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Greening for the greater good

The case of Action Against Desertification in Northern Nigeria

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Abstract

We analyse the socioeconomic impact of Action Against Desertification (AAD), a landscape restoration initiative in Northern Nigeria. Our goal is to assess the project's impact at five years from the start of its implementation on household livelihood diversification and food security. These impacts are the expected outcomes of increased income generation from restoration activities and a better ecosystem for agricultural activities. By using a multimethod strategy, we seek to generate more rigorous evidence on landscape restoration and its impacts at household level. Using pre-restoration remote-sensing data, a machine-learning algorithm is used for the identification of similar pieces of land to AAD restoration sites. Comparison households were then selected from communities bordering these sites through a replication of the AAD targeting process. Finally, the impact analysis is based on propensity score adjustment techniques, applied to survey data. Overall findings suggest that participation in landscape restoration influenced household-livelihood strategies towards climate-resilient options, including a reduction of crop sales accompanied by an increase in the commercialization of livestock and livestock by-products. Households also planted more trees on their individual land, because of restoration of communal and public lands. While this occurred without harming food security, we don't observe a substantial increase in food security within treatment households. This suggests that food security support could be strengthened as part of restoration activities and/or that impacts of opportunity-led diversification may need a longer period to accrue. Larger impacts observed within the early takers of the programme reinforce these conclusions. Overall, the analysis also provides an innovative approach to *ex post* evaluations settings.

Keywords: diversification, landscape restoration, food security, climate change adaptation.

JEL codes: O13, Q12, Q23, Q57.

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1 Introduction

Land degradation – the reduction in the physical, chemical or biological status of land (Eswaran *et al.*, 2001) – negatively affects the livelihoods of about 3.2 billion people globally (IPBES, 2018). The Sahel region in sub-Saharan Africa is particularly vulnerable to this phenomenon, where biophysical factors interact with anthropogenic ones, contributing to increased food insecurity and poverty (UNEP, 1992; UNEP, 2012). On the one hand, rising temperatures and shifting rainfall patterns caused by climate change are hastening the degradation of natural resources in the Sahel (Batterbury and Warren, 2001; USAID, 2017). In particular, hotter and dryer conditions make the natural regeneration process less effective, contributing to overall reduction of biomass.[1] On the other hand, anthropogenic factors in this region, including exponential population growth (Raynaut, 2001), is leading to an excessive pressure on natural resources. This is observed in the reduction of fallow periods, extensive cultivation, overgrazing, and increase collection of firewood by local populations (Olsson *et al.*, 2005; Doso, 2014).

Land restoration is seen as an important mechanism to tackle land degradation and desertification in ways that improve both ecosystem functionality and the well-being of land users. The Great Green Wall for the Sahara and the Sahel Initiative (GGW) aims at elevating the restoration efforts through the establishment of a transitional zone between the arid Sahara Desert and the humid Savannas to the south, across eight Sahelian countries (GGW, 2022).[2] While achieving their biophysical goals, the projects implemented under the GGW also aim at improving the livelihoods and food security of local people. These effects are seen as strategic for sustaining restoration investments in the long run. Their main premise is that a restored natural environment will lead to improved conditions for agricultural production, the processing and commercialization of a wide range of non-timber forest products (NTFP), and the provision of other critical ecosystem services. As farmers contribute to land restoration and protect its natural environment, they also improve their livelihoods and income generating opportunities, supporting the maintenance of restoration investments in the longer term (GGW, 2022). While these assumptions already influence the design of many restoration interventions, the literature still lacks evidence on the causal impacts of land restoration on socioeconomic outcomes (Malan *et al.*, forthcoming; Barbier and Hochard, 2018; Prince *et al.,* 2018).

Our analysis is placed within one pioneer land restoration project in the GGW, the Action Against Desertification (AAD) programme, which supported land restoration activities in six countries of the Sahel during 2016 and 2020. The AAD model combined large-scale mechanized restoration with a range of livelihood support activities to incentivize participation of the local population and maximize welfare improvements from landscape restoration. Our study investigates the socioeconomic impacts of AAD implemented in Northern Nigeria through an *ex post* quasi-experimental framework. The main research question is whether the restoration of the natural environment, implying important changes in local natural resource

[1] Soil erosion (and its consequent soil nutrient loss), degradation of crust development, and salinization are particularly stringing in this region (UNEP, 2012).

[2] AAD was implemented by the Food and Agriculture Organization of the United Nations (FAO) with funding from the European Union. The countries covered by AAD in the GGW were Burkina Faso, Ethiopia, the Gambia, the Niger, Nigeria, and Senegal. AAD has since expanded to other countries not under the GGW. Haiti, Fiji, and the countries of the Southern African Development Community (SADC).

management and livelihood strategies, can lead to improved, lower-risk livelihoods, and to food security. We use a novel approach to identify a valid comparison group for this study. First, we use a machine-learning algorithm on pre-intervention spatial data to identify restoration locations with similar characteristics to the AAD ones. We then mimic the targeting process at household level to address issues of selection bias. These methods are promising for future evaluations of land restoration and similar climate-related projects, where random assignment of treatment is difficult and where budgets for evaluation are often quite limited.

The analysis finds that AAD in Northern Nigeria was successful in fostering more climate-resilient livelihood strategies, with decreased sales from climate sensitive crop production, and increased sales from livestock and livestock by-products, particularly of small and medium animals. These changes were facilitated by AAD's restoration and training activities which promoted the preservation of communal land restoration and fostered additional livelihood opportunities. This is reflected in findings that AAD participating households were more likely to engage in communal land through the provision of household labour and collecting specific resources from these lands including NTFP such as Balanites. On the other hand, we found that AAD did not use communal resources for grazing cattle or fodder collection. These households were also more likely to have received agricultural information and training on agroforestry and marketing of NTFP, including more involvement of women and youth in such trainings. Households also planted more trees on their individual land as a result of restoration of communal and public lands. Overall, we find that these livelihood adjustments occurred without damaging food security, and with evidence that ADD led to improvements in some aspects of food security (including worrying less about not having enough to eat, skipping less meals, and not running out of food). The overall impact on food security (measured with Food Insecurity Experience Scale [FIES]) is small, suggesting that the support to local populations' livelihoods could be further strengthened as part of restoration activities and/or that impacts of opportunity-led diversification may need a longer period to accrue.

The rest of the paper is organized as follows. Section 2 details AAD's approach and the context in which it operated in Northern Nigeria. Section 3 presents the analytical framework. Section 4 presents the data used in the analysis and sampling design. Section 5 provides details on the empirical strategy, including the econometric approach. Section 6 presents the results and Section 7 concludes.

2 Background

In 2014, AAD was launched to restore drylands along Africa's GGW in multiple countries, including Nigeria.[3] Its implementation effectively began in 2016, helping restore about 35 000 hectares of land across six countries of the Sahel by the end of the programme in 2020. Together with the National Agencies for the Great Green Wall (NAGGW), the AAD established criteria for the selection of sites to be restored in each country, and provided spatial analysis as well as feasibility studies at community level.[4]

Once sites were established in each country, AAD engaged with local communities to start the restoration activities. Previous research defined the selection of tree species; however, the programme also emphasized the participation of local communities in the selection of trees and plants, in support to their income generating activities. The programme worked to mobilize the production and distribution of quality seeds needed for restoration and provided trainings on restoration practices, and the use and commercialization of NTFP (Sacande *et al.*, 2020). The principal intervention of AAD is large-scale restoration and its related preparatory activities at community level. Delfino ploughs were used to plough deep half-moons in restoration areas.[5]

Our evaluation of AAD focuses on the restoration activities in Northern Nigeria, in the states of Bauchi, Jigawa, and Sokoto (Figure 1). Between the period of 2007 and 2015, these states had experienced a 50 percent decrease in forest cover, with nearly all of it converted to croplands.

The locations of AAD in Northern Nigeria are mainly agricultural. Crop production is focused on subsistence production of groundnuts, cotton, millets, beans, Guinea corn, cassava, yam, and maize (Abdulkadir, 2017; Nigerian Government, 2021). Croplands are predominately rain-fed, and thus are highly vulnerable to the effects of climate change (Abdulkadir, 2017; Nigerian Government, 2021). Croplands account for nearly two-thirds of land use in the states that received AAD restoration, with implications for forest loss (Sacande *et al.,* 2018).

Cattle rearing is another important livelihood strategy in the project areas (Abdulkadir, 2017). The majority of beef and milk production in the country is produced by seasonally-nomadic pastoralists (Abdulkadir, 2017). Also, Nigeria's milk and indigenous meat's respective gross production index number (GPIN) had been higher than that of crops before AAD's project formulation, during the period of 2011–2015 (FAO, 2023).[6] Additionally, the hides, skins, and

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[3] AAD was implemented by the Food and Agriculture Organization of the United Nations (FAO) with funding from the European Union. The countries covered by AAD in the GGW were Burkina Faso, Ethiopia, the Gambia, the Niger, Nigeria, and Senegal. AAD has since expanded to other countries not under the GGW. Haiti, Fiji, and the countries of the Southern African Development Community (SADC).

[4] Selection criteria required that community land is available for restoration (50 hectares at min/100 hectares max) per village (not necessarily one piece); suitability for community-based resource management around cultivation, grazing, or forestry; easily accessible by villagers; and where an agreement-in-principle with the local population had been reached to initiate restoration activities (Sacande *et al*., 2020).

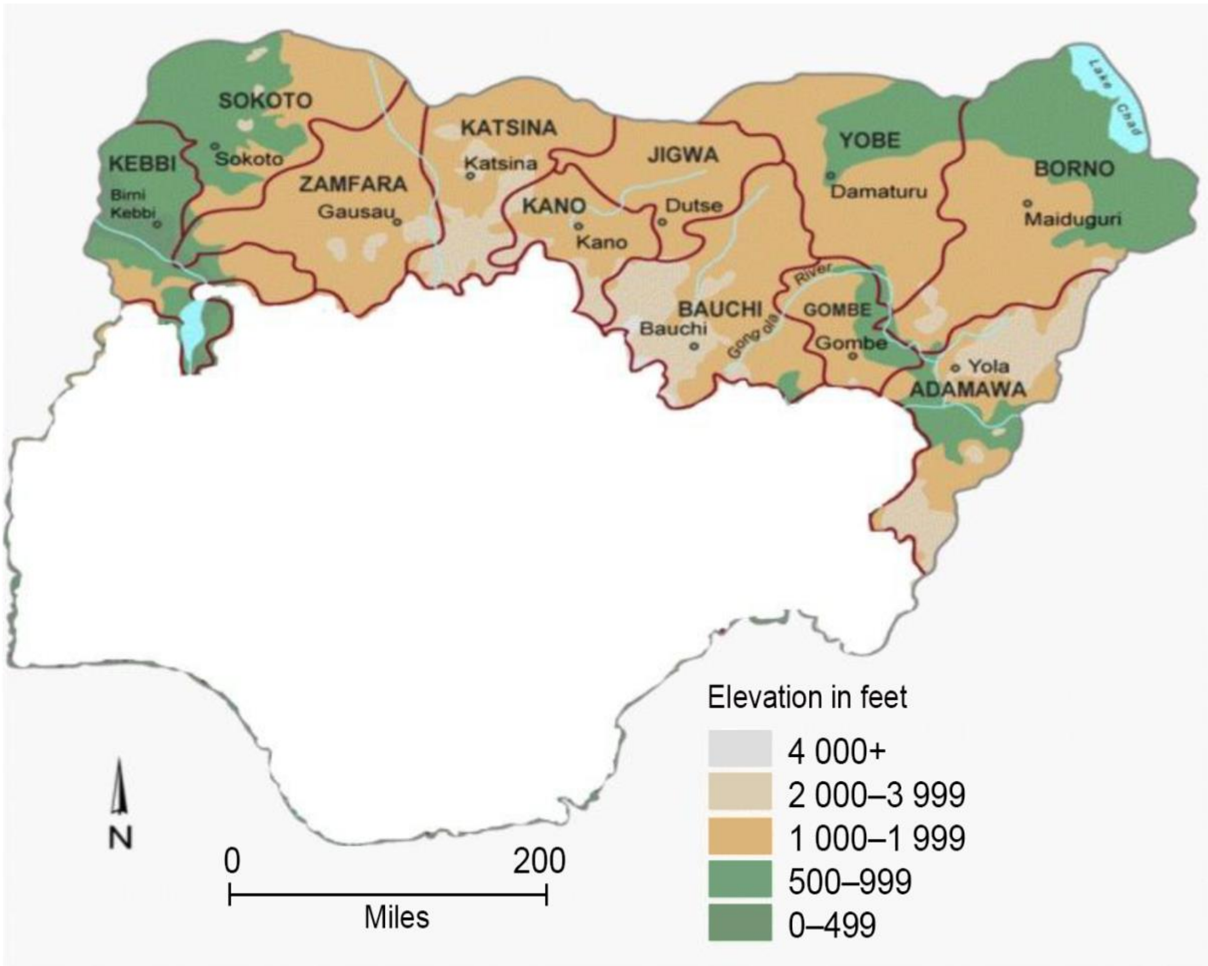
[5] These ploughs have a capacity of land preparation of 15–20 hectares a day. The ploughs were not available for all communities in Nigeria, especially at the start of the project, so some communities started large-scale restoration activities later.

[6] The average GPIN for the period 2011–2015 was 105 for milk, 96 for indigenous meat, and 89 crops respectively (FAO, 2023).

leather from cows, sheep, and goats are an important income source (Sacande and Parfondry, 2018). Agropastoral groups, mostly of Fulani origin, rear small ruminants (e.g. sheep) to provide meat for their families. Cattle is instead used for capital, investment, and prestige (Doso, 2014). Transhumant Fulani travel through the lands of farming communities as their cattle feed on the stover and fallows on farmlands, which tend to be managed by Hausa peoples (Suttie *et al.*, 2005).

Beyond agriculture and livestock, NTFP are a means of generating income in Northern Nigeria. NTFP refer to useful substances, materials or commodities obtained from forests that do not require the harvesting of trees (Sacande and Parfondry, 2018). Best estimates of NTFP as share of income for rural households in Nigeria range from 30 to 80 percent (Suleiman, 2017; Jimoh *et al.*, 2013). Also, work in Southern Nigeria has found that over 40 percent of household meals contained NTFP (Chukwuone and Okeke, 2012), making it also relevant for household food security and nutrition. Honey, Arabic gum and Balanites oil were identified in the project as having the potential to improve household livelihoods (Sacande and Parfondry, 2018).

Figure 1. Northern Nigeria: states prioritized by the Nigerian Agency for the Great Green Wall (NAGGW) in consultation with Action Against Desertification



Source: Nigerian Government. 2021. *National Strategic Action Plan for the Implementation of GGW Programme, 2021–2025.* 2021. Abuja.

3 Analytical framework

Landscape restoration activities are motivated by interlinked environmental and socioeconomic objectives. Environmental objectives include restoring and preserving ecosystems and its related services, protecting biodiversity, halting, or controlling desertification and mitigating climate change (van Oosten, 2013; Locatelli *et al.,* 2015). Restoration activities also seek to improve the well-being of people that rely on the natural environment for their livelihoods. Sustaining local communities' livelihoods is necessary to preserve the outcomes of restoration (GGW, 2022). Both objectives can be mutually reinforcing when the restoration of ecosystems leads to improvements in livelihoods, to a level where sufficient incentives are created for households to preserve the outcomes of restoration. However, tension often exists. Restoration activities depend on changing the ways people use and derive benefits from landscapes. Successful restoration activities must, therefore, manage potential trade-offs and enhance the synergies between socioeconomic and environmental objectives (Mansourian *et al.*, 2020; Cumming and Allen, 2017). The AAD model sought to address this tension by including in the landscape restoration activities the needs of the local populations.[7]

Socioeconomic benefits from landscape restoration can be generated through multiple direct and indirect channels (Adams *et al*., 2016). Directly, restoration activities can improve incomes and other welfare indicators through cash payments generated by the intervention. Depending on the restoration modality, this can include payments for ecosystem and carbon mitigation services (Jindal *et al.*, 2012; He and Sikor, 2015; Liang *et al.*, 2012), payments received through employment activities generated by the programme itself, and through the creation of new markets for restoration products, such as seeds and seedlings, or other NTFP.[8] Despite not having a direct payment component (like a cash transfer), projects like AAD can generate income effects through increased sales from NTFP, and diversification into higher value climate-resistant crops and tree products, as seen in other similar projects in the Niger (Haglund *et al.*, 2011), Burkina Faso, Mali, Senegal (Binam *et al.,* 2015), Ghana (Weston *et al*., 2015), and Ethiopia (Lemenih and Kassa, 2014). Also, from sales of seed by local households to support restoration activities (Sanches 2015; Durigan *et al.*, 2013).

Indirectly, landscape restoration can enhance incomes through several channels. First, improvements in soil quality and animal feed availability (e.g. fodder) can enhance agricultural and livestock productivity. These indirect benefits have been observed in several studies of forest landscape restoration, including increased average cereal yields in the Niger (Reij *et al.*,

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[7] Evidence from the implementation of landscape restoration interventions suggests that the extent to which local people are involved in the design and implementation of the restoration activities plays a determining role in managing trade-offs between socioeconomic and environmental objectives (Sacande and Berrahmouni 2016; Adams *et al*., 2016). A review of programmes from Reducing Emissions from Deforestation and Forest Degradation (REDD) + for forest restoration, including in Africa's drylands, suggests that bottom-up approaches (like that of the AAD model) produce better socioeconomic impacts than those initiatives developed and implemented by central governments, which often follow a top-down approach (Adams *et al.*, 2016; Duchelle *et al.,* 2017). Several studies also suggest that when communities and local individuals are excluded from decision-making processes and resources, restoration efforts often generate negative or minimal socioeconomic and food security impacts (He and Sikor 2015; Barr and Sayer 2012; Wandersee *et al*., 2012; Ros-Tonen *et al.,* 2013).

[8] As described earlier, the AAD programme focused specifically on the latter two, and did not include direct payments for ecosystem services.

2009; Reij and Garrity, 2016; Binam *et al.*, 2105); increased availability of fodder and water, livestock reproduction, and the availability of manure[9] (Franzel *et al.,* 2014; Reij, 2009). AAD focused specifically on developing these impact pathways through the digging of demi-lunes and the planting of fodder and economically valuable tree and shrub species in the restored lands. Evidence from regions in Ethiopia estimates that the NTFP derived from the dry forests account for 23 percent of household income, with NTFP helping to keep an estimated 20 percent of households above the poverty line (Walle and Nayak, 2022). Finally, reductions in time allocated to gathering wood and fodder can support opportunity-led household diversification, including that of women who often carry-out these tasks. A study of as restoration programme by Sendzimir *et al.,* (2011) found that the time saved in the collection of wood was dedicated to a range of activities, including education, food production and preparation, non-farm businesses, and greater participation in local leadership positions (Reij *et al.,* 2009, Sendzimir *et al.,* 2011, Weston *et al.,* 2015).

As a result of their direct and indirect impacts, landscape restoration activities promote the diversification of households' income strategies, both for direct beneficiaries and within the broader community (Adams *et al.*, 2016). In Indonesia, participants in a reforestation initiative were able to leverage the knowledge learned from the intervention to find wage employment with NGOs, oil palm producers, and in seedling nursery's (Pohnan *et al.*, 2015). In Ghana, a system to restore forest systems led to the creation of non-farm opportunities in cocoa production and processing, as well as petty trading (Ros-Tonen *et al.,* 2013). By enabling diversification of livelihoods across activities with varying levels of exposure to weather and market variability risks, and supporting ecosystem functionality, landscape restoration activities can support improvements in household's resilience to shocks (Mohammed *et al.*, 2021; Ngigi *et al.*, 2021).

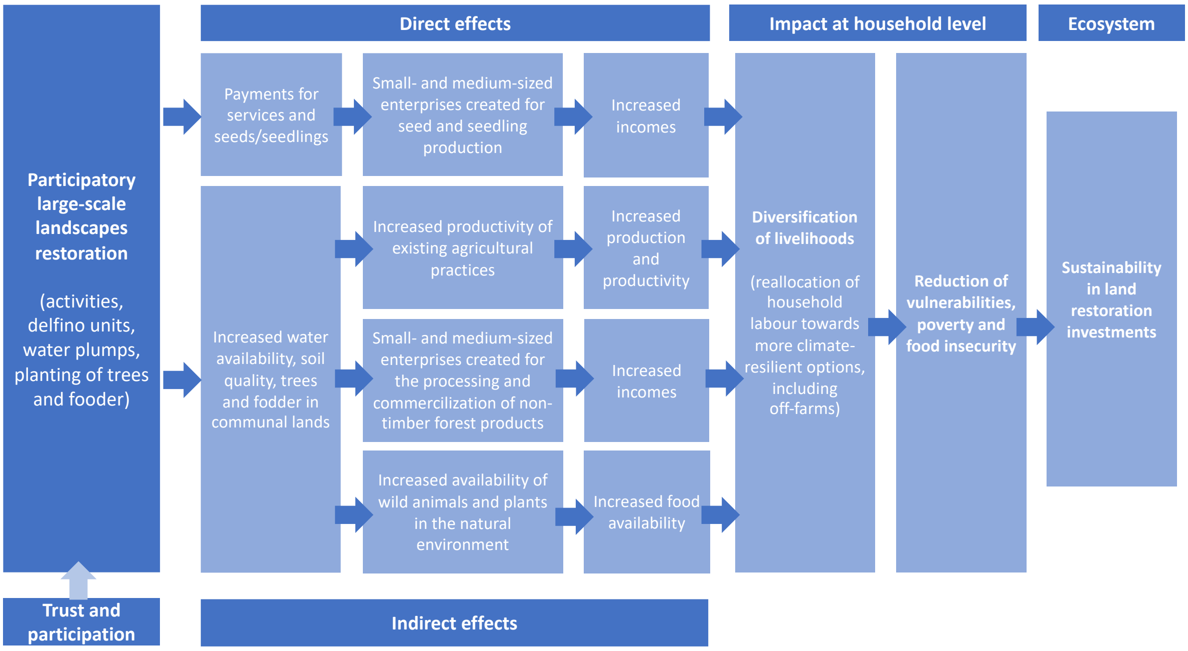
Finally, landscape restoration activities can have beneficial impacts on the food security of direct beneficiaries and community members. These impacts derive from improvements in the availability (and diversity) of foods from a restored natural environment, and increased access to food through improved incomes and food availability (e.g. from NTFP). In Burkina Faso and the Niger, restoration activities seem to have reduced participating households' seasonal food deficits (Reij *et al.,* 2009). Improvements in dietary diversity were also observed, with an increased number of households consuming wild plants and animals (Weston *et al.*, 2015; Reij and Garrity, 2016).

The final piece of this analytical framework concerns how more resilient livelihoods that reduce poverty will sustain land restoration outcomes. At a macro-level, there is evidence of a strong relationship between environmental degradation and poverty (Masron and Subramaniam, 2019; Baloch *et al.,* 2020). At the household level, analysis in Indonesia and Malaysia identifies poverty as the leading factor in deforestation and that reducing poverty leads a reduction in deforestation (Miyamoto, 2020). However, there is not conclusive evidence about how landscape restoration of forests can achieve both ecological and poverty reduction goals

[9] Manure availability, in turn, has been found to support further improvements in soil quality and crop yields, and the emergence of a market for manure and transportation (Reij, 2009).

(Hajjar *et al.*, 2021; Lawlor *et al.*, 2019; Cheng *et al.*, 2019).[10] While our study lacks the length and information necessary to test AAD's impacts on the nexus between long-term sustainability and poverty reduction, we believe this is an area worth considering in future studies. In Nigeria, about 40 percent of the population live below the poverty line, of which 75 percent live in the north of the country (World Bank, 2021; Ibrahim *et al.*, 2021). If increasing poverty leads to deforestation, identifying economic opportunities requiring a healthy landscape becomes relevant for achieving both sustainable landscape improvements and poverty reduction altogether. These theoretical pathways are summarized in Figure 2.

Figure 2. Theoretical impact pathway of landscape restoration at household level



Source: Authors' elaboration.

[10] Instead, there is some evidence on the links between poverty reduction and other related areas such as ecotourism, community forest management, agroforestry and, to a lesser degree, payments for ecosystem services (PES) (Hajjar *et al.*, 2021).

4 Data

4.1 Data sources

The analysis of AAD's impact draws on a combination of data sources, including a household and community-level socioeconomic survey implemented four years after the start of AAD on the ground. In addition, we use high resolution socioeconomic and biophysical remote-sensing data of the sites of the project for the selection of comparison sites as well as in the analysis of impacts.

The household data analysed in this study was collected from 1 325 households in 102 communities of 25 Local Government Areas (LGAs) across four states of Northern Nigeria – Bauchi, Jigawa, Kano and Katsina states (shown in map A of Figure 3). The sample is comprised of 546 AAD (treatment) households and 779 comparison households. Treatment households for the survey were identified through the programme participant list; while comparison households were selected following a targeting exercise on a hypothetical programme (see Annex 5 for a detailed description of this approach).[11] Community data was collected from the community leader or another knowledgeable individual in each of the 102 AAD and non-AAD communities.[12]

We also use different sources of remote sensing data from the areas of the study (including processed data through machine learning techniques) to increase performance in the identification of the comparison group, as well as to address potential differences in unobservable characteristics between both treated and comparison communities. The data includes a risk measure of extreme weather events, an asset wealth index, and a vegetation index. We create the risk measure summing the number of extreme weather events that occurred in the ten years prior to the start of the programme, from 2006 to 2016.[13] Extreme weather events are assessed from the Standardized Precipitation-Evapotranspiration Index (SPEI).[14] The asset wealth information is from ATLAS-AI[15] (Atlas AI, 2021; based on Yeh *et al.*, 2020); and the vegetation index is the Normalized Difference Vegetation Index (NDVI),

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[11] The household questionnaire was designed specifically for the evaluation of AAD. It was administered to the household head or other knowledgeable adult of 15 years or older. Sections of the questionnaire covered multiple topics including household demographics, agriculture, use and commercialization of NTFP, off-farm employment, migration, shocks and coping strategies, and perceptions of climate change, among others. The data was collected between 16 October and 16 November 2021, immediately following the rainy season, and six years after the start of the AAD programme.

[12] The community questionnaire aimed to assess topics such as features of the community; presence of support programmes; access to markets, health facilities, schools, and other services; presence of community groups; use of communal lands; perceptions and methods of adaptation to climate change; and incidences of conflict. The community questionnaire was collected at the same time as the household questionnaire.

[13] Formal statistical tests differences between treated and comparison distributions were conducted. The test were: Welch (it is based on the t-student statistic, hence it assumes a normal distribution); Wilcoxon (it is based on the rank sum, hence it is a non-parametric test); and Kruskal-Wallis (it is based on rank sum, hence it is very similar to the Wilcoxon test). The tests were performed on the mean, standard deviation, and kurtosis.

[14] SPEI is a normalized index that combines precipitation and temperature to identify significant variations relative to long-term trends, specifically droughts or floods (Vicente-Serrano *et al.,* 2010). This can be parametrized to specific time periods, in our case three-months.

[15] See Annex 3 for details on the construction of the ATLAS-AI asset wealth variable.

both estimated for 2016 from the 5 km radius of the centre of each community surveyed. Additional remotely-sensed data was utilized for the identification of the counterfactual and will be discussed in the following section. For a full list of this data see Annex 2.

4.2 Sampling design and identification of comparison group

Since the selection of communities for participation into AAD was based on landscape criteria, namely proximity to communal land with specific characteristics, we identified the potential counterfactual communities by first identifying similar land areas to those of AAD and then selected nearby communities. We identified the geographical coordinates of each of the AAD restoration areas and used remote sensing data prior to the start of AAD's activities (year 2016). Biophysical and socioeconomic data were used to build a profile of the restoration sites and then to find similar parcels of land in neighbouring LGAs.[16] A Support Vector Machine (SVM), a computer-vised machine-learning algorithm, was used to identify similar plots of land to those restored by AAD at baseline. The SVM is an algorithm used for classification or regression challenges when handling multiple variables, both categorical and continuous (Vapnik, 1995). The algorithm learns by example to assign labels to objects (Noble, 2006), which produces classes or types to which data is classified into. In our case those classes were classified as "similar or not similar" to those restored by AAD.

SVM learned which variables were significant in the assignment of the AAD restoration activities by examining data on each pixel of restored land, at 10 m^2 spatial resolution.[17] It then used that information to train the algorithm to find pixels with similar properties in the area of interest – initially the whole area of the four states, then its northern areas (shown in Figure 3). The result of this similarity analysis was a map indicating areas where pixels outside of AAD areas were similar to the restoration sites prior to the start of AAD restoration activities (Figure 3b). Through a visual inspection, we then identified the densest clusters of similar pixels and selected the closest communities to these clusters.

The approach has both advantages and disadvantages for the performance of similarity analysis. In terms of advantages, it allows more flexibility in terms of data input. The unsupervised classification as input of the SVM integrates well the existing Land Use/Land Cover (LULC) 2016 map and possible inaccuracies since it is a product created for national scale analysis. On the other hand, the results can be affected by the training data input and therefore, when only few or very small sites are used in the modelling, uncertainties around the results can be expected. In our case, given the small size of AAD restoration sites, the sites had to be clustered in ten groups, as shown in Table A4 (Annex). To test if the approached performed satisfactorily, we assess the pre-treatment parallel trends of both treated and

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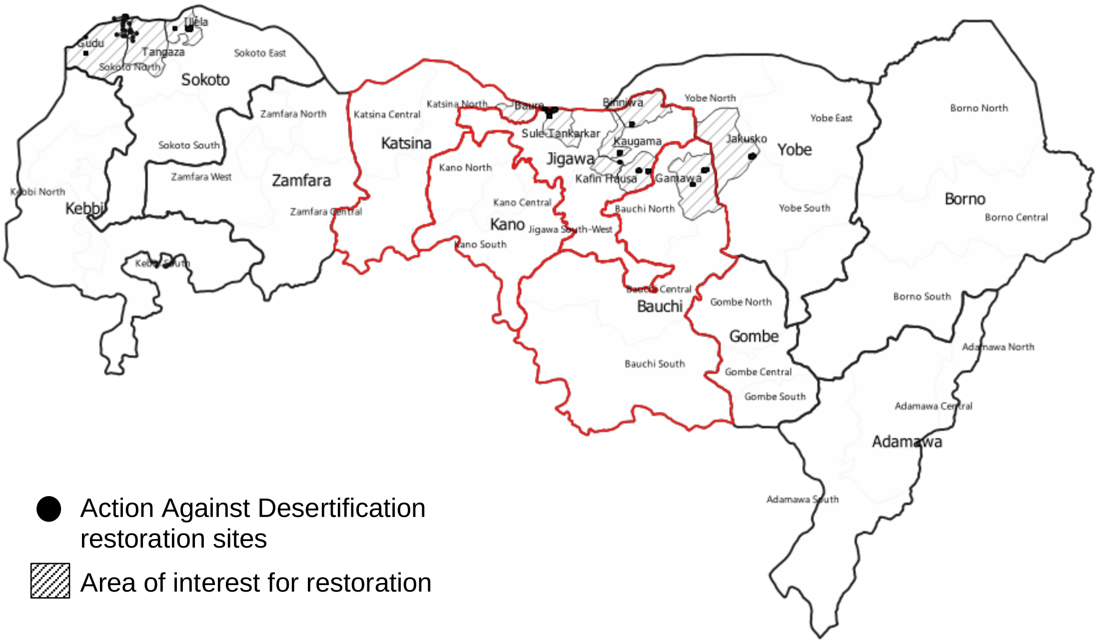
[16] The indicators that were used to find plots with similar characteristics are: slope and elevation, soil texture, soil drainage, soil type, normalized difference vegetation index (NDVI), Modified soil-adjusted vegetation index (MSAVI), Normalized difference moisture index (NDMI), bare soil index (BSI), road network, travel time to health services, national land use and land cover map, asset wealth index, electrification status. Annex 4 reports description and sources for each indicator.

[17] An unsupervised machine learning algorithm would see us feeding data in and asking the algorithm to determine patterns. In this case, we are telling the algorithm what the pattern is, i.e. this is the land that has been restored.

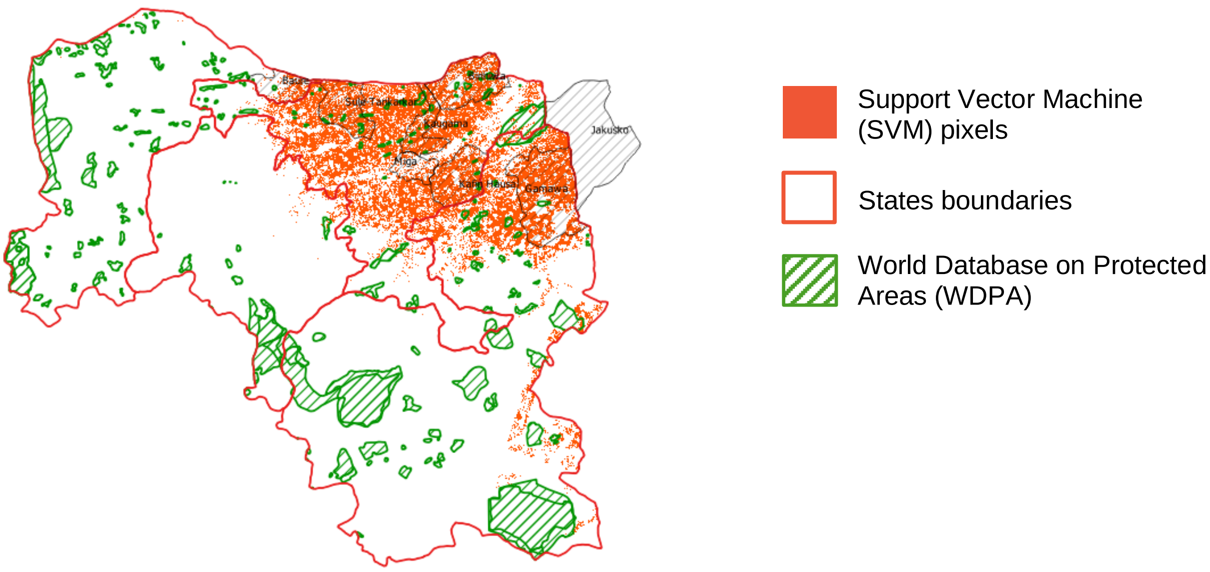
comparison sites based on wealth, vegetation and climate spatial information with overall satisfactory results (see results in Figure A1).

Figure 3. Northern Nigeria: restored areas by Action Against Desertification and similar areas at baseline, based on Support Vector Machine modelling

a. Area of interest for restoration and Action Against Desertification restoration sites



b. Similarity analysis output based on Support Vector Machine modelling. Orange areas denote similar areas to those restored by Action Against Desertification at baseline (year 2016)



Notes: The first map (a) shows the areas of interest for the study, covering mainly four states (Katsina, Kano, Bauchi and Jigawa), underlined in red. The dashed areas indicate the LGAs (Local Government Areas) for restoration, while the black dots mark AAD sites of restoration.

Source: GADM. 2022. *GADM Maps*. https://gadm.org, modified by the authors.

While we did not find other studies that apply this technique for the identification of a comparison group in a landscape-based project, there are examples of SVM applications of this technique to identify suitable land for project implementation, including land suitability for cultivated wheat in Iran (Sarmadian *et al.*, 2014), land use/land cover suitability in Indonesia (Safitri *et al.*, 2021), and peatland restoration in Indonesia (FAO, 2021).

After the selection of comparison sites, survey data was collected in 102 communities, (all 42 AAD and 60 as counterfactual) from 25 Local Government Areas (LGAs) in the four states of Northern Nigeria – Bauchi, Jigawa, Kano and Katsina states. The average size of restoration sites was 41 hectares, with a maximum of 255 hectares and a minimum of 2 hectares. Treated households for the survey were identified through the programme participant list. Comparison households, on the other hand, were selected by mimicking the process of selection of AAD participants to minimize as much as possible the selection bias. The selection process was led by the Zonal Forest Officers (ZFO) and the village heads who decided which households and individuals to assign to each of the seven-project activities (i.e. community management committees (CMC), community watch groups, micro-gardens, nurseries, seed collection, land restoration and value chain training). To replicate the same selection process that was used to select participant households, a targeting exercise on a hypothetical programme was conducted in each community. In practice, we approached ZFOs and village heads of comparison villages, described the features of AAD and asked them to provide a list of households that would have been selected if a project like AAD were to be implemented in their communities.[18] From the list of households that the village head nominated to work on hypothetical project tasks, which contained at least 30 households, 13 households per community were randomly selected for administering the questionnaire.

To select the treated households, AAD administrative data was used to create a list of beneficiary households that was presented to the village head for verification upon arrival of the data collection team. Once verified, the data collection team randomly selected from the list 13 households per community for administering of the questionnaire.

4.3 Definition of outcome indicators

The outcome indicators used in this analysis are linked to the project's theory of change and are grouped by intermediary outcomes, namely (1) use of communal lands; (2) agroforestry information and practices; and final outcomes, namely (3) livelihood and diversification strategies; and (4) food security.

We measure engagement with communal land by looking at whether households provided any labour to work related to community land (e.g. for planting or for restoration), whether households used communal land for grazing cattle or collecting any NTFP and fuelwood, and whether households participated in community groups. The list of groups included agricultural/livestock producer's group, water users' group, forest users' group, and trade/business association. All these variables are constructed as dummies.

[18] It is worth stressing that we explained that this was only a hypothetical scenario, and that there was no plan to implement such project in those communities. This point was emphasized and reiterated periodically to avoid raising false expectations and ensure the ethical standards of conducting research (see Annex 4 for the script of the interaction and for a detailed description of this approach).

For access to agroforestry-related information, we use three indicators: whether anyone in the family had access to any information learning opportunity (dummy); the number of topics they had access to (from zero to seven), and; whether women or youth (15 to 25 years old) were the recipients of this information (dummy).[19] For agroforestry practices, we proxy whether the involvement of households in agroforestry by looking at whether someone in the household planted any tree in the previous three years (dummy).

Livelihood strategies are proxied by four indicators: number of income sources, livestock ownership, hired labour for agricultural activities (dummy), and borrowing resources for agriculture production (dummy) as an additional indicator of increased crop production. The number of income sources ranges from zero to six and include the following categories: crop sales, livestock by-products sales (e.g. hides, milk, eggs, etc.), livestock sales, sales of timber and NTFP, remittances, salaried employment. Animal stock is expressed in Tropical Livestock Units (TLUs).[20] In addition to the overall value of livestock, we also construct three indicators, differentiating by large (e.g. cattle and donkeys), medium (e.g. goats and sheep) and small (e.g. chicken, and guinea fowls) animals.

Livelihood diversification measures examine whether households engage in agricultural activities, whether they engage both in agriculture and in off-farm activities, or in agriculture and timber-NTFP-related sales (all dummy variables). Other indicators used to measure income diversification include the number of cultivated crops, number of crops sold, number of types of livestock sold, number of types of livestock by-products sold, and the number of NTFP extracted. All these indicators were asked with a reference period of the previous 12 months.

Finally, food insecurity is measured with the FIES. The set of eight questions have been included in the household questionnaire, seeking to capture the intensity of the food insecurity experience over the last 12 months previous to the survey. The data collected from these eight questions are analysed by applying a Rasch model from which a probability of food insecurity – both severe and moderate – is obtained (Cafiero *et al.,* 2018).

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[19] Households were asked if they had received information on growing crops well suited to the soil and weather conditions, collecting seeds, agroforestry, timber and NTFP collection and management, natural resource management, cooperative management, and marketing of NTFP.

[20] Tropical Livestock Units refers to a 250 kg animal (e.g. cow). The following conversions from the International Livestock Research Institute for sub-Saharan Africa were used: cattle 1, donkeys 0.8, sheep 0.2, goats 0.2, chickens 0.04, and Guinea fowl 0.04 (Njuki *et al*., 2011).

5 Empirical strategy

Since AAD's landscape restoration activities were not randomly allocated, the effect of AAD on livelihood strategies and food insecurity are estimated using a quasi-experimental framework.

We use a propensity score-based approach for assessing AAD's socioeconomic impacts. Specifically, we use the doubly robust inverse-probability-weighted regression-adjustment (IPWRA) estimator.[21] Given the complex design of AAD's intervention (including the fact that several components of the project reached different types of beneficiaries), IPRWA's doubly-robustness to misspecification, of both the participation and the impact estimation, makes it a suitable approach for this context (Wooldridge, 2010; Linden *et al.*, 2015).

IPWRA estimators first use a model to estimate treatment status, and then, use a second model to predict the outcomes. IPWRA estimators use weighted regression coefficients to compute averages of each treatment-level predicted outcomes, where the weights are the estimated inverse probabilities of treatment (Cattaneo, 2010; Stata Corp, 2021). The comparison of these estimation averages provides the estimated treatment effects, which is, the mean of all treatment-specific predicted outcomes.

Propensity scores Pr(Z) are obtained from a maximum likelihood estimation based on the probability of a household being treated by AAD, as a function of pre-treatment household-level characteristics (Z), as follows:

$$P(Z)=Pr(Ti=1 \mid Z) \tag{1}$$

At this stage, IPWRA estimates the parameters of the treatment model and computes inverse-probability weights. For treated households their weight is calculated in equation three (3) and for comparison households it is calculated by equation four (3).

$$W(Z) = 1/P(Z) \tag{2}$$

$$W(Z) = 1/1 - P(Z) \tag{3}$$

The usual challenge of finding a valid counterfactual is further exacerbated in a context of *ex post* evaluation, particularly when generating propensity scores with *ex post* information. Ideally, propensity scores would be derived from baseline information related to selection criteria of the programme, and other variables that influence the final outcomes to be evaluated. In an *ex post* evaluation, these variables are not available, except for variables that

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[21] We use the command *teffects* in Stata that allows for generalized method-of-moments (GMM) estimators. When weights are specified in the model, these are applied to the estimating equation just as GMM applies user-specified weights. This command is used as it easily calculates the standard errors.

are used as criteria for the selection but that are not affected by the programme (e.g. household demographics).[22]

For the treatment equation, we use a vector of (*ex post*) control variables intended to reflect the factors that affected participation in AAD.[23] With that in mind, the treatment equation includes household variables (Z), namely the gender of the household head, the number of adult females in the household, and the number of working-age youth (15–25 years) in the household, along with marital status of the household head and whether the household uses an improved source for lighting[24] (the latter intended to act as a wealth proxy).

We also include in the equation one community level variable, a climate risk measure, which used the SPEI to count the number of extreme weather events that occurred in the ten years prior to the start of AAD. We believe that most factors affecting the selection of communities into AAD were captured by the work with the SVM, however only variables from the first year of the programme were used. There was no indicator of longer-term vulnerability to weather events, which we hypothesize could influence whether a community was selected (or not) to received restoration. For that reason, the risk measure was included in the treatment equation.

Table 1 shows descriptive statistics on the variables selected for generating the propensity scores before adjustment based inverse probability weighting. The comparison group has slightly more female-headed households, households with slightly less married household heads, more adult women, and young adults. Additionally, comparison households are more likely to use have access to improved lighting source. The comparison group has also experienced more weather-related shocks in the ten years prior to 2017.

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[22] The approach that we used to design the sample and identify the counterfactual should have accounted for several of these characteristics and for possible unobservable dynamics happening during the selection process. By replicating the targeting exercise in comparison communities, we also reduced to a minimum the threat to internal validity and relaxed the Conditional Independent Assumptions (CIA). This approach addressed critical limitations that a propensity-score based technique would have in cases of lack of baseline information on the outcomes of the programme. Also, when estimating a difference-in-difference approach was not possible, which would have removed unobservable characteristics that can usually produce bias.

[23] AAD did have specific requirements in terms of age and gender of participants, however, village leaders were also encouraged to select households that would benefit from participation in AAD. No specific guidance was provided on income levels of participants.

[24] Improved lighting includes the following sources: electricity, kerosene, solar power, and generator.

Table 1. Means of covariates by treatment status before adjustment with inverse probability weights

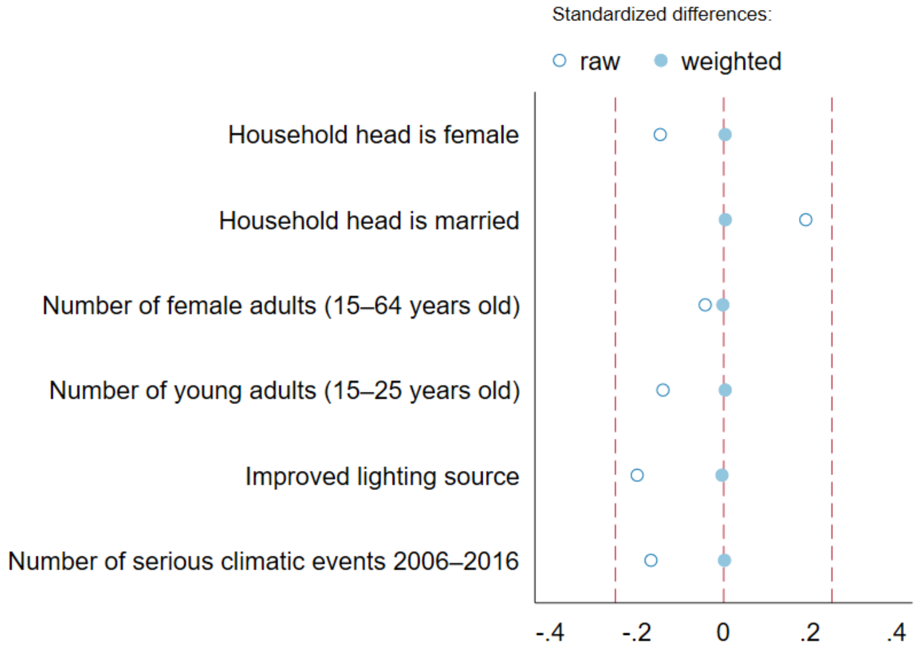
	All	Action Against Desertification early takers	Comparison	Difference
Household head is female	0.045	0.024	0.053	0.028*
Household head is married (monogamous and polygamous)	0.952	0.979	0.942	–0.037**
Number of female adults in the household (16–65 years old)	2.187	2.136	2.205	0.069
Number of young adults in the household (15–25 years old)	2.062	1.878	2.130	0.252*
Improved lighting source	0.122	0.077	0.139	0.062**
Climate risk (2006–2016)	2.172	2.045	2.218	0.173*
Household head age in years	45.901	45.671	45.985	0.313
Household head education in years	4.319	2.339	5.046	2.707***
Household size	9.508	8.937	9.718	0.781*
Household head is of the ethnic majority (Hausa)	0.617	0.430	0.685	0.255***
Asset wealth (2016)	–0.373	–0.357	–0.379	–0.022***
Log of Normalized Difference Vegetation Index (NDVI) (at 5 km radius of comm centre in 2016)	7.902	7.882	7.909	0.027***
The community experienced drought (one year)	0.439	0.455	0.434	–0.021
The community experienced flood (one year)	0.354	0.409	0.334	–0.075*
The community experienced crop disease (one year)	0.696	0.545	0.751	0.206***
The community experienced livestock disease (one year)	0.671	0.545	0.718	0.172***
Observations	1 065	286	779	1 065

Notes: Regression to calculate the weights includes the following covariates in the first equation: female-headed household (dummy), household head married (dummy), number of adult females in the household, number of adult youths in the household (15 to 25), household has access to improved source of lighting (dummy), measure of extreme weather events (2006 to 2016). * p<0.1 ** p<0.05; *** p<0.01.

Source: Authors' elaboration.

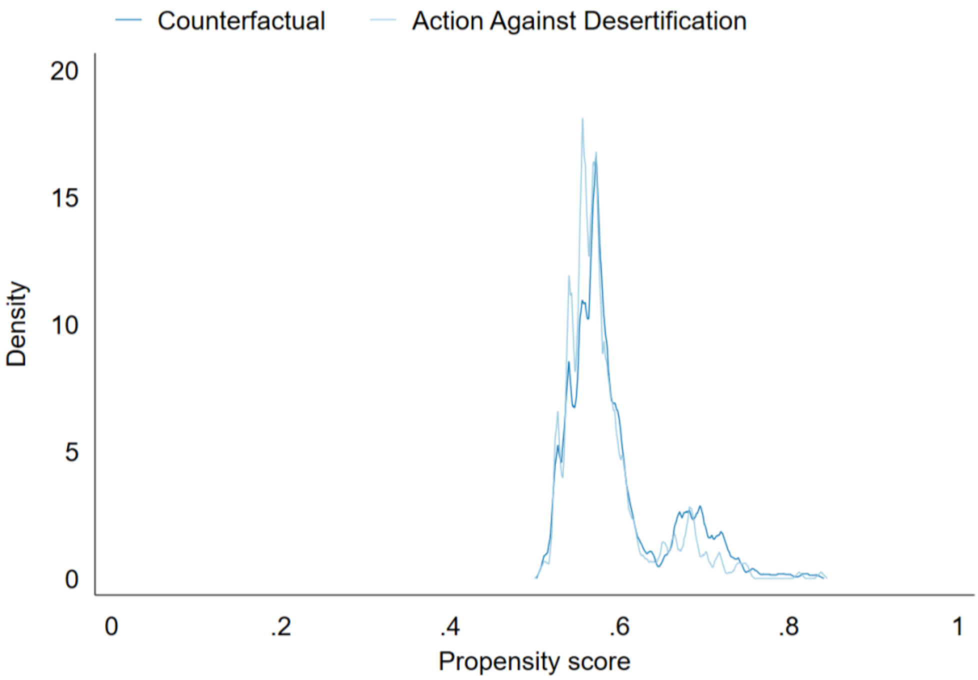
To assess the goodness of our model, we first check the balance of covariates. Figure 4 and Table A3 report the standardized differences between treated and comparison households for each variable used for the participation equation, and the variance ratio. The weighted standardized differences are well below the threshold of 0.25, they are all less than 0.01 and the variance ratios are all close to one. Overall, the model passes the overidentification test, not being able to reject the null hypothesis that the IPWRA model balanced all six base covariates. The unconfoundedness, or overlap, condition is also satisfied. Figure 5 reports kernel density of the probabilities of being in any group after reweighting. There is a very good overlap, which shows that the two groups have similar probabilities of being in either group, there are no spikes, and there is no concentration of observations in the extremes of the distribution.

Figure 4. Balance of covariates



Source: Authors' elaboration.

Figure 5. Overlap assumption (density of the probability of households' participation in Action Against Desertification restoration activities by treatment and comparison groups)



Source: Authors' elaboration.

Using the estimated inverse-probability weights, the model then fits weighted regression of outcome Y based on treatment level, obtaining the predicted outcomes for each household. Finally, the Average Treatment Effects of the Treated (ATET) coefficients are computed as the difference of the mean of all “treatment-specific” predicted outcomes. The IPWRA estimates are obtained by regressing the outcomes Y of household “h” of community “j“ against control variables and the treatment variable through weighted probit or poisson modelling (depending on the nature of the outcome variable used), as follows:

$$Y_{hj} = \propto + \beta_T \text{Treat} + \delta X_{hj} + \mu_j + \varepsilon_{hj} \tag{4}$$

Where Y_{hj} is the outcome of interest for household h from village j and β_T is the intent-to-treat (ITT) estimators. δX_{hj} represents a set of covariate variables and μ_j and ε_{hj} are iid errors across villages and across households within villages. The standard errors are clustered at the village level. We utilize two different specifications for different outcomes.

For the intermediate outcomes the control variables include those household characteristics used in the first equation plus the age of the household’s head, household head’s years of education, and household size. These additional variables are intended to capture the household’s ability to access and utilize the opportunities provided by AAD. To control for differences in livelihoods between ethnic groups, we include a dummy variable for Hausa households, as they tend to be more sedentary and oriented to crops’ production than the Fulani, whose livelihoods, on average, are more livestock oriented (and who could have more livestock). At the community level, the controls include the risk measure that we included also in the treatment equation, the NDVI and, the ATLAS-AI Wealth Index in 2016. NDVI is included to capture the biophysical state within the community prior to restoration, which could determine the success of the restoration. Similarly, the ATLAS-AI Wealth Index in 2016 was included to account for the well-being of the community at the start of AAD activities.

The estimation of the impact on food security is modelled by including all the covariates used for the intermediate outcomes, plus a dummy variable about whether the community reported instances of drought, flood, crop, and livestock disease during the 12 months years. The addition of the shock variables is intended to capture the occurrence of any recent events that would directly impact household’s food security.

6 Results

Tables 2 and 3 present the impact of AAD on a set of intermediary and final outcomes. Results are shown in the first and third columns of the table, including results from the overall sample (households in communities which lands were restored from 2017 to 2020) and the "early takers" (households in communities that started restoration earlier, in years 2017 and 2018). In the presentation of results, we focus on results of the early takers as these show stronger results, in line with the trends observed in the overall treated sample. This is expected as final outcomes as a result from restored environments, particularly those related to livelihood diversification and food security, would have needed a longer time to materialize. Finally, the fifth column shows the comparison group's mean as a reference to the level of impact.

Results on intermediary outcomes, namely patterns in land use, participation in community groups and access to agroforestry information, provides a sense of the level of engagement in AAD activities, the effective implementation of the programme and the mechanisms through which livelihood diversification and food security outcomes could have materialized. We find positive effects, with AAD households more likely to have allocated household labour for work in communal land (14.4 percentage points) in the previous three years compared to households from non-AAD communities. ADD households are also more likely to collect products from communal lands for their livelihood (14 percentage points). When looking at the different items that were collected from communal lands, we observe that treatment households are more likely to collect NTFP (4.6 percentage points), in particularly, Balanites (8.3 percentage points) which is one of the main NTFP promoted in AAD trainings for processing. At the same time, we observe that AAD households are less likely to collect fuelwood (17.1 percentage points) and fodder (29.1 percentage points) from any land, and as suggested by the results, the decrease mostly occurred from non-communal lands, and without affecting patters of communal land use. AAD households were also less likely to graze cattle in any land (9.1 percentage points). These results suggest an improvement of natural resource management by AAD communities as restored lands were protected to allow regeneration (and as promoted by the programme).

In terms of AAD agroforestry activities and training, we observe proof of households' participation and take up of practices. AAD households received agricultural information (whether through specialized trainings or community-wide discussions) regarding the collection seeds, NTFP collection and use, agroforestry, natural resource management, cooperative management, and species best suited for the weather conditions of the community. Results show that households in AAD communities were more likely to receive agroforestry-related information (16.3 percentage points), and of a wider range of topics considering the higher number of different information received. Because of the intent of the project to include women and youth, we disaggregated this indicator by demographics and found that, AAD also increased the probability of women and youth being involved in activities of knowledge sharing (7.5 percentage points). As an effect of AAD's orientation, households also planted more trees in their private lands (12 percentage points), indicating that agroforestry activities within households' own farms was reinforced with the new information received.

We also find that AAD households are not statistically more likely to have participated in any communal group in the three years before the survey. However, membership becomes significant when the analysis is run for the overall the sample. This is potentially an indication that community groups are formed, and function mostly, in the early stages of AAD's engagement, but are not sustained over time once restoration activities end.

Moving to Table 3 on changes in livelihood strategies and diversification, we observe some important impacts at household level. Overall, results suggest a shifting diversification strategy pattern away from the commercialization of crop products, and toward livestock-related production. We hypothesize that a reduction of crop sales and an increase in medium and small livestock sales (and their by-products) reflect households' preferences towards less risky activities, as livestock activities are less sensitive to mild rainfall and temperature anomalies than crop production. This shift clearly emerges from a decrease in deriving income from crop sales (15 percentage points), and an increase in deriving income from sales from both livestock (7.1 percentage points) and livestock by-products (15.5 percentage points). The increased sales are mostly observed in small and medium animals, so we hypothesize that these changes occurred without increasing the collection of fodder or grazing. AAD households are also more likely to derive income from the sales of timber and NTFP (8.7 percentage points), which is consistent with AAD's promotion and training in processing and commercialization of high-value NTFP such as for Balanites oil. On the other hand, there is no impact on whether households derive income from receiving remittances or earning income form salaried employment.

Estimates on the indicators on specialization and diversification strategies lead to similar results. AAD households are 10 percentage points less likely to solely engage in agriculture activities (crop and livestock) compared to non-AAD households, while there is some indication of specialization in livestock activities, when considering the overall sample. These patterns are also supported by additional evidence that AAD households sold less types of crops, but increased the number of types of livestock and livestock by-products sold. AAD households' ownership of livestock also increased, particularly within medium and small animals requiring less feed from fodder or grazing, as large livestock.

Finally, we find no evidence that these changes at household level had negative implications for food security after three to four years from the start of the programme. This is an important finding as populations in the areas of the project show high prevalence of food insecurity, as measured by FIES. Beyond the lack of negative impacts, there is also some indication that the livelihood diversification patterns observed may be working towards a decrease in moderate food insecurity, as well as in some respects related to accessing food. Out of the eight FIES indicators, three are positive and statistically significant for both early-taker households and the overall sample, including impacts in worrying less about not having enough to eat, skipping less meals, and not running out of food.

Table 2. Action Against Desertification impacts on intermediate outcomes (mechanisms)

	Average Treatment Effects of the Treated (ATET) (all sample vs comparison)	Standard errors	ATET (early takers vs comparison)	Standard errors	Comparison mean
	(1)	(2)	(3)	(4)	(5)
a. Use of communal and private lands					
Provided labour to communal lands (planting, reforestation)	0.118***	(0.023)	0.144***	(0.031)	0.121
Used resources from communal lands for livelihoods	0.111***	(0.023)	0.140***	(0.030)	0.118
Collected timber and non-timber forest product (NTFP) (from communal land)	0.049**	(0.021)	0.049*	(0.027)	0.130
Collected NTFP (no timber, from any land)	0.046*	(0.025)	0.066**	(0.032)	0.175
Collected timber and NTFP (from any land)	–0.095***	(0.026)	–0.166***	(0.033)	0.811
Collected fuelwood (from communal land)	0.027	(0.018)	–0.004	(0.021)	0.098
Collected fuelwood (from any land)	–0.093***	(0.027)	–0.171***	(0.035)	0.755
Collected fodder (from communal land)	–0.011	(0.268)	–0.000	(0.013)	0.033
Collected fodder (from any land)	–0.241***	(0.030)	–0.291***	(0.038)	0.653
Collected Balanites (from any land)	0.061***	(0.013)	0.083***	(0.018)	0.013
Grazed cattle (in communal land)	0.028	(0.030)	0.035	(0.038)	0.413
Grazed cattle (in own pasture)	0.030	(0.031)	0.091**	(0.040)	0.366
b. Group formation, agroforestry information and practices (Action Against Desertification activities)					
Received agroforestry information (last three years)	0.116***	(0.026)	0.163***	(0.034)	0.277
Number of different agroforestry information received (last three years)	0.394***	(0.087)	0.629***	(0.123)	0.619

	Average Treatment Effects of the Treated (ATET) (all sample vs comparison)	Standard errors	ATET (early takers vs comparison)	Standard errors	Comparison mean
	(1)	(2)	(3)	(4)	(5)
Women or youth received agroforestry information (last three years)	0.058***	(0.017)	0.075***	(0.023)	0.078
Planted new trees (in the last three years)	0.087***	(0.029)	0.121***	(0.037)	0.300
Number of new trees planted (in the last three years)	1.164***	(0.447)	1.900***	(0.664)	2.265
Membership in community groups	0.045*	(0.027)	0.043	(0.034)	0.317
Observations	1 324	1 324	1 065	1 065	779

Notes: Types of agricultural information received included: agroforestry, seeds, use of NTFP (non-timber forest products) and NRM (natural resource management), marketing. Stars denote p-values as follows: * p<0.1 ** p<0.05; *** p<0.01.

Source: Authors' elaboration.

Table 3. Action Against Desertification impacts on final diversification strategies and food security

	Average Treatment Effects of the Treated (ATET) (all sample vs comparison)	Standard errors	ATET (early takers vs comparison)	Standard errors	Comparison mean
	(1)	(2)	(3)	(4)	(5)
a. Livelihood strategies, specialization and diversification					
Number of income sources (one year)	0.045	(0.065)	–0.150**	(0.071)	1.913
Derived income from crop sales (one year)	–0.162***	(0.031)	–0.145***	(0.040)	0.639
Derived income from livestock by-product sales (one year)	0.100***	(0.023)	0.105***	(0.030)	0.103
Derived income from livestock sales (one year)	0.052*	(0.028)	0.071**	(0.036)	0.745
Derived income from timber and non-timber forest product (NTFP) sales (one year)	0.013	(0.028)	0.087**	(0.042)	0.177
Received income from remittances (one year)	–0.014	(0.016)	–0.020	(0.019)	0.107

	Average Treatment Effects of the Treated (ATET) (all sample vs comparison)	Standard errors	ATET (early takers vs comparison)	Standard errors	Comparison mean
	(1)	(2)	(3)	(4)	(5)
Derived income from salaried employment (one year)	0.025*	(0.015)	0.001	(0.019)	0.108
Specialized in agricultural activities (crop and livestock)	–0.097***	(0.031)	–0.100**	(0.040)	0.501
Specialized in livestock activities only	0.048*	(0.024)	0.033	(0.031)	0.153
Engaged in both agricultural and off-farm activities	0.012	(0.014)	–0.006	(0.018)	0.060
Engaged in both agricultural activities and timber and NTFP sales	–0.026	(0.017)	–0.009	(0.023)	0.087
b. Agricultural activities					
Hired labour for agricultural activities (last 12 months)	–0.148***	(0.030)	–0.182***	(0.039)	0.629
Number of crops cultivated (last 12 months)	–0.087	(0.073)	–0.087	(0.097)	3.469
Number of types of crops sold (last 12 months)	–0.296***	(0.065)	–0.285***	(0.081)	1.063
Number of types of livestock sold (last 12 months)	0.372***	(0.090)	0.488***	(0.118)	1.635
Number of types of livestock by-products sold (last 12 months)	0.136***	(0.032)	0.142***	(0.043)	0.119
Number of NTFP types extracted (last 12 months)	–0.139**	(0.054)	–0.150**	(0.071)	0.879
Processed timber and NTFP	0.018*	(0.010)	0.038**	(0.016)	0.018
Total animal stock in Tropical Livestock Unit (TLU) (last 12 months)	0.136**	(0.064)	0.227***	(0.084)	1.835
Number of large livestock owned (last 12 months)	0.003	(0.065)	0.098	(0.083)	1.140
Number of medium livestock owned (last 12 months)	0.166**	(0.081)	0.262**	(0.105)	2.376

	Average Treatment Effects of the Treated (ATET) (all sample vs comparison)	Standard errors	ATET (early takers vs comparison)	Standard errors	Comparison mean
	(1)	(2)	(3)	(4)	(5)
Number of small livestock owned (last 12 months)	0.440***	(0.103)	0.519***	(0.131)	2.153
Borrowed money to support any agricultural activity	–0.038	(0.026)	–0.054*	(0.032)	0.281
c. Food security					
Probability of moderate food insecurity (Food Insecurity Experience Scale [FIES] mod)	–0.046*	(0.027)	–0.045	(0.033)	0.763
Probability of severe food insecurity (FIES severe)	–0.041	(0.025)	–0.030	(0.029)	0.289
Total FIES score (0–8)	–0.356*	(0.190)	–0.344	(0.215)	5.365
(1) Worried you would not have enough food to eat	–0.051*	(0.029)	–0.054*	(0.032)	0.831
(2) Unable to eat healthy and nutritious food	–0.030	(0.027)	–0.025	(0.031)	0.838
(3) Ate only a few kinds of foods	–0.033	(0.028)	–0.028	(0.031)	0.828
(4) Had to skip a meal	–0.089**	(0.036)	–0.088**	(0.040)	0.632
(5) Ate less than you thought you should	–0.058*	(0.031)	–0.047	(0.035)	0.789
(6) Household ran out of food	–0.070*	(0.037)	–0.072*	(0.041)	0.578
(7) Were hungry but did not eat	–0.042	(0.037)	–0.033	(0.040)	0.615
(8) Went without eating for a whole day	–0.042	(0.036)	0.043	(0.040)	0.255
Observations	1 324	1 324	1 065	1 065	779

Note: Stars denote p-values as follows: * p<0.1 ** p<0.05; *** p<0.01.

Source: Authors' elaboration.

7 Conclusion

In this paper, we shed light on the impacts of landscape restoration at household level, on both important intermediary (use of communal lands, receiving agroforestry information and planning more trees on household farms) and final outcomes (household-livelihood diversification and food security). Acquiring a better understanding under which mechanisms these impacts are realized is not only important, but also urgent for sustaining the biophysical outcomes from investments in restoration. People living across the Sahel, including those that make part of the AAD project in Northern Nigeria, are at the forefront of climate change and its devastating effects on their livelihoods. More evidence on mechanisms that work in similar contexts can help improve the design of related project and improve their effectiveness.

This study finds that AAD's approach was effective in achieving its goals. Households that participated in the AAD restoration programme increased their access to agricultural and forestry information, engaged more with communal lands for restoration, while decreased their overall land use for grazing and for fodder. There is also indication that the extraction of some NTFP with market value, such as Balanites, is increasing. Furthermore, AAD enabled a shift away from high-risk, rain-fed crop agriculture for sales, towards more diversified livelihood options with market potential. This is reflected by participant households owning more livestock and selling more livestock and its by-products. Not only are these activities less sensitive to rainfall and temperature fluctuations, but the diversification of livelihood strategies decreases livelihoods risk. The study also found small, but positive, impact on overall food security and on some of its aspects. Nevertheless, the study also suggests that the promotion of behavioural change in the use of natural resources, namely decreasing grazing in communal lands for restoration and a temporary halt to forest products extraction, is possible without affecting food security, if alternative livelihood pathways are available – as in the markets of small and medium livestock and livestock by-products and high value NTFP in this case.

Our study is not without limitations. The lack of income quantities collected, which prevents us from determining whether diversification of livelihood strategies translated to higher income. Moreover, it was not possible to assess whether the lack of a positive impact on food security was due to lack of increase in income or a better environment for food access (e.g. through NTFP or higher productivity). Similarly, the lack of baseline information prevented to assess whether higher diversification also fostered household livelihood resilience, another driver of food security.

The limited impact of AAD on food security suggests that similar programmes should further investigate its relationship with household diversification as well as with changing natural resources management behaviour. Also, food security is affected by multiple factors and a more in-depth analysis is needed to identify them and design projects or additional components that specifically address these. We can speculate on some of the causes. One reason could be that more time is needed for some of the intermediate channels to translate to higher food security, via, access to food from higher levels of income. Some of the tree species that were planted, like Gum Arabic and Balanites, typically require five or more years before bearing fruit and thus becoming a more substantial source of income. The lagged effect of these interventions on outcomes is something that needs to be considered not only in the design of the project but also when evaluating impacts. We can claim that this study captured only the short-medium term effects, but most likely could not capture the effects coming from these other sources of income. It would be interesting to test this hypothesis, collect a second round of data and assess the effect of those project component that need longer time to materialize.

Another final concern is related to the external validity of our findings. The project areas and communities are not representative of all populations near potential restoration sites. In our sample, some populations are also more linked to markets than others, as reflected by the different levels of wealth at baseline. The *ex post* nature of our evaluation prevented us from addressing these issues with an experimental framework. However, diversification patters in potential restoration areas will be likely different in future project contexts as well, as targeting of restoration actions is not based on population characteristics, but on land suitability.

Finally, this paper also contributes to the data and techniques for improving *ex post* impact evaluation in land restoration projects. In this study, we leveraged the growing availability of remote-sensing data and spatial data to identify a suitable comparison group, specifically, the use of machine learning techniques for enabling an accurate identification of comparable sites. At field level, we also enhanced the identification of households in comparison areas through mimicking the targeting criteria of AAD for the selection of the survey sample. Going forward we see this approach being refined and applied, not only in similar *ex post* impact evaluation settings, but also, *ex ante* when evaluators struggle to identify a counterfactual. Furthermore, given the archives of remotely sensed data, there is the possibility to return to older restoration projects to examine their impacts. Combined with administrative data or nationally representative surveys, there is the potential to create a catalogue of land restoration programmes, their features, and their impact to aid in designing better interventions in the future.

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Annexes

Annex 1. Additional tables

Table A1. Action Against Desertification households by start year of project

Year	Number of households	Percent
2017	78	14
2018	208	38
2019	13	2
2020	247	45
Total	546	100

Source: Authors' elaboration.

Table A2. Outcome means by treatment status (unweighted)

	Action Against Desertification		Counterfactual		Difference	
	mean	standard deviation	mean	standard deviation	b	t
Provided labour to communal lands	0.229	0.421	0.121	0.326	–0.108***	(–5.047)
Used resources from communal lands	0.216	0.412	0.118	0.323	–0.098***	(–4.648)
Household collected timber and non-timber forest products (NTFP) (from communal land)	0.159	0.366	0.130	0.336	–0.030	(–1.502)
Household collected NTFP (no timber, from any land)	0.216	0.412	0.175	0.380	–0.042	(–1.865)
Household collected timber and NTFP (from any land)	0.725	0.447	0.811	0.392	0.086***	(3.627)
Household collected fuelwood (from communal land)	0.110	0.313	0.098	0.297	–0.012	(–0.721)
Household collected fuelwood (from any land)	0.685	0.465	0.755	0.430	0.070**	(2.774)
Household collected fodder (from communal land)	0.018	0.134	0.033	0.180	0.015	(1.745)
Household collected fodder (from any land)	0.434	0.496	0.653	0.476	0.219***	(8.053)
Household collected Balanites (from any land)	0.079	0.270	0.013	0.113	–0.066***	(–5.393)
Household grazed cattle (in communal lands)	0.504	0.500	0.413	0.493	–0.090**	(–3.254)
Household grazed cattle (in own pasture)	0.403	0.491	0.366	0.482	–0.037	(–1.363)
Membership in community groups	0.304	0.460	0.317	0.466	0.013	(0.505)
Household received agricultural information in the last three years	0.333	0.472	0.277	0.448	–0.056*	(–2.173)

	Action Against Desertification		Counterfactual		Difference	
	mean	standard deviation	mean	standard deviation	b	t
Number of agricultural information received in the last three years	0.875	1.672	0.619	1.331	–0.257**	(–2.986)
Women or youth in the household received agricultural information	0.117	0.322	0.078	0.269	–0.039*	(–2.314)
Household planted new trees in past three years	0.363	0.481	0.300	0.459	–0.062*	(–2.363)
Number of new trees planted in past three years	3.471	8.538	2.265	5.427	–1.206**	(–2.851)
Number of household income sources (excluding government support)	1.830	1.106	1.913	1.083	0.083	(1.357)
Household sold or bartered crops produced last year	0.445	0.497	0.639	0.481	0.194***	(7.094)
Household sold livestock by-products	0.211	0.408	0.103	0.304	–0.108***	(–5.244)
Household sold livestock (dead or alive) in the last year	0.771	0.421	0.745	0.436	–0.027	(–1.112)
Household sold or bartered some of the timber or NTFP collected	0.184	0.388	0.177	0.382	–0.007	(–0.288)
Household received income from remittances	0.071	0.258	0.107	0.309	0.035*	(2.248)
Household has at least one person in a salaried job	0.095	0.294	0.108	0.310	0.013	(0.750)
Household sold fruit or vegetables from their garden/orchard	0.011	0.104	0.014	0.118	0.003	(0.509)
Household hired labour for agricultural activities in the last year	0.421	0.494	0.629	0.483	0.208***	(7.600)
Number of crops cultivated by household last year	3.271	1.095	3.469	1.238	0.197**	(3.060)
Number of crops household sold or bartered in the last year	0.731	1.004	1.063	1.046	0.332***	(5.824)
Number of types of livestock household sold last year	1.923	1.519	1.635	1.391	–0.288***	(–3.513)
Number of types of livestock by-products household sold last year	0.269	0.583	0.119	0.379	–0.150***	(–5.272)
Number of timber and NTFP household extracts	0.758	0.952	0.879	0.781	0.121*	(2.450)
Household processed timber or NTFP before selling	0.038	0.192	0.018	0.133	–0.020*	(–2.153)
Total animal stock in Tropical Livestock Unit (TLU), last 12 months	1.979	1.134	1.835	0.991	–0.144*	(–2.399)
Number of large livestock owned	1.249	1.166	1.140	0.979	–0.110	(–1.800)

	Action Against Desertification		Counterfactual		Difference	
	mean	standard deviation	mean	standard deviation	b	t
Number of medium livestock owned	2.434	1.359	2.376	1.237	–0.058	(–0.793)
Number of small livestock owned	2.569	1.605	2.153	1.739	–0.416***	(–4.486)
Borrowed money to support any agricultural activity	0.201	0.401	0.281	0.450	0.080***	(3.382)
Specialized in agricultural activities (crop and livestock)	0.418	0.494	0.501	0.500	0.083**	(2.998)
Specialized in livestock activities	0.207	0.405	0.153	0.360	–0.054*	(–2.507)
Engaged in both agricultural and off-farm activities	0.062	0.242	0.060	0.238	–0.002	(–0.144)
Engaged in both agricultural activities and timber and NTFP sales	0.055	0.228	0.087	0.282	0.032*	(2.301)
Probability of moderate food insecurity (Food Insecurity Experience Score [FIES])	0.792	0.349	0.763	0.362	–0.029	(–1.460)
Probability of severe food insecurity (FIES)	0.343	0.340	0.289	0.319	–0.054**	(–2.915)
Total FIES score (0–8)	5.661	2.466	5.365	2.510	–0.297*	(–2.139)
Worried about not having enough food to eat	0.839	0.368	0.831	0.375	–0.008	(–0.385)
Unable to eat nutritious and healthy food	0.853	0.354	0.838	0.368	–0.015	(–0.758)
Ate only a few kinds of foods	0.846	0.361	0.828	0.378	–0.018	(–0.895)
Had to skip a meal	0.667	0.472	0.632	0.483	–0.035	(–1.320)
Ate less than you thought you should	0.797	0.403	0.789	0.408	–0.007	(–0.320)
Ran out of food	0.630	0.483	0.578	0.494	–0.052	(–1.896)
Hungry but do not eat	0.679	0.467	0.615	0.487	–0.065*	(–2.435)
Went without eating for a whole day	0.352	0.478	0.255	0.436	–0.096***	(–3.736)
Observations	546		779		1 325	

Source: Authors' elaboration.

Table A3. Balance test (full results)

	Standardized difference		Variance ratio	
	Raw	Weighted	Raw	Weighted
Household head is female	–0.146	0.003	0.480	1.021
Household head is married (monogamous and polygamous)	0.190	0.004	0.378	0.975
Number of female adults in the household (16–65 years old)	–0.043	–0.002	1.134	1.288
Number of young adults in the household (15–25 years old)	–0.140	0.004	0.898	1.125
Improved lighting source	–0.200	–0.004	0.596	0.988
Climate risk (2006–2016)	–0.168	0.002	0.978	0.904

Source: Authors' elaboration.

Annex 2. Implementation of Action Against Desertification in Northern Nigeria

The AAD programme in Northern Nigeria was implemented in two phases. The first phase involved community engagement to obtain their buy-in for labour support in AAD's restoration activities and the establishment of community level interventions. The second phase is mainly focused on the large-scale restoration of communal lands, using the Delfino units. In all activities, AAD emphasized the participation of women and youth from the community. Based on needs assessments conducted in phase one, AAD facilitated several community-level interventions to incentivize participation of community members. In Nigeria, AAD drilled large, solar-powered boreholes to improve community access to water and established micro-gardens. The community then allocated some of their members to work in these micro-gardens. AAD conducted trainings for the micro-gardens and provided with 5-kilo bags of seeds each of assorted vegetables for planting.

Once the buy-in of the community is confirmed and members engaged, land restoration activities started. First, village-level technicians were trained on quality seed collection of tree and fodder species. These technicians then mobilized the community, sharing information from the training, and then organize tree and fodder seed collection. The seeds were then used in the communal land restoration. The AAD provided compensation for the seeds, creating additional incentives for engagement through increased incomes. When new species were not available locally, seed exchange within communities was facilitated by AAD. After seeds were collected, nurseries were established near the boreholes constructed in the first phase. The nursery attendants were trained by AAD on how to germinate and rear seedlings.

Once the seedlings were ready, Delfino units (tractors) were brought in to mechanically prepare the land, digging the demi-lunes (half-moons) for adequate rainwater harvesting. In this phase, community members were trained on planting the seeds/seedlings in the demi-lunes. Both woody and fodder seeds/seedlings were planted on the same restoration sites to grow together on the same piece of land for maximum access to the rain waters harvested.

With the land planted, a community watch group, comprised of five young men, was established to protect restoration sites from encroachments (fencing around the land was cost prohibitive). These watch groups were given high-visibility vests and flashlights, and were renumerated for patrolling the land planted with the seeds and seedlings, which are highly vulnerable. Additionally, within the first one to two years after the restoration, community members were requested to avoid grazing their cattle on the fodder that had grown on restored land. This was intended to protect the seedlings during their most vulnerable stage. Yet to sustain buy-in and support economic benefits from the restoration, users were permitted to harvest fodder from the restoration site to feed their cattle at their respective homes.

To complement the restoration work, AAD also established CMC to be responsible for natural resource management, including water and land management. The CMC was comprised of a mix of professions—including farmers, herders, and traders – and required a large participation of women (around 40 percent women) and with one youth representative. As the community waited for the restored lands to bear fruit, AAD engaged in value chain training.[25] If a cooperative did not exist in the community, AAD would assist the community in forming one with the interested people, normally around 30 people. Trainings were then conducted by the Nigerian Raw Materials Research and Development Council on topics related to beekeeping and Balanites oil. AAD then assisted cooperatives in obtaining the necessary tools and equipment to utilize their new knowledge. It is important to note that all these activities, from the engagement with communities to restoration to training, occurred on a rolling basis from the start until the end of the programme in 2020. The implication of this is that AAD communities were at various stages in the restoration process when data collection for this analysis was conducted in 2021.

[25] Fodder is one to two years as for the trees, it depends on the species. With regards to the real money-making species, Arabic gum can be harvested six to eight years after tree planting and Balanites trees begin flowering and setting fruit after five to seven years.

Annex 3. Remote sensing data description

This section describes the indicators and data used for the selection of comparable communities using a Support Vector Machine (SVM).

1. **Slope and elevation:** The slope and elevation maps come from the Shuttle Radar Topography Mission (SRTM). This effort obtained digital elevation models on a near-global scale and is provided by National Aeronautics and Space Administration (NASA) Jet Propulsion Laboratory (JPL) at a resolution of one arc-second (approximately 30 m). Slope (%) and elevation (metres) are available at the GEE catalogue.

2. **Soil texture:** The soil texture map uses the textural class (USDA) of the soil fine earth fraction, aggregated over routable depth and the top 30 cm, mapped at 1 km resolution. The map is the result of digital soil mapping techniques using input data from 28 000 soil profiles from across sub-Saharan Africa (Leenaars *et al.*, 2018).

3. **Soil texture classes**, of the USDA system/triangle, are: (1) clay; (2) silty clay; (3) sandy clay; (4) clay loam; (5) silty clay loam; (6) sandy clay loam; (7) loam; (8) silty loam; (9) sandy loam; (10) silt; (11) loamy sand; (12) sand.

4. **Soil drainage:** The soil drainage map is defined according to the Guidelines for Soil Description (FAO, 2006) and predicted using the Africa Soil Profiles Database (AfSP) v1.2. The map can be found here. Soil drainage classes are: (1) very poor; (2) poor; (3) imperfect; (4) moderate; (5) well; (6) somewhat excessive; (7) excessive, (255) no data available. (Details available in Hengl *et al.*, 2015).

5. **Soil type:** The soil type map uses the World Reference Base (WRB), an international system for classification of soils, and map legend contains 29 soil types. The soil type map is at 250 m spatial resolution and description of the dataset can be found here: predictions were derived using a digital soil mapping approach based on Random Forest, drawing on a global compilation of soil profile data and environmental layers.

6. **Normalized Difference Vegetation Index (NDVI):** NDVI is an index with a value between –1 and 1, which represents the difference between near infrared (NIR) and visible (RED) reflectance of vegetation (Tucker, 1979). When sunlight hits a plant, some wavelengths are absorbed, and others reflected; the difference between these is driven by the health of the plant (Weier and Herring 2000). NDVI=(NIR-RED)/(NIR+RED).

7. **Modified Soil-Adjusted Vegetation Index (MSAVI):** MSAVI is a vegetation index used in areas with a small amount of vegetation because it minimizes the soil background influence increasing the range of vegetation signal (Qi *et al.*, 1994). This index is generally applied to the areas with a high degree of exposed soil surface. The formula is the following: MSAVI2=(2*NIR+1-√(〖(2*NIR+1)〗^2–8*(NIR-RED)))/2

8. **Normalized Difference Moisture Index (NDMI):** The NDMI measures the difference between NIR and short-wave infrared (SWIR), which reveals the moisture content or water stress level of vegetation (Gao, 1996). NDMI=(NIR-SWIR)/(NIR+SWIR)

9. **Bare Soil Index (BSI):** The BSI is best suited for estimations of vegetation status when there isn't much vegetation present (Rikimaru, 2002). It looks at the difference between visible RED and SWIR, and NIR and visible BLUE. BSI=(((RED+SWIR)-(NIR+BLUE)))/(((RED+SWIR)+(NIR+BLUE)))

10. **Road network:** The road network map is from EnergyData.Info. The dataset was extracted from OpenStreetMap, with a 1-, 2- and 5-kilometre buffers. The map contains every road that is tagged as a motorway, a primary, a secondary, or a tertiary road and highlight areas that are within a particular distance from a major road.
11. **Travel time (motorized transport and walking only) to health services:** The travel time to healthcare maps represent the estimated travel time to the nearest healthcare facility. Both motorized and walking maps are included to highlight the stark differences faced both by residents of rural communities and those with and without access to motorized transport (Weiss *et al.*, 2020).
12. **National land use and land cover map (2016):** The national dataset is part of the mapping component of the country REDD+ initiative and report can be found here. There are 12 classes based on the revised LULC classification scheme of FORMECU project (from the Forest Monitoring and Coordination Unit 1995). The classification scheme followed the Anderson 1976 Classification scheme. Land use and land cover classifications are (1) undisturbed forest; (2) mangrove; (3) forested freshwater; (4) forest plantation; (5) disturbed forest; (6) savanna woodland; (7) grassland; (8) arable land; (9) tree crop plantation; (10) settlement; (11) bare surfaces; (12) water body.
13. **Asset wealth index:** The wealth index data is a machine learning generated dataset by ATLAS-AI. They use wealth data from DHS surveys available for sub-Saharan Africa, to first generate an asset index using principal component analysis (PCA) for all households in all the surveys and all years available, such that the index is comparable across time and space. Averages for each locality – village for rural areas/clusters for urban areas – are computed based on the household scores. In the second step, the authors model and train spatially coarse public imagery Landsat surface reflectance and night-time lights images available on Google Earth Engine (GEE). In this way, the model learns the features of imagery that predicts the asset wealth, namely its changes over time and space. The model is therefore able to predict the values of asset wealth in places at locations and in years for which the survey data does not exist. The output is a dataset of asset wealth index, a continuous variable, that are given at a resolution of approximately 2 km x 2 km for each year of the period 2003 to 2020. Atlas AI's asset wealth layer estimates household asset wealth based on asset ownership. More information could be found at Asset Wealth – Atlas AI Public Documentation. The 2-kilometre spatial resolution is the result of a deep learning model that predicts survey-based estimates from satellite imagery.
14. **Electrification status:** Atlas AI's Electrification Status layer estimates the availability of access to the electricity grid at a particular location, i.e. the presence or absence of electrification. At any snapshot in time, the Electrification Status is binary – either "yes" or "no". Details of the layer can be found at Electrification – Atlas AI Public Documentation.

Annex 4. Steps for the identification of a valid counterfactual using a Support Vector Machine (SVM)

Identifying the counterfactual was the most problematic challenge to overcome in the analysis. We had a listing of households were selected to participate in AAD, however, selection into the programme, occurred at the landscape level. To address this challenge, we identified the geographical coordinates of each of the AAD restoration plots and accessed remotely sensed data of those plots prior to the start of AAD's work (year 2016). We hypothesized that we could use biophysical and socioeconomic data from 2016 to build a profile of each of the restoration sites and then find similar parcels of land in neighbouring states and LGAs. An SVM, which is a computer-vised machine-learning algorithm, was used to identify similar plots of land to those restored by AAD at baseline.

SVM is an algorithm often used for classification or regression challenges when handling multiple variables, both categorical and continuous (Vapnik, 1995). The algorithm learns by example to assign labels to objects (Noble, 2006), which produces "classes" that the data is classified into. In our case those classes were classified as "similar or not similar" to those restored by AAD. While innovative in its application to an *ex post* evaluation of socioeconomic impact, this approach is not without precedent. SVM is very popular in medical fields for neuroimaging analysis because of its ability to classify images even when the sample size is small and the dimensionality is high (Pisner and Schnyer, 2020). Furthermore, SVMs have been shown to perform well in both binary and multiclass classifications of remotely sensed data (Foody and Mathur, 2004). Examples of SVM applications include land suitability for cultivated wheat in Iran (Sarmadian *et al.*, 2014), rice paddy classification in China (Xu *et al.*, 2018), land use/land cover suitability in Indonesia (Safitri *et al.*, 2021), and peatland restoration in Indonesia (FAO, 2021). Nevertheless, in our review of the literature, we did not identify a single study that employed the classifying capacities of SMV in an *ex post* effort to identify a comparison group for impact evaluation. The data used for the SVM process have been summarized in Annex 2.

Prior to implementing the SVM similarity analysis, grouping of the restoration sites was necessary due to the number of sites and because of their variation in size. Running analysis on each site would have resulted in 33 different outputs, which would have been difficult to manage. Additionally, small sites and the resulting small number of pixels meant insufficient data to train the machine learning algorithm. The average size of restoration sites was 41 hectares, with a maximum of 255 hectares, a minimum of 2 hectares, and a median size of 22 hectares. For this reason, group of sites were put together as shown in Table A4. To overcome concerns about which variables to group by and the resulting distance between pieces of land in said groups, we decided to cluster in the most obvious way, by proximity. This was a useful approach because in many cases sites were bordering or around 1 km from one another. The result were ten groups of restoration sites, which were then analysed by the SVM.

Table A4. Groupings of sites based on proximity

State	Local government areas	Site numbers
Jigawa	Sule-Tankarkar	9, 22
Jigawa	Sule-Tankarkar	7, 8, 20, 21, 18
Jigawa	Sule-Tankarkar	10, 11, 44, 45
Jigawa	Sule-Tankarkar	5, 6, 23
Jigawa	Birimiwa	12, 13, 14, 15
Jigawa	Kaugama	26, 38, 47
Jigawa	Kafin Hausa	24, 25, 36, 37, 46
Bauchi	Gamawa	4, 17, 33, 34
Bauchi	Gamawa	43, 18
Jigawa	Kafin Hausa	41, 42

Source: Authors' own elaboration.

With the groupings defined, the then SVM learned which of the above variables were significant in the assignment of the AAD restoration activities by examining data on each pixel of restored land, at 10 m^2 spatial resolution.[26] It then used that information to train the algorithm to find pixels with similar properties in the area of interest.[27] More specifically, the method computes a One-Class SVM (OCSVM) classification which utilizes pixel level information from where the ADD activities were implemented to classify pixels that are outside of the project areas as similar or not to the project pixels. The result of this similarity analysis was one map per group indicating areas where pixels outside of AAD areas were like the properties of restoration sites prior to the start of AAD restoration activities. The output was a binary variable indicating if the pixel was similar to the restored sites of AAD (in their *ex ante* conditions).

The next step in this process was to identify the communities to visit for data collection. Once the map with the binary variable indicating similarity was produced for each group of restoration sites, we visually inspected and manually identified the densest clusters of similar pixels.[28] We did not aim for a one-to-one match. Instead, we identified the densest clusters on the map for each grouping. From there, a map of communities in Nigeria from 2016 was overlaid on each of the maps of a map of settlements on top of the sites map. Then the six closest communities to the densest clusters were selected for data collection.

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[26] An unsupervised machine learning algorithm would see us feeding data in and asking the algorithm to determine patterns. In this case, we are telling the algorithm what the pattern is, i.e. this is the land the has been restored.

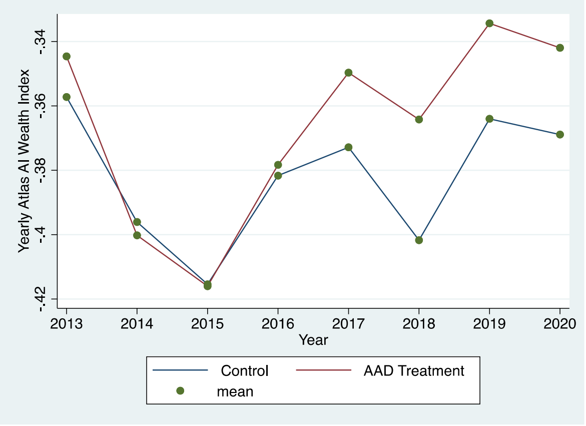
[27] The area of interest included the same LGAs where AAD restoration had occurred and the LGAs in Kano and Katsina states that had been identified as possible targets for future restoration activities in the form of the SURAGGWA project.

[28] Ideally, once the clusters of pixels were identified, field teams would have visited and catalogued all the hamlets, villages, and towns in the vicinity. From that list we would have then selected the communities. However, this was not possible due to various financial and security constraints. The best alternative was to overlay a map of settlements on top of the map resulting from the similarity analysis. Future evaluations could ensure financial resources for making the listing.

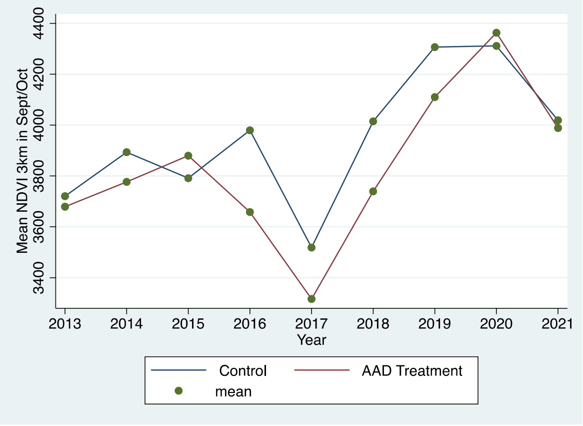
Figure A1 shows the progression of the wealth index (ATLAS-AI), vegetation (NDVI) and climate (SPEI) in both ADD treated communities and selected control communities before the programme and until the end of the programme implementation in 2020. These is a selection of the variables used for the selection of sites. The figures show that the selection of communities was satisfactory for our purpose, with treated and control communities being at similar levels in terms of asset wealth and climate conditions when the programme started in 2016.

Figure A1. Progression of socioeconomic, biophysical and climate indicators across treatment and control sites, before and during the intervention

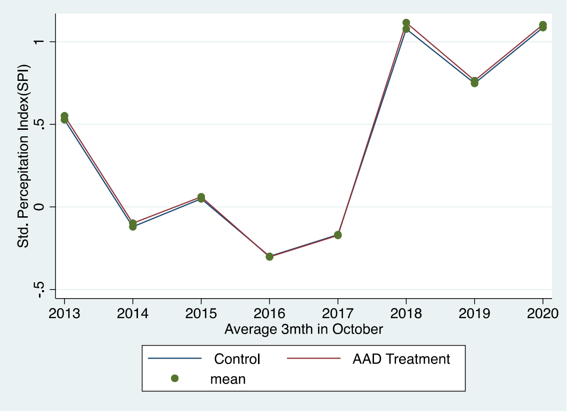
a. Asset wealth (ATLAS-AI)



b. Normalized Difference Vegetation Index (NDVI)



c. Standard Precipitation Index (SPI)



Notes: ADD stands for Action Against Desertification, and it starts in 2016. ALTAS-AI shows predicted asset wealth index for a 3-km radius around the restoration sites; Normalized Difference Vegetation Index (NDVI) for a 3-km radius around the restoration sites; and Standardized Precipitation Index (SPI) for a 5-km radius around the restoration sites.

Source: Authors' elaboration.

Step-by-step identification of Action Against Desertification comparison communities (Gamawa)

Below we provide an example of the selection of comparison communities, using spatial data for Bauchi state and the application of the SVM.

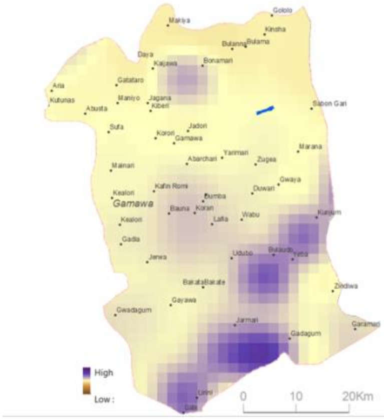
- Panel A shows a map of Bauchi state and the LGA of Gamawa, where AAD sites 4, 17, 33 and 34 were restored.
- Panel B shows a map of Gamawa with the Atlas AI Wealth Index for 2016. The blue rectangle in the top right is AAD restoration site.
- Panel C maps the soil drainage property of the LGA.
- Panel D shows the pixels identified by the SVM that are similar to those of the AAD restored sites.
- Panel E shows the SVM-identified pixels with the names of settlements, for the selection of comparison communities.
- Panel F shows the SVM-identified pixels and the settlements selected for data collection, highlighted in red.

These steps were repeated for all states and sites of AAD in our study.

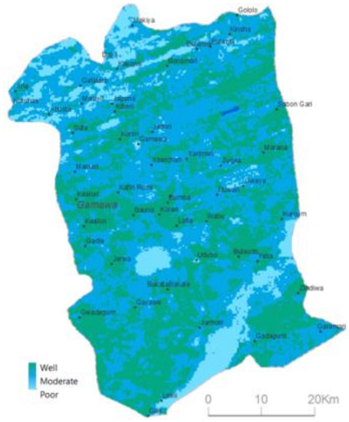
Figure A2. Panels used for comparing sites similar to Action Against Desertification locations

a. Action Against Desertification site in Gamawa Local Government Areas

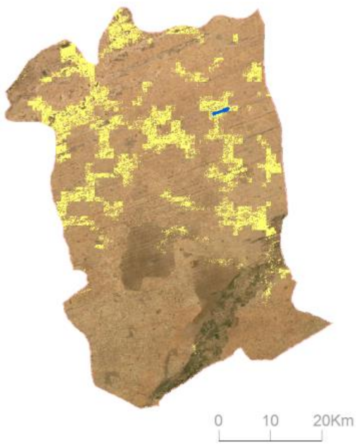
b. Altas-AI Wealth Index



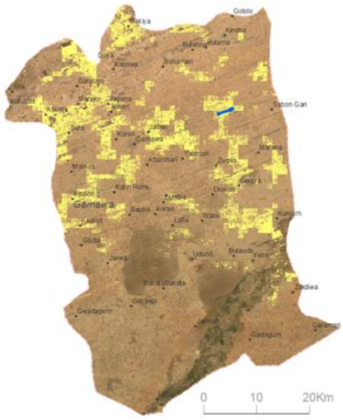
c. Soil drainage



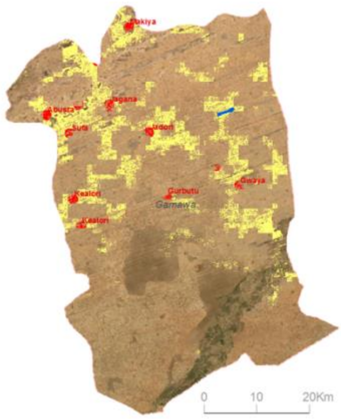
d. Similar pixels to Action Against Desertification site selected for data collection



e. Settlements



f. Final selection of settlements



Source: United Nations Geospatial. 2020. *Bauchi State, Northern Nigeria*. [shapefiles]. New York, USA, United Nations, modified by the authors.

Annex 5. Participation script used to identify comparable households to those participating in Action Against Desertification

As explained, once the communities were selected, the final step was to identify suitable comparison households for the survey. The strategy we adopted was replicating as closely as possible the selection process that was conducted for AAD. The selection of households was based on project criteria that guided the ZFO and the village heads to identify the beneficiaries for each of the seven project tasks (i.e. CMC, community watch groups, micro-gardens, nurseries, seed collection, land restoration and value chain training). In practice, we approached ZFOs and village heads of comparison villages, described the features of AAD and asked them to provide a list of households that would have been selected had a project like AAD were to be implemented in their communities using the same criteria that were used for AAD.[29] From the list of households that the village head nominated to work on hypothetical project tasks, which contained at least 30 households, 13 households were randomly selected for administering the questionnaire with another five selected as backups.

To select the treated households, AAD administrative data was used to create a list of beneficiary households that was presented to the village head for verification upon arrival of the data collection team. Once verified, the data collection team randomly selected from the list 13 households per community for administering of the questionnaire with another five selected as replacements.

Questionnaire script

Thank you, [village leader], for agreeing to continue with this imaginary situation with us.

Next, we are going to describe seven different types of activities that are related to this imaginary land restoration project. Each activity includes payments for the time spent working in the activity. For each activity, I will ask you to specify members of the community that fit the criteria. As would be the case if the restoration project was actually occurring, it is important that the opportunities are spread across as many households as possible. Additionally, if possible, having the same person involved in more than one activity should be avoided. If you are unsure of who would be best for an activity, please feel free to consult with the Zonal Forest Officer. If any of these activities already exists in your community, please tell me so and tell me the names of the people currently participating in the activity.

The first activity is the **community management committee (CMC).** This committee would be responsible for the management of the community's natural resources, including water and land management activities. This committee can have between five and nine people. There should be a mix of professions, including farmers, herders, and traders. Almost half, about 40 percent, of the people selected should be women. And there should also be one youth representative, a male under the age of 25.

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[29] It is worth stressing that we explained that this was only a hypothetical scenario, and that there was no plan to implement such project in those communities. This point was emphasized and reiterated periodically to avoid raising false expectations and ensure the ethical standards of conducting research (see Annex 4 for the script of the interaction).

Does a committee like this already exist in your community? One yes, One no

[If Not] Based on the information I have given you; can you please provide five to nine names of community members you feel would be suitable and willing to participate?

[If Yes] Can you please provide the names of the community members involved in this committee?

_______________________ _____________________

_______________________ _____________________

The second activity is the **community watch group**. This group would supervise and protect any restoration sites from encroachments since fencing around the land would not be used. This activity would be led by the youth representative on the Community Management Committee and will include 5 more young males.

Does an activity like this already exist in your community? One yes, One no

[If Not] Based on the information I have given you; can you please provide five names of community members you feel would be suitable and willing to participate?

[If Yes] Can you please provide the names of the community members involved in this activity?

_______________________ _____________________

_______________________ _____________________

The next activity would be **micro gardens**. Micro gardens would be established around a borehole that the project would drill and comprise about 3 hectares of fenced land. Trainings for the micro gardens would be conducted and trainees would receive a 5-kilo bags of seeds each of assorted vegetables for planting. Of the ten people to be named, at least six should be women, two should be 25 years old or younger, and two should be 65 years old or older.

Does an activity like this already exist in your community? One yes, One no

[If Not] Based on the information I have given you; can you please provide ten names of community members you feel would be suitable and willing to participate?

[If Yes] Can you please provide the names of the community members involved in this activity?

_______________________ _____________________

_______________________ _____________________

The next activity is the **nursery**. For this imaginary land restoration, your community would establish nurseries (near the borehole) to care for the seeds that would be planted on the restored land. There would be six nursery attendants in total, of which, at least four should be women.

Does an activity like this already exist in your community? One yes, One no

[If Not] Based on the information I have given you; can you please provide six names of community members you feel would be suitable and willing to participate?

[If Yes] Can you please provide the names of the community members involved in this activity?

______________________ ____________________

______________________ ____________________

The fifth activity is related to **seed** collection and these people are called **village technicians**. These people would learn how to collect, process, and store the seeds that would be used for planting during restoration.

Does an activity like this already exist in your community? One yes, One no

[If Not] Based on the information I have given you; can you please provide five names of community members you feel would be suitable and willing to participate?

[If Yes] Can you please provide the names of the community members involved in this activity?

______________________ ____________________

______________________ ____________________

This next activity is related to the **land restoration** itself. This can include anyone for the community who is physically able and willing to assist in planting the seedlings needed for the restoration.

Does an activity like this already exist in your community? One yes, One no

[If Not] Based on the information I have given you; can you please provide ten names of community members you feel would be suitable and willing to participate?

[If Yes] Can you please provide the names of the community members involved in this activity?

______________________ ____________________

______________________ ____________________

The final activity is **training on processing, value-added, marketing,** and other topics in the areas of beekeeping and Balanites oil. This activity assumes that with the newly restored land, community member will be able to pursue one or both moneymaking activities. After the training, participants should be willing to share this knowledge with other community members.

Does an activity like this already exist in your community? One yes, One no.

[If Not] Based on the information I have given you; can you please provide five names of community members you feel would be suitable and willing to participate?

[If Yes] Can you please provide the names of the community members involved in this activity?

______________________ ____________________

______________________ ____________________

Thank you, [village leader], for helping me to create this list of community members. Now I kindly request if you could help me to group members of the same household together. Once that is done, I will randomly select ten households to interview and five more as backups.

At this time, do you have any questions for me? [If yes answer any questions that arise. If no or once all questions are answered, continue.]

Thank you again, [village leader], for your time and willingness to work with us. I am leaving with you a copy of all the information that I have spoken about with you today. Included in this document are the contact information of the persons in charge of this research.

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