Analysis of the effects of armed conflict on farmland ownership using spatial regression techniques

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Abstract

In recent years, the frequency and intensity of armed conflict increased in West Africa. The agricultural sector is likely to beindirectly and directly affected by armed conflict. Given that agriculture is critical to the rural economies of West Africa, it is important to understand the effects that armed conflict has on aspects such as agricultural land use in this region. In this paper, we explore the relationship between armed conflict and farm land ownership in a cross-country context. In contrast to previous studies that focused on a single country, our study is based on household data from five neighboring countries in West Africa, thereby naturally including their borderlands. These border regions experience some of the highest conflict intensities and are therefore important to capture the entire effects in the region. We employ a cross-sectional spatial approach incorporating data from Benin, Burkina Faso, Mali, Niger, and Nigeria. We find an ambiguous relationship between conflict and farm land ownership. By differentiating conflict events by distance to the household, we find that the effect of armed conflict on farm land ownership is not constant across distance. A conflict-related fatality in close proximity to a household is for example associated with a decrease in the number of plots owned whereas an fatality far away increases the latter. Against findings from previous, single-country studies, we therefore argue that the impact of conflict on farm land ownership is too heterogeneous to aggregate to a clear linear relationship.

Keywords: Armed Conflict, Land Ownership, Smallholders, Spatial Analysis, West Africa
JEL Code: Q15, D74

1 Introduction

In West Africa, agriculture is the backbone of the rural economy. In many countries in the region, more than half of all employed people work in the agricultural sector. Agriculture in the region is characterized by a high share of small-scale farmers relying on labor-intensive production techniques (Allen et al. 2018). Due to its economic importance, the agricultural sector is crucial to ensure food security and economic growth in West Africa (Merem et al. 2019). Therefore, improved land access and efficient land use in agriculture are critical to short-term livelihoods and long-term economic transformation.

From 2010 onward, some regions in Western Africa have seen a severe increase in violent conflict. According to the International Rescue Committee, three of the ten top emergency countries are West African countries, namely Niger, Mali and Burkina Faso (International Rescue Committee 2023). In particular, the border region of these countries as well as north-eastern Nigeria have been affected by intense conflict. In the region, one third of all conflict-related fatalities were located within a 50 km distance of a country border (OECD/SWAC 2020). Sparsely controlled borders in the region facilitate the exchange of fighters and weapons, the recruiting of new fighters, and the set-up of temporary basis (OECD/SWAC 2020).

Furthermore, the share of conflict that specifically targets civilians increased over the last decade (Nsaibia 2023, OECD/SWAC 2020). Previously, most fatalities were caused by battle between armed groups and state forces, but in recent years the number of deaths of civilians killed in attacks, kidnappings or sexual assaults exceeded battle-related deaths. This change is partly due to the fact that armed groups are increasingly driven by identity politics that aim at creating areas that are homogeneous in terms of ethnicity or religion (Nsaibia 2023, OECD/SWAC 2020).[1]

The direct and indirect effects of armed conflict on civilians, including farmers, give rise to the question what impact the regional activities of armed groups have on the agricultural sector. More specifically we are interested in the effects of changes in agricultural land as agricultural land can be directly affected (e.g. if

[1] These armed groups are heterogeneous in terms of actions, ideologies and religious motives. More information about the different actors in the region can be found for instance in Nsaibia (2022), Nsaibia & Marco (2023), and Nsaibia (2023).

battles take place on fields), but also indirectly if farmers take different farm land ownership decisions due to conflict in the area. A thorough understanding of the effects of conflict on agriculture is crucial to understand the impact of the increase in conflict on livelihood of farmers in the region.

Several studies assessed the effect of conflict on land use variables in different contexts and find clear effects such as an increase of land left fallow as a consequence of armed conflict (e.g., Adelaja & George (2019*b*), Nyssen et al. (2022)). The analyses are typically focused on a particular conflict and the analyzed geographic area is limited to a single country (e.g., Eklund et al. (2017), Nyssen et al. (2022). This is a valid approach to take if violent incidents can clearly be attributed to a single conflict and if all the conflict-related events stayed within country boundaries. However, if borderlands play an important role for the armed conflict - as is the case in West Africa - limiting the geographic area to a single country imposes an artificial boundary to the study area such that conflict-related fatalities that happen just across the border are not taken into account. To the best of our knowledge, there is no study yet that assesses the effects of conflict on farm land ownership in West Africa on a regional scale.

Furthermore, there is some indication that incidents of armed conflict may not only affect living conditions in close geographic proximity. George et al. (2022) find that Boko Haram attacks in one state increase the likelihood of attacks by the Fulani Ethnic Militia in neighboring states. While this relates to activities of armed groups, van der Haar & van Leeuwen (2019) theorize that conflict events may lead to an increase in demand for land, even in areas relatively far away, as internally displaced people aim to relocate and rebuild their livelihoods. In other words, incidents of armed conflict may have effects on farmland ownership even beyond the immediate conflict zone, but this has not been empirically tested so far.

This paper aims at contributing to the understanding of the relation between conflict and farm land ownership in West Africa by explicitly including borderlands. We address two research questions: what is the effect of conflict on land use, i.e. the number of plots owned, the farmland owned, and the percentage of free land acquired, when including cross-border regions? Is the effect of conflict on farm land ownership consistent across increasing distance between the conflict-related fatality and the household?

We overcome the negligence of cross-border effects by conducting our analysis in a trans-national setting. Our analysis spans Mali, Burkina Faso, Benin, Niger and Nigeria and consequently also their border regions. The pronounced number and intensity of incidents of armed conflict in border regions underlines the necessity to include these regions in the analysis. Taking a trans-national approach also allows us to test whether earlier identified effects of conflicts on farm land ownership that were found for Nigeria (Adelaja & George 2019*b*) also hold for the larger region.

We fit a cross-sectional regression model to nationally representative data from the five mentioned countries. As opposed to many previous studies that used household survey data, we cannot rely on panel data in this setting. This makes abstracting from the effects of unobserved household heterogeneity more difficult. To cope with this problem, we use spatial smoothing splines to control for spatially distributed unobserved variables. The spatial smoothing splines also absorb spatial autocorrelation in the dependent variables (Fahrmeir et al. 2013). Thereby, we reduce possible bias in both the coefficient estimators and the variance estimators.

We add to existing studies (1) by taking a transnational approach and (2) by observing the effect of conflict on farm land ownership across different distances. We determine the size of local and also non-local influence of conflict on farm land ownership as well as the range over which such influence can be observed. To do so, we use regressors that incorporate information on conflict within several distances from the location of the observed households. This approach allows to systematically investigate heterogeneity in the effects of conflict across different distances.

A key finding of our study is the substantial heterogeneity of the relation between conflict and farm land ownership across distances. We demonstrate that effects of conflict on agricultural land size observed for farms in close proximity to incidents with conflict-related fatalities may differ substantially or even contradict the effects of conflict-related fatalities in far distance from a farming household. Our results are not in line with the findings of earlier literature on the effect of conflict in West Africa regardless of the distance considered.

The remainder of the article is structured as follows. Section 2 presents a review of existing literature regarding the relation between conflict and land use. Subsequently, we introduce the data sets that are used in the trans-national analysis in Section 3. In Section 4, we describe the structure of our model and discuss the methodological requirements to claim causality of results of this analysis. Descriptive information on underlying data are shown in Section 5 along with analytical results. Section 6 summarizes the main findings, discusses limitations of the analytical approach, and suggests areas of further research.

2 Literature Review

This paper builds on previous studies on the question how conflict influences farm land ownership. To revisit existing evidence, we differentiate between studies that are primarily based on satellite imagery and studies analyzing survey data.

Studies that used satellite imagery to determine land use and its changes during conflict periods showed that agricultural land use often decreased as a consequence of the armed conflict. Suthakar & Bui (2008) observed that agricultural land reduced by 50 percent during the two decades after the war between the government of Sri Lanka and the Liberation Tigers of Tamil Eelam (1983 - 2002). Similarly, Wilson & Wilson (2013) find that agricultural land used also decreased during the civil war in Sierra Leone from 1991 to 2002. The underlying assumption is that this decline is caused by farmers being killed or displaced.

This hypothesis is also supported in two studies analyzing more recent conflicts, namely the Islamic State Insurgency in Iraq and Syria in 2014 and 2015 (Eklund et al. 2017) and the conflict in north Ethiopia in the Tigray region in 2021 (Nyssen et al. 2022). Both studies find an increase in land left fallow in some of the analyzed regions and assume that this is primarily due to displacement. However, both studies also find that in other part of the analyzed regions the cropland did increase (Eklund et al. 2017) or at least stay constant (Nyssen et al. 2022). Eklund et al. (2017) hypothesize that agriculture might be used strategically during times of conflicts to generate revenue and guarantee supply of fighters and local population. Given the different context in Ethiopia, Nyssen et al. (2022) rather assume that small-scale farmers were able to adapt to the conflict, e.g., by shifting from commercial crops to crops that need less irrigation systems.

Using geocoded household and armed conflict data allows to produce a more nuanced picture of the effects of armed conflict on agricultural production systems.

Several studies looked at armed conflict in Nigeria and used the Living Standards Measurement Survey (LSMS) dataset and data on armed conflict from the Armed Conflict Location & Event data (ACLED) dataset from 2010 to 2016 (Adelaja & George 2019*a*,*b*, Fadare et al. 2022, 2023, George et al. 2021). Adelaja & George (2019*a*) and George et al. (2021) find that both, Boko Haram attacks as well as conflict with the Fulani ethnic militia (FEM), reduce total agricultural output and agricultural productivity. Armed conflict also decreases herd sizes (Fadare et al. 2022, George et al. 2021), but Fadare et al. (2022) specify that this is only the case for households who do not have access to larger areas of land. Regardless of land access, conflict that leads to more fatalities was associated with smaller herd sizes in their study (Fadare et al. 2022). Adelaja & George (2019*a*) further find that with increasing conflict intensity the hours of hired labour and of agricultural wages decrease while family labour input remains unchanged. Brugger & Zongo (2023) discover that agriculture contracts due to the massive displacement of farmers caused by widespread violence against civilians perpetrated by Salafist groups, local militias, and state security actors in Burkina Faso, while artisanal mining expands. Adelaja et al. (2023) findings indicate that increased conflict intensity decreases the probability of smallholder farmers expanding to a larger scale, particularly among those who primarily depend on farm incomes as opposed to off-farm incomes for their livelihoods.

With regard to farm land ownership, findings derived from survey data are similar to the findings from Eklund et al. (2017) and Nyssen et al. (2022). Adelaja & George (2019*a*) did not observe an effect of the conflict intensity of the Boko Haram insurgence in Nigeria on the total area harvested or in overall agricultural land productivity. Adelaja & George (2019*b*)[2] analyzed the same conflict and find that households affected by conflict possess more agricultural land with a larger percentage of it being acquired for free compared to households less affected by conflict. They hypothesize that this observation might be the result of free transfer of land from farmers abandoning the fields in the conflict area. In line with findings from the satellite imagery studies, they also find that conflict leads to more land

[2]Despite the fact that there were doubts about the internal validity of this study raised by Ölkers et al. (2023), we refer to this study as the authors of the original study provided full replication packages (Adelaja & George 2024). Their study is the closest to the present research study and therefore of major importance for this paper.

left fallow and lower land value.

Besides, there is evidence for a change in cropping patterns due to armed conflict. Arias et al. (2019) use household data on Colombian rural households from 2010. They distinguish between the time period a non-state armed actor has been present in the area and the occurrence of a violent incidence. With every year of additional presence of a non-state armed actor or if there is a violent shock, farmers reduce the amount of land used for seasonal crops and increased the share of mixed cropping and cattle ranching. This is also consistent with Adelaja & George (2019*b*) who found that casualties of armed conflict disincentivize mono-cropping and rather encourage mixed cropping. Arias et al. (2019) further found that if there is an incident of armed conflict while a non-state armed actor is present, the share of land dedicated to seasonal crops substantially increases. Households seem to shift their agricultural production to methods that are less risky and less investment intense. This aligns with findings from Nino et al. (2023). Using information on the Colombian peace agreement, Nino et al. (2023) conclude that one mechanism through which conflict inhibits agricultural development may be due to decreased investment.

While some conflicts remain within national borders, other conflicts develop in and around borderlands and span several countries, thereby rendering data availability more difficult. None of the discussed studies focused on borderlands despite the fact that, particularly in North and West Africa, borderlands experience more violence than other regions (OECD/SWAC 2020). In West Africa, borderlands are historically places with weak state control as movements are hard to control (OECD/SWAC 2020). Throughout the last decades, rebel groups and armed extremists organizations increasingly made use of this weakness by orchestrating and executing attacks from neighboring countries (Radil et al. 2022). Against this background, Zheng et al. (2023) analyzed global land cover change in borderlands related to armed conflict and find high forest loss rates caused by armed conflict. Zheng et al. (2023) do not address the question how armed conflict affects farm land ownership in borderlands, thereby leaving it open for investigation in this paper.

3 Data and Variable Definition

3.1 Measures of Conflict

Data on armed conflict is provided in the ACLED data set (Raleigh et al. 2023), which provides "disaggregated incident information on political violence, demonstrations, and select related non-violent developments around the world" (ACLED 2022*b*). This data set contains not only geo- and time-coded information on the occurrence of violent incidents, but also information on the number of fatalities resulting from the incidents as well as information on who was responsible for them. The ACLED data can be downloaded for free on the ACLED website (ACLED 2022*a*).

We quantify conflict intensity by aggregating the number of fatalities in the respective region one year prior to the survey months of the household[3]. This is necessary because Ubilava et al. (2023) show that there exist a harvest-related seasonality of conflict in Africa. We differentiate between three different radii: Fatalities of attacks within radius of 0 - 25 km, 50 - 100 km and 0 - 100 km of household location. Furthermore, in addition to the different conflict predictors, we provide robustness checks that use the number of incidents and a dummy for more than zero fatalities instead of the number of fatalities as conflict regressors (see Section 5.3 and Table A.7 and A.8 in the Appendix). Table A.1 in the Appendix provides an overview of the definitions of the ACLED variables used in our analysis.

3.2 Land Use Variables

The land use variables are based on on two main data sources. We use household data from the LSMS and "Enquête Harmonisée sur les Conditions de Vie des Ménages 2018 - 2019" (EHCVM). Both data sets are publicly available and can be downloaded online for free. For Nigeria, the LSMS data is collected as part of the General Household Survey (GHS) by the Nigerian National Bureau of Statistics. GHS-Panel households were visited twice: first after the planting season (post-planting) and second after the harvest season (post-harvest). The data sets

[3]We include all ACLED fatalities from October 1, 2017, to September 30, 2018.

include, among others, information on the demography, education, expenditure, and agricultural land use of households.

For Benin, Burkina Faso, Mali and Niger, we use cross-sectional data collected in the course of the LSMS project through the EHCVM 2018 - 2019. Overall, with minor deviations in the exact construction of the variables, the EHCVM contains similar information as the GHS data set. However, as the EHCVM lacks information on precipitation, we use precipitation levels at the household locations derived from data from the Climate Research Unit (University of East Anglia 2022). To allow us to estimate a model with data from these four countries as well as with data from Nigeria, for which the EHCVM data has not been collected, we combine the EHCVM data with data from the 2018 - 2019 wave of the GHS data set.

The GHS survey wave of 2018 - 2019 includes in total 5,116 Nigerian households. As we only include respondents involved in agricultural activities, the final sample size reduces to 3,062 households, as we have excluded households where the household head is older than 100 years old or if the household's total plot size is larger than 1,000,000 square meters. We identify farming households based on information provided in post-planting and post-harvest surveys, as only farmers responds to these questions.

The final sample size for the Benin sample is 3,775 households out of 8,012. For Burkina Faso, 4,344 households out of 7,010 are included; for Mali, 3,150 households out of 6,602 are included, and for Niger, 3,586 households out of 6,024 are included. We only include farmers in our analysis, which explains the reduction in the sample size. We identify farming households based on information provided in agricultural modules of the EHCVM data, as only farmers responds to these questions. Again, we have excluded households where the household head is older than 100 years old or if the household's total plot size is larger than 1,000,000 square meters.

Figure 1 shows the locations of the households contained in this combined EHCVM/GHS data set as grey dots and the location of incidents reported in the ACLED data set in red, while Figure A.1 in the Appendix show fatalities in different radii around household.

We have three key variables of interest, which we define as follows. The first one is the number of plots owned, determined through the information provided by

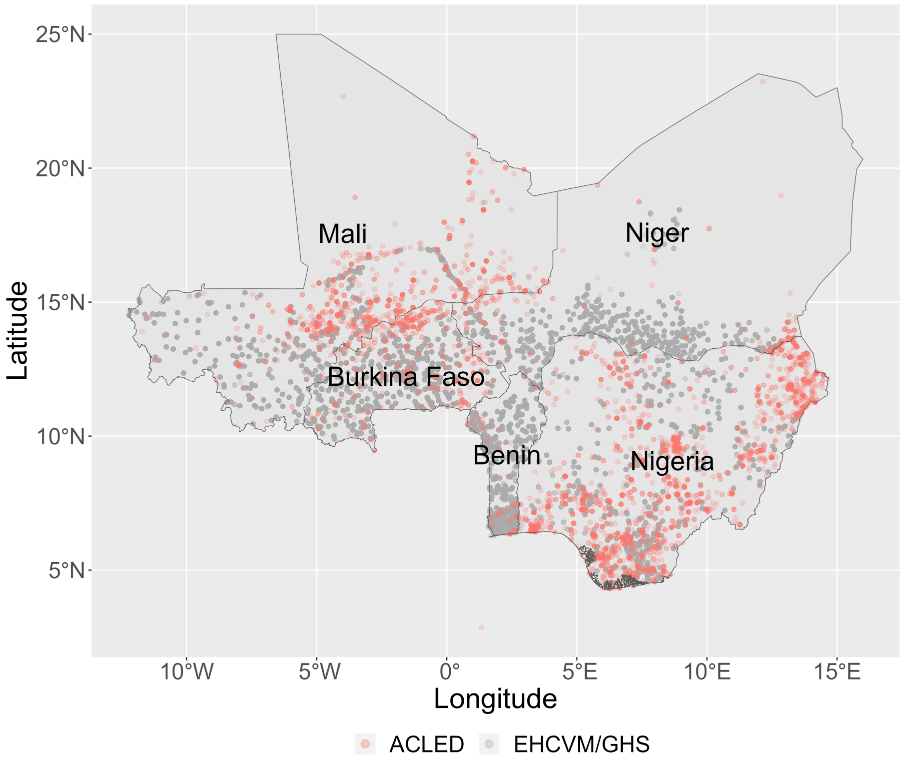

Figure 1: Geographic locations of surveyed households (EHCVM/GHS data) and of incidents of armed conflict (ACLED data)

farming households in the EHCVM about their respective plots. The farmers were asked questions regarding their plots, enabling the computation of the number of plots owned. Second, the land owned is measured in square meters, representing the sum of each plot owned by the farming household[4]. Third, farmers are asked how they acquired each of the plots they own. Based on this information, we can calculate the percentage of free land acquired[5].

3.3 Control Variables

Table A.2 and A.3 in the Appendix contains more specific information on which variables we use in our analyses. Table A.2 shows the variable definition and the

[4]In the data, the size of the plots is estimated based on both self-reported information and GPS data. We rely on the self-reported measures.

[5]Table A.2 and A.3 show the variable names of the respective variables of interest as well as of all control variables that we include in our estimation in the original GHS and EHCVM data set.

variable name in the GHS data and Table A.3 shows the same information for the EHCVM data. The set of household control variables encompassing the age, gender, religion, ethnicity, nationality, and education of the household head. Additionally, household controls include factors such as access to phone and internet, the food security situation, exposure to shocks, annual precipitation experienced by the household, and homeownership.

4 Methodology

In Subsection 4.1, we outline the analytical procedures that we apply to get a first understanding of the spatial influence of conflict on agricultural land use by means of exploratory data analysis. In Subsection 4.2, we introduce the trans-national cross sectional model to quantify the spatial effects of armed conflict on farm land ownership in Benin, Burkina Faso, Mali, Niger and Nigeria.

4.1 Exploratory data analysis

In a first step, exploratory data analysis techniques are applied to detect structures in the data. This analysis focuses on the relation between different measures for farmland ownership and conflict and detects spatial patterns that emerge in these variables.

To properly quantify the pure effect of conflict on these measures, i.e., to answer our key research question, more elaborate analytical tools were required. These tools need to incorporate the two types of spatial dependence that we expect to find: spatial autocorrelation in the dependent variables, i.e., farm land owned, and a spatially lagged effect of conflict on agricultural land use.

First, farm land owned is likely to exhibit positive spatial autocorrelation. In this context, positive spatial autocorrelation means that households located closer to each other tend to exhibit more similar land use characteristics than households located farther away from each other. Such correlation can be detected by calculating, for instance, Moran's I.

The global Moran's I can be calculated from the following formula (Moran 1948):

$$I = \frac{n}{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}} \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}\left(y_i - \bar{y}\right)\left(y_j - \bar{y}\right)}{\sum_{i=1}^{n}\left(y_i - \bar{y}\right)^2} \quad (1)$$

where n is the number of spatial units. $\overline{y}$ is the mean value of the respective variable of interest across the entire data. y_i and y_j are the value of the respective variable of interest for household i and j. w_{ij} is the weight matrix which describe the relationship for each pair of household i and j.

The values of global Moran's I range from "-1" to "1". If Moran's I is above 0, there is positive spatial correlation. A positive Moran's I statistic would indicate positive spatial autocorrelation. The larger this value is, the stronger the correlation will be. Inversely, if Moran's I is below 0, negative spatial correlation exists (Anselin 1988). To calculate Moran's I, the neighbourhood structure of the data needs to be specified (Ward & Gleditsch 2018). We provide two alternative specifications, one including all households in a range of 200 km and one including the 100 nearest neighbours of a household. The latter results in a set of neighbours that is within a range of less than 50 km for most households and is thus a more local neighbourhood definition. Both specifications use equal weights for all neighbours. We suspect that this spatial autocorrelation arises from underlying variables such as soil, climate conditions peer effects and neighborhoods that influence the dependent variables and are again distributed in certain patterns across space. The Moran's I correlation coefficients provided in the summary statistics (Table 1) indicate the presence of weak to medium positive spatial autocorrelation.

The second type of spatial dependence that we expect to find is the influence of conflict on farmland owned across spatial lags, i.e., across different distances from the respective household location. To this end, we have defined the measures of conflict in a set of Euclidean distances around the respective household as indicated in 3.1.

4.2 Trans-national cross-sectional model

We aim at quantifying the spatial effects of armed conflict farm land ownership in Benin, Burkina Faso, Mali, Niger and Nigeria by means of regression with spatial smoothing splines. The model is characterized by

$$y_{is} = \beta_1\, confl_{s,0-25} + \beta_2\, confl_{s,25-50} + \beta_3\, confl_{s,50-100} + X_i\, \gamma + f(\boldsymbol{s}_i) + \epsilon_{is} \quad (2)$$

where y_{is} is the value of the respective dependent variable of household i at location s. For the dependent variable, we consider size of land owned, number of plots owned, and the percentage of land acquired for free. $confl_{s,r}$ are aggregated conflict fatalities for a specified radius r (0 km to 25 km, 25 km to 50 km, or 50 km to 100 km) around the household at location s and X_i is a set of household control variables, encompassing the age, gender, religion, ethnicity, nationality, and education of the household head. Additionally, household controls include factors such as access to phone and internet, the food security situation, exposure to shocks, annual precipitation experienced by the household, and homeownership. $\boldsymbol{s}_i$ is the location given in coordinates of household i and f is a smoothing function.

We assume the following composition of the residual:

$$\epsilon_{is} = \zeta_s + \eta_i \quad (3)$$

The residual ϵ_{is} of household i at location s consists of the remaining unobserved variance ζ_s that affect all households at location s. The residual might comprise household specific unobserved variables η_i.

As a smoothing function we use tensor product splines of the coordinates. Tensor product splines are multivariate smoothing splines that are constructed by applying a smoothing function (in our case cubic regression splines) to all univariate margins (Fahrmeir et al. 2013). Here, these margins are longitude and latitude of the households. To arrive at a multivariate smoothing function, the marginal smoothing function of one variable - say longitude - needs to be allowed to vary in the other variable, i.e., latitude. To do so, the parameters of the smoothing function of longitude are allowed to vary in latitude and are modeled by the marginal smoothing function of latitude. Inserting the modeled smoothing function parameters of longitude in the smoothing function for longitude obtains a smoothing function that depends on both longitude and latitude.[6] The

[6]For more details, see, for example, Wood (2006).

tensor product splines give a flexible function of household locations, thus they will incorporate nearly all remaining spatial dependence so that the residuals are not spatially dependent. Furthermore, the spatial splines cover the effect of omitted variables that are not household specific. To implement tensor product splines, the *gam* function from the package *mgcv* was used (Wood 2011). However, household heterogeneity cannot be captured by the splines. Thus, adding spatial splines will most likely reduce but not eliminate bias in both the coefficient estimators and the variance estimators.

It should be noted that the splines might also absorb some of the effect of the conflict regressors in this model specification. The spatial structure of conflict contributes - among many other variables - to the spatial structure observed in the dependent variables. Spatial effects, however, are mostly attributed to the spatial splines. This could be prevented by restricting the splines to be orthogonal to the conflict regressors. This, again, would prevent the spatial splines from absorbing omitted spatial variables that are correlated to conflict (Fahrmeir et al. 2013). Therefore, we decided not to restrict the splines. Hence, the resulting conflict coefficient estimates should be considered a lower bound for the effect size.

In the regression, we apply weights to the observations that are based on the weights provided in GHS and EHCVM data. According to the LSMS data documentation, the weighting of the data is necessary to obtain representative data for the respective populations (World Bank 2021). To ensure that the weights are coherent across countries, we scale the weights for the observations from GHS by a constant factor. This factor is chosen such that population ratio between Nigeria and the EHCVM countries in 2018 is accurately reflected by the weighted data.[7]

To check the robustness of the results, we also provide a model specification that excludes Nigerian households. The reason for excluding specifically Nigerian households is twofold. As mentioned in Section 3, data on Nigerian households comes from the GHS survey while the remaining data comes from the EHCVM survey which was harmonized across countries. Thus, the GHS data is the only data in this analysis whose construction might deviate. Second, the population of Nigeria in 2018 was more than twice the population of the other four countries combined (World Bank 2022). However, the number of recorded households in

[7]Population estimates are taken from World Bank Data Catalog (2021).

Nigeria is similar to the number of households in the other countries. To accurately reflect the underlying population, the Nigerian households are assigned weights that are substantially larger. Consequently, the observations from Nigeria are far more influential in the analyses and are likely to dominate the results.

5 Empirical results

5.1 Descriptive results

Figure 2 depicts the spatial distribution of households from GHS and EHCVM in the considered region in 2018. In Burkina Faso and Nigeria, nearly all households in the dataset experienced armed conflict. While the intensity was uniformly low in Burkina Faso, it was high in central and eastern parts of Nigeria. In terms of border regions Niger's southern border to Nigeria seems to be particularly affected. In Mali, the households closer to the border with Burkina Faso experienced a higher conflict intensity than those further away. The varying intensity and number of incidents especially in the border regions emphasizes the need for a trans-national analysis. In both the GHS and EHCVM data, a substantial share of households is unaffected by conflict altogether in the sense that no incidents with fatalities happened in their direct surroundings. 71% of the households have not been affected by any fatality within 0 to 25 km of their homes, while 56% of the households have not experienced a fatality within 25 to 50 km, and 24% have not been affected by fatalities within 50 to 100 km of their homes.

Table 1 shows summary statistics of the key variables in our analysis, i.e., dependent variables and conflict measures (land owned in square meters (sqm), number of plots owned, and the share of free land acquired). Figures A.2 to A.4 in the Appendix display the distribution of the dependent variables. While we included sampling weights in the regression analysis, sampling weights were not applied to derive the summary statistics. All variables show considerable deviations from the total average when considering only Nigeria (column (3)). Particularly, average fatalities in the surroundings of the sample households are larger in Nigeria. Figures A.5 and A.7 in the Appendix display the spatial correlation for the dependent variables of interest. All dependent variables show a weak to medium positive

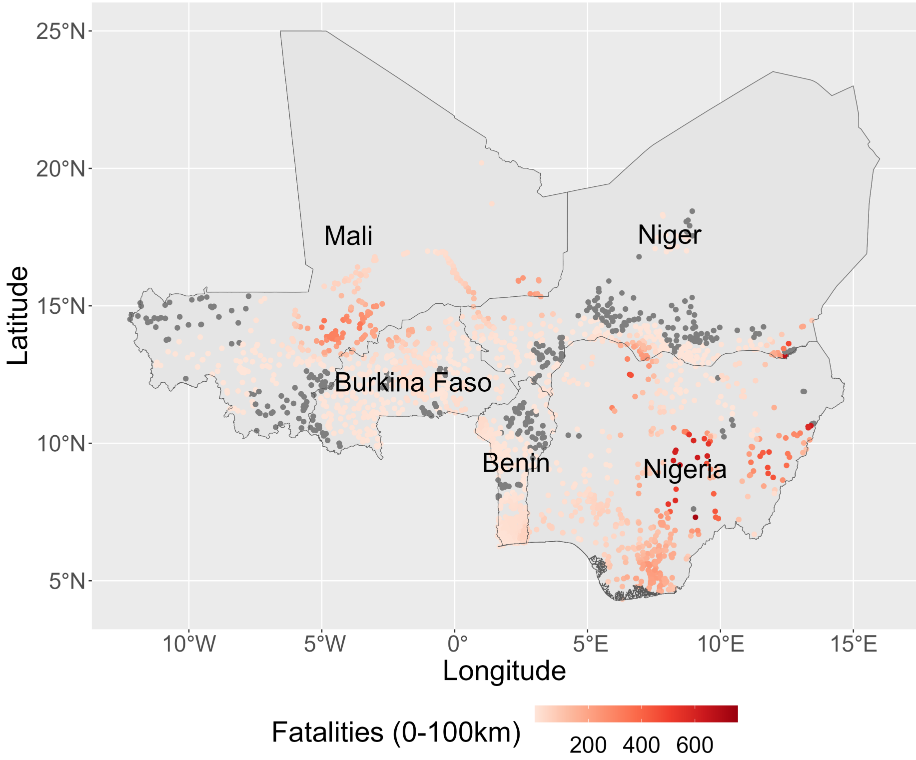

Figure 2: Exposure to armed conflicts within 100km radius of surveyed households (households not exposed to any fatalities within 100 km radius are depicted in grey. Source: Own visualization.

spatial autocorrelation but the exact extend depends strongly on the neighborhood structure. Table 1 also displays the three explanatory variables of interest, namely, the three conflict regressors that incorporate spatial lags at varying distances from the respective household locations. We generate predictors for conflict within 0 km to 25 km, 25 km to 50 km, and 50 km to 100 km radii. As anticipated, fatalities exposure increases with greater distance from the conflict zone. Once again, the variables exhibit deviations from the overall average when focusing solely on Nigeria (column (3)).

Since this paper focuses specifically on the spatial dimension of the relation between conflict and farm land ownership, we emphasize the spatial correlation that can be found in the variables of interest. Figure 3 depicts the positive spatial autocorrelation of the number of plots owned by a household with the number of

Table 1: Summary statistics of key variables in EHCVM/GHS cross-sectional data

Variable	(1) Obs.	(2) Mean	(3) Median	(4) Stddev.	(5) MI (dist.)	(6) MI (n.n.)
Land owned (sqm)	17,869	34,257.46	22,755.50	62,314.42	0.02	0.07
No. of plots owned	17,917	2.40	3.19	1.51	0.15	0.26
Share free land acquired (%)	16,057	8.12	13.53	26.07	0.00	0.06
Fatalities (0 km to 25 km)	17,917	3.64	8.38	11.64	0.21	0.62
Fatalities (25 km to 50 km)	17,917	9.61	27.11	26.61	0.27	0.62
Fatalities (50 km to 100 km)	17,917	42.87	119.80	91.25	0.48	0.84
Incidents (0 km to 25 km)	17,917	2.756	1	6.23	0.32	0.65
Incidents (25 km to 50 km)	17917	6.14	2	11.23	0.32	0.64
Incidents (50 km to 100 km)	17,917	23.32	10	31.38	0.26	0.69
Fatalities dummy (0 km to 25 km)	17,917	0.29	-	-	0.32	0.65
Fatalities dummy (25 km to 50 km)	17,917	0.44	-	-	0.32	0.64
Fatalities dummy (50 km to 100 km)	17,917	0.76	-	-	0.26	0.69

Note: MI is the Moran's I correlation coefficient used to determine spatial autocorrelation in the variables. To calculate Moran's I, the neighborhood structure of the data needs to be specified (Ward & Gleditsch 2018). We provide two alternative specifications, one including all other households in a range of 200 km **MI (dist.)** and one including the 100 nearest neighborhoods **MI (n.n.)**. The latter results in a set of neighborhoods that is within a range of less than 50 km for most households and is thus a more local neighborhood definition. Both specifications use equal weights for all neighborhoods.

0.24% of all households included in our analysis did not experience a fatality within 50 to 100 km of their homes. Out of 17,917 households, 10,025 (approx. 0.56%) did not experience a fatality within 25 to 50 km of their homes, while 0.71% did not experience one within 0 to 25 km.

plots owned by neighboring households. The linear fit to the average number of plots of neighbouring households clearly shows a positive relation similar to the spatial autocorrelation as measured by Moran's I in Table 1. As mentioned earlier in Subsection 4.1, the magnitude of the positive autocorrelation depends on the exact definition of neighbours.

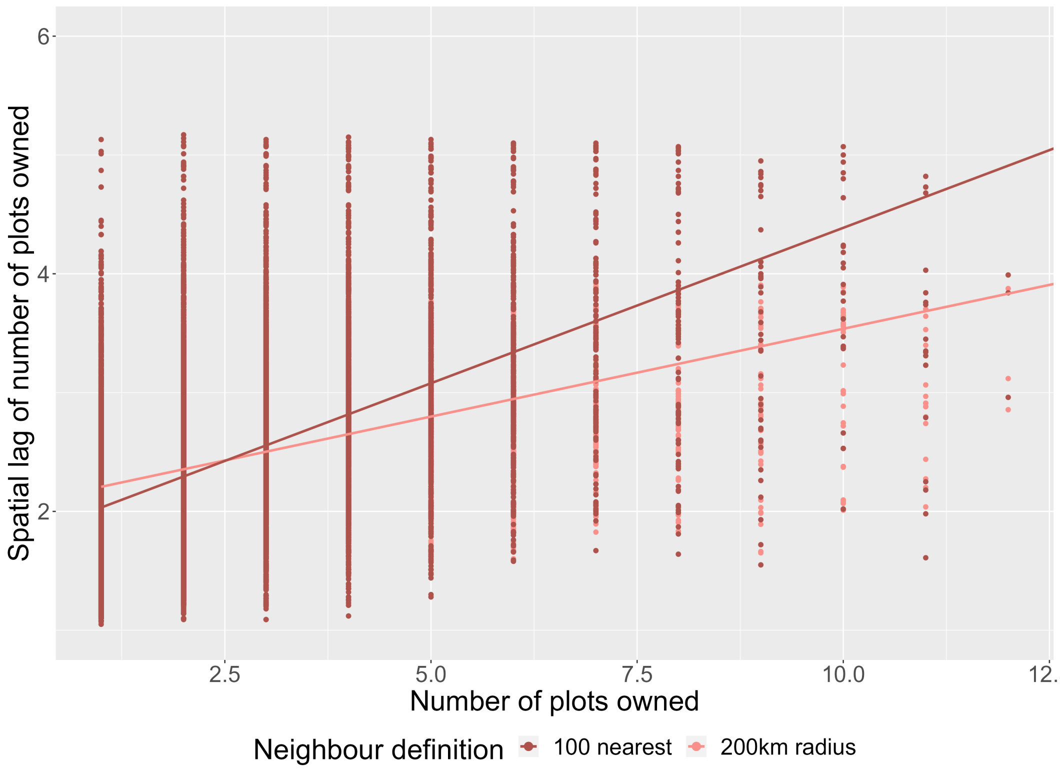

Figure 3: Spatial autocorrelation in number of plots of households using different neighborhood structures.
Source: Own visualization.

When considering local fatalities and the area of land owned, there seems to be evidence for a negative relationship, as shown in Figure 4. The linear fit in Figure 4 suggests a statistically significant, but in terms of magnitude relatively small negative relation. Again, the Figure shows that this result is most likely strongly influenced by outliers in both variables.

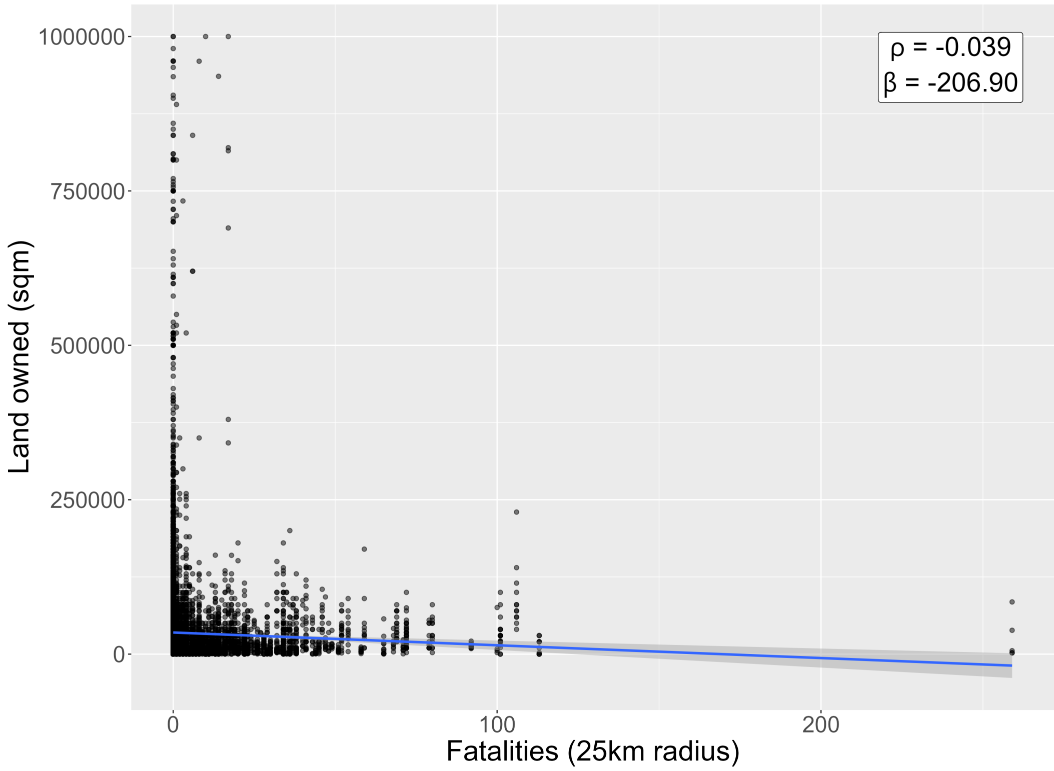

Figure 4: Relation between fatalities and land owned (EHCVM/GHS). ρ is the estimated unconditional correlation, β the coefficient estimator from a bivariate linear model.
Source: Own visualization.

5.2 Trans-national cross-sectional model

The regression results for the trans-national cross-sectional model can be found in Table 2. In Table 2 the dependent variables are the number of plots owned, the land owned in square meters, and the percentage of land acquired for free. We focus on the results from the model that includes spatial smoothing splines since we expect results of the models that do not adequately account for spatial heterogeneity to be substantially biased. The Table 2 show the results for one dependent variable each, which is listed at the top of the regression results. Model (1) is an OLS regression, while models (2) and (3) contain tensor product splines of the coordinates (compare equation 2). Models (1) and (2) contain the EHCVM data set and the GHS data set from Nigeria, while the data basis for model (3) is the EHCVM data set without the GHS data.

When considering the number of plots owned by a household (compare Table 2), local conflict is associated with a statistically significant decrease in the number of plots, whilst conflict farther away is positively associated with the number of plots. However, the effects are small in magnitude; an incident with one casualty is associated with a change in number of plots that is close to zero, only with increasing number of casualties, the associated effects become economically important.

With regard to the number of plots owned, these findings are contrary to what we expected to find based on the hypothesis that households remaining in conflict areas receive plot transfers from households leaving the area (see e.g. Adelaja & George (2019*b*)). In addition, these results do not hold when excluding Nigerian households. The direction of the effect changes and the results are no longer statistically significant.

Regarding the agricultural land owned (see Table 2), we obtain similarly inconclusive results. Casualties caused by local conflict are negatively associated with farmland owned. Fatalities caused by medium and long range conflict are positively associated with land owned, but only the medium range effect is statistically significant. The direction of the effects match the observed effects for number of plots when using the same model specification. For land owned, the direction of the effect remains the same when excluding Nigerian households, but none of the effects is statistically significant. Again, the effects are rather small compared to the influence of some covariates such as the gender of the household head or a farm being located in an urban area. Similar to the number of plots, we do not see supporting evidence that households in conflict areas receive additional farm land from migrating households.

The percentage of land that was acquired for free is positively associated with local conflict in all model specifications (see Table 2). However, it is not statistically significant in the main cross-sectional model including all five countries and spatial splines. With respect to conflict farther away, the direction of the observed effect reverses. Here, conflict is negatively associated with the percentage of freely acquired plots. Again, the direction of the effect is consistent across all model specifications. This finding is coherent with the hypothesis that households receive free transfers of land in conflict affected areas. It remains unclear, however,

Table 2: Shortened cross sectional regression results.

	Dependent variable:		
	No. of plots owned		
	(1)	(2)	(3)
	OLS	Spatial splines	Sp. spl. w/o Nigeria
Fatalities (0 - 25 km)	-0.002***	-0.005**	0.00003
	(0.001)	(0.002)	(0.004)
Fatalities (25 - 50 km)	-0.002***	0.007***	-0.005**
	(0.0003)	(0.001)	(0.002)
Fatalities (50 - 100 km)	0.002***	0.004***	0.001*
	(0.0001)	(0.0005)	(0.001)
Adjusted R^2	0.188	0.350	0.353
Obs.	17,005	17,005	14,807
	Land owned (sq. meters)		
	(1)	(2)	(3)
	OLS	Spatial splines	Sp. spl. w/o Nigeria
Fatalities (0 - 25 km)	-203.525***	-84.209	-1.164
	(30.098)	(59.652)	(205.017)
Fatalities (25 - 50 km)	183.310***	61.041**	56.231
	(11.496)	(24.440)	(97.514)
Fatalities (50 - 100 km)	-28.543***	18.416	27.452
	(5.312)	(13.616)	(28.840)
Adjusted R^2	0.092	0.168	0.155
Obs.	16,961	16,961	14,763
	Percentage of free land acquired		
	(1)	(2)	(3)
	OLS	Spatial splines	Sp. spl. w/o Nigeria
Fatalities (0 - 25 km)	0.283***	0.048	0.189***
	(0.017)	(0.044)	(0.060)
Fatalities (25 - 50 km)	-0.073***	-0.067***	-0.003
	(0.008)	(0.017)	(0.032)
Fatalities (50 - 100 km)	-0.012***	-0.024**	-0.025**
	(0.003)	(0.011)	(0.011)
Adjusted R^2	0.087	0.247	0.100
Obs.	15,608	15,608	14,723

*Note: *p<0.1; **p<0.05; ***p<0.01. We included country dummies and a set of control variables (e.g. age and gender of household head, religion, educational level, phone and internet access, past experience with shocks, precipitation). For full results see Table A.4 to A.6.*

why this effect reverses for spatially lagged conflict. Overall, the results from this approach do not support the hypothesis of households gaining additional farm land via free transfers in conflict areas.

Estimating spatial autocorrelation of the residuals for all three dependent variables by using Moran's I shows that the inclusion of spatial splines succeeds in absorbing spatial dependence. While the residuals from the model without splines for the number of plots owned show statistically significant positive autocorrelation (0.150), the residuals for the same dependent variable from the model with splines are completely uncorrelated (-0.004).[8]

In summary, we answer our main research questions as follows. First, the study does not provide evidence for a linear, clearly identifiable positive or negative effect of conflict on measurements of agricultural farm land ownership in this trans-national setting. Statistically insignificant and small estimates suggest no or only heterogeneous effects on the total land owned. Even though coefficient estimates are highly statistically significant when considering the number of plots owned, their small size and sensitivity to the inclusion of Nigerian households suggests no strong common trans-national effect of conflict. We find the percentage of land acquired for free to be most clearly affected by conflict. The coefficient estimates suggest that this effect is dependent on the distance to conflict incidents. The percentage of free land acquired is larger in regions with more local conflict. However, in regions situated farther away from conflict incidents, a statistically significant negative association on the percentage of free land acquired can be observed. While we find more free transfers in conflict affected areas, we cannot identify a statistically significant increase in plots or land owned. Hence, free transfers might exist, but if they do, their effect on land possession might be offset by land loss to a similar or even greater extent. With regard to our second research question on the effect of conflict across distances, we therefore have to conclude that there is no obvious linearly decreasing trend in the effects of armed conflicts of measures of land use. Again, the picture is more nuanced as several heterogeneous effects could be observed.

[8]Here, we used the 100 nearest neighbors and equal weights to define the neighborhood structure which proved to result in stronger spatial autocorrelations compared to the distance based approach. We used the R package 'spdep', develoepd by Bivand (2022), to estimate the Moran's I.

5.3 Robustness tests: Using alternative definitions of the conflict measures

We apply several alternative model specifications to check the robustness of the relationships that were observed in the previous section. In Subsection 5.2, the sensitivity of the relation between conflict and farm land ownership to the exclusion of Nigerian households has already been noted.

Another modification concerns the construction of the conflict regressors. Instead of aggregating the number of fatalities in a certain region and period, we construct alternative regressors that aggregate the number of incidents and dummy-code more than zero fatalities, respectively. Tables A.7 and A.8 of the Appendix show that some coefficients flip signs and substantially change levels of statistical significance when using the alternative conflict measures. This finding underlines the instability of the results on the effect of conflict on farm land ownership.

Overall, these further robustness checks complete a picture that was already implied by previous sections: statistically significant association of conflict on farm land ownership can be found in several model specifications. However, these findings are highly sensitive to specifications made, e.g., in terms of spatial extend of the analysis and construction of the conflict measure.

6 Discussion and Conclusion

Agricultural land use is a key determinant for prosperity and food security in West Africa (Merem et al. 2019). In recent years, the region is strongly affected by incidents of armed conflict with and without fatalities (OECD/SWAC 2020). Since previous studies focused on a single country context, the effects that conflicts that span entire regions across country borders can have on farm land ownership are not yet well understood. Our study aims at closing this gap. In terms of methodology, we add to existing studies that rely on household survey data from a single country by exploring household data from five neighboring countries in West Africa. To our knowledge, this study is the first to consider spatial dimensions and trans-national effects of conflict on farm land ownership.

In contrast to the previous literature, the results of our transnational analysis, which naturally encompasses cross-border regions, reflect the ambiguity in the relation between conflict and farm land ownership that has already been observed before. The exploratory data analysis yields no reliable results on the relation between conflict and farm land ownership. Too many confounding factors affect the farm land ownership of households to draw a clear picture from bivariate considerations only. By means of transnational regression analysis, we gained more insights, but the emerging picture is still heterogeneous. We find evidence for a positive association of local conflict on the percentage of plots acquired for free, but the effect size is small and sensitive to different regression specifications. This finding is only statistically significant when excluding Nigerian households, while the inclusion of Nigerian households suggests no strong common trans-national effect of conflict. Additionally, the effect reverses when conflict is farther away.

Against expectations and previous findings, we cannot validate the finding that more local conflict results in more farm land possessed by households. According to our estimations, the coefficient estimates suggest that this effect is dependent on the distance to conflict incidents. The percentage of free land acquired is larger in regions with more local conflict. However, in regions situated farther away from conflict incidents with casualties, a statistically significant negative association with the percentage of free land acquired was observed. We find a highly statistically significant relation between conflict and number of plots owned. For local conflict, this relation is negative but the sign of the relation reverses in farther distances. However, this finding is not robust when dropping Nigerian households. The effects are so small that they are only economically relevant for households that experience incidents of armed conflicts with very large numbers of fatalities.

A key finding of our study is the heterogeneity of the relation between conflict and land use. Our different analyses, including several robustness checks, do not result in a stable linear relation. We expect this finding to be driven by substantial heterogeneity in the relation across different spatial and temporal extends of conflict, across different survey areas, and across households as well as by non-linearity of the relation.

Regarding heterogeneity across different spatial extends of conflict, we demonstrate that effects on farmland ownership observed in small distances to the conflict-related fatality might mitigate or even reverse when considering larger distances. Similarly, heterogeneity might also be observable when considering conflict in different temporal periods, a factor that was not considered in our analysis. Hence, future research in this area should be precise on the spatial and temporal distance in which the effects of conflict are measured.

Furthermore, the effect of conflict on land use might be non-linear. One could imagine, e.g, a substantial difference in land use between households not affected by conflict and households affected by one or more fatality, but less significant differences between households affected by conflict in different intensities. Thus, the relation in this example would be similar to a saturation curve. Hence, clearer relations might be observable when allowing for non-linearity, e.g., by including polynomials or a flexible semi-parametric approach. Additional research is required that allows for non-linearity in this context. This might a promising avenue for future research.

We assume that the largest source for heterogeneity in the effect of conflict on farm land ownership is household heterogeneity. When exposed to conflict, households perceive this conflict differently and develop different coping strategies. Consider a politically motivated conflict: the perceived risk from this conflict will - in many cases - depend strongly on the political views of the household. Even if conflict is perceived similarly, coping strategies might differ substantially. Regression approaches can only identify an average of the effect conflict has on households (Angrist & Pischke 2009). Therefore, if households react diametrically to conflict in terms of their farm land ownership, effects might not be observable in the aggregate. Future qualitative research might go deeper in this direction to investigate these motives.

To obtain more robust findings in future research, we suggest to focus on the impact channels of conflict on farm land ownership. Additionally to relating conflict and farm land ownership directly, mediator variables could be considered in additional analyses. Such mediators might be migration, land transfers, death or disability of household members, and perceived risk of losing property. These more direct effects of conflict might be more homogeneous across households. However, data availability is a considerable obstacle to mediator analyses and also hindered the analysis of impact channels in this study.

Another limitation for the analysis of effects of armed conflict in border regions is the absence of trans-national panel household surveys. With cross-sectional data, we limit the analysis to households that are currently engaged in agriculture since no information is available whether the household has been engaged in agriculture previously. In panel data, households quitting agricultural activity would be observable. Hence, future research could employ panel data to further investigate this research question. As data availability improves, future research should take this into account, but this was beyond the scope of this study. Finally, ACLED primarily gathers reported incidents from newspapers and other media sources, potentially omitting some relatively low-profile incidents. Consequently, our analysis might result in an overrepresentation of more lethal events and an underrepresentation of relatively less violent events, as also noted by Adelaja et al. (2023).

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Appendix

Table A.1: Variable definitions of ACLED data set.

Variable Name	**Variable Description**
Incidents (0 - 25km)	No. of attacks within radius of 0 - 25 km of household location
Incidents (25 - 50km)	No. of attacks within radius of 25 - 50 km of household location
Incidents (50 - 100km)	No. of attacks within radius of 50 - 100 km of household location
Fatalities (0 - 25km)	Fatalities of attacks within radius of 0 - 25 km of household location
Fatalities (25 - 50km)	Fatalities of attacks within radius of 25 - 50 km of household location
Fatalities (0 - 100km)	Fatalities of attacks within radius of 50 - 100 km of household location
Fatalities $>$ 0 (0 - 25 km)	More than zero fatalities of attacks within radius of 0 - 25 km of household location (dummy variable)
Fatalities $>$ 0 (25 - 50 km)	More than zero fatalities of attacks within radius of 25 - 50 km of household location (dummy variable)
Fatalities $>$ 0 (50 - 100 km)	More than zero fatalities of attacks within radius of 50 - 100 km of household location (dummy variable)

Note: All variables contain data within the region as described in the table for a period of one year prior to the collection of the respective household data.

Table A.2: Variable definitions of GHS data set.

Variable Name	Reference Category	Variable name in GHS
Control Variables		
Year of survey	/	surveyprd
Local Government Area (LGA) code	/	lga
Urban HH	Rural HH	sector
HH size	/	hhsize
Age of HH	/	s1q4, s1q6
Female HH	Male HH	s1q2
Religion (Islam)	Religion (Christianity)	s1q12, s1q18, s1q18a
Religion (Other)	Religion (Christianity)	s1q12
Phone access of HH	No phone access of HH	s5q8, s4bq8
Internet access of HH	No internet access of HH	s5q14, s4bq14
Food security of HH	Food insecurity of HH	s9q5
Annual Precipitation	/	af_bio_12
Distance to population center	/	dist_popcenter, dist_popcenter2
Distance to market	/	dist_market
Distance to administration center	/	dist_admctr
Distance to nearest border crossing	/	dist_borderpost, dist_border2
Dependent Variables		
Land owned (sq. meters)	/	s11aq4d, s11aq4c
No. of plots owned	/	plotid
Average distance of plots from HH	/	dist_HH
Percentage of free land acquired	/	s11bq4, s11b1q4

Table A.3: Variable definitions of EHCVM data set.

Variable Name	Reference Category	Variable name in EHCVM
Control Variables		
HH size	/	hhsize
Country (Burkina Faso)	Country (Benin)	country
Country (Mali)	Country (Benin)	country
Country (Niger)	Country (Benin)	country
Country (Nigeria)	Country (Benin)	country
2nd survey wave	1st survey wave	vague
Urban HH	rural HH	milieu
Age of HH	/	hage
Female HH	Male HH	hgender
Religion (Islam)	Religion (Christianity)	hreligion
Religion (Other)	Religion (Christianity)	hreligion
Education (Primary)	Education (None)	heduc
Education (Secondary)	Education (None)	heduc
Education (Tertiary)	Education (None)	heduc
Phone access of HH	No phone access of HH	s01q36
Internet access of HH	No internet access of HH	s01q39_1
Food security of HH	Food insecurity of HH	s08aq01
Shock to HH member	No shock to HH member	s14q01, s14q02
Ecological shock	No ecological shock	s14q01, s14q02
Economical shock	No economical shock	s14q01, s14q02
Foreigner	Citizen	s01q15
Owns house	Does not own house	s11q04
Annual Precipitation	/	CRU data set
Dependent Variables		
Land owned (sq. meters)	/	s16aq09a
No. of plots owned	/	s16aq09a
Percentage of free land acquired	/	s16aq10, s16aq12

Table A.4: Cross sectional regression results: number of plots.

	Dependent variable: No. of plots owned		
	(1)	(2)	(3)
	(OLS)	(Spatial Splines)	(Sp. spl. w/o Nigeria)
Constant	0.440***	0.506	0.477
	(0.103)	(0.475)	(0.473)
Fatalities (0-25km)	−0.002***	−0.005**	0.000
	(0.001)	(0.002)	(0.004)
Fatalities (25-50km)	−0.002***	0.007***	−0.005**
	(0.000)	(0.001)	(0.002)
Fatalities (50-100km)	0.002***	0.004***	0.001*
	(0.000)	(0.0005)	(0.001)
Household size	0.090***	0.084***	0.064***
	(0.004)	(0.004)	(0.003)
Country (Burkina Faso)	0.536***	0.877	0.722
	(0.073)	(0.596)	(0.446)
Country (Mali)	0.034	0.815	1.079**
	(0.079)	(0.662)	(0.463)
Country (Niger)	−0.132*	0.549	0.586*
	(0.073)	(0.405)	(0.332)
Country (Nigeria)	0.854***	1.102***	
	(0.073)	(0.408)	
2nd survey wave	−0.129***	−0.135***	−0.158***
	(0.043)	(0.043)	(0.022)
Urban	−0.255***	−0.274***	−0.240***
	(0.043)	(0.047)	(0.038)
Age of household head	0.005***	0.006***	0.004***
	(0.001)	(0.001)	(0.001)
Female household head	−0.137***	−0.214***	−0.299***
	(0.042)	(0.038)	(0.032)
Religion (Islam)	−0.206***	−0.196***	−0.204***
	(0.039)	(0.050)	(0.041)
Religion (Other)	−0.155**	−0.271***	−0.052
	(0.075)	(0.074)	(0.047)
Education (Primary)	0.044	0.136***	0.088***
	(0.035)	(0.033)	(0.031)
Education (Secondary)	0.114***	0.264***	−0.014
	(0.042)	(0.041)	(0.047)

Education (Tertiary)	−0.039	0.031	−0.239*
	(0.073)	(0.068)	(0.139)
Phone access	−0.064*	−0.053	0.139***
	(0.039)	(0.036)	(0.023)
Internet access	−0.129***	−0.142***	−0.202***
	(0.038)	(0.036)	(0.054)
Food security	0.220***	0.153***	0.125***
	(0.028)	(0.027)	(0.021)
Shock to household member	0.043	−0.035	0.098***
	(0.037)	(0.034)	(0.023)
Ecological shock	0.156***	0.147***	0.201***
	(0.029)	(0.029)	(0.021)
Economical shock	0.069**	0.125***	0.125***
	(0.029)	(0.028)	(0.024)
Foreigner	0.196	0.053	−0.004
	(0.413)	(0.374)	(0.184)
Owns house	0.761***	0.608***	0.048
	(0.034)	(0.033)	(0.031)
Annual precipitation	0.000***	−0.000	0.001
	(0.000)	(0.000)	(0.001)
Observations	17,005	17,005	14,807
Adjusted R^2	0.188	0.350	0.353

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$
Source: Own visualization.

Table A.5: Cross sectional regression results: land owned (sq. meters)

	Dependent variable: Land owned (sq. meters)		
	(1)	(2)	(3)
	(OLS)	(Spatial Splines)	(Sp. spl. w/o Nigeria)
Constant	$13,781.150^{***}$	$1,582.785$	$-16,534.170$
	$(3,850.984)$	$(14,604.890)$	$(24,010.210)$
Fatalities (0-25km)	-203.525^{***}	-84.209	-1.164
	(30.098)	(59.652)	(205.017)
Fatalities (25-50km)	183.310^{***}	61.041^{**}	56.231
	(11.496)	(24.440)	(97.514)
Fatalities (50-100km)	-28.543^{***}	18.416	27.452
	(5.312)	(13.616)	(28.840)
Household size	770.620^{***}	727.293^{***}	$2,369.436^{***}$
	(143.689)	(147.501)	(141.488)
Country (Burkina Faso)	$-2,516.051$	$-16,932.920$	$41,949.150^{*}$
	$(2,724.762)$	$(15,042.340)$	$(23,715.600)$
Country (Mali)	$1,822.429$	$-27,862.650$	$19,238.930$
	$(2,962.005)$	$(17,773.060)$	$(24,245.530)$
Country (Niger)	$-10,442.950^{***}$	-562.383	$30,295.200^{*}$
	$(2,756.221)$	$(11,289.270)$	$(16,874.190)$
Country (Nigeria)	$-6,699.795^{**}$	$8,686.343$	
	$(2,742.266)$	$(11,144.740)$	
2nd survey wave	$-3,789.618^{**}$	$-4,584.847^{***}$	$-6,247.877^{***}$
	$(1,629.743)$	$(1,660.168)$	$(1,095.367)$
Urban	$-8,838.365^{***}$	$-7,966.354^{***}$	$-6,240.493^{***}$
	$(1,597.350)$	$(1,784.607)$	$(1,874.582)$
Age of household head	515.852^{***}	569.699^{***}	167.658^{***}
	(37.042)	(37.394)	(35.279)
Female household head	$-8,625.973^{***}$	$-6,005.613^{***}$	$-10,313.140^{***}$
	$(1,566.150)$	$(1,539.728)$	$(1,595.346)$
Religion (Islam)	$7,442.355^{***}$	$-3,503.990^{*}$	$-1,685.249$
	$(1,455.407)$	$(1,935.187)$	$(2,022.866)$
Religion (Other)	$3,242.559$	$-2,294.850$	$1,415.183$
	$(2,812.921)$	$(2,952.566)$	$(2,323.854)$
Education (Primary)	65.678	819.927	$-2,480.281$
	$(1,299.160)$	$(1,333.615)$	$(1,513.260)$
Education (Secondary)	$3,199.828^{**}$	$4,909.718^{***}$	$-1,730.730$
	$(1,571.311)$	$(1,639.723)$	$(2,327.695)$

Education (Tertiary)	$-2,272.440$	$1,569.773$	$-2,840.182$
	$(2,726.499)$	$(2,730.794)$	$(6,860.390)$
Phone access	$9,881.391^{***}$	$9,182.002^{***}$	$5,508.087^{***}$
	$(1,447.737)$	$(1,436.411)$	$(1,155.770)$
Internet access	$1,667.221$	$1,831.170$	$-2,590.108$
	$(1,435.411)$	$(1,430.260)$	$(2,664.207)$
Food security	$-4,191.050^{***}$	$-6,432.613^{***}$	$4,459.809^{***}$
	$(1,037.925)$	$(1,062.710)$	$(1,036.702)$
Shock to household member	$4,784.133^{***}$	$3,871.075^{***}$	$2,584.325^{**}$
	$(1,383.506)$	$(1,359.549)$	$(1,149.240)$
Ecological shock	$2,618.345^{**}$	-74.210	$1,653.872$
	$(1,094.533)$	$(1,139.765)$	$(1,021.601)$
Economical shock	$8,556.875^{***}$	$10,084.840^{***}$	$1,647.581$
	$(1,079.007)$	$(1,098.057)$	$(1,174.832)$
Foreigner	$-6,186.796$	$-11,790.360$	$-8,349.497$
	$(15,563.920)$	$(15,126.310)$	$(9,111.894)$
Owns house	$2,774.894^{**}$	258.236	-891.058
	$(1,264.823)$	$(1,331.627)$	$(1,521.433)$
Annual precipitation	-19.467^{***}	8.296	5.621
	(1.355)	(12.034)	(22.568)
Observations	16,961	16,961	14,763
Adjusted R^2	0.092	0.168	0.155

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Source: Own visualization.

Table A.6: Cross sectional regression results: Percentage of free land acquired.

	Dependent variable: Percentage of free land acquired		
	(1)	(2)	(3)
	(OLS)	(Spatial Splines)	(Sp. spl. w/o Nigeria)
Constant	-4.829^{***}	11.149	18.513^{**}
	(1.783)	(10.268)	(8.875)
Fatalities (0-25km)	0.283^{***}	0.048	0.189^{***}
	(0.017)	(0.044)	(0.060)
Fatalities (25-50km)	-0.073^{***}	-0.067^{***}	-0.003
	(0.008)	(0.017)	(0.032)
Fatalities (50-100km)	-0.012^{***}	-0.024^{**}	-0.025^{**}
	(0.003)	(0.011)	(0.011)
Household size	0.194^{***}	0.057	0.026
	(0.073)	(0.072)	(0.061)
Country (Burkina Faso)	7.245^{***}	2.473	2.723
	(1.046)	(13.106)	(7.119)
Country (Mali)	8.294^{***}	-13.870	-9.917
	(1.161)	(13.794)	(7.714)
Country (Niger)	4.891^{***}	-3.258	-5.907
	(1.093)	(8.148)	(5.900)
Country (Nigeria)	4.203^{***}	-5.920	
	(1.163)	(8.491)	
2nd survey wave	-0.869	-0.373	-0.546
	(0.617)	(0.676)	(0.454)
Urban	-2.157^{***}	-2.997^{***}	-1.512^{*}
	(0.803)	(0.933)	(0.784)
Age of household head	-0.026	-0.002	-0.057^{***}
	(0.018)	(0.018)	(0.015)
Female household head	3.189^{***}	3.888^{***}	0.325
	(0.760)	(0.741)	(0.684)
Religion (Islam)	2.341^{***}	1.532	1.523^{*}
	(0.715)	(0.939)	(0.848)
Religion (Other)	-4.198^{***}	-0.580	-0.443
	(1.147)	(1.190)	(0.988)
Education (Primary)	1.315^{*}	3.390^{***}	-0.955
	(0.693)	(0.683)	(0.648)
Education (Secondary)	0.547	-1.017	-0.653
	(0.850)	(0.846)	(0.996)

Education (Tertiary)	3.171**	4.286***	2.643
	(1.596)	(1.584)	(2.945)
Phone access	1.660**	0.740	−0.125
	(0.652)	(0.636)	(0.496)
Internet access	0.257	0.317	−0.733
	(0.770)	(0.764)	(1.142)
Food security	1.644***	1.561***	2.314***
	(0.511)	(0.513)	(0.444)
Shock to household member	−0.850	−1.464**	1.599***
	(0.634)	(0.606)	(0.492)
Ecological shock	1.747***	−0.128	0.929**
	(0.515)	(0.518)	(0.435)
Economical shock	3.710***	3.998***	0.243
	(0.541)	(0.552)	(0.503)
Foreigner	5.563	6.093	8.844**
	(5.849)	(5.472)	(3.873)
Owns house	−7.773***	−5.484***	0.480
	(0.625)	(0.677)	(0.648)
Annual precipitation	0.011***	0.003	−0.010
	(0.001)	(0.008)	(0.009)
Observations	15,608	15,608	14,723
Adjusted R^2	0.087	0.247	0.100

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$
Source: Own visualization.

Table A.7: Robustness check: Using alternative conflict measure - conflict incidents.

	Dependent variable:		
	Plots owned	Land owned (sqm)	Free land (%)
	(1)	(2)	(3)
Constant	0.404	$-2,133.310$	10.984
	(0.464)	(12, 769.190)	(10.069)
Incidents (0-25km)	0.011^{***}	-180.869^{**}	-0.498^{***}
	(0.003)	(86.352)	(0.074)
Incidents (25-50km)	0.025^{***}	79.713	-0.330^{***}
	(0.003)	(59.325)	(0.055)
Incidents (50-100km)	0.009^{***}	31.398	-0.068^{**}
	(0.001)	(33.522)	(0.030)
Household size	0.084^{***}	682.439^{***}	0.050
	(0.004)	(146.904)	(0.072)
Country (Burkina Faso)	0.800	$-23,729.780^{*}$	3.486
	(0.576)	(12, 527.260)	(12.676)
Country (Mali)	0.709	$-29,158.250^{*}$	-12.476
	(0.644)	(15, 046.240)	(13.418)
Country (Niger)	0.388	$-1,963.338$	-3.160
	(0.389)	(9, 480.352)	(7.958)
Country (Nigeria)	1.039^{***}	1, 683.756	-5.782
	(0.390)	(8, 763.017)	(8.263)
2nd survey wave	-0.133^{***}	$-4,820.716^{***}$	-0.256
	(0.043)	(1, 647.015)	(0.672)
Urban	-0.268^{***}	$-7,867.312^{***}$	-2.240^{**}
	(0.047)	(1, 769.511)	(0.936)
Age of household head	0.006^{***}	558.890^{***}	-0.001
	(0.001)	(37.282)	(0.018)
Female household head	-0.220^{***}	$-6,367.181^{***}$	3.733^{***}
	(0.038)	(1, 537.155)	(0.740)
Religion (Islam)	-0.205^{***}	$-3,923.863^{**}$	1.553^{*}
	(0.050)	(1, 908.301)	(0.933)
Religion (Other)	-0.276^{***}	$-2,239.896$	-0.494
	(0.074)	(2, 934.054)	(1.188)
Education (Primary)	0.129^{***}	729.348	3.267^{***}
	(0.033)	(1, 330.456)	(0.682)
Education (Secondary)	0.265^{***}	$4,861.598^{***}$	-0.773

	(0.041)	(1,633.500)	(0.845)
Education (Tertiary)	0.038	1,702.011	4.250***
	(0.068)	(2,727.032)	(1.579)
Phone access	−0.048	9,550.511***	0.684
	(0.036)	(1,434.035)	(0.635)
Internet access	−0.154***	1,546.559	0.579
	(0.036)	(1,422.651)	(0.761)
Food security	0.152***	−6,510.211***	1.505***
	(0.027)	(1,060.007)	(0.513)
Shock to household member	−0.034	3,892.043***	−1.427**
	(0.034)	(1,357.759)	(0.605)
Ecological shock	0.150***	−166.101	−0.143
	(0.029)	(1,132.106)	(0.517)
Economical shock	0.124***	9,808.529***	4.121***
	(0.028)	(1,091.560)	(0.552)
Foreigner	0.091	−12,963.100	6.119
	(0.374)	(15,117.640)	(5.462)
Owns house	0.600***	967.327	−5.396***
	(0.034)	(1,328.235)	(0.676)
Annual precipitation	−0.000	16.854	0.005
	(0.000)	(11.060)	(0.008)
Observations	17,005	16,961	15,608
Adjusted R^2	0.350	0.165	0.248

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$
Source: Own visualization.

Table A.8: Robustness check: Using alternative conflict measure - conflict fatalities dummy.

	Dependent variable:		
	Plots owned	Land owned (sqm)	Free land (%)
	(1)	(2)	(3)
Constant	1.122**	3,530.724	15.243
	(0.470)	(13,260.180)	(10.309)
Fatalities dummy (0-25km)	−0.119**	−3,357.932*	−7.946***
	(0.054)	(1,719.084)	(1.148)
Fatalities dummy (25-50km)	−0.122**	−1,639.923	−0.425
	(0.059)	(1,851.366)	(1.149)
Fatalities dummy (50-100km)	0.010	−2,658.594	−1.955
	(0.073)	(2,370.625)	(1.459)
Household size	0.084***	695.566***	0.050
	(0.004)	(147.092)	(0.072)
Country (Burkina Faso)	0.851	−21,585.840*	2.790
	(0.580)	(13,096.310)	(13.010)
Country (Mali)	0.789	−28,837.460*	−14.868
	(0.647)	(15,673.260)	(13.724)
Country (Niger)	0.525	−181.953	−3.082
	(0.394)	(9,743.216)	(8.095)
Country (Nigeria)	1.160***	3,004.572	−5.829
	(0.395)	(8,978.643)	(8.440)
2nd survey wave	−0.136***	−4,942.489***	−0.201
	(0.044)	(1,659.364)	(0.675)
Urban	−0.300***	−8,220.731***	−2.441***
	(0.047)	(1,780.041)	(0.931)
Age of household head	0.006***	560.726***	0.003
	(0.001)	(37.334)	(0.018)
Female household head	−0.227***	−6,279.460***	3.806***
	(0.038)	(1,536.959)	(0.740)
Religion (Islam)	−0.227***	−3,999.558**	2.233**
	(0.050)	(1,895.346)	(0.930)
Religion (Other)	−0.282***	−2,228.153	−0.238
	(0.075)	(2,937.721)	(1.187)
Education (Primary)	0.129***	695.863	3.296***
	(0.033)	(1,333.079)	(0.682)

Education (Secondary)	0.257***	4,816.616***	−0.703
	(0.041)	(1,636.572)	(0.845)
Education (Tertiary)	−0.005	1,249.013	4.751***
	(0.068)	(2,724.722)	(1.577)
Phone access	−0.054	9,526.871***	0.750
	(0.036)	(1,435.987)	(0.635)
Internet access	−0.168***	1,438.412	0.631
	(0.036)	(1,422.040)	(0.761)
Food security	0.155***	−6,439.068***	1.538***
	(0.027)	(1,061.093)	(0.512)
Shock to household member	−0.035	3,889.940***	−1.491**
	(0.034)	(1,359.028)	(0.605)
Ecological shock	0.150***	−263.408	−0.317
	(0.029)	(1,134.808)	(0.518)
Economical shock	0.129***	9,990.323***	4.120***
	(0.028)	(1,092.503)	(0.552)
Foreigner	0.094	−12,746.340	6.029
	(0.375)	(15,124.700)	(5.464)
Owns house	0.613***	988.075	−5.383***
	(0.034)	(1,331.304)	(0.676)
Annual precipitation	−0.001	13.965	−0.0003
	(0.000)	(11.289)	(0.008)
Observations	17,005	16,961	15,608
Adjusted R^2	0.345	0.166	0.248

Note: *p<0.1; **p<0.05; ***p<0.01

Source: Own visualization.

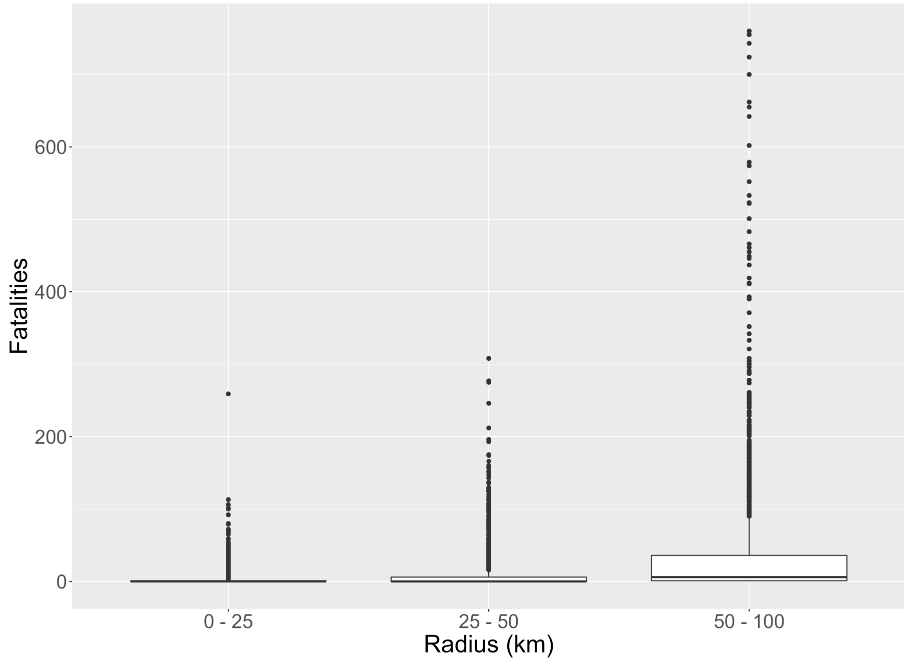

Figure A.1: Fatalities in different radii around household (EHCVM/GHS).
Source: Own visualization.

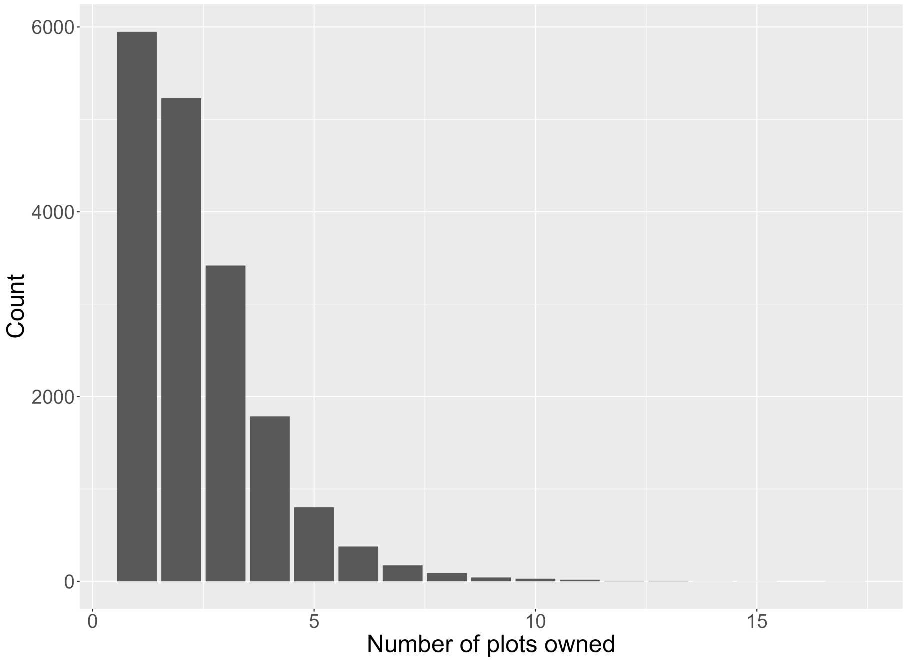

Figure A.2: Number of plots owned by households (EHCVM/GHS).
Source: Own visualization.

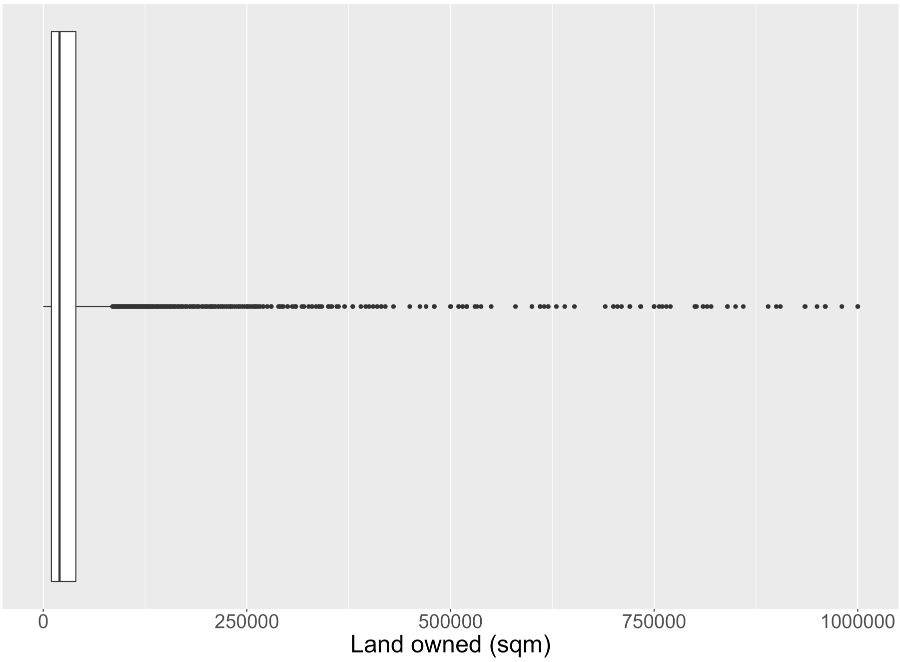

Figure A.3: Land owned by households (EHCVM/GHS).
Source: Own visualization.

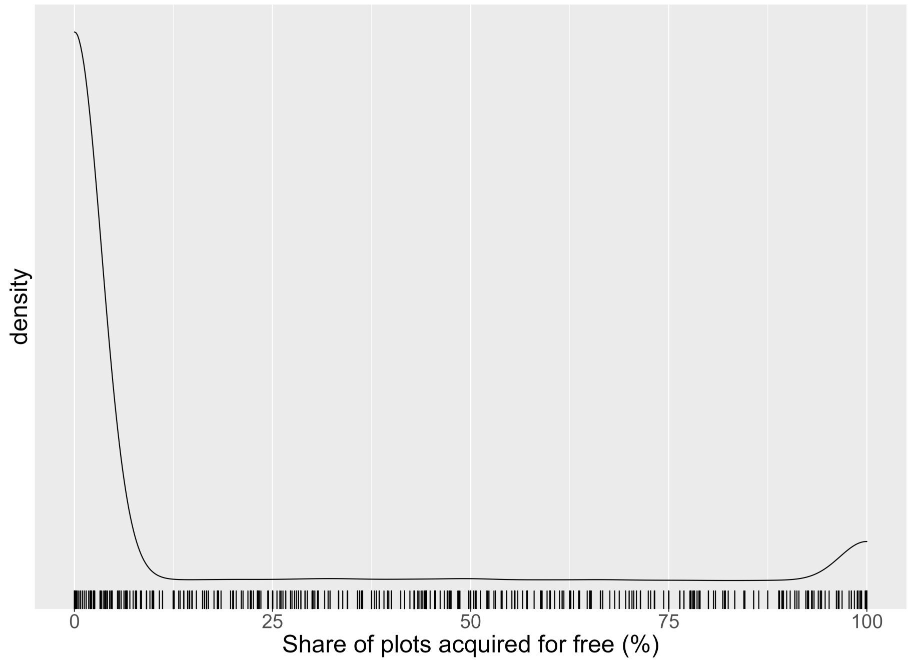

Figure A.4: Share of plots acquired for free (EHCVM/GHS).
Source: Own visualization.

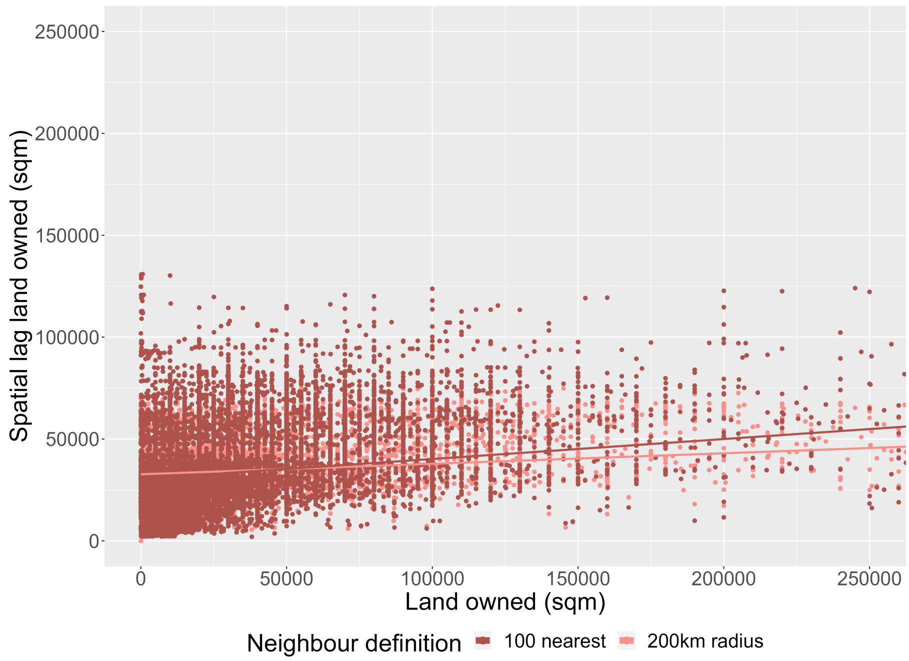

Figure A.5: Spatial correlation in land owned (EHCVM/GHS).
Source: Own visualization.

Figure A.6: Spatial correlation in share of free plots (EHCVM/GHS). Source: Own visualization.