Project Evaluation Series

Evaluation of the project “Action Against Desertification in support of the implementation of the Great Green Wall for the Sahara and the Sahel Initiative and of the UNCCD action plans in Fiji and Haiti, and South-South cooperation in the Africa Caribbean and Pacific countries”

Project code: GCP/INT/157/EC

Annex 1. Quasi-experimental satellite evidence of the impacts

FOOD AND AGRICULTURE ORGANIZATION OF THE UNITED NATIONS
Rome, 2022

Contents

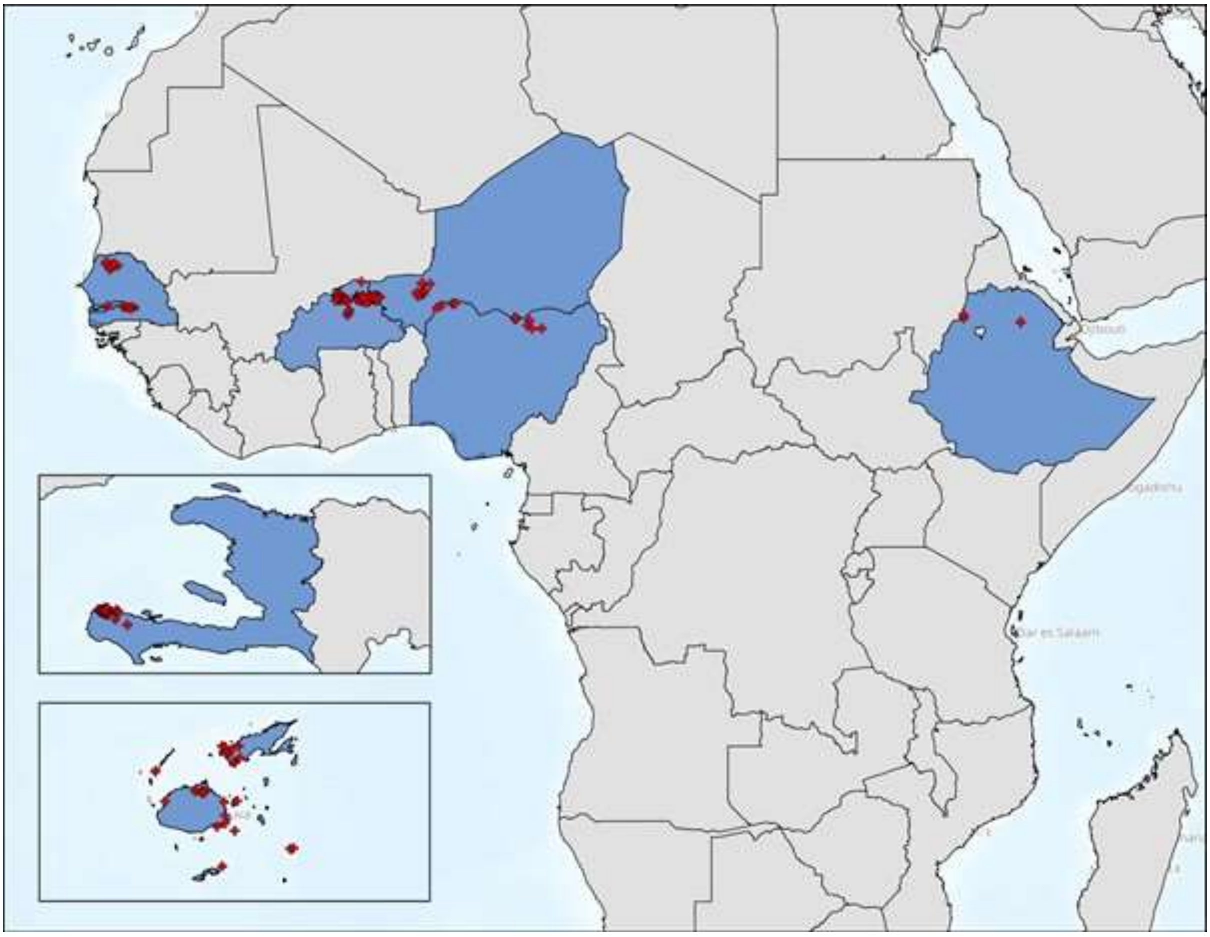
Acknowledgements

This document was prepared by Dr. Dan Runfola, Ms. Jiaying Chen, Ms. Emily Maison, Ms. Laura Mills, in close collaboration with Emilia Bretan (Evaluation Manager) and Luisa Belli (Evaluation Officer) from the FAO Evaluation Office (FAO OED). We would like to thank the FAO OED and AAD staff for their invaluable inputs in the preparation of this document. The evaluation benefited from the inputs of many stakeholders and organizations. Dr. Moctar Sacande (AAD International Coordinator) was instrumental in promoting the collection of and providing geographic information on project implementation locations. The Office of Evaluation extends its thanks to the U.S. National Aeronautics and Space Administration, who provisioned much of the satellite information used in this evaluation.

Abbreviations and acronyms

AAD	Action Against Deforestation
ACP	Africa, Caribbean, and Pacific countries
DLDD	Desertification, land degradation and drought
EVI	Enhanced vegetation index
FAO	Food and Agriculture Organization of the United Nations
GCF	Green Climate Fund
NDVI	Normalized difference vegetation index
GGW	Great Green Wall
GGWSSI	Great Green Wall for Sahara and the Sahel Initiative
M&E	Monitoring and evaluation
NGO	Non-governmental organization
NRM	Natural resource management
SDG	Sustainable Development Goal
QGI	Quasi-observational geographic interpolation

Figure 1. Host countries of Action Against Deforestation projects assessed in this evaluation



Notes: Inset maps represent Haiti and Fiji, respectively. Red crosses indicate project locations assessed in this report.

Source: FAO. 2021. *Host countries of Action Against Deforestation projects assessed in this evaluation*. Rome. Map conforms with UN. 2018. Map No. 4045; UN. 2020. Map of Haiti; and UN. 2009. Map of Fiji.

Executive summary

Introduction

1. This report assesses and presents satellite-based evidence of the impact of "Action Against Desertification in support of the implementation of the Great Green Wall for the Sahara and the Sahel Initiative and South-South cooperation in the Africa Caribbean and Pacific countries" ("AAD") (GCP/INT/157/EC). The AAD project is implemented by FAO and partners with funding from the European Union under the framework of the Tenth European Development Fund (EDF). The total project budget funded by the European Commission amounts to USD 19 930 479, of which USD 15 763 479 correspond to the Africa component, and USD 4 167 000 correspond to the Pacific/Caribbean component.

2. The specific objective of the AAD project is to 'improve the conditions and productivity of the agrosilvopastoral landscapes affected by DLDD and/through south-south cooperation in ACP countries' (c.f., AAD terms of reference, GCP/INT/157/EC). Recognizing this goal, the main objective of this study is to provide a satellite based, objective accounting of the impact of AAD activities on land productivity. The focus is reflective of the key study questions, specifically:

   i. Alignment & relevance. What was the trajectory of land productivity in the intervention area, as contrasted to other potential sites?

   ii. Effectiveness. What was the impact of AAD activities on land productivity within intervention areas, as contrasted to similar regions with no AAD activities? How large of a region did these activities influence?

   iii. Sustainable Development Goal 13 (SDG 13; Climate Action). What is the estimated global benefit of AAD activities' contributions to the mitigation of carbon emissions?

3. To obtain evidence of the performance of AAD on each of these dimensions, we leveraged the following approaches:

   i. Measurement. The change in gross primary productivity (GPP) of each AAD implementation zone was estimated for every year starting the year before project implementation (baseline) through the most recent full year available (2019). To facilitate robustness checks, two proxy indicators of GPP measured from satellite data are used: the normalized difference vegetation index (NDVI) and the enhanced vegetation index (EVI) (c.f., Sims et al. 2006).

   ii. Baseline targeting. A contrast between areas chosen for intervention and a random selection of areas not selected for intervention is made, both visually and with a Mann-Whitney / Wilcox test for differences.

   iii. Experimental effectiveness. A quasi-experimental geographic interpolation (QGI) approach is employed, in which AAD intervention sites are matched to comparable locations with no interventions. These pairs are contrasted over varying geographic distances to estimate the variation of impact effect over distance (c.f. Runfola et al. 2020).

   iv. Global benefits & SDG13. Given the impacts estimated in the experimental effectiveness analysis, and recognizing concomitant uncertainties, the total carbon emissions sequestered or avoided are estimated using a range of models in the literature. Additionally, an initial valuation of FAO AAD activities is calculated on the basis of a range of carbon valuations (GEF-IEO, 2017).

Main findings

4. As contrasted to areas with similar environmental and demographic characteristics that could have been selected as intervention sites, AAD activities tended to be implemented in areas with a higher baseline EVI value - the proxy variable for gross primary productivity used in this study - with exceptions in Burkina Faso and the Niger.

5. AAD activities in Ethiopia, the Niger and Fiji tended to be implemented in communities with a higher baseline rate of improvement than surrounding, similar communities. This is reflective of intervention activities focused around enrichment activities.

6. AAD activities in all but one region – Nigeria – occurred in communities that had a higher level of EVI in 2019 than during the pre-implementation period.

7. Communities in which AAD activities occurred had a larger positive change in EVI than similar control locations in Ethiopia, Haiti and Senegal; the remaining countries have not illustrated a significant change in either direction at this time.

8. In a controlled quasi-experimental trial, the global estimated effect of AAD activities on EVI was found to be both positive and statistically significant, with AAD intervention locations experiencing approximately 1.5 percent larger increases in EVI than control communities.

9. Quasi-experimental evidence in a controlled trial indicate that AAD interventions influenced the regions around them, with positive and statistically significant effects observable to approximately 1 km from the border of intervention areas. Initial qualitative findings suggest this could primarily be attributed to wind transport.

10. Within-country tests of significance were limited due to the relatively small number of observations within countries and short period of implementation observed; at this time, only AAD interventions in Senegal were found to have a statistically significant impact (positive).

11. AAD projects have an estimated contribution of between 384 thousand and 1.27 million tonnes of carbon sequestered (an increase of 2.2 percent to 9.3 percent from baseline), for a median valuation of USD 3.9 million.

Recommendations

Recommendation 1. The geographic spillover of intervention effects to neighboring communities can increase the reach and impact of FAO projects, and should be considered during site selection.

12. Findings in this study suggest that – globally – AAD activities have positive impacts on neighbouring communities, up to approximately 1 km from project boundaries. This finding is highly variable based on the individual country context being studied, but represents an important attribute of project effect that could be incorporated into future planning. For example, dispersing interventions a minimum of 1 km away could result in a larger outcome on average, but in-country practitioners should carefully assess their own environment to establish an appropriate threshold.

Recommendation 2. The global carbon benefits of many small FAO interventions seeking to improve vegetative productivity can add up to large gains, and represent co-benefits that should be accounted for.

13. While the primary goal of the AAD is to improve local conditions, these activities have benefits that accrue at the global scale. This has particular importance for understanding the contributions of FAO activities towards climate mitigation efforts as related to the Sustainable Development Goals.

Recommendation 3. The collection of high resolution geospatial information on both intervention sites and similar control locations can enable more precise understanding of efficacy, and should be collected where possible.

14. The AAD project team has curated detailed geospatial information on intervention areas, and it is recommended this continue for future efforts. A core limitation of the study presented is that it is quasi-observational in nature: we seek to identify comparable control sites retrospectively, and remotely. While evidence suggests that the matches identified here are both statistically and qualitatively similar, without on-the-ground identification of adequate controls at baseline considerable uncertainty remains as to the underlying match quality.

1. Introduction

1.1 Purpose of this analysis and intended users

1. The satellite imagery analysis presented here contributes to the final evaluation of "Action Against Desertification in support of the implementation of the Great Green wall for the Sahara and the Sahel Initiative and South-South cooperation in the Africa Caribbean and Pacific countries" (AAD) (GCP/INT/157/EC). In addition to the descriptive findings presented here, the quasi-experimental design presented allows for a quantitative, satellite-data based estimate of project performance in a similar way to a clinical trial – contrasting locations with AAD interventions to those without. Further, preliminary estimates of the value of carbon sequestration that may be attributable to FAO activities are modelled based on ancillary spatial data sources.

2. This study is not designed to replace other traditional modalities of evaluation. As with all data sources, satellite data is subject to errors, noise (i.e., clouds), and different modelling assumptions. Rather, the results presented here can be used as a part of a broader triangulation process to identify what works.

3. We specifically seek to achieve the goal of using satellite information to provide quasi-experimental evidence of the effectiveness – or lack thereof – of FAO conservation and restoration policies in reducing desertification, land degradation, and drought (DLDD) in African, Caribbean and Pacific (ACP) countries.

4. The primary audience for this study is the FAO Office of Evaluation (OED) as a component of the final evaluation of AAD. Practitioners within the FAO with experience using geographic information systems (GIS), remotely sensed satellite data, and statistical software such as R may further find this document of interest as a guide for the implementation of causally identified geo-spatial approaches.

1.2 Related studies

5. This analysis contributes to a growing ecosystem of tools and techniques for the use of satellite imagery for monitoring and evaluation of AAD – and more broadly, Great Green Wall (GGW) – projects. These include the *Collect Earth* tool (Saah et al. 2019), which has been used extensively for the planning and monitoring of the AAD projects analysed here; data and tools from the AGRHYMET drought monitoring center (Traore et al. 2014), and a number of recent high profile publications establishing the potential for dryland restoration (Bastin et al. 2019; Bastin et al. 2017).

6. In this study, we extend the methods pioneered by these groups to include a Quasi-experimental study design based on propensity score matching. Unlike the descriptive analyses generally used with spatial data, this method leverages a matching technique to identify "twins" – in this case, areas with AAD interventions and those with no known intervention, but otherwise as similar and geographically close as possible. By exploring the difference between these twins in terms of remotely-sensed characteristics, we illustrate a relatively novel approach to capturing the likely impact of interventions. This builds on previous work by a range of scholars examining similar topics (Runfola et al. 2020; Runfola

et al. 2017; Buchanan et al. 2016; Zhao et al. 2017; BenYishay et al. 2017) using geospatial data in the context of matched study designs.

1.3 Scope and objective of the study

7. By design, this study is tightly bound in scope to focus on aspects of AAD which can be assessed through the use of geo-spatial and satellite information. The scope is thus defined as:

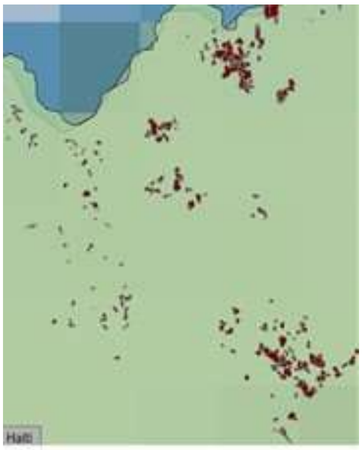
   i. **Unit of observation and geography:** All AAD interventions with geo-spatially recorded boundary information (N=607), as seen in Figure 1. This encompasses demarcated intervention sites in Burkina Faso (N=90), Ethiopia (N=10), Fiji (N=27), the Gambia (N=10), Haiti (N=340), the Niger (N=67), Nigeria (N=37) and Senegal (N=26). Details on the collection methodology are presented later in this document.

   ii. **Time period:** Project implementation began in 2016, with many on-the-ground activities commencing in 2018. The pre-implementation baseline is adjusted on a per-intervention-site basis according to when activities began at a given location. This analysis ends in December 2019, representing the last full year of satellite data available.

   iii. **Target population:** This study will focus on the direct impacts of activities on gross primary productivity (GPP), as measured by satellite proxy. No human target population is intentionally specified. Though it is recognized that many co-benefits may accrue unevenly to different human populations, such an analysis is beyond the scope of this study.

   iv. **Evaluated components:** This study is limited in scope to project components that are reflected in increases in green vegetation at the intervention site. The outcome(s) of other AAD activities, such as the promotion of south-south cooperation, information sharing, capacity development, or monitoring and evaluation (M&E) cannot be captured by satellite imagery over the relatively short time period examined here. We acknowledge and highlight that not all contributions of any activity can be measured solely by satellite imagery.

Figure 2. Example of demarcated intervention areas in Haiti



Notes: See Figure 1 for a global map of all project locations.
Areas delineated in red represent examples of the geographic area-of-intervention tested in this study.
Source: FAO. 2021. *Example of demarcated intervention areas in Haiti*. Rome. Map complies with UN. 2020. Map of Haiti.

8. The core **objectives** of this study are to i) provide quantitative evidence for the effectiveness – or lack thereof – of AAD project activities, as bound by the above scope, and ii) illustrate an evaluative approach which can be used as an input into future M&E efforts. It contributes to the evaluation key questions (formulated in the AAD evaluation terms of reference [TOR]) summarized in Table 1.

Table 1. Summary of key evaluation questions, research questions explored in this report, and methodological approach

Evaluation questions (AAD evaluation TOR)	***Research questions***	***Methodology***
1. Alignment and relevance 1.2 How relevant was the project for the 8 AAD countries, for the Great Green Wall and generally for other dryland areas/regions (e.g. southern Africa and Horn of Africa) affected by land degradation (including FAO technical support, its methodology, approaches and tools)?	Is there a significant difference between intervention sites chosen by the FAO and those not chosen based on pre-implementation trends in vegetation, as detected by satellite imagery?	1) Calculate pre-trend proxy variable for vegetative productivity: A) For all intervention sites. B) For unchosen sites. 2) Contrast using (a) visual distribution inspection, and (b) Mann Whitney U Test
2. Potential impact 2.0 To what extent (and how effectively) has the project contributed to improving the conditions and productivity of the agrosilvopastoral landscapes affected by DLDD and/through south-south cooperation in ACP countries? 2.7. (How) do the results achieved contribute to the achievement of the SDG 13 (Climate Action)?	Did areas within or proximate to AAD intervention zones present with a faster rate of vegetative growth than those outside of AAD intervention zones? If activities positively impacted vegetative growth, what (if any) are the concomitant valuations of carbon sequestered?	1) Calculate satellite and other geospatial variables for all intervention sites and a large sample (n=10 000) of controls. 2) Contrast these groups by matching FAO intervention locations to near-identical locations without FAO intervention using the QGI approach. 3) Estimate the value of carbon sequestration that could be attributed to FAO interventions, given the findings from step 2.

Source: FAO. 2021. *Summary of key evaluation questions, research questions explored in this report, and methodological approach*. Rome.

1.4 Methodology

15. **Methodological approach:** A four-phase approach was selected to answer each of the research questions summarized in Table 1:

i. Data collection & integration.

- AAD intervention sites were mapped by AAD actors during project implementation (see Figure 1 and 2, above).
- A synthetic sample of 10 000 sites at which no known AAD interventions occurred was created.
- For all intervention and synthetic sites, satellite information was extracted and integrated into a common dataset for analysis (see Table 2). We specifically focus on the enhanced vegetation index (EVI) as our outcome, a value which ranges from -1 to 1. Values from 0 to 1 can be interpreted as a proxy

measurement for vegetative productivity, with values approaching 1 indicating higher productivity.

ii. Targeting & descriptive analysis

- Descriptive statistics on pre-implementation states were estimated for each of the two groups (intervention and synthetic sites). This was done independently for each country.
- This is repeated twice, once for baseline levels and once for baseline trends.

iii. Quasi-experimental impact estimation

- AAD project intervention sites are matched to similar, "twin", synthetic sites at which no intervention occurred, with similarity measured based on variables described in Table 2.
- Intervention and non-intervention synthetic sites are contrasted to estimate the effect on a satellite-derived vegetative productivity proxy (EVI).
- This process is repeated for different spatial distances from AAD intervention locations to detect the geographic distance(s) from AAD projects where effects can be detected.

iv. Global benefits: potential carbon sequestration

- The estimates derived for the impact of FAO projects on vegetative productivity in stage iii are used as inputs into a range of models that capture the relationship between proxy variables for GPP (i.e., EVI) and carbon.
- Based on the geographic scope of implementation, we estimate the range of tonnes of carbon sequestration (or avoided emissions) that may be attributable to AAD activities.
- Based on a collected range of valuations for tonnes of carbon, we produce the average and range of valuations attributable to AAD activities.

9. **Sample Frame**. During project implementation, the area of project activities was captured at 607 AAD intervention sites by on-the-ground partners (see Figures 1 and 2, above). These regions are used as the unit of observation for this study. Additionally, 10 000 random points were dropped at distances from approximately 1 meter up to 150 km away from FAO projects, excluding all known intervention areas and with an approximately equal number of random points proximate to each cluster of intervention sites. Each of these points is buffered to create a circle with an area approximately equal to the average AAD intervention site (0.5 km^2). After removing points dropped in invalid locations (i.e., for which satellite measurements are not available due to cloud cover or other irregularities), a total of 9 982 eligible locations remained. These "synthetic sites" are used in a variety of contrasts, as described below.

10. **Intervention area delineation.** Detailed geographic data on the locations at which AAD interventions were undertaken was collected through a number of in-situ visits to each country by both AAD managers and implementing partners, GPS units mounted to plows, as well as delineated by satellite as a part of multiple multi-stakeholder workshops coordinated by the FAO. Geographic conflict, COVID-19 related challenges, and the timing of training activities limited data collection in some regions; the lack of data is most evident in Ethiopia (N=10) and the Gambia (N=10). Of note, due to the relatively small geographic-

scale nature of interventions in Fiji (small scale farming and agroforestry), locations are only known based on a latitude-and-longitude location, modestly increasing the spatial uncertainty associated with the analysis in that country.

11. **Satellite data collection & integration.** For each polygon described in our sample frame (intervention sites and synthetic sites), satellite and other geospatial information was collected from a range of sources, summarized in Table 2. In order to aggregate all data into a common frame, a weighted reducer approach was used to aggregate satellite imagery data values within each intervention area into a single estimate. This approach followed a three-step process in which:

i. All pixels with a minimum of 0.5 percent of their geographic area within the intervention area are selected from a global satellite image.

ii. The area of each pixel that falls within a given intervention area is calculated (i.e., a pixel on the border of an intervention area may be split so that not the entire pixel of data falls within the border).

iii. A weighted average of each pixel is calculated based on these overlaps.

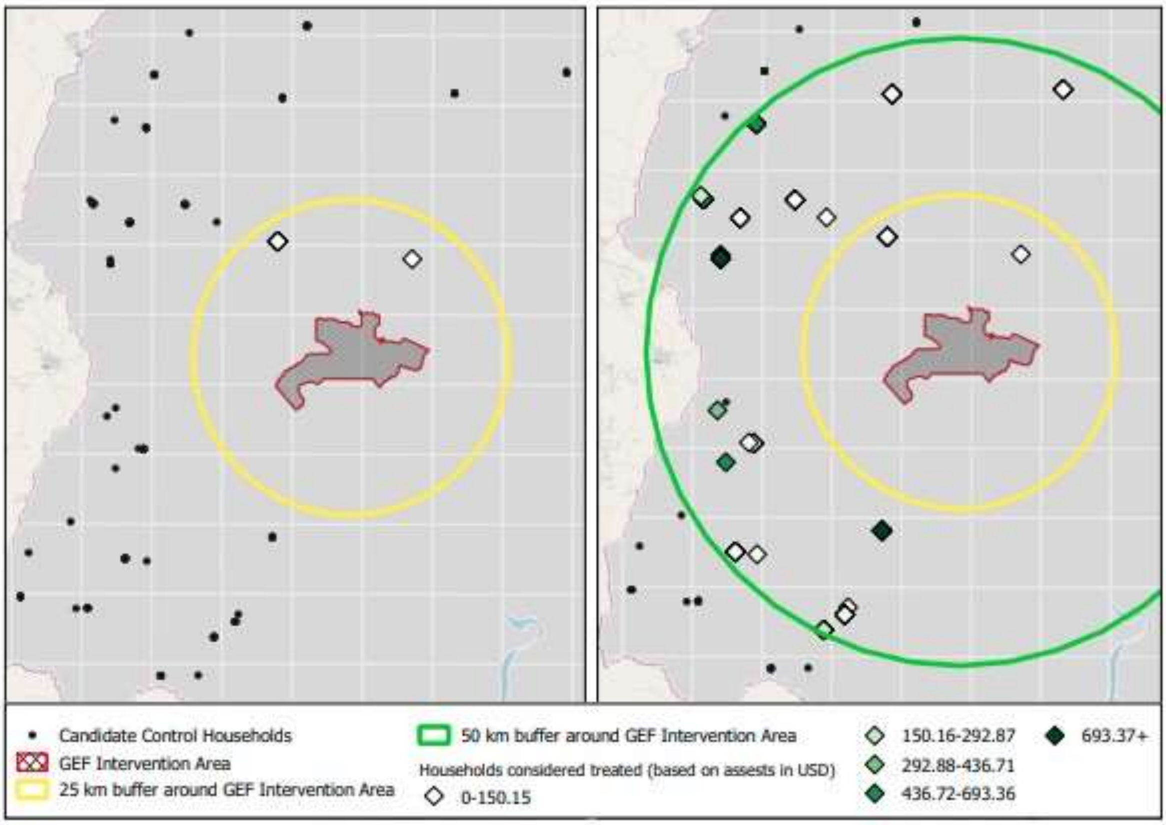
Table 2. Data sources used in this analysis

Feature	Source	Resolution
Global Administrative Zones	geoBoundaries Administrative Zones	Variable
NDVI	NASA LP DAAC at the USGS EROS Center	250 m
EVI	NASA LP DAAC at the USGS EROS Center	250 m
Land Surface Temperature	NASA LP DAAC at the USGS EROS Center	1000 m
Nighttime Lights	Earth Observation Group, Payne Institute for Public Policy, Colorado School of Mines	1 km
Population	NASA SEDAC at the Center for International Earth Science Information Network	1 km
Topography	NASA / CGIAR	90 m
Precipitation	ECMWF / Copernicus Climate Change Service	0.25 arc degrees
Air Temperature	ECMWF / Copernicus Climate Change Service	0.25 arc degrees
Surface Pressure	ECMWF / Copernicus Climate Change Service	0.25 arc degrees
Soil Moisture	University of California Merced	2.5 arc minutes
Palmer Drought Severity Index	University of California Merced	2.5 arc minutes
Actual Evapotranspiration	University of California Merced	2.5 arc minutes
Reference Evapotranspiration	University of California Merced	2.5 arc minutes
Runoff	University of California Merced	2.5 arc minutes
Climate Water Deficit	University of California Merced	2.5 arc minutes
Downward Surface Shortwave Radiation	University of California Merced	2.5 arc minutes

Source: FAO. 2021. *Data sources used in this analysis*. Rome.

12. **Targeting & descriptive analysis.** Two related approaches are applied to explore the spatial distribution of AAD projects. First, the pre-implementation vegetative productivity of all intervention areas is visually contrasted to matched (i.e., the most similar) synthetic regions, both globally and by country. This contrast is designed to inform us as to if the geographic areas the AAD interventions targeted were less or more productive than potential alternative areas that might have been selected. The second approach is designed to descriptively explore the baseline and contemporary levels of GPP by country, as well as for all projects. While this descriptive step cannot be understood as causal, as a number of confounding variables are not controlled for (see our analysis of effectiveness in the next section), it provides a quick overview of on-the-ground conditions in each implementation region.

Figure 3. Illustrative example of QGI approach



Notes: To establish the effect of the project outlined in red, all observations within the yellow circle (25km from GEF projects in this example) are considered to have been treated by the intervention, and contrasted to locations outside of the green circle (50km away), representing the maximum expected area of influence. This process is repeated hundreds of times for varying distance bands.

Source: Adapted from Runfola, D., Batra, G., Anand, A., Way, A. and Goodman, S. 2020. Exploring the socioeconomic co-benefits of Global Environment Facility projects in Uganda using a quasi-experimental geospatial interpolation (QGI) approach. *Sustainability: Science Practice and Policy,* 12(8): 3225.

13. **Local benefits: effectiveness of AAD activities in increasing GPP.** A quasi-observational geographic interpolation (QGI) approach is employed to assess the impact of AAD activities on the EVI, a proxy indicator of gross primary productivity. The QGI procedure builds on traditional propensity matching approaches, contrasting observed outcomes of areas proximate or within AAD intervention areas to areas far away from AAD intervention areas, but otherwise as similar as possible (see figure 3). The full procedure and mathematical underpinnings for QGI is outlined in Runfola et al. (2020), but can be summarized as:

   i. The selection of an upper distance band beyond which no impact is expected. In this case, we iteratively explore different distance thresholds to identify a distance at which no AAD project influence is observable; this distance band is variable depending on the country being analysed. For the global case of all AAD projects, we use a 5 km threshold.

   ii. We identify all of the 10 000 synthetic sites in our sample frame that are at least 5 km away from a AAD activity. This subset is used as a counterfactual for all modelling.

14. The following is then done 1 000 times, for distances ranging from 0 to a maximum of 6 km away from AAD projects (incrementing by 5 meters at each step):

i. We identify all of the sites (synthetic or AAD intervention) that fall within distance *d* of an AAD intervention, and add them to our "intervention" set. In the first iteration (distance *d* of 0), the intervention set would only include the AAD intervention sites themselves; in the 200th iteration (distance *d* of 1 000 meters), the intervention set would include all AAD intervention sites as well as all synthetic sites that fall within 1 km of AAD intervention sites.

ii. We match each of these intervention sites to one of the control sites identified in step ii, following a propensity matching approach that seeks to control for bias in project site selection.

iii. Based on this matched sample, we model the effect of the treatment using a linear model and record the treatment effect estimate, standard errors, and distance band.

15. Once the above process is complete, a distance decay curve is fit and the standard errors of the models are displayed over distance, allowing for the examination of impacts as a function of distance from project implementation location. This process is repeated for individual countries with adequate sample sizes, limiting eligible control sites to within the borders of each country.

16. **Match balance.** To explore the comparability of our match sampled (AAD intervention areas to areas without an AAD intervention), we conduct both a quantitative comparison of the matched pairs underlying statistics (see Table 4), as well as a qualitative comparison of the imagery from the matched geographic areas (see Figure 4). Because no historic control sample was determined using on-the-ground interviews or observations, we are reliant on remote methods to assess comparability (i.e., a quasi-observational study). While we constrain the matches in many ways – i.e., all matches are designed to be within the same country, are generally close together, are biophysically and demographically similar – differences between the matches still remain a source of uncertainty and potential error in this study. Matched pairs might include areas with no population (in the case of large-scale plowing interventions), or communities (in the case of more localized interventions). Figure 4 provides example satellite imagery for a small selection of the matched cases.

Figure 4. Qualitative comparison of two control and treatment locations selected on the basis of the variables presented in Table 2

Source: FAO. 2021. *Qualitative comparison of two control and treatment locations*. Rome.

17. In addition to these contrasts, in an interview with the AAD International Project Coordinator we sought to understand the limitations of the matching framework within the study countries. Because we matched cases within countries (i.e., an intervention location at which plowing was conducted but otherwise had no population would be contrasted to a location that also had no population, but plowing was conducted, within the same region), we were primarily interested in remaining heterogeneity that might be unaccounted for (for example, large scale cultural differences within a single country across intervention areas). Of note in this interview was that while the implementation regions selected within most regions are fairly homogeneous, in the case of the Gambia our ability to identify "control" locations was likely heavily limited due to the generally small geographic area which is eligible for intervention. Because the Gambia had relatively few observations, and in light of this concern, we withheld individual country results in that case.

18. **Global benefits: carbon sequestration.** To estimate the value of carbon either sequestered or avoided emissions due to a prevention of land degradation by AAD projects, we employ an approach similar to that used in GEF-IEO (2017). First, through a literature review we collect a set of equations that establish the relationship between EVI and carbon. Taking into account the impact of AAD projects on EVI established by QGI, the geographic size of each intervention, and total time of implementation, we use these equations to estimate total carbon biomass either sequestered or avoided. Noting these models are both geographically sensitive and have significant uncertainties, we derive estimates from four models relating EVI to carbon (see Table 3). Finally, we note that these models all seek to model slightly different outcomes – i.e., total living carbon, aboveground carbon, or forest aboveground carbon. We leverage each of these outcomes in our totals, as they inherently provide different assumptions about sequestration (i.e., that AAD interventions impact all biomass or only above ground biomass).

Table 3. Equations used to estimate carbon sequestered on the basis of shifts in EVI and NDVI

Equation	Indicator	Study
TC = -39.76 + 151.7 * EVI	Total Carbon Stock	(Situmorang et al., 2016)
TC = 40.73 + -65 * ln(EVI)	Total Carbon Stock	(Kumar and Ghose, 2017)
TLB (t/ha) = -84.22 + 280.93 * X TLC = 0.47 * TLB	Total Living Biomass (TLB) – converted to Carbon Biomass based on field study plots (500) at 47% scale.	(Gizachew et al., 2016)
AGTB = 2924.85*e* ^ (10.8*EVI) TC = 0.5 * AGTB	Above Ground Total Biomass Total Carbon	(Adeniyi and Ezekiel, 2017)

Source: FAO. 2021. *Equations used to estimate carbon sequestered on the basis of shifts in EVI and NDVI*. Rome.

19. We use the model estimates of total carbon sequestered or emissions avoided as input into a second model, which calculates a range of possible carbon valuations based on a review of published carbon prices from carbon markets and government tax bodies. The product of these valuations and the estimated tonnes of carbon sequestered are used to estimate a final distribution of project valuations, which are aggregated at the global scale. Of note, we do not provide regional estimates due to the large variation in the relationship between EVI and carbon biomass across different floral regimes; further information on this challenge, and the convergence of accuracy at global scales, can be found in (Gizachew et al. 2016; Labrecque et al. 2006; Jakubauskas and Price 1997). Values are derived from

carbon taxes or markets which generally do not establish specific time horizons for how long carbon is to be sequestered; rather, prices are generally set based on market or political desire to return to lower-carbon emission states for a region by a target date, which can be variable.

1.5 Limitations

20. There are four major limitations to the findings of this study. First and foremost, only elements of AAD activities which are reflected in fluctuating EVI are considered. This inherently limits the scope of this analysis to one key variable, GPP. AAD activities have had many other goals and benefits, which are not considered in this work. As this study seeks to contribute to a larger evaluation on AAD activities, this challenge should be mitigated through the multiple techniques and approaches being leveraged.

21. The second major limitation is in our valuation strategy. By design, it only considers project value from avoided carbon emissions and sequestered carbon. We do not attempt to capture other sources of value promoted by AAD activities (i.e., other ecosystem services).

22. The third major limitation is in data – in some implementation regions, it was difficult or impossible to collect the geographic information necessary to conduct this analysis. The core limitation of this is that country-specific estimates for the Gambia and Ethiopia are not possible at this time. We discuss this limitation further in our above notes on the geographic delineation of intervention areas.

23. The fourth limitation is in the design of the study itself. By design, AAD interventions tend to be located in areas that are at relatively low risk of deforestation, for a range of reasons. This means that traditional analyses that would explore avoided deforestation – an outcome that can be observed over relatively short timespans – are not of use in this context. Furthermore, because data on reforestation is not available at this time (with a period of only ~three years since implementations began), we are currently limited in our ability to explore the impacts of AAD projects on forest-growth related metrics. Similarly, we do not anticipate a significant capability to detect avoided desertification over the relatively short time spans explored here.

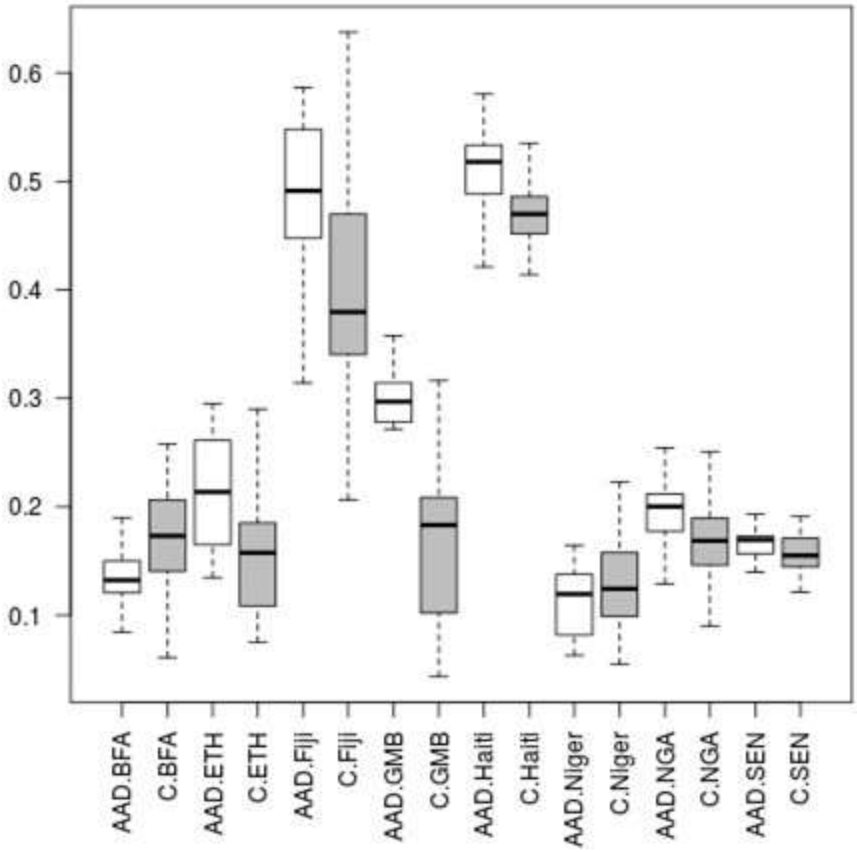
2. Findings

2.1 Research question 1

Is there a significant difference between intervention sites chosen by the FAO and those not chosen based on pre-implementation trends in vegetation, as detected by satellite imagery?

Finding 1.1. Contrasted to areas with similar environmental and demographic characteristics, AAD activities tended to be implemented in areas with higher baseline EVI, with exceptions only in Burkina Faso and the Niger.

Figure 5. EVI baseline – AAD vs. matched controls



Notes: This figure illustrates the distribution of EVI baseline values within all AAD intervention areas and comparable synthetic sites with no intervention, with higher values indicating a higher level of GPP.

Source: FAO. 2021. *Contrasting baseline EVI between control and treatment groups*. Rome.

Table 4. Summary of balance between control and treatment classes across all ancillary variables

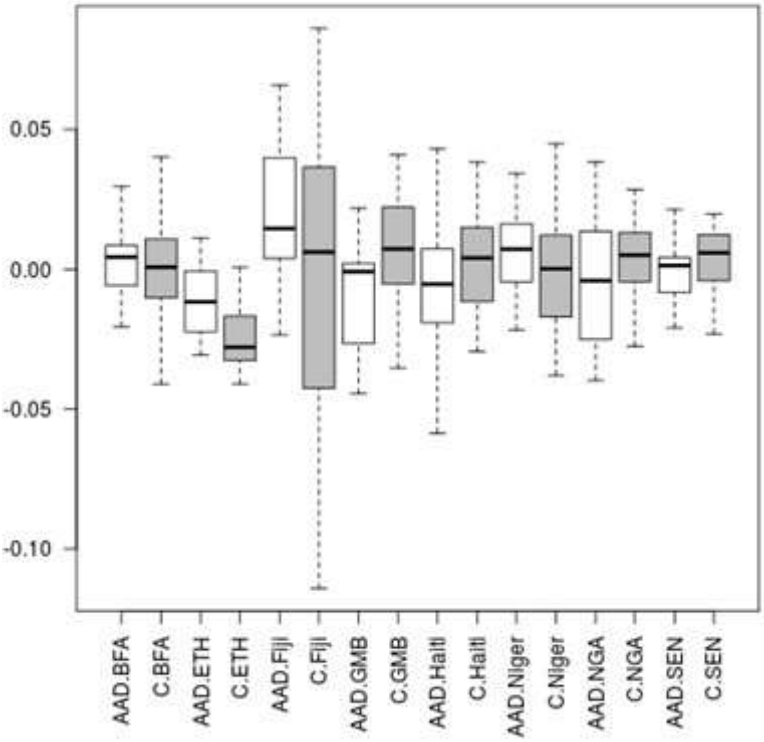
	Mean		SD		
	Control	AAD	Control	AAD	Histogram
Population	11.52	20.34	10.63	12.97	
Elevation	300.30	244.88	227.26	196.57	
Years of implementation	1.87	1.39	0.99	0.79	
Baseline EVI	0.19	0.37	0.10	0.18	
Baseline EVI Trend	0.00	-0.00	0.02	0.02	
Baseline NDVI Trend	0.00	0.01	0.03	0.03	
Baseline Precipitation	0.05	0.06	0.04	0.04	
Baseline Air Temperature	301.81	300.59	1.79	1.60	
Baseline Land Surface Temperature	15416.35	15213.03	124.49	209.44	
Baseline Surface Pressure	97783.08	99568.50	2787.05	2356.36	
Baseline Soil Moisture	225.16	709.50	305.31	493.64	
Baseline PDSI	89.37	228.57	271.78	188.97	
Baseline Actual Evapotranspiration	524.42	814.69	188.18	300.70	
Baseline Runoff	17.97	56.46	41.45	51.88	
Baseline Water Deficit	1195.80	618.78	385.19	605.70	
Baseline Reference Evapotranspiration	1726.85	1432.29	205.59	305.58	
Baseline Shortwave Radiation	2406.56	2270.47	137.82	165.56	
AAD_Activity	0.00	1.00	0.00	0.00	

Source: FAO. 2021. *Summary of balance across ancillary variables*. Rome.

24. When contrasting baseline EVI values within intervention areas, we find that – on average – AAD interventions tend to target areas with a baseline state that is more vegetatively productive than other areas that are otherwise comparable (Figure 5). This is confirmed through a Wilcox Rank Sum test of medians (significant at $\alpha = 0.05$); values for all covariates can be seen in Table 4.

Finding 1.2. AAD interventions in Ethiopia, the Niger and Fiji illustrated bias towards areas that were improving at a faster rate before AAD activities began.

Figure 6. EVI trend baseline – AAD vs. matched controls



Notes: Illustration of the baseline trends of EVI in the years leading up to activity implementation. Y-axis represents annual rate of change in EVI between 2000 and the year before implementation.

Source: FAO. 2021. *Contrasting baseline trends in EVI between control and treatment groups*. Rome.

25. Figure 6 shows, for every project, the annual rate of change of EVI between the year 2000 and the year before project activities commenced. The visualizations provide a contrast between the matched synthetic controls most like the AAD implementation areas, and actual AAD implementation areas within each country. As this figure illustrates, some countries did not have any bias in implementation – i.e., the distribution of AAD projects' EVI baseline trend is similar to the generated synthetic controls. However, three countries have notable biases in selection towards areas that had higher baseline trends than our random sample. These three countries are Ethiopia, the Niger and Fiji. Conversely, the Gambia, Haiti and Nigeria appear to have targeted areas with lower baseline trends.

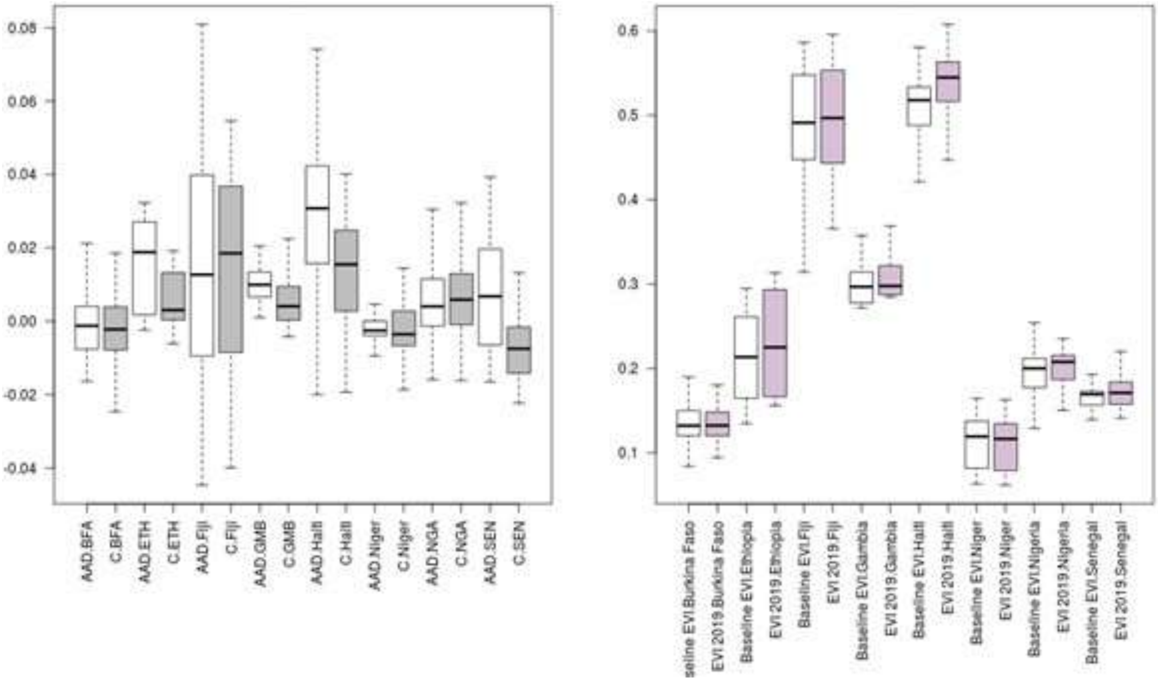
2.2 Research question 2

Did areas within or proximate to AAD implementation zones present with a faster rate of vegetative growth than those outside of AAD implementation zones?

Finding 2.1. From baseline to 2019, the increase of EVI in AAD intervention locations was significantly ($\alpha = 0.05$) higher than in synthetic control sites with no interventions.

26. In an uncontrolled comparison (i.e., no covariates or potentially confounding variables are considered), across all FAO projects there was a significantly ($\alpha = 0.05$, Wilcox rank sum test with continuity correction) higher median increase in EVI. Across the implementation period, AAD implementations have an observed median positive increase of 0.0145, contrasted to a median positive increase of .005 for all control cases. These increases are relative to an overall baseline median of 0.206 – i.e., the median AAD project resulted in a ~7 percent higher EVI than control cases (Figure 7).

Figure 7. EVI absolute change (AAD vs. controls) and AAD only EVI change baseline to 2019



Notes:
A) Contrast between all synthetic control locations and AAD project intervention locations, in terms of the absolute change between 2019 and the year project implementation began.
B) Change from baseline (white) to 2019 (purple) for each country.

Source: FAO. 2021. *Contrasting change in EVI between intervention and non-intervention locations*. Rome.

Finding 2.2. In a controlled quasi-experimental trial, the global estimated effect of AAD activities on EVI was found to be positive and statistically significant.

27. Table 5 presents the results from a quasi-experimental model built on a propensity score matching approach. This approach is built on a Rubin Causal Model, in which we seek to match geographic areas that contained an AAD intervention to areas that did not contain an AAD intervention, but are otherwise as similar as possible (similar to "twins" in a clinical trial, but retrospective and thus quasi-experimental). Table 4 and paragraph 15 provide more information on the relative similarity of each class (AAD and synthetic control). The first column of Table 5 shows the result from the fully matched model with all covariates and fixed effects. As this shows, after controlling for all covariates and matching to similar control sites, AAD activities are estimated to have increased EVI by 0.003 on average (or approximately 1.5 percent of the median EVI baseline).

28. Additionally, the country fixed effects in the matched model give us an opportunity to explore the relative (not absolute) effectiveness of AAD activities within each country. This global view suggests that Haiti, Ethiopia, the Gambia and Senegal are all performing at a level higher relative to the baseline (Burkina Faso), while the Niger is performing at a lower level. Results for Nigeria and Fiji were not statistically significant.

Table 5. Globally matched models with country fixed effects

	Matched Model	Propensity Model	Model A	Model B	Model C	Model D	Model E
Impact Estimate of AAD Activity	0.003*** (0.002)		0.017*** (0.000)	0.006*** (0.000)	0.005*** (0.000)	0.005*** (0.000)	0.004*** (0.000)
Intercept	-0.680* (0.096)	117.818*** (0.009)	0.001* (0.096)	-0.010*** (0.000)	-0.010*** (0.000)	-0.009*** (0.000)	-0.003*** (0.002)
Population	0.000 (0.900)	0.003 (0.704)					
Elevation	-0.000 (0.129)	-0.001 (0.211)					
Tree Cover Area (2000)	-0.000 (0.512)	-0.000*** (0.000)					
Years of Implementation	-0.000 (0.846)	-0.060 (0.382)				-0.000 (0.398)	
Baseline EVI	-0.069*** (0.000)	-11.021*** (0.000)		0.059*** (0.000)	0.059*** (0.000)	0.059*** (0.000)	
Baseline EVI Trend	-0.174*** (0.000)	12.276 (0.166)			-0.203*** (0.000)	-0.203*** (0.000)	
Baseline NDVI Trend	0.054** (0.048)	2.776 (0.641)					
Baseline Precipitation	-0.195*** (0.001)	-0.989 (0.924)					
Baseline Air Temperature	0.005*** (0.002)	-0.526*** (0.005)					
Baseline Land Surface Temperature	-0.000*** (0.001)	0.000 (0.807)					
Baseline Surface Pressure	-0.000** (0.020)	0.000 (0.847)					
Baseline Soil Moisture	0.000** (0.034)	0.005*** (0.000)					
Baseline PDSI	-0.000* (0.079)	-0.001*** (0.004)					
Baseline Actual Evapotranspiration	0.000 (0.761)	-0.001 (0.639)					
Baselrie Runoff	0.000 (0.532)	-0.010 (0.312)					
Baseline Water Deficit	-0.000 (0.122)	-0.007*** (0.000)					
Baseline Reference Evapotranspiration	-0.000 (0.704)	0.008*** (0.000)					
Baseline Shortwave Radiation	-0.000 (0.139)	0.011*** (0.000)					
Country Fixed Effects (BFA Baseline): Ethiopia	0.027*** (0.010)	-3.461*** (0.001)					0.013*** (0.000)
Fiji	0.027 (0.134)	8.902*** (0.001)					0.015*** (0.000)
Gambia	0.014** (0.038)	1.307* (0.073)					0.008** (0.013)
Haiti	0.023*** (0.008)	4.614*** (0.000)					0.027*** (0.000)
Niger	-0.004** (0.040)	0.433* (0.100)					-0.001 (0.276)
Nigeria	0.004 (0.272)	2.462*** (0.000)					0.007*** (0.000)
Senegal	0.013* (0.051)	1.200* (0.058)					0.001 (0.792)

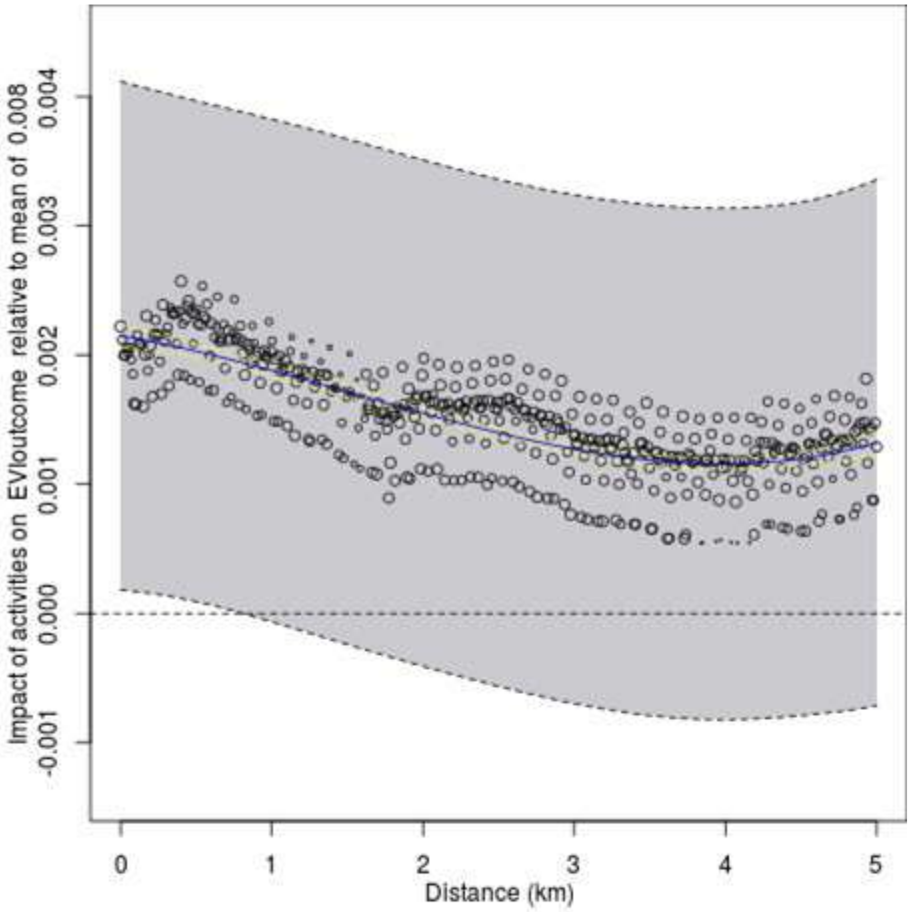
* p < 0.1, ** p < 0.05, *** p < 0.01

Notes: Models A-E are for reference. Propensity model is representative of the model used to match control and intervention locations.

Source: FAO. 2021. *Global matched models with country fixed effects*. Rome.

Finding 2.3. AAD interventions influenced the regions around them, with positive and statistically significant effects observable to approximately 1 km from the border of intervention areas.

Figure 8. Results of a quasi-experimental geographic interpolation model

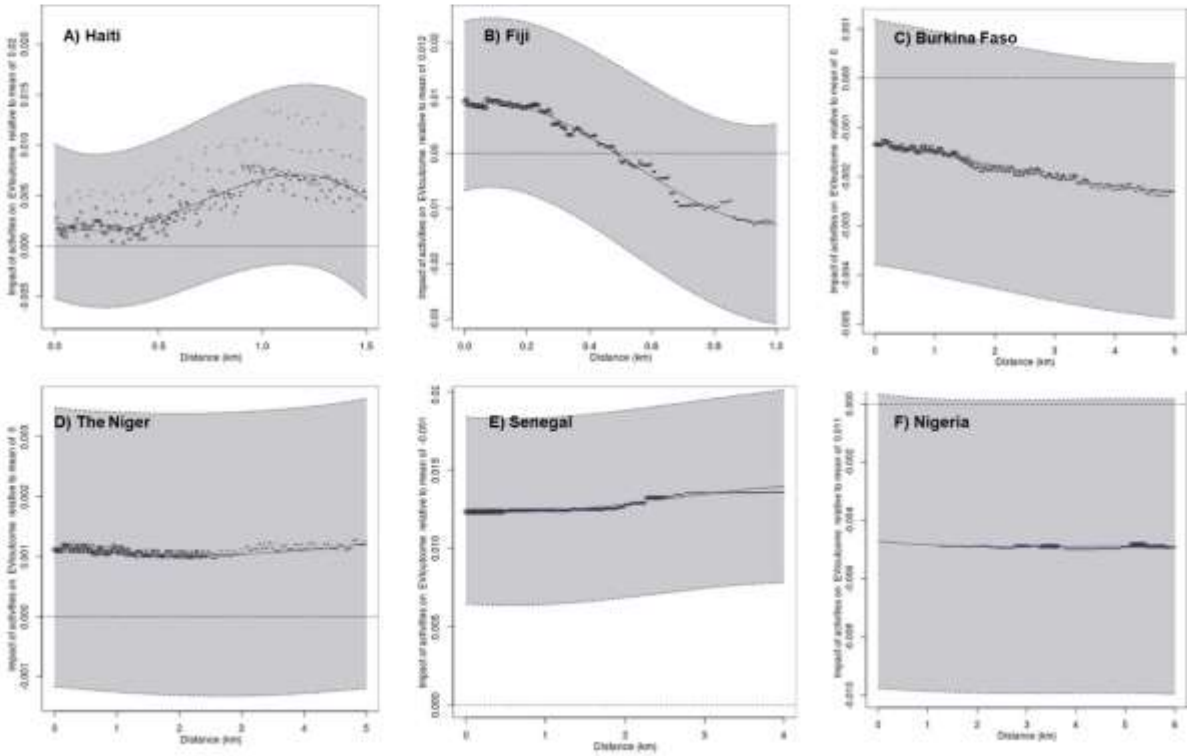


Notes: Each point on this graph represents a matched model similar to that introduced in table 4. The location of each point on the y-axis is equivalent to the estimated coefficient for the impact of AAD interventions; the location of each point on the x-axis represents the distance away from AAD interventions the effect is being tested for. The grey region represents a 95 percent confidence interval of the relationship between distance and effect.

Source: FAO. 2021. *Results of a quasi-experimental geographic interpolation model*. Rome.

29. For both the global and individual country cases, we constructed a quasi-experimental geographic interpolation model to explore how impact effects vary – both within countries and over space. Figure 7 illustrates the global relationship between distance and effect. The detected effect on EVI of AAD interventions remained significant – and positive – up to a distance of 1 km from each AAD implementation area, as indicated by the grey bands in Figure 8 (where the grey area intersects the dotted line is representative of a loss of statistical significance). No significant effects were identified beyond that distance. This finding highlights the spillover effects that might be expected from AAD activities. Further, non-significant findings suggest that spillover may expand further from AAD activities.

Figure 9. Results of a quasi-experimental geographic interpolation model conducted within each country



Notes: Each point on this graph represents a matched model similar to that introduced in Table 4. The location of each point on the y-axis is equivalent to the estimated coefficient for the impact of AAD interventions within a given country; the location of each point on the x-axis represents the distance away from AAD interventions the effect is being tested for. The grey region represents a 95 percent confidence interval of the relationship between distance and effect.

Source: FAO. 2021. *Results of quasi-experimental geographic interpolation across different countries*. Rome.

Finding 2.4. Within-country experiments provide further evidence of the effectiveness of projects in Senegal, but are still inconclusive for remaining countries.

30. Figure 9 presents the country-specific findings for QGI for each country that had a positive detected impact at any distance. Unlike the global models presented above, these models can be interpreted as the absolute impact an AAD intervention had within a given country. Because of the smaller sample size within each country, it is rare that these findings are significant – we identify no statistical significance in Haiti (Figure 8A), Fiji (8B), Burkina Faso (8C), the Niger (8D) or Nigeria (8F). Only in Senegal is the evidence statistically significant (figure 8E) for all measured distances. Of note, both the Gambia and Ethiopia lacked enough samples (N=10 in both cases) to fit meaningful within-country models.

2.3 Research question 3

Global co-benefits: If activities positively impacted vegetative growth, what (if any) are the concomitant valuations of carbon sequestered?

Finding 3.1. AAD projects have contributed between 384 000 and 1.27 million tonnes of carbon sequestered since activities began (an increase of 2.2 percent to 9.3 percent from baseline).

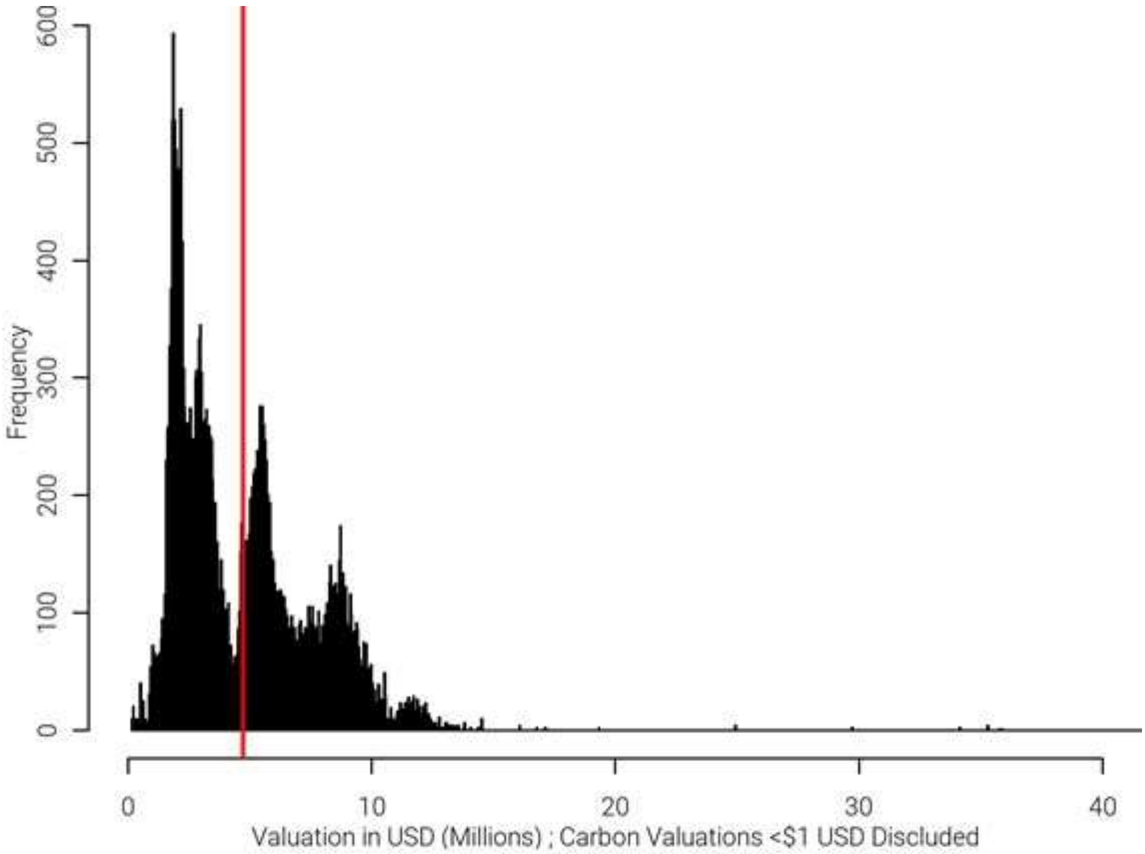
31. Four different models (Table 3) were applied to estimate the impact of AAD activities on carbon sequestration and avoided emissions. Each of the four models are calibrated based on a different study, allowing for a range of uncertainties regarding the relationship

between EVI and carbon. Accounting for the annual rate of change promoted by AAD activities, between 2016 and 2019 the four models suggested AAD activities led to a total of (in ascending order; letters indicate model by author initial): 176 825 tonnes (G); 203 158 tonnes (S); 518 772 tonnes (A); 518 942 tonnes (K).

32. Because each model made different assumptions (i.e., total carbon vs. above-ground biomass), we also present the percentage increases observed in each case. These were 2.5 percent (G); 4.7 percent (S); 3.4 percent (A); and 1.4 percent (K). As these values illustrate, despite model K indicating the highest absolute increase in tonnes of carbon attributable to AAD projects, this same model approach also has the smallest percentage increase (1.4 percent), indicating that model K estimates higher baseline levels of carbon than G, S or A.

Finding 3.2. Considering a wide range of valuations for carbon (8 093) from carbon markets, taxes, and other mechanisms, we estimate that on average AAD projects have contributed USD 4.7 million (median USD 3.9 million) in benefits in terms of carbon sequestration and/or avoided emissions.

Figure 10. Range of potential valuations of AAD activities in terms of carbon mitigation, USD



Source: FAO. 2021. *Range of potential valuation of AAD activities in terms of carbon mitigation, USD*. Rome.

33. There is considerable uncertainty in what the valuation of carbon should be, ranging from under a USD 1 to over USD 100 when various social, economic, political, and other factors are taken into account. Figure 6 shows the range of potential valuations when both model uncertainty (described in finding 3.1) and valuation uncertainty is accounted for. When

carbon valuations under USD 1 are included, the mean estimated value of AAD sequestration is approximately USD 4.4 million, with a median of USD 3.5 million. If carbon values of USD 1 a tonne and lower are excluded, this value increases to USD 4.7 million with a median of USD 3.9 million.

34. These values can be interpreted relative to project costs – i.e., the project budget of USD 19 930 479 or USD 23 614 628 at current exchange rates. Using the most conservative of the above valuations, this suggests a return on investment of approximately USD 0.15 for every USD 1 of investment including only value related to carbon sequestration and avoided emissions. As this was not a stated objective of AAD, this return on investment can be understood as additional value, or a global co-benefit, of investments to date.

3. Conclusions and recommendations

3.1 Conclusions

Conclusion 1. *Alignment and relevance* – AAD activities tended to be implemented in areas with a higher baseline EVI (as a proxy for GPP).

35. Relative to similar communities that could have been targeted by AAD activities, in most countries there was an apparent bias towards communities with a higher baseline level of EVI (with the exception of Burkina Faso and the Niger). In communication with project staff, this is reflective of the targeting of enrichment activities in many countries.

Conclusion 2. *Potential impact* - Quasi-experimental analysis shows AAD activities have likely resulted in a positive, statistically significant increase (~1.5 percent) in EVI relative to communities with no interventions. The positive impact of AAD activities is also reflected in a median descriptive increase of 7 percent.

36. Multiple strategies to explore the impact of AAD projects on EVI were explored, including calculating the EVI within each project implementation site at baseline and 2019; matching AAD sites to synthetic control sites and contrasting outcomes; and the implementation of a range of different propensity score modelling approaches (see Table 5). At the global scale, every modelling approach applied suggested that AAD activities have had a modest, statistically significant impact on EVI, even over the relatively short time period examined here. Further, for one country in which sufficient evidence was available (Senegal), AAD activities also suggested a positive impact on EVI.

Conclusion 3. *Potential impact* - Geospatial evidence suggests that AAD activities have had a positive, statistically significant impact in communities up to approximately 1 km away from the border of intervention areas. While extensive heterogeneity in this relationship exists across countries, there is insufficient evidence to calibrate the distance decay relationship at this time.

37. By iteratively matching different groups of controls at varying distances from AAD activities (QGI), Figure 8 illustrates the relationship between distance and estimated effect of AAD interventions. These findings highlight a 1 km area around AAD interventions at which statistically significant effects can still be detected. Because of the need for a large quantity of data, Figure 8 only shows the global relationship: Figure 9 shows the same figures for each country, which in (nearly) all cases resulted in statistical insignificance, and thus limits our ability to draw conclusions.

Conclusion 4. *Potential impact* - We estimate that the global benefits of AAD activities include carbon sequestration and avoided emissions of between 384 000 and 1.27 million tonnes of carbon (2.2 percent to 9.3 percent increase from baseline).

38. By extrapolating the global findings attributable to AAD projects, we are able to make an estimate of the total carbon sequestered (or avoided emissions) across the portfolio of measured interventions. This conclusion is limited to the global scale due to inherent uncertainty regarding the relationship between EVI and carbon across different floral regimes; while we capture some of this uncertainty by using multiple model strategies, the body of knowledge on this relationship is too imprecise to warrant more specific (country level) conclusions at this time.

3.2 Recommendations

Recommendation 1. The geographic spillover of intervention effects to neighboring communities can increase the reach and impact of FAO projects, and should be considered during site selection.

39. Findings in this study suggest that - globally - AAD activities have positive impacts on neighbouring communities, up to approximately 1 km from project boundaries. This finding is highly variable based on the individual country context being studied, but represents an important attribute of project effect that could be incorporated into future planning. For example, dispersing interventions a minimum of 1 km away could result in a larger outcome on average, but in-country practitioners should carefully assess their own environment to establish an appropriate threshold.

Recommendation 2. The global carbon benefits of many small FAO interventions seeking to improve vegetative productivity can add up to large gains, and represent co-benefits that should be accounted for.

40. While the primary goal of the AAD is to improve local conditions, these activities have benefits that accrue at the global scale. This has particular importance for understanding the contributions of FAO activities towards climate mitigation efforts as related to the Sustainable Development Goals.

Recommendation 3. The collection of high-resolution geospatial information on both intervention sites and similar control locations can enable more precise understanding of efficacy, and should be collected where possible.

41. The AAD project team has curated detailed geospatial information on intervention areas, and it is recommended this continue for future efforts. A core limitation of the study presented is that it is quasi-observational in nature: we seek to identify comparable control sites retrospectively, and remotely. While evidence suggests that the matches identified here are both statistically and qualitatively similar, without on-the-ground identification of adequate controls at baseline considerable uncertainty remains as to the underlying match quality.

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