RESEARCH PROGRAM ON
Climate Change, Agriculture and Food Security

CGIAR CCAFS

The impacts of climate-smart agricultural practices on household income and food security: evidence from Doyogena and Basona climate-smart landscapes

October 2021

Abonesh Tesfaye, James Hammond, Maren Radeny, John W. Recha, Abebe Nigussie, Gebermedihin Ambaw, Mark T. van Wijk, Lulseged Tamene, Wuletawu Abera, Dawit Solomon

Alliance
Bioversity International
CIAT International Center for Tropical Agriculture
Since 1967 Science to cultivate change

This project is funded by the European Union

The impacts of climate-smart agricultural practices on household income and food security: evidence from Doyogena and Basona climate-smart landscapes

Technical Report

CGIAR Research Program on Climate Change, Agriculture and Food Security (CCAFS)

October 2021

Abonesh Tesfaye, James Hammond, Maren Radeny,

John W. Recha, Abebe Nigussie, Gebermedihin Ambaw,

Mark T. van Wijk, Lulseged Tamene, Wuletawu Abera,

Dawit Solomon

To cite this technical report

Tesfaye A, Hammond J, Radeny M, Recha JW, Nigussie A, Ambaw G, van Wijk MT, Tamene L, Abera W, Solomon D. 2021. The impacts of climate smart agricultural practices on household income and food security: evidence from Doyogena and Basona climate-smart landscapes in Ethiopia. CCAFS Technical Report. Wageningen, the Netherlands: CGIAR Research Program on Climate Change, Agriculture and Food Security (CCAFS).

About CCAFS reports
Titles in this series aim to disseminate interim climate change, agriculture and food security research and practices and stimulate feedback from the scientific community.

About CCAFS
The CGIAR Research Program on Climate Change, Agriculture and Food Security (CCAFS) is led by the International Center for Tropical Agriculture (CIAT), part of the Alliance of Bioversity International and CIAT, and carried out with support from the CGIAR Trust Fund and through bilateral funding agreements. For more information, please visit https://ccafs.cgiar.org/donors.

Contact us
CCAFS Program Management Unit, Wageningen University & Research, Lumen building, Droevendaalsesteeg 3a, 6708 PB Wageningen, the Netherlands. Email: ccafs@cgiar.org

Abstract

The aim of this paper is to assess the impacts of CSA practices on household income and food security in Ethiopia. Data was collected from 796 randomly selected smallholder farmers from the two climate-smart villages of Doyogena (399) and Basona (397) districts. Half of the selected farmers were implementing CSA practices, while the remaining half were farmers who were not implementing CSA practices. Using a propensity score matching approach, the paper examined the contribution of CSA practices on farm household income and food security. The estimated results show that the adoption of CSA practices has enhanced household food security in Doyogena, whereas in Basona, implementation of CSA practices improved the average annual income of households. This study suggests that introducing CSA practices and scaling up of these practices should be site-specific but not be one-size-fits-all approach. Promoting and scaling up of these practices may require assessing the needs and priorities of communities living in different locations.

Keywords: Climate-smart agriculture; propensity score matching; food security; household income; improved breed; improved seed; soil and water conservation; Ethiopia.

About the authors

Abonesh Tesfaye is a consultant based in Addis Ababa, Ethiopia, working with the CGIAR Research Program on Climate Change, Agriculture and Food Security (CCAFS) in East Africa on the socio-economic impact assessment of climate-smart agricultural practices in Ethiopia.

James Hammod is a Scientist, Farming system Analysis, working at International Livestock Research Institute, Sustainable Livestock Systems, Nairobi.

Maren Radeny is a Science Officer of the CGIAR Research Program on Climate Change, Agriculture, and Food Security (CCAFS) East Africa.

John Walker Recha is a Scientist on Climate-Smart Agriculture and Policy of the CGIAR Research Program on Climate Change, Agriculture and Food Security (CCAFS) East Africa.

Abebe Nigussie is Assistant Professor – soil fertility/quality at Jimma University, Ethiopia.

Gebermedihin Ambaw is a research associate for the CGIAR Research Program on Climate Change, Agriculture, and Food Security (CCAFS) in East Africa.

Mark T. van Wijk is a Scientist - Crop-livestock modeling, Sustainable livestock futures working at the International Livestock Research Institute, Nairobi.

Lulseged Tamene is a Senior Scientist - landscape ecology, restoration, systems analysis, geospatial analysis, the Alliance of Bioversity and CIAT, Ethiopia.

Wuletawu Abera is **a** Scientist at CIAT- analysis, and modeling of hydrology, water budget, hydrogeomorphology, ecohydrology, agriculture, and ecosystem services.

Dawit Solomon is the Regional Program Leader of the CGIAR Research Program on Climate Change, Agriculture and Food Security (CCAFS) East Africa.

Acknowledgments

The authors are grateful to the European Union for providing the EU-funded grant that supports this survey which will assess the socio-economic impacts of CSA practices on farmers in Doyogena and Basona climate smart villages. A word of thanks also goes to Inter Aide, Areka Agricultural Research Center and Central Statistics Authority Debre Berhan branch for recruiting experienced enumerators for the data collection. We would also like to thank the International Center for Tropical Agriculture (CIAT), Feed the Future Africa RISING program of the United States Agency for International Development (USAID), International Center for Agricultural Research in the Dry Areas (ICARDA) and International Livestock Research Institute (ILRI) for their cooperation. Special thanks go to Sasu Tadesse from Gudoberet Ketema Agricultural office and Mesele Gintamo and Mesfin Desalegn from Inter Aide Doyogena project office for their kind cooperation in the organization of the survey.

Contents

Acronyms

ATT	Average Treatment Effect on the Treated
CCAFS	CGIAR Research Program on Climate Change Agriculture Food Security
CCAFS-EA	CGIAR Research Program on Climate Change Agriculture Food Security East Africa

CGIAR	Consultative Group for International Agricultural Research
CIS	Climate information services
CSA	Climate-Smart Agriculture
CSV	Climate-Smart Village
EU	European Union
FIES	Food Insecurity Experience Scale
HDDS	Household Dietary Diversity Score
HDDS-LS/FS	Household Dietary Diversity Score - Lean Season/Flush Season
M.A.S. L	Meter Above Sea Level
ODK	Open Data Kit
PSM	Propensity Score Matching
RHoMIS	Rural Household Multi Indicator Survey
SNNPR	Southern Nations, Nationalities, and People's Region
SWC	Soil and water conservation
TLU	Tropical Livestock Unit

Introduction

Background information

Ethiopia is one of the most vulnerable countries to climate variability and climate change due to its high dependence on rain-fed agriculture and natural resources, and relatively low adaptive capacity to deal with these expected changes (World Bank 2020). Climate variability and indeed food insecurity, have always been a feature of Ethiopia (Lewis 2017). There are many routes by which climate change can impact food security. One major route is through climate change affecting the amount of food, both from direct impacts on yields and indirect effects through climate change's impacts on water availability and quality, pests and diseases (FAO 2015). Among the many development options that exists, climate smart agriculture (CSA) is a sustainable approach that can enhance agricultural productivity and income through adopting adaptation strategies while promoting resilience to climate change and reducing greenhouse gas emissions (FAO 2013, Engel and Muller 2016).

The CSA approach is an integrated process to managing landscapes such as cropland, livestock, forests and fisheries that address the interlinked challenges of food security and climate change (FAO 2013). Technologies considered climate-smart and the "smartness" of a given CSA technology is context-specific, and can vary considerably between different production systems and locations (World Bank 2019). The CGIAR Research Program on Climate Change, Agriculture and Food Security (CCAFS), is partnering with farmers, development organizations, and national and international agricultural research organizations in east Africa to test and promote a portfolio of CSA technologies and practices with the aim of scaling up and giving out the appropriate options. CCAFS started piloting the climate smart villages (CSV) approach in east Africa in 2012. In each CSV, a portfolio of climate-smart interventions are introduced depending on the agro-ecological characteristics of the CSV, level of development, capacity and the interests of farmers and local government partners (Recha et al. 2017).

In Ethiopia, CCAFS has collaborated with local communities, government and non-government organizations to establish two climate-smart landscapes: Doyogena in southern Ethiopian and Basona in central Ethiopia. In these sites, locally appropriate CSA practices are being tested and promoted. Despite the significant global action and investment being oriented towards CSA and the growing recognition of the potential of CSA in developing countries, relatively few studies have quantified the impacts of these practices on farm household income and food security (CCAFS 2016). There are some stories of success of CSA technologies and practices that are positively changing the lives of farmers in Asia and Latin America. Monitoring and evaluation results from CSVs have shown that climate smart agriculture increased farmers' productivity, income and household food security in these regions (e.g. Hasan et al. 2018, Pal and Kapoor 2020, WFO 2020). Evidence from some east and southern African countries also suggest that the introduction of CSA practices among farmers contribute to adaptation to a changing climate by improving agricultural income and food security (e.g. Wekesa et al. 2018, Siziba et al. 2019, Ogada et al. 2020, Mugabe 2020, Mujeyi et al. 2021). However, the impact of these CSA practices on food security and income of Ethiopian farmers is not well documented and understood.

Objectives

The main objective is to assess the impacts of CSA practices on household income and food security in Doyogena and Basona CSVs. Estimation of the socio-economic impacts of these practices seek to contribute to fill the knowledge gap and highlight on the scaling up of the appropriate CSA options. The specific objectives include:

- Estimate the impacts of CSA practices on household income and food security.
- Document the role of CSA practices in enhancing the income and food security of farmers.
- Provide evidence that can help donors and decision makers to justify funding and guide priorities in scaling up the adoption of CSA technologies and practices.

Methodology

Propensity score matching

An impact evaluation is essentially a problem of missing data (Ravallion 2005). Determining the counterfactual is the pillar of a sound impact evaluation (Heinrich et al. 2010). The standard setup in the treatment effect literature for the basic impact evaluation that measures the direct effect of a program on outcomes can be stated as follows (Gertler et al. 2011):

$$Y_i = \alpha X_i + \beta T_i + \varepsilon \qquad (1)$$

Where Y_i denotes the outcomes (e.g. income or food security of household) i and T_i is a dummy variable that is equal to 1 for households who participate in the program (in this case implementing CSA practices) and 0 otherwise. X_i is a set of observable household characteristics that influence household income or food security and ε is an error term representing unobserved factors that affect household income or food security. The problem with estimating equation 1 is that participating in the CSA program is not random because of reasons such as purposive program placement, that is, CSA programs can be implemented based on the need of communities and self-selection into the program given program design and placement. Self-selection could be based on both observed and unobserved factors (Heckman 2004). In the case of unobserved factors, the error term ε in the estimating equation 1 will contain variables that are also correlated with the CSA program dummy T. In such a situation, one cannot measure and account for these unobserved factors in equation 1, which leads to unobserved selection bias that violates one of the assumptions of ordinary least squares, that is, no correlation between explanatory variables and the error term (e.g. Berry 1993). Randomized controlled trails are considered the gold standard approach for estimating the impacts of a program on outcomes because random treatment allocation ensures that treatment status will not be confounded with either measured or unmeasured characteristics (Greenland et al. 1999). However, randomly assigning a treatment/program raises concerns including ethical issues, external validity, partial or lack of compliance, and spillovers (Khandker et al. 2010).

Propensity score matching (PSM) method is an alternative approach to estimate the impact of a program when random assignment of households into a program is not feasible (Rosenbaum and Rubin 1983). The propensity score is defined as the probability of assignment to a particular treatment conditional on a vector of observed covariates (Rosenbaum and Rubin 1983). There are two stages in a PSM method. In the first stage, using the entire sample and the binary outcome model, PSM estimates the probability of participating in the CSA program using observed household characteristics x. This generates propensity score $P(x)$, that is, the probability that a household with a vector of characteristics x will participate in

CSA practices. The vector x represents those observable variables that determine whether a household implements CSA practices. Households with similar observable characteristics are likely to have similar propensity scores $P(x)$. Based on similarity in propensity scores, PSM constructs statistical comparison groups, that is, households with similar propensity scores $P(x)$ where one group has participated in CSA practices and the other group has not participated in CSA practices. Participants are then matched based on this probability or propensity score to non-participants and unmatched units are dropped (Rubin 2001). There are different matching techniques in implementing PSM. These include nearest neighbor matching, radius matching, kernel matching and stratification or interval matching (Rosenbaum 1999, Rubin 2007). After matching, a covariate balancing test is required to ensure that the differences in the covariates in the two groups of matched samples are removed for the matched groups to be credibly counterfactual (Ali and Abdulai 2010). The second stage of the PSM calculates the average outcome for participants and non-participants and then estimates the impacts of CSA practices as the difference in average outcomes between the two groups of households which is called the average treatment effect on the treated (ATT). The ATT can be defined as follows.

$$ATT = E_{P(x \setminus T=1)}[E\{Y_1 \setminus T = 1, P(x)\} - E\{Y_0 \setminus T = 0, P(x)\}] \qquad (2)$$

There are two assumptions underlying the PSM method. Un-confoundedness is the first assumption which states that uptake of the program is based entirely on observed characteristics (Rosenbaum and Rubin 1983). The second is the assumption of the common support or overlap condition. This condition ensures that treatment observations have comparison observations nearby in the propensity score distribution (Heckman et al. 1999).

Survey location and data collection

Household interviews were carried out in Ethiopia, across two regions: Amhara and Southern Nations, Nationalities, and People's Region (SNNPR). Figure 1 shows the two survey locations.

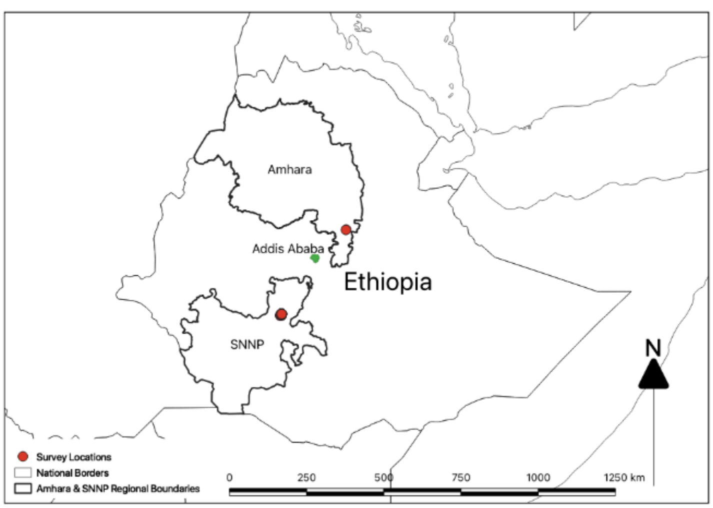

Figure 1. Survey locations at the SNNP (Doyogena) and Amhara (Gudoberet) regions

The Doyogena district is located in the SNNPR of Ethiopia. The altitude ranges from 2420 to 2740 meters above sea level (m.a.s.l). The mean annual rainfall ranges from 1,000 to 1,400 mm, while the temperature ranges from 12.6°C to 20°C. The farming system is characterized by Enset (*Ensete ventricosum*) – cereal - livestock production system. Main crops grown include wheat, barley, legumes and vegetables like potato. Enset which is an important source of food is grown in the area by almost all households. The average cropland size in the area is 0.6 hectare. Livestock production includes cattle, sheep and poultry. The subsistence farming in the area that is mainly rain-fed is increasingly threatened by climate related changes such as greater variability in the expected onset and cessation of rain, heavy rain, strong wind, low temperature, frost and drought. Due to the steep slope topography, the area also suffers from land degradation and loss of soil fertility which results in declining crop production and lack of feed for livestock (Bonilla-Findji and Eitzinger 2019). To address these challenges, locally relevant CSA practices that are both sustainable and resilient to climate change are being tested and promoted to improve the livelihood of farmers. About 11 CSA practices are being implemented in the Doyogena climate-smart landscape. These include soil and water conservation (SWC) practices such as soil bunds with Desho grass (*Pennisetum pedicellatum*); controlled grazing; improved wheat seeds (high yielding, disease resistant and early maturing varieties); improved bean seeds (high yielding varieties); improved potato seeds (high yielding, bigger tuber size varieties); cereal/potato-legume crop rotation (N fixing and non-N fixing); residue incorporation of wheat or barley; green manure: vetch and/or lupin during off-season (N fixing in time); improved breeds for small ruminants; agroforestry (woody perennials and crops) and cut and carry system for animal feed.

The Basona district is located in the Amhara Regional State of Ethiopia. The altitude ranges from 1,300 to 3,650 m.a.s.l. Average temperature ranges between 6 and 20^0 C, while the mean annual rain fall varies from 950 to 1200 mm. The main farming system is mixed crop-livestock. Major crops grown include barley and wheat. The average cropland size in the area is less than 1.4 hectare. The Basona landscape is suffering from climate variability, soil erosion and land degradation. Food insecurity and feed scarcity are the main challenges adversely affecting the livelihoods of farmers in the area. In addition, crop diseases, especially of faba bean are major concern (Tigist 2016, Tamene et al. 2017). To address the dual challenges of climate change and declining food security, CCAFS has established CSVs in the district. Within each CSV with the support of development partners, agricultural research institutes and CGIAR centres, locally appropriate CSA practices and policies are being tested. The portfolio of CSA practices being implemented in Bosana include improved breed (small ruminants and cattle), improved seed varieties, SWC such as soil bunds, soil bunds with biological measures e.g. phalaris and tree lucerne, trenches, enclosures, percolation pits, check-dams (gabion check-dams and wood check-dams) and gully rehabilitation.

The Rural Household Multi-Indicator Survey (RHoMIS) tool was employed to monitor the impacts of CSA practices on household income and food security in the two sites. RHoMIS is a household survey tool designed to rapidly characterize the state and change in farming households by a series of standardized indicators. It includes a modular survey tool, a digital platform to store and aggregate incoming data as well as analysis code to quantify indicators and visualize results. For further details, the reader is referred to the RHoMIS website: https://www.rhomis.org.

Simple random sampling technique was employed to select respondents from each district. Data was collected from 796 randomly selected smallholder farmers from the two sites, 399 from Doyogena and 397 from Basona. Half of the sample farmers were from the group implementing CSA practices (beneficiary group) while the remaining half were from farmers who were not implementing CSA practices (control group). Prior to data collection, enumerator training was conducted on the use of the RHoMIS tool and the questionnaire which runs on ODK software to ensure that they are confident with using the software and the digital interface of data collection. Next to the training, a field practice was organized to test the survey tool in the field with real farmers where nine household heads from each district participated. The data was collected from December 24, 2020 to January 05, 2021 in Doyogena and from February 4 to 16, 2021 in Basona district.

The main topics covered in the survey included farm household demographic characteristics, farm size, land management, provision of climate information services (CIS) and extension services, SWC practices, crop and livestock production, farm and off farm income and household food security. The two household food security indicators generated from the data collected were the household dietary diversity score (HDDS) and the food insecurity experience scale (FEIS). The HDDS is meant to reflect, in a snapshot form, the economic ability of a household to access a variety of foods (Swindale and Bilinsky 2006, FAO 2013). An increase in dietary diversity score is associated with socio-economic status and household food security. In this survey, the HDDS was calculated by asking respondents the frequency at which they consumed 10 different food groups within the last month. The typical FIES survey module contains eight questions focused on food-related behaviors and experiences associated with difficulties in accessing food due to resource constraints in the last 12 months (Ville et al. 2019). These experiences were linked to different severities of food insecurity in the survey: severely food insecure, moderately food insecure, mildly food insecure and food secure. Higher number (numbers ranging from 0 to 8) indicates more experience of hunger (Radimer et al. 1990, 1992, Smith et al. 2017).

Results

General household characteristics

The summary of variables used in the empirical analysis together with the X^2 and t-test results of the two districts (Doyogena and Basona) are presented in Table 1. A distinction is made between beneficiary households implementing CSA and the control households (not implementing CSA).

Doyogena:

Majority of the respondents both in the beneficiary and control groups were men, with an average age of 45 years and mean family size of 7 and 6 for beneficiary and control groups, respectively. The household size in male adult equivalent (MAE) was 5.8 in the beneficiary group and 4.9 in the control group. More than one third of respondents from the control group were illiterate while majority of respondents from the beneficiary group were literate. The average land holding in both groups was 0.6 hectare and the average cultivated land in control group was 0.6 and in the beneficiary group it was 0.5. The average livestock holding was 2.7 and 2.5 TLU[1] in the beneficiary and control groups, respectively. Average total income in the last 12 months was reported to be US$ 1164 in the control and US$ 1945 for the beneficiary group. The total value of households' income and agricultural production for the control and beneficiary groups is presented in Figure 2. The height of each bar represents the total value in terms of USD per household member per day. The colours within the bars show where that income or value came from such as crops consumed, crops and livestock sold and paid off-farm activities. Note that due to the differing number of interviews in each CSV, there are differing numbers of vertical bars, as each bar represents one household. Beneficiary households are better-off than control households. Although both

[1] Total livestock holding per household is aggregated into tropical livestock unit (TLU), where one TLU equals 250 kg life weight.

groups display similar patterns in terms of added value sources, the beneficiary households reported greater value derived from selling livestock.

Almost all beneficiaries and 41% of the control group were involved in SWC practices. Nearly a third of beneficiaries and one- fifth of control group practice agroforestry. According to sample respondents, CIS was being communicated to 58% of the beneficiaries and 44% of control group. Similarly, 60% of the beneficiaries and 16% of the control farmers received advice from extension agents. A fifth of the beneficiaries adopted improved seed when only a few used it in the control group. The use of improved breed was widespread among the beneficiaries than in the control group where less than half of them adopted it. Households in the beneficiary group reported medium food insecurity scoring 5 out of a possible 8 while the control group experienced severe food insecurity scoring 7 out of 8. The HDDS shows that control households performed better than beneficiary households in both the flush and lean seasons. Control households scored 3 out of 10 and 5 out of 10 in the lean and flush seasons respectively. Whereas the beneficiary households scored 2 out of 10 and 4 out of 10 in the lean and flush seasons respectively[2]. The X^2 test demonstrates strong evidence of a significant relationship between most of the farm household characteristics and whether the household is in the control or beneficiary group. The t-test shows that there is significant difference in household size, household size MAE, income, FIES and HDDS-LS between the control and beneficiary group.

Basona:

Most of the respondents in both the beneficiary and the control groups were male with average age ranging between 45 and 47 years and mean family size of 4. The household sizes in male adult equivalent were 4 and 3 in control and beneficiary groups respectively. More respondents were illiterate in the control group compared to the beneficiary group. Similarly, the proportion of respondents who participated in adult education was higher in the beneficiary than the control group. In both groups, less than half of the respondents have completed primary and secondary school. The average land holding in both groups was 1.4 hectare while the average cultivated land for both groups was 1.2 hectare. The average livestock holding was 4.5 and 4.8 TLU in the control and beneficiary groups respectively. Average total income in the last 12 months was reported to be US$ 1366 and US$ 3349 in the control and beneficiary groups, respectively. Figure 3 shows the total value of households' income and agricultural production in both groups. The height of each bar represents the total value in terms of USD per household member per day while the colours within the bars show the sources of the income or value, that is, crops consumed, crops sold, livestock sold and paid off-farm activities. Each bar represents one household, the differing number of vertical bars shows the differing number of interviews in each CSV. Beneficiary households were wealthier than the control group. The main driver appears to be the value of livestock sold (orange) and crops consumed (green). The control group presents similar pattern to beneficiary households but without the value gained from livestock sales.

Almost all beneficiaries and control farmers were involved in SWC practices while agroforestry was rarely reported in both groups. CIS was being communicated to 64% of the beneficiaries and 45% of control group while extension services were delivered to only 37% of beneficiaries and 35% of control groups. Less than a fifth of the respondents in both groups have adopted improved seed. There were more adopters of improved breed in the beneficiaries than in the control group. Both beneficiary and control households scored mild food insecurity scoring 2 out of 8. Regarding HDDS, both beneficiary and control

[2] Scoring higher number relates with having improved food security.

households scored similar HDDS (4 out of 10) in the flush season but in the lean season beneficiary households scored more (4 out of 10) and control group scored less, that is, 3 out of 10.

According to the t-test, household size, household size MAE, income and HDDS-FS were statistically significantly different between the control and beneficiary groups. When we look at the X^2 test, there is strong evidence of association or correlation between the level of education, receiving CIS, use of improved breed and whether the household is in the control or beneficiary group.

In summary, the descriptive analysis exhibits a difference between the two districts with regard to household characteristics, farm income and productivity, adoption of CSA practices, and household food security. In Basona, average household size, measured in MAE, was smaller than Doyogena. Beneficiary households in Basona tend to be a similar size to control households, whereas in Doyogena, beneficiary households tend to be 1MAE larger than control households. Cultivated land was almost twice as big in Basona as Doyogena. In both districts, beneficiary farms tend to be very similar in size to control farms. Livestock holdings were almost 2 TLUs larger in Basona than in Doyogena. In Basona, beneficiary households were wealthier than the control households and both household groups in Doyogena. Similarly, the second wealthiest group was the control households in Basona, which presented a similar pattern to the beneficiary households but without the value gained from livestock sales. Comparing beneficiary and control households in Doyogena, the former were wealthier than the latter, however, both household groups were less wealthy than both household groups in Basona.

Almost all respondents in Basona and beneficiary households in Doyogena have implemented soil and water conservation practices. There was better adoption of improved breed in both groups in Doyogena compared to Basona. With improved seed adoption, Basona was doing relatively better than Doyogena. Regarding the FIES, both household groups in Basona reported mild food insecurity whilst beneficiary and control households in Doyogena experienced medium and high food insecurity respectively. On the other hand, the HDDS suggested that there was a nutritionally inadequate and relatively scarce diet across the survey population.

Table 1. Descriptive statistics of sample respondents in the two districts

Variables	Doyogena		Basona		Doyogena	Basona
	Control	Beneficiary	Control	Beneficiary	t-test/X^2	t-test/X^2
Household characteristics						
Average age (years)	45	45	45	47	0.64	0.26
Share male (%)	80	87	89	86	0.08	0.38
Education level (%)					0.00^{***}	0.03^{***}
- No schooling	35	23	42	27		
- Adult education	0.5	0.5	17	20		
- Primary school	42	62	35	41		
- Secondary school	18	12	6	10		
- College	5	2	0.5	0.9		
Household size (persons)	6	7	4	4	0.00^{***}	0.00^{***}
Household size in MAE	4.9	5.8	4	3	0.00^{***}	0.00^{***}
Land holding (ha)	0.6	0.6	1.4	1.4	0.47	0.82
Cultivated land (ha)	0.6	0.5	1.2	1.2	0.29	0.38
Total income (US$/year)	1163	1945	1365	3348	0.02^{***}	0.00^{***}
Livestock holding (TLU)	2.5	2.7	4.5	4.8	0.18	0.62
CSA practices						
SWC (%)	41	96	98	99	0.00^{***}	0.55
Agroforestry (%)	21	32	1.1	4.3	0.02^{***}	0.05
Improved breed (%)	46	62	28	49	0.00^{***}	0.00^{***}
Improved seed (%)	6	20	12	15	0.00^{***}	0.43
Agro advisory services						
Extension services (%)	16	60	35	37	0.00^{***}	0.62
CIS (%)	44	58	45	64	0.00^{***}	0.00^{***}
Household food security						
FIES (Median)	7	5	2	2	0.00^{***}	0.08
HDDS (Median)						
- Lean season	3	2	3	4	0.00^{***}	0.07
- Flush season	5	4	4	4	0.21	0.00^{***}

Note: *, **, and *** mean values are significantly different at the 10%, 5%, and 1% levels respectively.

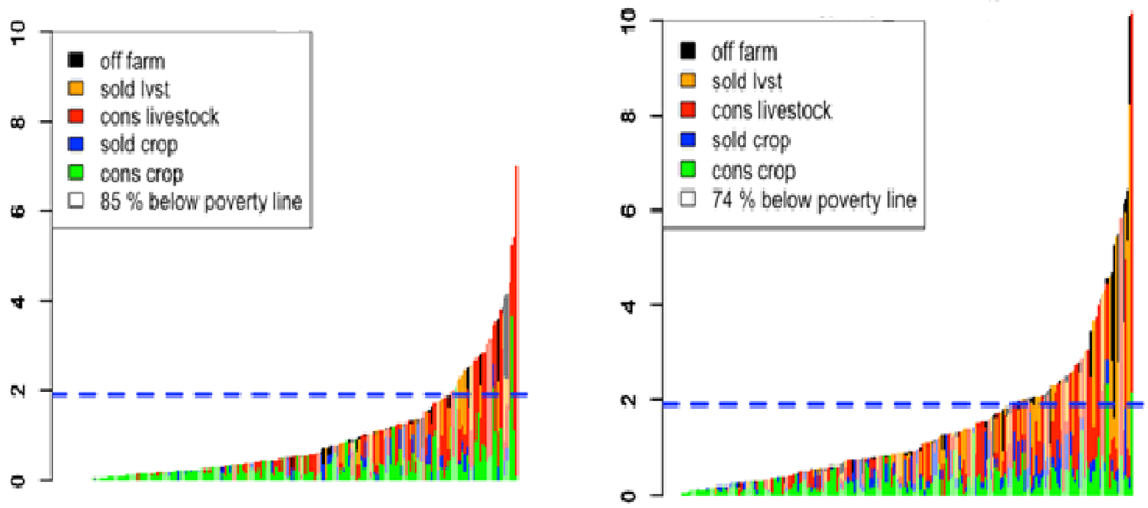

Figure 2. Total values of activities in Doyogena district - control and beneficiary groups from left to right

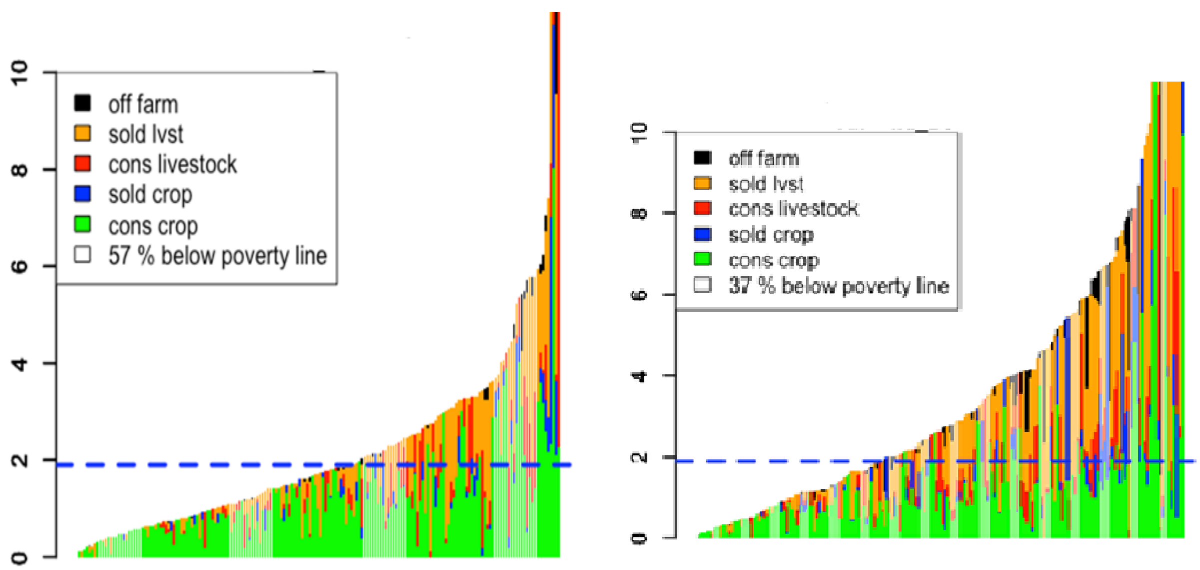

Figure 3 Total values of activities in Basona district - control and beneficiary groups from left to right

Econometric model results

The impact of CSA practices on household income and food security is estimated using the propensity score matching procedure. The food security indicator selected for this analysis is the food insecurity experience scale (FIES) instead of the household dietary diversity score (HDDS). The main reason being that FIES is a new approach introduced very recently and it is the only food insecurity measure that provides the opportunity to generate internationally comparable, standard measures of food insecurity with details on levels of severity (Ville et al. 2019). In this analysis, the matching procedure was conducted using *psmatch2* command in STATA version 15. The analysis employed kernel and nearest neighbor matching algorithms and imposed the common support condition to ensure proper matching. The results of the average treatment effect on the treated (ATT) is compared between the two matching algorithms. The probit model and the ATT estimation results for Doyogena and Basona are presented in Table 2 - Table 5. The predicted outcome of the probit model represents the estimated probability of participation, that is, the propensity score and hence it is not the focus of this study to discuss the relationship between the covariates and the dependent variable (probability of participation).

In Doyogena, improved breed and SWC practices are the two CSA practices used to examine their impacts on outcome variables. Estimation result indicates that beneficiary households who adopted improved breed gained significant average annual income that ranges between US$ 517 (ETB 21,197) and US$ 537 (ETB 22,017) compared to the control group who did not adopt improved breed. In addition, there is a significant inverse relationship between the adoption of improved breed and household food insecurity experience scale. This implies that beneficiary households who adopted improved breed managed to reduce their food insecurity experience (experience of hunger) by a scale of 1.2 to 1.4 compared to the control households. The adoption of soil and water conservation practices has similar significant positive impact on the income of beneficiary households. Accordingly, the implementation of soil and water conservation practices improved the average annual income of adopters between US$ 349 (ETB 14,309) and US$ 504 (ETB 20,664). Comparing the food insecurity experience scale of those who implemented soil and water conservation and those who didn’t implement, the former group showed significant reduction of food insecurity experience (experience of hunger) by a scale of 1.7 for both matching algorithms.

In Basona, improved breed and improved seed are the two-climate smart agricultural practices used to examine their impacts on household income and food security. The adoption of improved breed among beneficiary farmers significantly increased the average annual income between US$ 1610 (ETB 66,010) and US$1825 (ETB 74,825). Similarly, beneficiaries who adopted improved seed variety gained significant amount of average annual income that ranges between US$ 1245 (ETB 51,045) and US$ 1380 (56,580) compared to the control group. Looking at food security status, the adoption of improved breed among beneficiary farmers reduced the food insecurity experience by a scale of 0.3 to 0.7 compared to the control households. However, there was no significant relationship between the adoption of improved seed and food security status.

Table 2. Probit model for adoption of improved breed and SWC in Doyogena

Independent variables	Improved breed VS income		Improved breed VS FIES		SWC VS income		SWC VS FIES	
	Coefficients	SE	Coefficients	SE	Coefficients	SE	Coefficients	SE
Age	0.00	0.00	0.00	0.00	0.00	0.01		
Education	0.24***	0.06	0.21***	0.06				
Gender	0.01	0.18	0.05	0.18	0.16	0.19		
Land holding							0.11**	0.05
Cultivated land	0.02	0.05			-0.06	0.08		
Household size	0.03	0.03			0.06**	0.03		
Household size in MAE			0.02	0.04			0.07*	0.04
TLU							-0.02	0.04
Total income			0.00***	0.00			0.00**	0.00
Agroforestry			0.21	0.15				
Extension service	0.44***	0.14			1.30***	0.17	1.34***	0.18
CIS	-0.07	0.13					-0.03	1.15
Constant	-0.66**	0.36	-0.53	0.35	-0.37	0.37	-0.34	0.24
No. of observation	399							
LR X^2 (7)	32.26							
LR X^2 (6)			31.26					
LR X^2 (5)					78.74			
LR X^2 (6)							89.10	
Prob > X^2	0.00		0.00		0.00		0.00	
Pseudo R^2	0.06		0.06		0.16		0.18	

Note: *, **, and *** mean values are significantly different at the 10%, 5%, and 1% levels respectively.

Table 3. Probit model for adoption of improved breed and seed in Basona

Independent variables	Improved breed VS income		Improved breed VS FIES		Improved seed VS income		Improved seed VS FIES	
	Coefficients	SE	Coefficients	SE	Coefficients	SE	Coefficients	SE
Age	0.00	0.00	0.00	0.00	0.01	0.01	0.01	0.01
Education	-0.00	0.06	0.01	0.06	0.16**	0.08	0.15*	0.08
Gender	0.42**	0.22			0.04	0.24	0.01	0.25
Land holding			0.02	0.03				
Cultivated land	0.11	0.08			-0.25*	0.15	-0.29**	0.15
Household size	0.04	0.04	0.07*	0.04	-0.01	0.05		
Household size in MAE							-0.00	0.06
TLU	0.01	0.01						
Total income							0.00**	0.00
Agroforestry							0.10	0.47
Extension service	0.12	0.14			-0.16	0.17	-0.11	0.17
CIS					0.05	0.16		
Constant	-1.19***	0.37	-0.82***	0.34	-1.32***	0.46	-1.38***	0.46
No. of observation	396							
LR X^2 (7)	13.75							
LR X^2 (4)			4.86					
LR X^2 (7)					10.00			
LR X^2 (8)							14.32	
Prob > X^2	0.05		0.30		0.19		0.07	
Pseudo R^2	0.03		0.01		0.03		0.04	

Note: *, **, and *** mean values are significantly different at the 10%, 5%, and 1% levels respectively.

Sensitivity analysis

Matching aims to achieve balance on observed covariates, but there is no guarantee that matching will result in balance on unobserved covariates and entirely reduce hidden bias. A sensitivity analysis appraises how the conclusions of a study might be altered by hidden biases of various magnitudes (Rosenbaum 2010). According to Diprete and Gangle (2004), if the value of gamma in sensitivity analysis is lowest and encompasses zero then the probability of unobserved characteristics is relatively high and the estimated impact is sensitive to the existence of unobservable characteristics. To analyze the degree to which selection on unobservable may bias our inferences about the impacts of CSA practices on household income and food security, this study employed Rosenbaum's (2002) procedure. Table 4 and 5 show the sensitivity analysis results for the two districts.

The result of the Rosenbaum sensitivity analysis test shows that in Doyogena district the critical level of Γ at which we would have to doubt the results of the positive impacts of improved breed and SWC practices on total income is between 1.1 and 1.2, which is highly sensitive to the presence of possible hidden bias due to unobserved confounders. Whereas the critical level of Γ at which we would have to question the estimated results of the positive impacts of improved breed and SWC on food security are between 1.9 – 2.0 and 2.4 - 2.5, respectively. This means that our results are less sensitive to having the conclusions influenced by hidden bias.

In Basona district, for the estimation result of the impact of improved breed on total income to be sensitive to unobserved confounders, the critical level of Γ have to attain values between 1.7 and 1.8 which indicates the robustness of the result to hidden bias. Unlike the above result, the impact of improved seed on total income is the least robust to the possible presence of selection bias with a critical Γ value of 1.1 to 1.2. The sensitivity test for the impact of improved breed on food security shows that the critical level of Γ at which we would have to defend our conclusion of the positive impact of improved breed on food security is between 1.4 and 1.5 (kernel matching) and between 1.5 and 1.6 (nearest neighbor matching).

Table 4. Average treatment effect (ATT) of improved breed and SWC and sensitivity analysis in Doyogena

Matching algorithm	Livelihood outcome	ATT	T-statistics	Critical value (Γ)	Beneficiary (n)	Control (n)
Average treatment effect of improved breed						
Kernel	Income (US$/yr.)	517	2.95^{***}	1.1-1.2	213	183
	FIES	-1.2	-4.12^{***}	1.9-2.0	202	183
Nearest neighbor	Income (US$/yr.)	537	2.78^{***}	1.1-1.2	213	183
	FIES	-1.4	-3.82^{***}	1.8-1.9	202	183
Average treatment effect of SWC						
Kernel	Income (US$/yr.)	349	2.14^{**}	1.1-1.2	235	124
	FIES	-1.7	-3.88^{***}	2.4-2.5	237	124
Nearest neighbor	Income (US$/yr.)	504	3.02^{***}	1.1-1.2	236	124
	FIES	-1.7	-2.9^{***}	2.3-2.4	237	124

Note: *, **, and *** mean values are significantly different at the 10%, 5%, and 1% levels respectively.

Table 5. Average treatment effect (ATT) of improved breed and seed and sensitivity analysis in Basona

Matching algorithm	Livelihood outcome	ATT	T-statistics	Critical value (Γ)	Beneficiary (n)	Control (n)
Average treatment effect of improved breed						
Kernel	Income (US$/yr.)	1825	4.3^{***}	1.7-1.8	151	242
	FIES	-0.3	-1.73	1.4-1.5	154	242
Nearest neighbor	Income (US$/yr.)	1610	3.71^{***}	1.6-1.7	154	242
	FIES	-0.7	-2.72^{***}	1.4-1.5	154	242
Average treatment effect of improved seed						
Kernel	Income (US$/yr.)	1245	1.83^{*}	1.1-1.2	55	341
	FIES	-0.1	-0.35	-	54	341
Nearest neighbor	Income (US$/yr.)	1380	1.84^{*}	1.1-1.2	55	341
	FIES	-0.7	-1.79^{*}	-	55	341

Note: *, **, and *** mean values are significantly different at the 10%, 5%, and 1% levels respectively.

Balancing test

The covariate balancing test was conducted using the *pstest* command in STATA 15. The *pstest* calculates several measures of the balancing of covariates before and after matching for the two districts in Table 6 and 7. From the results of the balancing test, it is obvious that after the variables are matched, they are balanced between the treatment group and the control group. For each outcome variable in each district, the sample differences in the unmatched case surpasses the samples of matched cases indicating that the matching process resulted in significant bias reduction and a higher degree of covariate balance between the control and treatment samples used in the estimation procedure. Similarly, the insignificant t-test and the percentage bias reduction which is less than 5% after matching in almost all the cases is an indication of achieving balance through the matching process. Other important balancing indicators that confirmed the covariate balancing across the two groups include the low pseudo R^2, the insignificant p-value of the likelihood ratio and the low mean and median bias which is below 5%.

Table 6. Matching quality test for Doyogena

Matching algorithm		Pseudo R^2	LR X^2	P> X^2	Mean bias	Median Bias
Impact of improved breed on income						
	U	0.05	32.26	0.00	18.7	16.5
Kernel	M	0.00	0.82	0.99	2.8	8.8
	U	0.05	32.26	0.00	18.7	16.5
Nearest neighbor	M	0.00	1.60	0.98	3.2	2.1
Impact of improved breed on FIES						
	U	0.05	31.26	0.00	23.2	19.0
Kernel	M	0.00	0.88	0.99	2.9	1.9
	U	0.05	31.26	0.00	23.2	19.0
Nearest neighbor	M	0.01	5.91	0.43	5.8	3.2
Impact of SWC on income						
	U	0.15	78.74	0.00	34.5	20.8
Kernel	M	0.01	8.25	0.14	6.9	3.0
	U	0.15	78.74	0.00	34.5	20.8
Nearest neighbor	M	0.00	3.16	0.67	3.5	3.1
Impact of SWC on FIES						
	U	0.17	86.19	0.00	38.7	23.7
Kernel	M	0.00	1.72	0.88	4.5	4.0
	U	0.17	86.19	0.00	38.7	23.7
Nearest neighbor	M	0.00	1.72	0.88	2.6	2.4

Note: U= Unmatched; M=Matched.

Table 7. Matching quality test for Basona

Matching algorithm		Pseudo R^2	LR X^2	P> X^2	Mean bias	Median Bias
Impact of improved breed on income						
	U	0.02	13.75	0.05	15.0	19.3
Kernel	M	0.03	15.11	0.03	4.6	2.5
	U	0.02	13.75	0.05	15.0	19.3
Nearest neighbor	M	0.00	2.38	0.94	4.4	4.1
Impact of improved breed on FIES						
	U	0.01	4.86	0.30	10.7	9.7
Kernel	M	0.00	0.63	0.96	4.1	3.9
	U	0.01	4.86	0.30	10.7	9.7
Nearest neighbor	M	0.00	1.56	0.82	5.2	4.4
Impact of improved seed on income						
	U	0.03	10.01	0.18	14.8	13.9
Kernel	M	0.00	0.25	1,00	3.1	9.4
	U	0.03	10.01	0.18	14.8	13.9
Nearest neighbor	M	0.01	1.80	0.97	4.7	1.6
Impact of improved seed on FIES						
	U	0.04	14.32	0.07	16.0	13.6
Kernel	M	0.00	0.99	0.99	4.1	2.6
	U	0.04	14.32	0.07	16.0	13.6
Nearest neighbor	M	0.01	2.81	0.90	11.5	11.1

Note: U= Unmatched; M=Matched.

Discussion and conclusion

Discussion

The paper examines the impacts of climate smart agricultural practices on household income and food security status in two districts in Ethiopia. Data was collected from 796 randomly selected smallholder farmers from the two districts where 399 were selected from Doyogena and 397 from Basona district. Half of the sample farmers were from the group that implement climate smart agricultural practices (beneficiary group) while the remaining half were from farmers who do not implement climate smart agricultural practices (control group). Using a propensity score matching approach, the study examined the contribution of climate smart agricultural practices on the farm household food security and income. The PSM method is the widely used approach when there is no baseline data and hence the reason for adopting this approach in our study.

The econometric model results show that in Doyogena district, beneficiaries who adopted improved breed and soil and water conservation practices significantly increased their average annual income where the significance of the increase was associated with a t-value of 2.95 and 2.78 for kernel and nearest neighbor matching algorithms respectively. However, the sensitivity analysis shows that these conclusions are prone to hidden bias due to unobserved confounders. Nonetheless it is very important to recognize that while the sensitivity analysis provides information about the level of uncertainty contained in matching estimators by indicating the influence of a confounding variable, one cannot totally rule out the presence of a true positive impacts of the use of improved breed and soil and water conservation on household income in this study. This is because sensitivity analysis results are worst-case scenarios or the most extreme situation that can happen (Diprete and Gangle 2004). When we look at the impacts of these CSA practices on household food security, there was significant improvement in household food security status, that is, a reduction in food insecurity experience scale which can also be described as reduction in the experience of hunger. This result is illustrated in a significant t-value of -4.12 and -3.82 for kernel and nearest neighbor matching algorithms respectively. The plausibility of this result was confirmed with sensitivity test result that was highly robust to the possible presence of selection bias. This finding is in line with Mujeyi et al (2021), Ogada et al (2020) and Fentie and Beyene (2018) who assessed the impacts of climate smart agricultural practices on household livelihood outcomes in Zimbabwe, Kenya and Ethiopia respectively.

Turning to the Basona district, results indicate that due to the adoption of improved breed and seed beneficiary households achieved significant amount of average annual income gain. The t-statistics supported the significance of the results with t-value of 4.3 and 3.7 for improved breed and seed for kernel and nearest neighbor matching algorithms respectively. The sensitivity test conducted was also in agreement with these results showing the robustness of the results. Our finding is consistent with Mujeyi et al (2021) who investigated the positive impact of climate smart agricultural technologies on household food security and income in smallholder integrated crop-livestock farming system in Zimbabwe. Similarly, Wordofa et al (2021) reported that in eastern Ethiopia beneficiary households who adopted improved crop and livestock technologies gained higher annual income compared to the control group. Regarding the food security status, our result indicated that household food security status has improved for those who keep improved breed. That is, there was a significant reduction in the experience of hunger among beneficiaries who adopted improved breed that was demonstrated in T-statistics of -1.73 and -2.72 for kernel and nearest neighbor matching algorithms respectively. The sensitivity test revealed some degree of robustness of the estimation result to hidden bias. Similar studies such as Wekesa et al (2018) and Kifle (2020) that studied the impacts of climate smart agricultural practices on household food security in Kenya and Ethiopia have reported the potential of CSA practices to alleviate food insecurity among smallholder farmers.

Our result demonstrates that implementation of climate smart agricultural practices have contributed differently in the two districts. In Doyogena, these CSA practices were important to reduce the incidences of hunger and improve food security status of households whereas in Basona district the CSA practices increased households' annual income. These results are in line with our descriptive analysis where beneficiaries in Doyogena reported higher food insecurity experience scale compared to beneficiaries in Basona where food insecurity is not much of a concern.

Conclusion

The introduction of CSA practices and scaling up of these practices should not be one size fits all approach. Promoting and scaling up of these practices may require assessing the needs and priorities of communities living in different locations. In food insecure communities, the type of CSA practice that has to be introduced may need to consider those practices that contribute more towards the enhancement of household food security. On the other hand, in food secure communities, the kind of practices that has to be promoted may need to be related to income generating CSA practices. Identifying the appropriate CSA option for a specific location can help decision makers and funding agencies to guide priorities in scaling up the adoption of CSA practices.

Finally, one caveat of our study is the lack of a baseline data that resulted in the use of cross-sectional data and the PSM approach. This may influence the estimation results due to some limitations associated with the use of the PSM approach. In impact analysis, a powerful form of measuring the impact of a treatment is by using panel data collected from a baseline survey administered to both participants and nonparticipants before the program was implemented and after the program has been operating for some time. Estimation of impact analysis using panel data alleviates unobserved variable bias (Khandker et al. 2010). Nonetheless, our study can be an important first step that provides useful baseline information for the upcoming monitoring and evaluation of CSA practices in the two districts.

References

Ali A, Abdulai A. 2010. The adoption of genetically modified cotton and poverty reduction in Pakistan. *Journal of Agricultural Economics* 61: 175-192.

Berry WD. 1993. Understanding regression assumptions. SAGE University Paper series on Quantitative Applications in the Social Sciences, 07-092 Newbury Park, CA: sage.

Bonilla-Findji O, Eitzinger A. 2019. Training workshop report: implementation of the CSA monitoring to assess adoption of climate smart agricultural options and related outcomes in Doyogena climate-smart landscape (Ethiopia). Wageningen, the Netherlands: CGIAR Research Program on Climate Change, Agriculture and Food Security (CCAFS).

CCAFS 2016. Climate-Smart Villages. An AR4D approach to scale up climate-smart agriculture. Copenhagen, Denmark: CGIAR Research Program on Climate Change, Agriculture and Food Security (CCAFS). Available online at: www.ccafs.cgiar.org

Diprete TA, Gangl M. 2004. Assessing bias in the estimation of causal effects: Rosenbaum bounds on matching estimators and instrumental variables estimation with imperfect instruments. *Sociological Methodology* 34: 271-310.

Engel S, Muller A. 2016. Payments for environmental services to promote climate-smart agriculture? Potential and challenges. *Agricultural Economics* 47: 173–184.

FAO 2013. Guidelines for measuring household and individual dietary diversity. Rome, Italy: Food and Agriculture Organization of the United Nations.

FAO 2013. Climate smart agriculture: Sourcebook. Rome, Italy: Food and Agriculture Organization of the United Nations.

FAO 2015. Climate changes and food security: risks and responses. Rome, Italy: Food and Agriculture Organization of the United Nations.

Fentie A, Beyene AD. 2018. Climate smart agricultural practices and welfare of rural smallholders in Ethiopia: Does planning method matter? Environment for Development Discussion Paper Series. EFD DP 18-08.

Gertler PJ, Martinez S, Premand P, Rawlings LB, Vermeersch CMJ. 2011. Impact evaluation in practice, First Edition. World Bank. © World Bank. https://openknowledge.worldbank.org/handle/10986/2550 License: CC BY 3.0 IGO.

Greenland S, Pearl J, Robins J M. 1999. Causal diagrams for epidemiologic research. *Epidemiology* 10: 37–48.

Hasan MK, Desiere S, D'Haese M, Kumar L. 2018. Impact of climate-smart agriculture adoption on the food security of coastal farmers in Bangladesh. *Food Security* 10:1073–1088.

Heckman J, LaLonde JR, Smith J. 1999. The Economics and Econometrics of Active Labor Market Programs. In Handbook of Labor Economics, vol. 3, ed. Orley Ashenfelter and David Card, 1865–2097. Amsterdam: North-Holland.

Heckman J, Navarro S. 2004. Using matching, instrumental variables, and control functions to estimate economic choice models. *Review of Economics and statistics* 86: 30-57.

Heinrich C, Mafioli A, Vasquez G. 2010. A primer for applying propensity score matching, impact evaluation guidelines, office strategic planning and development effectiveness. Inter-American Development Bank.

Khandker SR, Koolwal GB, Samad HA. 2010. Handbook on Impact Evaluation: Quantitative Methods and Practices. World Bank, Washington, D.C.

Kifle T. 2020. Climate-Smart agricultural practices and its implications to food security in Siyadebrina Wayu District, Ethiopia. *African Journal of Agricultural Research* 17:92-103.

Lewis k. 2017. Understanding climate as a driver of food insecurity in Ethiopia. *Climatic Change* 144:317–328.

Mugabe PA. 2020. Assessment of Information on Successful Climate-Smart Agricultural Practices/Innovations in Tanzania. In W. Leal Filho (Eds.) Handbook of Climate Change Resilience. Cham: Springer International Publisher.

Mujeyi A, Mudhara, M, Mutenje M. 2021. The impact of climate smart agriculture on household welfare in smallholder integrated crop–livestock farming systems: evidence from Zimbabwe.

Nutrition and Consumer Protection Division, Food and Agriculture Organization of the United Nations.

Ogada MJ, Rao EJO, Radeny M, Recha JW, Solomon D. 2020. Climate-smart agriculture, household income and asset accumulation among smallholder farmers in the Nyando basin of Kenya. *World Development Perspectives* 18:100203.

Pal BD, Kapoor S. 2020. Intensification of climate-smart agriculture technology in semi-arid regions of India: Determinants and impact. CCAFS Working Paper no. 321. Wageningen, the Netherlands: CGIAR Research Program on Climate Change, Agriculture and Food Security (CCAFS).

Radimer KL, Olson CM, Campbell CC. 1990. Development of indicators to assess hunger. *The Journal of Nutrition* 120: 1544–1548.

Radimer K L, Olson CM, Greene J C, Campbell CC, Habicht JP. 1992. Understanding hunger and developing indicators to assess it in women and children. *Journal of Nutrition Education* 24(1): 36S–44S.

Ravallion M. 2005. Evaluating anti-poverty programs. World Bank, Policy Research Working Paper Series 3625.

Recha J, Kimeli P, Atakos V, Radeny M, Mungai C. 2017. Stories of success: climate smart villages in east Africa. Nairobi, Kenya.

Rosenbaum PR, Rubin DB. 1983. The central role of the propensity score in observational studies for causal effects. *Biometrika* 70:41–55.

Rosenbaum PR. 1999. Choice as an alternative to control in observational studies. *Statistical Science* 14: 258-304.

Rosenbaum PR. 2002. Observational studies. New York: Springer.

Rosenbaum PR. 2010. Design of observational studies. Springer, New York.

Rubin DB. 2001. Using propensity scores to help design observational studies: application to the tobacco litigation. *Health Services and Outcomes Research Methodology* 2: 169–188.

Rubin DB. 2007. The design versus the analysis of observational studies for casual effects: parallels with the design of randomized trails. *Statistics in Medicine* 26: 20-36.

Siziba S, Nyikahadzoi K, Makate C, Mango N. 2019. Impact of conservation agriculture on maize yield and food security: evidence from smallholder farmers in Zimbabwe. *African Journal of Agricultural and Resource Economics* 14: 89-105.

Smith MD, Kassa W, Winters P. 2017. Assessing food insecurity in Latin America and the Caribbean using FAO's Food Insecurity Experience Scale. *Food Policy* 71: 48–61.

Smith MD, Rabbitt MP, Coleman-Jensen A. 2017. Who are the world's food insecure? New evidence from the food and agriculture organization's food insecurity experience scale. *World Development* 93: 402–412.

Swindale A, Bilinsky P. 2006. Household dietary diversity score (HDDS) for measurement of household food access: indicator guide (v.2). Washington, D.C.: FHI 360/FANTA. United Nations, Rome.

Tamene L, Adimassu Z, Ellison J, Yaekob T, Woldearegay K, Mekonnen K, Thorne P, Quang Bao Le. 2017. Mapping soil erosion hotspots and assessing the potential impacts of land management practices in the highlands of Ethiopia. *Geomorphology* 292:153–163.

Tigist B. 2016. Assessment of surface water resource and irrigation practices in Gudo Beret Kebele, Amhara Region, Ethiopia. Thesis Presented to Addis Ababa University, Ethiopia.

Ville AS, Tsun Po JY, Sen A, Bui A, Melgar-Quiñonez H. 2019. Food security and the food insecurity experience scale (FIES): ensuring progress by 2030. *Food Security* 11:483–491.

Wekesa BM, Ayuya OI, Lagat JK. 2018. Effect of climate-smart agricultural practices on household food security in smallholder production systems: micro-level evidence from Kenya. *Agriculture and Food Security* 7:80.

WFO 2020. Climate smart agriculture supports resilience of Latin American farmers. Available at https://www.wfo-oma.org/frmletter-3_2020/climate-smart-agriculture-supports-resilience-of-Latin-American-farmers/.

Wordofa MG, Hassen JY, Edris GS, Aweke CS, Moges DK. 2021. Adoption on improved agricultural Tech nology and its impact on household income: a propensity score matching estimation in eastern Ethiopia. *Agriculture and Food Security* 10:5.

World Bank 2019. Climate smart agriculture investment plan: Mali. The World Bank Group. Washington DC.

World Bank 2020. Climate Risk Profile: Ethiopia 2020. The World Bank Group. Washington DC.