Impact Evaluation of Climate Smart Agriculture Program Investments in Food Security Using Machine Learning Estimators

by

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Abstract

Smallholder farmers in rural regions of developing countries are often vulnerable to climate events. Climate Smart Agriculture (CSA) seeks to sustain or improve agricultural yields while mitigating climate change. The CGIAR Research Program on Climate Change, Agriculture and Food Security (CCAFS) has made substantial investments in developing and scaling CSA programs in developing countries. Using a multi-country dataset, this paper runs two complementary analyses. The first uses a double/debiased machine learning approach to estimate the impact of participating in a CCAFS CSA program on household food security. I estimate this impact for the entire sample and within three sub-samples, which categorize households according to their CSA adoption strategy (i.e., non-adoption, specialized adoption, or diversified adoption). Results indicate that the probability of a household being food secure is 6.0 percentage points higher ($p<0.05$) if it participated in a CCAFS program. The food security benefits of CCAFS program participation are most clearly demonstrated among households that adopted a diverse set of CSA practices, where CCAFS training increased the probability of being food secure by 9.7 percentage points ($p<0.05$). On the other hand, the food security benefits of CCAFS training were negligible among households that did not adopt CSA practices or adopted a specialized set of practices. The second analysis combines traditional machine learning tools with future climate data to predict and compare the future food security of CCAFS program participants and non-participants. Results show that participating households are more likely to be food secure than non-participating households across all periods. Overall, the food security gap between participating and non-participating households is expected to increase over time.

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1. Introduction

Smallholder farmers in rural regions of developing countries are particularly vulnerable to climate events (Morton, 2007). While rising temperatures, shifting rainfall patterns, and strong storms will have consequences for food security worldwide, climate concerns are especially relevant for agriculture-based economies in countries that already face malnutrition (Aragon et al., 2021; Mendelsohn, 2008; Wheeler & von Braun, 2013). For the many smallholder farmers that rely on subsistence agriculture and local food markets, climate-caused decreases in crop yields pose a direct and alarming threat to food security (Brown & Funk, 2008; Funk & Brown, 2009). Moreover, developing countries will likely experience the most immediate and intense climate change impacts due to their hot, dry climates and minimal adaptive capacity (Aragon et al., 2021; Mendelsohn, 2008; Wheeler & von Braun, 2013).

In addition to being influenced by climate change, agriculture also contributes to climate change (Agovino et al., 2019). For example, rice paddies and livestock produce sizable methane emissions (Sejian et al., 2012; Zhang et al., 2016), while soils under cultivation often emit nitrous oxide – a process that is enhanced by the application of fertilizers and manure (Davidson, 2009). Furthermore, agriculture-driven land use change (e.g., conversion of forested areas to farms) also contributes substantially to climate change (Pendrill et al., 2019).

The reciprocal impacts between agriculture and climate change create complex negative feedback that impacts food security (Agovino et al., 2019; Wheeler & von Braun, 2013). Therefore, it is imperative to design and implement adaptation measures that help farmers maintain or increase yields in the face of climate change, and mitigation measures that help reduce greenhouse gas (GHG) emissions produced by farming (Harvey et al., 2014).

Adaptation and mitigation measures can be integrated, allowing farmers to jointly pursue both objectives (Locatelli et al., 2015; Smith & Olesen, 2010). Such synergies provide the foundation for climate-smart agriculture (CSA), which encompasses adaptive and sustainable practices that weaken the negative feedback loop between agriculture and the environment

(Harvey et al., 2014; Lipper et al., 2014).[1] The concept of CSA was first introduced in a 2009 report (Food and Agriculture Organization of the United Nations [FAO], 2009; Lipper & Zilberman, 2018). This report was followed by a Food and Agriculture Organization of the United Nations (FAO) paper that defined CSA as "agriculture that sustainably increases productivity, resilience (adaptation), reduces/removes GHGs (mitigation), and enhances achievement of national food security and development goals" (FAO, 2010, p. ii). Since then, the FAO has produced a comprehensive CSA Sourcebook, which details the purpose of CSA, the management of various agricultural facets through CSA (e.g., water, soil, energy, livestock), and how to implement, finance, and monitor CSA on both local and national scales (FAO, 2013).[2]

There are numerous types of CSA activities. For example, adaptation measures include weather monitoring, intercropping, minimal tillage, water conservation measures, integrated pest management, obtaining insurance, altering crop planting schedules, using improved crop varieties, and diversification of cropping, livestock, and aquaculture activities (Howden et al., 2007; Karttunen et al., 2017). Mitigation measures include reduced deforestation, land reclamation, agroforestry, agricultural intensification, biochar use, and fertiliser reduction (Intergovernmental Panel on Climate Change [IPCC], 2022; Wilkes et al., 2013). There is substantial overlap in the above practices; for instance, reducing soil erosion and nutrient leaching can simultaneously improve yields, reduce emissions, and increase soil carbon storage (Smith & Olesen, 2010). In addition, intensifying agricultural production on existing farmland can support both adaptation and mitigation goals (IPCC, 2022).[3] Therefore, CSA encompasses many of the above practices, as well as measures such as water harvesting, irrigation, and improved soil nutrient management through composting or the use of nitrogen-fixing plants (FAO, 2010). One commonly referred-to subset of CSA practices is conservation agriculture (CA), which includes minimum soil disturbance/reduced tillage, maintaining permanent organic

[1] While the overall collection of CSA practices supports both adaptation and mitigation, individual practices do not have to simultaneously contribute to both objectives to be considered CSA (Lipper et al., 2014).

[2] The Sourcebook is currently in its second edition and available online as a living document at *https://www.fao.org/climate-smart-agriculture-sourcebook/en/*.

[3] In fact, CSA shares many characteristics with the sustainable intensification approach to agriculture (Campbell et al., 2014).

soil cover, and crop diversification or crop rotation (Boillat et al., 2019; Giller et al., 2015; Makate et al., 2018).

Over the past decade, several authors have expressed the need to develop and analyse CSA practices (e.g., Sain et al., 2017; Steenwerth et al., 2014). Along these lines, organizations such as the World Bank and CGIAR have made substantial investments in developing and scaling CSA programs (Abegunde et al., 2019; García de Jalón et al., 2017). Government ministries in nations such as Ghana, Bangladesh, Zambia, and Vietnam have also collaborated with various organizations to promote CSA (Arslan et al., 2015; Hasan et al., 2018; Ho & Shimada, 2019; Zakaria et al., 2020b).[4]

As interest and investment in CSA expanded, a growing body of program evaluation research emerged to investigate how, and whether, these programs are effective (Li et al., 2022). For example, some authors have identified factors that influence CSA adoption (e.g., Amadu et al., 2020a), while others have quantified the impacts of CSA on socioeconomic outcomes such as food security and economic returns (e.g., Branca et al., 2021; Cholo et al., 2019; Komarek et al., 2019).

It is difficult to overstate the importance of program evaluation research, as scholars, politicians, and activists have long debated the most effective ways to improve the lives of people in developing countries (Banerjee & Duflo, 2012). For example, will CSA programs improve the current and future food security of smallholder farmers, or will they simply divert time, focus, and finances from more effective solutions? Such questions cannot be answered by theory alone. Instead, empirical research that can address bias and make causal links between a program and its outcomes is needed (Banerjee & Duflo, 2012). In the context of CSA, this means comparing outcomes for those who have access to a CSA program, to the outcomes for those who do not – a comparison that will assess whether CSA is generating its intended benefits. As donors continue to invest in CSA programs, these assessments will inform future programs so that they build upon past successes and improve upon past shortcomings.

[4] See Appendix A for background on CSA programs around the world.

On the whole, CSA impact evaluation research has concluded that CSA has the potential to increase crop yields, food security, household welfare, and even national gross domestic product (GDP) (e.g., Arslan et al., 2015; Komarek et al., 2019; Siziba et al., 2019). However, the benefits of CSA are not universal, with numerous studies finding that CSA can have no impact on, or can even decrease, yields and food security (e.g., Arslan et al., 2015; Branca et al., 2021; Tesfaye, Blalock, & Tirivayi, 2021). For example, in reviewing the effectiveness of CA (a popular sub-set of CSA practices), six meta-analyses found wide-ranging impacts on yield (Giller et al., 2015; Huang et al., 2018; Pittelkow et al., 2015; Steward et al., 2018; Su et al., 2021; Thierfelder et al., 2017).

Such seemingly contradictory results reveal that the question of whether CSA can improve the livelihoods of smallholder farmers is difficult to answer for three broad reasons: 1. Different CSA practices and CSA adoption strategies (e.g., specialization vs. diversification) can result in different impacts (e.g., Andersson & D'Souza, 2014), 2. The impacts of CSA vary by the location and socioeconomic context in which it is applied (e.g., Andersson & D'Souza, 2014), and 3. The evidence/data we rely upon to study CSA is often riddled with selection bias, making it difficult to identify the causal impacts of CSA.

The purpose of this study is to estimate the average treatment effect of participating in CGIAR's most recent CSA programs on food security, while providing insights into each of these areas of complexity. The results of this study contribute to the growing body of impact evaluation research by estimating this effect for the entire sample and for various groups of CSA adopters. Additionally, this work explores whether CCAFS program participation may continue to enhance food security in the context of future climate. In generating this work, several research contributions arise.

Firstly, CSA is a broad term that encompasses a plethora of diverse practices, and its impacts can differ not only by the type of practice adopted, but also by the combination of practices adopted. Authors such as Alam and Sikka (2019), Makate et al. (2019), and Tran et al. (2019) have attempted to identify optimal combinations of CSA practices. Other authors explore how CSA impacts change as the number of CSA practices adopted increases (e.g., Sardar et al., 2021). However, to my knowledge, a broad comparison between farmers that adopt a specialized set of CSA practices and those that adopt a diverse set of CSA practices has not been done. In the first analysis, I investigate whether CSA programs improve the food security of smallholder farmers. Using a split-sample analysis, I explore how non-adopters, specialized adopters, and diversified adopters may not benefit equally from CSA programs.

Secondly, CSA adoption and impacts vary widely due to biophysical, social, economic, and political factors (e.g., Mutenje et al., 2019). For example, Prestele and Verburg (2020) argue that spatial variability critically alters the efficacy of CSA and call upon future CSA research to account for this heterogeneity. One reason for this heterogeneity is that CSA impacts are particularly dependent upon climatic factors such as rainfall (e.g., Pittelkow et al., 2015; Su et al., 2021), which vary both spatially and temporally. Therefore, it is useful to conduct multi-country analyses that can identify trends in CSA impacts across landscapes. However, few such studies exist. One multi-country study was primary research that used a global biophysical simulation to explore the impacts of CSA (de Pinto et al., 2020). Other studies conducted meta-analyses that focused solely on no-till farming or CA (Huang et al., 2018; Pittelkow et al., 2015; Steward et al., 2018; Su et al., 2021). In contrast, this research employs econometric approaches to investigate a multi-country CGIAR dataset and explore the impacts of a diverse array of CSA practices. The dataset spans Latin America, Africa, and Asia, and was collected from 2017-2020. These data were based on CGIAR's latest programs, and to my knowledge, this paper is the first to analyse this recent dataset.

Finally, the third key factor that complicates CSA impact evaluation is not inherent in CSA itself, but in the data we use to study it. Often, the gold standard of identification is experimentation, which eliminates bias through random assignment of treatment and facilitates the identification of causal impacts. While economists such as Banerjee and Duflo (2012) advocate for the use of such experiments in program evaluation research, they are often impractical or impossible in practice. For example, organizations often select households to participate in development programs based on factors such as convenience or presumed need. Once selected by the organization, households may then choose whether to participate in the program (i.e., self-select). Both forms of selection can introduce selection bias into the resulting data, as both may cause program participants to differ from non-participants in ways that impact the outcome of the program. Therefore, CSA researchers cannot simply attribute differences between CSA program participants and non-participants to CSA programs. As such, overcoming bias has been a primary challenge for many CSA impact evaluations. While some authors address bias via methods such as propensity score matching (PSM) (e.g., Ho & Shimada, 2019;

Jamil et al., 2021; Khonje et al., 2015) and endogenous switching regression models (e.g., Issahaku & Abdulai, 2020; Martey et al., 2021; Tesfaye et al., 2021), others do not and are unable to identify causal links between CSA and its outcomes (Hasan et al., 2018; Ighodaro et al., 2020).

Uniquely, I employ a cutting-edge double/debiased machine learning (DML) technique that addresses selection bias without assuming that the relationship between the explanatory variables and program outcome is linear. While machine learning offers many advantages, its uptake has been slow within the CSA impact evaluation literature. Authors such as de Nijs et al. (2014) and Su et al. (2021) are exceptions; however, traditional machine learning methods are often unsuitable for identifying causal impacts due to their inability to address selection bias or provide standard errors. Therefore, there is a need to build upon previous papers through the consideration of bias and the use of new machine learning methods. In addition to addressing bias, the application of DML favors nonparametric estimation with high-dimension data (i.e., data in which the ratio of explanatory variables to observations is relatively high), as DML is not plagued by the curse of dimensionality.

Another notable feature of this paper is the distinction made between program participation and adoption of CSA. While related, the two are not synonymous; for example, a farmer that participates in a CSA program may not necessarily choose to implement CSA practices on their own farm. However, they may still benefit from the program due to, for example, increased communication with other farmers or increased knowledge of farming systems. Similarly, farmers that do not directly participate in CSA programs may be exposed to CSA as participating neighbors, family, or friends share their knowledge. Non-participants may then adopt CSA; however, they may benefit differently than program participants due to differences in CSA knowledge. Therefore, it is important to study the intersecting, but distinct, impacts of both program participation and CSA adoption. Thus far, most CSA impact evaluation research has focused solely on CSA adoption (e.g., Martey et al., 2020a; Ngoma, 2018). If program participation is considered, it is often only included as an explanatory variable. A few studies have separated and studied the effects of both adoption and program participation (Amadu et al., 2020b; Ho & Shimada, 2019; Martey et al., 2021). However, these studies do not make use of global datasets or machine learning, and do not study specialized vs. diversified adoption.

A final distinct feature of this paper is the analysis of CSA's future impacts. Because the impacts of CSA vary with climatic conditions, climate change may substantially alter CSA's effects. I've identified seven analyses that explored this possibility. Of these analyses, five (Brouziyne et al., 2018; de Pinto et al., 2020; Olajire et al., 2020; Xin & Tao, 2020; Zizinga et al., 2022) used biophysical, rather than econometric, models. As in my study, the remaining two papers (de Nijs et al., 2014; Su et al., 2021) used machine learning to study CSA; however, they relied on CSA impact data from previous studies and only employed one machine learning method (Bayesian belief networks and random forests, respectively). In contrast, I generate primary research while employing four machine learning methods.

The remainder of the paper is structured as follows. The next section provides a review of relevant literature (Section 2), which is followed by a description of the CCAFS CSA program and the study sites (Section 3). I then describe the two sets of data used in the paper (Section 4) before discussing the theory, methods, and results of the impact evaluation analysis (Section 5). Next, the theory, methods, and results of the future climate analysis are presented (Section 6). Finally, I draw conclusions based on both analyses (Section 7).

2. Literature Related to CSA

2.1 Introduction to CSA Literature

The expansion of CSA activity has been associated with a rapidly growing body of research. Overall, CSA literature seeks to determine whether, and under what conditions, CSA programs and practices are effective. More specifically, most CSA literature studies either the household, farm, biophysical, and institutional factors that influence CSA adoption, or the ability of CSA practices to improve agricultural yields, welfare outcomes, or environmental outcomes.

The CSA literature has grown sufficiently large, such that authors have sought to identify a number of themes. For example, Li et al. (2022) have reviewed various trends within the CSA literature including contributions of international organizations and individual authors, the most cited CSA papers, and where the majority of CSA research has been conducted (i.e., Sub-Saharan Africa, with most remaining studies focusing on Asia or Latin America). Comprehensive reviews, meta-analyses, and discussions of CSA literature have also been conducted by several authors (e.g., Andersson & D'Souza, 2014; Jat et al., 2020; Pittelkow et al., 2015; Su et al., 2021).

This review focuses on those parts of the literature that are most relevant to the models that I develop. First, I summarize CSA adoption research, as understanding why different adoption strategies are employed by farmers (e.g., specialized or diversified) provides the foundation for my split-sample analysis of various adoption strategies. Secondly, I summarize research on CSA impacts to understand how previous authors have measured the efficacy of CSA, the benefits and drawbacks of various impact evaluation methods, the factors that impact evaluation authors most often control for, and the findings of previous impact evaluation research. When summarizing such findings, I highlight studies that provide clues as to whether specialization or diversification in CSA adoption is more beneficial, as well as those that distinguish between the impacts of program participation and CSA adoption. Finally, I discuss research on the impacts of climate change on CSA's impacts, reviewing the seminal work that paves the way for my analysis of the impacts of future climate.

2.2 CSA Adoption

While a clear picture of global CSA adoption is difficult to obtain, estimates of the level of CSA adoption indicate that there is at least some uptake of CSA in countries such as Zambia, Zimbabwe, and Malawi (Andersson & D'Souza, 2014; Cavanagh et al., 2017). To better understand this phenomenon, many economists have sought to identify the factors that lead to adoption (Andersson & D'Souza, 2014).

Most economists examine similar determinants, including: demographics (e.g., age, farming experience, gender, education, and household size), income and wealth-related factors (e.g., assets, off-farm income, livestock ownership, land ownership, and farmland size), access to extension (e.g., extension and advisory services, contact with agricultural extension), access to other services (e.g., proximity to market, access to or use of credit, participation in agriculture or CSA training, and membership in an agricultural organization or group), and rainfall (e.g., Amadu et al., 2020a; Khatri-Chhetri et al., 2017; Kpadonou et al., 2017).[5] Overall, authors have found education, income and wealth-related factors, and access to other services to positively impact CSA adoption, while having a female head of household negatively impacts adoption (e.g., Branca & Perelli, 2020; Mazhar et al., 2021; Mutenje et al., 2019). On the other hand, factors such as age, household size, farming experience, generation of off-farm income, and access to extension have varying impacts on CSA adoption (e.g., Makate et al., 2019; Oladimeji et al., 2020; Ouédraogo et al., 2019).

Such variation in impacts may be attributed to the diversity of CSA practices available, as well as regional characteristics. Numerous studies have found that variation in CSA practices (e.g., Cavanagh et al., 2017; de Sousa et al., 2018; Kpadonou et al., 2017) and locations (e.g., Branca & Perelli, 2020; Tran et al., 2019) significantly alter both adoption rates and the impact of various adoption-influencing factors. For example, age, household size, and farming experience can positively impact the adoption of some practices, but negatively impact the adoption of others (e.g., Amadu et al., 2020a; Kpadonou et al., 2017; Makate et al., 2019). Such heterogeneity is somewhat intuitive, as different practices require different inputs, are associated with different costs, are designed to address different climatic and regional challenges, and have varying levels of social, technical, economic, and environmental compatibility (e.g., Abegunde et al., 2020; Amadu et al., 2020a; Khatri-Chhetri et al., 2017).

When confronted with a diverse array of CSA practices, it is common for farmers to adopt multiple practices simultaneously (e.g., Kpadonou et al., 2017; Zakaria et al., 2020a). One explanation for this behaviour is that adoption decisions are not made independently; instead, farmers first take stock of all available practices, then select a combination that will maximize their benefits (e.g., utility, profits), subject to their constraints (e.g., Aryal et al., 2018; Mutenje et al., 2019). This idea is supported by research that finds some practices to be complementary, and others to be substitutable, based on correlations between the adoption of various CSA practices (e.g., Branca & Perelli, 2020; Kpadonou et al., 2017; Zakaria et al., 2020a). For example, farmers often combine: crop rotation and intercropping, mulching and cover cropping, and

[5] Note that agricultural extension and CSA programs are not synonymous. While CSA programs may be considered a form of extension, the term ‘extension’ may refer to a wide variety of supports that are unrelated to CSA.

minimum tillage and cover cropping (Branca & Perelli, 2020); fertilizer use and crop diversification, irrigation and crop diversification, and agroforestry and crop diversification (Kurgat et al., 2020); and practices that increase soil nutrients with practices that conserve rainwater (a combination that agronomic experiments have shown to be effective) (Kpadonou et al., 2017). In fact, authors have found significant and positive correlations amongst 70% of CSA practice pairs studied (Zakaria et al., 2020a) and amongst nearly 95% of CSA practice pairs studied (Branca & Perelli, 2020), leading them to conclude that farmers most often adopt synergistic packages of CSA practices.[6] On the other hand, irrigation and livestock diversification, crop diversification and minimal tillage, and drought tolerant varieties and tied ridging are rarely implemented in these pairs, suggesting incompatibility, substitutability, or simply an absence of complementarity between the practices (Aryal et al., 2018; Branca & Perelli, 2020; Kurgat et al., 2020).

Such findings lead to the following idea: when CSA practices are substitutable or incompatible, it may be more beneficial for farmers to specialize in adopting a single practice or type of practice. Conversely, when CSA practices are complementary, it may be more beneficial for farmers to adopt diverse sets of such practices. Using this idea, my research explores whether households that are specializing or diversifying in CSA practice adoption receive greater benefit from CSA programs.

2.3 CSA Impact Evaluation

By definition, CSA aims to increase agricultural productivity and income, increase resilience to climatic changes, and reduce GHG emissions (Lipper et al., 2014). In investigating indicators of CSA's success or failure, most studies used crop yields per unit area (e.g., Amadu et al., 2020c; Arslan et al., 2015; Komarek et al., 2019) or agricultural/crop income (e.g., Berhanu et al., 2021; Khonje et al., 2015; Martey et al., 2020b). However, several authors also measured poverty outcomes. For example, a few authors used poverty headcount (i.e., proportion of households

[6] For example, if an author studied 5 CSA practices, there would be 10 possible pairings of different CSA practices. If the author found significant and positive correlations amongst 70% of CSA practice pairs studied, this means that for 7 of the 10 possible pairings, the adoption of one practice was significantly and positively correlated with the adoption of the other practice.

below the poverty line), and poverty gap (i.e., poverty intensity), with some making use of indices developed by Foster, Greer, and Thorbecke (1984) (Khonje et al., 2015; Shahzad & Abdulai, 2021; Tesfaye et al., 2021). Others measured poverty severity (i.e., wealth inequality) (Tesfaye et al., 2021), used a dummy variable to represent poverty (Jamil et al., 2021), or measured the overall income reported by households (Ighodaro et al., 2020). Lastly, a few authors focused on CSA's impacts on resource use efficiency (Imran et al., 2019, 2022) or technical efficiency (Ho & Shimada, 2019; Salat & Swallow, 2018).

In addition to yields, poverty, income, and efficiency, the success of CSA can be evaluated through its impact on food security. As with poverty, there are many measures of food security. For example, several authors used the household food insecurity access scale (HFIAS), the household dietary diversity score (HDDS), or measures of food expenditure to measure food security (e.g., Cholo et al., 2019; Hasan et al., 2018; Shahzad & Abdulai, 2021). Other authors used household potential food availability (Lopez-Ridaura et al., 2018) or a simple dummy variable (Khonje et al., 2015; Pan et al., 2018) as an index for food security.

There are myriad ways to investigate the impacts of CSA on a chosen indicator. For example, field experiments are commonly used to explore CSA's impacts in a controlled setting (e.g., Blaser et al., 2018; Gong et al., 2021; Kakraliya et al., 2018). Researchers have also created biophysical models to predict CSA's impacts on outcomes such as food security and GHG emissions (de Pinto et al., 2020), water availability (Alam & Sikka, 2019), crop yields, gross domestic product (GDP), and poverty (Komarek et al., 2019). Such models have been created for national (Komarek et al., 2019) and global (de Pinto et al., 2020) analysis. In addition, authors can conduct meta-analyses that summarize and compare the results of various forms of primary research (e.g., field experiments, econometric and biophysical models). Most meta-analyses first create an outcome measure that is comparable across studies (e.g., natural log of the response ratio: ln([yields under CSA]/[yields under conventional practices])), then summarize the results across studies (e.g., Huang et al., 2018; Pittelkow et al., 2015; Steward et al., 2018). Some follow up by conducting meta-regressions that control for the impacts of factors such as precipitation balance, climate stress, CSA duration, location, and year (Steward et al., 2018). Uniquely, Su et al.'s (2021) meta-analysis used a random forest machine learning model to estimate the response ratio as a function of crop type, soil, climate, and management. Next, they used climate projections to predict the impact of future climate on the efficacy of CSA (Su et al., 2021).

However, because meta-analyses rely on the results of other studies, they tend to have a limited ability to control for confounding variables due to inconsistencies across studies and datasets, and may have a shallow understanding of individual datasets. In addition, it is difficult for meta-analyses to address the bias that is often present in studies that have been previously undertaken. Such bias exists because it is difficult to conduct experiments for program evaluation; instead, organizations often select program participants non-randomly, and participants must willingly choose to partake.

Indeed, overcoming endogeneity in the form of selection bias is the greatest challenge for many studies that rely on real-world data. As a result, a variety of econometric techniques have been used for impact evaluation, including PSM (e.g., Ho & Shimada, 2019; Jamil et al., 2021; Khonje et al., 2015), endogenous switching regression models (e.g., Issahaku & Abdulai, 2020; Martey et al., 2021; Tesfaye et al., 2021), a double hurdle model (Amadu et al., 2020c), a correlated random effects model (Arslan et al., 2015), and a zero-stage probit model with fixed effects (Michler et al., 2019). While PSM is commonly used in impact evaluation to eliminate bias that is linked to observable characteristics, this approach cannot always address bias that is linked to unobservable characteristics.[7] On the other hand, endogenous switching regression models are a popular method of controlling for this type of 'unobservable' bias. One important feature of endogenous switching regression models is that they must contain at least one explanatory variable that directly influences selection into the treatment, but does not directly influence the outcome. For example, several authors use farmers' experience with or perception of climate events, access to CSA extension (e.g., distance of a household from CSA extension buildings), access to information about CSA, or membership in a farmers' association as variables that influence whether a household chooses to adopt CSA, but not outcomes such as food security, income, or crop yields (e.g., Khonje et al., 2015; Martey et al., 2020a; Ngoma, 2018).

Both PSM and endogenous switching regression rely on the assumption that the outcome variable is linearly related to the explanatory variables. However, links between outcomes (e.g.,

[7] More specifically, PMS assumes that participants who are equivalent in terms of observable characteristics will also be equivalent in terms of unobservable characteristics; therefore, unobservable characteristics will not create bias if this assumption is true.

food security, crop yields) and their determinants (e.g., household characteristics, climate, CSA practices, agricultural extension) are not always linear (e.g., Bakhtsiyarava et al., 2021; Bala et al., 2014; Schlenker & Roberts, 2009). If researchers incorrectly impose a linear model on a non-linear relationship, the model will be biased. Therefore, there is a need for more flexible models that can accommodate less straightforward relationships.

Accordingly, authors such as Su et al. (2021) and de Nijs et al. (2014) have taken a machine learning approach to CSA impact evaluation, using a random forest and a Bayesian belief network (respectively) to estimate the effects of CSA. Uniquely, Bala et al. (2014) modelled the non-linear impacts of CSA practices and agricultural extension on food security using a system dynamics approach. Such analyses, while rare, allowed these authors the flexibility to establish non-linear relationships between CSA outcomes and their explanatory variables. However, none of these approaches are designed to address selection bias.

In this study, I apply the double/debiased machine learning (DML) approach developed by Chernozhukov et al. (2018a). This method is designed to address selection bias by using orthogonalization and cross-fitting to estimate how a set of explanatory variables impacts both selection into the treatment (i.e., participation in a CSA program) and the CSA outcome (i.e., food security). Like PSM, DML is designed to address bias stemming from observable characteristics. Additionally (as with PSM and endogenous switching regression) the DML method cannot overcome omitted variable bias. However, it does allow for the use of multiple machine learning methods that can estimate non-linear relationships (e.g., trees, random forest, boosting), as well as methods that estimate linear ones (e.g., lasso). Ultimately, the DML method enables researchers to obtain consistent estimates under the assumption of selectivity based on observables, while also accommodating non-linear relationships.

When applying their chosen method of addressing selection bias, economists often include a wide array of factors that might influence both the treatment (e.g., adoption, selection into a CSA program) and the outcome (e.g., productivity, food security). These control variables often include demographic variables (e.g., age, gender, education, and farming experience of the household head, household size), farm and household characteristics (e.g., food aid, access to credit, assets, income, land ownership, land size, livestock ownership), and location (e.g., Amadu et al., 2020c; Cholo et al., 2019; Ho & Shimada, 2019). Such variables have often been shown to impact participation in a CSA program, CSA adoption, and CSA outcomes (e.g., Branca et al., 2021; Branca & Perelli, 2020; Martey et al., 2021).

So, what has the literature concluded regarding the ultimate question: Does CSA increase agricultural yields, household income, and/or food security? Because of the challenges inherent in determining the efficacy of CSA, it is prudent to look not at single studies, but at the literature as a whole. There are at least eleven literature reviews and meta-analyses that summarize CSA impact evaluation research (Giller et al., 2015; Gram et al., 2020; Huang et al., 2018; Jat et al., 2020; Khatri-Chhetri & Aggarwal, 2017; Kichamu-Wachira et al., 2021; Lamanna et al., 2016; Magombeyi et al., 2018; Pittelkow et al., 2015; Steward et al., 2018; Su et al., 2021; Thierfelder et al., 2017). Several such studies found that CSA generates significant increases in crop yields, water use efficiency, soil carbon, and economic returns, as well as decreased global warming potential, across South Asia (Jat et al., 2020; Khatri-Chhetri & Aggarwal, 2017) and Africa (Gram et al., 2020; Kichamu-Wachira et al., 2021; Magombeyi et al., 2018). However, CSA's effects are not always consistent. For example, in a systematic review that summarizes the impacts of a broad suite of CSA practices, Lamanna et al. (2016) find that while nutrient management practices consistently increase productivity, the impacts of practices such as agroforestry vary by location. Such results suggest that one of the key features influencing CSA's efficacy is the type of CSA practice implemented.

Practices such as CA, agroforestry, soil and water conservation measures, high-quality seeds, and genetically improved crop varieties have been widely studied and vary in their impacts. CA is the most analysed set of practices, with studies showing that CA can increase crop productivity, economic returns, resistance to drought, and technical efficiency (e.g., Boillat et al., 2019; Steward et al., 2019; Tong et al., 2019). Of CA's components, crop diversification (i.e., crop rotation and intercropping) appears to be a particularly popular strategy, with evidence showing that it can increase crop yields, economic returns, and nutrition/dietary diversity while reducing food insecurity (Baba & Abdulai, 2021; Makate et al., 2016). The separate implementation of minimal till farming and intercropping is also supported by authors who found them to increase crop yields and reduce the probability of low yields (Arslan et al., 2015; Ngoma, 2018; Nyirenda, 2019). When combined with other CSA practices, such as improved varieties of legumes and maize, fertilizer and green manure, or seed priming, there is evidence that CA increases both crop productivity and income (e.g., Berhanu et al., 2021; Makate et al., 2019; Setimela et al., 2018). The benefits of such combinations have been shown to outweigh their costs, allowing farmers to receive positive economic returns (Branca et al., 2021; Mutenje et al., 2019).

However, at least six meta-analyses and literature reviews find that, contrary to popular belief, the impacts of CA are not overwhelmingly positive and vary widely by context (Giller et al., 2015; Huang et al., 2018; Pittelkow et al., 2015; Steward et al., 2018; Su et al., 2021; Thierfelder et al., 2017). For example, Pittelkow et al. (2015) find that while no-till farming reduces crop yields, these reductions can be minimized (or even reversed) when no-till is implemented alongside residue retention and crop rotation. CA outcomes also vary substantially by climate; for example, CA often reduces yields and increases GHG emissions in wet or humid climates, but can lead to significant yield increases and reduced emissions when practiced in dry climates or during years of low rainfall (e.g., Huang et al., 2018; Pittelkow et al., 2015; Steward et al., 2018; Su et al., 2021). Therefore, depending on location, weather, and the combination of CA practices applied, CA can have insignificant impacts on crop yields (Arslan et al., 2015; Gong et al., 2021), increase yields and income, decrease yields and income (Michler et al., 2019; Tesfaye et al., 2021), or even decrease food security (Cholo et al., 2019). Furthermore, it can take between 2-5 years for farmers to achieve increased yields through CA (Thierfelder et al., 2017). Such variation in CA outcomes leads Giller et al. (2015) to contend that integrated management strategies, tailored to local contexts, are required for farmers to observe the purported benefits of CA.

In addition to CA, agroforestry (in which forest cover is integrated into crop systems), soil and water conservation measures (e.g., rainwater harvesting), and high-quality seeds/genetically improved crop varieties (particularly improved maize) have been heavily studied. While some authors find mixed results regarding whether agroforestry can increase economic returns and aid in climate change adaptation (Blaser et al., 2018; Branca et al., 2021), others find agroforestry or tree planting to positively impact maize yields (Amadu et al., 2020b; Amadu et al., 2020c) and food security (Cholo et al., 2019). Soil and water conservation measures provide more reliable benefits, with most authors finding them to reduce risk while increasing crop yields, farmer incomes, drought resilience, and resource use efficiency (e.g., Imran et al., 2019; Imran et al., 2022; Kosmowski, 2018). Similarly, fertilizers have been found to provide consistent increases in yield (Hammed et al., 2019; Kiwia et al., 2019; Sanou et al., 2016). There is also strong evidence supporting the use of high quality seeds and improved crop varieties, with numerous authors finding them to decrease poverty while increasing yields, consumption expenditures, and food security (e.g., Khonje et al., 2015; Martey et al., 2020a; Martey et al., 2020b). Lastly, some authors simultaneously examined diverse sets of crop, nutrient, and water management CSA practices, finding that they resulted in improved productivity, profit, GDP, and food security, as well as decreased GHG emissions, water use, and national poverty (e.g., de Pinto et al., 2020; Kakraliya et al., 2018; Komarek et al., 2019).

While literature suggests that the impacts of CSA are generally positive, several studies showed that these impacts can also vary depending on the number of CSA practices adopted (e.g., Makate et al., 2019; Tran et al., 2019), the location (e.g. Berhanu et al., 2021; Boillat et al., 2019), and the weather patterns of a given growing season (e.g. Arslan et al., 2015; Boillat et al., 2019). In general, authors found adoption of multiple CSA practices to provide greater benefits than adoption of single practices (e.g., Makate et al., 2019; Mutenje et al., 2019; Tran et al., 2019). Such studies almost always made specific comparisons between particular practices and combinations. In contrast, I found no studies that made broad comparisons between specialized and diversified CSA adoption. Closest to this approach is Sardar et al. (2021), who studied CSA impacts by the number of CSA practices adopted, finding that yields and farm income generally increased along with the number of CSA practices adopted.

Although CSA program participation and CSA adoption are distinct actions that may both influence CSA outcomes, research has almost exclusively focused on CSA adoption. Most often, CSA research includes access to agricultural extension programs as an explanatory variable, but does not have specific information on CSA program participation (e.g., Bala et al., 2014; Imran et al., 2019; Makate et al., 2019).[8] A few studies have strayed from this trend. Ogada et al. (2020) and Amadu et al. (2020b) studied the combined effects of CSA program participation and adoption by first matching villages that had CSA programs with comparable villages that lacked CSA programs, then assessing the impacts of adoption within those villages. Martey et al. (2021), Amadu et al. (2020c), Fuchs et al. (2019), and Pan et al. (2018) examined

[8] It is also common for studies to use access to agricultural extension programs as a variable that influences adoption, but not the outcome (e.g., food security), when controlling for bias through an endogenous switching regression model (e.g., Khonje et al., 2015; Martey et al., 2020a; Ngoma, 2018).

how participation in a CSA program impacted CSA adoption, crop productivity, income, and food security. Lastly, Ho and Shimada (2019) estimated two separate PSM models: one that addressed selection bias due to CSA program participation and measured the program's impacts, and one that addressed selection bias due to self-selection of adoption strategies and measured the impacts of adoption. Generally, these authors concluded that CSA programs increase CSA adoption, productivity, technical efficiency, income, and food security (e.g., Amadu et al., 2020c; Ho & Shimada, 2019; Martey et al., 2021).

2.4 Impact of Climate Change on the Impacts of CSA

While there is a rapidly expanding body of literature exploring the current impacts of CSA programs, far fewer studies predict how CSA impacts may change along with changing future climates. Additionally, the studies that do are often from a biophysical, rather than an economic, standpoint. At least four such biophysical studies have been conducted on a local or national scale (i.e., in Morocco, Nigeria, China, and Uganda) (Brouziyne et al., 2018; Olajire et al., 2020; Xin & Tao, 2020; Zizinga et al., 2022), while at least one has modelled global impacts (de Pinto et al., 2020). Most of these authors combine climate models with crop growth or hydrological models to predict the impacts of CSA on crop yields, for periods ranging from 2010 to 2059 (e.g., Brouziyne et al., 2018; Olajire et al., 2020; Zizinga et al., 2022). Generally, they find CSA practices to increase water use efficiency and crop yields, while dampening the negative impacts of climate change (Brouziyne et al., 2018; Xin & Tao, 2020; Zizinga et al., 2022). Some even predict that CSA may increase future crop yields in the face of climate change, contributing to decreased food prices worldwide (de Pinto et al., 2020; Olajire et al., 2020).

Because of the detailed biophysical inputs (e.g., soil properties, topography), farming practice inputs, calibration, and validation required to run process-based biophysical models, it can be difficult to predict future CSA impacts using such models due to the extensive data and computational requirements (Chetty, 2009; Islam et al., 2016a), especially when modelling large, heterogeneous areas. On the other hand, reduced-form economic models that do not require the same types of inputs often require less data (Chetty, 2009; Islam et al., 2016a). Additionally, because process-based biophysical models rely on a robust understanding of the pathways that run between inputs and outputs, it may be difficult to account for random, unexpected, or illunderstood phenomena that can impact those pathways. For example, farmers may initially choose to implement CSA practices, but later choose to abandon them in favour of seeking non-agricultural income. In contrast, econometric models that use real-world data do not require a complete understanding of causal pathways; such phenomena are already present within the data and will be reflected in model results.

Therefore, while complex biophysical models, such as the ones listed above, are most commonly used to predict the impacts of CSA under future climate conditions, broad economic approaches are also valuable research tools. One such approach was taken by Su et al. (2021), who compiled a CA dataset using 422 research papers, then used random forest machine learning to create a global model that predicted crop yields as a function of climate, crop type, soil properties, and farming practices. The authors then input future climate projections into the model, predicting global crop yields under CA farming from 2051-2060. They found that the potential future benefits of CA varied widely across the globe (Su et al., 2021). But overall, they predicted that while CA is more likely to increase yields in future climates, it will still produce smaller yields than traditional agriculture in many regions from 2051-2060.

A second machine learning approach was taken by de Nijs et al. (2014), who created a Bayesian belief network to predict the benefits of CSA under current and future climate conditions in Malawi. While results varied substantially due to variability between sites (e.g., topography and soil type), they found that CSA significantly reduced vulnerability to climate change (de Nijs et al., 2014).

3. The Program and Study Sites

Between the mid-2010s and 2021, the CGIAR Research Program on Climate Change, Agriculture and Food Security (CCAFS) ran CSA programs throughout villages in Africa, South Asia, and Latin America. Villages where CSA programs took place were labelled climate-smart villages (CSVs). Each CSV was sub-divided into several neighborhoods (localities) for the purpose of data collection and organization. My study focuses on 13 CSVs that, collectively, contain 87 localities (Figure 1).

Figure 1: Map of climate-smart villages (CSVs) included in this study.

Within Latin America, there are CSVs in Colombia, Guatemala, Honduras, and Nicaragua. In Colombia, the Cauca CSV spans the northwest portion of Popayán municipality (Osorio-García et al., 2020). The agricultural sector (particularly coffee and sugarcane cultivation) forms Cauca's economic foundation (Osorio-García et al., 2020). On average, Cauca farms are 1.3 ha in size, owned by the farmer, and primarily used for cash crops (i.e., sugarcane or coffee) instead of subsistence agriculture (Osorio-García et al., 2020). Such farms face diminishing soil and water quality due to deforestation and burning, and climate change has led to increased temperatures, erratic rainfall, and more frequent floods and droughts (Osorio-García et al., 2020; Twyman et al., 2015). Although Olopa CSV lies in eastern Guatemala's department of Chiquimula, and Santa Rita CSV lies in western Honduras's department of Copán, the two CSVs are less than 50 km apart and share several similarities (Bonilla-Findji et al., 2020a). Both Olopa and Santa Rita farmers primarily grow coffee as a cash crop; however, grains (e.g., corn, beans) and livestock (e.g., poultry, pigs) are also farmed for subsistence and income (Bonilla-Findji et al., 2020a; Bonilla-Findji et al., 2020b). While Santa Rita farms are often larger than

Olopa farms (1-5 ha vs. <1 ha, respectively), farmers in both CSVs face unpredictable rainy seasons and a lack of rainfall (Bonilla-Findji et al., 2020b). In Santa Rita, increasingly frequent droughts have been accompanied by higher temperatures, while Olopa has seen reduced rainfall in the summer season (Bonilla-Findji et al., 2020b). The final Latin American CSV is Tuma la Dalia, which is located in the northern portion of Nicaragua's Matagalpa Department (Wattel & Van Asseldonk, 2018). As in Olopa and Santa Rita, farmers in Matagalpa primarily grow maize, beans, and coffee, and partake in horticulture and raising livestock (Wattel & Van Asseldonk, 2018). While over half of Tuma la Dalia farms are between 1 and 5 ha, around one quarter of farmers have less than 1 ha (Climate Change Agriculture and Food Security [CCAFS], 2022).

Within Africa, there is one CSV located in each of Senegal, Ghana, Uganda, and Ethiopia. While all four CSVs have an agriculture-based economy that is threatened by irregular rainfall, the characteristics of the farms in each region remain unique (Bonilla-Findji et al., 2018; Bonilla-Findji et al., 2020c; Ouédraogo et al., 2020; Recha et al., 2016; Sam et al., 2020; Tadesse et al., 2021). Firstly, the CSV of Kaffrine lies in Senegal, between the Sahelian and Sudan Savannah zones (Ouédraogo et al., 2020). Despite a dry season that lasts for 8-9 months of the year, Kaffrine is characterized by small-scale (~ 9 ha) crop and livestock farms (Bonilla-Findji et al., 2018; Ouédraogo et al., 2020). Staple crops include peanut, cowpea, and millet, and major climate risks include floods, droughts, and strong winds in addition to irregular rainfall (Ouédraogo et al., 2020). The CSV of Lawra-Jirapa is composed of households that are within either the Lawra or Jirapa Districts of Ghana's Upper West Region (Partey et al., 2020). Lawra-Jirapa is less than 50 km from the border of Burkina Faso and lies within the Guinea Savannah Zone. Though the area typically has a high mean annual temperature and a rainy season with a single period of peak rainfall, farmers have recently faced more frequent droughts in addition to erratic rainfall (Bonilla-Findji et al., 2018; Partey et al., 2020; Sam et al., 2020). Most Lawra-Jirapa farms are approximately 3 ha in size and grow crops such as millet, maize, sorghum, yams, cowpeas, and groundnut (Bonilla-Findji et al., 2018; Partey et al., 2020). It is also common for Lawra-Jirapa farmers to raise animals such as guinea fowl, goats, sheep, and cows (Bonilla-Findji et al., 2018; Partey et al., 2020). The CSV of Hoima lies on the west side of Uganda, near the country's border with the Democratic Republic of Congo (Eriksen et al., 2019). Most Hoima residents rely on agriculture for work and income, and on subsistence agriculture for food (Recha et al., 2016). Frequently farmed crops include maize, sweet potato, beans, and cassava, as well as coffee and tea, which are common cash crops (Eriksen et al., 2019). Many households also raise livestock, including chickens, pigs, goats, and cattle (Recha et al., 2016). In Hoima, climate change has led to declining annual rainfall, increased temperatures, and rainfall variability (Recha et al., 2016). These changes further threaten food security in a community where two-thirds of residents are food insecure (Recha et al., 2016). Lastly, the Doyogena CSV is part of the Southern Nations, Nationalities, and Peoples' Region (SNNPR) of Ethiopia (Tadesse et al., 2021). Its climate is characterized by temperatures between 12 and 20 ºC and two rainy periods throughout the year (Tadesse et al., 2021). In addition to increased rainfall intensity and variability, Doyogena is subject to erosion and loss of soil fertility (Bonilla-Findji et al., 2020c). Most Doyogena farmers tend to mixed cereal, livestock, and agroforestry systems (Tadesse et al., 2021). While enset is most widely grown and plays a key role in farmer food security, other staple crops include wheat, barley, and faba bean (Tadesse et al., 2021). Subsistence agriculture predominates the region, with the average Doyogena farm being less than 0.5 ha in size (Tadesse et al., 2021).

Within Asia, there are three CSVs in Nepal and two CSVs in Bangladesh. The Nepalese CSVs of Bardiya, Nawalparasi, and Mahottari are located near the country's border with India, but are on the western, central, and eastern sides of Nepal, respectively (Bonilla-Findji & Khatri-Chhetri, 2017). The average farm is approximately 0.5 ha in all three Nepalese CSVs, and commonly grown crops include rice, wheat, potato, and pigeon pea (Bonilla-Findji & Khatri-Chhetri, 2017). Farmers in Bardiya, Nawalparasi, and Mahottari often raise livestock such as buffalo, goats, and chicken (Bonilla-Findji & Khatri-Chhetri, 2017). The primary climate challenges facing such farmers are droughts, floods, and insect pests (Bonilla-Findji & Khatri-Chhetri, 2017). In Bangladesh, the CSVs of Khulna and Barisal are less than 50 km apart and sit near the coast on the south side of the country (Bonilla-Findji & Khatri-Chhetri, 2017). As in Nepal, the average farm size in both CSVs is less than 1 ha (Bonilla-Findji & Khatri-Chhetri, 2017). It is common to grow rice and brinjal and to raise poultry, goats, cows, and fish (e.g., tilapia and carp) in both Khulna and Barisal (Bonilla-Findji & Khatri-Chhetri, 2017). However, wheat, chillies, cucumber, and cauliflower are more common in Khulna, while pulses, sweet gourd, and bitter gourd are more common in Barisal (Bonilla-Findji & Khatri-Chhetri, 2017). While both CSVs are susceptible to droughts and flooding, Khulna also faces storms, sea level rise, high salinity, and pollution, while Barisal is more threatened by high temperatures and unpredictable rain (Bonilla-Findji & Khatri-Chhetri, 2017).

Within each CSV, CCAFS ran CSA programs that trained farmers to adopt CSA practices. The programs also provided non-monetary support, such as seeds for improved crop varieties.[9] The set of CSA practices introduced varied by CSV, as practices were selected according to each CSV's unique set of climate challenges and local context. Farmers or households that participated in a CCAFS CSA intervention (and therefore, received CSA training and support) are referred to as "beneficiaries", while farmers or households that did not participate in a CCAFS CSA intervention are referred to as "non-beneficiaries".

Program beneficiaries were generally selected according to local systems and willingness to participate in the CSA program. For example, CCAFS often approached local authorities (e.g., a village chief or committee), which helped determine which farmers should be offered a place within the CSA program. In some CSVs (such as those in Vietnam), beneficiaries were also selected so that there would be similar numbers of men and women, and of young, middle age, and senior farmers (Eisen Bernard Bernardo, personal communication, 07/12/2021).[10]

Once they received training, beneficiaries could choose not to implement CSA practices, or to implement any combination of the CSA practices offered to them. Knowledge sharing often occurred between beneficiaries and non-beneficiaries, allowing some non-beneficiaries to also implement CSA practices. It is also possible that some farmers had already learned CSA practices through alternate channels (e.g., invention/discovery, another organization) prior to CCAFS's programs.

Once the CSA programs had been run, CCAFS surveyed beneficiaries and non-beneficiaries. As with the selection of beneficiaries, selection of survey participants was non-random. While all beneficiary households were surveyed, non-beneficiary survey respondents were selected through local systems (e.g., the recommendations of the village committee or chief) and willingness to participate.

[9] Appendix B contains a more comprehensive description of the supports offered to program participants.

[10] See Appendix B for more examples of how households were selected to participate in the CCAFS program.

The surveys were first piloted in 2017, then launched globally in 2018. In 2019, the surveys were revised in response to feedback received from the 2018 surveys. Therefore, the survey format used in 2017 and 2018 was slightly different than the format used in 2019 and 2020.

All surveys consisted of several modules, each targeted towards a certain theme. For example, in the 2017 and 2018 survey format, there were five survey modules: M0 Demographic and farm information; M1 Climate events; M2 Climate services; M3 Livelihood security and financial services; M4 Food security; and M5 Climate-smart options. CCAFS aimed to survey two members of each household: the household head and a second household member of the opposite gender. However, not all household members completed all survey questions. For example, in the 2019 and 2020 survey versions (and in some 2017 and 2018 surveys), only the household head of agricultural decisions filled out the climate events module and some of the demographic questions, and only female household members filled out the food security module (unless no female household members were available).

These surveys, when collected, cleaned, and prepared, resulted in the survey dataset used in this paper.

4. Data

Two sets of data were used in this study: survey data and climate data.

4.1 Survey Data

The survey data originated from the CCAFS CSA program described above and have been shared by CCAFS. The data contains survey responses that were recorded in 13 distinct CSVs between 2017 and 2020 (Table 1). The data from each CSV contains responses from multiple localities within the village, with an average of seven localities per CSV.

Table 1: Survey sampling design.

Region	Country	CSV	Survey Year			
			2017	2018	2019	2020
West Africa	Ghana	Lawra-Jirapa	X			
	Senegal	Kaffrine			X	
East Africa	Uganda	Hoima		X		
	Ethiopia	Doyogena			X	
South Asia	Bangladesh	Barisal		X		
		Khulna		X		
	Nepal	Bardiya		X		
		Mahottari		X		
		Nawalparasi		X		
Latin America	Colombia	Cauca		X	X	
	Guatemala	Olopa		X		X
	Honduras	Santa Rita		X		X
	Nicaragua	Tuma la Dalia		X		

There are a total of 4,573 survey responses in the dataset.[11] Since this study is conducted at the household level, 4,573 individual survey responses translates to 2,580 households. For all variables except those related to food security and CSA adoption, individual-level data were aggregated to the household level by taking the responses of the household head, then filling in any blank responses with the responses of the other surveyed household member.[12] Food security metrics, such as the HFIAS and the HDDS, direct food security questions to the household member who primarily prepares food and meals (Coates et al., 2007; Swindale & Bilinsky, 2006); most often, this member is a woman (Ali & Niehof, 2007; Fingleton-Smith, 2018;

[11] Each instance of a person filling out some, or all, of the survey modules counts as a survey response. The number of survey responses does not equal the number of unique survey respondents because several households in the Cauca, Olopa, and Santa Rita CSVs were surveyed twice; once in 2018, and once in 2019 or 2020.

[12] If there was more than one surveyed household head, the response of the oldest household head was used Similarly, if there was more than one non-household head, the response of the oldest non-head was used.

Wolfson et al., 2021). Because CCAFS used HFIAS questions in the surveys, individual-level food security data was aggregated to the household level by taking the responses of the female household member, then filling in any blank responses with the responses of the other surveyed household member.[13] Lastly, a household is considered a CSA practice adopter if at least one household member reports that the household previously adopted, or currently adopts, the practice.

Because some households (n=99) in the Cauca, Olopa, and Santa Rita CSVs were surveyed twice (once in 2018, and once in 2019 or 2020), I wanted to ensure that these households were not weighted more heavily in the analysis than households that were surveyed once. Because most surveys in the dataset were conducted in 2018, the 2019/2020 responses of such duplicate households were dropped to maintain consistency with respect to reporting years within the dataset. Ultimately, this process meant that there was one observation in the dataset per household surveyed, resulting in a total of 2,580 households. A breakdown of the number of household responses by CSV and year is given in Table 2.

[13] The food security responses of household members were prioritized in the following order: 1. Oldest female household head 2. Younger female household head 3. Oldest female non-household head 4. Younger female non-household head 5. Oldest male household head 6. Younger male household head 7. Oldest male non-household head 8. Younger male non-household head.

Table 2: Number of survey responses by CSV and year.

Year	CSV	# Household survey responses
2017	Lawra-Jirapa	193
2018	Hoima	344
	Barisal	149
	Khulna	147
	Bardiya	157
	Mahottari	169
	Nawalparasi	144
	Cauca	163
	Olopa	156
	Santa Rita	142
	Tuma la Dalia	147
2019	Cauca	114
	Kaffrine	166
	Doyogena	140
2020	Olopa	106
	Santa Rita	143
Total		**2,580**

To investigate specialized vs. diversified adoption, households were categorized according to three adoption strategies: non-adopters, specialized adopters, and diversified adopters. To establish these categories, the various CSA practices offered by CCAFS were organized into five broad themes (Table 3). These themes were informed by the Evidence for Resilient Agriculture (ERA) database's hierarchical structure of CSA practices (Rosenstock et al., 2020; World Agroforestry (ICRAF), 2020).[14] While not all CSVs offered all themes in Table

[14] More information on the ERA database can be found online at *https://era.ccafs.cgiar.org/*. A list of ERA database CSA practice themes can be found at *https://era.ccafs.cgiar.org/analysis/quick-start/* under the heading "Assess climate-smartness across practices".

3, 15 of the 16 CSVs offered at least two themes and 13 CSVs offered at least 3 themes.[15] Diversified adopters are households that adopted CSA practices that are housed within at least two separate themes. Specialized adopters are households that adopted a practice, or practices, that are housed within a single theme. Non-adopters are households that did not adopt any CSA practice. Note that both beneficiaries and non-beneficiaries may be either non-adopters, specialized adopters, or diversified adopters.

Table 3: CSA practice themes.

Themes	**# of CSVs that offered the theme**	**Descriptions of themes**
Agroforestry	9	The agroforestry theme includes practices that involve tree planting (e.g., for the purpose of harvesting fruit, providing windbreaks, or providing shade for livestock). It also includes farmer-managed regeneration of natural forested areas.
Animals	6	The animal theme includes practices in which farmers raised fish, poultry, or livestock. It also includes practices that enhance the production of fish, poultry, or livestock (e.g., controlled grazing, improved sheep varieties).
Crop Management	16	The crop management theme includes practices such as crop rotation, intercropping, improved crop varieties, the building of vegetable towers or gardens, and the building of solar grain dryers.
Soil, nutrient, and pest management	11	The soil, nutrient, and pest management theme includes practices that improve the management of the soil and its nutrients, or the management of pests. For example, it includes minimum or zero tillage, composting, the incorporation of plant residues into soil, cover cropping, and the use of pesticides and fertilizers.
Water management	13	The water management theme includes practices that improve water or runoff management, such as rainwater harvesting and storage, irrigation, and the building of structures to manage rainwater (e.g., ditches, bunds, and terraces).

[15] Note that the CSA practices offered to CSVs differed by both location and year. For example, Olopa was offered different CSA practices in 2018 and in 2020. Therefore, in this footnoted sentence (and in Table 3), CSVs are considered distinct if they differ in location or year (e.g., Olopa 2018 is distinct from Olopa 2020).

Finally, all households for which there was incomplete information were removed from the sample. Since two separate analyses (in Sections 5 and 6) were conducted, each with its own set of explanatory variables, two final datasets were assembled. Summaries of the households in the final datasets for the impact evaluation and future climate models are provided in Tables 4 and 5, respectively.

Table 4: Summary of households in the impact evaluation final dataset.

	Non-beneficiary	**Beneficiary**	**Total**
Non-adopter	201	35	**236**
Specialized adopter	249	249	**498**
Diversified adopter	410	483	**893**
Total	**860**	**767**	**1,627**

Table 5: Summary of households in the future climate analysis final dataset.

Non-beneficiary	**Beneficiary**	**Total**
1,049	895	**1,944**

4.2 Climate Data

Climate data were generated by the World Climate Research Programme's (WCRP's) Coupled Model Intercomparison Project (CMIP), which brings together and compares climate models from over 30 research groups worldwide (Eyring et al., 2016; World Climate Research Programme [WRCP], 2017). CMIP is a foundation of global climate science and its results are used in both IPCC Assessment Reports and international climate negotiations (Eyring et al., 2016; WRCP, 2017). To ensure that all models included in the project (i.e., endorsed MIPs) are comparable, all endorsed MIPs must meet CMIP criteria and standards, and must use the same climate scenarios (Eyring et al., 2016; WRCP, 2017).[16] While the results of each endorsed MIP are reported individually, CMIP also averages the results from all endorsed MIPs to create a multi-model ensemble result (WRCP, 2017).

There have been multiple iterations of CMIP as climate models are updated and refined to align with current research (WRCP, 2017). The latest iteration is CMIP Phase 6 (CMIP6), which includes 23 endorsed MIPs (WRCP, 2022) and uses four of the climate scenarios outlined in the IPCC's Sixth Assessment Report (AR6): shared socio-economic pathways (SSPs) 1-2.6, 2-4.5, 3-7.0 and 5-8.5 (IPCC, 2021; WorldClim, 2022a). CMIP6 data is available via the WorldClim website (WorldClim, 2022a).

For each locality within each CSV, CCAFS obtained historical climate data (for the years 1970-2000) (Fick & Hijmans, 2017; WorldClim, 2022b) and future climate predictions (for the years 2021-2040 and 2041-2060) from the CMIP6 multi-model ensemble via WorldClim (WorldClim, 2022a).[17] I use future climate predictions based on SSP 5-8.5 – a high-emissions pathway in which fossil fuel use drives rapid economic and social development, causing global surface temperatures to rise by 3.3°C to 5.7°C (relative to 1850-1900 temperatures) by 2081-2100 (IPCC, 2021; Riahi et al., 2017).

The dataset contains several bioclimatic variables that may influence crop range/distribution, crop growth, and food security in developing countries (e.g., Cotterman et al., 2020; Koch et al., 2022; Madani et al., 2018): Annual mean temperature (°C), maximum temperature of warmest month (°C), mean temperature of driest quarter (°C), annual precipitation (mm), precipitation of driest month (mm), precipitation of driest quarter (mm), precipitation of wettest month (mm), precipitation of wettest quarter (mm), and precipitation seasonality (coefficient of variation). These variables are investigated in Section 6.

[16] Climate scenarios represent potential global futures and are based on varying assumptions about future socio-economic conditions and GHG emissions (IPCC, 2021).

[17] Due to an error in the dataset, the localities within the CSVs of Khulna and Barisal were assigned the same coordinates (and therefore, the same set of climate data). However, there is likely little difference in the climate projections for these CSVs due to their close proximity (less than 50 km) and the large scale of the CMIP6 data.

5. Impact Evaluation

5.1 Empirical Strategy

5.1.1 The Model

In the impact evaluation model, the goal is to identify the effect of a treatment (i.e., being a CCAFS beneficiary household) on food security, while controlling for confounding variables. When treatment is allocated randomly through experimentation, researchers avoid introducing selection bias (i.e., a form of endogeneity in which the probability of receiving treatment is correlated with other determinants of food security). As a result, consistent average treatment effect (ATE) estimates can be generated without considering selection bias. While experimentation offers advantages in ATE estimation, randomization of treatment assignment is often not feasible in practice. For example, even if households are randomly selected to be part of a development program, not all households may choose to participate. In the absence of experiments, selection bias generates an identification problem that prevents researchers from disentangling treatment effects from the impacts of other determinants of food security, complicating program evaluation and the estimation of ATE.

Many approaches for dealing with endogeneity rely on instrumental variables (IVs) (i.e., variables that impact treatment but do not directly influence the outcome). Yet when it comes to the evaluation of CCAFS interventions on food security, it is difficult to differentiate the variables that affect the probability of becoming a beneficiary from those that affect food security. In fact, most socioeconomic determinants that are available in the data (and discussed in the literature review and Appendix B) are likely to influence both, making it difficult to obtain appropriate IVs. However, the need for IVs can be avoided if selection into the treatment is based on observable characteristics. This assumption is commonly made by impact evaluation researchers (e.g., Ho & Shimada, 2019; Jamil et al., 2021; Khonje et al., 2015); indeed, it forms the foundation for econometric methods such as PSM.

Additionally, standard approaches to estimate impacts and control for selection bias rely on the specification of linear models (or models where a latent variable is assumed to have a linear relationship with the explanatory variables). However, the relationships between control and outcome variables and control and treatment variables are complex and often unknown. For example, research has revealed non-linear relationships between livestock ownership, climate, and food security (Bakhtsiyarava et al., 2021), between CSA practices, agricultural extension, and food security (Bala et al., 2014), and between climate and crop yields (Frelat et al., 2016; Schlenker & Roberts, 2009; Wei et al., 2014). In such cases, incorrectly imposing linear relationships can significantly bias ATE estimates.

The approach here is to develop a flexible food security model that addresses the above challenges to estimate the ATE of CCAFS interventions. Formally, the model to be estimated is (Chernozhukov et al., 2018a):

$$Y_i = \alpha T_i + g(X_i) + \varepsilon_i \quad (1)$$

$$T_i = m(X_i) + \mu_i \quad (2)$$

where Y_i represents food security for a household i, *T* is a treatment indicator (i.e., CCAFS non-beneficiary or beneficiary), and *X* are outcome and selection confounding variables. The terms μ and ε are error terms with the properties $E(\mu \mid X) = 0$ and $E(\varepsilon \mid X, T) = 0$. Equation 1 is the outcome equation and allows both the program intervention *T* and confounding factors *X* to determine food security *Y*. Note that while the impact of *T* on *Y* is assumed to be linear, the model is general regarding the shape of the influence of *X* on *Y* and makes no assumptions about how those determinants of food security operate. The function g(.) operationalizes this general approach and accommodates unknown and complex forms of nonlinearities. Equation 2 explains selection into the treatment based on observable *X*. Similarly, there is a general relationship between *X* and the probability of receiving treatment (*T*) via a general and unknown function (m(.)).

The main parameter of interest is α, which corresponds to the marginal effect of being a CCAFS beneficiary on food security. The next section describes the approach used to estimate α.

5.1.2 The Estimation Approach

To maintain the flexibility of the model described by Equations 1 and 2, and to perform valid inference (based on a root-N estimator) I apply the double/debiased machine learning (DML) approach developed by Chernozhukov et al. (2018a). In this orthogonalization procedure, the dataset is randomly split into two sub-samples: a main sample and an auxiliary sample. The auxiliary sample is then used for two purposes: 1) To acquire a preliminary estimate of g(.) using Equation 1, and 2) To partial out the effect of *X* from *T* and obtain an estimate of μ_i (i.e., $\hat{\mu}_i$), using Equation 2. Both estimates are obtained via machine learning methods. Next, the main sample is used to compute an estimate of the ATE parameter α, where:

$$\hat{\alpha} = (\frac{1}{n}\sum \hat{\mu}_i T_i)^{-1} \frac{1}{n}\sum \hat{\mu}_i (Y_i - \hat{g}(X_i)) \tag{3}$$

Finally, the roles of the main and auxiliary samples are reversed (i.e., the old main sample becomes the new auxiliary sample, and the old auxiliary sample becomes the new main sample), the above orthogonalization steps are repeated to obtain a new estimate of α, and the two estimates of α are averaged. This process of sample-splitting, role-reversal, and averaging is called "cross-fitting" (Chernozhukov et al., 2018a, p. C6). Overall, the DML approach is defined as the above combination of machine learning, orthogonalization, and cross-fitting.

In this paper, the DML approach is applied via 100 iterations of its cross-fitting orthogonalization procedure. The final mean ATE estimate is the average estimate of α over the 100 iterations.

While its ability to estimate non-linear relationships is an advantage in econometric applications, machine learning has traditionally been used to model non-causal relationships and make predictions (Wager & Athey, 2018). In fact, traditional machine learning methods are often unsuitable for the estimation of causal impacts due to the presence of overfitting and regularization biases, slow convergence rates, and lack of consideration of selection bias.

Overfitting occurs when an estimated machine learning model closely tracks the idiosyncrasies of a sample, rather than reflecting the overall trends of a population. As a result, an overfit model will provide accurate in-sample predictions, but poor out-of-sample predictions, and can produce biased estimates of α (Chernozhukov et al., 2018a). While regularization (via regularized estimators such as lasso and boosting) is often used to address overfitting, it can also introduce bias into an estimated model (Chernozhukov et al., 2018a). This is especially true in Equation 1, where the causal parameter of interest is a low-dimensional parameter that exists alongside high-dimensional nuisance parameters (e.g., the function g(.)). Moreover, machine learning estimators often display convergence rates that are much slower than the typical parametric rate of $\sqrt{n}$-consistency (Gao et al., 2022).[18] Therefore, while traditional machine learning methods can be used to estimate Equation 1, they will often fail to provide unbiased or $\sqrt{n}$-consistent estimation of α.

In the DML method, overfitting and regularization biases are eliminated through cross-fitting and orthogonalization, respectively (Chernozhukov et al., 2018a). Firstly, the process of cross-fitting combines sample splitting with role-reversal and averaging to address overfitting while maintaining the efficiency of the estimator ($\hat{\alpha}$).[19] Secondly, orthogonalization effectively addresses regularization bias and achieves $\sqrt{n}$-consistency by combining the estimation errors produced when estimating Equations 1 and 2.[20] This orthogonalization procedure is rooted in the Frisch-Waugh-Lovell theorem (Frisch & Waugh, 1933; Lovell, 1963, 2008) and Robinson (1988).[21] Additionally, the DML method's use of Equation 2 in the orthogonalization procedure allows it to address selection bias more effectively than traditional machine learning methods. Like an IV, orthogonalization helps remove the effect of nuisance variables and isolate the impact of the treatment on the outcome; indeed, the estimator ($\hat{\alpha}$) can be thought of as a linear IV estimator (Chernozhukov et al., 2018a).

Finally, while traditional nonparametric and semi-parametric approaches can be used to estimate the functions g(.) and m(.) (Robinson, 1988), it is well-known that such nonparametric econometrics estimators do not perform well when given small samples and high-dimensional applications. This phenomenon is often referred to as the "curse of dimensionality". DML is

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[18] If an estimator is not unbiased, it should (at least) be $\sqrt{n}$-consistent. This means that as the sample size (n) increases, the estimation error (i.e., $\hat{\alpha} - \alpha$) converges upon 0 at a rate of $\frac{1}{\sqrt{n}}$. If the convergence rate is slower than $\frac{1}{\sqrt{n}}$ (e.g., $\frac{1}{\sqrt[4]{n}}$), the estimation error shrinks more slowly and the estimator is no longer $\sqrt{n}$-consistent.

[19] When used in isolation, sample splitting addresses overfitting, but reduces the efficiency of the estimator. Subsequent role-reversal and averaging restore the efficiency of the estimator.

[20] Since each of the estimation errors converge at a rate of $\frac{1}{\sqrt[4]{n}}$, the product of the estimation errors converges at a rate of $\frac{1}{\sqrt{n}}$.

[21] The DML orthogonalization described above is analogous to the following orthogonalization approach: 1) A machine learning method is used to predict *T* from *X* and obtain the resulting residuals, 2) A machine learning method is used to predict *Y* from *X* and obtain the resulting residuals, and 3) The estimate of α ($\hat{\alpha}$) is obtained by residual-on-residual linear regression. This three-step process is an extension of the Frisch-Waugh-Lovell theorem (Frisch & Waugh, 1933; Lovell, 1963, 2008), which uses linear regression throughout each of the three steps, and of Robinson (1988), who uses non-parametric regression in the first two steps and linear regression in the third step.

uniquely positioned to address high-dimensional data due to its use of machine learning and cross-fitting.

However, the validity of the DML approach used in this paper rests on three key assumptions. Firstly, the partially linear model described by Equations 1 and 2 allows for non-linearities in the functions g(.) and m(.), but assumes linearity in the relationship between T and Y. Secondly, the property of the error term μ ($E(\mu \mid X) = 0$) implies that, conditional upon X, there is no selection bias. In other words, like PSM, the model assumes that selectivity effects can be fully accounted for via the observables included in X. Thirdly, the property of the error term ε ($E(\varepsilon \mid X, T) = 0$) implies that there is no omitted variable bias, as (like most econometric methods) DML cannot identify causal impacts when excluded variables are correlated with both included explanatory variables and the outcome. When the above assumptions are met, DML allows us to maintain the causal interpretation of the ATE parameter and construct valid confidence intervals while modeling flexible, non-linear relationships. In this way, it combines the identification advantages of classic econometrics methods with the flexibility of machine learning, providing a unique angle from which to study the impacts of CSA programs.

5.1.3 The Model Specification

The variables for the model specification are contained in Table 6. The food security outcome (Y) is a binary variable that indicates whether the household is food secure (i.e., Y=1 if the household is food secure, 0 otherwise). This variable was constructed based on the following survey question: "*Have there been any months within the last twelve where you or anyone in your household did not have access to enough food?*".

The variable T is a binary indicator that is equal to 1 if the household is a CCAFS beneficiary and equal to 0 otherwise. As described in Section 3, a CCAFS beneficiary is a household that participated in the CCAFS CSA program (and therefore, received CSA training and support).[22] Of the 1,627 households in the sample, 767 are beneficiaries.

[22] See Appendix B for a description of the supports offered to beneficiaries by the CCAFS program.

A matrix of controls, *X*, was chosen based on information from the literature review and the factors that influenced selection into the CCAFS CSA program.[23] Firstly, the adoption strategy chosen by the household (non-adoption, specialized adoption, or diversified adoption) is included in *X*. Secondly, I include several socioeconomic characteristics that can affect both food security and selection into a CCAFS program: age, gender, education, household size, farm size, land ownership, farming of one of the top 3 most popular crops in the sample (i.e., beans, maize, rice), whether animals are raised on the farm, the type(s) of animals raised on the farm, the primary household income source, use of a loan or credit, ability to make savings, and climate events. Lastly, I include CSV and year dummy variables to control for fixed effects.[24]

The model assumes that the matrix *X* fully captures the probability of selection into the CCAFS program. As described in Appendix B, CCAFS offered the CSA program to households based on factors such as age, gender, farming system, and willingness to participate. While age, gender, and farming system information (e.g., farm size, whether households grew different crops or raised various animals) are included in the dataset, willingness to participate (i.e., self-selection) is captured by the adopter type dummy variables (as those who are willing to implement CSA practices are more likely to sign up for the CCAFS program), and by the wide array of socioeconomic characteristics included in *X*. The inclusion of socioeconomic characteristics is supported by literature that finds variables such as age, household size, and farm size to influence participation in a CSA program (Ho & Shimada, 2019; Martey et al., 2021). Additionally, the inclusion of fixed effects accounts for the impacts of any selection-influencing factors that are linked to either location or year (e.g., internet access, access to health services, cultural differences, climate events). For example, if program participation is affected by unobserved climate variation, the fixed effects will control for climate shocks that are common to all households in a given year or in a particular CSV. Overall, the variables included in *X* are comparable to those used by existing CSA impact evaluations that make similar assumptions (e.g., Jamil et al., 2021; Khonje et al., 2015). Moreover, CSA impact evaluations

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[23] See Section 2 (Literature Review) for control variables that are commonly included in CSA impact evaluations. See Appendix B for examples of how households were selected to participate in the CCAFS program.

[24] Third-degree polynomials of all non-binary variables (i.e., age, household size, farm size, climate events) were also included when using the least absolute shrinkage selection operator (Lasso) machine learning method.

that have applied both PSM and techniques designed to control for unobservable factors (e.g., endogenous switching regression, conditional mixed process) to the same data have found both methods to produce similar results (Khonje et al., 2015; Martey et al., 2021; Ogada et al., 2020). Such findings indicate that CSA selection bias can be adequately addressed via observable characteristics.

To further investigate the assumption that X captures the probability of being a CCAFS beneficiary, I generated a random forest model that predicted selection into the CCAFS program (T) using the matrix X. I then used 3x 10-fold cross-validation to evaluate the accuracy of the model.[25] The model correctly classified households as CCAFS beneficiaries or non-beneficiaries 84% of the time.

To better understand interactions between the CCAFS program and CSA adoption strategies, the model described by Equations 1 and 2 is estimated four times: once for the entire sample (n=1,627), once for a sub-sample of non-adopters (n=236), once for a sub-sample of specialized adopters (n=498), and once for a sub-sample of diversified adopters (n=893). Summary statistics for each sample are listed in Table 6.

[25] See Appendix D for more information on cross-validation and accuracy.

Table 6: Summary statistics for the impact evaluation model.[α]

Variable	Variable Definition [β]	All observations (n=1,627)	Non-adopters (n=236)	Specialized adopters (n=498)	Diversified adopters (n=893)
Outcome (*Y*)					
Food security	1 if household is food secure.	0.486 (0.500)	0.407 (0.492)	0.522 (0.500)	0.487 (0.500)
Treatment (*T*)					
CCAFS beneficiary	1 if household is a CCAFS beneficiary.	0.471 (0.499)	0.148 (0.356)	0.500 (0.501)	0.541 (0.499)
Confounding Factors (*X*)					
CSA adoption	1 if household chose that adoption strategy.[γ]				
No adoption (baseline)		0.145 (0.352)	–	–	–
Specialized adoption		0.306 (0.461)	–	–	–
Diversified adoption		0.549 (0.498)	–	–	–
Age	Age of household head (HH) in years.	49.385 (14.094)	47.131 (14.489)	48.048 (12.869)	50.727 (14.505)
Female	1 if HH is female.	0.168 (0.374)	0.136 (0.343)	0.155 (0.362)	0.185 (0.388)
Education	1 if HH has that level of education.				
No education (baseline)		0.358 (0.480)	0.182 (0.387)	0.365 (0.482)	0.401 (0.490)
Primary education		0.393 (0.489)	0.508 (0.501)	0.363 (0.481)	0.380 (0.486)
Secondary education		0.210 (0.408)	0.267 (0.443)	0.239 (0.427)	0.179 (0.384)
Technical/college/ university education		0.038 (0.192)	0.042 (0.202)	0.032 (0.177)	0.040 (0.197)
Household size	Number of individuals living in the household.	6.443 (4.233)	4.517 (2.625)	6.066 (3.858)	7.162 (4.580)
Farm size	Total productive area of household farm (in hectares).	2.500 (6.288)	2.322 (2.988)	2.128 (3.255)	2.756 (7.979)
Land ownership	1 if household owns most of the farmed land.	0.813 (0.390)	0.729 (0.446)	0.811 (0.392)	0.837 (0.370)

Variable	Variable Definition $^{\beta}$	All observations (n=1,627)	Non-adopters (n=236)	Specialized adopters (n=498)	Diversified adopters (n=893)
Types of crops	1 if household grows that crop.$^{\delta}$				
Beans		0.554 (0 .497)	0.212 (0.409)	0.578 (0.494)	0.630 (0.483)
Maize		0.505 (0.500)	0.216 (0.412)	0.566 (0.496)	0.546 (0.498)
Rice		0.372 (0.484)	0.483 (0.501)	0.460 (0.499)	0.295 (0.456)
Livestock	1 if household raises livestock.	0.842 (0.365)	0.678 (0.468)	0.789 (0.408)	0.915 (0.279)
Types of livestock	1 if household raises that type of livestock.$^{\varepsilon}$				
Bovine animals		0.341 (0.474)	0.263 (0.441)	0.321 (0.467)	0.373 (0.484)
Aquatic animals		0.054 (0.226)	0.110 (0.314)	0.066 (0.249)	0.032 (0.177)
Horses		0.117 (0.321)	0 (0)	0.082 (0.275)	0.167 (0.373)
Goats		0.303 (0.460)	0.093 (0.291)	0.317 (0.466)	0.351 (0.477)
Pigs		0.128 (0.334)	0.034 (0.181)	0.074 (0.263)	0.183 (0.386)
Poultry		0.503 (0.500)	0.297 (0.458)	0.394 (0.489)	0.619 (0.486)
Sheep		0.132 (0.338)	0 (0)	0.064 (0.245)	0.204 (0.403)
Income source	1 if that is the household's primary income source.$^{\theta}$				
Agricultural activities on their farm (baseline)		0.648 (0.478)	0.547 (0.499)	0.562 (0.497)	0.722 (0.448)
Other activities		0.320 (0.466)	0.436 (0.497)	0.394 (0.489)	0.247 (0.432)
Remittance or external Aid		0.033 (0.178)	0.017 (0.129)	0.044 (0.206)	0.030 (0.171)

Variable	Variable Definition $^{\beta}$	All observations (n=1,627)	Non-adopters (n=236)	Specialized adopters (n=498)	Diversified adopters (n=893)
Loan or credit	1 if household used a loan or credit for agricultural activities in the past 12 months.	0.251 (0.434)	0.254 (0.436)	0.227 (0.419)	0.263 (0.441)
Savings	1 if household's agricultural income allowed it to make savings in the past 12 months.	0.443 (0.497)	0.373 (0.485)	0.392 (0.489)	0.489 (0.500)
Climate events	Number of main climate events that affected on-farm production or income in the past 12 months.	0.982 (1.006)	0.864 (0.809)	1.026 (1.031)	0.988 (1.037)
Climate-smart village (CSV)	1 if household is in that CSV.				
Bardiya (baseline)		0.065 (0.247)	0.047 (0.211)	0.112 (0.316)	0.044 (0.204)
Barisal		0.086 (0.281)	0.263 (0.441)	0.076 (0.266)	0.045 (0.207)
Cauca		0.065 (0.247)	0.123 (0.329)	0.058 (0.234)	0.054 (0.226)
Doyogena		0.080 (0.271)	0 (0)	0.002 (0.045)	0.144 (0.352)
Hoima		0.100 (0.300)	0.072 (0.259)	0.118 (0.323)	0.096 (0.295)
Kaffrine		0.077 (0.266)	0 (0)	0.108 (0.311)	0.080 (0.271)
Khulna		0.085 (0.280)	0.271 (0.446)	0.112 (0.316)	0.021 (0.144)
Lawra-Jirapa		0.111 (0.314)	0 (0)	0.002 (0.045)	0.200 (0.401)
Mahottari		0.057 (0.231)	0 (0)	0.068 (0.252)	0.065 (0.247)
Nawalparasi		0.077 (0.266)	0.055 (0.229)	0.127 (0.333)	0.055 (0.228)
Olopa		0.122 (0.328)	0.106 (0.308)	0.149 (0.356)	0.112 (0.316)

Variable	Variable Definition $^{\beta}$	All observations (n=1,627)	Non-adopters (n=236)	Specialized adopters (n=498)	Diversified adopters (n=893)
Santa Rita		0.036 (0.185)	0.064 (0.244)	0.048 (0.214)	0.021 (0.144)
Tuma la Dalia		0.040 (0.196)	0 (0)	0.018 (0.133)	0.063 (0.243)
Years	1 if household was surveyed in that year.				
2017 (baseline)		0.111 (0.314)	0 (0)	0.002 (0.045)	0.200 (0.401)
2018		0.661 (0.473)	0.996 (0.065)	0.861 (0.346)	0.461 (0.499)
2019		0.176 (0.381)	0.004 (0.065)	0.129 (0.335)	0.249 (0.432)
2020		0.052 (0.221)	0 (0)	0.008 (0.089)	0.090 (0.286)

$^{\alpha}$ Mean values are reported without parentheses. Standard deviations are reported in parentheses.

$^{\beta}$ For all variables that apply to the household head, the response of the oldest respondent was taken if the household head did not respond to the survey.

$^{\gamma}$ The adoption strategy dummy variables ('no adoption', 'specialized adoption', and 'diversified adoption') were only included in the model run for the entire sample, as each sub-sample (non-adopter, specialized adopter, diversified adopter) only contained households that practiced the respective adoption strategy.

$^{\delta}$ The 'beans' dummy variable includes various types of beans, such as bambara beans, black beans, red beans, and soy beans.

$^{\varepsilon}$ The 'bovine animals' dummy variable includes cattle, buffalo, and oxen. The 'aquatic animals' dummy variable includes fish, prawns, and shrimp.

$^{\theta}$ The 'other activities' dummy variable includes agricultural activities that do not take place on their own farm and non-agricultural activities. If a household gained equal income from agricultural activities on their farm and other farms, or from agricultural and non-agricultural activities, its primary income source was 'other activities'.

Within the entire sample, nearly 50% of households face food insecurity and there is an approximately even split of CCAFS beneficiaries and non-beneficiaries. It is noteworthy that non-beneficiaries account for nearly half of the specialized and diversified adopter sub-samples, indicating that many households have implemented CSA without direct contact with CCAFS. Such households may have discovered CSA through neighbours, friends, community associations, organizations other than CCAFS, news articles, the internet, or ingenuity. In fact, relatively few households (15%) did not adopt CSA practices, with the majority (55%) selecting a diversified adoption strategy.

Over 80% of households in the sample are headed by males. While there is substantial variation in age, the average household head is 49 years old and lacks education beyond the primary level. The average household contains just over six people, owns the land it farms, raises livestock (primarily poultry, goats, or bovine animals), and relies primarily on its farmed land for income. However, less than half of households are able to save parts of their agricultural income. While there is some variation, the average farm is 2.5 ha in size and was impacted by one main climate event in the year prior to the survey. Lastly, each CSV is well-represented within the sample, with the smallest percentage of households located in Santa Rita (4%), and the largest percentage in Olopa (12%).

5.2 Results and Discussion

The DML machine learning approach is implemented using four machine learning methods for the estimation of g(.) and m(.): least absolute shrinkage and selection operator (Lasso), trees, random forests, and boosting.[26] Results for each of these methods are contained in Table 7. In addition, I follow Chernozhukov et al. (2018a) and compute another ATE estimate where the machine learning methods used for estimation of g(.) and m(.) are the ones with the best average out-of-sample prediction. This means that a mix and match approach is used, where the estimates used in each step of orthogonalization are based on the method that outperformed others in terms of prediction accuracy. This mix and match approach is referred to as the 'best' method.[27]

To put the treatment effect estimates in context, an average baseline food security ($\overline{g(X)}$) for each estimation method and sample is computed, where:

$$\overline{g(X)} = \bar{Y} - \hat{\alpha}\bar{T} \tag{4}$$

[26] The use of tree-based methods (e.g., trees, random forests, and boosting) is supported by the findings of Schlenker and Roberts (2009) and Bakhtsiyarava et al. (2021), who found that relationships between some outcomes (i.e., crop yields and food security) and some of their determinants are characterized by thresholds. Since tree-based methods are designed to find thresholds that best predict the outcome, they are well-suited to model such relationships.

[27] To investigate the robustness of the results, I performed a sensitivity analysis in which groups of variables were systematically removed from the control variable matrix *X*, and the models were re-run with the smaller set of control variables using 25 iterations. There was little change in estimated ATEs and their significances across these sensitivity runs.

This calculation is consistent with the model's assumption that mean residuals resulting from the estimation of Equation 1 are zero (i.e., $E(\varepsilon \mid X, T) = 0$).

Table 7: Estimates of ATE parameter α and $\overline{g(X)}$.

Sample	Sample Size	Parameter	(1) Lasso	(2) Trees	(3) Random forest	(4) Boosting	(5) Best
All observations	1,627	$\hat{\alpha}$	0.0661** (0.0277)	0.0415 (0.0361)	0.0602** (0.0299)	0.0697** (0.0297)	0.0602** (0.0299)
		$\overline{g(X)}$	0.4550	0.4666	0.4578	0.4533	0.4578
Non-adopters	236	$\hat{\alpha}$	0.1565 (0.1035)	0.0731 (0.1123)	0.0929 (0.0911)	0.1673* (0.1006)	0.0804 (0.0995)
		$\overline{g(X)}$	0.3836	0.3959	0.3930	0.3820	0.3948
Specialized adopters	498	$\hat{\alpha}$	0.0134 (0.0500)	-0.0147 (0.0622)	0.0078 (0.0436)	0.0169 (0.0448)	0.0075 (0.0436)
		$\overline{g(X)}$	0.5154	0.5295	0.5182	0.5136	0.5183
Diversified adopters	893	$\hat{\alpha}$	0.0830 (0.0555)	0.0926* (0.0509)	0.0974** (0.0494)	0.1156** (0.0507)	0.0974** (0.0494)
		$\overline{g(X)}$	0.4422	0.4370	0.4344	0.4246	0.4344

Standard errors are reported in parenthesis.
*p<0.1 **p<0.05 ***p<0.01

Table 7 presents DML estimates of the parameter α when using different machine learning methods for estimation (across columns) and different samples (across rows). In general, the results for the full sample indicate a significant and positive ATE (Table 7). All but one machine learning method delivers an ATE estimate between 0.060 and 0.070 (p<0.05), with the remaining estimate being insignificant. The random forest model provides the best fit for the data, as its results are equivalent to those of the 'best' column. This 'best' estimate indicates that being a CCAFS beneficiary increases the probability of food security by 6.0 percentage points (p<0.05). Additional information is provided by the 'best' estimate of $\overline{g(X)}$, which indicates that a household's probability of being food secure rises from 45.78% to 51.80%, on average, when it participates in CCAFS programs.

Previous studies show that participation in CSA programs can increase crop yields by between 15% and 20%, increase income by 24%, and increase technical efficiency by between 5% and 8% (Amadu et al., 2020c; Ho & Shimada, 2019; Martey et al., 2021). Most similarly to my study, Pan et al. (2018) found CSA programs to increase overall food security by 5.4 percentage points in participating villages. My results add to existing evidence by revealing that CSA programs can increase the probability of being food secure by 6.0 percentage points, or 13%, amongst participating households.[28,29] Collectively, the findings demonstrate that CSA programs can significantly improve the livelihoods of their participants.

In addition to quantifying the direct benefits of CSA programs, authors find that CSA programs increase the adoption of both individual CSA practices (Martey et al., 2021) and combinations of CSA practices (Amadu et al., 2020c), and that CSA adoption can improve yields and welfare outcomes (e.g., Jat et al., 2020; Kichamu-Wachira et al., 2021; Komarek et al., 2019). Taken together, these relationships imply that CSA programs and CSA adoption have interconnected and positive impacts on welfare. My study is among the few to dive deeper into these relationships.

The lower rows of Table 7 show estimates of models on sub-samples of the data, which explore the impact of CCAFS programs on households that chose different CSA adoption strategies. In general, the ATE estimates are statistically insignificant within the non-adopter sub-sample. We cannot reject the null hypothesis that CCAFS training has no impact on food security amongst households that do not adopt CSA practices. I find a similar result for specialized adopters. These two findings suggest that CSA program participation generates few food security benefits within these two groups of households. The non-adopter finding is supported by authors who find that CSA programs primarily benefit farmers through encouraging CSA adoption (i.e., CSA programs are ineffective when participants do not adopt)

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[28] This percentage is computed as the ratio of the ATE (6.02 percentage points) to the baseline food security (45.78%), expressed as a percentage.

[29] To contextualize these results, examples of previous research on the impacts of various development programs on food security are presented in Appendix C (Table 10).

(Amadu et al., 2020b; Pan et al., 2018). For example, Amadu et al. (2020c) find that CSA program participation increases crop yields, conditional upon participants adopting CSA.

The results for the diversified adopter sub-sample indicate a positive and significant ATE that is consistent across all but one machine learning method. Four of five methods estimate that being a CCAFS beneficiary increases the probability of being food secure by between 9.3 and 11.6 percentage points ($p<0.10$; $p<0.05$). As with the results for the entire sample, we see that the random forest model generates the best fit for the data. Using this 'best' estimate, a non-beneficiary diversified adopter's probability of being food secure will increase, on average, from 43.4% to 53.2% when they participate in CCAFS programs.

While it is generally accepted that CSA programs increase CSA adoption, which in turn increases welfare (Amadu et al., 2020b; Amadu et al., 2020c; Pan et al., 2018), these findings imply that the benefits of CSA programs extend beyond simply prompting adoption.[30] When it comes to diversified adoption, such programs may both encourage adoption and enhance its success. For example, the information and non-monetary supports offered by CSA programs may magnify CSA's benefits by helping participants adopt a diverse suite of practices in an ideal manner (e.g., selecting an optimal, complementary set of CSA practices, then implementing those practices properly). In contrast, non-participants may lack critical information or materials, making them unable to apply diverse sets of CSA practices effectively.

Even so, questions remain regarding why CSA programs improve the food security of diversified adopters, but not specialized ones. One possibility is that adopting a diverse suite of CSA practices is inherently more knowledge and resource-intensive than adopting a narrower set of practices, making CSA program support more influential for diversified adopters. However, clues provided by the baseline food security values point to other possibilities. Without CCAFS intervention, specialized adopters have (on average) a 52% chance of being food secure, while diversified adopters have a 43% chance of being food secure – a difference that is statistically

[30] This conclusion is implied, since if CCAFS programs simply prompted diversified adoption, but provided no further benefits, there would be no welfare difference between those who were prompted to adopt diverse practices through participation in the CCAFS program (i.e., beneficiary diversified adopters), and those who were prompted in other ways, such as through friends, neighbours, agricultural organizations, or ingenuity (i.e., non-beneficiary diversified adopters). Instead, we see that participation in the CCAFS program has boosted the welfare of beneficiary diversified adopters beyond that of the non-beneficiary diversified adopters.

significant ($p<0.01$).[31,32] Yet when diversified adopters participate in CCAFS programs, this gap narrows considerably, and we cannot reject the null hypothesis that there is no food security difference between specialized adopters and beneficiary diversified adopters ($p>0.10$). Therefore, it is possible that those who are relatively well-off (i.e., more food secure, specialized adopters) can access the information and infrastructure required for effective CSA adoption without the help of CSA programs. But for their less well-off, diversifying counterparts, CSA programs may be the key to unlocking these resources, applying effective CSA, and closing the welfare gap. A third possibility is discussed by Banerjee et al. (2015), who examined the impacts of a development program on multiple outcome measures including food security, income, assets, and access to financial services. As in my study, they found that their studied development program only increased the food security of households with relatively low food security (Banerjee et al., 2015). In contrast, they found that the program only improved access to financial services within households with relatively good financial service access (Banerjee et al., 2015). Therefore, it is possible that CCAFS programs simply benefit different household types in different ways. For example, while relatively food insecure, diversified adopter households may be more likely to benefit through increased food security, relatively well-off, specialized adopter households may be more likely to benefit through improved access to services such as banks, loans, and insurance.

Ultimately, the large differences in treatment effects amongst different adopter types reveal significant heterogeneity in the effects of CSA programs. However, further analysis is needed to identify additional causes of these differences. Such analysis of the heterogeneous effects of development programs has been conducted by authors such as Mullally et al. (2021), who apply the methods of Chernozhukov et al. (2018b).[33] Similar analysis has also been applied to CSA program participation, with Martey et al. (2021) finding that characteristics such as

[31] Statistical significance is determined using a two-tailed two-sample t-test.

[32] Because I did not eliminate the self-selection bias that occurred when households chose an adoption strategy, I cannot make causal links between adoption strategy and food security. Therefore, it is unclear why this gap in baseline food security exists.

[33] Chernozhukov et al. (2018b) use machine learning to identify whether a treatment has heterogeneous effects, and to examine differences in the characteristics of those most impacted and least impacted by a treatment.

gender, household size, farming experience, and membership in agricultural, savings, and loan organizations can impact the degree to which farmers benefit from CSA training.

Overall, the results from the diversified adopter sub-sample parallel existing literature that finds CSA adoption and agricultural extension to have separate (but significant) impacts on CSA outcomes (Imran et al., 2019), as well as literature that highlights the importance of CSA programs and extension access in improving both adoption and welfare (Martey et al., 2021; Wossen et al., 2017). This study adds to this literature by suggesting that CSA programs (which can be considered a form of extension) primarily improve the food security of those who have relatively low welfare and choose a diversified CSA adoption strategy.

6. Food Security in Future Climates

6.1 Empirical Strategy

6.1.1 The Model

While the results of Section 5 suggest that CSA programs may benefit participating households in the near-term, limited evidence exists regarding their long-term impacts. As climates continue to shift, such evidence is vital to ensure that farmers that invest in CSA programs and practices are not sacrificing long-term benefits for short-term gains. Therefore, the goal of the future climate model is to provide an exploratory analysis that estimates, predicts, and compares the food security (Y) of non-beneficiary and beneficiary households under future climate conditions.[34] Formally, the model to be estimated is:

$$Y_i = f(Z_i) + \tau_i \tag{5}$$

where Y_i represents food security for a household i, Z is a matrix of climate variables that may impact the productivity and food security of smallholder farms within my regions of study, and τ

[34] While I also explored a split-sample analysis that compared the food security of non-adopter, specialized adopter, and diversified adopter households, the results were not meaningful due to the small sub-sample sizes created by this sample split (non-adopter [n=386], specialized adopter [n=632], diversified adopter [n=1,099]). Unlike the DML approach, the straightforward use of machine learning methods (e.g., random forests, boosting) is not well-suited to small sample sizes and can lead to inconclusive results when there are too few observations.

is an error term with the property $E(\tau \mid Z) = 0$.[35] Current food security and historical (1970-2000) climate data is used to estimate Equation 5.

Once the function f(.) is estimated, food security predictions are made using the following equation:

$$\hat{Y}_{i,k} = \hat{f}(Z_{i,k}) \tag{6}$$

where $\hat{Y}_{i,k}$ is the predicted food security for a household i in period k (i.e., 1970-2000, 2021-2040, or 2041-2060), and $Z_{i,k}$ is the climate in household i's location during period k. Therefore, both current food security and future food security are predicted for each household (by inputting historical and future climate data, respectively).[36]

6.1.2 The Estimation Approach

While linear models can be used to estimate Equation 5, existing literature indicates that relationships between climate and crop yields can be non-linear (Frelat et al., 2016; Schlenker & Roberts, 2009; Wei et al., 2014). Because crop yields and food security are closely linked in the rural smallholder farming communities of developing countries (Brown & Funk, 2008; Funk & Brown, 2009), I infer that relationships between climate and food security may also be non-linear within my sample. Therefore, the goal of this analysis is to use flexible machine learning methods to estimate Equation 5. Ultimately, Equation 5 is estimated using classification tree, random forest, boosting, and lasso methods with a split-sample approach to predict and compare future food security outcomes for different household types.

6.1.3 The Model Specification

The model specification is based on the variables and summary statistics contained in Table 8. I control for a matrix of climatic variables *Z*, which was chosen based on the climatic factors most likely to influence productivity, and the climate challenges faced by my regions of study. *Z* includes: mean annual temperature (°C), maximum temperature of warmest month (°C), mean

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[35] To maintain the simplicity of the model and diminish the curse of dimensionality, I do not include socioeconomic characteristics within the matrix *Z*. The matrix *Z* is clearly exogenous, as climate is not impacted by food security.

[36] This process will produce reliable predictions if we assume that the relationship between climate and food security remains fixed over time.

temperature of driest quarter (°C), annual precipitation (mm), precipitation of driest month (mm), precipitation of driest quarter (mm), precipitation of wettest month (mm), precipitation of wettest quarter (mm), and precipitation seasonality (coefficient of variation). The model is run three times using each machine learning method: once on the entire sample (n=1,944), once on the sub-sample of non-beneficiary households (n=1,049), and once on the sub-sample of beneficiary households (n=895). Table 8 contains summary statistics for each sample.

Table 8: Summary statistics for the future climate model.$^{\alpha}$

Variable	All observations (n=1,944)	Non-beneficiaries (n=1,049)	Beneficiaries (n=895)
Outcome (Y)			
Food security	0.54 (0.50)	0.49 (0.50)	0.59 (0.49)
Climatic Variables (Z)			
Historical Period (1970 – 2000)			
Mean annual temperature (°C)	23.42 (3.26)	24.14 (2.74)	22.57 (3.60)
Maximum temperature of warmest month (°C)	32.46 (4.36)	33.07 (4.09)	31.74 (4.54)
Mean temperature of driest quarter (°C)	20.94 (3.90)	22.19 (3.88)	19.47 (3.37)
Annual precipitation (mm)	1,543.24 (522.27)	1,449.90 (528.49)	1,652.64 (493.16)
Precipitation of driest month (mm)	17.20 (20.61)	16.47 (18.85)	18.05 (22.47)
Precipitation of driest quarter (mm)	74.15 (74.98)	70.31 (68.74)	78.65 (81.50)
Precipitation of wettest month (mm)	326.84 (132.79)	302.29 (123.63)	355.61 (137.37)
Precipitation of wettest quarter (mm)	842.39 (330.17)	781.73 (318.40)	913.48 (329.71)
Precipitation seasonality	89.67 (33.51)	89.84 (34.93)	89.47 (31.77)
Future Period (2021 – 2040)			
Mean annual temperature (°C)	26.72 (3.20)	27.46 (2.70)	25.85 (3.51)
Maximum temperature of warmest month (°C)	37.80 (4.35)	38.44 (4.12)	37.06 (4.49)

Variable	All observations (n=1,944)	Non-beneficiaries (n=1,049)	Beneficiaries (n=895)
Mean temperature of driest quarter (°C)	23.69 (4.29)	25.05 (4.38)	22.10 (3.59)
Annual precipitation (mm)	1,637.30 (549.15)	1,533.09 (549.56)	1,759.45 (523.15)
Precipitation of driest month (mm)	17.84 (21.57)	17.22 (20.01)	18.57 (23.26)
Precipitation of driest quarter (mm)	76.78 (79.56)	73.54 (74.24)	80.59 (85.26)
Precipitation of wettest month (mm)	358.80 (155.58)	330.89 (144.19)	391.50 (162.03)
Precipitation of wettest quarter (mm)	905.58 (374.48)	838.26 (354.36)	984.47 (382.15)
Precipitation seasonality	90.77 (34.66)	91.01 (36.11)	90.49 (32.91)
Future Period (2041 – 2060)			
Mean annual temperature (°C)	27.76 (3.23)	28.49 (2.71)	26.90 (3.55)
Maximum temperature of warmest month (°C)	38.84 (4.43)	39.46 (4.17)	38.12 (4.61)
Mean temperature of driest quarter (°C)	24.78 (4.22)	26.12 (4.30)	23.21 (3.53)
Annual precipitation (mm)	1,679.00 (594.70)	1,560.67 (594.03)	1,817.69 (565.06)
Precipitation of driest month (mm)	18.64 (22.54)	18.05 (21.15)	19.33 (24.06)
Precipitation of driest quarter (mm)	79.77 (82.60)	76.71 (78.16)	83.36 (87.43)
Precipitation of wettest month (mm)	368.61 (170.56)	337.51 (157.46)	405.06 (178.03)
Precipitation of wettest quarter (mm	931.83 (418.97)	854.60 (395.54)	1,022.35 (427.67)
Precipitation seasonality	90.71 (34.69)	90.88 (35.94)	90.50 (33.19)

$^{\alpha}$ Mean values are reported without parentheses. Standard deviations are reported in parentheses.

In Table 8, we see that by 2021-2040, the mean annual temperature is predicted to rise by more than 3 ºC across all samples. This warming trend is especially noticeable in the maximum temperature of the warmest month, which rises by over 5 ºC across all samples. Precipitation, as well as precipitation seasonality, is also expected to increase across all samples. By 2041-2060, the mean annual temperature is predicted to rise by another 1 ºC across all samples, and all precipitation variables (excluding seasonality) are also expected to increase. Differences between non-beneficiaries and beneficiaries increase over time in terms of annual precipitation and precipitation in the wettest month and quarter.

6.2 Results and Discussion

After estimating Equation 5 and producing models for each sample using each machine learning method, I compare the fit of the models by running 3x 10-fold cross-validation and computing the average accuracy, precision, recall, and F1 score for each one.[37] Cross-validation results are displayed in Table 9.

[37] Accuracy, precision, recall, and F1 score are standard metrics used to compare fit amongst machine learning models. For more information, see Appendix D.

Table 9: Comparison of model fit.

Metric	Sample	(1) Lasso	(2) Trees	(3) Random forest	(4) Boosting
Accuracy	All observations (n=1,944)	0.701	0.780	0.791	0.787
	Non-beneficiary households (n=1,049)	0.592	0.745	0.755	0.758
	Beneficiary households (n=895)	0.673	0.827	0.827	0.829
Precision	All observations (n=1,944)	0.667	0.762	0.780	0.768
	Non-beneficiary households (n=1,049)	0.603	0.725	0.741	0.741
	Beneficiary households (n=895)	0.599	0.833	0.817	0.834
Recall	All observations (n=1,944)	0.714	0.765	0.765	0.774
	Non-beneficiary households (n=1,049)	0.582	0.824	0.802	0.812
	Beneficiary households (n=895)	0.573	0.729	0.739	0.727
F1 Score	All observations (n=1,944)	0.688	0.760	0.772	0.769
	Non-beneficiary households (n=1,049)	0.589	0.765	0.768	0.772
	Beneficiary households (n=895)	0.582	0.771	0.773	0.774

When comparing the fit of each machine learning method (Table 9), we see that the trees, random forest, and boosting models perform similarly in terms of all metrics (i.e., accuracy, precision, recall, and F1 score). Across all three methods, and all four metrics, values range between 0.725 and 0.834. On the other hand, the values for the metrics of the lasso model range between 0.582 and 0.714, indicating that the lasso model does not fit the data well. Therefore, the discussion of results focuses on the trees, random forest, and boosting models.

The models are then applied to Equation 6 to predict the food security of each observation within three periods: historical (1970-2000), 2021-2040, and 2041-2060. When averaged over all observations in a sample, the food security value (i.e., mean food security) represents the probability that an individual household within the sample is food secure. The predicted mean food securities for each sample, within each period, are displayed in Figures 2 and 3.[38]

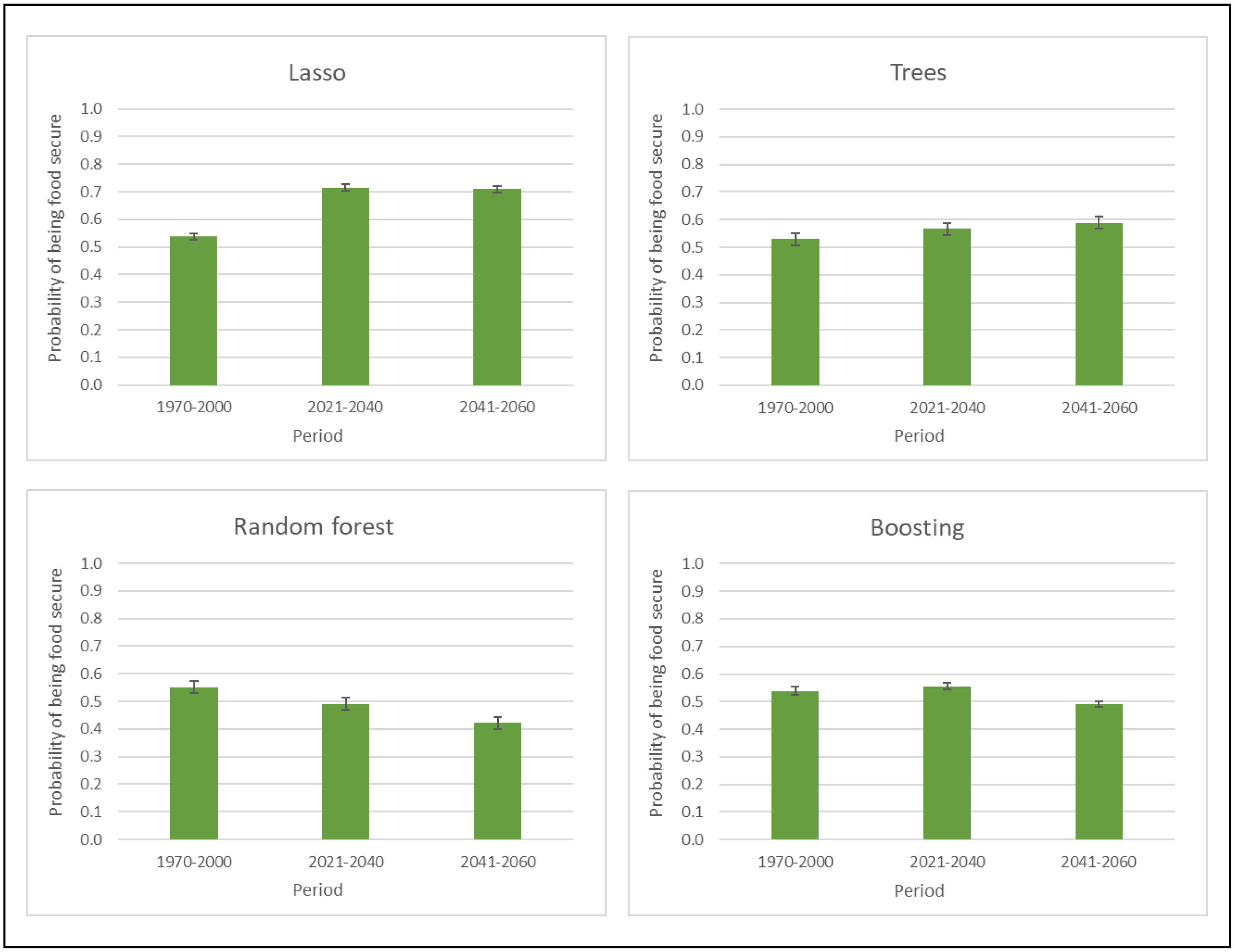

Figure 2: Bar charts of food security predictions for entire sample. Error bars represent 95% confidence intervals.[39]

[38] A table displaying the predicted mean food securities can be found in Appendix E (Table 11).

[39] 95% confidence intervals are calculated by calculating the standard error of all predictions within the sample or sub-sample, multiplying it by the critical t-value, then adding and subtracting the resulting number from the mean predicted value.

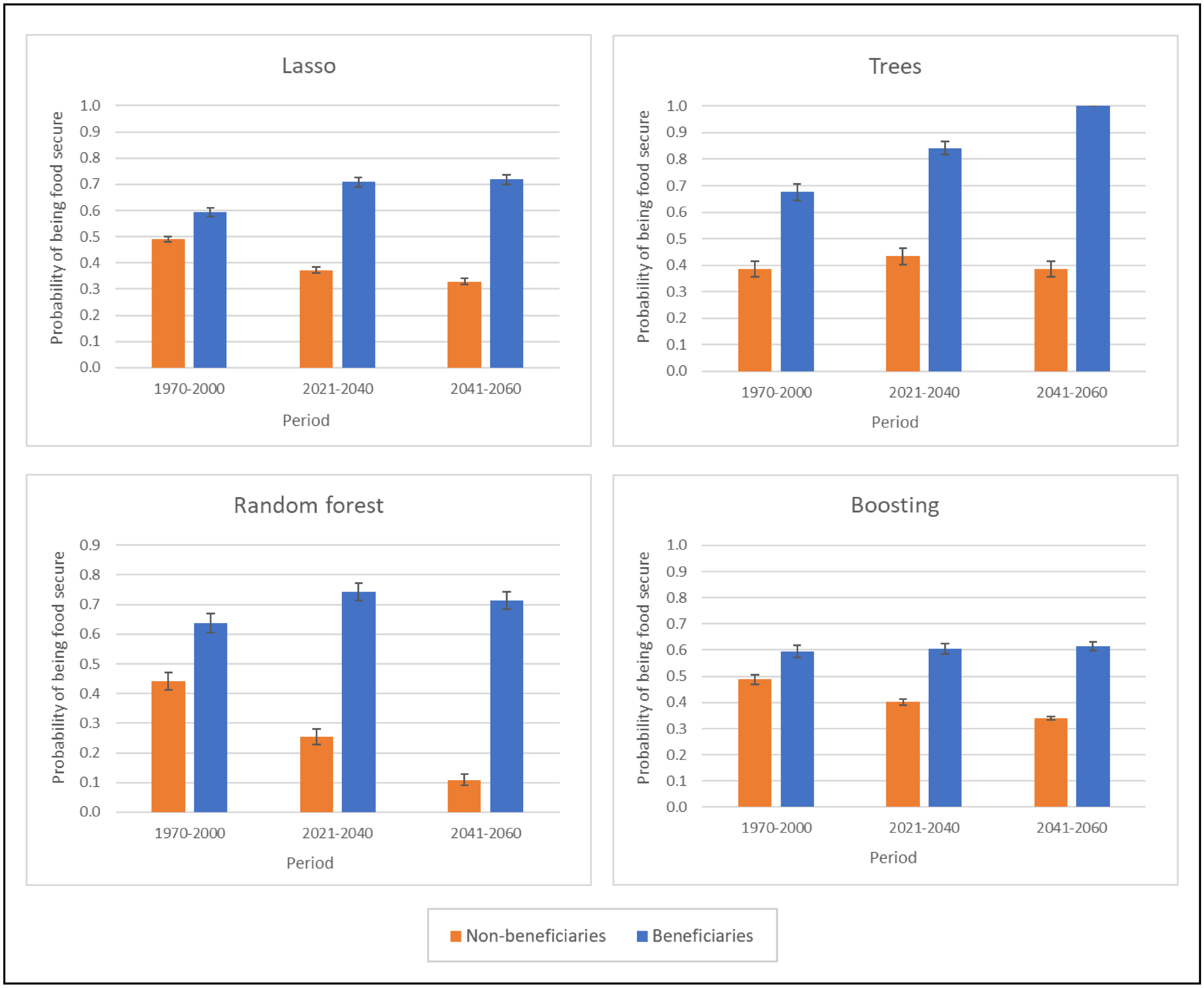

Figure 3: Bar charts of food security predictions for non-beneficiary and beneficiary sub-samples. Error bars represent 95% confidence intervals.

Figure 2 displays that predictions for the entire sample are somewhat inconsistent across machine learning methods. While the trees model predicts that food security will remain constant over time, the random forest model predicts a steady decline. Finally, the boosting model predicts that food security will remain constant in the first two periods, but decline in the last period.

Splitting this sample into non-beneficiary and beneficiary households reveals distinct differences in food security between the two groups. All machine learning methods predict that in every period, beneficiaries are more likely to be food secure than non-beneficiaries.[40] However, the magnitudes of these differences, as well as the overall trajectory of each sub-sample (i.e., increasing or decreasing food security) differ between machine learning methods. While the trees and random forest methods predict large differences in the probabilities of non-beneficiaries and beneficiaries being food secure, the boosting method predicts a more moderate difference.

Overall, the food security of non-beneficiaries is predicted to either decline or remain steady over time. Although the impacts of climate change on crop growth will vary across the globe and across crop types (Olajire et al., 2020; Su et al., 2021), existing research suggests that in general, future crop yields will decline without intervention (Xin & Tao, 2020). Such literature supports the predictions of the random forest and boosting methods.

Beneficiary households display the opposite trajectory, with all models predicting that the food security of this sub-sample will increase, or be maintained, over time. These findings are consistent with predictions that the yield benefits of CSA will counteract, or even outweigh, the negative impacts of climate change (Brouziyne et al., 2018; de Pinto et al., 2020; Zizinga et al., 2022).

Ultimately, all models predict divergence in the food security of non-beneficiaries and beneficiaries, causing the existing food security gap to grow over time. This trend corroborates existing evidence that CSA practices may result in greater yield benefits in future periods than in current ones (Su et al., 2021; Zizinga et al., 2022).

7. Conclusions

Developing countries are disproportionately vulnerable to climate fluctuations – a feature that is particularly noticeable in smallholder farming communities, where climate-caused yield reductions can threaten food security. In response, CSA has emerged as a way of breaking the

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[40] As discussed in Section 3, the CCAFS program relied on non-random methods when selecting beneficiary households and survey respondents. Therefore, predicted food security differences between non-beneficiary and beneficiary households cannot be attributed to the CCAFS program. Instead, I simply predict and compare future changes in the food security of the two groups.

destructive links between climate change and agriculture. As interest in CSA has expanded, organizations and governments have made substantial investments in CSA programs. Recognizing the need to evaluate how, and whether, such programs are effective, researchers worldwide have sought to identify the causal impacts of CSA programs on farmer welfare. While such studies are vital for informing future programs, many questions remain unanswered.

This paper contributes to CSA literature while highlighting the importance of investing in, and expanding, future CSA programs. In general, it adds to the growing body of literature that suggests that CSA can increase the food security of smallholder farmers in developing countries. But while most existing literature examines the impacts of CSA adoption, this study contributes to a smaller collection of evidence that CSA programs have a critical role in welfare outcomes.

My impact evaluation on food security uses the DML approach to address bias stemming from program participant selection while modelling flexible, non-linear relationships. This method facilitates the identification of causal links between CCAFS program participation and food security. Overall, results indicate that participation in a CCAFS program results in a significant increase in food security – a finding that corroborates and adds to the results of previous research. More uniquely, a split sample analysis is used to explore the relationships between CSA programs, adoption, and welfare outcomes. The insignificant findings from the non-adopter sub-sample support the idea that CSA programs primarily improve welfare outcomes via CSA adoption and offer few benefits to those who do not adopt CSA. This insignificant result is mirrored in the specialized adopter sub-sample results, possibly because specialized adopters benefit in areas other than food security (which are not investigated in this research). However, the analysis provides new evidence that CSA program participation is crucial for improving food security through a diversified adoption strategy. Such a result invites further research to identify which specific aspects of CSA programs generate their food security benefits (e.g., CSA training, access to CSA researchers, provision of seeds and tolerant crop varieties, weather forecasts). Moreover, the analysis reveals that while diversified adopters have the lowest baseline food security of any adopter type, CSA programs allow them to close the welfare gap and achieve the same level of food security as their specialized adopter counterparts. Ultimately, these results suggest that CSA programs not only encourage adoption (as discovered by previous literature), but also enhance the quality of adoption for those who have relatively low food security and/or who choose a diversified adoption strategy. Therefore, future CSA programs may be able to maximize food security impacts by targeting supports towards diversified adopters. With such distinct results amongst the various adopter types revealing heterogeneity in the effects of CSA programs, future research should aim to understand the characteristics that separate specialized adopters from diversified adopters, and to explore the mechanisms behind the baseline food security gap between specialized and diversified adopters. When considered alongside results from previous research, the impact evaluation supports findings that CSA helps farmers adapt to climate change, helps back the substantial investments that have been made in CSA programs, and lends justification for continued investment. Furthermore, the global nature of this analysis demonstrates that CSA can provide benefits across diverse climates and cultures, supporting the expansion of CSA programs to new areas.

While the above results are a promising indicator of CSA's potential to improve farmer welfare in the short-term, it is likely that CSA's impacts will change along with changing future climates. Such changes may create temporal trade-offs that must be considered before participating in CSA programs and implementing CSA. This paper's future climate section provides an exploratory analysis that builds upon the impact evaluation by investigating potential trends in the welfare of non-beneficiary and beneficiary households over time. Results suggest that the food security of non-beneficiary households will either decline or remain constant, while the food security of beneficiary households will either increase or remain constant. When combined, these trends create a growing gap in food security between the two groups of households. When considered alongside evidence of CSA programs' current benefits, these findings suggest that CSA programs may continue to improve the welfare of their participants over the coming decades. However, notable limitations of the future climate analysis include: its reliance on, and application of, food security data collected during a four-year period (2017-2020) to climate data that spans nine decades (1970-2060); and its use of historical climate data (1970-2000) to represent climate conditions at the time of food security data collection. Despite these limitations, the analysis serves as a preliminary indicator of CSA's long-term relevance to climate change adaptation while paving the way for more robust future analyses.

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Appendix A – CSA programs around the world

Since its emergence, CSA has been implemented in a wide variety of countries and through various organizations. While CSA in sub-Saharan Africa has been most extensively discussed in the literature, CSA projects have also been conducted in Asia, Latin America, and Europe. For example, CGIAR has conducted projects in India (Aryal et al., 2018), Bangladesh, Laos, Cambodia, Vietnam, the Phillippines, Guatemala, Honduras, Nicaragua, and Colombia (Bonilla Findji et al., 2019). In Central America, the Mesoamerican Environmental Program (MAP) has also encouraged CSA adoption through Farmer Field Schools (FSS) from 2009 to 2017 (de Sousa et al., 2018). Finally, the European Union has also encouraged member states to promote CSA, resulting in CSA uptake in countries such as Italy (Pagliacci et al., 2020).

To date, some of the largest CSA initiatives have been conducted by the World Bank and CGIAR. For example, the World Bank-funded West Africa Agricultural Productivity Program (WAAPP) promoted CSA in 13 west African countries (Abegunde et al., 2019). The World Bank also joined the Swedish government in co-funding the Kenya Agricultural Carbon Project (KACP), which promotes CSA practices to local farmers' groups and purchases the carbon credits they generate (Cavanagh et al., 2017). Similarly, CGIAR has promoted CSA practices in countries including Burkina Faso, Ghana, Mali, Niger, Senegal, Ethiopia, Kenya, Tanzania, and Uganda (García de Jalón et al., 2017), as well as throughout Latin America and Asia (Bonilla Findji et al., 2019).

Other non-governmental organizations promoting CSA include the International Maize and Wheat Improvement Center (CIMMYT), which, in collaboration with other organizations, conducts CA projects in countries such as Malawi (Abegunde et al., 2019), Zimbabwe (Mujeyi et al., 2020), Mozambique, and Zambia (Mutenje et al., 2019). The International Fund for Agricultural Development (IFAD), a United Nations agency, has also funded CSA projects in southern Africa (e.g. Zimbabwe and Malawi) (Makate et al., 2019). Malawi has also been the focus of CSA programs run by the World Agroforestry Centre (ICRAF) (Jew et al., 2020), as well as the US Agency for International Development (USAID)-funded Wellness and Agriculture for Life Advancement (WALA) project, which was administered from 2009 to 2014 through seven non-governmental organizations (Amadu et al., 2020a; Amadu et al., 2020c). While this project did not focus solely on CSA, one of WALA's key components was reducing risk through watershed development and CSA (Amadu et al., 2020a). Similar projects, which include CSA practices as part of a broader landscape-level strategy, have also been conducted in other African and Asian countries (Amadu et al., 2020a). Finally, the Federal University of Agriculture, Abeokuta (FUNAAB) collaborated with the Regional Agency for Agriculture and Food (RAAF) on a CSA promotion project in Nigeria (Oyawole et al., 2019).

Government programs, such as Bangladesh's Comprehensive Disaster Management Programme (CMDP), have also played a role in promoting CSA (Hasan et al., 2018). In Ghana, the Ministry of Agriculture (MoFA) has collaborated with non-governmental organizations such as Deutsche Gesellschaft für Internationale Zusammenarbeit (GIZ) to teach farmers CSA practices through the Integrated Climate Risk Management (ICRM) project, which was active from 2015 to 2019 (Zakaria et al., 2020b). In Bangladesh, the government has collaborated with donor organizations (including the United Nations and the European Union) to run the Comprehensive Disaster Management Programme (CDMP), which teaches CSA practices to farmers via climate field schools (Hasan et al., 2018). In Zambia, the government has provided subsidies for inputs such as fertilizer since 1997, and the Ministry of Agriculture and Livestock (MAL) has collaborated with various agencies to promote CA (Arslan et al., 2015). Lastly, government agencies have also promoted and run CSA pilot programs in Vietnam (Ho & Shimada, 2019).

Though CSA has been carried out under the funding and guidance of governments and non-governmental organizations, literature also indicates that some farmers have been independently developing, adopting, and expanding new practices to combat changing weather patterns (e.g., Maung Swe et al., 2015; Nindi & Mhando, 2012).

Appendix B – Description of CCAFS program

Most generally, CCAFS beneficiary households (BHs) are households that took part in a CCAFS activity related to the implementation and/or evaluation of CSA practices and technologies. BHs had access to training provided by the CCAFS regional team and/or CCAFS partners. In general, BHs were selected according to local processes and willingness to participate in the CCAFS program. The following text contains specific examples of how BHs were selected, as well as the training and support offered to BHs in Vietnam, Cambodia, and Myanmar. Information for this text was kindly provided by Eisen Bernard Bernardo of the International Rice Research Institute on December 7, 2021.

Vietnam

In Vietnam, households that volunteered for the CCAFS program or that championed the implementation of CSA practices were often selected to be BHs. Additionally, CCAFS aimed for an even gender balance amongst BHs (i.e., the group of BHs contained 50% men, 50% women), as well as an age balance amongst young, middle-aged, and senior farmers.

Several parties provided CSA training to Vietnamese BHs. These parties included CIAT researchers, NOMFASI, and local extensionists/CCAFS researchers. In addition, champion farmers who mastered the CSA practices and activities often began training other local farmers.

The Vietnam field team had a field researcher who lived and worked in the CSV full-time between 2015 and 2018. This field researcher worked with farmers on a daily basis. Because of the strong partnerships developed between the research team and the farmers in the CSV, the local authorities, and local leaders, CCAFS support has continued from 2018 until today.

The CSA program taught BHs how to implement CSA practices, but also provided support to facilitate CSA implementation. For example, BHs were offered microorganisms (e.g., organisms used for rice straw processing, vermicomposting, and biological bedding), tolerant crop varieties (including rice and cassava), forage grass seeds, and cut-and-carry livestock production (e.g., goat, cows, buffalo), among other supports. The CSA program also offered micro financing starting with $700 USD, which enabled poor farmers to purchase a mother cow. The calves produced would then be given to other poor families, and male calves would be sold to finance the purchase of more mother cows.

In addition, the CSA program taught farmers how to run a CSV; for example, it aided the operation of a village community library and provided books, supported daily weather forecasts projected through the village loudspeaker system, and coordinated information with other CSVs.

Lastly, the CSA program ran photovoice activities, which trained farmers to capture the impacts of climate change through photography and present these photos to local and provincial leaders to spur immediate and more appropriate support.

Cambodia and Myanmar

In Cambodia and Myanmar, the CCAFS CSA program was primarily run by the Institute of Rural Reconstruction (IIRR). BHs were selected through a participatory and consultative process. While the IIRR allowed households to express interest in participating in the program, the IIRR prioritized creating a group of BHs that represented a diverse set of farming systems. Therefore, the households that expressed interest and contributed to a diverse set of farming systems within the program became BHs. On occasion, female-headed households were also targeted for selection into the program. In recent years, the IIRR has aimed to avoid elite capture by ensuring that at least 25 households within each section of the village are targeted.

Several parties provided CSA training to CSVs in Cambodia and Myanmar. While the IIRR and the local government initially provided training, experienced farmers later trained other farmers.

The IIRR ran learning groups that met regularly and as needed. The meetings and CSA program training was led by learning group members and was a community-driven process. IIRR staff were stationed in CSVs, and BHs had the opportunity to visit the IIRR or local government staff when they visited the market.

CSA training consisted of one day training sessions, orientations, farmer to farmer events, and cross visits. However, the IIRR did not just train farmers; for example, the organization distributed nearly 10,000 coffee trees (50 trees per household) in designated coffee impact areas. In another village, the IIRR targeted 36 women and their households for fruit tree culture. In the Mynmar, Cambodia, and Philippines CSVs, the IIRR typically targeted 25 households in each village and provided each one an economically significant numbers of trees (or small livestock). However, these supports were limited by local financing mechanisms. In Cambodia, the IIRR set up village saving and funding groups to support CSA adoption.

Appendix C – Comparison of impacts on food security across interventions

Table 10: Estimated impacts of various interventions on food security.

Intervention	Food security impact	Study
CCAFS CSA program	6.0 percentage point increase (13% increase) in the probability of being food secure.	This paper
BRAC program (Provided a productive asset, training, and support to poor households.)	0.11 standard deviation increase (as measured by a food security index). 7.5% increase in food consumption.	Banerjee et al. (2015)
Malawi Social Action Fund public works program (Provided short-term employment to poor households.)	Insignificant impact on food security.	Beegle et al. (2017)
PROACT project (Provided cash crop program [training and agricultural inputs] and nutrition education to farmers.)	Cash crop program and nutrition education (combined) increased household dietary diversity score (HDDS), women's dietary diversity score (WDDS), and children's dietary diversity score (CDDS) by 0.2 food groups, 0.35 food groups (or 6.1%), and 0.24 food groups (or 6.43%), respectively.	Bonuedi et al. (2022)
Household economic strengthening (HES) intervention (Provided food packages and loans to start businesses.)	45% increase in the probability of being food secure.	Exavery et al. (2022)
Cash transfers or food baskets (Transfers and baskets were of equivalent value and provided during the most food insecure period.)	Relative to cash transfers, food baskets resulted in a 9.4 to 11.8 percentage point increase in the probability of having an acceptable food consumption score (FCS).	Hoddinott et al. (2018)
Microcredit program	3% increase in household calorie availability. 4% decrease in food poverty. Insignificant impact on dietary diversity.	Islam et al. (2016b)

Appendix D – Comparing the fit of machine learning models

Accuracy, precision, recall, and F1 scores are all standard metrics used to quantify how well a categorical machine learning model fits data, and how well it predicts the outcome variable when using new data. These metrics are all based on the confusion matrices produced during cross-validation.[41]

During each repetition (i.e., fold) of cross-validation, the training data is used to build a model, the testing data is used to test the model, and a confusion matrix is produced. The confusion matrix displays the number of correctly and incorrectly classified observations within the testing data. The following figure outlines the design of a confusion matrix:

		Actual food security	
		0	**1**
Predicted food security	**0**	True negatives (TN)	False negatives (FN) Type II error
	1	False positives (FP) Type I error	True positives (TP)

Figure 4: Design of a confusion matrix.

The accuracy of the confusion matrix is calculated as:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

Therefore, accuracy is the proportion of testing data observations that are correctly classified by the model. While accuracy is an intuitive way to quantify the efficacy of a model, it should only be used when there is a balanced proportion of observations that have actual outcome variable values of 0 and 1. If there is an unbalanced proportion of 0s and 1s, a model that is simply predicting that all observations have the same outcome variable value may have a deceivingly

[41] In an n-fold cross-validation procedure, the data is randomly and evenly split into n sub-samples. The first nine sub-samples are used as training data (i.e., to create/train the model), while the last sub-sample is used as testing data (i.e., to test how well the model makes predictions). This process is repeated n times, until each sub-sample has been used to test the data.

high accuracy. For example, if 90% of observations in the sample are food insecure, a model that predicts that all observations will be food insecure will be 90% accurate, even though the model fails to capture the complexity of the data and will be unable to make meaningful predictions about food security.

The precision of the confusion matrix is calculated as:

$$Precision = \frac{TP}{(TP + FP)}$$

Therefore, precision is the proportion of all positive predictions that are true positives. The model with the highest precision will be the model that minimizes false positives.

The recall of the confusion matrix is calculated as:

$$Recall = \frac{TP}{(TP + FN)}$$

Therefore, recall is the proportion of all observations that have an actual outcome variable value of '1' that are correctly classified. The model with the highest recall will be the model that minimizes false negatives.

The F1 score of the confusion matrix is calculated as:

$$F1\ Score = \frac{2(Precision\ *\ Recall)}{Precision + Recall}$$

The F1 score is the harmonic mean of precision and recall. It is used to represent how well the model fits the data when there is unbalanced proportion of actual outcome variable values (i.e., an uneven proportion of 0s and 1s).

Because one confusion matrix is produced for each fold of cross-validation, we produce one accuracy, precision, recall, and F1 score value per fold. These values can then be averaged across all folds. For example, when running a 3x 10-fold cross-validation, the overall accuracy can be produced by averaging the 30 accuracy values produced.

Appendix E – Future climate analysis results table

Table 11: Food security predictions from the future climate model.

Sample	Period	(1) Lasso	(2) Trees	(3) Random forest	(4) Boosting
All observations (n=1,944)	1970-2000	0.538 (0.006)	0.529 (0.011)	0.551 (0.011)	0.539 (0.008)
	2021-2040	0.714 (0.006)	0.566 (0.011)	0.491 (0.011)	0.556 (0.005)
	2041-2060	0.709 (0.006)	0.588 (0.011)	0.421 (0.011)	0.492 (0.005)
Non-beneficiary households (n=1,049)	1970-2000	0.490 (0.006)	0.385 (0.015)	0.441 (0.015)	0.487 (0.010)
	2021-2040	0.372 (0.006)	0.434 (0.015)	0.254 (0.013)	0.401 (0.006)
	2041-2060	0.329 (0.006)	0.385 (0.015)	0.109 (0.010)	0.340 (0.004)
Beneficiary households (n=895)	1970-2000	0.593 (0.009)	0.676 (0.016)	0.637 (0.016)	0.595 (0.012)
	2021-2040	0.709 (0.009)	0.841 (0.012)	0.743 (0.015)	0.606 (0.010)
	2041-2060	0.718 (0.009)	1.000 (0.000)	0.713 (0.015)	0.614 (0.009)

Mean predicted values are reported without parentheses.
Standard errors are reported in parenthesis.