CESifo WORKING PAPERS

10423
2023

Original Version: May 2023
This Version: January 2024

Insuring Peace: Index-Based Livestock Insurance, Droughts, and Conflict

Kai Gehring, Paul Schaudt

CESifo

Impressum:

CESifo Working Papers
ISSN 2364-1428 (electronic version)
Publisher and distributor: Munich Society for the Promotion of Economic Research - CESifo GmbH
The international platform of Ludwigs-Maximilians University's Center for Economic Studies and the ifo Institute
Poschingerstr. 5, 81679 Munich, Germany
Telephone +49 (0)89 2180-2740, Telefax +49 (0)89 2180-17845, email office@cesifo.de
Editor: Clemens Fuest
https://www.cesifo.org/en/wp
An electronic version of the paper may be downloaded
· from the SSRN website: www.SSRN.com
· from the RePEc website: www.RePEc.org
· from the CESifo website: https://www.cesifo.org/en/wp

CESifo *Working Paper No. 10423*

Insuring Peace: Index-Based Livestock Insurance, Droughts, and Conflict

Abstract

We provide quasi-experimental evidence of how an innovative market-based solution using remote-sensing technology can mitigate drought-induced conflict. Droughts are a major driver of conflict in Africa, particularly between nomadic pastoralists and sedentary farmers. The Index-Based Livestock Insurance (IBLI) piloted in Kenya provides automated, preemptive payouts to pastoralists affected by droughts. Combining plausibly exogenous variation in rainfall and the staggered rollout of IBLI in Kenya over the 2001-2020 period, we find that IBLI strongly reduces drought-induced conflict. Key mechanisms are an income smoothing effect and reduced migratory pressure for pastoralists, reducing the likelihood of miscoordination with other land users. Our study suggests that market-based solutions are a scalable, cost-effective pathway to mitigate conflict, complementing political solutions such as institutional reforms.

JEL-Codes: D740, G220, G520, O130, Q340, Q540.

Keywords: conflict, conflict resolution, climate change, droughts, pastoralism, insurance, ICT, resources.

Kai Gehring
Department of Economics &
Wyss Academy for Nature
University of Bern / Switzerland
kai.gehring@unibe.ch

Paul Schaudt
Department of Economics
University of St. Gallen / Switzerland
paul.schaudt@unisg.ch

Janaury 2024
We thank Nathaniel Jensen and the International Livestock Research Institute (ILRI) for kindly sharing their data on insurance rollout and payments with us. Dylan Philippe and Amelia Libeau provided excellent research assistance. Kai thanks the Wyss Academy Hub Kenya for support in organizing his trips to Kenya and local workshops and meetings. Paul Schaudt acknowledges funding from the Swiss National Science Foundation Ambizione project PZ00P1208916. We are grateful for helpful suggestions by Lorenzo Casaburi, Beatrix Eugster, Roland Hodler, Valentin Lang, Joris Mueller, and Dominic Rohner, as well as comments from seminar participants at the University of St. Gallen, theWorkshop: Resources, conflict, and the environment, the EPCS 2023 conference, the Beyond Basic Question conference, and the DENS conference. None of the authors has any financial interest in the results of this study or received money from involved actors.

1. Introduction

Mitigating violent conflict caused by extreme weather events is a major challenge of the 21st century. Extreme weather events constitute large economic shocks that can cause and escalate conflicts, particularly in low-income countries without adequate social protection schemes (Burke et al., 2024). An important example are droughts, which constitute a root cause of the widespread conflicts between nomadic pastoralists and sedentary farmers in Africa (Eberle et al., 2023; McGuirk and Nunn, 2023). Droughts intensify competition over scarce resources by forcing pastoralists to migrate out of their traditional grazing grounds into areas with other land users. As climate change leads to more and longer droughts, such conflicts are predicted to increase by up to a third if no countervailing measures are taken (Eberle et al., 2023). Thus, identifying scalable and cost-effective conflict-mitigation interventions for countries with weak fiscal and state capacity is essential to protect vulnerable populations from widespread conflict and instability.

Our paper provides quasi-experimental evidence highlighting the potential of index-based livestock insurance (IBLI) in mitigating drought-induced conflict in Africa. Without access to insurance, pastoralists hold excess livestock as pre-cautionary saving devices, which means that droughts often force pastoralists to migrate into mixed areas also used by other land users to feed those animals. Insurance schemes can provide a targeted approach to mitigate adverse events like droughts, but traditional insurance models are often impractical due to high monitoring costs and delayed payouts. IBLI solves those issues by using remote sensing to automatically trigger preemptive payouts if a pre-determined drought threshold is crossed. IBLI coverage can mitigate conflicts by smoothing pastoralists' incomes and by setting an incentive for smaller herd sizes (Jensen et al., 2017), which limits the extent of necessary drought migration. Hence, while index-based insurance schemes are an increasingly popular social protection scheme, they can also constitute a cost-effective and scalable conflict-mitigation tool for low- and middle-income countries.

We focus on the conflict-mitigation potential of IBLI in Kenya, whose large pastoralist population (8.8 out of 53 million Kenyans) faces increased competition for resources due to the expansion of various other land uses. We illustrate how droughts in the traditional grazing grounds of pastoralists increase conflict in a wider region using survey data from a central, semi-arid region close to Mount Kenya. During years of sufficient rainfall, pastoralists typically stay within their traditional territories, where established community-led negotiations are often effective in resolving disputes. However, during droughts, the necessity for pastoralists to migrate further in search of grazing land leads to an increased frequency of conflicts. The risk of escalation is especially pronounced when their drought migration routes cross into areas of expanded farmland, urban developments, and nature reserves. Hence, IBLI availability to pastoral communities is most likely to reduce the probability of conflict during droughts in the neighborhood of those communities.

Our main specification estimates to which degree IBLI coverage reduced the effect of drought on conflict in Kenya over the 2001-2020 period. The dependent variable is the probability of conflict in a 0.1×0.1-degree gridcell (roughly 10 x 10 km) based on the Armed Conflict Location and Event Dataset (ACLED). The treatment variable combines exogenous changes in the rainfall deficit in the neighborhood of the cell with variation in insurance coverage from the staggered IBLI rollout across eligible areas. Our neighborhood approach captures conflict spillovers in line with the patterns observed in the case study and McGuirk and Nunn (2023), who show that conflicts occur mainly in neighboring areas that are the destinations of the pastoralists' drought migration movements. Our main results suggest that the drought-conflict semi-elasticity is reduced by about 23% for a one standard deviation increase in neighborhood IBLI coverage.

The main identification concern in our setting is that the insurance rollout across locations is potentially endogenous.[1] IBLI was piloted in Northern Kenya in 2010 as a social protection scheme for pastoralists and later rolled out to eligible pastoralist areas in five steps. Technical challenges are reported as the key factors influencing the initial location and rollout pattern (Fava et al., 2021). Cell-fixed effects capture cross-sectional differences between eligible and ineligible areas. However, we are still concerned that the timing until an eligible area receives IBLI might be correlated with the prior drought-conflict elasticity or with other interventions that could mitigate drought-induced conflict.

The first type of potential omitted variables are unobserved factors that explain the rollout pattern and also correlate with conflict and droughts. For instance, if eligible areas with a higher, latent, drought-conflict elasticity would receive IBLI coverage earlier, this would lead to an upward bias in an estimated conflict-reducing effect. The worry in our analysis would be a downward bias, which could occur if areas with a higher drought-conflict elasticity would receive IBLI coverage later. We show that the estimated pre-treatment drought-conflict elasticity explains neither IBLI eligibility nor the timing of receiving IBLI coverage, and different placebo tests indicate no conflict-mitigation effect of actual IBLI eligibility or coverage in the pre-treatment period. Furthermore, we find no indication of differences in rainfall trends that would indicate a dynamic adaption of the rollout pattern to changes in drought patterns.

The second type of potential omitted variables are other interventions that both affect drought-induced conflict and correlate with the rollout pattern of IBLI and droughts. The Hunger Safety Net Program (HSNP), which provides cash transfers to vulnerable households, is one such program. It covers most of the areas that also receive IBLI and could also work as a mitigating factor by providing cash to households that are pushed under the eligibility line due to droughts. Similarly, World Bank aid projects with a focus on the agricultural sector (e.g., irrigation) are a concern. We run regressions controlling for both interventions at the cell and neighborhood level and find no indications that they are causing a bias in our main estimates.

Our results are robust to varying core assumptions regarding the conceptualization of the neighborhood, using alternative conflict measures and drought proxies, computing standard error in various ways, and further robustness tests regarding the IBLI roll-out. Most importantly, we employ an alternative specification based on the insights from the case study that the likelihood of pastoralist migration triggering conflict is higher if the pastoralists encounter other land users. This allows us to leverage differences in the expected treatment

[1] Endogenous insurance payouts that are manipulated or delayed due to drought-induced conflict are a problem with traditional insurance. They are unlikely in the case of IBLI because payouts are automatically triggered based on remote-sensing-based drought proxies pre-defined by the independent International Livestock Research Institute (ILRI).

intensity within rollout clusters by including rollout-cluster-times-period fixed effects in our regression. These fixed effects absorb any omitted variables related to the potentially endogenous rollout steps. Even in such a restrictive specification, we find a sizeable conflict-mitigating effect of IBLI.

We then turn to the mechanisms. Jensen et al. (2017) suggest that IBLI sets an incentive to reduce herd size and invest more in cattle health, but also successfully smooths pastoralists' income. Smaller herd sizes could mitigate conflicts by reducing the extent of necessary drought migration. To demonstrate that less migratory pressure is a key mechanism, we follow Eberle et al. (2023) and match conflict actors to ethnic homelands (Murdock, 1967). We then show that if an ethnic homeland has IBLI coverage, the distance between the homeland centroid and conflict events involving that group decreases. We also demonstrate the income-smoothing effect of IBLI with geo-coded data from Afrobarometer, suggesting that higher opportunity costs of fighting also contribute to the overall conflict-mitigating effect.

Finally, we provide an estimate of the cost-effectiveness of the program. To this end, we predict the plausible drought-induced conflict fatalities in Kenya over our pre-treatment period and calculate the yearly number of lives saved based on our main estimates. We then relate the monetary value of saved lives in relation to public spending in the form of subsidies by the Kenyan government. We find that even for the comparably low values of statistical life (VSL) estimates from the World Health Organization or the World Bank, IBLI provides a pure fatality saving of between 10 and 22 cents per dollar spent on subsidizing the program.

We contribute to various strands of literature. Our study is inspired by the literature on climate and conflict (e.g., Hsiang et al., 2013; Burke et al., 2015). In particular, we build on McGuirk and Nunn (2023) and Eberle et al. (2023), who document droughts as a cause of pastoral-farmer conflicts in Africa and establish key mechanisms. Those studies show heterogeneity in the drought-conflict sensitivity can be mitigated by inclusive political institutions (see also Fetzer and Kyburz, 2022). We provide novel evidence that index-based insurance schemes are not just a promising welfare intervention but can also comprise a cost-effective conflict mitigation intervention. An important feature of market-based interventions such as IBLI is that they can be scaled up quickly and do not require institutional changes, making them an important complement to necessary political reforms.

The potential to scale up matters as pastoralism is practiced in 43% of the African landmass, covering 36 countries, and contributes to the livelihood of about 268 million people (FAO, 2018). Moreover, climate change is predicted to further amplify challenges to pastoralism in many regions, particularly in the Sahel and Horn of Africa (H.-O. Pörtner, 2022). The World Bank and private equity are currently planning to expand their engagement for pastoralists in East Africa with close to 900 million dollars over the 2023 to 2027 period.[2] Hence, the findings of this study are relevant for understanding the potential and role of IBLI as part of such engagements and provide further justifications to invest in or at least explore such schemes in additional countries and settings.

We also complement existing papers studying the direct effects of IBLI on pastoralist

[2]See the DRIVE project https://www.worldbank.org/en/news/press-release/2022/06/23/world-bank-boosts-pastoral-economies-and-climate-action-in-the-horn-of-africa.

welfare in Kenya (Jensen et al., 2017) and on direct conflict exposure in Ethiopia (Sakketa et al., 2023). Sakketa et al. (2023) provide important complementary evidence to this paper on individual take-up, for which we lack data. They conduct a mediation analysis based on a randomized encouragement program in southern Ethiopia and show that insurance uptake is the decisive channel leading to a lower likelihood of conflict for the insured pastoralists themselves. Our study, in turn, examines the regional conflict mitigation potential of IBLI at scale and focuses on conflict mitigation for a broader set of conflicts in the neighborhood of an affected cell. Thus, our results include spillovers from insured pastoralists to non-insured pastoralists and non-pastoralists in the entire country. We show that the conflict-mitigation potential of neighborhood IBLI coverage is highest in cells with mixed-land use where pastoralists encounter other land users in a competition for scarce resources.

By demonstrating the potential of remote-sensing-based insurances with automated payouts, we contribute to a growing literature studying technology for development (ICT) (Blumenstock, 2016; Fabregas et al., 2019). ICT ranges from simple tools like SMS messaging that help farmers increase yields (Casaburi et al., 2019) to hotline services that solve free-riding problems (Casaburi et al., 2019), and the use of remote-sensing technology for insurance design (Benami et al., 2021). One big challenge is insufficient demand for insurance, which could be partly explained by high upfront costs in settings with liquidity constraints and present bias (see Casaburi and Willis, 2018). Incomplete land markets pose another challenge, but (Acampora et al., 2022) show that subsidies can help to cope with these frictions. Our results further justify well-designed subsidies and other measures to foster insurance adoption.

Our results also contribute to the large economics of conflict literature. Within that literature, most related are studies highlighting how conflict depends on competition between groups (Gassebner et al., 2023; Gehring et al., 2022; Morelli and Rohner, 2015), studies considering long-term sources of conflict in Africa (Michalopoulos and Papaioannou, 2016; Moscona et al., 2020; McGuirk and Burke, 2020), and studies focusing on resources as a source of conflict (Berman et al., 2017; Gehring et al., 2023; Hodler et al., 2023). While historical tensions and inequalities are an important source of conflict, external shocks cause new conflicts to break out or existing tensions to intensify (Bazzi and Blattman, 2014; Berman and Couttenier, 2015; Dube and Vargas, 2013). We study how an external shock, droughts, intensifies long-term conflicts between pastoralists and herders about water and land and show that IBLI can act as a buffer against such an external shock.

This links our study to the small but growing literature studying possibilities for conflict mitigation. As Fetzer (2020) describes: "Any public intervention that helps households smooth incomes has the potential to reduce conflict by breaking this key link." However, while better public health and education correlate with a lower likelihood of violence (Berlanda et al., 2022; Rohner and Saia, 2019), those systems are highly persistent and hard to change. Public work programs can be an effective tool (Fetzer, 2020), but require substantial state capacity, while the evidence on cash transfers is mixed (Blattman and Annan, 2016; Crost et al., 2016; Premand and Rohner, 2023). International interventions can provide some relief but are very costly (Rohner, 2022), while development aid has a mixed record (Nunn and Qian, 2014). Jensen et al. (2017) highlight a crucial difference in the cost structure of index insurance compared to social welfare schemes like cash transfers or public work programs. While the initial investment in the technology and set-up is costly, the marginal costs are much lower, suggesting a high potential for further expansion and upscaling.

The remainder of the paper is structured as follows. Section 2 provides details on IBLI and introduces our setting. Section 3 introduces our data and main variables. Section 4 presents our identification strategy and discusses our identifying assumptions. Section 5 presents our main results and sensitivity analysis. Section 6 presents evidence on the main channels, and Section 7 quantifies the effect of IBLI in relation to expenditures. Section 8 concludes and discusses implications for public policy.

2. Setting

2.1. Index-Based Livestock Insurance (IBLI) in Kenya

Index-Based Livestock Insurance (IBLI) represents an innovative financial tool designed to address the unique challenges faced by pastoralists in regions vulnerable to climate risks, particularly in areas where conventional livestock insurance proves impractical. Distinguished by its reliance on a predetermined index, typically linked to environmental factors like rainfall or vegetation cover, IBLI triggers payouts based on specific pre-defined index threshold conditions, thereby bypassing the need for direct loss assessment. This approach not only enhances objectivity and transparency but also mitigates issues inherent in traditional insurance models, such as moral hazard and adverse selection. IBLI's efficiency and scalability offer a cost-effective, accessible insurance option crucial for supporting livelihoods and ensuring the economic stability of communities heavily reliant on livestock. Some versions of IBLI are implemented in diverse regions, including Asia (particularly India and Mongolia), Latin America (particularly Mexico), and Southern and Eastern Africa.

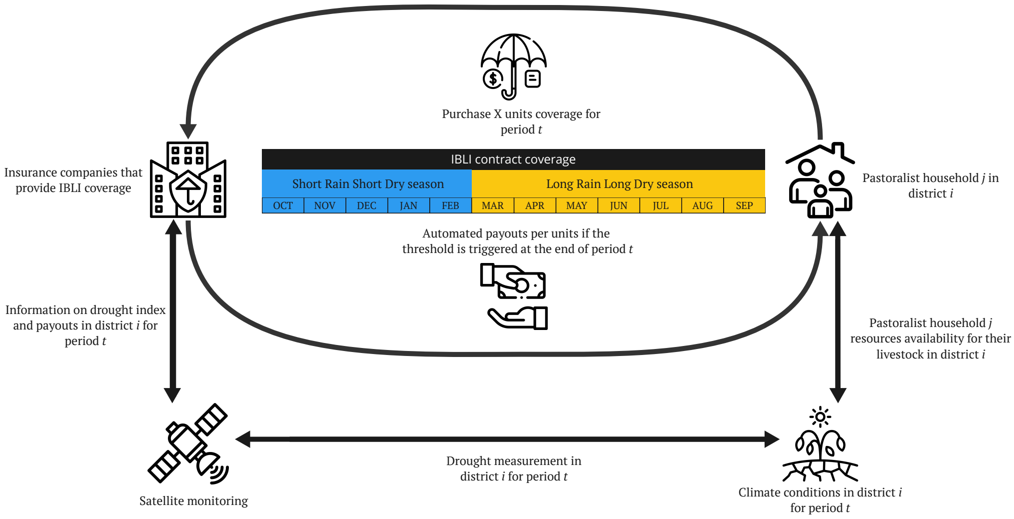
In Kenya, IBLI was initially developed, among others, by the International Livestock Research Institute (ILRI) and the World Bank to protect pastoralists in arid and semi-arid areas against climatic shocks and improve their living conditions. IBLI was successfully piloted in the Northern Marsabit region in 2010 and afterward rolled out to all eligible areas across Kenya (Johnson et al., 2019; Fava et al., 2021). All traditionally pastoralist areas are eligible and were divided into 146 insurance districts. As of summer 2023, IBLI coverage is available in 93 insurance districts, and the Kenyan government and the World Bank's DRIVE initiative aim to extend coverage further.

Figure I illustrates how IBLI works in Kenya. If an insurance district has IBLI coverage, IBLI insurance plans are offered and distributed by private Kenyan insurance agencies.[3] Following initial success, the Kenyan Government relabeled IBLI domestically, the Kenyan Livestock Insurance Program (KLIP) in 2015 (Fava et al., 2021), and fully subsidizes coverage for up to five TCUs per household. Pastoralist households in that district can purchase IBLI for a specific number of tropical livestock units (TLUs, one TLU corresponds to one cattle or ten goats/sheep). Instead of following the calendar year, an IBLI contract always covers a

[3]Those companies include UAP Insurance Company, Oromia Insurance Company (OIC), APA Insurance Ltd., and Takaful Insurance of Africa (see https://ibli.ilri.org/index/).

one-year period following the two rain and dry seasons in Kenya.

FIGURE I
Index-Based Livestock Insurance (IBLI) in Kenya



Notes: The figure provides a simplified scheme of the processes underlying IBLI.

The payouts of insured pastoralist households depend on the drought conditions in their insurance district. In an initial step, ILRI estimated the size of expected drought-induced damage for each insurance district (Jensen et al., 2017). Based on this damage function, satellite data and remote sensing are used to calculate if and by how much a district-specific drought threshold is crossed. If the threshold in their insurance district is crossed, pastoralists receive immediate automated payments from insurance companies.[4] The widespread use of mobile payment systems in Kenya (e.g., MPESA) enables fast payments even to remote households (Fava et al., 2021).

2.2. Case study: Droughts, conflict, and insurance in central Kenya

While there is no comprehensive data on pastoralists drought migration routes for all of Kenya, we can illustrate the spatial pattern and mechanisms underlying drought-induced conflicts for the Samburu-Laikipia-Isiolo-Meru region in central Kenya based on detailed survey data from Lengoiboni et al. (2010).

Panel A of Figure II displays the home village of three pastoralist communities as triangles: the Namelock in the West, the Lodungkowe in the North, and the Ngaremara in the East. Based on in-depth surveys in 2008, Lengoiboni et al. (2010) also elicit and georeference the potential migration routes out of each of these villages during droughts. We show those routes originating from each village in the same color as the village triangle. Those routes are

[4] It is an intentional feature that insured pastoralists might receive payouts without actually occurring livestock losses (Vrieling et al., 2014; Fava and Vrieling, 2021), as IBLI aims to prevent the loss of cattle rather than only compensating for damages (Chantarat et al., 2013). The design also implies that it is not decisive where pastoralists are located at the moment the drought conditions are calculated, but rather the drought conditions in their home insurance district. In years with sufficient rain, pastoralists mostly remain within their district (average size $2817 km^2$, but droughts make it necessary to travel further (Chelanga et al., 2017; Jensen et al., 2017).

approximations and are subject to frequent change, but they can nevertheless provide a good indication of the extent and direction of drought migration. In addition, the map differentiates four types of land use with distinct patterns: pastoral areas, protected areas such as parks and forests, commercial agriculture in the form of farms and ranches, and urban areas. We further complement the map with all geo-referenced conflict events taking place in the landscape during our sample period. They are derived from the Armed Conflict Location and Event Data (ACLED, Raleigh et al., 2020) and shown as red crosses.

The drought-migration routes out of the three villages differ strongly in length and pattern, but all cross into areas characterized by other types of land use. Usually, women and younger children remain in the home villages throughout the year, together with smaller livestock such as goats and poultry (Jensen et al., 2017). The men leave the village with the cattle to roam the grazing grounds in search of pasture. In years with sufficient rain, the time away from the family is limited, and the spatial extent of the migration is mostly restricted to pastoral areas. However, in drought periods with a large rainfall deficit, the migration routes reach far into other land-use areas. This is risky as it increases the likelihood of encounters and potential conflicts with other land users.

Panel B of Figure II documents encounters and conflicts with pastoralists reported by the three other types of land users in 2008. The graph on the left-hand side shows that during drought periods, about 60% of survey respondents in urban areas report encounters with pastoralists, 70% of those in farms and ranches, and almost 90% of those in forests and parks.[5] With sufficient rain, those encounters are usually peaceful. However, during droughts, reported conflict events involving pastoralists are widespread (see right graph of panel B). Compared to encounters with pastoralists in parks and forest areas, encounters in urban locations or on farm and ranch land turn into violent conflict much more often. One likely reason is that urban and agricultural areas have expanded strongly in the last decades and contain more private property. Agricultural businesses compete with pastoralists for insufficient water resources in dry periods, and property owners in urban areas protect their property against intrusion by pastoralists with force if necessary.

We add the georeferenced ACLED conflict events during our sample period to the map to validate if conflicts indeed accumulate where pastoralists' drought migration routes cross into other land use areas. Take pastoralist migration out of Namelok, depicted in yellow in Panel A, as an example. Their drought migration route crosses the urban area of Isiolo in the east and the farms and ranches in the west. The red crosses show a clear and strong accumulation of conflict events in those two parts of the map. Similar accumulations of conflict events occur where the drought migration routes of pastoralists out of Lodungokwe and Ngaremara cross into the urban areas of Meru and Laikipia or into agricultural areas, while events in protected areas along the drought migration routes are much less frequent. There are significantly fewer conflict events along migration routes within pastoralist areas, usually caused by resource competition among pastoralists. While ACLED doesn't contain all conflicts in the survey and

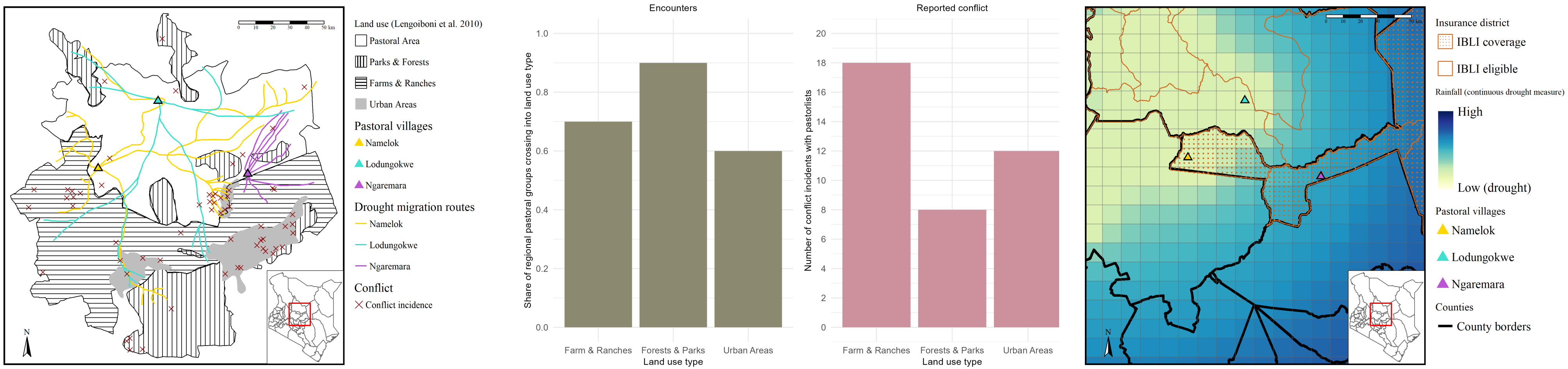
[5]Parks and forests are public or private areas with the purpose of conservation or partly tourism. Farms and ranches refer to both farm agriculture, small subsistence and large export-oriented farms, and large private estates with animal farming. Urban areas are more densely populated with residential and commercial housing, which often have gardens that feature grass and bushes as potential forage for cattle.

FIGURE II
Droughts, conflicts, and IBLI in the Samburu-Laikipia-Isiolo-Meru counties

(A) Pastoralist migration routes during 2010 drought

(B) Encounters & conflicts of pastoralists with non-pastoral land users during droughts

(C) Drought exposure across IBLI districts



Notes: Panel A shows the digitized map from Lengoiboni et al. (2010) with the different land use types for the Samburu-Laikipia-Isiolo-Meru region and the drought migrations routes and villages for the Namelok, the Lodungokwe, and the Ngaremara pastoral groups. Panel B plots reported encounters and conflicts by land use types in the study region based on Lengoiboni et al. (2010). Conflict incidents are from ACLED (Raleigh et al., 2020). Panel C shows counties and insurance districts to illustrate the variation in IBLI coverage based on whether a county is eligible and on the timing of eligible counties receiving IBLI coverage. Samburu is the county in the North (IBLI coverage in 2017), Laikipia in the South-West (not eligible), Meru in the South-East (not eligible), and Isiolo in the East (IBLI coverage in 2013) (Fava et al., 2021). Rainfall is used to approximate the drought conditions in an insurance district during the Short Rain Short Dry (SRSD) and Long Rain Long Dry (LRLD) seasons that comprise our 12-month periods.

often lacks information on groups involved in a conflict event, the most important insight for our study is that it captures the locations and spatial patterns of conflicts well.

Drought-induced conflicts in the case study region occur mostly in the neighborhood of the pastoralist areas, in particular in other land use areas where the likelihood of encountering other land users is highest. Meru and Laikipia counties in the South are not the home of the pastoralist communities but the goal of pastoralist drought migration. The former observation supports McGuirk and Nunn (2023), who show the importance of estimating the effect of drought in one location on conflict events in the neighborhood. The latter observation is in line with Eberle et al. (2023), who document that the likelihood of conflicts during the pastoralists' drought migration is highest in areas characterized by mixed settlements of different ethnic groups and mixed land use. Hence, our empirical strategy to estimate changes in drought-induced conflict in Kenya needs to explicitly account for these two observations.

Panel C of Figure II illustrates the spatial and temporal variation in drought patterns as well as in IBLI eligibility and coverage. The two arid or semi-arid counties in the east and north, Isiolo and Samburu, are both eligible for IBLI. However, based on the stepwise rollout pattern, Isiolo County in the east already received coverage in 2013. Samburu in the north is also eligible and even closer to the initial Marsabit pilot county but only received coverage in 2017. Meru and Laikipia counties in the South have fewer pastoralists and are not eligible for IBLI as of now. Therefore, the spatial variation in IBLI coverage comes first from being eligible or not – which relies mostly on a high enough share of pastoralists – and among those eligible from receiving coverage at different points in time.

When and where can IBLI coverage affect conflict in the region? Panel C illustrates the drought conditions in the respective insurance districts within the counties using hypothetical rainfall deficits. In the example, both the Namelock and Lodungokwe communities face drought conditions in their home village, but only the Namelock can purchase IBLI. The men from Namelock can avoid long and risky drought migration if they use insurance payouts to buy forage for their cattle (as documented in Jensen et al., 2017). To the extent they engage in their traditional drought migration, IBLI payments help smooth their incomes and thus increase the opportunity cost of fighting (Grossman, 1991). All this should reduce the likelihood of drought-induced conflicts in the neighborhood of Namelock compared to the neighborhood of Lodungokwe. Hence while other studies document the positive effects of IBLI on insured pastoralists in a specific region, we use this neighborhood approach to estimate the effect on insured pastoralists, but also non-insured pastoralists and other land users in Kenya.

3. Data

Our spatial units of analysis are grid cells of 0.1 $\times$ 0.1 degrees (roughly 10 x 10 km) covering the landmass of Kenya (580,000 km^2), following the native resolution of our preferred drought proxy. Our temporal units of analysis are 12-month periods from October to September of the following year, covering 20 periods from October 2000 to September 2020. As explained in Section 2.1, this reflects the two rain and dry seasons and the purchasing options of IBLI. The combination of cells and periods results in 94,300 cell-periods, our units of observation.

We are interested in measuring whether and by how much IBLI coverage mitigates the likelihood of conflict in a specific cell and period. However, the case study highlights that conflicts due to droughts in pastoral areas do not primarily occur in the pastoral areas themselves but along the drought migration routes where pastoralists encounter other land users (see Section 2.2). This means that in our setting, we need to capture how conflict in one cell is affected by droughts and IBLI coverage in other cells surrounding it. We explain in this section how we capture this dynamic and the majority of relevant conflicts by measuring drought and IBLI in these other cells with a neighborhood approach. We begin by introducing our outcome variable measuring conflict at the cell level and then continue by explaining the construction of our main variables of interest at this neighborhood level.

Other variables for testing balance, sensitivity, or mechanisms, both at the cell and neighborhood level, are introduced when being used for the first time. Details and sources for all cell and neighborhood variables used in this study are provided in Online Appendix A. Table A-1 provides summary statistics.

3.1. Outcome variable: Conflict at the cell-level

Our main outcome variable $Conflict_{i,t}$ is a binary variable taking on the value one if at least one conflict event is recorded in a cell i within a period t, and zero otherwise. We use the Armed Conflict Location and Event Data (ACLED, Raleigh et al., 2020) as a source of conflict data, in line with related studies on farmer-herder conflicts in Africa (McGuirk and Nunn, 2023; Eberle et al., 2023). The case study helped to validate that the geolocated conflict events in ACLED capture the spatial pattern of the relevant conflict events in Kenya well. ACLED does not cover all possible conflict events, but it covers many more conflict events in Kenya than alternative data sources like UCDP/PRIO Armed Conflict Dataset (Sundberg and Melander, 2013) or the Social Conflict Analysis Database (Salehyan et al., 2012). ACLED reports the actors involved in a conflict event, but close inspection reveals that the assignment is frequently missing or imprecise in our sample (e.g., actors labeled as "unknown" or just "raiders"). To avoid arbitrary classification, we use all conflict events in the construction of our baseline measure and demonstrate the robustness of our results by focusing on particular actors or event types.

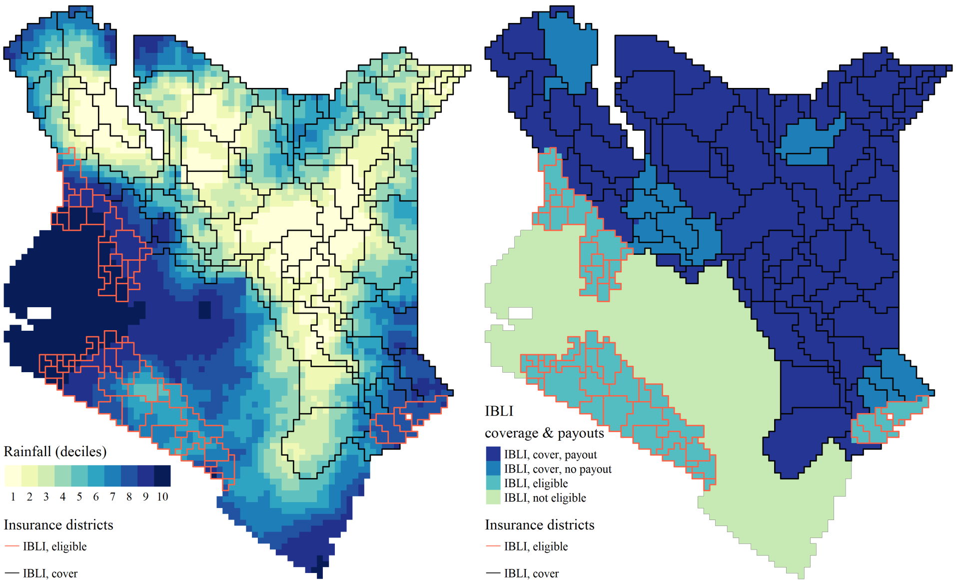
3.2. Variables of Interest: Droughts and IBLI coverage in the neighborhood

Data on IBLI eligibility and availability comes from the International Livestock Research Institute (ILRI) and Fava et al. (2021). ILRI kindly shared geospatial data about the insurance districts that are nested within the Kenyan counties. Information on whether a district is eligible for IBLI and the timing of receiving coverage comes from Fava et al. (2021). There are no publicly available data on actual IBLI payouts by insurance district and period, but we obtained data from ILRI for the years 2016 to 2019. Even for those years, the only information reliably available is whether there was a payout in a district, not the exact amount. Hence, we use payouts only in some robustness checks and focus on IBLI coverage.

Our main proxy to capture droughts is based on monthly rainfall data in millimeters, available from NASA's GPM (Huffman et al., 2017) for grid cells of 0.1 × 0.1 degrees. We prefer rainfall over more complex measures because it is (i.) readily available with a high spatial- and temporal resolution, (ii.) widely employed in the literature and easily interpreted, and (iii.) exogenous to human behavior that might be related to conflict and can affect forage availability. For robustness tests, we also compute a phytomass proxy based on dry matter productivity (DMP, from Copernicus Global Land Service, 2019) that reflects the availability of forage more directly, as well as an aridity index (Abatzoglou et al., 2018) that also incorporates temperature, soil, and wind conditions.

FIGURE III
Droughts (proxied by rainfall) IBLI coverage and payouts

(A) Rain (16/17 period) (B) IBLI payouts (16/17 period)



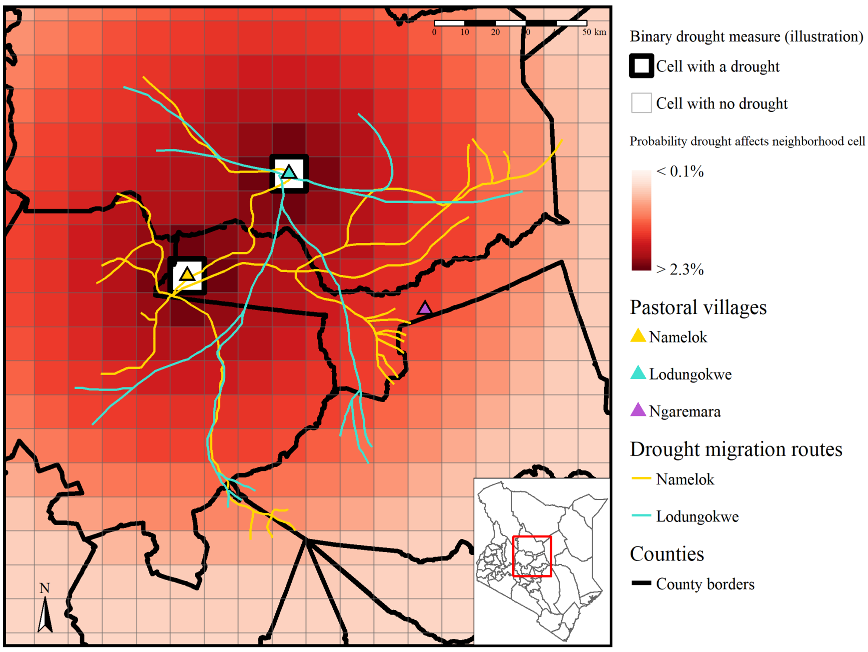
Notes: Panel A plots the average rainfall (in deciles) during the Short Rain Short Dry (SRSD) and Long Rain Long Dry (LRLD) seasons overlapping over the years 2016 and 2017 (Oct 2016 to Sep 2017). Panel B shows the insurance districts that received IBLI payouts either in February or August 2017. IBLI coverage and payouts are given by the International Livestock Research Institute (ILRI). The different variables are processed at a $0.1° \times 0.1°$ gridcell-level.

Panel A of Figure III illustrates the spatial variation in IBLI coverage and rainfall using the 2016/2017 period as an example. All areas covered by an insurance district are IBLI-eligible; those with black district borders already received IBLI coverage by 2016. Naturally, rainfall is lower in the IBLI-eligible semi-arid areas, but Panel A also highlights considerable variation in rain within those areas. Panel B verifies that lower rainfall approximates the drought conditions that trigger IBLI payouts in an insurance district during a specific period.

Neighborhood definition The first challenge for a neighborhood approach is to approximate the potential conflict risk in terms of drought migration from another cell j to an outcome cell i. We cannot rely on fixed, georeferenced migration routes that steer drought migration of certain pastoralists in specific directions. Beyond a few regions and periods, such data is not systematically available. More importantly, in contrast to roads or train tracks, those routes themselves are not exogenously given but continuously change over time, shaped by conflicts, general drought patterns, or changes in infrastructure (Flintan et al., 2013). Even without such fixed routes or information on group-specific travel costs, it is plausible to assume that the probability of migration is smaller for cells that are further away. Longer migration implies psychological costs (e.g., time away from family, economic costs (general travel costs, cattle health, see acaps, 2022), and potential costs from conflicts when passing through areas with other land users. Our neighborhood approach, therefore, reflects that, on average, the likelihood of a pastoralist group from another cell j in the neighborhood migrating into a cell i declines in distance.

The second challenge is that from the perspective of a cell i, the neighborhood approach has to approximate the potential conflict risk of not one but all other cells j surrounding it. The cell might be affected by drought migration from more than one pastoralist group, as their routes overlap and change over time. It would be misleading to use a specific distance to select which other cells j matter, as pastoralist group sizes and migration distances differ drastically from 50km to more than 400km. For each of the other cells, the drought conditions and insurance coverage influence the probability and length of pastoralist migration. Therefore, our neighborhood approach aggregates across all other cells by multiplying the cell-specific values with a distance-weighted probability.

FIGURE IV
Neighborhood weight illustration based on inverse distance weights



Notes: The figure depicts how we distribute the drought impact hypothetically occurring in two pastoral villages (highlighted in white) across cells based on the 1/distance weights. County borders depicted in black are from the GADM database.

Figure IV returns to the case study region to illustrate in more detail how this neighborhood approach accommodates the two challenges. Consider a hypothetical case with a binary drought indicator, where the pastoral villages Namelok and Lodungkowe are affected by a drought, but Ngaremara village in the East is not. We can capture the risk that the pastoralists from the drought-affected village cells j migrate into another cell i by multiplying the values in the j cell by $distance_{i,j}^{(-k)}$. Using a weight of $k = -1$ and a binary drought indicator, the red colors indicate the probability that the drought-affected pastoralists migrate to a specific cell in the entire neighborhood. The dark red indicates a probability of around 2.5% for cells in the direct neighborhood. The lighter red indicates that the probability for cells beyond a distance of 100km is non-zero but smaller than 0.1%. As $k = -1$ generates plausible probabilities corresponding to common drought-migration patterns, we select it as our baseline decay but conduct robustness tests for a range of other distance decays.

To capture the aggregate risk of pastoralist drought migration, we need to combine the inverse-distance weighted probabilities from all other cells. In the simple illustrative example in Figure IV, this is easy to understand by comparing cells located between the two drought-affected villages with cells that are in the south-west of Namelock or the north-east of Lodungokwe. Cells between both villages face the risk of being affected by drought migration from both communities, which requires adding up the respective probabilities. The dark red colors indicate this overlapping of probabilities, while the colors show a continuously declining probability in the southwest and northeast. Summing up probabilities is more easily illustrated with two drought-affected cells and a binary drought-measure, but can equally be applied to continuous measures and variation in all other cells. To account for all other cells j and to use our continuous measures, we compute neighborhood variables as $Neighborhood \quad variable_i = \sum_{j \neq i}^{J} \frac{\text{Cell-level variable}_j}{distance_{i,j}^{(-k)}}$.

Cell-level variable The first step in computing the neighborhood measure is to define the cell-level drought and IBLI coverage variables. $Rain \ deficit_{i,t}$ is computed as the log annual rainfall in millimeters for a grid-cell i over a period t, multiplied by minus one. We construct the rain deficit this way to interpret its effect as semi-elasticity between a percentage decrease in annual rainfall and the likelihood of conflict. $IBLI_{i,t}$ measures the availability of the insurance in a cell i and period t, based on IBLI coverage in the respective insurance district over that period.

Neighborhood-level variables: The neighborhood level rain deficit for cell i in period t is computed as the inverse distance weighted average of the continuous cell-level rain deficit as $Rain \ deficit \ neighborhood_{i,t} = \sum_{j \neq i}^{J} \frac{Rain \ deficit_{j,t}}{distance_{i,j}^{(-k)}}$. Compared to the simple binary drought indicator example, using the continuous rain deficit allows for differences in drought intensity. Using the aggregation of probabilities in the whole neighborhood also captures that the probability of drought migration into a cell i is the sum of all probabilities in the neighborhood cells. The neighborhood rain deficit has no natural interpretation, but using the logarithm allows us an easy interpretation of effects as an elasticity later. Insurance coverage in the neighborhood is computed for cell i in period t as the inverse distance weighted average of the cell-level IBLI coverage indicators as $IBLI; neighborhood_{i,t} = \sum_{j \neq i}^{J} \frac{IBLI_{j,t}}{distance_{i,j}^{(-k)}}$. To ease interpretation, we z-standardize this variable to have mean zero and a standard deviation of one.

4. Empirical strategy

4.1. Estimating equation

Our baseline specification estimates the effect of neighborhood IBLI coverage on drought-induced conflict using a linear probability model:

$$
\begin{aligned}
Conflict_{i,t} = &+ \delta_1 Rain\ deficit\ neighborhood_{i,t} + \delta_2 IBLI\ neighborhood_{i,t} \\
&+ \delta_3 (Rain\ deficit\ neighborhood_{i,t} \times IBLI\ neighborhood_{i,t}) \\
&+ \mathbf{X}'_{\mathbf{i,t}} \xi + \eta_i + \tau_t + \epsilon_{i,t}
\end{aligned}
\tag{1}
$$

$Conflict_{i,t}$ is the binary conflict indicator at the level of the cell i during period t. $Rain\ deficit\ neighborhood_{i,t}$ and $IBLI\ neighborhood_{i,t}$ capture drought conditions and IBLI coverage in the neighborhood of a cell. $\mathbf{X_{i,t}}$ is a vector containing further cell-level control variables, always including $Rain\ deficit_{i,t}$, $IBLI_{i,t}$, and their interaction. η_i are cell-fixed effects, absorbing time-invariant determinants of conflict and IBLI, such as climate, geography, local political institutions, or the historical presence of pastoralists. γ_t are period-fixed effects absorbing country-wide shocks, such as democratization, national elections, general trends in conflict, IBLI availability, and droughts. Online Appendix B show that even net of the fixed effects, there is considerable variation in the neighborhood variables and their interaction. $\epsilon_{i,t}$ are spatially clustered standard errors (Conley, 1999), accounting for the spatial dependence in the neighborhood measures. Our main distance cutoff is 200km, but we employ various cutoffs in robustness checks.

We are interested in assessing if there is a statistically significant drought-conflict mitigation effect, as well as in measuring the magnitude of such an effect in a meaningful way. Regarding the statistical significance of the effect, our main interest is in δ_3, the coefficient measuring the effect of the interaction between $Rain\ deficit\ neighborhood_{i,t}$ and $IBLI\ neighborhood_{i,t}$. To compute the magnitude of this conflict mitigation effect, it is helpful to set it in relation to the baseline effect of $Rain\ deficit\ neighborhood_{i,t}$, captured by δ_1. By dividing δ_3 by δ_1, we can compute the reduction in drought-induced conflict by IBLI in percent. To reduce clutter, our plots and tables focus on the two main terms and their interaction, as well as this ratio $\frac{\delta_3}{\delta_1}$; the coefficients of control variables are displayed in appendix tables.

4.2. Identification

The main concern for the causal interpretation of the interaction coefficient δ_3 is that this specification interacts a plausibly exogenous variable ($Rain\ deficit\ neighborhood_{i,t}$) with a potentially endogenous variable ($IBLI\ neighborhood_{i,t}$). We need to assume that conditional on the fixed effects, the cell-level controls, and the respective main terms, δ_3 is exogenous (Borusyak and Hull, 2023). δ_1, the effect of the neighborhood rain deficit on conflict can plausibly be considered as causal following the common assumption that rainfall patterns are exogenous with respect to conflict (e.g., Miguel et al., 2004). Assuming exogeneity of δ_2, the estimate of the neighborhood IBLI coverage on conflict is more problematic as the insurance rollout could correlate with many other factors influencing conflict.

We can also think about our specification as a triple-difference estimator (Gruber, 1994) with two continuous variables.[6] The identifying assumption in such a triple-difference specification is easier to understand with two discrete treatment variables at the cell level but more complex with two continuous variables at the neighborhood level.[7] For instance, unlike the treatment variable in classical two-way fixed effect difference-in-differences specification, the interaction of the neighborhood variables always takes on a non-zero value for every cell after IBLI was first introduced. Hence, thinking in terms of never-takers and discrete counterfactual groups is much more complicated than in the discrete difference-in-difference literature (concerns center around treatment dossage Callaway et al., 2021). Instead of trying to justify a more complicated common trend assumption, we instead turn to the omitted variable bias formula to precisely evaluate potential identification concerns in our setting. Conditional on the fixed effects and main terms, we can derive that the estimated $\hat{\delta}'_3$ captures the true δ_3 plus a potential bias term.

$$\hat{\delta}'_3 = \delta_3 + \alpha_4 \cdot \frac{\text{Cov}((Rain\ deficit\ neighborhood_{i,t} \times IBLI\ neighborhood_{i,t}), Z_{i,t})}{\text{Var}((Rain\ deficit\ neighborhood_{i,t} \times \text{IBLI}_{i,t}))}(I.) \qquad (2)$$

$Z_{i,t}$ represents potential omitted variables that varies over space and periods t. To cause a bias in $\hat{\delta}'_3$, the $Z_{i,t}$ need to directly influence conflict (captured by α_4) and correlate with both $Rain\ deficit\ neighborhood_{i,t}$ and $IBLI\ neighborhood_{i,t}$. Given that rainfall is plausibly exogenous with respect to local conflict, the formula illustrates that a potential bias could occur if the potential endogenous rollout of IBLI would correlate with such $Z_{i,t}$.

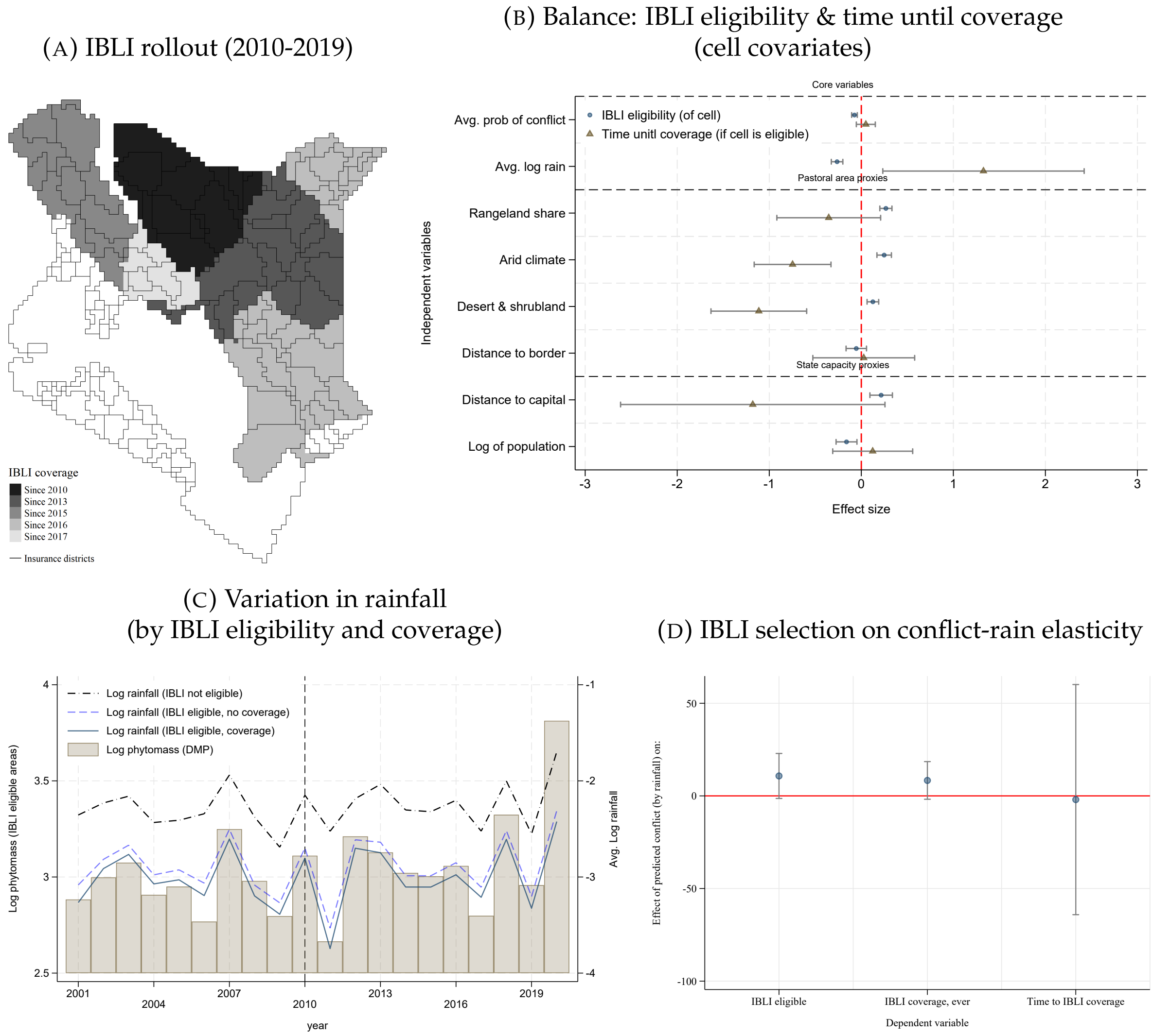
Panel A of Figure V shows the rollout pattern over the 2010-2019 period. IBLI was piloted in the Northern Marsabit region in 2010 as a social protection scheme for pastoralists and later rolled out to eligible pastoralist areas in five steps. Those steps follow the county boundaries to the extent that one county and the IBLI insurance districts nested within it always receive coverage at the same time. Fava et al. (2021), and official statements report that technical challenges had the biggest impact on the time until an area received coverage. The lack of any obvious spatial pattern in Panel A is in line with that evidence. By 2019, around 80% of IBLI-eligible areas have received coverage.

Panel B of Figure V shows two types of balance tests regarding IBLI eligibility and rollout timing, focusing on the probability of conflict, rainfall, geographic and climatic conditions, distance to the capital, and population. Considering IBLI eligibility, the eligible pastoral areas naturally have less rain, a more arid climate, a higher share of rangeland, and are

[6] Triple difference designs are robust to common types of model misspecification in geospatial conflict research. A common concern is the size of the gridcells when using linear probability models for estimation. Large gridcells likely lead to a downward bias due to a high unconditional conflict probability, while small cells tend to lead to an upward bias. δ_3 would not be affected because the upward or downward bias in δ_1 would not be correlated with neighborhood IBLI coverage (Olden and Møen, 2022).

[7] For instance, "strong parallel trends" (Callaway et al., 2021) in our setting means that the average conflict probability over time conditional on rainfall for a high-IBLI coverage area is a good counterfactual for the outcome in a low-IBLI coverage group if they had been assigned the same degree of coverage. In this case, δ_3 with two-way fixed effects identifies weighted averages of the differential in the average causal responses of conflict to neighborhood drought intensity at different treatment intensities of the neighborhood IBLI coverage (Callaway et al., 2021).

FIGURE V
Evaluating concerns about potential endogenous IBLI rollout



Notes: Panel A of the figure plots the rollout of IBLI coverage across Kenya (based on Johnson et al., 2019; Fava et al., 2021). Black lines highlight insurance district borders. The grey lines plot the 146 insurance districts. The white area in the center of panel A are non-eligible areas (IBLI is not planned to be offered there). Panel B reports results from bi-variate balancing tests. We regress the average of a set of variables (depicted on the y-axis) between 2001 and 2009 on the probability that a cell is designated to potentially receive IBLI (blue dots) or the years until coverage conditional on eligibility (green triangles). Panel C plots the average rainfall for areas that are never eligible for IBLI (black dashed line), eligible areas (bright blue dashed line), and areas that receive IBLI coverage (dark blue line) over our sample period. In addition, we plot the log level of available pythomass (Dry Matter Productivity) in IBLI-eligible areas as a proxy for forage scarcity in pastoral areas. We report the interaction coefficient of the neighborhood rainfall deficit with either insurance proxy and their 95% confidence intervals. Panel D plots how predicted conflict by the rain deficit in the cell and neighborhood predicts IBLI eligibility, eventual IBLI coverage, or the time until coverage among cells that eventually receive IBLI. The 95% CI in panels B and D are based on Conley standard errors and are implemented using the acreg package in Stata (Colella et al., 2019), with a distance cutoff of 200km.

characterized by desert and shrubland conditions compared to the non-eligible rest of the country. Conditional on eligibility, the time until receiving coverage also correlates with some of those variables. To the extent that this correlation does not vary over time, the cell-fixed effects would capture those cross-sectional differences. As shown above, we would be worried about a potential bias from omitted variables either dynamically determining the IBLI rollout or correlating with IBLI coverage, droughts, and conflict over time.

The first type of such variables are unobserved factors that explain the rollout pattern and also correlate with conflict and droughts. One possibility is that the effect of the cross-sectional balance variables like arid climate or soil type (Z_i) on the IBLI rollout varies by period t. To account for this, we run robustness tests controlling for the interaction of the cross-sectional variables with the neighborhood rain deficit. Other options are that the rollout pattern could correlate with the prior drought-conflict elasticity or is dynamically adjusted to drought and conflict patterns.

Panel C of Figure V provides no indication that the IBLI rollout is dynamically adjusted to rainfall patterns. While the black dashed line indicates that ineligible areas obviously differ in having considerably more rainfall, there are no differences in rainfall patterns between those eligible areas that receive coverage during our sample period and those that do not. The graph also verifies that the rainfall variable provides a good proxy for the available phytomass in an area. However, this does not capture the drought-conflict elasticity and its potential effect on the rollout pattern.

Suppose that the government intervenes to adjust the time until receiving coverage based on observing the likelihood that drought causes a conflict in an area. If areas with a higher drought conflict elasticity receive IBLI coverage earlier, δ_3 would be biased upward. A bigger concern to measure a conflict-mitigating effect would be if those areas receive IBLI coverage later, which would cause a downward bias. Panel D of Figure V shows that the pre-2010 rain-conflict elasticity has a small and insignificant positive correlation with IBLI eligibility but clearly no systematic correlation with the time until IBLI coverage.

A second category of omitted variables that is harder to rule out ex-ante are other interventions that both affect drought-induced conflict and correlate with the rollout pattern of IBLI and droughts. Assume the government or other actors introduce a program that is also targeted at areas with a high drought-conflict sensitivity, with a rollout pattern that correlates strongly with IBLI. If this program would also succeed in lowering conflict, we could wrongly attribute its success to IBLI. If it would instead foster conflict, we would underestimate the conflict-mitigating effect of IBLI. To address this, we will identify potentially problematic existing programs and interventions and control for their effect in robustness tests.

5. Results

In this section, we provide evidence that IBLI coverage meaningfully decreases the effect of droughts on the probability of conflict, after which we provide evidence that our results are unlikely to be explained by spatial correlates to the IBLI rollout. Moreover, we document that our effects are stable when controlling other programs implemented in Kenya's pastoral areas and are not sensitive to the specific coding decisions taken regarding our variables of interest or the spatial decay employed in constructing our neighborhood measures. Finally, we present results based on an alternative identification strategy that leverages local differences in potential conflict exposure based on ex-ante-defined characteristics within IBLI rollout clusters.

5.1. Main results

Table I displays our main results, sequentially adding the respective rain deficit and IBLI variables at the cell and neighborhood levels. Column 1 shows that cells experiencing a higher rain deficit in their neighborhood are indeed more likely to experience conflict compared to cells with a lower rain deficit in their neighborhood. Column 2 shows that, on average, more IBLI coverage in the neighborhood correlates with less conflict. Column 3 adds the interaction term of rain deficit and with IBLI coverage at the neighborhood level. The interaction coefficient is negative and statistically significant, indicating that IBLI coverage in the neighborhood of a cell reduces the conflict-inducing effect of less rainfall in its neighborhood.

TABLE I
Baseline results

	Dependent variable: Conflict$_{i,t}$		
	(1)	(2)	(3)
NEIGHBORHOOD			
Rain deficit (δ_1)	0.0756		0.0692
	(0.0337)		(0.0295)
IBLI (δ_2)		-0.0160	-0.0243
		(0.0043)	(0.0051)
Rain deficit $\times$ *IBLI* (δ_3)			-0.0158
			(0.0052)
Dep. var. mean	0.0245	0.0245	0.0245
Conflict mitigation	–	–	-22.79%
Cell level treatment controls	✓	✓	✓
Cell-fixed effects	✓	✓	✓
Time-fixed effects	✓	✓	✓
Obs	93400	93400	93400

Notes: The table reports the results of regressing the probability of conflict at the cell level on the rain deficit (log(rainfall)×-1), Index-Based Livestock Insurance (IBLI) coverage, and the respective interaction at the cell and neighborhood level. The level estimates are relegated to Table B-2. Conflict mitigation values in percent are the reduction in the semi-elasticity of the rain deficit on the probability of conflict for a standard deviation increase in the neighborhood IBLI coverage (δ_3/δ_1). The neighborhood variables are based on the 1/distance weighting scheme. Conley standard errors are implemented using the acreg package in Stata (Colella et al., 2019), with a distance cutoff of 200km.

The magnitude of the mitigation in column 3 has a straightforward interpretation, given the log transformation of the rainfall deficit and the standardization of IBLI coverage at the neighborhood level. A one percentage point increase in the rainfall deficit is associated with a 6.92 percentage point increase in the conflict probability for the average IBLI coverage in the neighborhood. If IBLI coverage increases by one standard deviation, the same rain deficit only leads to a 6.92 - 1.58 = 5.34 percentage point increase. A reduction of 1.58 percentage points is a sizeable effect compared to the baseline likelihood of conflict in a cell of roughly 2.5%.

A more intuitive quantification of the conflict mitigation is the percentage change in the effect of the neighborhood rainfall deficit on conflict (δ_3/δ_1), which corresponds to a reduction of 23%. Note that we find no evidence against a constant effect interpretation. Figure B-5 shows that the mitigating effect of IBLI coverage does not decrease with drought intensity (proxied by binning the rainfall deficit).[8]

IBLI coverage in the cell itself, which buffers against income shocks and raises the opportunity costs of fighting, shows a negative and statistically significant coefficient. Without attaching a causal interpretation to this, it is reassuring for the interpretation of our main results that IBLI coverage in a cell does not correlate with conflict.

5.2. Sensitivity analysis

In this subsection, we provide evidence in favor of our identifying assumptions and interpretation of our main results. We start by testing for the potential selection of IBLI with respect to cell characteristics and address the issue of few spatial rollout clusters. We then provide evidence that our results are not driven by cash transfers or development aid programs in pastoral areas, after which we provide a general sensitivity test with respect to the measurement of our variables of interest, standard error construction, and more. The section closes with an alternative identification strategy that leverages within rollout cluster variation.

5.2.1. IBLI rollout concerns and inference with few rollout clusters

We run various robustness tests to probe if differences between IBLI-eligible and non-eligible locations somehow drive our results through some unobserved interaction with time-varying rainfall patterns. Panel A of Figure VI shows that our coefficient of interest remains stable when adding interactions between the neighborhood rainfall deficit and several correlates of IBLI coverage (reported in panel B of Figure V), such as the log of population, the share of rangeland, and indicators for different climate and biome zones.[9]

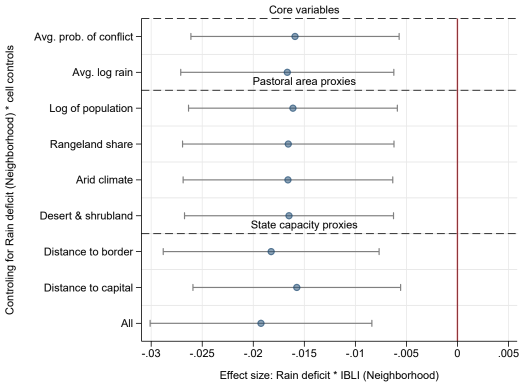
Further evidence against the idea that conflict mitigation, which we attribute to IBLI coverage, is caused by some other factor correlated with the IBLI rollout is provided by a placebo test of eventual IBLI coverage on pre-treatment conflict. If the rollout were caused by an underlying omitted variable that ultimately causes a conflict-mitigating effect instead of IBLI itself, we would expect this pattern to be visible in the pre-treatment period before the rollout. Panel B of Figure VI, reports results from placebo tests where we interact the neighborhood rain deficit with either a time-invariant neighborhood IBLI eligibility or a neighborhood variable capturing if an eligible area received IBLI coverage within the sample period. The positive point estimates indicate that pre-treatment, there was, if anything, a stronger drought-conflict sensitivity in IBLI areas. This would suggest some upward bias, which would imply that we underestimate the mitigation potential, but both coefficients are statistically insignificant.

[8]The estimates of the cell-level rain deficit and IBLI coverage (see Table B-2) align with the previous literature. Similar to McGuirk and Nunn (2023), we find a negative estimate of the rain deficit in the cell itself, but it is small and not statistically significant. Their interpretation is that the search for forage drives pastoralists, making cells without rainfall unlikely locations for conflicts between pastoralists and farmers.

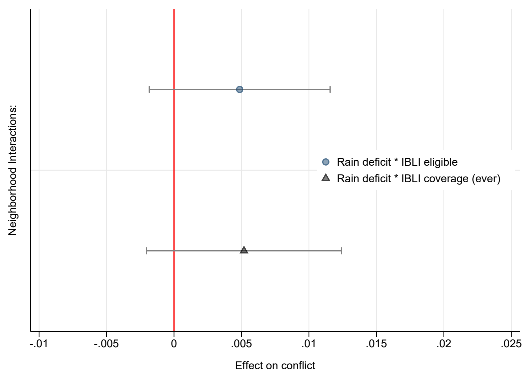
[9]We also replicate the exercise at the neighborhood-level, weighing all those covariates with the identical distance decay as IBLI coverage and the rainfall deficit. Again, our results remain stable (see Table B-6). Using a single dimension for poor soil quality also does not alter our results (see Table B-7 and Table B-8). See Figure A-5 for maps of the cell soil classification.

FIGURE VI
Dynamic effect of cross-sectional covariates and randomization inference

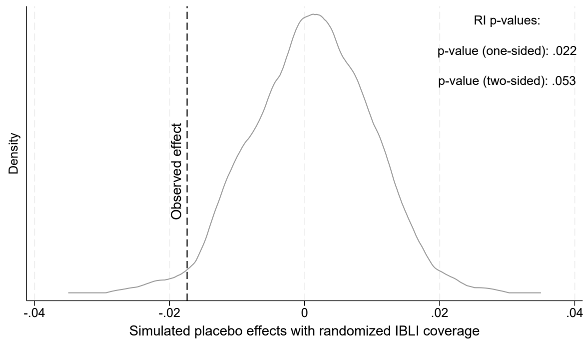
(A) IBLI mitigation effect controlling for cross-sectional covariates × rainfall deficit



(B) Placebo: IBLI mitigation effects (pre-IBLI rollout 2001-2009)



(C) Randomization Inference (random IBLI assignment with 7 clusters)



Notes: Panel A of the figure plots our interaction coefficient of interest δ_3 based on our main specification (column 3 of Table I). In addition, we add the cell-level controls shown as potentially correlated with IBLI coverage (see panel B of Figure V) and interact them with our neighborhood rain deficit measure. Panel B reports the results from a placebo regression covering the period 2001 to 2009 (based on eq. 1) in which we use IBLI eligibility (cell located in IBLI-eligible areas) or IBLI coverage, ever (cell located in IBLI-eligible area), instead of the time-varying coverage measure. Panel C plots the distribution of our neighborhood interaction term between the rain deficit and IBLI cover based on 1000 randomized IBLI coverage across the rollout clusters. The vertical line represents our obtained estimate from the observational data. The p-value is the exact p-value documenting the share of point estimates obtained from the randomized samples equal to or below our point estimates obtained from the real data.

The relatively few spatial IBLI rollout clusters are another concern for identification in our setting. The IBLI rollout occurred in six distinct waves, covering most of the arid and semi-arid regions of Kenya. Hence, our estimates could be driven by unobserved factors that vary with the neighborhood rain deficit across rollout clusters over time. Such unobserved factors would not be covered by our fixed effects but would correlate both with the cell-level and neighborhood-level IBLI coverage. If some other unobserved factor across rollout clusters drives our results over time, we would expect that the actual assignment of IBLI in our data should not matter and our results are reproducible for any variable that varies across the IBLI rollout clusters over time, as long as the variable is interacted with the observed neighborhood rainfall deficit.

To test for this possibility, we randomly assign IBLI cover across the six rollout clusters in each year, recalculate our neighborhood measure of IBLI coverage, and replicate our main specification (column 3 of Table I). Randomly assigning cell-level IBLI coverage by rollout cluster preserves the spatial dependence between cells within a cluster with respect to IBLI coverage. Calculating the neighborhood measures from the randomized data, in turn, ensures that the neighborhood measure has the same relation to the cell-level coverage as in the observed data.

Panel C of Figure VI provides evidence against the idea that another factor that varies across IBLI rollout clusters over time produces our results. Panel B plots the distribution of the neighborhood interaction between the rain deficit and IBLI coverage resulting from 1000 randomizations and our interaction coefficient obtained from the observed data (the vertical line). The exact p-value indicates that we only obtain an estimate smaller or equal to the size of our actual point estimate in 2.2% of the cases. The number falls to zero if we account for the size of the t-statistic, indicating that the randomized data also produces much less precise estimates. Hence, it is unlikely to obtain our interaction effect of interest for other variables that align with the spatial rollout clusters but have a differing temporal variation than the actual IBLI rollout.

5.2.2. Other interventions potentially affecting drought and conflict

A potential alternative explanation for our observed neighborhood effects are other interventions, either by domestic or international actors, that mitigate conflict due to droughts in pastoral grazing areas. The most prominent alternatives are unconditional cash transfers provided by the Kenyan government's "Hunger Safety Net Programme" (HSNP) to vulnerable households and relief efforts of international aid agencies, such as the World Bank. Both issues are of particular concern because they are likely to condition the effect of droughts on conflict.

The HSNP plausibly mitigates the effects of droughts because households that are pushed below the vulnerability threshold due to drought are eligible to receive cash transfers. Moreover, the spatial rollout pattern of the HSNP is somewhat correlated with the rollout of IBLI (see Figure A-2).[10] In fact, HSNP was introduced around the pilot stage of IBLI in northern Kenya (covering four pastoral counties) and expanded to the eight counties currently covered by IBLI in April 2019. Hence, the spatial overlap in the programs could bias our neighborhood measures for IBLI coverage. Moreover, if droughts increase the probability of conflict because they push pastoralists into poverty, HSNP could absorb part of this shock by providing unconditional cash transfers.

Development organizations, such as the World Bank, have implemented interventions during the last decades to relieve famine (a common consequence of droughts) and set up aid projects to increase the resilience of the agricultural and livestock sectors to climate change (e.g., irrigation projects). Moreover, additional aid (e.g., food aid) is often disbursed to locations where international aid agencies are already active, although the effects with respect to conflict are less clear (e.g., Crost et al., 2014; Nunn and Qian, 2014; Gehring et al., 2022).[11]

[10] For details see https://www.hsnp.or.ke/index.php/as/objectives.

[11] See Figure A-4 for the spatial distribution of World Bank development aid projects and commitments (AidData, 2017), before and during the IBLI rollout.

TABLE II
Controlling for other interventions

	Dependent variable: $\text{Conflict}_{i,t}$				
		Controlling for relief variable:			
		HSNP		Aid	
	(1)	(2)	(3)	(4)	(5)
NEIGHBORHOOD					
$Rain\ deficit\ (\delta_1)$	0.0692	0.0692	0.0599	0.0777	0.0882
	(0.0295)	(0.0298)	(0.0314)	(0.0301)	(0.0302)
$IBLI\ (\delta_2)$	-0.0243	-0.0239	-0.0257	-0.0256	-0.0253
	(0.0051)	(0.0067)	(0.0067)	(0.0052)	(0.0051)
$Rain\ deficit \times IBLI\ (\delta_3)$	-0.0158	-0.0161	-0.0253	-0.0178	-0.0169
	(0.0052)	(0.0054)	(0.0074)	(0.0053)	(0.0052)
NEIGHBORHOOD RELIEF CONTROLS					
$Relief$		-0.0013	0.0025	0.0072	0.0127
		(0.0043)	(0.0046)	(0.0038)	(0.0053)
$Rain\ deficit \times Relief$			0.0131		0.0082
			(0.0063)		(0.0062)
Dep. var. mean	0.0245	0.0245	0.0245	0.0245	0.0245
Conflict mitigation	-22.79%	-23.30%	-42.24%	-22.91%	-19.16%
Cell level treatment controls	✓	✓	✓	✓	✓
Cell-fixed effects	✓	✓	✓	✓	✓
Time-fixed effects	✓	✓	✓	✓	✓
Obs	93400	93400	93400	93400	93400

Notes: The table reports the results of regressing the probability of conflict at the cell level on the rain deficit (log(rainfall)×-1), Index-Based Livestock Insurance (IBLI) coverage, and the respective interaction at the cell and neighborhood level. In columns 2 and 3, we add controls for the cell and neighborhood-level coverage of HSNP. In columns 4 and 5, we control for the number of active aid projects (targeted at agriculture) at the cell and neighborhood level as well as their interaction with the respective rain deficit. The cell level estimates are relegated to Table B-3. Conflict mitigation values in percent are the reduction in the semi-elasticity of the rain deficit on the probability of conflict for a standard deviation increase in the neighborhood IBLI coverage (δ_3/δ_1). The neighborhood variables are based on the 1/distance weighting scheme. HSNP coverage is given by the Hunger and Safety Net Programme (HSNP). Data on World Bank development aid projects comes from (AidData, 2017). Conley standard errors are implemented using the acreg package in Stata (Colella et al., 2019), with a distance cutoff of 200km.

We directly test for the potential that domestic or international interventions confound our effects by adding cell and neighborhood-level proxies for HSNP coverage and the number of active aid projects (targeted to the agricultural sector) as well as their interactions with the rain deficit to our main specification.[12]

Table II documents that the mitigating effect of IBLI of the rain deficit conflict semi-elasticity remains close to identical if we control for the cell and neighborhood-level coverage of HSNP or active aid projects (comparing δ_3 in column 1 to δ_3 in columns 2 and 4 Table II).[13] The mitigation effect of IBLI coverage increases if we control for the interaction at the cell and neighborhood level of the rain deficit with HSNP availability (see column 3), and remains stable when controlling for the interaction of the rain deficit with the number of active aid projects at (see column 5). The neighborhood-level interaction effects of the rain deficit and

[12] Applying the same distance decay in the neighborhood measures as with our treatment variables of interest.
[13] The estimates of cell-level controls from the specifications in Table II are reported in Table B-3.

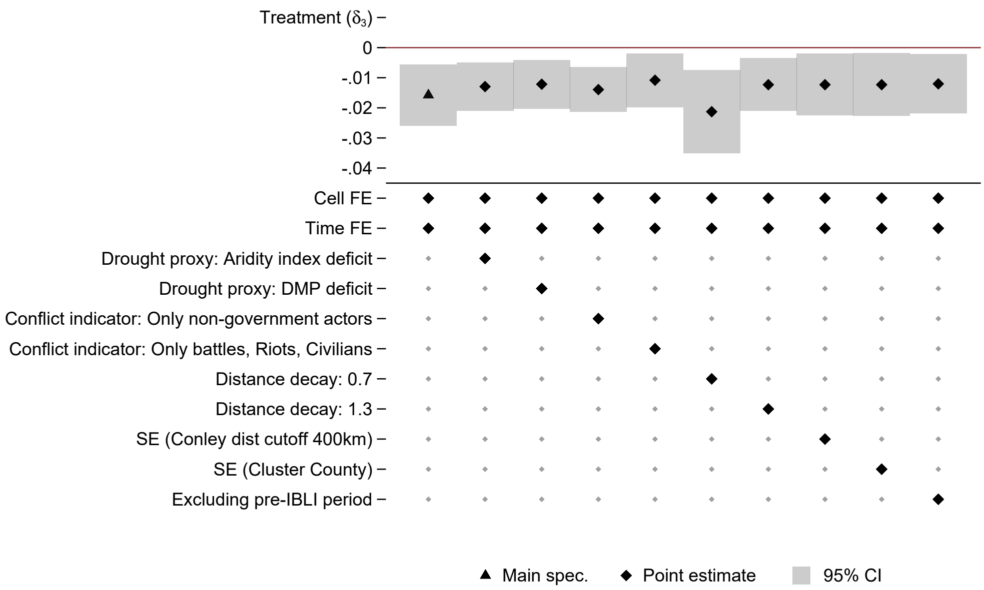
HSNP or aid enter positive but are only borderline significant in the case of HSNP. While we do not interpret those interaction coefficients as causal, they align with previous evidence on the effects of unconditional cash transfers (Premand and Rohner, 2023) and development aid (Nunn and Qian, 2014) on conflict.[14]

In summary, we conjecture that neither HSNP nor development aid projects are likely alternative explanations for the conflict-mitigating effect of IBLI coverage during droughts. Moreover, given the stability of our coefficient of interest, we reject HSNP and aid project coverage as a potential omitted variable.

5.2.3. Further sensitivity tests

We show that our results are robust to alternative drought and conflict proxies, varying assumptions on the computation of the neighborhood measures, and differing calculations of the standard errors (see Figure VII for an overview of the sensitivity analysis).

FIGURE VII
Overview: Sensitivity tests



Notes: The figure reports our coefficient of interest δ_3 over perturbations of our main specification (column 3 of Table I) depicted as a diamond. We introduce alternative drought proxies and conflict measures, add our balancing variables at the cell and neighborhood level, and employ alternative distance decay functions and standard errors. If not indicated differently, the drought proxy is the rain deficit, and 95% CI are based on Conley standard errors with a distance cutoff of 200km. The aridity index is the ratio of precipitation over potential evapotranspiration (Abatzoglou et al., 2018). Dry Matter Productivity (DMP) is a phytomass indicator measured by the dry biomass increase of the vegetation (in kg/ha/year, from the Copernicus Global Land Service 2019).

Figure VII shows that our results are qualitatively similar if we use the Aridity Index or Dry Matter Productivity (DMP) as drought proxies.[15] Moreover, we document that we obtain

[14]The results remain similar when leveraging the number of all aid projects or the log value of aid commitment in millions of US dollars (see Table B-4).

[15]Full results provided in Table B-5.

similar results when focusing only on conflict events that do not involve the government or events classified as battles, riots, or violence against civilians. Figure B-6 in the appendix documents similar patterns for various additional subcategories of events or actors included in ACLED. However, precision is somewhat reduced in part of the specifications due to discarding some conflict observations.

Figure VII also documents that the specific way we construct our neighborhood measures does not drive our results. We test if the results are sensitive to using different spatial decays or alternative cut-offs for the Conley standard errors. Figure B-7 shows that our results hold for a wide range of weight functions ranging from small decays to steep ones ($distance^{-0.5}$ to $distance^{-1.5}$). In fact, we observe that while our coefficients of interest δ_1 and δ_3 scale in response to the chosen distance decays, the estimated mitigation δ_3/δ_1 remains stable. Moreover, we plot the resulting t-statistics from varying the Conley standard errors with cut-offs between 25 and 400km in Figure B-8. We observe that the interaction effect always keeps a t-statistic above two and remains stable when increasing the cutoff from 200km up to 400km. We also observe that our results are not sensitive to excluding the pre-IBLI period (2000 to 2009), i.e., only leveraging the intensity of the neighborhood IBLI coverage across locations over time.

Finally, in addition to our reduced form effect, we can use an instrumental variable specification to approximate the effect of actual IBLI payouts. Given data limitations on the payout data, we only aim to confirm that drought-predicted payouts do not positively affect conflict, which would indicate some omitted variable bias. Note that there is an important limitation to this analysis. We only have information on the occurrence of payouts in IBLI insurance areas during a period, not the payout amount. We assign a value of one for each cell located in an insurance area that received IBLI payouts and zero otherwise. Hence, this reflects only the extensive margin of insurance payouts and assumes a uniform distribution of payouts within the IBLI area. In our first stage, we instrument the inverse-distance weighted IBLI payouts in the neighborhood $IBLI\ \ payout\ \ neighborhood_{i,t}$ (z-standardized to ease interpretation) with the interaction of $Rain\ deficit\ neighborhood_{i,t}$ with $IBLI\ neighborhood_{i,t}$.

Table B-9 in Online Appendix B provides results in line with the idea that the rain deficit in a neighborhood triggers payouts if the neighborhood is covered by IBLI. Moreover, we document that the occurrence of payouts in the neighborhood of a cell significantly reduces the probability of conflict by around 150% compared to the baseline risk.

5.3. Heterogeneity and within rollout-cluster-year evidence

No version of our baseline specification can rule out with certainty that an omitted variable exists; varying across cells and time biases our estimates because it correlates with conflict, the neighborhood rain deficit, and the IBLI rollout. However, our setting allows us to exploit one additional source of variation that offers plausibly exogenous variation in treatment intensity within the spatial IBLI rollout clusters. Specifically, our case study suggests that the drought-conflict relationship is particularly severe in areas characterized by other land use close to pastoral grazing areas, referred to as mixed land use areas by related studies (Eberle et al., 2023; McGuirk and Nunn, 2023).[16]

We leverage differences in expected treatment intensity based on pre-determined mixed land use data to estimate the conflict-mitigating effect within IBLI rollout clusters. $Mixed\ land\ use_i$ is an indicator variable equaling one if a cell is located within an area designated as mixed and zero otherwise. The designation is based on an official land use map published by the government of Kenya in 1984 (prior to our sample), which we digitized and georeferenced for our purposes (see panel A of Figure A-3). Following Eberle et al. (2023), we add interaction with the $Mixed\ land\ use_i$ indicator and our cell and neighborhood level variables for IBLI coverage and the rain deficit to estimate:

$$
\begin{aligned}
Conflict_{i,t} = &+ \delta_1 Rain\ deficit\ neighborhood_{i,t} + \delta_2 IBLI\ neighborhood_{i,t} \\
&+ \delta_3(Rain\ deficit\ neighborhood_{i,t} \times IBLI\ neighborhood_{i,t}) \\
&+ \psi_1(Rain\ deficit\ neighborhood_{i,t} \times Mixed\ land\ use_i) \\
&+ \psi_2(IBLI\ neighborhood_{i,t} \times Mixed\ land\ use_i) \\
&+ \psi_3(Rain\ deficit\ neighborhood_{i,t} \times IBLI\ neighborhood_{i,t} \times Mixed\ land\ use_i) \\
&+ \mathbf{X}_{\mathbf{i,t}}^{'}\xi + \eta_i + \gamma_{r,t} + \epsilon_{i,t}
\end{aligned}
\tag{3}
$$

where our coefficient of interest is ψ_3, capturing the differing drought mitigation effect of IBLI on the conflict between cells located in mixed land use locations and those that are not. $\mathbf{X}_{\mathbf{i,t}}^{'}$ still includes the cell-level variables of IBLI coverage, the rain deficit, and their interactions, but now also contains their respective interactions with the $Mixed\ land\ use_i$. $\gamma_{r,t}$ are IBLI-rollout-cluster times year period fixed effects that replace γ_t. Those $\gamma_{r,t}$ fully capture the influence of potentially omitted variables that correlate with the pattern and timing of the IBLI rollout across rollout clusters r in which a cell i is located. Hence, we only compare the differential impact of IBLI conflict mitigation within rollout clusters over time.

Table III presents results consistent with the idea that IBLI mitigates drought-induced conflict, particularly within mixed land-use locations. Similar to the main result, we phase in the different components of our specification, starting with the rain deficit and IBLI coverage, before including our interactions and triple-interactions of interest and finally $\gamma_{r,t}$. Columns (2) to (4) report our coefficients of interest δ_3 and ψ_3 and confirm that the semi-elasticity of drought on conflict is indeed significantly more mitigated by IBLI coverage in cells located in the mixed land use areas compared to those outside. The conflict mitigating effect is about four times as large in $Mixed\ land\ use_i$ (9 times when fully accounting for IBLI rollout in column 4).[17] This is consistent with the expected treatment heterogeneity. The widespread presence of IBLI in the neighborhood of cells prone to drought-induced conflict should experience the highest

[16] The issue is amplified in locations close to homeland borders (mixed settlement areas) that are more sensitive to the neighborhood effect of droughts on the probability of conflict because droughts push pastoralists into other homelands in which traditional informal conflict resolution mechanisms between the different actors are less developed. Thus increasing the chance of violent incidents.

[17] In robustness exercises, we replace the mixed land use indicator with an indicator for cells below the median distance to ethnic homeland borders to proxy for mixed settlement areas (see panel B Figure A-3). Results of those specifications posit a mitigation effect, which is two to four times compared to cells outside the mixed settlement areas (see Table B-11).

TABLE III
Triple-interaction results: Mixed land use

	Dependent variable: $\text{Conflict}_{i,t}$			
	(1)	(2)	(3)	(4)
NEIGHBORHOOD				
$Rain\ deficit\ (\delta_1)$	0.0731		0.0673	0.1252
	(0.0330)		(0.0291)	(0.0379)
$Rain\ deficit \times Mixed\ land\ use\ (\psi_1)$	-0.0255		-0.0229	-0.0036
	(0.0278)		(0.0259)	(0.0287)
$IBLI\ (\delta_2)$		-0.0160	-0.0243	-0.0135
		(0.0043)	(0.0051)	(0.0071)
$IBLI \times Mixed\ land\ use\ (\psi_2)$		0.0026	-0.0107	-0.0224
		(0.0058)	(0.0073)	(0.0084)
$Rain\ deficit \times IBLI\ (\delta_3)$			-0.0158	-0.0077
			(0.0052)	(0.0057)
$Rain\ deficit \times IBLI \times Mixed\ land\ use\ (\psi_3)$			-0.0183	-0.0301
			(0.0127)	(0.0144)
Dep. var. mean non-mixed land use	0.0226	0.0226	0.0226	0.0226
Dep. var. mean mixed land use	0.0543	0.0543	0.0543	0.0543
Conflict mitigation			-23.41%	-6.19%
Conflict mitigation (mixed land use)			-76.83%	-31.12%
Cell level treatment controls	✓	✓	✓	✓
Cell-fixed effects	✓	✓	✓	✓
Time-fixed effects	✓	✓	✓	–
Rollout-cluster-time-fixed effects	–	–	–	✓
Obs	93400	93400	93400	93400

Notes: The table reports the results of regressing our indicator for any conflict event on the log of rainfall deficit (log(rainfall)×-1) at the neighborhood level, the standardized insurance coverage neighborhood measure, and the interactions of neighborhood level rain deficit and IBLI coverage. The cell level variables are relegated to Table B-10 to conserve space. Moreover, we include interactions of all our variables with an indicator variable for a cell located within a mixed land use area. Mixed land use areas indicate areas where both agriculture, ranging, and pastoral land use are practiced and are obtained from an official land use map of the Kenyan government (1984) prior to our study sample. Conflict mitigation values in percent are the reduction in the semi-elasticity of the rain deficit on the probability of conflict for a standard deviation increase in the neighborhood IBLI coverage (δ_3/δ_1). The neighborhood variables are based on the 1/distance weighting. Conley standard errors are implemented using the acreg package in Stata (Colella et al., 2019), with a distance cutoff of 200km.

reduction in the probability of conflict. We take this as further evidence that the reduction in the drought-conflict semi-elasticity is caused by the presence of IBLI.

6. Channels: Reduced income shocks and migratory pressure

IBLI has the potential to mitigate drought-induced conflict in at least three ways. First, smoothing incomes by buffering against shocks can lower conflict by increasing the opportunity costs of fighting. Jensen et al. (2017) show that IBLI helps to smooth and increase pastoralists' incomes in the initial pilot area over the 2009 to 2012 period. We provide suggestive evidence that IBLI successfully reduces negative drought-related income shocks for pastoralists across Kenya, leveraging six waves of survey data from the Afrobarometer (2005-2019). In Section C-1, we show that local differences in drought exposure between pastoralists residing in districts with IBLI coverage are less predictive of the probability of experiencing hunger compared to those in insurance districts without coverage.

Second, IBLI is linked to smaller herd sizes and higher investments in the health of animals during droughts (see evidence in Jensen et al., 2017). Hence, when a drought shock hits, there are fewer animals to feed, and the pastoralists are, on average, better equipped to survive the shock. Third, IBLI payouts can enable pastoralists to buy forage from markets, conditional on market access and overall supply. All three factors should reduce the migratory pressure, i.e., for a given drought shock, pastoralists migrate not as far away from their traditional grazing grounds, reducing the likelihood of conflict.

To test if IBLI reduced drought-induced migratory pressure for pastoralists in Kenya, we build on the spread-of-violence specification employed by Eberle et al. (2023) for Africa. They calculate the distance between a pastoralist homeland and conflict events involving members of the same group to highlight how negative weather shocks in the homeland lead to conflict elsewhere. We follow their approach and match the actors identified in the georeferenced ACLED conflict events to their ethnic homelands (based on Murdock, 1967), details in Table A-3, and adapt the other variables to the homeland level. The small map in panel A of Figure VIII depicts all ethnic homelands in Kenya and the conflict event locations for all matched conflict events. Absent systematic data on pastoralist migration, we also use this distance measure to proxy for the migratory distances of an ethnic group in a period.

The main map in panel A of Figure VIII illustrates our approach using the Turkana homeland in the northwest of Kenya. It plots all conflict locations involving the Turkana group within our sample, with different colors indicating the respective severity of the rainfall shortage in the Turkana homeland at the time of the event. Pluses and dots indicate if there was IBLI coverage or not. The example illustrates that the frequency of conflict locations involving the Turkana, on average, decreases in distance to the homeland. Moreover, conflict events occur further away from the Turkana homeland if there are more severe droughts (orange and red icons). However, for droughts of similar intensity, the distance between the conflict events and the homeland seems smaller for the years where the Turkana were covered by IBLI (comparing dot- and plus-icons of the same color). In summary, the Turkana example illustrates that our approach is able to capture changes in the migratory pressure related to IBLI coverage.

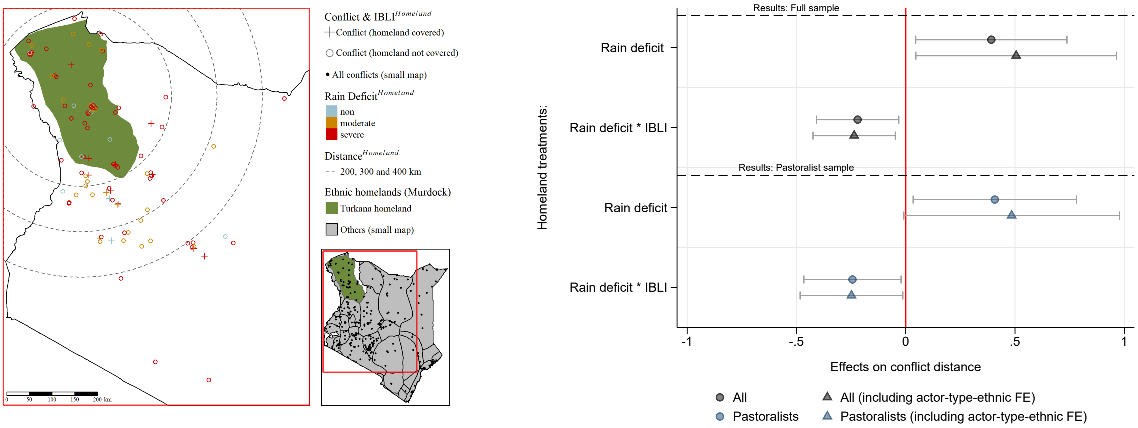
To provide more systematic evidence, we estimate the following specification:

$$\begin{aligned} Log\ Distance_{k,i,e,t}^{Homeland} = {} & \delta_1 Rain\ deficit_{e,t}^{Homeland} + \delta_2 IBLI_{e,t}^{Homeland} \\ & + \delta_3 (Rain\ deficit_{e,t}^{Homeland} \times IBLI_{e,t}^{Homeland}) + \eta_e + \gamma_t + \epsilon_{k,i,e,t} \end{aligned} \tag{4}$$

where Log $Distance_{k,i,e,t}^{Homeland}$ is the log of geographic distance between the geolocation of a conflict event k, involving actor i matched to ethnic homeland e that occurs in period t. $Rain\ deficit_{e,t}^{Homeland}$ is the log averaged rainfall in a homeland during period t, which we multiply by minus one (resulting in the log average rainfall deficit) assigned to all actors i that are matched to homeland e. $IBLI_{e,t}^{Homeland}$ is the share of the homeland e that IBLI covers during period t for actors i matched to homeland e (again z-standardized with mean zero and variance of one). η_e are homeland fixed effects that capture time-invariant features of ethnic homelands like their size, border location, or geographic features, which could bias our results if they correlate with the likelihood of receiving IBLI and experiencing droughts. γ_t are time-fixed effects that capture period-specific shocks and standard errors $\epsilon_{k,i,e,t}$ are clustered at the homeland level, the level of treatment (Abadie et al., 2023).

FIGURE VIII
Droughts, IBLI, and conflict distance to ethnic homelands in Kenya

(A) Turkana illustration (B) Regression results



Notes: Panel A of the figure plots the conflict locations (ACLED, Raleigh et al., 2020) involving Turkana pastoralists over our sample. Different colors indicate the severity of the rainfall deficit (log(rainfall)×-1) in the Turkana homeland (highlighted in green). Blue icons refer to years during abundant rainfall in the Turkana homeland, orange icons refer to locations during moderate droughts in the Turkana homelands, and red icons indicate conflict locations involving Turkana during severe droughts in their homeland. Moreover, the icon type (+ and ∘) indicates if the Turkana homeland was covered by IBLI at the time of the conflict event. The Turkana homeland has been covered by IBLI from 2015 onward (homeland area covered at 98% by IBLI since 2015, see panel A of Figure V). The rings show the 200, 300, and 400km distance from the Turkana homeland centroid. The small map in panel A depicts the different Murdock homelands within Kenya (Murdock, 1967) digitized by Nunn (2008). All conflict locations involve actors we could match to members of the ethnic groups traditionally inhabiting the Murdock homelands. Panel B plots the point estimates (δ_1 and δ_3) from our conflict-location homeland-level regressions from equation 4. The upper part shows the point estimates and 95% confidence intervals based on our full sample. The lower part shows the results using pastoralist groups only. In both parts of the plot, symbols show the results of the same regression using different fixed effects. ∘ represent point estimates including ethnic FE and △ point estimates including an actor-type-ethnic FE. 95% confidence intervals are obtained from standard errors clustered at the homeland (treatment) level. See Table A-3 for details on Actor-Type-Ethnic association and List A-1 for the pastoral classification of ethnic groups.

Our main interest is in δ_1, capturing the effect of the exogenous homeland rainfall shortage, and δ_3, capturing again the extent to which IBLI can mitigate this effect. Panel B of Figure VIII plots the coefficients together with 95% confidence intervals. The black dots show that with our baseline specification, the homeland rainfall deficit has a statistically significant and positive effect on distance. For average homeland IBLI coverage, this can be translated into a rain deficit-distance elasticity of about 0.39. Increasing IBLI coverage by one standard deviation significantly reduces the elasticity by more than half to 0.17.

Those results are robust to replacing the homeland fixed effect with more restrictive actor-type-times-homeland fixed effects. These fixed effects absorb time-invariant differences between three different actor types (unorganized groups, militias, or organized groups), which we assign to each actor i linked to a homeland (see Table A-3). Homelands differ in the composition of actor types, which could bias our results if different actor types react differently to drought and IBLI coverage. Moreover, we can replicate the results when restricting the sample to actors associated with homelands of pastoralist groups (depicted as blue dots and triangles).[18]. Taken together, those results highlight that income smoothing and reduced migratory pressure on pastoralists are important mechanisms by which IBLI reduces conflicts during droughts in the neighborhood of pastoralists.

7. Quantification

IBLI benefits include both the direct benefits on the well-being of pastoralists and the indirect benefits due to mitigating conflict. We can think of those effects as an externality occurring to everyone affected by drought-induced pastoral migration and competition over scarce resources. Within the scope of this paper, we aim to approximate the benefits of this externality alone, thus measuring only one part of the overall benefits.

Any such quantification relies on various assumptions, creating uncertainty about the estimates in several dimensions. Hence, we present the value of the externality as a range of possible benefits. We assess the number of avoided conflict incidents and incident-related fatalities and provide a range of return-to-investment estimates based on insurance subsidies in relation to the "saved" value of statistical life. Thus, we relate the avoided loss of life to the public investment into IBLI (see Carleton et al., 2022, for more general quantification on climate-related loss of live valuation).

Computation of drought-induced conflicts: In a first step, we predict the conflict probability within each of our 4670 cells based on our baseline regression using a restricted sample consisting of only the years prior to the IBLI introduction (2000-2009). We then use the point estimate and the lower and upper bound of the 95% confidence intervals to sum up these probabilities over cells to approximate the number of drought-induced conflict events within a year.[19] The number of country-wide drought-induced conflicts ranges between 34 and 122. Finally, by taking the average fatality per incident during this period, which is 1.37, we can approximate the range of conflict-related deaths due to droughts to be between 47 and 167. Using our regression estimates to extrapolate for all cells in Kenya, a one standard deviation increase in aggregate IBLI coverage avoided between 8 and 28 conflicts and between 11 to 38 conflict-related deaths every year.

Computation return to public investment: To put the conflict externalities in perspective to the public (taxpayer) costs of IBLI (proxied by government subsidies), we calculate the financial return on investment for each dollar spent on IBLI subsidies in 2017 (for which we have cost information). We extrapolate the rainfall-induced loss of life for the 2017 rainfall

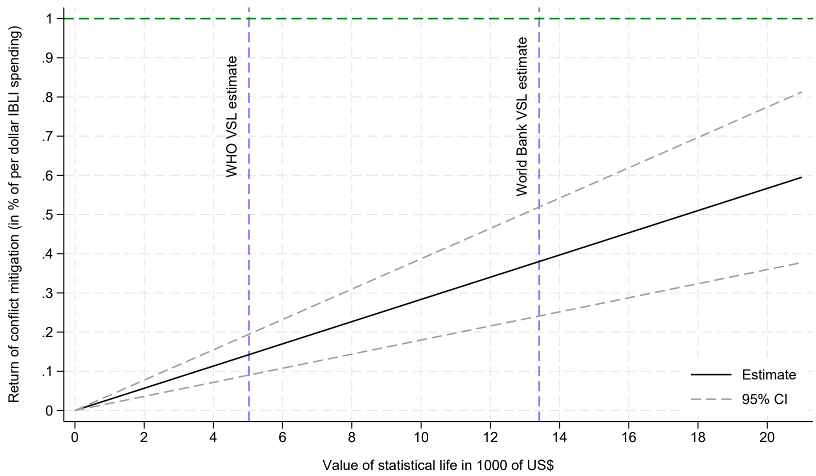
[18]List A-1 documents which groups are classified as pastoral groups. Our classification roughly corresponds to a transhumant pastoral value of above 0.5 as in McGuirk and Nunn (2023), or the nomad/pastoral dummy in Eberle et al. (2023). Reassuringly, the homelands of groups not classified as pastoralists in this way do not receive IBLI coverage.

[19]Note that the aggregation has a natural interpretation, as it sums all the extensive margin probabilities of at least one conflict event in a cell during a period.

values, obtaining a range between 103 and 219 fatalities. Multiplying the obtained fatalities with 0.2279 results in an estimated number of lives saved, ranging from 27 to 57.

Recall that the 22.79% reduction is estimated based on a counterfactual rainfall shock with a one standard deviation higher coverage of IBLI in the neighborhood, which corresponds in the aggregate to IBLI coverage in 2017 compared the absence of the program. This allows us to put a return to investment value on the saved lives in relation to the costs paid by the Government of Kenya in subsidies, documented at 1.2 million US$ in 2017 (Macmillan, 2017).

FIGURE IX
Conflict mitigation return per IBLI dollar spent in 2017 (for VSF)



Notes: The solid black line depicts the return on investment per dollar spent on the IBLI subsidy based on our average estimate for the "Reduction in Drought-Induced Loss of Live" (RDILF). Specifically, return on investment $= \frac{(RDILF \times VSL)}{TCS}$ where VSL is the Value of Statistical Life (in US$) and TCS is the Total Cost of the Subsidies (1.2 million US$). The grey dotted lines represent the upper and lower bound estimates based on the 95% CI around the estimates of drought-induced conflict incidents (avoided due to IBLI). The first blue vertical line represents the World Health Organization Choosing Interventions that are Cost-Effective (WHO-CHOICE, Edejer et al. (2003)) threshold for cost-effectiveness interventions (less than 3× the GDP per capita, 1675 US$ for Kenya in 2017). The second blue vertical line depicts a VSL based on a transfer function from a study conducted by the World Bank ($VSL = 0.00013732 \times (GDP\ per\ capita)^{2.478}$ with VSL and GDP per capita expressed in 2005 international dollars, Milligan et al. (2014)).

We compute the return on investment value of the conflict externality for a whole range of VSL ranging from 0 to 20.000 US$, instead of choosing a specific VSL for Kenya in 2017. The return to investment is calculated by dividing the costs (1.2 million) from the estimated "saved" fatalities valued between 0 and 20.000$ each, which yields the estimated return per dollar for differing VSL.

Figure IX presents the results. The black line plots the return to investment based on saved VSL over our range of VSL. The horizontal green line depicts the size of the conflict externality that would equal the total costs of IBLI for the Government of Kenya. This is reached for a VSL of roughly 22000$ for the upper drought-induced fatality bound, which is about four times the WHO VSL estimate for 2017 and about 50% larger than the World Bank's estimate for the corresponding year. However, our predictions point to the fact that the avoided fatalities alone can account for between roughly 0.1 and 0.22 $ for each dollar spent under the VSL of the WHO and between 0.25 and 0.58$ for each dollar spent for the World Bank VSL estimate.

8. Conclusion

This study provides quasi-experimental evidence that index-based livestock insurance (IBLI) can significantly mitigate drought-induced conflict. We find that higher insurance coverage reduces the drought-conflict elasticity by about 23%. We show that key mechanisms through which IBLI mitigates conflict are by smoothing drought-induced negative income shocks and by reducing the migratory pressure on pastoralists.

Those results highlight the importance of market-based mechanisms such as IBLI as a complement to institutional reforms in mitigating the negative effects of climate change on conflict in low- and middle-income countries. Based on our results, the current "De-risking, Inclusion and Value Enhancement of Pastoral Economies in the Horn of Africa (DRIVE)" (World Bank, 2022) is a promising initiative. DRIVE provides 327.5 million in public funds in combination with 572 million in private capital to expand IBLI in Kenya and make it widely available in Djibouti, Ethiopia, and Somalia over the 2023 to 2027 period. In Kenya alone, IBLI public funding is expected to increase ten times and fully expand coverage to all semi-arid and arid areas. A crucial next step will be to investigate how IBLI intensification in already covered areas affects the conflict mitigation potential. To this end, proper data collection and monitoring are essential, allowing future studies to go beyond the reduced-form effects provided in this paper.

Our findings contribute to the broader literature on conflict-mitigating interventions and the role of technology in development. They highlight the importance of innovative solutions, like remote-sensing-based index-insurance, in addressing the challenges posed by climate change in conflict-prone settings. By demonstrating the potential of IBLI to reduce conflict and promote economic development, our study provides a strong case for well-designed subsidies and other measures (e.g., inducement programs for uptake) to foster insurance adoption in fragile regions, given the additional positive external effects of IBLI on reducing conflict.

The implications of our analysis extend beyond Kenya to other regions experiencing similar challenges. As climate change continues to threaten fragile ecosystems and livelihoods, it is crucial for governments, international organizations, and the private sector to explore and implement innovative solutions like IBLI. These efforts can help reduce the likelihood of conflict, promote economic development, and improve the resilience of communities affected by climate change.

References

Abadie, A., S. Athey, G. W. Imbens, and J. M. Wooldridge (2023). When should you adjust standard errors for clustering? *Quarterly Journal of Economics 138*(1), 1–35.

Abatzoglou, J. T., S. Z. Dobrowski, S. A. Parks, and K. C. Hegewisch (2018). Terraclimate, a high-resolution global dataset of monthly climate and climatic water balance from 1958–2015. *Scientific Data 5*(1), 1–12.

Acampora, M., L. Casaburi, and J. Willis (2022, September). Land rental markets: Experimental evidence from Kenya. Working Paper 30495, National Bureau of Economic Research.

acaps (2022, December). Kenya impact of drought: Turkana and marsabit counties. Accessed December 18, 2023. Available at https://www.acaps.org/fileadmin/Data_Product/Main_media/20221207_acaps_thematic_report_horn_of_africa_impact_of_drought_in_kenya_0.pdf.

AidData (2017). `WorldBank_GeocodedResearchRelease_Level1_v1.4.2` geocoded dataset. Aid Data Williamsburg, VA and Washington, DC. AidData. Accessed on February 9, 2020. Available at http://aiddata.org/research-datasets.

Bazzi, S. and C. Blattman (2014). Economic shocks and conflict: Evidence from commodity prices. *American Economic Journal: Macroeconomics 6*(4), 1–38.

Benami, E., Z. Jin, M. R. Carter, A. Ghosh, R. J. Hijmans, A. Hobbs, B. Kenduiywo, and D. B. Lobell (2021). Uniting remote sensing, crop modelling and economics for agricultural risk management. *Nature Reviews Earth & Environment 2*(2), 140–159.

Berlanda, A., M. Cervellati, E. Esposito, D. Rohner, and U. Sunde (2022, March). Medication against conflict. Discussion Paper 17125, Centre for Economic Policy Research.

Berman, N. and M. Couttenier (2015). External shocks, internal shots: The geography of civil conflicts. *Review of Economics and Statistics 97*(4), 758–776.

Berman, N., M. Couttenier, D. Rohner, and M. Thoenig (2017). This mine is mine! How minerals fuel conflicts in Africa. *American Economic Review 107*(6), 1564–1610.

Blattman, C. and J. Annan (2016). Can employment reduce lawlessness and rebellion? A field experiment with high-risk men in a fragile state. *American Political Science Review 110*(1), 1–17.

Blumenstock, J. E. (2016). Fighting poverty with data. *Science 353*(6301), 753–754.

Borusyak, K. and P. Hull (2023). Non-random exposure to exogenous shocks. *Econometrica*, Forthcoming.

Burke, M., J. Ferguson, and E. Miguel (2024). New evidence on the economic of climate and conflict. *Handbook of the Economics of Conflict*, Forthcoming.

Burke, M., S. M. Hsiang, and E. Miguel (2015). Climate and conflict. *Annual Review of Economics 7*(1), 577–617.

Callaway, B., A. Goodman-Bacon, and P. H. Sant'Anna (2021). Difference-in-differences with a continuous treatment. *arXiv preprint arXiv:2107.02637*.

Carleton, T., A. Jina, M. Delgado, M. Greenstone, T. Houser, S. Hsiang, A. Hultgren, R. E. Kopp, K. E. McCusker, I. Nath, et al. (2022). Valuing the global mortality consequences of climate change accounting for adaptation costs and benefits. *Quarterly Journal of Economics 137*(4), 2037–2105.

Casaburi, L., M. Kremer, S. Mullainathan, and R. Ramrattan (2019, September). Harnessing ICT to increase agricultural production: Evidence from Kenya. Working paper, Private Enterprise Development in Low-Income Countries.

Casaburi, L., M. Kremer, and R. Ramrattan (2019, October). Crony capitalism, collective action, and ICT: Evidence from Kenyan contract farming. Working paper, Private Enterprise Development in Low-Income Countries.

Casaburi, L. and J. Willis (2018). Time versus state in insurance: Experimental evidence from contract farming in Kenya. *American Economic Review 108*(12), 3778–3813.

Chantarat, S., A. G. Mude, C. B. Barrett, and M. R. Carter (2013). Designing index-based livestock insurance for managing asset risk in northern Kenya. *Journal of Risk and Insurance 80*(1), 205–237.

Chelanga, P., D. Khalai, F. Fava, and A. Mude (2017). Determining insurable units for index-based livestock insurance in northern Kenya and southern Ethiopia. ILRI Research Brief 83, ILRI, Nairobi, Kenya.

Colella, F., R. Lalive, S. O. Sakalli, and M. Thoenig (2019, August). Inference with arbitrary clustering. Discussion Paper 12584, IZA Institute of Labor Economics.

Conley, T. G. (1999). GMM estimation with cross sectional dependence. *Journal of Econometrics 92*(1), 1–45.

Crost, B., J. Felter, and P. Johnston (2014). Aid under fire: Development projects and civil conflict. *American Economic Review 104*(6), 1833–1856.

Crost, B., J. H. Felter, and P. B. Johnston (2016). Conditional cash transfers, civil conflict and insurgent influence: Experimental evidence from the Philippines. *Journal of Development Economics 118*, 171–182.

Dube, O. and J. F. Vargas (2013). Commodity price shocks and civil conflict: Evidence from Colombia. *Review of Economic Studies 80*(4), 1384–1421.

Eberle, U. J., D. Rohner, and M. Thoenig (2023). Heat and hate: Climate security and farmer-herder conflicts in Africa. *Review of Economics and Statistics*, Forthcoming.

Edejer, T. T.-T., R. Baltussen, T. Tan-Torres, T. Adam, A. Acharya, R. Hutubessy, D. Evans, and C. Murray (2003). *Making choices in health: WHO guide to cost-effectiveness analysis*, Volume 1. World Health Organization.

Fabregas, R., M. Kremer, and F. Schilbach (2019). Realizing the potential of digital development: The case of agricultural advice. *Science 366*(6471), p. eaay3038.

FAO (2018). *Pastoralism in Africa's drylands: Reducing risks, addressing vulnerability and enhancing resilience.* Food and Agriculture Organization of the United Nations (FAO), Rome, Italy.

Fava, F. and A. Vrieling (2021). Earth observation for drought risk financing in pastoral systems of Sub-Saharan Africa. *Current opinion in environmental sustainability 48*, 44–52.

Fava, F. P., D. Nathaniel, J. Sina, G. Andrew, and B. Maher (2021). *Building financial resilience in pastoral communities in Africa: Lessons learned from implementing the Kenya Livestock Insurance Program (KLIP).* World Bank, Washington, D.C.

Fetzer, T. (2020). Can workfare programs moderate conflict? Evidence from India. *Journal of the European Economic Association 18*(6), 3337–3375.

Fetzer, T. and S. Kyburz (2022). Cohesive institutions and political violence. *Review of Economics and Statistics*, 1–46.

Flintan, F. E., R. Behnke, and C. Neely (2013). Natural resource management in the drylands in the horn of Africa: Brief prepared by a technical consortium hosted by CGIAR in partnership with the FAO investment centre. *Technical Consortium Brief*.

Gassebner, M., P. Schaudt, and M. H. Wong (2023). Armed groups: Competition and political violence. *Journal of Development Economics 162*, 103052.

Gehring, K., L. C. Kaplan, and M. H. Wong (2022). China and the World Bank—how contrasting development approaches affect the stability of African states. *Journal of Development Economics 158*, 102902.

Gehring, K., S. Langlotz, and S. Kienberger (2023). Stimulant or depressant? Resource-related income shocks and conflict. *Review of Economics and Statistics*, 1–47.

Grossman, H. I. (1991). A general equilibrium model of insurrections. *American Economic Review*, 912–921.

Gruber, J. (1994). The incidence of mandated maternity benefits. *American Economic Review 84*(3), 622–641.

H.-O. Pörtner, D.C. Roberts, M. T. E. P. K. M. A. A. M. C. S. L. S. L. V. M. A. O. B. R. e.

(2022). *IPCC, 2022: Climate Change 2022: Impacts, Adaptation, and Vulnerability. Contribution of Working Group II to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*. Cambridge, UK and New York, USA: Cambridge University Press.

Hodler, R., P. Schaudt, and A. Vesperoni (2023, January). Mining for peace. Discussion Paper 17807, Centre for Economic Policy Research.

Hsiang, S. M., M. Burke, and E. Miguel (2013). Quantifying the influence of climate on human conflict. *Science 341*(6151), 1235367.

Huffman, G., E. Stocker, D. Bolvin, E. Nelkin, and J. Tan (2017). Gpm imerg final precipitation l3 1 month 0.1 degree x 0.1 degree v06. *Greenbelt, MD, Goddard Earth Sciences Data and Information Services Center (GES DISC)*. Accessed November 13, 2022. Available at: https://doi.org/10.5067/GPM/IMERG/3B-HH/06.

Jensen, N. D., C. B. Barrett, and A. G. Mude (2017). Cash transfers and index insurance: A comparative impact analysis from northern Kenya. *Journal of Development Economics 129*, 14–28.

Johnson, L., B. Wandera, N. Jensen, and R. Banerjee (2019). Competing expectations in an Index-based livestock insurance project. *Journal of Development Studies 55*(6), 1221–1239.

Lengoiboni, M., A. K. Bregt, and P. van der Molen (2010). Pastoralism within land administration in Kenya—The missing link. *Land Use Policy 27*(2), 579–588.

Macmillan, S. (2017). Record payouts being made by Kenya government and insurers to protect herders facing historic drought. Accessed June 14, 2023. Available at https://news.ilri.org/2017/02/21/record-payouts-being-made-by-kenya-government-and-insurers-to-protect-herders-facing-historic-drought/.

McGuirk, E. and M. Burke (2020). The economic origins of conflict in Africa. *Journal of Political Economy 128*(10), 3940–3997.

McGuirk, E. F. and N. Nunn (2023). Transhumant pastoralism, climate change, and conflict in Africa. *Review of Economic Studies*, Forthcoming.

Michalopoulos, S. and E. Papaioannou (2016). The long-run effects of the scramble for Africa. *American Economic Review 106*(7), 1802–1848.

Miguel, E., S. Satyanath, and E. Sergenti (2004). Economic shocks and civil conflict: An instrumental variables approach. *Journal of Political Economy 112*(4), 725–753.

Milligan, C., A. Kopp, S. Dahdah, and J. Montufar (2014). Value of a statistical life in road safety: A benefit-transfer function with risk-analysis guidance based on developing country data. *Accident Analysis Prevention 71*, 236–247.

Morelli, M. and D. Rohner (2015). Resource concentration and civil wars. *Journal of Development Economics 117*, 32–47.

Moscona, J., N. Nunn, and J. A. Robinson (2020). Segmentary lineage organization and conflict in Sub-Saharan Africa. *Econometrica 88*(5), 1999–2036.

Murdock, G. P. (1967). Ethnographic atlas: A summary. *Ethnology 6*(2), 109–236.

Nunn, N. (2008). The long-term effects of Africa's slave trades. *Quarterly Journal of Economics 123*(1), 139–176.

Nunn, N. and N. Qian (2014). US food aid and civil conflict. *American Economic Review 104*(6), 1630–1666.

Olden, A. and J. Møen (2022). The triple difference estimator. *The Econometrics Journal 25*(3), 531–553.

Premand, P. and D. Rohner (2023). Cash and conflict: Large-scale experimental evidence from Niger. *American Economic Review: Insights*, Forthcoming.

Raleigh, C., A. Linke, and C. Dowd (2020). Armed Conflict Location and Event Dataset (ACLED). *Codebook Version 2*.

Rohner, D. (2022). Mediation, military, and money: The promises and pitfalls of outside interventions to end armed conflicts. *Journal of Economic Literature*, Forthcoming.

Rohner, D. and A. Saia (2019, February). Education and conflict: Evidence from a policy experiment in Indonesia. Discussion Paper 13509, Centre for Economic Policy Research.

Sakketa, T. G., D. Maggio, and J. McPeak (2023, March). The protective role of index insurance in the experience of violent conflict: Evidence from Ethiopia. Working Paper 385, Households in Conflict Network.

Salehyan, I., C. S. Hendrix, J. Hamner, C. Case, C. Linebarger, E. Stull, and J. Williams (2012). Social conflict in Africa: A new database. *International Interactions 38*(4), 503–511.

Sundberg, R. and E. Melander (2013). Introducing the UCDP Georeferenced Event Dataset. *Journal of Peace Research 50*(4), 523–532.

Vrieling, A., M. Meroni, A. Shee, A. G. Mude, J. Woodard, C. K. de Bie, and F. Rembold (2014). Historical extension of operational NDVI products for livestock insurance in Kenya. *International Journal of Applied Earth Observation and Geoinformation 28*, 238–251.

World Bank (2022). World bank boosts pastoral economies and climate action in the horn of africa. Accessed June 14, 2023. Available at https://www.worldbank.org/en/news/press-release/2022/06/23/world-bank-boosts-pastoral-economies-and-climate-action-in-the-horn-of-africa.

Online appendix – Insuring Peace: Index-based livestock insurance, droughts, and conflict

Appendices

A. Data Appendix

A-1. Variables and sources

Measures of conflict

- *Conflict*: Indicator variable that is one if at least one conflict event is recorded in a cell in a given year.
- *I(Battles)*: Indicator variable that is one if at least one battle event occurs in a given year and cell.
- *I(Battles, riots, violence civilians)*: Indicator variable that is one if at least one battle, riots, or violence against civilians event occurs in a given year and cell.
- *I(Explosion)*: Indicator variable that is one if at least one explosion event occurs in a given year and cell.
- *I(Government)*: Indicator variable that is one if at least one conflict involving the State occurs in a given year and cell.
- *I(Non-government)*: Indicator variable that is one if at least one conflict that does not involve the state occurs in a given year and cell.
- *I(Outside metropolis)*: Indicator variable that takes value one if a conflict event occurs outside the Nairobi and Mombasa metropolitan area in a given year and cell (OECD/SWAC, 2020).
- *I(Pastoral)*: Indicator variable that is one if at least one conflict event involving a pastoral ethnic group occurs in a given year and cell. Following McGuirk and Nunn (2023), we define pastoral as an ethnic group with ″Nomadic or fully migratory″ or ″Seminomadic″ settlement patterns from Murdock's Geographic Atlas (Murdock, 1967).
- *I(Protests)*: Indicator variable that is one if at least one protest event occurs in a given year and cell.
- *I(Riot)*: Indicator variable that is one if at least one riot event occurs in a given year and cell.
- *I(Strategic deployment)*: Indicator variable that is one if at least one strategic deployment occurs in a given year and cell.
- *I(Violence civilians)*: Indicator variable that is one if at least one event with violence against civilians occurs in a given year and cell.

Source: ACLED (Raleigh et al., 2020)

Index-Based Livestock Insurance (IBLI) variables

- *IBLI coverage*: Indicator variable that is one if the centroid of a cell is located within an insurance district that offers the Index-Based Livestock Insurance (IBLI) in a given year.
- *IBLI*: Indicator variable of *IBLI coverage* for a given cell and year.
- *IBLI coverage, ever*: Indicator variable that is one if the centroid of a cell is located within an insurance district that received or will receive the Index-Based Livestock Insurance (IBLI) at some point between 2010 and 2020.
- *IBLI eligible*: Indicator variable that is one if the centroid of a cell is located within an insurance district that is eligible to the Index-Based Livestock Insurance (IBLI) in a given year.
- *IBLI not eligible*: Indicator variable that is one if the centroid of a cell is not located within an insurance district that is eligible to the Index-Based Livestock Insurance (IBLI) in a given year.
- *IBLI neighborhood*: Continuous variable computed taking the inverse-distance weighted average of the *IBLI coverage* of all surrounding cells of a given cell.
- *IBLI payouts*: Indicator variable that is one if the centroid of a cell is located within an insurance district that received payouts from the Index-Based Livestock Insurance (IBLI) in a given year.
- $IBLI^{Homeland}$: Indicator variable that is one if an ethnic homeland is covered by IBLI for a given year. Ethnic homelands are defined according to Murdock's Geographic Atlas (Murdock, 1967).
- *IBLI availability*: Indicator variable that is one if an insurance district is covered by the Index-Based Livestock Insurance (IBLI) program in a given year.
- *Time to IBLI coverage*: Variable that uses a year until coverage received count (from 2010 onward) for the set of cells that are ever covered by the Index-Based Livestock Insurance (IBLI) over our sample period.

Source: The International Livestock Research Institute (ILRI)

Drought proxies

- *Log AI*: Continuous variable constructed taking the logarithm of the Aridity Index, where AI is calculated as the ratio of precipitation (P) over Potential Evapotranspiration (PET). The index is computed using monthly data provided by the TerraClimate dataset and aggregated at the cell year level. World Atlas Desertification (Cherlet, 2018), TerraClimate (Abatzoglou et al., 2018)
- *AI deficit*: Continuous variable constructed taking minus *Log AI*.

- *Rainfall*: Continuous variable indicating the mean precipitation in millimeters per year for a given year and cell. NASA's GPM product (Huffman et al., 2017).

- *Log rainfall*: Continuous variable constructed by taking the logarithm of *Rainfall* for a given year and cell.

- *Rain deficit*: Continuous variable constructed by taking minus the logarithm of (*Rainfall*) for a given year and cell.

- *Rain deficit neighborhood*: Continuous variable constructed by taking the inverse distance weighted average of *Rain deficit* for all surrounding cells of a given cell.

- *Rain deficit*^{Homeland}: Continuous variable indicating the average *Rain deficit* in a given ethnic homeland. Rainfall data are taken from NASA's GPM product (Huffman et al., 2017). Ethnic homelands are defined according to Murdock's Geographic Atlas (Murdock, 1967).

- *Log DMP*: Continuous variable constructed by taking the logarithm of the Dry Matter Productivity (DMP) for a given year and cell. The DMP is a continuous variable indicating the overall growth rate or dry biomass (phytomass) increase of the vegetation (kg/ha/year). Copernicus Global Land Service (2019).

- *DMP deficit*: Continuous variable constructed by taking minus *Log DMP*.

Land use and land cover, climate and biomes

- *Arid climate*: Indicator variable that takes value one for cells predominantly located in the arid climate zone following the Köppen-Geiger climate classification (Beck et al., 2018).

- *Desert & Shrubland*: Indicator variable that takes value one for cells predominantly located in the desert & shrubland climate zone following the Köppen-Geiger climate classification (Beck et al., 2018).

- *Mixed land use area*: Indicator variable that takes value one if a cell is predominantly located in an area defined as Mixed land use following the historical land use map of Kenya (Kenya Rangeland Ecological Monitoring Unit, 1983).

- *Rangeland share*: Continuous variable indicating the rangeland share for a given cell (in %) built following the Climate Change Initiative Land Cover (CCI CL) classification (European Space Agency (ESA)).

- *Excess salt*: Dummy variable that takes value one if the soil of a given cell is defined to have excess salt (cells associated with classes 3, 4, or 5 (Severe limitations, Very severe limitations, and Mainly non-soil)) (Nachtergaele et al., 2009).

- *Nutrient availability*: Dummy variable that takes value one if the nutrient availability of a given cell is defined to be of poor quality (cells associated with classes 3, 4, or 5 (Severe limitations, Very severe limitations, and Mainly non-soil)) (Nachtergaele et al., 2009).

- *Nutrient retention capacity*: Dummy variable that takes value one if the nutrient retention capacity of a given cell is defined to be of poor quality (cells associated with classes 3, 4, or 5 (Severe limitations, Very severe limitations, and Mainly non-soil)) (Nachtergaele et al., 2009).
- *Oxygen availability*: Dummy variable that takes value one if the soil oxygen availability of a given cell is defined to be of poor quality (cells associated with classes 3, 4, or 5 (Severe limitations, Very severe limitations, and Mainly non-soil)) (Nachtergaele et al., 2009).
- *Rooting condition*: Dummy variable that takes value one if the soil rooting condition of a given cell is defined to be of poor quality (cells associated with classes 3, 4, or 5 (Severe limitations, Very severe limitations, and Mainly non-soil)) (Nachtergaele et al., 2009).
- *Toxicity*: Dummy variable that takes value one if the soil of a given cell is defined to be toxic (cells associated with classes 3, 4, or 5 (Severe limitations, Very severe limitations, and Mainly non-soil)) (Nachtergaele et al., 2009).
- *Workability*: Dummy variable that takes value one if the soil workability of a given cell is defined to be of poor quality (cells associated with classes 3, 4, or 5 (Severe limitations, Very severe limitations, and Mainly non-soil)) (Nachtergaele et al., 2009).

Other variables

- *Log pop*: Continuous variables constructed taking the logarithm of population estimates from the GHSL population raster data (2000 estimates) for a given cell.
- *Mixed settlement*: Indicator variable that is one if the geographic distance from a cell's centroid to the border of an ethnic homeland is less than the median distance of the sample. Murdock's Geographic Atlas (Murdock, 1967).
- *Log distance*^{Homeland}: Continuous variable indicating the geographic distance between the geolocation of a conflict event (Raleigh et al., 2020) involving an actor matched to an ethnic homeland from the Murdock's Geographic Atlas Murdock (1967).
- *Dist. border*: Continuous variable indicating the geographic distance between a cell's centroid and the national border of Kenya.
- *Dist. capital*: Continuous variable indicating the geographic distance between a cell's centroid and Nairobi.
- *Value of statistical life*:
  - *WHO VSL estimate*: Indicator variable indicating the VSL dollar amount (the threshold for cost-effectiveness intervention) following the World Health Organization Choosing Intervention that is Cost -Effective (WHO-CHOICE Edejer et al. (2003)); less than $3\times$ the GDP per capita, 167US$ in 2017.

  - *WB VSL estimate*: Indicator variable indicating the VSL dollar amount following the World Bank that uses a transfer function ($VSL = 0.00013732 \times (GDPpercapita)^{2.478}$) with VSL and GDP expressed in 2005 international dollars (Milligan et al., 2014).

- *HSNP*: Indicator variable that takes value one if the cell's centroid is located in an area that is eligible to receive payouts from Hunger and Safety Net Programme (HSNP) for a given year.

Afrobarometer variables

- $Hunger_{r,g,w}$: Indicator variable for wether a respondent r surveyed on gridcell g during wave w has experienced hunger during the last 12 month. The indicator takes one if the respondent answers the question, "Over the past year, how often, if ever, have you or anyone in your family gone without enough food to eat?" with either "Always", "Many times", or "Several times" and zero otherwise.

- *Pastoral group identification*: Indicator variable if a respondent identifies with one of the pastoral groups in our sample List A-1. The underlying Afrobarometer question is: "What is your tribe? [Interviewer: Prompt if necessary: You know your ethnic or cultural group.]...".

- *Female*: Indicator variable taking unity if the respondent indicates to be a woman and zero otherwise.

- *Age*: Age in years, self-reported by the respondent.

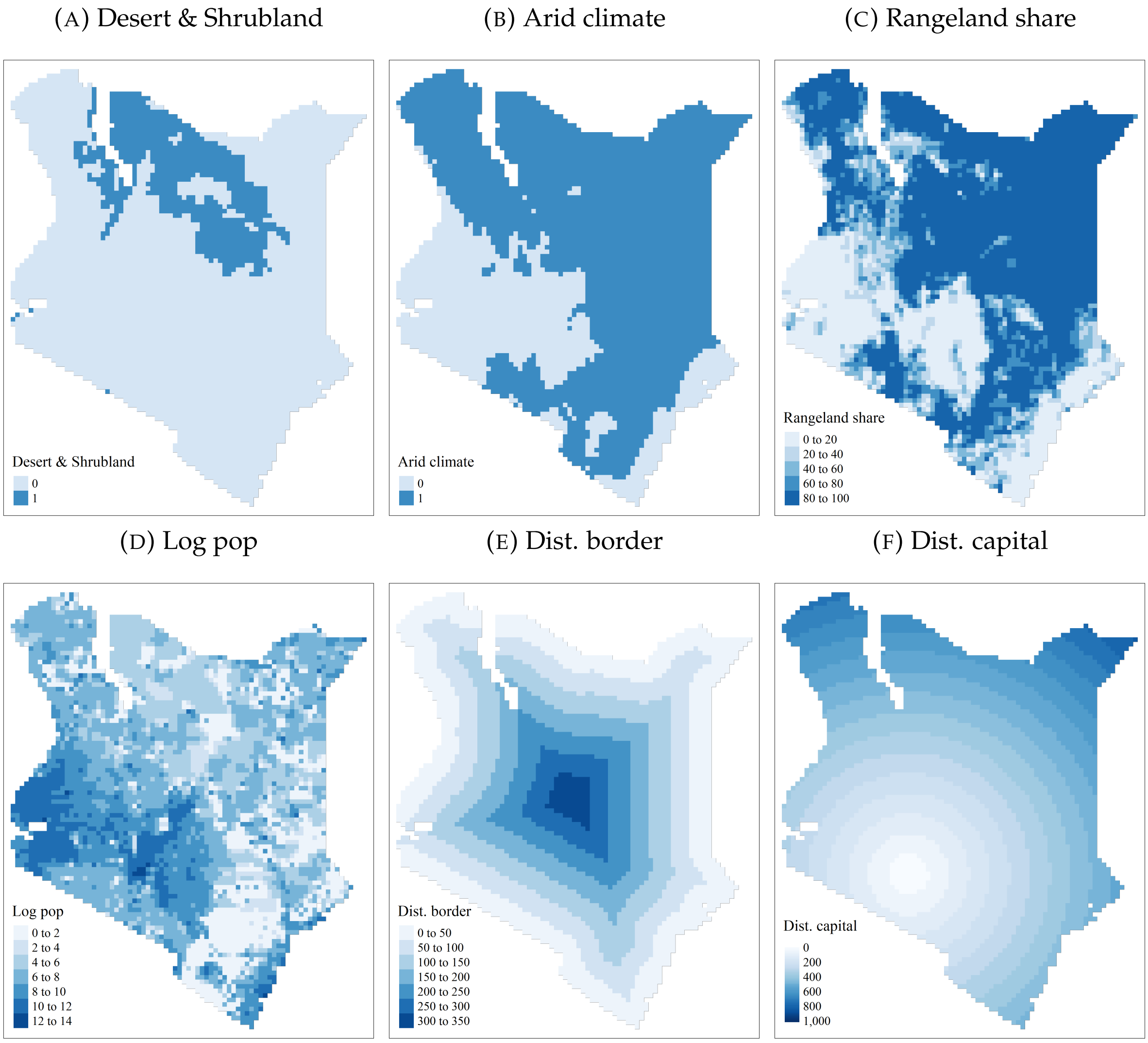
- *Urban*: Indicator variable equal to one if the survey location is in an urban location and zero otherwise.

- *Completed primary education*: Indicator variable equal to one if the respondent indicates to have completed primary education and zero otherwise. Based on self-reported education level.

- *Some secondary education*: Indicator variable equal to one if the respondent indicates to have completed primary education and taken some secondary education, and zero otherwise. Based on self-reported education level.

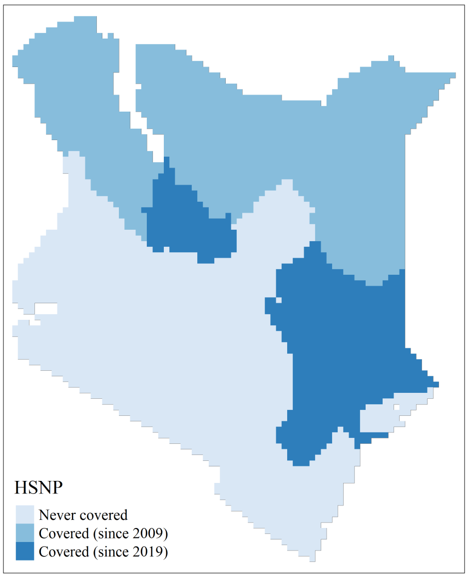
- *Secondary education or more*: Indicator variable equal to one if the respondent indicates to have completed secondary education or more and zero otherwise. Based on self-reported education level.

FIGURE A-1
Land cover, population and distances



Notes: Panels A and B show the desert & shrubland and the arid climate zone indicator variable that takes value one for cells predominantly located in these climate zones following the Köppen-Geiger climate classification from Beck et al. (2018). The share of rangeland in panel C is built following the Climate Change Initiative Land Cover (CCI CL) classification (European Space Agency (ESA)). Panel D shows the log of population from the GHSL population raster data (estimates from 2000). Panel E shows the geographic distance between a cell's centroid and the national border of Kenya. Panel G shows the geographic distance between a cell's centroid and Nairobi. All variables are processed at a 0.1° × 0.1° grid-cell level.

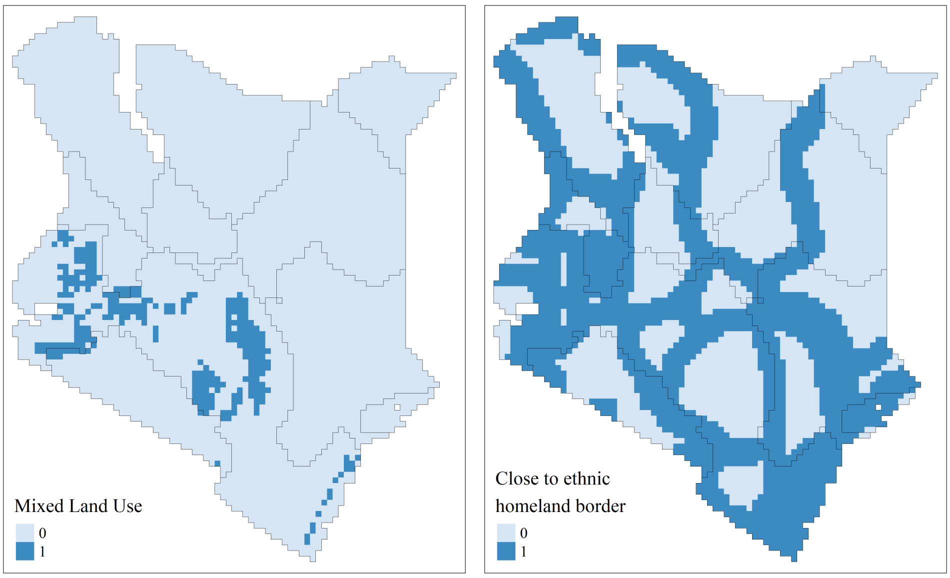
FIGURE A-2
Human Safety Net Program (HSNP) rollout



Notes: The figure represents the area eligible to receive payouts from the Human Safety Net Program (HSNP), first in 2009 and then in 2019.

FIGURE A-3
Mixed land use and distance to ethnic homeland

(A) Mixed land use | (B) Close to ethnic homeland border

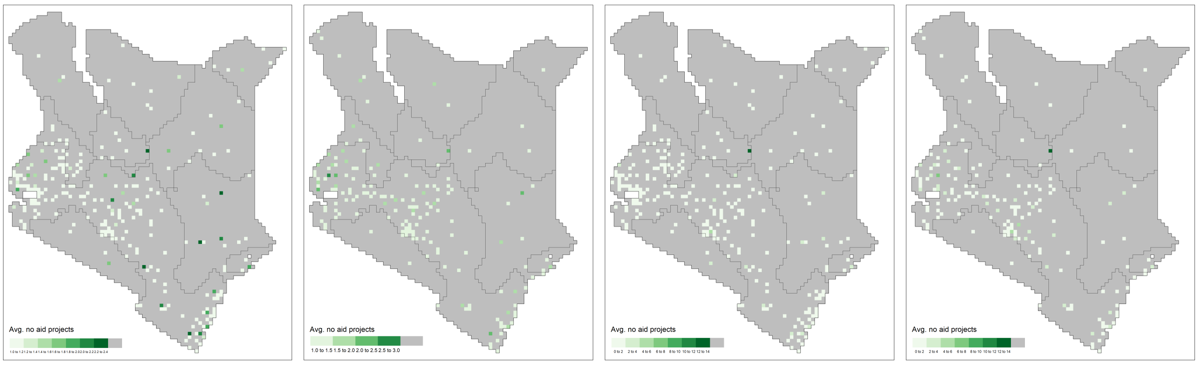


Notes: Panel A plots the Mixed land use area indicator that takes value one if a cell is predominantly located in an area defined as Mixed land use following the historical land use map of Kenya (Kenya Rangeland Ecological Monitoring Unit, 1983). Panel (B) shows the proximity to an ethnic homeland border. The variable is one if the geographic distance from a cell's centroid to the border of an ethnic homeland is less than the median distance of the sample (Murdock's Geographic Atlas (Murdock, 1967)). The variables are processed at a $0.1^\circ \times 0.1^\circ$ grid-cell level.

FIGURE A-4

Development aid projects coverage (pre- and IBLI-rollout period)

(A) Pre-rollout (agricultural projects) | (B) Post-rollout (agricultural projects) | (C) Pre-rollout (all projects) | (D) Post-rollout (all projects)

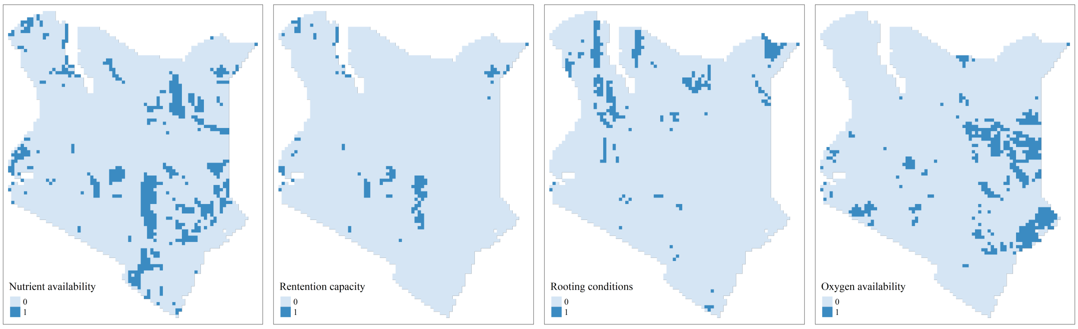


Notes: Panel A of the figure plots the average number of development aid projects (classified as agricultural aid) running in the pre-rollout period (2001-2009). Panel B plots the average number of development aid projects (classified as agricultural aid) running in the rollout period (2010-2020). Panels C and D report the corresponding distributions of all aid projects. Variables are processed at a 0.1° × 0.1° grid-cell level. World Bank aid projects and commitments are obtained from AidData (2017).

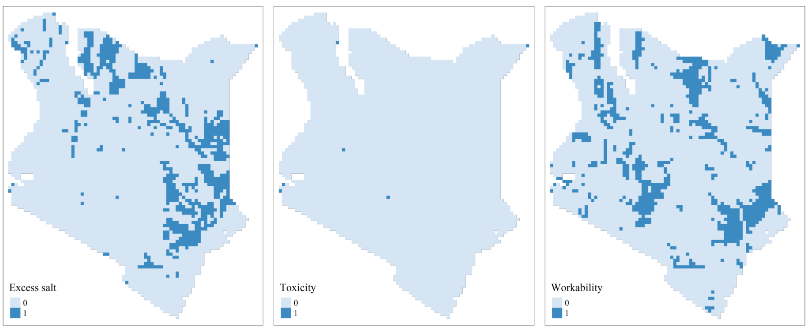
FIGURE A-5

Soil characteristics

(A) Nutrient availability | (B) Nutrient retention cap. | (C) Rooting conditions | (D) Oxygen availability



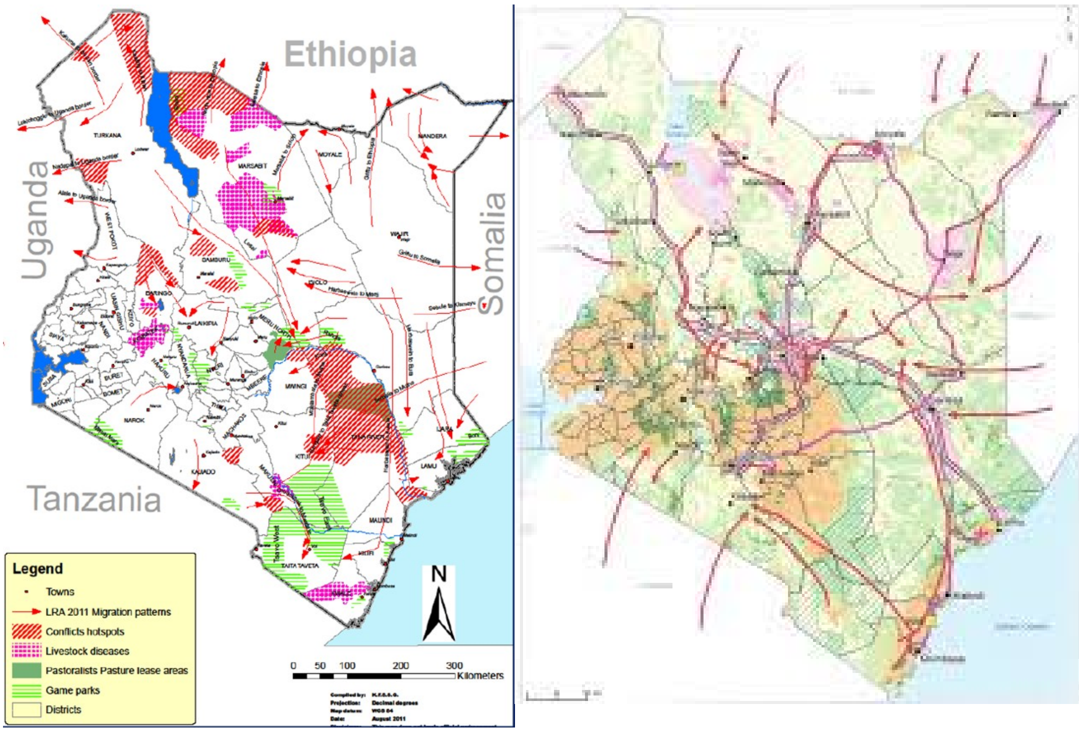
(E) Excess salts | (F) Toxicity | (G) Workability



Notes: The soil characteristics are indicator variables taking value 1 (poor soil quality) if a cell's location is associated with class 3, 4, or 5 (severe limitations, very severe limitations, and mainly non-soil). Harmonized World Soil Database (Nachtergaele et al., 2009). All variable are processed at a 0.1° × 0.1° grid-cell level.

FIGURE A-6
Pastoral migration route estimates for all Kenya

(A) 2011 (B) 2013



Notes: Beyond the Isiolo-Meru-Samburu region shown in Figure II, there are no reliable, comprehensive, and precise estimates of migration routes for the whole country. The figures shown here indicate that estimates by different authors differ considerably. This could be due to actual changes in migration routes between years that were analyzed or differences in assessment. Moreover, comparing those figures to Figure II reveals that those estimates for the whole country cover only a small fraction of the existing routes. Panel A is a sketch of the migration routes as depicted in (KFSSG) (2012) figure 1.3. Panel B sketches some of the migration routes during 2013 as depicted in figure 2 of Flintan et al. (2013).

TABLE A-1
Summary statistics

Variable	Mean	SD	Min	Max	N
Cell sample					
Outcomes					
Conflict$_{i,t}$	0.02	0.15	0.00	1.00	93,400
I(Government)	0.01	0.10	0.00	1.00	93,400
I(Non-Government)	0.02	0.14	0.00	1.00	93,400
I(pastoral)	0.00	0.06	0.00	1.00	93,400
I(Outside metropolis)	0.01	0.11	0.00	1.00	93,400
I(Battles, riots, violence civilians)	0.02	0.14	0.00	1.00	93,400
I(Battle)	0.01	0.08	0.00	1.00	93,400
I(Riot)	0.01	0.09	0.00	1.00	93,400
I(Violence civilians)	0.01	0.10	0.00	1.00	93,400
I(Protests)	0.01	0.09	0.00	1.00	93,400
I(Explosions)	0.00	0.04	0.00	1.00	93,400
I(Strategic deployments)	0.00	0.03	0.00	1.00	93,400
Treatments (cell level)					
Log rain deficit	2.72	0.57	1.10	5.05	93,400
Log aridity index deficit	1.08	0.69	-1.56	3.00	93,400
Log dry matter productivity deficit	-3.03	0.94	-4.96	0.08	93,000
IBLI, eligible	0.71	0.45	0.00	1.00	93,400
IBLI (coverage ever)	0.60	0.49	0.00	1.00	93,400
IBLI coverage	0.20	0.40	0.00	1.00	93,400
Log rain deficit * IBLI coverage	0.61	1.22	0.00	4.99	93,400
Log aridity index deficit * IBLI coverage	0.29	0.61	-0.40	3.00	93,400
Log dry matter productivity deficit * IBLI coverage	-0.52	1.08	-4.77	0.08	93,000
Mixed land use (farmland and pastoral)	0.10	0.29	0.00	1.00	93,400
Mixed settlement area	0.50	0.50	0.00	1.00	93,400
HSNP coverage	0.24	0.43	0.00	1.00	93,400
Controls (cell level)					
No. of agricultural aid projects	0.03	0.21	0.00	4.00	93,400
No. of aid projects (all)	0.04	0.36	0.00	19.00	93,400
Log of population	5.89	3.15	0.00	13.99	93,400
Rangeland share	0.65	0.38	0.00	1.00	93,400
Arid climate	0.70	0.46	0.00	1.00	93,400
Desert & shrubland (biomes)	0.17	0.37	0.00	1.00	93,400
Log distance border	4.30	1.12	-3.47	5.85	93,400
Log distance capital	5.75	0.61	1.52	6.69	93,400
Poor soil quality	0.41	0.49	0.00	1.00	93,400
Poor nutrient availability	0.12	0.33	0.00	1.00	93,400
Poor retention capacity	0.03	0.16	0.00	1.00	93,400
Poor rooting condition	0.05	0.23	0.00	1.00	93,400
Poor oxygen availability	0.09	0.29	0.00	1.00	93,400
High excess of salt	0.16	0.36	0.00	1.00	93,400
High toxicity	0.00	0.04	0.00	1.00	93,400
Poor workability condition	0.17	0.38	0.00	1.00	93,400
Treatments (neighborhood level)					
Log rain deficit	-0.24	0.34	-1.19	0.96	93,400
Log aridity index deficit	-1.95	0.39	-3.11	-0.75	93,400
Log dry matter productivity deficit	-6.16	0.36	-6.92	-4.74	93,400
IBLI coverage	0.00	1.00	-0.75	2.61	93,400
IBLI payouts	-0.00	1.00	-0.42	4.88	93,400
Log rain deficit * IBLI coverage	-0.03	0.44	-2.32	0.75	93,400
Log aridity index deficit * IBLI coverage	-0.06	2.02	-6.68	2.11	93,400

Continued on next page

Table A-1 – *Continued from previous page*

Variable	Mean	SD	Min	Max	N
Log dry matter productivity deficit * IBLI coverage	0.06	6.05	-16.72	5.14	93,400
Controls (neighborhood level)					
HSNP coverage	-0.00	1.00	-0.98	2.40	93,400
No. of aid projects	-0.00	1.00	-1.75	5.10	93,400
No. of aid agricultural projects	0.00	1.00	-1.55	6.86	93,400
Actor-homeland (Murdock) sample					
Log distance Actor-location to homeland (Conflict)	4.63	0.95	1.55	6.58	1,003
Avg. log rain deficit (Homeland)	2.50	0.57	1.43	4.27	1,003
IBLI coverage (Homeland)	0.00	1.00	-0.36	3.53	1,003
Pastoral group (Homeland)	0.56	0.50	0.00	1.00	1,003
Afrobarometer respondent sample					
$Hunger_{r,g,w}$ (Respondent)	0.30	0.46	0.00	1.00	7,882
Rain deficit cell (Respondent)	2.19	0.49	1.34	3.99	7,882
IBLI coverage cell (Respondent)	0.04	0.20	0.00	1.00	7,882
Pastoral group identification (Respondent)	0.20	0.40	0.00	1.00	7,882
Female indicator (Respondent)	0.50	0.50	0.00	1.00	7,882
Age in years (Respondent)	35.89	13.78	18.00	99.00	7,882
Urban indicator (Respondent)	0.37	0.48	0.00	1.00	7,882
Completed primary education (Respondent)	0.20	0.40	0.00	1.00	7,852
Some secondary education (Respondent)	0.13	0.34	0.00	1.00	7,852
Secondary education or more (Respondent)	0.44	0.50	0.00	1.00	7,852

Notes: The table reports the summary statistics of our variables of interests across samples. See Data Appendix A for more details on the variables.

TABLE A-2
Correlation of drought proxies

Panel (A): Cell level cross-correlations			
	Log rain deficit	Log AI	Log DMP
Log rain deficit	1		
Log AI	-0.839	1	
Log DMP	-0.811	0.807	1
Panel (B): Neighborhood level cross-correlations			
	Log rain deficit	Log AI	Log DMP
Log rain deficit	1		
Log AI	-0.906	1	
Log DMP	-0.537	0.567	1

Notes: The table reports the correlations between our different drought proxies. Rain deficit (log(rainfall × -1)) has been computed using rainfall data from NASA's GMP product (Huffman et al., 2017). The Aridity Index (AI) is the ratio of precipitation over potential evapotranspiration (Abatzoglou et al., 2018). Dry Matter Productivity (DMP) is a phytomass indicator measured by the dry biomass increase of the vegetation (in kg/ha/year, from the Copernicus Global Land Service 2019).

TABLE A-3
ACLED actor, actor type, ethnic group matches

Murdock group	Actor	Actor type
Bararetta	Ajuran Ethnic Militia	Semi-organized
Bararetta	Auliyan Ethnic Militia	Semi-organized
Bararetta	Degodia Ethnic Militia	Semi-organized
Bararetta	Garre Ethnic Militia	Semi-organized
Bararetta	Jibril Clan Militia	Semi-organized
Bararetta	Matan Clan Militia	Semi-organized
Bararetta	Somali Ethnic Militia	Semi-organized
Bararetta	Unidentified Ethnic Militia (Bararetta)	Semi-organized
Bararetta	Unorganized group members (Bararetta)	Unorganized
Bararetta	Wardei Ethnic Militia	Semi-organized
Boni	Abduwak Ethnic Militia	Semi-organized
Boni	Unorganized group members (Boni)	Unorganized
Boran	Borana Ethnic Militia	Semi-organized
Boran	Gabra Ethnic Militia	Semi-organized
Boran	OLF: Oromo Liberation Front	OLF: Oromo Liberation Front
Boran	Orma Ethnic Militia	Semi-organized
Boran	Oromo Ethnic Militia	Semi-organized
Boran	Unorganized group members (Boran)	Unorganized
Dorobo	Kapshoi Clan Militia	Semi-organized
Dorobo	Ndorobo Ethnic Militia	Semi-organized
Dorobo	Ogiek Ethnic Militia	Semi-organized
Dorobo	Unorganized group members (Dorobo)	Unorganized
Gusii	Kisii Communal Militia	Semi-organized
Gusii	Kisii Ethnic Militia	Semi-organized
Gusii	Unorganized group members (Gusii)	Unorganized
Kikuyu	Akorino Sect Militia	Semi-organized
Kikuyu	Kiambu Ethnic Militia	Semi-organized
Kikuyu	Kieleweke	Semi-organized
Kikuyu	Kikuyu Ethnic Militia	Semi-organized
Kikuyu	Mau Mau War Veterans	Semi-organized
Kikuyu	Mungiki Militia	Mungiki Militia
Kikuyu	Unorganized group members (Kikuyu)	Unorganized
Kipsigi	Kipsigi Ethnic Militia	Semi-organized
Kipsigi	Unorganized group members (Kipsigi)	Unorganized
Luo	Luo Ethnic Militia	Semi-organized
Luo	Unorganized group members (Luo)	Unorganized
Masai	Maasai Ethnic Militia	Semi-organized
Masai	Moran Ethnic Militia	Semi-organized
Masai	Siria Clan Militia	Semi-organized
Masai	Unorganized group members (Masai)	Unorganized
Meru	Imenti Ethnic Militia	Semi-organized
Meru	Meru Ethnic Militia	Semi-organized
Meru	Tharaka Ethnic Militia	Semi-organized
Meru	Unorganized group members (Meru)	Unorganized
Nandi	Marakwet Ethnic Militia	Semi-organized
Nandi	Nandi Ethnic Militia	Semi-organized
Nandi	Unorganized group members (Nandi)	Unorganized
Pokomo	Pokomo Ethnic Militia	Semi-organized
Pokomo	Unorganized group members (Pokomo)	Unorganized
Samburu	Isiolo Communal Militia (Samburu)	Semi-organized
Samburu	Pokot Ethnic Militia (Samburu)	Semi-organized
Samburu	Samburu Ethnic Militia	Semi-organized

Continued on next page

Table A-3 – *Continued from previous page*

Murdock group	Actor	Actor type
Samburu	Unorganized group members (Samburu)	Unorganized
Sonjo	Sonjo Ethnic Militia	Semi-organized
Suk	Unorganized group members (Suk)	Unorganized
Topotha	Toposa Ethnic Militia	Semi-organized
Turkana	Turkana Ethnic Militia	Semi-organized
Turkana	Unidentified Ethnic Militia (Turkana)	Semi-organized
Turkana	Unorganized group members (Turkana)	Unorganized
Wanga	Kabasiran Clan Militia	Semi-organized
Wanga	Luhya Ethnic Militia	Semi-organized
Wanga	Unorganized group members (Wanga)	Unorganized

Notes: The table reports the Murdock groups in our sample (Murdock, 1967), the actors reported in ACLED (Raleigh et al., 2020) matched by the association between actor and Murdock groups, and the actor type classification we employ. We classify actors as "unorganized" if they are just members of an ethnic group/tribe but are not organized as a militia. Militias are classified as "semi-organized" because multiple smaller village- or regional militias can be encompassed by the actor name. Actors with an individual name and a formal organization are classified as an individual actor-type (e.g. The Oromo Liberation Front).

List A-1
Murdock homelands pastoral/non-pastoral classification

Bajun, Bararetta (P), Boni, Boran (P), Chaga, Didinga (P), Digo, Dorobo (P), Duruma, Gusii, Gyriama, Jie, Kamba, Karamojong (P), Keyu, Kikuyu, Kipsigi, Luo, Masai (P), Meru, Nandi, Pare, Pokomo, Rendile (P), Reshiat (P), Sabei (P), Samburu (P), Sanye (P), Segeju, Shambala, Shashi, Sonjo, Suk (P), Teita, Topotha, Turkana (P), Wanga,

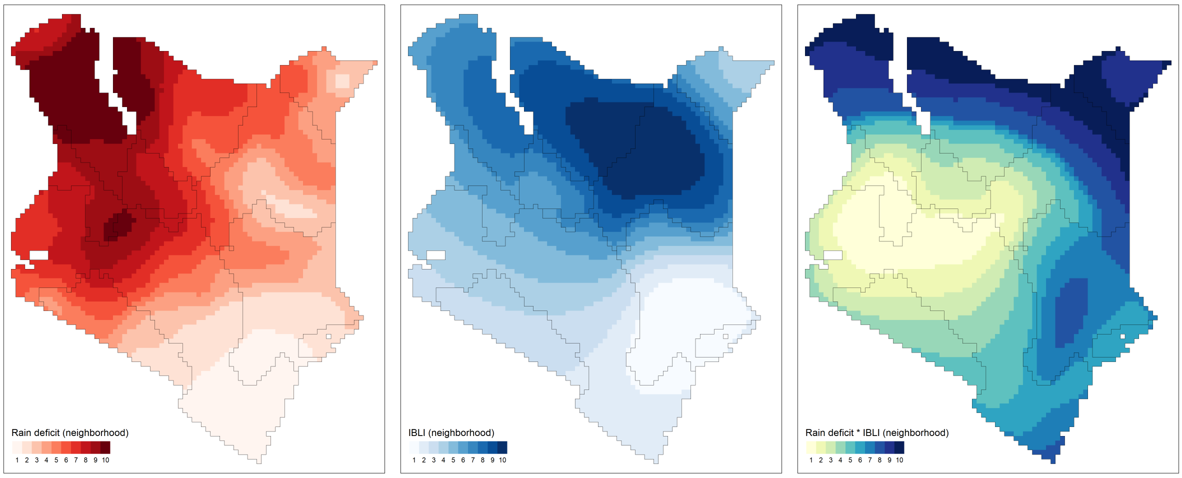
Notes: The list reports our classification of Murdock groups into pastoral and non-pastoral. Groups that are classified as pastoral groups have a (P) next to their name. Our classification corresponds to the nomad classification in (Eberle et al., 2023), roughly a transhumant pastoralists value of 0.5 and higher in McGuirk and Nunn (2023)

B. Additional results

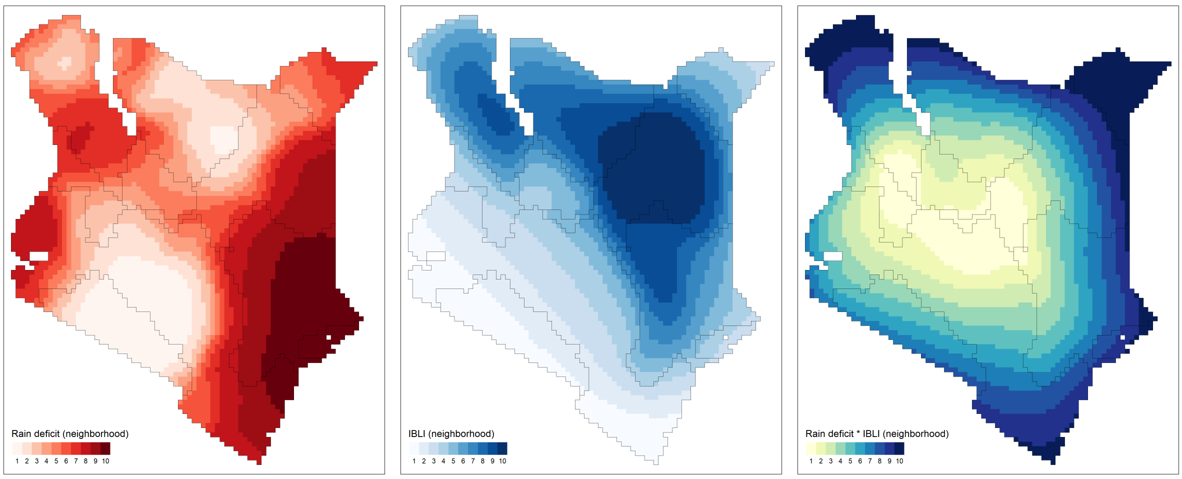
B-1. Additional figures

FIGURE B-1
Variation variables of interest (neighborhood)

(A) Rain deficit 2014/2015 | (B) IBLI 2014/2015 | (C) Rain deficit ×IBLI 2014/2015

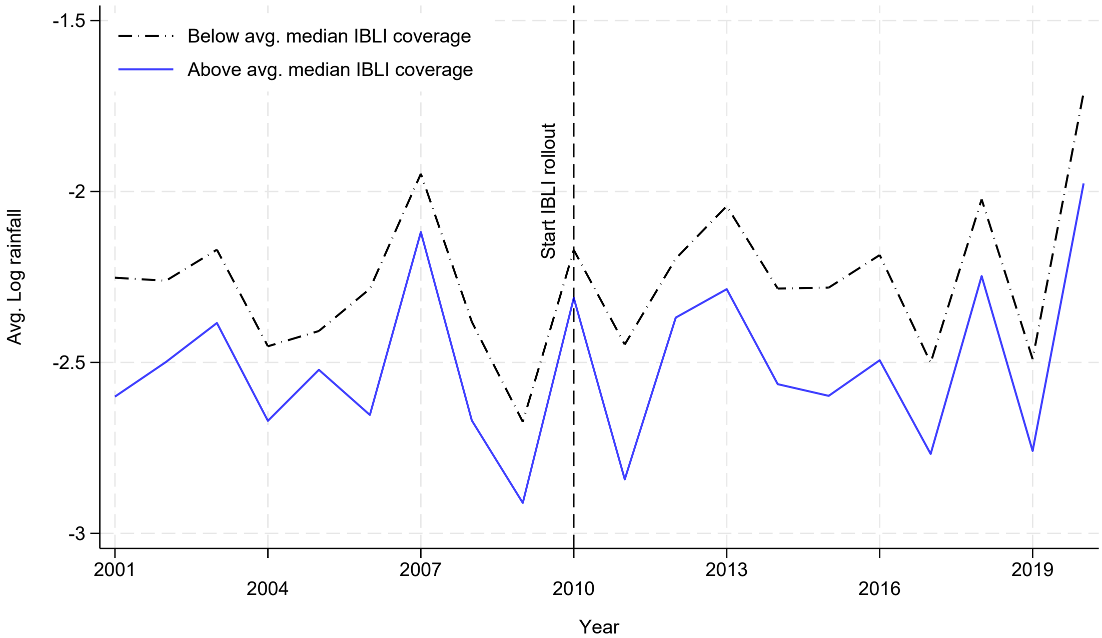


(D) Rain deficit 2015/2016 | (E) IBLI 2015/2016 | (F) Rain deficit ×IBLI 2015/2016



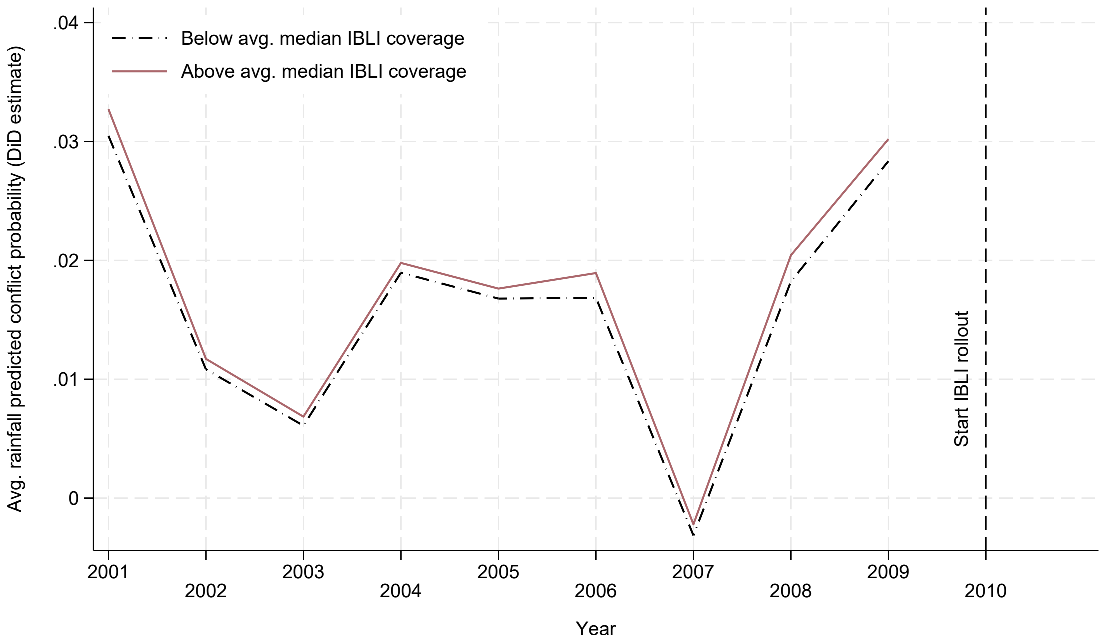
Notes: The figure plots the identifying variation used in our main specification, specifically our neighborhood variables of interest net of cell and period fixed effects. Panel A of the figure plots the average neighborhood version of the rain deficit (log rainfall ×-1) between October 2014 and September 2015. Panel B plots the corresponding neighborhood measure of IBLI coverage, and panel C the interaction of the two. Panels D to F plot the same variables for the October 2015 to September 2016 period. To ease interpretation, we plot the variables in percentiles.

FIGURE B-2
Rainfall trends over IBLI coverage



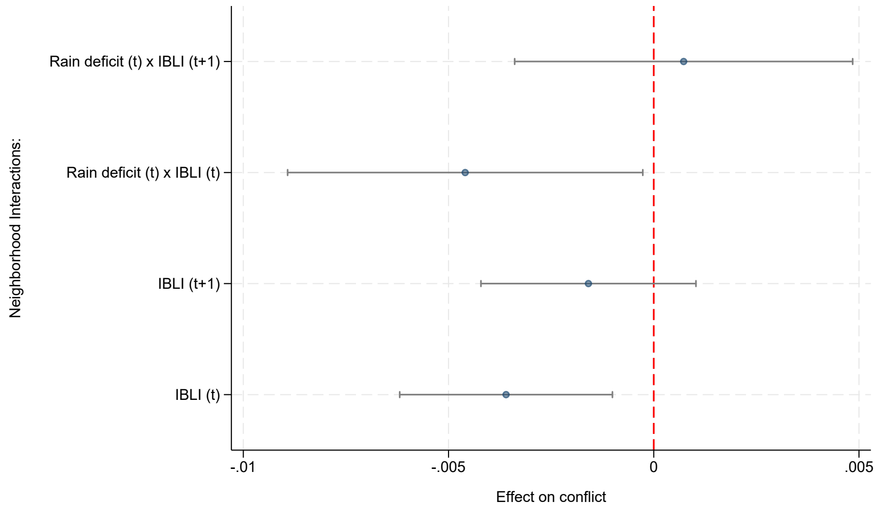
Notes: The figure plots the average neighborhood rainfall for cells with below and above time-averaged IBLI coverage

FIGURE B-3
Pre-IBLI drought-conflict elasticity trends



Notes: The figure plots the conflict predicted by the rain deficit in the cell and neighborhood (based on column 1 of Table I) for cells that have above (below) median IBLI coverage in the neighborhood over the pre-rollout period of IBLI.

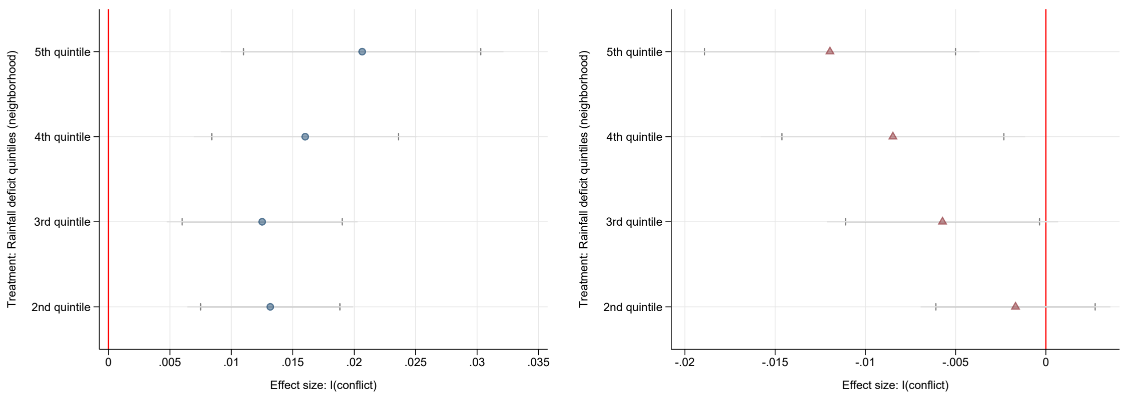
FIGURE B-4
Controlling for next periods IBLI coverage



Notes: The figure plots the coefficients of interest for adding a lead in the IBLI coverage and the interaction with current rainfall to our main specification reported in column 3 of Table I. The 95% confidence intervals are based on Conley standard errors are implemented using the acreg package in Stata (Colella et al., 2019), with a distance cutoff of 200km.

FIGURE B-5
Rainfall quintiles

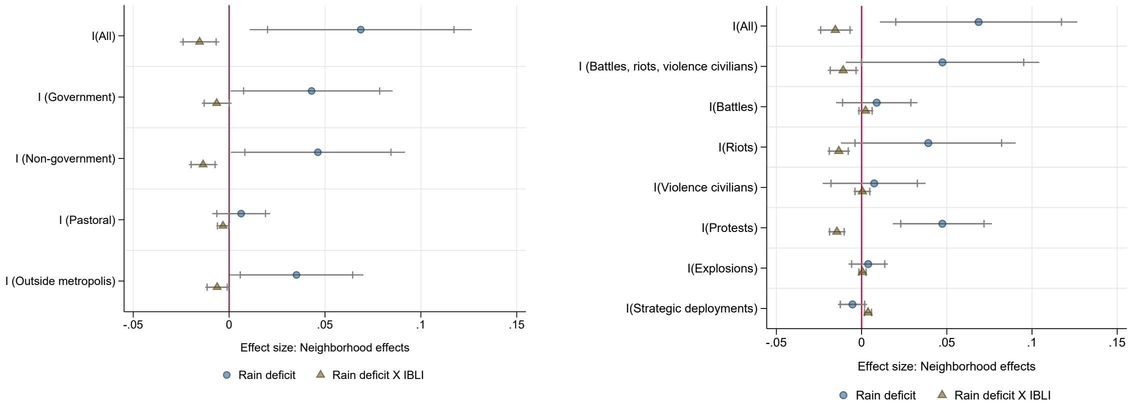
(A) Rain deficit (δ_1) (B) Rain deficit $\times$ IBLI (δ_3)



Notes: Panels A and B of the figure report our point estimates of interest (δ_1 and δ_3) and 95% confidence intervals for binned rainfall deficits (quintiles) following the specification in column 3 of Table I. Panel A reports the obtained δ_1 for the differing rain deficit quintiles. Panel B reports the corresponding δ_3. The 95% confidence intervals are based on Conley standard errors, implemented using the acreg package in Stata (Colella et al., 2019), with a distance cutoff of 200km.

FIGURE B-6
Main results: Alternative conflict measures

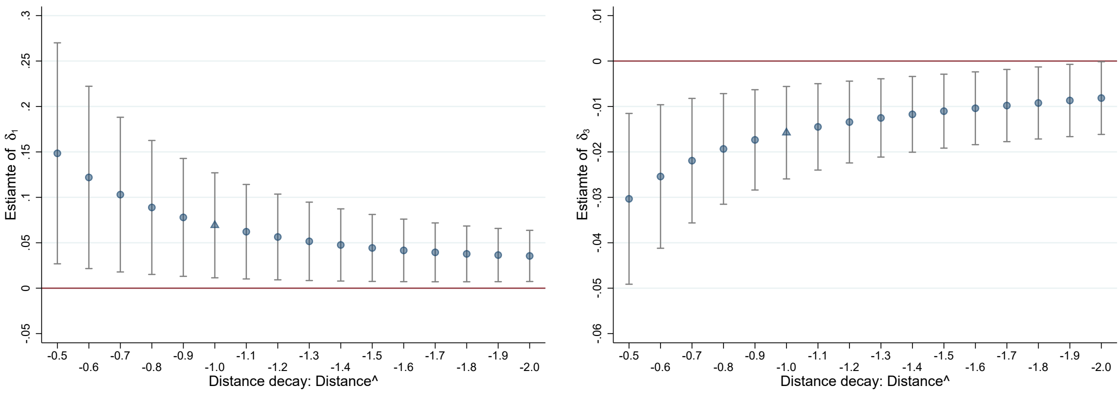
(A) Different actors (B) Different events



Notes: The figure reports our point estimates of interest (δ_1 and δ_3) and 95% confidence intervals for alternative conflict measures from the ACLED dataset (Raleigh et al., 2020) regressed on the specification in column 3 of Table I. *All* considers all associated actors and types of incidents. *Government* are incidents that involve the government (*Non-Government* when it does not). We also use an indicator for at least a conflict event on the groups of events consisting of *Battles, Riots, Violence against civilians* as in Eberle et al. (2023). *Riots* are only riots incidents. *Civilians* are incidents involving violent events against civilians. *Pastoral* are incidents that involve an ethnic group defined as pastoralist following the classification by McGuirk and Nunn (2023). Panel A reports the obtained δ_1. Panel B reports the corresponding δ_3. The 95% confidence intervals are based on Conley standard errors, implemented using the acreg package in Stata (Colella et al., 2019), with a distance cutoff of 200km.

FIGURE B-7
Main results: Alternative distance decay neighborhood effects

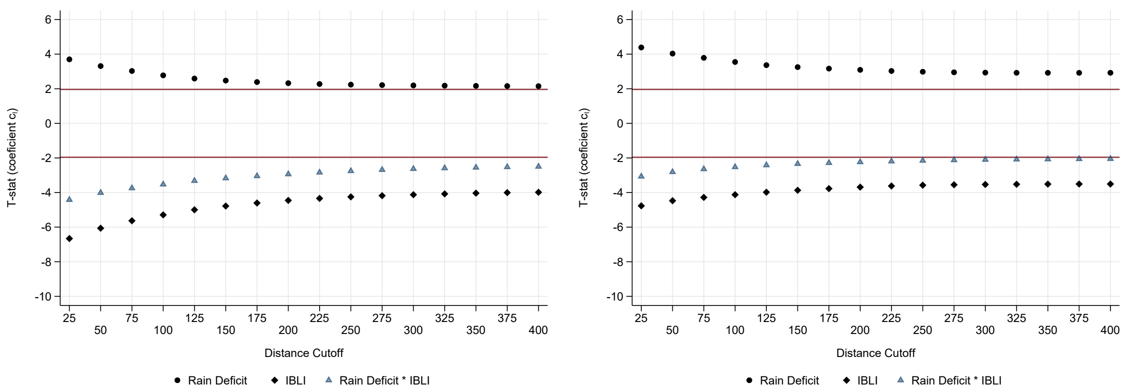
(A) Rain deficit (Neighborhood) (B) Rain deficit $\times$ IBLI (Neighborhood)



Notes: The figure plots the point estimates and 95% confidence intervals of the log of neighborhood rainfall deficit (log(rainfall) $\times -1$) (panel A), and its interaction with the standardized neighborhood IBLI coverage (panel B) for varying distance decays (based on our main specification column (3) of Table I). The confidence intervals in grey are based on Conley standard errors, implemented using the acreg package in Stata (Colella et al., 2019), with a distance cutoff of 200km.

FIGURE B-8
Main results: Spatial cutoffs

(A) Cell & year FE (B) Cell & pastoral-area-year FE



Notes: Panel A of the figure plots the t-statistics for our coefficients of interest (δ_1, δ_2, and δ_3) based on our baseline specification (column 3 of Table I) for varying distance cutoffs in the spatial clustering. Panel B replicates Panel A but adds IBLI-area-period fixed effects, corresponding to the specification reported in column 4 of Table I.

B-2. Additional tables

TABLE B-1
IBLI payout in insurance district

	Dependent variable: IBLI payout			
	(1)	(2)	(3)	(4)
IBLI	0.4032	1.1732	0.0853	1.4769
	(0.0548)	(0.1085)	(0.0770)	(0.1817)
DROUGHT PROXY				
$Rain\ deficit$	0.3147			0.7397
	(0.3116)			(0.3594)
$DMP\ deficit$		0.0857		0.0369
		(0.0997)		(0.0807)
$AI\ deficit$			-0.3236	-0.1344
			(0.0553)	(0.0664)
DROUGHT PROXY × IBLI AVAILABILITY				
$Rain\ deficit$	0.5092			0.3978
	(0.0835)			(0.1127)
$DMP\ deficit$		0.2900		0.3029
		(0.0303)		(0.0474)
$AI\ deficit$			0.2324	-0.1766
			(0.0464)	(0.0564)
$Conflict_{i,t+1}$	0.0098	0.0020	0.0086	0.0035
	(0.0339)	(0.0330)	(0.0344)	(0.0306)
$Conflict_{i,t}$	0.0040	-0.0090	-0.0016	-0.0057
	(0.0297)	(0.0310)	(0.0287)	(0.0286)
$Conflict_{i,t-1}$	-0.0015	-0.0169	-0.0010	-0.0011
	(0.0348)	(0.0334)	(0.0340)	(0.0334)
Unit-fixed effects	✓	✓	✓	✓
Time-fixed effects	✓	✓	✓	✓
Adj. R2	0.6982	0.7038	0.6913	0.7221
Obs	765	765	765	765

Notes: The table reports the regression results of regressing an indicator for IBLI payouts on different drought proxies; rainfall deficit (log(rainfall) $\times -1$) from NASA's GMP product (Huffman et al., 2017), Dry Matter Productivity deficit (log(DMP) $\times -1$) from the Copernicus Land Service (2019), and the aridity index deficit (ratio of precipitation over potential evapotranspiration, (log(AI) $\times -1$)) from Abatzoglou et al. (2018), as well as their interaction with IBLI availability within insurance districts (or Unit Insurance Area UIA, see Fava et al., 2021) over our periods. Index-Based Livestock Insurance (IBLI) coverage and payouts are given by the International Livestock Research Institute (ILRI) and conflict events from ACLED (Raleigh et al., 2020). The different variables are processed at a 0.1° × 0.1° grid-cell level. Unit-fixed effects are UIA fixed effects. Standard errors are clustered at the IBLI-unit level.

TABLE B-2
Baseline results (cell level coefficients)

	Dependent variable: Conflict$_{i,t}$		
	(1)	(2)	(3)
CELL			
$Rain\ deficit$	-0.0073		-0.0089
	(0.0059)		(0.0059)
$IBLI$		-0.0097	-0.0409
		(0.0046)	(0.0145)
$Rain\ deficit \times IBLI$			0.0134
			(0.0049)
Dep. var. mean	0.0246	0.0246	0.0246
Cell-fixed effects	✓	✓	✓
Time-fixed effects	✓	✓	✓
Obs	93400	93400	93400

Notes: The table reports the cell level variables omitted from the output in Table I. Conley standard errors are implemented using the acreg package in Stata (Colella et al., 2019), with a distance cutoff of 200km.

TABLE B-3
Relief results (cell level coefficients)

	Dependent variable: Conflict$_{i,t}$				
		Controlling for relief variable:			
		HSNP		*Aid*	
	(1)	(2)	(3)	(4)	(5)
CELL					
$Rain\ deficit$	-0.0089	-0.0089	-0.0065	-0.0108	-0.0118
	(0.0059)	(0.0060)	(0.0061)	(0.0060)	(0.0060)
$IBLI$	-0.0409	-0.0427	-0.0512	-0.0505	-0.0529
	(0.0145)	(0.0143)	(0.0164)	(0.0149)	(0.0149)
$Rain\ deficit \times IBLI$	0.0134	0.0138	0.0172	0.0166	0.0172
	(0.0049)	(0.0049)	(0.0056)	(0.0051)	(0.0050)
NEIGHBORHOOD RELIEF CONTROLS					
$Relief$		0.0025	0.0235	-0.0066	0.0295
		(0.0041)	(0.0134)	(0.0107)	(0.0330)
$Rain\ deficit \times Relief$			-0.0087		-0.0159
			(0.0046)		(0.0139)
Cell level treatment controls	✓	✓	✓	✓	✓
Cell-fixed effects	✓	✓	✓	✓	✓
Time-fixed effects	✓	✓	✓	✓	✓
Obs	93400	93400	93400	93400	93400

Notes: The table reports the cell level variables omitted from the output in Table II. Conley standard errors are implemented using the acreg package in Stata (Colella et al., 2019), with a distance cutoff of 200km.

TABLE B-4

Accounting for development aid

	Dependent variable: Conflict$_{i,t}$			
	Controlling for:			
	No aid project		*Log aid commitments*	
	(1)	(2)	(3)	(4)
NEIGHBORHOOD				
Rain deficit (δ_1)	0.0777	0.0772	0.0751	0.0755
	(0.0300)	(0.0295)	(0.0300)	(0.0301)
IBLI (δ_2)	-0.0244	-0.0238	-0.0244	-0.0242
	(0.0051)	(0.0051)	(0.0051)	(0.0050)
Rain deficit $\times$ *IBLI* (δ_3)	-0.0166	-0.0170	-0.0157	-0.0156
	(0.0052)	(0.0052)	(0.0051)	(0.0051)
NEIGHBORHOOD CONTROLS				
Aid	0.0163	-0.0005	0.0235	0.0274
	(0.0091)	(0.0165)	(0.0153)	(0.0208)
Rain deficit $\times$ *Aid*		0.0102		-0.0037
		(0.0076)		(0.0087)
CELL CONTROLS				
Rain deficit	-0.0107	-0.0163	-0.0100	-0.0075
	(0.0060)	(0.0075)	(0.0060)	(0.0079)
IBLI	-0.0484	-0.0513	-0.0456	-0.0446
	(0.0149)	(0.0148)	(0.0149)	(0.0148)
Rain deficit $\times$ *IBLI*	0.0159	0.0167	0.0150	0.0146
	(0.0051)	(0.0050)	(0.0051)	(0.0050)
Aid	0.0018	0.0214	0.0044	0.0487
	(0.0073)	(0.0145)	(0.0140)	(0.0383)
Rain deficit $\times$ *Aid*		-0.0086		-0.0201
		(0.0063)		(0.0171)
Dep. var. mean	0.0245	0.0245	0.0245	0.0245
Conflict mitigation	-21.40%	-22.08%	-20.88%	-20.71%
Cell level treatment controls	✓	✓	✓	✓
Cell-fixed effects	✓	✓	✓	✓
Time-fixed effects	✓	✓	✓	✓
Obs	93400	93400	93400	93400

Notes: The table reports the results of regressing the probability of conflict at the cell level on the rain deficit (log(rainfall)$\times$-1), Index-Based Livestock Insurance (IBLI) coverage, and the interaction of the two at the cell and neighborhood level. The level estimates are relegated to Table B-3. In addition, we control for the number of aid projects (columns 1 and 2) and the log value of aid commitments in US dollars (columns 3 and 4), as well as their interaction with the rain deficit at the cell and neighborhood level. Conflict mitigation values in percent are the reduction in the semi-elasticity of the rain deficit on the probability of conflict for a standard deviation increase in the neighborhood IBLI coverage (δ_3/δ_1). The neighborhood variables are based on the 1/distance weighting scheme. The development aid data is obtained from AidData (2017). Conley standard errors are implemented using the acreg package in Stata (Colella et al., 2019), with a distance cutoff of 200km.

TABLE B-5
Alternative drought proxies

	Dependent variable: Conflict$_{i,t}$	
	(1)	(2)
NEIGHBORHOOD		
$DMP\ deficit$ (δ_1)	0.0218	
	(0.0308)	
$DMP\ deficit \times IBLI$ (δ_3)	-0.0119	
	(0.0042)	
$AI\ deficit$ (δ_1)		0.0944
		(0.0287)
$AI\ deficit$ × IBLI (δ_3)		-0.0124
		(0.0041)
$IBLI$ (δ_2)	-0.0876	-0.0450
	(0.0262)	(0.0099)
CELL		
$DMP\ deficit$	0.0020	
	(0.0038))	
$DMP\ deficit \times IBLI$	0.0000	
	(0.0027)	
$AI\ deficit$ (δ_1)		-0.0228
		(0.0076)
$AI\ deficit$ × IBLI (δ_3)		0.0163
		(0.0049)
$IBLI$	-0.0039	-0.0236
	(0.0081)	(0.0070)
Dep. var. mean	0.0245	0.0245
Cell-fixed effects	✓	✓
Time-fixed effects	✓	✓
Obs	93000	93000

Notes: The table replicates columns 3 of Table I, switching the rain deficit (log(rainfall)×-1) for alternative drought proxies. In column 1, we use a phytomass measure (the Dry Matter Productivity–DMP from the Copernicus Global Land Sevice, 2019). In column 2, we leverage the Aridity Index (AI) which is the ratio of precipitation over potential evapotranspiration (with data from Abatzoglou et al. (2018)). As with our rain deficit measure, we log both measures and multiply them by -1 to mimic the scaling of our main specification. Conley standard errors are implemented using the acreg package in Stata (Colella et al., 2019), with a distance cutoff of 200km.

TABLE B-6
Baseline: Further controls (Neighborhood level)

	Dependent variable: $\text{Conflict}_{i,t}$								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
NEIGHBORHOOD									
Rain deficit (δ_1)	0.0637	0.0659	0.0642	0.0608	0.0554	0.0674	0.0726	0.0621	0.0511
	(0.0310)	(0.0290)	(0.0303)	(0.0293)	(0.0291)	(0.0295)	(0.0296)	(0.0302)	(0.0289)
IBLI (δ_2)	-0.0242	-0.0245	-0.0242	-0.0243	-0.0242	-0.0241	-0.0246	-0.0241	-0.0243
	(0.0051)	(0.0051)	(0.0051)	(0.0051)	(0.0051)	(0.0051)	(0.0051)	(0.0051)	(0.0052)
Rain deficit × *IBLI* (δ_3)	-0.0157	-0.0192	-0.0157	-0.0186	-0.0189	-0.0174	-0.0177	-0.0176	-0.0192
	(0.0052)	(0.0057)	(0.0052)	(0.0057)	(0.0056)	(0.0054)	(0.0055)	(0.0056)	(0.0058)
Rain deficit neighborhood × **NEIGHBORHOOD CHARACTERISTICS**									
Avg. conflict (00–09)	-0.0019								0.0138
	(0.0052)								(0.0204)
Avg. Rain deficit (00–09)		0.0072							0.0391
		(0.0033)							(0.0270)
Log pop			-0.0018						-0.0304
			(0.0046)						(0.0286)
Rangeland share				0.0065					-0.0176
				(0.0035)					(0.0121)
Arid climate					0.0080				-0.0058
					(0.0040)				(0.0219)
Desert & shrubland						0.0048			0.0043
						(0.0025)			(0.0037)
Dist. border							0.0044		-0.0036
							(0.0031)		(0.0076)
Dist. capital								0.0050	-0.0123
								(0.0034)	(0.0136)
Cell-fixed effects	✓	✓	✓	✓	✓	✓	✓	✓	✓
Time-fixed effects	✓	✓	✓	✓	✓	✓	✓	✓	✓
Obs	93400	93400	93400	93400	93400	93400	93400	93400	93400

Notes: The table reports the results of regressing our indicator for any conflict event (ACLED Raleigh et al., 2020) on the log of rainfall deficit (log(rainfall)×-1) at the cell and neighborhood level, the insurance cover indicator at the cell level, the standardized insurance coverage neighborhood measure, and the respective interactions at the cell and neighborhood level. Throughout columns 1 to 9, we add interactions of the rainfall deficit at the neighborhood level with neighborhood versions of the cell level controls shown as potentially correlated with IBLI coverage (see panel B of Figure V). Cell-level variables are omitted from the table. Conley standard errors are implemented using the acreg package in Stata (Colella et al., 2019), with a distance cutoff of 200km.

TABLE B-7
Baseline: Soil quality controls (cell level)

	Dependent variable: Conflict$_{i,t}$						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
NEIGHBORHOOD							
Rain deficit (δ_1)	0.0677	0.0685	0.0691	0.0702	0.0680	0.0687	0.0730
	(0.0297)	(0.0296)	(0.0296)	(0.0297)	(0.0297)	(0.0295)	(0.0297)
IBLI (δ_2)	-0.0235	-0.0235	-0.0235	-0.0235	-0.0235	-0.0235	-0.0235
	(0.0053)	(0.0053)	(0.0053)	(0.0053)	(0.0053)	(0.0053)	(0.0053)
Rain deficit × *IBLI* (δ_3)	-0.0154	-0.0154	-0.0154	-0.0154	-0.0154	-0.0154	-0.0154
	(0.0052)	(0.0052)	(0.0052)	(0.0052)	(0.0052)	(0.0052)	(0.0052)
Rain deficit neighborhood× **POOR SOIL CELL CHARACTERISTICS**							
Nutrient availability	0.0042						
	(0.0052)						
Nutrient retention capacity		0.0066					
		(0.0125)					
Rooting condition			-0.0061				
			(0.0081)				
Oxygen availability				-0.0072			
				(0.0066)			
Excess salts					0.0016		
					(0.0039)		
Toxicity						0.0286	
						(0.1033)	
Workability							-0.0127
							(0.0073)
Cell-fixed effects	✓	✓	✓	✓	✓	✓	✓
Time-fixed effects	✓	✓	✓	✓	✓	✓	✓
Obs	93400	93400	93400	93400	93400	93400	93400

Notes: The table reports the results of regressing our indicator for any conflict event (ACLED Raleigh et al., 2020) on the log of rainfall deficit (log(rainfall)×-1) at the cell and neighborhood level, the insurance cover indicator at the cell level, the standardized insurance coverage neighborhood measure, and the respective interactions at the cell and neighborhood level. Throughout columns 1 to 7, we add interactions of the rainfall deficit at the neighborhood level with a poor soil indicator at the cell level based on soil characteristics from the Harmonized World Soil Database (Nachtergaele et al., 2009). For each one of the soil characteristics, a location is considered to be of poor quality when it is associated with class 3, 4, or 5 (severe limitations, very severe limitations, and mainly non-soil). In cases where some locations encompass a soil characteristic defined as both of poor and good quality, we assign to the location the quality that covers most of the area of that location. The neighborhood variables are based on the 1/distance weighting. Cell-level variables are omitted from the table. Conley standard errors are implemented using the acreg package in Stata (Colella et al., 2019), with a distance cutoff of 200km.

TABLE B-8

Baseline: Soil quality controls (neighborhood level)

	Dependent variable: $\text{Conflict}_{i,t}$						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
NEIGHBORHOOD							
$Rain\ deficit\ (\delta_1)$	0.0657	0.0693	0.0691	0.0692	0.0614	0.0701	0.0675
	(0.0294)	(0.0297)	(0.0295)	(0.0296)	(0.0297)	(0.0289)	(0.0295)
$IBLI\ (\delta_2)$	-0.0236	-0.0236	-0.0234	-0.0235	-0.0234	-0.0235	-0.0235
	(0.0053)	(0.0053)	(0.0053)	(0.0053)	(0.0053)	(0.0053)	(0.0053)
$Rain\ deficit \times IBLI\ (\delta_3)$	-0.0158	-0.0155	-0.0155	-0.0153	-0.0166	-0.0154	-0.0160
	(0.0053)	(0.0053)	(0.0053)	(0.0053)	(0.0054)	(0.0052)	(0.0055)
NEIGHBORHOOD $Rain\ deficit$ × **POOR SOIL NEIGHBORHOOD CHARACTERISTICS**							
Nutrient availability	0.0025						
	(0.0024)						
Nutrient retention capacity		0.0012					
		(0.0030)					
Rooting condition			0.0011				
			(0.0030)				
Oxygen availability				-0.0004			
				(0.0025)			
Excess salts					0.0044		
					(0.0030)		
Toxicity						0.0008	
						(0.0047)	
Workability							0.0021
							(0.0038)
Cell-fixed effects	✓	✓	✓	✓	✓	✓	✓
Time-fixed effects	✓	✓	✓	✓	✓	✓	✓
Obs	93400	93400	93400	93400	93400	93400	93400

Notes: The table reports the results of regressing our indicator for any conflict event (ACLED Raleigh et al., 2020) on the log of rainfall deficit (log(rainfall)×-1) at the cell and neighborhood level, the insurance cover indicator at the cell level, the standardized insurance coverage neighborhood measure, and the respective interactions at the cell and neighborhood level. Throughout columns 1 to 7, we add interactions of the rainfall deficit at the neighborhood level with a poor soil indicator at the cell level based on soil characteristics from the Harmonized World Soil Database (Nachtergaele et al., 2009). For each one of the soil characteristics, a location is considered to be of poor quality when it is associated with class 3, 4, or 5 (severe limitations, very severe limitations, and mainly non-soil). In cases where some locations encompass a soil characteristic defined as both of poor and good quality, we assign to the location the quality that covers most of the area of that location. The neighborhood variables are based on the 1/distance weighting. Cell-level variables are omitted from the table. Conley standard errors are implemented using the acreg package in Stata (Colella et al., 2019), with a distance cutoff of 200km.

TABLE B-9
2SLS results: Insurance payouts

	2SLS 1st stage	2SLS 2nd stage
	Dependent variable:	
	IBLI payout	$\text{Conflict}_{i,t}$
	(1)	(2)
NEIGHBORHOOD		
Rain deficit (δ_1)	0.6606	0.0930
	(0.2830)	(0.0319)
IBLI (δ_2)	0.8150	0.0051
	(0.0864)	(0.0085)
Rain deficit × *IBLI* (δ_3)	0.4374	
	(0.0644)	
IBLI payouts (δ_4)		-0.0361 7
		(0.0118)
CELL		
Rain deficit	-0.0963	-0.0123
	(0.0622)	(0.0066)
IBLI	-0.9510	-0.0752
	(0.3159)	(0.0240)
Rain deficit × *IBLI*	0.1972	0.0205
	(0.1140)	(0.0072)
Dep. var. mean	0	0.0245
F-stat 1st stage	45.638	
Cell-fixed effects	✓	✓
Time-fixed effects	✓	✓
Obs	93400	93400

Notes: The table reports the 1st stage results (columns 1 and 3) of regressing the neighborhood weighted IBLI payout indicator (z standardized, with mean zero and standard deviation of one) on the cell level log of rainfall deficit (log(rainfall)×-1), the IBLI cover indicator, the interaction of the two, as well as the neighborhood level log of rainfall deficit, the neighborhood level IBLI coverage (standardized), and the interaction of the two. The neighborhood variables are based on the 1/distance weighting. Columns 2 and 4 report the second stage results with the probability of conflict ($\text{Conflict}_{i,t}$) as the dependent variable, where the interaction of the neighborhood level log of rainfall deficit and the neighborhood IBLI coverage is the excluded instrument. Cell-level variables are omitted from the table. Conley standard errors are implemented using the acreg package in Stata (Colella et al., 2019), with a distance cutoff of 200km.

TABLE B-10

Triple-interaction results cell level: Mixed land use

	Dependent variable: $\text{Conflict}_{i,t}$			
	(1)	(2)	(3)	(4)
CELL				
Rain deficit	-0.0072		-0.0087	-0.0084
	(0.0058)		(0.0059)	(0.0063)
Rain deficit ×Mixed land use	0.0182		0.0223	0.0061
	(0.0205)		(0.0218)	(0.0240)
IBLI		-0.0094	-0.0394	
		(0.0046)	(0.0151)	
Rain deficit × *IBLI*			0.0129	-0.0028
			(0.0051)	(0.0066)
Cell level treatment controls	✓	✓	✓	✓
Cell-fixed effects	✓	✓	✓	✓
Time-fixed effects	✓	✓	✓	–
Rollout-cluster-time-fixed effects	–	–	–	✓
Obs	93400	93400	93400	93400

Notes: The table reports the cell level treatment variables from the specification reported in Table III Conley standard errors, implemented using the acreg package in Stata (Colella et al., 2019), with a distance cutoff of 200km.

TABLE B-11
Triple-interaction results: Mixed settlement

	Dependent variable: Conflict$_{i,t}$			
	(1)	(2)	(3)	(4)
NEIGHBORHOOD				
Rain deficit (δ_1)	0.0740		0.0671	0.1209
	(0.0343)		(0.0296)	(0.0375)
Rain deficit × *Mixed settlement*(ψ_1)	0.0059		0.0038	0.0077
	(0.0101)		(0.0103)	(0.0092)
IBLI (δ_2)		-0.0170	-0.0244	-0.0141
		(0.0045)	(0.0052)	(0.0072)
IBLI × *Mixed settlement* (ψ_2)		0.0024	-0.0028	-0.0040
		(0.0030)	(0.0031)	(0.0031)
Rain deficit × *IBLI* (δ_3)			-0.0119	-0.0046
			(0.0052)	(0.0056)
Rain deficit × *IBLI* × *Mixed settlement*(ψ_3)			-0.0098	-0.0105
			(0.0043)	(0.0043)
CELL				
Rain deficit	-0.0074		-0.0080	-0.0086
	(0.0060)		(0.0058)	(0.0062)
Rain deficit × *Mixed settlement*	0.0190		0.0215	0.0166
	(0.0371)		(0.0365)	(0.0316)
IBLI		-0.0059	-0.0269	
		(0.0045)	(0.0141)	
IBLI × *Mixed settlement*		-0.0406	-0.0922	-0.0930
		(0.0158)	(0.0670)	(0.0604)
Rain deficit × *IBLI*			0.0091	-0.0030
			(0.0048)	(0.0066)
Rain deficit × *IBLI* × *Mixed settlement*			0.0193	0.0251
			(0.0209)	(0.0188)
Dep. var. mean non-mixed settlement	0.0183	0.0183	0.0183	0.0183
Dep. var. mean mixed settlement	0.0845	0.0845	0.0845	0.0845
Conflict mitigation	–	–	-17.78%	-3.76%
Conflict mitigation (mixed settlement)	–	–	-30.63%	-11.67%
Cell level treatment controls	✓	✓	✓	✓
Cell-fixed effects	✓	✓	✓	✓
Time-fixed effects	✓	✓	✓	–
Rollout-cluster-time-fixed effects	–	–	–	✓
Obs	93400	93400	93400	93400

Notes: The table reports the results of regressing our indicator for any conflict event on the log of rainfall deficit (log(rainfall)×-1) at the neighborhood level, the standardized insurance coverage neighborhood measure, and the interactions of neighborhood level rain deficit and IBLI coverage. Moreover, we include interactions of all our variables with an indicator variable for cells located in mixed settlement areas, defined as cells below the median proximity to an ethnic homeland border (roughly below 30km). The proximity to a homeland border is defined via a cell's centroids geographic distance to the closed non-coethnic homeland cell based on Murdocks Geographic Atlas (Murdock, 1967). The neighborhood variables are based on the 1/distance weighting. Conley standard errors, implemented using the acreg package in Stata (Colella et al., 2019), with a distance cutoff of 200km.

C. Income effects: Individual level evidence

In this appendix, we provide suggestive evidence in favor of the idea that IBLI mitigates drought-induced income shocks, leveraging survey data from several survey rounds of the Afrobarometer. Section C-1 presents the data and our empirical specification, and Section C-2 presents results.

C-1. Individual level evidence: Data and specification

We construct a repeated cross-section of Afrobarometer respondents in Kenya matching their cell locations to local drought conditions and IBLI coverage based on our cell-level outcomes. Specifically, we match 7882 respondents interviewed in six survey waves, occurring between 2003 and 2019, to our cells.[1] Geocodes for waves 3 to 6 are obtained from BenYishay et al. (2017), while waves 7 and 8 provide GPS coordinates for the survey clusters. The grey dots in Figure C-1 document the spatial coverage of survey clusters over the different waves.

We have no direct measure of income because Afrobarometer does not include survey questions about it. However, there is a question if a respondent has experienced hunger during the last 12 months. We take this variable and construct an indicator that equals unity in case a respondent has "always gone hungry, "mostly gone hungry", or gone "hungry several times" and zero otherwise. We then take information on the month and year in which the survey was conducted and calculate the 12-month average rainfall and insurance coverage at the cell in which a respondent has been surveyed with respect to the interview data. Note that due to the timing of the surveys, we still obtain an indicator for insurance coverage. The corresponding rainfall measure is plotted in Figure C-1. Black lines indicate IBLI insurance districts, and red lines the borders of insurance districts that already have IBLI coverage during the preceding 12 months.

We take this repeated cross-section to test if the cell level rain deficit increases the likelihood of respondents going hungry (or proxy for a negative income shock) and if IBLI reduces the effect of drought on the probability of going hungry. Unlike in our main specification, we do not have proper panel variation. Hence, we only test if differing local drought conditions between respondents within an insurance district are more severe compared to respondents in insurance districts that already have IBLI coverage. Our expectation is that while local drought exposure should matter in uninsured areas, it should matter less across respondent pairs within already covered insurance districts.

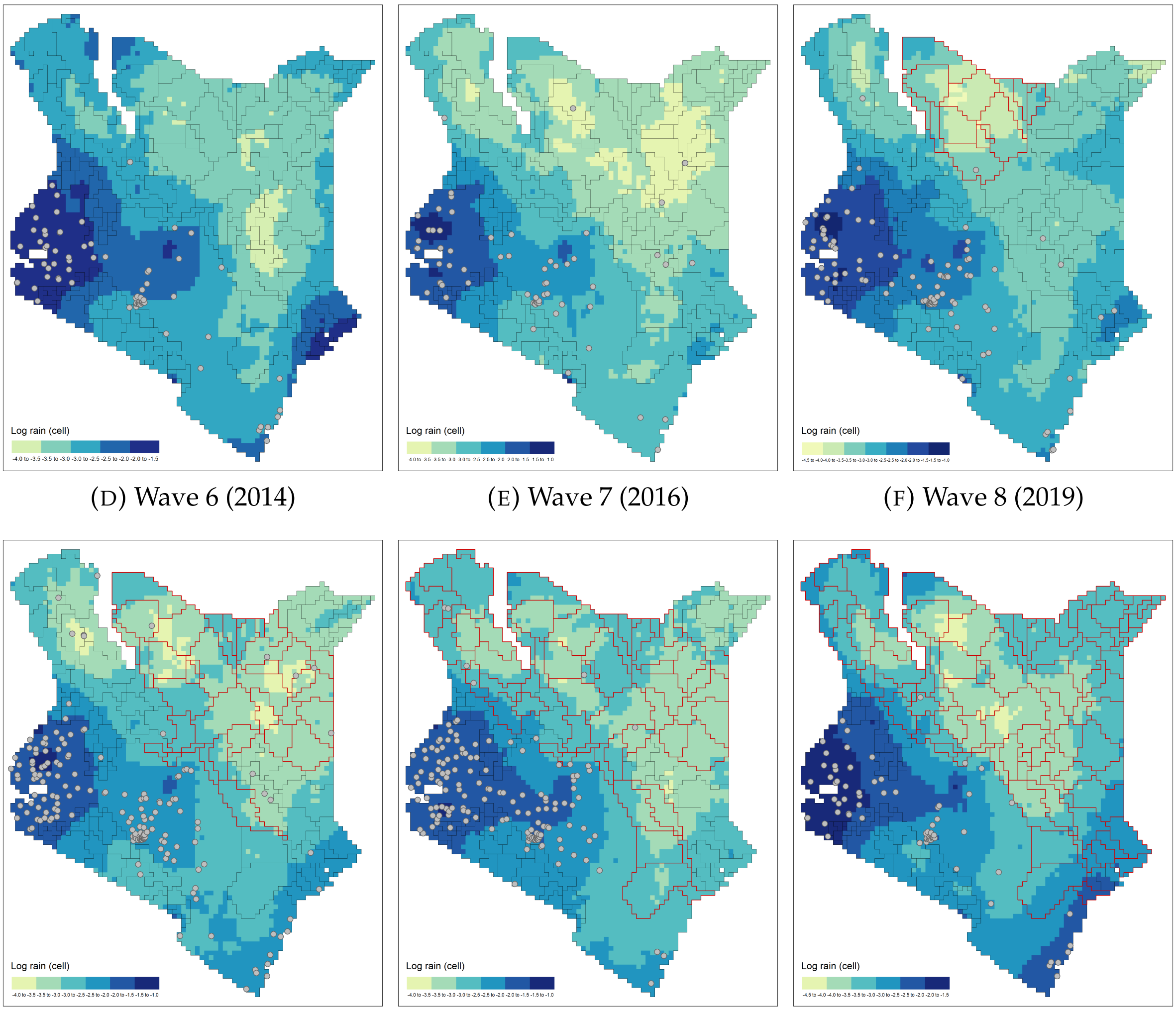
Our main specification leveraging the repeated cross-section of Afrobarometer respondents is defined as:

$$\text{Hunger}_{r,g,w} = \beta_1 \text{Rain deficit}_{g,w} + \beta_2(\text{Rain deficit}_{g,w} \times \text{IBLI}_{g,w}) + \mathbf{X}'_{\mathbf{r,g,w}}\xi + \tau_w^{id} + \epsilon_{id,w} \quad \text{(C-1)}$$

where $\text{Hunger}_{r,g,w}$ is an indicator variable that is unity in case a respondent r, surveyed on gridcell g located in insurance-district d during wave w has suffered hunger. β_1 and β_2 are our coefficients of interest. β_1 captures the effect of the average rain deficit on gridcell g during

[1] See https://www.afrobarometer.org/ for details.

FIGURE C-1
Afrobarometer clusters, avg. log precipitation and IBLI coverage over cells



(A) Wave 3 (2005) (B) Wave 4 (2008) (C) Wave 5 (2011)

(D) Wave 6 (2014) (E) Wave 7 (2016) (F) Wave 8 (2019)

Notes: Panels A to F of the figure plot the Afrobaromter survey locations over the different waves across Kenya. We also plot the log rainfall averaged across the 12 months before the respective Afrobarometer survey over the cell. Black lines are IBLI insurance districts. Red lines are IBLI insurance districts that have IBLI coverage during the 12 months before the respective survey wave. Afrobarometer survey locations for waves 3 to 6 are obtained from BenYishay et al. (2017). For waves 7 and 8, we use GPS coordinates directly provided by Afrobarometer (https://www.afrobarometer.org/). Rainfall data comes from NASA's GMP product (Huffman et al., 2017).

wave w on the probability of hunger, and β_2 is the rain deficit heterogeneity with respect to IBLI coverage. Note that the level effect IBLI coverage is captured by the insurance-district-wave fixed effect, as is any variable related to rollout. $\mathbf{X}'_{\mathbf{r,g,w}}$ is a vector of respondent level controls: age, a gender dummy, an urban dummy, and several indicators for education levels. Standard errors are clustered at the insurance-district level.

C-2. Income effects: Results

Table C-1 presents the results. Columns 1 and 2 document a clear positive relationship between the cell-level rain deficit and the probability that a respondent has been going hungry during the last 12 months. The mitigating effect of IBLI, in turn, is close to zero and statistically insignificant. However, as soon as we limit the sample to respondents who identify with ethnic groups in which pastoralism is a common practice, we observe our previously documented pattern.[2] Once more, local variation in the rain deficit between respondents residing within the same county and insurance district is correlated with the probability that respondents went hungry in the expected direction. However, those local differences do no longer matter once a district is covered by IBLI.

Taken together, we take this as suggestive evidence that IBLI reduces the negative income effects of droughts for pastoralists (echogin findings by Jensen et al., 2017) while not for others.

TABLE C-1
Individual level results: Income effect

	Dependent variable: $\text{Hunger}_{i,t}$			
	All respondents		*Pastoral group members*	
	(1)	(2)	(3)	(4)
$Rain\ deficit$	0.4668	0.3837	0.3424	0.3112
	(0.0044)	(0.0038)	(0.0220)	(0.0258)
$Rain\ deficit \times IBLI$	-0.0206	0.0797	-0.3431	-0.2627
	(0.1963)	(0.1099)	(0.1120)	(0.1164)
Dep. var. mean	0.3030	0.3030	0.3260	0.3260
Individual level controls	–	✓	–	✓
IBLI-district-county-wave effect	✓	✓	✓	✓
Respondents	7882	7882	1542	1542

Notes: The table reports the results from regressing the probability of going hungry on the cell level rain deficit and cell level insurance cover, averaged across the 12 months preceding the respective Afrobarometer survey wave w. In columns 1 and 2, we use all survey respondents. In columns 3 and 4, we only include survey respondents in the regression that identify with an ethnic group in which mobile pastoralism is a common practice (the Boran, Kalenjin, Rendile, Maasai, Samburu, Somali, and Turkana). Individual controls include a gender dummy, age in years, an indicator for urban survey locations, a dummy for receiving below primary level education, a dummy for receiving primary level education, a dummy for receiving some secondary education, and a dummy for receiving secondary education or more. All columns include IBLI-insurance district times county times year fixed effects. Standard errors are clustered at the IBLI-insurance district times county level.

Additional references

Abatzoglou, J. T., S. Z. Dobrowski, S. A. Parks, and K. C. Hegewisch (2018). Terraclimate, a high-resolution global dataset of monthly climate and climatic water balance from 1958–2015. *Scientific Data* 5(1), 1–12.

AidData (2017). `WorldBank_GeocodedResearchRelease_Level1_v1.4.2` geocoded dataset. Aid Data Williamsburg, VA and Washington, DC. AidData. Accessed on February 9, 2020. Available at http://aiddata.org/research-datasets.

Beck, H. E., N. E. Zimmermann, T. R. McVicar, N. Vergopolan, A. Berg, and E. F. Wood (2018). Present and future Köppen-Geiger climate classification maps at 1-km resolution. *Scientific Data* 5(1), 1–12.

[2] Note that the Afrobarometer does not include any information that would allow us to know if respondents are pastoralists directly.

BenYishay, A., R. Rotberg, J. Wells, Z. Lv, S. Goodman, L. Kovacevic, and D. Runfola (2017). Geocoding afrobarometer rounds 1–6: Methodology and data quality. Technical report, AidData.

Cherlet, M., H. C. R. J. H. S. S. v. M. G. (2018). *World Atlas of Desertification*. Publication Office of the European Union, Luxembourg.

Colella, F., R. Lalive, S. O. Sakalli, and M. Thoenig (2019, August). Inference with arbitrary clustering. Discussion Paper 12584, IZA Institute of Labor Economics.

Eberle, U. J., D. Rohner, and M. Thoenig (2023). Heat and hate: Climate security and farmer-herder conflicts in Africa. *Review of Economics and Statistics*, Forthcoming.

Edejer, T. T.-T., R. Baltussen, T. Tan-Torres, T. Adam, A. Acharya, R. Hutubessy, D. Evans, and C. Murray (2003). *Making choices in health: WHO guide to cost-effectiveness analysis*, Volume 1. World Health Organization.

Fava, F. P., D. Nathaniel, J. Sina, G. Andrew, and B. Maher (2021). *Building financial resilience in pastoral communities in Africa: Lessons learned from implementing the Kenya Livestock Insurance Program (KLIP)*. World Bank, Washington, D.C.

Flintan, F. E., R. Behnke, and C. Neely (2013). Natural resource management in the drylands in the horn of Africa: Brief prepared by a technical consortium hosted by CGIAR in partnership with the FAO investment centre. *Technical Consortium Brief*.

Huffman, G., E. Stocker, D. Bolvin, E. Nelkin, and J. Tan (2017). Gpm imerg final precipitation l3 1 month 0.1 degree x 0.1 degree v06. *Greenbelt, MD, Goddard Earth Sciences Data and Information Services Center (GES DISC)*. Accessed November 13, 2022. Available at: https://doi.org/10.5067/GPM/IMERG/3B-HH/06.

Jensen, N. D., C. B. Barrett, and A. G. Mude (2017). Cash transfers and index insurance: A comparative impact analysis from northern Kenya. *Journal of Development Economics 129*, 14–28.

Kenya Rangeland Ecological Monitoring Unit (1983). Land use map of Kenya. *Survey of Kenya 500/3/83*.

(KFSSG), K. F. S. S. G. (2012). *The 2011 long rain season assessment report*. Government of Kenya. Nairobi.

McGuirk, E. F. and N. Nunn (2023). Transhumant pastoralism, climate change, and conflict in Africa. *Review of Economic Studies*, Forthcoming.

Milligan, C., A. Kopp, S. Dahdah, and J. Montufar (2014). Value of a statistical life in road safety: A benefit-transfer function with risk-analysis guidance based on developing country data. *Accident Analysis Prevention 71*, 236–247.

Murdock, G. P. (1967). Ethnographic atlas: A summary. *Ethnology 6*(2), 109–236.

Nachtergaele, F., H. Velthuizen, L. Verelst, and D. Wiberg (2009). Harmonized world soil database (hwsd). *Food and Agriculture Organization of the United Nations, Rome*.

OECD/SWAC (2020). Africapolis (database). Accessed August 24, 2023. Available at www.africapolis.org.

Raleigh, C., A. Linke, and C. Dowd (2020). Armed Conflict Location and Event Dataset (ACLED). *Codebook Version 2*.