FP073

Strengthening Climate Resilience of Rural Communities in Rwanda "Green Gicumbi Project"

Impact evaluation endline report

September 2026

IEU's Learning-Oriented Real-Time Impact Assessment programme

GREEN CLIMATE FUND | Independent Evaluation Unit

TRUSTED **EVIDENCE**.
INFORMED **POLICIES**.
HIGH **IMPACT**.

GREEN CLIMATE FUND | Independent Evaluation Unit

September 2026

Learning-Oriented Real-Time Impact Assessment Programme (LORTA)

Impact evaluation endline report for FP073: Strengthening Climate Resilience of Rural Communities in Rwanda "Green Gicumbi Project"

Summary

This report presents the endline findings of an impact evaluation of the GCF FP073: Strengthening climate resilience of rural communities in Northern Rwanda, known as the Gicumbi project. The overall objective of the FP073 project is to increase the resilience of vulnerable communities to climate change in Gicumbi District in Northern Rwanda. The impact evaluation by the IEU LORTA team focuses on two sub-components of this project: watershed protection and climate resilient agriculture, sustainable forest management.

The Green Gicumbi project (FP073) ran from 2019 to 2025 in the Gicumbi District, northern Rwanda, with USD 33.2 million from the GCF. It supported terracing, agroforestry, climate-resilient farming, forest restoration, clean cookstoves, water storage and training. This report provides evidence of the impact achieved and learnings useful for project design, implementation, and adoption.

175, Art center-daero
Yeonsu-gu, Incheon 22004
Republic of Korea
Tel. (+82) 032-458-6450
Email: ieu@gcfund.org
https://ieu.greenclimate.fund

First Edition

Citation
The suggested citation for this report is:
Independent Evaluation Unit. *Impact evaluation endline report for FP073: Strengthening Climate Resilience of Rural Communities in Rwanda "Green Gicumbi Project"*. Independent Evaluation Unit, Green Climate Fund, 2026.

Credits
Head of the GCF Independent Evaluation Unit: Andreas Reumann
Evaluation task lead: Marco d'Errico, Impact Evaluation Officer, Independent Evaluation Unit
Editing: Toby Pearce
Layout: Giang Pham
Cover design: Therese Gonzaga
Cover image: Rural landscape Rwanda, ©atosaн, licensed via Canva Pro.

A FREE PUBLICATION

Printed on eco-friendly paper

Acknowledgements

The authors (Paul Winter, Alvaro Altamirano, and Marco d'Errico) express their gratitude to colleagues whose names are listed as follows for their help in the development of the report.

- Martin Prowse (University of East Anglia)
- Andreas Reumann (Independent Evaluation Unit of the Green Climate Fund)
- Susumu Yoshida (Independent Evaluation Unit of the Green Climate Fund)
- Michell Dong (Independent Evaluation Unit of the Green Climate Fund)
- Yeonji Kim (Independent Evaluation Unit of the Green Climate Fund)
- Therese Gonzaga (Independent Evaluation Unit of the Green Climate Fund)
- Sean Tan (Independent Evaluation Unit of the Green Climate Fund)
- Giang Pham (Independent Evaluation Unit of the Green Climate Fund)
- Toby Pearce (Senior Editing Expert)
- Ghida Karbala (Center for Evaluation and Development)
- Clementine Sadania (Center for Evaluation and Development)
- William Mugabo (Ministry of Environment of Rwanda)
- Christian Manzi (Ministry of Environment of Rwanda)
- Steven Mugenyi (Ministry of Environment of Rwanda)
- Frank Murenzi (Ministry of Environment of Rwanda)

List of Authors

The authors of the LORTA report are (in alphabetical order of the surnames):

Full name	**Affiliation**
Alvaro Altamirano	Research Assistant, University of Notre Dame
Marco d'Errico	Independent Evaluation Unit of the Green Climate Fund
Paul Winters	Associate Dean for Academic Affairs, Keough–Hesburgh Professor of Sustainable Development, University of Notre Dame

Table of Contents

List of Tables

List of Figures

Abbreviations

CRA	Climate-resilient agriculture
CRI	Climate Resilience Index
CSI	Coping Strategies Index
DDD	Triple difference
DiD	Difference-in-differences
EWS	Early warning systems
FHH	Female-headed households
GoR	Government of Rwanda
HDDS	Household dietary diversity score
HH	Household
HHH	Household head
IE	Impact evaluation
IPW	Inverted probability weighting
LORTA	Learning-Oriented Real-Time Impact Assessment Programme
MHH	Male-headed households
MoE	Ministry of Environment of Rwanda
RWF	Rwanda franc
SE	Standard error
TEK	Traditional environmental knowledge
TLU	Tropical livestock units
ToC	Theory of change

Executive summary

The Green Gicumbi project (FP073 "*Strengthening Climate Resilience of Rural Communities in Northern Rwanda*") ran from 2019 to 2025 with USD 33.2 million in GCF funding. It was implemented by the Ministry of Environment and FONERWA in nine sectors of Gicumbi District, and combined watershed protection and climate-resilient agriculture (CRA), forest and energy interventions, resilient settlements, and knowledge transfer. This report presents the endline impact evaluation carried out under the IEU's LORTA programme, following the 2020 baseline and the 2024 midline.

Impacts are estimated by comparing beneficiary households in the project sectors with households in a comparison area in the south of the district. The analysis uses difference-in-differences on repeated cross-sections (1,299 households at baseline, 1,285 at endline, in the same 125 villages), weighted on baseline characteristics, with a balanced village-level panel as a robustness check. The two approaches give very similar answers, which is the main reason for confidence in the results below.

Adoption of climate-resilient agriculture rose by 43 percentage points relative to the comparison group; households used 1.5 more CRA techniques and reported 2.2 more CRA skills in use. In standardized terms, these are effects of 1.7 to 2.4 standard deviations, and they hold at both household and village level. Adoption in project areas rose from 57 per cent to 90 per cent, while it fell in comparison areas from 63 per cent to 53 per cent. This is not simply distribution of inputs: households took the practices into their production systems and kept using them.

At baseline, project villages were worse off than comparison villages on food security, dietary diversity, livestock and production. By endline the ranking had reversed. Food shortage fell from 50 per cent to 7 per cent among beneficiaries while rising from 34 per cent to 50 per cent in the comparison group. The midline data show that this was a gradual process rather than a late jump: the CRA effects were already significant in 2024 at roughly a third of their final size, and then roughly doubled. Benefits accumulated as adoption spread and as investments matured.

Food shortage fell by 60 percentage points relative to comparison households, dietary diversity rose by about 0.8 points on a 0–10 scale, and livestock holdings rose by 0.26 tropical livestock units. Crop count also held up better in project areas, though it declined in both groups. These are the outcomes usually treated as intermediate markers of resilience: households were able both to protect what they had and to accumulate.

Total crop value, the number of income sources, and the Coping Strategies Index show no significant effect (the coping index is marginal at village level only, and is measured only among food-insecure households, so it is hard to compare across waves). This is not evidence of failure. Crop income depends on weather, prices and markets well beyond farming practice, and the project was not designed to push households into non-farm activities. Adaptation investments tend to stabilize production before they raise incomes, and the sequencing here is consistent with that.

The Climate Resilience Index (CRI; a 0–100 composite combining survey data with remote-sensing measures of vegetation, rainfall, temperature and drought anomalies) increased by about 10 points, significant at the 1 per cent level and stable across specifications. Because the index includes fixed geographic components, the difference-in-differences removes location effects, so the estimated gain reflects the household and community dimensions of resilience rather than any change in exposure. The CRI result reconciles the two strands above: households can become more resilient by reducing vulnerability and protecting assets even when income is flat.

On CRA adoption, techniques and skills, and on food shortage, female- and male-headed households benefited on the same terms. However, the gains did not convert equally. Dietary diversity improved for male-headed households (+0.64) and not at all for female-headed households (−0.12). The resilience index rose by 8.7 points for male-headed households and 4.5 points for female-headed ones, a gap that is significant on the village panel. The problem is not therefore access to the project, it is the conversion of adoption into welfare, which is constrained by labour, liquidity and market access. The same pattern was found in the IEU's Madagascar impact evaluation.

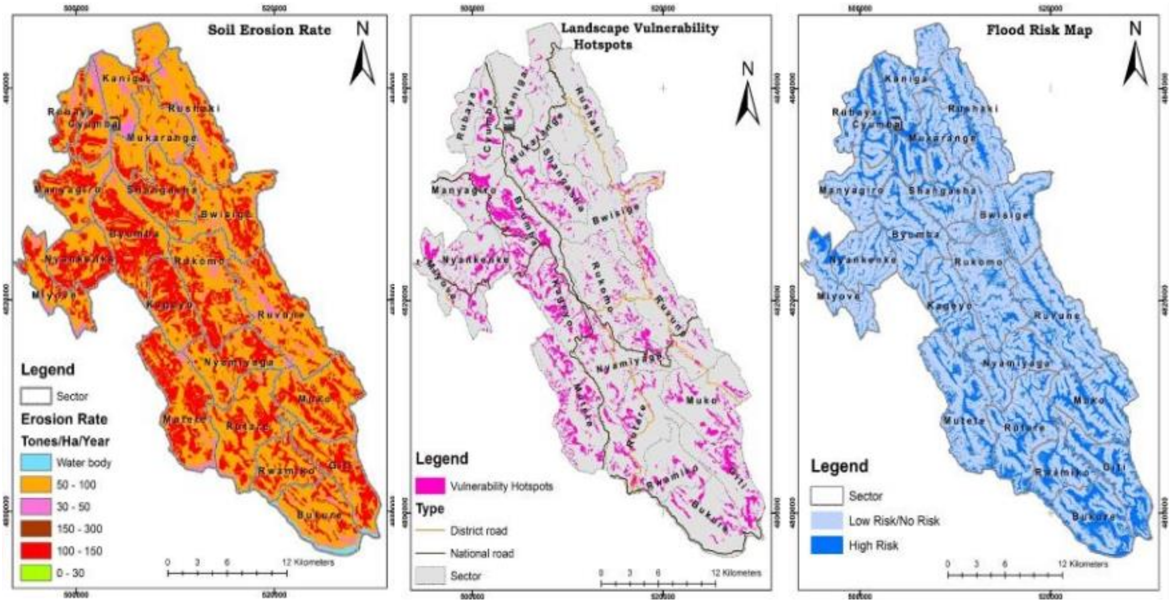
The project's core delivery logic worked as designed. Where the original theory of change was optimistic in assuming that adoption would carry through to livelihood transformation on its own, and that reaching female-headed households would be enough for them to benefit proportionally. Three lessons follow: adoption should be treated as a mid-point rather than an end point, with attention to what turns it into sustained livelihood gains; resilience-building needs longer time horizons than adaptation projects usually assume; and technical support needs to be paired with measures addressing the structural constraints (labour, credit, market access) that determine who can convert adoption into welfare.

Introduction

1. Ranked 159th (out of 193) for the Human Development Index,[1] Rwanda remains in the **"Low Human Development"** tier. Its historical trajectory is notable in that its Human Development Index score has more than doubled since the mid-1990s, marking one of the fastest average growth rates in human development globally over the past three decades. This, combined with a real gross domestic product growth rate of 7.2 per cent in 2026 and **9.4 per cent** in 2025,[2] places Rwanda as the **third fastest-growing economy in Africa** (trailing only South Sudan and Guinea).
2. Rwanda's sensitivity to climate change is high while its adaptive capacity is low. In recent years, Rwanda has witnessed a series of climate-related hazards such as floods, landslides, and droughts, that have left devastating effects particularly on those with low adaptive capacity and resilience to climate change. The high dependency on rainfed agriculture, the hilly topography, low access to climate information, and the depletion of forest stocks have been identified as some of the factors exacerbating Rwanda's vulnerability to such hazards.
3. Data from the national survey on the assessment of climate change in Rwanda shows that in the northern province, Gicumbi District ranks highest in exposure to climate hazards and ranks second highest in sensitivity to climate-related impacts.[3] The two indicators signal that Gicumbi is likely to suffer considerably from climate hazards. According to this report, the high vulnerability of Gicumbi District to climate change is based on an increase in average temperature, frequent and longer heatwaves, more intensive rainfall and frequent floods, and increases in severe droughts. Moreover, the Gicumbi District has one of the highest rates of households experiencing crop loss, food insecurity, animal disease and fluctuations in livelihoods due to weather hazards.
4. To provide a visual sense of the geographical spread of hazards across Gicumbi, Figure 1 shows the 2017 Gicumbi regional maps for flood, soil erosion exposure, and landscape vulnerability spots defined by overlaying the following four criteria: low tree cover, high erosion rate, and landslide vulnerability and flood risk. As seen in the maps, climate hazards are widespread.

[1] Theglobaleconomy.com, "Rwanda: Human development."
[2] Worldometers, "Rwanda GDP (2026)."
[3] Green Climate Fund, *Funding Proposal FP073: Strengthening climate resilience of rural communities in Northern Rwanda*.

Figure 1: Geographic distribution of hazards in the Gicumbi District



Source: G. Karbala, A. Riviere and C. Sadania. *Impact Evaluation Design Report Rwanda* (2019).

5. The "**Strengthening Climate Resilience of Rural Communities in Northern Rwanda**" project, also referred to as the Green Gicumbi Project, aims to increase the resilience of the targeted vulnerable communities to climate change. The project targets nine sectors out of the 21 sectors in Gicumbi where there is high potential to address climate hazards. According to the project proposal submitted by the Rwanda team, an estimated 248,907 people or 63 per cent of the district's population live in the targeted areas.[4] The nine sectors fall within sub-catchment B of the Muvumba river and includes 252 villages.

6. The high dependency of the targeted population on agriculture as a source of food and income makes them highly vulnerable to the degradation processes occurring within the catchment. Particularly at risk are tea and coffee farmers as both crops are highly sensitive to climate change and adverse losses in productions are already evident. The estimated annual loss of production from climate variability at the Mulindi tea plantations (2,300 hectares) in Gicumbi over the last six years ranges from 2.0 million to 3.3 million tons of green leaf per year, with an equivalent market loss of USD 2.5 million to USD 4.1 million. Such losses directly affect the income of smallholders. However, the degradation of the watershed is accelerated not only by climate change but also by poor land management, the steep topography, and the shallow soils of the surrounding sectors, which make it particularly vulnerable to weather events.

7. The Green Gicumbi Project's goal was to restore and enhance ecosystem services of sub-catchment B of the Muvumba watershed, increasing the capacity of communities to renew and sustainably manage forest resources, and supporting smallholders to adopt climate-resilient agriculture (CRA). The project invested in green settlements for vulnerable families currently living in high-risk areas.

8. This report presents the findings of the post-treatment impact evaluation (IE) of the Green Gicumbi Project. Building on baseline, midline, and endline surveys, it assesses the extent to which the project contributed to strengthening climate resilience, food security, and climate-resilient agricultural practices among beneficiary households.

[4] Ibid.

9. This report is structured as follows: Section I introduces the Green Gicumbi Project, and particularly its implementation progress to date. Section II presents the evaluation strategy and the theory of change (ToC) of the Green Gicumbi Project, that is, the intended path from inputs to goals and key underlying assumptions. Section III provides descriptive statistics. Section IV offers the results of the IE, and section V discusses the results and draws conclusions.

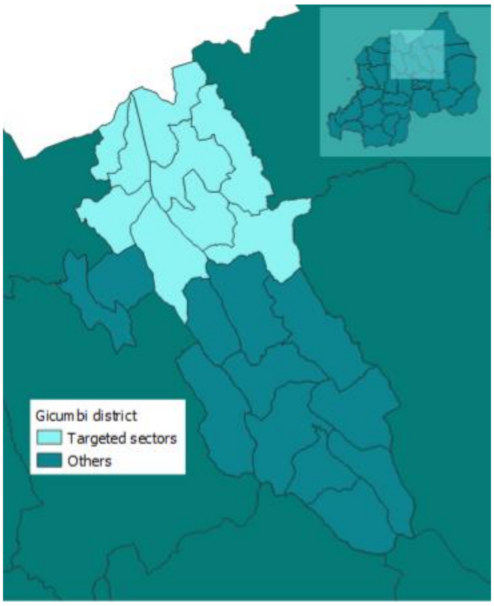
10. This document is part of the Learning-Oriented Real-Time Impact Assessment (LORTA) programme and presents evidence of the impact of the project on projected outcomes.

I. Background

1.1. General information

11. The Green Gicumbi Project is a six-year project (2019–2025) with funding of USD 33.2 million, implemented in the nine northern sectors of the Gicumbi District surrounding the sub-catchment B of the Muvumba watershed (Figure 2). This project aims to increase the resilience of vulnerable communities to climate change through the restoration and enhancement of ecosystem services of the watershed through an increase in the capacity of communities to renew and sustainably manage forest resources, and by supporting smallholders to adopt CRA. The project will also invest in green settlements for vulnerable families currently living in high-risk areas. The Green Gicumbi Project's accredited entity is the Ministry of Environment (MoE) of Rwanda. The project activities are executed directly by the National Fund for Environment (FONERWA) and implemented by Government of Rwanda (GoR) agencies at district or sector level.

Figure 2: Intervention areas of the Green Gicumbi Project



Source: Independent Evaluation Unit, *Impact Evaluation Midline Report for FP073 – The Green Gicumbi Project* (2024).

12. The Green Gicumbi Project is aligned with the GoR's commitment to sustainable environmental and climate change management initiated in the year 2000.[5] GoR's commitment has been further renewed in the Vision 2050 ("Vision 2050: For Rwanda to be a developed climate-resilient, low-carbon economy by 2050"), to which the Green Gicumbi Project contributes.[6]

13. The project interventions are organized around four main components:

(a) Watershed protection and CRA

[5] Rwanda, *Third National Communication: Report to the United Nations Framework Convention on Climate Change*.
[6] Green Climate Fund, *Funding Proposal FP073: Strengthening climate resilience of rural communities in Northern Rwanda*.

(b) Sustainable forest management and sustainable energy use

(c) Climate-resilient settlements

(d) Knowledge transfer and mainstreaming

14. These components are further split into 27 sub-components for a total of 143 activities. Communities within each of the nine targeted sectors will receive assistance in prioritizing activities based on need assessments. For each community, this exercise will lead to the development of a local adaptation plan describing the package of interventions that the community will receive. Part of the IE then is to assess if this community-based decision-making process is effective at delivering on anticipated outcomes.

15. The quantitative impacts of the Green Gicumbi Project are assessed by comparing changes in outcomes of interest between a group of beneficiaries and a group of non-beneficiaries that has similar characteristics to the beneficiary group. After discussions with the project team, the southern part of the Gicumbi District, situated around the Nyabugogo catchment, was designated as particularly suitable to serve as a comparison area. This area shares more similar agroecological characteristics than the upper part of the Muvumba catchment, located in the eastern neighbouring districts (Nyagatare and Gatsibo) of the project intervention area. Of course, the pretreatment similarities between the beneficiaries and non-beneficiaries need to be verified. This is discussed more fully below.

1.1.1. Implementation status

16. The project is now completed and, over the past six years, have achieved significant results across its four components, strengthening both climate resilience and community livelihoods. In line with its core objective of empowering local communities to adapt to climate shocks, multiple interventions have been carried out, bringing the overall implementation status to nearly 90 per cent. This IE is designed to verify if the stated objectives of the project have been achieved through these interventions.

17. A summary of the current implementation progress and key achievements, based on project reports, is presented below.

18. **Watershed protection and CRA:** A total of 1,450 hectares of land were terraced including 600 hectares with radical terraces and 850 hectares with progressive terraces to control erosion on steep slopes and boost agricultural productivity. Additionally, 50 hectares of upland tea and 40 hectares of coffee plantations were established, potentially providing communities with long-term income sources and strengthening their resilience to climate shocks. The project also planted 10,000 hectares of agroforestry trees and established 1,370 hectares of protective trees along roadsides and rivers.

19. **Sustainable forestry management and sustainable energy:** Over 2,200 hectares of degraded forests were rehabilitated across the nine intervention sectors, and 31,000 improved cookstoves were distributed to low-income households, in the hope of helping them to save energy and reduce pressure on forests. The restoration of degraded forests is expected to strengthen soil retention, reduce erosion, and support uninterrupted agricultural activities in the watershed. Additionally, new forest harvesting and management techniques were piloted, accompanied by training for forest cooperatives.

20. **Climate-resilient settlements:** Two integrated green settlements were constructed for 100 vulnerable households, incorporating environmental features, such as solar lighting and robust rainwater harvesting systems. In addition, more than 2,500 water harvesting tanks were distributed or built at both household and institutional levels, with a combined capacity of 8,700 m^3. To manage runoff and reduce erosion across the watershed, 35 water ponds were developed, capturing 6,670 m^3 of water, while 16,900 infiltration ditches were established to enhance water capture and slow runoff to minimize erosion impacts.

21. **Knowledge transfer and mainstreaming:** The project has prioritized generating and sharing knowledge to support the scale-up and replication of effective community climate adaptation practices. To date, it has reached over 158,000 direct and 464,000 indirect beneficiaries, with more than 25,000 people trained on climate resilience. As the project nears completion, this component remains key to sustaining impact, facilitating community knowledge transfer, and reinforcing long-term results. The project is estimated by the GoR to have created over 99,000 green jobs, including 54,000 direct jobs, and to have helped avoid approximately 214,000 tons of CO_2 equivalent emissions.

1.1.2. The LORTA programme and the Green Gicumbi impact evaluation

22. The LORTA programme has engaged with the Green Gicumbi Project since its inception, embedding rigorous IE and data-driven learning into the project's implementation cycle. Through this engagement, LORTA has accompanied the MoE and FONERWA in designing a robust evaluation framework, developing survey instruments, determining the sampling strategy, and generating evidence at multiple stages of implementation. The baseline survey carried out in 2020 established a comprehensive starting point on household livelihoods, exposure to climate-related hazards, agricultural practices, adaptive capacity, and access to basic services in both the intervention and comparison areas of Gicumbi District.

23. Building on this, the 2024 midline analysis assessed the emerging effects of the project's watershed rehabilitation, CRA, improved forest management, and household-level adaptation measures. Early results showed meaningful progress in the adoption of climate-resilient agricultural practices, increased use of certain adaptation technologies, and short-term gains in food security and cropping outcomes, while also highlighting areas where longer-term improvements are expected to materialize only after continued implementation.

24. Within this long-term partnership, the post-treatment IE serves as the final analytical assessment of the project's effectiveness. The evaluation draws on evidence generated through the baseline, midline and endline surveys and applies a set of complementary empirical approaches to assess project impacts. It draws lessons and evidence generated from the baseline and midline phases and sets out the empirical strategies, key indicators, and quality checks that will guide the analysis of the endline data. The endline data collection allowed the team to rigorously assess the project's final impacts across its main adaptation pathways. This report is therefore not only a technical document but also the continuation of a learning process that has characterized the collaboration between LORTA, the GoR, and the Green Gicumbi implementing partners.

1.2. Theory of change

25. While the ToC has been thoroughly presented over the course of baseline and midline reports, here we summarize the ToC of the project.

26. The Green Gicumbi Project was designed to strengthen the climate resilience of vulnerable rural communities in Northern Rwanda through an integrated package of watershed restoration, CRA, sustainable forest management, climate-resilient settlements, and knowledge transfer activities. The underlying ToC assumes that improvements in natural resource management and household adaptive capacities would reduce vulnerability to climate-related shocks and contribute to more resilient livelihoods.

27. Through its four main components and 27 subcomponents, the project's intervention logic can be summarized in five interconnected pathways:

(a) Improved natural resource management

The rehabilitation of degraded watersheds, terracing of agricultural land, agroforestry expansion, forest restoration, and erosion control measures were expected to improve soil fertility, reduce land degradation, enhance water retention, and strengthen ecosystem services. These environmental improvements provide the foundation for more sustainable agricultural production under changing climatic conditions.

(b) Adoption of CRA

Training, extension support, demonstration activities, and access to climate-resilient agricultural technologies were expected to increase farmers' adoption of improved practices. Increased adoption of CRA was expected to improve agricultural productivity, reduce vulnerability to climatic shocks, and strengthen households' adaptive capacity.

(c) Strengthened household assets and adaptive capacity

Investments in productive assets, water harvesting infrastructure, livestock systems, community organizations, and access to climate information were expected to strengthen households' ability to prepare for, respond to, and recover from adverse climatic events. Enhanced adaptive capacity would allow households to better manage risk and maintain livelihoods during periods of stress.

(d) Improved food-security and livelihood outcomes

Through increased agricultural resilience and stronger livelihood assets, the project was expected to reduce food shortages, improve dietary diversity, protect productive assets, and strengthen overall household welfare. These improvements represent the intermediate outcomes through which resilience gains become visible at household level.

(e) Enhanced climate resilience

The ultimate objective of the project was to increase the resilience of rural communities to climate change. Resilience is understood as the capacity of households to absorb climatic shocks, adapt to changing environmental conditions, and sustain livelihoods despite increasing climatic uncertainty. Improvements in climate-resilient agricultural practices, food security, productive assets, and adaptive capacities are therefore expected to translate into higher overall climate resilience.

28. Taken together, the ToC suggests a progression from environmental restoration and behavioural change to improved livelihood outcomes and ultimately stronger resilience. The IE assesses whether these expected pathways materialized and whether observed changes among beneficiary households are consistent with the project's intended adaptation strategy.

II. Evaluation strategy

2.1. Evaluation questions, hypothesis to be tested, and data

29. 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 underlying hypotheses of the project's ToC.

Table 1: Evaluation questions and impact indicators

Evaluation questions (EQ)	Key indicators
Output level	
EQ1: Do the adaptation interventions 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 II 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 lead to an increase in food security and diversity?	• Household dietary diversity score (HDDS) • Experienced a food shortage in the last year • Number of days last year in which experienced food shortage
EQ4: Do activities lead to an increase in smallholder farmers' resilience? What dimensions of resilience are the most influenced by the project activities?	• Coping Strategies Index (CSI)[7] • Agricultural production (size of harvest) • Total value of harvest • Share of agricultural production not for consumption • Ownership of tropical livestock units (TLU) • Number of sources of livelihood • Climate Resilience Index
Impact level	
EQ5: Do 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 the household head
Do the impacts of the project differ by the gender of 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

[7] D. Maxwell and R. Caldwell, *The Coping Strategies Index: Field Methods Manual* (2008).

EVALUATION QUESTIONS (EQ)	KEY INDICATORS
	• Experienced a food shortage in last year by gender of the household head • Number of days in last year in which a food shortage was experienced by gender of the household head • CSI by gender of the household head

Source: Evaluation team's elaboration on project data.

30. 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 coping strategies, food security, production, income and resilience. 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.

31. Beyond the indicators listed under each evaluation question in Table 1, this section elaborates on two analytical tools that require additional explanation: the Climate Resilience Index (CRI), listed among the EQ4 indicators, and a traditional environmental knowledge (TEK) module, which cuts across several of the EQ1 and EQ4 indicators.

32. Table 1 lists a set of discrete outcome measures under EQ3 and EQ4, each capturing a specific aspect of household welfare. The CRI is included among the EQ4 indicators because these discrete measures, while informative individually, do not answer EQ4's second question: what dimensions of resilience are most influenced by the project. The CRI is a tool designed to answer that question directly by synthesizing absorptive, adaptive, and transformative capacities together with households' exposure to climate stressors into one composite score. It allows the evaluation to characterize which components of resilience the Green Gicumbi Project moved, and to compare that resilience profile across sectors and against other LORTA evaluations using the same CRI architecture. The subsection below sets out how the index is constructed from the underlying EQ3/EQ4 indicators and additional geospatial data.

33. TEK is introduced for a different reason. EQ1 asks whether project interventions increase the adoption of CRA practices, and Table 1 explicitly tracks not just the proportion and number of practices adopted but their type. This last element matters because the project's ToC assumes that resilience gains flow from farmers adopting modern climate-smart techniques, an assumption that risks overlooking whatever traditional practices households already use to manage climate risk, and how those two sets of practices interact. Evidence from comparable agricultural contexts shows traditional and modern practices can substitute for one another and complement one another; the question here is, are traditional practices revitalized rather than displaced? Which of these patterns has direct implications for interpreting both the "type of CRA practice adopted" indicator under EQ1, and the resilience-dimension breakdown the CRI is designed to produce under EQ4. The TEK module, collected as a dedicated set of survey questions at endline, is therefore included to ensure that observed shifts in practice adoption and resilience capacity can be adequately analysed rather than read as a simple story of modern replacing traditional.

2.1.1. **Outcome indicators**

34. Table 2 lists the 13 outcome indicators used in this evaluation. The table includes how the variable is constructed for use in the study. Since the creation of the CRI and the TEK are more involved than the other variables, they are discussed in detail below.

Table 2: Data analysis plan outcome indicators

#	Indicator	EQ	Construction
1	CRA adoption rate	EQ1	Binary: adopted ≥ 1 CRA technology
2	CRA technology count	EQ1	Count of 7 technologies adopted (0–7)
3	CRA skills in use	EQ1	Count of 14–15 skills currently applied
4	Dietary diversity score	EQ3	Count of 10 food groups consumed (0–10)
5	Food shortage	EQ3	Binary: experienced shortage in last 12 months
6	Coping Strategies Index	EQ4	Frequency-weighted sum of 12 coping strategies[a]
7	Tropical livestock units	EQ4	FAO-weighted livestock count[b]
8	Income sources	EQ4	Count of income-generating activities
9	Number of crops	EQ4	Count of crop types cultivated
10	Total crop value	EQ4	Production × price (RWF)
11	Female-headed household	EQ5	Binary: HH head is female (roster-derived)
12	Climate Resilience Index	EQ1–5	Index ranging from 0 (low) to 100 (high)
13	TEK	EQ1-5	Categorical variables

Source: Evaluation team's elaboration on project data.
Notes: [a] Severity weights (workshop consensus): seed conservation = 2, feed for work = 2, reduce meals = 1, borrow food = 2, limit portions = 2, purchase on credit = 1, skip entire days = 4, beg = 4, restrict adults = 3, eat elsewhere = 3, gather wild food = 2, eat less preferred = 1.
[b] FAO TLU conversion factors: cattle = 0.70, pigs = 0.20, goats = 0.10, sheep = 0.10, chickens = 0.01, ducks = 0.03, rabbits = 0.01.
HH=household

2.1.2. **Climate Resilience Index**

35. For this analysis, the CRI is incorporated as an integrative, conceptually grounded measure intended to summarize the main factors that contribute to households' resilience in the context of the Green Gicumbi Project. This index combines information on three broad domains that are consistently highlighted in the resilience literature: (i) the **capacities** households possess to manage climate risks (including absorptive, adaptive, and transformative elements), (ii) the **climate stressors** to which they are subject, and (iii) their **degree of exposure** linked to geographical, environmental, and livelihood characteristics. The index therefore provides a synthetic view of resilience that goes beyond any single indicator and allows the evaluation to track whether households benefiting from project interventions show signs of strengthened resilience relative to comparison groups.

36. Following standard practice, Table 3 provides the different elements of the CRI as defined for the Green Gicumbi Project. The variables were selected to operationalize each of the five pillars underlying the CRI, ensuring that every dimension of household resilience is captured by at least one measurable indicator. *Adaptive capacity* is proxied through travel time variables, reflecting physical access to services and markets that shape a household's ability to adjust to shocks. *Transformative capacity* draws on asset-based indicators (livestock, land, tree cover, and durable goods) which represent the stock of resources households can draw on or convert to build longer-term resilience. *Absorptive capacity* is captured through participation in social safety nets and cooperatives, both of which provide buffering mechanisms against short-term shocks. *Climate stressors* are measured through self-reported exposure to hazard-induced losses (crop, housing, food), representing the direct impact of climate events on the household. Finally, *degree of exposure* combines livelihood

diversification, income, and knowledge-based indicators, capturing both structural vulnerability and the household's informational capacity to respond. Together, these variables ensure the CRI reflects the multidimensional nature of resilience rather than any single proxy.

37. Importantly, the CRI used in this report should be understood as an operational tool rather than a finalized theoretical construct. Its purpose is to guide the analysis by offering a consistent framework for organizing available data and interpreting changes over time. As the broader methodological work on climate resilience measurement continues to evolve,[8] this index provides a pragmatic starting point for assessing how the Green Gicumbi Project contributes to reducing climate vulnerability and supports climate-resilient development pathways.

Table 3: Components of a Climate Resilience Index

PILLARS	INDICATORS
Adaptive capacity	Travel time to the closest all-weather road
	Travel time to the closest market for food products
	Travel time to the closest market for animal products
	Travel time to the closest primary school
	Travel time to the closest health centre
	Travel time to the closest drinkable water
Transformative capacity	Household assets ownership
	Livestock
	Land holding
	Tree area
	Durable assets
Absorptive capacity	Reception of social safety net
	Cooperative membership
Climate stressors	Losses in agricultural products following climate hazards
	House damaged by climate hazards
	Food shortage because of climate hazards
Degree of exposure	Off-farm employment
	Number of crops grown
	Income
	Income diversification
	Number of self-reported adaptive capacities
	Knowledge of climate-resilient practices
	Knowledge of erosion control practices

Source: Evaluation team's elaboration on project data.

[8] Both within the Green Climate Fund and in the wider academic and policy community.

2.1.3. Traditional environmental knowledge

38. TEK refers to the cumulative body of knowledge, practices, and beliefs that communities develop over generations about their relationship with the surrounding environment. It is transmitted through observation, experimentation, and lived experience, and is typically embedded in local agricultural systems, land management practices, and resource-use norms rather than codified in formal scientific terms. Far from being a residual category associated only with poverty or a lack of access to modern inputs, TEK is increasingly recognized as a substantive body of adaptive expertise in its own right, one that can be integrated into contemporary climate and natural resource management frameworks rather than simply being displaced by them. The role and relevance of TEK, especially for Indigenous Peoples, is well stated and documented in the literature.[9] However, there is evidence of tension between the adoption of modern smart agriculture techniques and the use of TEK. This seems to be particularly relevant for projects like the Green Gicumbi Project, where the objective of achieving greater resilience is supposed to be achieved through the adoption of modern farming techniques.

39. For smallholder farming communities such as those in Gicumbi, TEK is manifested through practices accumulated over time to manage terraced hillside agriculture, respond to rainfall variability, and preserve soil fertility under conditions of land scarcity. These practices reflect a detailed, place-specific understanding of local agroecological conditions that formal agricultural extension systems do not always capture. At the same time, households in this context are also exposed to modern climate-smart agriculture interventions introduced through the Green Gicumbi Project, including improved terracing, agroforestry, and soil and water conservation techniques. Table 4 introduces the variables adopted for assessing the use of TEK.

Table 4: Traditional environmental knowledge variables

#	Indicator (Question)	Construction
Adoption and practice		
13.1	Practices any TEK (Q13.1.1)	Binary: household reports practising ≥ 1 traditional technique
13.2	Applies TEK every season (Q13.1.4)	Binary: technique applied every agricultural season (versus occasionally)
13.3	Practice is individual or collective (Q13.1.6)	Categorical: individual only / collective only / both
Perceived effectiveness and change over time		
13.4	Perceived effectiveness of TEK (Q13.2.1)	Categorical: very effective / moderately effective / not effective
13.5	Practice changed over time (Q13.2.2)	Binary: practice modified or adapted since first learned
Knowledge transmission		
13.6	Shared/taught technique to others (Q13.3.2)	Binary: has transmitted TEK to another person
13.7	Young people still learning TEK (Q13.3.4)	Binary: perceives youth actively learning TEK

[9] T. Dorji et al., "Understanding How Indigenous Knowledge Contributes to Climate Change Adaptation and Resilience: A Systematic Literature Review," *Environmental Management* 74, no. 6 (2024); J.M. Robinson et al., "Traditional Ecological Knowledge in Restoration Ecology: A Call to Listen Deeply, to Engage with, and Respect Indigenous Voices," *Restoration Ecology* 29, issue 4 (2021).

#	Indicator (Question)	Construction
13.8	Everyone in community uses TEK (Q13.3.5)	Binary: perceives TEK as universally practised locally
13.9	Source of TEK knowledge[a]	Multi-select (5 categories): parents, elders, farmer field schools, cooperatives, NGOs
TEK – Modern CRA interface		
13.10	Conflict with modern CRA methods (Q13.4.1)	Binary: reports tension between TEK and project-promoted practices
13.11	Combines TEK with project techniques (Q13.4.3)	Binary: jointly applies TEK and modern CRA
13.12	Areas of TEK–CRA complementarity[a]	Multi-select (3 categories): soil conservation, pest and weed control, water use
Early warning systems (EWS)		
13.13	Knows what an EWS is (Q13.5.1)	Binary: aware of the early warning system concept
13.14	Community has EWS practices (Q13.5.2)	Binary: community reportedly uses early warning practices
13.15	Traditional signs still work (Q13.5.4)	Binary: perceives traditional indicators as still reliable
13.16	Channel of early warning receipt[a]	Multi-select (3 categories): radio, local/traditional signs, project alerts

Source: Evaluation team's elaboration on project data.
Note: [a] Multi-select item; question numbering to be confirmed against the endline questionnaire annex.

40. The relationship between traditional and modern approaches can be understood through at least three lenses: a **substitution perspective**, in which modern techniques are expected to progressively displace traditional practices; a **complementarity perspective**, in which the two are combined to jointly reinforce household resilience; and a **revitalization perspective**, which emphasizes recovering and strengthening traditional practices eroded by past marginalization. Distinguishing between these pathways matters for evaluation purposes, since the extent to which households retain, combine, or abandon traditional practices alongside climate-smart agriculture adoption has direct implications for how resilience gains are generated and sustained. This evaluation therefore treats TEK not as a control variable to net out, but as a substantive dimension of household adaptive capacity to be examined alongside the CRI and climate-smart agriculture adoption outcomes.

2.2. Identification strategy

41. The Green Gicumbi Project was implemented geographically rather than at the household level. All intervention sectors received project activities, while neighbouring sectors with similar agroecological characteristics served as comparison areas. As a result, villages within a given sector were either entirely treated or entirely non-treated. Treatment status therefore reflects programme placement decisions rather than household self-selection. Consequently, the main sources of potential bias arise from geographic and contextual factors (such as agroecological conditions, market access, and local institutions) rather than from household-level characteristics.

42. The evaluation combines three independent cross-sectional surveys conducted in the same 125 villages: baseline (N = 1,299), midline (N = 1,299), and endline (N = 1,285). Because households

were sampled independently at each survey round, the analysis relies on a repeated cross-section design. This approach uses the full representative sample available in each survey wave and compares outcomes between treatment and comparison villages over time.

43. Treatment effects are estimated using a difference-in-differences (DiD) approach:

$$\hat{\delta} = \left(\bar{Y}_{T,EL} - \bar{Y}_{T,BL}\right) - \left(\bar{Y}_{C,EL} - \bar{Y}_{C,BL}\right) \quad (1)$$

where $Y_{g,t}$ denotes the average outcome for group $g \in \{T, C\}$ at survey wave (t). In practice, this estimator is implemented through the interaction between treatment status and survey wave in a regression framework, with standard errors (SEs) clustered at the village level. By focusing on changes over time, the DiD approach removes time-invariant differences between treatment and comparison areas, including unobserved geographic characteristics that may have influenced project placement.

44. The validity of this approach relies on a conditional parallel trends assumption. Following recent methodological guidance, we assume that, after accounting for observable baseline characteristics, outcomes in treatment and comparison areas would have followed similar trajectories in the absence of the project.[10] To support this assumption, treatment effects are estimated using inverse-probability weighting based on propensity scores calculated from baseline characteristics. These characteristics are measured prior to project implementation and are therefore not affected by the intervention.

45. We assess the plausibility of the parallel trends assumption through complementary analyses, including a three-wave event-study specification and estimates based on a balanced village-level panel. We probe the trends assumption through the three-wave event study and the village-level panel.

46. Our specification exploits the survey's repeated cross-section design: the baseline (1,299 households) and endline (1,285 households) are independent, representative samples of the same 125 villages, so a DiD that pools the two cross-sections rests on each wave's full sample. We estimate

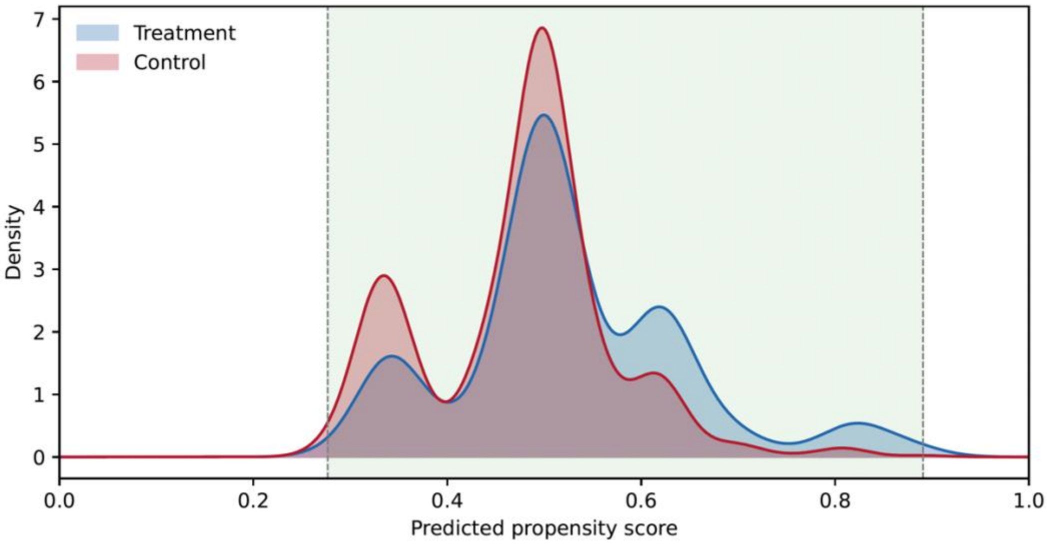
$$Y_{iw} = \alpha + \beta_1 Post_w + \beta_2 Treat_i + \delta(Post_w \times Treat_i) + \varepsilon_{iw} \quad (2)$$

where w indexes waves; δ is the DiD estimate. To carry the propensity adjustment across waves, we estimate the propensity score on the baseline using 13 covariates measured comparably in both waves (age, household size, female-headed household, literacy, distance to water, distance to health centre, radical terraces, urban/rural location, a harmonized four-level education scheme, and married/widowed indicators), and predict it forward onto the endline cross-section using the baseline coefficients. Education is harmonized to none, primary, secondary (junior plus higher secondary), and university; marital status is reduced to married and widowed indicators, the two categories populated comparably in both waves.

47. Figure 3 presented propensity scores showing that treatment and control overlap almost completely (common support [0.28, 0.89], containing 99.8 per cent of households). This indicates the range of characteristics across treatment and control households are similar, facilitating the ability to create a counterfactual.

[10] A. Baker, et al., "Difference-in-Differences Designs: A Practitioner's Guide," *Journal of Economic Literature* 64, no. 2 (2026).

Figure 3: Propensity score distributions by treatment status



Source: Evaluation team's elaboration on project data.
Note: Repeated cross-section propensity score overlap. Kernel density estimates of the predicted propensity score for treatment (blue) and control (red) under the 13-covariate harmonized model estimated on the baseline. The shaded band marks the common support region [0.28, 0.89], which contains 99.8 per cent of households.

III. Descriptive statistics

3.1. Data

48. Three waves of household survey data are available and used in this analysis. They are a repeated cross-section of the same villages making the data amenable to a pseudo-panel analysis. The waves are as follows:

(a) Baseline (2020): 1,299 households across 125 villages (651 beneficiary, 648 control) collected prior to programme implementation.

(b) Midline (2022–2023): 1,299 households (651 treatment, 648 control) collected during implementation.

(c) Endline (2026): 1,285 households (641 beneficiary, 644 control) collected after project completion.

49. Because the data collection is a repeated cross-section of the same villages, rather than household-level panel data, and the sample sizes in each round of data collection is similar, attrition is not an issue that needs to be addressed.

3.2. Endline survey and analytical sample

50. The endline (2026) is the key round of data collection for this evaluation since it was collected after project completion. As such, we describe the survey and analytical sample in more detail than the earlier waves. It re-surveyed the same 125 villages (62 beneficiary, 63 control) with a questionnaire that extended the baseline instrument. Alongside the core modules included in the earlier rounds of data collection (household roster, agricultural production and parcels, food security and coping strategies, livestock, income sources, and the CRA technologies and skills that define the primary outcomes) the endline added modules on cooking energy, group membership, TEK, and the intra-household dimensions of technology adoption.

51. Because the evaluation is designed as a repeated cross-section, the analytical sample is the full baseline (1,299 households) and the full endline (1,285 households), and the estimates do not condition on whether an endline household is a re-interview or a replacement. The design therefore draws on each wave's complete, representative sample and is unaffected by the differential recontact rate; the re-interview count is reported here only to document the composition of the endline survey.

3.3. Baseline balance

52. Table 5 reports baseline summary statistics for the full sample by treatment group. Several indicators show statistically significant differences at baseline. Food-shortage prevalence is higher among beneficiaries (49.8 per cent versus 33.6 per cent, $p < 0.001$), dietary diversity is lower (4.45 versus 5.09, $p < 0.001$), total crop value is lower (Rwandan franc (RWF) 64,414 versus RWF 110,957, $p = 0.005$), TLU is lower (0.49 versus 0.55, $p = 0.001$), and the number of crops cultivated is lower (2.89 versus 3.25, $p < 0.001$). These differences are present in the full baseline sample, indicating they originate from the non-random, sector-level selection of treatment and control communities.

53. Figure 4 displays standardized mean differences across all indicators. The baseline differences suggest that the treatment group is generally worse off than the control group with lower dietary diversity, more food shortages, lower Coping Strategies Index (CSI), etc. This raises some concern about the measurement of impact since the starting point is lower in the treatment and control. As seen in the

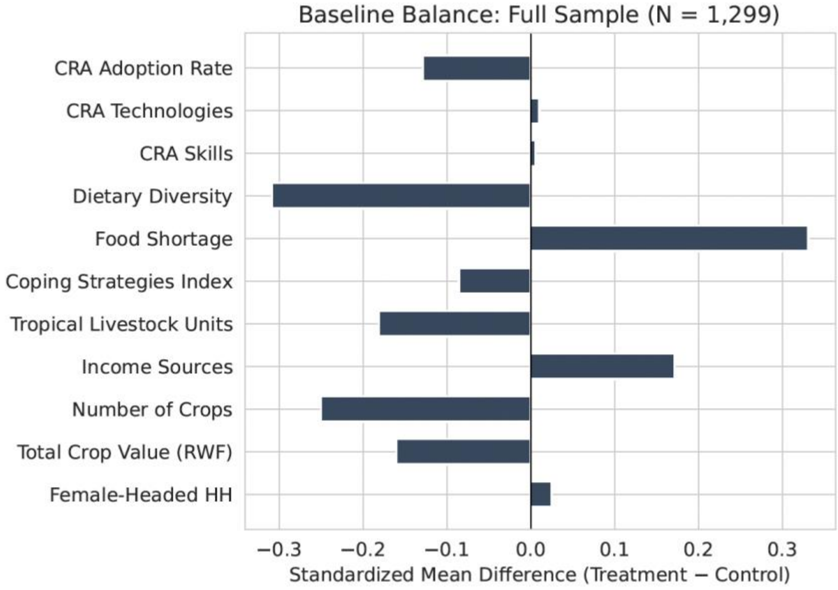
subsequent text, any estimate of impact is likely to be a lower bound estimate. Therefore, every estimation took this aspect into consideration before presenting results.

Table 5: Baseline summary statistics by treatment group (full sample, N = 1,299)

Indicator	Treatment mean	Treatment SD	Treatment N	Control mean	Control SD	Control N	*p*-value
CRA adoption rate	0.571	0.495	651	0.634	0.482	648	0.021**
CRA technologies	1.134	1.197	651	1.122	1.112	648	0.855
CRA skills in use	0.808	2.354	651	0.795	2.228	648	0.917
Dietary diversity	4.453	1.877	651	5.088	2.225	648	<0.001***
Food shortage	0.498	0.500	651	0.336	0.473	648	<0.001***
Coping Strategies Index	15.497	16.279	324	17.174	22.425	218	0.343
Tropical livestock units	0.487	0.365	651	0.552	0.350	648	0.001***
Income sources	1.932	0.890	651	1.787	0.804	648	0.002***
Number of crops	2.892	1.352	609	3.247	1.491	594	<0.001***
Total crop value (RWF)	64,414	350,894	603	110,957	214,138	614	0.005***
Female-headed household	0.203	0.402	651	0.193	0.395	648	0.656

Source: Evaluation team's elaboration on project data.

Figure 4: Baseline balance



Source: Evaluation team's elaboration on project data.
Note: Standardized mean differences at baseline, full sample (N = 1,299): the mean treatment−control difference for each indicator, scaled by the pooled standard deviation.

3.4. Endline sample characteristics

54. Table 6 summarizes the endline analytical sample by treatment and control group. Beneficiary and comparison households are similar in the age, headship, and marital status of the household head and in literacy, but differ on several dimensions that echo the geographic, sector-level selection documented at baseline. Beneficiary households are smaller (3.2 versus 3.9 members, $p < 0.01$) with fewer working-age members, somewhat better educated (secondary schooling 19.0 per cent versus 12.1 per cent; primary 61.5 per cent versus 68.8 per cent), are marginally more likely to own land, and are markedly closer to public infrastructure; 0.9 per cent of beneficiary households are more than an hour from water against 17.2 per cent of comparison households, and 5.3 per cent versus 31.1 per cent for a health centre. As with the baseline differences, these are level gaps that reflect where the intervention was placed rather than its effects. The expectation is that the DiD design removes the time-invariant component.

Table 6: Endline sample characteristics by treatment group (N = 1,285)

CHARACTERISTIC	TREATMENT (N=641)	CONTROL (N=644)	*p*-VALUE
Age of household head (years)	49.69	48.34	0.125
Household size	3.17	3.88	0.000***
Working-age members	2.25	2.45	0.011**
Female-headed household	20.3%	17.9%	0.289
Head is literate	79.9%	77.3%	0.266
Head is married	78.2%	78.1%	0.981
Education: none	17.8%	18.8%	0.642

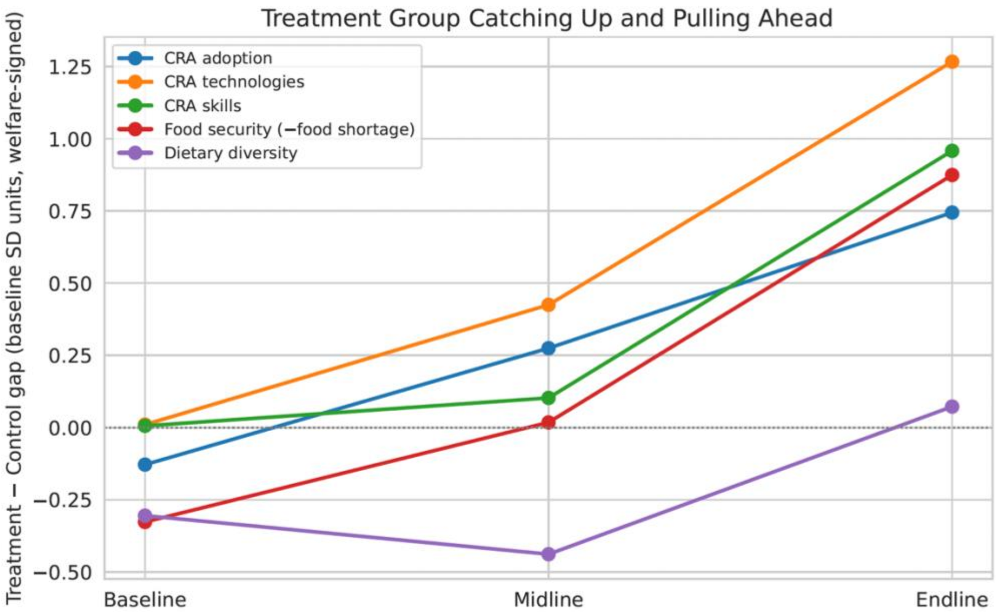
Characteristic	Treatment (N=641)	Control (N=644)	p-value
Education: primary	61.5%	68.8%	0.006***
Education: secondary	19.0%	12.1%	0.001***
Education: university	1.7%	0.3%	0.012**
Owns land	93.9%	91.1%	0.059*
Distance to water > 1 hour	0.9%	17.2%	0.000***
Distance to health centre > 1 hour	5.3%	31.1%	0.000***

Source: Evaluation team's elaboration on project data.
Note: Means for continuous variables, shares for binary p-values from Welch's t-test. *p < 0.10, **p < 0.05, ***p < 0.01.

3.5. Outcome trajectories

55. Pooling the three cross-sections allows the treatment and control trajectories to be traced across baseline, midline, and endline. This identifies general trends in key variables and initial assessment of whether the trends are consistent with programme impact. Figure 5 summarizes the pattern: for the welfare outcomes. As seen in the figure and highlighted previously, the treatment group begins at or below the control group at baseline, closes the gap by midline, and pulls clearly ahead by endline. This catching-up-then-takeoff pattern is the descriptive signature of a programme whose effects accumulate as adoption diffuses. The CRA indicators show the cleanest progression; dietary diversity follows a J-shape, dipping at midline before recovering above the control group at endline, consistent with the adjustment costs of an agricultural transition.

Figure 5: Outcome trajectories



Source: Evaluation team's elaboration on project data.
Note: Treatment−control gap across the three waves, in baseline standard deviation units and signed so that higher is better. Every welfare outcome starts at or below zero at baseline and is positive by endline.

56. Figure 6 displays unweighted outcome means by treatment group and wave on the full cross-sections. These trajectories are descriptive, not causal, but they help contextualize the impact estimates presented above.

57. The climate-resilient agriculture indicators (CRA adoption rate, technology count, and skills) diverge sharply and consistently: treatment households increase steadily across all three waves, while control households remain essentially flat, producing a widening gap by endline. Dietary diversity follows a different shape: both groups start close together, dip slightly at midline, and then rise, with treatment pulling clearly ahead of control by endline, consistent with a delayed nutritional payoff from the agricultural transition.

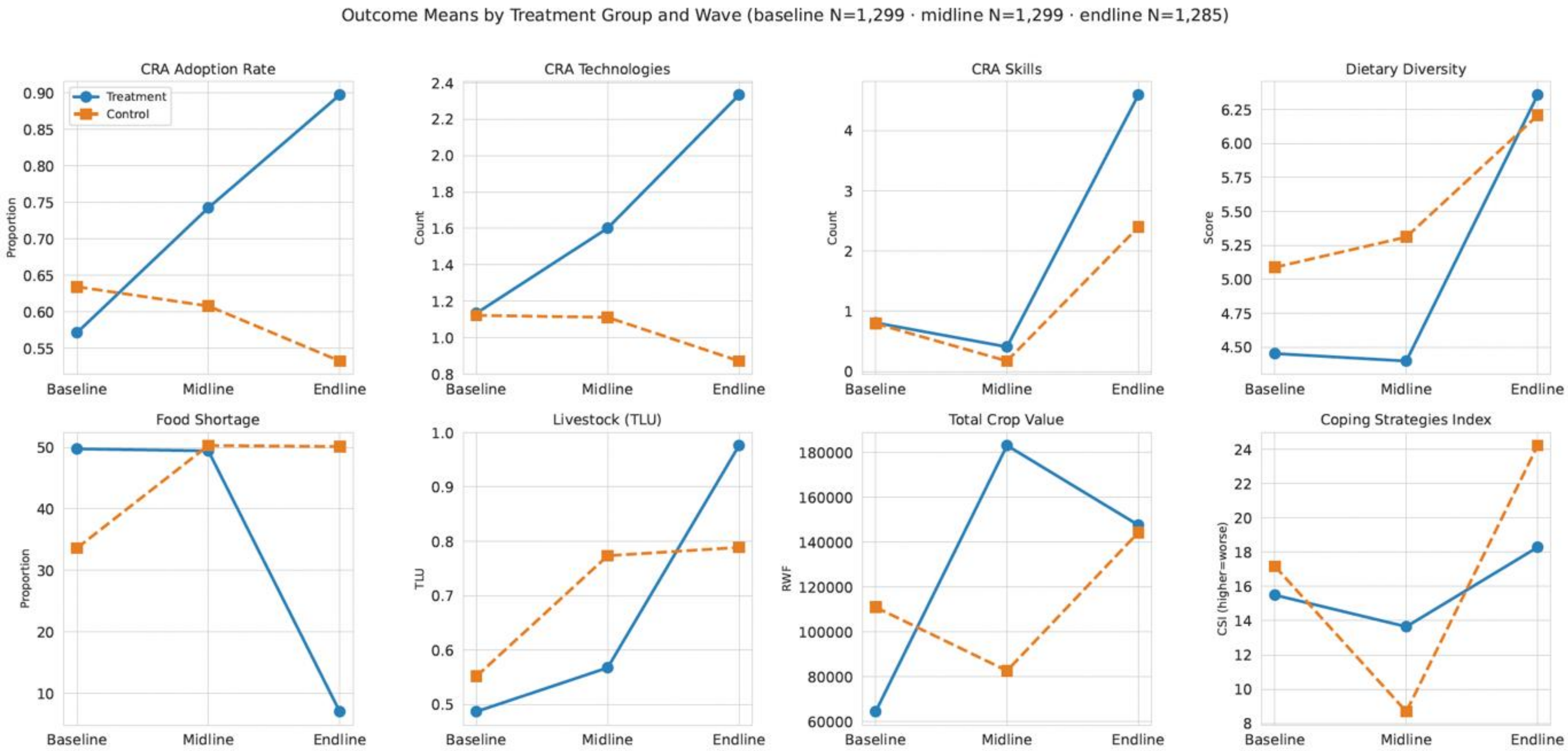
58. Food-security variable shows that food-shortage prevalence among treatment households falls steadily from 49.8 per cent at baseline to roughly 7 per cent at endline, while among control households it rises from 33.6 per cent to just over 50 per cent. The two groups start close together and end nearly 45 percentage points apart, with the divergence driven as much by control deterioration as treatment improvement.

59. TLU shows a converging pattern: control households start with visibly higher holdings at baseline, treatment households close most of that gap by midline, and the two groups are nearly indistinguishable by endline, which is consistent with the null impact estimates reported for this indicator. Total crop value moves in the opposite direction of the CRA and food-security panels: treatment households start below control, overtake them by midline, but control households recover and pull back ahead by endline, reflecting the volatility in crop value already discussed in the production and yield estimates above.

60. The CSI is the most volatile of the eight series: both groups fall from baseline to midline, but from midline to endline the control group’s score rises sharply (nearly doubling) while the treatment group’s increase is more moderate, leaving treatment households with a markedly lower (better) score than control by endline, despite both groups looking similar at baseline.

61. Taken together, the eight panels show three distinct patterns: steady divergence (CRA indicators, food shortage), late convergence (livestock), and volatility with a late-stage reversal (crop value, coping strategies), once again reaffirming that the endline DiD estimates should be read alongside these trajectories rather than as a single-point comparison.

Figure 6: Outcome means by treatment group and wave



Source: Evaluation team's elaboration on project data.
Note: Outcome means by treatment group and wave, full cross-sections (baseline N = 1,299, midline N = 1,299, endline N = 1,285).

Box 1: Building a credible counterfactual: Lessons from the evaluation design

A central challenge of the evaluation was the identification of a credible counterfactual against which to assess project impacts. Because the Green Gicumbi Project was assigned geographically at the sector level rather than randomly at the household level, treatment and comparison communities exhibited important baseline differences in welfare and agricultural outcomes. The evaluation team therefore explored several alternative analytical strategies before settling on the final estimation approach.

The first strategy relied on constructing a household panel by tracking the same households across survey rounds. However, household re-interview rates proved substantially lower than anticipated and differed across treatment and comparison groups. While panel estimators remained informative as robustness checks, the resulting sample was no longer representative of the original population and risked introducing attrition bias.

A second strategy explored inverse-probability-weighted regression adjustment and related matching approaches to create a balanced comparison group based on observable household characteristics. These methods improved balance on individual-level covariates but did not eliminate the baseline differences in key outcomes. Additional analyses using entropy balancing reached similar conclusions, suggesting that the residual imbalance reflected geographic and sector-level factors rather than household-level selection.

The evaluation team also considered focusing on a pseudo-panel approach based on aggregated village-level outcomes. These models proved useful. However, given the study design and limitations of the counterfactual identified in the baseline descriptive statistics, the approach was not adequate as the sole or the primary estimation strategy.

The final evaluation strategy therefore relies on a repeated cross-section DiD design combined with inverse-probability weighting based on baseline characteristics. This approach uses the full representative samples collected at baseline, midline, and endline while accounting for observable differences between treatment and comparison households. Identification rests on a conditional parallel trends assumption: after conditioning on baseline characteristics, outcomes in treatment and comparison villages would have followed similar trajectories in the absence of the project. The plausibility of this assumption is assessed through multiple robustness checks, including three-wave outcome trajectories, village-level panel estimates, overlap diagnostics, and sensitivity analyses based on alternative weighting and trimming specifications.

3.6. Traditional environmental knowledge versus modern climate-resilient agriculture

62. This section provides descriptive statistics on the adoption level of modern CRA as compared to the TEK. These are analysed from two different angles: gender of household head, and treatment versus control groups. Since the TEK module was not collected during baseline and midline, this analysis holds validity for the endline only, with no attempt to make causal attribution to the project.

3.6.1. Gender of household head

63. Table 7 presents descriptive statistics for the full TEK module disaggregated by gender of the household head. Tests of statistically significant difference by gender are presented. Normally, these

would be indicated through an asterisk, but since there are no gender differences in terms of statistical significance none are indicated in the table.

64. The most striking finding is the near-perfect consistency of responses across all thematic dimensions. Adoption rates are virtually identical (25.8 per cent for male-headed versus 22.7 per cent for female-headed households), and this homogeneity extends throughout the module: frequency of application, individual versus collective practice, perceived effectiveness, knowledge transmission to younger generations, and engagement with EWS all show differences of less than five percentage points, none of which approach statistical significance. The pattern holds equally for the TEK-modern CRA interface: conflict with project-promoted methods is reported by 13.2 per cent of male-headed and 13.3 per cent of female-headed households, while the share combining TEK with new project techniques is 23.0 per cent and 18.7 per cent respectively.

65. Taken together, these figures suggest that TEK practice in the project area is a community-level phenomenon shaped by local agroecological and cultural conditions rather than by intra-household gender dynamics. Importantly, the data show no evidence of systematic collision between traditional knowledge systems and the climate-smart agriculture practices promoted by the intervention: the large majority of households (and regardless of the gender of the head) report no conflict, and a substantial share actively combine both approaches, with soil conservation, pest and weed control, and water use identified as the main areas of perceived complementarity.

Table 7: TEK versus CRA uptake by gender of household head

Indicator	Male HHH (N=356)	Female HHH (N=75)	Difference (F–M, pp)
TEK adoption and practice			
Practices any TEK (Q13.1.1)	25.8	22.7	–3.1
Applies technique every season (Q13.1.4)	76.4	75.0	–1.4
Practice is collective or both (Q13.1.6)	82.0	82.7	+0.7
Perceived effectiveness and change over time			
Rates TEK as “very effective” (Q13.2.1)	35.1	35.8	+0.7
Rates TEK as “not effective” (Q13.2.1)	21.3	21.3	0.0
Practice has changed over time (Q13.2.2)	41.6	45.3	+3.7
Knowledge transmission			
Shared/taught technique to others (Q13.3.2)	84.8	82.7	–2.1
Young people still learning TEK (Q13.3.4)	81.5	80.0	–1.5
“Everyone” in community uses TEK (Q13.3.5)	50.0	57.3	+7.3
Where TEK was learned (multi-select, % mentioning)			
From parents	53.9	52.0	–1.9
From elders	43.3	36.0	–7.3
From farmer field schools	35.4	33.3	–2.1
From cooperatives	23.6	25.3	+1.7
From NGOs	11.5	6.7	–4.8
TEK-modern CRA interface			

Indicator	Male HHH (N=356)	Female HHH (N=75)	Difference (F–M, pp)
Reports conflict with modern methods (Q13.4.1)	13.2	13.3	+0.1
Combines TEK with project techniques (Q13.4.3)	23.0	18.7	–4.3
Areas of TEK–CRA complementarity (multi-select, % mentioning)			
Soil conservation	83.4	86.7	+3.3
Pest and weed control	55.3	58.7	+3.4
Water use	44.4	49.3	+4.9
Early warning systems			
Knows what an EWS is (Q13.5.1)	57.6	54.7	–2.9
Community has EWS practices (Q13.5.2)	54.2	52.0	–2.2
Traditional signs still work (Q13.5.4)	67.7	68.0	+0.3
How early warnings are received (multi-select, % mentioning)			
Radio	75.0	72.0	–3.0
Local/traditional signs	55.9	61.3	+5.4
Project alerts	40.2	48.0	+7.8

Source: Evaluation team's elaboration on project data.
Note: HHH = household head. Male HHH = female_hhh_bl==0; Female HHH = female_hhh_bl==1 (sex of HHH at baseline). Duration of practice (adopters only): male-headed HHs mean 10.0 years (median 5), female-headed HHs mean 6.8 years (median 5). pp = percentage points. * indicates statistically significant with 90 per cent confidence, ** with 95 per cent confidence. No * indicates difference is not different from a statistical standpoint.

3.6.2. Control versus treatment communities

66. Table 8 reveals a more differentiated picture than the gender analysis, with substantial and statistically significant differences between treatment and control households across nearly all dimensions of the TEK module. Notably, overall TEK adoption rates are similar between the two groups (27.2 per cent versus 21.7 per cent, chi-squared p = 0.207), suggesting that exposure to the project did not displace traditional practice at the extensive margin. The more striking contrasts emerge at the intensive margin and in the quality of engagement. Among adopters, treatment households apply TEK every season at a far higher rate than control households (92.1 per cent versus 39.4 per cent) and are substantially more likely to report that their traditional practices have evolved over time (50.2 per cent versus 27.6 per cent). This pattern suggests active behavioural change rather than passive retention of inherited knowledge.

67. The transmission of TEK to younger generations also appears more robust in the treatment group (86.0 per cent versus 73.0 per cent reporting that young people are still learning), and treatment households are markedly more likely to describe TEK as highly effective compared to modern methods (58.6 per cent versus 1.9 per cent). Together, these findings suggest that project exposure may have deepened households' conscious engagement with traditional knowledge rather than eroding it, with beneficiaries demonstrating a clearer awareness of how TEK and CRA practices can coexist and complement each other. This is particularly true in soil conservation, pest control, and water management, where perceived complementarity is consistently higher in the treatment group.

68. Reported conflict between TEK and CRA remains low in both groups, though it is somewhat more frequent among the treatment group (17.6 per cent versus 5.3 per cent), which likely reflects greater day-to-day exposure to the interface between the two systems rather than fundamental incompatibility.

69. Finally, the early warning system data warrant careful interpretation: control households report stronger reliance on traditional warning signs (84.2 per cent say they still work, versus 58.8 per cent among the treatment group), but this gap appears to reflect a compositional shift in information channels among project participants rather than a deficit. In fact, beneficiaries are far more likely to receive alerts through project-provided systems (52.7 per cent versus 19.1 per cent), suggesting a partial substitution of modern early warning channels for traditional ones as a result of intervention exposure.

Table 8: TEK versus CRA uptake by treatment group

Indicator	Beneficiaries (N=279)	Control (N=152)	Difference (C–B, pp)
TEK adoption and practice			
Practices any TEK (Q13.1.1)	27.2	21.7	–5.5
Applies technique every season (Q13.1.4)	92.1	39.4	–52.7**
Practice is collective or both (Q13.1.6)	84.2	78.8	–5.4
Perceived effectiveness and change over time			
Rates TEK as “very effective” (Q13.2.1)	58.6	1.9	–56.7**
Rates TEK as “not effective” (Q13.2.1)	10.5	36.8	+26.3**
Practice has changed over time (Q13.2.2)	50.2	27.6	–22.6**
Knowledge transmission			
Shared/taught technique to others (Q13.3.2)	84.2	84.9	+0.7
Young people still learning TEK (Q13.3.4)	86.0	73.0	–13.0**
“Everyone” in community uses TEK (Q13.3.5)	66.7	23.0	–43.7**
Where TEK was learned (multi-select, % mentioning)			
From parents	32.3	92.8	+60.5**
From elders	38.0	46.7	+8.7
From farmer field schools	46.2	16.4	–29.8**
From cooperatives	29.4	14.5	–14.9**
From NGOs	11.1	9.9	–1.2
TEK-modern CRA interface			
Reports conflict with modern methods (Q13.4.1)	17.6	5.3	–12.3**
Combines TEK with project techniques (Q13.4.3)	20.4	25.7	+5.3
Other projects encourage modern only (Q13.4.7)	76.7	94.7	+18.0**
Areas of TEK–CRA complementarity (multi-select, % mentioning)			
Soil conservation	89.6	75.0	–14.6**

Indicator	Beneficiaries (N=279)	Control (N=152)	Difference (C–B, pp)
Pest and weed control	63.1	40.8	–22.3**
Water use	53.4	31.6	–21.8**
Early warning systems			
Knows what an EWS is (Q13.5.1)	52.7	65.1	+12.4**
Community has EWS practices (Q13.5.2)	48.4	63.8	+15.4**
Traditional signs still work (Q13.5.4)	58.8	84.2	+25.4**
How early warnings are received (multi-select, % mentioning)			
Radio	69.9	79.6	+9.7*
Local/traditional signs	62.4	50.0	–12.4**
Project alerts	52.7	19.1	–33.6**

Source: Evaluation team's elaboration on project data.
Note: Beneficiaries = treatment==1; Control = treatment==2 (baseline assignment). Duration of practice (adopters only): Beneficiaries mean 9.6 years (median 5), Control mean 8.9 years (median 5). Overall TEK adoption (chi-squared p = 0.207) is not statistically significant. pp = percentage points. * indicates statistically significant with 90 per cent confidence, ** with 95 per cent confidence. No * indicates difference is not different from a statistical standpoint.

IV. Results

70. This section presents the evaluation's impact estimates in four steps. Section 4.1 reports repeated cross-section DiD estimates for the main outcome indicators identified in Table 1: CRA practice adoption and technology use (EQ1), food security and dietary diversity (EQ3), and production and asset accumulation (EQ4). Section 4.2 turns to the CRI, the composite EQ4 indicator that synthesizes these and other dimensions into a single resilience score. Section 4.3 checks the robustness of both sets of estimates using a fully balanced village-level panel. Finally, section 4.4 examines whether these impacts were shared equally by male- and female-headed households through a triple-difference analysis (EQ5). Together, these four steps move from indicator-specific effects to a synthesized resilience measure, to a robustness check, to a distributional check on who benefited.

4.1. Estimates of impact

71. Table 9 reports the repeated cross-section DiD estimates with cluster-robust SEs, unweighted and inverted probability weighting (IPW)-weighted. Note that weighting barely changes the repeated cross-section estimates, because the high level of common support indicates significant overlap in treatment and control.

72. Looking at the results, the project effects are clear: food shortage falls (−0.61, $p < 0.01$); dietary diversity is positive and significant (+0.77, $p < 0.05$), matching the village-level estimate in section 4.7; TLU and number of crops rise; and CRA adoption, techniques, and skills are all large and highly significant. Income sources, the CSI, total crop value, and female-headed household status are not statistically significant in the repeated cross-section.

Table 9: Repeated cross-section DiD estimates

Indicator	Unweighted DiD (δ)	SE	IPW-weighted DiD (δ)	SE
Food shortage (binary)	–0.602***	(0.061)	–0.612***	(0.061)
Dietary diversity score	+0.756**	(0.373)	+0.771**	(0.380)
Coping Strategies Index	-3.878	(4.737)	–3.954	(4.428)
Tropical livestock units	+0.257***	(0.077)	+0.262***	(0.079)
Crop value (RWF, '000)	+45.607	(58.064)	+36.621	(57.045)
Number of crops	+0.339**	(0.137)	+0.384***	(0.137)
Income sources	+0.007	(0.131)	–0.012	(0.130)
CRA adoption (binary)	+0.426***	(0.070)	+0.465***	(0.072)
CRA techniques count	+1.458***	(0.222)	+1.559***	(0.222)
CRA skills count	+2.197***	(0.470)	+2.312***	(0.497)
Female-headed HH (binary)	+0.014	(0.029)	+0.011	(0.030)

Source: Authors' calculations based on survey data.
Note: DiD (δ, the Post×Treat coefficient) on the pooled baseline (1,299) and endline (1,285) cross-sections; the repeated cross-section is free of household-level attrition. Unweighted: pooled OLS. IPW-weighted: inverse-probability weights from the baseline-estimated 13-covariate propensity, predicted forward to the endline. Cluster-robust SEs (village level) in parentheses. Crop value in RWF thousands. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

73. Table 10 reports the underlying baseline and endline means by treatment group, organized by evaluation question, alongside the repeated cross-section DiD. The descriptive trajectories make the effects concrete: among beneficiaries, food shortage falls from 49.8 per cent to 7.0 per cent while among controls it rises from 33.6 per cent to 50.2 per cent; CRA technology counts roughly double in treatment areas while declining in control areas; and dietary diversity rises faster among beneficiaries.

Table 10: Outcome means by treatment group

Indicator	Baseline treat	Baseline control	Endline treat	Endline control	DiD
EQ1: Climate-resilient agriculture					
CRA adoption rate	0.571	0.634	0.897	0.533	0.427***
CRA technologies	1.134	1.122	2.334	0.871	1.451***
CRA skills in use	0.808	0.795	4.593	2.398	2.182***
EQ3: Food security					
Dietary diversity (0–10)	4.453	5.088	6.357	6.207	0.786**
Food shortage	0.498	0.336	0.070	0.502	–0.593***
EQ4: Livelihoods and assets					
Coping Strategies Index	15.497	17.174	18.293	24.230	–4.259
Tropical livestock units	0.487	0.552	0.976	0.789	0.252***
Income sources	1.932	1.787	1.754	1.606	0.003
Number of crops	2.892	3.247	1.181	1.194	0.343**
Total crop value (RWF)	64,414	110,957	147,596	144,328	49,810
EQ5: Gender					
Female-headed HH	0.203	0.193	0.203	0.179	0.014

Source: Authors' calculations based on survey data.
Note: Means on the full cross-sections (baseline N = 1,299, endline N = 1,285). DiD is the repeated cross-section Post×Treat coefficient (Table 9); cluster-robust p-values (village). Crop value in RWF. *p < 0.1, **p < 0.05, ***p < 0.01.

74. Table 11 probes the robustness of these estimates to the weighting and trimming rule, testing whether a richer specification and trimming clean up the residual baseline imbalance. Weighting on the 13 baseline covariates reduces the average absolute standardized baseline difference from 0.088 to 0.006 (maximum across covariates from 0.296 to 0.012), so balance is essentially exact. Trimming the sample on the propensity score changes almost nothing, because overlap is already strong (only 0.2 per cent of observations have a propensity above 0.9 and none below 0.1), and the DiD estimates are stable across all four specifications. The convergence of the repeated cross-section and village-level estimates provides the most credible reading of the project's impact.

Table 11: Repeated cross-section estimates pool the baseline

	UNWEIGHTED	IPW	IPW + TRIM 0.1	IPW + TRIM 0.05
Baseline covariate balance (13 covariates)				
Mean |std. diff.|	0.088	0.006	0.006	0.006
Max |std. diff.|	0.296	0.012	0.012	0.012
Observations	2,534	2,534	2,529	2,533
Difference-in-differences estimates				
Dietary diversity	+0.76**	+0.77**	+0.77**	+0.77**
Food shortage	–0.60***	–0.61***	–0.61***	–0.61***
Livestock (TLU)	+0.26***	+0.26***	+0.26***	+0.26***
Total crop value (RWF)	45,607	36,621	35,968	35,820
CRA adoption	+0.43***	+0.47***	+0.46***	+0.47***
CRA technologies	+1.46***	+1.56***	+1.56***	+1.56***
CRA skills	+2.20***	+2.31***	+2.31***	+2.31***
Coping Strategies Index	–3.88	–3.95	–3.99	–3.96
Climate Resilience Index	+10.26***	+10.63***	+10.63***	+10.62***

Source: Authors' calculations based on survey data.
Note: Repeated cross-section pools the full baseline (N = 1,299) and endline (N = 1,285) cross-sections. Propensity estimated on the baseline with 13 pretreatment covariates (pseudo-R2 = 0.038) and predicted forward; common support [0.26, 0.96]. IPW is Hajek-normalized (ATE-type). Trimming columns drop units with estimated propensity outside the stated interval. Standardized differences are treatment−control at baseline, averaged (and maximized) over the 13 covariates; values below 0.10 indicate negligible imbalance. Cluster-robust SEs (village). *p < 0.1, **p < 0.05, ***p < 0.01.

4.2. Climate Resilience Index

75. As a summary outcome, we estimate the project's effect on the CRI, a composite measure on a 0–100 scale that combines household survey responses with remote sensing inputs (vegetation, rainfall, temperature, and drought/heat anomalies extracted via Google Earth Engine) across capacity, sensitivity, and exposure dimensions, constructed with equal weights. Like the other indicators, the CRI is imbalanced at baseline (treatment sectors begin roughly nine points higher as shown in Table 12) so the level difference is differenced out by the DiD rather than interpreted directly. Estimated on the repeated cross-section, the project raises the CRI by about 10 points, significant at the 1 per cent level, with the IPW-weighted estimate essentially identical to the unweighted one. One interpretive caveat: because the CRI embeds geographic and remote sensing components (notably exposure, which is largely fixed location characteristics), the DiD nets out the time-invariant geographic portion, so the estimated gain reflects the household- and community-responsive dimensions of resilience rather than changes in fixed exposure.

Table 12: Climate Resilience Index: Treatment effects (repeated cross-section)

Indicator	Baseline T–C gap	Repeated cross-section DiD Unweighted	Repeated cross-section DiD IPW
Climate Resilience Index (0–100)	+9.34***	+10.26***	+10.63***

Source: Authors' calculations based on survey data.
Note: CRI on a 0–100 scale, integrating household survey and remote sensing inputs. Baseline T−C gap: raw difference on the full baseline (N = 1,299), Welch t-test. Repeated cross-section DiD pools the baseline (1,299) and endline (1,285) cross-sections; IPW uses the baseline-estimated 13-covariate propensity. Cluster-robust SEs (village). ∗p < 0.1, ∗∗p < 0.05, ∗∗∗p < 0.01.

4.3. Village-level estimates

76. As a robustness check on the household-level estimates presented in sections 4.1 and 4.2, this section reports DiD estimates using the village-level panel. Table 13 reports DiD estimates using the village-level panel (125 villages × 3 waves), where household outcomes are aggregated to village means within each wave. Because all 125 villages are observed in all waves, this panel is balanced by construction and provides an aggregation-level check on the household estimates.

77. The village-level results confirm the repeated cross-section findings for the CRA indicators. CRA adoption shows a village-level DiD of +0.43 (p < 0.001), CRA techniques +1.47 (p < 0.001), and CRA skills +2.20 (p < 0.001) for the baseline-to-endline comparison. These effects are large in standardized terms (1.7–2.4 SD) and track the household-level estimates closely.

78. For food security, the village-level food-shortage DiD is −0.60 (p < 0.001), matching the repeated cross-section estimate (−0.61). Dietary diversity shows a positive DiD of +0.82 (p = 0.027) at the village level, in line with the positive repeated cross-section estimate (+0.77). The CSI shows a marginally significant village-level DiD of −8.08 (p = 0.061), whereas the household-level estimate is insignificant. This difference should be interpreted cautiously: CSI items were administered only to food-shortage households, so at the village level. CSI mean aggregates over a changing and potentially non-comparable subset of households across waves. TLU shows a positive village-level DiD of +0.25 (p = 0.001), consistent with the repeated cross-section result (+0.26). Number of crops is significant at the village level (+0.40, p = 0.007), and total crop value is positive but imprecisely estimated at the village level (p = 0.355), as in the repeated cross-section; the severe baseline imbalance in this indicator complicates interpretation at both levels.

Table 13: DiD estimates based on the balanced village-level panel

Indicator	Period	DiD	SE	p-value	Effect size	N_v
Food shortage (binary)	BL→EL	–0.595***	(0.060)	<0.001	–2.466	125
Food shortage (binary)	BL→ML	–0.169***	(0.048)	<0.001	–0.699	125
Dietary diversity score	BL→EL	+0.821**	(0.368)	0.027	+0.656	125
Dietary diversity score	BL→ML	–0.243	(0.260)	0.351	–0.195	125
Coping Strategies Index	BL→EL	–8.077*	(4.272)	0.061	–0.513	125
Coping Strategies Index	BL→ML	+3.330	(3.091)	0.283	+0.212	125
Tropical livestock units	BL→EL	+0.251***	(0.076)	0.001	+1.848	125

Indicator	Period	DiD	SE	p-value	Effect size	N_v
Tropical livestock units	BL→ML	–0.142***	(0.037)	<0.001	–1.050	125
Total crop value (RWF)	BL→EL	+48,073.804	(51,779.920)	0.355	+0.380	125
Total crop value (RWF)	BL→ML	+140,382.300	(86,774.546)	0.108	+1.111	125
Number of crops	BL→EL	+0.403***	(0.146)	0.007	+0.511	125
Number of crops	BL→ML	+0.275	(0.211)	0.195	+0.350	125
Income sources	BL→EL	+0.021	(0.132)	0.875	+0.044	125
Income sources	BL→ML	–0.187*	(0.106)	0.081	–0.400	125
CRA adoption (binary)	BL→EL	+0.433***	(0.070)	<0.001	+1.730	125
CRA adoption (binary)	BL→ML	+0.192***	(0.057)	<0.001	+0.766	125
CRA techniques count	BL→EL	+1.473***	(0.218)	<0.001	+2.440	125
CRA techniques count	BL→ML	+0.472***	(0.143)	0.001	+0.782	125
CRA skills count	BL→EL	+2.198***	(0.461)	<0.001	+1.969	125
CRA skills count	BL→ML	+0.229	(0.199)	0.252	+0.206	125
Female-headed HH (binary)	BL→EL	+0.016	(0.030)	0.600	+0.114	125
Female-headed HH (binary)	BL→ML	–0.000	(nan)	1.000	0.000	125

Source: Authors' calculations based on survey data.
Note: Effect size = DiD / baseline pooled SD. 125 villages × 3 waves. ∗p < 0.1, ∗∗p < 0.05, ∗∗∗p < 0.01.

4.4. Gender responsiveness: Heterogeneity by sex of household head

79. Having established the project's average effects on the indicators and the CRI above, we now assess whether project impacts were distributed equitably across household types. This section presents a triple-difference (DDD) analysis comparing treatment effects for female-headed households (FHH) and male-headed households (MHH). The estimating sample comprises 132 and 125 FHH in the treatment and control arms at baseline, and 126 and 110 at endline, making FHH estimates less precise than the full-sample counterparts. The triple-difference coefficient captures the differential treatment effect for FHH relative to MHH and is estimated on the repeated cross-section. All estimates use village-clustered SEs.

80. Table 14 reports male-headed and female-headed DiD estimates alongside the DDD and its p-value. For the CRA indicators the DDD coefficients are small and statistically indistinguishable from zero (p = 0.91, 0.86, and 0.34 respectively), indicating that both household types benefited equally from the project's capacity-building activities. Similarly, the reduction in food-shortage prevalence is comparable across household types (DDD +0.06, p = 0.50), and the livestock (TLU) differential is modest and only marginally significant on the village panel (−0.20, p ≈ 0.10).

81. Two outcomes, however, reveal a statistically significant gap. Dietary diversity gains accrued almost entirely to male-headed households (+0.64 HDDS points), while the effect for FHH is near zero (−0.12), yielding a triple-difference of −0.76 (p = 0.073), which is confirmed on the village panel (−0.75, p < 0.10). A similar pattern is observed for the CRI: male-headed households gained approximately 8.7 points, while FHH gained only 4.5 points, a triple-difference of −4.26 (p = 0.064) that strengthens on the village panel (−5.27, p = 0.046). Together, these results suggest that the welfare and composite resilience benefits of the project were less fully realized by FHH, even as agricultural practice adoption proceeded at the same rate. This pattern is consistent with greater

constraints on the conversion of productive knowledge into consumption and asset outcomes among FHH, including more limited access to markets, labour, and complementary inputs, and warrants attention in the design of future project cycles.

Table 14: DDD estimates by sex of household head (repeated cross-section and village panel)

INDICATOR	MHH DID	FHH DID	DDD	*p*	VILLAGE DDD
CRA adoption	+0.39	+0.38	−0.01	0.911	−0.02
CRA technologies	+1.26	+1.31	+0.04	0.863	+0.00
CRA skills	+1.85	+1.42	−0.43	0.340	−0.64
Food shortage	−0.59	−0.53	+0.06	0.503	+0.04
Dietary diversity	+0.64	−0.12	−0.76*	0.073	−0.75*
Livestock (TLU)	+0.26	+0.14	−0.12	0.191	−0.20*
Climate Resilience Index	+8.73	+4.48	−4.26*	0.064	−5.27**

Source: Authors' calculations based on survey data.
Note: All estimates on the baseline-to-endline repeated cross-section with village-clustered SEs; village panel as robustness. DDD = [FHH – MHH] treatment effect. *p < 0.10, **p < 0.05. FHH N: 132/125 (BL treat/control), 126/110 (EL treat/control).

V. Discussion and conclusions

5.1. Theme 1. From adoption to outcomes: Evidence of behavioural change

82. The evaluation findings indicate that the Green Gicumbi Project successfully changed agricultural practices among participating households. CRA adoption, the number of techniques used, and reported skills are all large and significant at the 1 per cent level (Table 9); the village-level panel confirms this with DiD estimates of +0.43, +1.47, and +2.20 respectively (all $p < 0.001$), corresponding to standardized effects of 1.7–2.4 SD. These effects are large, statistically significant, and consistently observed across alternative estimation approaches.

83. Importantly, these findings suggest that the project achieved more than the simple dissemination of agricultural inputs or technologies. The results lead to sustained behavioural change, whereby households not only gained access to climate-resilient practices but also incorporated them into their production systems. Such behavioural changes are particularly relevant in adaptation programming, where long-term resilience depends not only on asset provision but also on the capacity of households to modify production strategies in response to changing climatic conditions.

84. The consistency of the effects across adoption, technology uptake, and skills use provides strong evidence that the intervention successfully influenced the mechanisms through which resilience gains were expected to occur.

5.2. Theme 2. Recovery and overtake

85. One of the most notable findings of the evaluation is the trajectory followed by beneficiary households over time. At baseline, treatment communities were systematically worse off than comparison communities across several key dimensions, including food security, dietary diversity, livestock ownership, and agricultural production. For example, food-shortage prevalence stood at 49.8 per cent among future beneficiaries versus 33.6 per cent among comparison households at baseline. By endline this had reversed: beneficiary food shortage fell to 7.0 per cent while the comparison group's rose to 50.2 per cent (Table 10). The baseline-to-midline estimates corroborate this trajectory: CRA adoption was already significant at midline (+0.19, $p < 0.001$), roughly a third of the endline effect (+0.43) (Table 13), consistent with a cumulative rather than one-off effect. These differences likely reflect the geographic targeting of the intervention towards more vulnerable areas.

86. However, the three-wave evidence reveals a clear pattern of recovery and overtake. On food security, the reversal is stark: by endline, beneficiary food shortage had fallen to 7.0 per cent while the comparison group's had risen to 50.2 per cent, a reversal of over 59 percentage points. The same pattern holds for practice adoption: CRA adoption and technique-use effects were already significant at midline (+0.19 and +0.47, both $p < 0.001$) and roughly doubled by endline (+0.43 and +1.47, Table 13), indicating the gap closed progressively across waves rather than emerging only at the final round. Beneficiary households gradually closed the initial gap observed at baseline and, by the endline, outperformed comparison households on a range of outcomes. This pattern is particularly visible for CRA adoption, food security, and livestock assets.

87. The observed trajectory is consistent with the ToC underlying many climate adaptation interventions. Adoption of new practices often requires an initial adjustment period during which households experiment with unfamiliar technologies, reorganize labour allocation, and absorb implementation costs. Benefits may therefore emerge gradually rather than immediately. The fact that improvements strengthened between midline and endline suggests that project impacts accumulated over time as adoption became more widespread and technologies matured.

88. This temporal pattern strengthens confidence in the evaluation findings. Rather than observing a short-lived or isolated effect, the evidence suggests a progressive process through which households improved their capacity to cope with climatic and livelihood risks.

5.3. Theme 3. Food-security and asset accumulation

89. Food shortage declined by 0.61 points on the repeated cross-section ($p < 0.01$) and 0.60 at the village level ($p < 0.001$); dietary diversity rose by 0.77 ($p < 0.05$) and 0.82 ($p = 0.027$), respectively (Table 9 and Table 13). At the same time, beneficiary households accumulated significantly larger livestock holdings (TLU DiD +0.26 in the repeated cross-section, +0.25 at the village level, $p = 0.001$).

90. These findings are important because they correspond to outcomes that are often considered intermediate achievements of resilience. Livestock represents a productive asset that can be mobilized during periods of stress, while improvements in food consumption indicate greater capacity to maintain welfare despite climatic and economic shocks.

91. The combination of improved agricultural practices, stronger food-security outcomes, and increased asset ownership suggests that the project successfully strengthened households' absorptive and adaptive capacities. Rather than generating gains through a single channel, the intervention appears to have influenced multiple dimensions of household well-being simultaneously.

92. The livestock results are particularly noteworthy because they indicate that households were able not only to protect existing assets but also to accumulate new ones. This suggests that project benefits extended beyond short-term coping and contributed to longer-term livelihood strengthening.

5.4. Theme 4. Missing impacts

93. Not all outcomes showed statistically significant improvements. Crop value remained insignificant at both estimation levels ($p = 0.355$ at the village level, Table 13), income sources showed no significant change, and the CSI was insignificant on the repeated cross-section though only marginally significant at the village level (−8.08, $p = 0.061$), a difference plausibly explained by the changing composition of food-insecure households this indicator is conditioned on.

94. These findings should not necessarily be interpreted as evidence of project failure. First, agricultural income is influenced by a wide range of factors beyond production practices, including weather variability, market conditions, input prices, and local demand. Improvements in resilience may therefore materialize before measurable gains in agricultural income become evident. Adaptation interventions often strengthen the stability and reliability of production rather than maximizing short-term output or profits.

95. Second, the absence of significant effects on income diversification is broadly consistent with the project's objectives. The Green Gicumbi Project sought primarily to improve the resilience and productivity of agricultural systems rather than encourage households to diversify into non-farm activities. The lack of measurable change in the number of income sources therefore does not necessarily contradict the project's ToC.

96. Third, the CSI presents a more nuanced picture. Although food shortage declined substantially, coping behaviour did not improve significantly. One possible explanation is that coping strategies reflect broader perceptions of risk and vulnerability that may persist even after food security improves. Households may continue precautionary behaviours despite experiencing fewer food shortages. In addition, the index is measured only among households experiencing food insecurity, making it inherently more variable and potentially less responsive than other food-security indicators.

97. Taken together, these results suggest that the project generated stronger evidence of resilience and food-security gains than of immediate income gains. This pattern is consistent with the expected sequencing of impacts in climate adaptation interventions.

5.5. Theme 5. Climate resilience as an integrating outcome

98. The CRI provides an integrated perspective on project performance by combining information on resilience capacities, exposure to climatic stressors, and livelihood conditions. While individual outcome indicators provide evidence on specific dimensions of change, the CRI captures the broader objective of strengthening households' ability to absorb, adapt to, and recover from climatic shocks.

99. The project raised the CRI by approximately 10 points on a 0–100 scale, significant at the 1 per cent level, with the IPW-weighted estimate essentially unchanged (Table 12). The positive and statistically significant impact observed on the CRI is therefore particularly important. It indicates that the improvements documented across agricultural practices, food security, and asset ownership translate into measurable gains in overall resilience.

100. The CRI results also help reconcile the apparent contrast between strong improvements in adaptation practices and the absence of significant effects on some income-related indicators. Resilience and income maximization are often results of completely different policies. A household may become more resilient by reducing vulnerability, stabilizing consumption, protecting productive assets, and increasing adaptive capacity even when immediate income gains remain modest.

101. Viewed collectively, the evidence suggests that the Green Gicumbi Project successfully strengthened the resilience of participating households. The observed improvements in CRA, food security, livestock ownership, and the CRI are consistent with a pathway in which behavioural change translated into enhanced capacity to manage climatic risks and sustain livelihoods under increasingly uncertain environmental conditions.

5.6. Theme 6. Unequal transmission: Female-headed households at the margin of welfare gains

102. The triple-difference analysis reveals a structurally important asymmetry in the distribution of project benefits. While the intervention succeeded in promoting the adoption of climate-resilient agricultural practices uniformly across household types, the transmission of these gains into welfare outcomes was significantly weaker for FHH. The triple-difference coefficients for the CRA indicators are statistically indistinguishable from zero ($p = 0.91, 0.86, 0.34$), confirming equal access across household types (Table 14). By contrast, the dietary diversity triple-difference is −0.76 ($p = 0.073$ on the repeated cross-section, −0.75 at the village level, $p < 0.10$), and the CRI triple-difference is −4.26 ($p = 0.064$), strengthening to −5.27 ($p = 0.046$) at the village level. The equal adoption and unequal welfare conversion suggests an *access* rather than a *returns-to-adoption* problem.

103. For five of the seven indicators examined, the triple-difference coefficients confirm that both household types participated in, and benefited from, the project's capacity-building activities on broadly equal terms. Food shortage declined at comparable rates, and livestock accumulation, while marginally lower for FHH on the village panel, did not reach conventional significance thresholds in the primary repeated cross-section estimates. These findings are consistent with the project's delivery model which appears to have been inclusive at the point of engagement.

104. However, the picture changes sharply for outcomes that depend on the ability to convert agricultural knowledge and practices into consumption and asset welfare. Dietary diversity gains accrued almost exclusively to MHH; and the pattern is even more pronounced for the CRI. This transmission gap is unlikely to reflect differential engagement with the intervention. Rather, it is consistent with a broader

pattern documented in the gender and agriculture literature whereby FHH face compounding constraints that limit their ability to realize the full welfare returns of productivity-enhancing investments. These include more limited access to complementary labour (particularly for land preparation and harvest operations that often require hired or reciprocal male labour), tighter liquidity constraints that reduce the ability to invest in inputs at the right moment in the agricultural calendar, more restricted market access and bargaining power in output markets, and, in some contexts, higher dependency ratios that divert food and income towards immediate consumption needs rather than dietary diversification. The project did not specifically target these structural bottlenecks, and the DDD results suggest they were consequential.

105. The finding carries direct implications for the project's gender marker and for the design of future interventions. Achieving gender-responsive outcomes (rather than gender-neutral access) requires moving beyond inclusive delivery of training and technology to actively address the constraints that prevent FHH from converting adoption into welfare gains. This could include dedicated support for labour-sharing arrangements or collective production models, targeted input credit or subsidy schemes for FHH, and gender-differentiated market linkage support. Without such measures, the risk is that well-designed agricultural interventions reproduce, rather than reduce, intra-community welfare disparities.

106. This finding aligns with the results of the Madagascar IE led by the Independent Evaluation Unit.[11] In the case of Madagascar, results showed that FHH were unable to sustain the adoption of conservation agriculture practices over time. Also, and consistently with the results showed here, it emerged that the initial disparities (between FHH and MHH) reflected structural constraints, such as time, labour shortages and vulnerability to shocks, rather than lack of interest or awareness. This evidence clearly shows the need for a more accurate assessment of initial and structural differences when considering gender dimensions.

5.7. Revisiting the theory of change: What worked, what did not, and why?

107. The Green Gicumbi Project was originally designed more than a decade ago, with the funding proposal first developed in 2015 and subsequently approved by the Green Climate Fund in 2018. The project's ToC was built around the premise that investments in watershed restoration, CRA, sustainable forest management, resilient settlements, and knowledge transfer would strengthen the adaptive capacity of vulnerable communities, reduce their exposure to climate risks, and ultimately improve livelihoods and resilience. Particular emphasis was placed on vulnerable populations, including FHH, who were identified as being disproportionately exposed to climate-related risks.

108. The endline evaluation provides an opportunity to reflect on these assumptions and assess not only whether the project generated impacts, but also whether the causal pathways envisioned in the original ToC operated as expected.

109. The evaluation findings provide strong evidence that the project successfully influenced behavioural change and practice adoption. Beneficiary households adopted climate-resilient agricultural practices, increased their use of climate-smart technologies, and improved their knowledge and skills related to climate adaptation. These findings suggest that the project's core delivery mechanisms functioned largely as originally designed back in 2015.

110. The results further indicate that these behavioural changes translated into improvements in several key welfare outcomes. Beneficiary households experienced reductions in food shortages, improvements in dietary diversity, and gains in livestock ownership. Moreover, positive impacts were observed on the

[11] Independent Evaluation Unit, *Impact Evaluation Endline Report for FP026: Sustainable Landscapes in Eastern Madagascar* (2026).

CRI, suggesting that project interventions contributed to strengthening households' overall capacity to cope with and adapt to climate-related shocks.

111. Taken together, these findings support the central premise of the ToC that investments in adaptive capacity and climate-resilient practices can contribute to improved household welfare and resilience.

112. While the project successfully promoted the adoption of climate-resilient practices, the evidence suggests that the pathway from adoption to broader livelihood transformation was less straightforward than originally anticipated.

113. Several outcomes that would be expected to improve through enhanced agricultural productivity and livelihood diversification showed weaker or less consistent effects. In particular, impacts on crop value, income diversification, and some dimensions of coping capacity were limited. This suggests that while households adopted new practices, these changes did not always translate into sustained economic gains.

114. The findings therefore point to an important distinction between the adoption of resilience-enhancing practices and the realization of resilience-enhancing outcomes. The former appears to have occurred relatively successfully; the latter was more uneven.

115. The gender-disaggregated analysis provides perhaps the most revealing "stress test" of the original ToC.

116. The project's Gender Action Plan explicitly recognized FHH as a particularly vulnerable group and incorporated a range of measures intended to improve their participation in project activities. The underlying assumption was that increased access to project interventions would enable women and FHH to benefit proportionately from project investments.

117. The evaluation findings suggest that this assumption was only partially correct. FHH appear to have adopted climate-resilient practices at rates broadly comparable to MHH, indicating that the project was successful in reaching women and promoting participation. However, the gains in dietary diversity and overall resilience were smaller among FHH than among MHH.

118. These findings suggest that access to adaptation technologies and knowledge, while necessary, may not be sufficient to generate equivalent welfare gains across different household types. FHH may face additional structural constraints that reduce their ability to convert technical gains into broader improvements in well-being and resilience.

119. In this respect, the evaluation does not indicate a failure of implementation. Rather, it suggests that the original ToC may have underestimated the importance of complementary constraints that shape households' ability to benefit from adaptation investments.

Lessons for future adaptation programming

120. The evidence highlights three lessons that may be relevant for future climate adaptation investments.

121. First, adoption of climate-resilient technologies should not be viewed as an end in itself. Greater attention may be needed to the mechanisms through which adoption translates into sustained livelihood improvements.

122. Second, resilience-building is likely to be a longer-term process than originally assumed. Many project interventions (including watershed restoration, agroforestry, forest regeneration, and livelihood diversification) may require longer time horizons before their full benefits become visible.

123. Third, future interventions may need to complement technical adaptation support with measures that address structural barriers faced by vulnerable groups. Improving access to technologies and knowledge may not be sufficient if households lack the assets, labour, market access, or institutional support required to convert these opportunities into lasting resilience gains.

124. Viewed through this lens, the Green Gicumbi Project serves not only as an example of successful climate adaptation programming, but also as a learning opportunity to better understand what lies beyond adoption. The evaluation suggests that technical support, training, and asset provision are necessary but may not always be sufficient to generate lasting and equitable resilience gains. Understanding the additional social, economic, and institutional conditions required for households to transform adaptation investments into resilience outcomes represents an important contribution to the design of future climate resilience programmes in Rwanda and across the Green Climate Fund ecosystem.

5.8. Conclusions

125. The Green Gicumbi Project represents one of the longest-running climate adaptation investments supported by the Green Climate Fund. From the initial conception of the project in 2015 (i.e. right after the Paris Agreement, within a very new – and different – Green Climate Fund), through approval in 2018, implementation, and eventual completion, the project spans more than a decade of sustained engagement. Such a long time horizon is particularly usual and relevant in the context of climate adaptation, where many of the intended changes require years before their full effects become visible.

126. Throughout the course of this evaluation, one observation consistently emerged from discussions with stakeholders, local authorities, implementing partners, and beneficiary communities: the Green Gicumbi Project is widely regarded as a success story. This perception extends beyond the immediate intervention area and reflects the strong ownership demonstrated by the GoR and the MoE throughout the design and implementation of the project. The visibility of the project's achievements, combined with the strong institutional commitment surrounding it, has contributed to establishing Green Gicumbi as a reference point for climate adaptation programming within Rwanda and beyond.

127. The evaluation findings presented in this report provide support for this broader perception. Beyond the specific impacts observed at household level, the project demonstrates the value of sustained investments in climate resilience and the potential for adaptation interventions to generate tangible benefits for vulnerable communities when implemented at scale and over an extended period.

128. An equally important finding emerging from this evaluation concerns country ownership. Following the approval and implementation of Green Gicumbi, the MoE continued to mobilize climate finance through additional Green Climate Fund instruments, including Project Preparation Facility support and subsequent project proposals. This reflects not only the successful implementation of a single project but also the strengthening of national capacities to identify, prepare, and manage climate investments. In this regard, Green Gicumbi can be viewed as an example of country ownership in practice: national institutions moving beyond project implementation to actively shape and expand their climate adaptation agenda.

129. The project also offers important lessons regarding scalability and replication. The integrated approach adopted by Green Gicumbi addresses multiple dimensions of climate vulnerability simultaneously. While adaptation interventions are inherently context-specific, many of the principles underpinning the Green Gicumbi model appear transferable to other vulnerable regions within Rwanda and potentially beyond. The project's emphasis on local ownership, long-term engagement, and the integration of environmental restoration with livelihood improvement provides a useful framework for future adaptation programming.

130. Ultimately, the legacy of the Green Gicumbi Project extends beyond its immediate results. It demonstrates the potential of long-term climate finance to support locally owned adaptation pathways, strengthen national institutions, and create foundations for future investments in resilience. As climate risks continue to intensify across many developing countries, the experience of Green Gicumbi offers valuable lessons for both the GoR and the wider Green Climate Fund portfolio.

Appendix 1. Data issues

1.1. Data quality issues

Differential attrition. 66.8 per cent overall attrition, with beneficiaries retained at nearly twice the rate of controls (42.9 per cent versus 23.5 per cent). This is the primary threat to internal validity of the household-level estimates.

Baseline imbalance. Food shortage and total crop value show significant baseline differences between treatment and control. These imbalances are present in the full baseline sample (N = 1,299; food shortage $p < 0.001$, crop value $p = 0.005$), confirming they originate from randomization rather than attrition.

Conditional CSI at baseline. CSI items were only administered to food-shortage households, limiting the baseline CSI sample to 542 of 1,299 households (193 of 431 in the panel).

Missing household heads. 50 endline households have no roster member coded as "head." All 50 have other members (spouse, son/daughter, etc.). Their head demographics are flagged (no_head_flag = 1) and set to missing.

Total crop value outliers. Self-reported production and prices produce extreme values in some households (maximum RWF 1,945,000 in the panel). The distribution is right-skewed with a large mass at zero (141 of 261 treatment HHs, 51 of 148 control HHs). Winsorizing at the 95th percentile reduces the baseline imbalance but preserves the significant DiD (RWF 150,416, $p < 0.001$).

1.2. Data-processing notes

Several data issues were identified and addressed during panel construction:

- Baseline variable coding. All binary indicators (CRA technologies, skills, dietary diversity items, income sources) used 1 = Yes / 2 = No coding. These were recoded to 1/0 before aggregation. CSI items used 999 for "did not use this strategy," recoded to 0.
- Midline string variables. The midline SPSS import produced string-typed variables ("Yes"/"No") for several indicator sets. These were encoded to numeric 1/0.
- Midline duplicate variable sets. The merged midline file contains both baseline carryover and midline-specific versions of several instruments. Missingness analysis determined that the _midline/_New_midline suffix variables are the primary instruments (96.6 per cent coverage versus ~40 per cent for carryover sets).
- CSI item ordering. The 12 coping strategies are ordered differently across waves. Weights were mapped by strategy label, not column position.
- Endline HHH demographics. Head demographics were derived from the household roster (relation = "Head"), yielding 18.4 per cent FHH at 4 endline. 50 endline households have no member coded as "Head" in the roster; their head demographics are flagged as missing.
- Endline multi-response strings. CRA technologies, skills, dietary diversity, and income sources are stored as space-delimited strings in the endline data. These were parsed into component counts via keyword matching in a Python preprocessor.
- Crop production data. Total crop value was recovered from raw crop-level files: Seasons.dta (baseline, crop × season) and Plot_2.sav (midline, wide format per crop). Both were aggregated to household-level totals.

1.3. Variable crosswalk

Table 15 maps each data analysis plan outcome indicator to its source variables in each survey wave and documents the construction method.

Table 15: Outcome variable crosswalk across survey waves

Indicator	Baseline	Midline	Endline	Construction
CRA adoption	j_4_1... j_4_7	j_4_*_midline	cra_tech (multi-response)	≥ 1 technology = 1
CRA tech. count	j_4_1... j_4_7	j_4_*_midline	cra_tech (multi-response)	Sum of adopted items (0–7)
CRA skills	k_17_1... k_17_14	k_17_*_midline	skills_used (multi-response)	Sum of skills (0–14)
Diet. diversity	h_3_1... h_3_9, h_3_8_1	h_3_*_midline	foods_eaten (multi-response)	Count of food groups (0–10)
Food shortage	h_6	h_6_midline	food_shortage	Binary (yes = 1)
CSI	h6_1... h6_12	h_7_*_New_midline	csi_* (12 items)	Weighted sum
TLU	c_3_1... c_3_7	c_3_*_midline	el_cows... el_rabbits	FAO-weighted sum
Income sources	c_1_1... c_1_10	c_1_*_midline	income_sources (multi-response)	Count of sources
Number of crops	Seasons.dta (crop names)	Plot_2.sav (dominant crops)	n_crops (precomputed)	Distinct crop count
Total crop value	Seasons.dta ($kg \times price$)	Plot_2.sav ($kg \times price$)	total_crop_value (precomp.)	$\sum produced \times price$ (RWF)
Female-headed HH	b_2	b_2	Roster: relation = Head	Binary (female = 1)

Source: Authors' calculations based on survey data.
Note: CSI item ordering differs between baseline (h6_*) and midline (h_7_*_New_midline). Weights mapped by strategy label, not column position. See Table 2 for weights. Baseline lacks ducks (c_3_6); duck TLU weight (0.03) applied at midline and endline only. BL/ML binary variables recoded from 1=Yes/2=No to 1/0. BL CSI 999 values recoded to 0 ("did not use strategy"). ML string variables ("Yes"/"No") encoded to numeric 1/0. EL multi-response strings parsed via keyword matching.

1.4. Attrition analysis

Table 16 compares baseline characteristics of retained and attrited households. Treatment status is the strongest predictor of retention: beneficiary households are retained at nearly twice the rate of controls. Among the outcome indicators, only CRA technology count differs significantly between retained and attrited households ($p = 0.033$). The remaining indicators do not differ at conventional significance levels, suggesting that attrition is driven primarily by treatment status rather than by baseline outcome levels.

Table 16: Baseline characteristics: retained versus attrited households (N = 1,299)

Variable	Retained (N = 431)	Attrited (N = 868)	Difference	*p*
Treatment group[a]	1.353	1.571	–0.219	< 0.001***
CRA adoption rate	0.636	0.586	0.049	0.085*
CRA technologies	1.225	1.079	0.146	0.033**
CRA skills in use	0.722	0.841	–0.119	0.374
Dietary diversity	4.782	4.764	0.018	0.883
Food shortage	0.448	0.402	0.046	0.118
Tropical livestock units	0.514	0.522	–0.008	0.716
Income sources	1.886	1.847	0.040	0.431
Number of crops	3.093	3.055	0.037	0.668
Total crop value (RFW)	83,332	90,205		0.645
Female-headed HH	0.174	0.210	–0.036	0.120

Source: Authors' calculations based on survey data.
Note: ***$p < 0.01$, **$p < 0.05$, *$p < 0.10$. p-values from Welch's t-test. [a] Treatment coded 1 = Beneficiaries, 2 = Control. Lower mean among retained reflects higher beneficiary retention.

1.5. Climate Resilience Index

To complement the analysis of individual outcome indicators, this evaluation adopted an innovative CRI designed to provide an integrated measure of household resilience to climate change. The index follows the analytical framework which conceptualizes climate resilience as the combined result of household capacities, the climate stressors households face, and their level of exposure to those stressors.[12]

The CRI combines three dimensions:

1. Drivers and capacities

This dimension captures the resources and capabilities that enable households to anticipate, absorb, adapt to, and recover from climate shocks. Indicators include household assets, livelihood

[12] M. d'Errico, and M.A. Constas, "Climate Resilience: An Analytical and Measurement Framework for Evaluation," forthcoming.

diversification, agricultural practices, access to services, and other variables collected through the household survey.

2. Climate stressors

Climate stressors represent the environmental conditions experienced by households during the project period. These indicators were extracted from remote sensing products using Google Earth Engine and include:

- Vegetation condition (NDVI and EVI)
- Rainfall anomalies (CHIRPS)
- Temperature anomalies (ERA5-Land)
- Frequency of drought and heat stress events

3. Exposure

Exposure reflects the extent to which households depend on climate-sensitive livelihoods and operate in environmentally vulnerable locations. It combines geographical exposure to climatic hazards with the degree of dependence on agricultural land surrounding each household.

For each sampled household, remotely sensed indicators were extracted within a 500-metre buffer around the household GPS location. Climatic anomalies were calculated relative to a 2010–2019 climatological baseline, while project conditions were measured over the 2020–2024 implementation period.

All indicators were normalized to a common scale before aggregation. The three dimensions were first combined into sub-indices and subsequently aggregated into a single CRI according to:

$$CRI = w_1 D + w_2(1 - S) + w_3(1 - E)$$

where:

- D represents household drivers and capacities
- S represents climate stressors
- E represents household exposure

Higher CRI values indicate greater climate resilience. Equal weights were adopted for the aggregation of the three dimensions in this evaluation, reflecting the exploratory nature of the index and the absence of an established empirical weighting scheme.

The resulting CRI should be interpreted as a synthetic indicator that complements, rather than replaces, the individual outcome measures presented throughout this report.

References

Arriagada, R.A., P.J. Ferraro, E.O. Sills, S.K. Pattanayak, and S. Cordero-Sancho. "Do Payments for Environmental Services Affect Forest Cover? A Farm-Level Evaluation from Costa Rica." *Land Economics* 88, no. 2 (2012): 382–399.

Baker, A., B. Callaway, S. Cunningham, A. Goodman-Bacon, and P.H.C. Sant'Anna. "Difference-in-Differences Designs: A Practitioner's Guide." *Journal of Economic Literature* 64, no. 2 (2026): 498–557.

Blackman, A. "Evaluating Forest Conservation Policies in Developing Countries Using Remote Sensing Data: An Introduction and Practical Guide." *Forest Policy and Economics* 34 (2013): 1–16.

Chhetri, N., M. Stuhlmacher, and A. Ishtiaque. "Nested pathways to adaptation." *Environmental Research Communications* 1, 015001 (2019).

d'Errico, M., and M.A. Constas. "Climate Resilience: An Analytical and Measurement Framework for Evaluation." Forthcoming.

Dorji, T., K. Rinchen, A. Morrison-Saunders, D. Blake, V. Banham, and S. Pelden. "Understanding How Indigenous Knowledge Contributes to Climate Change Adaptation and Resilience: A Systematic Literature Review." *Environmental Management* 74, no. 6 (2024):1101–1123.

Fedele, G., C.I. Donatti, C.A. Harvey, L. Hannah, and D.G. Hole. "Transformative Adaptation to Climate Change for Sustainable Social-Ecological Systems." *Environmental Science and Policy* 101 (2019): 116–125.

Food and Agriculture Organization of the United Nations. "Guidelines for the Preparation of Livestock Sector Reviews." *Animal Production and Health Guidelines* 5 (2011).

Frölich, M., and S. Sperlich. *Impact Evaluation: Treatment Effects and Causal Analysis*. Cambridge University Press, 2019.

Green Climate Fund. *Funding Proposal FP073: Strengthening Climate Resilience of Rural Communities in Northern Rwanda*. GCF/B.19/22/Add.21. Green Climate Fund, 2017.

Guo, S., M. Fraser, M., and Q. Chen. "Propensity Score Analysis: Recent Debate and Discussion." *Journal of the Society for Social Work and Research* 11, no. 3 (2020): 463–482.

Hainmueller, J. "Entropy Balancing for Causal Effects: A Multivariate Reweighting Method to Produce Balanced Samples in Observational Studies." *Political Analysis* 20, no. 1 (2012): 25–46.

Iacus, S.M., G. King, G., and G. Porro. "Causal Inference Without Balance Checking: Coarsened Exact Matching." *Political Analysis* 20, no. 1 (2012): 1–24.

Imbens, G.W., and D.B. Rubins. *Causal Inference for Statistics Social, and Biomedical Sciences: An Introduction.* Cambridge University Press, 2015.

Independent Evaluation Unit. *Impact evaluation endline report for FP026: Sustainable Landscapes in Eastern Madagascar*. Independent Evaluation Unit, Green Climate Fund, 2026. https://ieu.greenclimate.fund/document/impact-evaluation-report-fp026.

Independent Evaluation Unit. *Impact Evaluation Midline Report for FP073 – Strengthening climate resilience of rural communities in Northern Rwanda*. Independent Evaluation Unit, Green Climate Fund, 2024. https://ieu.greenclimate.fund/document/impact-evaluation-midline-report-fp073.

Karbala, G., A. Riviere, and C. Sadania. *Impact Evaluation Design Report Rwanda*. Independent Evaluation Unit, Green Climate Fund, 2019.

Kates, R.W., W.R. Travis, and T.J. Wilbanks. "Transformational Adaptation When Incremental Adaptations to Climate Change Are Insufficient." *Proceedings of the National Academy of Sciences of the United States of America* 109, no. 19 (2012): 7156–7161.

King, G., and R. Nielsen. "Why propensity scores should not be used for matching." *Political Analysis* 27, no. 4 (2019): 435–454.

Lavell, A., M. Oppenheimer, C. Diop, et al. "Climate Change: New Dimensions in Disaster Risk, Exposure, Vulnerability, And Resilience." In *Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation*, edited by C.B. Field et al. Cambridge University Press, 2012.

Lee, D.S. "Training, wages, and sample selection: Estimating Sharp Bounds on Treatment Effects." *Review of Economic Studies* 76, no. 3 (2009): 1071–1102.

Maxwell, D., and R. Caldwell. *The Coping Strategies Index: Field Methods Manual*." 2nd ed. Cooperative for Assistance and Relief Everywhere, 2008.

Ripollone, J.E., K.F. Huybrechts, K.J. Rothman, R.E. Ferguson, and J.M. Franklin. "Evaluating the Utility of Coarsened Exact Matching for Pharmacoepidemiology Using Real and Simulated Claims Data." *American Journal of Epidemiology* 189, no. 6 (2020): 613-622.

Robinson, J.M., N. Gellie, D. MacCarthy, J.G. Mills, K. O'Donnell, and N. Redvers. "Traditional Ecological Knowledge in Restoration Ecology: A Call to Listen Deeply, to Engage With, and Respect Indigenous Voices." *Restoration Ecology* 29, no. 4 (2021): e13381.

Rosenbaum, P.R. "Sensitivity Analysis for m-Estimates, Tests, and Confidence Intervals in Matched Observational Studies." *Biometrics* 63, no. 2 (2007): 456-464.

Rosenbaum, P.R., and D.B. Rubin. "The Central Role of the Propensity Score in Observational Studies for Causal Effects." *Biometrika* 70, no. 1 (1983): 41–55.

Rwanda Environmental Management Authority. *Rwanda Climate Change Vulnerability Assessment and Index 2018 – Final Report*. Rwanda Environmental Management Authority, 2019.

Rwanda. *Third National Communication: Report to the United Nations Framework Convention on Climate Change*. Rwanda, 2018.

Sant'Anna, P.H.C., and J. Zhao. "Doubly Robust Difference-in-Differences Estimators." *Journal of Econometrics* 219, no. 1 (2020): 101–122.

Schulz, K.F., and D.A. Grimes. "Sample Size Slippages in Randomised Trials: Exclusions and the Lost and Wayward." *The Lancet* 359, no. 9308 (2002): 781–785.

Stuart, E. A. "Matching Methods for Causal Inference: A Review and a Look Forward." *Statistical Science* 25, no. 1 (2010): 1–21.

Swindale, A., and Bilinsky, P. *Household Dietary Diversity Score (HDDS) for Measurement of Household Food Access: Indicator Guide – v.2*. Food and Nutrition Technical Assistance Project (FANTA). FHI 360, 2006.

Theglobaleconomy.com. "Rwanda: Human development." Accessed June 18, 2026. https://www.theglobaleconomy.com/Rwanda/human_development/.

"United Nations Climate Change." Accessed December 2019. https://www4.unfccc/int/sites/sdcmicrosite/Pages/SD-Tool.aspx.

Wooldridge, J.M. *Econometric Analysis of Cross Section and Panel Data*. 2nd ed. The MIT Press, 2010.

Worldometers. "Rwanda GDP (2026)." Accessed June 18, 2026. https://www.worldometers.info/gdp/rwanda-gdp.