476)	−0.066 (0.045)
Child had to skip a meal (dummy)	0.360 (0.481)	0.309 (0.464)	0.388 (0.488)	−0.079 (0.046)*
Child was hungry but could not afford food (dummy)	0.244 (0.430)	0.212 (0.410)	0.261 (0.440)	−0.048 (0.041)
Child did not eat for a whole day (dummy)	0.155 (0.362)	0.139 (0.347)	0.163 (0.370)	−0.023 (0.035)
Child food insecurity score (CFIES) (0–4)	1.081 (1.418)	0.939 (1.374)	1.156 (1.438)	−0.217 (0.137)
Resilience to food insecurity				
Resilience capacity index (RCI)	37.197 (15.580)	38.994 (17.187)	36.232 (14.581)	2.762 (1.500)*
Access to basic services (ABS)	49.467 (26.307)	55.599 (26.059)	46.172 (25.886)	9.427 (2.505)***
Assets (AST)	21.847 (11.548)	25.101 (13.664)	20.098 (9.820)	5.003 (1.092)***
Social Safety Nets (SSN)	22.745 (18.555)	25.875 (21.504)	21.062 (16.552)	4.813 (1.779)***
Adaptive capacity (AC)	38.012 (20.802)	42.581 (20.254)	35.556 (20.710)	7.026 (1.984)***
Food consumption score (FCS)	43.160 (17.775)	44.418 (16.397)	42.484 (18.463)	1.934 (1.715)
Household characteristics				
Distance to extension office in kilometres (in natural log)	1.379 (0.766)	1.549 (0.781)	1.288 (0.744)	0.261 (0.073)***
Extension visit (dummy)	0.722 (0.448)	0.909 (0.288)	0.622 (0.486)	0.287 (0.041)***
Premium respondent was willing to pay for biochar and compost (GHS) (in natural log)	4.313 (0.733)	4.547 (0.487)	4.187 (0.810)	0.360 (0.069)***
Quantity of inorganic fertilizer application (kilograms) (in natural log)	5.078 (2.033)	5.022 (2.180)	5.109 (1.953)	−0.087 (0.196)
Household head's risk attitude (#)	5.727 (2.822)	5.806 (2.845)	5.684 (2.812)	0.122 (0.273)
Membership of farmer group (dummy)	0.608 (0.489)	0.727 (0.447)	0.544 (0.499)	0.183 (0.046)***
Household practises irrigated agriculture (dummy)	0.307 (0.462)	0.382 (0.487)	0.267 (0.443)	0.115 (0.044)***
Household practises monocropping farming system (dummy)	0.549 (0.498)	0.552 (0.499)	0.547 (0.499)	0.004 (0.048)
Number of household members (#)	4.875 (2.091)	5.055 (2.234)	4.779 (2.007)	0.276 (0.202)
Household head is a male (dummy)	0.697 (0.460)	0.679 (0.468)	0.707 (0.456)	−0.028 (0.044)
Household head is a Muslim (dummy)	0.523 (0.500)	0.558 (0.498)	0.505 (0.501)	0.053 (0.048)
Household head is a farmer (dummy)	0.725 (0.447)	0.782 (0.414)	0.694 (0.462)	0.088 (0.043)**
Age of household head (in completed years)	48.021 (13.838)	48.412 (12.792)	47.811 (14.384)	0.601 (1.337)
The square of household head's age (completed years)	2497.110 (1427.469)	2506.376 (1322.749)	2492.130 (1482.772)	14.245 (137.938)
Married Household head (dummy)	0.756 (0.430)	0.788 (0.410)	0.739 (0.440)	0.048 (0.041)
Household head has completed at least basic school (dummy)	0.227 (0.419)	0.242 (0.430)	0.218 (0.414)	0.024 (0.040)
West Mamprusi (dummy)	0.358 (0.480)	0.358 (0.481)	0.358 (0.480)	−0.001 (0.046)
Lawra municipal (dummy)	0.322 (0.468)	0.242 (0.430)	0.365 (0.482)	−0.122 (0.045)
Bawku municipal (dummy)	0.320 (0.467)	0.400 (0.491)	0.277 (0.448)	0.123 (0.045)***

Notes: Descriptive statistics on household characteristics have been previously reported in Okyere and Kornher (2023). Results reported in Columns (1)–(3) are the means and standard deviation (in parentheses) for participants and non-participants. In Column (4), we report the mean differences standard error (in parentheses) and their statistical significance. *** Significant at the 1% level, ** Significant at the 5% level, * Significant at the 10% level.

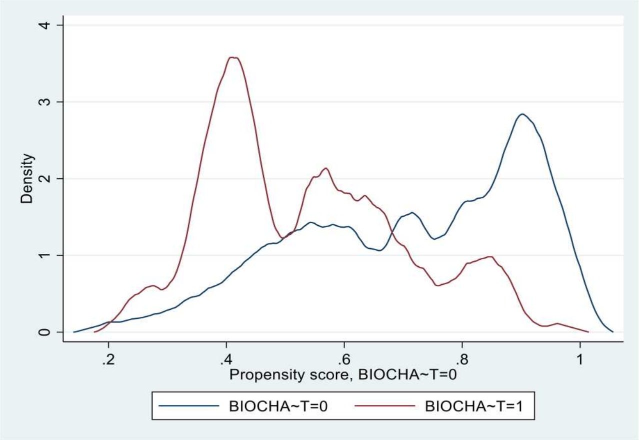

Figure 2. Overlap plots of carbon farming training.

we also observe significant overlap between the two plots, indicating a non-violation of the overlap assumption. This is confirmed by the results of overidentification test for covariate balance using the variables in Table 1 ($\text{Chi}^2 = 18.024$; $\text{Prob} > \text{chi}^2 = 0.454$). The test results indicate that we cannot reject the null hypothesis that the covariates are balanced between the households that received the carbon farming training and those that did not participate in the training.

Table 2 reports the results on the effect of carbon farming training on resilience capacity and food security in Northern Ghana. The results from two main models – IPWRA and TEL-ASSO – are reported for each outcome variable. For each of the two models, results from both clustered standard errors (odd numbered columns) and robust standard errors (even numbered columns) are also reported. The use of the different models/estimators and the variation in the assumptions

Table 2. Effects of carbon farming training on food security and resilience.

Indicators	Model 1: IPWRA		Model 2: TELASSO	
	Clustered SE	Robust SE	Clustered SE	Robust SE
Panel A: Household resilience	**(1)**	**(2)**	**(3)**	**(4)**
Resilience capacity index (RCI)	2.342	2.342+	2.524	1.885
	(2.095)	(1.509)	(2.114)	(1.498)
Access to basic services (ABS)	7.732***	7.732***	7.288**	7.747***
	(2.839)	(2.755)	(2.961)	(2.694)
Assets (AST)	3.169***	3.169***	4.135***	4.304***
	(1.068)	(1.088)	(1.445)	(1.228)
Social Safety Nets (SSN)	4.480+	4.480**	5.472*	5.224***
	(2.853)	(1.892)	(3.051)	(1.912)
Adaptive capacity (AC)	3.413+	3.413*	3.053+	3.053+
	(2.290)	(2.042)	(2.037)	(1.946)
Panel B: Food security				
Food consumption score (FCS)	3.494*	3.494**	3.871**	4.302**
	(1.907)	(1.606)	(1.976)	(1.726)
Child food insecurity score (CFIES) (0–4)	−0.133	−0.133	−0.169	−0.169
	(0.170)	(0.143)	(0.177)	(0.144)
Household food insecurity experience scale (FIES) (0–8)	−0.161	−0.161	−0.149	−0.151
	(0.323)	(0.281)	(0.360)	(0.300)
Moderately food insecure (FIES> = 4; dummy)	−0.030	−0.030	−0.012	−0.032
	(0.058)	(0.048)	(0.065)	(0.050)
Severely food insecure (FIES> = 7; dummy)	−0.005	−0.005	−0.004	−0.012
	(0.039)	(0.039)	(0.043)	(0.040)
Household dietary diversity score (HDDS) (0–12)	1.085***	1.085***	1.265***	1.133***
	(0.370)	(0.264)	(0.452)	(0.285)
No. of observations (N)	**472**	**472**	**472**	**472**
Controls	**Yes**	**Yes**	**Yes**	**Yes**

Notes: The following control variables are included in the treatment and outcome models: natural log of distance to extension office in kilometres, access to extension visit, natural log of quantity of inorganic fertilizer application, risk attitude, irrigation, natural log of the maximum bid for biochar and compost in GHS, monocropping farming system, household size; male-headed households, Muslim household head, age of household and its squared, marital status, household head's educational status, dummies for West Mamprusi and Lawra municipals. Count outcome measures (FIES score and HDDS) are estimated using Poisson model. *** Significant at the 1% level, ** Significant at the 5% level, * Significant at the 10% level and +Significant at the 15% level. We report both robust (even numbered columns) and clustered standard errors at the 38 communities (odd numbered columns).

about standard errors serve as robustness check on the estimated results. It is interesting to note that our results are found to be robust to the different estimators, as Table 2 shows no qualitative differences in the results from different models/estimators for the outcome variables considered. The main model of this paper is reported in Column 1 using the clustered standard errors adjusted estimates from the IPWRA method.

From Table 2, we find no statistically significant effect of participation in CF training on the overall measure for household resilience capacity (that is, RCI). Interestingly, there was marginal improvement (results with *p*-value closer to 10%) in the RCI for robust error adjusted estimates using IPWRA method (Column 2). However, participation in CF training has statistically significant and positive effect on the key components of household resilience capacity. Across the results from the different models presented in Table 2, we find that participation in CF training had statistically significant and positive influence on two of the four components of household resilience capacity in Northern Ghana at the traditional levels of statistical significance. These components are access to basic services and assets. Indeed, the effect of CF training on ABS and AST are statistically significant at 1% significance level in most of the models. Similarly, we found marginal improvement in SSN and AC (results with *p*-value closer to 10%) in the preferred model reported in Column 1. Interestingly, these results are statistically significant at different (and generally better) confidence intervals as per the results from the IPWRA model with robust standard errors and TELASSO model with clustered and robust standard errors (refer to Columns (2) to (4)), respectively.

The results in Table 2 show further that participation in CF training is associated with an increase in FCS and HDDS. In the case of the FCS, the effect is statistically significant at 10% and 5% in the IPWRA model with clustered and robust standard errors, respectively, and 5% significance level in both TELASSO models. Similarly, the effect on HDDS is highly statistically significant in all the models – the effect is actually statistically significant at 1% level in all four models including the two TELASSO models. However, we find no statistically significant effects on other food and nutrition insecurity indicators (that is, FIES and CFIES). The results on food and nutrition insecurity do not change when dummies based on moderate (FIES> = 4) and severe (FIES> = 7) food insecurity indicators are used. The null effects of CF training on household and child food insecurity experience scale (FIES and CFIES) could be largely due to the longer reference period (12 months) used for the questions soliciting information on the indicators used for measuring household and child food insecurity. It is possible for these results to change substantially if a much shorter reference period (such as the past 24 hours, last 7 or 30 days) were used to derive the indicators on FIES and CFIES. This explanation is arguably reasonable in the light of the fact that we found a statistically significant effect of CF training on FCS and HDDS which were derived from indicators with a much shorter reference period (that is, 7 days).

As previously reported in Okyere and Kornher (2023), carbon farming training led to increased farm performance and poverty reduction. Additional descriptive analysis (results available upon request) suggests that the benefits from long-term carbon farming training led to investment in assets and basic amenities (such as water and sanitation) which are integral component of the indicators used in computing the RCI and its sub-components. This partly support the positive results we report in this study on key components of resilience and food security. Besides, the result on social safety nets is interesting as it points to the fact that carbon farming training could strengthen social networks which have implications on the receipt of both formal and informal transfers. This result could also be explained by well-known 'concept of reciprocity' in social science literature. For instance, increased farm performance and the associated increase in returns on agricultural production could lead to farm households providing support (both cash and in-kind) to relatives and non-relatives (i.e. social networks) in the community and beyond. This support for social networks could lead to reciprocal receipt of gifts and transfers to support farm households to enhance agricultural production and consumption smoothening.

The findings that participation in CF training improves aspects of household resilience to food insecurity and has positive effect on household food consumption score and dietary diversity is generally consistent with the recent literature on the impact of climate smart agricultural practices on household welfare in other developing country contexts (see for example, Lal, 2004; Martey et al., 2020; Mujeyi et al., 2021; Nkonya et al., 2023; Shahzad & Abdulai, 2021). These studies show that climate smart agricultural practices, which involve practices for soil carbon sequestration help improve household welfare and food security situation through several channels but particularly by increasing farm yield (see Lal, 2004; Okyere & Kornher, 2023). Similarly, a study by Michler et al. (2019) assessed the impact of conservation agriculture and find that it is effective at helping to mitigate the negative impact of variability in rainfall in Zimbabwe while Fentie and Beyene (2019) also show that climate smart agricultural practices (row planting) have significant impact on per capita consumption and crop income per hectare. Although our results are generally consistent with the above-mentioned studies in terms of positive welfare implications, this article is distinctive in terms of its focus on CF training particularly on biochar and compost production training and its effect on household resilience. Also, the focus of the paper on vulnerable smallholder agricultural households in relatively deprived regions of Ghana, a developing country, show the potential for CF training and related climate smart agricultural programmes to help build the resilience of vulnerable households in deprived communities.

It is important to note that the effect of CF training on household welfare found in the study area of this article (Northern Ghana) may have occurred through several channels including productivity gains from participation in CF training. In a previous study which focused on the same study area, Okyere and Kornher (2023) showed that CF training allowed farm households to adopt organic fertilizer, increasing perceptions of soil quality, maize productivity as well as returns on maize production. This intermediate impact may have happened as a result of the positive effect of CF training on the farmers' participation in farmer group activities leading to higher knowledge on resilience to climatic shocks, and adoption of soil health practices. These intermediary outcomes represent development goals (see for instance, the Sustainable Development Goals 1 and 2) by themselves and the finding of positive effects shows the importance of agricultural capacity building initiatives leading to welfare improvement in a much broader sense. While Okyere and Kornher (2023) documented greater expenditure and poverty reduction effects due to CF training, they did not interrogate the effect of CF training on equally important welfare indicators such as household resilience and food security.

Our findings also align with studies on the effect of training or capacity building on agricultural practices on household welfare among smallholder farmers in Ghana and other developing country contexts (see for example, Atta-Ankomah & Danso-Mensah, 2022; Chesterman et al., 2019; Fafchamps et al., 2020; Martey et al., 2021; Rhebergen et al., 2018; Zakaria et al., 2020). The results on development resilience have policy relevance as recent studies in the international development literature have focused on determinants and impacts of social interventions including digital financial inclusion and cash transfers in enhancing household resilience to shocks/stressors (see for example, D'Errico et al., 2020; Otchere and Handa, 2022; Suri et al., 2021; Yao et al., 2023). However, our results are novel as we show that climate change capacity building initiatives (i.e. carbon farming training) could lead to broader development outcomes such as improvements in key indicators on food security and household resilience beyond the agricultural productivity, consumption and expenditure outcomes.

3.3. Sensitivity analyses

Based on previous findings reported in Section 3.2, it is essential to understand the project components underlying the results. We accomplish this task by exploring heterogeneity in treatment effects estimations based on participation in the broader USAID-UG Project. We find that the results, which are reported in Table 3, are similar to those reported in Section 3.2. This suggests that the results are robust to alternative definition of project participation and also estimation strategies. This is not surprising as the training on biochar and compost production was the key component of the USAID-UG Project. Figure 3 indicates a non-violation of the overlap assumption when participation in the broader USAID-UG project is used as the treatment variable, and this is further confirmed by overidentification test for covariate balance between the participating and non-participating farm households (i.e. H_0: Covariates are balanced; $\text{Chi}^2 = 16.820$; Prob $> \text{Chi}^2 = 0.536$).

Table 3. Effects of USAID-UG project on food security and resilience.

Indicators	Model 1: IPWRA		Model 2: TELASSO	
	Clustered SE	Robust SE	Clustered SE	Robust SE
Panel A: Household resilience	**(1)**	**(2)**	**(3)**	**(4)**
Resilience capacity index (RCI)	1.224	1.224	1.048	0.849
	(2.240)	(1.508)	(2.169)	(1.645)
Access to basic services (ABS)	5.172+	5.172*	6.812*	7.760**
	(3.483)	(3.124)	(3.574)	(3.006)
Assets (AST)	2.047+	2.047**	2.918*	3.208**
	(1.252)	(1.028)	(1.634)	(1.325)
Social Safety Nets (SSN)	1.972	1.972	3.865	2.829
	(2.784)	(1.861)	(3.031)	(2.021)
Adaptive capacity (AC)	2.786	2.786	3.073+	3.073+
	(2.047)	(2.115)	(1.878)	(2.071)
Panel B: Food security				
Food consumption score (FCS)	3.912*	3.912**	2.761	3.523*
	(2.035)	(1.722)	(2.234)	(1.935)
Child food insecurity score (CFIES) (0–4)	−0.146	−0.146	−0.073	−0.073
	(0.160)	(0.154)	(0.165)	(0.150)
Household food insecurity experience scale (FIES) (0–8)	−0.322	−0.322	−0.092	−0.092
	(0.350)	(0.301)	(0.375)	(0.305)
Moderately food insecure (FIES> = 4; dummy)	−0.029	−0.029	0.001	−0.011
	(0.061)	(0.050)	(0.066)	(0.053)
Severely food insecure (FIES> = 7; dummy)	−0.027	−0.027	−0.012	−0.020
	(0.034)	(0.041)	(0.039)	(0.042)
Household dietary diversity score (HDDS) (0–12)	0.952***	0.952***	1.105***	0.925***
	(0.352)	(0.280)	(0.430)	(0.343)
No. of observations (N)	**472**	**472**	**472**	**472**
Controls	**Yes**	**Yes**	**Yes**	**Yes**

Notes: Refer to Table 2 on the controls included in the models. *** Significant at the 1% level, ** Significant at the 5% level, * Significant at the 10% level and +Significant at the 15% level. We report both robust (even numbered columns) and clustered standard errors at the 38 communities (odd numbered columns).

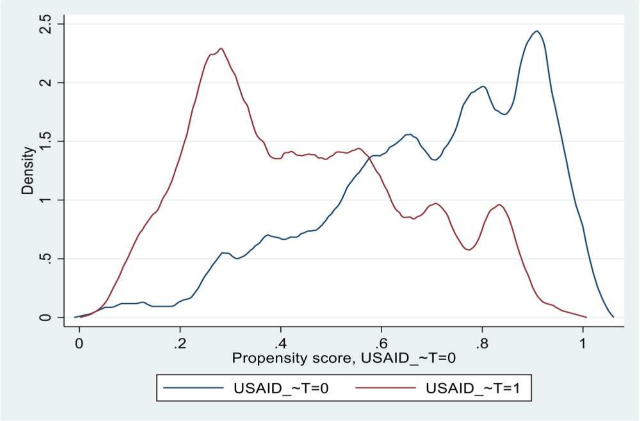

Figure 3. Overlap plots of USAID-UG project.

4. Conclusion

This study presents evidence on the effects of carbon farming training on food security and development resilience in Northern Ghana. Our study relies on data from the promotion of soil carbon mitigation strategies in which farmers in three semi-arid regions of Northern Ghana were trained on biochar and compost production. We relied on newly collected data from 472 farm households in three semi-arid regions in Northern Ghana and also employed rigorous data analysis techniques such as IPWRA and TELASSO methods to address potential selection bias and heterogeneity. It is also interesting to note that internationally standardized indicators of welfare (e.g. FAO's RCI, FIES, FCS, CFIES and HDDS) were used as the outcome measures.

We found evidence that carbon farming training increases some components of resilience capacity index (RCI) such as access to basic services (ABS) and assets (AST). We also found positive effects on the food and nutrition security indicators, including the food consumption score (FCS) and household dietary diversity score (HDDS) but no effects on FIES and CFIES scores. Overall, our results suggest that promoting soil carbon mitigation strategies could be one of the avenues for achieving food security and development resilience of farm households in developing countries. The main policy implications are that agricultural training programs, particularly climate change adaptation capacity building initiatives could have a much broader effect on welfare beyond the farm performance, income and consumption pathways. We recommend that policy makers and stakeholders in the agricultural sector of developing countries should implement carbon farming capacity building strategies to boost the welfare of farm households.

Finally, we have identified several areas for future research. Given that we only examine the effect of carbon farming training, additional insights could be gained from future research examining the adoption of carbon farming practices and its effects on carbon sequestration at farm level. Similarly, panel data analysis relying on nationally representative surveys from the scaling up of the soil carbon mitigation strategies could shed additional light on the long-term food security and resilience effects in developing countries. Gender and age disaggregated data analysis could be one of the future research opportunities on the heterogeneity in treatment effects of carbon farming training and techniques on food security and resilience in developing countries.

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