World Development 179 (2024) 106597

Contents lists available at ScienceDirect

World Development

journal homepage: www.elsevier.com/locate/worlddev

Regular Research Article

The impact of large-scale land acquisitions on child food insecurity in Africa

Antoine Castet

UMR Développement & Sociétés, Sorbonne Institute of Development Studies (IEDES), Paris 1 Panthéon-Sorbonne University, 12 place du Panthéon, 75005 Paris, France

ARTICLE INFO

JEL:
I15
O13
Q15

Keywords:
LSLA
Food insecurity
Agriculture
Difference-in-differences

ABSTRACT

Food insecurity is a major concern in most African countries. Large-scale land acquisitions (LSLAs) frequently have a negative impact on local communities. In this paper, I examine the impact of LSLAs on the nutritional status of neighboring children. To this end, I use a difference-in-differences methodology applied to LSLAs in a large number of African countries at different times since the early 2000s. I analyze data from Demographic and Health Surveys combined with data from the Land Matrix Initiative, supplemented by my own research, ultimately covering 18,276 children living in the vicinity of 45 LSLAs. I show that LSLAs have had a significant negative impact on child nutrition in Africa over the past two decades. Specifically, the dietary diversity scores of children living close to LSLAs were reduced by 20 per cent after acquisition. The results are robust to various statistical tests. I find no changes in work status or household assets. While the impact of LSLAs may be positive for agricultural practices, it is negative for child food security. The analysis highlights the importance of supporting local communities following foreign agricultural investment.

1. Introduction

The 2008 global food price crisis and increasing demand for biofuels have accelerated the demand for lands suitable for agriculture, leading to a surge in land investment. The acquisition of these lands is often referred to as 'large-scale land acquisition' (LSLA) or 'land grabbing.' Since 2000, 54 million hectares, an area roughly the size of Spain, have been acquired through LSLAs, according to the Land Matrix Initiative (The Land Matrix, 2021).

The scale and speed of this wave of investment has prompted many researchers to study its economic and social impact. Many qualitative studies have been carried out, usually in the form of case studies on a single context (a region, a district, or even a single LSLA). Individually, they contribute to a better understanding of the processes behind LSLAs and their consequences for local populations, but they remain context-specific and lack external validity (Lay et al., 2021a).[1]

In addition, several researchers have analyzed the impact of LSLAs using quantitative methods. As a foreign direct investment, an LSLA is expected to have positive spillovers on local economic activity. In Mozambique, Deininger & Xia (2016) estimate the spillovers of large land-based investments on agricultural practices. Small farms in the vicinity of these land-based investments experienced a positive significant change in their agronomic practices shortly after the acquisition. In Zambia, Lay et al. (2021a) find that smallholder yields increased when located near large farms.

However, these encouraging results need to be tempered. In many cases, LSLAs shift local smallholder production towards export-oriented cash crops (among others, see Borras et al., 2011; Moreda, 2017; Mechiche-Alami et al., 2021; Müller et al., 2021). On the one hand, this reduction in the local food supply could have a negative impact on food security. On the other hand, additional income from cash crops and additional employment opportunities could offset this negative effect. The impact of LSLAs on local food security is therefore unclear, with studies showing mixed results. The overall conclusion is that the impact is likely to be limited (Lay et al., 2021b).

Two recent quantitative papers, Anti (2021) and Müller et al. (2021), provide evidence that LSLAs can worsen the food situation of neighboring households. Anti (2021) finds in Cambodia that household

E-mail address: antoine.castet@univ-paris1.fr.

[1] For comprehensive reviews of case study findings, see Hufe & Heuermann (2017), Oberlack et al. (2016), or Yang & He (2021).

https://doi.org/10.1016/j.worlddev.2024.106597
Accepted 4 March 2024
Available online 21 March 2024
0305-750X/© 2024 The Author(s). Published by Elsevier Ltd. This is an open access article under the CC BY license (http://creativecommons.org/licenses/by/4.0/).

expenditures, especially food expenditures, decreased after land grabs. Müller et al. (2021), using data from 11 African countries, find a negative effect of LSLAs on children's dietary diversity scores. This is an important finding, but one that requires caution not only because it is not based on a difference-in-differences method, but also because its significance depends on two LSLAs in Liberia,[2] limiting both its internal and external validity.

This paper makes several contributions to the literature. Firstly, I empirically assess the impact of LSLAs on child nutritional status using a difference-in-differences methodology across African countries over the past two decades. Secondly, I extend the Land Matrix dataset by searching for each LSLA that has not yet been geolocated by the Land Matrix Initiative, using a variety of sources including company websites, organization reports, research papers, and Google Maps. This work has allowed me to geolocate 131 transactions, which can be added to the 229 already geolocated by Land Matrix and are compatible with my study. To the best of my knowledge, this is the largest and most reliable dataset on large-scale land acquisitions in Africa. Thirdly, I analyze the possible transmission channels that lead to nutritional consequences, namely changes in individual work status and household wealth, while making sure that the migration channel does not drive the results.

I find that the nutritional status of children living close to LSLAs deteriorates relative to that of children living farther away. This result is significant and robust to a number of robustness checks. Specifically, the two dietary diversity scores examined, namely the women's dietary diversity score and the minimum dietary diversity score of children living close to LSLAs, i.e. within about 15 km, decrease by more than 0.5 points on a 10-point scale, with an average score of 2.35, and by almost 0.4 points on a 7-point scale, with an average score of 2.04. The dietary diversity scores of the other children do not change after LSLAs, which means that LSLAs reduce the dietary diversity scores of neighboring children by 20 %. This decrease is mainly due to a decrease in the most expensive food sources, leading to an increase in the prevalence of stunting. Finally, there is no significant change in individual work status or household wealth as a result of LSLAs.

The remainder of the paper is structured as follows. Section 2 discusses the local impact of LSLAs, and in particular, its empirical implications for child food insecurity. Section 3 describes and presents the LSLAs and household data available. Section 4 outlines the empirical strategy. The results are presented in Section 5. A series of robustness checks are proposed in Section 6, while Section 7 discusses the findings and concludes.

2. The local consequences of Large-Scale land acquisitions

2.1. Empirical and theoretical considerations

In most cases, LSLAs occur on land already occupied by smallholder households. Messerli et al. (2014) find that investors actually tend to target areas that are already occupied, rather than 'idle' or 'marginal' areas. Arezki et al. (2015) and Lay & Nolte (2018) estimate that LSLA investors target countries with weak tenure security, but only for projects under 10,000 ha. Targeting land that is already in use and smallholders with insecure local land rights ensures both that the land is suitable for cultivation and that local labor is available should the future crop require it.

To better understand how investors manage an LSLA when people live on the land in question, a number of qualitative studies have been carried out. For example, Bae (2023) in Zambia, Engström et al. (2022) in Tanzania, and Obuene et al. (2022) in Nigeria focus on the processes through which governments grant investors the right to farm land that is already in use. These processes can culminate in violent, forced evictions, leaving the people affected with no choice but to leave their land (Bae, 2019; Feldman & Geisler, 2012).

In addition to the violence that accompanies them, LSLAs have an impact on local communities' economic life in a number of ways. For example, farming practices differ between large and small farms. Deininger & Xia (2016) compare the use of improved seeds, fertilizers, and pesticides between large and small farms in Mozambique, and find significant differences. Rice is the best example, with improved seeds used by 73 % of large farms and only 5 % of small farms, and similar results for fertilizers (73 % vs. 3 %) and pesticides (68 % vs. 1 %). These differences between farms may lead to technology spillovers. Smaller farms may imitate the farming practices of larger farms and benefit from easier access to agricultural inputs, which is exactly what Deininger & Xia (2016) find: a change in farming practices and an increase in input use for small farms in the vicinity of large farms. Ali et al. (2019) find similar results for fertilizer use in Ethiopia, while Lay et al. (2021a) find no such change in input use in Zambia, but an increase in yields. In addition, the latter find that smallholders in the vicinity of large farms adapt their crop portfolio. Neighboring smallholders shift from a diversified crop portfolio to a more corn-centric one, reducing the area planted in crops such as sorghum and millet, but increasing the area planted in corn. This attempt by local smallholders to maximize the benefits of technology spillovers has led to reduced crop diversity in the region, particularly when it comes to food crops.

This decline in food crop diversity is compounded by the fact that LSLAs themselves reduce food crop diversity. Several case studies provide insights into how LSLAs change local food production. Borras et al. (2011) show how an agrofuel investment in Mozambique, located on prime land, competed with local food production. In Laos, Friis & Nielsen (2016) find that foreign investors dismantled the existing agricultural infrastructure in order to establish banana plantations for export. Moreda (2017) analyzes how the Ethiopian government granted land that was considered 'underutilized' or 'unused' to export-oriented investments in food and agrofuels, despite the value of this land for pastoralists and shifting cultivators. This shift from local food crops to export-oriented crops has also been studied at the macro level. Using the Land Matrix dataset and based on LSLA investors' decisions, Mechiche-Alami et al. (2021) estimate that 63 % of planned crops in Africa are for export. Müller et al. (2021) confirm that the export crop that LSLA investors want to grow is usually not the one that was grown in the past. The remote sensing dataset of crops grown prior to LSLAs shows that investors have shifted from local staple crops, such as cereals and pulses, to cash crops, such as sugar and oils.

While this shift reduces the local food supply, the demand for labor after LSLAs is also closely linked to the crops chosen by LSLA investors. Capital-intensive crops such as wheat, soybeans, or corn require fewer workers than labor-intensive crops such as tea, bananas, or coffee (Deininger & Byerlee, 2012; Nolte & Ostermeier, 2017). Only if the crops chosen are labor-intensive can they provide employment opportunities for local people and thus stimulate rural development (Anti, 2021; Baumgartner et al., 2015; Kleemann & Thiele, 2015).

In a study focusing on two deals in Tanzania, Herrmann (2017) finds a positive effect on income after the investment (also see Herrmann & Grote (2015) in Malawi). Both contract farmers and wage workers benefitted from the arrival of LSLAs and saw their income rise. These positive impacts mainly occur when investors meet their compensation commitments, which often include hiring local workers. However, a common theme in many case studies is the failure of investors to deliver on their promises. In many cases, investors renege on their employment commitments after acquiring the land (Gyapong, 2020; Hall, 2013; Li, 2011; White et al., 2012). In Cambodia, Anti (2021) uses household surveys to analyze the impact of land acquisition on both employment and income. Individuals living in the neighborhood switch from

[2] The methodology of Müller et al. (2021) does not require having observations before and after each LSLA. Of the 11 countries studied, 7 have no observations before an LSLA and 1 has no observations after it. Moreover, while their full sample consists of 4,520 observations, 2,671 observations are close to these two Liberian deals.

independent agricultural activities to on-farm employment. LSLAs reduce the food and non-food expenditures of nearby households.

LSLAs target populated areas, shift local food production towards export, and have an unclear impact on employment and income. This raises concerns about local food security. Aha & Ayitey (2017) in Ghana, Atuoye et al. (2021) in Tanzania, Fitawek et al. (2020) in Madagascar, and Shete & Rutten (2015) in Ethiopia find that LSLAs may have negative impacts on local food security. By contrast, a more systematic review of studies suggests that the impact of LSLAs on food security is limited or at least inconclusive (Hufe & Heuermann, 2017; Lay et al., 2021b; Oberlack et al., 2021). The complexity of the evidence concerning the link between LSLAs and food security is best illustrated by the case of a sugarcane plantation in Sierra Leone, studied in three different papers, with three different conclusions: increase (Yengoh & Armah, 2015), decrease (Bottazzi et al., 2018), and stagnation (Hofman et al., 2019). Even Fitawek et al. (2020), who find a negative effect on food security in Madagascar, also find a positive effect for the local population employed by LSLAs. The study that comes closest to mine is Müller et al. (2021), both in terms of the LSLAs analyzed and the measure of food security. Examining 28 LSLAs in 11 countries, they find that children's dietary diversity is negatively affected after a land investment.

To summarize, LSLAs are most common near populated areas; they reduce the diversity of food crops and the area available for local food consumption; their impact on the labor market and income is unclear and depends on the type of crop and whether the compensation promised is actually paid; investors in LSLAs favor export-oriented crops, switching from local staples to cash crops; and technological spillovers may increase production in the area, but may also lead nearby farmers to have a less diverse crop portfolio. The impact on food security is therefore mixed.

2.2. Hypotheses

This research evaluates two main hypotheses about the local consequences of LSLAs:

1.a. LSLAs have a negative impact on the nutritional status of children, as measured by dietary diversity scores and anthropometric indicators.

1.b. LSLAs negatively affect children's food consumption, especially protein sources.

2. LSLAs increase the number of people working in agriculture without affecting their wealth

First, I assess the impact of the proximity to LSLAs on child food security. Although agricultural investment is often proposed as a solution to alleviate food insecurity in Africa, potentially increasing crop production and creating employment opportunities, the evidence suggests a more intricate situation. Mechiche-Alami et al. (2021) show that LSLAs may not adequately address the food security challenges faced by African countries. Shifting production from local staples to cash crops reduces the local food supply, which in turn may lead to an increase in food prices, although to my knowledge this specific price change has not been studied. In addition, although the impact of LSLAs on income is uncertain, there is evidence of decreasing income. An increase in food prices and decrease in income is expected to lead to a change in food consumption: individuals may shift from more expensive to less expensive foods. Lack of purchasing power has often been cited as an explanation for the low consumption of animal products (Iannotti et al., 2012; Haileselassie et al., 2020; Shen & Zhong, 2023).

Second, I examine the impact of LSLAs on the labor market and wealth. Due to data limitations, it is not possible to look at the exact occupation or income, which would be the most appropriate. However, it is possible to obtain information on whether individuals work in agriculture or not (regardless of status, whether formal/informal/contracted-farmer/employee/temporary), and on their wealth. The literature is unclear on the effect of LSLAs on employment, but there is evidence of an increase in the number of people reporting that they work in agriculture. Unlike income, wealth is not expected to change negatively, as it reflects long-term assets (type of house wall/roof/floor, type of toilet, cars, etc.) which are not affected by recent shocks, either negatively or positively. The impact on agricultural activity and income is expected to be heterogeneous according to the crops grown by the LSLAs, but data limitations do not allow this heterogeneity to be analyzed.

These hypotheses are based on the broader assumption that the impact of LSLAs on local communities depends on distance. The households living closer to the areas affected by LSLAs will be more affected than those living farther away. The quantitative literature on LSLAs often relies on this assumption to estimate the impact of LSLAs on different outcomes (Anti, 2021; Bunte et al., 2018; Deininger & Xia, 2016; Lay et al., 2021a; Wegenast et al., 2022). Anti (2021) provides a theoretical explanation for such an assumption. Households do not always live on the land that they farm, and those living nearby are more likely to have their land rights expropriated. Moreover, the proximity to LSLAs determines the intensity of the effect, as transmission channels are expected to be localized. Thus, employment opportunities, food price changes, and technology spillovers depend on distance. The farther individuals live from LSLAs, the greater the distance they must travel. As LSLAs take place in rural areas with limited transport infrastructure, the impact is therefore spatially limited to the surrounding area.

3. Data

3.1. Large-Scale land acquisitions

Information on the location and size of large-scale land acquisitions (LSLAs) comes from the Land Matrix Initiative, a platform that consolidates data on LSLAs and acts as an independent land monitoring entity, committed to transparency and accountability in LSLA approval decisions in low- and middle-income countries. It gathers information from a variety of sources, including the media, international and non-governmental organizations, and academic research.

To be included in the study, LSLAs must: i) have taken place between 2000 and 2021; ii) cover an area of 200 ha or more; iii) have involved at least one foreign buyer; iv) have involved a transfer of ownership; v) not be for mining or oil/gas extraction; and vi) have a known location.

The Land Matrix Initiative is constantly refining and expanding its data through ongoing research. I have conducted further research to identify additional locations to supplement the Land Matrix data. For each LSLA in Africa whose geolocation was not disclosed by the Land Matrix Initiative, I used various resources such as company websites, reports, research papers, and Google Maps to identify the geolocation. As a result, I was able to identify the locations of 131 LSLAs that now accompany the 229 transactions previously geolocated by the Land Matrix Initiative, as shown in Figure 1 and Figure A1. While the Land Matrix data does not provide the exact shape of the LSLA for each transaction, an approximate shape can be derived by forming a circle representing the area acquired around the geolocation provided by the Land Matrix data.[3] This extended database is, to my knowledge, the most comprehensive geo-referenced dataset of LSLAs in Africa and a pioneering use of the exact shapes of LSLA areas for a sub-sample of transactions.

3.2. Household-Level data and outcome variables

The information on household characteristics is taken from Demographic and Health Surveys (DHS), which provide a representative sample of the national population. All the surveys conducted in Africa

[3] Müller et al. (2021) estimate that in Cambodia about 75% of the area actually surveyed was in agreement with the approximated circles.

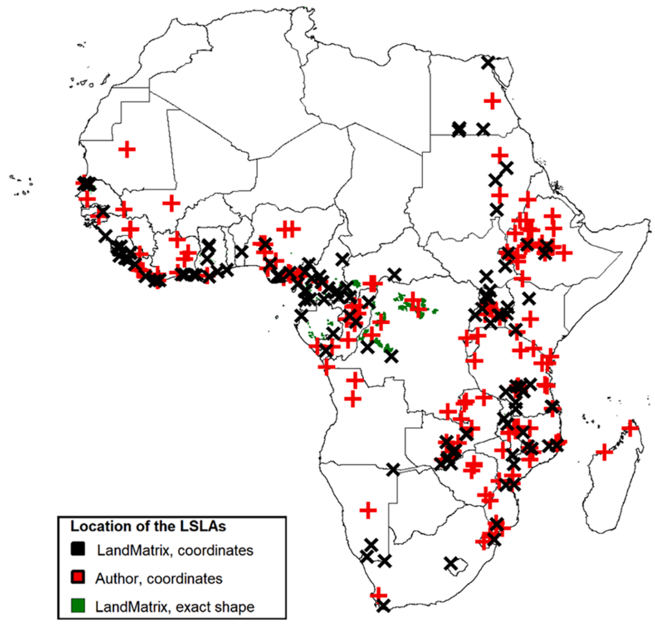

Fig. 1. Map of LSLAs in Africa. Note: The figure shows the location of LSLAs from 2000 to 2021. The black crosses represent the location geolocated by Land Matrix where the exact shape of the area is unknown, the red crosses represent the location geolocated by the author and the green shapes represent the exact areas of the transactions for which it is known. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

for which GPS coordinates were available were merged to create a repeated cross-sectional database.[4] They serve as a comprehensive and comparable source of household-level data, as the survey questions are consistent across countries and years, although they are not panel surveys. In each household, all women aged 15–49 who are either usual residents or who stayed there the night before the survey are eligible for the household survey. These surveys include a specific set of questions for each child born to the women interviewed in the five years prior to the survey. A similar procedure is used when interviewing men.

Table A1 provides a detailed description of the variables included: age and sex of the household head and child, mother's literacy, access to water and improved sanitation, urban or rural setting, number of household members, and wealth quintile (country and survey specific).

The child's nutritional status is assessed using dietary diversity scores and anthropometric indicators. Two dietary diversity scores were calculated by summing the number of food groups consumed by a child in the past 24 h.[5] The Women's Dietary Diversity Score (WDDS) includes ten food groups, while the Minimum Dietary Diversity Score (MDDS) includes seven groups. The Food and Agriculture Organization recommends the WDDS for women aged 15–49 years, while the World Health Organization recommends the MDDS for children aged 6–23 months. Although the MDDS theoretically consists of eight groups, breast milk is excluded in order for the MDDS to be applied to children over 23 months, in line with Diop et al. (2021), who suggest that both indicators are relevant for children aged 6–59 months. These scores and their component groups are detailed in Table A2 in the Appendix.

The anthropometric indicators collected by DHS include weight-for-height (WFH), height-for-age (HFA), and weight-for-age (WFA). For each indicator, a z-score below minus 2 respectively indicates that the child is wasted, stunted, or underweight. Wasting increases children's risk of death, while stunting hinders their ability to reach their full physical and cognitive potential.

To account for household characteristics, data on household composition and socioeconomic profile are included. Table A2 in the Appendix provides a more detailed description of the variables.

4. Identification strategy

The analysis is based on cross-sectional Demographic and Health Surveys (DHS) conducted in Africa between 2005 and 2018. The aim is to identify the impact of large-scale land acquisitions (LSLAs) on health indicators, exploiting both spatial and temporal variation through a 'difference-in-differences' approach. The methodology is similar to that used by Deininger & Xia (2016) but applied to multiple countries where LSLAs occurred at different points in time.

4.1. Assignment to treatment

The spatial treatment variation corresponds to the distance of a household from an LSLA site. Households are classified as treated or control based on their proximity to an LSLA. The hypothesis underlying this categorization is that the intensity of exposure to the shock may vary with distance from LSLAs. Indeed, the methodology is essentially based on the assumption that the impact of LSLAs diminishes with distance, with households located closer to LSLA sites being assumed to be more exposed to the associated shocks.

In the preferred estimation, a household is classified as treated if the nearest LSLA area is within a radius of 15 km, and as control if the distance is between 15 and 50 km. Households living outside this range are not included in the study. The aim is to compare people living close to LSLAs and those farther away. The distance thresholds chosen are consistent with the existing literature.[6] The analysis also presents results using alternative distance thresholds and a continuous distance variable.

Figure 2 illustrates the spatially varying treatment. The areas corresponding to the treated or control groups of households for each LSLA area are hereafter referred to as 'buffers.' At this stage, out of the 360 LSLAs, 296 meet the spatial treatment condition of having at least one respondent in both the control and treated buffers and may therefore be included in the study.

Figure 3 illustrates the rationale behind the identification strategy by plotting the mean Women's Dietary Diversity Score (WDDS) as a function of distance, both before and after the occurrence of the LSLA. The graphs show that children living close to or within the acquired area had a higher WDDS before the LSLA and that this effect decreases with distance. The graphs also show that children living closer to the LSLA experienced a decrease in their WDDS after the LSLA, a trend that is not observed for children living slightly farther away. Further illustrations using the Minimum Dietary Diversity Score (MDDS) can be found in Figure A2 in the Appendix.

4.2. Temporal variation

The temporal variation is derived from the date of occurrence of LSLAs. This date is identified as the year when the contract leading to the transfer of land rights from locals to foreign investors was signed, or if this date is not available, the date when the project entered the 'start-up phase' or became 'operational.' The reason for choosing to use the year

[4] This database was created using Integrated Public Use Microdata Series (IPUMS) resources, which harmonize the names and codes of the different DHS variables across countries and waves.

[5] A 24-hour period is used as the reference period for the dietary diversity score. The appropriateness of this timeframe has been discussed by Gina Kennedy & Nutrition Division (2011), who largely favor it due to its lower recall error, ease for the respondent, and alignment with the recall period used in many dietary diversity studies.

[6] Among others, see Anti (2021) who uses 20 km, Bunte et al. (2018) 25 km, Deininger & Xia (2016) 25 and 50 km, Lay et al. (2021a) 10, 20, and 50 km, and Wegenast et al. (2022) 10 km.

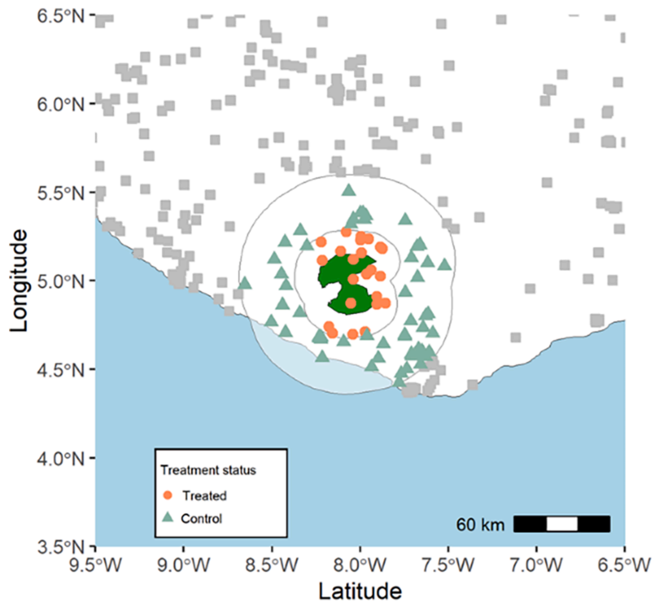

Fig. 2. Household treatment assignment: An example. Note: The figure illustrates the treatment assignment. The green shape represents the LSLA area. Children living within the narrower circle (15 km), marked by orange dots, are considered treated. Children living between the first and second circles (50 km), marked by turquoise triangles, are considered as control. Children outside these two areas are considered too far away to be included in the study. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

when the contract was signed rather than when it took effect was motivated by the potential negative impacts on local people even if the project was not actually implemented (see, for example, Engström, (2018), Borras et al. (2022), and Broegaard et al. (2022) who show that the preparatory process leading up to implementation can negatively affect local smallholder households regardless of whether the project materializes).

The difference-in-differences (henceforth DiD) approach requires at least two time points - before and after the shock - for both the treated and control households. To qualify for inclusion in the study, an LSLA area must have at least one treated and one control household in its vicinity both before and after the LSLA. In addition, the interview must have taken place shortly before or after the land acquisition in order to accurately measure the shock effect. Households interviewed more than five years after the LSLA are thus excluded to ensure close temporal proximity to the event. This methodological constraint significantly reduces the number of LSLAs that can be analyzed. Of the 296 LSLAs that satisfy the spatially varying treatment, only 45 LSLAs have at least one treated and one control household both before and after the LSLA, thus satisfying the temporal treatment condition. Of these 45 LSLAs, 44 had only one interview before and only one had two. For consistency, households interviewed during the earlier survey were excluded. These 45 LSLAs can be compared to the 28 studied by Müller et al. (2021), which did not have such strict inclusion rules.

The sample of 18,276 observations is detailed in Table 1 and Table A3. Although there are differences between treated and control observations, they either have the same sign before and after or are not statistically significant at the standard confidence level. Treated children have a significantly better dietary diversity score than control children before LSLAs and a significantly worse score after LSLAs.

4.3. Estimation

Equation (1) is estimated to assess the impact of LSLAs on nutrition indicators:

$$Y_{i,b,j,t} = \alpha + \beta(Treated_{i,b,j,t} \times Post_t) + \delta X_{i,b,j,t} + \mu_b + \eta_t + \zeta_g + \epsilon_{i,b,j,t} \quad (1)$$

where $Y_{i,b,j,t}$ represents either the dietary diversity score or the anthropometric indicators of child i residing in buffer b of country j in year t. $Treated_{i,b,j,t}$ is a binary variable that takes the value 1 if child i is located within 15 km of an LSLA in country j in period t, and 0 if the child is between 15 and 50 km. Alternatively, the continuous variable $Distance_{i,b,j,t}$ is used, indicating the distance to the LSLA. $Post_t$ is a binary variable equal to 0 if the year is before the LSLA contract was signed, and

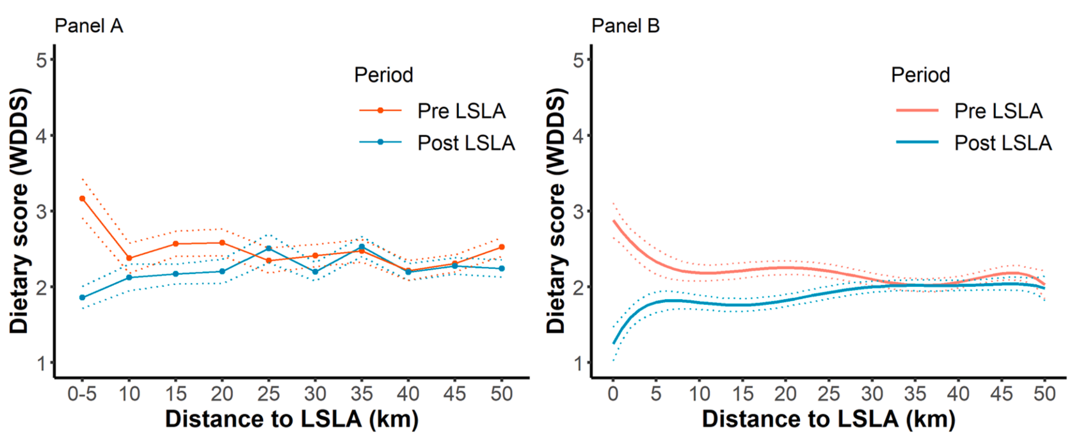

Fig. 3. Nutrition score by distance – WDDS. Note: Panel A (left) shows the simple WDDS means by distance group before (red) and after (blue) LSLAs. Panel B (right) shows the prediction of a 6th degree polynomial estimate of the WDDS by distance. The dashed lines indicate a confidence interval of 0.95. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

1 if it is after; $X_{i,b,j,t}$ includes a set of variables[7] describing the characteristics of the child and their household; μ_b is a buffer fixed effect, η_t is a year fixed effect, ζ_g is an administrative area fixed effect (GADM)[8] described in Table A4, and $\epsilon_{i,b,j,t}$ is the error term. Standard errors are clustered at the buffer level consistent with the level of treatment assignment (Bertrand et al., 2004; Abadie et al., 2017). All the estimates are weighted using individual DHS weights.

This equation estimates the change in nutritional status between children living close to LSLAs (treated) and those living farther away (control), relative to the period before the LSLAs had taken place. The analysis assumes that without LSLAs, both the treated and control groups would have followed the same path with respect to their nutritional status. A negative coefficient β indicates that the nutritional status of children living closer to LSLAs deteriorated compared to those living farther away after the LSLAs took place. The inclusion of buffers and GADM fixed effects controls for spatial differences between children, while the year fixed effect absorbs time-specific shocks that may have occurred in a given year. Robustness checks include estimations with other fixed effect specifications, such as country-year fixed effects, and alternative levels of clustering.

4.4. Parallel trends assumption

The DiD methodology relies on the 'parallel trends' assumption, according to which without treatment, the treated and control groups would have followed the same trend for the outcomes studied. This assumption is crucial because it helps to ensure that the observed effects after treatment are due to the treatment itself and not to pre-existing trends.

This assumption can be tested by looking at outcome trends before treatment. However, there are data limitations in the present study that prevent establishing parallel pre-treatment trends. In particular, only one of the LSLAs in the study was assessed twice before treatment. Nevertheless, there is much that suggests that, despite their differences, the treated and control children were following parallel trends.

First, I provide evidence of parallel pre-treatment trends for a separate sub-group of households, namely those who were interviewed twice before treatment, even though they were not interviewed after treatment. Panel A and Panel B in Figure A3 respectively show the WDDS and MDDS means for this sample. The results support the claim of parallel trends.

Second, an event study design can be used to test for prior trends among the treatment and control groups. To estimate this event study, Equation (1) was modified with the inclusion of leads and lags, according to the time distance between the survey and the LSLAs, interacted with the treatment. The aim of this estimation was to check for WDDS diverging trends prior to the LSLAs. For each year relative to the LSLAs, a separate coefficient was estimated. These coefficients show how the dependent variable differs between the treatment and control groups at each time relative to the LSLAs. There should be no significant difference between the treated and control groups before treatment. Panel A and Panel B in Figure A4 respectively show the event study results for the sample of interest and for a larger sample including children over all time periods (without removing observations more than five years from the LSLAs). In this larger sample, there are no significant differences between treated and control children (except 10 and 13 years before the LSLAs). The lack of significant results after the LSLAs may be due to the lack of observations in each period. Event studies are more appropriate when the treated and control groups are observed many periods before and after. In this study, they were observed only one period before and one period after, with only a variation in the timing of observation. Nevertheless, this result is interesting for observing the trend over time between the treatment and control groups. For the sample under study, the results indicate that there are also no significant differences between the treatment and control groups of children before the shock. However, a negative and significant effect is observed in the year following the shock. The significance then disappears in subsequent years. The parallel trends assumption is consistent with these results.

Thirdly, the proximity of the treatment and control groups adds further support to the hypothesis of parallel trends. Individuals living within 50 km of each other are likely to follow the same trends in outcomes due to their proximity. It is possible to simulate these expected parallel trends scenario by randomly shifting each geolocated LSLA, and then assigning the children within 15 km as treated, and those between 15 and 50 km as control. This simulation is used to verify that, without shock, the distance between treated, and control groups is reduced enough to state that similar trends should be expected. I implemented this randomization process 5,000 times using two different methods: i) I randomly distributed LSLAs across the whole of Africa; and ii) I randomly distributed LSLAs across Africa, with the number of LSLAs in each country being the true sample distribution. Examples of this random reallocation are shown in Figure A5. Equation (1) was then estimated using these 10,000 datasets. As shown in Table A5, the effect is insignificant in most cases, again supporting the parallel trends assumption. The average coefficient is close to zero (0.006), the average p-value is around 0.484, and about 6.64 % of the results are significant (at 0.95). This is close to what could be expected if the regression was run randomly. This result indicates that, in the absence of a shock, individuals living in close proximity to each other follow the same trend with respect to the outcome of interest.

Finally, following Benshaul-Tolonen (2019, 2022), Figure A6 shows that the treated and control areas have similar trends in night lighting, which is often used as a proxy for economic development. This implies that economic development is not significantly different in these areas.

5. Results

5.1. Nutritional status

The main results for the impact of LSLAs on children's dietary diversity are presented in Table 2. The table displays the results from estimating Equation (1) under different treatment thresholds and definitions.

Columns 1–4 show the estimates obtained with a treatment threshold of 10 km, while the threshold is 15 km in columns 5–8. Regardless of the treatment threshold, a consistent control group threshold of 50 km is maintained across all estimates. Finally, columns 9–10 use a continuous measure of distance, eliminating discrete thresholds for the treated and control groups. Every child within a 50 km radius is included if at least one has been surveyed before and after, for each LSLA.

The estimates in columns 1, 2, 5, and 6 are derived using a binary definition of treatment. By contrast, the remaining columns use a continuous measure of distance to define treatment. Each estimate is first presented without the inclusion of control variables (odd-numbered columns). This is followed by a presentation that includes a set of control variables (even-numbered columns). These control variables are included to account for the socio-economic characteristics of the children in the study, as discussed in Section 3.

The coefficient in column 1 indicates that a significant decrease in the WDDS of 0.540 points out of 10 affects children within 10 km of LSLAs relative to children farther away. This effect needs to be put into perspective with the mean value of the WDDS, which is around 2.35 for

[7] The variables include the child's age and gender, the mother's literacy, water access, toilet access, the household head's age and gender, the household member count, the wealth level, and urban or rural setting.

[8] The households' administrative location data is sourced from the "Global Administrative Areas" (GADM) database, corresponding to the "boundary level 2," which is often referred to as a "district." On average, individuals in the vicinity of an LSLA are spread out over 6.6 administrative sites.

Table 1
Summary statistics.

	Before			After		
Variables	**Control (15–50 km)**	**Treated (0–15 km)**	**Difference**	**Control (15–50 km)**	**Treated (0–15 km)**	**Difference**
WDDS	2.397	2.644	−0.247 ***	2.295	2.076	0.219 ***
	(0.028)	(0.066)		(0.025)	(0.044)	
MDDS	2.070	2.228	−0.158 ***	2.008	1.811	0.198 ***
	(0.022)	(0.049)		(0.021)	(0.036)	
Age	28.763	27.715	1.048	22.553	22.476	0.077
	(0.295)	(0.643)		(0.193)	(0.366)	
Literacy	0.520	0.490	0.030 **	0.587	0.509	0.078 ***
	(0.006)	(0.012)		(0.006)	(0.011)	
Imp. water	1.668	1.679	−0.011	1.561	1.660	−0.099 ***
	(0.011)	(0.022)		(0.009)	(0.019)	
Imp. toilet	0.503	0.389	0.115 ***	0.562	0.460	0.102 ***
	(0.006)	(0.012)		(0.006)	(0.011)	
Time to water	0.987	1.030	−0.043 ***	0.959	1.082	−0.122 ***
	(0.008)	(0.013)		(0.008)	(0.012)	
Urban	0.249	0.147	0.102 ***	0.280	0.221	0.059 ***
	(0.005)	(0.009)		(0.005)	(0.009)	
Head age	39.009	38.761	0.248	38.526	37.663	0.863 ***
	(0.153)	(0.297)		(0.145)	(0.269)	
Head sex	0.804	0.754	0.050 ***	0.793	0.792	0.001
	(0.005)	(0.01)		(0.005)	(0.009)	
Members	6.575	6.406	0.169 **	6.426	6.330	0.096
	(0.037)	(0.065)		(0.035)	(0.069)	
Poor	0.169	0.267	−0.098 ***	0.195	0.241	−0.046 ***
	(0.005)	(0.011)		(0.005)	(0.01)	
Rich	0.218	0.105	0.113 ***	0.186	0.116	0.070 ***
	(0.005)	(0.008)		(0.004)	(0.006)	
Observations	6937	1716		7874	2185	

Note: Means are estimated using DHS individual weights. The stars correspond to the Student's *t*-test p-value.
* p < 0.1, ** p < 0.05, *** p < 0.01.

Table 2
Dietary diversity scores.

Treatment cutoff	**10 km**				**15 km**				**Without**	
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**
WDDS										
Treated X Post	−0.540**	−0.542**			−0.522***	−0.509***				
	(0.269)	(0.263)			(0.18)	(0.183)				
Distance X Post			0.008*	0.010*			0.012**	0.012**	0.008*	0.008*
			(0.005)	(0.005)			(0.005)	(0.005)	(0.004)	(0.004)
Mean Before	2.349	2.349	2.349	2.349	2.351	2.351	2.351	2.351	2.338	2.338
MDDS										
Treated X Post	−0.377*	−0.379**			−0.391***	−0.379***				
	(0.193)	(0.187)			(0.135)	(0.136)				
Distance X Post			0.007*	0.008**			0.009**	0.009***	0.005	0.006*
			(0.004)	(0.004)			(0.004)	(0.004)	(0.003)	(0.003)
Mean Before	2.033	2.033	2.033	2.033	2.037	2.037	2.037	2.037	2.035	2.035
Observations	15,638	15,638	15,638	15,638	18,712	18,712	18,712	18,712	24,496	24,496
Number of LSLAs	30	30	30	30	45	45	45	45	78	78
Controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes

Note: WDDS is a score from 0 to 10. MDDS is a score from 0 to 7. The control group has a maximum distance of 50 km. All columns include year, buffer and GADM fixed effects. The inclusion or not of control variables is indicated at the bottom of each estimate. All estimates are weighted with DHS individual weights. Standard errors clustered at the buffer level are shown in parentheses.
* p < 0.1, ** p < 0.05, *** p < 0.01.

the full sample. Therefore, it represents a 20 percent decrease in their score compared to children living farther. According to the FAO, the minimum threshold for adequate dietary diversity using the WDDS is 5, while the WHO recommends a minimum threshold of 4 with the MDDS. On average, the children studied here were below the recommended threshold. This low WDDS pre-treatment is similar to that calculated by Müller et al. (2021).

Column 2 shows that the effect decreases slightly when the set of controls is added, with a coefficient of 0.542 points. These results are confirmed in columns 3 and 4 using continuous distance for the same sample. One additional kilometer of distance from LSLAs increases the WDDS score by almost 0.01. The results are quite similar when using the MDDS as the dependent variable, with a decrease of about 0.37 between the treated and control groups. The coefficient is lower for the MDDS than for the WDDS, but this is explained by the fact that MDDS scores are out of 7 instead of 10.

The results in columns 5 to 8 with a treatment threshold of 15 km are close to those with a treatment threshold of 10 km, but with a higher level of significance. As, this sample contains more observations, the statistical power is higher.

Unlike columns 3, 4, 7, and 8 which use the same sample with the binary treatment, columns 9 and 10 present the results with the continuous distance treatment, with every observation below 50 km. The results are similar to the previous ones, increasing respectively by

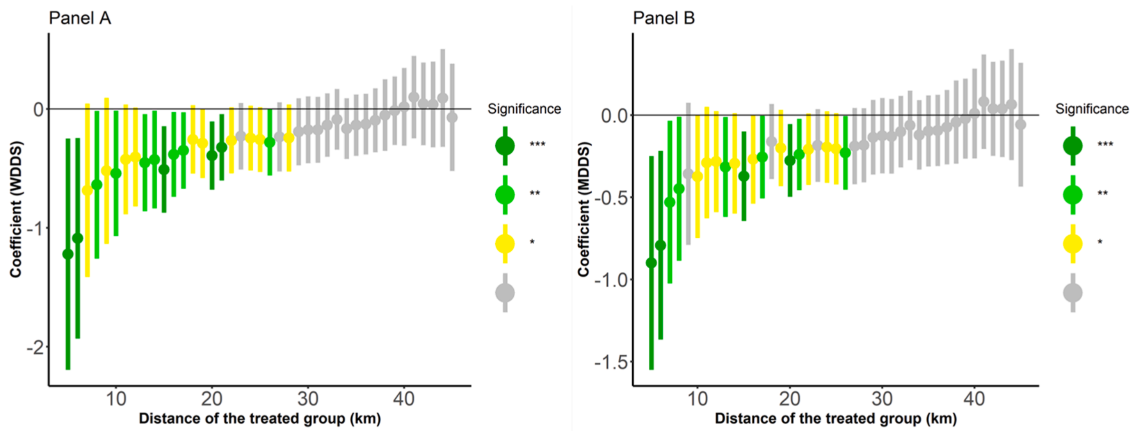

Fig. 4. Dietary diversity score loops. Note: The figures show coefficients and confidence intervals from 40 regressions of Equation (1), including year, buffer, GADM fixed effects and controls. In each regression, the treatment group distance increases by one kilometer from 5 km to 45 km. The control group has a maximum distance of 50 km. The dependent variable is the WDDS for Panel A (left) and the MDDS for Panel B (right). Confidence intervals are at 0.95.

Table 3
Food groups.

	Dairy	Grains	Vit. A	Others	Eggs	Meat	Legumes
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Without controls							
Treated X Post	−0.081***	−0.027	−0.032	−0.061*	−0.056**	−0.085***	−0.050
	(0.029)	(0.038)	(0.036)	(0.031)	(0.026)	(0.028)	(0.033)
With controls							
Treated X Post	−0.076***	−0.028	−0.030	−0.059*	−0.054**	−0.083***	−0.049
	(0.028)	(0.037)	(0.036)	(0.031)	(0.025)	(0.027)	(0.034)
Mean Before	0.276	0.604	0.358	0.171	0.135	0.309	0.183
Observations	18,712	18,712	18,712	18,712	18,712	18,712	18,712
Number of LSLAs	45	45	45	45	45	45	45

Note: Each food variable is a dummy that takes the value 1 if the corresponding food group is consumed and 0 otherwise. The control group has a maximum distance of 50 km. All columns include year, buffer and GADM fixed effects. All estimates are weighted with DHS individual weights. Standard errors clustered at the buffer level are shown in parentheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

about 0.008 and 0.007 points per km for the WDDS and MDDS.

Figure 4 shows the results of 40 estimations where the difference lies in the treatment distance threshold. The results show that the coefficient increases with increasing treatment distance. The closest LSLAs have the lowest WDDS (Panel A) and MDDS (Panel B). The coefficients are negative and significant when the treatment threshold is between 5 and 20 km. When the treatment threshold is around 25 km, the effect is not significantly different from zero anymore.

The estimates of Equation (1), using each component of the MDDS as the dependent variable, are presented in Table 3. The aim is to understand whether there is a decrease in the consumption of a particular type of food as a result of proximity to LSLAs. The significance of the results of the estimations in columns 1 (dairy), 5 (eggs), and 6 (meat) points to the presence of heterogeneity in the food consumption change. In particular, there is a significant decrease in the consumption of animal protein. When it comes to the remaining components, i.e. grains, vitamin A, legumes, and other foods, no significant results are found. The proximity to LSLAs has a negative effect on the diversity of children's diet, especially on their consumption of animal protein.

The lack of access to a variety of foods can lead to malnutrition. A standard way of measuring child malnutrition is to use anthropometric measurements. The three main indicators are weight for height (WFH), height for age (HFA), and weight for age (WFA), which respectively indicate wasting, stunting, and being underweight. For each indicator, a z-score or standard deviation from the mean below minus 2 indicates that the child is wasted, stunted, or underweight. WFH, HFA, and WFA are dummy variables. They take the value 1 if the child's score is at least 2 standard deviations (SD) below the mean of child growth standards set by the World Health Organisation, and 0 otherwise. Table 4 and Figure 5 present the results assessing the impact of LSLAs on malnutrition. The results suggest that children living in close proximity to LSLAs are more stunted than those living farther away, but less wasted. Logically, the lack of effect on the underweight status follows from these two opposite effects. The positive, and significant effect of HFA at 10 km with no significant effect on WFH, and WFA, suggests that the children are shorter than expected for their age but not heavier or lighter than expected for their height or age. This result can indicate that children are eating less nutrient dense foods, leading to shorter height, but an appropriate amount of energy dense foods for that height. However, the coefficients in Figure 5 suggest that children closest to LSLAs are less wasted, even if not significantly, when the threshold is precisely at 10 km. This effect on wasting reduction may be due to the consequences of a lower height combined with an increased calorie intake due to switching from protein to grains.

A diet that is nutritionally poor, low in protein, and plant-based is associated with stunting (Millward, 2017). The findings on undernutrition support previous findings of reduced dietary diversity.

5.2. Work status and wealth

Malnutrition is a sign of lack of purchasing power, and the worsening nutritional status of children living near LSLAs may simply reflect a lower income for the treated households. However, it is not possible to test the lower income hypothesis directly as the DHS does not ask about individual income. The best that can be done with DHS data is to look at individual work status and household assets. Although work status is not

Table 4
Anthropometric status indicators.

Treatment cutoff	10 km				15 km				Without	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
WFH										
Treated X Post	−0.027	−0.028			−0.020	−0.021*				
	(0.019)	(0.019)			(0.012)	(0.013)				
Distance X Post			0.001	0.001			0.001*	0.001*	0.00	0.000
			(0.000)	(0.000)			(0.000)	(0.000)	(0.000)	(0.000)
Mean Before	0.06	0.06	0.06	0.06	0.062	0.062	0.062	0.062	0.065	0.065
Observations	11,951	11,951	11,951	11,951	15,130	15,130	15,130	15,130	20,735	20,735
Number of LSLAs	30	30	30	30	45	45	45	45	78	78
HFA										
Treated X Post	0.088**	0.089***			0.044	0.041				
	(0.033)	(0.033)			(0.030)	(0.030)				
Distance X Post			−0.001	−0.001			0.000	0.000	−0.001	−0.001
			(0.001)	(0.001)			(0.001)	(0.001)	(0.001)	(0.001)
Mean Before	0.292	0.292	0.292	0.292	0.298	0.298	0.298	0.298	0.301	0.301
Observations	11,945	11,945	11,945	11,945	15,119	15,119	15,119	15,119	20,718	20,718
Number of LSLAs	30	30	30	30	45	45	45	45	78	78
WFA										
Treated X Post	0.024	0.024			−0.003	−0.005				
	(0.024)	(0.025)			(0.023)	(0.023)				
Distance X Post			−0.001	−0.001			0.000	0.000	0.000	−0.001
			(0.001)	(0.001)			(0.001)	(0.001)	(0.001)	(0.001)
Mean Before	0.123	0.123	0.123	0.123	0.129	0.129	0.129	0.129	0.137	0.137
Observations	11,979	11,979	11,979	11,979	15,163	15,163	15,163	15,163	20,776	20,776
Number of LSLAs	30	30	30	30	45	45	45	45	78	78
Controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes

Note: WFH, HFA and WFA are binary variables corresponding to the anthropometric status indicators weight for height, height for age and weight for age respectively. They take the value 1 if the child is two points below the median of the WHO standards for child growth, otherwise 0. The control group is a maximum of 50 km. All columns include year, buffer and GADM fixed effects. The inclusion of control variables is indicated at the bottom of each estimate. All estimates are weighted with DHS individual weights. Standard errors clustered at the buffer level are shown in parentheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

an exact proxy for household income, a decrease in the number of individuals reporting that they worked could indicate decreasing work opportunities and hence earnings.

Formally, the following equations are estimated:

$$WorkStatus_{i,b,j,t} = \alpha + \beta(Treated_{i,b,j,t} \times Post_t) + \delta X_{i,b,j,t} + \mu_b + \eta_t + \zeta_g + \epsilon_{i,b,j,t} \tag{2}$$

where $WorkStatus_{i,b,j,t}$ represents either the work status of women/men i residing in buffer b of country j in year t. The work status is a dummy equal to 1 if the respondent reports that they work. The other parts of the equation are similar to Equation (1).

$$Wealth_{h,b,j,t} = \alpha + \beta(Treated_{h,b,j,t} \times Post_t) + \delta X_{h,b,j,t} + \mu_b + \eta_t + \zeta_g + \epsilon_{h,b,j,t} \tag{3}$$

where $Wealth_{h,b,j,t}$ represents the value of the wealth index of household h residing in buffer b of country j in year t. The other parts of the equation are similar to Equation (1).

Table 5 and Figure A7 present the results of Equation (2) using the work status of the women and men surveyed, i.e. 'women of reproductive age (15–49) and men aged 15–59.' I find no effect on the work status of either women or men, regardless of their sector of activity with the DiD estimation. Continuous dependent variable estimates with a sample reduced to 15 km indicate a negative effect on men's work status. However, this result is not significant with the full sample, in columns 9 and 10. As for household assets, the DHS constructs a household wealth index using 'easily collected data on the ownership of selected assets by the household.' Although this index allows looking at the accumulation of wealth by a household, it does not provide much information on recent changes in income. Indeed, since it is constructed only using long-lived products and not short-lived ones, a recent income shock may not lead to a reduction in value. Table A6 and Figure A8 show the results of Equation (3) using the household wealth index. There is no effect of LSLAs on this index. This result is reassuring as it suggests that households before and after LSLAs are similar in terms of long-term accumulated wealth.

6. Robustness checks

To ensure the robustness of the main results, several robustness checks were performed.

6.1. Migration

One concern in accurately identifying the effects of LSLAs is that they could lead to migration. On the one hand, LSLAs could encourage neighboring households to migrate to LSLA areas because of expected job opportunities, leading to in-migration. These migrants could be negatively selected, thereby lowering the results. On the other hand, the wealthiest inhabitants could decide to leave LSLA areas, causing out-migration. The data do not allow a direct examination of migration patterns. The DHS provides the year of residence but not in every survey. The sample that could be examined by retaining only households that have not migrated in the last five years is too small for analysis. Nevertheless, Figure B1 presents the results estimating the same specification as in Figure 4 with this reduced sample. The coefficients and trend are quite similar but, as expected with greater confidence intervals. However, significant migration, which is likely to affect the results, seems to be contradicted by several observations.

Firstly, Table B1 in the Appendix shows that household characteristics are not affected by LSLAs. In particular, households are neither poorer nor richer after LSLAs than they were before. These results suggest that my main finding is unlikely to be biased by the inclusion of self-selected in-migrants or out-migrants.

Secondly, Figure B2 show the population density around LSLAs using geospatial data from the Gridded Population of the World (GPW) and Global Human Settlement (GHS). Panels A and B show the results for the 45 LSLAs selected, while Panels C and D include all geolocated LSLAs.

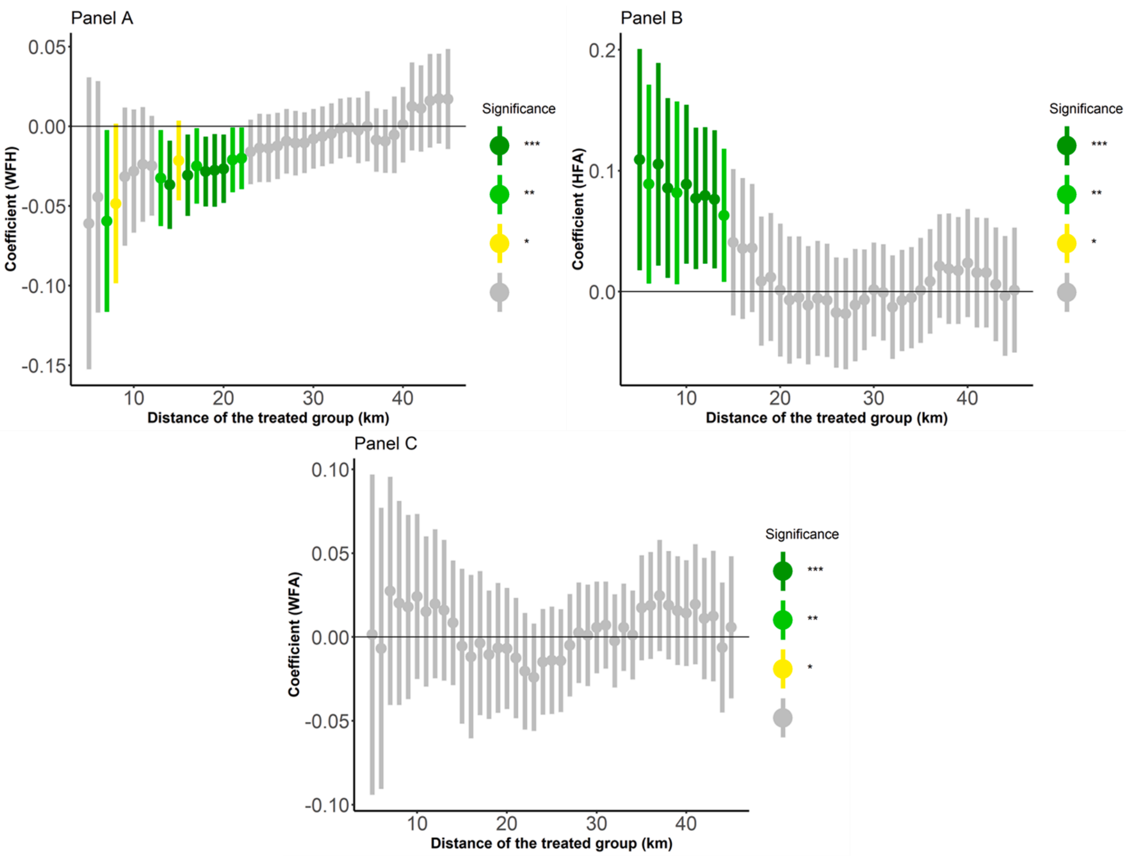

Fig. 5. Anthropometric status indicators loops. Note: The figures show coefficients and confidence intervals from 40 regressions of Equation (1), including year, buffer, GADM fixed effects and controls. In each regression, the treatment group distance increases by one kilometer from 5 km to 45 km. The control group has a maximum distance of 50 km. The dependent variable is WFH for Panel A (top left), WFA for Panel B (top right), and HFA for Panel C (bottom). Confidence intervals are at 0.95.

Table 5
Work status.

Treatment cutoff	10 km				15 km				Without	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Women working										
Treated X Post	0.007	0.023			−0.008	−0.003				
	(0.045)	(0.030)			(0.048)	(0.030)				
Distance X Post			0.000	0.000			0.000	0.000	0.000	0.000
			(0.001)	(0.001)			(0.001)	(0.001)	(0.001)	(0.001)
Mean Before	0.563	0.563	0.563	0.563	0.568	0.568	0.568	0.568	0.572	0.572
Observations	31,558	31,558	31,558	31,558	38,159	38,159	38,159	38,159	53,729	53,729
Number of LSLAs	30	30	30	30	46	46	46	46	83	83
Men working										
Treated X Post	−0.018	−0.029			−0.077*	−0.069*				
	(0.052)	(0.048)			(0.045)	(0.038)				
Distance X Post			0.002*	0.001			0.003***	0.002**	0.001	0.001
			(0.001)	(0.001)			(0.001)	(0.001)	(0.001)	(0.001)
Mean Before	0.754	0.754	0.754	0.754	0.766	0.766	0.766	0.766	0.776	0.776
Observations	10,385	10,385	10,385	10,385	14,325	14,325	14,325	14,325	23,492	23,492
Number of LSLAs	19	19	19	19	35	35	35	35	72	72
Controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes

Note: The work status of men and women is a binary variable. They take the value 1 if they are currently working, otherwise 0. The control group has a maximum distance of 50 km. All columns include year, buffer and GADM fixed effects. The inclusion of control variables is indicated at the bottom of each estimate. All estimates are weighted with DHS individual weights. Standard errors clustered at the buffer level are shown in parentheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Panels A and C of Figure B2 show long-term population density from 1975 to 2015, while panels B and D are more short-term, from 2000 to 2020. On average, the population density observed in different 10 km buffers from LSLAs followed the same trends.

Thirdly, Kleemann & Thiele (2015) note that case studies point to limited and more often seasonal job opportunities in LSLA areas. The wages of LSLA workers are below the national minimum wage and even below the income of pre-LSLA farmers (Veldman & Lankhorst, 2016). This reduces the incentives for a poor neighborhood worker to seek job opportunities in investment farms, thus reducing the possibility of negatively selected migration.

Fourthly, Tsikata & Yaro (2011) and Veldman & Lankhorst (2016) find that large farms attract migrant workers. However, these migrants are positively selected as employers seek highly skilled workers. The effect of the arrival of skilled workers could lead to an upward bias in the estimate, rather than a downward one, if they were interviewed. Taken together, these four points suggest that the impact of migration on the main estimates is only of minor importance.

6.2. Subsample analysis

Firstly, the results estimating the same specification as in Table 2-column 6 above, i.e. with controls and a treatment threshold at 15 km, dropping one country at a time, are presented in Table B2. The coefficients remain negative and significant regardless of which country is dropped.

Secondly, Figure B3 presents the results estimating the same specification as in Figure 4, but varying the control distance threshold instead of the treatment distance threshold. Keeping the treatment threshold at 15 km, the results remain significant.

Thirdly, information on the 'implementation status' of an LSLA is not always available in the Land Matrix dataset. Table B3 shows the results as in Table 2, dropping the observations for which a contract was signed but its implementation is unknown. The results are very similar.

Fourthly, in order to maintain a similar number of observations and to allow comparisons between columns, observations with missing values in the control variables are dropped from the sample. Table B4 presents the main results without control, as in Table 2-column 5, retaining observations with missing values. Table B5 also presents the results with additional control variables, thus increasing the number of observations dropped. These various modifications to the variables and to the sample from which the estimates are calculated do not lead to any significant changes.

Finally, the DHS randomly moves the coordinates of DHS clusters. Rural clusters are moved by up to five kilometers in 99 % of cases. Observations in the control group may move to the treatment group and vice versa. To ensure that the results are robust to these random shifts, Table B6 estimates Equation (1) with a treatment distance threshold of 10 km but a control distance of 20 km, and with a treatment distance of 15 km and a control distance of 25 km. In this specification, it is certain that the treated children are less than 15 km away and the control children are more than 15 km away, or 20 km away in the 15/25 specification. The results are robust to this check.

6.3. Alternative econometric specifications

The results remain valid if a number of changes are made to the specification of Equation (1).

Firstly, Figures B4–B6 present the results of respectively Table 2, 3, and 4 using the Wooldridge (2021, 2023) extended two-way fixed effects (eTWFE) estimator. The aim of the eTWFE estimator is to overcome the weights bias that arise when the treatment effects vary across periods and groups. To this end, the eTWFE includes all possible interactions between treatment and time variables including treatment cohorts and all other covariates. The results are of the same sign and remain significant.

Secondly, Table B7 presents the results using a different level of clustering. The signs and significance are not affected by the different levels of clustering. Thirdly, Table B8 presents the results with fixed effects introduced one at a time. Columns 9 and 10 also report the results using country-time fixed effects. Finally, one might think that the differences between the treatment and control groups in Table 1 are important. These potential imbalances between the treatment and control groups are addressed using the reweighting method proposed by Hainmueller (2012). Balanced samples were constructed, and the main results were recalculated using these weights. The results presented in Table B9 show the robustness of the main results again.

7. Conclusion

The sudden increase in LSLAs in developing countries has sparked mixed reactions. Some saw it as an opportunity to develop an underinvested agricultural sector while others as a threat to the rights and livelihoods of already vulnerable populations. Assessing the consequences of LSLAs is therefore of particular interest for policy makers. Understanding the positive/negative impacts that LSLAs can have on economies and populations can help to better tailor policies that support foreign investors while protecting local populations. Previous research highlights mixed effect on employment and income, agricultural practices, and food security.

My paper contributes to this ongoing debate regarding the consequences of LSLAs on local populations. In particular, it suggests that LSLAs have had a negative impact on child nutrition indicators in Africa over the past two decades. To empirically assess these consequences, I geolocated an additional 131 LSLAs to thus already included in the Land Matrix dataset, and, for the first time, I used their exact shape when known.

By combining this extended Land Matrix dataset with DHS data, I was able to examine the impact of 45 LSLAs in 10 African countries on the nutritional status of 18,712 children. First, the nutritional indicators of the closest children to them are negatively affected by these LSLAs. Dietary diversity scores fall by 20 %, on average, shortly after an LSLA, and nearby children are also more stunted. Second, the decrease in dietary diversity is driven by a decrease in the consumption of protein sources, the most expensive type of food. Third, there is no significant effect on the work status or wealth of the treated households.

For the moment, data limitations do not allow for an in-depth understanding of the mechanisms driving this decline in child food security. At the very least, it would appear that changes in household employment do not seem to have been the cause of this decline. The hypothesis of rising local food prices, especially for protein sources, could explain this finding, but would need to be tested empirically. A better understanding of the mechanisms driving the decrease in dietary diversity is needed.

The results of this paper suggest that policy makers should implement additional policies to mitigate the negative consequences on food security. Potential gains in terms of employment or agricultural productivity, highlighted in previous analyses, may mask the detrimental effects on individual livelihoods. Also, monitoring and enforcing promises made to local populations during LSLA process, appear to be a crucial first step to ensure fairer transaction.

CRediT authorship contribution statement

Antoine Castet: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Resources, Software, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The authors do not have permission to share data.

Acknowledgement

I would like to express my gratitude to the editor, Christelle Dumas, and the two anonymous reviewers for their insightful comments and suggestions that greatly improved this article. I am very grateful to my thesis director, Alain Desdoigts, for his precious help. Additionally, I would like to acknowledge Eliane El Badaoui, Rémi Bazillier, Antoine Boucher, Jean-Baptiste Guiffard, Karine Marazyan, Jessica Meyer, Jérémy Do Nascimento Miguel, Yohan Renard, Josselin Thuilliez, Alexandre Touw, Thomas Vendryes, and the participants of the AFEDEV Doctoral Days, Doctorissimes, MIASA, ICDE, AFSE, and IEA conferences for their comments and suggestions. Finally, I am also thankful to UMR DEVSOC (Panthéon-Sorbonne University) and Sciences Po Paris for their support.

Appendix A

Table A1
Description of the variables.

Variables	Description	Units	Source
WDDS	Women's Dietary Diversity Score of child	Score (0–10)	DHS
MDDS	Minimum dietary diversity score of child	Score (0–7)	DHS
Age	Child's age	Months	DHS
Literacy	Mother's literacy	Binary	DHS
Urban	Urban	Binary	DHS
Improved water	WHO definition of improved water supply	Binary	DHS
Improved toilet	WHO definition of improved sanitation	Binary	DHS
Time to water	Time to access water	0; 1, <30 min; 2, >30 min	DHS
Head age	Household head's age	Year	DHS
Head sex	Household head's sex	Binary	DHS
Members	Number of members living in the household		DHS
Poor	Belongs to the poorest quintile of wealth	Binary	DHS
Rich	Belongs to the richest quintile of wealth	Binary	DHS

Note: This table presents the variables, their units, source, and a description.

Table A2
Composition of dietary diversity scores.

	WDDS		MDDS
1	Cereal grains	1	Cereal grains, white tubers and root foods
2	White tubers, and root foods		
3	Vitamin A-rich fruits	2	Vitamin A-rich fruits and vegetables (including dark leafy green)
4	Vitamin A-rich vegetable/tubers		
5	Dark leafy greens		
6	Other fruits and vegetables	3	Other fruits and vegetables
7	Meat, poultry and fish	4	Meat, poultry, and fish
8	Eggs	5	Eggs
9	Legumes/nuts/seeds	6	Legumes/nuts/seeds
10	Milk and milk products	7	Milk and milk products

Note: This table presents the food groups which compose each dietary diversity score.

Table A3
Number of children per country and DHS survey year.

Country	2005	2006	2007	2008	2010	2011	2012	2013	2014	2015	2016	2018	Total
Egypt	0	0	0	547	0	0	0	0	1,049	0	0	0	1,596
Ethiopia	656	0	0	0	519	0	0	0	0	0	113	0	1,288
Ghana	0	0	0	268	0	0	0	0	386	0	0	0	654
Guinea	0	0	0	0	0	0	552	0	0	0	0	521	1,073
Liberia	0	0	1,673	0	0	0	0	2,242	0	0	0	0	3,915
Malawi	0	0	0	0	1,529	0	0	0	0	1,140	0	0	2,669
Nigeria	0	0	0	1,234	0	0	0	925	0	0	0	0	2,159
Uganda	0	531	0	0	0	1,211	0	0	0	0	2,039	0	3,781
Zambia	0	0	314	0	0	0	0	334	0	0	0	0	648
Zimbabwe	97	0	0	0	411	0	0	0	0	421	0	0	929
Total	753	531	1,987	2,049	2,459	1,211	552	3,501	1,435	1,561	2,152	521	18,712

Note: This table presents the number of observations by year and country for the baseline sample with cutoff distance at 15 km.

Table A4
Summary statistics for administrative areas.

Country	Level name	N	Mean	Median	St.Dev	Min	Max
Egypt	Kism/Markaz	343	2,868.12	154.18	16,476.74	0.41	267,901.59
Ethiopia	Zone	79	14,297.73	11,247.00	13,935.27	8.66	62,048.40
Ghana	District	137	1,739.59	1,180.96	1,696.57	126.66	9,839.51
Guinea	Prefecture	34	7,200.48	5,653.94	4,614.68	419.98	17,672.26
Liberia	District	66	1,453.30	1,249.92	1,015.04	106.15	4,550.06
Malawi	Traditional authority	256	461.05	290.45	716.76	3.67	7,864.74
Nigeria	Local authority	775	1,172.14	694.17	1,421.38	11.59	10,314.90
Uganda	County	166	1,454.46	1,027.58	2,403.11	4.78	28,402.66
Zambia	District	72	10,423.48	9,157.58	7,850.28	465.36	39,398.22
Zimbabwe	District	60	6,511.34	5,445.94	4,801.64	458.31	29,787.91

Note: Summary statistics of each administrative area in kilometer square for country included in the study. Data are from Global Administrative Areas and correspond to Level 2.

Table A5
Results following the randomisation of LSLA locations.

	Mean coeff	Median coeff	Mean p-value	Median p-value	Mean obs	Median obs	Percent p-values	Percent coeff
Random	0.009	0.007	0.438	0.418	8,017	7,638	12.58	3.4
Random country	0.006	0.005	0.484	0.480	18,286	17,992	6.46	0.2

Note: This Table presents the results of, respectively, (1) 5,000 estimations with random locations of LSLAs accross Africa, and (2) 5,000 random locations of LSLAs respecting the real distribution between countries. Columns 1, and 2 present the mean and median coefficients, Columns 3, and 4 the mean and median p-value, Columns 4, and 5 the mean and median number of observations. Column 6, present the percentage of significant results at 0.95. Column 7, present the percentage of coefficient below the study one, 0.509. The treated group has a maximum distance of 15 km. The control group has a maximum distance of 50 km. All estimations include year, buffer, and GADM fixed effects, and the control variables. All estimates are weighted using DHS individual weights. Standard errors are clustered at the buffer level.

Table A6
Wealth index.

Treatment cutoff	10 km				15 km				Without	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Wealth index										
Treated X Post	−0.086	−0.161			−0.402	−0.397				
	(0.403)	(0.427)			(0.474)	(0.458)				
Distance X Post			0.002	0.004			0.006	0.008	−0.002	−0.001
			(0.008)	(0.009)			(0.010)	(0.011)	(0.007)	(0.006)
Mean Before	0.39	0.39	0.39	0.39	0.319	0.319	0.319	0.319	0.184	0.184
Observations	15,351	15,351	15,351	15,351	18,293	18,293	18,293	18,293	35,779	35,779
Number of LSLAs	30	30	30	30	45	45	45	45	78	78
Controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes

Note: The wealth index is a composite indicator of the wealth of the household. The control group has a maximum distance of 50 km. All columns include year, buffer and GADM fixed effects. The inclusion of control variables is indicated at the bottom of each estimate. All estimates are weighted with DHS individual weights. Standard errors clustered at the buffer level are shown in parentheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

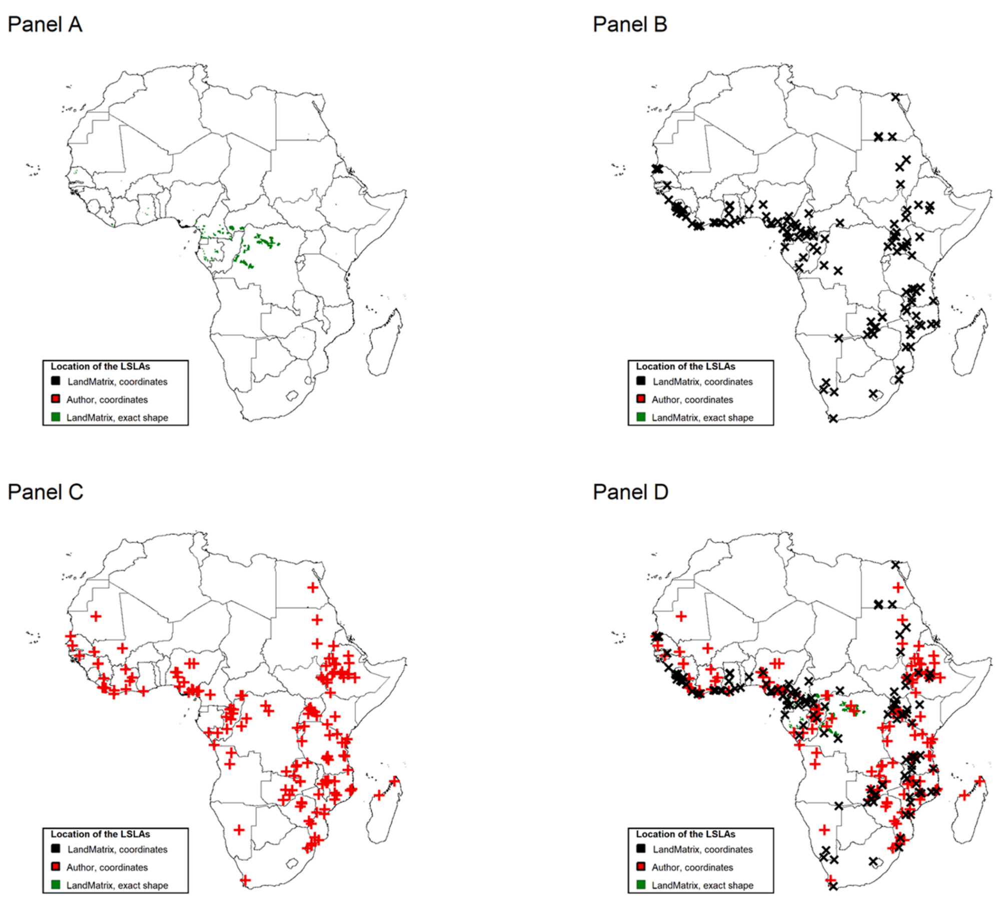

Fig. A1. Map of LSLAs in Africa – Disentangled. Note: The figures show LSLAs located from 2000 to 2021. Panel A (top left) represents the exact areas of the transactions for which it is known. Panel B (top right) represents the location as geolocated by the author. Panel C (top right) represents the location geolocated by Land Matrix, where the exact shape of the area is unknown. Panel D (bottom right) combines all the above.

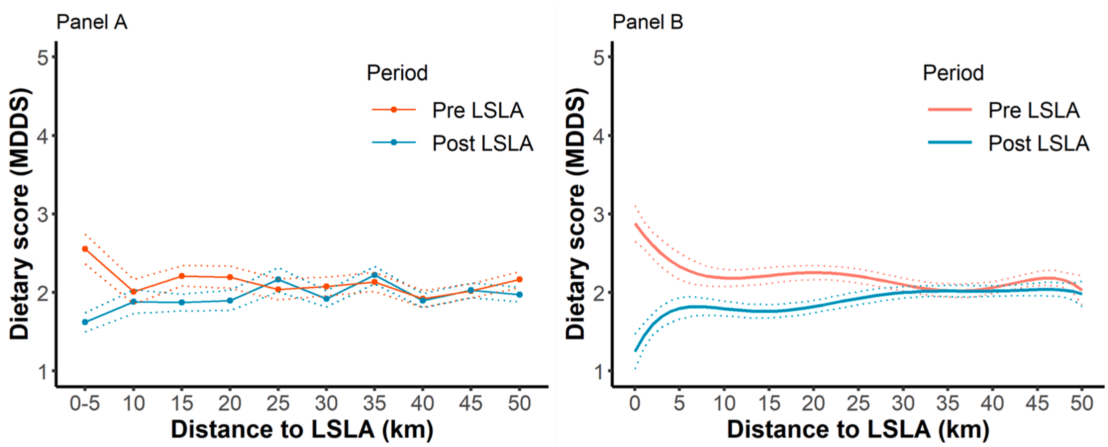

Fig. A2. Nutrition score by distance – MDDS. Note: Panel A (left) shows the simple MDDS means by distance group before (red) and after (blue) LSLAs. Panel B (right) shows the prediction of a 6th degree polynomial estimate of the MDDS by distance. The dashed lines indicate a confidence interval of 0.95.

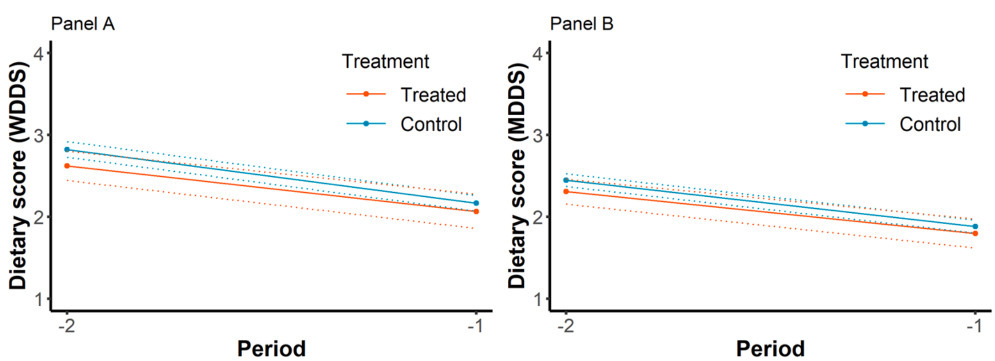

Fig. A3. Ex ante parallel trends for surveys with two periods of pre-treatment. Note: Panel A (left) and Panel B (right) show the simple WDDS and MDDS means two and one periods before treatment, respectively. The dashed lines indicate a confidence interval at 0.95.

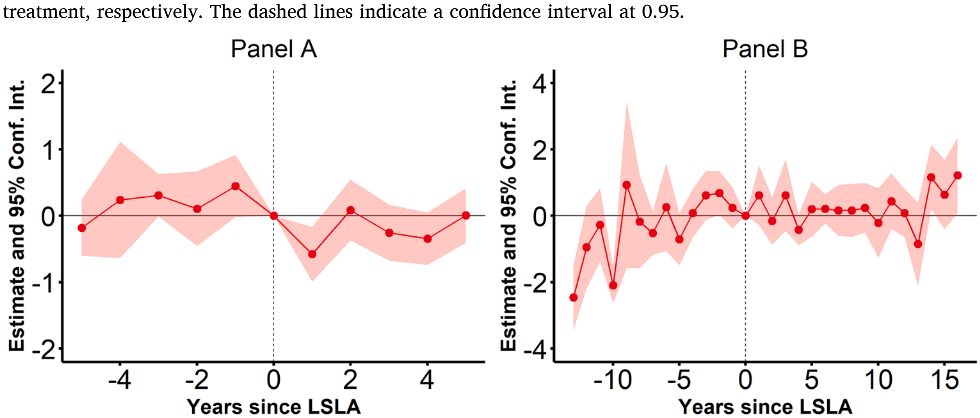

Fig. A4. Event-study estimations. Note: Panel A (left) and Panel B (right) show the results for the baseline sample and the event study specific sample respectively. The dependent variable is WDDS for both panel. The estimations include year, LSLA, and GADM fixed effects. The control variables are included. Confidence intervals are at 0.95.

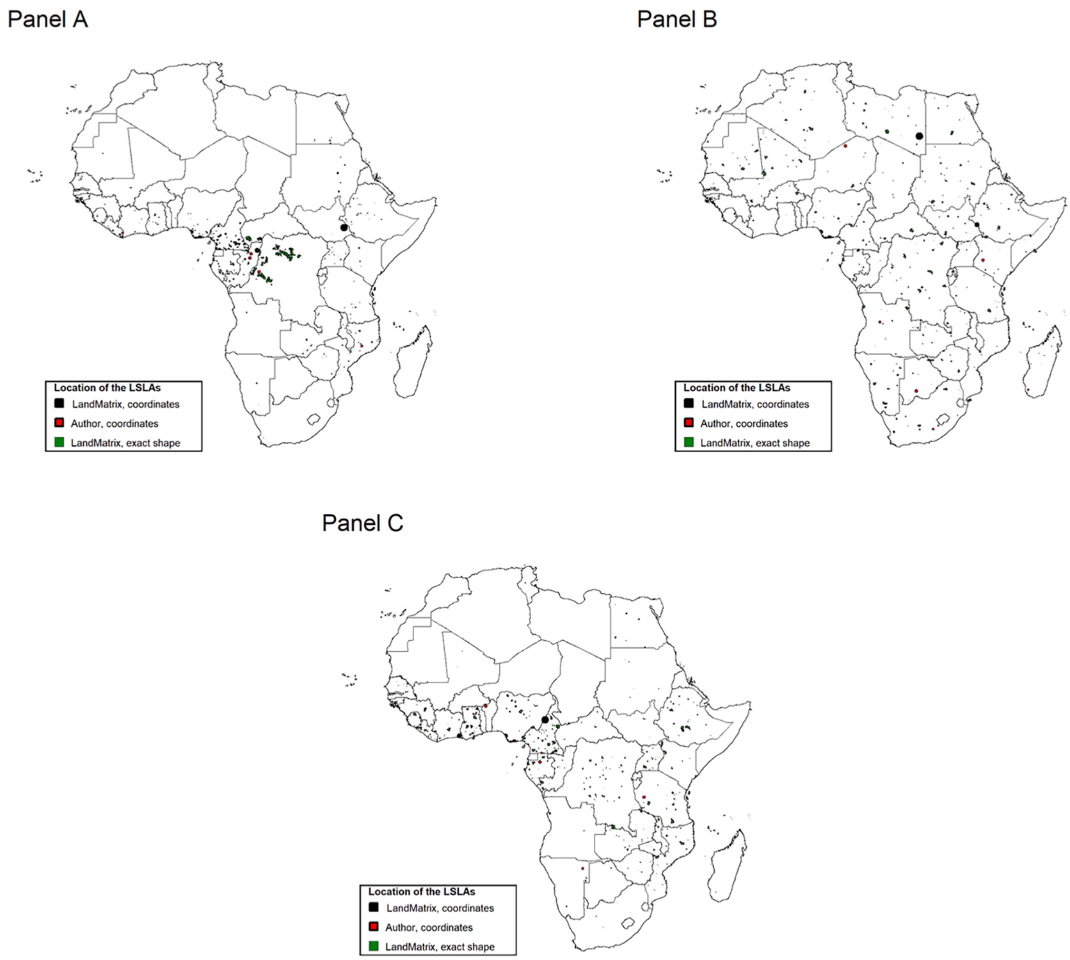

Fig. A5. Location of the LSLAs randomized. Note: Panel A (top left) shows the map with the real location of the LSLAs. Panel B (top right) shows the map with the randomized location of LSLAs across Africa. Panel C (bottom) shows the map with the randomized location of LSLAs, respecting the real distribution between countries.

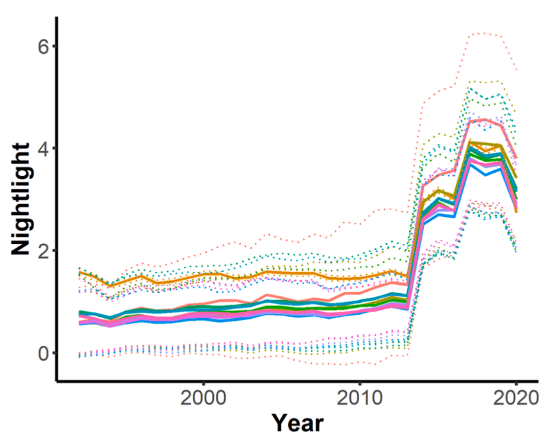

Fig. A6. Trends in night-time lighting by LSLA distance. Note: Panel A (left) shows the simple mean of the night light value measured by DMSP_VIIRS as a function of the area distance to LSLAs. Panel B (right) shows the prediction of a degree 3 polynomial estimating the population according to the distance ring. The available years are from 1992 until 2020. Only the 45 LSLAs of the preferred estimation (15 km treatment and 50 km control) are included.

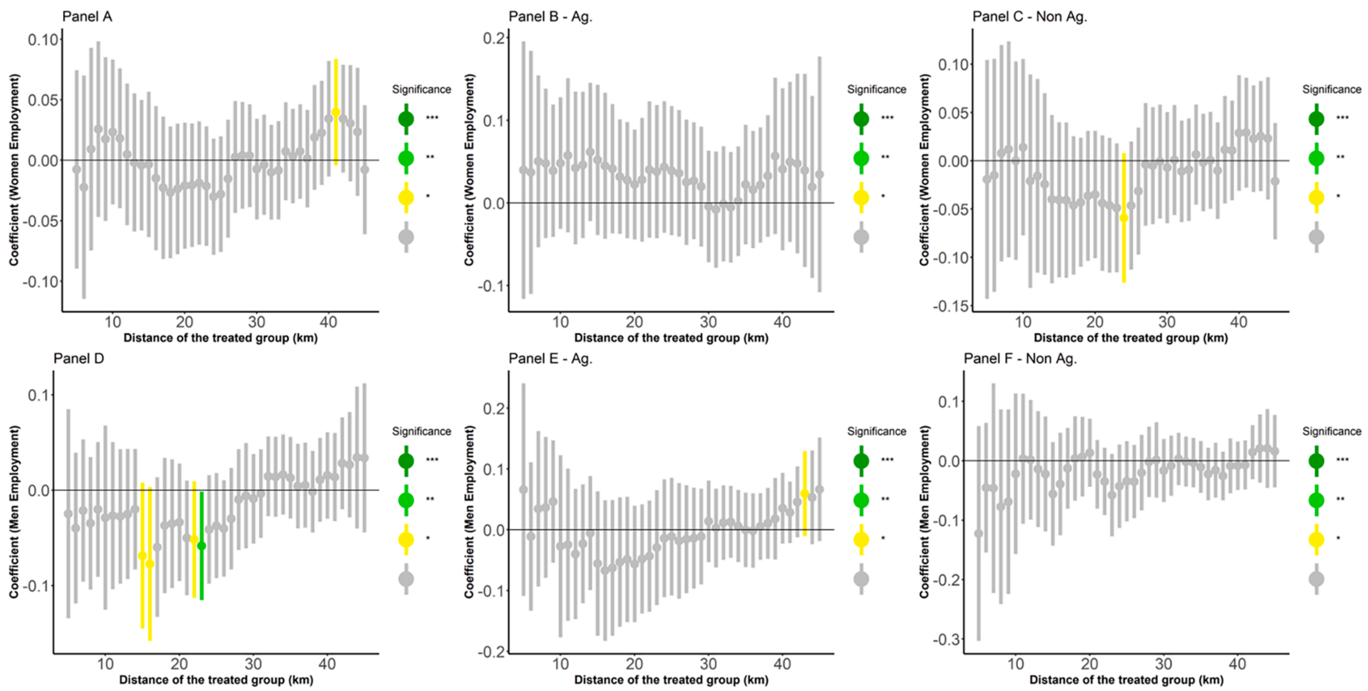

Fig. A7. Work status loops. Note: The figures show the coefficients and confidence intervals associated with 40 regressions of Equation , including year, buffer and GADM fixed effects and controls. In each regression, the distance assigned to the treated group increases by one kilometer from 5 to 45 km. The control group has a maximum distance of 50 km. The dependent variable is the work status of women for the top panels A, B and C and the work status of men for the bottom panels D, E and F. Panel B (E) includes only women (men) who report working in agriculture, while panel C (F) include women (men) who report not working in agriculture. Confidence intervals are at 0.95.

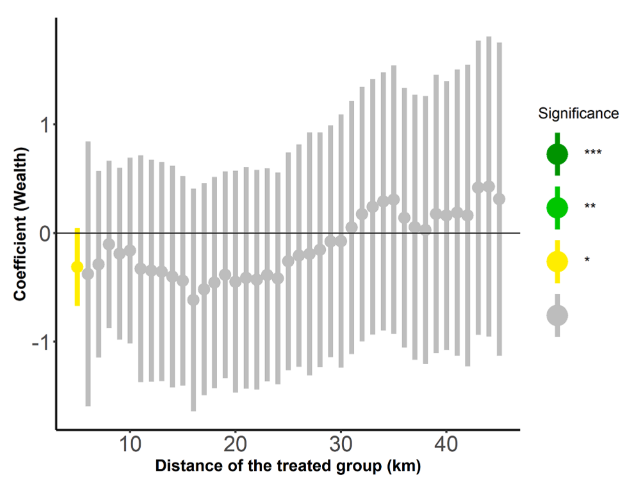

Fig. A8. Wealth index loop. Note: The figure shows the coefficients and confidence intervals associated with 40 regressions of Equation , including year, buffer and GADM fixed effects and controls. In each regression, the distance assigned to the treated group increases by one kilometer from 5 to 45 km. The control group has a maximum distance of 50 km. The wealth index is the dependent variable. The confidence intervals are at 0.95.

Appendix B. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.worlddev.2024.106597.

References

Abadie, A., Athey, S., Imbens, G. W., & Wooldridge, J. (2017). When should you adjust standard errors for clustering? (working paper 24003). National Bureau of economic. *Research.*. https://doi.org/10.3386/w24003

Aha, B., & Ayitey, J. Z. (2017). Biofuels and the hazards of land grabbing : Tenure (in) security and indigenous farmers' investment decisions in Ghana. *Land Use Policy, 60*, 48–59. https://doi.org/10.1016/j.landusepol.2016.10.012

Ali, D., Deininger, K., & Harris, A. (2019). Does large farm establishment create benefits for neighboring smallholders? *Evidence from Ethiopia. Land Economics, 95*(1), 71–90. https://doi.org/10.3368/le.95.1.71

Anti, S. (2021). Land grabs and labor in Cambodia. *Journal of Development Economics, 149*, Article 102616. https://doi.org/10.1016/j.jdeveco.2020.102616

Arezki, R., Deininger, K., & Selod, H. (2015). What drives the global "land rush"? *World Bank Economic Review, 29*(2), 207–233. https://doi.org/10.1093/wber/lht034

Atuoye, K. N., Luginaah, I., Hambati, H., & Campbell, G. (2021). Who are the losers? gendered-migration, climate change, and the impact of large scale land acquisitions on food security in coastal Tanzania. *Land Use Policy, 101*, Article 105154. https://doi.org/10.1016/j.landusepol.2020.105154

Bae, Y. J. (2019). A displaced community's perspective on land-grabbing in Africa : The case of the kalimkhola Community in Dwangwa, Malawi. *Land, 8*(12), Art. 12. https://doi.org/10.3390/land8120187

Bae, Y. J. (2023). Analyzing the connection between customary land rights and land grabbing: A case study of Zambia. Art. 1 *Land, 12*(1). https://doi.org/10.3390/land12010200.

Baumgartner, P., von Braun, J., Abebaw, D., & Müller, M. (2015). Impacts of large-scale land investments on income, prices, and employment : Empirical analyses in Ethiopia. *World Development, 72*, 175–190. https://doi.org/10.1016/j.worlddev.2015.02.017

Benshaul-Tolonen, A. (2019). Local industrial shocks and infant mortality. *The Economic Journal, 129*(620), 1561–1592. https://doi.org/10.1111/ecoj.12625

Benshaul-Tolonen, A. (2022). Industrial gold mining and female empowerment. *Economic Development and Cultural Change*. https://doi.org/10.1086/723215

Bertrand, M., Duflo, E., & Mullainathan, S. (2004). How much should we trust differences-in-differences estimates? *The Quarterly Journal of Economics, 119*(1), 249–275. https://doi.org/10.1162/003355304772839588

Borras, S. M., Fig, D., & Suárez, S. M. (2011). The politics of agrofuels and mega-land and water deals : Insights from the ProCana case. *Mozambique. Review of African Political Economy, 38*(128), 215–234. https://doi.org/10.1080/03056244.2011.582758

Borras, S. M., Franco, J. C., Moreda, T., Xu, Y., Bruna, N., & Afewerk Demena, B. (2022). The value of so-called 'failed' large-scale land acquisitions. *Land Use Policy, 119*, Article 106199. https://doi.org/10.1016/j.landusepol.2022.106199

Bottazzi, P., Crespo, D., Bangura, L. O., & Rist, S. (2018). Evaluating the livelihood impacts of a large-scale agricultural investment : Lessons from the case of a biofuel production company in northern Sierra Leone. *Land Use Policy, 73*, 128–137. https://doi.org/10.1016/j.landusepol.2017.12.016

Broegaard, R. B., Vongvisouk, T., & Mertz, O. (2022). The impact of unimplemented large-scale land development deals. *Frontiers in Sustainable Food Systems, 6*. https://doi.org/10.3389/fsufs.2022.789809

Bunte, J. B., Desai, H., Gbala, K., Parks, B., & Runfola, D. M. (2018). Natural resource sector FDI, government policy, and economic growth : Quasi-experimental evidence from Liberia. *World Development, 107*, 151–162. https://doi.org/10.1016/j.worlddev.2018.02.034

Deininger, K., & Byerlee, D. (2012). The rise of large farms in land abundant countries : Do they have a future? *World Development, 40*(4), 701–714. https://doi.org/10.1016/j.worlddev.2011.04.030

Deininger, K., & Xia, F. (2016). Quantifying spillover effects from large land-based investment : The case of Mozambique. *World Development, 87*, 227–241. https://doi.org/10.1016/j.worlddev.2016.06.016

Diop, L., Becquey, E., Turowska, Z., Huybregts, L., Ruel, M. T., & Gelli, A. (2021). Standard minimum dietary diversity indicators for women or infants and young children are good predictors of adequate micronutrient intakes in 24–59-month-old children and their nonpregnant nonbreastfeeding mothers in rural Burkina Faso. *The Journal of Nutrition, 151*(2), 412–422. https://doi.org/10.1093/jn/nxaa360

Engström, L. (2018). Development delayed. *Acta Universitatis Agriculturae Sueciae, 2018*, 40. https://res.slu.se/id/publ/104202.

Engström, L., Bélair, J., & Blache, A. (2022). Formalising village land dispossession? an aggregate analysis of the combined effects of the land formalisation and land acquisition agendas in Tanzania. *Land Use Policy, 120*, Article 106255. https://doi.org/10.1016/j.landusepol.2022.106255

Feldman, S., & Geisler, C. (2012). Land expropriation and displacement in Bangladesh. *The Journal of Peasant Studies, 39*(3–4), 971–993. https://doi.org/10.1080/03066150.2012.661719

Fitawek, W., Hendriks, S., Reys, A., & Fossi, F. (2020). The effect of large-scale agricultural investments on household food security in Madagascar. *Food Security, 12*(6), 1349–1365. https://doi.org/10.1007/s12571-020-01055-6

Friis, C., & Nielsen, J.Ø. (2016). Small-scale land acquisitions, large-scale implications : Exploring the case of chinese banana investments in northern Laos. *Land Use Policy, 57*, 117–129. https://doi.org/10.1016/j.landusepol.2016.05.028

Gina Kennedy, T. B., & M. D. & Nutrition Division. (2011). Guidelines for measuring household and individual dietary diversity. *FAO*. https://www.fao.org/publications/card/fr/c/5aacbe39-068f-513b-b17d-1d92959654ea/.

Gyapong, A. Y. (2020). How and why large scale agricultural land investments do not create long-term employment benefits : A critique of the 'state' of labour regulations in Ghana. *Land Use Policy, 95*, Article 104651. https://doi.org/10.1016/j.landusepol.2020.104651

Haileselassie, M., Redae, G., Berhe, G., Henry, C. J., Nickerson, M. T., Tyler, B., & Mulugeta, A. (2020). Why are animal source foods rarely consumed by 6–23 months old children in rural communities of northern Ethiopia? a qualitative study. *PLOS ONE, 15*(1), e0225707.

Hainmueller, J. (2012). Entropy balancing for causal effects : A multivariate reweighting method to produce balanced samples in observational studies. *Political Analysis, 20*(1), 25–46. https://doi.org/10.1093/pan/mpr025

Hall, D. (2013). Primitive accumulation, accumulation by dispossession and the global land grab. *Third World Quarterly, 34*(9), 1582–1604.

Herrmann, R. T. (2017). Large-scale agricultural investments and smallholder welfare : A comparison of wage labor and outgrower channels in Tanzania. *World Development, 90*, 294–310. https://doi.org/10.1016/j.worlddev.2016.10.007

Herrmann, R. T., & Grote, U. (2015). Large-scale agro-industrial investments and rural poverty : Evidence from sugarcane in Malawi. *Journal of African Economies, 24*(5), 645–676. https://doi.org/10.1093/jae/ejv015

Hofman, P., Mokuwa, E., Richards, P., & Voors, M. (2019). Local economy effects of large-scale agricultural investments. Biodiversity and Economics for Conservation (BIOECON)(Wageningen, The Netherlands, September 2019).

Hufe, P., & Heuermann, D. F. (2017). The local impacts of large-scale land acquisitions : A review of case study evidence from sub-saharan Africa. *Journal of Contemporary African Studies, 35*(2), 168–189. https://doi.org/10.1080/02589001.2017.1307505

Iannotti, L. L., Robles, M., Pachón, H., & Chiarella, C. (2012). Food prices and poverty negatively affect micronutrient intakes in Guatemala. *The Journal of Nutrition, 142*(8), 1568–1576. https://doi.org/10.3945/jn.111.157321

Kleemann, L., & Thiele, R. (2015). Rural welfare implications of large-scale land acquisitions in Africa : A theoretical framework. *Economic Modelling, 51*, 269–279. https://doi.org/10.1016/j.econmod.2015.08.016

Lay, J., & Nolte, K. (2018). Determinants of foreign land acquisitions in low- and middle-income countries. *Journal of Economic Geography, 18*(1), 59–86. https://doi.org/10.1093/jeg/lbx011

Lay, J., Nolte, K., & Sipangule, K. (2021a). Large-scale farms in Zambia : Locational patterns and spillovers to smallholder agriculture. *World Development, 140*, Article 105277. https://doi.org/10.1016/j.worlddev.2020.105277

Lay, J., Anseeuw, W., Eckert, S., Flachsbarth, I., Kubitza, C., Nolte, K., & Giger, M. (2021b). Taking stock of the global land rush : Few development benefits, many human and environmental risks. *Analytical Report III.*

Li, T. M. (2011). Centering labor in the land grab debate. *The Journal of Peasant Studies, 38*(2), 281–298. https://doi.org/10.1080/03066150.2011.559009

Mechiche-Alami, A., Yagoubi, J., & Nicholas, K. A. (2021). Agricultural land acquisitions unlikely to address the food security needs of african countries. *World Development, 141*, Article 105384. https://doi.org/10.1016/j.worlddev.2020.105384

Messerli, P., Giger, M., Dwyer, M. B., Breu, T., & Eckert, S. (2014). The geography of large-scale land acquisitions : Analysing socio-ecological patterns of target contexts in the global south. *Applied Geography, 53*, 449–459. https://doi.org/10.1016/j.apgeog.2014.07.005

Millward, D. J. (2017). Nutrition, infection and stunting : The roles of deficiencies of individual nutrients and foods, and of inflammation, as determinants of reduced linear growth of children. *Nutrition Research Reviews, 30*(1), 50–72. https://doi.org/10.1017/S0954422416000238

Moreda, T. (2017). Large-scale land acquisitions, state authority and indigenous local communities : Insights from Ethiopia. *Third World Quarterly, 38*(3), 698–716. https://doi.org/10.1080/01436597.2016.1191941

Müller, M. F., Penny, G., Niles, M. T., Ricciardi, V., Chiarelli, D. D., Davis, K. F., Dell'Angelo, J., D'Odorico, P., Rosa, L., Rulli, M. C., & Mueller, N. D. (2021). Impact of transnational land acquisitions on local food security and dietary diversity. Proceedings of the National Academy of Sciences, 118(4). 10.1073/pnas.2020535118.

Nolte, K., & Ostermeier, M. (2017). Labour market effects of large-scale agricultural investment : Conceptual considerations and estimated employment effects. *World Development, 98*, 430–446. https://doi.org/10.1016/j.worlddev.2017.05.012

Oberlack, C., Giger, M., Anseeuw, W., Adelle, C., Bourblanc, M., Burnod, P., Eckert, S., Fitawek, W., Fouilleux, E., Hendriks, S., Kiteme, B., Masola, L., Mawoko, Z. D., Mercandalli, S., Reys, A., da Silva, M., van der Laan, M., Zaehringer, J., & Messerli, P. (2021). Why do large-scale agricultural investments induce different socio-economic, food security, and environmental impacts? evidence from Kenya, Madagascar, and Mozambique. *Ecology and Society, 26*(4). https://doi.org/10.5751/ES-12653-260418

Oberlack, C., Tejada, L., Messerli, P., Rist, S., & Giger, M. (2016). Sustainable livelihoods in the global land rush? archetypes of livelihood vulnerability and sustainability potentials. *Global Environmental Change, 41*, 153–171. https://doi.org/10.1016/j.gloenvcha.2016.10.001

Obuene, H. U., Akanle, O., & Omobowale, A. O. (2022). Land grabbing and resistance of indigenous landowners in Ibadan. *Nigeria. International Sociology, 37*(1), 143–159. https://doi.org/10.1177/02685809211046408

Shen, Q., & Zhong, T. (2023). Did household income loss have an immediate impact on animal-source foods consumption during the early stage of the COVID-19 pandemic? *Foods (Basel, Switzerland), 12*(7), 1424. https://doi.org/10.3390/foods12071424

Shete, M., & Rutten, M. (2015). Impacts of large-scale farming on local communities' food security and income levels – empirical evidence from Oromia region, Ethiopia. *Land Use Policy, 47*, 282–292. https://doi.org/10.1016/j.landusepol.2015.01.034

The Land Matrix. (2021). Deals Accessed Date, 26th October 2021. https://landmatrix.org/list/deals/

Tsikata, D., & Yaro, J. (2011). Land market liberalization and trans-National Commercial Land Deals in Ghana since the 1990s. *Future Agricultures.* https://www.future-agricultures.org/news/land-market-liberalization-and-trans-national-commercial-land-deals-in-ghana-since-the-1990s/.

Veldman, M., & Lankhorst, M. (2016). Socio Economic Impact of Commercial Exploitation of Rwandan Marshes : A Case Study of Sugar Production in Rural Kigali (p. 40). ILC. https://landportal.org/node/36003.

Wegenast, T., Richetta, C., Krauser, M., & Leibik, A. (2022). Grabbed trust? the impact of large-scale land acquisitions on social trust in Africa. *World Development, 159*, Article 106038. https://doi.org/10.1016/j.worlddev.2022.106038

White, B., Borras, S. M., Jr., Hall, R., Scoones, I., & Wolford, W. (2012). The new enclosures : Critical perspectives on corporate land deals. *The Journal of Peasant Studies, 39*(3–4), 619–647. https://doi.org/10.1080/03066150.2012.691879

Wooldridge, J. M. (2021). Two-Way Fixed Effects, the Two-Way Mundlak Regression, and Difference-in-Differences Estimators (SSRN Scholarly Paper 3906345). 10.2139/ssrn.3906345.

Wooldridge, J. M. (2023). Simple approaches to nonlinear difference-in-differences with panel data. *The Econometrics Journal, 26*(3), C31–C66. https://doi.org/10.1093/ectj/utad016

Yang, B., & He, J. (2021). Global land grabbing : A critical review of case studies across the world. *Land, 10*(3), Art. 3. https://doi.org/10.3390/land10030324

Yengoh, G. T., & Armah, F. A. (2015). Effects of large-scale acquisition on food insecurity in Sierra Leone. *Sustainability, 7*(7), Art. 7. https://doi.org/10.3390/su7079505