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Charles Yaw Okyere and Lukas Kornher

Carbon Farming Training and Welfare: Evidence from Northern Ghana

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Zentrum für Entwicklungsforschung (ZEF)
Center for Development Research
Genscherallee 3
D – 53113 Bonn
Germany
Phone: +49-228-73-1861
E-Mail: zef@uni-bonn.de
Website: www.zef.de

The authors:

Charles Yaw Okyere, Department of Agricultural Economics and Agribusiness, University of Ghana, Legon, Contact: okyerecharles@gmail.com; cyokyere@ug.edu.gh
Lukas Kornher, Center for Development Research, University of Bonn.

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Declaration of Competing Interest

Charles Yaw Okyere declares that he participated in pilot studies undertaken by the Department of Agricultural Economics and Agribusiness, University of Ghana, Legon, during the project implementation which may be deemed as a source of potential competing interest.

Abstract

Carbon farming, particularly soil carbon climate strategies, has emerged as a popular tool in addressing climate change and variability in worldwide agriculture. Yet, there is a paucity of evidence on its application, and even more so, limited evidence exists on the welfare impacts in developing countries, where the negative impacts of climate change and variability remain disproportionately higher. This paper presents the results of a study on biochar and compost production training and its welfare effects on farm households in Northern Ghana using doubly robust estimators. We find that the intervention had statistically significant positive effects on agricultural productivity and welfare outcomes. The results show the prospect of using soil carbon climate strategies in improving the welfare of farm households in developing countries.

Keywords: Climate-smart Agriculture, Carbon Farming; Biochar; Compost; Welfare; Poverty; Northern Ghana

JEL classification: Q12; Q15; Q16; Q18; Q57; C21; I31; I32

1. Introduction

Currently, more than one-third of the worldwide population suffers from moderate or severe food insecurity, and between 700 to 828 million are considered undernourished; an increase of about 150 million from before Covid-19 level in 2019 (FAO et al., 2022). Similarly, about 8.6 percent of the global population lives in poverty (The World Bank, 2021a). These figures make it appears very unlikely to achieve the United Nation's (UN's) Sustainable Development Goals (SDGs) related to welfare (UN, 2021) such as: poverty reduction (Goal 1), zero hunger (Goal 2), good health and wellbeing (Goal 3), and gender equality (Goal 5) (UN, 2013; 2016).

Evidently, economic wellbeing is determined by several factors related to the lack of adequate infrastructure (Morgan et al. 2020; Shively, 2017; Shively and Thapa, 2017), conflict and war (FAO et al., 2021; World Bank, 2021a), price volatility (Kalkuhl et al. 2016), lack of improved agricultural technologies and inputs (Suri and Udry, 2022), limited access to extension services (Tambo and Matimelo, 2021; Sheahan and Barret, 2017; Aker, 2011), and climate change and variability (FAO, 2015; FAO et al., 2021; World Bank, 2021a; Wheeler and von Braun 2013). These factors either singly or in combination, affect farm performance in terms of yields, technical efficiency, income and therefore, contributing to the vicious poverty cycle or intergenerational poverty mostly found in farm households in developing countries.

In addition, climate change and weather variability threaten economic growth and development of many low-and-middle-income countries (LMICs) (Lomborg, 2020). They are ranked topmost among the factors affecting agricultural production in rainfed agricultural systems. Thus, climate change and weather variability negatively affect global food systems, particularly in the arid and semi-arid regions of Sub-Saharan Africa (SSA) (FAO et al., 2021; World Bank, 2021a; Wheeler and von Braun, 2013). The food system is interlinked with neighbouring systems, such as the health, ecological and energy system. Therefore, agriculture and climate are directly interdependent (von Braun et al. 2021). Specifically, climate change and weather variability affect farm performance whilst the food system also has implication for climate change as the main greenhouse gas (GHG) emitter.

To address the challenges posed by the interlinkage between climate change and agricultural production, several innovative approaches, broadly classified as climate-smart agriculture (CSA), have been developed and adopted (World Bank, 2021b; Lipper et al. 2014). CSA includes climate-resilient agriculture (CRA) (Reddy, 2015; Alvar-Beltran et al. 2021), an approach to develop production methods and farming systems, such as integrated soil fertility management (ISFM) (Vanlauwe et al. 2015), that better cope with increasing climate variability. Additionally, the application of organic fertilisers including compost has positive effects on soil fertility (Ouédraogo et al. 2001; D'Hose et al. 2014; Hernández et al. 2016).

Carbon farming (CF) has gained prominence as CSA approach in worldwide agriculture for simultaneously mitigating the negative impacts of climate change and variability, and also contributing to lower GHG emission. CF encompasses approaches to optimise soil carbon sequestration (McDonald et al. 2021; Nyssens, 2021). Previous studies (Amelung et al. 2020;

FAO, 2019) have showed the potential link of soil carbon sequestration to food and nutrition security through improvement of soil health. According to FAO (2021), soil organic carbon is the primary indicator for assessing soil health. Additionally, recent initiatives promoted to improve soil carbon include FAO's "recarbonization of global soils (RECSOIL)" programme (Amelung et al. 2020; FAO, 2019) which aims at improving farm households' income, and food and nutrition security (FAO, 2019). Therefore, improving soil fertility is essential for rural poverty reduction in SSA (Vanlauwe et al. 2015).

As another approach, the application of biochar (i.e. biological charcoal)-*a product from partial pyrolysis of organic matter*- has been proven to be effective in improving soil carbon sequestration (Gwenzi et al. 2015; Bach et al. 2016). Biochar is relatively stable in soils in the long-term and the abundant availability of biomass in countries like Ghana makes it suitable for large scale production (Duku et al. 2011). Similarly, previous studies have shown that the use of compost or organic fertilizer improve crop yield through higher gains in soil fertility (D'Hose et al. 2014; Hernández et al. 2016; Ouédraogo et al. 2001). Improvement of soil carbon sequestration through the application of biochar and compost could be useful in improving soil fertility, moisture retention and soil structure. For instance, a meta-analysis by Gross and Glaser (2021) found that biochar application improves nutrient availability and soil organic carbon (SOC) in a variety of different contexts. Mohammadi et al. (2017) found that the application of biochar increased the net present value of rice production by 12 percent in North Vietnam. Additionally, Kim et al. (2017) found that biochar application increases rice yield and also reduces CH_4 emissions. Similar results have been reported on economic and agricultural productivity benefits for the application of biochar together with either organic or inorganic fertilizer (Zheng et al. 2017; Badu et al. 2019; Frimpong et al. 2021; MacCarthy et al. 2020).

Interestingly, recent high prices for fertiliser and agricultural inputs require redoubling of efforts to local production of organic resources (i.e. biochar and compost) for farming in SSA. Promoting own production of organic resources from locally available raw materials is important for the sustainability of agricultural production in SSA. For instance, organic resources will make farming more efficient and boost soil health and yields in SSA. Besides, the application of biochar-compost (i.e. co-compost) mixtures combines the advantages of different CSA approaches and support soil fertility, restores degraded lands, and mitigates climate changes through carbon sequestration (Agegnehu et al. 2017; Gross and Glaser 2021; D'Hose et al. 2014; Gwenzi et al. 2015; Bach et al. 2016). In return, increased agricultural productivity could lead to high income, food and nutrition security, poverty reduction, among other welfare outcomes (see for example, FAO, 2019). While there is abundant evidence in the agronomic literature on the importance of biochar and compost as adaptation strategies to climate change and variability, soil fertility and agricultural productivity (Gwenzi et al. 2015; Bach et al. 2016; Mohammadi et al. 2017; Gross and Glaser, 2021; Kim et al. 2017; Zheng et al. 2017; Badu et al. 2019; Frimpong et al. 2021; MacCarthy et al. 2020), there is limited evidence on the determinants and economic benefits of adoption of these technologies by farm households in developing countries (see a review on biochar by Gwenzi et al. 2015; Bach et al. 2016), particularly in settings where climate change is a threat to agricultural productivity. Unsurprisingly, the literature on adoption of biochar as soil amendment strategy in worldwide agriculture is dominated by studies in developed countries with limited evidence coming from Sub-Saharan Africa (Gwenzi et al. 2015). Previous studies have shown that the application of organic resources (including biochar and compost) in worldwide agricultural system is affected by several constraints including high cost of production, lack of appropriate technology in production, land tenure system, and high application rate required per hectare (Gwenzi et al. 2015; Bach et al. 2016; Ouédraogo et al. 2001).

Most importantly, the adoption of carbon farming techniques involves a complex mix of resources and policy frameworks. Therefore, training farmers on owned production of organic resources as soil carbon mitigation strategies is a crucial step in the adoption of such technologies. We find that the biochar and compost production training have a positive and statistically significant effect on diverse welfare outcomes, such as farm performance and poverty reduction. Specifically, relative to the comparison group, participating farm households increase the use of compost or organic fertilizer by 25.8 percent; the yield of maize by 487.49 kilograms per hectare (kg/ha); maize gross revenue per hectare by GHS 760.75 (US$ 107); maize farming expenses by GHS 201.44 (US$ 29); per capita monthly food consumption expenditure by GHS 33.93 (US$ 5); and per capita total yearly expenditure by GHS 481.03 (US$ 68). Interestingly, probability of poverty likelihood decreased by 5.39 percent.

This study contributes to filling the gap in the literature with respect to welfare implications of carbon farming, specifically biochar-compost mixture, in tropical agricultural systems. Previous studies (Ouédraogo et al. 2001; Badu et al. 2019; Frimpong et al. 2021; MacCarthy et al. 2020) in developing countries context have analysed the potential of using biochar and/or compost to improve agricultural productivity in field experimental settings. This study takes a step further in analysing the decision to participate in biochar and compost production training and also subsequent application on farmer fields. Specifically, we examine the welfare effects of a 5-year (2015-2020) project implemented by the University of Ghana in Northern Ghana in which farmers were offered training on biochar and compost production using locally available resources. The project had additional components such as: household waste sorting training; technical and business skills training; and biotechnology awareness programme. This is an important step in the empirical literature in adopting biochar and compost as carbon farming mechanisms in developing countries. To our knowledge, we present the first study on biochar and compost production training in SSA context; the region most affected by climate change and variability.

Second, we add to the rapidly burgeoning literature on the effects of CSA practices on farm performance and welfare, particularly in the social science literature on moving agricultural production technologies from field experiments to farm household level. This is essential in the adoption of new and improved agricultural technologies, as many promising technologies and innovations developed for agricultural production in developing countries are largely abandoned at the field experiment level without actual use by farm households. Additionally, issues of endogeneity due to non-random adoption of these techniques persist leading to potentially biased estimates. We rely on rigorous econometric techniques with several robustness checks such as doubly robust treatment effect estimations to address potential selection bias to generate evidence on the impact of biochar and compost production training on the welfare of farm households in the semi-arid regions of Ghana.

Third, the project targeted multiple crops including staple (maize and rice) and cash crop (soya) cultivated by farm households and this is an important addition to the empirical literature. Previous studies (Badu et al. 2019; Ouédraogo et al. 2001; Frimpong et al. 2021; MacCarthy et al. 2020) have targeted one crop and largely concentrated on either staples or vegetables which are mainly cultivated on small piece of plot, particularly in experimental studies. By concentrating on multiple crops, the results from the training programme suggest that soil carbon mitigation strategies could have broader appeal to rural farm households in developing countries and that such technologies have the prospect of improving the welfare of farm households.

Finally, the study shows that properly designed carbon farming techniques, particularly training programmes on soil climate mitigation strategies can relax the constraints in the adoption of soil fertility practices and increase the agricultural productivity of farm households, allowing them to purchase food and other essential goods and services, and thereby contribute to welfare improvement such as poverty reduction. The results suggest that the project could be replicated in other developing countries and the impacts could be much more if targeted to high valued horticultural crops including vegetables which tend to have higher profitability margins. Therefore, our results are more likely to be lower bound of the potential welfare impacts of soil climate mitigation strategies in developing countries.

The rest of the paper is arranged as follows: Section 2 describes the concept of carbon farming. Section 3 describes the methodology and data while Section 4 presents the results and discussion. Section 5 concludes the study by indicating the policy implications and areas for future research.

2. Background

2.1 Carbon Farming

The concept of “carbon farming” has become one of the popular mechanisms in worldwide agricultural system, particularly in developed countries as a tool for climate change and variability mitigation and/or adaptation. Even though it is a relatively new concept in the literature, the term follows the footsteps of antecedents in addressing climate change and variability such as CSA, CRA, CA, and IFM. In the literature, CF is largely discussed in relation to land use management practices in improving soil carbon sequestration. The European Environmental Bureau (EEB), for example, defines carbon farming 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*" (Nyssens, 2021) while McDonald et al. (2021) refer to carbon farming as "… *sequestering and storing carbon and/or reducing GHG emissions at farm level*". The common theme through these definitions is the idea that CF reflects the ability of land use management practices to increase soil carbon sequestration to address climate change and variability. By explicitly contributing to mitigating GHG emissions and carbon sequestration, CF goes beyond most existing CSA and CRA approaches. However, implementation of carbon farming techniques including soil climate mitigation strategies is complex and resource intensive, and at times with uncertain outcomes (see for example, McDonald et al. 2021). Interestingly, carbon farming does not occur in isolation from the existing farming systems but involves the application of certain good agricultural practices which have long been associated with climate change and variability mitigation and/or adaptation, such as organic fertilisation through composting and biochar. As such, training farmers on the production of carbon farming resources as soil carbon mitigation strategies is an important component of the adoption of such technologies.

McDonald et al. (2021) classified CF into five main components, such as: *managing peatlands; agroforestry; maintain and enhance SOC on mineral soils; livestock and manure management; nutrient management on croplands and grasslands.* Furthermore, each category of CF addresses different source of actions, per hectare mitigation potential, benefits to farmers and society, and associated risks (see McDonald et al. 2021 for details), although they all fit as mitigation and/or adaptation strategies for climate change and variability. For instance, SOC option has mitigation potential of 0.5-7 $tCO_{2\text{-}e}$ per hectare per year (tCO_2-e/ha/yr) and the benefits for applying this option include increased soil water retention capacity and yields (McDonald et al. 2021). Therefore, CF factor in diverse options of land use management in improving soil carbon sequestration (see for example, McDonald et al. 2021; Nyssens, 2021). More importantly, the SOC component of carbon farming is applicable to "any farming system" (McDonald et al. 2021) and its potential risk include the application of contaminated biochar and compost that could have negative effect on soil health and biodiversity (McDonald et al. 2021). However, it remains an empirical issue to understand if CF options in developing countries could have economic welfare benefits through reducing the effects of climate change and variability.

2.2 Study Setting

The importance of agriculture for welfare improvement is more evident in Northern Ghana, where in some regions (Upper East and Upper West), over 80% of the population depends on it for their livelihoods (Ghana Statistical Service (GSS), 2019). However, agricultural production in Northern Ghana is characterized by poor soil fertility and increased climate variability leading to low productivity (see for example, Ministry of Food and Agriculture (MoFA), 2021). Therefore, it is not surprising that poverty, hunger, and malnutrition are disproportionately higher in Northern Ghana compared to Southern Ghana (GSS, 2019). In

Northern Ghana, agricultural production is undertaken under rainfed system with limited application of improved agricultural technologies. Agricultural production is undertaken from May of the year with harvesting taking place in December, meaning that only one major planting season per year. Furthermore, most of the agricultural production are undertaken by smallholder farmers for subsistence purposes with limited commercialization (MoFA, 2021).

In recent times, climate change and variability have become more visible with low levels of rainfall for agricultural production in Northern Ghana (i.e. the semi-arid part of Ghana). Northern Ghana experiences daytime temperatures as high as above 40 ^{0}Celcius (MoFA, 2021). The 10-year average rainfall was 1,069 mm, 940 mm, and 675 mm for Northern, Upper East and Upper West regions, respectively. In 2020, the average rainfall was 1000 millimetres (mm) in Sudan Savannah and 1100 mm in the Guinea Savannah agro-ecological zones compared to 1800 mm in the rain forest agro-ecological zone. Besides, Northern, Upper West and Upper East regions experienced 32.9%, 0.3% and 38.3% less rainfall in 2020 compared to 2019, respectively (MoFA, 2021). Previous studies have shown the importance of both CSA practises (Issahaku and Abdulai, 2019) and conventional agricultural training and improved technologies (Bedi et al. 2022) to address climate change and variability in the region.

Therefore, several programmes (e.g, National Climate Change Master Plan (2015–2020); Climate Change Adaptation in Northern Ghana; and Resilient and Sustainable Livelihoods Transformation in Northern Ghana) have been undertaken to address climate change and variability in Ghana with varying degree of success (refer to Etwire et al. 2022 for discussion on this topic). Similarly, soils in Northern Ghana are poor with low soil organic matter and phosphorus levels (MoFA, 2021). For instance, soil organic matter was 0.00-6.74%, 0.54-6.74%, and 0.77-6.74% in Northern, Upper East, and Upper West regions, respectively. These figures are low compared to other food production regions such as Ashanti and Brong Ahafo regions (0.00-13.83%) (MoFA, 2021). The general low-quality soils in Northern Ghana have led to the implementation of soil health and land use management interventions such as the Alliance for a Green Revolution in Africa (AGRA)'s Soil Health Project (SHP) (refer to Martey and Kuwornu, 2021 for additional information).

2.3 USAID-UG Project

In light of previous soil health interventions, the School of Agriculture, College of Basic and Applied Sciences, University of Ghana, Legon worked with smallholder farmers in three districts in Northern Ghana (refer to Figure 1 for the map of the study area): Lawra district, Upper West; West Mamprusi municipal, North East region (formerly part of Northern region); and Bawku municipal, Upper East region through the various Departments of Agriculture based on the production of crops of interest (i.e. maize, rice and soyabean) and previous experience on similar programmes. The Department of Agriculture is a government institution responsible for supporting farmers in the adoption of improved agricultural technologies. The project districts are located in the Guinea and Sudan savannah agroecological zones which experience monomodal rainfall pattern (MoFA, 2021; Etwire et al. 2022; Martey and Kuwornu, 2021).

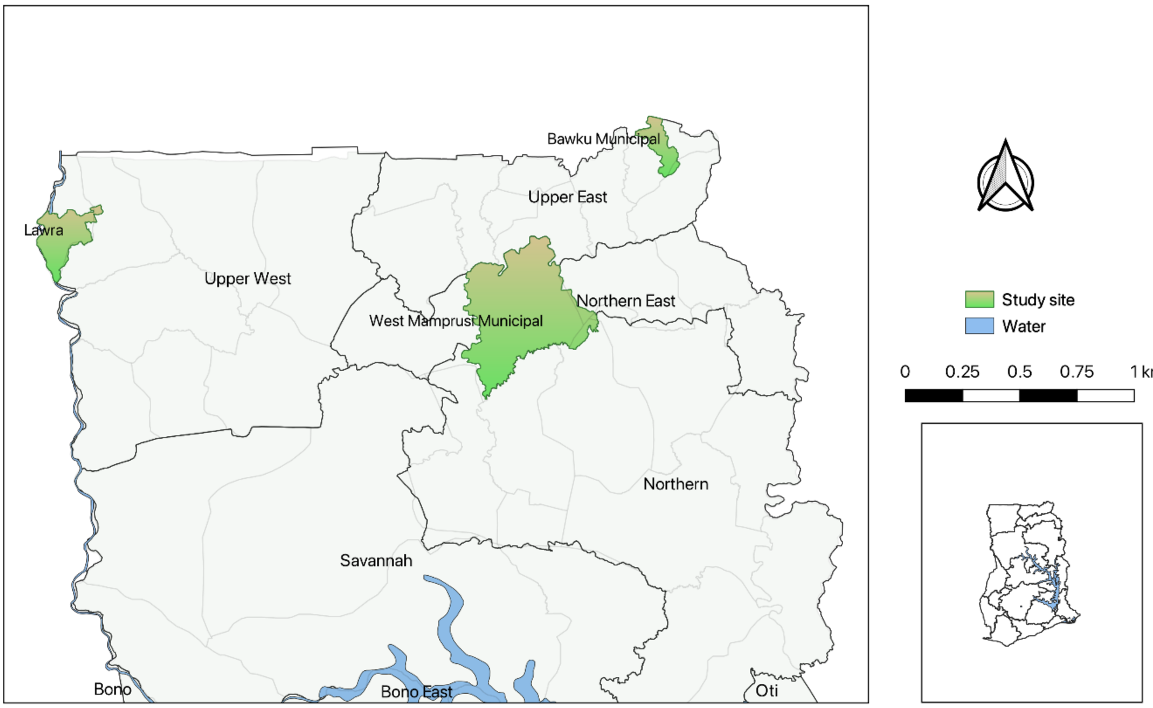
The USAID-UG Institutional Capacity Building for Agriculture Productivity Project (i.e. USAID-UG Project) involved Departments of Crop Science, Soil Science, Agricultural Extension, and, Agricultural Economics and Agribusiness. The main goal of the project was to increase agricultural productivity, food security and poverty reduction in farming communities through strengthening the capacity of households, farmer groups and agricultural extension agents to promote the adoption of soil carbon climate mitigation strategies (i.e. CF practices). Specifically, the project aimed at increasing the productivity of rice, maize and soya beans through the production and scaling up of biochar, and combination of biochar and compost (Co-compost); and undertaking a series of capacity building initiatives of stakeholders such as household waste sorting training; technical and business skills training; and biotechnology awareness programme. Additionally, the project undertook pilot study on evaluating the impact of project components on smallholder farmers in the three districts in Northern Ghana.

Farmer groups in the project sites were selected in 2016 based on previous experience with the various Departments of Agriculture. In 2017, training on the various components was undertaken where 10 farmers from each district, making a total of 30 farmers were selected for a short capacity building on carbon farming strategies, business support, among others at the University of Ghana, Legon. Participants were nominated by the farmer groups for the training programme. After this initial training programme, further training programmes were organized in the various districts where 30 farmers from each district, making a total of 90 farmers were taken through various components of the projects. Facilitators from the School of Agriculture designed the training protocols and implemented with the various Departments of Agriculture.

Beginning from the 2018 farming season, experimental fields, compost platforms, locally manufactured kilns, among other equipment were procured to produce biochar and compost for field experiments and on-farm field trials. These activities were undertaken with the active participation of the farmers and the agricultural extension agents (AEA) from the Departments of Agriculture. At this stage, all farmer group members were entitled to participate in the project activities.

Since 2018, each farmer group met weekly at the project venue for the collection of raw materials, charring and compost preparation. In 2018 and 2019 farming seasons, the field experiments demonstrated the different application rates for biochar and inorganic fertilizer. Similarly, during the 2020 farming season, the project experimented the application of biochar with compost known as “co-compost”. Interestingly, since the completion of the project in 2020, the farmer groups continue to meet regularly to produce biochar and compost for agricultural production. More significantly, some of the farmers produced their own biochar and compost for farming activities. Lastly, whilst biochar and compost were produced by the various farmer groups based on training and logistical arrangements, the products were shared to the farmers for the use on their plots. Since the inception of the project in 2015, about 200 farmers have participated in the biochar and compost production project either been originally selected by their farmer groups or through project activities at the farmer group levels.

Figure 1: Map of the Project Sites



3. Methodology and Data

3.1 Research Design and Sample Selection

The study was granted ethical approval from the Ethics Committee of the Basic and Applied Sciences (ECBAS), University of Ghana, Legon in December 2021. The study employed a multistage sampling procedure to select 472 farm households in Northern Ghana. The study selected farm households who participated in the USAID-UG Project and similar farm households in non-project communities. We relied on the list of 90 participants[1] from the Project Secretariat that was used in previous pilot surveys in 2020 and 2021. We undertook a census where participants on the list formed the initial sampling frame. Additional tracking was undertaken based on information from project and farmer group leaders to identify all members who have participated in the project activities. In total, we identified 192 farm households with participants in the USAID-UG project activities, of which 165 participated in the biochar and compost component (i.e. the focus of this study).

[1] This was defined as farm households originally selected as participants by their farmer groups for project activities.

Furthermore, the pilot surveys identified 47 non-participant farm households [2] in the project communities and we relied on this list to form the first half of the comparison group. We then proceeded to adjoining non-project communities to randomly select additional farm households to form the other half of the comparison group, making a total of 280 comparison farm households. Sampling of farm households from non-project communities was undertaken by dividing the communities into four quadrants based on the principal streets. Then in each quadrant, every fourth (4^{th}) household was interviewed for the survey. Interviews were conducted with the household head or spouse based on their knowledge of climate change and variability adaptation practices, sociodemographic, food and nutrition security and agricultural production characteristics. At the end of the household survey, we enumerated 151, 152 and 169 farm households in Bawku municipal[3], Lawra district and West Mamprusi municipal, respectively.

Taking into consideration the COVID-19 safety protocols and the location of residence of the field data enumerators, the study adopted several innovative approaches for the data collection exercise. First, we employed experienced field data enumerators with tertiary education and also able to speak the local language of the farm households in the respective project districts. Second, the survey instruments were shared with the field data enumerators about five days prior to the training workshop for the data collection. This was to ensure that the field data enumerators acquainted themselves with the survey instruments before the virtual training workshop. Third, a 2-day online (virtual) training was undertaken using Zoom software for all the field data enumerators based on the paper survey instruments. Constant roll-calls and tasking of field data enumerators to read and explain portions of the survey instruments were undertaken to ensure punctuality and understanding of the survey instruments.

Fourth, after the virtual training workshop, each field data enumerator was tasked to identify and interview two farm households in their communities using the revised paper-based survey instruments. Fifth, a 2-day in-person training sessions were organized for each survey team in the project districts using an electronically developed CAPI programme based on CsPro software. Another round of pretesting and role plays were undertaken by the field data enumerators before the commencement of the actual data collection. In total, 5 days of training and pretesting activities were undertaken before data collection exercise. Sixth, robust data quality mechanism was put in place to monitor in real time the submitted data

[2] This included farmers who were not originally selected by their farmer groups to participate in the project activities and also non-farmer group members. Therefore, we relax this definition in this study and include farm households who have participated in the project activities as participants leaving out the non-farmer group members as the non-participants. In all, about 30 farmers were re-classified as participants.

[3] Due to ethnic conflict in Bawku municipal during the data collection, the study based on ethical reasons did not undertake data collection in the city center and also communities affected by the conflict such as Kpalore, etc. Therefore, periphery communities were targeted for the data collection to avoid risking the lives of the data enumerators. In addition, residents and district agricultural extension agents with tertiary education used for the pilot surveys in 2020 and 2021 were recruited for the data collection due to their knowledge on the terrain in the municipality.

by the field data enumerators. Data delivered by the field data enumerators to the servers were occasionally checked and field data enumerators were promptly informed on the outcomes of their interviews. Seventh, all field data enumerators were advised to follow strictly the COVID-19 safety protocols. Lastly, participating farm households were given three pieces of soap as a token of appreciation for responding to the survey instruments.

The survey was conducted in March-April 2022 on the 2021 farming season together with socioeconomic characteristics. For project crops of interest (i.e. rice, maize and soya), a recall data collection for the 2020 and 2019 farming seasons was undertaken where production information was collected to create a 3-year recall panel[4] (i.e. 2019, 2020 and 2021). Previous studies (Atta-Ankomah et al. 2022; Benin, 2015) have employed this technique to collect household and firm level data on performance and mechanization services in Ghana. The detailed household survey instrument included modules on location and identification including GPS coordinates of dwelling and community; dwelling characteristics and household possession; integrated soil fertility management, climate change and variability; agricultural production; household income and expenditure; Innovations for Poverty Action (IPA)'s poverty probability index (PPI); food security; business enterprises; shocks and environmental resource scarcity; institutional and business support services, social capital and risk attitude; beneficiary module; and willingness to pay for biochar and compost; among others. Similarly, a short community questionnaire was designed to identify existing rural infrastructure and agricultural production activities in the project sites. In total, data collection was undertaken in 38 communities with the breakdown as follows: 15, 12, and 11 communities in Bawku municipal, Lawra district and West Mamprusi municipal, respectively.

3.2 Treatment Effects Estimations

The main objective of the study is to examine the effects of the biochar and compost production training (i.e. carbon farming training) on six indicators of welfare of farm households in Northern Ghana: maize productivity (kg/ha), gross maize revenue (GHS/ha), maize farming expenses (GHS/ha), per capita food expenditure (GHS), per capita total expenditure (GHS), and poverty likelihood (%). This could be achieved by employing a standard econometric technique, for example, ordinary least squares (OLS) to estimate the basic regression model, specified as follows:

$$W_i = \beta + \gamma P_i + X_i \delta + \varepsilon_i \tag{1}$$

where W_i is the welfare measure (for instance, poverty likelihood status) of farm household i. Let P_i represents an indicator variable for participation in biochar and compost production training measured as 1 if a farm household had a participant in the project and 0 for the comparison group, and γ represents the coefficient for the treatment effect estimates. In all regression models, we include a vector of household and community characteristics including

[4] Whilst this approach is cost-effective in creating a panel data, it may be affected by recall bias. However, since this study deals with agricultural production which forms part of household daily activities, the effect of recall bias should be minimum.

district dummies, which is represented as X_i and, ε_i represents the error term. Clustered standard errors adjusted at the 38 communities are reported.

However, this approach could lead to biased estimates of the effects of biochar and compost production training due to non-random selection of participants leading to endogeneity problems. As described in Section 3, selection bias due to self-selection and the influence of farmer group leaders could possibly affect participation in the project. Therefore, without adequately addressing these potential selection bias and endogeneity scenarios could result in upward biased estimates of the treatment effects. Similarly, participating farm households may be systematically different from the non-participating farm households, and this could also lead to biased estimates of the treatment effects.

We address these endogeneity issues related to the non-random selection of participants by estimating treatment effects using the inverse probability weighting regression adjustment (IPWRA) (Imbens & Wooldridge, 2009; Cattaneo, 2010; Drukker, 2016). The IPWRA has been employed by several empirical papers (Okyere and Ahene-Codjoe, 2022; Okyere et al., 2022; Manda et al., 2018; Okyere, 2021; Okyere & Usman, 2021; Tambo & Mockshell, 2018) based on its doubly robust property (Imbens & Wooldridge, 2009; Cattaneo, 2010; Drukker, 2016), where correct specification of either the treatment or outcome model generates robust estimates of the effects of carbon farming training on welfare. The IPWRA estimator allows the comparison of the expected welfare of farm households with participants in the biochar and compost production training to their counterparts that did not participate in the training. As previously shown in literature (Cattaneo, 2010; Manda et al., 2018), we estimate an average treatment effect on the treated (ATT) using the following basic regression model:

$$ATT = E(W_{1i}|P_i = 1) - E(W_{0i}|P_i = 1) \quad (2)$$

where $E()$ represents the expectation operator, P_i is a dummy variable measured as 1 if the farm household had a participant in the biochar and compost production training, W_{1i} and W_{0i} represent welfare outcomes of participating and non-participating farm households, respectively. In estimating the effects of participation in carbon farming training, we compare the average outcomes for participating farm households with the outcomes of non-participating farm households. Additionally, we estimate the effects of the project on not only the direct outcomes but also the indirect effects including poverty likelihood. This study expects that the project will increase the adoption of soil health strategies, increase resilience to climatic shocks, and increase technical efficiency leading to increased agricultural productivity, and finally, reduction in poverty likelihood in the project sites. Specifically, the study anticipates that the project will increase farm households' knowledge and perceptions on soil fertility practices and increase the adoption of good agricultural practices which will translate to higher technical efficiency, agricultural productivity, and ultimately, reduction in poverty likelihood in Northern Ghana.

We undertake robustness checks by employing least absolute shrinkage and selection operator treatment effects (TELASSO) method. Lasso is a machine learning technique that allows the selection of relevant covariates for a model and its treatment effect model has the doubly robust property (Chernozhukov et al. 2018; Koch et al. 2018; StataCorp. 2021).

4. Empirical Results

4.1. Descriptive Statistics

Table 1 presents the summary statistics on indicators for the USAID-UG Project. We find that majority of the farm households (56%) were aware of the project in their communities. Interestingly, 41 percent of the farm households participated in at least one component of the project whilst about 35 percent of the farm households were participants in the biochar and compost production component. The average period of participation in the project was 40 months (equivalent over 3 years). Overwhelming majority of the farm households were satisfied with the application of biochar and/or compost for agricultural production and would like to partake in the project in the future. On average, 93.43 kilograms (kg) of biochar and/or compost were applied on farmer plots during the 2021 farming season. Lastly, majority of the farm households (64.8%) rely on inorganic fertilizer only for maize farming in the study sites, followed by the application of both organic and inorganic fertilizer (23.6%). About 3.9 percent of the households rely on organic fertilizer only for maize farming in the study sites.

Table 1: Summary Statistics of USAID-UG Project Indicators

Indicators	Mean	S.D.
	(1)	(2)
Awareness of USAID-UG Project (dummy)	0.561	0.497
Participated in the USAID-UG Project (dummy)	0.407	0.492
Participated in the biochar and compost component of the USAID-UG Project (dummy)	0.350	0.477
Number of months of participation in the USAID-UG Project (number) [a]	40.516	16.089
Partake in the USAID-UG Project in the future (dummy)[a]	0.990	0.102
Respondent is very satisfied or satisfied with the use of biochar and/or compost [b]	0.990	0.100
Amount of biochar and/or compost applied to farm during 2021 farming season (kg) (including 0s)	93.432	273.744
Household used neither organic nor inorganic fertilizer	0.078	0.268
Household used inorganic fertilizer only	0.648	0.478
Household used organic fertilizer only	0.039	0.194
Household used both organic and inorganic fertilizer	0.236	0.425

Notes: a reports results for participating farm households and S.D. indicates standard deviation. b represents only farm households using biochar and/or compost.

Table 2 present the summary statistics of fertilizer application and farm performance. Results show that adoption of both organic and inorganic fertilizer leads to higher maize yield and gross revenue. Surprisingly, application of neither organic nor inorganic fertilizer application generates higher yields compared to use of inorganic or organic fertilizer only. This is counterintuitive and may be due to the relatively small samples for the neither organic nor inorganic, and organic fertilizer only categories. Another plausible explanation could be the lag effects of fertilizer application on farmer fields (i.e., benefit of previous usage of fertilizer on the plots).

Table 2: Summary Statistics of Fertilizer Application and Farm Performance

Indicators	Maize yield (kg/ha)	Maize gross margin (GHS/ha)	Maize gross revenue (GHS/ha)
	(1)	(2)	(3)
Neither organic nor inorganic fertilizer	868.574 (155.725)	993.980 (325.262)	1713.163 (279.9778)
Inorganic fertilizer only	753.845 (77.880)	371.184 (86.547)	1689.255 (88.823)
Organic fertilizer only	754.615 (162.511)	1303.241 (312.271)	1768.859 (291.790)
Both organic and inorganic fertilizer	1234.225 (137.847)	630.713 (211.317)	2198.911 (203.892)

Notes: Standard errors in parentheses.

Table 3 presents the summary statistics for our data, disaggregated by participants and non-participants in the biochar and compost production training. The results showed that majority of the farm households in Northern Ghana are male-headed and have an average household size of five members. The average household head is about 48 years and largely illiterate (i.e. cannot read and write in English) or with low educational status. Agricultural production in Ghana is dominated by smallholder farmers (MoFA, 2021) and this is evident in our sample where average maize farm size is about 1.42 hectares and total land under cultivation was about 2.21 hectares. Most of the farm households are risk neutral based on perceived risk attitude and this is similar to previous results found in Rwanda and Zambia (Tambo and Matimelo, 2021; Tambo et al. 2021). Interestingly, we find that most of the household head characteristics were similar for both participating and non-participating farm households.

However, we find statistically significant differences in farm and household socio-economic characteristics between participating and non-participating farm households in the biochar and compost production. For instance, participating farm households were more likely to belong to farmer groups, have larger farm area under cultivation and have better off-farm business activities. Compared to non-participating farm households, participating farm households have longer distance from their dwelling to agricultural extension offices, agro-dealer shops, and markets, but have better access to extension services. Table 3 also presents the descriptive statistics on farm performance. Unsurprisingly, participating farm households have better farm performance such as maize productivity and gross revenue compared to non-participating farm households. Similarly, participants have higher perception on soil quality compared to non-participant, but do not adopt more climate change and variability adaptation strategies than their non-participating farm households. Compared to non-participating farm households, participating farm households are more likely to purchase or use compost or organic fertilizer, herbicides, insecticides, seeds and irrigation for agricultural production during the 2021 farming season. Participating farm households have higher premium for compost and biochar compared to their non-participating farm household counterparts. Interestingly, both groups are similar when it comes to the adoption of monocropping farming system, sloppiness of farm land, and hiring of farm labour.

Finally, Table 3 also presents the welfare measures. Similarly, per capita household and food consumption expenditure were higher for participating farm households compared to non-participating farm households. Additionally, using IPA (2019)'s PPI score, we find poverty likelihood to be high in Northern Ghana (see also GSS, 2019). The IPA's PPI is based on ten questions ranging from consumption of meat and eggs in the past one month to ownership of television, fan, refrigerator to housing construction materials. Based on the PPI, 55.78 percent, 29.10 percent and 17.50 percent of the farm households in our sample were likely to be poor based on the national poverty, extreme poverty and US$ 1.25 per person per day poverty lines, respectively. Significantly less participating farm households were poor than non-participating farm households. Overall, our results suggest that farm households participating in the biochar and compost production are more productive, spend more on food and non-food items, and less poor than non-participating farm households, and thus give an indication of positive association of the training on farm performance and welfare. The next sub-section ascertains using doubly robust econometric analyses on whether this positive relationship is the causal effect of the carbon farming training after accounting for differences in 20 covariates among the participating and non-participating farm households.

Table 3: Summary Statistics and Balance Test for Biochar and Compost Production Training

Variable	Full sample (1)	Participant farm households (2)	Non-participant farm households (3)	Differences (4)
Household socio-demographic characteristics				
Age of household head (years)	48.021 (13.838)	48.412 (12.792)	47.811 (14.384)	0.601 (1.337)
Household size (number)	4.875 (2.091)	5.055 (2.234)	4.779 (2.007)	0.276 (0.202)
Male headed household (dummy)	0.697 (0.460)	0.679 (0.468)	0.707 (0.456)	-0.028 (0.044)
Household head is educated to at least Junior High School level (dummy)	0.227 (0.419)	0.242 (0.430)	0.218 (0.414)	0.024 (0.040)
Household head is illiterate (i.e. cannot read and/or write in English) (dummy)	0.773 (0.419)	0.764 (0.426)	0.779 (0.416)	-0.015 (0.040)
Household head is married (dummy)	0.756 (0.430)	0.788 (0.410)	0.739 (0.440)	0.048 (0.041)
Household head is Muslim (dummy)	0.523 (0.500)	0.558 (0.498)	0.505 (0.501)	0.053 (0.048)
Farming is main activity of household head (dummy)	0.725 (0.447)	0.782 (0.414)	0.694 (0.462)	0.088 (0.043)**
Household resides in Bawku municipal (dummy)	0.320 (0.467)	0.400 (0.491)	0.276 (0.448)	0.123 (0.045)***
Household resides in West Mamprusi municipal (dummy)	0.358 (0.480)	0.358 (0.481)	0.358 (0.480)	-0.001 (0.046)
Household resides in Lawra district (dummy)	0.322 (0.468)	0.242 (0.430)	0.365 (0.482)	-0.122 (0.045)***
Household member belongs to a farmer group (dummy)	0.608 (0.489)	0.727 (0.447)	0.544 (0.499)	0.183 (0.046)***
Perceived risk attitude of respondent (number)	5.727 (2.822)	5.806 (2.845)	5.684 (2.812)	0.122 (0.273)
System on mutual aid among farmers (dummy)	0.506 (0.500)	0.582 (0.495)	0.466 (0.500)	0.116 (0.048)**
Household has participated in survey in the last 3 years	0.644 (0.479)	0.897 (0.305)	0.508 (0.501)	0.389 (0.043)***
Off-farm business activity (dummy)	0.328 (0.470)	0.424 (0.496)	0.277 (0.448)	0.147 (0.045)***
10 year average rainfall (mm)	900.850 (164.614)	921.885 (150.946)	889.544 (170.679)	32.341 (15.837)**
30 year average rainfall (mm)	1034.430 (100.356)	1025.558 (105.927)	1039.199 (97.073)	-13.641 (9.677)
Distance from dwelling to extension office (km)	4.376 (4.947)	5.289 (5.345)	3.886 (4.655)	1.403 (0.474)***
Distance from dwelling to extension office (mins)	57.824 (49.987)	65.418 (50.514)	53.743 (49.301)	11.676 (4.800)**
Distance from dwelling to agro-dealer (km)	3.350 (5.085)	4.312 (5.126)	2.832 (4.995)	1.480 (0.487)***
Distance from dwelling to agro-dealer (mins)	45.722 (48.484)	55.145 (51.005)	40.658 (46.372)	14.487 (4.637)***
Distance from dwelling to market (km)	3.875 (5.211)	4.294 (4.946)	3.650 (5.342)	0.644 (0.503)
Distance from dwelling to market (mins)	49.956 (44.438)	53.327 (45.978)	48.143 (43.556)	5.184 (4.287)

Distance from dwelling to all-weather road (km)	2.427 (5.178)	3.414 (5.427)	1.896 (4.968)	1.518 (0.495)***
Distance from dwelling to all-weather road (mins)	25.422 (32.628)	34.994 (41.037)	20.277 (25.693)	14.717 (3.079)***
Household participate in extension services (dummy)	0.722 (0.448)	0.909 (0.288)	0.622 (0.486)	0.287 (0.041)***
Awareness of climate change and variability (dummy)	0.801 (0.400)	0.830 (0.377)	0.785 (0.411)	0.045 (0.039)
Total number of climate change and variability adaptation strategies (number; 0-8)	2.835 (1.776)	2.891 (1.838)	2.805 (1.744)	0.086 (0.172)
Farm soil quality perceived to be poor (dummy)	0.208 (0.406)	0.151 (0.360)	0.238 (0.426)	-0.086 (0.039)**
Total agriculture land ownership (ha)	2.665 (3.062)	3.365 (4.303)	2.289 (2.025)	1.076 (0.292)***
Total cultivated land (ha)	2.211 (1.976)	2.439 (2.090)	2.088 (1.905)	0.351 (0.190)*
Farm performance indicators				
Household cultivated maize during 2021 farming season (dummy)	0.926 (0.262)	0.927 (0.260)	0.925 (0.264)	0.002 (0.025)
Maize area under cultivation (ha)[b]	1.421 (1.290)	1.630 (1.604)	1.308 (1.071)	0.322 (0.129)**
Maize yield (kg/ha) [b]	875.604 (1266.244)	1210.713 (1156.026)	689.714 (1288.363)	521.000 (127.817)***
Maize gross margin (GHS/ha) [b]	506.364 (1613.269)	937.828 (1880.731)	286.621 (1412.263)	651.207 (166.415)***
Maize farming expenditure (GHS/ha) [b]	1164.922 (763.135)	1313.939 (818.615)	1089.028 (723.107)	224.911 (79.414)***
Maize gross revenue (GHS/ha) [b]	1808.572 (1600.747)	2397.898 (1841.532)	1508.551 (1372.396)	889.348 (160.538)***
Household purchases seeds (dummy) [b]	0.239 (0.427)	0.346 (0.477)	0.182 (0.387)	0.164 (0.042)***
Household purchases inorganic fertilizer (dummy) [b]	0.883 (0.321)	0.850 (0.359)	0.901 (0.299)	-0.052 (0.032)
Total inorganic fertilizer application (kg/ha) [b]	364.112 (276.787)	367.587 (277.791)	362.240 (276.717)	5.347 (27.788)
Total amount spent on inorganic fertilizer (GHS/ha) [b]	701.995 (596.585)	744.425 (613.546)	678.975 (586.997)	65.450 (59.889)
Household purchases organic fertilizer (dummy) [b]	0.273 (0.446)	0.449 (0.499)	0.179 (0.384)	0.270 (0.042)***
Total organic fertilizer and/or biochar application during 2021 farming season (including 0s; kg)	93.432 (273.744)	238.182 (388.159)	15.635 (131.233)	222.547 (24.379)***
Household purchases weedicides/herbicides (dummy) [b]	0.582 (0.494)	0.667 (0.473)	0.536 (0.500)	0.131 (0.049)***
Household purchases insecticides/pesticides (dummy) [b]	0.336 (0.473)	0.417 (0.495)	0.292 (0.456)	0.125 (0.047)***
Household uses irrigation (dummy)	0.307 (0.462)	0.382 (0.487)	0.267 (0.443)	0.115 (0.044)***
Household uses hired labour (dummy) [b]	0.474 (0.500)	0.526 (0.501)	0.447 (0.498)	0.079 (0.050)
Farmland perceived to be flat (dummy)	0.629 (0.484)	0.630 (0.484)	0.629 (0.484)	0.002 (0.047)
Monocropping farming system (dummy)	0.549 (0.498)	0.552 (0.499)	0.547 (0.499)	0.004 (0.048)
WTP for biochar (GHS)	43.083 (25.109)	51.176 (24.256)	38.733 (24.511)	12.443 (2.357)***

WTP for compost (GHS)	45.735 (25.294)	52.782 (23.507)	41.948 (25.445)	10.834 (2.393)***
WTP for both biochar and compost (GHS)	88.818 (48.877)	103.958 (46.971)	80.681 (48.007)	23.277 (4.599)***
Welfare indicators				
Household monthly food expenditure per capita (GHS)	69.082 (111.503)	95.844 (150.349)	54.699 (80.177)	41.145 (10.606)***
Household yearly food expenditure per capita (GHS)	828.983 (1338.040)	1150.124 (1804.191)	656.382 (962.119)	493.742 (127.276)***
Non-food yearly expenditure per capita (GHS)	635.836 (866.128)	705.882 (951.375)	598.189 (815.797)	107.694 (83.548)
Total yearly expenditure per capita (GHS)	1464.819 (1806.090)	1856.007 (2328.380)	1254.571 (1410.119)	601.436 (172.307)***
National poverty line PPI scorecard	22.561 (12.647)	24.370 (13.984)	21.590 (11.776)	2.780 (1.215)**
National poverty likelihood status	55.776 (21.690)	52.936 (23.597)	57.302 (20.470)	-4.366 (2.086)**
Extreme poverty line PPI scorecard	15.693 (10.094)	17.758 (11.293)	14.583 (9.217)	3.175 (0.964)***
Extreme poverty likelihood status	29.097 (16.622)	26.435 (17.138)	30.528 (16.186)	-4.093 (1.595)**
Poverty likelihood PPI scorecard (US$1.25/person/day)	22.112 (12.731)	25.030 (13.837)	20.544 (11.824)	4.486 (1.213)***
Poverty likelihood status (US$1.25/person/day)	17.498 (13.301)	14.990 (12.965)	18.846 (13.305)	-3.856 (1.273)***
No. of observations	472	165	307	---

Notes: [b] reports summary statistics for only maize growers during 2021 farming season. Columns (1)-(3) presents the means and standard deviation (in parentheses) for each group. Column (4) indicates the mean differences and standard error (in parentheses). Results on maize productivity and household expenditure are controlled for outliers and therefore are fitted within 95 percentile.

4.2 Effects of Carbon Farming Training on Farm Performance and Welfare

We rely on several farm performance and welfare measures such as adoption of organic fertiliser, agricultural productivity, maize gross revenue, expenditure, and poverty status. We first present the balance diagnostics tests on whether the overlap and covariate balancing conditions are satisfied (see also Tambo et al. 2021; Okyere et al. 2022; Okyere and Ahene-Codjoe, 2022) in Figure 2. It shows that there is sufficient overlap of the propensity score distribution between participating and non-participating farm households. Furthermore, we found no statistically significant Chi-squared (*p*-value of 32.29) overidentification test for the 20 covariates included in the treatment model. Similarly, the covariate balancing tests shows that the mean and variance are closer to zero and one, respectively, after weighting. Therefore, we can safely conclude that the IPWRA estimator generates comparability between the participating and non-participating farm households, and therefore the assumptions underlying treatment effects estimates are satisfied. Lastly, we rely on another doubly robust estimator-TELASSO- which controls for the choice of important covariates to be included in the models using machine learning technique. The results from TELASSO reported in Columns (3) and (4) are very similar to those obtained from our preferred IPWRA estimator (i.e. Columns 1 and 2).

Figure 2: Overlap Plot for IPWRA Estimator

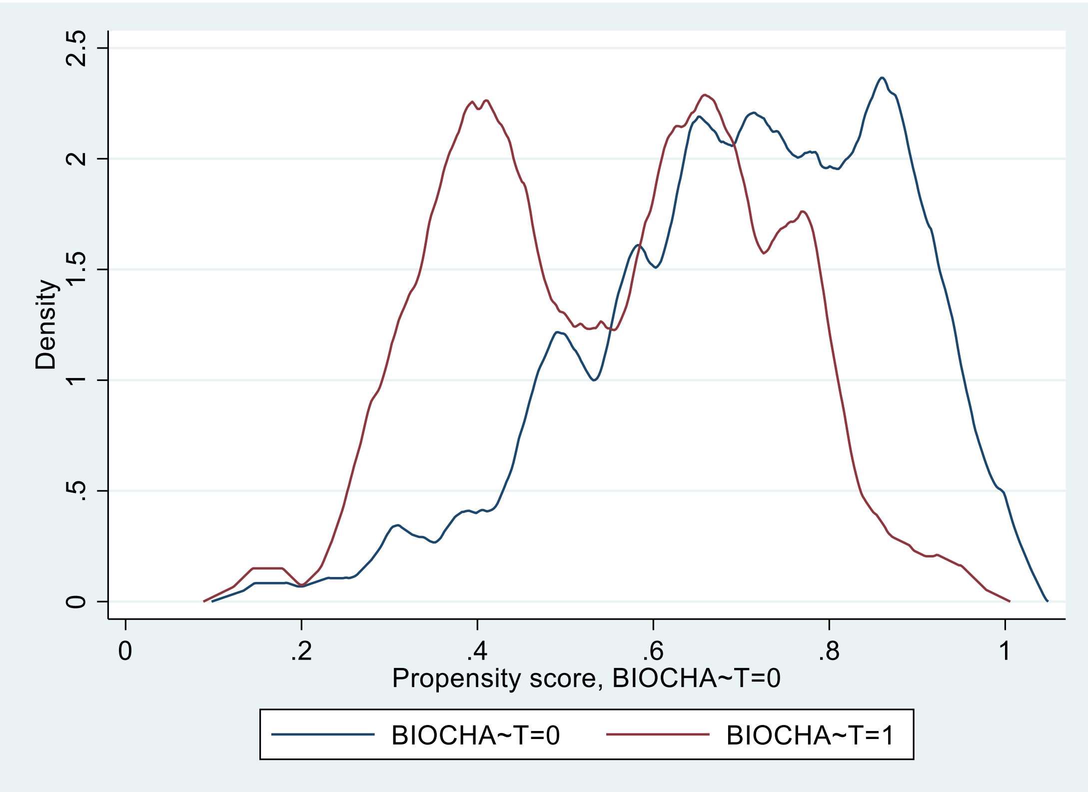


Table 4 presents the effects of CF training on farm performance and welfare. First and foremost, participating farm households are about 25.8 percent more likely to use compost or organic fertilizer and 9.7 percent less likely to report that their soil quality is poor. However, we find that participation in carbon farming training does not statistically and significantly increase climate change and variability adaptation strategies. These results are not counterintuitive as farm households may have perceived the project to be related to soil health improvement rather than broader climate change and variability adaptation strategies. Besides, several climate change and variability adaptation strategies have been promoted in the project sites and therefore, farmers are widely aware of its negative effects. The results on the adoption of organic fertilizer and perception on soil quality are interesting findings, since soil fertility is essential for poverty reduction in SSA (Vanlauwe et al. 2015), and in recent times there has been global urgency of improving soil health including soil carbon (Amelung et al. 2020; FAO, 2019).

We also found statistically significant positive effects of CF training on maize yield, revenue and expenses. In particular, participants obtained 487.49 kg/ha maize yield increase relative to non-participants. Similarly, participating in carbon farming training is statistically and significantly associated with GHS 201.44 increase in maize farming expenses and GHS 760.75 increase in gross maize revenue. Taken together, the results suggest that CF training increases agricultural investment decisions and productivity, and this concurs with previously reported studies in the literature on the increase in agricultural productivity due to the adoption of climate change and variability adaptation strategies (Etwire et al. 2022) and CA (Tambo and Mockshell, 2018, Tambo and Kirui, 2021) and organic fertilizer (Martey, 2018).

Table 4 also reports that participation in CF training statistically and significantly contributes to a reduction in the likelihood that a household is poor. The results show that relative to non-participating farm households, farm households that participated in the carbon farming training are 5.39 percent less likely to be poor based on IPA's PPI national poverty line. These are interesting findings considering that the semi-arid regions of Ghana (i.e., project sites) have the highest number of populations living in poverty or extreme poverty. Finally, we find that participation in carbon farming training increases total household expenditure and food consumption expenditure. Taken together, our results show that CF training generates positive effects on important welfare indicators, and this partly confirms Vanlauwe et al. (2015) and Martey (2018)'s study on the importance of improving soil health for poverty reduction in SSA.

Table 4: Effects of Carbon Farming Training on Farm Performance and Welfare

	Model 1: IPWRA		**Model 2: TELASSO**	
	ATT	**Clustered SE**	**ATT**	**Clustered SE**
	(1)	**(2)**	**(3)**	**(4)**
Farm performance				
Compost or organic fertilizer (dummy)	0.258***	0.056	0.295***	0.061
Poor soil quality (dummy)	-0.097**	0.047	-0.085**	0.035
Adoption of climate change and variability adaptation practices (#; 0-8)	-0.193	0.223	-0.089	0.223
Maize yield (kg/ha)	487.489***	151.691	546.242***	161.271
Maize gross revenue (GHS/ha)	760.753***	231.451	722.383***	174.888
Maize farming expenses (GHS/ha)	201.437**	80.230	202.487***	77.759

Welfare measures				
Household monthly food expenditure per capita (GHS)	33.932**	14.449	41.977**	17.340
Total yearly expenditure per capita (GHS)	481.027**	240.100	634.099**	281.032
National poverty likelihood (%)	-5.389**	2.676	-5.747*	3.257
No. of observations (N)	**472**		**472**	
Controls	**Yes**		**Yes**	

Notes: 20 covariates included in both treatment and outcome models are: natural log of distance to market and district extension office, natural log of quantity of inorganic fertilizer application, off-farm business activities, risk attitude, farmer group membership, irrigation, monocropping farming system, natural log of maximum willingness to pay for both biochar and compost, male-headed households, age of household and its squared, marital status, religion of household, household head's educational status, dummies for West Mamprusi and Lawra districts.

4.3 Multiple Hypotheses Testing of Outcome Measures

This section presents results on multiple hypothesis testing of the outcome measures as it is possible that some of the statistically significant treatment effect estimates are due to chance. We address this problem using the false discovery rate (FDR) approach (Benjamini and Hochberg 1995; Arouna et al 2021; Tambo et al. 2020) by undertaking multiple hypothesis testing. FDR was chosen due to computational convenience as its applications are relatively easier including the option of manual estimation. Our results (available upon request) show that all the statistically significant results reported in Table 4 maintain their significance, except for poverty likelihood results from the TELASSO estimator. This further shows that our results are robust to alternative specifications.

5. Conclusion

In Sub-Saharan Africa (SSA), climate change and variability are widely recognised as one of the major factors for low agricultural productivity. This evidence has necessitated the promotion of several climate change and variability adaptation strategies in which various land use management practices are adopted for agricultural production. In recent times, CF, particularly soil carbon mitigation strategies are gaining prominence in worldwide agriculture as one of the mechanisms for climate change and variability mitigation and/or adaption strategies. However, few empirical studies have been undertaken on the uptake and effect on economic welfare of farm households in developing countries. More so, little is known about CF training on farm performance and welfare in developing countries. This study attempts to fill these gaps in the literature by examining the welfare effects of carbon farming training, particularly soil carbon mitigation strategies in which farmers received training on biochar and compost production in three semi-arid regions of Ghana. Our results have policy relevance, especially based on recent global urgency in improving soil health, particularly soil carbon towards achieving agricultural productivity, food security, poverty reduction and wellbeing; which are key components of the SDGs.

Using data from 472 farm households, we analysed whether participation in the training led to increased adoption of organic fertiliser, climate change and variability adaptation strategies, maize productivity and returns, household expenditure, and finally, reduction in poverty. In consonance with previous studies (Etwire et al. 2022; Tambo and Mockshell, 2018, Tambo and Kirui, 2021; Martey, 2018) on climate change and variability adaptation, conservation agriculture and organic fertilizer, our results show that training on carbon farming generates positive effects on key welfare outcomes. Our findings show that participation in carbon farming training encourages the use of organic fertiliser leading to significant maize productivity and gross return gains of 487.49 kg/ha and GHS 760.75, respectively. Additionally, CF training is statistically and significantly associated with an increase in household expenditure and also a reduction of poverty likelihood.

In conclusion, our results suggest that CF training is beneficial in terms of adoption of organic fertiliser, perception on soil quality, increased productivity and achieving poverty reduction. While there are recent efforts in improving soil carbon at the global level, biochar and compost production could be considered as possible avenues for such interventions. More importantly, policy support for the training of farm households on the production of soil carbon resources (i.e. biochar and compost) could be a viable option to pursue in addressing climate change and variability in the global south. Specifically, our results suggest the need to provide comprehensive training programmes on carbon farming techniques to encourage smallholder farmers to adopt soil carbon mitigation strategies in SSA.

Lastly, our study has some limitations that could serve as areas for future research. First, relying on a relatively small sampled observational data limits the ability of making strong causal inferences on the long-term effects of carbon farming training. Similarly, we do not undertake soil quality analysis on carbon sequestration. Therefore, we recommend a longitudinal analysis combining survey, plot level data, and soil quality data analysis to examine the social, economic, and environmental welfare effects of carbon farming techniques. Another interesting area to consider is the design of sustainable business models for the production and scaling up of carbon farming practices in the global south. This is important as Jefferey et al. (2017) showed that the application of biochar to tropical soils could achieve higher productivity gains compared to temperate soils. Due to limited samples and estimation challenges, we do not consider heterogeneity in treatment effects based on gender, age, and socio-economic status, and this is important in closing productivity and gender gaps in agriculture, thereby achieving women’s economic empowerment and gender equality.

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