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Impact of conservation agriculture and biochar interventions on labour demand and productivity in Uganda: evidence from a field experiment

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Abstract

Conservation agriculture (CA) and the use of biochar as a soil amendment can promote productive, resilient, and sustainable smallholder farming. However, adopting these practices requires a shift from conventional methods, potentially changing labour use and returns, the extent of which remains poorly understood. Using data from a randomized controlled trial (RCT) of 400 farmers designed to be representative of smallholder farmers in two districts of Uganda, this study assesses how an informational intervention (delivered through instruction and participatory field demonstrations) on CA methods with and without biochar affect labour use and productivity. Control group farmers were compared to those receiving (i) CA and (ii) CA+BIOCHAR interventions. First difference and inverse probability-weighted regression-adjustment model results indicate that the CA+BIOCHAR intervention increased labour use, with no significant labour productivity gains, compared to the control group. Labour input rose by about 36%, driven by a 54% increase in family labour, while hired labour input declined. Extra work was hence met by family labour rather than paid work. Labour savings occurred only in land preparation, and overall returns to labour were roughly 45% lower than conventional practice. The shifts in labour use and productivity are largely attributable to the information intervention, which increased cultivated area, area under minimum tillage, crop diversity, and biochar application. Taken together, these findings show that, over the study period following the intervention, the promoted CA and biochar package was associated with higher labour demand and no clear labour productivity gains. Bundling training with complementary interventions that tackle the labour burden inherent in smallholder agriculture may be necessary to achieve both labour-saving and labour productivity gains from CA and biochar adoption.

Keywords Climate-smart agriculture, Biochar, Labour requirements, Labour productivity, Randomized control trial, Uganda

JEL Codes O13, Q16, Q12, Q21, C93

Introduction

Food demand in Sub-Saharan Africa (SSA), including Uganda, is rising sharply due to population growth, urbanisation, increasing incomes, and shifting dietary preferences (Giller 2020; Van Ittersum et al. 2016; IPCC 2022). Rapid demographic expansion and increasing urbanisation rates¹ are expected to intensify the demand for staples such as grains, vegetables, and protein sources, posing significant challenges to achieving food security², especially as current production struggles to meet demand (Giller 2020; Van Ittersum et al. 2016). Achieving food security is further hindered by the severe impacts of climate change, such as prolonged dry spells, floods and erosion (IPCC 2014, 2022).

Agricultural systems worldwide already contribute to more than 20% of global greenhouse gas emissions, are a major driver of habitat loss and deforestation, are a leading cause of water, air, and soil pollution, and use 70% of global freshwater withdrawals (IPCC 2022; Potapov et al. 2022; Rosegrant et al. 2009). Smallholder farmers, who cultivate on average less than two hectares, make up 84% of all farms globally, produce about 35% of the world's food, and support two-thirds of the rural population in developing countries (Lowder et al. 2021; Rapsomanikis 2015). In SSA, agriculture provides vital employment, income, and food security, engaging over half of the regional workforce (ILO 2017). Despite its importance, agricultural productivity in SSA is stagnating, with substantial yield gaps attributed to socioeconomic constraints, government and market inefficiencies, soil degradation and the disproportionate impacts of climate change on smallholder farmers (IPCC 2022; Ortiz-Bobea et al. 2021; Ray et al. 2012; Suri and Udry 2022). In addition, conventional agricultural methods are labour-intensive, locking up much of the active labour force that could be freed for use in the off-farm sector. Improving smallholder land and labour productivity is, hence, essential to achieving sustainable development goals, especially those focused on eradicating poverty (SDG 1) and hunger (SDG 2).

Climate-smart agriculture (CSA), which aims to simultaneously achieve productivity, adaptation, and mitigation goals while maximising synergies between these goals and minimising potential trade-offs, is one approach touted to sustainably increase agricultural production in agro-based societies (FAO 2010; Lipper et al. 2014). The successful adoption of CSA practices holds substantial promise for transforming smallholder farming under climate stress in SSA. While no single set of practices universally defines CSA, it generally encompasses strategies that enhance productivity and climate resilience while minimising negative environmental impacts, particularly greenhouse gas emissions (FAO 2010; Lipper et al. 2014). Conservation agriculture (CA) and biochar are two promising CSA practices with strong potential to increase yields, strengthen climate resilience, and reduce emissions. CA, which involves minimal soil disturbance (no-till or reduced tillage), crop rotation, and permanent soil cover (FAO 2015), can play an essential role in smallholder farming systems by preserving soil health, reducing water use, enhancing soil carbon capture, and boosting crop yields (Corbeels et al. 2020; Johansen et al. 2012; Pisante et al. 2015). Similarly, biochar³, a carbon-rich material produced

¹ Urbanization rates in Sub-Saharan Africa (SSA) and Uganda have increased by nearly 27% points (from 15% to 46%) and 22% points (from 4% to 26%), respectively, between 1960 and 2022 (World Bank, 2022).

² According to the FAO, the prevalence of undernourishment in the region is increasing, with a rise of more than 2% points (from 17.6% to 19.1% in 2019) over a five-year period between 2014 and 2019 (FAO et al. 2020).

³ In agricultural applications, biochar is commonly applied in powdered or crushed form and mixed into the topsoil by hand or with basic implements as a soil amendment.

from agricultural waste through pyrolysis in a low-oxygen environment, offers benefits such as improving soil quality, increasing soil water retention, supporting crop productivity, aiding climate change mitigation, and promoting efficient resource use (Kapoor et al. 2022; Campion et al. 2023; Schmidt et al. 2021). CA and biochar, taken together, can serve as key pillars of sustainable agriculture by providing a strong foundation to improve productivity, resilience, and sustainability in smallholder farming (Cornelissen et al. 2013; Martinsen et al. 2014; Obia et al. 2020).

CA and biochar hold promise for enhancing land productivity and resilience in smallholder farming, but their adoption is often complex and not autonomous. These practices face context-specific constraints, including challenges in accessing feedstock for biochar production due to competing uses for residues and/or insufficient biomass production, especially on the poorest soils where biochar is most effective (Scholz et al. 2014; Zilberman et al. 2023). More broadly, although no single binding constraint limits adoption, various context-specific barriers often impede promising innovations in developing regions, including liquidity constraints, inadequate risk-management instruments, high transaction costs in input and output markets, and information gaps (Binswanger-Mkhize and McCalla 2010; de Janvry and Sadoulet 2019; Suri and Udry 2022). In addition, the adoption of CA and biochar often requires a shift away from conventional farming methods, which can significantly alter labour demands across various production stages (Farnworth et al. 2016; Montt and Luu 2020; Pannell et al. 2014). Knowledge gaps exist regarding the net labour effects of minimum tillage, a central practice of CA, which may reduce labour at initial stages like land preparation but can increase labour at later stages, such as weeding, if herbicides are not used due to a higher weed burden (Giller et al. 2009; Pannell et al. 2014; Rusinamhodzi 2015). Likewise, combining CA with biochar may increase overall labour requirements due to the added work involved in producing and applying biochar compared to conventional methods (Bruckman and Pumpanen 2019; Owsianiak et al. 2021; Sparrevik et al. 2014). It may further raise total labour demands per unit of output during later stages, such as harvesting and post-harvest handling, following yield improvements (Farnworth et al. 2016; Montt and Luu 2020). Nevertheless, the anticipated improved harvest outcomes with successful CA and biochar implementation (Cornelissen et al. 2013; Martinsen et al. 2014; Obia et al. 2020) suggest that the combination of potential labour savings and increased output can alter overall labour productivity. The nature and extent of these possible changes in labour input and in the allocation of labour between family and hired labour, as well as the resulting returns across different contexts, remain uncertain.

Therefore, this paper assessed the contributions of CA and biochar interventions to labour use, costs, and productivity in smallholder farming in rural Uganda using data from a randomised controlled trial (RCT) involving 400 farmers. Specifically, it quantified to what extent the access to training in CA or both CA and biochar (CA+BIOCHAR) led to (i) significant shifts in total labour use, both overall and across specific stages of production (e.g., land preparation, planting, fertilizer application, weeding, and harvesting), (ii) changes in the use of family and hired labour, and in overall labour costs, and (iii) changes in crop output per unit of labour used when compared with control groups. The analysis was based on data from an RCT conducted across two districts, Alebtong in Northern Uganda and Mubende in Central Uganda, with baseline data collected in 2021 and endline data in 2024. The study contributes to the literature by using an RCT to

analyse how access to CA and biochar interventions, compared to conventional farming methods, impacts labour use, costs, and productivity in smallholder farming in Uganda, a question that has received limited experimental attention. In doing so, we situate CSA adoption within the broader context of smallholder agricultural growth, considering both labour use and productivity, to provide insights into potential pathways for rural development under climate stress. The results can inform the design of CSA interventions by guiding the identification of strategies that simultaneously reduce excess labour and improve output per unit of labour, supporting both efficiency and broader rural development goals.

Research methods

Context

Uganda is predominantly an agricultural country, with agriculture playing a crucial role in its economy and the livelihoods of approximately 73% of its population, most of whom reside in rural areas. Although agriculture's share of GDP has declined over time, it still contributes around 24% of Uganda's GDP and accounts for 72% of total employment (Roser et al. 2024). Cereals are an important category of crops in the Ugandan diet, with current cereal yields averaging 2.29 tonnes per hectare per year, above the African average (1.74 tonnes/hectare) and that of other low-income countries (1.44 tonnes/hectare), though still significantly lower than in Asia (4.40 tonnes/hectare) and high-income countries (5.87 tonnes/hectare)(ibid.).

The agricultural sector remains heavily reliant on manual labour and locally sourced inputs. Production is predominantly rain-fed, low-input, and managed by small-scale, resource-poor farmers, who receive minimal support from advisory and extension services. For example, only 0.5% of cultivated land is irrigated, below that of neighbouring countries such as Burundi (1.6%), Kenya (2%), and Tanzania (3.6%) (Ministry of Water and Environment 2017). In addition, the use of improved seeds is limited, with roughly 70–95% of farmers using farmer-saved seeds or those sourced through informal seed exchanges (Bagamba et al. 2022). Fertiliser use is similarly low, averaging just 2.4 kg per hectare of arable land, compared to 13.61 kg in other low-income countries, 85.44 kg in Europe and Central Asia, and 138.71 kg in high-income countries (Roser et al. 2024).

Agricultural growth achieved in recent years has largely stemmed from expanding cultivated areas rather than increasing productivity per unit of land. Farmland grew from 10.68 million hectares in 1980 to 14.42 million hectares by 2021. The lack of productivity growth in Uganda's smallholder agriculture sector is primarily due to declining soil fertility, the growing impacts of climate change, and other socioeconomic challenges, including frequent extreme weather events and soil erosion (BFS/USAID. 2017; Nkonya et al. 2008; World Bank, 2021).

Theory of change and hypotheses

To understand the connection between access to transformative training on climate-smart agriculture methods and changes in agricultural outcomes, including labour use, the study drew on theoretical and empirical evidence addressing key constraints to agricultural modernisation, along with proposed solutions, in developing regions, including Africa (e.g., (Barrett et al. 2020; de Janvry and Sadoulet 2019; Suri and Udry 2022)). Key barriers to agricultural transformation are often attributed to government and

market failures, which create three main constraints: (i) low profitability of innovations for smallholder farmers, (ii) limited availability of innovations locally, and (iii) barriers to adoption even when innovations are available and profitable (de Janvry and Sadoulet 2019; Goyal and Nash 2017). These constraints are exacerbated by factors such as limited access to credit and savings, challenges in risk management, poor infrastructure and lack of information on new technologies (Binswanger-Mkhize and McCalla 2010; de Janvry and Sadoulet 2019; Suri and Udry 2022).

Literature suggests two primary approaches to overcoming these barriers: (i) creating incentives for modernization through value chain development and integration, and (ii) ensuring the local availability of profitable innovations while addressing barriers to demand and adoption through institutional improvements and better technology dissemination (Bridle et al. 2019; de Janvry and Sadoulet 2019; Magruder 2018). Information constraints remain one of the most frequently highlighted barriers to the adoption and proper implementation of agricultural innovations in developing countries, including Uganda, suggesting that access to training is a crucial pathway for driving transformative change (Abdulai 2023; Aker 2011; Shikuku 2019; Shikuku et al. 2019).

Training helps address these information constraints by equipping farmers with the knowledge needed to understand, assess, and adapt innovations, fostering both awareness and confidence in applying new practices effectively within their local contexts. The conventional way of achieving this in Uganda is through private and publicly provided extension services. However, they face multiple challenges that limit effectiveness. For example, in Uganda, public agricultural extension is constrained by limited funding, high farmer-to-extension worker ratios, logistical and mobility constraints, low extension worker motivation, poor infrastructure, bureaucratic inefficiencies, and restricted access to modern technologies for effective demonstration (Kabunga et al. 2016; MAAIF, 2016). As a result, fewer than 11% of the agricultural population reports having ever received information from extension services in one year (Kabunga et al. 2016), and extension staff-to-farmer ratios are way below the recommended ratios (MAAIF, 2016). Given the challenges faced by Uganda's extension system, providing training to farmers can help bridge these gaps by equipping them with the knowledge and practical skills needed to implement CSA methods, thereby promoting uptake and driving transformative changes in both labour use and productivity.

The study therefore, implemented an RCT that introduced a series of training and practical demonstration sessions teaching farmers best practices in the application of climate-smart innovations, including (i) principles and practices of CA, (ii) CA basin and rip line making and planting techniques, (iii) weed management, (iv) pest and disease management, (v) post-harvest handling and storage, (vi) biochar production using crop residues (e.g., pigeon-pea residue), and (vii) biochar application and planting. The training provided in the RCT was designed to equip farmers with the necessary skills to adopt these CSA practices, potentially inducing changes in labour use and productivity. This study explores these presumed links by addressing the following research question and hypotheses.

Research question

- 1) Does access to training in two specific CSA methods (CA and CA+biochar) change labour use, costs and productivity in smallholder farming?

Hypotheses

- a) Access to training in CSA methods reduces total labour use and costs, including both family and hired labour, in agricultural production.
- b) Access to training in CSA methods reduces labour use in land preparation and planting but increases labour use in weeding and harvesting.
- c) Access to training in climate-smart agriculture methods increases labour productivity.

Data and variables

The data for this study come from a randomised controlled trial (RCT) conducted in two districts of Uganda, Alebtong in Northern Uganda and Mubende in Central Uganda. The baseline survey was conducted in May 2021, and an endline survey was carried out in July 2024. The initial sample consisted of 400 households, evenly distributed across the two districts (200 households per district) and eight villages (four villages per district). Within each village, 50 households were randomly selected to participate in the RCT. In each district, four villages were assigned to one of three treatments, with one village serving as the control group, one village receiving CA training, and two villages receiving both CA and biochar training. The selection of control and intervention villages was done to minimize potential spillover effects while maintaining comparability across study sites. On average, the separation between control and intervention villages (using village centers as a reference) ranged from 3 to 5 km, which was assumed sufficient to substantially limit spillover effects, although some information sharing through social networks or markets may not be completely ruled out. Formal tests for spillover effects, however, show no significant spillover effects in our study.

After the baseline survey in 2021, households in the treatment groups participated in a series of training sessions facilitated by field officers from Rural Enterprise Development Solutions (REDS Uganda), a local partner with extensive experience in delivering agricultural extension services focused on sustainable farming practices. Training sessions for treatment groups in both Mubende and Alebtong districts were conducted over a period spanning August 2021 and March 2022. The training and demonstrations provided to farmers focused on hands-on guidance for implementing CA and biochar practices, as well as general principles for efficient production, management, harvesting, and post-harvest handling of output. Farmers in each treatment group were trained once and left to implement the practices independently on their farms without further follow-up from experts. Compliance with the training sessions was exceptionally high, with 90% of households attending. On average, households in the CA training group attended 4.5 out of 5 sessions (90% attendance rate), while those in the combined CA and biochar training group attended 6.3 out of 7 sessions (90% attendance rate). This confirmed that the treatment assignment closely resembled the actual treatment reception.

Data collection was conducted using structured questionnaires that collected data on both household socioeconomic characteristics and plot-level production activities, including labour use. Data were collected through in-person interviews conducted by well-trained and experienced enumerators familiar with the local context and languages, and were recorded centrally using KoBo Collect open-source software to ensure standardized data capture and real-time quality checks. These data are used to define key outcome variables for analysis, including total labour use, family labour use, and hired labour use, measured both in physical quantities (person-days per hectare) and in

monetary terms (costs per hectare in Ugandan shillings, UGX). Costs of hired labour reflect direct expenses incurred by the households that used hired off-farm labour, while family labour costs reflect the opportunity cost⁴ of family labour. All costs are expressed in real 2021 values to facilitate the comparison of costs between the baseline (2021) and endline (2024) surveys. Conversion to real UGX values is done using the Consumer Price Index (CPI) data for Uganda from the World Bank (World Bank 2024). Labour productivity is measured both for all crops grown⁵ and for specific key crops (maize and beans) and crop groups, such as cereals (maize, millet and sorghum) and legumes (beans, soybeans, groundnut, pigeon peas and cowpeas). For the general measure, productivity is expressed as the total value of harvested output⁶ per person-day worked (USD/person-day). For specific crops (maize and beans), productivity is measured in both physical quantities (kg/person-day) and the value of harvested output (USD/person-day).

Information about the farm and the households collected in the baseline and endline surveys allowed for the measurement of various household characteristics (household size, female ratio⁷, household asset wealth index⁸, farm size (ha), and male adult equivalent labour units⁹), characteristics of the household head (age and gender), and farm characteristics (e.g., the main form of land tenure, measured as dummy variables for customary, private (freehold or leasehold), and mailo tenure¹⁰). Rainfall conditions during the season in which the data were collected (the short season of 2024, between January and June) were also included, alongside long-term averages (1990–2023) computed using farm-specific location data derived from the Climate Hazards Group Infra-Red Precipitation with Station (CHIRPS¹¹).

⁴ The Ugandan Bureau reports that the median wage from agriculture in 2021 was about 220 000 UGX/month which translate to roughly 7,333.33 UGX/day or about USD 2.04/day after adjusting for inflation and using an average exchange rate of about 3,586.57 to 1 USD. We assume that the opportunity cost of family labour equals the prevailing median agricultural wage, and that family and hired labour are valued at the same unit cost when translating labour inputs into monetary terms. Family labour costs are therefore interpreted as an opportunity-cost measure based on prevailing agricultural wages rather than on observed household-specific off-farm earnings. Accordingly, the data do not allow us to determine whether additional family labour on the farm displaced off-farm employment, domestic work, or leisure.

⁵ The survey primarily covered food crop production, including key cereals, legumes and other crops including maize, beans, sunflower, soybeans, cassava, Irish potatoes, coffee, millet, groundnuts, sorghum, pigeon peas, matooke, rice, sesame, sweet potatoes, seed cotton, cowpeas, and tomatoes.

⁶ The value of crop harvest per household is estimated by converting the physical quantities of harvested output (grain in kilograms) into monetary terms using average prices observed in the central and northern regions of Uganda, as reported by various sources (refer to the supplementary material for a table detailing average prices per kilogram of output across different years).

⁷ The household female ratio captures the proportion of household members that are female.

⁸ The asset index is computed by Principal Components Analysis (PCA) (Filmer and Pritchett 2001) using the list of assets included in the household socioeconomic questionnaire, including tractors, tractor rippers, tractor ploughs, animal-drawn power (ADP) equipment, knapsack sprayers, generators, motor vehicles, motorcycles, bicycles, radios, solar panels, televisions, and other asset indicators (e.g., ownership of livestock and type of household roofing material).

⁹ Household male adult-equivalent labour units are approximated by assigning values of 1, 0.8, and 0.5 to an adult male, an adult female, and children between 5 and 15 years of age, respectively, as in previous studies using related data (e.g. (Makate et al. 2024; Tione and Holden 2021)).

¹⁰ Uganda has four types of land tenure systems, including: (i) customary tenure, which allows land use without formal titles and is often governed by traditional practices; (ii) freehold, which grants exclusive ownership rights; (iii) leasehold, involving time-bound rental agreements (up to 99 years) between landlords and tenants; and (iv) Mailo, a hybrid system characterized by overlapping and often undocumented rights between landowners and occupants (Pedersen et al. 2012).

¹¹ CHIRPS is a 35 + year global rainfall dataset (1981–present) that combines satellite imagery, in-situ station data, and climatology to provide high-resolution gridded rainfall time series for trend analysis and drought monitoring across latitudes 50°S to 50°N. More information on the database is available here: <https://www.chc.ucsb.edu/data/chirps>.

Attrition

Of the initial 400 households surveyed in 2021, 332 households remained in the complete panel, reflecting a 17% attrition rate. The primary causes of attrition identified were mortality and relocation. To determine if the attrition was random, the study examined patterns of attrition across the treatment and control groups, including whether households with certain characteristics were more or less likely to drop out of the panel. A probit regression model with a dummy variable indicating dropout from the complete panel (1 = yes; 0 = no) as the outcome variable and controlling for household socioeconomic characteristics, district dummies, and baseline treatment assignment as covariates revealed that attrition was not random. Female-headed households ($p < 0.05$), households with more assets ($p < 0.10$), and households from Mubende district ($p < 0.01$) in central Uganda were significantly more likely to drop out. Additionally, households from treatment villages were more likely to drop out compared to those in control villages (Table 1).

Due to the unsystematic dropout of households from the sample, attrition weights were generated using an attrition probit model to test and correct for potential attrition bias in regressions identifying treatment effects. Specifically, the inverse Mills ratio (IMR) was constructed from the probit model and incorporated as an additional regressor in robustness analyses that accounted for extra covariates. The IMR, reflecting attrition weights, helps adjust for potential selection bias by compensating for non-random dropout of households, ensuring that estimated treatment effects are less likely to be biased due to attrition.

Verification of random assignment to treatment

Random treatment assignment was intended to create comparable control and treatment groups at baseline, enabling the identification of treatment effects post-intervention. In this paper, treatment was defined as the assignment of farmers into one of three groups: (i) the control group (no intervention), (ii) CA treatment, or (iii) CA+BIOCHAR

Table 1 Patterns of attrition in the sample of participants in the RCT

	Dropped out from the complete panel (1 = yes)	
	coefficient	se
Female-headed household (1 = yes)	0.509**	(0.214)
Household size (#)	-0.035	(0.033)
Head of household age (years)	-0.004	(0.004)
Household asset wealth index	0.084*	(0.051)
Total farm size(ha)	0.010	(0.046)
Private land tenure(1 = yes)	0.062	(0.256)
Mailo land tenure(1 = yes)	0.202	(0.274)
Unknown land tenure(1 = yes)	-0.196	(0.274)
Control village (1 = yes) (reference)	0.000	(.)
CA training village (1 = yes)	0.736***	(0.259)
CA + BIOCHAR training village (1 = yes)	0.538**	(0.235)
Alebtong district (1 = yes) (reference)	0.000	(.)
Mubende district(1 = yes)	0.648**	(0.286)
Constant	-1.589***	(0.380)
Households	400	

Notes: Standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; Reference category for land tenure is the main form of land tenure (customary tenure)

treatment. In order to test the quality of random assignment at baseline, an assessment was made of whether the means of selected baseline variables for households in the treatment groups differed statistically from those in the control group. The baseline variables included primary outcome variables (labour use and productivity variables), socio-economic variables described earlier, and attrition. Specifically, a multivariate regression model was specified, as shown in the following equation:

$$d_j = \theta_0 + \sum_{i=1}^2 \delta_j treat_j + \epsilon_j \quad (1)$$

Where d_j represents all baseline outcome and control variables, and $treat_j$ denotes the treatment group assignments at baseline, with values of 1 (CA training), and 2 (CA + BIOCHAR training), compared against the control group (no intervention). The error term (ϵ_j) captures the residual (unexplained) variation in the dependent variable (d_j). We report heteroskedasticity-robust standard errors to account for potential variability in error terms across observations.

The results, summarised in Table 2, include the constant term (θ_0 ; indicating the estimated mean of the dependent variable in the control group) and the estimated coefficients of the treatment dummies ($treat_j = 1$ and $treat_j = 2$, respectively), which show how much (d_j) deviated positively (+) or negatively (−) from the control group mean. The p-value of the F-test, which evaluated whether the coefficients of all treatment indicators were jointly equal to zero for each baseline variable, was reported. Hotelling's F-statistic was also included to test whether the means of all baseline covariates were jointly equal between each treatment group and the control group.

Results comparing control and treatment groups at baseline showed that most variables were balanced, as the F-tests of the joint null hypothesis that all treatment-indicator coefficients were zero were not statistically significant ($p > 0.05$) (Table 2). However, a few key differences at the 5% significance level were evident, including family labour person-days, family and total labour costs, farmer age, and attrition (Table 2). These differences require an empirical specification that mitigates potential biases in treatment effects arising from (i) regression to the mean¹², (ii) differences in observed covariates, and (iii) attrition bias. (Wooldridge 2010)

Identifying average treatment effects of the intervention

The average treatment effect of two interventions, exposure to CA training and CA+BIOCHAR training, was estimated for various labour-related outcomes, including total labour (person-days/ha), family labour (person-days/ha), hired labour (person-days/ha), and total labour cost (UGX/ha). Labour use was also assessed across different production stages, including land preparation, planting, fertilization, weeding, and harvesting, measured in both person-days/ha, and the contributory shares of labour at each stage to total labour used (%). Labour productivity was approximated as the value of harvested crop output per person-day (USD/person-day) for all crops grown, the main

¹² Regression to the mean is a statistical tendency for extreme baseline values of outcome variables to move closer to the group mean in subsequent measurements due to random fluctuations, measurement errors, or natural variation. This phenomenon can produce artificial treatment effects in RCTs if baseline differences are not properly controlled, leading to overestimation or underestimation of treatment effects.

Table 2 Covariate balance at baseline ($N=400$ households)

	Control		CA training		CA + BIO training		F-test p-value
Total labour (person-days/ha)	203.05	(17.622)	-3.26	(24.984)	-34.69	(21.600)	0.173
Family labour (person-days/ha)	138.68	(12.349)	16.46	(17.509)	-25.06	(15.138)	0.018*
Hired labour (person-days/ha)	61.25	(8.034)	-19.57	(11.391)	-9.33	(9.848)	0.230
Family labour cost (100,000 UGX/ha)	10.17	(0.906)	1.21	(1.284)	-1.84	(1.110)	0.018*
Hired labour cost (100,000 UGX/ha)	0.35	(0.112)	-0.07	(0.158)	0.19	(0.137)	0.117
Total labour cost (100,000 UGX/ha)	10.44	(0.940)	1.20	(1.333)	-1.77	(1.153)	0.029*
Total labour cost (USD/ha)	291.11	(26.217)	33.58	(37.169)	-49.49	(32.135)	0.029*
Labour land preparation(person-days/ha)	52.73	(6.225)	16.25	(8.825)	-1.11	(7.630)	0.063
Labour planting(person-days/ha)	26.51	(44.149)	87.01	(62.593)	-6.92	(54.116)	0.201
Labour fertilization(person-days/ha)	2.37	(0.523)	-0.73	(0.742)	-1.28*	(0.641)	0.134
Labour weeding(person-days/ha)	88.23	(12.752)	-21.65	(18.079)	-28.98	(15.630)	0.178
Labour harvesting(person-days/ha)	42.50	(4.639)	-2.88	(6.577)	-4.50	(5.686)	0.732
Value of crop output per day worked(USD/ person-day)	3.21	(0.316)	0.42	(0.448)	0.76	(0.388)	0.142
Maize output per day worked(kg/ person-day)	7.21	(0.957)	0.55	(1.357)	-0.75	(1.173)	0.520
Value of cereal output per day worked (USD/person-day)	2.58	(0.331)	0.18	(0.469)	-0.29	(0.406)	0.481
Bean output per day worked(kg/ person-day)	1.43	(0.198)	0.28	(0.280)	-0.53*	(0.243)	0.002**
Value of legume output per day worked (USD/person-day)	1.62	(0.232)	0.21	(0.330)	-0.06	(0.285)	0.630
Customary tenure (1 = yes)	0.52	(0.050)	0.11	(0.071)	-0.00	(0.061)	0.176
Private tenure (1 = yes)	0.19	(0.039)	-0.06	(0.056)	0.04	(0.048)	0.149
Mailo tenure (1 = yes)	0.16	(0.039)	0.04	(0.056)	0.04	(0.048)	0.699
Unknown tenure(1 = yes)	0.22	(0.036)	-0.09	(0.051)	-0.09*	(0.044)	0.102
Age of household head(years)	40.62	(1.302)	6.10**	(1.846)	3.21*	(1.596)	0.005**
Female-headed household(1 = yes)	0.18	(0.038)	0.04	(0.054)	-0.03	(0.047)	0.311
Female ratio (#female/household size)	0.36	(0.021)	0.01	(0.030)	0.01	(0.026)	0.937
Bank account (1 = yes)	0.17	(0.037)	0.02	(0.052)	-0.03	(0.045)	0.506
Household labour units	4.45	(0.202)	-0.08	(0.286)	-0.48	(0.247)	0.089
Total farm size(ha)	1.56	(0.187)	0.38	(0.265)	0.44	(0.229)	0.153
Household wealth index(normalized)	0.30	(0.022)	0.00	(0.032)	0.01	(0.027)	0.915
Rain (Jan-Jun, mm)	528.52	(6.037)	-5.24	(8.559)	-1.14	(7.400)	0.806
Historical rain (Jan-jun, mm) (1990–2024)	572.29	(47.789)	5.34	(63.896)	4.23	(55.992)	0.822
Attrition (1 = yes)	0.07	(0.037)	0.17**	(0.053)	0.12*	(0.046)	0.004**
Hotelling F-statistic (p-value)			3.66 (0.000)		2.74 (0.000)		

Notes: Robust standard errors in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. The first column (Control) reports the coefficients of the constant, while CA training and CA+BIOCHAR training present the respective treatment indicators from an OLS regression of each baseline variable or incidence of attrition on the two treatment indicators. The last column shows the p -value for the F-test assessing whether the coefficients of all treatment indicators are jointly equal to 0 for each baseline variable. Hotelling's F-statistic tests the equality of the means of all baseline variables jointly between each treatment group and the control group

crops (maize and beans), and for cereals (maize, sorghum, millet) and legumes (beans, soybeans, groundnut, pigeon peas and cowpeas) combined.

Treatment assignment corresponded closely with actual participation, as most farmers received their assigned pieces of training, averaging 4.5 out of 5 in the CA group and 6.3 out of 7 in the CA+BIOCHAR group, with at least 94% receiving at least one training. The high compliance rate suggests that the intention-to-treat (ITT) closely reflects the actual treatment. As a result, the study used treatment assignment at baseline as the actual treatment. ITT estimates are valuable for policymakers because they provide insights into the real impact of development interventions with less-than-perfect

compliance, which is common in programs offering training services without the capacity to enforce full participation. In such cases, recommendations from the RCT literature (e.g., (Duflo et al. 2007, 2011) advise reporting the average treatment effect on the treated group (ATT) to accurately measure the impact of actual training attendance. The primary specification for identifying treatment effects is a first-difference regression model that includes both treated and control households, expressed as in Eq. 2:

$$\Delta Q_j = \vartheta_0 + \sum_{i=1}^2 \varphi_j \text{treat}_j + R_r + \epsilon_j \quad (2)$$

Where ΔQ_j represents the difference in labour use and productivity outcomes for farmer j between endline (2024) and baseline (2021), treat_j denotes the two treatment groups, R_r accounts for regional fixed effects (district¹³), and ϵ_j is the error term. The intercept ϑ_0 , captures the mean change in labour use and productivity outcomes for control group farmers. The key parameter φ_j estimates treatment effects for each intervention relative to the control group. Heteroskedasticity-robust standard errors are reported to account for potential variability in error terms across observations. Outliers in the main outcome variables were inspected and managed using winsorization techniques¹⁴ (Barnett and Lewis 1994; Dixon and Tukey 1968). All the analysis was done in STATA software version 17 (Albright and Marinova 2015; StataCorp 2013).

Robustness and supplementary analysis

In the robustness analysis, the sensitivity of the treatment effects from the first-difference model was assessed by adjusting for baseline imbalances in covariates, attrition bias, and baseline differences in outcome variables using an alternative approach. To achieve this, the inverse-probability-weighted regression adjustment (IPWRA) model, which combines two powerful techniques (inverse probability weighting and regression adjustment), was used. First, inverse probability weighting balances treated and control groups by accounting for differences in who receives treatment (selection bias). Second, regression adjustment models outcomes conditional on observed covariates. The IPWRA is also advantageous because of its doubly robust property that ensures consistent treatment effect estimates even if either the treatment or outcome model is misspecified. The primary model, the first-difference model, effectively eliminates time-invariant unobserved household heterogeneity, such as fixed household characteristics, preferences, or initial conditions, that could otherwise confound the estimates. However, it does not address time-varying unobserved heterogeneity. The IPWRA model, while not directly controlling for unobserved factors, adjusts for differences in observed covariates between treatment and control groups and enhances the precision of treatment effect estimates. By combining inverse-probability weighting and regression adjustment, IPWRA can indirectly mitigate bias caused by time-varying unobserved heterogeneity if

¹³ We include district fixed effects not for direct interpretation, as we lack a valid hypothesis for comparing the two districts, but to account for potential unobserved heterogeneity that could influence the dependent variables.

¹⁴ The reported results reflect winsorization at the 3rd and 96th percentiles. While the trends in the results without winsorization of outliers in outcome variables align with those in the winsorized data, the standard errors and coefficients are slightly inflated, leading to greater uncertainty in the results (when outliers are ignored). Testing different levels of winsorization revealed that applying it at the 3rd (bottom) and 96th (upper) percentile minimized the impact of extreme outliers, with no changes in results when increasing the levels up to the maximum permissible level of 10% (i.e. winsorization between the 10th and 90th percentiles).

those unobserved factors are correlated with the observed covariates. This dual adjustment ensures robustness, making it a valuable complementary approach to validate findings and address potential residual biases that the first-difference model alone may overlook. Following guidance from the RCT literature (e.g., Duflo et al. (2007), covariates were selected ex-ante (i.e., as defined at baseline). In addition to the first difference and IPWRA models, we further evaluate our results using alternative difference-in-differences models estimated with random and fixed effects.

To understand the potential mechanisms that explain differences in labour use outcomes across treatments, the study also compared the CA and CA+BIOCHAR treatments to the control group at the endline concerning the following variables: (1) total cultivated area (ha) and cultivated area per household adult-equivalent labour unit (ha/LU); (2) Crop diversity, indicated by the number of crops cultivated per hectare and per adult-equivalent labour unit; (3) the number of CSA management practices¹⁵ Implemented per ha and per adult-equivalent labour unit; (4) the cultivation of any legumes crop (1 = yes) or specifically pigeon pea (1 = yes); and (5) area under minimum tillage (ha) and area under minimum tillage per household adult-equivalent labour unit (ha/LU), as well as the amount of biochar applied (kg/ha and kg/LU). To make the training-to-adoption pathway more explicit, we interpret these variables as indicators of the uptake and intensity of implementation of the promoted CSA components. Because treatment assignment was randomized but adoption itself was not, this analysis is not a formal mediation analysis. Rather, it provides evidence on whether access to training translated into observable behavioural change on the farm and whether such changes are consistent with the labour-use patterns identified in the main treatment-effect estimates.

In addition, we tested for potential spillover effects of the RCT intervention by examining whether households in control villages adjust their labour use or labour productivity as a function of geographic proximity to treated villages. Although treatment was assigned at the village level, households may interact across village boundaries, leading to spillover effects. Using household GPS data, we constructed a variable that captures proximity to treated villages in the sub-sample of control groups. This approach is motivated by theories of social learning and the spatial diffusion of information and technologies (e.g., Conley and Udry (2010), as well as empirical approaches that proxy potential exposure to treatment among control units using proximity to treatment sites (Heitzig and O’Keeffe-O’Donovan 2024). Focusing on households in control villages, we estimated whether labour use and labour productivity vary systematically with proximity to treated villages. A statistically significant relationship between distance and outcomes is interpreted as suggestive evidence of spillover effects, while a null relationship indicates that treatment effects are spatially contained (no spillover effects). We find no evidence of spillover effects (see supplementary material, Table F1).

Lastly, although our primary focus is on labour productivity, we also incorporate, as a supplementary analysis, land productivity measured as the value of harvested crop output per hectare as an outcome variable. We find no statistically significant differences in land productivity between treatments and the control groups.

¹⁵ Climate-Smart-Agriculture (CSA) management practices that were implemented were counted, specifically those classified under the following categories: the implementation of minimum tillage practices (such as rip lines, basins, zero till), crop diversification (including intercropping, the incorporation of legumes such as beans, and practices of crop rotation), and the application of biochar.

Study limitations

Although our study provides evidence on how CSA interventions can affect labour use and productivity, contributing to broader goals of improving farm efficiency and supporting rural development, it is not without limitations. The RCT was small-scale, conducted in only two districts and 8 villages in Uganda, and the context-specific nature of the data may limit the generalizability of results beyond these locations. Another important limitation of the study is that relying solely on baseline and endline data restricts our understanding of short-term dynamics in CSA adoption, like temporary shifts in practice or fluctuations in labour allocation. Consequently, we can identify overall changes in adoption and treatment effects but cannot precisely track the timing or order of household adjustments. Also, the survey did not collect sufficiently detailed panel data on the allocation of family labour between own-farm and off-farm activities, local labour market access, or off-farm earnings, which limits our ability to quantify welfare effects associated with any possible displacement of off-farm employment or to distinguish temporary adjustment costs from more persistent changes in labour allocation and farm management across adopters. Reliance on farmer self-reports for CSA adoption, labour use, farm size, and other socioeconomic characteristics introduces potential measurement error. The limited number of clusters (eight villages) reduces statistical power and the ability to detect small differences between treatments, so some effects may not reach conventional levels of statistical significance despite potentially meaningful magnitudes. Nevertheless, the results provide preliminary insights into patterns of labour use and productivity under CSA adoption. Future research could improve insights into this topic by incorporating larger, more geographically diverse samples, collecting more detailed longitudinal data on labour use and CSA adoption, and using objectively measured variables alongside farmer reports to improve accuracy and better capture the dynamics of household decision-making and farm outcomes.

Results

Tables 3 and 4 summarize the average treatment effects on labour use, costs and productivity outcomes, estimated using the first-difference model and the inverse-probability-weighted regression adjustment (IPWRA) model, respectively. The results reported compared the mean outcomes for the control group (non-intervention) with those for households exposed to the CA and the combined CA and biochar (CA+BIOCHAR) interventions, highlighting the extent to which average labour use, costs and productivity under these treatments were above or below the control group mean. The treatment effects on labour use at specific production stages (land preparation, planting, fertilization, weeding, and harvesting) are summarized in Fig. 1, while the full tables are provided in the supplementary material (Tables B1-B2 and D1-D2). Figure 2 summarizes treatment effects on labour productivity outcomes.

Impact on labour use and costs

Results show that total labour use and costs were higher ($p < 0.05$) in intervention groups, particularly in the CA + BIOCHAR treatment, compared to the control group (Table 3). The average total labour use in the CA + BIOCHAR treatment per season was 65 person-days/ha higher than the estimated average of 179 person-days/ha that would have occurred without exposure to the treatment (control). Accordingly, the estimated

Table 3 Average treatment effects on total labour, family labour, hired labour use, and labour productivity (results from the first difference model)

Panel A: Labour use (person-days/ha) and costs (UGX/ha)						
	Total labour		Family labour		Hired labour	
	(person-days/ha)	(100,000 UGX/ha)	(person-days/ha)	(100,000 UGX/ha)	(person-days/ha)	(100,000 UGX/ha)
CA	24.307 (42.524)	1.772 (2.650)	15.232 (32.868)	1.198 (2.517)	-2.406 (18.018)	-0.506 (0.436)
CA+BIOCHAR	65.345** (33.149)	5.813*** (1.824)	70.379*** (22.068)	5.462*** (1.716)	-2.438 (16.282)	- 1.282*** (0.419)
Mubende(1 =yes)	56.803* (29.911)	1.134 (1.831)	-14.269 (22.152)	-1.173 (1.710)	69.708*** (13.473)	2.196*** (0.329)
Constant	-19.814 (29.115)	0.002 (1.458)	-16.197 (18.152)	-0.153 (1.407)	-19.900 (14.683)	1.430*** (0.338)
Control group mean (se)	178.811 (7.362)	9.811 (0.455)	128.917 (5.467)	9.476 (0.422)	49.650 (3.266)	0.521 (0.092)
r2	0.035	0.070	0.033	0.048	0.009	0.233
n	332	332	332	332	332	332
Panel B: Labour productivity (value of grain USD/person-day)						
	All crops	Maize	Cereals	Bean	Le-gumes	
	(USD/ person-day)	(USD/person-day)	(USD/ person-day)	(USD/ person-day)	(USD/ person-day)	
CA	-1.441 (0.898)	-0.525 (0.723)	-0.512 (0.742)	-0.871*** (0.335)	- 1.285*** (0.491)	
CA+BIOCHAR	-1.736** (0.720)	-0.036 (0.621)	0.030 (0.638)	0.549* (0.309)	0.216 (0.471)	
Mubende(1 =yes)	-0.779 (0.630)	0.701 (0.518)	0.243 (0.532)	1.159*** (0.256)	-0.511 (0.391)	
Constant	2.184*** (0.668)	-0.502 (0.584)	-0.148 (0.596)	-1.026*** (0.262)	0.379 (0.428)	
Control group mean (se)	3.787 (0.157)	2.343 (0.129)	2.440 (0.132)	1.018 (0.063)	1.721 (0.096)	
r2	0.020	0.007	0.003	0.108	0.036	
n	332	332	332	332	332	

Notes: Robust standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; Panel A presents results for labour use outcomes, including total labour, family labour, and hired labour, measured in both physical quantities (person-days per hectare) and monetary terms (expressed in 100,000 Ugandan Shillings per hectare). Panel B presents results on labour productivity outcomes in value of crop output per person-day (USD/day) for all crops, maize, beans, cereals, and legumes. The dependent variables represent the first difference (ΔQ_{jt}) in the respective outcome variables between the baseline and endline. The district of Alebtong serves as the reference category. The results in this table are derived from the first-difference model specification outlined in Eq. 2

treatment effects of the CA+BIOCHAR treatment group indicate that total labour costs per hectare during the entire season were 581, 300 UGX/ha higher than the control group (Table 3).

Specifically, comparing labour use by source (whether family or hired), the study found that, on average, family labour use and costs increased substantially in the CA+BIOCHAR treatment following the intervention, while hired labour costs decreased (Table 3). The treatment effects show that family labour, both in terms of quantities (person-days/ha) and costs (UGX/ha), increased by 70 person-days/ha and approximately 546,200 UGX/ha, compared to the control group, which had, on average, insignificant changes in family labour quantities and costs (Table 3). Relative to the control group, where total and family labour use averaged approximately 179 and 129 person-days/ha,

Table 4 Average treatment effects on total labour, family labour, hired labour use, and labour productivity (results from the inverse-probability-weighted regression adjustment model)**Panel A: Labour use (person-days/ha) and costs (UGX/ha)**

	Total labour		Family labour		Hired labour	
	(person-days/ha)	(100,000 UGX/ha)	(person-days/ha)	(100,000 UGX/ha)	(person-days/ha)	(100,000 UGX/ha)
CA	15.979 (33.740)	3.600** (1.732)	39.563* (20.265)	3.010* (1.616)	-24.232 (15.667)	-0.394 (0.466)
CA+BIOCHAR	49.365 (33.748)	5.881*** (1.812)	69.146*** (21.709)	5.487*** (1.748)	-7.487 (16.496)	-0.678 (0.423)
Potential outcomes mean	204.454*** (25.476)	10.336*** (0.900)	105.750*** (10.573)	8.728*** (0.870)	72.636*** (14.023)	2.671*** (0.416)
Baseline controls	YES	YES	YES	YES	YES	YES
n	332	332	332	332	332	332

Panel B: Labour productivity (value of grain USD/person-day)

	All crops	Maize	Cereals	Bean	Le-gumes
	(USD/day)	(USD/day)	(USD/day)	(USD/day)	(USD/day)
CA	-0.954 (0.812)	0.005 (0.538)	-0.207 (0.568)	-0.674*** (0.237)	-0.758** (0.340)
CA+BIOCHAR	-1.005 (0.694)	-0.246 (0.447)	-0.315 (0.489)	0.117 (0.282)	0.516 (0.419)
Potential outcomes mean	4.924*** (0.586)	1.860*** (0.387)	2.250*** (0.416)	0.805*** (0.234)	1.576*** (0.291)
Baseline controls	YES	YES	YES	YES	YES
n	332	332	332	332	332

Notes: Robust standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Controls include the age of the household head, number of labour units, household wealth index, total farm size, district dummy, attrition weights, and the baseline value of the dependent variable, all (controls) measured at baseline. The district of Alebtong serves as the reference category. A detailed table displaying all covariates is available in the supplementary material

respectively, the additional 65 and 70 person-days/ha in the CA+BIOCHAR treatment correspond to increases of about 36% in total labour use and 54% in family labour use¹⁶. Family labour was thus a major contributor to total labour use and costs. However, hired labour costs for the CA+BIOCHAR treatment decreased by about 128,000 UGX/ha compared to the control group (Table 3).

Results from the robustness analysis in Table 4 confirm the main finding that average labour use and costs for the CA+BIOCHAR and CA treatment groups were higher than those in the control group. The results show that total labour costs and family labour costs were significantly higher, approximately 57% and 63%, respectively, in the CA+BIOCHAR treatments compared to the control group (Table 4).

Further assessment of labour use at different stages of production showed that, on average, the treatment groups did not significantly differ from the control groups in terms of labour use and costs in fertilization, harvesting and weeding. However, during land preparation, the CA+BIOCHAR treatments incurred significantly lower labour use and costs compared to the control groups (Fig. 1). For instance, on average, the share of labour used for land preparation in the CA+BIOCHAR treatment was 3% lower

¹⁶ Percentage changes are calculated by dividing the estimated treatment effect by the corresponding control-group mean.

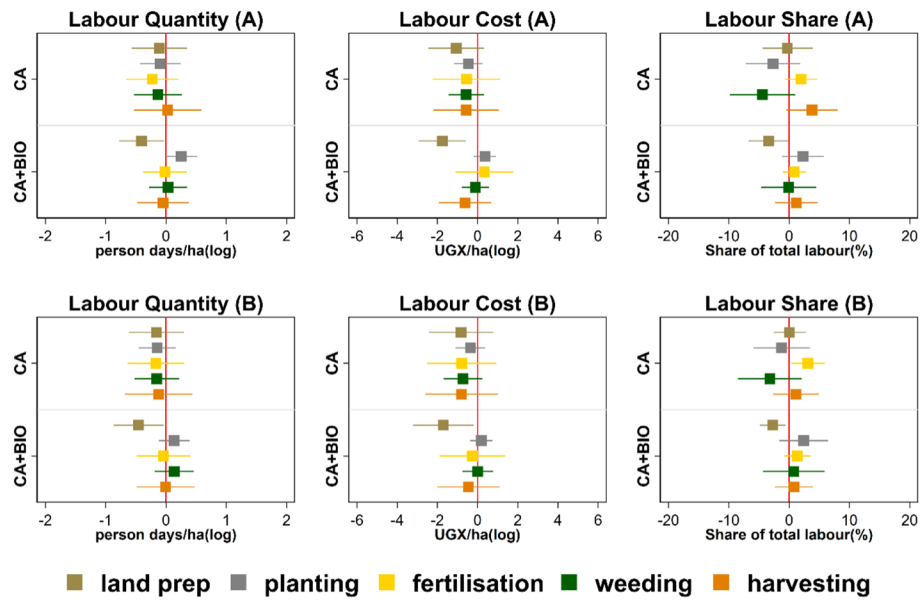


Fig. 1 Average treatment effects on total labour use at different stages of production (land preparation, planting, fertiliser application, weeding, and harvesting). The average treatment effects are based on the first difference model (A) and the inverse-probability-weighted regression adjustment model (B). Labour quantities and costs are log-transformed. Summarized results showing treatment effects for log-transformed and non-log-transformed data, side by side, are shown in the supplementary (Table B0), while detailed results are shown in Tables B1-B2, C1-C3

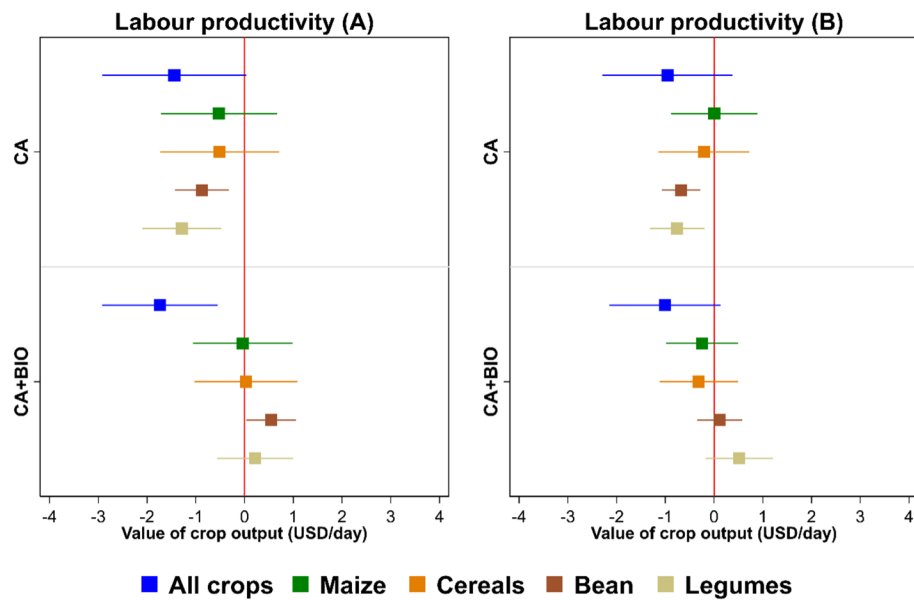


Fig. 2 Average treatment effects of the interventions on labour productivity outcomes, measured as the value of crop harvest per person-day, for all crops combined(all crops grown), maize, cereals (maize, millet, sorghum), beans, and legumes (beans, soybeans, groundnuts, pigeon peas, and cowpeas). The left panel (A) summarises results from the first difference model, while the right panel (B) report results from the inverse-probability-weighted regression adjustment model

than the total labour used by the household compared with the control group (Fig. 1). However, re-examining the stage-specific treatment effects using both untransformed and log-transformed labour measures (Supplementary Table B0) and simple bar plots of mean labour by treatment (Supplementary Figure B) suggests substantial idiosyncratic noise that reduces power and makes single-stage estimates unstable. We therefore emphasize results based on aggregate labour use measures, which pool across stages, reduce variance, and better recover the cumulative treatment effect. Overall, results show that exposure to the CA and biochar treatment greatly increased farmers' overall labour input requirements. The overall increased labour demand in the CA+BIOCHAR treatment is met through greater reliance on family labour rather than paid work.

Impact on labour productivity

The results reporting the impact of treatments on labour productivity outcomes (bottom panels of Tables 3 and 4; Fig. 2) show that compared to the control group, the CA and CA+BIOCHAR treatments did not significantly affect labour productivity for cereals (maize, sorghum and millet), and maize in terms of value of harvested crops in USD/person-day. However, when considering all crops grown, the treatment effect on the value of crop output per person-day for the CA+BIOCHAR treatment was significantly lower by about USD 1.74 per person-day when compared to mean changes in the control group. Relative to the control group, which had an average labour productivity of USD 3.8/person-day, the USD 1.74 reduction observed in the CA+BIOCHAR treatment represents a 45% decrease in labour returns. In addition, the treatment effect on the value of legume output was significantly lower in the CA treatment compared to the control group. The value of legume output per person-day in the CA treatment was lower by between USD0.8 and USD1.30, as reported in the IPWRA and first-difference models, respectively. For beans, the treatment effect of the CA treatment was also significantly lower, by between USD0.7 and USD0.9 per person-day, compared to the control group, indicating lower labour productivity for legumes in the CA treatment compared to the control group.

In supplementary analyses (see supplementary material, Table G3), we find no statistically significant differences in land productivity between the treatment and control groups, suggesting that the observed reductions in labour productivity are not accompanied by corresponding changes in land productivity.

Potential mechanisms linking CSA training to labour use and productivity

Since the intervention randomized access to training rather than adoption itself, it is important to examine whether the training translated into greater implementation of promoted CSA practices. Table 5, therefore, reports treatment effects on adoption-related outcomes measured at endline, including cultivated area, area under minimum tillage, crop diversity, legume cultivation, the number of CSA practices implemented, and biochar application. The results (Table 5) show that, at the endline survey, the CA+BIOCHAR treatment group, on average, exhibited a 0.5-ha increase in total cultivated area and a 0.2-ha increase in cultivated area per adult-equivalent labour unit compared to the control group. In addition, the number of crops grown per labour unit was 0.2 higher, and the number of CSA management practices implemented was 0.5 higher in the CA+BIOCHAR group. The probability of growing any legume and, specifically,

Table 5 Potential mechanisms explaining differences in labour use among treatments compared to the control group

	(1)	(2)	(3)	(4)	(5)	(6)
	Area planted		Crop diversity		CSA practices	
	Ha	Ha/LU	Count/Ha	Count/LU	Count/Ha	Count/LU
CA	-0.021 (0.136)	-0.005 (0.055)	0.195 (0.160)	0.039 (0.076)	0.261 (0.362)	0.100 (0.155)
CA+BIOCHAR	0.458*** (0.116)	0.174*** (0.062)	-0.011 (0.120)	0.164** (0.064)	0.480 (0.296)	0.519*** (0.130)
Constant	1.210*** (0.078)	0.396*** (0.041)	1.709*** (0.093)	0.520*** (0.050)	3.271*** (0.234)	1.012*** (0.096)
	(7)	(8)	(9)	(10)	(11)	(12)
	Legume cultivation		Minimum tillage		Biochar application	
	Pigeon pea	Any legume	Ha	Ha/LU	Kg/Ha	Kg/LU
CA	0.005 (0.028)	0.210*** (0.073)	-0.060 (0.067)	0.024 (0.037)	10.296 (6.782)	4.260 (3.050)
CA+BIOCHAR	0.146*** (0.030)	0.130** (0.057)	0.118** (0.054)	0.113*** (0.027)	48.113*** (9.779)	19.716*** (4.849)
Constant	0.032* (0.018)	0.326*** (0.048)	0.345*** (0.047)	0.114*** (0.019)	-0.000 (0.000)	0.000 (0.00)

Notes: Columns (1)–(2) report total cultivated area in hectares and cultivated area per household adult-equivalent labour unit (ha/LU). Columns (3)–(4) measure crop diversity as the number of crops cultivated per hectare and per adult-equivalent labour unit. Columns (5)–(6) report the number of CSA management practices implemented per hectare and per adult-equivalent labour unit. Columns (7)–(8) show legume cultivation, defined as pigeon pea cultivation (1 = yes) and cultivation of any legume crop (1 = yes). Columns (9)–(10) report area under minimum tillage in hectares and per adult-equivalent labour unit. Columns (11)–(12) report the quantity of biochar applied per hectare and per adult-equivalent labour unit (kg/LU). Standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

pigeon peas was 13% and 15% higher, respectively, in the CA+BIOCHAR treatment compared to the control. In addition, the area under minimum tillage increased by 0.12 ha per household and 0.11 ha per household adult-equivalent labour unit, while biochar application averaged 48 kg/ha and 20 kg per labour unit in the CA+BIOCHAR treatment, as opposed to no biochar application in the control group. These results suggest that the estimated labour effects are linked to training-induced changes in farm practices. In particular, the increase in cultivated area, greater implementation of minimum tillage, higher crop diversity, and the addition of biochar provided plausible channels through which the intervention increased labour demand, especially family labour. At the same time, the size of these changes also suggests partial rather than full adoption of the promoted practices, which is consistent with the modest and uneven treatment effects observed across outcomes.

Discussion

The study provides valuable insights into the labour demand and labour productivity impacts of training in climate-smart agriculture (CSA) methods, particularly conservation agriculture (CA) and biochar, based on data from a randomized control trial in Uganda. The findings challenge the hypothesis linking access to CSA training to possible reductions in total labour use and costs, as significant increases in both labour use and costs, particularly in the CA+BIOCHAR treatment, were observed. These findings are consistent with the substantial implementation demands associated with the promoted CSA package, particularly where households expanded cultivated area, increased minimum tillage, and biochar application. This finding aligns with literature and theory that emphasizes the upfront increase in resource demands, including labour, associated

with innovation adoption in smallholder systems constrained by market imperfections and liquidity shortages (Barrett et al. 2020; de Janvry and Sadoulet 2019; Montt and Luu 2020).

The reliance on family labour highlights the critical role of household resource reallocation in response to the demands of transitioning to relatively new combinations of CSA practices (e.g., CA and Biochar). The observed increase in family labour costs and decline in hired labour costs further suggest substitution effects, with households prioritizing internal resources to offset cash constraints. This reallocation may have partly come at the expense of off-farm work or other household activities, implying potential welfare trade-offs that our data cannot directly quantify. This pattern is also consistent with the rural contexts in developing countries, including Uganda, where households often rely on family labour due to the limited availability and high cost of hired labour (Foster and Rosenzweig 2010; Montt and Luu 2020; Teklewold et al. 2013).

The production stage-specific effects on labour costs observed in the study provide further insights. Labour use during land preparation decreased significantly in the CA+BIOCHAR treatment, reflecting the labour-saving potential of minimum tillage in land preparation (Giller et al. 2009; Pannell et al. 2014). However, this was not the case for subsequent production stages, such as planting, weeding, and harvesting, where labour demands were comparable to conventional practice (control group). These findings align with literature emphasizing the point that while CSA practices involving minimum tillage may save labour in land preparation, they often require additional effort in other stages of production, particularly in resource-poor settings where mechanization is limited (Andersson and D'Souza 2014; Farnworth et al. 2016; Giller et al. 2009; Montt and Luu 2020; Pannell et al. 2014; Rusinamhodzi 2015).

The lack of overall labour savings in both CA and CA+BIOCHAR treatments compared to control groups likely contributed to the observed lack of improvement in labour productivity outcomes. Reductions in overall labour productivity (value of crop output per person-day) and specifically in legume productivity further underscore the challenges of achieving short-term labour productivity gains from CSA innovations. The hypothesized labour productivity benefits from CSA innovation adoption may require higher adoption rates and a longer time horizon to materialize (if soil quality improvements and farmer expertise in these methods evolve). However, previous studies (e.g., Phiri et al. (2025) found soil quality improvements to be unlikely even after five seasons, while early gains in soil water retention were more probable and essential for enhancing crop productivity and resilience to dry spells. More broadly, these findings, coupled with no significant improvements in land productivity, could imply that CSA adoption, at least in the short-to-medium term (with minimal adoption), may not relax the fundamental land-labour trade-offs that underpin productivity growth in smallholder farming systems. In early-stage rural economies, structural transformation theory emphasizes the need for complementary growth in land and labour productivity so that agriculture can release labour without reducing output, thereby supporting broader economic diversification (Barrett et al. 2017).

The lack of labour savings and productivity benefits in the treatment groups could also indicate the ineffectiveness of one-off training without follow-up throughout the entire production season or in subsequent seasons, as was the case in this study. Hence, follow-up trainings might be another complementary action needed to ensure long-term

labour-productivity benefits from CSA adoption materialize. This notion is also consistent with evidence indicating that the benefits of CA and similar practices often accrue over extended periods as implementation becomes optimized and practices are adapted to local conditions (Corbeels et al. 2020; Lalani et al. 2017; Makate et al. 2025; Rusinamhodzi 2015; Suri and Udry 2022). Also, low-cost, simple technologies that harness Indigenous and local environmental knowledge, along with information and communication technologies, are recommended in order to enhance labour productivity in smallholder agriculture while promoting social inclusion and ecological sustainability (Adenle et al. 2019; Rajkhowa and Baumüller 2024).

Overall, the observed increases in labour use and costs, coupled with limited labour productivity gains, highlight the transitional challenges of CSA adoption in developing countries. While CSA practices offer long-term economic and environmental benefits, the short- to medium-term costs pose significant barriers for resource-constrained farmers. However, these short-run labour costs do not necessarily imply that CSA adoption is irrational, since farmers may still value expected longer-term productivity, resilience, or soil improvement benefits that are not fully captured by current-season labour productivity measures. As noted by Magruder (2018), the profitability of agricultural innovations depends not only on breaking information constraints but also on addressing both adoption costs and complementary constraints, such as access to inputs, credit, and infrastructure. Seen in a broader context, the limited short-term productivity gains associated with CSA adoption are consistent with Uganda's pattern of agricultural growth, which has historically relied more on extensification than on sustained improvements in land productivity, suggesting that the transitional labour and cost burdens observed here may partly reflect structural constraints at the sectoral level rather than CSA-specific inefficiencies.

Training in CSA methods remains a pivotal tool for overcoming information asymmetries and promoting the adoption of CSA practices (Abdulai 2023; Aker 2011; Shikuku 2019; Tambo et al. 2019). This is also evident from our findings, which show that shifts in labour use and productivity were mainly explained by the clear improvement in uptake of promoted components (minimum tillage, biochar application, and crop diversity) associated with the information intervention. However, because adoption itself was not randomized, we interpret these results as supportive evidence that training led to observable changes in farm management, rather than as a formal causal mediation analysis. By equipping farmers with knowledge of complex practices or combinations such as biochar integration and minimum tillage, training has the potential to increase the uptake of innovations. However, training alone may not be sufficient to foster transformative change in labour-saving and productivity outcomes. This notion aligns with the agricultural technology adoption literature in developing countries, particularly in Africa, that shows little or no transformational effects of extension and information programs implemented alone on technology adoption (and impact), except where the technology is completely new (Caldwell et al. 2019; Suri and Udry 2022). Similar studies in Uganda found extension service provision alone to be insufficient in bringing change in farmers' practices or income and productivity growth (e.g., Bold et al. (2022)). However, bundling training with complementary measures such as improved access to markets, institutional innovations, and affordable inputs is often found to be essential to enhance the viability, scalability and transformative benefits of CSA practices (Barrett et al. 2020;

Bold et al. 2022). For example, previous studies in Uganda (Kaweesa et al. 2020, 2021) recommend reconciling market policies, credit and financial environment in addition to awareness and information for effective scaling of sustainable farming practices such as conservation agriculture.

Conclusions and policy implications

The study underscores the opportunities and challenges of CSA adoption in smallholder systems. During the study period, adoption of the promoted CSA package was associated with increased labour demands and costs, which may discourage sustained uptake despite the potential longer-term agronomic and environmental benefits often associated with these practices when fully adopted. Recognizing the interplay between resource constraints and adoption dynamics is therefore important for effectively integrating new CSA practice combinations in labour-intensive agricultural systems like those in Uganda.

Addressing these transitional challenges requires patient capital, supportive policies, and targeted interventions to sustain farmers through the adjustment period. To facilitate successful CSA adoption and labour productivity benefits, it is essential to enhance support systems that reduce immediate labour and cost barriers while fostering long-term sustainability. The role of training in overcoming information gaps should, however, never be underestimated. While the study demonstrated the importance of hands-on, practical training for farmers in driving adoption of CSA, it also highlighted that once-off training alone may be insufficient to support a smooth transition to CSA. Follow-up training is required to help farmers optimize CSA implementation across production stages and ensure productivity benefits per labour unit increase. Also, training should be paired with other interventions, for example, institutional reforms that address farmers' inherent constraints in reducing the labour burden in agriculture and resource limitations in accessing complementary inputs, to ensure the scalability and long-term success of innovations, such as those involving the combination of CA and biochar.

Bundling solutions that address knowledge constraints, such as transformative training, with interventions that address other farmers' inherent constraints, such as low-cost labour-saving technologies, improved market access, infrastructure improvements, and other institutional support, may be needed to enable smallholder farmers to adopt CSA and biochar and achieve labour-saving and productivity benefits from adoption. Future research could focus on evaluating the effectiveness of bundled solutions that combine transformative training with other complementary components that address farmers' inherent constraints, such as affordable labour-saving technologies and complementary institutional support (e.g., market access), in enhancing labour productivity benefits from CSA. Such research would help identify the most cost-effective approaches that farmers can use to achieve long-term sustainability benefits from CSA implementation.

Supplementary Information

The online version contains supplementary material available at <https://doi.org/10.1186/s40100-026-00515-5>.

Supplementary Material 1

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Author contributions

C.M: Conceptualization, Data curation, Formal analysis, Methodology, Visualization, Writing – original draft, Writing – review and editing. G.C: Conceptualization, Funding acquisition, Investigation, Methodology, Project administration, Supervision, Writing – review and editing, Validation. J.M: Conceptualization, Funding acquisition, Investigation, Methodology, Project administration, Supervision, Writing – review and editing, Validation. V.M: Conceptualization, Funding acquisition, Investigation, Methodology, Project administration, Supervision, Writing – review and editing, Validation. B.O: Data curation, Project administration, Writing – review and editing, Validation. J.B.W: Conceptualization, Data curation, Methodology, Project administration, Supervision, Writing – review and editing, Validation. A.O: Project administration, Writing – review and editing, Validation. G.K: Project administration, Writing – review and editing, Validation. Ø.N.H: Conceptualization, Funding acquisition, Methodology, Project administration, Supervision, Writing – review and editing, Software, Validation.

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Data availability

Data availability statement The findings from this study are supported by data, which will be uploaded at <https://dataverse.no/dataverse/nmbu>.

Declarations

Competing interests

The authors declare no competing interests.

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