Working paper RWA-25103

March 2026

The forest cover impacts of improved cookstoves

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The Forest Cover Impacts of Improved Cookstoves

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March 24, 2026

Abstract

Improved cookstove programs are widely promoted for their health and energy benefits, yet there is little causal evidence on whether they reduce deforestation or increase forest cover. We study Tubeho Neza in Rwanda, a large-scale carbon-financed intervention that has distributed more than 1.5 million improved cookstoves since 2014. Exploiting the program's staggered rollout across rural Rwanda, we estimate the effect of stove receipt on forest cover using the Mundlak difference-in-differences estimator. We combine stove distribution records with satellite-based measures of forest and non-forest vegetation including bespoke classifications predicted through Machine Learning algorithms. We supplement our empirical findings with qualitative fieldwork including focus group discussions, district leader interviews, and community forest visits. Our estimates indicate that Tubeho Neza resulted in increased vegetation cover on average. Treated cells experienced a 0.61 percentage point increase in forest cover, a 1.256 percentage point increase in non-forest vegetation, and a 1.866 percentage point decline in non-vegetated area. We also find substantial heterogeneity: cells with relatively high pre-treatment forest cover experience larger forest gains, while cells with lower baseline forest cover mainly gain non-forest vegetation. Taken together, the results suggest that large-scale improved cookstove distribution can improve landscape outcomes, including forest cover in ecologically favorable areas.

Acknowledgments

This research was funded by Canadian Social Sciences and Humanities Research Council (SSHRC) and The International Growth Center (IGC). We are grateful to the staff at NjordFrey for excellent research support with fieldwork management. We thank DelAgua Health Rwanda Implementation Ltd., particularly David Kitt, for providing access to program data and for helpful discussions about the Tubeho Neza program. We also extend a thanks to our research assistants Adeline Akansobe, Thomas Bilintoh and Shiven Diwakar for their excellent research assistance with this project. We are also thankful to the conference participants at Canadian Economic Association (2024), Agricultural and Applied Economics Association (2025), and the Economics Seminar at Villanova University for excellent feedback.

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1 Introduction

"For most of her 60 years, Ms. Anasthasie watched the daylight seep away with a sense of dread, anxious that darkness might fall before she could find enough wood to cook a meal. The forests that once surrounded her village had been dismantled and hacked into firewood. She and her neighbors wandered for hours into the surrounding mountains looking for sticks."

- *New York Times from Buzuta Rwanda, Dec. 2018* (Goodman, 2018)

An improved, or "clean" cookstove is a cooking technology intended to replace high-emissions, energy-intensive traditional cooking methods. While clean cooking technologies can vary widely in terms of their technological sophistication and fuel input, they share a common objective of reducing the energy requirement for meal preparation. Cooking technology interventions are far from new: efforts to transition developing country households to more efficient cookstoves date back to at least the mid-20th century (Raju, 1954). Decades of research have yielded substantial evidence that household adoption of improved stove technologies can yield benefits in adult and child health, including reductions in respiratory infections, blood pressure, lung cancer risk, and diarrheal illness. (Barstow et al., 2019; Grieshop et al., 2011; LaFave et al., 2021; Wassie and Adaramola, 2021). These health improvements can be tied to indirect benefits such as improved school performance (Biswas and Das, 2022; Ninan, 2024). Other benefits include time savings, especially for women (Barstow et al., 2014; Krishnan et al., 2023) and reduced biomass consumption (Brooks et al., 2016; Mekonnen et al., 2022).

Surprisingly little is known about the impacts that improved cookstove technologies have on forest cover. In fact, past scholarship has cast doubts on whether these interventions abate deforestation at all (Foley et al., 1984; Urmee and Gyamfi, 2014). Our study is a first step towards causally evaluating the impact of improved cookstoves on forest cover. We focus on the *Tubeho Neza* program carried out in Rwanda by DelAgua Health Rwanda Implementation Ltd. (henceforth DelAgua) in partnership with the Rwandan government. Since 2014, Tubeho Neza has delivered over 1.5 million improved cookstoves to Rwandan households. Over 900,000 of these stoves remain active. As part of the program, beneficiary households receive an EcoZoom Dura stove, a rocket style stove designed to burn firewood and crop residue more efficiently than the three-stone stoves Rwandan households otherwise use. The Tubeho Neza program applies a bottom-up approach involving village community health workers (CHWs), who assist with household training and annual household visits. The Tubeho

Neza program also includes marketing campaigns, educational supports, and assistance with repairs and replacements. The program design has resulted in high take up and usage, as demonstrated by our qualitative focus group discussions (FGDs) and past program evaluations. These characteristics make Rwanda's Tubeho Neza program a suitable "natural experiment" to understand the impact of improved cookstoves on deforestation.

We use proprietary and geospatial data sources to generate a panel of information characterizing Rwandan cells - the country's fourth administrative division (ADM4) - for years 2000-2023. We use proprietary data from DelAgua to determine cell stove distributions by year. We use two primary sources for forest and vegetation data. First, we use the MODIS Terra Continuous Fields 250m data (2000-2023), which provides the percent of land cover characterized as forest, non-forest vegetation, or non-vegetated. We also use 30m "hard" (discrete) land cover classifications derived from the Landsat satellite. These data were developed for this project, and the machine learning algorithms used to generate them were trained exclusively on observations from Rwanda.

We implement a differences-in-differences (DID) approach estimating the impact of cookstove distribution on forest and non-forest vegetation. Our primary estimation strategy draws on the MODIS Terra data and identifies the effect of cookstove receipt on percent forest and vegetation cover at the extensive margin: we classify treatment cohorts based on the first year a cookstove distribution occurs in the administrative cell. We address potential estimation bias from the staggered timing of treatment (Goodman-Bacon, 2021) by adopting an event study identification strategy based on the Mundlak regression (Wooldridge, 2025), which is flexible to heterogeneous treatment timing.

We present several robustness checks. First, we estimate our DID framework using an alternative event study estimator from De Chaisemartin and d'Haultfœuille (2024). This robustness check further provides evidence of the program's intensive margin effects. Because the estimator allows for continuous and increasing treatments, we can define treatment as the cumulative number of stoves distributed per 100 residents in the cell. Second, we re-estimate our Mundlak regression using an alternative land cover data source. Specifically, we use "hard" (discrete) land cover classification maps with 30m spatial resolution developed from the Landsat satellite series.

Combining data on cumulative stove delivery over time with geospatial data on forest and non-forest vegetation cover, we find that the rollout of the Tubeho Neza program at the cell level increases vegetation cover, but the effect is heterogeneous. Cells with prior healthy forests experience a 2.5 percent point increase in forest cover. Cells with prior less healthy forests do not experience an increase in forest cover but they also see a 1.3 percent increase in non-forest vegetation. Our results our robust to a set of robustness checks including choice of satellite data and the choice of DID estimation parameter, and our claim of causality is further supported by placebo tests.

We further augment our empirical study with qualitative fieldwork comprising of focus group discussions (FGDs), district leader interviews, and community forest visits. In August and September 2025, we conducted ten FGDs each with rural men and women, respectively. We also spoke with key informants from district leadership whose partnership was necessary for Tubeho Neza rollout. The FGDs helped us gain firsthand evidence of stove usage, user satisfaction and biofuel consumption practices among households. The key informant interviews shed light on the leaders' decision to participate in the program. The qualitative fieldwork helps ensure that (a) our estimates are not confounded by unaddressed factors, and (b) our approach takes into account the user demand and competition from substitute provider programs. Our qualitative fieldwork was crucial for identification, revealing two potential confounders: the entry of competing cookstove programs following the sharp rise in demand for carbon credits tied to cookstoves and nature-based solutions around 2020, and the adoption of improved cookstove targets across all levels of government under Rwanda's five-year development plans. Moreover, the FGDs shed light on household energy sources and energy usage and demand, directing our focus towards more plausible mechanisms.

Our study of Tubeho Neza is an important contribution to development and environmental economics research on clean technology, forest and vegetation extraction, and household welfare. To the best of our knowledge, we are the first to causally evaluate the impact of a clean cookstove intervention on forest cover. There is a longstanding literature on improved cookstoves studying adoption, health benefits, and other benefits such as gender equity and increased school attendance (Barstow et al., 2019; Brooks et al., 2016; Grieshop et al., 2011; Kirby et al., 2019; Krishnan et al., 2023; LaFave et al., 2021; Mekonnen et al., 2022; Nagel et al., 2016; Ostwald et al., 2021; Thomas et al., 2016), yet the claims of reduced deforestation embedded in carbon credit methodologies have never been empirically verified. Forests are a common property resource yielding both market and non-market ecosystem services (Johnson et al., 2023), and forest products provide an important source of income and energy for rural Rwandan households (Heal et al., 2026). Worldwide, forests face threats from agricultural expansion, logging, and household energy consumption as populations grow (Allen and Barnes, 1985), but the relative importance of fuelwood harvesting as a driver of deforestation remains unclear. By studying a large-scale program with high rates of adoption and sustained usership, we provide new evidence on the relationship between cooking fuel demand and forest stock.

The study also provides suggestive evidence on whether improved cookstoves represent a legitimate basis for carbon credit issuance. Since the advent of carbon financing,[1] academic literature has evaluated the opportunities and challenges of financing clean cookstove interventions through carbon credits (Lambe et al., 2015; Simon et al., 2012). Notably, Tubeho Neza is financed primarily through the sale of carbon credits generated by the program. While accreditation methodologies have evolved over time, demonstrating additionality[2] continues to rely on assumptions about program-stimulated reductions in non-renewable biomass consumption. The lack of standardization in credit definitions, combined with the absence of adequate additionality checks across multiple markets, has created legitimacy concerns. For example, Gill-Wiehl et al. (2024) document widespread over-crediting across a sample of improved cookstove projects, though the Tubeho Neza program implemented by DelAgua was not included in their analysis. We contribute to this literature by providing the first causal estimates of forest cover impacts for a carbon-financed cookstove program.

Last, we contribute to the literature on technology adoption in low- and middle-income countries. This literature focuses heavily on uptake and learning of agricultural technology, such as seeds and fertilizers. Clean cookstoves have faced low demand historically, owing to factors related to consumer tastes and preferences, cultural suitability of stove technology, and high opportunity cost of adoption for cash constrained households, particularly women (Miller and Mobarak, 2013; Mobarak et al., 2012). We study a context characterized by free distribution of a clean cooking technology but supplemented by regular household training and engagement, and conducted through an existing network of community health workers with strong connections to the area. This challenges the conventional wisdom that giving something for free leads to low uptake and usage, especially for repeat-purchase goods, since the consumer places a very low value on the good (Shukla et al., 2022). However, it can be considered an intervention that provides the technology free of cost but with incentives; and such interventions have been shown to have higher uptakes in different contexts (Banerjee et al., 2010). We contribute to the literature that studies the effect of pricing on uptake relative to the effects of information and framing (Ashraf et al., 2010; Cohen and Dupas, 2010; Dupas, 2009).

The paper proceeds as follows. Section 2 provides important information about the Tubeho Neza intervention as well as the study context. Our description of the study context draws on the results of our qualitative fieldwork (further described in Appendix B). In Section 3, we describe the

[1] Carbon financing creates markets in which emissions reductions are assigned monetary value, allowing carbon credits to be bought and sold. Credits are generated through activities that reduce or sequester carbon, including deforestation prevention and cleaner energy use. Improved cookstove programs qualify for carbon credits on the grounds that they reduce both fuelwood demand (and thereby deforestation) as well as ambient air pollution.

[2] An activity is considered "additional" if it leads to emissions reductions that would not have occurred in its absence.

geospatial and proprietary data used for our study, which we aggregate at the administrative cell level to generate a cell-year panel. Section 4 describes the Mundlak regression event study method in detail, and we report main results in Section 5. We explore heterogeneity in outcomes by forest endowment, treatment cohort, and road proximity in Section 6. We describe and report the results of our robustness checks in Section 7. Section 8 concludes.

2 Background

We divide this section into two parts. The former provides information on DelAgua's Tubeho Neza clean cookstove program's characteristics. The latter details key insights from our fieldwork in Rwanda. The details in this section inform our identification strategy later.

2.1 Tubeho Neza

Tubeho Neza ("Live Well" in Kinyarwanda) was launched by DelAgua, a social enterprise, in partnership with the Rwandan government. Since its inception, Tubeho Neza has been financed through carbon credits and has delivered over 1.5 million free cookstoves to Rwandan households. Recipient households receive the EcoZoom Dura, a rocket stove designed to burn fuelwood and crop residue more efficiently than traditional three-stone fires. During the earliest years (2012-2016) of Tubeho Neza, beneficiary households received a EcoZoom Dura model with a rated lifespan of seven years, as well as a LifeStraw Family 2.0 gravity-fed water filter (Barstow et al., 2016). Earlier estimates suggest that the EcoZoom Dura stove cost approximately USD 35 per unit during the 2014 and 2016 distributions, with additional annual costs of around USD 7 per stove for replacements, repairs, and associated support systems (Barstow et al., 2019).

The *Tubeho Neza* rollouts occurred in several phases, and the program's structure evolved over time. Pilot testing (Phase 1) took place in 2012: the implementing partners distributed cookstoves and water filters to 1,943 households in 15 non-randomly selected villages in Rwanda's Western province (Barstow et al., 2014). The distribution was not means-tested, meaning that households obtained EcoZoom cookstoves regardless of their *Ubudehe* (Rwandan wealth classification). Participating households received training in using the technology through community meetings. The program also partnered with Rwanda's existing community health worker (CHW) program, which allocates three CHW's in each rural village (Barstow et al., 2016). CHW's additionally encouraged technological adoption and provided user support (Barstow et al., 2014).

A follow-up study examining adoption rates up to six months after the pilot rollout found that

90% of program beneficiaries reported using the EcoZoom Dura as their primary cooking technology. Yet 71% continued using traditional stoves alongside it. The use of traditional stoves alongside improved stoves, known as “stove stacking”, is a common challenge (Shankar et al., 2020) that complicates carbon financing, which relies on careful accounting based on the assumed displacement of less energy efficient technology with the more efficient alternative (Gill-Wiehl et al., 2024).

Our 2025 focus group discussions shed light on stove-stacking behavior and Tubeho Neza: participants noted that the EcoZoom performed poorly with wet wood, required more active fire management, and, with only a single burner, could not meet households’ full cooking needs simultaneously. Users also continued relying on three-stone stoves for home heating, as the EcoZoom reaches very high temperatures but does not meaningfully radiate heat beyond the cooking surface.

Crucially, however, ongoing use of traditional stoves does not appear to preclude meaningful reductions in biofuel consumption. Indeed, even without eliminating traditional stove use, the 2012 pilot found that Tubeho Neza receipt was associated with a 65.8% reduction in fuelwood consumption across treated households (Barstow et al., 2014).

Prior to large-scale rollout, the implementing partners modified the intervention using insights from the pilot study, including stove design improvements and augmented materials for teaching households about the benefits and use of the technology (Barstow et al., 2016). Phase 2 of the distribution drive in 2014 targeted all households classified as *Ubudehe* 1 and 2 (the poorest quarter of Rwandan households) residing in 72 of the 96 sectors of the Western province (Barstow et al., 2016)[3]. Households that participated in the Phase 1 pilot received new versions of the cookstoves and water filters, modified based on feedback from the pilot program. Phase 2 included comprehensive public outreach and education, including social marketing campaigns, community promotion and demonstrations of the technologies, visual aides on how to use the stove and filter, and direct user support for each household provided by CHW’s (Barstow et al., 2016). In total, 101,788 households (representing 457,778 individuals) received the cookstove and water filter technology during Phase 2 (Barstow et al., 2016).

In a follow-up survey implemented 10 months after Phase 2 rollout, 89% of recipient households reported that the improved cookstove was their primary cooking source. About 80% of respondents claimed to use the improved cookstove the last time they prepared food. Similar to pilot study findings, households reported that they continued to use traditional stoves when they did not have access to dry firewood, when food preparation required more than one stove, and to warm their

[3] As per the reports (Barstow et al., 2016, 2014), the remaining sectors were excluded in this phase to facilitate a Randomized Control Trial for studying the health benefits of the program.

homes (Barstow et al., 2016). Evidence suggests that the intervention reduced fuelwood consumption substantially: a long-run assessment estimated that the program resulted in a reduction of firewood consumption by 458,000 tons over the next five years (Barstow et al., 2019).

Past impact assessments show that the Phase 2 stove distribution led to significant health improvements for recipient households. A short-run evaluation found that although indoor air pollution levels were unchanged, childhood acute respiratory illness fell by 25% (Kirby et al., 2019). The Phase 3 rollout started in 2016 and targeted *Ubudehe* 1 and 2 households across the entire Eastern province. Tubeho Neza continued delivering stoves and the water filter to the lowest income rural households, though the rollout was smaller in magnitude.

Around 2020, demand for carbon credits generated by improved cookstoves increased substantially, facilitating higher-volume stove rollouts. Both the technology's design and the intervention design underwent substantial revisions before distribution began. First, the program adopted an improved version of the EcoZoom Dura that has a ten year lifespan as opposed to seven. Second, the water filter component of the intervention was discontinued. This programmatic adjustment was undertaken in coordination with the Government of Rwanda to better align the intervention with national strategic priorities and the needs identified in rural communities. Finally, the program relaxed its *Ubudehe*-based wealth eligibility requirement, distributing stoves to all households in targeted rural villages. The heightened value of carbon credits, along with the aforementioned program changes, resulted in a substantial intensification of stove rollouts. From 2020 to 2023, Tubeho Neza distributed 1.2 million stoves across the Eastern, Western, Southern, and Northern provinces.

2.2 Central Planning and Increased Cookstove Demand

Prior to 2019, improved cookstove activities in Rwanda were limited. To our knowledge, DelAgua was the only large-scale provider operating in rural Rwanda at this time. This began to change around 2020, driven not only by the rising demand for carbon credits but also by central government planning. As part of Rwanda's long-term Vision 2050 development agenda, the National Strategy of Transformation Round (NST) 1 (2017-2024) set explicit targets for reductions in biofuel consumption and clean cookstove adoptions for rural households. These benchmarks matter: Rwanda's organized, hierarchical governance structure is institutionally robust enough to hold local leadership accountable for meeting their targets.

In 2019, the improved cookstove component of NST1 became operational (World Bank, 2020), and as part of their Energy Access and Quality Improvement Project (EAQIP), the World Bank and Rwandan government launched an improved cookstove subsidy program in which subsidies could be used to finance the consumption of cookstoves meeting minimum performance standards.[4] Investments in the subsidy program have been substantial, with nearly half a million households receiving a subsidized stove as of 2025.

At the time of writing, we are unfortunately unable to incorporate information about the World Bank distribution directly into our analysis. This may confound estimates for groups that first received stoves in 2020 or later.

We also identified One Acre Fund's large-scale tree distribution drive, which occurred concurrently with our study period, as a potential—though less likely—confounding factor. The initiative promotes agroforestry by providing farmers with free saplings suitable for agricultural land. This initiative also began in 2020, so like the World Bank subsidy program and NST1 incentives, the concurrent nature of the intervention may confound our findings for groups first treated 2020 and later. Because our outcome measure captures forest cover—which in Rwanda is typically located outside agricultural areas except for plantations—this program is unlikely to meaningfully confound our estimated treatment effects.

2.3 Insights from Qualitative Fieldwork

The components of the fieldwork comprised of Focus Group Discussions (FGDs) with men and women separately, interviews with district leaders [5], and observance of any community forests [6] collectively owned by villages. Appendix C provides details on the contents of each component. Tables B1 through B3 provide details on the questions and themes included in the FGDs, district leader interviews and forest visits.

The purpose of the fieldwork was to develop an improved understanding of the user experience, primarily through FGDs, and understand the district leaders' motivation behind participation in the improved cookstove program. The results helps us to (a) understand any potential endogenous sorting of districts into the intervention, (b) learn about the presence of any confounding interventions that may affect forest cover or vegetation, (c) accurately interpret the results from our differences-in-differences and event study estimations, and (d) recommend most efficient policies.

[4] The subsidy program works as follows: retailers are tasked with selling the technology to households, a departure from the Tubeho Neza model of pro bono distribution. Companies then submit proof that the technology was delivered and installed. Auditing teams confirm technology receipt and also determine whether the technology remained operational for at least one year. Once these confirmations are completed, the firm receives a subsidy. See Zhang (2025).

[5] Rwanda is administratively distributed into 30 districts. District leaders decide if their district would participate in the improved cookstove program.

[6] In Rwanda, forests can be owned be community owned, district owned, province owned or state owned.

Table 1: Summary of Cookstove Field Findings

Theme	**Key Findings**
User Experience	Extensive use of improved cookstoves; older recipients (2016 or earlier) often require maintenance and may stop usage without it; newer recipients (2020 onwards) report active use with minimal maintenance; strong demand for pro-bono cookstove provision.
Energy Resources and Constraints	Fuelwood access is seasonal with higher prices in the rainy season; households adjust cooking by avoiding long-cooking meals; energy supply depends on market distance, season, forest ownership, community forest presence, and prices; rainy season and remoteness exacerbate constraints.
Competitors	Quality Engineering emerged as a major competitor from 2020 onwards; villages typically received cookstoves from only one provider; Quality Engineering stoves burn less wood but are heavy and fragile; training and maintenance are primarily provided by DelAgua.
Pros & Cons	Reduced fuelwood use and expenditure (spending decreases from 10,000 Rwandan Francs (RWF) ($\sim$ 7 USD) to 3,000–4,000 RWF ($\sim$ 2–3 USD)); time savings for firewood collectors, particularly children, and reduced likelihood of children missing school to collect firewood; increased flexibility for women's cooking; reduced indoor smoke and likelihood of respiratory infections; limitations include single-pot cooking and stoves heating too quickly.
FGD Results by Gender	No major gender differences in perceived benefits or usage; some differences in views on forest governance and regulations; minor differences in market access and energy constraints.
Community Forest Use	Most villages lack community forests; individual forest ownership exists; where a community forest is present, forest use is regulated by access and cutting rules (such as penalties and permits); past lack of regulation led to deforestation ("tragedy of the commons"); cultural and religious significance of forests reported in one village.

Notes: This table summarizes findings from qualitative fieldwork conducted in August–September 2025 across 10 rural villages in Rwanda. In each village, two focus group discussions (FGDs) were conducted—one with men and one with women—with approximately 10 participants per group (20 FGDs total). Discussions lasted 60–90 minutes and covered stove usage, household energy practices, fuelwood collection, and market access. Participants were primarily rural households spanning multiple *Ubudehe* (wealth) categories. Findings reflect self-reported behaviour and perceptions and are intended to complement the quantitative analysis. Currency conversions are approximations.

In August and September 2025, we talked to household wood collectors and cookstove users about their experience with the cookstoves and its effectiveness, their attitude towards the program, household energy resources and expenditures, and wood collection practices including any rules about community forests. All in all, we conducted 20 FGDs in 10 villages across 5 districts within 4 Rwandan provinces. In every village, we conducted two 60-90 minutes focus group sessions, one with a group of men and one with a group of women. Each group included 10 participants.

The mean age of respondents in our FGDs was about 44 years, and it was roughly the same for men and women. Participants' age ranged between 27 and 70, with majority of them falling in the 40-49 age group. The average household size for respondents' households was 5.1, with mean number of children under 5 years being 0.57 [7]. Almost 51% of our participants were in Ubudehe category 2 followed by 44% of participants in category 3. About 2% of the participants belonged to categories 2 and 5, respectively. However, there were meaningful differences in Ubudehe categories between female respondents and male respondents. While 53% of the male respondents' households fell into category 3 and 47% fell into category 4, only about 36% of the female respondents' households fell into category 3 and about 55% fell into category 4. This suggests that the households of female respondents in our FGDs were poorer on average.

Our findings are summarized in Table 1. To begin with, participants in most FGDs reported being energy constrained. The severity of the constraint mainly depended on seasonality, distance to the market, presence of sellers in the market, and ownership of individual forests. Fuelwood shortages were reported in villages which are far from the nearest tarmac road or, in some instances, when fuelwood markets are not saturated enough even if nearby. Similarly, rainy season can lead to severe shortages such that households do not cook meals, such as beans, that need a longer cooking time. Last, these shortages are exacerbated for those that do now own an individual forest, they may have to skip a meal when the household is severely energy constrained.

When it comes to uptake and user experience, the FGDs revealed a daily and consistent use of cookstoves as long as they had not broken down or needed maintenance. This corroborates with DelAgua's report the at least 900,000 out of 1.5 million cookstoves are active as of August 2025. While there was a high interest in uptake, there was also a clear and consistent demand for a cookstove design that allows for two saucepans instead of one so that multiple foods can be cooked simultaneously. It was also clear that the traditional and improved cookstoves were being used together.

[7] The average houshold size and the mean number of children aged below 5 were slightly lower among female participants, at 4.9 and 0.52, respectively.

The most common reported benefits included reduction in expenditure on fuelwood (participants across multiple FGDs quoted a reduction from 10,000 Rwandan Francs to 3000-4000 Rwandan Francs), decreased reliance on children for procuring firewood as bundles last longer - leading to a reduction in the likelihood of children missing school, light weight of the stove allowing the cooking to take place anywhere in the house, and decrease in respiratory infections. The three limitations reported across all FGDs included the constraint of one saucepan at a time, the stove heating too quickly, and older stoves (distributed in 2016 or earlier) having broken down.

It was also apparent that Rwanda did not have forest management rules in the past but that is not the case anymore. Any community owned forest or state forest cannot be used for wood harvesting or collection, or any other activites, until permission from the relevant sector officials [8] has been sought and granted. Regulations focus on the type of trees that can be harvested, the maximum height if a branch or shrub that can be cut down, the frequency of such activities, and the penalties for violating these regulations. However, it is also clear that these rules existed in cells and villages where improved cookstoves have not yet been distributed [9]. Thus, any nonrandom presence of community forest rules in cells that received improved cookstoves seems unlikely.

As part of our fieldwork, we also scanned for competing clean cookstove programs as well as other initiatives by NGOs and the government that can affect forest cover and vegetation. According to the respondents in our FGDs, a major producer and distributor known as Quality Engineering began delivering cookstoves in 2020, as part of the World Bank subsidy program. However, our respondents reported much lower user satisfaction with the Quality Engineering stoves, with numerous respondents reporting that they stopped working after 2-3 years.[10]

Notably, we did not find major differences by gender in our qualitative fieldwork. Comparing the responses in male FGDs with those in female FGDs, participants' responses on experience with DelAgua/Tubeho Neza and competitors, market access, and main benefits were almost similar. There were some minimal differences user experience, energy resources and constraints. While both groups list the same benefits, women emphasized user experience and main benefits to cookstove use and daily coking workflow while men focused more on fuel efficiency and fuel savings. The same differences show up when they talked about energy constraints: women focused more on how stove stacking affects meals and timing while men emphasized energy access more frequently. Similarly, when it came to user experience, women focused more heavily on the design issues and while men mentioned them too, they placed higher emphasis on material durability and fuel compatibility.

[8] Cell is the fourth administrative division of Rwanda, below district and above village.
[9] We visited at least two such villages.
[10] Respondents also disliked that the Quality Engineering stoves were heavy and difficult to move.

Women also gave a substantially richer explanation of how their households cope with fuel scarcity and fuel constraints. Men generally perceive forests to be safer than women.

We also conducted brief Key Informant Interviews (KII) with district leaders. Rwanda is administratively divided into 30 districts. District leaders decide if they will sign an MOU with an entity like DelAgua that will carry out the cookstove intervention in their district. It is important to understand their motivation because sorting into the program can be endogenous to time-varying unobserved district characteristics. Therefore, we conducted KIIs with 8 district leaders. Appendix Table B4 summarizes the responses of district leaders. No district leader highlighted a specific district characteristic that motivated their decision to sign the MOU. Despite being asked specifically, all responses broadly mention increasing the rural welfare and promoting the government's agenda of being environmentally sustainable. However, climate stress is generally cited by the interviewees when asked about the environmental health of their district.

Information elicited through FGDs and KIIs informs our conceptual framework, identification strategy, and the interpretation of and event study estimates. First, it is clear that improved cookstoves are regularly used and their uptake is high. This explains the downstream reported benefits in the form of reduced energy expenditure, improved health outcomes, and less reliance on children for fuelwood collection.

Next, any policies and initiatives that can confound our estimates, such as competing cookstove programs and other forestry initiatives, started around 2020. As discussed in section 2.1 first two phases of DelAgua's cookstove distribution were completed in 2014 and 2016, which gives us about 5-7 years of post-intervention time periods in which the event study estimates should not be confounded by other policies. Besides, our study period ends in 2023 owing to geospatial data limitations; since other interventions began towards the tail end of our study period, we do not expect these to confound our event study estimates because forest growth and recovery is very limited in the short-run.

3 Data

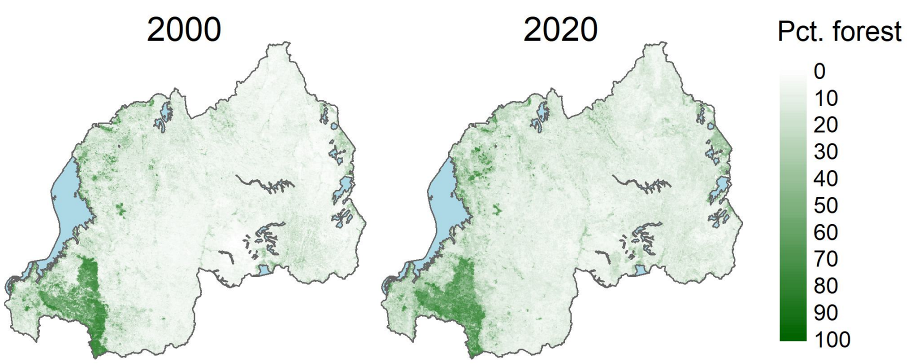
While the qualitative data discussed in section 2.3 is an auxiliary component of this study, the study mainly combines geospatial data on forest cover and vegetation, and proprietary cookstove distribution data.

3.1 Geospatial Data

We use two sources of data for measuring Rwanda's landscape characteristics. The first is the MODIS Terra Vegetation Continuous Fields (VCF) product, hereby referred to as VCF. The VCF is a global secondary spatial product that provides estimated grid-cell percent forest, nonforest vegetation, and nonvegetative cover at 250m resolution for years 2000–2024 (DiMiceli et al., 2021). In this classification, *forest cover* corresponds to the proportion of a grid cell occupied by tree canopy above a minimum density threshold, while *nonforest vegetation* captures all remaining vegetated land cover, including shrubs, grasses, sparse tree cover and tree saplings, cropland, and agroforestry systems that do not meet the forest canopy criteria. The *nonvegetated* category reflects bare ground, built-up areas, and other non-vegetated surfaces.

Figure 1 uses the VCF data to show the percent forest cover in Rwanda in 2000 and in 2020. Given Rwanda's high population density and the rural population's dependence on agriculture for livelihoods, low forest cover rates characterize much of the country throughout the study period. We discern increasing forest cover in some areas of the country, notably in the northwest. Nevertheless, forest cover rates remained low throughout the study period in many areas.

Figure 1: Percent Forest Cover in Rwanda, 2000 and 2020



Notes: Forest cover is measured as the percentage of each 250m grid cell classified as tree canopy using the MODIS Vegetation Continuous Fields (VCF) dataset. Forest is defined as vegetation exceeding a minimum canopy density threshold. Maps illustrate spatial variation in forest cover across Rwanda at the beginning and near the end of the study period (DiMiceli et al., 2021).

Last, we use raw data from the Landsat satellite to build bespoke land cover maps at 30m resolution for Rwanda. Map production requires machine learning models that use spectral Landsat imagery from the dry season broadly defined as (May to October) to predict "hard", or discrete, land cover classes. We use the following categories: dense vegetation, sparse vegetation, agriculture, bare ground and urban areas.

The hard classification's primary advantage is that it is developed exclusively using training data collected from Rwanda, abating measurement error issues common with globally calibrated spatial products. But a major weakness of these data are that we cannot clearly characterize the years 2012 or 2013, due to technical problems with the Landsat 7 satellite. The failure of a satellite component caused systematic wedge-shaped data gaps across each image collected, leaving about 22% of pixels missing near the scene edge (U.S. Geological Survey, 2023). Because Landsat 7 is the only satellite in the Landsat series that captured May-October imagery for years 2012 and 2013, our pre-treatment data is likely affected by measurement error to an extent that may complicate DID identification, particularly for the groups that first received cookstoves in 2014 and 2016.

We use additional spatial data for our analysis. We account for population differences using the WorldPop gridded population of the world database (WorldPop, 2025). Drawing on the most recent and available resources, we rely on WorldPop 100m resolution data for 2000-2020 and 1km resolution data for 2021-2023. We account for climatic variation (cumulative precipitation and maximum temperature) using the TerraClimate global data product (Abatzoglou et al., 2018).

We are also interested in road proximity. Tarmac road proximity is especially important for market access in Rwanda given its hilly and mountainous topography and the difficulty of traversing steep dirt roads, particularly in wet conditions. Market access influences household wealth, but it can also influence the treatment effect, particularly if households exhibit a "rebound effect" by selling their unused firewood in local markets. We use road linestring data published by the Rwanda Transport Development Agency (RTDA) (Africa GeoPortal, 2022), restricting to paved national and primary roads.

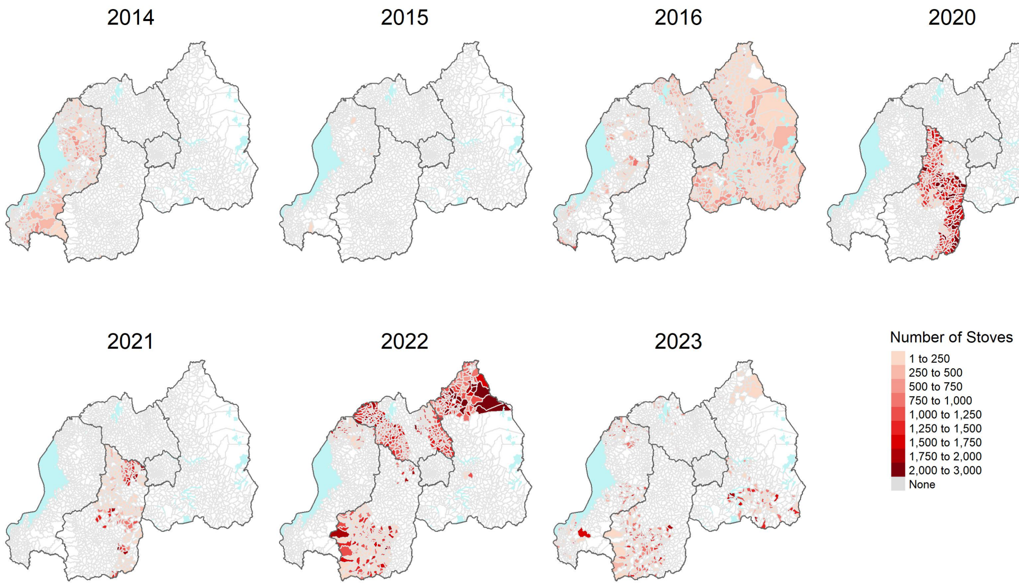
3.2 Stove Distribution Data

Our study benefits from the use of proprietary cookstove distribution data provided by DelAgua, which includes the universe of all cookstoves distributed by DelAgua to date [11]. The data is very granular, providing the beneficiary's administrative location down the the village level (ADM5, 14,387 villages), as well as a timestamp documenting when the cookstove was first delivered to the household. Hence, there is temporal variation in terms of the year of cookstove delivery, and there is additional spatial variation with respect to which villages received stoves.

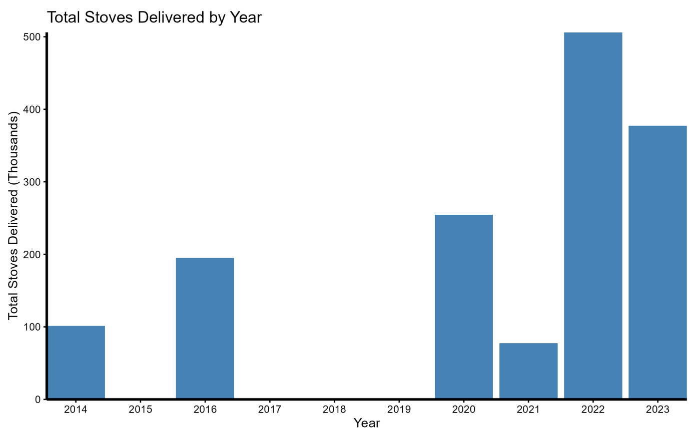
[11] DelAgua has also shared with us ancillary data such as Kitchen Performance Tests on a subsample of the cookstove recipients and user satisfaction surveys.

Figure 2: Distribution of Tubeho Neza stove disbursements by administrative division and year

(a) Cookstove distribution intensity by administrative cell and year



(b) Total cookstoves first delivered by year



Notes: Panel (a) maps cookstove distribution intensity by administrative cell (ADM4) and year using proprietary data from DelAgua. Panel (b) aggregates these data to show the total number of cookstoves first delivered in each year.

Figure 2 presents data on cookstove distributions across Rwanda. Figure 2a maps out annual distribution by Rwanda's 4 provinces -namely Northern, Southern, Western and Eastern provinces [12]. Figure 2b presents a bar chart showing the total cookstoves distributed by DelAgua annually. The roll-outs in 2014 and 2016 targeted the Western and the Eastern provinces, respectively. The number of cookstoves distributed were moderate relative to the numbers distributed after 2020, and we observe a sizable increase in cookstove distribution 2020 onwards, particularly in 2022 and 2023. As previously discussed (Section 2.2), we attribute this rise to the boosted demand for cookstove-associated carbon credits as well as heightened demand in response to central planning and national cookstove distribution targets. In the program's more recent years, the Northern and Southern provinces have been the largest beneficiaries of cookstove distributions, although districts in Eastern and Western provinces have received cookstoves as well since 2022.

3.3 Data Assembly

We use publicly available polygon data of Rwanda's administrative boundaries to collect zonal statistics for each of Rwanda's 2,148 administrative cells. Using the MODIS VCF data, we estimate mean percent forest, nonforest vegetation, and nonvegetated cover 2000-2023. We use the Landsat-based mappings to estimate cell percent dense vegetation, sparse vegetation, open land, and agricultural land 2012-2023. Using WorldPop, we estimate the cell's annual population 2000-2023, and from TerraClimate we derive the cell's cumulative rainfall and maximum annual temperature 2000-2023. We characterize cell road proximity based on the cell centroid's distance to the nearest paved road.

Table 2 reports descriptive statistics of our cell-year panel. Land cover in Rwandan cells is predominantly vegetated: vegetation accounts for roughly 70 percent of land cover on average, while about 14 percent is forest, and the remaining 16 percent is non-vegetated. Treatment timing varies across cells, 17.7 percent of administrative cells were in the earliest (2014) treatment group, while many cells first entered the stove program in 2016 (35.7 percent) and 2022 (23.9 percent). While 2016 distributions included many administrative cells, the means tested nature of the intervention at this time means that per-cell receipt was lower than in later year (see Figure 2b). Only 8.9 percent of cells never receive a stove during the study period. Rwanda's administrative divisions are predominately rural, with only 11.7 percent of cells classified as urban. Cells lie on average 5.8 kilometers from the nearest paved road with considerable variation and are on average small, covering roughly 11.3 square kilometers. Over time, forest cover rises modestly—from about 11

[12] The fifth province is Kigali City, which houses the capital, but it is almost entirely urban and hence, not part of the cookstove intervention.

Table 2: Descriptive statistics of cell-year panel data 2000-2023

	Overall	2005	2009	2014	2019	2023
Time-Varying						
Forest Cover (%)	13.87	11.02	13.04	13.06	15.82	15.79
	(8.94)	(7.85)	(7.65)	(7.57)	(8.46)	(8.87)
Vegetation (%)	69.78	73.35	70.70	70.22	69.78	67.42
	(7.49)	(6.86)	(6.83)	(6.40)	(6.60)	(7.73)
Non-Vegetation (%)	16.35	15.62	16.26	16.73	14.40	16.78
	(5.88)	(5.28)	(5.05)	(5.91)	(5.13)	(6.81)
Precipitation (mm)	98.19	81.75	104.79	86.89	64.84	115.82
	(25.86)	(14.16)	(14.22)	(15.85)	(12.22)	(21.45)
Max Temperature (°C)	25.52	25.91	26.07	24.89	25.82	26.24
	(1.98)	(1.92)	(1.90)	(2.03)	(2.02)	(1.98)
Population	4230.92	3483.24	3860.65	4450.91	5218.86	5478.08
	(2701.06)	(1713.39)	(1966.46)	(2591.54)	(3689.92)	(3577.21)
Stoves Distributed	29.32	0.00	0.00	47.11	0.00	175.66
	(174.37)	(0.02)	(0.02)	(113.83)	(0.00)	(405.29)
Time-Invariant						
Distance to Paved Road (km)	5.79					
	(5.04)					
Area (sq. km)	11.34					
	(19.61)					
Urban (%)	11.7					
	(32.1)					
2014 Group (%)	17.7					
	(38.2)					
2016 Group (%)	35.7					
	(47.9)					
2020 Group (%)	11.2					
	(31.5)					
2021 Group (%)	1.4					
	(11.5)					
2022 Group (%)	23.9					
	(42.6)					
2023 Group (%)	0.2					
	(4.3)					
Never Treated (%)	8.9					
	(28.5)					
N	51,552	2,148	2,148	2,148	2,148	2,148

Note: Means reported with standard deviations in parentheses on the line below. Statistics reported for entire panel and by selected reference years. Group rows (ex: "2014 Group") represent the percent of cells that were first treated in the listed year. Forest, vegetation, and non-vegetated cover derived from the MODIS VCF spatial product (DiMiceli et al., 2021). Population data generated using WorldPop annual gridded population estimates (WorldPop, 2025). Stoves distributed reflect Tubeho Neza stoves first received by beneficiaries living in the estimation unit (administrative cell) during a given reference year.

percent in 2005 to nearly 16 percent by the end of the sample, while non-vegetative cover declines slightly and overall vegetation remains broadly stable.

4 Empirical Strategy

This study implements a staggered DID approach to estimate the effect of the *Tubeho Neza* program on forest cover. We do this by estimating versions of the following model using ordinary least squares (OLS),

$$y_{it} = \beta_0 + \beta_1 TubehoNeza_{it} + X_{it} + \gamma_t + \phi_i + \mu_{p*t} + \epsilon_{it}, \quad (1)$$

where y_{it} is an outcome of interest related to landscape cover for village or cell i in time period t, $TubehoNeza_{it}$ is a binary variable equal to one if the village had received stoves through *Tubeho Neza* in time period t and zero otherwise, X_{it} is a vector of cell-level time-variant controls that includes annual precipitation and maximum temperature as well as population. The γ_t term is a vector of cell fixed effects controlling for all time-invariant qualities of the cell , ϕ_i is a vector of year fixed effects controlling for time-specific shocks, and μ_{p*t} is a vector of province-time trends controlling for anything changing linearly over time at the province level (Angrist and Pischke, 2009). In this model, the coefficient of interest is β_1, the average treatment effect on the treated (ATT) of the program on the outcome assuming parallel trends holds and homogeneous effects by treatment cohort Goodman-Bacon (2021).

Several concerns have been raised in the recent econometrics literature about two-way fixed effects estimation in the context of a treatment staggered over time (Goodman-Bacon, 2021). To address this, we use Wooldridge (2025)'s "Extended Two-Way Fixed Effects" estimator. To implement this, we follow Nagengast et al. (2026) and estimate the following amended version of Equation (1),

$$Y_{it} = \beta_0 + \sum_{g \in G} \sum_{t=t_0}^{g-1} \theta_{gt}^{-} TubehoNeza_{igt} + \sum_{g \in G} \sum_{t=g}^{T} \theta_{gt}^{+} TubehoNeza_{igt} + X_{it} + \gamma_t + \phi_i + \mu_{p*t} + \epsilon_{it}. \quad (2)$$

where G is a set that indicates at what time treatment started for all treated observations, T is the last period of the analysis, t_0 is the first period in the analysis. This model allows us to estimate cohort-specific effects over time relative to a common starting time period. We can then use these cohort-time effects, the θ_{gt}^{+} vector, to calculate an average treatment effect on the treated (ATT) according to the following formula,

$$ATT = \frac{\sum_i^N \widehat{ATT}_i \times w_{it} \times R_{it}}{\sum_i^N w_{it} \times R_{it}} \tag{3}$$

where $R_{it} = 1$ if $t \geq g$ for $i \in g > 0$, and zero otherwise, and $\widehat{ATT}_i = \hat{Y}(obs) - \hat{Y}(0)$, $\hat{Y}(obs)$ is i's predicted outcome under the observed covariates, $\hat{Y}(0)$ is i's predicted outcome under the counterfactual scenario of no treatment. and w_{it} is the weight of the observation used in the estimation model. We also use these estimates from Equation (2) to estimate period-specific effects to create event study estimates. The calculation of these estimates follows Equation (3), but we define $R_{it} = 1$ if $t - g = e_c$ and $e \neq -2$, and zero otherwise, where e_c is the event of interest (Nagengast et al., 2026).

We define the reference period as occurring one years before the first year the *Tubeho Neza* is active since we see anticipation of the arrival of the program to be unlikely for reasons we explain below in Section 4.1. We only use the never treated as the comparison group in all estimations, which avoids scenarios in which already-treated units inadvertently serve as part of counterfactual estimation for later-treated units (Goodman-Bacon, 2021). This is also consistent with other estimators of this class that have emerged addressing the worry outlined by Goodman-Bacon (2021) (Callaway and Sant'Anna, 2021; Nagengast et al., 2026; Sun and Abraham, 2020). We remove all cells that were treated with pilot programs from all estimations.

We also combine our group-time ATT estimates to generate event studies that report outcomes over different relative time periods. There are two benefits to our event studies. First, the impacts of *Tubeho Neza* may vary over time and event studies allow insight into any evolution of an effect over time. Second, our event study plots also provide some evidence of whether the parallel trends assumption holds for a given outcome by examining whether the pre-treatment effects, estimated using the θ^+_{gt}s from Equation (2), are systematically significantly different than zero. If they are, it would suggest that the parallel trends assumption is not justified and our DID approach is biased in this setting.

4.1 Threats to Identification

Before we present our main estimation results, we briefly review the threats to our identification strategy such as selection bias, confounding treatment estimates, or anticipation effects.

Selection bias: District leaders decide if they want their district to be part of the improved cookstove program by signing MOUs with NGOs such as DelAgua. In other words, the treatment is assigned at the district level, though it does not imply that each cell within the district is treated. However, in the absence of a district leader's decision to participate, no cell within a district receives cookstoves or is treated.

One concern is that districts deciding to participate in the program are non-randomly different from districts yet to participate, or districts that decided to participate earlier are systematically different from other districts. For this purpose, we conducted Key Informant Interviews (KIIs) with the district leaders, as discussed in section 2.3. For instance, these districts might have faced higher rates of deforestation in the past, or their population growth rate may be faster, or more villages may be excluded from the markets because of the distance. In the KIIs, we explicitly asked what factors informed their decision to participate in the program. However, all answers revolved around improving living standards and achieving government objectives. Thus, we are reasonably confident that there was no endogenous sorting or selection into the improved cookstove intervention.

Confounding treatment estimates: Another major concern for our identification strategy is the presence of other programs, policies, and interventions that can affect deforestation and vegetation. For instance, a ban on any cutting of trees around the time of improved cookstoves distribution in a district will make it harder to cleanly tease out the effects of improved cookstoves on forest cover. In this regard, we inquired both district leaders and participants of FGDs about other environmental programs in the district, and experience with competing improved cookstove distributors, respectively. We also met with staff of other NGOs in Rwanda such as OneAcre Fund as well as with the government officials in the Ministry of Agriculture (MINIAGRI) and National Institute of Statistical Research (NISR).

Our conclusion from our fieldwork is that all other programs that can affect forest cover started after 2020-21. These include the introduction of other cookstove distributors and other NGO-led programs, such as the distribution of seeds and branches for tree plantation. Our period of study is until 2023, and since these programs started towards the tail end of our study time period, it is not likely that they will affect the forest cover in any meaningful way. In any case, the event study estimates until 2020 should not be confounded by other policies and interventions.

Anticipation Effects: One threat to the parallel trends assumption is that households switch to a different village in anticipation of the improved cookstove distribution. This is extremely unlikely, however, because (a) rural households' welfare is entwined with the complex village economy based around terraced farming, agro-forestry, and other activities; and (b) participants in our FGDs whose improved cookstoves had broken down or expired expressed no willingness to move in order to benefit from the cookstove receipt in a different village or sector.

Other concerns: The cookstove receipt alone is not enough to guarantee an effect on our outcomes of interest. The program should not have any effect on forest cover or deforestation if households do not use the improved cookstoves due to concerns related to tastes and preferences, or if they break down easily. Similarly, if a village or sector does not rely on fuelwood in the pre-treatment time periods, then the improved cookstove intervention is unlikely to impact forest cover. Our results in section 2.3 reveal that beneficiaries of improved cookstoves actively use them and subsequently report a reduction in energy expenditure. They also reveal energy constraints that are exacerbated during the rainy season, particularly in villages with poor road/market connectivity.

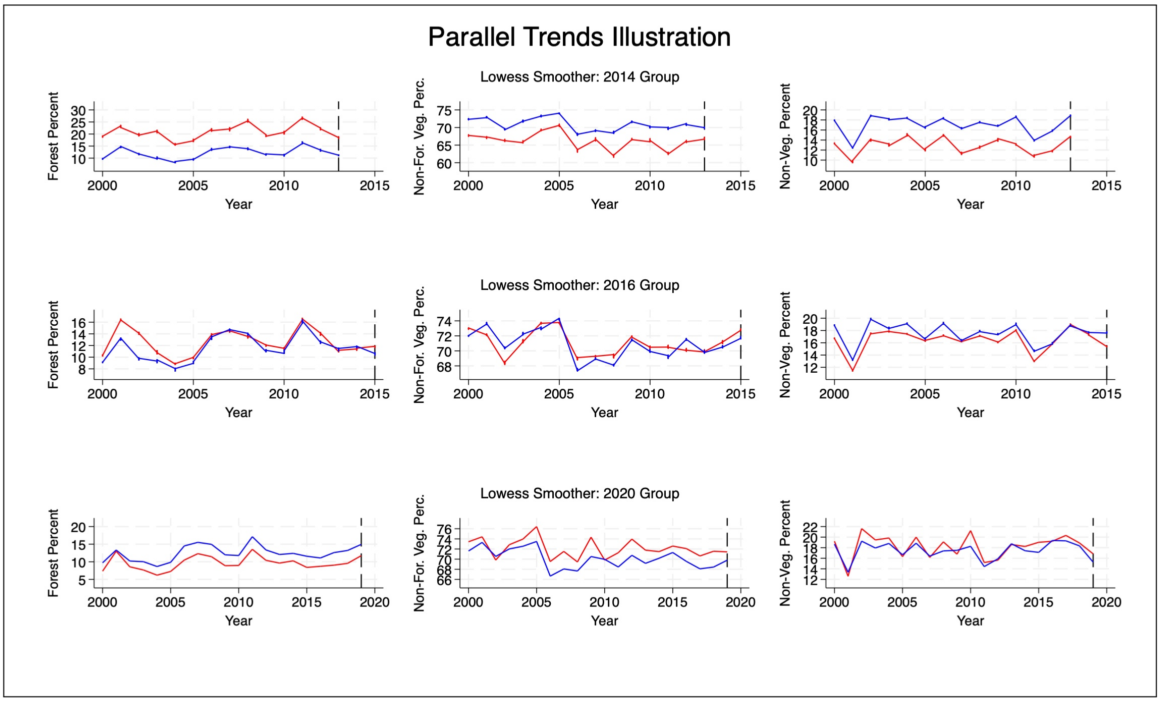
5 Main Results

We begin by examining a short nonparametric analysis of parallel trends in the outcome variables for the first three cohorts in the study. We do this by using the Lowess Smoother to illustrate the evolution of the outcome variables for the treated cells and the untreated cells prior to treatment. These are contained in Figure 3. We allow for a bandwidth of 0.1 to allow for the Lowess measure to be relatively sensitive and pick up variation from year to year.

Figure 3 presents the evolution of outcome for each treatment cohort, and never treated cohort - we discuss the generalized parallel trends for all treatment cohorts aggregated together when we present the event study results later. Given that the MODIS VCF data is not available only until 2022, we can only compare treatment and control groups for the three treatment cohorts until 2021. Using the VCF data in Figure 3, we compare the evolution of outcomes for three outcomes of interest: percent forest vegetation (first column), percent non-forest vegetation (second column), and percent non-vegetation (third column). Thus, we have three outcomes of interest and three treatment cohorts, yielding nine comparisons of how an outcome of interest evolves between the treated cohort and the control group. In all cases, we see that uniformly the treated and control groups evolve similarly over time, providing confidence that the parallel trends assumption is justified in our setting.

Table 3 presents the ATT estimates for our three outcome variables, estimated using the MODIS VCF data. Here, the ATT estimates are calculated at the most aggregate level. The result in column 3 shows an unambiguous, statistically significant decrease in areas classified as non-vegetation by 1.866 percentage points (ppt). Furthermore, these results show that treated cells experienced statistically significant increases both in the percent of their territory classified as forest and in non-

Figure 3: Pre-Treatment Trends in Forest and Vegetation Outcomes



Notes: Lowess-smoothed trends in outcome variables for treated and never-treated administrative cells prior to treatment, shown separately by treatment cohort. Outcomes include percent forest cover, percent non-forest vegetation, and percent non-vegetated area. Treatment timing is defined by the first year in which Tubeho Neza stoves were distributed in the administrative cell. Forest, vegetation, and non-vegetated cover are derived from the MODIS VCF spatial product (DiMiceli et al., 2021). Treatment status is constructed using proprietary DelAgua stove distribution records.

Table 3: Average Treatment Effects on the Treated, Mundlak estimator and MODIS VCF data

	Forest Percent	Non-For. Veg. Percent	Non-Veg. Percent
ATT	0.610**	1.256***	-1.866***
	(0.245)	(0.393)	(0.333)
Sample Mean	13.742	69.840	16.418
R-squared	0.863	0.731	0.780
Observations	48,168	48,168	48,168
Satellite	MODIS	MODIS	MODIS
Years Covered	2000 - 2023	2000 - 2023	2000 - 2023

Notes: Table reports average treatment effects on the treated (ATT) from the Mundlak event study estimator described in Wooldridge (2025). The unit of observation is the administrative cell-year. Treatment is defined as the first year in which Tubeho Neza cookstoves were distributed within a cell. Outcome variables measure the percentage of land area within each cell classified as forest, non-forest vegetation, and non-vegetated cover using the MODIS Vegetation Continuous Fields (VCF) dataset (DiMiceli et al., 2021). Forest cover corresponds to tree canopy above a minimum density threshold, while non-forest vegetation includes shrubs, grasses, and sparse tree cover below this threshold. ATT estimates represent the average post-treatment effect across all treated cohorts and periods. Sample means are calculated over the full estimation sample. Standard errors clustered at the sector level are reported in parentheses. All models include cell fixed effects, year fixed effects, province-specific linear time trends, and controls for precipitation, maximum temperature, and population (coefficients omitted for brevity). *** p<0.01, ** p<0.05, * p<0.1.

forest vegetation. Tree canopy (forest) cover increased by 0.61 percentage points: given the sample mean, this finding translates into a 4.4% increase in forest cover in response to Tubeho Neza. In absolute terms, this represents an average increase in forest cover by 9.7 football pitches annually.[13]

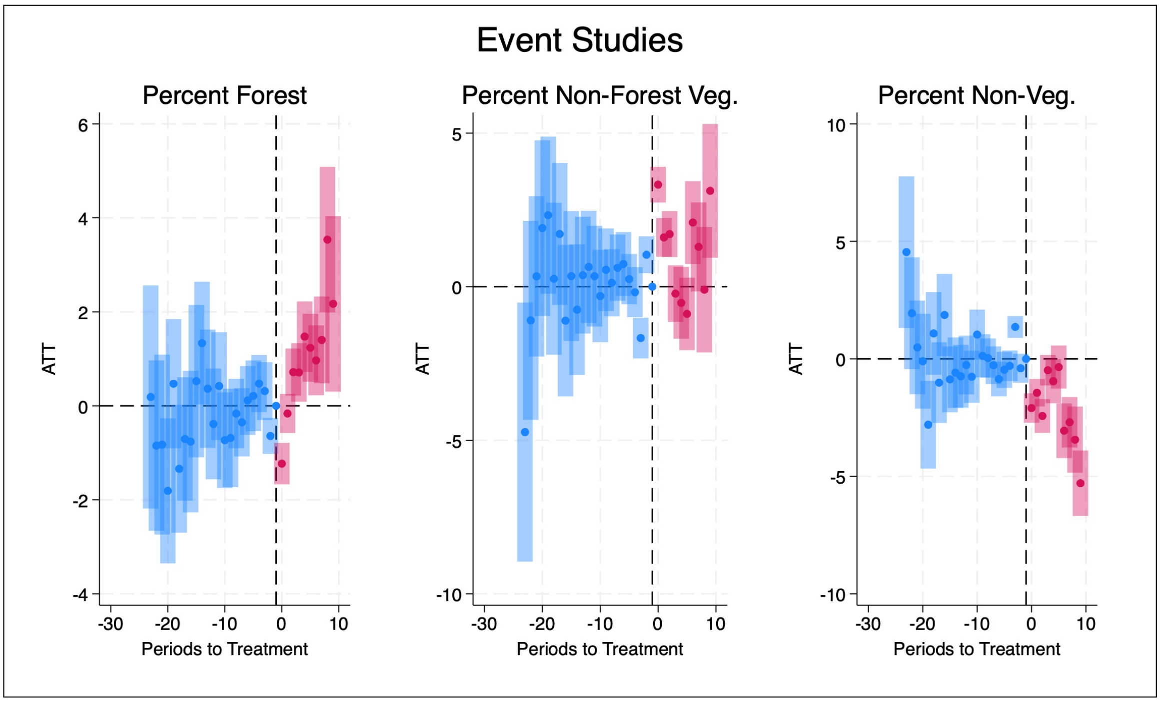
The significant 1.26 ppt. increase in non-forest vegetation represents additional verdant land cover that does not qualify as closed canopy. This can include shrubland and grasslands, but it can also include sparsely treed landscapes. This pattern is consistent with ecological recovery in areas with low baseline forest cover, where reduced pressure on biomass may first manifest as increases in sparse or mixed vegetation, including low-density tree cover that does not meet the threshold for forest classification. These gains in vegetation are mirrored by declines in non-vegetated area, consistent with previously cleared or degraded land transitioning into vegetated states. The effect is equivalent to a marginal increase of cover by 19.9 football pitches each year.

The decline in non-vegetated area further reinforces this interpretation. The annual 1.87 ppt. reduction (equivalent to 29.6 football pitches) indicates that land previously classified as bare or built-up is transitioning into vegetated cover. This is consistent with reduced pressure on biomass allowing degraded or sparsely covered areas to recover, even if this recovery initially takes the form of non-forest vegetation rather than dense canopy forest.

The fact that the increase in non-forest vegetation does not crowd out forest cover holds significance important in Rwandan context. Specifically, Rwanda's economy significantly relies on coffee exports; and the European Union's Deforestation Regulation (EUDR) can have significant consequences for Rwanda in terms of trade restrictions if coffee production grows at the expense of forest cover. Our results, however, strongly suggest that while the cookstove distribution intervention leads to an increase in non-forest vegetation, in does not come at the expense of forest cover. Unfortunately, the VCF data does not allow further decomposition of forest and non-forest vegetation so we are unable to make a definitive claim on the relationship between agricultural expansion and forest cover. However, we shed some light on this when we discuss our results using Landsat data in section 7.1.

[13] The average size of an administrative cell is 11.34 km^2. To convert percentage point treatment effects into land area, we multiply the estimate by average administrative cell size (e.g., $11.34 \times 0.0061 \approx 0.069$ km^2, or 6.9 hectares for forest). The same conversion applies to other land-cover categories (e.g., $0.01256 \times 11.34 \approx 0.142$ km^2 for non-forest vegetation, and $0.01866 \times 11.34 \approx 0.212$ km^2 for non-vegetated area). A standard football pitch is about 0.714 hectares, so these correspond to roughly $6.9/0.714 \approx 9.7$, $14.2/0.714 \approx 19.9$, and $21.2/0.714 \approx 29.6$ football pitches, respectively.

Figure 4: Dynamic Effects of Cookstove Distribution on Land Cover Outcomes



Notes: Event study estimates of the impact of Tubeho Neza cookstove distribution on percent forest cover, non-forest vegetation, and non-vegetated area. Coefficients are estimated relative to the year prior to treatment and are plotted with 95% confidence intervals, with standard errors clustered at the sector level. Blue points represent pre-treatment periods, while red points represent post-treatment periods. Outcome variables are derived from the MODIS Vegetation Continuous Fields (VCF) dataset (DiMiceli et al., 2021), and treatment status is constructed using proprietary DelAgua stove distribution data. All models control for precipitation, maximum temperature, and population

Next, we turn to the presentation and discussion of our event study estimates. Figure 4 shows the event studies for the three main outcome variables. Figure 4 presents further evidence in favor of the parallel trends assumption. The third figure with with percent non-vegetation area as the outcome provides the strongest evidence in favor of the parallel trends assumption. The periods leading up to the first treatment period show no difference in outcome between the treatment and the control group. The coefficient estimates are small in absolute size and are not statistically different from zero. The first two charts present similar evidence in favor of the parallel trends assumption, with percent forest cover and percent non-forest vegetation as outcomes, respectively. These two charts show mostly statistically insignificant results prior to treatment with no clear pattern.

The post-treatment period shows a clear pattern in gains in both the percent forest cover and non-forest vegetation. A corresponding decrease in percent non-vegetation area also takes place. Figure 4 shows that the changes in our outcomes of interest show up a few years after receiving treatment. This is not surprising, specially in the case of percent forest cover, because it takes time for vegetation to grow and also, be large enough and dense enough to be detected by the satellite. This is perhaps why it takes a few years before we see increase in percent forest cover in the first chart and decrease in percent non-vegetation in the third chart.

Surprisingly, we see a decrease in percent non-forest vegetation for three years, after an initial post-treatment increase. This decrease is corresponded by a noticeable simultaneous gain in percent non-vegetation. This may reflect measurement or classification error between percent non-vegetation area and percent non-forest vegetation, either during these three years, or during the time periods after treatment but preceding these three years.

6 Heterogeneity

Before we discuss the sensitivity of our findings to the choice of satellite data and the choice of estimation method, we present heterogeneity in our findings. This is because the chosen estimation method allows estimating ATT by treatment cohorts, using equation 3, which are of particular interest in any empirical study based on an event study approach.

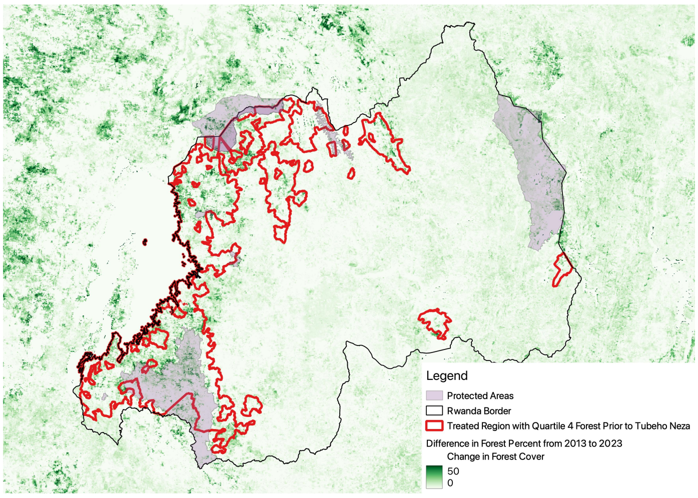
6.1 Heterogeneity by Forest Cover

We first examine heterogeneity in the effects by the type of forest cover the cells had in the five years prior to treatment. Here we group the treated sample into quartiles based on the average percentage of their territory classified as forest in the five years prior to treatment. We label Quartile 1 as the quartile with the lowest percent of their area classified as forest, and Quartile 4 as the one with the highest. We then rerun our estimates. Table 4 contains the results.

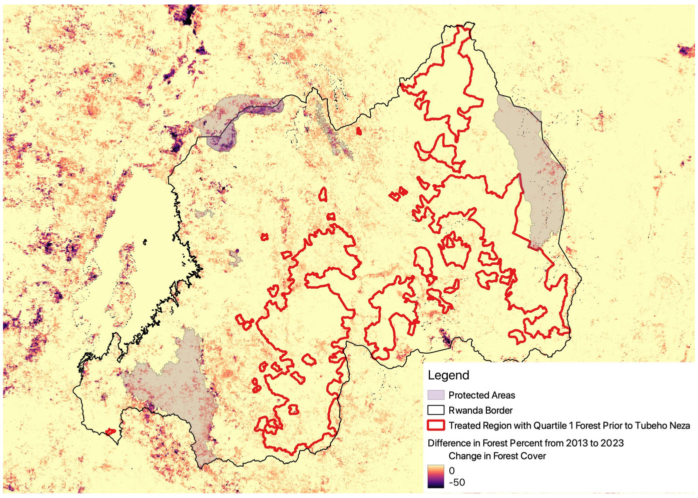
There are several patterns to note. First, all treated cells, regardless of quartile, experienced a statistically significant increase in its area classified as nonvegetated, with the largest being in quartile 3, a 2.691 percentage point decrease in area classified as vegetation. Second, gains in non-forest vegetation were not evenly distributed across quartiles. Notably, cells in quartile four did not experience a statistically significant increase in non-forest vegetation. This is consistent with areas that already have relatively high forest cover experiencing recovery primarily through increases in dense canopy (forest), while areas with lower initial forest cover exhibit gains in more diffuse or early-stage vegetation. Third, gains in area classified as forest were also not evenly distributed across the quartiles with only quartile 4 -that is quartiles with relatively abundant forest cover prior to treatment- experiencing gains in forest cover, and cells in quartile 1 actually experiencing a decline in forest cover.

Figure 5: Forest Growth and Decline by Baseline Forest Endowment

(a) High baseline forest cover (Quartile 4 cells)



(b) Low baseline forest cover (Quartile 1 cells)



Notes: Panel (a) shows forest growth and treated locations among administrative cells in the highest quartile of baseline forest cover, while Panel (b) shows forest decline and treated locations among cells in the lowest quartile. Forest cover is measured using the MODIS Vegetation Continuous Fields (VCF) dataset, which reports the percentage of land area classified as tree canopy at 250m resolution (DiMiceli et al., 2021). Treatment status is constructed using proprietary DelAgua stove distribution data.

Table 4: Heterogeneous ATT Estimates by Baseline Forest Cover (Quartiles)

	Panel 1: Percent Forest			
Sample	Forest Quart. 1	Forest Quart. 2	Forest Quart. 3	Forest Quart. 4
ATT	-0.900***	0.162	0.402	2.255***
	(0.240)	(0.222)	(0.281)	(0.696)
Sample Mean	8.205	10.055	12.142	19.791
R-squared	0.716	0.715	0.732	0.868
Observations	15,456	15,648	15,360	15,312
	Panel 2: Percent Non-Forest Veg.			
Sample	Forest Quart. 1	Forest Quart. 2	Forest Quart. 3	Forest Quart. 4
ATT	1.865***	1.516***	2.288***	-0.125
	(0.471)	(0.394)	(0.415)	(0.720)
Sample Mean	71.283	71.057	70.386	64.695
R-squared	0.715	0.704	0.692	0.789
Observations	15,456	15,648	15,360	15,312
	Panel 3: Percent Non-Vegetation			
Sample	Forest Quart. 1	Forest Quart. 2	Forest Quart. 3	Forest Quart. 4
ATT	-0.965**	-1.678***	-2.691***	-2.130***
	(0.415)	(0.368)	(0.365)	(0.377)
Sample Mean	20.511	18.887	17.472	15.514
R-squared	0.820	0.848	0.869	0.898
Observations	15,456	15,648	15,360	15,312
Satellite	MODIS	MODIS	MODIS	MODIS
Years Covered	2000 - 2023	2000 - 2023	2000 - 2023	2000 - 2023

Notes: This table reports average treatment effects on the treated (ATT) estimated using the Mundlak event-study approach described in Wooldridge (2025), stratified by quartiles of baseline forest cover. The unit of observation is the administrative cell-year. Treatment is defined as the first year in which Tubeho Neza cookstoves were distributed within a cell. Cells are grouped into quartiles based on their average percent forest cover in the two years prior to treatment, with Quartile 1 representing the lowest baseline forest cover and Quartile 4 the highest. Each panel reports results for a different outcome: percent forest cover (Panel 1), percent non-forest vegetation (Panel 2), and percent non-vegetated area (Panel 3). Outcome variables are derived from the MODIS Vegetation Continuous Fields (VCF) dataset (DiMiceli et al., 2021), where forest cover corresponds to tree canopy above a minimum density threshold and non-forest vegetation includes shrubs, grasses, and sparse tree cover below this threshold. ATT estimates represent the average post-treatment effect within each quartile group. Sample means are calculated within each quartile-specific estimation sample. Standard errors clustered at the sector level are reported in parentheses. All models include cell fixed effects, year fixed effects, province-specific linear time trends, and controls for precipitation, maximum temperature, and population (coefficients omitted for brevity). *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Figure 5b provides a sense of where the growth occurred in the Quartile 4 cells that drives this result. The figure contains a map of Rwanda with the Quartile 4 cells in red. The green pixel layer shows where increases in forest happened between 2013 and 2023, where the darker the green the greater the increase in forest cover. Most of the forest growth that occurred in those years was in the western and northwestern regions of the country, particularly the areas far to the west relatively close to Lake Kivu. This is consistent with the results in Table 5, which show that the 2014 treatment cohort which was based in the Western Province, was the only cohort to experience growth in forest cover from *Tubeho Neza*. Figure 5a provides a sense of where the forest declined in regions with relatively less forest cover prior to *Tubeho Neza*. This figure shows Rwanda with the cells with the lowest pre-treatment forest outlined in red. The underlying pixel layer shows where declines in forest cover occurred, with the darker purple color reflecting more forest loss. The figure shows that generally there was no specific area or set of locations driving this result.

6.2 Heterogeneity by Treatment Cohort

More importantly, we also look at heterogeneity by treatment cohort. To do this we use the same set of estimates as described in Equation 2, but we aggregate ATT estimate by treatment cohort by using equation 3. Table 5 contains the results. It shows varied effects by cohort. While four out of the six cohorts (2014, 2016, 2020, and 2022) experienced a statistically significant increase in vegetation, only one, the 2014 cohort, experienced an increase in forest cover. The other four cohorts experiencing growth in vegetation achieved this through increases in non-forest vegetation.

Notably the 2020, 2022, and 2023 groups all experienced statistically significant declines in forest cover. These cohorts experience an increase in non-forest vegetation cover and a corresponding decrease in non-vegetation cover. Is non-forest vegetation substituting for forest cover for these cohorts? We think this is too soon to say since our results in section 5 show that the effect of cookstove distribution on percent forest cover takes a few years to show up and stabilize. In particular, it is hard to interpret the results for the 2022 and 2023 cohorts.

It is also possible that the 2020 cohort is a special group. While Figure 2a shows that the beneficiaries in this cohort are almost entirely based in the Southern province. Combining Figure 2a and Figure 5b, it can be seen that a substantial proportion of the 2020 treatment cohort resides in areas in Quartile 1 that is the quartile with the lowest percent of their area classified as forest. Hence, results in Table 5 support our findings in section 6.1 that forest cover only grows in regions with higher baseline forest cover before the intervention, while non-forest vegetation grows in all

Table 5: Heterogeneous ATT Estimates by Treatment Cohort (Year of First Stove Receipt)

	Forest Percent	Non-For. Veg. Percent	Non-Veg. Percent
ATT 2014 Group	3.093***	-0.70	-2.423***
	(0.577)	(0.677)	(0.439)
ATT 2016 Group	-0.403	1.540***	-1.137**
	(0.292)	(0.542)	(0.463)
ATT 2020 Group	-1.324**	4.866***	-3.542***
	(0.623)	(1.057)	(0.654)
ATT 2021 Group	0.248	-0.881	0.633
	(0.374)	(0.608)	(0.640)
ATT 2022 Group	-1.061***	3.718***	-2.657***
	(0.364)	(0.524)	(0.508)
ATT 2023 Group	-2.070*	4.001***	-1.930
	(1.247)	(1.065)	(1.587)
R-squared	0.863	0.731	0.780
Observations	48,168	48,168	48,168
Sample Mean	13.742	69.840	16.418
Satellite	MODIS	MODIS	MODIS
Years Covered	2000 - 2023	2000 - 2023	2000 - 2023

Notes: This table reports average treatment effects on the treated (ATT) estimated using the Mundlak event-study approach described in Wooldridge (2025), disaggregated by treatment cohort. The unit of observation is the administrative cell-year. Treatment cohorts are defined by the first year in which Tubeho Neza cookstoves were distributed within a cell (e.g., the "2014 Group" includes all cells first treated in 2014). Each row reports the average post-treatment effect for a given cohort. Outcome variables measure the percentage of land area within each cell classified as forest, non-forest vegetation, and non-vegetated cover using the MODIS Vegetation Continuous Fields (VCF) dataset (DiMiceli et al., 2021). Forest cover corresponds to tree canopy above a minimum density threshold, while non-forest vegetation includes shrubs, grasses, and sparse tree cover below this threshold. ATT estimates capture the dynamic response of land cover to cookstove distribution across cohorts that differ in timing of exposure. Sample means are calculated over the full estimation sample. Standard errors clustered at the sector level are reported in parentheses. All models include cell fixed effects, year fixed effects, province-specific linear time trends, and controls for precipitation, maximum temperature, and population (coefficients omitted for brevity). *** p<0.01, ** p<0.05, * p<0.1.

regions. This might be the case because stemming deforestation or increasing afforestation is easier in an ecosystem that supports tree growth.

Encouragingly, we notice a decrease in percent non-vegetation area for all treatment cohorts. The coefficient is not statistically significant for the 2023 cohort but that is not surprising given our earlier finding that changes in vegetation only start showing up in the satellite data after a while. The largest decrease is for the 2014, 2020 and 2022 treatment cohorts - with the caveat that it is hard to interpret the coefficient for the 2022 cohort, again because it received treatment very recently.

6.3 Heterogeneity by Road Distance

Table A1 in Appendix A contains heterogeneous effects by the amount of road constructed in the cell. [14] We again look at patterns in effects by quartile of distance to a paved road. We find that while non-vegetation area reduced by about the same amount, between 1.878 and 1.976 percentage points across all cohorts, this hides interesting heterogeneity in what type of vegetation grew. The results indicate that cells in the lowest road quartiles saw much more forest growth, over one percentage point, than cells with more roads, which saw much less forest growth. However, those areas that had more roads still saw significant increases in non-forest vegetation, over 1.75 percentage points.

The results hold important consequences when considered in the light of household separability between production and consumption. Households farther from the roads are much more likely to be those where time spent on fuelwood collection are also a function of household consumption and demographics. Thus, reduced reliance on wood for daily subsistence shall, in theory, improve the separability between fuelwood production and other decisions such as time spent on wage employment and household consumption of market goods.

7 Robustness Checks

7.1 Landsat Data

We check robustness by examining whether our results hold when we construct our own data using alternative satellite imagery. To do this, we use data available from the Landsat satellite from 2012 to 2023 to construct measures for the percentage of each cell covered in dense vegetation, sparse vegetation, open land, and agricultural land. We use Machine Learning algorithms to create bespoke maps and classification methods that best suit the Rwandan geographical and climate context.

[14] It is also likely that poor road connectivity is positively correlated with baseline or pre-treatment forest cover.

Table 6: Average Treatment Effects on the Treated Using Landsat-Derived Land Cover Measures

	Perc. Dense Veg.	Perc. Sparse Veg.	Perc. Open Land	Perc. Ag. Land
ATT	0.505*	2.259***	-0.557	0.583
	(0.271)	(0.676)	(0.791)	(1.517)
Sample Mean	2.261	7.106	7.891	21.142
R-squared	0.872	0.843	0.981	0.648
Observations	24,084	24,084	24,084	24,084
Satellite	Landsat	Landsat	Landsat	Landsat
Years Covered	2012 - 2023	2012 - 2023	2012 - 2023	2012 - 2023

Notes: This table reports average treatment effects on the treated (ATT) estimated using the Mundlak event-study approach described in Wooldridge (2025), using land cover measures derived from Landsat imagery. The unit of observation is the administrative cell-year. Treatment is defined as the first year in which Tubeho Neza cookstoves were distributed within a cell. Outcome variables measure the percentage of land area within each cell classified as dense vegetation, sparse vegetation, open land, and agricultural land based on Landsat-derived land cover classifications. These categories provide a more disaggregated view of land cover compared to the MODIS Vegetation Continuous Fields (VCF) measures used in the main analysis. ATT estimates represent the average post-treatment effect across all treated cohorts and periods. Sample means are calculated over the full estimation sample. Standard errors clustered at the sector level are reported in parentheses. All models include cell fixed effects, year fixed effects, province-specific linear time trends, and controls for precipitation, maximum temperature, and population (coefficients omitted for brevity). *** p<0.01, ** p<0.05, * p<0.1.

In this section, we repeat our main results and ATT estimates presented in section 5, as well as the heterogeneity in our findings presented in section 6, using the Landsat data. Besides serving as a robustness check on the choice of satellite data, the Landsat data allows us to decompose surface area into dense vegetation, sparse vegetation, agricultural land, and open or bare land. This is possible because the Landsat data is available at a much finer resolution of 30 meters, but with the caveat that it is only available from 2012 onwards, which means that only one pre-treatment time period is available for the 2014 treatment cohort. Nevertheless, this allows us to decompose our earlier finding of increase in non-forest vegetation. Crucially, we are able to report whether this increase is attributable to sparse vegetation or agricultural land.

Table 6 presents our ATT estimates from the estimation of equation 2. The coefficient on both percent dense forest and percent sparse vegetation, in Columns 1 and 2 respectively, is positive and statistically different from zero. The coefficient in Column 2 is about 4 times the size of the coefficient in Column 1 which supports our earlier finding in Table 3 using MODIS VCF data that increase in non-forest vegetation is greater than the increase in forest vegetation. [15] Given the sample mean, we observe a 22% increase in dense vegetation and a 32% increase in sparse vegetation. Further, while the coefficient for agricultural land in Column 4 is positive and about the same size as the coefficient for dense vegetation in Column 1, it is not statistically different from zero. [16]

[15] A comparison of the coefficient estimates between Table 3 and Table 6 is not feasible given that the outcomes are different. However, a qualitative comparison of estimates from VCF data and estimates from Landsat data is not only possible but warranted.

[16] Given the sample mean, it only translates to a 2.7% increase in agricultural land which is not economically meaningful.

While we observe a decrease in area covered by open land, it is not statistically different from zero. This is different from our estimates using VCF data in Table 3 that showed a substantial decrease in percent non-vegetation area. The coefficient size is also much smaller here suggesting that we find no decrease in percent of open land when using the Landsat data. Overall, the coefficients reported in Table 6 are qualitatively similar to the ones in Table 4: they show an increase in both forest vegetation and non-forest vegetation, with the effect being greater in magnitude for non-forest vegetation.

In Appendix A, Table A2 examines heterogeneity in the effects by the type of forest cover the cells had in the five years prior to treatment, and Table A3 explores heterogeneity by treatment cohorts. Table A2 shows that the coefficient of ATT on both sparse and dense vegetation (in Panel 1 and Panel 2, respectively) is positive for all but the first quartile. It is statistically different from zero in Columns 2 and 4 for dense vegetation, and in Columns 3 and 4 for sparse vegetation. For both the outcomes, the coefficient is negative and statistically different from zero for the quartile with the lowest forest cover in the five years prior to treatment (Column 1).

These findings compare well with the coefficient estimates reported in Table 4. They are qualitatively similar, with the only notable difference being that we found no increase in non-forest vegetation for quartile 4 when using VCF data -with the coefficient being negative, small in absolute size and not statistically different from zero, but we find a statistically significant increase in sparse vegetation for the same quartile when using Landsat data. This could be due to two reasons. First, it could be the case because non-forest vegetation may not be detected well by the MODIS VCF data in areas with high baseline forest cover, while our bespoke classifications reduce the measurement error. Second, it is also likely that there is not a one-to-one mapping between sparse vegetation (in Table A2) and non-forest vegetation (in Table 4) because the former isolates sparse vegetation from agricultural land while the latter does not.

In Table A3, we explore heterogeneity by treatment cohorts using the Landsat data. Column 1 reports the results for dense vegetation while Column 2 reports the results for sparse vegetation. Unlike in Table 5, we now find a positive ATT coefficient estimate for all treatment cohorts in Column 1. Overall. the coefficient estimates in Table A3 are more imprecisely estimated than the results for treatment cohorts using VCF data in Table 5. However, they reinforce the finding that the increase in non-forest vegetation is more salient than the increase in forest cover.

Overall, we can be confident that areas with higher baseline forest cover are more likely to see an increase in all types of vegetation as a result of this large-scale cookstove intervention. Crucially, our results using Landsat data suggest, albeit with weak empirical evidence, that the increase in vegetation is not the result of agricultural expansion. Thus, the intervention does not lead to the unintended spillover of increased carbon emissions and substitution of forest cover for agricultural expansion.

7.2 Dynamic DID estimator with continuous treatment

We also estimate treatment effects using the dynamic DID estimator proposed by De Chaisemartin and d'Haultfœuille (2024) (henceforth the DCDH estimator). Unlike the Mundlak estimator, a parametric model that uses fixed effects to estimate group-specific treatment effects, the DCDH estimator is a nonparametric method that uses comparisons between treated and never-treated groups to generate average treatment effects, aggregating across groups. The DCDH estimations provide evidence of whether our results are sensitive to a specific DID estimation strategy and its underlying assumptions.

The DCDH estimator accommodates treatments that vary continuously and increase over time. Our robustness check using this estimator also provides a sense of treatment effects at the extensive margin, to complement our main results focused on the intensive margin. A DID identification strategy with continuous treatment requires an additional assumption. Along with parallel pre-treatment trends, identification also depends on the *strong parallel trends assumption*: conditional on observables, cells receiving lower-intensity stove interventions would have experienced the same treatment response as cells receiving higher-intensity interventions if they had received the same level of treatment intensity (Callaway et al., 2024). This assumption cannot be tested directly but underlies our DCDH estimations.

We estimate the dynamic DID event study using the MODIS Terra Continuous Fields data, generating coefficients for 9 years prior to treatment and 10 years post-treatment. Outcome variables include percent forest, non-forest vegetation, and non-vegetated cover, in administrative cell i during year t. Our treatment indicator is the cumulative number of stoves distributed per 100 people in cell i as of year t.[17] Our estimation otherwise aligns with the main specification: we control for maximum temperature and cumulative rainfall in year t, and regressions are weighted using annual predicted population of cell i in year t. We cluster standard errors at the sector level.

We report DCDH event study results in Figure A1 (precise coefficient and standard error estimates in Table A4), and we include the cumulative average treatment effect (CATE) over the 10 year relative time window in Table A5.

As in the main findings, the DCDH estimates suggest a delayed impact on forest cover and an

[17] We rescale the treatment indicator so that the coefficient estimates are easier to interpret.

immediate reduction in nonvegetated cover. For forest cover, the estimated effects become positive and statistically significant beginning three years after treatment, with magnitudes ranging from roughly 0.03 to 0.12 percentage points (ppt) across later post-treatment periods. The CATE implies that an additional stove distributed per 100 residents increases forest cover by approximately 0.04 ppt, although this estimate is not statistically significant. In contrast, the results indicate a strong and persistent reduction in non-vegetative land cover. Across nearly all post-treatment years, the estimated coefficients are negative and statistically significant, with magnitudes between approximately 0.04 and 0.20 ppt. The cumulative estimate indicates that each additional stove per 100 residents is associated with a 0.33 ppt reduction in non-vegetative cover. Finally, the vegetation category (which includes non-forest vegetation) shows positive and statistically significant post-treatment effects beginning immediately after treatment, with a cumulative effect of roughly 0.29 ppt.

But the placebo estimates provide only limited support for the parallel trends assumption. Across the three outcomes, several pre-treatment coefficients are statistically different from zero. These patterns indicate that the identifying assumption underlying the event study specification is not strongly supported, and the estimated treatment effects should therefore be interpreted with caution. Nonetheless, the results remains consistent with the broader findings of the paper, suggesting that stove distribution is indeed having a positive impact on forest and vegetation cover and resulting in a reduction in nonvegetated landcover.

8 Conclusion

This paper studies whether a large-scale improved cookstove intervention can change forest and vegetation outcomes. Exploiting the staggered rollout of Rwanda's Tubeho Neza programme, we find that treated cells experienced an average increase in vegetation cover. In the MODIS data, stove receipt is associated with a 0.61 percentage point increase in forest cover, a 1.256 percentage point increase in non-forest vegetation, and a 1.866 percentage point decline in non-vegetated area. Event study estimates show little evidence of differential pre trends and indicate that treatment effects emerge gradually, which is consistent with the time required for vegetative recovery to become visible in satellite imagery. The robustness checks point in the same direction. Using bespoke Landsat classifications, we find increases in dense and sparse vegetation and little evidence of economically meaningful expansion in agricultural land. An alternative dynamic difference-in-differences specification with continuous treatment is harder to interpret because it requires stronger assumptions, but it qualitatively reinforces the main pattern of declining non-vegetative cover and improving vegetation outcomes over time.

Our qualitative fieldwork helps design the identification strategy, address potential identification confounders, and interpret our empirical findings. Focus group discussions indicate regular stove use (albeit with stove stacking), lower fuelwood expenditure, and less reliance on children for firewood collection. District leader interviews provide little evidence that rollout timing was driven by local environmental characteristics, and that major competing cookstove and tree-planting initiatives began only around 2020–21, near the end of the study period. These insights do not substitute for the econometric design, but they strengthen the case that the estimated land-cover effects are linked to the program itself.

The central substantive finding is that the environmental effects of improved cookstoves are positive but heterogeneous. Areas with stronger baseline forest conditions are more likely to experience forest regeneration, while areas with weaker initial forest cover tend to gain vegetation primarily outside the forest category. Importantly, these gains in non-forest vegetation should not be interpreted as limited ecological improvements, as they likely include increases in sparse or regenerating tree cover that do not meet the threshold for closed-canopy forest. This pattern suggests that lowering fuelwood demand need not translate uniformly into forest recovery everywhere; ecological starting conditions matter for whether reduced extraction pressure shows up as denser forest cover or as broader gains in vegetation.

These findings matter for two broader debates. First, they suggest that improved cookstove interventions can generate environmental benefits in addition to the health, time-use, and fuel-saving gains already documented in prior work. Second, they speak directly to current debates over carbon-financed cookstove programs. Our results do not by themselves resolve the full question of carbon additionality, but they do show that a large-scale cookstove intervention can measurably improve land-cover outcomes, including forest cover in ecologically favorable areas. In Rwanda, that matters not only for climate policy under Vision 2050, but also for sectors such as coffee that may face growing scrutiny under deforestation-linked trade regulation.

Future work can examine the cost-benefit of the program over time, integrating environmental gains with program costs as well as other benefits such as improved health outcomes, time savings, and reduced fuel expenditure. It can also further disentangle the mechanisms underlying the observed heterogeneity in impacts, including the role of ecological endowments, market access, and household income in shaping how reductions in fuelwood demand translate into landscape recovery.

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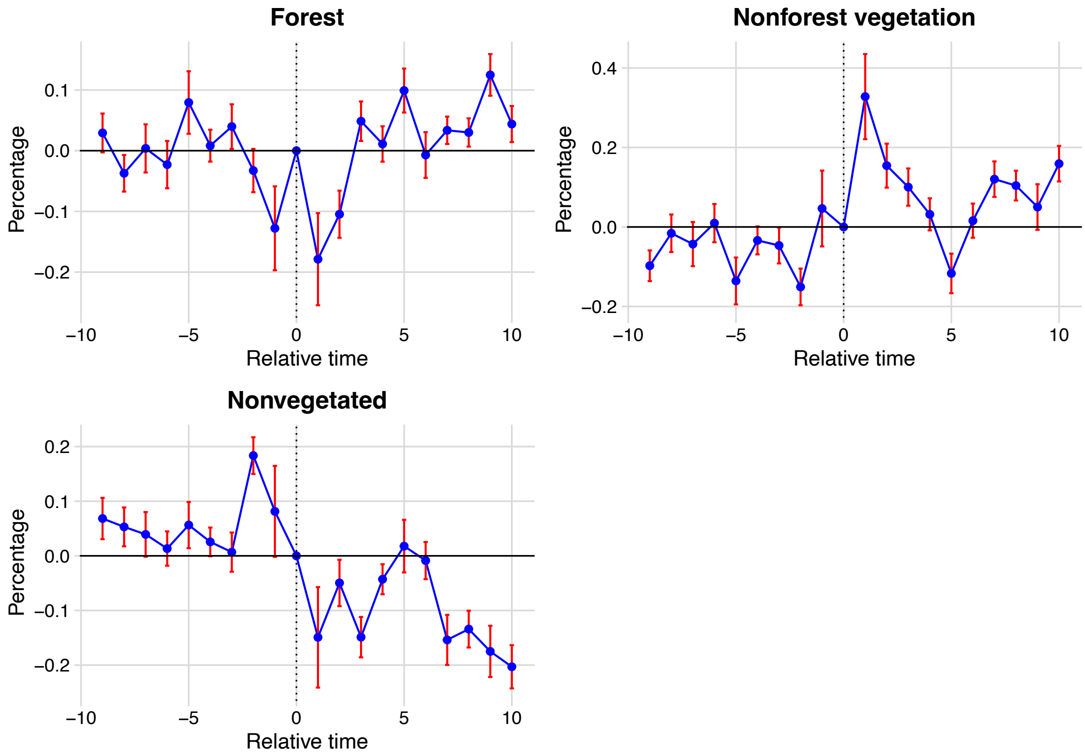
A Additional Figures and Tables

A.1 Additional Figures

Figure A1: Dynamic Treatment Effects Using Continuous Treatment Intensity (de Chaisemartin & D'Haultfoeuille Estimator)



Notes: Event-study estimates using the de Chaisemartin and D'Haultfoeuille estimator with a continuous treatment indicator. The treatment variable is defined as the cumulative number of Tubeho Neza cookstoves distributed within each administrative cell (ADM4). Coefficients are plotted with 95% confidence intervals, with standard errors clustered at the sector level. Regressions are weighted by estimated cell population. Outcome variables are derived from the MODIS Vegetation Continuous Fields (VCF) dataset (DiMiceli et al., 2021), and treatment data are constructed using proprietary DelAgua stove distribution records.

A.2 Additional Tables

Table A1: Heterogeneous Effects by Distance to Paved Roads (Quartiles)

	Panel 1: Percent Forest			
Sample	Road Quart. 1	Road Quart. 2	Road Quart. 3	Road Quart. 4
ATT	1.134***	1.059***	0.152	0.068
	(0.429)	(0.396)	(0.310)	(0.249)
Sample Mean	12.475	13.032	12.929	11.627
R-squared	0.739	0.875	0.880	0.897
Observations	14,040	15,960	16,200	15,576
	Panel 2: Percent Non-Forest Veg.			
Sample	Road Quart. 1	Road Quart. 2	Road Quart. 3	Road Quart. 4
ATT	0.842	0.819*	1.793***	1.872***
	(0.513)	(0.495)	(0.432)	(0.373)
Sample Mean	69.442	69.200	69.117	69.744
R-squared	0.724	0.769	0.776	0.776
Observations	14,040	15,960	16,200	15,576
	Panel 3: Percent Non-Vegetation			
Sample	Road Quart. 1	Road Quart. 2	Road Quart. 3	Road Quart. 4
ATT	-1.976***	-1.878***	-1.945***	-1.94***
	(0.375)	(0.354)	(0.363)	(0.354)
Sample Mean	18.083	17.768	17.954	18.630
R-squared	0.873	0.865	0.861	0.859
Observations	14,040	15,960	16,200	15,576
Satellite	MODIS	MODIS	MODIS	MODIS
Years Covered	2000 - 2023	2000 - 2023	2000 - 2023	2000 - 2023

Notes: Table reports average treatment effects on the treated (ATT) estimated using the Mundlak event-study approach (Wooldridge, 2025), stratified by quartiles of distance to paved roads. The unit of observation is the administrative cell-year. Treatment is defined as the first year in which Tubeho Neza cookstoves were distributed within a cell. Cells are grouped into quartiles based on their average distance to the nearest road, with Quartile 1 representing cells closest to roads and Quartile 4 representing the most remote cells. Outcome variables derived from the MODIS Vegetation Continuous Fields (VCF) dataset (DiMiceli et al., 2021), where forest cover corresponds to tree canopy above a minimum density threshold and non-forest vegetation includes shrubs, grasses, and sparse tree cover below this threshold. ATT estimates represent the average post-treatment effect within each quartile group. Standard errors clustered at the sector level are reported in parentheses. All models include cell and year fixed effects, province-specific linear time trends, and controls for precipitation, maximum temperature, and population (coefficients omitted for brevity). *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A2: Heterogeneous Effects by Baseline Forest Cover Using Landsat-Derived Vegetation Measures

	Panel 1: Percent Dense Vegetation			
Sample	Forest Quart. 1	Forest Quart. 2	Forest Quart. 3	Forest Quart. 4
ATT	-0.468**	0.383*	0.265	1.649***
	(0.226)	(0.215)	(0.322)	(0.508)
Sample Mean	0.527	0.810	1.256	5.558
R-squared	0.543	0.508	0.499	0.887
Observations	7,908	7,608	7,800	7,572
	Panel 2: Percent Sparse Vegetation			
Sample	Forest Quart. 1	Forest Quart. 2	Forest Quart. 3	Forest Quart. 4
ATT	-1.292***	0.703	4.031***	2.725***
	(0.450)	(0.639)	(0.870)	(0.891)
Sample Mean	3.165	5.240	7.497	7.753
R-squared	0.922	0.910	0.850	0.788
Observations	7,908	7,608	7,800	7,572
Satellite	Landsat	Landsat	Landsat	Landsat
Years Covered	2012 – 2023	2012 – 2023	2012 – 2023	2012 – 2023

Notes: This table reports average treatment effects on the treated (ATT) estimated using the Mundlak event-study approach described in Wooldridge (2025), stratified by quartiles of baseline forest cover using Landsat-derived vegetation measures. The unit of observation is the administrative cell-year. Treatment is defined as the first year in which Tubeho Neza cookstoves were distributed within a cell. Cells are grouped into quartiles based on their average percent dense vegetation in the two years prior to treatment, with Quartile 1 representing the lowest baseline vegetation and Quartile 4 the highest. Each panel reports results for a different outcome: percent dense vegetation (Panel 1) and percent sparse vegetation (Panel 2), both derived from Landsat land cover classifications. These measures provide a more disaggregated view of vegetation compared to the MODIS Vegetation Continuous Fields (VCF) data used in the main analysis. ATT estimates represent the average post-treatment effect within each quartile group. Sample means are calculated within each quartile-specific estimation sample. Standard errors clustered at the sector level are reported in parentheses. All models include cell fixed effects, year fixed effects, province-specific linear time trends, and controls for maximum temperature, precipitation, and population (coefficients omitted for brevity). *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A3: Heterogeneous Effects by Treatment Cohort Using Landsat-Derived Vegetation Measures

	Dense Veg.	Sparse Veg.
2014 Group	0.640	5.539***
	(0.482)	(0.859)
2016 Group	0.508*	1.045
	(0.289)	(0.644)
2020 Group	0.175	1.401
	(0.190)	(0.445)
2021 Group	0.565*	1.329**
	(0.340)	(0.599)
2022 Group	0.601***	0.387
	(0.136)	(0.310)
2023 Group	0.039	4.342***
	(0.357)	(0.511)
Sample Mean	2.261	7.106
R-squared	0.872	0.843
Observations	24,084	24,084
Satellite	Landsat	Landsat
Years Covered	2012–2023	2012–2023

Notes: This table reports average treatment effects on the treated (ATT) estimated using the Mundlak event-study approach described in Wooldridge (2025), disaggregated by treatment cohort. The unit of observation is the administrative cell-year. Treatment cohorts are defined by the first year in which Tubeho Neza cookstoves were distributed within a cell (e.g., the "2014 Group" includes all cells first treated in 2014). Outcome variables measure the percentage of land area within each cell classified as dense vegetation and sparse vegetation based on Landsat-derived land cover classifications. These categories provide a more disaggregated view of vegetation cover relative to the MODIS Vegetation Continuous Fields (VCF) measures used in the main analysis. Each row reports the average post-treatment effect for a given cohort. Sample means are calculated over the full estimation sample. Standard errors clustered at the sector level are reported in parentheses. All models include cell fixed effects, year fixed effects, province-specific linear time trends, and controls for maximum temperature, precipitation, and population (coefficients omitted for brevity). *** p<0.01, ** p<0.05, * p<0.1.

Table A4: Dynamic Treatment Effects per 100 Stoves Distributed (de Chaisemartin & D'Haultfoeuille Estimator)

	Forest	Vegetation	Non-Veg.
Placebo −9	0.0292*	-0.0976***	0.0683***
	(0.0163)	(0.0197)	(0.0193)
Placebo −8	-0.0372**	-0.0159	0.0531***
	(0.0154)	(0.0241)	(0.0181)
Placebo −7	0.0038	-0.0431	0.0393*
	(0.0202)	(0.0283)	(0.0208)
Placebo −6	-0.0229	0.0096	0.0133
	(0.0199)	(0.0245)	(0.0161)
Placebo −5	0.0794***	-0.1358***	0.0564***
	(0.0263)	(0.0300)	(0.0216)
Placebo −4	0.0083	-0.0338*	0.0256*
	(0.0134)	(0.0179)	(0.0134)
Placebo −3	0.0398**	-0.0466**	0.0068
	(0.0187)	(0.0230)	(0.0183)
Placebo −2	-0.0327*	-0.1508***	0.1836***
	(0.0182)	(0.0235)	(0.0172)
Placebo −1	-0.1278***	0.0464	0.0814*
	(0.0353)	(0.0486)	(0.0425)
Effect +1	-0.1787***	0.3279***	-0.1492***
	(0.0387)	(0.0546)	(0.0469)
Effect +2	-0.1047***	0.1543***	-0.0496**
	(0.0198)	(0.0282)	(0.0216)
Effect +3	0.0486***	0.1003***	-0.1489***
	(0.0166)	(0.0239)	(0.0189)
Effect +4	0.0111	0.0318	-0.0428***
	(0.0149)	(0.0206)	(0.0140)
Effect +5	0.0991***	-0.1168***	0.0178
	(0.0185)	(0.0254)	(0.0246)
Effect +6	-0.0071	0.0158	-0.0087
	(0.0192)	(0.0219)	(0.0174)
Effect +7	0.0336***	0.1203***	-0.1539***
	(0.0115)	(0.0228)	(0.0234)
Effect +8	0.0300**	0.1041***	-0.1341***
	(0.0119)	(0.0191)	(0.0172)
Effect +9	0.1248***	0.0501*	-0.1750***
	(0.0175)	(0.0293)	(0.0239)
Effect +10	0.0439***	0.1592***	-0.2031***
	(0.0152)	(0.0228)	(0.0202)

Notes: This table reports dynamic treatment effects estimated using the de Chaisemartin and D'Haultfoeuille estimator with a continuous treatment indicator. The unit of observation is the administrative cell-year. The treatment variable is defined as the cumulative number of Tubeho Neza cookstoves distributed within each administrative cell (ADM4), with coefficients interpreted as the effect per 100 stoves distributed. "Placebo" coefficients correspond to leads (pre-treatment periods), while "Effect" coefficients correspond to lags (post-treatment periods), both relative to the omitted reference period. Outcome variables measure percent forest cover, vegetation, and non-vegetated area derived from the MODIS Vegetation Continuous Fields (VCF) dataset (DiMiceli et al., 2021). Regressions are weighted by estimated cell population. All models control for precipitation and maximum temperature (coefficients omitted for brevity). Standard errors clustered at the sector level are reported in parentheses. *p<0.10, **p<0.05, ***p<0.01.

Table A5: Cumulative Treatment Effects per 100 Stoves Distributed (de Chaisemartin & D'Haultfoeuille Estimator)

Outcome	Cumulative ATE
Forest	0.042
	(0.037)
Vegetation	0.290***
	(0.055)
Non-vegetation	-0.333***
	(0.053)

Notes: This table reports cumulative average treatment effects estimated using the de Chaisemartin and D'Haultfoeuille estimator with a continuous treatment indicator. The unit of observation is the administrative cell-year. The treatment variable is defined as the cumulative number of Tubeho Neza cookstoves distributed within each administrative cell (ADM4), with coefficients interpreted as the effect per 100 stoves distributed. Estimates represent cumulative effects across post-treatment periods. Outcome variables measure percent forest cover, vegetation, and non-vegetated area derived from the MODIS Vegetation Continuous Fields (VCF) dataset (DiMiceli et al., 2021). Regressions are weighted by estimated cell population. Standard errors clustered at the sector (ADM3) level are reported in parentheses. *p<0.10, **p<0.05, ***p<0.01.

B Fieldwork Appendix

Table B1: Summary of focus group discussion (FGD) questionnaire themes

Section / Module	Men's FGD: themes covered (types of questions)	Women's FGD: themes covered (types of questions)
Community forest access and governance (current)	Whether a communal forest exists; forest characteristics and safety; how people use the forest (livelihood, cultural/religious uses); what resources are collected; local rules, enforcement, and customary practices; past vs. current harvesting norms (including cutting live trees); disputes and conflict resolution; access rights for other villages and outsiders.	Same themes: presence/role of communal forest; forest characteristics/safety; uses and values; resources collected; local governance and enforcement; harvesting norms then vs. now; conflicts and resolution; access rights for other villages and outsiders.
Community forest access (historical change / loss of access)	For villages that previously had communal forests: how access and use used to work; what changed and why; who has access now; how households adapted to obtain fuelwood/forest products after losing access.	Same themes: past access and use; drivers of change; current access arrangements; strategies to replace forest-sourced fuelwood/products.
If no communal forest: fuelwood acquisition constraints	Where people obtain fuelwood in the absence of a communal forest; major challenges and constraints in obtaining firewood.	Same themes: main sources of fuelwood without a communal forest; challenges/constraints.
Household/community energy use and burdens	Main cooking fuels used; whether fuels are purchased or collected; local market availability and seasonality (reliability/price changes); who is responsible for collection; time burden; stress/insecurity around fuel; coping strategies (including changing meals).	Same themes: fuel mix and procurement; market availability/seasonality; responsibility for collection; time burden; fuel insecurity/stress; coping and meal adjustments.
Community perceptions of NGOs and improved cookstoves (Tubeho Neza and others)	General experience with NGOs (helpful/harmful perceptions); understanding and attitudes toward Tubeho Neza; exposure to other improved cookstove programs; receipt and use patterns; maintenance practices; likes/dislikes and perceived fit.	Same themes: perceptions of NGOs; awareness and attitudes toward Tubeho Neza; experience with other improved cookstoves; adoption/use patterns; maintenance; satisfaction and concerns.
Perceived impacts of Tubeho Neza	Perceived overall community impacts; perceived health effects (with examples); perceived changes in fuelwood collection/procurement (with examples); perceived changes in communal forest conditions; other notable impacts.	Same themes: perceived overall impacts; perceived health effects; fuelwood procurement and time impacts; perceived forest impacts; other effects.

Table B2: Summary of District Leader (Key Informant) Interviews

Section / Module	**Brief, report-style summary of questions/themes**
Respondent background and leadership experience	Role in the district, time in current post, and years of experience in district administrative leadership.
District environmental conditions and perceived trends	Perceived environmental health of the district—especially forests/natural vegetation—and whether conditions are improving or worsening.
Deforestation-related programs over the past two decades	Environmental/deforestation programs active in the district over the past ˜20 years and what they involved.
Role of forests in the district	Role of state/district/community forests in local ecosystems and socioeconomic activities.
District partnerships with organizations (general experience)	Whether the district partnered with relevant organizations, what they implemented (and when), and how collaboration worked.
DelAgua partnership and program experience	Why partner with DelAgua; why take the decision in the reference year (including timing constraints); experience working with DelAgua; perceived community impacts.
Other cookstove actors and formal arrangements	Other cookstove providers (who/when); whether MOUs existed and what they implied (exclusivity/duration); links to World Bank subsidy programming; perceived satisfaction/complaints.
Influence of government planning on cookstove strategy	Whether government 5-year plans shaped district approaches to cookstove programs, priorities, or targets.

Table B3: Summary of Forest Visit Protocol

Section / Module	**What is observed / asked (summary of themes)**
Community forest observations: overall vegetation condition	Observe healthy vegetation and describe its density and extent.
Community forest observations: vegetation removal / extraction	Observe signs of vegetation cover removal, including visible tree removal, branches/stumps removed, the extent/intensity of removal, and (if possible) the tools used.
Community forest observations: deadwood	Observe presence of deadwood growth and describe its density and extent.
Community forest observations: ongoing resource use	Observe ongoing uses (e.g., herbs collection, firewood harvesting, edible plants) and document how collection occurs (e.g., cutting branches/live trees vs. removing whole plants/parts).
Community forest observations: evidence and sustainability of human activity	Assess whether there are signs of frequent human activity, whether it is ongoing vs. recent past, how much it has affected vegetation and whether it appears sustainable, and whether there is a seasonal dimension.

Table B4: Key Informant Interview Response Summary

Section / Module	**Synthesis across 8 responses**
Respondent background and leadership experience	Respondents are mainly district environment/forest & natural resources officers (plus one director-level role). Time in current role is typically a few years (often around ~3 years).
Years in district administrative leadership	Leadership experience ranges from ~2 to ~14 years, with several clustered around 3–6 years.
Environmental health of the district (esp. forests/natural vegetation)	Most describe conditions as good or improving, often citing forest restoration/planting; several emphasize drought/climate stress (especially in drier areas) as an ongoing constraint.
Environmental/deforestation programs in the past ~20 years	Commonly mentioned: tree planting/agroforestry and erosion control/terracing/wetland protection; several respondents report limited/no knowledge of older programs.
Role of forests in ecosystem and socioeconomic activities	Forests are described as supporting soil erosion control, microclimate/air quality, and livelihoods/income (tree harvesting and related revenues); a few link forest/clean cooking efforts to health improvements.
District partnerships with organizations (existence)	All 8 report the district has partnered with external organizations.
Partner programs and timing	Activities cited include tree planting, agroforestry, and improved cookstoves/clean cooking; timing is often described broadly, and some respondents provide limited detail.
Experience working with partner organizations	Collaboration is generally described as positive and beneficial, including support for environmental goals and (for some) improved capacity to pursue additional projects.
DelAgua partnership and timing (combined)	Reasons: reduce fuelwood pressure/deforestation, forest conservation/restoration, climate mitigation, and improved living standards via improved cookstoves; timing is usually attributed to when DelAgua approached/rolled out in the district (often 2022–2023, with one noting 2014), and a few report insufficient information.
Perceived community impacts of DelAgua	Most describe positive impacts: reduced fuelwood use/expense, health improvements (less smoke-related illness), time savings, and broader socioeconomic benefits; one respondent reported no positive impact.
Other cookstove actors (who/when combined)	Name all environmental programs beyond cookstoves (e.g., Tubura, Harcos, Ruriba, Rwanda Water Board), while others report no information; years of entry often unknown/not specified.
World Bank subsidy link for other initiatives	No: 6; Yes: 2.
General impression / satisfaction / complaints (other initiatives)	Where assessed, impressions are generally positive and recipients are described as happy; a main practical issue mentioned is proper use/requirements (e.g., needing dry wood); some could not assess due to limited information.
Influence of government 5-year plans on cookstove strategy	Most indicate yes: plans and district performance frameworks shape prioritization and planning for cookstove/environment initiatives; a couple gave limited detail/no response.

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