LORTA

Impact evaluation midline report for FP073

The Green Gicumbi Project

July 2024

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ABOUT LORTA

In 2018, the Independent Evaluation Unit initiated the Learning-Oriented Real-Time Impact Assessment (LORTA) Programme, within which it collaborates with the impact evaluation specialists and academics, project teams funded by the Green Climate Fund (GCF) and local evaluation teams. The LORTA programme incorporates state-of-the-art approaches for impact evaluations to measure results and raise awareness about the effectiveness and efficiency of GCF projects. In Rwanda, LORTA proudly partners with the Ministry of Environment of Rwanda (formerly the Ministry of Natural Resources).

The LORTA programme has a twofold aim: (i) to embed real-time impact evaluations into funded projects for generating evidence about what works and what not in climate adaptation and mitigation; and (ii) to build capacity within projects to design high-quality data sets for overall impact measurement. The purpose of the impact evaluations is to measure the change in key results areas of the GCF that can be attributed to project activities. The LORTA programme is informing about the impacts of GCF projects and helps GCF projects track implementation fidelity.

FOREWORD

This is a midline impact evaluation report of the project FP073 *Strengthening climate resilience of rural communities in Northern Rwanda*, commonly known as Green Gicumbi Project. The overall objective of the project is to increase the resilience of vulnerable communities to climate change in Gicumbi District in Northern Rwanda. The project aims to restore and enhance ecosystem services in one of the sub-catchments of the degraded Muvumba watershed, increase the capacity of communities to renew and sustainably manage resources, and support smallholders to adopt climate-resilient agriculture.

Knowledge and capacity developed during implementation will be mainstreamed at the local and national levels.

There are two expected outcomes from the project, linked to both mitigation and adaptation:

1) Improved management of land or forest areas contributing to emissions reduction.
2) Strengthened adaptive capacity and reduced exposure to climate risks.

The report was written by the LORTA team in the GCF-IEU with technical support from consultants of the Center for Evaluation and Development (C4ED). Data-collection was conducted by the Social Economic Studies, Surveys, Monitoring, and Evaluation Consult Limited (SESMEC Ltd), Kigali, Rwanda.

The focus of the midline evaluation is on the project's outcomes from its inception in May 2019 up to data-collection in March 2023. This report provides insights into the estimated impacts across beneficiary households that were part of the evaluation's treatment versus the control group comparison.

Overall, the findings presented in the midline impact evaluation report will contribute to the ongoing success and effectiveness of the Green Gicumbi Project. The report will support the Ministry of Environment in making informed decisions, fine-tuning project strategies, and achieving its goals of fostering climate resilience, sustainable resource management, and improved livelihoods within Gicumbi District.

Mr. Patrick Karera

Permanent Secretary

Ministry of Environment, Government of Rwanda

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ABBREVIATIONS

ATT	Average treatment on the treated
ANCOVA	Analyses of covariance
CAF	Community Adaptation Fund
CRA	Climate-resilient agriculture
CRI	Climate resilience index
CSI	Coping strategies index
DiD	difference-in-differences
EQ	Evaluation question
FAO	Food and Agriculture Organization of the United Nations
FE	Panel Fixed-Effects model
FFS	Farmer Field School
FONERWA	Rwanda Green Fund
GCF	Green Climate Fund
GHG	Greenhouse gas
HDDS	Household dietary diversity score
ICC	Intra-cluster correlation
IE	Impact evaluation
IEU	Independent Evaluation Unit of the Green Climate Fund
IPCC	Intergovernmental Panel on Climate Change
LORTA	Learning-Oriented Real-Time Impact Assessment Programme
MDES	Minimum Detectable Effect Size
MOE	Rwanda Ministry of Environment
OLS	Ordinary Least Square model
PSM	Propensity score matching
SESMEC	Social Economic Studies, Surveys, Monitoring, and Evaluation Consult
TLU	Tropical livestock unit
ToC	Theory of change
WCS	Weather and climate services

EXECUTIVE SUMMARY

Climate change is a pressing global challenge marked by rising temperatures, with projections indicating a potential 2-degree Celsius increase by 2050. Its consequences, including decreases in agricultural productivity, are likely to impact sub-Saharan African countries like Rwanda due to greater variance in temperatures and rainfall, leading to a greater frequency and severity of hazards like floods and droughts. Rwanda's topography, reliance on rain-fed agriculture, and limited access to climate information will likely reduce crop yield.

Vulnerability varies across the regions of the country. Gicumbi District ranks as the district in Rwanda with the greatest exposure to climate hazards. Gicumbi's households are relatively poor, with few completing secondary education. Many are overwhelmingly reliant on subsistence farming. The Rwandan government has committed to climate action through policies like Vision 2050 and the Green Growth and Climate Resilient Strategy. The "Strengthening climate resilience of rural communities in Northern Rwanda" project (FP073), funded by the Green Climate Fund and referred to as the Green Gicumbi Project, mainly aims at increasing the climate change resilience of targeted vulnerable communities. This midline report assesses its impact three years into the project's implementation.

The Green Gicumbi Project is implemented in nine sectors: an administrative unit below the district level and above the village level. The nine sectors fall within a sub-catchment zone of the Muvumba River, comprising around 252 villages. The zone is particularly prone to water run-off and associated land degradation processes. The high dependency on agriculture makes households highly vulnerable to the loss of fertility caused by land degradation. The Green Gicumbi Project aims to address these challenges through a cascading series of measures. The project's multiple activities are grouped into four main components: (i) watershed protection and climate-resilient agriculture; (ii) sustainable forest management and sustainable energy use; (iii) climate-resilient settlements; (iv) knowledge transfer and mainstreaming.

This report assesses the impact of the first two components of the project by comparing key outcome indicators across households in villages that have received project interventions with comparable households in villages in nine non-intervention sectors in Gicumbi. At the output level, the report assesses changes in adopting climate-resilient agricultural practices, the main source of fuel used for cooking, and the quantity of firewood and charcoal used for cooking. At the outcome level, the report assesses indicators of food security, such as household dietary diversity scores, household coping strategy indices, and whether households experienced food shortages in the past year. In addition, the report assesses indicators of agricultural production, the number of income sources, and a climate resilience index. Indicators are also presented separately for female- and male-headed (married) households.

Baseline data was collected in June–July 2020, while midline data was collected approximately three years later, in April 2023. Endline data-collection is scheduled to take place in 2025. Data was collected from 1,299 households across treatment and control groups in 18 sectors at baseline. At midline, data was obtained from 1,258 households across treatment and control groups in the same sectors. The report uses a repeated cross section design with a random sample of households from the same villages and sectors interviewed at baseline and midline.

The identification strategy applies two quasi-experimental methods. The report employs the difference-in-differences methodology using the repeated cross section data set where possible. This provides a causal estimate of the project's impact by assessing changes in the trends of indicators through time. Difference-in-differences estimates are provided for all indicators apart from two sets of outcomes. The report uses propensity score matching for two outcomes which cannot be assessed using the difference-in-differences methodology. Propensity score matching creates a comparison group by matching treated households to one or several control households on their estimated probability of receiving the intervention based on a range of observable characteristics. Matching estimates are provided for the coping strategy index scores and measures of agricultural production.

Turning to results, we find that **the treatment group has higher adoption rates of climate-resilient agricultural practices**. The proportion of treatment households adopting climate-resilient agricultural practices is 20 to 24 percentage points higher than comparison households, and adopt around 0.5 more climate-resilient agricultural practices per household. These aggregate results are driven by a greater proportion of treatment households adopting:

- methods to protect housing infrastructure against lightning (11.3 percentage points)
- rainwater harvesting (14.2 percentage points)
- household wastewater treatment (18.3 percentage points)
- alternative cooking fuels (3 percentage points)
- development of irrigation schemes (6.5 percentage points)
- radical terracing (14.5 percentage points)

Surprisingly, more control households have adopted climate-resilient crop varieties (0.6 percentage points) than treatment households.

Results are mixed when it comes to measures of agricultural production. At midline, the intervention enhanced the agricultural production of specific staple crops like beans and sweet potatoes. We found a significant increase in crop production for beans (between 92.4 kg and 92.9 kg) and sweet potatoes (between 1,226 kg and 1,242 kg). Significant improvements were not observed for other commonly grown crops such as potatoes, maize and sorghum. We found a decrease in production by the 67 treatment households that reported growing bananas of between 6,210 kg and 6,062 kg. This translates into a significantly lower value of production of between 858,543 and 898,990 Rwandan francs (equivalent to USD 769.48 to USD 803.95).

Turning to yields, the only crop that shows a statistically higher yield is beans, with treatment households now yielding an additional 1.72 to 1.78 tonnes of beans per ha compared to control areas. This is economically significant, considering control areas yield 1.34 tonnes per ha at midline. The share of bean production not for consumption in treatment households, which signifies the amount available for sale as a proportion of total production, decreased by 7.6 and 9.3 percentage points for beans across treatment households. This finding is surprising, given the increase in both bean production and yield. Our interpretation is that greater bean production is preferred for household consumption, given the nutritional attributes of households in Gicumbi.

Green Gicumbi Project activities increase short-term food security and reduce vulnerability to food shortages. A significantly smaller proportion of treatment households (17.6 percentage points) reported suffering from food shortages in the past year compared to control households. Furthermore, treatment households report lower coping strategy index scores (between 3.3 and 3.6 points lower), indicating that they resort less to harmful strategies in response to food shortages than control households. However, long-run dietary habits do not appear to be affected yet, as there is no significant difference between treatment and control households concerning household dietary diversity scores.

In terms of measures of smallholder farmers' resilience, at midline we observe no changes in tropical livestock units, or the climate resilience index (using a Food and Agricultural Organization tool). We also observe a decrease in income diversification. According to the impact evaluation's theory of change, the project was expected to diversify income sources. Instead, we observe a decrease in the average number of income sources for households in the treatment group of 0.15 standardized units. As there is potential for these outcomes to improve over time, they will be a key focus of the endline impact evaluation.

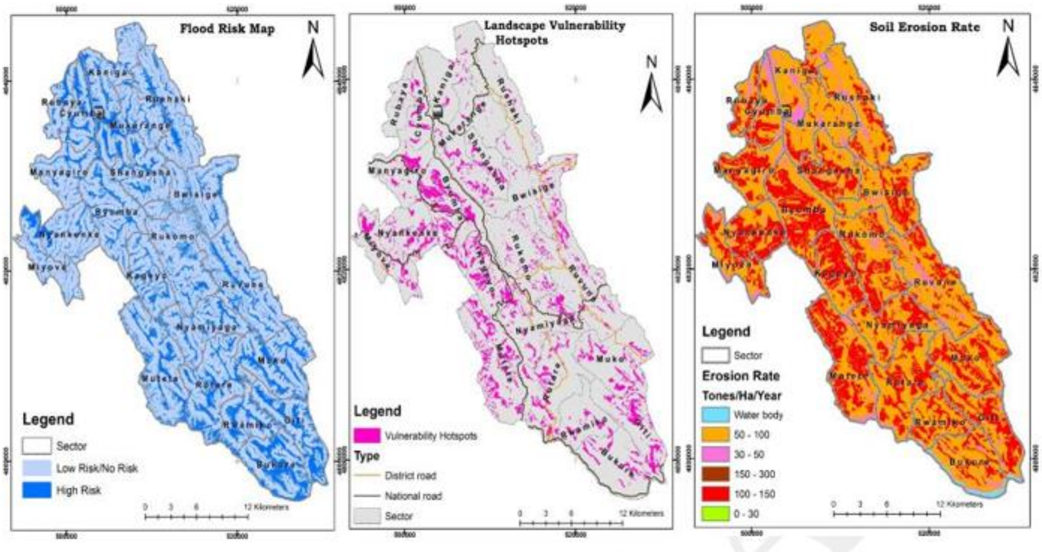
We observe mixed findings regarding the type of cookstoves used and the type and quantity of fuel used. The use of traditional stoves decreased from baseline to midline for both treatment and control households. However, the decrease was much greater for control households than treatment households who, at midline, were 31.9 percentage points more likely to be using traditional stoves (across both female- and male-headed households). The use of improved cookstoves also increased for both groups from baseline to midline. However, the increase was again more pronounced among control households, which were 29.4 percentage points more likely to use improved cookstoves. Treatment households reported very high utilization rates of improved cookstoves (88.1 per cent) following the receipt of these stoves from the project, suggesting there is scope for greater distribution of improved cookstoves by the project. The use of firewood bundles and charcoal sacks decreased over time across both treatment and control households. Yet these decreases were greater in control households due to the greater adoption of improved cookstoves.

Female-headed households consistently exhibit notable and statistically significant improvements in a range of output and outcome indicators. Female-headed households show a more pronounced adoption of climate-resilient agricultural practices. Whereas a greater proportion of male-headed treatment households (23 percentage points) have adopted a climate-resilient agricultural practice compared to control households, an even greater proportion of female-headed treatment households (27.6 percentage points) have done so. Female-headed treatment households also adopt more climate-resilient agricultural practices than male-headed treatment households (0.81 more practices versus 0.52 more practices). Additionally, female-headed households display a greater reduction of experiencing food shortages (23.4 percentage points) compared to a reduction of 17.9 percentage points for male-headed households. Female-headed households also show a significant decline in the use of coping strategies (8.5 points lower for female-headed households versus 2.2 points lower for male-headed households). Conversely, male-headed households exhibit an increase in the absolute number of days characterized by food shortages (with an increase of 19 days, significant at the 10 per cent level). When we look at the type and quantity of fuel used, female-headed households display an insignificant reduction in the number of firewood bundles (1.19) compared to a significant increase in male-headed households. These findings emphasize the importance of gender-specific considerations in project design and implementation.

I. INTRODUCTION AND CONTEXT

1. Climate change poses one of the greatest challenges to humanity. According to the Intergovernmental Panel on Climate Change (IPCC), temperatures are predicted to have already risen by 1.1 degrees Celsius from 1850-1900 to 2011-2020, with very rapid increases in recent years (Intergovernmental Panel on Climate Change, 2023). Climate science projections suggest temperatures will rise by up to two degrees Celsius by 2050. In terms of precipitation, climate models diverge, with both decreases and increases projected over the next 30 years (Austin and others, 2020). Aside from higher temperatures and more erratic rainfall, the consequences of climate change are predominantly negative, already leading to increased biodiversity losses, desertification, and losses in agricultural productivity (Intergovernmental Panel on Climate Change, 2023).
2. Low- and middle-income countries within sub-Saharan Africa, including Rwanda, face increased vulnerability to the impacts of climate change. Rwanda is projected to experience a range of detrimental climate impacts, including higher temperatures and more volatile precipitation (Rwanda, 2018). Indeed, Rwanda has already witnessed a series of climate-related hazards in recent years, including floods, landslides, and droughts (Rwanda, 2018). The high dependency on rain-fed agriculture, the hilly topography, low access to climate information, and the depletion of forest stocks have been identified as critical factors exacerbating Rwanda's vulnerability to such hazards.
3. In the context of crop productivity, Austin and others (2020) offers estimates of how the meteorological changes associated with climate change will influence the productivity of key crops across Rwanda. Based on assessments across 11 main staple crops within the country, Austin and others (2020) suggest the greatest impacts will be on maize, a variety of beans, and Irish potatoes, with yield reductions ranging from 10per cent to 15per cent. However, the impacts are not expected to be uniform across the country, with highland areas seeing possible increases in productivity in contrast to savannah areas.
4. Certain provinces and districts are more exposed to the negative consequences of climate change than others. Data from the national survey on the assessment of climate change in Rwanda (Rwanda Environment Management Authority, 2018) shows that, in the Northern Province, the Gicumbi District ranks the highest in terms of exposure to climate hazards and the second highest in terms of sensitivity to climate-related impact. The two indicators give Gicumbi the highest rank for climate vulnerability to hazards. According to this report, the high vulnerability of Gicumbi District to climate change is based on (i) an increase in temperature, (ii) frequent and longer heatwaves, (iii) intensive rainfall and frequent floods, and (iv) severe droughts and long dry spells. Moreover, Gicumbi District has one of the highest proportions of households experiencing crop losses, food insecurity, animal disease, and livelihood fluctuations due to weather hazards. Figure I–1 shows the 2017 Gicumbi regional maps for flood, soil erosion exposure, and landscape vulnerability spots. These are defined by overlaying the following four criteria: low tree cover, high erosion rate, landslide vulnerability, and flood risk.

Figure I–1. Geographic distribution of hazards in the Gicumbi District



Source: Karbala, Riviere and Sadania, 2019

5. Gicumbi District's heightened level of vulnerability and poverty can also be discerned from the baseline report. The report highlights that households in the Gicumbi District are, on average, poor and vulnerable to climatic shocks (Independent Evaluation Unit, 2020). Less than 10 per cent of household heads completed secondary school. Over 88 per cent of households own land, with the vast majority on hillsides, steep slopes, and marshlands. Almost all respondents reported the destruction of crops due to heavy rainfall, and around half reported the destruction of family properties from such extreme weather events. Almost all households used firewood and straw for cooking, and less than 1 per cent used electricity or gas. Only one-quarter used inorganic fertilizer for crop production.[1]
6. In response to the climate-related challenges at the national and local level, the Rwandan government has made substantial commitments to climate action, covering both adaptation and mitigation, including within policy frameworks such as Vision 2050, Nationally Determined Contributions under the Paris Agreement, and commitments made to attaining the Sustainable Development Goals. The Green Growth and Climate Resilient Strategy has informed the Rwandan National Strategy for Transformation (2018 – 2024) by offering a road map to improve sustainable land-use and water resource management, climate-smart agriculture, and improved planning and infrastructure.
7. In addition to national level policies, communities and community groups in Gicumbi are key actors and stakeholders in adjusting to climate change. For example, Clay and King (2019) argue that intercessions such as rural development interventions will likely have differential impacts on smallholder farmers' adaptive capacities and that existing social institutions can play important roles in managing climate risks. Clay and Zimmerer (2020) extend this argument by outlining how inclusive land-use planning and support for existing participatory and agroecological practices can enhance resilience. Moreover, Vermeire and others (2023) detail how agricultural cooperatives could help to tackle the greater time burden, and challenges experienced adjusting to changing climatic conditions, especially by females.
8. To this end, the "Strengthening climate resilience of rural communities in Northern Rwanda" project (FP073), also called the Green Gicumbi Project, was launched in 2019, with project

[1] Further details are provided in Appendix 4.

activities starting in 2020. The goal of this project, described in more detail in section II, is to increase the climate resilience of vulnerable communities in the Gicumbi District through both incremental adaptation and transformational adaptation. Incremental adaptation is defined, in the context of this project, as changes in the socio-ecological system to improve its resilience to climate change. Incremental adaptation may entail strategies that do not change the system completely but re-arrange and improve it to preserve the provision of benefits. On the contrary, transformational adaptation involves strategies that shift the socio-ecological system away from unsustainable or undesirable trajectories by overhauling its fundamental attributes (Kates, Travis and Wilbanks, 2012; Chhetri, Stuhlmacher and Ishtiaque, 2019; Fedele and others, 2019).

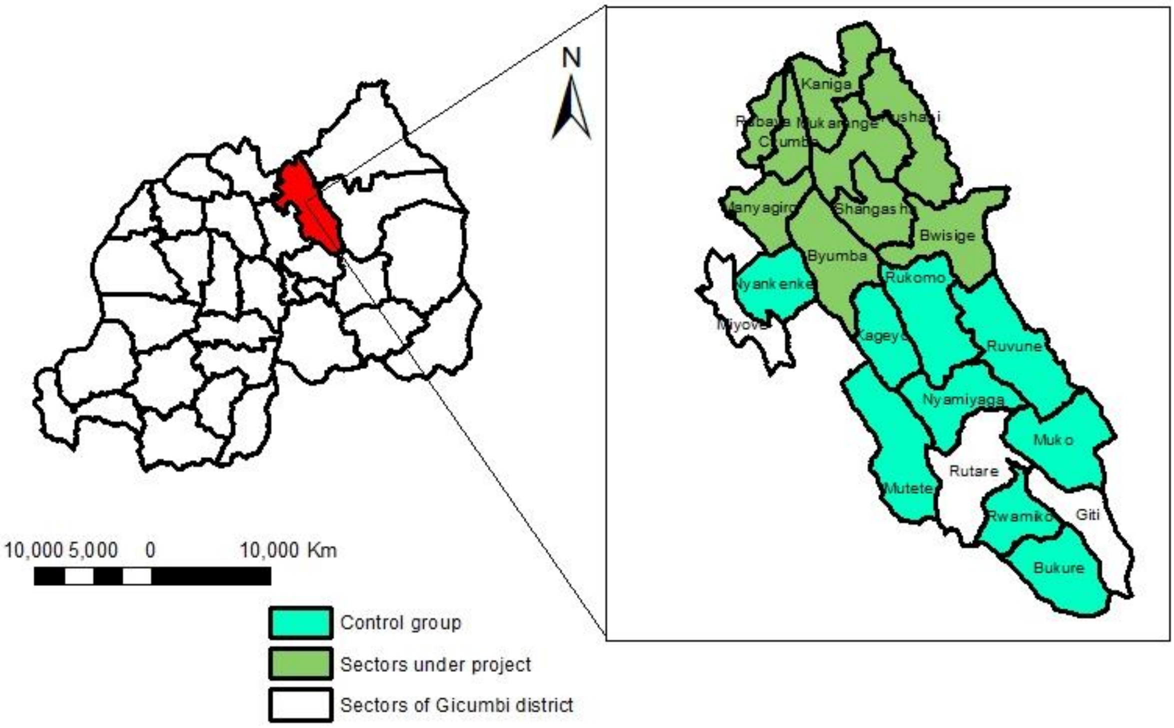
9. This midline report aims to present impact estimates for key project outputs and outcomes and assess the effectiveness of project activities at the project's midline three years after the start of project activities.

II. PROJECT (INTERVENTION) DESCRIPTION

10. The Green Gicumbi Project is a six-year project (2019–2025) valued at USD 33.2 million, funded by a Green Climate Fund (GCF) grant. The project aims to increase the resilience of vulnerable communities to climate change by restoring and enhancing the watershed's ecosystem services, increasing the capacity of communities to renew and sustainably manage resources, and supporting smallholders to adopt climate-resilient agriculture. The project also invests in green settlements for vulnerable families living in high-risk areas. The GCF Board approved the Green Gicumbi Project in March 2018 as FP073. The project's accredited entity is Rwanda's Ministry of Environment (MOE). The project activities are executed directly by the Rwanda Green Fund (FONERWA) and implemented by Government of Rwanda agencies at the district or sectoral level.

11. The project targets nine out of the 21 sectors in Gicumbi District. According to the project proposal, around 248,907 people, or 63 per cent of the district's population, live in the targeted areas (Rwanda, Ministry of Environment, 2018). The nine sectors fall within a sub-catchment zone of the Muvumba river and comprise around 252 villages, as depicted in Figure II–1.

Figure II–1. Project implementation area



Source: Rwanda, Ministry of Environment, 2020

12. The Green Gicumbi Project aims to achieve its goal of increasing targeted communities' climate resilience through restoring and enhancing ecosystem services of the sub-catchment zone of the Muvumba watershed, increasing the capacity of communities to renew and sustainably manage forest resources, and supporting smallholders to adopt climate-resilient agriculture. The project also invests in green settlements for vulnerable families living in high-risk areas.

13. The project interventions are organized around four main components:[2]
    - Watershed protection and climate-resilient agriculture
    - Sustainable forest management and sustainable energy use
    - Climate-resilient settlements
    - Knowledge transfer and mainstreaming
14. These components are further segregated into 27 sub-components, for 133 activities. Communities within each of the nine targeted sectors receive assistance in prioritizing activities based on assessing their needs. This exercise led to the development of a local adaptation plan describing the package of interventions that each community will receive.

A. DETAILS ON PROJECT ACTIVITIES

15. The project mainly focuses on adaptation, reducing vulnerability to climate change by enhancing the adaptive capacity of the targeted groups and reducing their exposure to climate risks. A key focus is making existing practices more resilient and embedding them within communities so they can continue adapting to future climate variability beyond the project's lifetime. In addition to this adaptation focus, the Green Gicumbi Project includes a mitigation component comprising activities that encourage alternative approaches to energy, such as using biogas and more efficient cookstoves. Sustainable forest management is also promoted. Finally, the project is planned around a gender-sensitive implementation strategy that ensures women can access project activities and benefits such as training, jobs and knowledge. The project also aims to reach gender parity in terms of access to benefits. Furthermore, some project activities, such as resettlement initiatives. specifically target or prioritize female-headed households. These activities increase women's chances of benefiting from the intervention by overcoming obstacles hindering their participation.[3]
16. Hereafter, we describe Green Gicumbi's main activities by component, restricting ourselves to the first two components, which are part of this impact evaluation (IE).

1. COMPONENT ONE: WATERSHED PROTECTION AND CLIMATE-RESILIENT AGRICULTURE

17. The first component focuses on reducing soil erosion and land degradation in cultivated areas, including tea and coffee plantations, and constructing buffer areas around the catchment and other public areas like rivers and roadsides. The component aims to identify high-risk sites in all nine sectors targeted by the project, including the Mulindi Tea Estate, which is particularly vulnerable to flooding and landslides.[4] Efforts to reduce soil erosion include (i) implementing mechanical soil stabilization techniques such as establishing radical and progressive terraces, (ii) replanting steep slopes with perennial grasses and shrubs, wattling, and brush layering, and (iii) replanting protective forests along roads and riversides. Local entities implement and supervise the activities who train

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[2] The project also includes a component related to knowledge transfer and mainstreaming. Based on lessons learned from the three main components and activities, the fourth component aims at ensuring results are mainstreamed and knowledge is disseminated. This component produces a range of knowledge products, including policy briefs and case studies.
[3] While Rwanda has made immense progress in equal gender representation in parliament, females still lag males in educational, economic, and health outcomes (World Economic Forum, 2023).
[4] The estimated annual loss of production from climate variability at the Mulindi tea plantation (2,300 ha) in Gicumbi over the last six years ranges from 2.0 to 3.3 million tonnes of green leaf per year, with an equivalent market loss of USD 2.5 to 4.1 million. Such losses affect the income of smallholders who work on the plantation within cooperatives. Smallholders who grow tea and coffee on their own land are also affected.

and hire community members. This approach is expected to generate employment for community members, especially in labour-intensive tasks like terrace construction.

18. In addition to targeting public areas, this component targets smallholder farmers. The project complements its soil erosion reduction measures, which benefit all farmers, by increasing the adaptive capacity of smallholder farmers by promoting climate-resilient agriculture (CRA) and agroforestry technologies. Smallholder farmers were trained on various CRA practices, such as rainwater harvesting, developing irrigation schemes, and adopting climate-resilient crop varieties.

2. Component Two: Sustainable forest management and sustainable energy

19. The second component assists forest owners and users in improving forest productivity and reducing deforestation. This is done via enhanced forest management techniques and reducing dependency on biomass for cooking fuel. This component provides high-quality seeds and plant material by implementing trial sites and assessments to match targeted sites with appropriate species. Following demonstration sites and technical capacity-building, forests covering over 2,261 hectares (ha) of the watershed are being restored. Moreover, capacity-building in forest management and maintenance targets different groups, including district staff, district technicians, and MOE and Rwanda Water and Forest Authority staff. Training also targets private forest owners, beekeeping associations, cooperatives, and contractors supported through demonstration nurseries and forest and agroforestry plots. The training ensures skills and management competence, raises awareness, and introduces new practices, techniques, and species to support and improve the livelihoods of communities.

20. For private landowners, the project covers the cost of improved woodlot management to facilitate the adoption of best management practices. The project supports the development of nurseries in communities and cooperatives for small woodlot owners. Altogether, the intervention is training 3,960 individuals over five years.

21. Finally, besides improving forest management, this component aims to mitigate greenhouse gas (GHG) emissions by encouraging biogas and modern, efficient cookstoves. This activity targets a wide group of beneficiaries, prioritizing households producing dairy products and institutions (including the Mulindi Tea Estate) by raising awareness of using alternative energy and encouraging investment in biogas. This also includes promoting and subsidizing cleaner, more efficient cookstoves, a key focus within this IE.

B. Implementation status

22. The implementation of Green Gicumbi Project activities started in some sectors in July 2019 and is expected to end in May 2025. Activities directed at target beneficiaries were delayed and only started after the baseline data-collection between June and July 2020. Despite the COVID-19 pandemic resulting in lockdowns in Rwanda, hindering travel and project meetings, most project activities progressed as planned. The third annual progress report, assessing project implementation in 2021, reported that component One activities fulfilled 82 per cent of the key results areas, including the training of smallholder farmers in CRA practices through demonstrations on plots in Farmer Field Schools (FFS) (Green Climate Fund, 2021). Component Two activities were assessed as having a 93 per cent overall completion rate. These activities include the provisioning of modern, improved cookstoves and training on their proper use, among other activities (Green Climate Fund, 2021). Overall, the activities of the two components assessed in this midline report have mostly been implemented successfully.

C. Theory of Change

23. Both components of the Green Gicumbi Project seek to address different core problems vulnerable communities face. Component One is concerned with the low adaptative capacity at the community and landscape levels. In contrast, Component Two focuses on enhancing forest productivity and reducing deforestation. Separate theories of change (ToCs) have been developed for these components, as shown in Figure II–2 and Figure II–3.

1. ToC of Component One: Watershed protection and climate-resilient agriculture

24. **Inputs**: GCF grants and funds from FONERWA, Gicumbi District, and the Wood Foundation are allocated to service providers and technical experts to purchase inputs. Communities also contribute to the project through labouring opportunities.

25. **Activities:** Component One activities comprise adaptation and mitigation. Adaptation activities include public awareness campaigns, training sessions, provision of inputs, and continuous technical assistance to smallholder farmers on CRA practices and terrace construction. Smallholder farmers were provided with CRA training through FFS demonstration plots. These activities are tailored to community needs and documented in local adaptation plans.[5] The adoption of CRA practices has been supported by the development of the Community Adaptation Fund (CAF), a revolving fund serving households and agricultural groups. Completing these activities depends on sufficient project funds, access to the required inputs and equipment, and suitable human capital in the project intervention area.

26. **Outputs:** The awareness and training activities are expected to increase the CRA capacity of sector and district technicians and the dissemination of risk reduction and adaptation practices. Component One activities will also provide smallholder farmers with inputs, technical assistance, CAF access, weather and climate services (WCS), and temporary employment constructing radical terraces. The activities will also implement soil conservation and water management measures and establish agroforestry systems in targeted areas. Completing these outputs relies on the project's ability to capture the needs of all target population segments and offer relevant activities. This will be ensured through the co-development of local adaptation plans. Component One's success also assumes that the target population is informed about and participates in the training sessions. WCS is delivered through media sources that the target population has access to, engages with and respects.

27. **Outcomes:** FFS technicians train smallholder farmers through repeated sessions and demonstration plots. Also, if the target group benefits from the output stage's elements, we expect a certain number of farmers to adopt these new risk reduction and adaptation practices. Risk reduction and adaptation practices include shade trees, grass strips, fodder banks, better pest management, and expanded upland coffee and tea production. They also include building and maintaining radical and progressive terraces. These intermediate outcomes will enhance the watershed's ability to absorb rainwater by increasing infiltration. This will reduce run-off and lessen the risk of flooding. It is also likely smallholders will increase their adaptive capacity by improving their agricultural and animal production productivity and diversifying their sources of livelihoods, resulting in higher incomes, which will be supplemented by temporary employment.

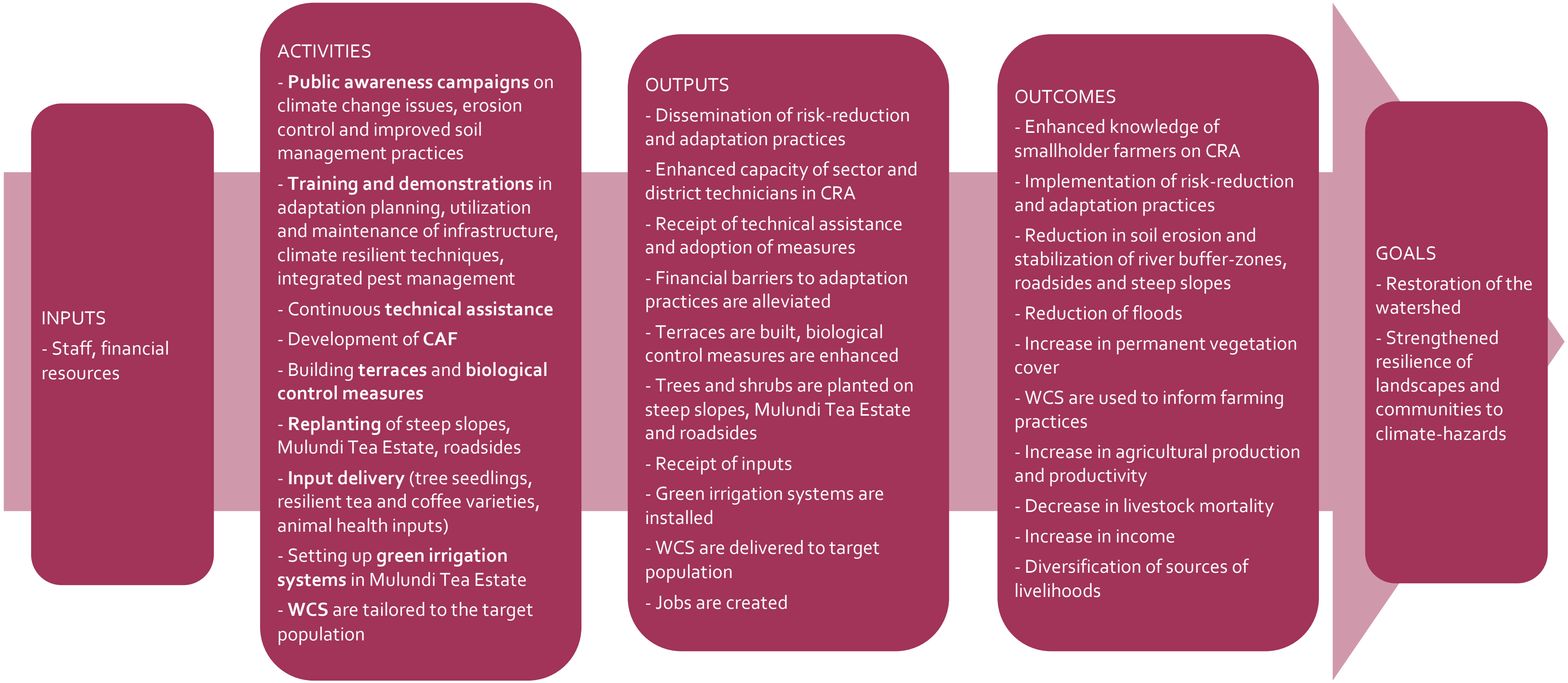
28. The ability of the project to achieve these outcomes relies on (i) delivering quality training tailored to the target population, (ii) project activities that address all barriers to adopting the prescribed

[5] Local adaptation plans were drafted with input from local communities. Communities received assistance in how to prioritize the activities that best respond to their needs and become more climate resilient.

practices, and (iii) effective maintenance of the project infrastructure. The target population also requires training on interpreting and acting upon WCS.

29. **Goals:** Component One activities aim to contribute to the watershed's restoration and strengthen the resilience of landscapes and communities to climate-related hazards. The ability of component One activities to contribute to these goals relies on the absence of barriers to the long-term adoption of the project's prescribed practices and the sustainable use of natural resources. These five stages are summarized in Figure II–2.

Figure II–2. Theory of change for component One activities



2. ToC of component Two: Sustainable forestry and energy use

30. **Inputs:** GCF grant and funds from FONERWA, Gicumbi District and the Wood Foundation are allocated to service providers and technical experts to purchase inputs. Communities also contribute to the project through work opportunities.

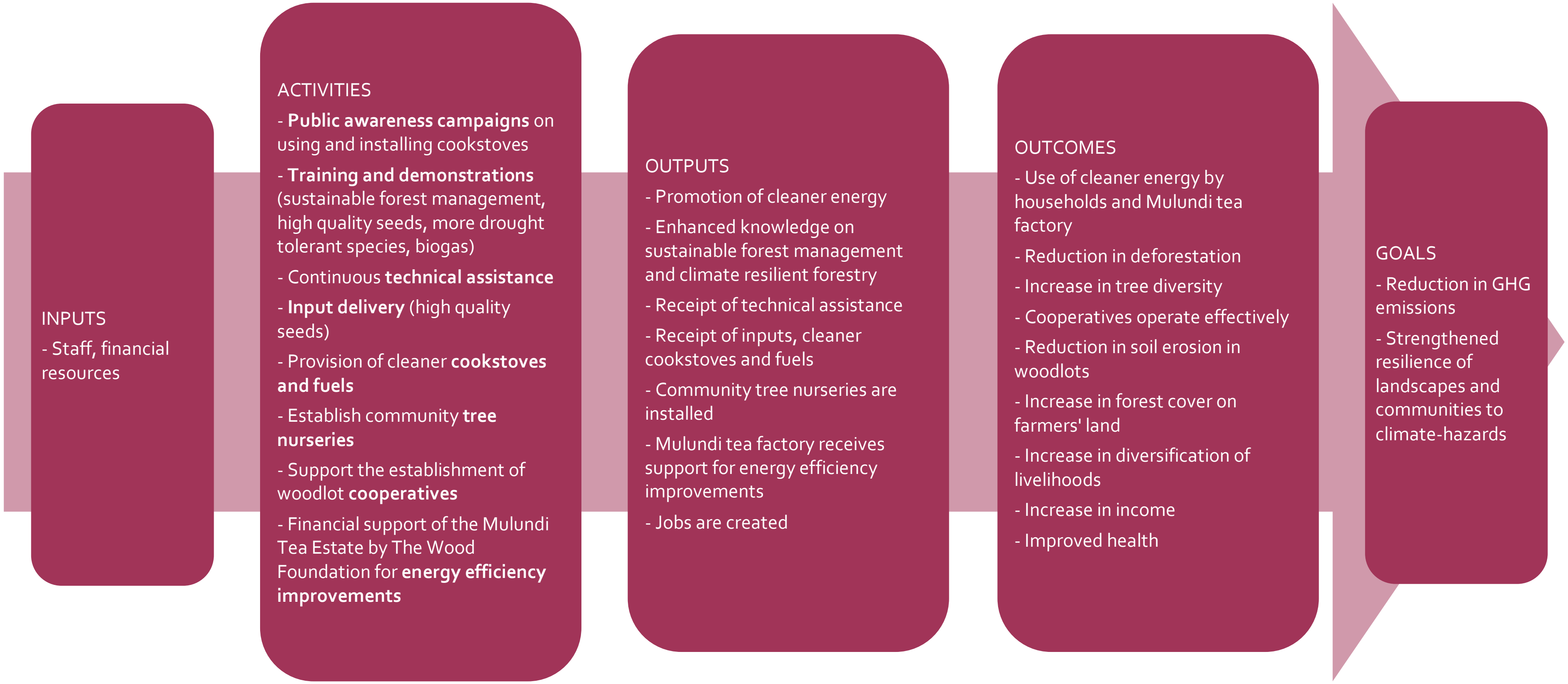
31. **Activities:** Component Two activities consist of adaptation and mitigation measures promoting cleaner energy and sustainable forest management. These activities include awareness campaigns, farmer training, inputs, technical assistance, cleaner cookstoves and fuels, community tree nurseries, and support for establishing woodlot cooperatives. Completing these activities depends on sufficient project funds, access to the required inputs and equipment, and suitable human capital in the project intervention area.

32. **Outputs:** Component Two activities are expected to result in farmers' enhanced knowledge of clean energy, sustainable and climate-resilient forestry, the reception of inputs, improved cookstoves, technical assistance, the establishment of tree nurseries, and job creation. Jobs are expected to be created by establishing and supporting businesses that manufacture and sell improved cookstoves. These businesses were trained in basic business skills, marketing, and bookkeeping. A key assumption at this stage is the project's ability to reach all segments of the target population and convince community members to participate in project activities.

33. **Outcomes:** The execution of component Two activities is expected to lead to the production and use of cleaner energy, for example, biogas, cleaner cookstoves and reduced household use of firewood. Improved woodlot management is increasing tree production and diversity and reducing soil erosion in woodlots. Training also supports adopting additional sources of livelihood from forestry products, contributing to job creation and increased income. Using cleaner energy sources is also expected to improve health and reduce firewood and charcoal use. The project's ability to achieve these outcomes relies on (i) effective transfer of knowledge to the target population, (ii) implementing project activities that address all barriers to adoption, (iii) delivering good quality equipment, (iv) changing attitudes and behaviours regarding forest resources and energy, and (v) ensuring the relevance of newly accessible forest products to people's livelihoods.

34. **Goals:** Component Two aims to strengthen the resilience of landscapes and communities to climate-related hazards and reduce GHG emissions. Component Two activities can help achieve these goals if the target population uses cleaner energy sustainably, which assumes access to affordable fuel, well-maintained equipment, regular use of improved cookstoves, and sustainable use of natural resources. Figure II–3 summarizes these five stages.

Figure II–3. Theory of change for component Two activities



III. EVALUATION QUESTIONS AND INDICATORS

A. EVALUATION QUESTIONS

35. The IE focuses on household level outcomes and aims to assess how effectively the Green Gicumbi Project contributes to incremental and transformational climate change adaptation. To assess the project's contribution to incremental and transformational climate change adaptation, the LORTA team and its partners prepared key evaluation questions derived from the ToCs' underlying hypotheses.

36. Evaluation questions 1 to 5 are answered using quantitative methods and focus on the impacts of component One and Two activities.[6] Table III–1 presents the evaluation questions and the specific impact indicators for answering them.

Table III–1. Evaluation questions and associated impact indicators

Evaluation question	Key indicator
Output level	
EQ1: Do the adaptation interventions in components One and Two lead to an increase in farmers' adoption of CRA practices?	Proportion of households adopting CRA practices
	Number of CRA practices adopted
	Type of CRA practices adopted
EQ2: To what extent do the mitigation activities in component Two lead to the production and use of cleaner energy for cooking?	Quantity of firewood used for cooking
	Quantity of charcoal used for cooking
	Main source of fuel for cooking
Outcome level	
EQ3: Do the adaptation activities in components One and Two lead to an increase in food security and diversity?	Household dietary diversity score
	Experienced a food shortage in the last year
	Number of days in last year in which experienced food shortage
	Coping Strategies Index (Maxwell and Caldwell, 2008)
EQ4: Do component One and Two activities lead to an increase in smallholder farmers' resilience? What dimensions of resilience are the most influenced by the project activities?	Agricultural production (size of harvest)
	Total value of harvest
	Yield of harvest
	Share of agricultural production not for consumption
	Ownership of tropical livestock units
	Number of sources of livelihood
	Climate resilience index
Impact level	
EQ5: Do components One and Two's activities contribute to an increase in women's participation in economic life?	Proportion of households adopting CRA practices by gender of the household head
	Number of CRA practices adopted per household by gender of

[6] Components Three and Four activities are outside the scope of this evaluation.

EVALUATION QUESTION	KEY INDICATOR
Do the impacts of the project differ by the gender of the household head?	the household head
	Quantity of firewood used for cooking by gender of the household head
	Proportion of households using a traditional stove by gender of the household head
	Household dietary diversity by gender of the household head
	Experienced a food shortage in last year by gender of the household head
	Number of days in last year in which experienced food shortage by gender of the household head
	Coping Strategies Index (Maxwell and Caldwell, 2008) by gender of the household head

37. EQ1 and EQ2 identify key steps towards achieving the goal of household resilience by focusing on output level indicators, such as providing training in CRA practices, adopting clean cookstove solutions and reducing firewood use. EQ3 and EQ4 focus on the ability of the project to contribute to strengthening the resilience of households by focusing on outcome level indicators, such as food security, production, and income. EQ5 allows the assessment of the gender responsiveness of project activities, which will be answered through a heterogeneity analysis of survey data. This evaluation will assess the sustainable development co-benefits of the project at endline.

B. IMPACT INDICATORS

38. This section briefly introduces and explains the composite indices and scores used during the following impact assessment.

1. CLIMATE RESILIENCE INDEX

39. In line with the GCF proposal submitted by the project team, this evaluation presents resilience as one of the main indicators of interest. It should be noted that while the concepts of resilience and vulnerability are interconnected, differences exist between the two. Vulnerability is defined as susceptibility to harm and a potential for a change or transformation of the existing system when confronted with a hazard (for early discussions on this, see Adger, 2000; Prowse, 2003). As a result, vulnerability assessment is often linked to the assessment of different components, such as risk of exposure or sensitivity to hazard. In contrast, Gallopín (2006) states that resilience relates to the capacity of the response component of vulnerability. The IPCC defines resilience as “the ability of a system and its component parts to anticipate, absorb, accommodate, or recover from the effects of a potentially hazardous event in a timely and efficient manner, including through ensuring the preservation, restoration, or improvement of its essential basic structures and functions” (Lavell and Oppenheimer, 2012).

40. Despite these definitions, no single measure of resilience to climate change exists [see Weldegebriel and Prowse (2013); Mahmud and Prowse (2012) for different approaches]. This IE adapts the resilience tool proposed by the Food and Agriculture Organization of the United Nations (FAO) (2016), the Resilience Capacity Index. The Resilience Capacity Index is organized around five pillars: (i) access to basic services, (ii) assets, (iii) social safety nets, (iv) sensitivity, and (v) adaptive capacity. The evaluation team defined a list of components to be part of the climate resilience index

(CRI) based on the information from the baseline survey (see Table III–2). The index can be computed as a simple average of its components for ease of implementation and interpretation.

Table III–2. Components of a climate resilience index

PILLAR	INDICATOR
Access to basic services	Travel time to the closest all-weather road
	Travel time to the closest market
	Travel time to the closest primary school
	Travel time to the closest health centre
	Travel time to the closest drinkable water
Asset	Literacy
	Livestock
	Landholding
Social safety net	Reception of social safety net
	Cooperative membership
Adaptive capacity	Off-farm employment
	Income
	Income diversification

Source: Adopted from Food and Agriculture Organization of the United Nations (2016)

2. COPING STRATEGIES INDEX

41. The coping strategies index (CSI) was developed to measure the strategies that households employ quickly and practically when faced with a food shortage (Maxwell and Caldwell, 2008). Surveyed households are asked how many days they implemented a particular coping strategy from a pre-defined list of strategies in the past week. Depending on the local context and norms, these strategies are then given a severity ranging from one to four. A final CSI score is calculated by multiplying the number of days each strategy was employed during the last week with its severity weight and taking the sum of all coping strategies.

42. Table III–3 presents the midline survey's list of strategies alongside their respective severity weights. The weights are taken from the Comprehensive Food Security and Vulnerability Analysis (World Food Programme, 2016), completed by the Government of Rwanda and the World Food Programme.[7]

Table III–3. Coping strategies and associated weights

IN THE PAST SEVEN DAYS, HOW OFTEN HAS YOUR HOUSEHOLD HAD TO RESORT TO THE FOLLOWING WHEN YOU DID NOT HAVE ENOUGH FOOD OR MONEY TO BUY FOOD?	SEVERITY WEIGHT
Rely on less preferred and less expensive food?	1
Limit portion size at mealtime?	1
Reduce number of meals eaten in a day?	1
Borrow food or rely on help from a friend or relative?	2

[7] While coping strategies can be provided with a severity weight of four, this weight was not used in the case of Rwanda.

In the past seven days, how often has your household had to resort to the following when you did not have enough food or money to buy food?	Severity weight
Purchase food on credit?	2
Gather wild food, hunt, or harvest immature crops?	2
Consume seed stock held for next season?	2
Sent household members to eat elsewhere?	3
Restrict consumption by adults for small children to eat?	3
Feed working household members at the expense of non-working members?	3
Skip entire days without eating?	3
Send household members to beg?	3

Source: Comprehensive Food Security and Vulnerability Analysis (World Food Programme, 2016)

3. Household dietary diversity score

43. The household dietary diversity score (HDDS) used in this report is a small variation of the measure used widely by the FAO and other organizations. The HDDS measures how many food groups a household consumes over a certain period, thereby proxying for the nutrient adequacy of a household's diet (Kennedy, Ballard and Dop, 2013). The midline survey asked households what they recall consuming from a list of 10 food items. These 10 items were classified into six food groups, following FAO guidelines (Kennedy, Ballard and Dop, 2013). The food groups considered in the report are (i) cereals, (ii) white root tubers, (iii) vitamin A vegetables, (iv) other vegetables, (v) other fruits, and (vi) legumes and nuts. Therefore, in the present report, HDDS ranges from a minimum of 0 to a maximum of 6.

4. Tropical livestock units

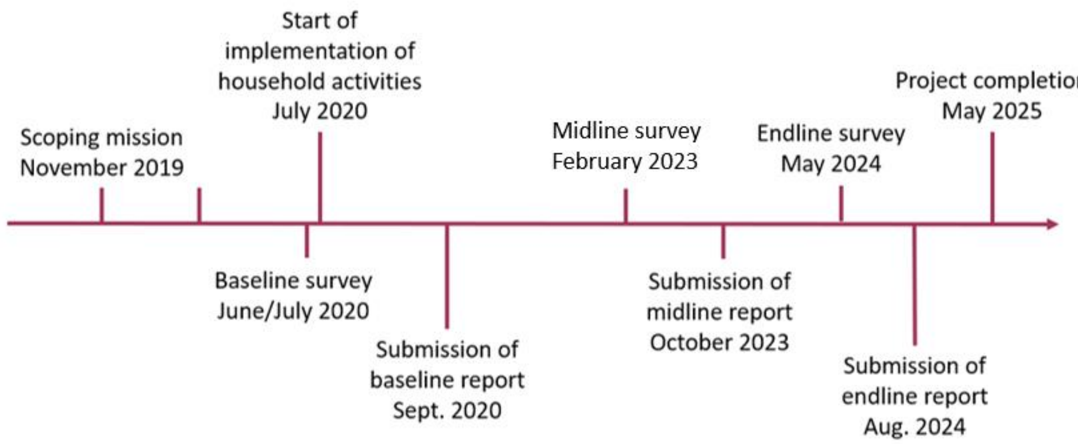
44. Estimates of livestock ownership are reported in the number of tropical livestock units (TLU) per household. The TLU simply converts reported livestock numbers to a common unit by assigning a certain weight to each reported livestock. For this report, cattle are given a weight of 0.5 units, pigs 0.2, goats and sheep 0.1, and chickens, ducks, and rabbits 0.01.

IV. EVALUATION STRATEGY AND DESIGN

45. The Green Gicumbi Project's IE comprises three waves of data-collection. The baseline was conducted in June-July 2020, the midline in April 2023, and the endline is scheduled for 2025. The project terminates in May 2025.

46. Figure IV–1 illustrates the timeline of the IE activities in parallel with the project's implementation timeline.

Figure IV–1. Timeline



47. The quantitative impacts of the Green Gicumbi Project are assessed by comparing changes in outcomes of interest between a group of beneficiaries and non-beneficiaries. After discussions with the project team, the southern part of the Gicumbi District, situated around the Nyabugogo catchment, was designated as a suitable comparison area. This area shares more similar agroecological characteristics than the upper-part of the Muvumba catchment, located in the project intervention area's eastern districts of Nyagatare and Gatsibo. The primary units of analysis are smallholder farmers. Hence, this approach led to the precise measurement of changes in farmers' outcomes of interest.

A. Description of the units for decision-making, the intervention and for analysis

48. Beneficiary sectors and the constituent villages were pre-selected by the project team based on proximity to and dependency on the sub-catchment of the Muvumba watershed. Consequently, the evaluation team selected a quasi-experimental design to assess the Green Gicumbi Project quantitatively. Due to the complementary nature of project activities and the necessity to tailor activities to each community's characteristics and needs, the team is evaluating the overall impact of the Green Gicumbi Project and distinguishing between specific project activities. The team decided that a difference-in-differences (DiD) approach combined with matching was the most suitable evaluation design for assessing the overall impact of components One and Two.

49. At the design stage, the evaluation team initially proposed an approach solely involving DiD analysis (see section E for details on sampling). However, the feasibility of this approach hinged on the ability to identify and track the same households at both baseline and midline stages. Due to constraints during fieldwork, consistent household identification was not possible. The evaluation proceeded with the DiD analysis using two cross-sections instead of panel data, ensuring that variables were defined consistently throughout. Due to significant changes in some survey modules from baseline to midline, it was not possible to merge variables related to agricultural production, yield, sale values, and non-consumption shares. Where these variables were not consistently defined across baseline and midline data-collection, matching methods were used with midline data to draw reliable and credible causal estimates. Matching involves employing statistical methods to create a comparison group. In this process, each treated unit is paired with a non-treated unit exhibiting the most similar observable characteristics. The next section explores the empirical strategy in more detail.

B. IDENTIFICATION AND EMPIRICAL STRATEGY

50. The DiD approach estimates project effects by comparing changes in outcomes over time between beneficiaries and non-beneficiaries using a comparison group. As every community in the intervention area will ultimately receive the intervention, the comparison group comprises smallholders in communities outside the nine sectors targeted by the project. Due to the non-random selection of communities and direct beneficiaries, beneficiaries and the comparison group were expected to systematically differ at baseline.[8] Therefore, a pure ex-post comparison of both groups would have prevented isolating the project’s effects.

51. Instead, the DiD approach allows for comparing changes in outcomes between the two groups, acknowledging potential initial differences. Alternatively, matching methods allow for closer comparisons by creating a balance between the treatment and control groups by aligning their observable characteristics.

52. The DiD design accounts for initial observable and unobservable differences between beneficiaries and the comparison group. Assuming that the initial difference impacting the outcomes of interest is constant over time in the absence of the intervention, DiD enables the causal identification of the project’s impact. This approach is also robust to external shocks, assuming these shocks affect both groups equally. The crucial assumption of this technique is that the change in the outcomes of beneficiaries and the comparison group over time would have been the same without the intervention. This is called the “parallel trends assumption”. The project's impacts are then estimated by computing the difference in outcomes between beneficiaries and the comparison group after the project with the difference in outcomes between the same groups at the beginning of the project.

53. However, the parallel trends assumption is unlikely to hold under practical settings and cannot be tested directly.[9] It is also impossible to test for pre-trends when historical time series data is unavailable. Instead, the validity of the parallel trends assumption is reinforced by the greater similarity between the groups at the beginning of the project. Therefore, at the design stage, the evaluation team suggested complementing this approach with matching at the household level (see section E for details on sampling). Matching consists of using statistical techniques to construct an

[8] Although the two groups are fairly balanced at baseline, they do differ in some important respects. See Appendix 3 for details.

[9] One way to gain confidence in its validity is to test this assumption on past data. If the outcomes of the group of future beneficiaries and the comparison group were evolving in parallel in the past, it is likely they would have kept evolving in parallel in the future, whether the project was implemented or not. This can be referred to as a placebo test, requiring data on at least two periods before the project’s implementation. In the case of the Green Gicumbi project, there is no available household data for both groups before the baseline survey. Hence, a placebo test cannot be conducted.

artificial comparison group such that every treated unit is matched with a non-treated unit that has the most similar observable characteristics.[10] This two-step approach aims to reduce the initial differences between these two groups. Any remaining time-invariant differences are accounted for by the DiD approach.

1. Heterogenous effects

54. Heterogeneity analysis between households headed by males or females is a fundamental component of the evaluation, especially since certain outcomes had a female empowerment or gender focus, as described in Table III–1. Although females enjoy strong political representation at the national level, and gains have been made in addressing gender inequality in broader society, gender inequality persists in health, education, and economic outcomes (World Economic Forum, 2023).[11] Researchers have also pointed out that females continue to face challenges in the agricultural sector due to lower access to seeds and fertilizers (Randell and McCloskey, 2014). In response to these challenges, the Green Gicumbi Project is dedicated to gender-sensitivity, training its staff in gender-mainstreaming, encouraging gender-balanced participation, and reserving various project activities for women.
55. For this reason, gender heterogeneity analysis is undertaken for four indicators to shed light on potential disparities and gender-specific nuances within critical domains.[12]
56. To measure CRA adoption it is helpful to determine if households headed by men and women equally access and benefit from sustainable agricultural practices. Examining the type of cooking fuel by gender informs energy and environmental policies by considering differences between men and women regarding energy access and environmental impact. The analysis of food security by gender acknowledges that men and women may experience food insecurity differently due to varying roles, enabling targeted interventions to address each group's specific challenges. Lastly, assessing CSI scores by gender uncovers gender-specific vulnerabilities and strengths in climate resilience and food security, guiding policies that account for these dynamics to foster greater equity and effectiveness.

2. Assumptions and limitations

57. Potential risks for the suggested IE design relate to the quality of matching, the possibility of spillovers, shocks affecting beneficiaries and the comparison group separately, and the inclusion of non-beneficiaries in the treated group. The quality of matching is dependent on the quality of baseline data collected. During the baseline, it became evident that adjustments to the survey tools were required to improve the data quality, especially for rosters used to collect agricultural data at parcel and plot levels. Such adjustments mostly refer to the programming of the survey and ensuring that all relevant variables essential for the analysis are properly measured. The field team encountered numerous challenges in consistently tracking and identifying baseline households during the midline assessment. Fortunately, this limitation has had a limited impact on the matching quality, as selected matching variables are mostly time-invariant variables associated with the probability of receiving the treatment. Nevertheless, it should be noted that the mentioned limitations influence the possibility of conducting DiD for certain outcome variables since they were not accurately measured at baseline and rely on a pure matching approach.

[10] We perform post-matching tests to confirm if our matching algorithms to compare pre- and post-matching bias. 1:1 matching reduced mean-bias across the selected variables from 7.6 per cent to 4.6 per cent, while nearest neighbour matching reduced bias from 7.6 per cent to 4.7 per cent.
[11] At baseline, 27 per cent of male and 56 per cent of female household heads reported receiving no education.
[12] The selection of these four variables was also guided by specifications run over the entire sample, indicating where potential discrepancies across gender might lie.

58. **Spillovers at midline**: Project activities will build the capacity of authorities and technicians working at the district level and, therefore, these actors will be active across both treatment and control sectors. The knowledge transfer may strengthen the adaptive capacity of communities in targeted sectors and communities in non-targeted sectors chosen as a comparison area. The existence of positive spillovers would influence estimating the Green Gicumbi Project's impacts. However, these activities represent a minor subset of all the interventions proposed by the project and do not address all the barriers smallholder farmers face in implementing adaptation and mitigation strategies. Therefore, spillover effects are expected to be small. Indeed, data collected at midline show that spillovers and contamination are unlikely to significantly affect the impact estimates. At midline, only seven out of the 630 (or slightly more than 1 per cent) of households living in control villages reported being a beneficiary of the Green Gicumbi Project.
59. **Shocks**: The parallel trend assumption behind the DiD approach would fail if an external shock affected only one of the two groups being compared, i.e., beneficiary or comparison communities. One such shock is the COVID-19 pandemic, which occurred between the baseline and midline evaluations. However, the COVID-19 pandemic affected all sectors in Gicumbi in a similar manner. Nonetheless, this situation did prompt the implementation of new interventions in the study area, which could have potentially influenced the comparison communities. It is worth noting that if any bias were introduced into our treatment effects, it would likely have been in a downward direction. In many cases, this is a preferable outcome, as downward biases tend to yield more conservative and reliable estimates.
60. **Non-beneficiaries**: Finally, at the time of baseline data-collection, individual beneficiaries of the Green Gicumbi Project were not yet identified. Instead, only beneficiary communities could be identified. As explained in section E, households were randomly selected for baseline data-collection. Hence, the sample includes households that are not direct project beneficiaries. Including households not directly benefiting from the project may result in underestimating the project's impact. Households were asked if they were beneficiaries of the Green Gicumbi Project. Only 27 of the 628 (or slightly more than 4 per cent) households living in treatment areas reported not being a beneficiary of the project, indicating very few non-beneficiaries in the treatment sample.

C. Empirical estimation

61. Our IE design relies on a DiD setting for indicators where both baseline and midline data was available. The basic model specification is given by equation (1):

$$Y_{jit} = \propto + \beta_1 . T_{ji} + \beta_2 . D_t + \beta_3 . T_{ji} . D_t + X_{it} + FE_i + \mu_{jit} \quad (1)$$

where Y_{jit} represents the outcome of interest for household *j* in treated community *i*, at time *t*. $\propto$ represents the intercept, and T_{ji} represents the treatment status for individual *j* in community *i*. T_{ji} takes a value of 1 if the household is in a treatment community (and therefore benefited from the activities of the Green Gicumbi Project), and 0 otherwise. D_t is a binary variable for time, taking a value of 1 for the midline, and 0 otherwise. X_{it} represents a matrix of control variables (such as household demographics and respondent characteristics), while FE_i is a matrix of fixed effects, including village fixed effects and occupation fixed effects[13]. μ_{jit} represents the error term for individual *j* located in village *i*, at time *t*. β_3 therefore captures the average treatment effect on the

[13] In various models, the outcome variables are intricately linked to agricultural practices. Given that a small fraction of respondents (less than 5 per cent) predominantly identifies as artisans or drivers, beyond their farming roles, it is imperative to account for cross-occupation variations. Addressing this aspect is crucial to mitigate potential omitted variable bias and discern the treatment-induced within-group (within-occupation) variation exclusively. Hence, our specifications incorporate occupation fixed effects for precise estimation.

treated (ATT); it measures the difference in Y_{jit}, from baseline to midline, for households receiving the treatment and households not receiving the treatment, while controlling for observable time-variant sociodemographic characteristics as well as village and occupation specific fixed effects $\boldsymbol{X}_i$.

62. In situations where certain indicators were only captured at midline, we adopt a matching design. Specifically, we make use of propensity score matching (PSM).[14] PSM creates a comparison group by matching treated households to one or several untreated households on their estimated probability of receiving the intervention (i.e. the activities offered by the Green Gicumbi Project), called propensity scores (Rosenbaum and Rubin, 1983). This probability is estimated based on a range of observable characteristics, called matching variables, that both predict receiving the project activities and key outcomes of interest, namely resilience and adaptation. We include matching variables at the household level. The propensity scores are estimated via a binary choice model (i.e. a probit or a logit model) as illustrated by equation (2).

$$T_i = \alpha + \delta M_{ji} + \mu_{ji} \tag{2}$$

63. In this equation, T_i represents the treatment dummy, which takes a value of 1 if household j is located in a treated community i, and 0 otherwise. α is a constant representing the average probability of treatment in the comparison group. δ is a set of coefficients capturing the impact of matching variables M_{ji} on the probability of treatment, and μ_{ji} is an error term. This equation is used to predict the probability of receiving the project activities for each household in our sample, based on their characteristics reflected by the selected set of matching variables. The predicted probability of treatment is illustrated by equation (3), where *p(m)* represents the propensity scores.

$$\Pr(T = 1|M = m) = p(m) \tag{3}$$

64. Eligibility to receive project activities was determined by the high dependency of local populations on agriculture as a source of food and income, making them vulnerable to the degradation occurring at the Muvumba watershed's sub-catchment. Consequently, the matching variables were meant to capture differences in characteristics between households in treated and control communities relating to dependency on agricultural activities and climate risk exposure, which also correlate with the outcomes of interest. Matching variables are identified by referring to the existing literature on the determinants of key outcomes of interest and by directly exploring correlations between this indicative set of determinants and these key outcomes. A final list of matching variables can be found in the probit regression model listed in Appendix 4.[15] The estimated propensity scores were then used to match treated and non-treated households.

65. Specifically, we estimate average treatment effects on the treated (ATT) across both the DiD and matching specifications, as represented by equation (4).

$$ATT = E\left(y_{ji}{}^1 - y_{ji}{}^0 \middle| T_i = 1\right) = E\left(y_{ji}{}^1 \middle| T_i = 1\right) - E(y_{ji}{}^0 | T_i = 1) \tag{4}$$

66. In this equation, y_{ji} represents the respective outcomes of interest for household j located in community i and T_i represents the treatment dummy, which takes the value of 1 if household j is located in a treated community i and 0 otherwise. The ATT corresponds to the difference in expectations (E) between the outcomes of the treatment group ($T_i = 1$) after receiving the project activities ($y_{ji}{}^1$) and the outcomes of the same group if this group had not received the project activities ($y_{ji}{}^0$). Both statuses cannot be observed simultaneously: a household either benefits from the project or does not. The latter situation, in which a treated household does not benefit from the project, is the one that we do not observe. This situation is referred to as the potential outcome and is estimated in a matching model.

[14] Variables only sufficiently captured at midline include the CSI and variables related to agricultural production, yield, harvest value, and share of harvest for non-consumption.
[15] As a robustness check, matching was also performed on a second set of variables.

D. Robustness checks

67. Five different regression models were used for all DiD estimates as presented in the tables above. Column (1) presents the baseline (ordinary least squares) OLS model, column (2) adds household demographics as control variables,[16] column (3) includes additional controls for respondent demographics,[17] column (4) adds further controls based on occupation or income source fixed effects which helps control for unobserved differences in patterns across different occupations. And column (5) adds village fixed effects to control for unobserved heterogeneity across villages. For matching estimates, an OLS regression was run with fixed effects as the baseline model. Five matching models were then run, including all four additional sets of control variables: (i) household demographics, (ii) additional controls for respondent demographics, (iii) further controls based on occupation or income source fixed effects, and (iv) village fixed effects to control for unobserved heterogeneity across villages.

68. In addition, we performed two robustness checks to test the consistency of the estimates derived from matching. Firstly, we use and report two different matching algorithms. We perform both nearest-neighbour matching and one-to-one matching. Furthermore, we perform matching on an alternative set of indicators, as shown in Appendix 5. Therefore, our matching results are robust when using different matching algorithms and propensity scores derived from different matching indicators.

E. Sampling strategy and sample size

69. As explained above, all the targeted sectors' farmers were eligible for some project activities. Hence, the evaluation team needed to identify a group of comparison communities outside the Green Gicumbi's intervention area. Following discussions, the project team identified the southern part of the Gicumbi District, situated around the Nyabugogo catchment, as particularly suitable for comparison, as it shared the most similar agroecological characteristics. Nonetheless, to further enhance the two areas' comparability, the LORTA team recommended conducting matching at the community level based on available secondary data. The local survey firm responsible for this step at baseline indicated that control villages were selected such that the distribution (average value) of key village level variables was as similar as possible between the beneficiary and control villages. Seven villages in each of the nine control sectors were selected according to secondary data on agroecological zones, exposure to hazard risks, distance to river/water bodies, distance to all-weather roads, population density, poverty level, elevation, main crops cultivated in the village/land-use, and exposure to other interventions or projects in agriculture and environmental protection (Bukure, Kageyo, Muko, Mutete, Nyankenke, Nyamiyaga, Rukomo, Ruvune and Rwamiko).[18] The local firm randomly selected the villages where it would conduct the household survey. Within each sample village, an equal number of households was randomly selected to be interviewed.

[16] The set of controls for household demographic includes the count of total household members, gender and age of the household head, and a continuous variable for the household monthly income.
[17] Controls for respondent characteristics include factors such as age, education, relationship to the household head, and respondent's marital status. These control variables help incorporate additional demographic aspects within the household by examining the characteristics of an adult in the household, distinct from the household head.
[18] The fairly strong balance achieved between treatment and control households at baseline (shown in Appendix 3) indicate that the selected control sectors were indeed similar to treatment sectors.

F. POWER CALCULATIONS

70. The number of households to be interviewed in the several rounds of the household survey was determined by power calculations. At baseline, a sample size of 1,200 households was considered sufficient to detect an impact of the project activities, considering an equal allocation ratio between treatment and control groups. Given this sample size, the Minimum Detectable Effect Size (MDES) was estimated for a power of 80 per cent and a statistical significance level of 5 per cent. As treatment and control households were clustered by village, power calculations must account for different intra-cluster correlation coefficient (ICC) values. The MDES was calculated for four different ICC values: 0.05, 0.10, 0.15, and 0.20.

71. Using one measure of vulnerability to climate hazards, the vulnerability index, a sample size of 1,200 households would allow us to detect a decrease in vulnerability of between 17.3 per cent and 28.7 per cent.[19] The sample size of 1,200 was adjusted to 1,260 households to obtain an equal dispersion of households in the intervention and control areas. Appendix 2 contains the formula used and the exact MDES values.

G. ATTRITION ANALYSIS

72. A key challenge when working with repeated cross-sections is that, depending on the sample size, the characteristics of midline and endline samples vary systematically from the baseline sample. Within a panel data study, this is referred to as attrition, which refers to missing observations. In other words, it concerns households disappearing from the sample due to death, destitution and migration, among other reasons.

73. Attrition reduces the power of a study and can affect the degree to which findings can be extrapolated to the wider population the sample was drawn from. Moreover, if different proportions of treatment or control units attrite from the sample at midline or endline, this can impart a degree of bias into samples. It is important to know whether the characteristics of households that disappear from the treatment and control groups vary systematically. Typically, evaluators check whether differential attrition has occurred by running a probit regression for the sample interviewed at baseline. In this approach, the dependent variable equals 1 if a household was not interviewed at midline and 0 otherwise. The independent variables are taken from the baseline survey and typically consist of key sociodemographic characteristics of the baseline household. This allows these variables to be held constant when calculating impact estimates.

74. In this repeated cross section design, a different approach is required. The sampling approach for this IE means that all households living in 18 of the 21 sectors of the Gicumbi District form the survey population. All nine sectors in which the Green Gicumbi Project was introduced form the treatment group. From the 12 remaining sectors in the district that did not benefit from project activities, nine were selected as the control group based on their similarity to the treatment sectors' population, socioeconomic and physical characteristics. Within each sector, a two-stage sampling approach was used. First, seven villages were randomly selected within each sector. Second, 10 households were selected from within each village. So, at baseline, 630 households were interviewed within treatment sectors, and 630 households were interviewed within control sectors.

[19] Gicumbi District scored 0.471 on the vulnerability index, which ranges from 0 to 1 and where higher numbers indicate increased vulnerability to hazards (Rwanda Environment Management Authority, 2018). Power calculations were performed using this variable as this was one measure of exposure to climate shocks for which pre-intervention data was available.

75. Appendix 1 illustrates the number of households interviewed at midline. We see, once again, the same seven villages targeted within each sector and 10 households selected from within each village. We also note several discrepancies with the original sampling design. For treatment households, we see that, instead of 630 households targeted for data-collection, only 620 households were targeted due to the exclusion of Kagera village, from the Rwankonjo cell, in the Cyumba sector. Moreover, we note that, for the remaining 62 villages, over half (32) had a different number of interviewed households than intended, ranging from six more households to two fewer households.[20] For example, we can see that Burambira and Gipandi villages, from the Nyambara cell, in the Cyumba sector, provided an additional four and six households, respectively.[21] Overall, 639 households were interviewed within treatment sectors.

76. When we turn to control households, we see that from the 10 households targeted for data-collection across the 63 villages, 21 villages provided either more or less than 10 observations, ranging from two more to one less. We also note that Sabiro village, from the Cyuru cell, in the Rukomo sector, was excluded at midline, with three additional households interviewed from other villages in the Rukomo sector. Overall, 641 households were interviewed at midline in control sectors, leading to a total of 1,280 households.

77. As explained above for panel data, differential attrition of treatment and control households can impart bias into impact estimates. Similarly, the observed discrepancies within the number of households interviewed per village can introduce bias into our estimates. Due to this, we need to assess the degree to which the values of key sociodemographic characteristics of the households interviewed at midline differ significantly from those provided at baseline. In contrast to panel data, where this is done through a probit regression, our approach here is to conduct a series of analyses of covariance (ANCOVA) models at village level.

78. Analysis of covariance tests the null hypothesis that there is no significant difference in a continuous variable between two or more groups, controlling for covariates. This is obtained from the variance. If the variance between the groups (based on the variance of group means from the total mean) is much greater than the variance within the groups (based on the variance from the group mean), this suggests a significant difference. This is the F-ratio (between-group variance by within-group variance). Our null hypothesis is that there is no significant difference in the dependent variable between baseline and midline surveys for each village. We also include further dependent variables as covariates. So, an ANCOVA is conducted for each village, comparing the variable's value across baseline and midline surveys.

79. Table IV–1 provides a concise overview of the results obtained from the village level ANCOVA analysis conducted on key sociodemographic household characteristics. The analysis reveals that, overall, there is no distinct or apparent trend in changes within household characteristics between the baseline and midline surveys. Statistical significance at the 5 per cent or 1 per cent level is seldom observed in the context of any demographic characteristic. When it does occur, it is typically linked to a specific village by chance. When we expand the criteria to a 10 per cent level of significance, a slightly larger proportion of villages exhibit some variations in demographic characteristics. Nonetheless, these instances remain within expectations for the 10 per cent level. In summary, we can confidently assert that attrition does not pose a significant threat to the reliability of our estimations. Moreover, the eight variables were included as covariates in DiD estimates and

[20] Some discrepancy is expected since enumerators were instructed to oversample respondents per sector. Some villages had fewer interviews than initially planned because respondents could not be tracked from baseline to midline and no suitable replacement respondents were found.

[21] This can be seen as a form of replacement for Kagera village, from the Rwankonjo cell, in the Cyumba sector by the survey firm.

as matching variables within PSM estimates. This ensured that any systematic differences between baseline and midline were controlled in impact estimates.

Table IV–1. ANCOVA significant effects across baseline and midline surveys – village level

	10% LEVEL	5% LEVEL	1% LEVEL	NO. OF VILLAGES
Age of household head	9	4	1	125
Gender of household head (male)	7	4	0	125
Household size	1	2	2	125
Household head can read or write	6	2	3	125
Dependency ratio	5	4	1	125
House located near a river or marshland	4	3	1	125
House located in high-risk zone	9	7	5	125
Tropical livestock units	5	4	0	125

H. DATA AND QUALITY ASSURANCE

80. This section briefly describes all the collected data sources relevant to this evaluation, starting with the baseline and midline surveys.

1. BASELINE SURVEY

81. The baseline survey was conducted in the last quarter of 2020. It captured a wealth of information, including general demographic, social, and economic characteristics of the respondents and the household. Given the outcome variables of interest, the survey tool included information on land property, farming, agricultural inputs, and practices by parcel and plots. Information was collected on each parcel's location, ownership, use, and size. Further, data was collected on the type of crops planted and other sustainable agriculture activities such as soil types and irrigation methods, pesticides, fertilizers, and CRA practices. The survey also covered the farmer's awareness of the consequences of climate change, experience of multiple natural hazards, and access, understanding, and use of WCS. In addition, data on other relevant outcome variables such as wealth, livestock health, food security, access to clean water, energy, transportation, and climate information was collected.
82. As mentioned earlier, baseline data suffered from measurement issues in some of the collected indicators, notably the level of disaggregation of agricultural production, cultivated area, and plot sizes. These errors were adjusted for during midline data-collection, and they do not affect the quality of matching. The baseline data set was used for the DiD estimates, including when matching individuals in treated communities to those in non-treated communities, using indicators that jointly affect project participation and the outcomes of interest.

2. Midline survey

83. The midline survey was conducted in January and February of 2023 by SESMEC, the contracted data-collection firm. A few adjustments were made to the baseline survey. One adjustment was the above-mentioned changes to the level of disaggregation on which agricultural production and cultivated areas were collected. Notably, these indicators were now captured at the plot rather than parcel level, as they were captured at baseline. While the midline survey more accurately captures agricultural production, it does mean that it could not be perfectly merged with the baseline survey, making a DiD estimation strategy impossible to follow for agricultural indicators. Data-collection took place using tablets and aimed at reaching a total sample of 1,260. Ultimately, 1,258 households were interviewed. As noted previously, the same individuals were not followed from baseline to midline, meaning the collected data takes the form of a repeated cross section rather than a panel data set.

84. The survey population was all households living in private dwellings during the interviewing period (January and February 2023) in the 18 sectors of the Gicumbi District, illustrated in Figure II–1. Nine of the 18 sectors were in the project intervention area, while the remaining nine served as a control group and lay outside the intervention area of the Gicumbi District.[22] The targeted group comprised selected disaggregated households sampled as described in sub-section E. The sample size was determined based on the power calculations described in sub-section E. It was clear that nine control sectors selected during the baseline study were maintained.[23]

3. Data-collection

85. In the fieldwork preparation phase, representatives from SESMEC Ltd, LORTA, MOE and FONERWA were actively involved in training sessions and analysing the questionnaire's suitability for data-collection. The translated questionnaire in Kinyarwanda was validated, digitized, and uploaded to the tablets using the KoboToolbox software app. This training helped fine-tune the questionnaire, train the enumerators on the fieldwork, and identify and address possible challenges in the field.

86. KoboToolbox was used to collect field data on a mobile device and transmit it to a server, from where the data could be extracted for subsequent analysis. The GPS facility incorporated in KoboToolbox helped to monitor geographical locations and the progress of the interviews. This enhanced the findings' quality, validity, and reliability. KoboToolbox facilitated compiling and submitting data progress reports showing the total interviews completed, remaining interviews, and the challenges faced in each case.

4. Pre-test of midline survey tool

87. A pre-test was undertaken after three days of training supervisors and enumerators to ensure the appropriateness of data-collection tools and the wording of the questionnaire. The key objective of the pre-test was to assess the data-collection procedures and identify any irregularities in the questionnaire. The pre-test also helped determine how many questionnaires an enumerator could complete daily. The pre-test was carried out in the Kigali Sector, Mwendo Cell, in the villages of Isangango and Umutekano, with respondents who shared characteristics similar to those in the

[22] Those in the intervention area include Bwisige, Byumba, Cyumba, Kaniga, Manyagiro, Mukarange, Rubaya, Rushaki, and Shangasha sectors. Bukure, Kageyo, Muko, Mutete, Nyankenke, Nyamiyaga, Rukomo, Ruvune and Rwamiko sectors served as control group.

[23] These sectors did not benefit directly from project interventions and did not benefit indirectly from project activities. These nine control sectors have similar as possible physical, demographic, and socio-economic characteristics to the treatment sectors.

Gicumbi District but were not part of either the treatment or control group. For the pre-test, the 20 enumerators were divided into four teams of five enumerators and one supervisor. Two teams were allocated to each village. Each enumerator was assigned to conduct at least two surveys. The fieldwork for data-collection began on 25 January and finished on 4 February 2023, with the enumerators and supervisors returning home on 4 February 2023. The planned number of interviews per village and the number of interviews performed can be found in Appendix 1.

I. CHALLENGES ENCOUNTERED WITH THE RESEARCH DESIGN, INCLUDING ATTRITION

88. Several challenges were encountered during the field data-collection exercise.
89. **Difficulty in accessing respondents**: Firstly, it was challenging to reach respondents who did not have access to mobile phones. Secondly, migration posed a challenge as people frequently moved, particularly along the border and in urban areas. Lastly, there were poor road networks and bridges in some areas. Sometimes, the survey team had to walk long distance to reach the sampled villages. The survey team coordinated with the local community leaders to improve the chances of reaching hard-to-access respondents and increase the response rate. However, after several attempts by the survey team to reach potential respondents failed, people of the same characteristics replaced the unreachable respondents after consultation with the survey manager.
90. **Survey fatigue**: The respondents found it challenging to complete the questionnaire because it required making complex estimates, such as land size, yields, fertilizer, pesticides and seeds. For instance, it was difficult to estimate yields for tea and coffee. Moreover, the large number of questions caused some respondents to lose interest. Also, respondents in control groups were not interested in participating in the interviews. To address this, the survey team took time with each question to help household members make reasonable estimations. In addition, the survey team used recall techniques to make estimates. To deal with the questionnaire's length, the survey team tried to be patient and used encouraging language. The survey team collaborated with community leaders to encourage control group members to participate.
91. **Incentivization**: Some interviewees requested money to participate in the research (*Insimburamubyizi*) to compensate for lost time. To address this, the survey team had to explain the purpose of the study to the respondents, emphasizing that no compensation was planned. Community leaders were also asked to inform household members that no budget was allocated for the research.
92. **Connectivity**: It was challenging for the survey team to keep constant and reliable communication with the respondents due to the lack of a communication network. The survey team addressed this challenge by liaising with the village chairperson to obtain the necessary information.

J. SOFTWARE AND CODE

93. The research team primarily used two different software apps to perform the IE. As noted, the field team used KoboToolbox to implement the survey and collect data for analysis. This data was stored in BoxCryptor before being exported for analysis in Stata. The research team used Stata to merge the collected midline data with baseline data. Stata was further used to clean the received data, such as identifying and trimming outliers. Following the data cleaning process, the DiD and matching impact estimates were performed using Stata. The code used to merge the data sets, clean the data, and run the impact estimates was recorded in Stata do-files. Table IV–2 lists all employed software.

Table IV–2. Software apps used during the evaluation's lifecycle

Software	Purpose	Project objects derived
KoboToolbox	Data-collection	Midline data set
BoxCryptor	Data storage	Storage of collected midline data set
Stata	Data merging, cleaning, and analysis	Merged baseline and midline data set Cleaned merged baseline and midline data set Impact estimates tables

K. Ethics

94. We stored the data collected in BoxCryptor. Strict protocols were in place to ensure that only designated investigative team members could access the data. Additionally, data was de-identified. Personal identifying information was separated and stored in an alternate data set with a common key linking the main de-identified data set to the data set with personal identifying information.
95. The data-collection was subject to ethical approval by relevant Rwandan authorities. The data-collection was underpinned by a commitment to integrity, honesty, and competence. Participation in data-collection was voluntary. All respondents gave their informed consent before participating in interviews, which were carried out privately, and anonymity was assured. Respondents were informed that consent could be revoked at any time without any repercussions.

V. PRESENTATION OF RESULTS

A. Baseline balance

96. Appendix 3 reports on baseline balance tests. Household sociodemographic characteristics are balanced at baseline, with the only significant difference being that the control household heads are significantly more likely to be literate, as shown in Table A - 3. At baseline, treatment households live in significantly riskier locations. However, they enjoy equal or better access to drinkable water, all-weather roads, food markets, primary education, and health facilities than control households, as seen in Table A - 4.

97. Treatment and control households are equally likely to be farmers and have equal household and durable assets (see Table A - 5). Control households own significantly more livestock (measured in TLUs) than treatment households. Finally, as Table A - 6 highlights, treatment and control households have indistinguishable financial characteristics at baseline.

98. To summarize, the baseline balance was relatively strong between treatment and control households. However, control households tend to be more literate, live in less risky locations, and own more livestock. In addition, our empirical approach further reduces any potential omitted variable bias. The DiD empirical strategy accounts for differences in time-invariant observable[24] and unobservable characteristics. At the same time, PSM narrows any time-variant differences based on observable characteristics.

B. Impact estimates

99. This section of the report displays the midline impact estimates. The DiD approach assesses the effects of the project on CRA practice adoption rates and the number of practices adopted, as well as changes in the types of cooking fuel used. It is also used to analyse measures of food security and adaptive capacity. On the other hand, matching techniques are employed in instances where we seek to estimate the influence of the project on outcomes, such as food security and the CSI, agricultural crop production, total value of production, harvest yield, and the share of production designated for non-consumption purposes. Impacts on output level indicators are presented first, answering EQ1 and EQ2. Impacts on outcome level indicators are presented second, answering EQ3 and EQ4. Impact estimates on the impact level are presented last, addressing EQ5.

1. Output level impact estimates

100. The output level impact estimates seek to answer EQ1 and EQ2 by analysing the impact of the Green Gicumbi Project on CRA adoption and the quantity and type of cooking fuel.

a. CRA adoption

101. Table V–1 presents DiD estimates on adopting at least one CRA practice, and the number of CRA practices adopted. In Panel A, the dependent variable is binary, indicating whether a farmer adopts any critical CRA practices.[25] This suggests that the treatment positively impacts the proportion of

[24] The literacy rates of household heads and geographic characteristics, such as living in more or less risky locations, are arguably time-invariant over the timespan of this evaluation.

[25] The DiD estimate suggests the percentage change in the adoption of CRA practices due to the treatment. Details of the five models are presented in the robustness section above. All control variables are taken from baseline and midline values.

treatment households adopting CRA practices. The magnitude of the effect slightly increases as we move from the basic OLS model (20.3 percentage points) and gradually control for potential confounders and fixed effects. We also see the accuracy of the models increasing from columns (1) to (5), as illustrated in the higher adjusted R-squared figures. The most robust specification is in column (5), which controls for household demographics, respondent characteristics, and fixed effects for income source and village, indicating a 23.9 percentage point increase in the proportion of treatment households adopting CRA practices. To put the magnitude of the estimate in context, 57 per cent of treatment farmers reported using at least one CRA practice at baseline.

102. Panel B presents analogous specifications to Panel A. The dependent variable is a continuous measure of the total number of suggested CRA practices[26] adopted by farmers. The specifications across columns (1) to (5) indicate an increase of 0.5 to 0.57 CRA practices adopted by treatment households, against a pre-treatment mean of 1.12 CRA practices adopted per household. Overall, the estimates consistently show that the treatment had a positive and statistically significant impact on the proportion of treatment households adopting CRA practices (Panel A) and the number of adopted practices (Panel B).

Table V–1. Adoption of CRA practices and number of CRA practices - DiD estimates[27]

	(1)	(2)	(3)	(4)	(5)
Panel A	**Dep Var=1 if farmer adopts CRA practices[28]**				
DiD estimate: time*treated	0.203***	0.214***	0.216***	0.233***	0.239***
	(0.060)	(0.059)	(0.058)	(0.057)	(0.037)
Time= Midline	-0.028	-0.045	-0.045	-0.019	-0.016
	(0.043)	(0.041)	(0.040)	(0.041)	(0.028)
Baseline mean	0.603	0.603	0.603	0.603	0.603
Observations	2557	2557	2557	2557	2557
Adjusted R-squared	0.017	0.035	0.045	0.088	0.179
Household demographics	No	Yes	Yes	Yes	Yes
Respondent characteristics	No	No	Yes	Yes	Yes
Income source fixed effects	No	No	No	Yes	Yes
Village fixed effects	No	No	No	No	Yes
Panel B	**Dep Var= No of CRA practices adopted by farmer**				
DiD estimate: time*treated	0.492***	0.527***	0.520***	0.550***	0.566***
	(0.162)	(0.161)	(0.156)	(0.154)	(0.095)
Time= Midline	-0.016	-0.059	-0.061	-0.019	-0.001
	(0.110)	(0.109)	(0.104)	(0.101)	(0.066)

[26] Out of a total of seven CRA practices suggested and displayed in Table V–2.
[27] In Panel A, the regression table reports the coefficients for whether a farmer adopts any CRA practices regressed on a DiD variable, which is an interaction between an indicator for treatment status of the observed farmer and an indicator representing the year/time of each observation. In Panel B, the regression table reports the coefficients associated with regressions of a variable that records the total number of CRA practices adopted by farmers, regressed on a DiD variable which is an interaction between an indicator for treatment status of the observed farmer and an indicator representing the year/time of each observation. Standard errors are clustered within village x-year cells.
[28] Dep Var is used in the report as shorthand for dependent variable.

	(1)	(2)	(3)	(4)	(5)
Baseline mean	1.13	1.13	1.13	1.13	1.13
Observations	2557	2557	2557	2557	2557
Adjusted R-squared	0.028	0.054	0.077	0.125	0.243
Household demographics	No	Yes	Yes	Yes	Yes
Respondent characteristics	No	No	Yes	Yes	Yes
Income source fixed effects	No	No	No	Yes	Yes
Village fixed effects	No	No	No	No	Yes

Note: *** p<0.01 **p<0.05 *p<0.1

103. Table V–2 shows the outcomes of DiD estimates on households adopting specific types of CRA practices. Across columns (1) through (5), the DiD estimates show a positive, statistically significant treatment effect on the proportion of treatment households adopting the practices being evaluated. The project led to a greater proportion of treatment households adopting wastewater treatment (18.3 percentage points), radical terracing (14.5 percentage points), rainwater harvesting (14.2 percentage points), lightening protection (11.3 percentage points), irrigation schemes (6.5 percentage points), as well as a greater proportion of treatment households adopting alternative fuels (by 3.1 percentage points). A slightly negative impact (0.6 percentage points) on farmers' adoption of crop varieties indicates a need for reflection by implementing agencies and a focus on this CRA practice in the endline evaluation.

Table V–2. Types of CRA practices - DiD estimates[29]

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A	**Dep Var=1 if farmer adopts specific type of CRA practice**[30]						
DiD estimate: time*treated	0.113***	0.142***	0.183***	0.031***	0.065*	-0.006*	0.145***
	(0.024)	(0.037)	(0.037)	(0.010)	(0.036)	(0.003)	(0.028)
Time= Midline	-0.067***	-0.005	-0.020	0.020***	0.068**	-0.001	-0.072***
	(0.017)	(0.028)	(0.028)	(0.007)	(0.026)	(0.002)	(0.019)
Dep-Variable (type of CRA)	Lightning protection	Rainwater harvesting	Wastewater treating	Alternative fuel	Irrigation schemes	Crop varieties	Radical terracing
Baseline mean	0.192	0.223	0.279	0.012	0.004	0.409	0.243

[29] The regression table reports the coefficients associated with regressions of an indicator variables for whether a farmer adopts a specific type of CRA practice regressed on a DiD variable. This is an interaction between an indicator for the treatment status of the observed farmer and an indicator representing the year of each observation, conditional on a set of controls for household and respondent demographics, the primary source of income for the household, and village-specific fixed effects. Standard errors are clustered within village x year cells.
[30] The DiD estimates show the proportion of treatment households adopting each type of CRA practice due to the treatment. All specifications controls for household demographics, respondent characteristics, and fixed effects for income source and village, while standard errors are clustered within village x year cells. In other words, the specification is the same as column (5) above. All control variables for DiD are taken from baseline and midline values.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Observations	2557	2557	2557	2557	2557	2557	2557
Adjusted R-squared	0.188	0.154	0.188	0.058	0.167	0.018	0.262
Household demographics	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Respondent characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Income source fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Village fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: *** p<0.01 **p<0.05 *p<0.1

b. Type of fuel used for cooking

104. Table V–3 displays the DiD estimates concerning various measures for the main source of fuel for cooking. Project activities are expected to increase the use of improved cookstoves, as these were provided to treatment households, and treatment households were strongly encouraged to use them.[31] In column (1), the dependent variable is the number of firewood bundles used per week. The OLS estimate (the coefficient on the indicator for "Time = Midline") shows a strong decrease in the number of firewood bundles used from baseline to midline. This decrease was found for both treatment and control households. However, the decrease was stronger for control households than for treatment households. The DiD point estimate indicates treatment households used an additional two firewood bundles used per week compared to control households. In column (2), the dependent variable is the weekly number of charcoal sacks used, where the point estimates suggest an additional amount of 0.18 charcoal sacks used per treatment household per week compared to control households. The negative coefficient on "Time=Midline" shows that charcoal consumption strongly decreased from baseline to midline. However, this decrease is greatest among control households.

105. The use of traditional stoves decreased from baseline to midline for both treatment and control households. However, this decrease was much stronger for control households than treatment households, leading to a positive coefficient for treatment households of 31.9 percentage points. The usage of improved cookstoves also increased for both groups from baseline to midline, although the increase is again more pronounced among control households. Improved cookstoves are more energy-efficient and require less firewood to operate than traditional cooking stoves. Therefore, the statistically significant higher levels of firewood usage among the treatment group can be ascribed to a slower rate when adopting improved cookstoves[32] from baseline to midline, compared to a higher rate in adopting improved cookstoves in the control group.

[31] Usage of improved cookstoves was high among households that reported receiving them. At midline, 60 per cent of treatment households reported receiving an improved cookstove from the Green Gicumbi project. Of these households, 88 per cent report using an improved cookstove, versus only 45 per cent of treatment households that did not report receiving an improved cookstove.

[32] Indeed, the OLS estimate indicates that, overall, the adoption of improved cookstoves increased overtime. The negative point estimate on the DID estimator for this measure is driven by an even higher positive rate for adoption of improved cookstoves among the control group.

Table V–3. Types of fuel used for cooking - DiD estimates[33]

	(1) Firewood bundles	(2) Charcoal	(3) Stove	(4) Improved stove	(5) Gas/ electric stove	(6) Other
	Dep Var = Source of fuel for cooking					
DiD estimate: time*treated	2.090***	0.180*	0.319***	-0.294***	-0.001	-0.025**
	(0.695)	(0.106)	(0.037)	(0.037)	(0.002)	(0.012)
Time = Midline	-9.094***	-0.893***	-0.442***	0.458***	-0.002	-0.014**
	(0.542)	(0.044)	(0.025)	(0.025)	(0.001)	(0.007)
Baseline mean	10.417	1	0.465	0.500	0.001	0.032
Observations	2384	1277	2485	2485	2485	2485
Adjusted R-squared	0.430	0.580	0.205	0.231	0.037	0.208
Household demographics	Yes	Yes	Yes	Yes	Yes	Yes
Respondent characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Income source fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Village fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

Note: *** p<0.01 **p<0.05 *p<0.1

2. Outcome level estimates

106. The outcome level estimates seek to answer EQ3 and EQ4 by analysing the Green Gicumbi Project's impact on household food security and agricultural resilience.

a. Food security

107. Regarding households' dietary diversity index score, the descriptive statistics in Table A - 16 show that treatment households displayed a significantly worse score (3.95) compared to control households (4.32), significant at the 1 per cent level.[34] In column (1) of Table V–4, the DiD estimates refine these descriptive statistics and show that, while treatment households report a slightly lower score, this remains insignificant after controlling for household and respondent demographics, source of income, and village-specific fixed effects.

108. When we look at column (2), the dependent variable is a binary measure indicating if the household faced any food shortage during the previous year. In the descriptive statistics at midline, both

[33] The regression table reports the coefficients associated with regressions of different measures for main source of cooking fuel regressed on a DiD variable. This is an interaction between an indicator for treatment status of the farmer/household and an indicator representing the year/time of each observation, conditional on a set of controls for household and respondent demographics, the major source of income for the household and village specific fixed effects. The dependent variable in column (1) is the number of firewood bundles used per week, the dependent variable in column (2) is the number of charcoal sacks used per week, while the dependent variables in columns (3) through (6) are indicator variables for various equipment used as the main mode of cooking. Standard errors are clustered within village x-year cells.

[34] This is in comparison to baseline values of 3.86 and 4.10 for treatment and control households respectively, significant at the 1 per cent level.

treatment and control households showed a very similar figure, with around 50 per cent reporting a food shortage.[35] Looking at the midline only estimates in Table V–4 (controlling for household and respondent demographics, source of income, and village-specific fixed effects), we observe a greater proportion of treatment households reporting food shortages in the past year to 18 per cent of households. However, when we look at the trend between baseline and midline values (as well as controlling for household and respondent demographics, source of income, and village-specific fixed effects), we note that a decrease in the proportion of treatment households reporting food shortages is 17.6 percentage points. Putting these three findings together (the descriptives, midline estimates with controls, and DiD with controls), these results suggest the project has a positive effect for treatment households but is mostly driven by increases in the food shortages experienced by control households and not by an improvement in the situation of treatment households.

109. When we look at column (3) of Table V–4, we see the number of days without sufficient harvest food reported by households. The descriptive statistics highlighted an insignificant difference of seven days less for treatment households for this indicator. The midline impact estimates (with controls) report an insignificant nine days less for treatment households. However, the DiD estimates (with controls) suggest an insignificant increase of 14 days for treatment households. The endline survey will need to pay careful attention to this particular issue.

Table V–4. Measures of food security - DiD estimates[36]

	(1) HDDS	(2) FOOD SHORTAGE	(3) DAYS OF SHORTAGE
	Dep Var: Measures of food security		
DiD estimate: time*treated	-0.120	-0.176***	14.224
	(0.108)	(0.033)	(9.309)
Time = Midline	0.074	0.179***	-9.844
	(0.083)	(0.022)	(7.283)
Baseline mean	3.978	0.417	69.751
Observations	2557	2557	1169
Adjusted R-squared	0.243	0.184	0.133
Household demographics	Yes	Yes	Yes
Respondent characteristics	Yes	Yes	Yes
Income source fixed effects	Yes	Yes	Yes
Village fixed effects	Yes	Yes	Yes

Note: *** p<0.01 **p<0.05 *p<0.1

b. Food security: CSI score

110. Table V–5 presents estimates for the household CSI. The CSI defines the coping strategies needed or used by each household to respond to food insecurity, with higher scores indicating a greater

[35] At baseline, around 33 per cent of control households reported having a food shortage, whereas the proportion of treatment households has stayed constant at around 50 per cent. The negative coefficient in column (2) is perhaps driven by an increase in food insecurity among control households.

[36] The regression table reports the coefficients associated with regressions of different measures of food security regressed on a DiD variable. This is an interaction between an indicator for treatment status of the farmer/household and an indicator representing the year/time of each observation, conditional on a set of controls for household and respondent demographics, major source of income for the household as well as village specific fixed effects. Standard errors are clustered within village x year cells. All control variables for DiD are taken from baseline and midline values.

number and severity of coping strategies. The descriptive statistics show that, at midline, treatment households reported a higher CSI score, with a difference of almost five units, with treatment households reporting a score of 13.791, and control units reporting a score of 8.613, significant at the 1 per cent level.

111. Table V–5 shows that when we control for household demographics, respondent characteristics, income source, and village fixed effects through OLS and PSM estimates,[37] we find negative estimates (ranging from -4 to -3.3 units) consistent across specifications.[38] The most robust estimate in column (3) suggests that treatment status is associated with a decrease of 3.3 points in the CSI score.[39] It is important to recognize that these figures are solely based on midline data, as the baseline data set did not allow for calculating the CSI. In this respect, the estimates do not capture any changes in time for the treatment sample relative to the control sample. Instead, the OLS and PSM estimates control for observable characteristics at baseline only.

112. Analysing this estimate with the estimates in Table V–4 suggests that the project led to a lower proportion of treatment households reporting food shortages, on average, and that these households were now using less severe coping strategies compared to control households.

Table V–5. CSI - matching estimates[40]

	(1) OLS	(2) 1-1 Match	(3) N-N match
	Dep Var: Measures of food security		
Treatment status = 1	-3.637***	-3.950***	-3.343***
	(0.866)	(1.139)	(0.885)
Midline mean	11.635	11.635	11.635
Observations	1257	948	1245
Adjusted R-squared	0.214	0.231	0.206
Household demographics	Yes	Yes	Yes
Respondent characteristics	Yes	Yes	Yes
Income source fixed effects	Yes	Yes	Yes
Village fixed effects	Yes	Yes	Yes

Note: *** p<0.01 **p<0.05 *p<0.1

c. Agricultural resilience: Crop production and value of production

113. Table V–6 presents an analysis of crop production based solely on midline data using two different estimation approaches: OLS with fixed effects in Panel A and matching estimates in Panel B. All specifications across Panels A and B use a full set of control variables and fixed effects. Panel A

[37] Details on matching variables and the associate probit model are presented in Appendix 5.
[38] The point estimate is a little lower in magnitude in column (2), which is explained by excluding some observations that did not qualify for the strict 1:1 matching algorithm.
[39] The mean CSI score across the midline sample is 11.2, ranging from 0–80 overall.
[40] This sample is restricted to midline observations only. The regression table reports the coefficients associated with regressions of a measure for the household CSI regressed on an indicator variable for the treatment status of the farmer/household, conditional on a set of controls for household and respondent demographics, the major source of income for the household, and village specific fixed effects. Column (1) presents estimates from a baseline OLS specification, the specification in column (2) matches control and treatment observations based on a 1:1 matching algorithm, while the specification in column (3) matches control and treatment observations based on a k-nearest neighbours matching algorithm. Standard errors are clustered within village x-year cells. All control variables for matching estimates are taken from baseline/midline values.

shows a significant increase in crop production for beans (92 kg, significant at the 1 per cent level), a 1,226 kg increase in sweet potatoes (significant at the 1 per cent level), and a substantial -6,062 kg reduction in bananas (significant at the 5 per cent level).[41] Panel B presents more reliable matching estimates. The positive estimates for beans and sweet potatoes and the negative estimates for bananas are consistent and remain statistically significant.[42] These estimates refine the descriptive statistics shown in Appendix 3 by reconfirming the increased production of sweet potatoes by treatment households and greater production of bananas for control households. They also show that treatment households increased bean production significantly but not maize production, as suggested in the descriptive statistics in Table A - 15.[43]

114. Table V–7 is analogous to Table V–6, apart from the dependent variable, which shows the total production value.[44] Table V–7 shows that only the difference in the value of bananas is statistically significant (with control households growing a greater value of this crop, at the 1 per cent level). The full set of control variables refine these estimates and show that the total value of bean production is not greater in treatment households, as suggested by the descriptive statistics presented in Table A - 15.

d. Agricultural resilience: Harvest yield

115. Table V–8 shows the yield per ha for different crops. OLS with fixed effects estimations are presented in Panel A, and matching estimates are presented in Panel B. All specifications across Panels A and B use a full set of control variables and fixed effects. Except for beans, treatment households do not experience higher yields.[45] The per ha yield for beans improved by 1.76 tonnes/ha for treatment households, more than the control mean of 1.339 tonnes/ha.[46] The higher yields for sweet potatoes shown in the descriptive statistics are not present in these refined impact estimates.

e. Agricultural resilience: share of production for non-consumption

116. In Table V–9, the non-consumption share of crops is examined. The non-consumption share is the harvest share households do not consume and, therefore, have available for sale. Estimates using OLS with fixed effects are presented in Panel A, and matching estimates are presented in Panel B.[47] Except for beans, none of the estimates are statistically significant. The point estimates across Panel A and B are consistently negative and statistically significant for beans. Indeed, the negative point estimate in the matching model is higher in magnitude, suggesting the non-consumption share dropped by 9.3 percentage points in treatment households. This means treatment farmers store or sell less of their crops than control farmers.[48]

[41] No significant impact on potatoes, maize or sorghum production was recorded.
[42] The magnitude of the treatment effect is almost consistent across the OLS/FE and matching models.
[43] It is important to recognize that these figures are based on only midline data. The estimates do not capture any changes over time for the treatment sample relative to the control sample. Instead, the OLS and PSM estimates control for observable characteristics at midline only.
[44] We use the price at which smallholder farmers reported selling their produce.
[45] This compares to the midline yield increases estimated by sector agronomists of 13 per cent for maize, 22 per cent for beans, 21 per cent for Irish potato and 7 per cent for wheat, as reported by the MOE. In both our findings and the secondary data, beans show the largest increase in yield. However, we do not detect any further significant increases in yield, possibly due to small observation numbers.
[46] It is important to recognize that these figures rely solely on midline data. The estimates do not capture any changes over time for the treatment sample relative to the control sample. Instead, the OLS and PSM estimates control for observable characteristics at midline only.
[47] All Panel A and B specifications use a full set of control variables and fixed effects.
[48] Results are similar when considering the total amount of crops sold. Only the point estimate on bananas is statistically significant (at the 1 per cent level), showing that treatment farmers sell 1,554 kg less than control farmers. While the point estimate for the amount of beans sold is negative, it does not reach statistical significance.

Table V–6. Crop production - matching estimates[49]

	(1) Beans	(2) Potatoes	(3) Maize	(4) Sorghum	(5) Sweet potato	(6) Banana	(7) Other
Panel A: OLS/FE[a]			**Dep Var: Total size of harvest (kg)**				
Treatment status = 1	92.875***	-679.583	74.859	62.015	1226.153***	-6062.038**	-77.438
	(12.056)	(3299.02)	(58.998)	(73.036)	(227.506)	(2455.111)	(512.90)
Midline mean	98.273	457.888	133.308	90.840	234.722	377.9641	278.221
Observations	691	107	348	268	252	167	113
Adjusted R-squared	0.049	0.436	0.060	0.370	-0.179	-0.043	0.678
Household demographics	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Respondent characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Income source fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Village fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Panel B: NN matching			**Dep Var = Total size of harvest (kg)**				
Treatment status = 1	92.357***	279.064	82.928	43.510	1242.551***	-6209.871**	-59.013
	(12.099)	(3635.257)	(69.341)	(60.190)	(236.148)	(2540.434)	(520.111)
Midline mean	98.273	457.888	133.308	90.840	234.722	377.9641	278.221
Observations	682	105	346	261	250	165	111

[49] In Panel A, the sample is restricted to midline observations only. The regression table reports the coefficients associated with regressions of measures for production of different crops regressed on an indicator variable for the treatment status of the farmer/household, conditional on a set of controls for household and respondent demographics, the major source of income for the household as well as village specific fixed effects. In Panel B, the sample is restricted to midline observations only. The regression table reports the coefficients associated with regressions of measures for production of different crops regressed on an indicator variable for the treatment status of the farmer/household, conditional on a set of controls for household and respondent demographics, major source of income for the household, and village specific fixed effects, but specifications in columns (1) through (7) match control and treatment observations based on a k-nearest neighbours matching algorithm. Standard errors are clustered within village x-year cells.

	(1) BEANS	(2) POTATOES	(3) MAIZE	(4) SORGHUM	(5) SWEET POTATO	(6) BANANA	(7) OTHER
Adjusted R-squared	0.011	0.533	0.092	0.457	-0.133	-0.045	0.668
Household demographics	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Respondent characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Income source fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Village fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: *** p<0.01 **p<0.05 *p<0.1
[a]OLS = Ordinary Least Square model; FE = Panel Fix-Effects model

Table V–7. Total value of production - matching estimates[50]

	(1) BEANS	(2) POTATOES	(3) MAIZE	(4) SORGHUM	(5) SWEET POTATO	(6) BANANA	(7) OTHER
Panel A: OLS/FE	**Dep Var = Total value (thousand Rwandan Francs) of harvest**						
Treatment status = 1	-7.998	189.787	27.668	48.658	8.713	-858.543***	9.066
	(13.209)	(743.552)	(75.952)	(47.318)	(25.974)	(314.296)	(161.650)
Midline mean	61.216	108.892	134.884	30.686	18.937	64.757	103.911
Observations	691	107	348	268	282	167	113
Adjusted R-squared	0.125	0.809	0.109	0.506	0.051	0.052	0.627
Household demographics	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Respondent characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Income source fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes

[50] In Panel A, the regression table reports the coefficients associated with regressions of standardized measures of value of total production for different crops regressed on an indicator variable for treatment status of the farmer/household, conditional on a set of controls for household and respondent demographics, major source of income for the household as well as village specific fixed effects. In Panel B, the sample is restricted to midline observations only, and the regression table reports the coefficients associated with regressions of standardized measures of value of total production for different crops regressed on an indicator variable for treatment status of the farmer/household, conditional on a set of controls for household and respondent demographics, major source of income for the household as well as village specific fixed effects, but specifications in columns (1) through (7) match control and treatment observations based on a k-nearest neighbours matching algorithm. Standard errors are clustered within village x year cells.

	(1) BEANS	(2) POTATOES	(3) MAIZE	(4) SORGHUM	(5) SWEET POTATO	(6) BANANA	(7) OTHER
Village fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Panel B: NN matching	**Dep Var = Total value (thousand Rwandan francs) of harvest**						
Treatment status = 1	-6.599	290.264	37.920	49.407	4.379	-896.992***	10.212
	(13.105)	(767.340)	(88.036)	(43.569)	(25.884)	(316.641)	(160.575)
Midline mean	61.216	108.892	134.884	30.686	18.937	64.757	103.911
Observations	682	105	346	261	281	165	111
Adjusted R-squared	0.152	0.756	0.135	0.568	0.174	0.126	0.578
Household demographics	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Respondent characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Income source fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Village fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: *** p<0.01 **p<0.05 *p<0.1

Table V–8. Total yield - matching estimates[51]

	(1) BEANS	(2) POTATOES	(3) MAIZE	(4) SORGHUM	(5) SWEET POTATO	(6) BANANA	(7) OTHER
Panel A: OLS/FE	**Dep Var = Yield per ha (tonnes)**						
OLS/FE estimate: 1 = Treatment	1.719***	-17.194	-0.006	-1.303	13.927	12.928	3.029
	(0.282)	(60.502)	(3.029)	(0.985)	(13.599)	(281.353)	(5.352)

[51] In Panel A, the regression table reports the coefficients associated with regressions of yield per ha for different crops regressed on an indicator variable for the treatment status of the farmer/household, conditional on a set of controls for household and respondent demographics, the major source of income for the household, and village specific fixed effects. In Panel B, the sample is restricted to midline observations only. The regression table reports the coefficients associated with regressions of yield per ha for different crops regressed on an indicator variable for the treatment status of the farmer/household, conditional on a set of controls for household and respondent demographics, the major source of income for the household, and village specific fixed effects, but specifications in columns (1) through (7) match control and treatment observations based on a k-nearest neighbours matching algorithm. Standard errors are clustered within village x-year cells.

	(1) BEANS	(2) POTATOES	(3) MAIZE	(4) SORGHUM	(5) SWEET POTATO	(6) BANANA	(7) OTHER
Midline mean	1.388	6.666	2.380	1.467	5.568	25.071	21.851
Observations	686	107	346	266	179	165	111
Adjusted R-squared	0.017	0.027	-0.257	0.228	-0.439	-0.396	0.999
Household demographics	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Respondent characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Income source fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Village fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Panel B: NN matching estimates				**Dep Var = Yield per ha (tonnes)**			
Matching estimate: 1 = Treatment	1.776***	-13.880	-0.353	-1.262	11.718	-1.796	3.219
	(0.246)	(59.893)	(3.091)	(1.124)	(11.721)	(282.042)	(5.419)
Midline mean	1.388	6.666	2.380	1.467	5.568	25.071	21.851
Observations	677	105	344	259	178	163	109
Adjusted R-squared	0.152	0.149	-0.255	0.300	-0.418	-0.387	0.999
Household demographics	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Respondent characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Income source fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Village fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: *** p<0.01 **p<0.05 *p<0.1

Table V–9. Total share of production not for own consumption - matching estimates[52]

	(1) BEANS	(2) POTATOES	(3) MAIZE	(4) SORGHUM	(5) SWEET POTATO	(6) BANANA
Panel A: OLS/FE	**Dep Var = Share available to sell/Total production**					
OLS/FE estimate: 1 = Treatment	-0.076**	-1.053	0.130	0.066	-0.045	-0.871
	(0.032)	(1.343)	(0.106)	(0.191)	(0.279)	(0.648)
Midline mean	0.204	0.375	0.188	0.274	0.125	0.305
Observations	687	103	335	261	174	152
Adjusted R-squared	0.069	0.785	0.152	0.006	0.029	0.382
Household demographics	Yes	Yes	Yes	Yes	Yes	Yes
Respondent characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Income source fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Village fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Panel B: NN matching estimates	**Dep Var = Share available to sell/Total production**					
Matching estimate: 1=Treatment	-0.093***	-1.112	0.139	-0.038	-0.029	-0.865
	(0.032)	(1.180)	(0.107)	(0.204)	(0.290)	(0.662)
Midline mean	0.204	0.375	0.188	0.274	0.125	0.305
Observations	678	101	333	254	173	150
Adjusted R-squared	0.068	0.816	0.185	0.073	-0.016	0.366

[52] In Panel A, the regression table reports the coefficients associated with regressions of non-consumption share of different crops regressed on an indicator variable for the treatment status of the farmer/household, conditional on a set of controls for household and respondent demographics, the major source of income for the household, and village specific fixed effects. In Panel B, the sample is restricted to midline observations only. The regression table reports the coefficients associated with regressions of non-consumption share of different crops regressed on an indicator variable for the treatment status of the farmer/household, conditional on a set of controls for household and respondent demographics, the major source of income for the household, and village specific fixed effects. Specifications in columns (1) through (6) match control and treatment observations based on a k-nearest neighbour matching algorithm. Standard errors are clustered within village x-year cells. Recognizing that these figures are solely based on midline data is important. The estimates do not capture any changes over time for the treatment sample relative to the control sample. Instead, the OLS and PSM estimates control for observable characteristics at midline only.

	(1) BEANS	(2) POTATOES	(3) MAIZE	(4) SORGHUM	(5) SWEET POTATO	(6) BANANA
Household demographics	Yes	Yes	Yes	Yes	Yes	Yes
Respondent characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Income source fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Village fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

Note: *** $p<0.01$ ** $p<0.05$ * $p<0.1$

f. Agricultural resilience: Measures of adaptive capacity

117. Table V–10 displays the results of a DiD analysis concerning measures of adaptive capacity.[53] The estimates are statistically insignificant for measures of total TLUs and the CRI.[54] The estimate for the standardized income diversification variable is statistically significant and negative. The coefficient shows a statistically significant decrease of 0.15 in the mean number of income sources for treatment households, indicating that treatment households showcase less income diversification.[55]

Table V–10. Measures of adaptive capacity - DiD estimates[56]

	(1) TLU	(2) INCOME DIVERSIFICATION[57]	(3) CRI
		Dep Var = Adaptive capacity	
DiD estimate: time*treated	0.029	-0.152*	-0.004
	(0.024)	(0.078)	(0.007)
Time = Midline	-0.044**	-0.169***	-0.000
	(0.022)	(0.060)	(0.005)
Baseline mean	0.397	0.155	0.518
Observations	2557	2557	1169
Adjusted R-squared	0.120	0.214	0.643
Household demographics	Yes	Yes	Yes
Respondent characteristics	Yes	Yes	Yes
Income source fixed effects	Yes	Yes	Yes
Sector and village fixed effects	Yes	Yes	Yes

Note: *** p<0.01 **p<0.05 *p<0.1

3. Impact level estimates – Heterogeneity analysis

118. This section reports the project's heterogenous gendered effects.

[53] Throughout columns (1) to (3), specifications control for household demographics, respondent characteristics, and fixed effects for income source and village. Standard errors are clustered within village x year cells.
[54] See section III for how these variables are constructed.
[55] Recall that the descriptive statistics reported that a greater proportion of treatment households (10 per cent) were engaged in non-farm activities.
[56] The regression table reports the coefficients associated with regressions of different measures of adaptive capacity regressed on a DiD variable. This is an interaction between an indicator for the treatment status of the farmer/household and an indicator representing the year/time of each observation, conditional on a set of controls for household and respondent demographics, the major source of income for the household, and village specific fixed effects. The dependent variable in column (1) is the total number of TLU, the dependent variable in column (2) is a standardized measure of income diversification, while the dependent variable in column (3) is a standardized measure of the CRI. Standard errors are clustered within village x-year cells.
[57] Households were asked, "What is the source of household income in last 12 months - January-December 2022?" (1) Food crops farming; (2) Cash crops farming (3) Business (4) Selling of logs, wood, timber and/or charcoal (5) Artisan (6) Part time wage employment (7) Full time wage employment (8) Renting property (9) Retirement allowances (10) Gifts/remittances (11) Mining and queries (12) Animal husbandry and products (13) Any other. The number of sources of income in January–December 2022 were standardized. The question in Kinyarwanda is "*Mu mezi 12 ashize (Kuva mukwa 1 kugeza mukwa 12 muri 2022), ni hehe mwakuraga ibitunga umuryango muri ibi bikurikira*?"

a. CRA adoption by gender

119. Table V–11 provides insightful heterogeneity estimates for the adoption of CRA practices, disaggregated by female and male-headed households. The analysis distinguishes between these gender categories, focusing on two distinct outcome variables: the adoption of any CRA practice (columns 1 and 2) and the total number of CRA practices adopted (columns 3 and 4).

120. In columns (1) and (2), the results reveal a notable gender-based disparity. Female-headed households exhibit a robust and statistically significant DiD estimate of 0.276 (significant at the 1 per cent level), signifying a substantial positive impact of the introduction of CRA practices on adoption within this group. Conversely, male-headed households demonstrate a slightly lower, yet still significant, DiD estimate of 0.230 (significant at the 1 per cent level). These findings underscore a gender-specific effect, suggesting that implementing CRA practices has a more pronounced and favourable influence on adoption among female-headed households than male-headed (married) households.

121. A similar pattern emerges when assessing the count of CRA practices adopted. In columns (3) and (4), female-headed households demonstrate a noteworthy DiD estimate of 0.813 (significant at the 1 per cent level), indicating a substantial increase in the total number of CRA practices embraced over time. In contrast, male-headed households also display a significant DiD estimate of 0.521 (significant at the 1 per cent level), suggesting a discernible rise in the count of CRA practices adopted, albeit to a lesser extent than the increase observed among female-headed households.

Table V–11. Adoption of CRA practices and number of CRA practices by gender – DiD estimates

Panel A	Adopt CRA practice		CRA practices (count)	
	(1) Female	**(2) Male**	**(3) Female**	**(4) Male**
DD estimate: time*treated	0.276***	0.230***	0.813***	0.521***
	(0.083)	(0.040)	(0.218)	(0.106)
Time = Midline	-0.049	-0.011	-0.166	0.023
	(0.081)	(0.030)	(0.215)	(0.072)
Baseline mean	0.598	0.609	1.126	1.131
Observations	509	2036	509	2036
Adjusted R-squared	0.176	0.177	0.200	0.245
Household demographics	Yes	Yes	Yes	Yes
Respondent characteristics	Yes	Yes	Yes	Yes
Income source fixed effects	Yes	Yes	Yes	Yes
Village fixed effects	Yes	Yes	Yes	Yes

Note: *** p<0.01 **p<0.05 *p<0.1

b. Type of fuel used for cooking by gender

122. Heterogeneity estimates for the type of fuel used for cooking are presented in Table V–12, utilizing a DiD approach. This analysis distinguishes between female and male-headed households, with a focus on variations in the use of firewood bundles and traditional stoves.

123. In columns (1) and (2), the DiD estimates reveal intriguing gender-specific patterns in the choice of cooking fuel. Female-headed households display a substantial and statistically significant DiD estimate of 1.189 fewer firewood bundles, suggesting a marked shift away from this traditional fuel source (significant at the 1 per cent level). In contrast, male-headed households exhibit a significantly higher DiD estimate of 2.686 (significant at the 1 per cent level), indicating a notable increase in the use of firewood bundles within this group. These findings highlight a gender-based divergence in fuel choices, with female-headed households moving away from firewood bundles. In contrast, male-headed households show an opposite trend.

124. Similar gender disparities are not observed in the use of traditional stoves, as demonstrated in columns (3) and (4). Female-headed households exhibit a highly significant DiD estimate of 0.327 (significant at the 1 per cent level), indicating an increased preference for traditional stoves. Male-headed households also display a significant DiD estimate of 0.337 (significant at the 1 per cent level), indicating a propensity to adopt traditional stoves over time.

Table V–12. Types of fuel used for cooking by gender– DiD estimates

Panel X	Firewood bundles		Traditional stove	
	(1) Female	**(2) Male**	**(3) Female**	**(4) Male**
DD estimate: time*treated	-1.189	2.686***	0.327***	0.337***
	(1.416)	(0.714)	(0.089)	(0.041)
Time = Midline	-6.994***	-9.406***	-0.482***	-0.440***
	(1.255)	(0.567)	(0.084)	(0.028)
Baseline mean	10.065	10.871	0.492	0.428
Observations	456	1914	499	1975
Adjusted R-squared	0.435	0.429	0.225	0.191
Household demographics	Yes	Yes	Yes	Yes
Respondent characteristics	Yes	Yes	Yes	Yes
Income source fixed effects	Yes	Yes	Yes	Yes
Sector and village fixed effects	Yes	Yes	Yes	Yes

Note: *** p<0.01 **p<0.05 *p<0.1

c. Food security by gender

125. Table V–13 presents heterogeneity estimates for different food security measures, distinguishing between male and female-headed households. Starting with the HDDS score in columns (1) and (2), we see that female-headed households demonstrate a DiD estimate of -0.286, although this coefficient lacks statistical significance. In contrast, male-headed households exhibit a DiD estimate of -0.107, which similarly fails to reach statistical significance. These results suggest that there may be no substantive gender disparities in the changes observed in HDDS.

126. Turning to the presence of food shortages, examined in columns (3) and (4,) our analysis uncovers intriguing gender-specific patterns. Female-headed households display a statistically significant DiD estimate of -0.234 (significant at the 1 per cent level), indicating a reduced likelihood of encountering food shortages over time. Male-headed households also exhibit a significant DiD

estimate of -0.179 (significant at the 1 per cent level), suggesting a decreased probability of food shortages. However, the point estimate is smaller in magnitude. Turning to columns (5) and (6), showing estimates for the absolute number of days of food shortages experienced during the previous year, the estimate for female-headed households is -5.466 days, although it lacks statistical significance. In contrast, male-headed households display a positive and notably higher DiD estimate of 19.182 days (significant at the 10 per cent level). This outcome implies that male-headed households may experience more days characterized by food shortages than female-headed households.

Table V–13. Types of fuel used for cooking by gender– DiD estimates

PANEL X	HDDS		FOOD SHORTAGE		DAYS OF SHORTAGE	
	(1) Female	**(2) Male**	**(3) Female**	**(4) Male**	**(5) Female**	**(6) Male**
DD estimate: time*treated	-0.286	-0.107	-0.234***	-0.179***	-5.466	19.182*
	(0.215)	(0.121)	(0.079)	(0.037)	(24.169)	(10.594)
Time = Midline	0.355*	0.053	0.229***	0.185***	-7.789	-15.482**
	(0.204)	(0.099)	(0.071)	(0.025)	(24.451)	(7.663)
Baseline mean	3.893	4.095	0.443	0.382	69.705	69.824
Observations	509	2036	509	2036	219	914
Adjusted R-squared	0.197	0.246	0.146	0.193	0.092	0.136
Household demographics	Yes	Yes	Yes	Yes	Yes	Yes
Respondent characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Income source fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Village fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

Note: *** p<0.01 **p<0.05 *p<0.1

d. Food security: CSI scores by gender

127. Table V–14 presents the matching estimates for the CSI, a crucial indicator of households' ability to cope with food security challenges. The analysis seeks to discern gender-specific disparities in food security measures and how treatment status influences these outcomes for female and male-headed households.

128. In columns (1) and (2), the results reveal distinct patterns in the context of food security measures. Female-headed households exhibit a noteworthy and statistically significant DiD estimate of -8.560 (significant at the 1 per cent level), indicating a substantial decline in resorting to coping strategies for food security. Conversely, male-headed households display a DiD estimate of -2.198 (significant at the 5 per cent level), suggesting a significant but less pronounced reduction in food security measures. These findings highlight a significant gender-based difference in the impact of treatment status on food security, with female-headed households experiencing a more substantial decline.

Table V–14. CSI by gender – Matching estimates

	N-N MATCH	
	(1) Female	**(2) Male**
Panel D	**Dep Var: Measures of food security**	
Treatment status = 1	-8.560**	-2.198*
	(3.297)	(1.274)
Midline mean	11.795	10.456
Observations	258	987
Adjusted R-squared	0.412	0.196
Household demographics	Yes	Yes
Respondent characteristics	Yes	Yes
Income source fixed effects	Yes	Yes
Sector and village fixed effects	Yes	Yes

Note: *** p<0.01 **p<0.05 *p<0.1

C. ROBUSTNESS CHECKS

129. As explained above, we perform two robustness checks to test the consistency of the estimates derived from matching, using nearest-neighbour matching and one-to-one matching. The estimates derived from matching stay consistent across these two algorithms. Furthermore, we perform matching on an alternative set of matching variables, as shown in Appendix 5. Results remain unchanged when using the propensity scores derived from the alternative matching indicators (not shown). Therefore, our matching results are robust when using different matching algorithms and propensity scores derived from different matching indicators.

VI. DISCUSSION

130. In this discussion, we analyse the midline results of the Gicumbi project, interpreting it considering the ToC, its underlying assumptions, broader social and economic theory, and insights from heterogeneity analyses. This discussion attempts to answer key questions related to the project's outcomes, heterogeneity, mechanisms at work, the reasons behind deviations from expectations, contradictions in results, the implications for the ToC, and possible implications for the evaluation strategy going forward.

131. Our first set of estimates examines farmers' adoption of CRA practices and technologies. In the treatment areas, there has been a notable increase in the proportion of households adopting CRA practices, ranging from 20.3 to 23.9 percentage points, compared to a midline mean adoption rate of 60.6 per cent among control households. This translates to an average of 0.5 to 0.57 additional CRA practices and technologies adopted per treatment household. The assessment of the number of CRA practices adopted shows how, on average, female-headed households have adopted 0.813 additional practices (significant at the 1 per cent level), compared to 0.521 by male-headed households (significant at the 1 per cent level).

132. The second key set of estimates relates to different outcomes for food security, where we find that treatment households have a similar HDDS to control households. In addition, we find that a smaller proportion of treatment households are reporting food shortages.[58] Regarding CSI scores, households in treatment areas report a reduction in CSI scores (ranging between 3.3 and 4 units – depending on the matching algorithm utilized) compared to control households. We do not find a consistent set of significant findings across the four food security measures, with no change in HDDS or the days of food shortage experienced. In contrast, the probability of experiencing a food shortage and household CSI scores decreased. Combining the findings on food security suggests a considerable improvement from baseline values for treatment households. However, there is still a large amount of work to be done. For example, changes in food security indicators have not substantially influenced household dietary diversity outcomes or the number of days when food shortages were experienced. This outcome is broadly in line with expectations, as the intervention's impact on immediate-term outcomes may differ from its longer-term effects, such as shifts in dietary diversity. Such outcomes often hinge on behavioural shifts and the sustained perception of income security, which might not manifest significantly in midline data-collection but has the potential to evolve. This will be a key focus within the endline IE.

133. When we look at the gender of the household head, female-headed households display a greater reduction of food shortages over time of -0.234 (significant at the 1 per cent level) compared to male-headed households (-0.179, significant at the 1 per cent level). Moreover, we can see that female-headed households show a greater improvement in CSI scores (a DiD estimate of -8.56, significant at the 1 per cent level) than male-headed households (who display a DiD estimate of -2.198, significant at the 5 per cent level). In addition, the number of days of food shortages experienced during the previous year is insignificant for female-headed households at -5.466 days, while male-headed households show an increase of 19.2 days (significant at the 10 per cent level). These findings suggest that the food security of female-headed households has improved due to project interventions. The reasons for these differences will be investigated in the endline IE.

134. The project's impact on agricultural production, productivity, value of production and income was also estimated. We find a significant increase in crop production for beans (between 92.4 kg and 92.9 kg), sweet potatoes (between 1,226 kg and 1,242 kg), and a decrease in bananas (between

[58] The point estimate shows a 17.5 percentage point reduction in the reported incidence of food shortage among treatment households.

6,210 kg and 6,062 kg). The decrease in banana production reported by 67 treatment households may be related to radical terracing activities within the plots and parcels of treatment households as treatment households substitute to crops more suited for growing in terraces. This issue can be investigated further at endline. Despite the greater production of beans and sweet potatoes in treatment areas, there are no increases in the value for these crops. In contrast, the greater production of bananas in control areas translates into higher values of between 858,543 and 898,990 Rwandan francs (equivalent to USD 769.48 to USD 803.95, using mid-market exchange rates on 3 April 2023). Turning to yields, the only crop that shows a statistically significant greater yield is beans, with treatment areas now yielding an additional 1.72 to 1.78 tonnes per ha compared to control areas. This is economically important, considering control areas yield 1.339 tonnes/ha at midline.

135. Interestingly, the share of bean production not for consumption in treatment households, which signifies the amount available for sale as a proportion of total production, has decreased by 7.6 and 9.3 percentage points for beans. This finding raises questions, as bean production and yields have increased. It suggests that treatment households may be inclined to sell less of this staple crop, possibly indicating limited food security within these households. Additionally, it could imply that beans are preferred for household consumption, given their nutritional attributes. In summary, at midline, the intervention enhanced the agricultural productivity of specific crops like beans and sweet potatoes. However, similar improvements were not observed for other key crops, such as potatoes, maize, and sorghum. Since agricultural yield was a central objective within the project's ToC, the endline IE will pay close attention to this.

136. More broadly, we can reflect on the broader findings on climate impacts on staple crops within the country (Austin and others, 2020), which suggest the greatest impacts will be on maize, a variety of beans, and Irish potatoes, with yield reductions ranging from 10 to 15 per cent. However, these climate impacts may not hold in highland areas. The improved bean yields suggest not only improved food production on the farm but also the potential for greater food access in due course through greater sales.

137. Turning to livelihoods, income diversification, and the CRI, we observe that TLUs and CRI scores in treatment area households are not significantly different from those in control areas. However, it is noteworthy that the standardized income diversification indicator reveals a statistically significant decrease of 0.15 standardized units in the average number of income sources for households in the treatment group. According to the ToC assumptions, the intervention was expected to lead to income source diversification and increased TLUs as direct outcomes. As there is potential for these outcomes to gradually improve as the intervention's effects propagate through the causal chain, these outcomes will be a key focus on the endline IE.

138. The final set of indicators relates to using cleaner energy for cooking. The use of firewood bundles and charcoal sacks decreased over time across both treatment and control households. However, the causal estimate based on the DiD estimates appears negative, as the adoption of cleaner cooking practices was even higher among control households compared to a positive, albeit lower, adoption rate among treatment households. Similarly, while adopting improved cookstoves increased among treatment households, the use of improved cookstoves increased at a greater rate among control households. The causal estimate indicates that the use of improved stoves and other cooking modes decreased by 29.4 percentage points among treatment households compared to control households. The utilization rates are almost twice as high among treatment households that reported receiving improved cookstoves (88.11 per cent) from the project than among treatment households that did not receive an improved cookstove (44.69 per cent). However, only 60 per cent of treatment households have reported receiving an improved cookstove, indicating significant scope for increasing improved cookstove usage through their more extensive distribution.

139. When we look at the gender of the household head, female-headed households display an insignificant reduction in the number of firewood bundles (1.189) compared to an increase by male-headed households (2.686, significant at the 1 per cent level). These findings highlight a gender-based divergence in fuel choices. Similar gender disparities are not observed in the use of traditional stoves. The reasons for the changed cooking practices of households in treatment areas will need to be captured fully at endline.

VII. CHALLENGES AND SHORTCOMINGS

140. As highlighted above, several challenges were encountered during the field data-collection exercise, including difficulty accessing respondents, survey fatigue, incentivizing respondents, and connectivity. In addition, the evaluation design evolved, as the initial approach involved matching and DiD analysis. Yet, the feasibility of this approach hinged on creating a panel data set linking the same household at baseline and midline. Due to constraints during fieldwork and other factors, the survey team could not maintain consistent household identification. There were also some differences in the questionnaires used at baseline and midline, making their merging difficult.

141. The evaluation proceeded with the DiD analysis using two cross-sections instead of panel data, ensuring that variables were defined consistently throughout. Where variables were not consistently defined across baseline and midline data-collection, matching methods were used to draw reliable and credible causal estimates. As mentioned, the baseline data suffered from measurement issues with some of the collected indicators. These notably included the level of disaggregation of agricultural production, cultivated area, and size of parcels and plots. These errors were adjusted for during midline data-collection through matching, which involved employing statistical methods to create a valid comparison group. In this process, each treated unit is paired with a non-treated unit exhibiting the most closely aligned observable characteristics.

142. The team also encountered a challenge related to attrition. In this repeated cross section design, a different approach is required to that used with panel data (using a probit model with the dependent variable equal to one when households attrite from the sample). Attrition can impart bias into impact estimates. Similarly, the observed discrepancies within the numbers of households interviewed per village can impart bias into our estimates. Due to this, we assessed the degree to which the values of key sociodemographic characteristics of the households interviewed at midline differ significantly from those provided at baseline through a series of ANCOVA models at the village level. The analysis revealed that, overall, there is no distinct or apparent trend in changes within household characteristics between the baseline and midline surveys. When significant differences occur, it is through chance, as shown by the increase in villages from 1 per cent to 5 per cent and 10 per cent levels of significance. We are confident the repeated cross section design does not pose a significant threat to the reliability of our estimates. Moreover, the eight variables were included as covariates in DiD estimates and as matching variables within PSM estimates, ensuring that any systematic differences between baseline and midline were controlled in our impact estimates.

VIII. CONCLUSION

143. The primary focus of the intervention revolves around climate change and its impacts, particularly in the context of Rwanda's vulnerable Gicumbi District. The Gicumbi District is exposed to various climate hazards and suffers from high poverty levels and dependence on traditional farming methods. The intervention under evaluation was launched in 2019, aiming to enhance the climate resilience of vulnerable communities in the district. Interventions included ecosystem restoration, sustainable forest management, and climate-smart agriculture. The IE of the Green Gicumbi Project comprises three waves of data-collection: baseline, conducted in June-July 2020; midline, conducted in April 2023; and endline, scheduled for 2025. The project terminates in May 2025.

144. This midline study evaluated project impacts through five key evaluation questions categorized by output, outcome, and impact levels. EQ1 and EQ2 focus on project outputs and assess the adoption of CRA practices and cleaner energy usage, respectively, using indicators such as the proportion of households adopting CRA practices and the quantity of firewood and charcoal used for cooking. EQ3, at the outcome level, examines the impact on food security and diversity, utilizing indicators like the HDDS and the CSI in assessing experiences of food shortages. EQ4, also at the outcome level, gauges the influence of project activities on smallholder farmers' resilience, considering factors like agricultural production, livelihood sources, and a CRI. Finally, at the impact level, EQ5 investigates whether project activities enhance female participation in economic life, analysing gender-specific indicators related to CRA practices adoption, fuel usage, dietary diversity, and coping strategies during food shortages.

145. Findings related to EQ1, concerning the adoption of CRA practices and technologies, reveal that treatment areas experienced a substantial increase in the proportion of households adopting these practices, often effectively doubling the number of practices per household.

146. Regarding food security and diversity (EQ3), treatment households report a reduction in the likelihood of food shortages and lower CSI scores (lowering by between 3.3 and 4 units). However, while immediate-term impacts on food security may have improved, these do not yet show in long-term improvements.

147. EQ4 assesses the impact on agricultural production and resilience. We found a significant increase in the production of beans and sweet potatoes. However, the non-consumption share of beans in treatment households has decreased, suggesting possible retention of this crop for food security. Findings regarding livelihoods and income diversification (EQ4) show that treatment households exhibit no significant changes in total livestock units and CRI scores. However, there is a statistically significant decrease of 0.15 standardized units in the average number of income sources for households in the treatment group, contrary to the project's expectations. This will be examined in detail at endline.

148. EQ2 examines the production and use of cleaner energy for cooking and finds that treatment households are adopting cleaner energy at a lower rate compared to control households. Despite some positive changes, such as a reduction in the use of firewood bundles and charcoal sacks and an increase in the adoption of improved stoves among treatment households, these improvements are smaller in magnitude when compared with control households. The reasons are unclear, but this underscores the potential and need to enhance the use of clean energy among treatment households. The project should also focus more on providing treatment households with improved cookstoves, as treatment households that received improved cookstoves are much more likely to use them than treatment households that did not. At the same time, the Green Gicumbi Project could investigate possible reasons for increased uptake among control households and use those lessons for learning. Again, this will be examined in detail at endline.

149. Finally, there are significant heterogeneous project effects across genders (EQ5), with female-headed households experiencing more pronounced positive impacts in various aspects, including adopting CRA practices, fuel choice, reduced food shortages, and lower reliance on food security coping strategies. In contrast, male-headed households exhibit positive changes to a slightly smaller extent and, in the case of food shortages, even an increase in the number of days characterized by shortages. This emphasizes the importance of gender-specific considerations in project design and implementation for equitable outcomes.

APPENDIX 1. HOUSEHOLDS VISITED PER VILLAGE COMPARED TO TARGET

Table A - 1. Midline data-collection per village

Sector	Cell	Village	Interviews (A)	Target (B)	Difference (B-A)
Bukure	Karenge	Kabuga	10	10	0
	Kigabiro	Gabiro	10	10	0
		Kanyogote	10	10	0
	Kivumu	Butare	10	10	0
		Karambo	10	10	0
	Rwesero	Gicaca	10	10	0
		Mugorore	10	10	0
Bwisige	Bwisige	Kavuruga	10	10	0
		Ndoha	9	10	1
	Gihuke	Nyakagera	10	10	0
		Nyamugari	10	10	0
	Mukono	Rwebisheke	10	10	0
		Rwondo	10	10	0
	Nyabushingitwa	Warufu	10	10	0
Byumba	Gacurabwenge	Gacurabwenge	11	10	-1
	Gisuna	Rebero	8	10	2
	Kivugiza	Mugandu	9	10	1
	Murama	Gacaca	14	10	-4
	Nyakabungo	Gacyamo	10	10	0
	Nyamabuye	Gatete	9	10	1
	Nyarutarama	Mukeri	12	10	-2
Cyumba	Gasunzu	Mugera	10	10	0
	Muhambo	Nyamabare	12	10	-2
	Nyakabungo	Remera	10	10	0
	Nyambare	Burambira	14	10	-4
		Gipandi	16	10	-6
	Nyaruka	Murore	10	10	0
Kageyo	Gihembe	Maya	10	10	0
	Horezo	Kigoma	10	10	0
	Muhondo	Munini	9	10	1
		Mwange	11	10	-1
		Nyaruvumu	10	10	0
	Nyamiyaga	kageyo	8	10	2

Sector	Cell	Village	Interviews (A)	Target (B)	Difference (B-A)
		Rukomo	9	10	1
Kaniga	Bugomba	Gatare	10	10	0
		Ryakabanda	11	10	-1
	Gatoma	Nyakibande	11	10	-1
	Mulindi	Gisunzu	10	10	0
		Taba	10	10	0
	Nyarwambu	Nyamabare	10	10	0
	Rukurura	Kabare	10	10	0
Manyagiro	Kabuga	Gabiro	11	10	-1
	Nyiragifumba	Rwamazi	10	10	0
	Nyiravugiza	Rusebeya	9	10	1
	Remera	Sangano	8	10	2
	Rusekera	Kavure	11	10	-1
		Rebero	11	10	-1
	Ryaruyumba	Gatsyata	9	10	1
Mukarange	Cyamuganga	Ndarama	11	10	-1
	Gatenga	Nyacyoroma	10	10	0
	Kiruhura	Burembo	11	10	-1
		Nyamutoko	9	10	1
	Mutarama	Kaziba	10	10	0
	Rugerero	Munyege	12	10	-2
	Rusambya	Rusambya	10	10	0
Muko	Cyamuhinda	Ntonyanga	10	10	0
	Kigoma	Cyerere	10	10	0
		Karambi	10	10	0
	Mwendo	Gikumba	9	10	1
	Nyange	Gasharu	10	10	0
	Rebero	Gasizi	12	10	-2
		Mayogi	10	10	0
Mutete	Gaseke	Gasharu	10	10	0
		Runyinya	11	10	-1
	Kabeza	Busabira	9	10	1
	Musenyi	Gataba	11	10	-1
		Rurama	10	10	0
	Mutandi	Karama	10	10	0
	Nyarubuye	Kavumu	11	10	-1
Nyamiyaga	Gahumuriza	Maya	11	10	-1
	Jamba	Byimana	11	10	-1

Sector	Cell	Village	Interviews (A)	Target (B)	Difference (B-A)
	Kabeza	Karambo	10	10	0
	Kabuga	Mubuga	10	10	0
	Karambo	Gaseke	11	10	-1
	Kiziba	Karambi	11	10	-1
	Mataba	Mataba	10	10	0
Nyankenke	Butare	Gikombe	10	10	0
	Kigogo	Gakoma	10	10	0
	Kinishya	Gashiru	9	10	1
	Rusasa	Birumba	11	10	-1
	Rutete	Kabingo	10	10	0
	Rwagihura	Mwendo	10	10	0
	Yaramba	Nturo	11	10	-1
Rubaya	Gihanga	Gomba	10	10	0
		Kirimbi	10	10	0
	Gishambashayo	Gashiru	11	10	-1
	Gishari	Kabaya	10	10	0
	Muguramo	Mabare	10	10	0
		Ngange	11	10	-1
	Nyamiyaga	Kabeza	11	10	-1
Rukomo	Cyeya	Birambo	11	10	-1
	Cyuru	Kabuga	10	10	0
	Gisiza	Gatare	10	10	0
		Rusumo	11	10	-1
	Kinyami	Gahondo	11	10	-1
	Mabare	Mburamazi	10	10	0
	Munyinya	Mataba	10	10	0
Rushaki	Gitega	Karambi	10	10	0
		Rubyiro	10	10	0
		Ryaruganzu	10	10	0
	Kamutora	Kamutora	11	10	-1
		Mabare	10	10	0
	Karurama	C. Rushaki	10	10	0
		Nyaruhanga	9	10	1
Ruvune	Cyandaro	Karambo	11	10	-1
	Gasambya	Kirara	10	10	0
	Gashirira	Nyarurama	10	10	0
	Kabare	Murehe	10	10	0
	Rebero	Gatare	10	10	0

Sector	Cell	Village	Interviews (A)	Target (B)	Difference (B-A)
		Taba	10	10	0
	Ruhondo	Kirwa	10	10	0
Rwamiko	Cyeru	Bugarura	10	10	0
		Gabiro	11	10	-1
	Kigabiro	Cyiri	10	10	0
		Kanyove	10	10	0
	Nyagahinga	Kabusunzu	11	10	-1
		Kigaga	10	10	0
		Ntaremba	10	10	0
Shangasha	Bushara	Gasura	11	10	-1
	Kitazigurwa	Iharama	10	10	0
	Nyabishambi	Gasiza	11	10	-1
		Kagali	8	10	2
	Nyabubare	Karuhanga	9	10	1
	Shangasha	Kajyanjyali	10	10	0
		Runaba	9	10	1
Grand total			**1280**		

APPENDIX 2. POWER CALCULATIONS

The number of households to interview in the several rounds of the household survey was determined by power calculations. Power calculations allow for determining the minimum sample size needed to detect the impact of a given intervention. At baseline, a sample size of 1200 households was considered sufficient to detect project activity impact, considering an equal allocation ratio between treatment and control groups.

Power calculations were performed by the LORTA team using the following power formula that relates the sample size to the MDES between the mean outcomes of the two groups:

$$MDES = (t_{1-\kappa} + t_{\alpha})\sqrt{\frac{1}{P(1-P)}}\sqrt{1+\rho(m-1)}\sqrt{\frac{\sigma^2}{N}}\sqrt{1-R^2}$$

where $t_{1-\kappa}$ and t_{α} are t-statistics representing the required power and level of statistical significance, P represents the proportion in one of the two compared groups (allocation ratio), ρ presents ICC, m is the number of individuals per cluster, σ^2 is the variance of the outcome of interest within our population, N is the total sample size and R^2 represents the extent to which baseline characteristics predict the endline outcome.

The MDES was estimated for a power of 80 per cent and a level of statistical significance of 5 per cent. Because the project interventions differ by community, we must account for the similarity of members within the same community. Hence, we consider a clustered design in which a cluster corresponds to a village. The ICC measures the similarity between farmers residing in similar villages, comparing the variance in outcomes within and between villages. When the similarity in outcomes within a village increases and, simultaneously, there is heterogeneity across villages, the variability of farmer responses to the interventions reduces. As a result, the sample size required to detect a significant difference between beneficiaries and the comparison group increases. Table A - 2 presents four different values of ICC: 0.05, 0.10, 0.15 and 0.20.

Table A - 2. Power calculations - vulnerability index

Mean	Baseline standard deviation	ICC	Total sample	R2	MDES in % points	Needed endline level	% change
0.472	0.50	20%	1200	30%	0.113	0.359	24.0%
0.472	0.50	20%	1200	0%	0.135	0.337	28.7%
0.472	0.50	15%	1200	30%	0.104	0.368	22.0%
0.472	0.50	15%	1200	0%	0.124	0.348	26.3%
0.472	0.50	10%	1200	30%	0.093	0.379	19.7%
0.472	0.50	10%	1200	0%	0.111	0.361	23.6%
0.472	0.50	5%	1200	30%	0.081	0.391	17.3%
0.472	0.50	5%	1200	0%	0.097	0.375	20.6%

Source: Vulnerability index from Rwanda Environment Management Authority (2018).

Using the formula above and referring to the vulnerability index, one measure of vulnerability to climate hazards for which pre-intervention data was available, Table A - 2 shows that a sample size of 1,200 would allow us to detect a decrease in vulnerability of between 17.3 per cent and 28.7 per cent. The sample size of 1,200 was adjusted to 1,260 households to obtain an equal dispersion of households in the intervention and control areas.

APPENDIX 3. DESCRIPTIVE STATISTICS

A. SOCIODEMOGRAPHIC INDICATORS AT BASELINE

Table A - 3 below details key household characteristics from the baseline survey conducted in 2020. It shows that both treatment and control households have similarly aged household heads (46), similarly sized households (4.8 members), and households with similar dependency ratios (0.41). Females head 20 per cent of households in both groups, and a similar number of household heads are married (just under 80 per cent). Only one household characteristic is unbalanced: whether the household head can read or write. Here, we see a significantly smaller proportion of treatment households (66 per cent) with literate household heads than 74 per cent of control households.

Table A - 3. Descriptive statistics for sociodemographic characteristics of the household at baseline

Variable	Treatment mean	Control mean	T-test p-value	# obs. treatment	# obs. control
Age of household head	46.808	46.503	0.699	651	648
Gender of household head (male)	0.797	0.807	0.656	651	648
Household size at baseline	4.834	4.801	0.756	651	648
Household head can read or write	0.663	0.735	0.046**	406	275
Marital status of household head	0.778	0.800	0.499	406	275
Dependency ratio at baseline	0.411	0.419	0.508	651	648

Note: Columns 4-5 display the p-value of t-tests for the differences in mean values between treatment and control households. Significance levels are indicated by * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A - 4 below displays the geographical characteristics of households at baseline. A range of characteristics are not balanced at baseline. The first two rows detail the proportion of households located near a river or marshland or in a high-risk zone. We see that a larger proportion of treatment households (9 per cent and 17 per cent , respectively) are positioned in these precarious locations, compared to 2 per cent and 12 per cent of control households (these differences are significant at the 1 per cent and 5 per cent levels, respectively).

In terms of proximity to a source of drinkable water, we see that, on average, treatment households are closer, with a greater proportion of control households over 30 minutes away from a source of drinkable water (significant at the 1 per cent level). On the other hand, we see that a greater proportion of control households are closer to an all-weather road, with significantly more treatment households taking between one to two hours to reach an all-weather road compared to control households (significant at 5 per cent level).

Turning to access to markets, we see mixed results. A greater proportion of treatment households access the closest food market within 30 minutes (14 per cent compared to 8 per cent of control households, significant at the 1 per cent level). However, more treatment households also report taking more than two hours to reach the closest food market (40 per cent of treatment households, compared to 27 per cent of control households, significant at the 1 per cent level). On the other hand, we find more control households (44 per cent) taking between one to two hours compared to 24 per cent of treatment households.

We see a broadly similar pattern in access to the closest primary school, with more treatment households (53 per cent) taking less than 30 minutes to reach this seat of learning, compared to control households (at 48 per cent of households, significant at the 10 per cent level). At the same time, a greater proportion of treatment households (3 per cent) take more than two hours compared to 2 per cent of control households (significant at the 10 per cent level).

Such mixed results are also visible when we observe the time to reach the closest health facility, with 43 per cent of treatment households taking less than 30 minutes (compared to 29 per cent of control households, significant at the 1 per cent level), In comparison, a greater proportion of control households take between 30 minutes and two hours (significant at a minimum 5 per cent level).

Overall, treatment households are located in significantly riskier locations. Yet, compared to control households, most have equal or better access to drinkable water, an all-weather road, a food market, primary education, and health facilities. Nevertheless, a minority of treatment households do appear much more isolated compared to control households, especially when it comes to access to food markets and the closest primary school.

Table A - 4. Descriptive statistics for geographical characteristics of the household at baseline

Variable	Treatment mean	Control mean	T-test p-value	# obs. treatment	# obs. control
House located near a river or marshland	0.089	0.018	0.000***	628	627
House located in high-risk zone	0.166	0.123	0.031**	628	627
Travel time to the closest drinkable water at baseline					
Less than 10 minutes	0.536	0.431	0.000***	651	648
Less than 30 minutes	0.255	0.230	0.293	651	648
Less than an hour	0.097	0.184	0.000***	651	648
More than an hour	0.112	0.156	0.021**	651	648
Travel time to the closest all-weather road					
Less than 30 minutes	0.158	0.151	0.706	650	643
Between 30 minutes and 1 hour	0.163	0.179	0.452	650	643
Between 1 and 2 hours	0.238	0.193	0.046**	650	643
More than 2 hours	0.44	0.477	0.177	650	643
Travel time to the closest market for food products					
Less than 30 minutes	0.141	0.083	0.001***	647	648
Between 30 minutes and 1 hour	0.218	0.207	0.624	647	648
Between 1 hour and 2 hours	0.238	0.441	0.000***	647	648
More than 2 hours	0.403	0.269	0.000***	647	648
Travel time to the closest primary school					
Less than 30 minutes	0.528	0.478	0.071*	651	646
Between 30 minutes and 1 hour	0.341	0.382	0.122	651	646
Between 1 hour and 2 hours	0.097	0.122	0.141	651	646

Variable	Treatment mean	Control mean	T-test p-value	# obs. treatment	# obs. control
More than 2 hours	0.034	0.017	0.055*	651	646
Travel time to the closest health centre					
Less than 30 minutes	0.431	0.286	0.000***	649	647
Between 30 minutes and 1 hour	0.305	0.385	0.003**	649	647
Between 1 hour and 2 hours	0.205	0.267	0.008***	649	647
More than 2 hours	0.059	0.062	0.805	649	647

Note: Columns 4-5 display the p-value of t-tests for the differences in mean values between treatment and control households. Significance levels are indicated by * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A - 5 displays the results for the proportion of household heads who are farmers, household participation in cooperatives, and livestock ownership, measured in TLU. We observe that 89 per cent of both treatment and control households farm, and we can see that a significantly larger proportion of treatment households (15 per cent) are enrolled in a cooperative compared to 10 per cent of control households (at the 5 per cent level). In contrast, control households own significantly more livestock, as reflected in a TLU score of 0.63, compared to 0.49 for treatment households. As livestock is a crucial source of wealth in rural Rwanda, this suggests that control households might, on average, be slightly wealthier than treatment households. This hypothesis is further supported by the finding that, at midline, control households tend to report higher levels of monthly income than treatment households (see Table A - 15 below).

Table A - 5. Descriptive statistics for livelihood profile at baseline

Variable	Treatment mean	Control mean	T-test p-value	# obs. treatment	# obs. control
Household head is a farmer at baseline	0.887	0.891	0.864	406	275
Belongs to a cooperative at baseline	0.154	0.096	0.016**	651	648
Tropical livestock units at baseline	0.493	0.633	0.000***	651	648
Household asset ownership at baseline[59]	-0.219	-0.226	0.876	651	647
Durable assets at baseline[60]	0.061	-0.020	0.164	651	648

Note: Columns 4-5 display the p-value of t-tests for the differences in mean values between treatment and control households. Significance levels are indicated by * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

However, when we observe the findings in Table A - 6, we see that treatment and control households share similar financial characteristics and reliance on social assistance. Both groups are

[59] An Anderson Index was constructed for this measure because it was determined that the principal component analysis was not adequately reducing dimensions of the variables going into the index. An Anderson Index is a standardized weighted index following a generalized least square weighting procedure as described in Anderson (2008). It offers a key advantage over the usual principal component analysis because it does not involve reduction in dimensions of the data. At the most basic level, this index is a weighted mean of several standardized outcomes. The weights are calculated to maximize the amount of information captured in the index. The index is generated by ensuring that higher values for variables included in the index represent more favourable outcomes. Variables are standardized so that the mean takes a value of 0, with a standard deviation of 1. The household asset index was generated by grouping the number of rooms a household has, the materials out of which the household's floors, walls, foundations, and roof were made, household ownership of durable assets, the kind of toilet available to households, and households' main source of drinking water.
[60] Ibid.

balanced in terms of the proportion of households that own a bank account (45 per cent overall), belong to a savings group (just under 49 per cent overall) and receive social assistance (at almost exactly 10 per cent of the total sample).

Table A - 6. Descriptive statistics for the financial characteristics of the household at baseline

Variable	Treatment mean	Control mean	T-test p-value	# obs. treatment	# obs. control
Owns a bank account at baseline	0.455	0.435	0.480	651	648
Belongs to a saving group at baseline	0.470	0.503	0.234	651	648
Reception of social assistance at baseline	0.108	0.094	0.423	651	648

Note: Columns 4-5 display the p-value of t-tests for the differences in mean values between treatment and control households. Significance levels are indicated by * p < 0.10, ** p < 0.05, *** p < 0.01.

B. Output indicators at midline

Moving from baseline to midline, we provide descriptive statistics for the project output indicators covering components One and Two (see Table III–1). We start with access to WCS.

Table A - 7 describes the proportion of treatment and control households that access WCS through different means.[61] We note that a greater proportion of treatment households (23 per cent) have no access to WCS (significant at the 10 per cent level) compared to control households (19 per cent). Moreover, we note that a greater proportion of control households (25 per cent) access WCS via meetings than treatment households (20 per cent). The slightly greater access to climate and weather information displayed by control households is reinforced through the frequency of access, with 28 per cent of control households accessing weather and climate information daily, compared to 22 per cent of treatment households (significant at the 5 per cent level). Moreover, a lower proportion of control households (45 per cent) access weather and climate information occasionally compared to treatment households (52 per cent, significant at the 5 per cent level). On the other hand, we also can see that 8 per cent of treatment households have received training on using weather and climate information, compared to only 5 per cent of control households (significant at the 5 per cent level).

The descriptive statistics indicate that project components support beneficiaries accessing and using WCS. However, more can be done to increase people's awareness and adoption of them. This is especially true considering fewer households report receiving WCS training at midline than baseline.[62]

Table A - 7. Descriptive statistics on access to WCS

Variable	Treatment mean	Control mean	T-test p-value	# obs. treatment	# obs. control
Modes of access to WCS					
No access to weather/climate information	0.234	0.190	0.059*	628	630
Radio	0.457	0.449	0.781	628	630

[61] The question asked was "How do you get access to weather/climate information?" In Kinyarwanda "*Amakuru agendanye n'iteganyagihe abageraho ate*?".
[62] At baseline, 13 per cent of control households report having received training on how to use weather and climate information, compared to 14 per cent of treatment households, with the difference being statistically insignificant.

Variable	Treatment mean	Control mean	T-test p-value	# obs. treatment	# obs. control
Mobile phone	0.422	0.414	0.782	628	630
Television	0.059	0.059	0.988	628	630
Journals	0.008	0.008	0.996	628	630
Meetings	0.202	0.249	0.046**	628	630
Other sources	0.021	0.016	0.523	628	630
Frequency of access to WCS					
Never	0.189	0.200	0.638	628	630
Per day	0.220	0.275	0.024**	628	630
Per week	0.053	0.073	0.135	628	630
Per month	0.014	0.005	0.081*	628	630
Occasionally	0.524	0.448	0.007***	628	630
Receipt of training on WCS					
Received training on how to use WCS	0.083	0.052	0.032**	628	630

Note: Columns 4-5 display the p-value of t-tests for the differences in mean values between treatment and control households. Significance levels are indicated by * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Another output of the project components is to enable farmers to reduce slope erosion to sustainable levels by promoting terracing. Table A - 8 shows that a greater proportion of treatment households (37 per cent) have radical terraces on their land, compared to only 17 per cent of control households (significant at the 1 per cent level).[63] Of those households that reported owning radical terraces (namely, 228 households in the treatment sample and 106 in the control sample), both groups reported a broadly similar area covered by radical terracing.[64]

Table A - 8. Descriptive statistics on radical terracing

Variable	Treatment mean	Control mean	T-test p-value	# obs. treatment	# obs. control
Radical terraces on farmland	0.366	0.170	0.000***	628	630
Area of farmland covered by radical terraces[65]	1 409,055	1 433,239	0.939	228	106

Note: Columns 4-5 display the p-value of t-tests for the differences in mean values between treatment and control households. Significance levels are indicated by * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

We now turn to another central project output: training in CRA practices. Table A - 9 shows the descriptive statistics for receiving training on CRA. It shows that more treatment households have received CRA training (9 per cent) compared to only 5 per cent of control households, significant at the 1 per cent level. Of households that received training, a much greater proportion of treatment

[63] The question was, “Do you have radical terraces in your farmland?”. In Kinyarwanda this translates as “*Waba baraciye amaterasi y’indinganire mu mirima yawe*?”. The area of terracing was asked through “*Muri metero kare*”.
[64] At baseline, 21 per cent of control households reported owning radical terraces, compared to 28 per cent of treatment households (significant at the 1 per cent level). From baseline to midline, the number of treatment farmers owning terraces increased by almost 10 percentage points, whereas the number of control farmers owning terraces decreased marginally.
[65] The units used for this variable include ha, acres, and square meters. Considering that no standard unit was used, the focus is not on the magnitude of the area reported, but the difference in the reported area between control and treatment households. A standard unit will be used at endline.

households received training on small-scale irrigation (21 per cent versus 3 per cent, significant at the 1 per cent level), tree nurseries (26 per cent versus 9 per cent, significant at the 10 per cent level), and improved seed preservation (36 per cent versus 16 per cent, significant at the 5 per cent level). We also see almost double the proportion of treatment households receiving training in tree planting (significant at the 1 per cent level), domestic animal treatments (at the 5 per cent level), terracing and slope maintenance (at the 1 per cent level), crop rotation (at the 5 per cent level), and accounting and improved management for farming (at the 10 per cent level). Overall, treatment households received a wider range of CRA training than control households.

Table A - 9. Descriptive statistics on climate-resilient agriculture

VARIABLE	TREATMENT MEAN	CONTROL MEAN	T-TEST P-VALUE	# OBS. TREATMENT	# OBS. CONTROL
Received any training on CRA	0.092	0.051	0.004***	628	630
Awareness of the adverse effects of climate change	0.672	0.695	0.375	628	630
Type of training received[66]					
Small-scale irrigation	0.207	0.031	0.023***	58	32
Tree nursery	0.259	0.094	0.062*	58	32
Rainwater collecting/harvesting	0.431	0.281	0.164	58	32
Improved grain drying/storage	0.241	0.125	0.191	58	32
Improved seed preservation	0.362	0.156	0.040**	58	32
Mulching of soils	0.190	0.219	0.745	58	32
Inter-cropping methods	0.603	0.531	0.512	58	32
Tree planting	0.672	0.344	0.002***	58	32
Pest and weed control	0.586	0.406	0.104	58	32
Use of organic manure	0.724	0.594	0.210	58	32
Domestic animal treatments	0.586	0.313	0.013**	58	32
Terracing and slope maintenance	0.603	0.313	0.008***	58	32
Crop rotation	0.569	0.344	0.041**	58	32
Mixing trees with crops	0.638	0.500	0.207	58	32
Accounting and improved management for farming	0.448	0.250	0.064*	58	32

Note: Columns 4-5 display the p-value of t-tests for the differences in mean values between treatment and control households. Significance levels are indicated by * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A - 10 displays the results for the sources of agricultural extension received by households. It shows that a greater proportion of treatment households (18 per cent) received extension advice from a project service provider compared to control households (10 per cent), significant at the 1 per cent level. There are no further differences between both groups in terms of the six further sources of agricultural extension, with most advice being received from sector agronomists, veterinary officers, and cooperative officers (with around 43 per cent, 38 per cent, and 23 per cent of households receiving extension from these agents, respectively). Overall, the project successfully

[66] In what percentage of your land did you apply the skill? (in per cent) – for all the categories.

increases the rates of agricultural extension services received by treatment households, doubling the rate of visits from project service provider staff from baseline.[67]

Table A - 10. Descriptive statistics on sources of agricultural extension

Variable	Treatment mean	Control mean	T-test p-value	# obs. treatment	# obs. control
Source of extension services					
Project service provider staff	0.175	0.100	0.000***	521	512
District agronomist	0.154	0.138	0.457	513	530
District veterinary officer	0.133	0.139	0.758	490	524
District cooperative officer	0.114	0.128	0.490	466	507
Sector agronomist	0.422	0.449	0.375	540	557
Sector veterinary officer	0.365	0.404	0.183	524	552
Sector cooperative officer	0.256	0.213	0.112	492	484

Note: Columns 4-5 display the p-value of t-tests for the differences in mean values between treatment and control households. Significance levels are indicated by * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A - 11 illustrates the proportion of households that have received agricultural inputs in the last 12 months and the proportion of households that grow tea and coffee. We can see that a broadly similar percentage of treatment and control households have received inputs and that this difference is not statistically significant. We also note that access to tea plantations by smallholders is significantly more widespread in treatment locations with 5 per cent of households compared to less than 1 per cent of control households. In contrast, 9 per cent of control households access to plantations, compared to less than 1 per cent of treatment households. Both these differences are significant at the 1 per cent level.

Table A - 11. Descriptive statistics on receipt of agricultural inputs and tea/coffee plantations

Variable	Treatment mean	Control mean	T-test p-value	# obs. treatment	# obs. control
Received agricultural inputs	0.161	0.132	0.145	628	630
Tea plantation	0.053	0.003	0.000***	628	630
Coffee plantation	0.008	0.094	0.000***	628	630

Note: Columns 4-5 display the p-value of t-tests for the differences in mean values between treatment and control households. Significance levels are indicated by * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

The final set of results on output indicators is shown in Table A - 12. The table shows that, while an equal proportion of treatment and control households report being a member of a cooperative (just under 9 per cent) and implementing rain harvesting infrastructure (around 7 per cent), a significantly greater proportion of treatment households (76 per cent) report using a kitchen garden compared to 68 per cent of control households (significant at the 1 per cent level).[68]

[67] At baseline, 9 per cent of treatment households and 7 per cent of control households reported receiving advice from a project service provider, with no statistically significant difference between the that two groups.
[68] At baseline, 65 per cent of control households reported using a kitchen garden, compared to 68 per cent of treatment households. This difference was not statistically significant.

Table A - 12. Descriptive statistics on output indicators for components Two and Three

Variable	Treatment mean	Control mean	T-test p-value	# obs. treatment	# obs. control
Cooperative membership	0.097	0.076	0.187	628	630
Kitchen garden	0.763	0.676	0.001***	628	630
Rain harvesting infrastructure	0.078	0.059	0.175	628	630

Note: Columns 4-5 display the p-value of t-tests for the differences in mean values between treatment and control households. Significance levels are indicated by * p < 0.10, ** p < 0.05, *** p < 0.01.

C. Outcome indicators at midline

As described in section II, the Green Gicumbi Project aims to contribute to various desirable outcomes for project beneficiaries. We now turn to descriptive statistics for these project outcome indicators.

The first set of outcome indicators presented here focuses on adopting CRA practices, an outcome associated with component One of the project. Table A - 13 shows that 75 per cent of treatment households report adopting CRA practices, which is 15 percentage points higher than control households (significant at the 1 per cent level). In addition, we can note that, on average, treatment households adopt 1.61 practices per household, compared to only 1.11 in control households (significant at the 1 per cent level).

In terms of specific practices, we note that a greater proportion of treatment households adopted housing infrastructure against lightning (21 per cent versus 13 per cent, significant at the 1 per cent level), rainwater harvesting and utilization (38 per cent versus 20 per cent , significant at the 1 per cent level), households wastewater management (45 per cent versus 27 per cent, at the 1 per cent level), alternative energy sources (7 per cent versus 3 per cent , at the 1 per cent level) and developed an irrigation scheme (5 per cent versus 1 per cent, at the 1 per cent level). We note that both groups have a similar proportion of households adopting climate-resilient crop varieties (around 46 per cent) and other technologies (less than 0.1 per cent).

Table A - 13. Descriptive statistics on the adoption of CRA practices

Variable	Treatment mean	Control mean	T-test p-value	# obs. treatment	# obs. control
Adoption of CRA practices	0.7468	0.6063	0.000***	628	630
Number of CRA practices adopted by farmers	1.609	1.106	0.000***	628	630
Type of CRA practices adopted by farmers					
Protection of housing infrastructure against lightning	0.217	0.133	0.000***	628	630
Rainwater harvesting and utilization	0.377	0.195	0.000***	628	630
Household wastewater management	0.446	0.268	0.000***	628	630
Use of alternative sources of cooking other than biomass energy	0.065	0.029	0.002***	628	630
Development of irrigation scheme	0.045	0.011	0.000***	628	630
Adoption of crop varieties	0.459	0.467	0.774	628	630

Variable	Treatment mean	Control mean	T-test p-value	# obs. treatment	# obs. control
Other climate-resilient technology	0.002	0.003	0.566	628	630

Note: Columns 4-5 display the p-value of t-tests for the differences in mean values between treatment and control households. Significance levels are indicated by * p < 0.10, ** p < 0.05, *** p < 0.01.

Table A - 14 shows that an unsatisfactory number of treatment and control households have adopted a wider range of prescribed CRA technologies, with around 4.8 technologies adopted in both groups. When we compare the specific practices listed in Table A - 14, we note the limited number of observations and the very similar proportions – none of the other prescribed practices show significant differences.

Table A - 14. Descriptive statistics on adoption of climate-resilient technologies

Variable	Treatment mean	Control mean	T-test p-value	# obs. treatment	# obs. control
Adoption of other prescribed practices	0.8979	1.000	0.124	49	22
Number of other prescribed practices	4.9387	4.7727	0.833	49	22
Rainwater collecting/harvesting	0.320	0.444	0.518	25	9
Tree nursery	0.200	0.333	0.637	15	3
Improved grain drying, storage	0.357	0.500	0.630	14	4
Improved seed preservation	0.333	0.600	0.289	21	5
Mulching of soils	0.364	0.429	0.798	11	7
Inter-cropping methods	0.857	0.882	0.807	35	17
Tree planting	0.718	0.818	0.513	39	11
Pest and weed control	0.735	0.769	0.816	34	13
Use of organic manure	0.905	1.000	0.170	42	19
Terracing and slope maintenance	0.514	0.800	0.112	35	10
Crop rotation	0.667	0.909	0.124	33	11
Mixing trees with crops	0.730	0.813	0.530	37	16

Note: Columns 4-5 display the p-value of t-tests for the differences in mean values between treatment and control households. Significance levels are indicated by * p < 0.10, ** p < 0.05, *** p < 0.01.

We now turn to the descriptive statistics on agricultural production. Here, we can observe that, of the households that report growing the specific crop, treatment households are producing more maize (around 75 kg, significant at the 5 per cent level) and sweet potatoes (around 73 kg, significant at the 10 per cent level). In contrast, a limited number of control households produce more peas (around 50 kg, significant at the 10 per cent level) and more bananas (around 300 kg, significant at the 5 per cent level). In terms of the value of crop production, we note that for beans and bananas, control households estimate a significantly higher value than treatment households (significant at the 5 per cent and 10 per cent levels, respectively). When we investigate yields, we find that the limited number of control households growing peas report significantly higher yields (at the 10 per cent level) and that the treatment households report significantly higher sweet potato yields of around 6.8 tonnes per ha, compared to 4.3 tonnes per ha for control households (significant at the 5 per cent level).

Table A - 15 also shows the crop area, the value of crop production per ha, and the average value. Here we find treatment households are farming about half the land area (0.45 ha, just over one acre) compared to control households (at 0.89 ha, over two acres), significant at the 1 per cent level. Due to this, we find a much higher value of crop production per ha for treatment households (although not significant at conventional significance levels) at 4,700,531 Rwandese francs, compared to 1,775,463 Rwandese francs in control households.

Table A - 15. Descriptive statistics on agriculture

VARIABLE	TREATMENT MEAN	CONTROL MEAN	T-TEST P-VALUE	# OBS. TREATMENT	# OBS. CONTROL
Crop-farming production of main crops					
Beans	96.103	100.474	0.733	348	343
Peas	29.375	81.706	0.099*	16	17
Cassava	386.667	173.824	0.123	9	17
Potato	478.310	444.692	0.893	42	65
Maize	162.754	87.956	0.041**	211	137
Sorghum	94.768	88.019	0.696	112	156
Sweet potato	270.9	196.1721	0.097*	130	122
Banana	203.3582	494.95	0.021**	67	100
Tea	395.588	508.000	0.715	17	10
Coffee	0	82.632	0.179	2	19
Other	294.2364	263.0345	0.859	55	58
Value of crop production					
Beans	50 933	71 648	0.040**	348	343
Peas	8 025	31 800	0.142	16	17
Cassava	38 333	15 970	0.236	9	17
Potato	130 088	95 196	0.681	42	65
Maize	114 196	166 746	0.123	211	137
Sorghum	33 035	29 000	0.779	112	156
Sweet potato	22 997	14 578	0.123	146	136
Banana	39 243	81 852	0.075*	67	100
Tea	50 767	109 440	0.298	17	10
Coffee	0	43 142	0.334	2	19
Crop yields of main crops					
Beans	1 436	1 339	0.684	344	342
Peas	300	1 389	0.058*	16	16
Cassava	2 351	5 528	0.316	6	11
Potato	7 650	6 030	0.491	42	65
Maize	2 919	1 558	0.270	209	137
Sorghum	1 680	1 317	0.234	110	156

VARIABLE	TREATMENT MEAN	CONTROL MEAN	T-TEST P-VALUE	# OBS. TREATMENT	# OBS. CONTROL
Sweet potato	6 846	4 187	0.034**	93	86
Banana	44 905	11 847	0.291	66	99
Tea	7 134	2 675	0.315	17	10
Coffee	0	3 825	0.302	2	19
Crop area	0.4582	0.8919	0.002***	507	482
Value of crop production per ha	4 700 531	1 775 463	0.428	480	505
Average value of sales across all crops and seasons	128 568	157 828	0.179	483	505
Average household monthly income in the last year					
<30, 000	0.640	0.598	0.127	617	627
30,000 – 100,000	0.321	0.332	0.684	617	627
100,000 – 200, 000	0.021	0.048	0.010***	617	627
>200,0000	0.018	0.022	0.572	617	627
Number of sources of income in the last year	1.935	2.006	0.096*	628	630

Note: Columns 4-5 display the p-value of t-tests for the differences in mean values between treatment and control households. Significance levels are indicated by * p < 0.10, ** p < 0.05, *** p < 0.01.

We now turn to the descriptive statistics for food security. When we compare food shortages in the last 12 months and the number of days without sufficient harvest food, we do not see significant differences between the two groups. However, when we look at the dietary diversity score, we again find that treatment households display a significantly worse score (3.95) compared to control households (4.32), which is significant at the 1 per cent level. Table A - 16 also shows the results for the CSI. We can see a statistically significant difference between treatment and control households regarding the CSI (full details of how this was computed are described below). This suggests that treatment households are conducting more and more severe coping strategies compared to control households. However, it is worth noting that the CSI score for both treatment and control households decreased from baseline to midline, indicating increased food security over time.[69]

[69] Although the sample size is much smaller, the CSI for treatment and control households was 17.57 and 15.28, respectively. The difference between the two was not statistically significant.

Table A - 16. Descriptive statistics for food security

Variable	Treatment mean	Control mean	T-test p-value	# obs. treatment	# obs. control
Coping strategies index	13.791	8.613	0.000***	627	630
Food shortage last 12 months	0.495	0.506	0.693	628	630
Number of days without sufficient harvest food	63.812	70.558	0.243	308	319
Dietary diversity score	3.946	4.313	0.000***	628	630

Note: Columns 4-5 display the p-value of t-tests for the differences in mean values between treatment and control households. Significance levels are indicated by * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A - 17 below shows the descriptive statistics for adaptive capacity and using cleaner energy for cooking. We can observe that a greater proportion of treatment households engage in non-farm activities (74 per cent) than control households (65 per cent). We can also see that control households (79 per cent) consider a greater number of adaptation measures as appropriate to deal with the effects of climate change compared to treatment households (68 per cent) at the 10 per cent level.[70] The knowledge of erosion control practices is very similar across both groups at 92 per cent. In contrast, we can observe a higher proportion of control households use improved stoves (90 per cent, compared to 70 per cent for treatment households), which may help to explain the greater quantity of firewood used by treatment households (significant at the 1 per cent level).

Table A - 17. Descriptive statistics for adaptive capacity and cleaner energy for cooking

Variable	Treatment mean	Control mean	T-test p-value	# obs. treatment	# obs. control
Off-farm employment	0.018	0.011	0.339	628	630
Non-farm employment	0.742	0.648	0.000***	628	630
Number of adoption measures considered as important to deal with climate change (knowledge)	0.675	0.786	0.059*	628	630
Knowledge of erosion control practices	0.924	0.917	0.689	628	630
Production of biogas	0.0015	0	0.317	628	630
Use of improved stoves	0.709	0.901	0.000***	609	619
Quantity of firewood used for cooking	2.635	2.311	0.000***	628	630

Note: Columns 4-5 display the p-value of t-tests for the differences in mean values between treatment and control households. Significance levels are indicated by * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

[70] Out of a list of 10 possible measures.

APPENDIX 4. PROBIT MODEL (PRIMARY SPECIFICATION)

Table A - 18. Probit estimates for matching models

	(1) MATCHING ESTIMATE: 1 = TREATMENT
Asset index	0.003
	(0.068)
Household size at baseline	-0.013
	(0.021)
Gender of household head (male)	-0.077
	(0.090)
Age of household head	0.008
	(0.007)
<= 30,000 Rwandan francs annually	-0.720*
	(0.388)
30,000 – 100,000 Rwandan francs annually	-0.846**
	(0.393)
100,000 – 200,000 Rwandan francs annually	-1.494***
	(0.449)
>200,000 Rwandan francs annually	-1.256**
	(0.500)
Dummy indicator==1 when income is unreported	0.000
	(.)
Age of respondent	-0.012*
	(0.007)
No education	0.000
	(.)
Primary school education	0.048
	(0.101)
Junior high school/Lower secondary education	0.198
	(0.166)
Higher school/Upper secondary education	0.365**
	(0.177)
University and higher education	0.965*
	(0.492)
Head of household	0.000
	(.)
Spouse of household head	-0.095
	(0.083)

	(1) MATCHING ESTIMATE: 1 = TREATMENT
Son/daughter of household head	-0.656***
	(0.247)
Grandchild of household head	0.120
	(0.745)
Single	0.000
	(.)
Married	-0.329
	(0.252)
Divorced	0.113
	(0.340)
Separated	-0.648**
	(0.322)
Polygamy	0.000
	(.)
Widow(er)	-0.215
	(0.268)
None/no job	0.000
	(.)
Farmer	-0.144
	(0.175)
Artisan	0.035
	(0.341)
Commerce/transport	0.308
	(0.314)
Civil servant	-0.080
	(0.357)
Private employee	0.752*
	(0.399)
Constant	1.505***
	(0.513)
Observations	1255
Pseudo R-squared	0.0320
LR chi2(25)	55.75

Note: * p < 0.10, ** p < 0.05, *** p < 0.01.

The probit estimates in Table A - 18 present the coefficients associated with factors that predict treatment assignment within the context of a matching model. Notably, income categories exhibit a negative gradient, indicating that higher income levels are associated with a reduced likelihood of being in the treatment group. Particularly, the ">200,000 Rwandan franc annually" category exhibits the strongest negative impact (-1.256). In contrast, higher education levels positively influence treatment assignment, with individuals with a university or higher education displaying a highly positive impact (0.965). Additionally, being a "Private employee" is linked to a significantly higher likelihood of being in the treatment group (0.752). Conversely, several variables, including "Asset Index," "Household size at baseline," "Gender of household head (male)," and others, do not demonstrate significant effects on treatment assignment. These findings collectively contribute to a nuanced understanding of the determinants of treatment assignment, emphasizing the role of income, education, and occupation in shaping participation in the treatment group. The pseudo R-squared value of 0.0320[71] suggests that the model explains a modest portion of the variation in treatment assignment. The LR chi-squared test with 25 degrees of freedom indicates that the model as a whole is statistically significant.

In conclusion, these probit estimates provide valuable insights into the determinants of treatment assignment, highlighting the significance of variables such as income, education, gender, and household composition in influencing the likelihood of being in the treatment group.

[71] Alternate matching variables show similar pseudo-R-squared values. This probably means that the treatment assignment is fairly random rather than based on observable characteristics.

APPENDIX 5. PROBIT MODEL (ROBUSTNESS CHECK)

Table A - 19. Alternative probit estimates for matching models

	(1) Matching estimate: 1 = Treatment
Age of household head	-0.003
	(0.003)
Gender of household head (male)	-0.074
	(0.092)
Household size at baseline	-0.026
	(0.021)
Respondent is literate	-0.078
	(0.065)
Married	-0.008
	(0.031)
Household dependency ratio at baseline	-0.368**
	(0.156)
Farmer	-0.290***
	(0.117)
Less than 50 metres from river or marshland	0.794***
	(0.159)
In high-risk (hilly or sloping) area	0.311*
	(0.174)
Less than 10 minutes from a water source	0.354**
	(0.148)
Less than 30 minutes from a water source	0.011
	(0.156)
Less than an hour from a water source	-0.070
	(0.198)
Tropical livestock units	-0.404***
	(0.099)
Any household member has a bank account	-0.107
	(0.076)
Any household member belongs to a cooperative	0.291**
	(0.135)
Household has received social assistance in the last year	0.286**
	(0.129)
Constant	0.673**
	(0.283)

	(1) MATCHING ESTIMATE: 1 = TREATMENT
Observations	1229
Pseudo R-squared	0.0557
LR chi2(16)	94.96

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

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