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Impacts of the Great Green Wall projects on children's health: Evidence from Nigeria

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Impacts of the Great Green Wall projects on children's health: Evidence from Nigeria

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Abstract

The Great Green Wall is a cross-country initiative to improve the environment of desertification areas in Sub-Saharan Africa. This paper refers to the implementation of Great Green Wall projects in Nigeria to document the local impact of environmental restoration on children's food security and health. Our identification strategy uses two types of variation to capture these effects. The spatial variation comes from the heterogeneous exposure of the 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 main outcome of interest, we find a significant and robust health improvement for 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 score for children living near orchards.

Keywords: Environmental Restoration, Food security, Nigeria, Nutrition, Impact evaluation

JEL Codes: 012, 013, Q18, Q23

1 Introduction

In the 1970s and 1980s, severe droughts struck Sub-Saharan Africa with harmful consequences on local populations. These tragic events motivated the adoption of The United Nations Convention to Combat Desertification (UNCCD) in 1994 with the dual objective of evaluating the desertification process and providing sustainable solutions against it.[1] During the 2000-2010 period, Sub-saharan Africa still experienced the largest increase (32%) in population living on degrading agricultural land (Barbier and Di Falco, 2021). Besides reducing agricultural productivity, land degradation damages livelihoods through food insecurity, water shortage, poverty, health problems and conflicts (Holden and Shiferaw, 2004; Couttenier and Soubeyran, 2014; Olagunju, 2015).

Following this warming assessment, eleven African countries committed to the creation of the Great Green Wall (GGW) in 2007.[2] They agreed to join forces to reforest the region through a 7000 km greenbelt across the continent. Initially designed as a continuous wall of vegetation, the project has evolved to become a mosaic of interventions to restore ecosystems and address the needs of local populations (Goffner et al., 2019). Whether such an ambitious environmental restoration project improves livelihoods of the surrounding households is still an under-explored research question (Benjaminsen and Hiernaux, 2019).[3] This paper bridges this evidence gap by assessing the impacts of the program on children's health in Nigeria.

The motivation for the GGW program implementation echoes the growing body of evidence showing that trees-based ecosystem services are correlated to human well-being through diet quality, nutrition or health. Tree land cover helps improving household livelihoods through its capacity to foster agricultural yields and to provide households with products that address basic needs in terms of food, fiber, energy and shelter (Angelsen et al., 2014; Ickowitz et al., 2014). Many

[1] The UNCCD defines desertification as "land degradation in arid, semi-arid and dry subhumid 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 Nature journal urged researchers to work on the evaluation of the GGW project and to guide policy-makers towards the achievement of GGW key goals: https://www.nature.com/articles/d41586-020-03080-z

case studies bring evidence on the benefit of forests when a shock occurs, such as a crop failure, to complement the income or meet with subsistence needs (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 an important change in the amount of land covered by trees and raises expectations of preliminary positive effects on welfare outcomes.

Although trees can have many benefits, little work has yet analyzed the positive impacts trees might have on children's well-being. Yet, early life conditions are known to be very important for individual development (Behrman and Rosenzweig, 2004; Black et al., 2007; Currie and Vogl, 2012). Malnutrition in early stages of life has long-term consequences on human capital attainments such as cognitive scores or health, educational and socio-economic achievements as adults (Glewwe et al., 2001). For instance, Hoddinott et al. (2013) show that individuals who enjoyed a correct growth in the first 3 years of life complete more schooling, score higher tests of cognitive skills 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 for 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 the child begins her life deserves special attention. Given that children in Northern Nigeria grow up in harsh environment with potential long-term negative impacts of droughts on their individual development, assessing the ability of GGW program to enhance the health during early childhood is a crucial task. This assessment is all the more important 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 region showed that net gains of such land restoration program 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, it is the first to document the local impact of the Great Green Wall program on children's health outcomes. Although Duboz et al. (2019) displayed some correlations between the implementation of GGW in Senegal and welfare and health outcomes, there is surprisingly no causal impact assessment of its consequences on local communities' welfare. Secondly, the distinct analysis conducted on the two main types of project launched by GGW program allows to determine the specific greening activity that benefits the most to children. Third, we investigate the food security channel to better capture the source of health improvement for children. Nutrition level is known as 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 health and food security, we exploit geographical heterogeneity of children in exposure 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 GGW projects, both geocoded, are combined to assign a treatment status to the community where the children reside. The distance cutoff 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 credible counterfactual given that the program was targeted and not randomly allocated to households. To overcome this challenge, we augment the estimations with propensity score reweighting and parallel trends checks for the period preceding the GGW projects. This empirical methodology stays constant when we investigate the changes in children nutrition proxied by their dietary diversity score.

The findings are twofold. First, the children living next 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 an important increase in height-to-age standard deviation. This positive impact on children's health becomes even more important 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 local children significantly and positively increases, bringing 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 may 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 are due to public employment, investments or the boost of local markets, they would be limited to the short run while one can expect more sustainable impacts from ecosystemic services in the long-term.

The remainder of the paper proceeds as follows. Section 2 introduces the context of the new 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 to slow down the expansion of the Sahara by planting a barrier of trees spreading 7000 kilometers from Senegal to Djibouti.

With the rising concerns about climate change in the Sahel region, the greenbelt intends to fill a new role: increasing 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 for its support.[5]

The project has been progressing at different scales among the eleven countries committed to give birth to the GGW.[6] In Nigeria, the implementation of the project has been starting 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 deciding and monitoring the implementation of the program at the national level. At the community level, the head of the community decides how to redistribute revenues or products from the activities across households.[7]

All these activities have generated about 20,000 jobs in Nigeria.[8] The UNCCD claims that the GGW initiative trained and engaged 498 youths as forest guards, several thousands in planting and other related activities and more than a thousand in drilling boreholes. According to Gadzama (2017), more than 100,000 people in the rural areas will be employed during the whole period of projects implementation, beside the 1000 forest guards and 450 extension workers that will be required.

Tree planting programs often face great challenges (Holl and Brancalion, 2020). Previous land restoration programs in Nigeria were actually suspected of weak integration and notable gaps in civil society participation, absence of use of indigenous knowledge, limited community and farmers implication, and limited maintenance (Jalam et al., 2020; Medugu et al., 2010). These limitations may have contributed the low observed survival rates of shelterbelts projects (Gadiga et al., 2015). To ensure a sustainable implementation of the current program, policymakers try to learn from past errors in national land restoration initiatives, notably by involving community members and vulnerable population in the land

[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 data on GGW implementation for other countries involved in the project.

[7] The land where the projects take place mainly belong to community members' institutions. The land that belongs to the community members are 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 gotten from the project.

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

use policy and redistribution of projects' revenues (Turner et al., 2021) and by adopting bottom-up approaches.

The implementation of the GGW project takes different forms in the country. Shelterbelts are rows of trees to protect soil from erosion and improve the quality of farmlands. Between 2013 and 2016, 642 kilometers of such shelterbelts grew along the northern part of the country. About 300 hectares of community orchard have also been established to provide edible products such as mangoes, guavas, cashews, or oranges among others. More than a hundred solar and wind-powered boreholes have been constructed to support the maintenance of shelterbelts and orchards, and are supposed to provide water to over 40,000 people and 150,000 livestock (PAG, 2018). Given that characteristics and channels associated with each type of project differ (as discussed in 2.1.3), we distinctively assess the impacts of orchards and shelterbelts on children's health.

2.1.2 The data

The first task to answer our research question is to locate the environmental restoration projects implemented through the GGW program. To this end, the NCGGW provided data on the localisation, type and year of implementation of about a hundred of orchards and boreholes and of more than two hundreds of shelterbelts as shown in table 1. Figure 1 provides an overview of the different types of projects implemented as part of the program between 2013 and 2016. Most of the boreholes are placed in the very vicinity of orchards or shelterbelts in order to increase the lifespan of both types of projects. 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]

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

Table 1: Distribution of GGW projects 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**

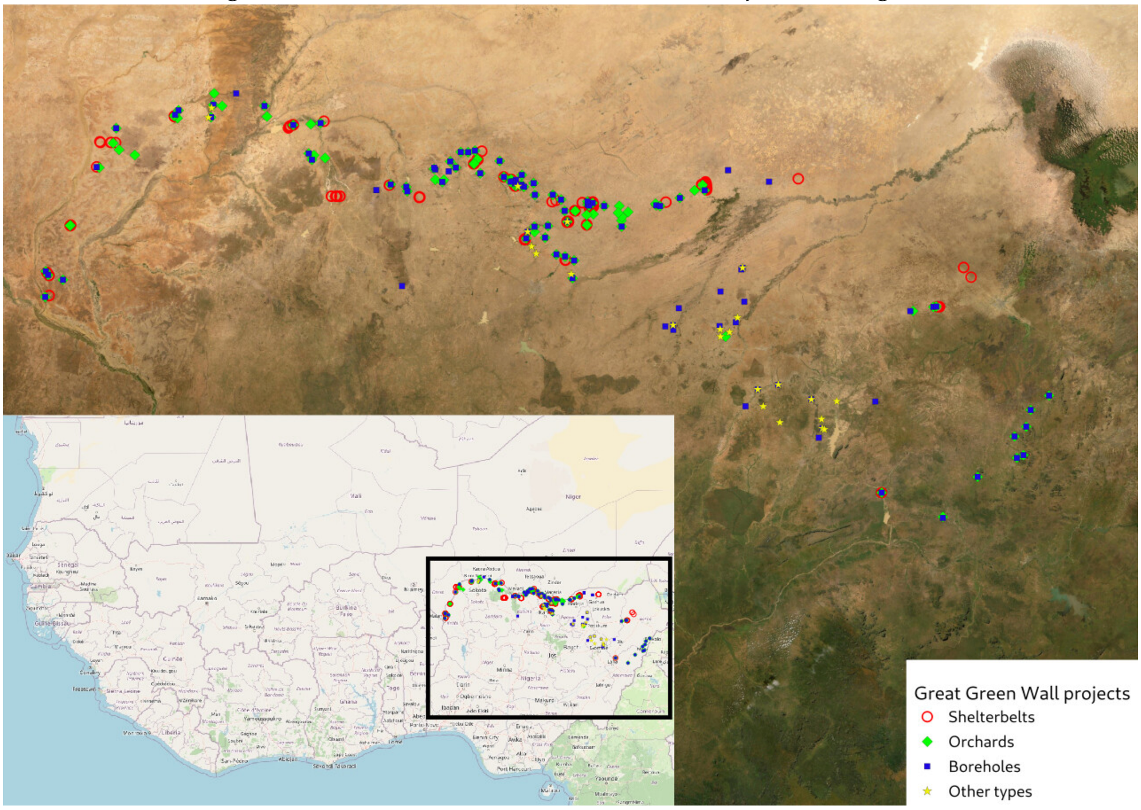
2.1.3 Ecosystemic services and other potential impacts

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

The most important impacts of shelterbelts on agricultural yields in arid environments probably comes from the limitation of soil erosion, the protection against windstorm and the run-off and evapotranspiration regulation (Wang et al., 2008). Limiting soil erosion has indeed been proved to positively impact crop growth yields in the Sahel (Michels et al., 1998). Such improvements in soil condition consequently result in vegetation development in areas where shelterbelts are established (Adesina and Gadiga, 2014). Kho et al. (2001) show that millet grown under acacia trees (*Faidherbia albida*) canopy in Niger had a yield 36% higher than those grown in open fields. Pest control plays also a key role in Nigeria: millet growing under acacia trees was not found infected by the millet pest striga, in contrast to surrounding areas (Gworgwor, 2007).

Planting trees in arid environments also provides water availability and reduce floods through water flow regulation: it limits rainfall run-off and favorises groudwater recharge by fostering water infiltration. By increasing water hold-

Figure 1: Location of Great Green Wall Projects in Nigeria



ing capacity, tree roots regulate the water cycle and limits downstream flooding by increasing evapotranspiration (Zhang et al., 2017; Zhang and Wei, 2021). McCarthy et al. (2021) show that green belts are effective to reduce flood risk for maize production in Malawi and Ilstedt et al. (2016) that tree densities influence groundwater recharge in Burkina Faso.

In addition to ecosystemic 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 species are identified to play 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 households characteristics, health and living conditions at the national. The data are geocoded at the DHS cluster/community level. 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 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]

*************************** HEIGHT TO AGE or HEIGHT FOR AGE ???? *************************

All surveyed women aged between 15 and 49 years old present at the time of the survey are interviewed. Each of their children who are less than 5 years old are subject to anthropometric measurements. In particular, height was measured in order to establish a height-for-age index and compare it to standards provided by the World Health Organization (WHO). The height-for-age indicator informs on the long-term nutritional status of the child and captures recurrent or chronic illness at an early age. When the height-for-age standard deviation (HAZ) 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 DHS Final Report conducted in Nigeria in 2018 reveals that 37% of Nigerian children below 5 years old are stunted. Investigating HAZ score allows us to

[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 broad objective of the NSPFS 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 receive field activities from the 2003 cropping season to 2006. More information about implementation and objectives of the program 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.

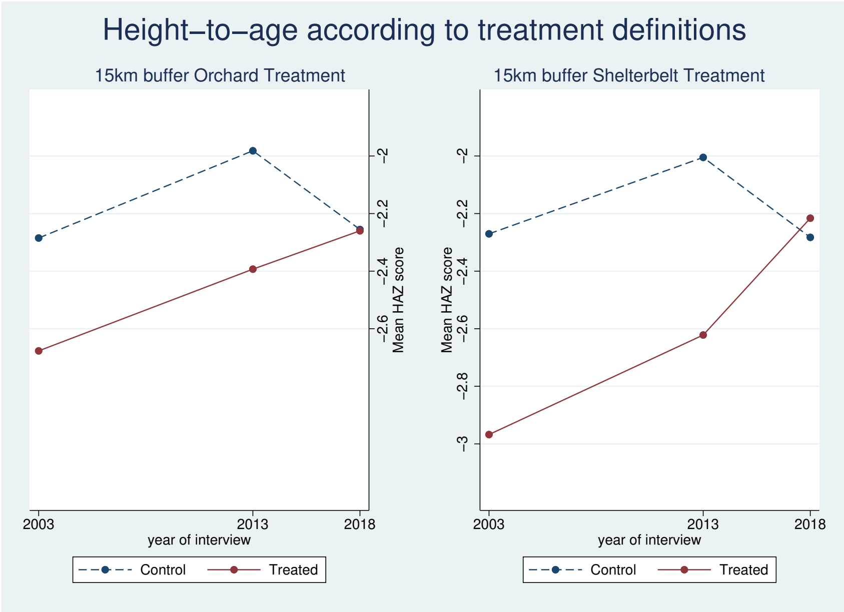


Figure 2: The evolution of height-to-age z-score under two treatment definitions

capture the impacts of environmental reforestation on children health and food security on a long term, independently from recent changes in dietary intakes.

The children are assigned with a treatment status according to the distance of their community to the 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 children across the three waves of DHS. Even though the 2003 average HAZ score is lower for the children living in the area selected for orchards implementation, both treated and control children experience health improvement following a parallel trend until 2013. During the period of orchards implementation, HAZ scores display downward health trends for control children (from -1.99 to -2.28, i.e. -15 %) and positive change in HAZ score for the treated group (from -2.39 to -2.26, i.e. +1%). If we consider the shelterbelt projects, we see that health conditions has increased in the treated group (from -2.62 to -2.22, i.e. +15%) while it has decreased for the control group (from -2.02 to -2.28, i.e. -13%). Further investigation helps understanding whether this difference in health evolution between treated and control children is driven by the implementation of environmental restoration projects.

3 Empirical Framework

The goal of this empirical study is to identify how the GGW projects affect children's health in the local communities. To this end, we explore variations across time (the project occurence) and space (children's community distance to the projects). This actually refers to a difference-in-difference (DiD) methodology. To do so, it is crucial to determine a treated and a control group at best.

Many empirical studies rely on geospatial DiD to assess 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 distance cutoff to the program used to identified treated and control groups. To our knowledge, there are no papers relying on a similar methodology to assess the impact of environmental restoration programs on health outcomes for 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 at 15 km from the 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 precise data, we might define closeness even more restrictively. However, in the context of available data, we think 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 increases the power of the results, all else equal.

The 15 km distance cutoff is eventually 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:

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

with Y_{ijmys} being 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 greening areas on the health of children who live next to 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} represent 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 on the period 1980-2000. To avoid as much as possible "fake controls" (children considered as control whereas they are treated), 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.

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

Propensity Score Reweighting In this study, the treatment assignment is not randomly operated. The table 2 brings evidence that there are persistent differences across treated and control groups at baseline. Among the multiple techniques that have been developed to help researchers capturing the impact of a program on individuals with different characteristics at baseline, we decide to employ the Inverse Probability Weighting (IPW) method. Its ability to recover unbiased estimates of 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 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 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 non-treated and treated observations respectively.[14]

The ideal approach to identify the set of covariates for the estimation of propensity score is to focus on the selection process that sorts participants into treatment and control conditions. However, relatively little is known about the factors that influence exposure to the GGW projects 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 variables that are observed at baseline. 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 with a large spike of control children with low probabilities of treatment, such that IPW will be necessary to ensure the robustness of our estimates. The final goal of propensity scores is to remove any selection bias that has made the groups different on those invariant

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

[14] The propensity score reweighting is separately executed for Orchard and Shelterbelt treatments.

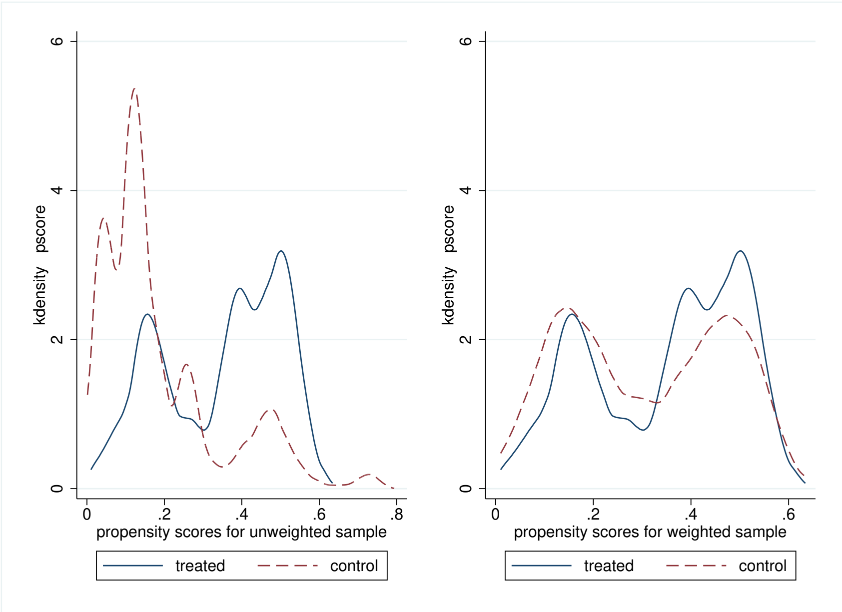


Figure 3: Distribution of propensity scores, before (left panel) and after (right panel) weighting

observed variables. A straightforward way to test the validity of the procedure is to compare the propensity scores for 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 children had similar health trends before the occurrence period. 2003 and 2013 DHS are two pre-treatment waves available to check for parallel trends. It allows to build a credible counterfactual for the control group and tests 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 2013 DHS wave are considered to belong 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 not anymore significantly different in the weighted samples. This also suggests that comparability between the two groups has been improved, although it is not fully achieved.

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. The results are introduced in section 4.3. 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 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.

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

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

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

We explore the possibility that our results could be unspecific to GGW activities, but rather due to other factors that would correlate with systematically better health around places where projects settled. For instance, we could suspect that the critical food insecurity 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. The 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, that is 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 10 rainfall zones correspond to the deciles of the distribution of long run 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 received at least one vaccine injection. The family planning variable is equal to one if the household 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 far from any Great Green Wall Project, including orchards, shelterbelts, and boreholes. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

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. They 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 orchard 15 km 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 at 15 km significantly increases the height-for-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 height-to-age z-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.

Results are robust to the exclusion of children born to recent migrants (A3). Excluding all mothers who arrived after the launch of orchard projects does not alter the magnitude of the results. This indicates that the positive impact of orchard activities on health is not driven by children from newly arrived households. The positive impact of orchards activities on children HAZ score 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 averages fixed effects (A5). Eventually, Table A7 shows that the magnitude of the impact is higher when the orchard is coupled with the creation of a borehole. Figure 4 plots the coefficient estimates for the three thresholds for treatment assignment and shows that the positive impact on health of being close to at least one orchard

Table 3: Impacts of orchards on children height-to-age z-score

	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 to 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

persists at 20 km.

Table 4 displays the results for 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 far from a shelterbelt as shown in A4. Figure 4 shows that positive impact of shelterbelt activities on children's health are expected on short distances, such as 10 km, but fails to benefit to further communities. Put together, the mixed evidence from the different specifications and robustness checks prevents us from concluding on a strong impact of shelterbelt activities on health of children living more than 10 km far from the projects.

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

	Shelterbelts 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 has Close if her community is less than 15 km to 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

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.

Table A6 in appendix introduces the coefficients when the treatment definition includes all type of projects together, such as orchards, shelterbelts or boreholes. Cumulative effects of the three types of projects show significant and greater magnitude than 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 activities. The awareness of family planning seems to decrease in households living close to shelterbelts. This mitigates the hypothesis that other health or development projects have been implemented in same areas than the GGW and strengthens the causal impact of the environmental restoration programs on health improvements.

4.2 Heterogeneous impacts

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

Table 5 shows the impact of these heterogeneity variables on children's health. It reveals that being exposed to an orchard that is one hectare bigger increases its effect on height-for-age by 0.10 to 0.15 standard deviations according to the specification. Being exposed longer or being treated at a younger age also amplifies the positive impact of GGW projects on HAZ scores. These results are consistent with evidence of a 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.

4.3 Channels

The previous results show to which extent the impact of the project plays a key role for health improvement of children who were living nearby, in particular

Table 5: Heterogeneous impacts of orchards and shelterbelts on children height-to-age z-score, 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 Close 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 Close 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 Close 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 Close 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 Close 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 Close 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 has Close if her community is less than 15 km to at least one orchard or one shelterbelt. Children residing 15-30 km from an orchard or 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

when community-based orchards are at stake. Following the literature, we consider that nutrition and food intake in early stages of life is a determining factor in health status. Therefore, we rely on additional information from DHS to study if this health improvement is supported by some changes in the dietary diversity for 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 the dietary diversity. These results are in line with the persistent health improvements for children living nearby orchard projects. The diet of children living in communities near shelterbelts do not appear to be significantly more diverse.

A first interpretation of these results relies on the capacity of orchards to provide edible products to the surrounding households, hence participating directly into food security improvement. This hypotheses is strengthened by the capacity of some fruit trees to bear fruits relatively early.[19] The second assumption builds on the 20,000 jobs created for GGW implementation in Nigeria and assumes that the more diverse food consumption reflects an additional income earned by local communities.[20] Unfortunately, DHS data do not allow to further investigate these transmission channels and to conclude on whether the impact of GGW projects on child health is directly linked to public expenditures, to an increased access to edible products or indirectly through increase of agricultural productivity.

[19]Mango trees start to bear fruits 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, trees are more commonly propagated via cuttings and layering. In this case, guava tree fruiting should occur when the tree is 3-4 years of age. Orange trees may bear fruits 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.

[20]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 when the project was created.

Table 6: Impacts of orchards and shelterbelts on children 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 has Close if her community is less than 15 km to 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).
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

5 Discussion

Western African households are particularly vulnerable to growing soil erosion under arid climate. This harmful process leaves them with fewer alternatives to find sources of edible products and to protect their lands. In 2007, policy makers across the continent committed to an environmental restoration program named the Great Green Wall. This paper presents the first evidence that an environmental restoration program, such as the GGW in Nigeria, improves children's health by providing better food access to the local populations. We match nationally representative socio-demographic surveys to precise location of Nigerian GGW environmental restoration projects to explore the impact of the program on children's height-to-age and dietary diversity score. The heterogeneous exposure to the projects in time and space allows to distinguish treated households from control one and establish a DiD model. Parallel trend estimations and IPW method 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 implication for program design since they inform about the specific types of GGW activities that benefit the most to local children. First, the estimates show a positive and long-distance impact of orchard activities on children health whereas shelterbelts are associated with strong health improvement of children at a short distance only. The orchards seem to have long distance impacts on children health since some positive spillovers are still captured at 20 km. We bring evidence that this health improvement is coupled with a higher dietary diversity for the surrounding children.

As first 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 program has been implemented heterogeneously across Sub-Saharan Africa. For instance, Niger decided to distribute grains to the local population whereas Burkina Faso tried to rehabilitate lands through the development of traditional practice in the communities. Therefore, our results are specific to the Nigerian case but does not provide an overall assessment of GGW effectiveness. The vast range of initiatives undertaken to restore lands deserve a cross-country and comparative analysis to better capture the specific greening activities that may benefit the most to the local population. 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 statistics of the projects

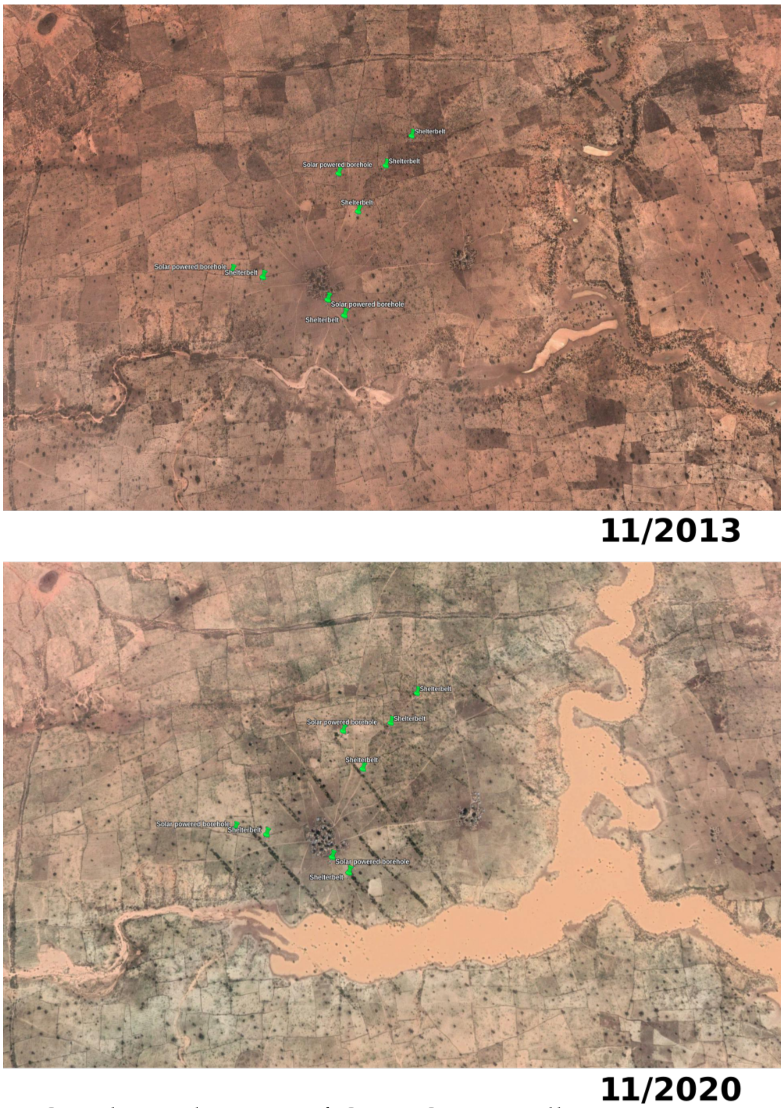

Figure A1: Two Google Earth views of Great Green Wall projects in Nigeria during the 2013-2020 period. Project in these views include 5 shelterbelts and 3 solar powered boreholes, which are observed during the winter, before (in 2013) and after (in 2020) their implementation (in 2015).

Table A1: Project size summary statistics

Variable	Mean	Std. Dev.	Min.	Max.	N
Shelterbelts lenght (km)	1.338	0.868	0.65	5	204
Orchards size (ha)	2.829	1.228	1	7	111

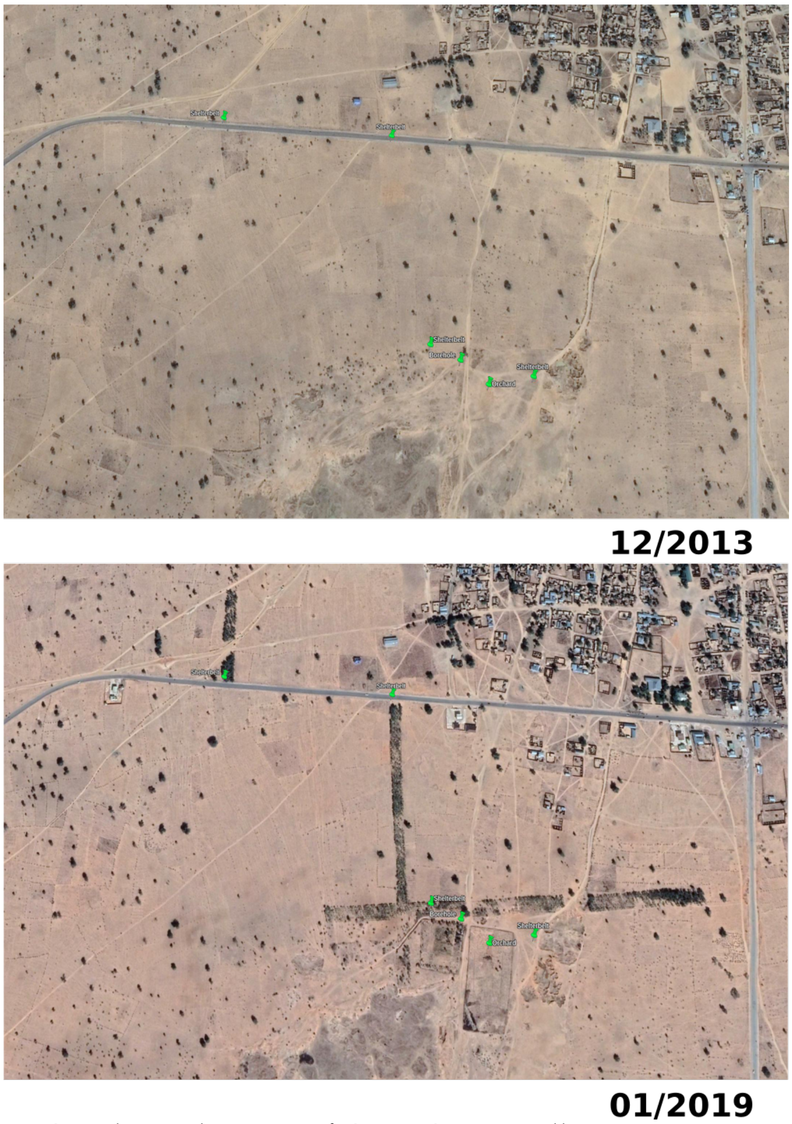

Figure A2: Two Google Earth views of Great Green Wall projects in Nigeria during the 2013-2020 period. Project in these views include 4 shelterbelts, a solar powered borehole and an orchard, which are observed during the winter, before (in 2013) and after (in 2019) their implementation (2014-2015).

Figure A3: Two Google Earth views of Great Green Wall projects in Tumbo, Bachaka, Kebbi, Nigeria (on the border between Niger and Nigeria) during the 2013-2020 period. Project 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 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 has Close if her community is less than 15 km to 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.

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 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 has Close if her community is less than 15 km to 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.

All children living in communities more than 100 km away from an orchard or a 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 averages fixed effects

Table A5: Impacts of orchards and shelterbelts on children 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 has Close if her community is less than 15 km to 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.

The child is defined has 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 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 closed (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 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 closed (less than 15 km) to a Orchard project joint with a borehole or to a Shelterbelt Project joint with a borehole. 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 has Close if her community is less than 15 km to 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

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