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Abstract

This paper looks at the implementation of Great Green Wall projects in Nigeria to analyze the local impact of environmental restoration on children's health and food security. Our identification strategy uses two types of variations to capture these effects. The spatial variation comes from the heterogeneous exposure of children to these new environmental restoration programs. The temporal variation comes from sudden changes between 2013 and 2016. Taking the height-to-age z-score as the main outcome of interest, we find significant and robust health improvements in children living next to community-based orchards, whereas proximity to shelterbelts generates mixed impacts. Gains in health (+0.5 standard deviation in the height index) coexist with higher dietary diversity scores in children living near orchards.

Keywords: Environmental restoration, Children's health, Nigeria, Nutrition, Impact evaluation, Great Green Wall, Desertification

JEL Codes: 012, 013, Q18, Q23

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1 Introduction

In the 1970s and 1980s, severe droughts struck Sub-Saharan Africa, wreaking harmful consequences on local populations. These tragic events motivated the creation of The United Nations Convention to Combat Desertification (UNCCD) in 1994 whose dual objective is to evaluate the desertification process in vulnerable climates and provide sustainable solutions against it.[1] However, Sub-Saharan Africa continued experiencing the largest increase (32%) in population living on degrading agricultural land during the 2000-2010 period (Barbier and Di Falco, 2021). In addition to reducing agricultural productivity, land degradation damages livelihoods through food insecurity, water shortages, poverty, health problems and conflicts (Holden and Shiferaw, 2004; Couttenier and Soubeyran, 2014; Olagunju, 2015).

In 2007, eleven African countries committed to the creation of the Great Green Wall (GGW), and agreed to join forces to reforest the region through a 7,000 km greenbelt spanning the continent.[2] Initially designed as a continuous wall of vegetation, the project has evolved to become a mosaic of green projects aimed at restoring ecosystems and addressing the needs of local populations (Goffner et al., 2019). Whether such an ambitious environmental restoration project improves the livelihoods of the surrounding households is still an under-explored research question.[3] This article answers this call and attempts to bridge the evidence gap by assessing the impacts of GGW projects on children's health in Nigeria.

The motivation for the GGW echoes the growing body of evidence showing that tree-based ecosystem services are correlated to improved health via enhanced diet quality and nutrition. Tree land cover helps improve household livelihoods through its capacity to foster agricultural yields and provide households with products, such as food, fiber and energy, that address basic needs and

[1] The UNCCD defines desertification as "land degradation in arid, semi-arid and dry sub-humid areas resulting from various factors, including climate variation and human activities".

[2] The eleven countries include Burkina Faso, Chad, Djibouti, Ethiopia, Eritrea, Mali, Mauritania, Niger, Nigeria, Senegal and Sudan.

[3] In November 2020, an editorial in the journal *Nature* urged researchers to evaluate the GGW project and help guide policy-makers towards achieving the project's key goals: https://www.nature.com/articles/d41586-020-03080-z

shelter (Angelsen et al., 2014; Ickowitz et al., 2014). Many case studies provide evidence on the benefit of forests and their capacity to complement lost income and meet subsistence needs when a shock, such as a crop failure, occurs. (Pattanayak and Sills, 2001; McSweeney, 2005; Fisher et al., 2010; Baland et al., 2018). Although trees planted as part of the GGW are unlikely to have reached the minimum height needed to be categorized as forest, high resolution data of some GGW projects in Nigeria show a significant change in the amount of land covered by trees there and raises expectations of preliminary positive effects on the welfare outcomes of local residents.

Although trees can provide many benefits, little work has yet analyzed the positive impacts they might have on children's well-being. Nevertheless, conditions in early life are known to be very important for an individual's overall development (Behrman and Rosenzweig, 2004; Black et al., 2007; Currie and Vogl, 2012). Malnutrition in the early stages of life has long-term consequences on human capital outcomes and health, educational and socio-economic achievements (Glewwe et al., 2001). For instance, Hoddinott et al. (2013) show that individuals who enjoyed normal growth in the first three years of life complete more schooling, score higher cognitive-skill test scores in adulthood, have better outcomes in the marriage market and are more likely to be employed in higher-paying jobs. Similarly, a strong correlation between drought conditions in early childhood and future health and socioeconomic outcomes has been shown in studies on many regions: Hyland and Russ (2019) show that women from Sub-Saharan Africa who experienced water deficits as children are less wealthy as adults, Maccini and Yang (2009) reach similar conclusions for Indonesian women. Therefore, the context in which a child begins her life deserves special attention. Given that children in northern Nigeria grow up in a harsh drought-prone environment that has potential long-term negative impacts on their individual development, assessing the ability of the GGW program to enhance health during early childhood is crucial. It is all the more important given that the ongoing process of forest loss in Nigeria has been shown to be associated with worsening children's health conditions (Berazneva and Byker, 2017) and that a recent cost-benefit analysis over the whole sub-Saharian region showed that net gains of a land restoration program such as the GGW initiative would be the highest in Nigeria (Mirzabaev et al., 2021).

This article contributes to the existing literature on environmental restoration and children's welfare in a number of aspects. To begin with, to our knowledge, it is the first to document the local impact of the Great Green Wall initiative on children's health outcomes. Although Duboz et al. (2019) highlighted some correlations between the GGW implementation in Senegal and health and welfare outcomes, there is surprisingly no causal impact assessment of its consequences on the welfare of local communities. Secondly, the distinct analysis conducted of the two main GGW project types launched in Nigeria allows us to determine the specific greening activity that most benefits children. Third, we investigate the food security channel to better capture the source of children's health improvements as nutrition level is known to be the most important factor affecting linear height growth and explains most of the differences in stature among humans (Grasgruber et al., 2014; Perkins et al., 2016).

To rigorously assess the impacts of environmental restoration on children's health and food security, we exploit the geographical heterogeneity of children exposed to GGW projects and conduct a difference-in-difference analysis. The 2013 and 2018 Nigeria Demographic and Health Survey and the information on the location of the country's GGW projects, both geocoded, are combined to assign a treatment status to the communities where the children reside. The cutoff distance used to define the treatment status of the community is set at 15 km in the main model. The identification relies on the variation in environmental restoration programs implemented between late 2013 and 2016 in the northern regions of Nigeria. However, the main strategy suffers from the lack of a credible counterfactual, given that the program was targeted at, and not randomly allocated to, households. To overcome this challenge, we augment the estimations with propensity score reweighting and parallel trend checks for the period preceding the implementation of the GGW projects. This empirical methodology stays constant when we investigate the changes in children's nutrition proxied by their dietary diversity score.

The findings are twofold. First, the children living close to areas where environmental restoration programs have been implemented appear to be in better health than those who live further from the projects. In particular, this result survives all the specifications and robustness checks when the local project is a community orchard, with a significant increase in children's height-to-age standard deviation. This positive impact on children's health becomes even greater when the orchard is coupled with the creation of a borehole. However, the estimated impacts of shelterbelts fluctuate and are not conclusive for some specifications. Second, the dietary diversity score of children located near orchards significantly and positively increases, providing evidence that health improvement coexists with better food access in the case of orchard treatment. Although these results are consistent with the presumption that access to fruit resources are likely to increase, the higher diversity in diets may also be driven by other potential channels that are likely to occur in the short run. Further research would thus be needed to better understand the channels that condition the persistence of the impacts. If the improvement of food access and health conditions is due to public employment, investments or the boost of local markets, it would be limited to the short run, while one can expect more sustainable impacts from ecosystem services over the long-term.

The remainder of the paper proceeds as follows. Section 2 introduces the context of the new GGW environmental restoration program implemented in Nigeria, as well as the data used in the analysis. Section 3 describes the identification strategy and Section 4 displays the results. Section 5 concludes.

2 Context and Data

2.1 The Great Green Wall in Nigeria

2.1.1 The program

The Great Green Wall is a Pan-African initiative spearheaded by the African Union and funded by the World Bank, the European Union and the United Nations. The idea was formally approved in 2007 as a means to slow down the expansion of the Sahara by planting a barrier of trees spanning 7,000 kilometers from Senegal to Djibouti.

With the rising concerns about climate change in the Sahel region, this greenbelt aims to increase the vegetation cover to eventually mitigate food insecurity, land conflicts and migration for millions of farmers living in the region. On its official website, the project promises "to bring life back to Africa's degraded landscapes at an unprecedented scale, providing food security, jobs and a reason to stay for the millions who live along its path".[4] To this end, more than eight billion dollars have been mobilized and pledged in support of the initiative.[5]

The initiative has been progressing at different scales among the eleven countries committed to the GGW.[6] In Nigeria, implementation of the initiative began in 2013 with about 6,000,000 plants produced mainly for shelterbelts and orchards managed at the community level. The program covers eleven northern states of the country. The National Council on the Great Green Wall (NCGGW) is the governing body that monitors the implementation at the national level. At the community level, the head of the community decides how to redistribute generated revenues or products across households.[7] All these activities have thus far generated about 20,000 jobs in Nigeria.[8] The UNCCD claims that the GGW initiative has trained and employed 498 youths as forest guards, more than a thousand to drill boreholes, and several thousands to plant and perform other related activities.

The implementation of the GGW program takes different forms throughout Nigeria. Shelterbelts are rows of trees that protect soil from erosion and improve the quality of farmlands. Between 2013 and 2016, 642 kilometers of such shelterbelts were planted along the northern part of the country. About 300 hectares of community orchards have also been established to provide edible products such as mangoes, guavas, cashews and oranges, among other fruits. More than a hundred solar and wind-powered boreholes have been constructed to support the maintenance of shelterbelts and orchards and are intended to provide water to over 40,000 people and 150,000 livestock (PAG, 2018).

[4]https://www.greatgreenwall.org/about-great-green-wall

[5]https://www.unccd.int/actions/great-green-wall-initiative

[6]The focus on the Nigerian case stems from the lack of national GGW implementation data on other countries involved in the project.

[7]The land where the projects are implemented mainly belongs to community member institutions and is voluntarily donated for the benefit that comes with the project, because after an agreed period of time, the community members will take over the sustainability of the land and enjoy whatever proceeds come from the projects.

[8]https://www.unccd.int/news-events/african-countries-accelerate-progress-great-green-wall

2.1.2 The data

In order to answer our research question, the first task is to locate the environmental restoration projects implemented through the GGW initiative. To this end, the NCGGW provided data on the localization, type and year of implementation of about a hundred orchards and boreholes and more than two hundred shelterbelts, as shown in Table 1. Figure 1 provides an overview of the different types of projects implemented between 2013 and 2016 as part of the GGW initiative. Most of the boreholes are placed in the very vicinity of orchards or shelterbelts in order to increase the lifespan of both. Figures A1, A2 and A3 illustrate the scope of such projects by showing remote sensing images of different types of projects before and after their implementation.[9]

Tree planting programs generally face great challenges (Holl and Brancalion, 2020). Previous land restoration programs in Nigeria were actually suspected of notable gaps in civil society participation, absence of the use of indigenous knowledge, limited community and farmer involvement, and limited maintenance (Jalam et al., 2020; Medugu et al., 2010). These limitations may have contributed to the observed low survival rates of shelterbelt projects in Nigeria (Gadiga et al., 2015). To ensure the sustainable implementation of the current program, policymakers are trying to learn from past errors in national land restoration initiatives by adopting bottom-up approaches and involving community members in decision-making on projects management (Turner et al., 2021). Unfortunately, variables that could be a good proxy for effectiveness of the current GGW activities, such as survival rates, are not available. We cannot exclude the possibility that some of the projects directly failed after their implementation and discuss the implication of this potential measurement error on results in section 4.

[9]A systematic monitoring and checking of the GPS data is very complex since many projects are not observed at the optimal date. The seasonality in vegetation makes it hard to distinguish among projects since an image is not available every year.

Table 1: Distribution of GGW projects in Nigeria over the 2013-2016 period

	Year of establishment				
	2013	2014	2015	2016	**Total**
Orchard	8	43	45	4	**100**
Shelterbelt	45	57	114	0	**216**
Borehole	10	50	43	1	**104**
Total	**63**	**150**	**203**	**4**	**420**

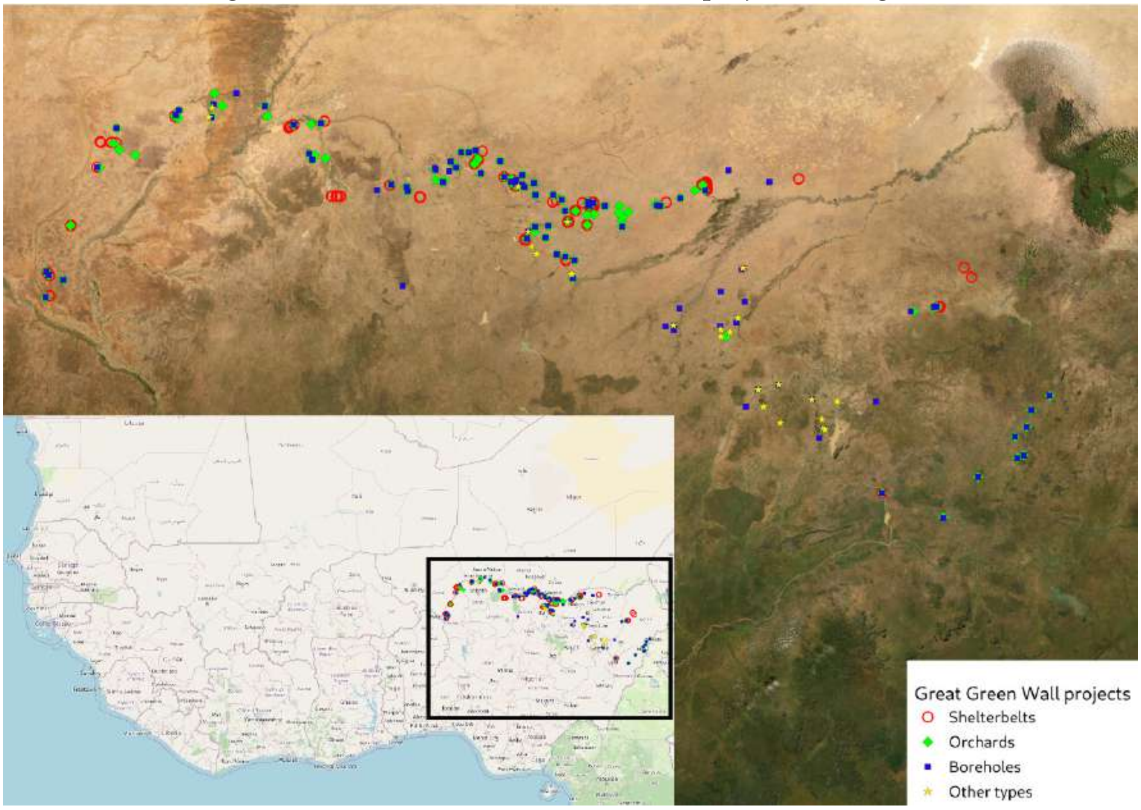
2.1.3 Ecosystem services and other potential impacts

Environmental restoration programs, including land restoration programs, are implemented to enhance various ecosystem services (Benayas et al., 2009). Woody vegetation in Sudano-Sahelian West Africa is known to provide numerous ecosystem services including pest control, soil nutrient concentration, erosion control, carbon storage, water flow regulation, shade provision and micro-climate regulation (Sinare and Gordon, 2015; Davies, 2017). These services impact local communities, mainly by fostering agricultural yields (Sinare et al., 2022), reducing the probability and impacts of floods or heatwaves, and contributing to groundwater recharge.

The greatest impacts of shelterbelts on agricultural yields in arid environments probably comes from the limitation of soil erosion, the protection against windstorm and run-off and evapotranspiration regulation. Indeed, limiting soil erosion has been shown to positively impact crop growth yields in the Sahel (Michels et al., 1998). Such improvements in soil conditions consequently result in vegetation development in areas where shelterbelts have been established (Adesina and Gadiga, 2014). Kho et al. (2001) show that millet grown under acacia tree (*Faidherbia albida*) canopy in Niger had a 36% higher yield than that grown in open fields. Pest control also plays a key role in Nigeria: millet growing under acacia trees was not found to be infected by the millet pest striga, in contrast to other millet plants in surrounding areas (Gworgwor, 2007).

Planting trees in arid environments also provides water availability, reduces floods through water flow regulation, limits rainfall run-off and promotes groundwater recharge by fostering water infiltration. By increasing water holding capac-

Figure 1: Location of Great Green Wall projects in Nigeria



ity, tree roots regulate the water cycle and limit downstream flooding by increasing evapotranspiration (Zhang et al., 2017; Zhang and Wei, 2021). McCarthy et al. (2021) show that greenbelts are effective in reducing flood risk for maize production in Malawi and Ilstedt et al. (2016) that tree densities influence groundwater recharge in Burkina Faso.

In addition to ecosystem services, fruit tree planting may also improve food security and diet diversification. Ickowitz et al. (2014) found a statistically significant positive relationship between tree cover and dietary diversity. Their findings suggest that children in Africa who live in areas with more tree cover have more nutritious diets. Some fruit tree species are identified as playing a major role during certain seasons or gain importance during drought years, compensating in case of crop loss (Sinare et al., 2016). Eventually, tree planting may also improve income from medicinal, social, cultural, food additive, energy and material uses (Sinare and Gordon, 2015).

2.2 Health of Nigerian Children

In this paper, the main source of socio-economic data is the nationally representative Nigeria Demographic and Health Surveys (DHS). DHS are cross-sectional surveys designed to provide information on household characteristics, health and living conditions at the national level. The data are geocoded at the DHS cluster/community levels. For confidentiality issues, the DHS program displaces the latitude and longitude of the clusters. In particular, urban locations are displaced 0-2 kilometers while rural locations are displaced 0-5 kilometers with 1% displaced 0-10 kilometers for anonymity purposes. We make use of data available for 2013 and 2018, two years surrounding the implementation of various GGW projects. To perform parallel trend tests, DHS are also extracted for the year 2003.[10] We restrict our sample to rural households belonging to the eleven Northern states where GGW projects have been implemented.[11]

All women of sampled households between 15 and 49 years old present at the time of the survey were interviewed. Each of their children under 5 years old was subject to anthropometric measurements. In particular, height was measured in order to establish a height-to-age index and compare it to height-to-age standards provided by the World Health Organization (WHO). The height-to-age indicator captures the long-term nutritional status of the child and recurrent or chronic illnesses at an early age. When the height-to-age standard deviation (HAZ score) from the WHO 2006 study medians is below minus two, the child is considered as stunted or chronically undernourished. Children whose HAZ score is below minus three standard deviations from the median are considered severely stunted. The Final Report of the 2018 DHS conducted in Nigeria reveals that 37% of Nigerian children below 5 years old are stunted. Investigating the HAZ score allows us to capture the impacts of environmental restoration projects on children's long-

[10] Nigerian DHS are available for the year 2008. However, the food security indexes that could be extracted from these data might be greatly distorted by the National Special Program for Food Security (NSPFS) implemented in Nigeria right before the 2008 DHS collection. The NSPFS's broad objective was to contribute to sustainable improvements in national food security through increases in agricultural productivity and food production. Several sites in Northern Nigeria were selected to implement the activities from the 2003 to the 2006 cropping season. More information about the program implementation and objectives is available here: www.fao.org/3/a-bd346e.pdf.

[11] These states are Adamawa, Bauchi, Borno, Gombe, Jigawa, Kano, Katsina, Kebi, Sokoto, Yobe and Zamfara.

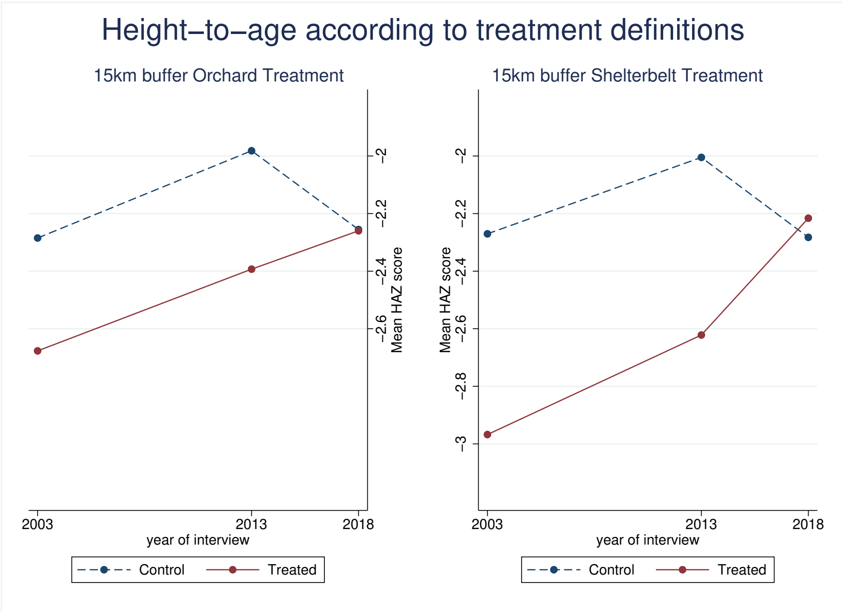


Figure 2: The evolution of height-to-age z-scores under two treatment definitions

term health and food security, independently from recent changes in dietary intake.

The children in our sample are assigned a treatment status according to the distance of their community to a GGW project, with a threshold established at 15 kilometers for the main specification. Table A2 shows the distribution of children across control and treated areas, defined by a 10 km, 15 km and 20 km buffer around the centroid of the project. Figure 2 plots the trends in average HAZ score for treated and control groups across the three waves of DHS. Even though the 2003 average HAZ score of the children living in the area selected for orchard implementation is lower than for the control group, both treated and control children experience health improvement, following a parallel trend until 2013. During the period of orchard implementation, HAZ scores display downward health trends for the children in the control group (from -1.99 to -2.28, i.e. -15 %) and positive changes in HAZ scores for the treated group (from -2.39 to -2.26, i.e. +1%). If we consider the shelterbelt projects, we see that health conditions have increased in the treated group (from -2.62 to -2.22, i.e. +15%) while they have decreased for the control group (from -2.02 to -2.28, i.e. -13%). Further investigation helps us understand whether or not this difference between the health conditions in the treated and control groups is driven by the implementation of GGW environmental restoration projects.

3 Empirical Framework

The goal of this empirical study is to identify how the GGW initiative affects children's health in local communities. To this end, we explore variations across time (project occurrence) and space (children's community distance to a project). We use a difference-in-difference (DiD) methodology.

Many empirical studies rely on geospatial DiD to assess the health impacts of programs or public policies (Friedman, 2018; Lucas and Wilson, 2018; Benshaul-Tolonen, 2019; Herrera-Almanza and Rosales-Rueda, 2020). This empirical strategy first consists in defining a physical distance from the program as a cutoff to identify treated and control groups. To our knowledge, there are no papers that rely on a similar methodology to assess the impact of environmental restoration programs on health outcomes of surrounding communities. Therefore, we learn from existing programs in other fields of economics and test several thresholds, from 10 to 20 km, with a baseline distance of 15 km from a GGW project. Apart from von der Goltz and Barnwal (2019) and Friedman (2018) who work on tight distances, most of the authors who study the health impact of interventions using displaced household locations define the treatment status using larger bandwidths. Benshaul-Tolonen (2019) and Lucas and Wilson (2018) work with a minimum baseline distance fixed at 10 km whereas Wilson (2012), Kotsadam and Tolonen (2016) and Aragon and Rud (2016) use a baseline cutoff of 20 km.

With more precise data, we might define closeness even more restrictively. However, in the context of available data, we believe that the 15 km distance cut-off is reasonable for two reasons: (1) the practice of jittering DHS cluster geolocations (displaced up to 5 km, and up to 10 km for 1% of the sample) risks introducing excessive noise if the cut-off is tight; and (2) the sample size of treated households increases rapidly with distance (see Table A2), which, all else equal, increases the power of the results.

The 15 km-distance cutoff is also motivated by empirical evidence on commuting distances in rural Africa, showing that areas of 10 or 15 km are likely integrated markets (Schafer, 2000; Amoh-Gyimah and Nimako Aidoo, 2013; Kung et al., 2014). At this distance, we can reasonably expect households to take part in the projects as direct employees or as potential buyers of food products from newly created orchards.

Once the exposition status has been assigned, we rely on DiD to assess the impact of the treatment on children's height-to-age standard deviation. The following equation illustrates the canonical set up with two units and two time periods, with one of the units being treated in the second period:

$$\begin{aligned} Y_{ijmys} = \beta_1 POST_j.CLOSE_j + \beta_2 POST_j + \beta_3 CLOSE_j + \\ \beta_4 X_{ijmys} + \beta_5 POST_j.X_{ijmys} + \alpha_m + \alpha_y + \alpha_{my} + \alpha_s + \epsilon_{ijmys}. \end{aligned} \tag{1}$$

where Y_{ijmys} is the anthropometric measurement for child i born in month m in year y and living in community j from state s. $POST_j$ and $CLOSE_j$ are dummy variables equal to one if the child's community is in the post-treatment period and one if the child is close to at least one project. β_1 is the coefficient of interest and captures an Intention-to-Treat effect; it gives the estimated impact of the change in exposure to the projects on the health of children who live near a GGW site. We control for the unobservable conditions during the very beginning of life by including month of birth m, year of birth y, and month by year of birth fixed effects. One specification includes geographic fixed effects at the state level s. X_{ijmys} represents covariates that may influence the initial estimates on health outcomes, such as sex and age of the head of the household, the size of the household, the birth order/birth interval/age/gender/twin status of the children, the education/marital/religion/body mass index of the mother, the distance to the nearest water source and the number of droughts registered during the period 1980-2000. To avoid "contamination" (children in the treated group who are erroneously considered as in the control group), we exclude from the analysis any children located between the distance cutoff and twice its distance.[12] $POST_j$ and X_{ijmys} are also interacted for sensitivity checks. In all models, we cluster standard errors at the DHS cluster level, which corresponds to community j.

Propensity Score Reweighting In this study, the treatment assignment is not randomly operated. Table 2 provides evidence that there are persistent differ-

[12]In the case of the 15 km treatment, for instance, the children located between 15 and 30 km of the site are dropped from the regressions.

ences across the treated and control groups at baseline. Among the multiple techniques that have been developed to help researchers capture the impact of a program on individuals with different characteristics baseline, we employ the Inverse Probability Weighting (IPW) method. Its ability to recover unbiased estimates of the average treatment effects in observational studies has made this method very attractive for causal inference (Hirano et al., 2003; Austin and Stuart, 2015). The approach consists in estimating the probability of the treatment assignment conditional on observed covariates, also called the propensity score, and using it to reweight each observation from the data in the DiD model described in equation 1. The estimated probability of being treated by a project for observation i, denoted by p_i, is computed based on the set of covariates X and the geographic fixed effects.[13] Using this probability, we derive weights $\frac{1}{1-p_i}$ and $\frac{1}{p_i}$ assigned to the non-treated and treated observations, respectively.[14]

The ideal approach to identify the set of covariates for the estimation of the propensity score is to focus on the selection process that sorts participants into treatment and control categories. However, relatively little is known about the factors that influence exposure to the GGW initiative, and it is difficult to identify all the variables that are related to differential exposure. The solution is usually to balance both groups based on observed baseline variables. Since the DHS is not a panel, we draw on Bargain et al. (2019) and use time-invariant characteristics to compute the propensity scores. The set of covariates includes the age and level of education of the household head, the religion of the household, the marital status of the mother, the household size and the number of drought episodes between 1980 and 2000.

The distribution of propensity scores among the two groups are reported on the left-hand side of figure 3 and appear quite different from each other, showing a large spike of control children with low probabilities of treatment, such that the IPW will be necessary to ensure the robustness of our estimates. The final goal of the propensity scores is to remove any selection bias that has made the groups different in terms of those invariant observed variables. A straightforward way to test the validity of the procedure is to compare the propensity scores for the

[13]In our case, this estimation relies on a logit estimator.

[14]The propensity score reweighting is separately executed for orchard and shelterbelt treatments.

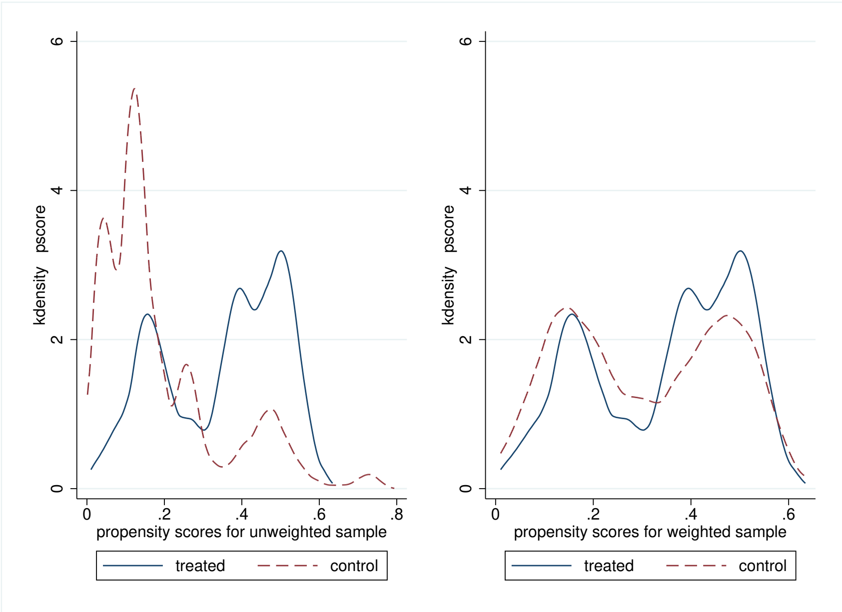


Figure 3: Distribution of propensity scores, before (left panel) and after (right panel) weighting

treatment and control groups after reweighting the sample. On the right-hand side of figure 3, the propensity scores between the groups are balanced on their entire distributions and suggest that the two samples suit our comparability requirements.[15]

Parallel trend checks The parallel trend estimations aim at checking whether treated and control group children had similar health trends before the occurrence period. 2003 and 2013 DHS are two pre-treatment waves that are available to check for parallel trends, allowing us to build a credible counterfactual for the control group and test if any difference occurs during the pre-treatment period. We do so by replicating the baseline estimations on the pre-treatment period, with the difference that children from the 2013 DHS wave are considered as belonging to the post-treatment period ($POST_j = 1$).

[15]By comparison with the balance table 2, the age of household head, the religion of the household and the number of drought episodes are no longer significantly different in the weighted samples. This also suggests that comparability between the two groups has been improved, although it has not been fully achieved. The weighted balance table is available upon request to the authors.

Heterogeneity in treatment effects We study the heterogeneity in impacts according to three main characteristics: the duration of exposure to GGW projects, the age at which the child is exposed, and the size of the project.[16] The variable $HETEROGENEITY_{ij}$ represents each of these characteristics and systematically equals 0 for children included in the control group. Equation 2 presents the model. We show that the larger the project size, the longer the exposure and the earlier the treatment, the higher the amplitude of the impacts (Table 5 Section 4.2).

$$\begin{aligned} Y_{ijmys} = \beta_1 POST_j.HETEROGENEITY_{ij} + \beta_2 POST_j + \beta_3 CLOSE_j + \\ \beta_4 X_{ijmys} + \beta_5 POST_j.X_{ijmys} + \alpha_m + \alpha_y + \alpha_{my} + \alpha_s + \epsilon_{ijmys}. \end{aligned} \tag{2}$$

Channels Investigation We use the same DiD model from equation 1 to investigate the change in dietary diversity for children surveyed in the DHS. To do this, we compute a dietary diversity score at the child level. This dietary diversity score is increasingly accepted as an essential component of healthy diets and associated with nutrient intake and thus recognized as a good proxy for food security (Ruel, 2002). In particular, many studies suggest that dietary diversity is significantly associated with the HAZ score, either as a main effect or in an interaction (Arimond and Ruel, 2004; Stey et al., 2006). We restrict the analysis to children between the ages of 12 and 60 months, because children are heavily dependent on breast milk during their first year and thus have limited diets. The dietary diversity score is the number of food groups consumed by a child during the last twenty-four hours. The score ranges from 0 to 10, 10 being the maximum number of nutritional food groups including cereals, roots and tubers, vegetables, fruits, eggs, meat, fish and seafood, milk and dairy products, pulses and nuts and beverages. The results are introduced in Section 4.3.

Robustness checks Several robustness checks are run to complement the main analysis and examine the persistence of the results with more detail. First, we alternatively control for geographic linear-time trends by using fixed effects at

[16] Project exposure depends on the year of the project implementation and the birth information of the surveyed children and varies from 2 to 5.5 years.

the annual cumulative rainfall level averages in A5.[17] To restrain the sample to areas with comparable environments, the tables A4 exclude from the analysis children located more than 100 km away from the closest GGW project site. In the Appendix A7, we compare the magnitude of the coefficient estimates when a borehole is jointly constructed with the project.

We explore the possibility that our results could be unspecific to GGW activities, and due rather to other factors that might correlate with systematically better health around areas where projects have been implemented. For instance, we could suspect that the critical health situation in the areas targeted by the GGW program could have also attracted new health or development programs. To rule out the hypothesis that HAZ score improvement is driven by local health programs such as initiatives related to malaria prevention, we run a fake treatment on alternative health outcomes, including the incidence of cough, diarrhea, and fever. Table A8 also shows the results for preventive health outcomes, such as vaccination and family planning, that should not be affected by the GGW program.[18]

Eventually, the analysis involves a concern about residential sorting, i.e., the possibility that households with different potential health outcomes may be selectively moving in or out of an area targeted by the GGW program. To control for this issue, we restrict model 1 to the sample of children belonging to households who have not moved between 2013 and 2018 (see Appendix A3).

[17] We built 10 rainfall zones, using average annual cumulative precipitations over the 1980-2015 period. The ten rainfall zones correspond to the deciles of the distribution of long-term average cumulative precipitations in all DHS clusters considered.

[18] The variables related to fever, diarrhea and cough are dummies equal to one if the child has been ill with this symptom for the last two weeks. The vaccination variable is a dummy equal to one if the child has received at least one vaccine injection. The family planning variable is equal to one if the household has heard of family planning in the last few months.

Table 2: Balance Table for Pre-Treatment variables for children in 2013 DHS

	Control group	Treatment group	Difference
Child variables :			
Height-to-age standard deviation	-1.973	-2.337	-0.365***
	(2.063)	(1.974)	(0.065)
Child's food diversity scale (from 0 to 10)	1.701	1.630	-0.071
	(1.801)	(1.653)	(0.051)
Birth order number	4.513	4.562	0.049
	(2.832)	(2.856)	(0.075)
1 if child is a girl, 0 if not	0.498	0.487	-0.011
	(0.500)	(0.500)	(0.013)
Age of child (months)	27.720	27.871	0.152
	(17.285)	(17.353)	(0.501)
Preceding birth interval (months)	33.949	33.446	-0.503
	(16.743)	(15.828)	(0.480)
1 if child is twin, 0 if not	0.044	0.036	-0.008
	(0.269)	(0.242)	(0.007)
Mother variables:			
Mother's body mass index	2,188.108	2,102.707	-85.401***
	(383.704)	(328.123)	(10.036)
Household variables:			
Number of household members	7.862	7.540	-0.322***
	(3.668)	(3.482)	(0.097)
1 if female headed-household, 0 if not	0.041	0.031	-0.010*
	(0.197)	(0.173)	(0.005)
Age of household head	41.202	40.260	-0.941***
	(11.735)	(11.267)	(0.309)
Education of household head (years)	1.297	0.553	-0.744***
	(3.005)	(1.937)	(0.075)
1 if respondent is Christian, 0 if not	0.056	0.003	-0.053***
	(0.230)	(0.053)	(0.006)
1 if respondent is Muslim, 0 if not	0.929	0.991	0.063***
	(0.258)	(0.092)	(0.006)
1 if respondent is currently married, 0 if not	0.974	0.991	0.017***
	(0.159)	(0.092)	(0.004)
Time to get to water source (minutes)	19.338	22.041	2.702***
	(28.120)	(24.261)	(0.730)
Cluster variables:			
Drought episodes	6.419	4.621	-1.798***
	(2.276)	(1.638)	(0.058)
Distance to GGW project	69.938	8.567	-61.371***
	(37.772)	(3.952)	(0.904)
Observations	7,420	1,751	9,171

Treatment group includes all the rural children who are less than 15 km from any Great Green Wall project site, including orchards, shelterbelts and boreholes. Children residing 15-30 km from a project are excluded from the sample. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

4 Results

4.1 Main results

The tables introducing the main results are split between the panel with children surveyed for the period of interest (2013 and 2018 DHS) and the children surveyed during the pre-treatment period (2003 and 2013 DHS) for parallel trend checks, which aim at checking whether treated and control children had similar health improvement trends before their exposure to environmental restoration projects.

Table 3 displays the results of the DiD estimation of the 15 km orchard buffer treatment on children's height-to-age standard deviations. The results show persistent positive and significant causality between orchard development and children's health, across all specifications. The coefficients range from 0.37 to 0.72, according to the specification at stake. Living in a community with at least one orchard within 15 km significantly increases the height-to-age by 0.50 standard deviations in the most conservative specification with IPW. The DiD estimates without IPW show lower but still substantial and significant improvement in children's HAZ scores. The lower panel in Table 3 shows that none of the parallel trend estimates of β_1 are statistically different from zero in the pre-treatment period. Living in the areas that would later be exposed to orchard activities did not imply a specific trend in terms of children's health improvement.[19]

Results are robust to the exclusion of children born to recent migrants (A3). Excluding all mothers who arrived after the launch of an orchard project does not alter the magnitude of the results. This indicates that the positive impact of orchard activities on children's health is not driven by children from newly arrived households. The positive impact of orchard activities on children's HAZ scores is also robust to the exclusion of children living further than 100 km from an orchard (A4) and to alternative specifications with annual cumulative rainfall average fixed effects (A5). Finally, Table A7 shows that the magnitude of the im-

[19]We cannot completely rule out the possibility that some projects failed to be sustainable after their implementation. However, the failure of projects between 2013 and 2016 would lead to downward biased estimates in our regression. Estimates, that are already substantial and positive, may be even higher if we could stop considering children exposed to deficient activities as treated.

Table 3: Impacts of orchards on children's height-to-age z-scores

	Orchard treatment at 15 km					
	Without IPW			With IPW		
	(1)	(2)	(3)	(1)	(2)	(3)
Period of interest: 2013 and 2018 DHS						
Post x Close	0.478***	0.437***	0.367**	0.724***	0.687***	0.496***
	(0.159)	(0.156)	(0.142)	(0.177)	(0.174)	(0.149)
Observations	7,352	7,350	7,350	6,600	6,597	6,597
R-squared	0.088	0.167	0.196	0.095	0.171	0.198
Placebo Period: 2003 and 2013 DHS						
Post x Close	0.177	0.227	-0.287	0.118	0.385	-0.145
	(0.249)	(0.276)	(0.234)	(0.224)	(0.233)	(0.212)
Observations	5,930	5,929	5,929	5,786	5,785	5,785
R-squared	0.087	0.166	0.198	0.094	0.190	0.208
Individual Controls X_{ijmys}	✓	✓	✓	✓	✓	✓
$POST_j$ x X_{ijmys}	✓	✓	✓	✓	✓	✓
Birth FE		✓	✓		✓	✓
State FE			✓			✓

DiD estimations based on 2003 and 2013 DHS for the parallel trend and on 2013 and 2018 DHS for the main period of interest. The child is defined as "Close" if her community is less than 15 km from at least one orchard. Children residing 15-30 km from an orchard are excluded from the regressions. Birth FE includes month of birth of child i, year of birth and the interaction between the two.

Standard errors in parentheses are clustered at the community level (DHS clusters).

*** p<0.01, ** p<0.05, * p<0.1

pact is higher when the orchard is coupled with the construction of a borehole. Figure 4 plots the coefficient estimates for the three treatment assignment thresholds and shows that the positive impact on the health of children living within 20 km proximity to at least one orchard persists.

Table 4 displays the results of the DiD estimation for the other main treatment assignment, that is, the proximity to shelterbelt projects. The positive and significant results identified in the first specifications do not hold when state fixed-effects are included, showing that the positive relationship between proximity to at least one shelterbelt and the improvement in HAZ score is affected by omitted variable bias due to factors that are constant over states. We find the same result when we estimate the regressions with annual cumulative rainfall average fixed effects (table A5 or restrict the sample to newly arrived migrants, table A3). However, the set of estimates becomes significant if we exclude all children who reside more than 100 km from a shelterbelt, as shown in A4. Figure 4 shows that shelterbelt activities have a positive impact on the health of children living

Table 4: Impacts of shelterbelts on children height-to-age z-scores

	Shelterbelt treatment at 15 km					
	Without IPW			With IPW		
	(1)	(2)	(3)	(1)	(2)	(3)
Period of interest: 2013 and 2018 DHS						
Post x Close	0.740**	0.747**	0.583**	0.931**	0.907***	0.503
	(0.355)	(0.326)	(0.289)	(0.361)	(0.302)	(0.347)
Observations	7,666	7,664	7,664	5,305	5,303	5,303
R-squared	0.087	0.168	0.196	0.083	0.165	0.176
Placebo Period: 2003 and 2013 DHS						
Post x Close	0.0934	0.262	-0.150	0.252	0.389	0.0403
	(0.361)	(0.305)	(0.279)	(0.301)	(0.457)	(0.456)
Observations	6,321	6,321	6,321	3,058	3,052	3,052
R-squared	0.083	0.165	0.194	0.069	0.176	0.183
Individual Controls X_{ijmys}	✓	✓	✓	✓	✓	✓
$POST_j$ x X_{ijmys}	✓	✓	✓	✓	✓	✓
Birth FE		✓	✓		✓	✓
State FE			✓			✓

DiD estimations based on 2003 and 2013 DHS for the parallel trend and on 2013 and 2018 DHS for the main period of interest. The child is defined as "Close" if her community is less than 15 km from at least one shelterbelt. Children residing 15-30 km from a shelterbelt are excluded from the regressions. Birth FE includes month of birth of child i, year of birth and the interaction between the two.
Standard errors in parentheses are clustered at the community level (DHS clusters).
*** p<0.01, ** p<0.05, * p<0.1

within short distances, such as within 10 km, but that they fail to benefit children in communities located farther away. Put together, the mixed evidence from the different specifications and robustness checks prevents us from concluding shelterbelt activities have a strong impact on the health of children living farther than 10 km from these projects.

Table A6 in the Appendix introduces the coefficients when the treatment definition includes all type of projects together, such as orchards, shelterbelts and boreholes. Cumulative effects of the three types of projects show a significant and greater magnitude than that of one type of project alone.

Eventually, Table A8 shows that alternative health outcomes, including fever, cough and diarrhea, and preventive health outcomes, such as the incidence of vaccination, are not significantly affected by the proximity to GGW project sites. The awareness of family planning seems to decrease in households living close to shelterbelts. This mitigates the hypothesis that other health or development

Figure 4: Evolution of coefficient estimates of HAZ scores following different treatment thresholds (10 km, 15 km, and 20 km). The coefficient estimates shown in this figure are the results of the most restrictive specification including covariates, all fixed effects and IPW.

projects have been implemented in the same areas as the GGW and strengthens the hypothesis of a causal impact of the environmental restoration programs on health improvements.

4.2 Heterogeneous impacts

Taking advantage of variations in birth and survey date (month) as well as project year, we compute the treatment duration and the age at treatment of each treated child, for orchards and shelterbelt projects, respectively. We also use available information about the project size (see Table A1) to look at heterogeneity of impact across these three metrics.

Table 5 shows the impact of these treatment heterogeneity variables on children's health. It reveals that being exposed to an orchard that is one hectare bigger increases its effect on height-to-age by 10 to 15% of one standard deviation, according to the specification. Being exposed longer or being treated at a younger age also amplifies the positive impact of GGW projects on children's HAZ scores. The last result is consistent with evidence of high sensitivity to food shortage and more generally to income shocks during early childhood (Hyland and Russ, 2019; Maccini and Yang, 2009). Results on shelterbelts show the same patterns but are, again, less significant, except for shelterbelt size.

4.3 Channels

The previous results show to what extent the GGW program plays a role in health improvement in children living nearby community-based orchards, in particular. Following the literature, we consider that nutrition and food intake in the early stages of life are determining factors in a child's health status. Therefore, we rely on additional information from DHS to study whether this health improvement is supported by changes in the dietary diversity of children belonging to exposed communities.

Table 6 displays significant changes in the dietary diversity score of children living within a 15 km buffer of at least one orchard. In the most conservative restriction, living close to at least one community-based orchard is associated with a 0.52 increase in dietary diversity score. These results are in line with the persistent health improvements of children living nearby orchard projects. The diet of children living in communities near shelterbelts do not appear to be significantly more diverse.

An initial interpretation of these results takes into account the capacity of orchards to provide edible products to surrounding households, hence contributing directly to food security improvement. This hypothesis is strengthened when we consider the capacity of some fruit trees to bear fruit relatively early.[20] The second assumption builds on the 20,000 jobs created for GGW implementation in Nigeria and assumes that the more diverse food consumption reflects additional income earned by local communities.[21] Unfortunately, DHS data do not allow

[20]Mango trees begin to bear fruit at the age of 5–6 years (Meena and Asrey, 2018). While a guava grown from seed will take up to 8 years to produce fruit, guava trees are more commonly propagated via cuttings and layering. As such, guava tree fruiting should occur when a tree is 3-4 years of age. Orange trees may bear fruit after three to four years. The traditional cashew tree takes three years from planting before it starts production and eight years before economic harvests can begin.

[21]Some analysis has been run on the impact of GGW projects on labor outcomes, but the main caveat is that the recall period for labor activities is 12 months and doesn't capture any employment at the time the project was created.

Table 5: Heterogeneous impacts of orchards and shelterbelts on children's height-to-age z-scores, depending on intensity of treatment and age at treatment

	Period of interest: 2013 and 2018 DHS					
	Without IPW			With IPW		
	(1)	(2)	(3)	(1)	(2)	(3)
	Orchards at 15 km					
Post x Size (ha)	0.0988***	0.0962**	0.0957**	0.149***	0.148***	0.120**
	(0.0380)	(0.0374)	(0.0388)	(0.0490)	(0.0505)	(0.0496)
Observations	7,508	7,506	7,506	7,114	7,111	7,111
R-squared	0.007	0.133	0.174	0.008	0.136	0.175
Post x Duration (month)	0.00991***	0.0103***	0.00999***	0.0135***	0.0139***	0.0122***
	(0.00345)	(0.00337)	(0.00314)	(0.00366)	(0.00365)	(0.00326)
Observations	8,775	8,773	8,773	7,897	7,894	7,894
R-squared	0.007	0.133	0.173	0.010	0.134	0.170
Post x Age (month)	-0.0220***	-0.00861**	-0.00695	-0.0224***	-0.00970**	-0.00792*
	(0.00372)	(0.00414)	(0.00436)	(0.00365)	(0.00412)	(0.00479)
Observations	8,775	8,773	8,773	7,897	7,894	7,894
R-squared	0.009	0.132	0.172	0.011	0.131	0.168
	Shelterbelts at 15 km					
Post x Size (km)	0.273	0.351*	0.381**	0.307*	0.408**	0.399**
	(0.214)	(0.211)	(0.179)	(0.168)	(0.175)	(0.175)
Observations	7,810	7,808	7,808	5,550	5,549	5,549
R-squared	0.008	0.134	0.172	0.004	0.132	0.151
Post x Duration (month)	0.0139**	0.0145**	0.0109*	0.0123**	0.0129**	0.00834
	(0.00674)	(0.00669)	(0.00595)	(0.00512)	(0.00522)	(0.00555)
Observations	9,162	9,160	9,160	6,379	6,378	6,378
R-squared	0.007	0.132	0.170	0.004	0.128	0.145
Post x Age (month)	-0.0255***	-0.0138	-0.00671	-0.0153**	-0.00226	0.00593
	(0.00953)	(0.00983)	(0.00967)	(0.00716)	(0.00778)	(0.00794)
Observations	9,162	9,160	9,160	6,379	6,378	6,378
R-squared	0.007	0.132	0.170	0.003	0.127	0.145
Individual Controls X_{ijmys}	✓	✓	✓	✓	✓	✓
$POST_j$ x X_{ijmys}	✓	✓	✓	✓	✓	✓
Birth FE		✓	✓		✓	✓
State FE			✓			✓

DiD estimations based on 2013 and 2018 DHS. The child is defined as "Close" if her community is less than 15 km from at least one orchard or shelterbelt. Children residing 15-30 km from an orchard or shelterbelt are excluded from the regressions. Birth FE includes month of birth of child i, year of birth and the interaction between the two.

Standard errors in parentheses are clustered at the community level (DHS clusters).

*** p<0.01, ** p<0.05, * p<0.1

Table 6: Impacts of orchards and shelterbelts on children's dietary diversity score

	Without IPW			With IPW		
	(1)	(2)	(3)	(1)	(2)	(3)
Orchard treatment at 15 km:						
Post x Close	0.0646	0.0539	0.0618	0.469**	0.450**	0.523**
	(0.204)	(0.186)	(0.188)	(0.223)	(0.209)	(0.209)
Observations	6,503	6,501	6,501	5,825	5,822	5,822
R-squared	0.093	0.317	0.325	0.090	0.313	0.323
Shelterbelt treatment at 15 km:						
Post x Close	0.247	0.231	0.253	0.339	0.126	0.0889
	(0.305)	(0.221)	(0.237)	(0.324)	(0.217)	(0.270)
Observations	6,761	6,759	6,759	4,453	4,451	4,451
R-squared	0.087	0.312	0.322	0.085	0.321	0.324
Individual Controls X_{ijmys}	✓	✓	✓	✓	✓	✓
$POST_j$ x X_{ijmys}	✓	✓	✓	✓	✓	✓
Birth FE		✓	✓		✓	✓
State FE			✓			✓

DiD estimations based on 2013 and 2018 DHS. The child is defined as "Close" if her community is less than 15 km from at least one specific GGW activity (orchard or shelterbelt, respectively). Children residing 15-30 km from the specific GGW activity are excluded from the regressions. Birth FE includes month of birth of child i, year of birth and the interaction between the two.
Standard errors in parentheses are clustered at the community level (DHS clusters).
*** p<0.01, ** p<0.05, * p<0.1

us to further investigate these transmission channels and conclude whether the impact of GGW projects on children's health is directly linked to public expenditures, to an increased access to edible products or indirectly through an increase in agricultural productivity.

5 Discussion

Western African households are particularly vulnerable to growing soil erosion. This harmful phenomenon leaves them with fewer alternatives to find sources of edible products and to protect their lands and harvests. In 2007, policy makers across the continent committed to an environmental restoration initiative called the Great Green Wall . This paper presents the first evidence that an environmental restoration program such as the GGW implemented in Nigeria improves children's health by providing better food access to local populations. We match nationally representative socio-demographic surveys to the precise location of Nigerian GGW environmental restoration projects to explore the impact of the program on children's height-to-age and dietary diversity scores. The heterogeneous exposure to the projects in time and space allows us to distinguish treated households from control ones and establish a DiD model. Parallel trend estimations and IPW methods enrich the empirical framework and control for the identification issues that may occur from the not-random location of the projects.

The results have important implications for program design since they inform about the specific types of GGW activities that most benefit local children. First, the estimates show a positive and long-distance impact of orchard activities on children's health whereas shelterbelts are associated with strong health improvement in children who live within a short distance only. The orchards seem to have long-distance impact on children's health, since some positive spillovers are still captured at 20 km. We provide evidence that this health improvement is coupled with higher dietary diversity in children among children who were exposed to orchard projects.

As an initial causal impact evaluation of the GGW program, we believe that this paper provides useful preliminary evidence on the positive spillovers of land restoration projects. However, the GGW initiative has been implemented heterogeneously across Sub-Saharan Africa. For instance, Niger chose to distribute grains to the local population whereas Burkina Faso has tried to rehabilitate lands through the development of traditional practices in its communities. Therefore, our results are specific to the Nigerian case but do not provide an overall assessment of the GGW initiative's effectiveness. The vast range of initiatives undertaken to restore lands deserves a cross-country and comparative analysis to better capture the specific greening activities that may most benefit local populations. The growing availability of remote sensing data and household surveys with GPS coordinates offer a promising path to investigate this question in other settings.

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A Appendices

A.1 Satellite view and summary project statistics

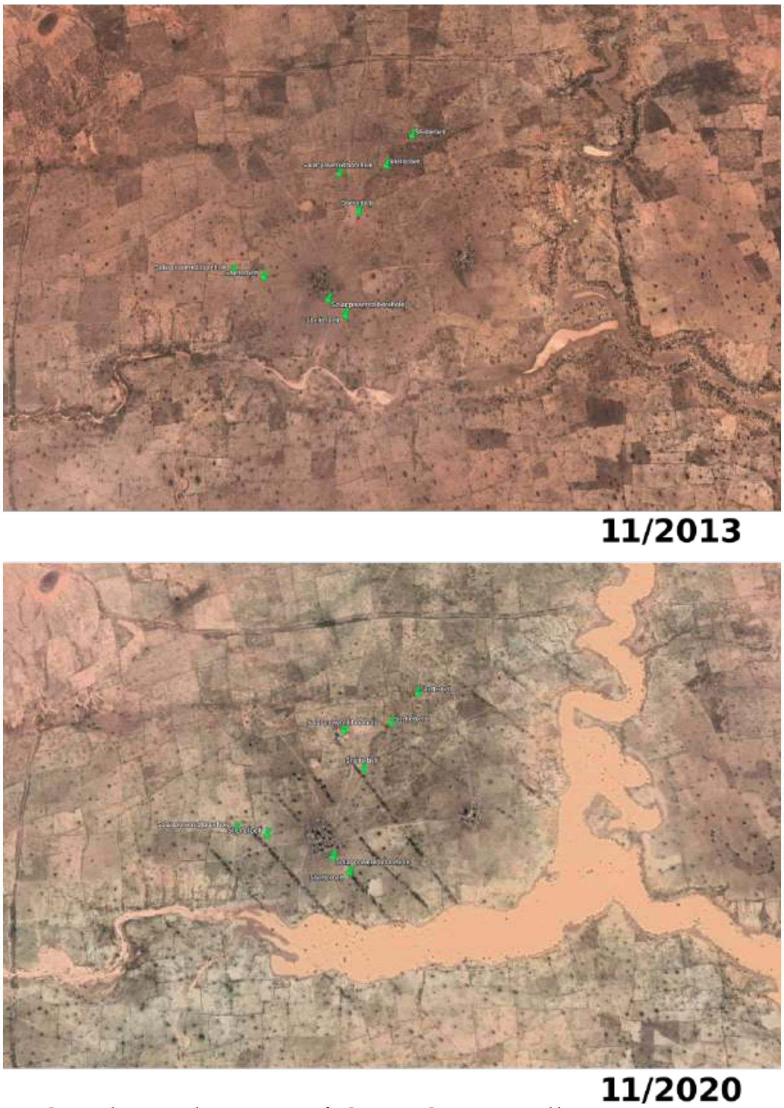

Figure A1: Two Google Earth views of Great Green Wall projects in Nigeria during the 2013-2020 period. Projects in these views include five shelterbelts and three solar powered boreholes, which are observed during the winter, before (in 2013) and after (in 2020) their implementation (in 2015).

Table A1: Project size summary statistics

Variable	Mean	Std. Dev.	Min.	Max.	N
Shelterbelt length (km)	1.338	0.868	0.65	5	204
Orchard size (ha)	2.829	1.228	1	7	111

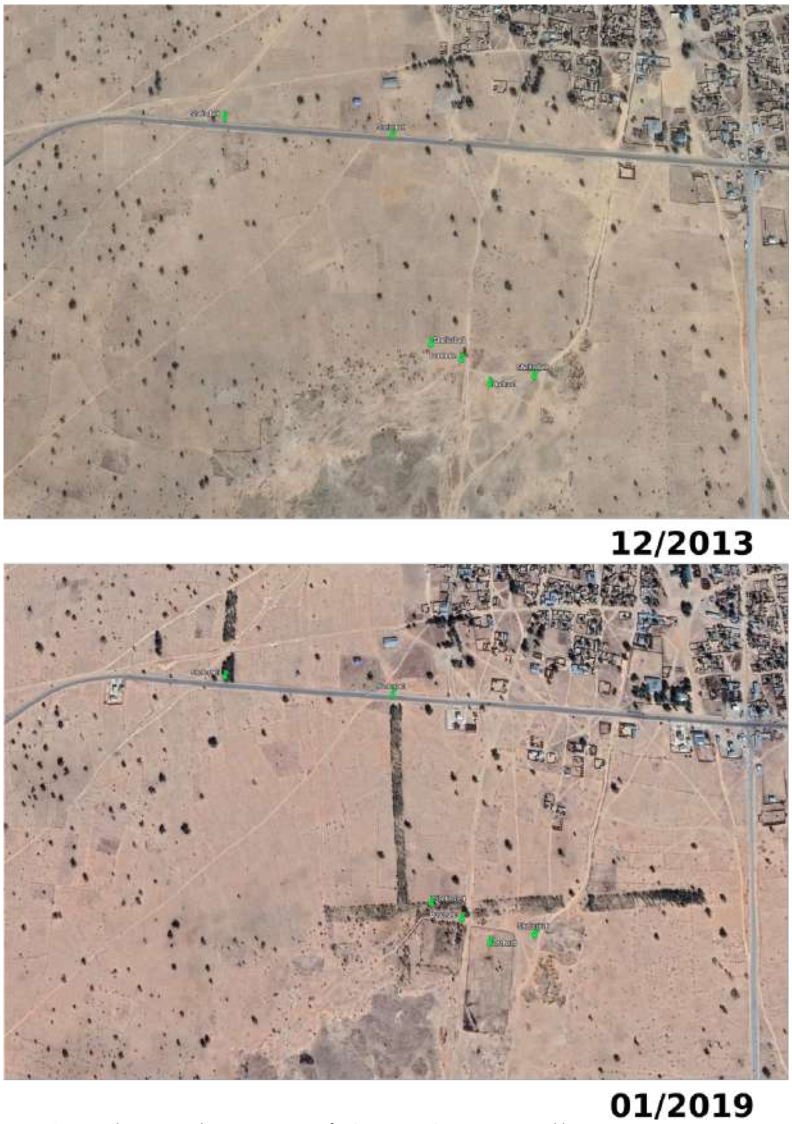

Figure A2: Two Google Earth views of Great Green Wall projects in Nigeria during the 2013-2020 period. Projects in these views include four shelterbelts, a solar powered borehole and an orchard, which are observed during the winter, before (in 2013) and after (in 2019) their implementation (2014-2015).

Figure A3: Two Google Earth views of Great Green Wall projects in Tumbo, Bachaka, Kebbi, Nigeria (on the Niger-Nigerian border) during the 2013-2020 period. Projects in these views include a shelterbelt and an orchard, which are observed during the winter, in 2014 and 2020.

A.2 Distribution of households across DHS waves

Table A2: Distribution of observations among treated and control groups in DHS surveys

	10 km				15 km				20 km			
	2013		2018		2013		2018		2013		2018	
	Treated (after 2013)	*Control*	*Treated*	*Control*	*Treated* (after 2013)	*Control*	*Treated*	*Control*	*Treated* (after 2013)	*Control*	*Treated*	*Control*
Orchard	865	9,081	941	8,921	1,441	7,575	1,663	7,498	2,257	6,613	6,313	2,339
Total Sample	9,766		9,862		9,016		9,161		8,870		8,652	
Shelterbelt	197	10,530	326	10,329	447	10,097	472	9,522	808	8,867	931	8,665
Total Sample	10,727		10,665		10,544		9,994		9,675		9,596	

A.3 Drop Newly Arrived Households in 2018

Table A3: Impacts of orchards and shelterbelts on children's height-to-age z-score

	Without IPW			With IPW		
	(1)	(2)	(3)	(1)	(2)	(3)
Orchard treatment at 15 km:						
Post x Close	0.487***	0.443***	0.363**	0.728***	0.683***	0.487***
	(0.162)	(0.157)	(0.142)	(0.178)	(0.175)	(0.151)
Observations	7,244	7,241	7,241	6,498	6,496	6,496
R-squared	0.088	0.167	0.196	0.095	0.171	0.198
Shelterbelt treatment at 15 km:						
Post x Close	0.779**	0.789**	0.636**	1.017***	0.966***	0.557
	(0.360)	(0.332)	(0.291)	(0.368)	(0.309)	(0.354)
Observations	7,557	7,555	7,555	5,248	5,246	5,246
R-squared	0.087	0.167	0.195	0.084	0.165	0.177
Individual Controls X_{ijmys}	✓	✓	✓	✓	✓	✓
$POST_j$ x X_{ijmys}	✓	✓	✓	✓	✓	✓
Birth FE		✓	✓		✓	✓
State FE			✓			✓

DiD estimations based on 2013 and 2018 DHS. The child is defined as "Close" if her community is less than 15 km from at least one specific GGW project (orchard or shelterbelt, respectively). Children residing 15-30 km from the specific GGW project are excluded from the regressions. Birth FE includes month of birth of child i, year of birth and the interaction between the two.
All children belonging to households who migrated between 2013 and 2018 are excluded from the analysis.
Standard errors in parentheses are clustered at the community level (DHS clusters).
*** p<0.01, ** p<0.05, * p<0.1

A.4 Exclusion of children above 100 km

Table A4: Impacts of orchards and shelterbelts on children's height-to-age z-score

	Without IPW			With IPW		
	(1)	(2)	(3)	(1)	(2)	(3)
Orchard treatment at 15 km:						
Post x Close	0.480***	0.414***	0.364**	0.765***	0.710***	0.547***
	(0.164)	(0.159)	(0.146)	(0.184)	(0.173)	(0.153)
Observations	5,954	5,953	5,953	5,489	5,488	5,488
R-squared	0.090	0.176	0.197	0.096	0.182	0.198
Shelterbelt treatment at 15 km:						
Post x Close	0.784**	0.817**	0.652**	0.938**	0.963***	0.596**
	(0.351)	(0.320)	(0.283)	(0.402)	(0.322)	(0.301)
Observations	4,667	4,665	4,665	3,675	3,675	3,675
R-squared	0.085	0.178	0.204	0.079	0.178	0.192
Individual Controls X_{ijmys}	✓	✓	✓	✓	✓	✓
$POST_j$ x X_{ijmys}	✓	✓	✓	✓	✓	✓
Birth FE		✓	✓		✓	✓
State FE			✓			✓

DiD estimations based on 2013 and 2018 DHS. The child is defined as "Close" if her community is less than 15 km from at least one specific GGW project (orchard or shelterbelt, respectively). Children residing 15-30 km from the specific GGW project are excluded from the regressions. Birth FE includes month of birth of child *i*, year of birth and the interaction between the two.

All children living in communities more than 100 km away from an orchard or shelterbelt are dropped from the analysis.

Standard errors in parentheses are clustered at the community level (DHS clusters).

*** p<0.01, ** p<0.05, * p<0.1

A.5 Annual cumulative rainfall average fixed effects

Table A5: Impacts of orchards and shelterbelts on children's height-to-age z-score

	Without IPW			With IPW		
	(1)	(2)	(3)	(1)	(2)	(3)
Orchard treatment at 15 km:						
Post x Close	0.478***	0.437***	0.475***	0.540***	0.505***	0.450**
	(0.159)	(0.156)	(0.172)	(0.173)	(0.160)	(0.180)
Observations	7,352	7,350	7,350	6,655	6,653	6,653
R-squared	0.088	0.167	0.176	0.087	0.165	0.182
Shelterbelt treatment at 15 km:						
Post x Close	0.740**	0.747**	0.895***	0.740*	0.713**	0.829**
	(0.355)	(0.326)	(0.315)	(0.381)	(0.322)	(0.339)
Observations	7,666	7,664	7,664	3,357	3,355	3,355
R-squared	0.087	0.168	0.178	0.088	0.177	0.195
Individual Controls X_{ijmys}	✓	✓	✓	✓	✓	✓
$POST_j$ x X_{ijmys}	✓	✓	✓	✓	✓	✓
Birth FE		✓	✓		✓	✓
Rainfall FE			✓			✓

DiD estimations based on 2013 and 2018 DHS. The child is defined as "Close" if her community is less than 15 km from at least one specific GGW project (orchard or shelterbelt, respectively). Children residing 15-30 km from the specific GGW project are excluded from the regressions. Birth FE includes month of birth of child *i*, year of birth and the interaction between the two.

The child is defined as "Close" if her community is less than 15 km to at least one orchard or one shelterbelt.

*** p<0.01, ** p<0.05, * p<0.1

A.6 Orchards, shelterbelts and boreholes together

Table A6: Impacts of all GGW projects on children's height-to-age z-score

	Without IPW			With IPW		
	(1)	(2)	(3)	(1)	(2)	(3)
Orchard or shelterbelt or borehole treatment at 15 km:						
Post x Close	0.414***	0.385**	0.300**	0.640***	0.602***	0.393***
	(0.155)	(0.151)	(0.144)	(0.179)	(0.173)	(0.151)
Observations	7,509	7,507	7,507	6,766	6,764	6,764
R-squared	0.087	0.165	0.193	0.092	0.168	0.193
Individual Controls X_{ijmys}	✓	✓	✓	✓	✓	✓
$POST_j$ x X_{ijmys}	✓	✓	✓	✓	✓	✓
Birth FE		✓	✓		✓	✓
State FE			✓			✓

DiD estimations based on 2013 and 2018 DHS. Treatment assignment is defined as being close (less than 15 km) to at least one orchard, one shelterbelt or one borehole. Children residing 15-30 km from any GGW activity are excluded from the regressions. Birth FE includes month of birth of child *i*, year of birth and the interaction between the two.

Standard errors in parentheses are clustered at the community level (DHS clusters).

*** p<0.01, ** p<0.05, * p<0.1

A.7 Joint Projects (Shelterbelt/Borehole and Orchard/Borehole)

Table A7: Impacts of joint projects on children's height-to-age z-score

	Without IPW			With IPW		
	(1)	(2)	(3)	(1)	(2)	(3)
Joint orchard/borehole treatment at 15 km :						
Post x Close	0.713***	0.732***	0.557***	0.851***	0.920***	0.645**
	(0.248)	(0.234)	(0.201)	(0.274)	(0.265)	(0.254)
Observations	7,363	7,361	7,361	4,345	4,344	4,344
R-squared	0.088	0.171	0.199	0.076	0.165	0.195
Joint shelterbelt/borehole treatment at 15 km:						
Post x Close	1.012***	1.034***	0.691**	0.918**	0.869***	0.331
	(0.371)	(0.301)	(0.315)	(0.389)	(0.322)	(0.374)
Observations	7,448	7,446	7,446	3,079	3,077	3,077
R-squared	0.091	0.172	0.200	0.103	0.196	0.205
Individual Controls X_{ijmys}	✓	✓	✓	✓	✓	✓
$POST_j$ x X_{ijmys}	✓	✓	✓	✓	✓	✓
Birth FE		✓	✓		✓	✓
State FE			✓			✓

DiD estimations based on 2013 and 2018 DHS. Treatment assignment is defined as being close (less than 15 km) to a joint orchard and borehole project or to a joint shelterbelt and borehole project. Children living close to orchard or shelterbelt projects alone are dropped from the analysis to avoid biased estimates.

Standard errors in parentheses are clustered at the community level (DHS clusters).

*** p<0.01, ** p<0.05, * p<0.1

A.8 Impacts on other health outcomes

Table A8: Impacts of orchards and shelterbelts on other health outcomes

	Fever		Diarrhea		Cough		Vaccination		Family planning	
Orchard treatment at 15 km:										
Post x Close	-0.00789	-0.0381	0.0726**	0.0259	-0.0116	-0.0286	0.104	0.0380	-0.0532	0.0301
	(0.0347)	(0.0382)	(0.0319)	(0.0322)	(0.0263)	(0.0325)	(0.0635)	(0.0670)	(0.0477)	(0.0500)
Observations	8,316	7,424	8,321	7,436	8,293	7,403	7,528	6,743	8,350	7,458
R-squared	0.146	0.147	0.120	0.137	0.111	0.115	0.202	0.172	0.127	0.126
Shelterbelt treatment at 15 km:										
Post x Close	0.0321	0.00927	0.0227	-0.00375	0.0201	0.0686	-0.0798	-0.0513	-0.248***	-0.183*
	(0.0534)	(0.0535)	(0.0536)	(0.0381)	(0.0344)	(0.0512)	(0.0901)	(0.102)	(0.0590)	(0.0950)
Observations	8,668	5,967	8,673	5,976	8,648	5,953	7,884	5,472	8,705	5,995
R-squared	0.141	0.145	0.110	0.122	0.107	0.126	0.206	0.178	0.126	0.121
Individual Controls X_{ijmys}	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
$POST_j$ x X_{ijmys}	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Birth FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
State FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
IPW		✓		✓		✓		✓		✓

DiD estimations based on 2013 and 2018 DHS. The child is defined as "Close" if her community is less than 15 km from at least one specific GGW project (orchard or shelterbelt, respectively). Children residing 15-30 km from the specific GGW project are excluded from the regressions. Birth FE includes month of birth of child i, year of birth and the interaction between the two.
Standard errors in parentheses are clustered at the community level (DHS clusters).
*** p<0.01, ** p<0.05, * p<0.1

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