INSURING PEACE: INDEX-BASED LIVESTOCK INSURANCE, DROUGHTS, AND CONFLICT*

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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 transhumant pastoralists and sedentary farmers. Index-Based Livestock Insurance (IBLI) piloted in Kenya provides automated, preemptive payouts to pastoralists affected by droughts. Combining variation in rainfall and the staggered rollout of IBLI in Kenya over the 2000-2020 period, we find that IBLI strongly reduces drought-induced conflict. Key mechanisms include a reduction in herd sizes, as well as income smoothing and asset-price stabilization, contributing to an overall reduced migratory pressure for pastoralists. Our study suggests that market-based solutions are a scalable, cost-effective pathway to mitigate conflict, complementing political solutions such as power-sharing agreements and institutional reforms.

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I. 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 transhumant pastoralists and sedentary farmers in Africa (Eberle, Rohner, and Thoenig 2025; McGuirk and Nunn 2025).[1] 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, Rohner, and Thoenig 2025). 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. 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. Index-based insurance schemes are an increasingly popular social protection scheme, but we are the first to examine whether they could also constitute a cost-effective and scalable conflict-mitigation tool for low- and middle-income countries.

We study the conflict-mitigation potential of IBLI in Kenya, a country whose large pastoralist population (8.8 out of 53 million Kenyans, see Wanyama 2020) faces increased competition for resources due to the expansion of various other land uses. We begin with a case study combining spatial and survey data in a central semi-arid Kenyan region to illustrate the conflict patterns. 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, pastoralists need to migrate further in search of grazing land. Survey data document an increased likelihood of pastoralist encounters with other land users. The spatial distribution of conflicts demonstrates that conflicts cluster around contested land use areas, where pastoralist drought migration routes cross into areas with expanded farmland, urban settlements, or nature reserves. Hence, the scope for IBLI to reduce drought-induced conflict is greatest in these contested land use areas.

IBLI can mitigate conflicts involving pastoralists through two interrelated mechanisms that link droughts to conflicts. First, a rapacity effect arises because drought reduces common-pool grazing resources -— such as communal pasture and shared water points —- intensifying competition over the remaining forage and water. This rapacity effect is the stronger, the larger the pastoralists' herd sizes when droughts hit.[2] IBLI has the potential to reduce herd sizes by limiting the need for pastoralists to hold excess livestock as precautionary savings. Pastoralists can even use timely IBLI payouts to prevent livestock losses by purchasing veterinary supplies or buying feed from local farmers, to the extent there

[1]Transhumant pastoralists maintain a permanent home settlement but seasonally move their herds between established grazing areas; they differ from fully nomadic pastoralists, who relocate entire households without a fixed base.

[2]Whereas the rapacity effect in Dube and Vargas (2013) stems from external price increases that raise the value of an appropriable commodity, in our case droughts increase the value of a shared resource base by raising its scarcity; in both cases, higher rents raise the incentive for violence.

is sufficient market access. Taken together, smaller herds and healthier cattle due to IBLI coverage can reduce the rapacity effect.

Second, IBLI can increase the opportunity costs of conflict by cushioning against severe adverse income shocks and stabilizing asset values. Droughts often force many pastoralists to simultaneously monetize their precautionary cattle savings to feed their family, leading to sometimes dramatic declines in local cattle prices. Sufficiently fast payouts, automatically triggered by IBLI, buffer against individual income shocks and reduce the pressure to sell. This not only benefits individual insurance holders, but also has a stabilizing general equilibrium effect on prices helping all drought-affected pastoralists in need of a sale. Taken together, IBLI has the potential to mitigate drought-related conflict through increased opportunity costs of conflict and a smaller rapacity effect - which also limit risky long-distance drought migration and the likelihood of conflictual encounters with other land users.

Our main empirical analysis estimates the degree to which IBLI coverage mitigates the effect of drought on conflict in a panel of 0.1×0.1-degree grid cells (roughly 11 x 11 km) in Kenya over the 2000-2020 period. Our dependent variable is the probability of conflict in a cell based on the Armed Conflict Location and Event Dataset (ACLED). To account for the conflict patterns in our case study, our treatment captures drought conditions and insurance coverage in the neighborhood of this cell. It combines variation from exogenous changes in the rainfall deficit with the staggered IBLI rollout across eligible areas. The calculation of the neighborhood measure assumes that both the likelihood of drought-induced migration into an outcome cell and IBLI's potential to mitigate conflict decline in spatial distance to neighboring cells. Using this approach, our main results suggest that the additional conflict likelihood caused by a one standard-deviation increase in drought severity in a cell's neighborhood is mitigated by about 25% by a one standard deviation increase in neighborhood IBLI coverage.

The main identification concern in our setting is that the rollout of IBLI across locations is potentially endogenous.[3] 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 potentially 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 the estimated conflict-reducing effect. Our main concern is a downward bias that could falsely indicate program effectiveness, which could occur if areas with higher drought-conflict elasticity 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 adaptation of the rollout pattern to changes in drought patterns.

[3] 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 – regardless of actual livestock loss – by remote-sensing-based drought proxies pre-defined by the independent International Livestock Research Institute (ILRI).

The second type of potentially 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, 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, grid-cell sizes, time periods, using alternative conflict measures and drought proxies, computing standard errors in various ways, and further robustness tests regarding the IBLI roll-out. Moreover, we obtain consistent results for a larger sample of East African countries, providing us with a much expanded control group that includes locations where drought migration is plausibly unaffected by IBLI. 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 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 provide empirical evidence supporting the postulated rapacity and opportunity cost mechanisms. County-level data from the Kenyan Ministry of Agriculture (2012–2018) show that IBLI-covered counties have significantly smaller cattle herds. This effect is particularly pronounced among mobile beef cattle, suggesting that IBLI reduces the need for precautionary savings and thus dampens the rapacity effect. In parallel, our analysis of cattle prices from 41 livestock markets and six rounds of Afrobarometer surveys shows that IBLI coverage mitigates the dramatic price declines and income shocks typically induced by droughts. By stabilizing these economic outcomes, IBLI effectively increases the opportunity cost of conflict.

These direct stabilizing effects also translate into a smaller rapacity effect and reduced migratory pressure. When households face less economic and resource stress, the need for costly long-distance drought migration diminishes, thereby lowering the likelihood of conflictual encounters with other land users. Encounters with other land users increase conflict risks over-proportionally, as transhumant pastoralists tend to have a strong in-group identity, but be hostile towards outgroup members – attitudes shaped by the challenges of their traditional lifestyle (Le Rossignol and Lowes 2022). To capture migratory pressure, we follow Eberle, Rohner, and Thoenig (2025) and match georeferenced ACLED conflict events with ethnic homelands (based on Murdock 1967), and calculate the distance from the centroid of each homeland to the conflict locations. Our findings indicate that under increased IBLI coverage, drought-induced conflict events occur closer to homelands, consistent with a lower likelihood of long and risky drought migration, and a lower likelihood of encounters and conflicts with other land users.

We also 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 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, IBLI provides a pure fatality saving of at least 10 to 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, Burke, and Miguel 2013; Burke, Hsiang, and Miguel 2015). In particular, we build on McGuirk and Nunn (2025) and Eberle, Rohner, and Thoenig (2025), who document droughts as a cause of pastoral-farmer conflicts in Africa and establish key mechanisms. Those studies show that heterogeneity in the drought-conflict sensitivity can be mitigated by inclusive political institutions (see also Fetzer and Kyburz 2024). We provide novel evidence that index-based livestock insurance is 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 (Pörtner et al. 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.[4] 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 welfare in Kenya (Jensen, Barrett, and Mude 2017) and on direct conflict exposure in Ethiopia (Sakketa, Maggio, and McPeak 2025). Sakketa, Maggio, and McPeak (2025) provide important complementary evidence to this paper on individual take-up, for which we lack data. Using a randomized encouragement program in southern Ethiopia, they show that insurance uptake is the key channel leading to a 17 to 50% lower likelihood of insured pastoralists being directly involved in a conflict. 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 contested land use where pastoralists encounter other land users in a competition for scarce resources.

By demonstrating the potential of remote-sensing-based asset insurance with automated payouts, we contribute to a growing literature studying information and communications technology for development (ICT4d) (Blumenstock 2016; Fabregas, Kremer, and Schilbach 2019). ICT4d 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, Kremer, and Ramrattan 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, Casaburi,

[4] 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.

and Willis (2025) 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, Schaudt, and Wong 2023; Gehring, Kaplan, and Wong 2022; Morelli and Rohner 2015), studies considering long-term sources of conflict in Africa (Michalopoulos and Papaioannou 2016; Moscona, Nunn, and Robinson 2020; McGuirk and Burke 2020), and studies focusing on resources as a source of conflict (Berman et al. 2017; Gehring, Langlotz, and Kienberger 2023; Hodler, Schaudt, and Vesperoni 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. 2024; 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, Felter, and Johnston 2016; Premand and Rohner 2024). International peacekeeping interventions can provide some relief but are very costly (Rohner 2024), while development aid generally has a mixed record (Nunn and Qian 2014; McGuirk and Nunn 2024). Jensen, Barrett, and Mude (2017) highlight a crucial difference in the cost structure of index insurance compared to social welfare schemes like cash transfers or public work programs. The initial investment in the technology and set-up is costly, but marginal costs are lower, suggesting a high potential for further expansion and upscaling.

The remainder of the paper is structured as follows. Section II provides details on IBLI and introduces our setting. Section III introduces our data and main variables. Section IV presents our identification strategy and discusses our identifying assumptions. Section V presents our main results, quantifies the effects, and sensitivity analysis. Section VI presents evidence on the main channels, and Section VII concludes and discusses implications for public policy.

II. Setting

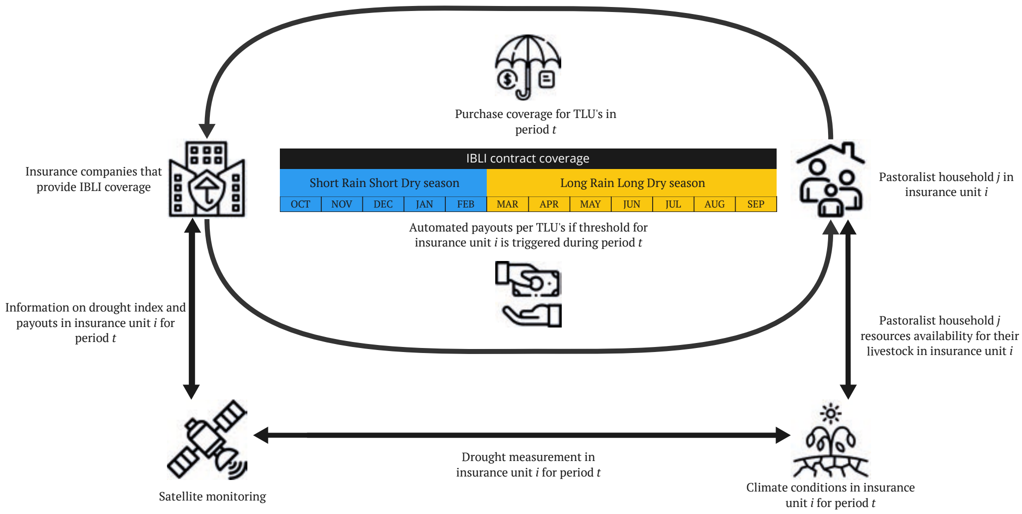
II.A. Index-Based Livestock Insurance (IBLI) in Kenya

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 is infeasible. IBLI triggers payouts for specific pre-defined index threshold conditions based on a livestock loss function (Chantarat et al. 2013), which is based on rangeland conditions that are proxied by the Natural Deviation in Vegetation Index (NDVI). Thus, it bypasses 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. Another version of IBLI has been implemented in Mongolia, while the one developed in Kenya is currently being scaled up in East Africa. Jensen et al. (2024) provide a detailed overview of IBLI, and discuss its current state in East Africa and options for further development.

In Kenya, IBLI was initially developed by researchers at Cornell University and the International Livestock Research Institute (ILRI) to protect pastoralists in arid and semi-arid areas against climatic shocks and improve their living conditions. IBLI was successfully piloted in the Marsabit district in 2010 and rolled out to eligible areas across Kenya (Johnson et al. 2019; Fava et al. 2021). All traditional pastoralist areas are eligible and were divided into 146 insurance units. As of summer 2023, IBLI coverage is available in 93 insurance units, fully covering 8 of Kenya's 13 eligible counties. 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 unit has IBLI coverage, IBLI insurance plans are offered and distributed by private Kenyan insurance agencies.[5] Pastoralist households in that district can purchase IBLI for a specific number of tropical livestock units (TLUs, one TLU corresponds to 0.7 camels, one cattle, or ten goats/sheep). Instead of following the calendar year, an IBLI contract always covers a one-year period covering the two rain and dry seasons in Kenya. Following initial success, the Kenyan government started to buy IBLI in bulk and distribute it to vulnerable households under the Kenyan Livestock Insurance Program (KLIP) in 2015 (Fava et al. 2021). Vulnerable pastoralist households targeted by KLIP are estimated to have on average 10-15 TLUs (Jensen et al. 2024), and KLIP provides fully subsidized coverage for up to five TLUs. Beyond five units, additional coverage can be obtained at market prices from insurance companies, which are responsible for handling all payouts.

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



Notes: The figure provides a simplified scheme of the processes underlying IBLI. An insurance contract can also start coverage in the long rain long dry season, i.e., running from March to February.

The payouts of insured pastoralist households depend on the drought conditions in their insurance unit. In an initial step, ILRI estimated the size of expected drought-induced damage for each insurance

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

unit (Chantarat et al. 2013). 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 unit is crossed, pastoralists receive automated payments from insurance companies proportional to the predicted loss. Following further innovations in the product, payments are made in anticipation of the expected loss of livestock, with the idea of preventing the loss of livestock rather than compensation for it (Vrieling et al. 2016). Hence, IBLI is now best understood as an asset protection rather than an asset replacement contract.[6] The widespread use of mobile payment systems in Kenya (e.g., M-PESA) enables fast payments even to remote households (Fava et al. 2021).

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

We begin by illustrating the spatial pattern and mechanisms underlying drought-induced conflicts in the Samburu-Laikipia-Isiolo-Meru region in central Kenya. To do so, we combine and geo-process various data sources, including detailed survey data from Lengoiboni, Bregt, and van der Molen (2010).

Panel A of Figure II displays the home villages 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, Bregt, and van der Molen (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 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, Kishi, and Linke 2023) 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, Barrett, and Mude 2017). The men leave the village with the larger livestock 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.[7] With sufficient rain, those encounters are usually

[6]The design also implies that what matters is not the pastoralists' location at the time when drought conditions are measured, but rather the drought conditions prevailing in their home insurance unit. In years with sufficient rain, pastoralists mostly remain within their insurance unit (average size 2817km^2, but droughts make it necessary to travel further (Chelanga et al. 2017; Jensen, Barrett, and Mude 2017).

[7]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.

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 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 in a way that is consistent with the survey evidence.

Drought-induced conflicts in the case study region occur mostly in the neighborhoods of the pastoralist areas, particularly 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 destination of pastoralist drought migration. The former observation supports McGuirk and Nunn (2025), 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, Rohner, and Thoenig (2025), 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.

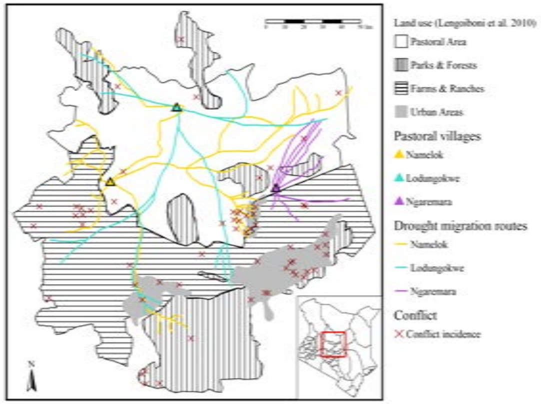
Panel C of Figure II illustrates the spatial and temporal variation in drought patterns and IBLI eligibility and coverage. The two arid or semi-arid counties in the east and north, Isiolo and Samburu, are eligible for IBLI. However, based on the stepwise rollout pattern, Isiolo County in the east already 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 is determined by the area being semi-arid or arid and historically characterized by pastoral land use – 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 units within the counties using hypothetical rainfall deficits. In the example, both the Namelock and Lodungokwe communities face drought conditions in their home

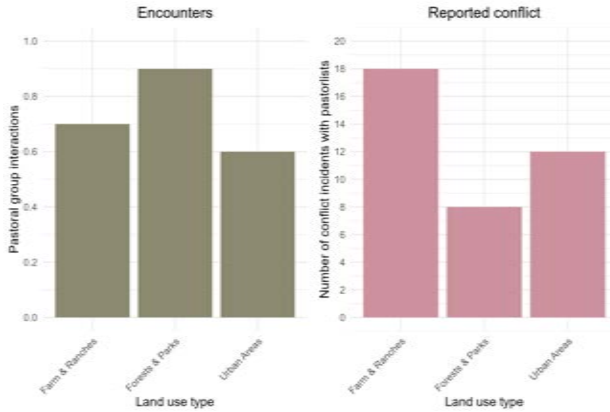
FIGURE II

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

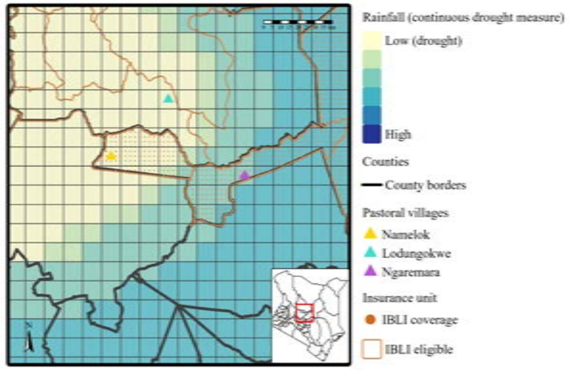
(A) Pastoralist migration routes during 2007/08 drought



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



(C) Drought exposure across IBLI units



Notes: Panel A shows the digitized map from Lengoiboni, Bregt, and van der Molen (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 41 respondents interviewed by Lengoiboni, Bregt, and van der Molen (2010). Conflict incidents are from ACLED (Raleigh, Kishi, and Linke 2023). Panel C shows counties and insurance units 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 unit during the Short Rain Short Dry (SRSD) and Long Rain Long Dry (LRLD) seasons that comprise our 12-month periods.

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 fodder for their livestock (as documented in Jensen, Barrett, and Mude 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, non-insured pastoralists and other land users in Kenya.

III. Data

Our spatial units of analysis are grid cells of 0.1×0.1 degrees (roughly 11 x 11 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 II.A, 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 but along the drought migration routes where pastoralists encounter other land users (see Section II.B). 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. In this section, we explain how we capture this dynamic and the majority of relevant conflicts by measuring drought and IBLI in these other cells using 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.

III.A. 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, Kishi, and Linke 2023) as a source of conflict data, in line with related studies on farmer-herder conflicts in Africa (McGuirk and Nunn 2025; Eberle, Rohner, and Thoenig 2025). 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.[8] ACLED reports notes

[8]The most prominent alternative geocoded conflict database, the Georeferenced Event Dataset from the Uppsala Conflict Data Program (UCDP) and Peace Research Institute Oslo (PRIO), has a dramatically worse and limited coverage for Kenya. Over our sample period, ACLED covers 6362 conflict events, compared to 632 in the UCDP's "Georeferenced Event Dataset" (GED). The coverage of events potentially linked to pastoralism in more remote settings is even more limited. In our case study region, for instance, it is 253 in ACLED versus 15 with UCDP (see Figure A-2). UCDP coverage is better in other East

describing the incident, the type (e.g., riot or battle), and the actors involved in a conflict event (see details in Table A-2). However, 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. We provide further details on the most important actors involved in the conflict in Kenya, their geographic distribution, and how likely they are affected by drought in Online Appendix C.

III.B. 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 units that are nested within the Kenyan counties. Information on whether an insurance unit 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 unit and period, but we obtained data from ILRI for the years 2016 to 2019. Even for those years, the only reliable information 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. 2022) 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 – including in closely related research by McGuirk and Nunn (2025) – 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 augments rainfall data with potential evapotranspiration (linked to temperature, land use or wind conditions). We do not use standardized drought proxies like the Standardized Precipitation Evapotranspiration Index (as in Harari and Ferrara 2018); because our neighborhood measures work better with non-standardized measures. Table A-5 shows that, as we would expect, all chosen drought proxies are highly correlated.

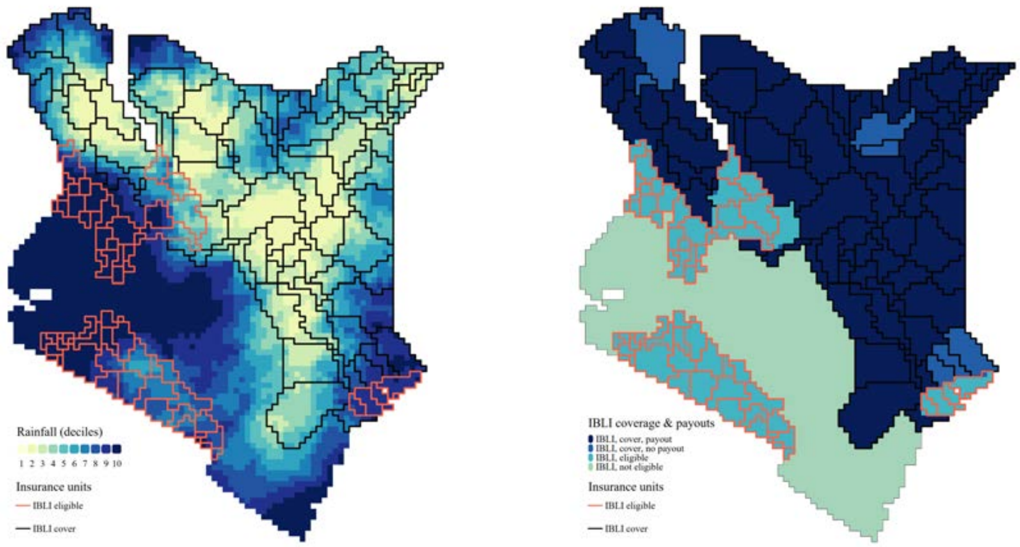
Panel A of Figure III illustrates the spatial variation in IBLI coverage and rainfall using the 2016/2017 period as an example. All areas covered by an insurance unit are IBLI-eligible; those with black borders already received IBLI coverage by the 2016/17 period. Naturally, rainfall is lower in the IBLI-eligible semi-arid and 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 unit during a specific period.

Neighborhood definition: The first challenge for a neighborhood approach is to approximate the potential conflict risk regarding 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 are not exogenously given but continuously

African countries, hence we use it in a robustness test for an extended sample later. Another possible source, the Social Conflict Analysis Database SCAD, has even fewer observations in Kenya and does not cover our full sample period.

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 units 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 $0.1° \times 0.1°$ grid-cell level.

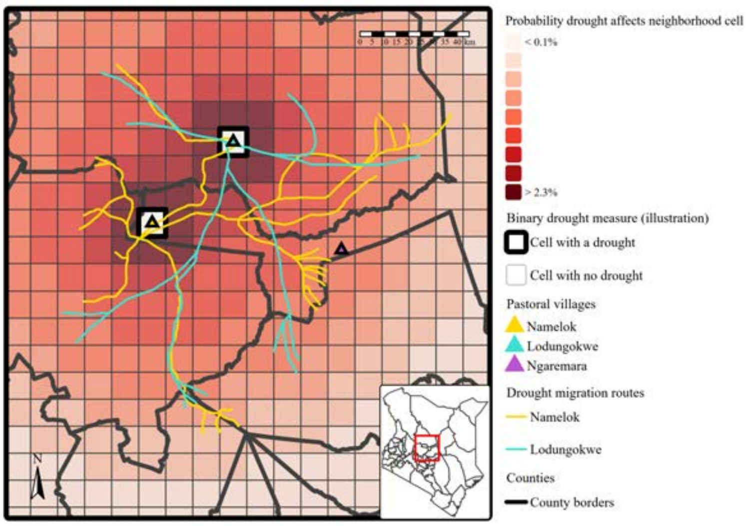
change over time, shaped by conflicts, general drought patterns, or changes in infrastructure (Flintan, Behnke, and Neely 2013). Even without such fixed routes or information on group-specific travel costs, it is plausible to assume that the probability of migration is smaller for cells that are further away. Longer migration implies psychological costs (e.g., time away from family, economic costs such as general travel costs and cattle health, see acaps 2022), and potential costs from conflicts when passing through areas with other land users. Therefore, our neighborhood approach 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 (see Figure A-1 for some illustrations from various studies). 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 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.[9]

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. Still, it 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 $Neighborhood\ \ variable_i = \sum_{j \neq i}^{J} \frac{Cell\text{-}level\ variable_j}{distance_{i,j}^{(-k)}}$.

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.

Cell-level variables: 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

[9] When using our baseline decay of 1, the average neighborhood contains 210 cells with weights greater than 0.05%, and around 60 cells have weights greater than 0.1%. For comparison, the average county encompasses around 90 cells and the average insurance unit encompasses around 23 cells.

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 unit 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 to easily interpret the 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.

IV. Empirical strategy

IV.A. Estimating equation

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

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

$Conflict_{i,t}$ 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. $\mathbf{X}_{\mathbf{i,t}}$ 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, historical political institutions, and 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. Figure B-1 shows that even net of the fixed effects, there is considerable spatial and temporal variation in both 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 in the main text 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.

IV.B. *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, the interaction is exogenous and δ_3 therefore identified (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, Satyanath, and Sergenti 2004). Causal interpretation 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. To precisely evaluate potential identification concerns in our setting, we turn to the omitted variable bias formula.[10] 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.

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

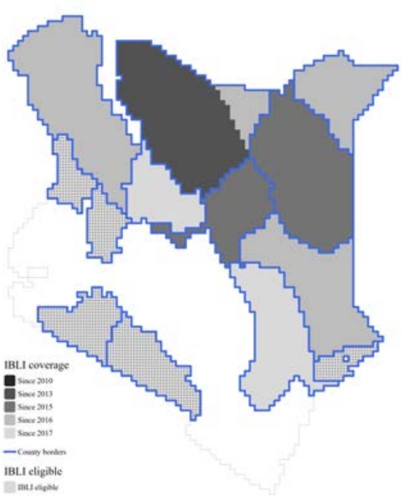
$Z_{i,t}$ represents a potential omitted variable that varies over space and periods t. To cause a bias in $\hat{\delta}_3'$, a $Z_{i,t}$ need to directly influence conflict (captured by α_4) and correlate with both $Rain\ deficit\ neighborhood_{i,t}$ and $IBLI\ neighborhood_{i,t}$. Given that rainfall 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 a $Z_{i,t}$.[11]

[10] Triple difference designs are robust to common types of model misspecification in geospatial conflict research. One key misspecification concern is the choice of the right grid-cell size when estimating a linear probability model. Large grid cells rather lead to a downward bias due to a high unconditional conflict probability, while small cells tend to lead to an upward bias. In our case, however, δ_3 would not be affected because the potential upward or downward bias in δ_1 is not correlated with the neighborhood IBLI coverage (see Olden and Møen 2022). 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. For instance, unlike the treatment variable in the 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 counter-factual groups is much more complicated than in the discrete difference-in-difference literature (see Roth et al. 2023, , for an overview).

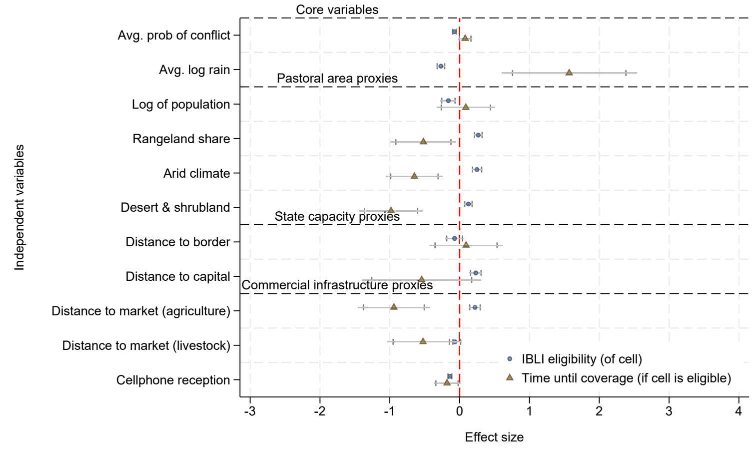
[11] A related concern is serial correlation in the time series of our variables of interest (see Christian and Barrett 2024). This concern is mitigated in our case by the fact that both variables of interest vary between cells and over time. Table B-1 shows no signs of a problematic serial correlation.

Figure V
Evaluating IBLI rollout and its relationship with conflict

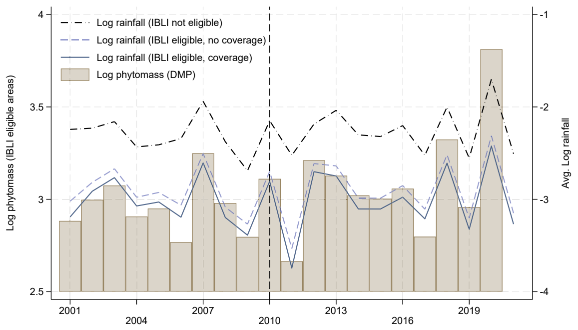
(a) IBLI rollout (2010-2020)



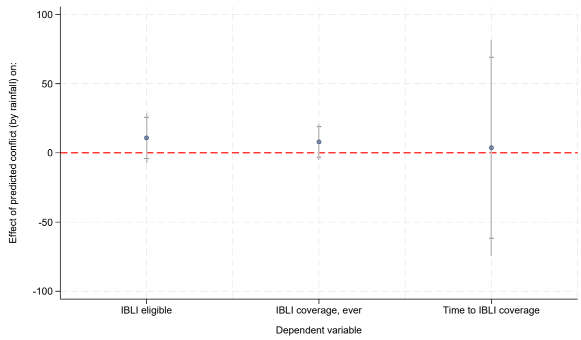
(b) Balance (cell level): IBLI eligibility & time until coverage



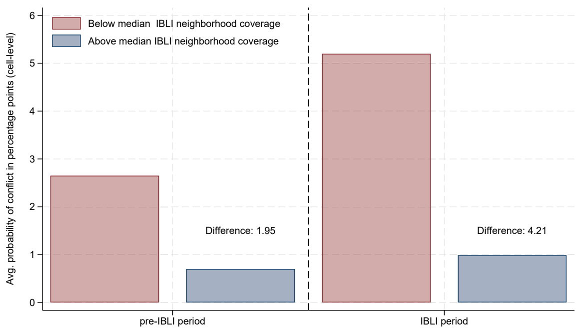
(c) Variation in rainfall
(by IBLI eligibility and coverage)



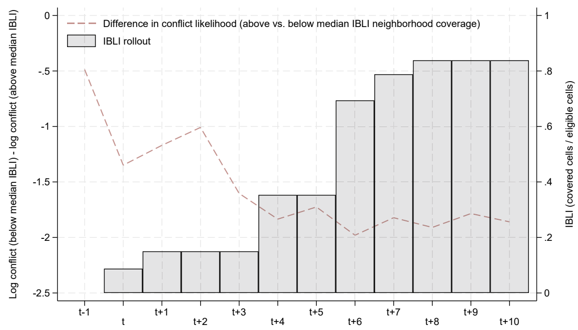
(d) IBLI selection on conflict-rain elasticity



(e) Conflict and IBLI neighborhood coverage
(pre-IBLI vs. IBLI period)



(f) Conflict and IBLI neighborhood coverage
(during IBLI rollout)



Notes: Panel A plots the rollout of IBLI across Kenya (based on Johnson et al. 2019; Fava et al. 2021). Blue lines are county borders within eligible areas, and white areas are non-eligible areas. Panel B shows results from bi-variate balancing tests, regressing the average of a set of variables (y-axis) from 2000-2009 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. It adds the log level of available pythomass (Dry Matter Productivity) in IBLI-eligible areas as a proxy for forage scarcity in pastoral areas. 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 rain-predicted conflict is the linear prediction of conflict resulting from regressing the conflict indicator on the rain deficit at the cell and neighborhood level, as well as cell level and period fixed effects. Median neighborhood IBLI coverage in panels E and F refers to the median of the average neighborhood coverage of a cell during our sample period. The 90% and 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.

Panel A of Figure V shows the rollout pattern over the 2010-2020 period. IBLI was piloted in the Marsabit district 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 units nested within it always receive coverage at the same time. Fava et al. (2021), and official statements report that technical challenges, such as cellphone reception, had the biggest impact on the time until an area received coverage. The lack of a continuous spread originating from the pilot region 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, population, distance to agricultural and livestock markets, and cellphone reception. Considering IBLI eligibility, the eligible pastoral areas naturally have less rain, a more arid climate, a higher share of rangeland, and are 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, particularly proximity to markets and cellphone reception, but not with the state capacity proxies. 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 and soil type (Z_i) on the IBLI rollout varies by period t. Another possibility are time-varying factors $Z_{i,t}$ such as cellphone coverage, which is positively correlated with IBLI expansion and plausibly related to conflict. To account for this, we run robustness tests controlling for the interaction of the cross-sectional variables with the neighborhood rain deficit.

The most worrying example of this type is the prior drought-conflict elasticity (Z_i) and possible dynamic adjustments of the rollout to rainfall 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 constitutes a good proxy for the available phytomass in an area. Figure B-2 also shows no trend differences in rainfall between areas with an average IBLI neighborhood coverage above the median compared to those with below median neighborhood coverage.

Suppose that the government intervenes to adjust the time until coverage is received 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 no systematic correlation with IBLI coverage during our sample. Another type of placebo test reveals no differences in drought-related conflict trends during the pre-IBLI period when comparing cells that will eventually end up having below versus those that will receive above median IBLI neighborhood coverage (see Figure B-3). We neither observe clear differential trends in the raw conflict data across areas that are non-eligible, eligible with or without coverage (see Figure A-5), nor across rollout clusters (see Figure A-6).

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 instead fosters 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.[12]

Before moving to more systematic regression evidence, we can also look more descriptively at the relationship between conflict and IBLI rollout in the neighborhood of a cell. For ease of exposition, we categorize cells into two groups, where one group consists of cells whose time-averaged IBLI neighborhood coverage is below the median and the other above. Panel E highlights two key features in the data. First, conflict is more common in locations that have low IBLI neighborhood coverage (red bars) compared to locations that have a high IBLI neighborhood coverage. Second, conflict is generally more frequent in Kenya during the IBLI period compared to the pre-IBLI period. However, the increase in conflict occurring in cells with above-median IBLI neighborhood coverage is less than half that in cells with below-median coverage. This is in line with the hypothesis that IBLI can mitigate conflicts.

Panel F zooms into the IBLI rollout period and depicts diverging conflict trends between above- and below-median IBLI neighborhood coverage. While panel E has indicated that IBLI is related to a relative reduction in conflict, we would expect that this difference gradually increases as the rollout proceeds. To investigate this, we plot the difference in the average conflict likelihood of cells with above-median IBLI neighborhood coverage compared to below-median (red line) together with the rollout over eligible cells over time (as grey bars). We see that the difference indeed gradually widens as IBLI coverage increases across cells. Figure B-4 suggests that this divergence is driven by a gradually declining drought-conflict sensitivity. Taken together, this suggests that IBLI plays an important role in reducing drought-induced conflict.

V. Results

In this section, we provide systematic evidence that IBLI coverage meaningfully decreases the effect of droughts on the probability of conflict. We then illustrate that our results are unlikely to be explained simply by variables correlating spatially with the IBLI rollout. Moreover, we document that our effects are stable when controlling for 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. We further show evidence for an extended sample, including all neighboring countries of Kenya. 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.

[12] An additional concern could be if the media-based ACLED conflict data are more likely to cover conflict events when cellphone coverage is better. Given that cellphone coverage correlates positively with the IBLI rollout, this could lead to non-classical measurement error. However, this would shift our estimates towards zero, biasing against a possible conflict-mitigating effect.

V.A. 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. While we refrain from assigning a causal interpretation to the effect of IBLI neighborhood coverage itself on conflict, Figure B-5 shows at least no obvious sign of worrying pre-trends.

We move to our main specification in column 3, adding the interaction term of the neighborhood-level rain deficit and IBLI. The interaction coefficient δ_3 is negative and statistically significant, indicating that IBLI coverage in the neighborhood of a cell reduces the conflict-inducing effect of droughts in its neighborhood.[13] Column 4 further adds local macro-cell-specific time trends (roughly 1 X 1 degree), which reduce concerns that the results are driven by spurious local conflict trends that correlate with the IBLI rollout.[14] Both the rain deficit and the interaction coefficient become smaller, remain negative, and stay precisely estimated.

The magnitude of the mitigation effect in column 3 has a straightforward interpretation. For the average IBLI neighborhood coverage, δ_1 indicates that a 100% increase in the rain deficit is associated with a 6.11 percentage point increase in the conflict probability. The coefficient of the interaction term, δ_3, indicates that increasing IBLI neighborhood coverage by one standard deviation lowers the sensitivity of conflict with regard to droughts by 1.56 percentage points. Put differently, this means that doubling the rain deficit would then lead to a smaller 6.11 (δ_1) - 1.56 (δ_3) = 4.55 percentage point increase in the likelihood of conflict. Another intuitive way to express the conflict-mitigating effect is, as explained above, to compute the change in drought-induced conflict in percent by dividing δ_3/δ_1. This way of computing the effect has the advantage that it is independent of the chosen grid-cell size. Calculated in this way, the mitigation effect of IBLI corresponds to a reduction of 25% (respectively 16.66% in column 4) in drought-induced conflict.[15]

In Online Appendix D, we analyze the cost-effectiveness of the program relative to its costs and current uptake. Using only pre-IBLI years and then applying the estimated mitigation leads to predictions of drought-induced conflict ranging from 34 to 122 incidents per year and from 47 to 167 deaths in Kenya (based on 90 percent confidence bounds). Based on our main mitigation estimate, IBLI prevents between

[13] Table B-2 shows the cell-level coefficients. The cell-level rain deficit coefficient is negative but insignificant. This absence of a conflict-inducing effect at the cell level itself aligns with the results in McGuirk and Nunn (2025), who argue that cells experiencing drought are not the locations that pastoralists target when seeking grazing opportunities. We generally refrain from interpreting the cell-level estimates, which constitute control variables in our specification. We will show in our sensitivity tests that our main neighborhood-level results are robust to omitting the cell-level variables, demonstrating that this specification choice is not driving the results.

[14] Macro cells are defined on a regular 1 X 1 degree grid using cell centroids. A few macro cells at the country border comprise only very few constituent 0.1 X 0.1 cells (as few as two cell centroids). Very small and very heterogenous macro cell sizes would add noise and potential bias if proximity to the border correlates with IBLI rollout. We therefore combine the 25% smallest incomplete macro-cells into four larger contiguous border clusters cells.

[15] One might also ask whether IBLI coverage successfully mitigates conflict for any level of rain deficit or whether its efficiency is smaller or greater for more or less extreme droughts. Figure B-6 bins the rain deficit in quintiles and shows that the conflict-mitigating effect is negative and significant for the third to fifth quintiles. The absolute interaction coefficient size increases by quintile, but the mitigation in percent remains roughly the same. IBLI payouts do increase in drought severity beyond the initial threshold that triggers payments (even though not captured in our data), so it is plausible that our reduced-form effect in percent remains similar across these quintiles. We can also bin the IBLI neighborhood coverage, although only in quartiles. The results highlight that higher coverage is correlated with a more substantial decrease for similar drought exposure.

TABLE I
Baseline results

	Dependent variable: $\text{Conflict}_{i,t}$			
	(1)	(2)	(3)	(4)
NEIGHBORHOOD				
Rain deficit (δ_1)	0.0708		0.0611	0.0579
	(0.0335)		(0.0297)	(0.0268)
IBLI (δ_2)		-0.0167	-0.0252	-0.0136
		(0.0043)	(0.0052)	(0.0069)
Rain deficit × *IBLI* (δ_3)			-0.0156	-0.0096
			(0.0052)	(0.0057)
Dep. var. mean	0.0246	0.0246	0.0246	0.0246
Conflict mitigation	–	–	-25.48 %	-16.66%
Cell-level controls	✓	✓	✓	✓
Cell fixed effects	✓	✓	✓	✓
Time fixed effects	✓	✓	✓	✓
Macro-cell time trends	–	–	–	✓
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)×-1), the standardized Index-Based Livestock Insurance (IBLI) coverage, and their respective interaction at both 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. Macro-cell time trends are linear trends on 1-degree by 1-degree grid cells, in which our 0.1-degree by 0.1-degree cells are nested. If fewer than 55 cells are within a macro cell (5% of the sample at the national borders) we group them into a common border-specific macro cell. Conley standard errors are implemented using the acreg package in Stata (Colella et al. 2019), with a distance cutoff of 200km.

8 and 28 incidents and 11 to 38 drought-induced deaths per year at the current uptake rate. For 2017 public subsidies of about 1.2 million US dollars, the return per public dollar is 0.10 to 0.22 using the WHO value of a statistical life, 0.25 to 0.58 with the World Bank values, and 1.1 based on IDinsight. Closing the remaining coverage gap of about 16 percent of eligible areas, about half a standard deviation, would avoid 4 to 14 incidents and 6 to 19 deaths per year at the current uptake rate. Of course, focusing solely on avoided deaths provides only a lower bound of the benefits, and increasing the current uptake rate could further improve the program's effectiveness.

V.B. 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.

V.B.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 rain deficit and several correlates of IBLI coverage (reported in panel B of Figure V), such as the log of population, the share of rangeland, proxies for state capacity or commercial infrastructure (distance to markets and cellphone reception), and indicators for different climate and biome zones.[16]

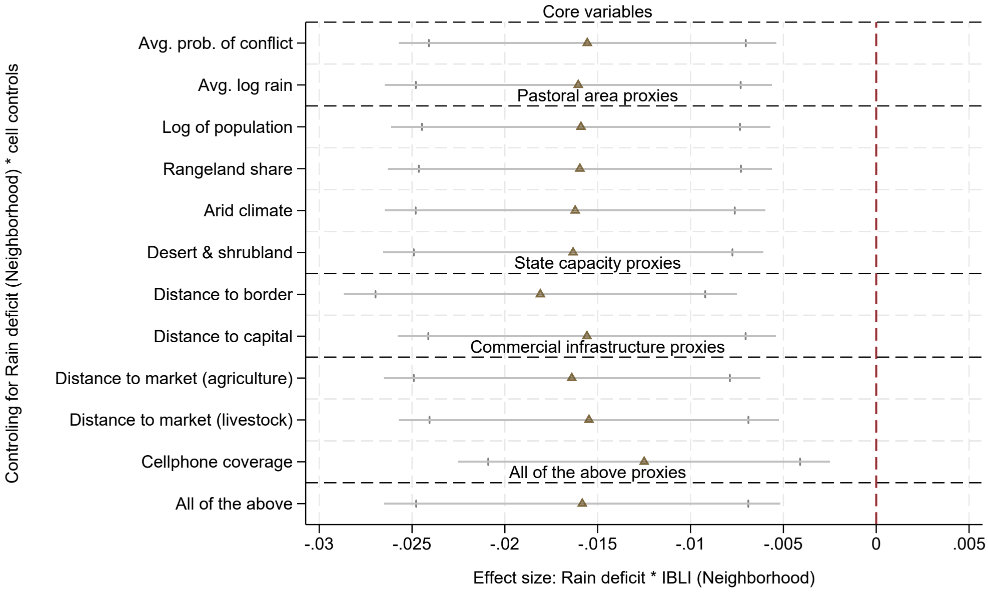
Further evidence against the idea that conflict mitigation, which we attribute to IBLI coverage, is caused by some other factor correlated with the IBLI rollout is provided by a placebo test of eventual IBLI coverage on pre-treatment conflict. If the rollout were caused by an underlying omitted variable 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, implying that we underestimate the mitigation potential, but both coefficients are statistically insignificant.[17]

[16]We also replicate the exercise at the neighborhood-level, weighing all those covariates with the identical distance decay as IBLI coverage and the rain deficit. Again, our results remain stable (see Table B-3). Using a single dimension for poor soil quality also does not alter our results (see Table B-4 and Table B-5). See Figure A-4 for maps of the cell soil classification.

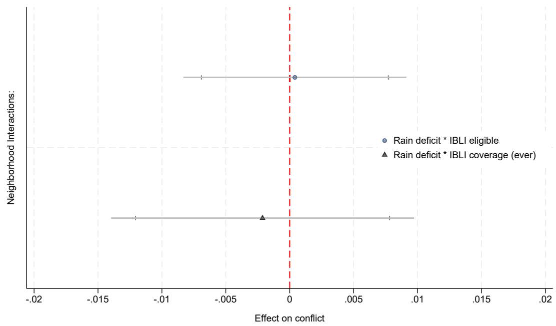
[17]We can also control for the next period IBLI coverage and its interaction with the rain deficit. Again, we find no evidence of an effect of future IBLI coverage or its interaction with the current rain deficit (see Figure B-7).

Figure VI
Dynamic effect of covariates and randomization inference

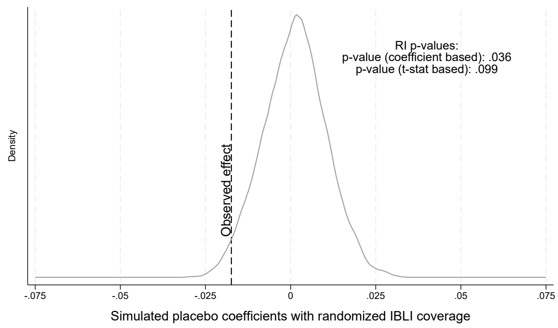
(a) IBLI mitigation effect controlling for covariates × rain deficit



(b) Placebo: IBLI mitigation effects (pre-IBLI rollout 2000-2009)



(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 2000 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 actual time-varying IBLI coverage. The estimation equation is: $(Conflict_{i,t} = \delta_1 Rain\ deficit\ neighborhood_{i,t} + \delta_2 IBLI\ neighborhood_i + \delta_3(Rain\ deficit\ neighborhood_{i,t} \times IBLI\ neighborhood_i) + \mathbf{X}'_{\mathbf{i,t}}\xi + \eta_i + \gamma_t + \epsilon_{i,t})$. 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 the estimate we obtain 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.

Another potential concern for identification and statistical inference is that 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 and 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 rain deficit. Few treated clusters also raise potential concerns about the validity of the p-values we report, which might over- or under-reject the null-hypothesis of no effect in such cases.

To address this issue, we follow MacKinnon and Webb (2020) and implement a randomization inference (RI) procedure to compare our estimate to a large distribution of placebo estimates. To implement a randomization procedure in our setting, 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 and emulates the real treatment assignment process. 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. RI allows computing finite-sample valid p-values without relying on distributional assumptions and provides more valid and conservative p-values than alternatives like the wild-cluster bootstrap (MacKinnon, Ørregaard Nielsen, and Webb 2023).

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 C 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 coefficient-based p-value is 0.036, further supporting a statistically significant conflict-mitigating effect of IBLI. Even with an alternative, particularly conservative t-statistics-based RI p-value, which is also robust to clusters differing strongly in size or variance (MacKinnon and Webb 2020), the interaction effect is still significant at the 10% level.

V.B.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 partly overlaps with the rollout of IBLI (see Figure A-7).[18] 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.

International development organizations like the World Bank have also set up aid projects aimed at alleviating famine and increasing the resilience of the agricultural and livestock sectors to climate change

[18]For more details, see https://www.hsnp.or.ke/index.php/as/objectives. Note that the partial, but limited, overlap has been intentional to evaluate the impact of the two programs (see Jensen, Barrett, and Mude 2017).

TABLE II

Controlling for other interventions

Other intervention:	Dependent variable: $\text{Conflict}_{i,t}$				
		HSNP		Aid	
	(1)	(2)	(3)	(4)	(5)
NEIGHBORHOOD					
$Rain\ deficit\ (\delta_1)$	0.0611	0.0600	0.0508	0.0710	0.0844
	(0.0297)	(0.0302)	(0.0318)	(0.0303)	(0.0304)
$IBLI\ (\delta_2)$	-0.0252	-0.0237	-0.0252	-0.0264	-0.0260
	(0.0052)	(0.0068)	(0.0069)	(0.0053)	(0.0052)
$Rain\ deficit \times IBLI\ (\delta_3)$	-0.0156	-0.0154	-0.0232	-0.0179	-0.0164
	(0.0052)	(0.0054)	(0.0072)	(0.0053)	(0.0053)
NEIGHBORHOOD INTERVENTION CONTROLS					
$Intervention$		-0.0021	0.0011	0.0076	0.0153
		(0.0043)	(0.0046)	(0.0039)	(0.0057)
$Rain\ deficit \times intervention$			0.0113		0.0112
			(0.0062)		(0.0065)
Dep. var. mean	0.0245	0.0245	0.0245	0.0245	0.0245
Conflict mitigation	-25.48%	-25.74%	-45.68%	-25.16%	-19.39%
Cell-level 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-6. 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 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.

(e.g., irrigation projects) during the last decades. Additionally, more short-term oriented aid, such as food aid, is often over-proportionally allocated to locations where international aid agencies are already active. Evidence about the net effect of aid on conflict is mixed (e.g., Crost, Felter, and Johnston 2014; Nunn and Qian 2014; Gehring, Kaplan, and Wong 2022; Christian and Barrett 2024; Moscona 2025). Figure A-8 shows the spatial distribution of World Bank development aid projects and commitments (AidData 2017), before and during the IBLI rollout. We directly test for a confounding effect of other interventions by adding cell- and neighborhood-level proxies for HSNP coverage, aid projects targeted to the agricultural sector, and their interaction with the rain deficit to our main specification. HSNP coverage is proxied by the spatial availability (exactly as we do for IBLI coverage). Aid projects are measured by the count of active projects, leveraging information on project start and end.

Table II documents that the conflict-mitigating effect of IBLI remains almost 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). 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 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 2024) and development aid (Nunn and Qian 2014) on conflict.[19]

In summary, we conclude 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, it seems implausible that overlapping coverage of IBLI with HSNP and or aid project coverage can explain the direction or significance of our main results.

V.B.3. Further sensitivity tests

We show that our results are robust to ($i.$) using alternative drought proxies, ($ii.$) different definitions of the conflict indicators, ($iii.$) varying aspects of the periods under consideration, ($iv.$) using plausible alternative ways of computing the neighborhood measures, ($v.$) changing how standard errors are calculated, and ($vi.$) alternative cell sizes. Panels A and B of Figure VII show the treatment effects with their confidence interval for each perturbation and the respective conflict mitigation in percent below. The first column always shows the baseline results for comparison, and the black diamonds indicate which aspect is being varied or added in which column.

The first concern we address is that using a single drought proxy can lead to measurement error, causing bias if it underestimates or overestimates the severity of the drought. Although rainfall is the most plausible exogenous drought proxy compared to alternatives with respect to conflict, the downside is that it less precisely captures drought conditions and feed availability for livestock than more specific indicators designed for that purpose. We confirm our findings using alternative proxies such as the Aridity Index and Dry Matter Productivity (DMP), indicating that the findings are not driven by mismeasurement of drought intensity. Similarly, different types of conflict may respond to drought differently, leading to measurement error if too many irrelevant conflict events are included. Our results remain stable when focusing on conflicts involving non-government actors or on battles, riots, or events with civilian casualties (as in Eberle, Rohner, and Thoenig 2025).[20] Moreover, we show that the results hold when focusing on events with the highest geographical precision category (e.g., a known town), addressing concerns about the precision of the event-based classification in ACLED.

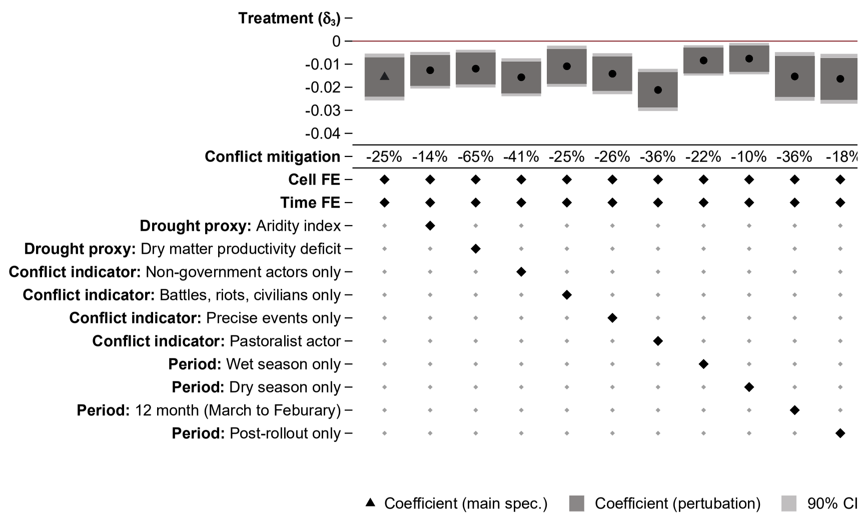
The most important alternative conflict indicator focuses on events plausibly involving pastoralists. The ACLED metadata includes the two main actors for all events and, for a subset of events, a finer distinction of associated actors and a text description for each event, which we use to classify events with dictionary-based approaches or an LLM. We classify events as (i.) involving pastoralists, (ii.) involving livestock, and (iii.) involving either one or the other. Our main indicator focuses on events where at least one of the two actors frequently features pastoralist groups as associated actors (at least 10% of incidents). Results remain similar. Figure B-9 shows that the treatment effect remains

[19] Table B-7 shows that results remain similar when using either the number of aid projects or the log of aid commitments in millions of US dollars. We also find similar results when controlling for aid from a larger set of 17 European donors, the US, India, and China (with data from Bomprezzi et al. 2024).

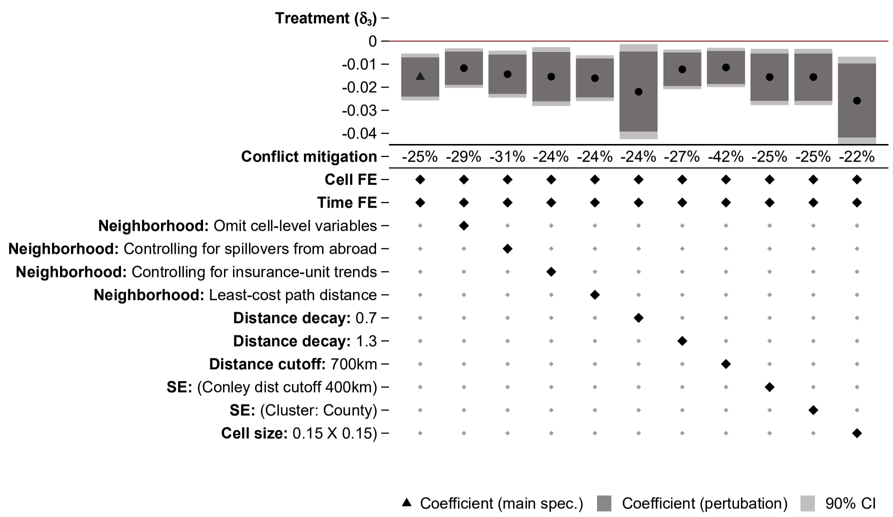
[20] Figure B-8 provides several additional alternative variables for events plausibly mitigated by IBLI and those unlikely to be affected, such as interstate conflict between governments. We can show that results are very similar for all conflict types plausibly affected by IBLI coverage for pastoralists, like riots, protests, non-fatal incidents, and events outside big cities. In contrast, it is reassuring to find that large conflicts (battles), strategic deployment of troops (war, civil war), violence by the government against civilians, unilateral violence by the government, and interstate conflict are not affected by our treatment. Finally, we find no effect with an outcome combining all other conflict types but excluding conflicts with pastoralist actors.

FIGURE VII
Overview: Sensitivity tests

(A) Perturbations: (In)dependent variables & sample period



(B) Perturbations: Neighborhood, standard errors, & cell size



Notes: The figure reports our coefficient of interest δ_3 over perturbations of our main specification (column 3 of Table I) depicted as a triangle. 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 90% and 95% CI (in dark and bright grey) are based on Conley standard errors with a distance cutoff of 200km. The aridity index is the ratio of precipitation over potential evapotranspiration. Dry Matter Productivity (DMP) is a phytomass indicator measured by the dry biomass increase of the vegetation (in kg/ha/year). Alternative conflict indicators refer to a subset of ACLED events that is used to construct the indicator variable, either based on actors involved, type of events, the geographic precision category provided by ACLED, or association of actors with pastoralists. The periods refer to alternative period constructions in which we use the rain deficit and conflict measures in the month of the dry or wet season only, use 12-month periods from March to February the following year, or drop all periods prior to the IBLI rollout. Controlling for spillovers from abroad controls for the neighborhood rain deficit and neighborhood IBLI coverage from cells within 700km of Kenya's national border. Insurance unit trends indicate the inclusion of a linear time trend for each of the 141 insurance units as well as the ineligible area. Least-cost path refers to neighborhood measures in which the inverse distance is based on a least-cost path based on Tobler's off-path hiking function (Tobler 1993) instead of geographic distance. Distance decays of 0.7 and 1.3 represent flatter and steeper distance decays in the construction of the neighborhood. The cutoff drops all cells beyond 700km in the construction of the neighborhood measures. The alternative standard errors use a higher distance cutoff when calculating Conley standard errors or cluster at the county level. Online Appendix A for details on the variable construction and sources.

statistically significant and that the conflict mitigation tends to be larger for these conflicts over various other plausible ways to approximate pastoralist participation. Although none of these approaches alone provides definitive evidence, the robustness of the results toward alternative classifications reassures us that ACLED constitutes a reliable source in our setting. As a final variation in the conflict outcome, Figure B-10 also shows an intensive margin conflict mitigation effect using either the logarithm or an inverse hyperbolic sine transformation of the number of incidents in a cell.

We conduct several tests concerning the definition of our sample period. First, in line with the arguments in McGuirk and Nunn (2025), we find stronger conflict mitigation in the wet season, though the interaction coefficient remains significant in both seasons. Moreover, while our definition of the 12-month-period aligns best with the initial IBLI sales windows, we show that results are not affected by defining a period from March to February. The final coefficient in panel A shows that excluding pre-IBLI years slightly reduces the precision of the point estimate without affecting the coefficient's size. Overall, panel A indicates that our results are robust to various choices or definitions of treatment, outcome, or period.

Panel B of Figure VII examines the sensitivity of our results to alternative neighborhood specifications, methods of calculating standard errors, and cell size. We demonstrate that our main neighborhood result is not driven by the decision to control separately for cell-level rain deficit and IBLI coverage by excluding all cell-level variables. Spillovers from neighboring countries, including areas where IBLI is absent (or very limited, as in Ethiopia), could bias our results by either introducing external conflicts or by omitting parts of the relevant neighborhood in our spatial measure. By incorporating controls for rain deficits, IBLI coverage, and their interaction across borders, we show that potential spillovers from migration and conflicts due to droughts abroad are not driving our results (see Figure A-9 for details on the bordering areas). Moreover, we show our results barely change when we include linear insurance-unit-specific time trends, to account for potentially different conflict dynamics or other factors trending across regions over time.

Using geographic distance could introduce measurement error if it does not account for natural barriers like mountains or lakes, leading to attenuation bias. To address these concerns, we show that our results hold when using the actual least-cost-path travel distances instead (using Tobler's off-path hiking function, see Figure A-10 for an illustration). We also examine a potential misspecification of the decay parameter, which could cause attenuation bias (if too steep) or overestimation (if too flat). The figure reports results for a flatter (0.7) and a steeper (up to 1.3) decay, and Figure B-11 shows results for a whole range of decays from 0.5 up to 2. A decay of 2 assigns 95% of weights to cells within a 340km radius. Our main result is robust to these alterations with regard to sign and significance, and the mitigation in percent is remarkably robust across the whole range.

A skeptical reader might also question whether the distance decay is sufficient to account for the maximum distances that different pastoralist groups migrate. Including cells outside the unobserved maximum migratory distance could potentially bias our results if these cells receive enough weight to shift our main coefficient of interest. To address this concern, we show that our results remain robust when applying an upper distance limit of 700 km to the neighborhood calculation (Figure B-12 shows results for a whole range of distance cutoffs). Relatedly, we show that we can increase the distance cutoff when computing the Conley standard errors without losing statistical significance and that results are robust when using standard errors clustered at the county level instead.[21]

Another concern is whether we have chosen the appropriate size for our grid cells. If cells are too large, there is too little variation in the probability of conflict. If cells are too small, imprecision in the conflict events could lead to wrongful assignment of the conflict probability across cells. Estimation of our main parameters of interest should be robust to the second issue due to the spatial smoothing employed in constructing our neighborhood measures. However, it is unclear at which cell size results start to vanish due to limited variation. We test the sensitivity of our results by varying cell size for robustness. Increasing cell size to 0.15 × 0.15 degrees leaves the conflict mitigation and statistical significance of δ_3 virtually unchanged. Figure B-14 shows results over a range of cell sizes up until 0.5 × 0.5 degrees, the size of the prominent PRIO-grid cells (Tollefsen, Strand, and Buhaug 2012).[22]

Finally, in Table B-9 we employ an instrumental variable (IV) approach to estimate the impact of IBLI payouts on the probability of conflict, addressing potential biases in the reduced-form analysis. The IV approach first helps to confirm that the interaction term we use in our main, reduced-form estimation strongly predicts actual payouts, with a robust F-statistic and individual significance in the first stage. We use a binary indicator for payouts due to data limitations, instrumenting inverse-distance weighted IBLI payouts with the interaction of neighborhood rain deficits and IBLI coverage. The results show that the payouts significantly reduce the likelihood of conflict. Although the effect size of binary payouts is limited in interpretation, it also remains within a plausible range and suggests that payouts contribute to conflict mitigation. The larger effect size with IV (column 3) compared to OLS (column 1) could be due to either measurement error (attenuation bias) or OLS underestimating the true effect due to an upward bias. Either argument would suggest that a possible bias in our reduced form estimates works against finding an effect of IBLI.

V.C. Extension with East African neighboring countries

In this section, we expand our sample to include all neighboring countries of Kenya. Panel A of Figure VIII shows that only small part of Ethiopia is covered by a version of IBLI, but adding Somalia, South Sudan, Uganda and Tanzania has two possible benefits. First, pastoralist migration does not stop precisely at country borders, and adding neighboring countries helps to account for this. Second, by adding these countries, our estimation sample now includes areas that are pastoralist but are so far away from Kenya that they cannot be plausibly affected by IBLI in Kenya. Hence, we can use this sample to run a specification with cells that are "never" treated by IBLI neighborhood coverage.

Specifically, we implement this by using the extended sample and computing neighborhood measures with a distance cutoff of 700km for cells j relative to a cell i, after which they are no longer included in the neighborhood measures of that cell i. A potential challenge with this extended sample is that some of the neighboring countries experience major regional conflicts unrelated to droughts that could add excessive noise to the estimation. We account for this in two ways. First, we add linear trends on macro-grid

[21] Another test of the plausibility of our estimates by checking if we can recover plausible macro-level trends using a completely different approach to operationalize the neighborhood. For that purpose, we take the replication data of McGuirk and Nunn (2025) for all of Africa, including their large grid cells and definition of what constitutes a neighborhood. Even in that setting, we find that after January 2010, when IBLI was introduced, pastoralist neighboring homelands are begin to be less strongly linked to conflict in Kenya compared to other countries (see Table B-10)

[22] Larger cells become problematic because the unconditional probability of having at least one conflict increases so much that there remains too little variation across cells and time. Moreover, such large cells would lead to less than 30 cells (located at least 50% in Kenya) (see Figure A-11).

cells g (1 degree × 1 degree) to account for regional conflict dynamics, as well as country-by-period fixed effects that fully absorb country-specific time trends in either conflict, drought, or IBLI availability. Second, we use our dictionary-based indicator to run tests focusing only on livestock-related conflict. In addition, we also show results using the UCDP conflict database, which has sufficient coverage when combining all the countries in one sample. The specification we estimate is:

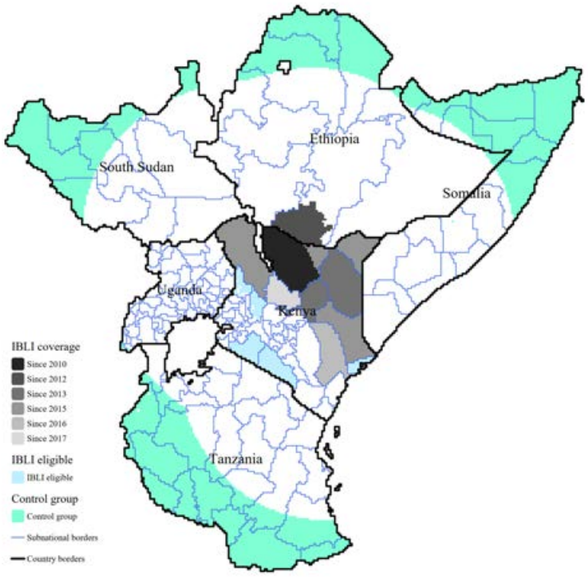
$$\begin{aligned} Conflict_{i,t} = &+ \delta_1 Rain\ deficit\ neighborhood_{i,t} + \delta_2 IBLI\ neighborhood_{i,t} \\ &+ \delta_3 (Rain\ deficit\ neighborhood_{i,t} \times IBLI\ neighborhood_{i,t}) \\ &+ \mathbf{X}_{\mathbf{i,t}}^{'} \xi + \eta_i + \tau_{(c),t} + \gamma_g t + \epsilon_{i,t} \end{aligned} \quad (3)$$

with $\gamma_g t$ representing the macro-cell-specific linear trends and $\tau_{(c),t}$ are either period or the country-by-period fixed effects. Specifications without country-by-period fixed effects use simple period fixed effects instead.

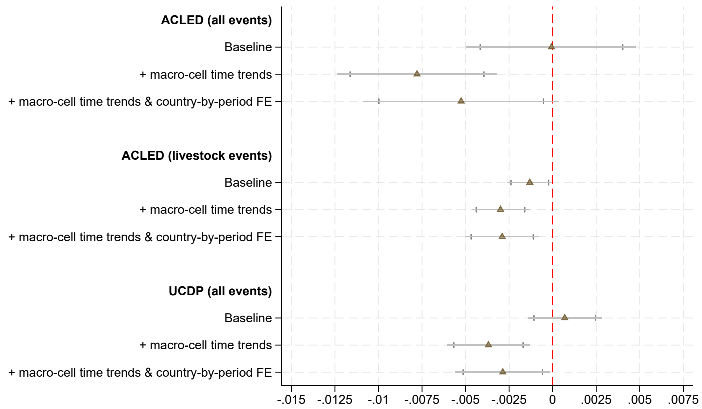
Figure VIII, Panel B, shows that the interaction coefficient is negative and statistically significant in all specifications that control for differential conflict dynamics using macro-cell-specific linear trends and country-by-period fixed effects. As expected, there is a lot of noise in the initial ACLED and UCDP specifications, but adding the controls or focusing on livestock events successfully addresses this issue. The magnitude of the coefficient cannot be easily compared to our main specification since a one-standard-deviation change in IBLI neighborhood coverage differs strongly in the extended sample. However, Table B-12 provides an approximation using a binary treatment indicator. The results indicate that in our preferred specification controlling for macro-trends, the percent reduction in drought-induced conflict corresponds to between 22 to 23%. Taken together, the results from the extended East Africa sample are very much in line with our main results focusing on Kenya.

Figure VIII
East Africa extension

(a) Sample



(b) Results



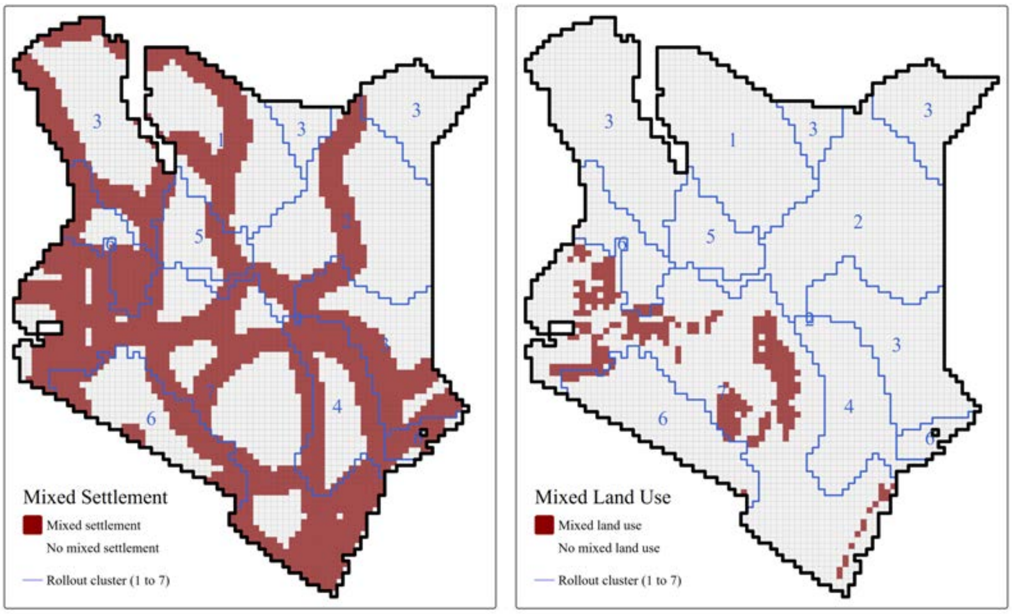
Notes: Panel A of the figure plots our East Africa sample, consisting of Kenya and its direct neighbors. The figure plots the rollout of IBLI coverage across Kenya and Ethiopia (based on Johnson et al. 2019; Fava et al. 2021). Blue lines highlight subnational borders. The white areas highlight ineligible locations in East Africa as of 2022. Green shaded areas do not receive any neighborhood IBLI coverage. Starting in 2023, the DRIVE program intends to provide IBLI to all of the neighbors. The variable is processed at a $0.1° \times 0.1°$ grid-cell level. Panel B of the figure reports coefficients, 90% and 95% confidence intervals from 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 for the East Africa sample. It displays our variable of interest, the interaction term at the neighborhood level, while all other coefficients can be found in Table B-11. The neighborhood variables apply a cut-off at 700km in this multi-country specification, i.e., cells j beyond a 700km distance do not contribute to the neighborhood measure of cell i. Standard errors are two-way clustered both at the PRIO-grid-cell level and the country-year level. Full regression results are provided in Table B-11.

V.D. *Heterogeneity and within rollout cluster-year evidence*

No version of our baseline specification can rule out with certainty that an omitted variable exists that varies 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 IBLI rollout clusters. Specifically, our case study suggests that the drought-conflict relationship is particularly severe in areas where land use is contested. Areas characterized by other land use and within the range of the pastoralist drought-migration routes, also referred to as mixed land use or fringe areas, are particularly affected by drought-induced conflict (Eberle, Rohner, and Thoenig 2025; McGuirk and Nunn 2025). The spatial conflict patterns in our case study region suggest this is also likely in Kenya. Hence, if IBLI mitigates this type of conflict by mitigating the drought shock for pastoralists, we would expect stronger mitigation effects in precisely those locations compared to others.

Figure IX
Contested land use classifications

(a) Mixed settlements (Murdock atlas) (b) Mixed land use (historical map)



Notes: Panel A shows our mixed settlement indicator, which is unity for all cells within a homeland with below median distance to the homeland border (based on Murdock's Geographic Atlas, Murdock 1967). Panel B 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). Blue lines indicate the borders of the insurance rollout clusters. The numbers within the cluster indicate the order in which the insurance clusters received IBLI. The variables are processed at a $0.1° \times 0.1°$ grid-cell level.

We use two proxies for contested land use cells, shown in Figure IX. Panel A shows the mixed settlement areas, defined as regions within ethnic homelands close to their borders, based on Murdock's Ethnographic Atlas (Murdock 1967). While the issue of contested land use is more complicated in reality and subject to open scholarly discussions, it is plausible that, on average, these areas have a higher likelihood of interaction between different ethnic groups and more competition for resources. Panel B depicts our second proxy mixed land use areas identified from a historical land use map of Kenya (Kenya Rangeland Ecological Monitoring Unit, 1983) that we digitized and georeferenced, where agricultural and pastoral activities overlap, increasing the potential for conflict over land and water resources. Both types of contested areas are highlighted in red on the map, with the blue borders indicating the IBLI insurance rollout clusters. These red regions, especially when facing drought conditions, are particularly prone to conflict due to competition between different land users and should experience the strongest conflict mitigation due to IBLI.

We test this hypothesis by taking our baseline specification and adding the contested land use proxies and the relevant interaction terms:

$$
\begin{aligned}
Conflict_{i,t} = {} & \delta_1 Rain\ deficit\ neighborhood_{i,t} + \delta_2 IBLI\ neighborhood_{i,t} \\
& + \delta_3 (Rain\ deficit\ neighborhood_{i,t} \times IBLI\ neighborhood_{i,t}) \\
& + \psi_1 (Rain\ deficit\ neighborhood_{i,t} \times Contested\ land\ use_i) \\
& + \psi_2 (IBLI\ neighborhood_{i,t} \times Contested\ land\ use_i) \\
& + \psi_3 (Rain\ deficit\ neighborhood_{i,t} \times IBLI\ neighborhood_{i,t} \times Contested\ land\ use_i) \\
& + \mathbf{X}'_{\mathbf{i,t}} \xi + \eta_i + \gamma_{r,t} + \epsilon_{i,t}
\end{aligned}
\tag{4}
$$

where $\mathbf{X}'_{\mathbf{i,t}}$ still includes the cell-level and neighborhood variables of IBLI coverage, the rain deficit, and their interactions, but now also contains their respective interactions with the $Contested\ land\ use_i$. It is this triple interaction coefficient ψ_3 and its significance that serves as a test of our hypothesis. One decisive difference to our main specification is that in further specifications, we can add $\gamma_{r,t}$, IBLI-rollout-cluster-by-time 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.

The two proxies have important differences in terms of identifying variation and overlap of IBLI with contested cells. Our preferred measure is based on Murdock's Geographic Atlas, which provides substantial variation between cells that receive IBLI coverage during our sample period and those that get it earlier or later during the rollout. The historical land use map reflects a more restricted definition of contested land use, and there is no overlap between contested land use cells and areas with IBLI coverage. The disadvantage is that this alternative option offers only variation within two rollout clusters. The advantage is that it serves as an even stricter test of our neighborhood approach; we examine conflict in cells that are only indirectly affected by IBLI through migrating pastoralists.

Table III presents results consistent with the idea that IBLI mitigates drought-induced conflict, particularly within contested land use locations. Our coefficients of interest are δ_3 and ψ_3, which captures the differential impact of IBLI drought mitigation in the contested land use locations. Column 1 confirms a significant and negative triple interaction effect, indicating that the conflict-mitigating effect is stronger in contested land use cells. Column 2 accounts for the potentially endogenous IBLI rollout by adding the rollout cluster times period fixed effects. Column 3 replicates the same result using the historical land use map.[23] All results show that conflict mitigation is much stronger in contested land use cells. In our favorite specification in column 2, we find a 6.84% reduction in non-contested cells, compared to an 18.75% reduction in contested land use cells.[24]

[23] Table B-14 shows qualitatively similar results using more recent data to classify mixed land use based on pastoral and agricultural suitability or the transition from grassland to cropland.

[24] By using the Murdock data to proxy for contested cells, we are oversimplifying. In reality, there are not necessarily always more conflicts between all distinct ethnic groups. Some ethnic groups in the dataset, like the Rendille and Samburu, share a common Masai culture (Murdock 1967) that makes it easier to establish informal conflict-resolution mechanisms. In contrast,

Table III
Triple-interaction results: Competing land use

Contested land use proxies:	*Dependent variable:* Conflict$_{i,t}$		
	Main: Murdock ethnographic atlas		*Alternative:* Historical land use map
	(1)	(2)	(3)
Neighborhood			
$Rain\ deficit$ (δ_1)	0.0587	0.0867	0.0899
	(0.0299)	(0.0338)	(0.0339)
$Rain\ deficit \times contested\ land\ use$ (ψ_1)	0.0039	0.0057	-0.0194
	(0.0105)	(0.0095)	(0.0360)
$IBLI$ (δ_2)	-0.0251	-0.0146	-0.0145
	(0.0053)	(0.0068)	(0.0067)
$IBLI \times contested\ land\ use$ (ψ_2)	-0.0030	-0.0048	-0.0223
	(0.0031)	(0.0033)	(0.0086)
$Rain\ deficit \times IBLI$ (δ_3)	-0.0122	-0.0059	-0.0097
	(0.0051)	(0.0057)	(0.0059)
Neighborhood mitigation heterogeneity			
$Rain\ deficit \times IBLI \times contested\ land\ use$ (ψ_3)	-0.0095	-0.0114	-0.0274
	(0.0043)	(0.0044)	(0.0141)
Dep. var. (non-contested)	0.0186	0.0186	0.0226
Dep. var. (contested)	0.0312	0.0312	0.0543
Conflict mitigation (non-contested)	-20.87%	-6.84%	-10.83%
Conflict mitigation (contested)	-34.72%	-18.75%	-52.73%
Cell-level controls	✓	✓	✓
Cell fixed effects	✓	✓	✓
Time fixed effects	✓	–	–
Rollout-cluster-by-time fixed effects	–	✓	✓
Obs	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. To conserve space, the cell-level variables are relegated to Table B-13. Moreover, we include interactions of all our variables with an indicator variable for a cell located within a contested land use area. Our main proxy is based on an indicator for all cells closer to their homeland border than the median cell in their homeland, based on Murdock's ethnographic atlas (Murdock 1967). The alternative proxy indicates areas where agriculture, ranging, and pastoral land use are practiced, based on a Historical land use map from the Kenyan government (1984). 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). Conflict mitigation in the contested land use is defined as $((\delta_3 + \psi_3)/(\delta_1 + \psi_3))$. 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.

VI. Mechanisms

This section provides evidence on the mechanisms by which IBLI affects drought-induced conflict, distinguishing between rapacity effects and opportunity cost effects. First, we examine the equilibrium effect of IBLI on herd sizes. Larger herds could amplify the rapacity effect during droughts because it

the Turkana are linked to the Karamojong culture group and, despite being neighbors with the Samburu, face higher obstacles to establishing such mechanisms. The Murdock data allows us to distinguish between ethnic border areas within and across cultural groups, as shown in Figure A-13. Figure B-15 shows that only the triple interaction with mixed settlement between different cultural groups is statistically significant. Due to the limited number of cultural groups and general limitations of using this source, we interpret these results as suggestive but in line with our general theory and approach.

intensifies competition for scarce resources, while smaller herds would contribute to mitigating it. IBLI could lead to larger herd sizes by increasing risk-adjusted returns to hold livestock (see Toth et al. 2017; Barrett et al. 2023). However, it is also plausible that without IBLI, pastoralists are forced to hold excess cattle beyond their desired optimum as precautionary savings.[25] By reducing the need for precautionary savings, IBLI can allow pastoralists to have smaller herds and invest more in the health of each animal, increasing their resilience to droughts (see evidence in Jensen, Barrett, and Mude 2017). We provide evidence that herd sizes are indeed smaller in counties covered by IBLI, thus decreasing the rapacity effect.

Second, we examine how IBLI affects the opportunity costs of conflict via its effect on income and asset values. Conflict and conflict-related activities are risky and costly, and better outside options allow pastoralists to avoid situations that risk escalating into a conflict or creating a vicious circle of action and retaliation (cf., Cao et al. 2025). Another more behavioral interpretation in our setting is that malnutrition, fear for their cattle, and general desperation increase the likelihood of violent behavior and spontaneous outbreaks of violence among pastoralists and between pastoralists and farmers. Tafere, Barrett, and Lentz (2019) find that IBLI coverage significantly improves subjective well-being and reduces self-reported stress among insured pastoralists in southern Ethiopia, even absent insurance payouts. In addition, we use price data from a panel of local livestock markets across Kenya to show that IBLI mitigates the drop in livestock asset prices during droughts. Moreover, results using six rounds of the Afrobarometer survey show that IBLI cushions against negative drought-related income shocks. Both higher incomes and asset values raise the opportunity cost of engaging in conflict, thereby reducing its likelihood.

Finally, the effects of IBLI of reducing herd sizes, as well as stabilizing incomes and asset values can not only directly reduce conflict by a reduction in the rapacity and increase in the opportunity cost effect, but could also contribute to reducing migratory pressure. If pastoralists are forced to migrate far from their traditional grazing grounds, the likelihood of conflictual encounters with other land users increases. Toth et al. (2017) use GPS devices to show for a small sample of 20 pastoral households in Northern Kenya that drought-migration routes are shaped by IBLI coverage. While we cannot provide quantitative evidence on it, IBLI could also ease migratory pressure in cases where pastoralists have sufficient market access to use IBLI indemnity payments to purchase animal feed (Boresha Consortium 2022). Although we cannot observe actual migration behavior, we combine ACLED with the ethnographic atlas from Murdock (1967) to provide supportive, albeit not definitive, evidence that IBLI reduces the migratory distances from pastoralists' ethnic homelands during droughts.

VI.A. Herd size and precautionary savings

In line with our proposed mechanism that IBLI reduces the rapacity effect by curbing excessive herd sizes, we first use county-level administrative data from the Kenyan Ministry of Agriculture to examine herd sizes. The Kenyan Ministry of Agriculture provides annual panel data on the total number of cattle (kept for beef and dairy production) across counties between 2012 and 2018.[26] Panel A of Figure X depicts the distribution of cattle, highlighting most cattle, especially those kept for beef production, are actually located in pastoralist areas. We then construct a county-year panel and regress the number of

[25] Barrett et al. (2023) provide complementary evidence for the precautionary-savings channel, showing that IBLI uptake substantially reduces distress sales of goats in the same region.

[26] The cattle numbers are based on agricultural censuses and supplemented with surveys for years without a census (see Section A-6 for further details).

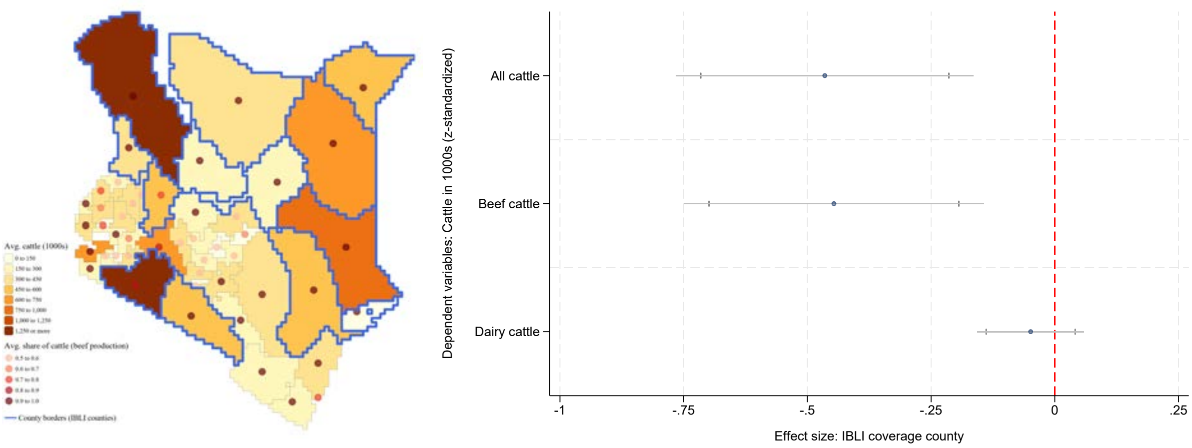
cattle on the share of a county's area where IBLI is available using the following specification:

$$\text{Herd size}_{c,t} = \beta_1 \text{IBLI}_{c,t} + \eta_c + \gamma_t + \epsilon_{c,t} \tag{5}$$

where Herd size$_{c,t}$ is the number of cattle (z-standardized) in county c during year t, IBLI$_{c,t}$ is the share of a county covered by insurance units. η_c are county fixed effects capturing time-invariant factors such as inherent IBLI eligibility and geographical characteristics, and γ_t are time fixed effects absorbing common trends in cattle numbers.

FIGURE X
Herd size

(A) Avg. cattle numbers (2012-2018) (B) IBLI coverage on cattle numbers (county)



Notes: Panel A of the figure plots the average number of cattle in millions across counties for the 2012 to 2018 period in shades of brown. It also depicts the share of cattle kept for beef production on all cattle. County borders of counties eligible for IBLI are highlighted in blue. The data is obtained from the Kenyan Ministry of Agriculture. Panel B reports the coefficient, 90% and 95% confidence intervals from regressing the number of cattle z-standardized (for all cattle, cattle kept for beef and dairy production) on county-averaged IBLI coverage. All specifications include county and time fixed effects. Standard errors are clustered at the county level. Full results are reported in Table B-15.

Figure X, Panel B shows that IBLI coverage correlates with an overall smaller amount of cattle. In counties with full IBLI coverage, the number of cattle drops by about half a standard deviation (roughly 200,000). This is consistent with the idea of a quantity-quality trade-off in Jensen, Barrett, and Mude (2017), where pastoralists with IBLI emphasize cattle health and quality more than the mere number of cattle, and in line with evidence of reduced precautionary savings due to IBLI in Barrett et al. (2023). Notably, when distinguishing between types of cattle, the reduction is entirely driven by cattle for beef production—those typically used by transhumant pastoralists, with no effect on dairy cattle. Dairy cows are much less common in IBLI eligible counties with an average share of 16%, compared to 47% in non-eligible counties. Dairy cattle are predominantly kept in the village and not taken away during the drought migration, and hence plausibly less affected by ILBI. Descriptively, the evidence supports the notion that IBLI, by reducing the need for precautionary savings for cattle, leads to smaller herds in equilibrium. Smaller herd sizes reduce competition for resources during droughts, thereby mitigating the rapacity effect.

VI.B. Asset prices and incomes

VI.B.1. Stabilizing returns to assets

To shed further light on the opportunity cost mechanism, we test if IBLI helps to stabilize pastoralists' livestock, which is their key asset. Droughts can force pastoralists to sell more on the local livestock markets than they initially intended because they "are desperate" and need to feed themselves or buy feed for the remaining cattle. Amplified by falling demand – as buyers often include other drought-affected actors – anecdotal evidence reports dramatically plummeting prices. One article mentions how during a severe drought year "prices have dropped threefold since last year" (see Xinhua 2023) and a Reuters report describes even steeper drops with cattle regularly selling for "60,000 or 65,000 shillings ($500-$530) (...) selling for only 1,500 Kenyan shillings ($12)" (see Waita 2022). To some extent, pastoralists can reduce their own consumption to avoid selling at low prices (Janzen and Carter 2019), but there are obviously limits to this coping strategy. IBLI coverage can help to limit the vicious cycle of emergency sales and price declines by reducing herd sizes and smoothing incomes during droughts.

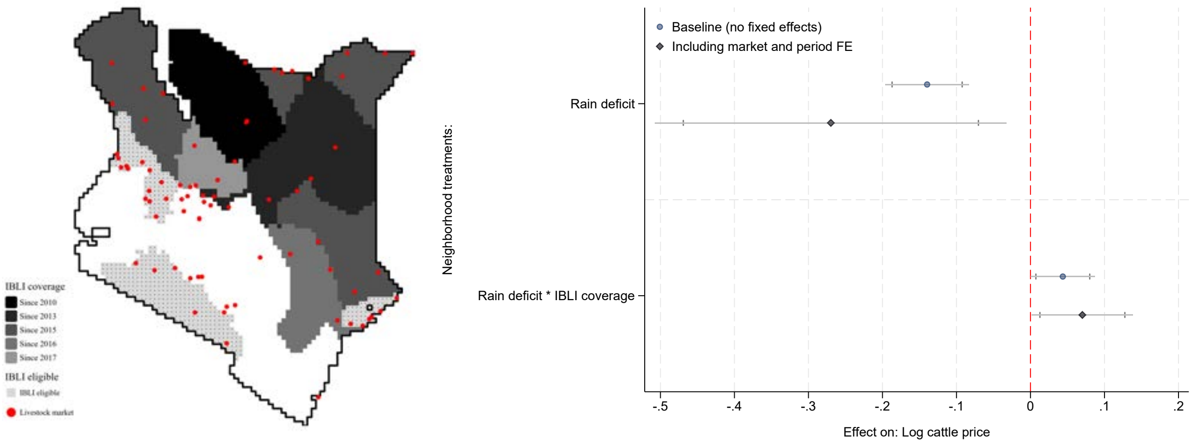
To examine this mechanism empirically, we gather livestock prices for 73 local livestock markets across Kenya (Kenya Livestock Market Information System 2024), which we geo-code and match to our grid cells (see panel A of Figure XI). Livestock prices are obtained via trained collaborators directly from the markets via text message (see Section A-6 for more details). We average monthly prices over our 12-month periods for each local market as our outcome of interest. Although price data are available for 73 markets, only 41 markets provide sufficient temporal coverage for a panel analysis. Hence, we end up with an unbalanced panel of markets with price data in at least two and for up to nine periods. We estimate the following specification.

$$\begin{aligned}\text{Log(livestock price)}_{m,i,t} = &+ \delta_1 Rain\ deficit\ neighborhood_{i,t} + \delta_2 IBLI\ neighborhood_{i,t} \\ &+ \delta_3 (Rain\ deficit\ neighborhood_{i,t} \times IBLI\ neighborhood_{i,t}) \\ &+ \eta_{m,i} + \gamma_t + \epsilon_{i,m,t}\end{aligned} \tag{6}$$

where $\text{Log(livestock price)}_{m,i,t}$ is the log of the period t averaged livestock price at a market m, located within cell i. δ_1 and δ_3 are our coefficients of interest. δ_1 is the coefficient of the neighborhood rain deficit, and δ_3 is the coefficient of the interaction between the neighborhood rain deficit and neighborhood IBLI coverage. $\eta_{m,i}$ capture time-invariant differences between livestock markets, and γ_t capture country-wide shocks (e.g., overall drought intensity or livestock price developments). The neighborhood variables are always computed from the perspective of the respective local market. Standard errors are spatially clustered as in the main specification.

FIGURE XI
Stabilizing returns to assets

(A) Livestock markets & IBLI access (B) Asset price effects (market level)



Notes: Panel A of the figure depicts livestock markets (red dots) and, in shades of black to bright grey, the timing of the IBLI rollout. Panel B depicts the coefficients, 90% and 95% confidence intervals from regressing the log cattle price on the market level on the neighborhood rain deficit, neighborhood IBLI coverage, and the interaction of the two. Dots represent results from a regression without market and period fixed effects, and diamonds represent results from regression, including both period and market fixed effects. Full results, including results on other livestock prices, are reported in Table B-16. The 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 XI shows results for the main effect of drought on cattle prices and the mitigating effect of IBLI, both with and without market and period fixed effects. The graph's upper part shows that a drought's equilibrium effect on cattle prices is negative and statistically significant. The magnitude of the coefficient suggests that a 100% increase in the rain deficit is associated with an on average 13 to 25% decrease in the cattle price. This is not of the same magnitude as the dramatic anecdotal examples, but a strong depreciation in asset value for pastoralists and broadly in line with prior findings by Barrett et al. (2003). Moving to another market with potentially higher prices is a costly alternative, and due to the spatial correlation in droughts neighboring markets are often also affected to some degree.

Regarding the mitigating effect of IBLI, the lower part of the coefficient plot shows that there is a positive and significant interaction effect with IBLI coverage of around 0.04 to 0.05, which corresponds to a mitigation effect of between 20 and 30% of the drought-induced price drop. This result is robust to using a simple specification and, despite the limited number of markets, also to using fixed effects and solely variation within the same market over time. These results are in line with the county-level trends linking IBLI coverage to smaller herd sizes, which can help to limit the additional supply of cattle pushed on the market during intense drought periods. This mechanism is particularly interesting as it points towards a positive externality of even limited IBLI take-up. Each pastoralist who does not have to engage in "distress sales" helps to limit the decline in prices for all market participants. Higher prices, all else equal, raise the opportunity cost of fighting for everyone, even for those who did not buy IBLI themselves.

VI.B.2. Mitigating adverse income shocks

To further assess the opportunity cost channel through which IBLI may reduce conflict, we test whether IBLI helps mitigate income shocks among pastoralists. We use survey data from the Afrobarometer (2019), which provides us with a repeated cross-section of six survey rounds collected during our sample period. Using the geolocations in the survey, we match 7882 respondents to our cells. Because Afrobarometer has no direct, continuous measure of income, we follow Desmet and Gomes (2023) and create two binary indicators based on two questions inquiring if a respondent has either (i.) experienced hunger or (ii.) gone without cash income during the last 12 months (see Section A-7 for details). We take the respondent-level information on the month and year when the survey was conducted and calculate the corresponding average rainfall and insurance coverage over the prior 12-month period in the cell where they are located. We compute both outcomes for the full sample and for a pastoralist sub-sample defined as respondents working in the agricultural sector or self-identifying with an ethnic group traditionally practicing pastoralism.[27]

We estimate the following specification:

$$\begin{aligned}\text{Adverse income shock}_{r,i,u,t} =& \beta_1 \text{Rain deficit}_{i,t} + \beta_2(\text{Rain deficit}_{i,t} \times \text{IBLI}_{u,t}) \\ &+ \mathbf{X}'_{\mathbf{r,t}}\xi + \tau_{u,t} + \psi_e + \epsilon_{r,i,u,t}\end{aligned} \tag{7}$$

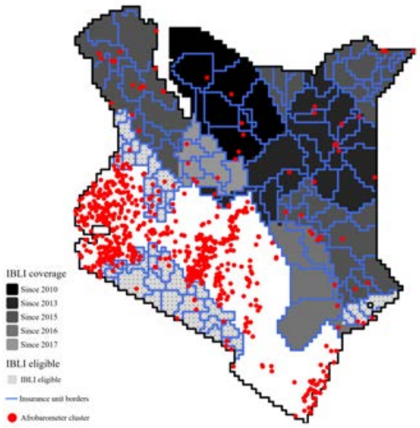
where the outcome Adverse income shock$_{r,i,t}$ is a binary variable that takes on the value 1 if a respondent r, surveyed on grid cell i, located in insurance unit u, reports suffering an income shock during the 12 months before the interview (t). β_1 and β_2 are our coefficients of interest. β_1 captures the effect of the average rain deficit on grid cell i during wave w on the probability of an income shock, and β_2 measures whether IBLI coverage can successfully mitigate this effect. The insurance unit-by-time fixed effects ($\tau_{u,t}$) capture the main effect of IBLI coverage. ψ_e are ethnic group fixed effects, capturing the prevalence of pastoralism within ethnic groups. $\mathbf{X}'_{\mathbf{r,t}}$ is a vector of respondent level controls: age, a gender dummy, an urban dummy, and proxies for education (see details in Section A-7). Standard errors are clustered at the insurance unit level to account for within-unit correlation in income shocks.

Panel B of Figure XII presents the regression results: the upper part demonstrates a clear and significant positive correlation between rain deficit and the probability of experiencing hunger or a adverse cash income shock, while the lower part shows that IBLI coverage significantly reduces these income shocks. These findings hold for both the full sample (depicted as circles) and the pastoralist subsample (depicted as triangles), although the magnitude of the effect on cash income is smaller in the full sample. Although the Afrobarometer data have inherent limitations as a repeated cross-section, our results provide descriptive evidence consistent with the hypothesis that IBLI raises the opportunity cost of conflict by mitigating income shocks.

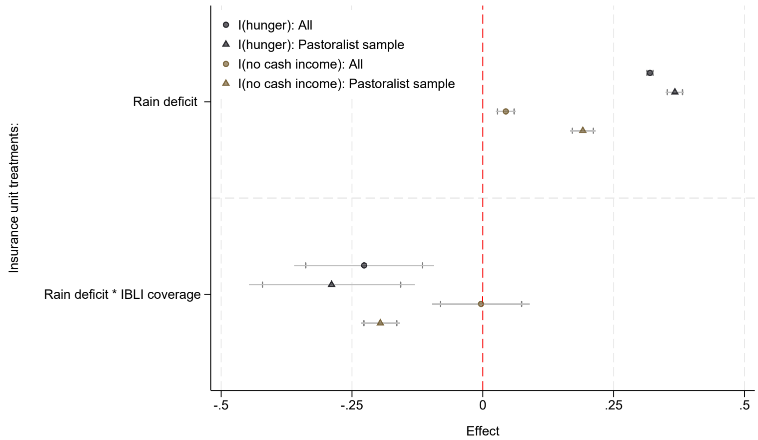
[27] Panel A of Figure XII shows sufficient coverage and variation in Afrobarometer locations for areas with and without IBLI coverage. Figure A-14 provides disaggregated spatial coverage of survey clusters and insurance coverage by survey round. In addition, it shows that there is also sufficient variation in the rain deficit over the survey clusters.

FIGURE XII
Smoothing adverse income shocks

(A) Afrobarometer cluster & IBLI units



(B) Income effect results (Individual level)



Notes: Panel A of the figure depicts the Afrobarometer survey cluster (red dots), the insurance unit borders (blue lines), and in shades of black to bright grey, the timing of the IBLI rollout. Panel B depicts the results from regressing the probability of going hungry on the cell-level rain deficit and its interaction with cell-level IBLI coverage, averaged across the 12 months preceding the respective Afrobarometer survey wave w. The dependent variables are our hunger (black dots and triangles) and no cash income indicators (olive dots and triangles). Dots represent results from a regression using all survey respondents. Triangles represent results from restricting the sample survey respondents in the regression that identify with an ethnic group in which pastoralism is a common practice (the Boran, Gabra, Kalenjin, Kipsigis, Rendile, Maasai, Samburu, Somali, Sabaot, Tugen, and Turkana). Full results are reported in Table B-17. 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 specifications include Insurance unit-by-time and ethnic-group fixed effects. We define administrative counties as insurance units for non-eligible areas when constructing the fixed effects. The 90% and 95% confidence intervals are based on standard errors are clustered at the insurance-unit-by-county level.

VI.C. Migratory pressure

Both smaller herd sizes (lowering the rapacity effect) and cushioning against income and asset price shocks (raising the opportunity cost effect) should lower the necessity for long-distance drought-migration. To examine whether this constitutes a relevant mechanism, we follow Eberle, Rohner, and Thoenig (2025) and match the actors recorded in georeferenced ACLED conflict events to ethnic homelands based on Murdock (1967) (see Table A-6 for details). We then compute the distance between the centroid of a pastoralist homeland—defined based on Murdock (1967) and each conflict event involving actors from that homeland. This distance serves as our proxy for the migratory distance of that ethnic group in a given period. We also compute the corresponding values of our key variables (such as rain deficit and IBLI coverage) at the ethnic homeland level, aligning this analysis with our prior specifications. The small map in panel A of Figure XIII illustrates this approach by displaying all ethnic homelands in Kenya alongside the conflict event locations for the matched events.

The main map in panel A of Figure XIII 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 rain deficit 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, this example illustrates the validity of our approach and is line with IBLI reducing migratory pressure.

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

$$\begin{aligned} Log\ Distance^{Homeland}_{k,i,e,t} = {} & \delta_1 Rain\ deficit^{Homeland}_{e,t} + \delta_2 IBLI^{Homeland}_{e,t} \\ & + \delta_3 (Rain\ deficit^{Homeland}_{e,t} \times IBLI^{Homeland}_{e,t}) + \eta_e + \gamma_t + \epsilon_{k,i,e,t} \end{aligned} \tag{8}$$

where Log $Distance^{Homeland}_{k,i,e,t}$ is the log of geographic distance between the geolocation of a conflict event k and the centroid of homeland e, involving actor i matched to ethnic homeland e that occurs in period t. $Rain\ deficit^{Homeland}_{e,t}$ is the log averaged rainfall in a homeland during period t, which we multiply by minus one (resulting in the log average rain deficit) assigned to all actors i that are matched to homeland e. $IBLI^{Homeland}_{e,t}$ is the share of the homeland e that IBLI covers during period t for actors i matched to homeland e (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 assignment (Abadie et al. 2023).

Our main interest is in δ_1, capturing the effect of the exogenous homeland rain deficit, and δ_3, capturing again the extent to which IBLI can mitigate this effect. Panel B of Figure XIII plots the coefficients together with 95% confidence intervals. The black dots show that with our baseline specification, the homeland rain deficit has a statistically significant and positive effect on distance. For average pastoral homeland IBLI coverage, this can be translated into a rain deficit-distance elasticity of about 0.26. Increasing IBLI coverage by one standard deviation reduces the elasticity by roughly half to 0.14.

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-6). 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).[28] Taken together, those results suggest that easing migratory pressure seems to constitute an important mechanism by which IBLI reduces drought-related conflicts.[29]

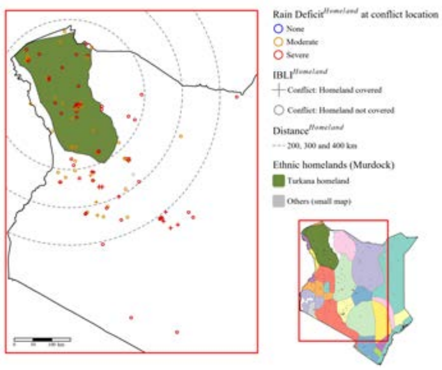
[28] List A-1 documents which groups are classified as pastoral groups. Our classification roughly corresponds to a transhumant pastoral value of above 0.5 as in McGuirk and Nunn (2025), or the nomad/pastoral dummy in Eberle, Rohner, and Thoenig (2025). Reassuringly, the homelands of groups not classified as pastoralists in this way do not receive IBLI coverage.

[29] To assess the risk of spurious spatial reallocation of conflict, we compare conflict rates inside and outside ethnic homelands under IBLI coverage. Figure A-15 shows that, despite a higher relative concentration of conflicts within homelands, IBLI reduces the absolute number of conflicts by roughly 50% outside and by 33% inside the homelands. This suggests that IBLI does not simply shift conflicts, but has an overall mitigating effect.

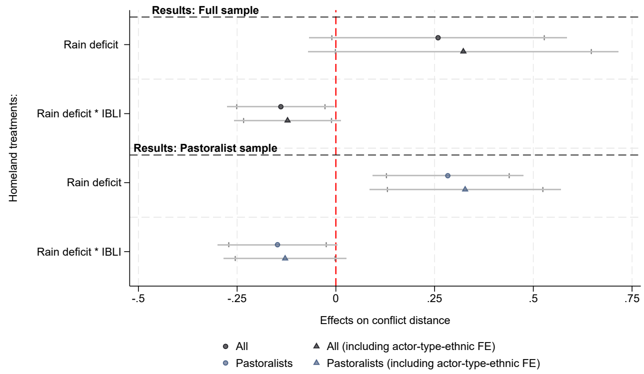
Figure XIII

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, Kishi, and Linke 2023) involving Turkana pastoralists over our sample. Different colors indicate the severity of the rain 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 whether 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 8. The upper part shows the point estimates and 90% 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. 90% and 95% confidence intervals are obtained from standard errors clustered at the homeland (treatment) level. See Table A-6 for details on Actor-Type-Ethnic association and List A-1 for the pastoral classification of ethnic groups. Full results are reported in Table B-18.

VII. 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 25%. We show that key mechanisms through which IBLI mitigates conflict are by reducing herd size, smoothing drought-induced negative income shocks, stabilizing livestock prices, 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 US$ in public funds in combination with 572 million US$ 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 with weak state and fiscal capacity. It seems promising to consider how the remote-sensing technology underlying IBLI could be combined with other ICT4d tools to develop a platform that monitors herds and provides real-time notifications to farmers, and optimizes migration routes for pastoralists in a way that minimizes disruptive encounters between different types of land users. 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, Alberto, Susan Athey, Guido W Imbens, and Jeffrey M Wooldridge, "When should you adjust standard errors for clustering?", *Quarterly Journal of Economics*, 138 (2023), 1–35

Abatzoglou, John T, Solomon Z Dobrowski, Sean A Parks, and Katherine C Hegewisch, "TerraClimate, a high-resolution global dataset of monthly climate and climatic water balance from 1958–2015", *Scientific Data*, 5 (2018), 1–12

Acampora, Michelle, Lorenzo Casaburi, and Jack Willis, "Land rental markets: Experimental evidence from Kenya", *American Economic Review*, 115 (2025), 727–771

acaps, "Kenya Impact of drought: Turkana and Marsabit counties", 2022

Afrobarometer, "Afrobarometer Data, Kenya, Rounds 3 to 8, 2003 - 2019", 2019

AidData, "WorldBank Geocoded Research Release Level1 v1.4.2 geocoded dataset", 2017

Barrett, Christopher B., Francis Chabari, DeeVon Bailey, Peter D. Little, and Layne D. Coppock, "Livestock Pricing in the Northern Kenyan Rangelands", *Journal of African Economies*, 12 (2003), 127–155 https://doi.org/10.1093/jae/12.2.127

Barrett, Christopher B, Nathaniel Jensen, Karlijn Morsink, Yuma Noritomo, Hyuk Harry Son, Rupsha Banerjee, and Nils Teufel, "Long-run Effects of Catastrophic Drought Insurance", DEEP Working Paper No. 18, Data and Evidence to End Extreme Poverty Research Programme: Oxford., 2023

Bazzi, Samuel, and Christopher Blattman, "Economic shocks and conflict: Evidence from commodity prices", *American Economic Journal: Macroeconomics*, 6 (2014), 1–38

Benami, Elinor, Zhenong Jin, Michael R Carter, Aniruddha Ghosh, Robert J Hijmans, Andrew Hobbs, Benson Kenduiywo, and David B Lobell, "Uniting Remote Sensing, Crop Modelling and Economics for Agricultural Risk Management", *Nature Reviews Earth & Environment*, 2 (2021), 140–159

Berlanda, Andrea, Matteo Cervellati, Elena Esposito, Dominic Rohner, and Uwe Sunde, "Medication against conflict", *Journal of Development Economics* (2024), 103306 https://doi.org/https://doi.org/10.1016/j.jdeveco.2024.103306

Berman, Nicolas, and Mathieu Couttenier, "External shocks, internal shots: The geography of civil conflicts", *Review of Economics and Statistics*, 97 (2015), 758–776

Berman, Nicolas, Mathieu Couttenier, Dominic Rohner, and Mathias Thoenig, "This mine is mine! How minerals fuel conflicts in Africa", *American Economic Review*, 107 (2017), 1564–1610

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

Blumenstock, Joshua Evan, "Fighting Poverty with Data", *Science*, 353 (2016), 753–754

Bomprezzi, Pietro, Axel Dreher, Andreas Fuchs, Teresa Hailer, Andreas Kammerlander, Lennart C Kaplan, Silvia Marchesi, Tania Masi, Charlotte Robert, and Kerstin Unfried, "Wedded to Prosperity? Informal Influence and Regional Favoritism", CESifo Working Paper No. 10969, CESifo, 2024

Boresha Consortium, "PROMOTING INDEX BASED LIVESTOCK INSURANCE IN KENYA, Technical Brief January 2022", 2022

Borusyak, Kirill, and Peter Hull, "Non-random exposure to exogenous shocks", *Econometrica*, 91 (2023), 2155–2185

Burke, Marschall, Solomon M. Hsiang, Joel Ferguson, and Edward Miguel, "New Evidence on the Economics of Climate and Conflict", NBER Working Paper No. 33040, National Bureau of Economic Research, 2024

Burke, Marshall, Solomon M Hsiang, and Edward Miguel, "Climate and conflict", *Annual Review of Economics*, 7 (2015), 577–617

Cao, Yiming, Benjamin Enke, Armin Falk, Paola Giuliano, and Nathan Nunn, "Herding, armed conflict, and a culture of honor: Global evidence", NBER Working Paper No. 29250, National Bureau of Economic Research, 2025

Casaburi, Lorenzo, Michael Kremer, Sendhil Mullainathan, and Ravindra Ramrattan, "Harnessing ICT to increase agricultural production: Evidence from Kenya", Working Paper, Private Enterprise Development in Low-Income Countries, 2019

Casaburi, Lorenzo, Michael Kremer, and Ravindra Ramrattan, "Crony Capitalism, Collective Action, and ICT: Evidence From Kenyan Contract Farming", Working Paper, Private Enterprise Development in Low-Income Countries, 2019

Casaburi, Lorenzo, and Jack Willis, "Time versus state in insurance: Experimental evidence from contract farming in Kenya", *American Economic Review*, 108 (2018), 3778–3813

Chantarat, Sommarat, Andrew G Mude, Christopher B Barrett, and Michael R Carter, "Designing index-based livestock insurance for managing asset risk in northern Kenya", *Journal of Risk and Insurance*, 80 (2013), 205–237

Chelanga, Philemon, Duncan C. Khalai, Francesco Fava, and Andrew Mude, "Determining insurable units for index-based livestock insurance in northern Kenya and southern Ethiopia", ILRI Research Brief No. 83, ILRI, Nairobi, Kenya, 2017

Christian, Paul, and Christopher B Barrett, "Spurious regressions and panel IV estimation: Revisiting the Causes of Conflict", *Economic Journal*, 134 (2024), 1069–1099

Colella, Fabrizio, Rafael Lalive, Seyhun Orcan Sakalli, and Mathias Thoenig, "Inference with arbitrary clustering", Discussion Paper No. 12584, IZA Institute of Labor Economics, 2019

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

Crost, Benjamin, Joseph Felter, and Patrick Johnston, "Aid under fire: Development projects and civil conflict", *American Economic Review*, 104 (2014), 1833–1856

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

Desmet, Klaus, and Joseph F Gomes, "Ethnic remoteness reduces the peace dividend from trade access", NBER Working Paper No. 30862, National Bureau of Economic Research, 2023

Dube, Oeindrila, and Juan F Vargas, "Commodity price shocks and civil conflict: Evidence from Colombia", *Review of Economic Studies*, 80 (2013), 1384–1421

Eberle, Ulrich J., Dominic Rohner, and Mathias Thoenig, "Heat and Hate: Climate Security and Farmer-Herder Conflicts in Africa", *Review of Economics and Statistics* (2025), 1–47 https://doi.org/10.1162/rest_a_01546

Fabregas, Raissa, Michael Kremer, and Frank Schilbach, "Realizing the potential of digital development: The case of agricultural advice", *Science*, 366 (2019), eaay3038 https://doi.org/10.1126/science.aay303

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

Fava, Francesco, Nathaniel Jensen, James Sina, Andrew Mude, and Barry Maher, *Building financial resilience in pastoral communities in Africa: Lessons learned from implementing the Kenya Livestock Insurance Program (KLIP)*, (World Bank, Washington, D.C., 2021)

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

Fetzer, Thiemo, and Stephan Kyburz, "Cohesive institutions and political violence", *Review of Economics and Statistics*, 106 (2024), 133–150 https://doi.org//doi.org/10.1162/rest_a_01156

Flintan, Fiona E, Roy H Behnke, and Constance Neely, "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* (2013), 1–44

Gassebner, Martin, Paul Schaudt, and Melvin HL Wong, "Armed groups: Competition and political violence", *Journal of Development Economics*, 162 (2023), 103052

Gehring, Kai, Lennart C Kaplan, and Melvin HL Wong, "China and the World Bank-How contrasting development approaches affect the stability of African states", *Journal of Development Economics*, 158 (2022), 102902

Gehring, Kai, Sarah Langlotz, and Stefan Kienberger, "Stimulant or depressant? Resource-related income shocks and conflict", *Review of Economics and Statistics* (2023), 1–47

Grossman, Herschell I, "A general equilibrium model of insurrections", *American Economic Review*, 81 (1991), 912–921

Gruber, Jonathan, "The incidence of mandated maternity benefits", *American Economic Review*, 84 (1994), 622–641

Harari, Mariaflavia, and Eliana La Ferrara, "Conflict, climate, and cells: A disaggregated analysis", *Review of Economics and Statistics*, 100 (2018), 594–608

Hodler, Roland, Paul Schaudt, and Alberto Vesperoni, "Mining for Peace", Discussion Paper No. 17807, Centre for Economic Policy Research, 2023

Hsiang, Solomon M, Marshall Burke, and Edward Miguel, "Quantifying the influence of climate on human conflict", *Science*, 341 (2013), 1235367

Huffman, George J., Erich F. Stocker, David T. Bolvin, Eric J. Nelkin, and Jackson Tan, "GPM IMERG Final Precipitation L3 1 month 0.1 degree x 0.1 degree V06", 2022

Janzen, Sarah A, and Michael R Carter, "After the drought: The impact of microinsurance on consumption smoothing and asset protection", *American Journal of Agricultural Economics*, 101 (2019), 651–671

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

Jensen, Nathaniel D et al., *Escaping Poverty Traps and Unlocking Prosperity in the Face of Climate Risk: Lessons from Index-Based Livestock Insurance*, (Cambridge University Press, 2024)

Johnson, Leigh, Brenda Wandera, Nathan Jensen, and Rupsha Banerjee, "Competing expectations in an index-based livestock insurance project", *Journal of Development Studies*, 55 (2019), 1221–1239

Kenya Livestock Market Information System, "Livestock Paramaters", Livestock Market Information System Kenya (LMISKE) Dataset. Accessed on November 4, 2024. Available at http://www.lmiske.go.ke/lmis/livestock.htm?action=getLivestockParameters, 2024

Kenya Rangeland Ecological Monitoring Unit, "Land Use Map of Kenya", 1983

Le Rossignol, Etienne, and Sara Lowes, "Ancestral livelihoods and moral universalism: Evidence from transhumant pastoralist societies", NBER Working Paper No. 30259, National Bureau of Economic Research, 2022

Lengoiboni, Monica, Arnold K Bregt, and Paul van der Molen, “Pastoralism within land administration in Kenya—The missing link”, *Land Use Policy*, 27 (2010), 579–588

MacKinnon, James G., and Matthew D. Webb, “Randomization inference for difference-in-differences with few treated clusters”, *Journal of Econometrics*, 218 (2020), 435–450 https://doi.org/https://doi.org/10.1016/j.jeconom.2020.04.024

MacKinnon, James G., Morten Ørregaard Nielsen, and Matthew D. Webb, “Cluster-robust inference: A guide to empirical practice”, *Journal of Econometrics*, 232 (2023), 272–299 https://doi.org/https://doi.org/10.1016/j.jeconom.2022.04.001

McGuirk, Eoin, and Marshall Burke, “The economic origins of conflict in Africa”, *Journal of Political Economy*, 128 (2020), 3940–3997

McGuirk, Eoin F, and Nathan Nunn, “Development Mismatch? Evidence from Agricultural Projects in Pastoral Africa”, NBER Working Paper No. 33191, National Bureau of Economic Research, 2024

McGuirk, Eoin F, and Nathan Nunn, “Transhumant Pastoralism, Climate Change, and Conflict in Africa”, *Review of Economic Studies*, 92 (2025), 404–441

Michalopoulos, Stelios, and Elias Papaioannou, “The long-run effects of the scramble for Africa”, *American Economic Review*, 106 (2016), 1802–1848

Miguel, Edward, Shanker Satyanath, and Ernest Sergenti, “Economic shocks and civil conflict: An instrumental variables approach”, *Journal of Political Economy*, 112 (2004), 725–753

Morelli, Massimo, and Dominic Rohner, “Resource concentration and civil wars”, *Journal of Development Economics*, 117 (2015), 32–47

Moscona, Jacob, “The management of aid and conflict in Africa”, *American Economic Journal: Economic Policy*, 17 (2025), 228–259

Moscona, Jacob, Nathan Nunn, and James A Robinson, “Segmentary Lineage Organization and Conflict in Sub-Saharan Africa”, *Econometrica*, 88 (2020), 1999–2036

Murdock, George Peter, “Ethnographic Atlas: A Summary”, *Ethnology*, 6 (1967), 109–236 http://www.jstor.org/stable/3772751

Nunn, Nathan, “The long-term effects of Africa’s slave trades”, *Quarterly Journal of Economics*, 123 (2008), 139–176

Nunn, Nathan, and Nancy Qian, “US food aid and civil conflict”, *American Economic Review*, 104 (2014), 1630–1666

Olden, Andreas, and Jarle Møen, “The triple difference estimator”, *Econometrics Journal*, 25 (2022), 531–553

Pörtner, Hans-Otto et al., *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, 2022)

Premand, Patrick, and Dominic Rohner, “Cash and Conflict: Large-Scale Experimental Evidence from Niger”, *American Economic Review: Insights*, 5 (2024), 137–153

Raleigh, Clionadh, Roudabeh Kishi, and Andrew Linke, “Political instability patterns are obscured by conflict dataset scope conditions, sources, and coding choices”, *Humanities and Social Sciences Communications*, 10 (2023), 1–17

Rohner, Dominic, “Mediation, military, and money: The promises and pitfalls of outside interventions to end armed conflicts”, *Journal of Economic Literature*, 62 (2024), 155–195

Rohner, Dominic, and Alessandro Saia, “Education and conflict: Evidence from a policy experiment in Indonesia”, Discussion Paper No. 13509, Centre for Economic Policy Research, 2019

Roth, Jonathan, Pedro HC Sant’Anna, Alyssa Bilinski, and John Poe, “What’s trending in difference-in-differences? A synthesis of the recent econometrics literature”, *Journal of Econometrics*, 235 (2023), 2218–2244

Sakketa, Tekalign Gutu, Dan Maggio, and John McPeak, “The Protective Role of Index Insurance in the Experience of Violent Conflict: Evidence from Ethiopia”, *Journal of Development Economics*, 174 (2025)

Tafere, Kibrom, Christopher B. Barrett, and Erin Lentz, "Insuring Well-Being? Buyer's Remorse and Peace of Mind Effects From Insurance", *American Journal of Agricultural Economics*, 101 (2019), 627–650 https://doi.org/10.1093/ajae/aay087

Tobler, Waldo, "Three presentations on geographical analysis and modeling: non-isotropic geographic modeling; speculations on the geometry of geography; and global spatial analysis (93-1)", Technical report 93-1, National Center for Geographic Information Analysis, 1993

Tollefsen, Andreas Forø, Håvard Strand, and Halvard Buhaug, "PRIO-GRID: A unified spatial data structure", *Journal of Peace Research*, 49 (2012), 363–374

Toth, Russell, Christopher B Barrett, Richard Bernstein, Patrick Clark, Carla Gomes, Shibia Mohamed, Andrew Mude, and Birhanu Taddesse, "Behavioural substitution of formal risk mitigation: Index insurance in East Africa", 2017

Vrieling, Anton, Michele Meroni, Andrew G Mude, Sommarat Chantarat, Caroline C Ummenhofer, and Kees CAJM de Bie, "Early assessment of seasonal forage availability for mitigating the impact of drought on East African pastoralists", *Remote Sensing of Environment*, 174 (2016), 44–55

Waita, Edwin, "Drought forces Kenya's Maasai to sell starving cattle for a pittance", 2022

Wanyama, Jacob Barasa, "Accounting for pastoralists in Kenya", Informational brief, League for Pastoral Peoples and Endogenous Livestock Development, LIFE – Africa Region, 2020

World Bank, "World Bank Boosts Pastoral Economies and Climate Action in the Horn of Africa", 2022

Xinhua, Li Yahui, "Kenya's livestock markets reeling from devastating impacts of acute drought", 2023

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

Appendices

A. Data Appendix

In this appendix, we provide an overview of our data sources and the variables we construct from them (Section A-1 to Section A-7), after which we provide summary statistics and spatial visualization of key variables in the study (Section A-8).

A-1. Conflict data

Our main source of conflict data is the Armed Conflict Location & Event Data Project (ACLED) dataset (Raleigh, Kishi, and Linke 2023) that systematically records conflict events across various countries, including Kenya. ACLED provides detailed information on the dates, actors, types, locations, and fatalities of political violence and protest events. It is widely used by researchers and policymakers to understand conflict dynamics, trends, and patterns.

The ACLED dataset categorizes conflict events into several distinct event types, each capturing a specific form of political violence or protest. Each event type is further divided into sub-event types, providing more granular detail about the nature of the event. Table A-2 lists the main event types and provides examples of associated sub-event types to illustrate the variety of conflict events recorded in the dataset.

ACLED also provides a text description of the conflict event in a variable called "notes". This can reflect the event type or actors but can also contain additional information about both or more general details. We can use text analysis to code additional event types, such as the location, involvement of livestock, or actors that are plausibly associated with pastoralists. We employ two approaches for generating event types based on notes: dictionary-based or LLM classification with GPT-4o.

Measures of conflict

- *Conflict*: Indicator variable equal to one if at least one conflict event is recorded in a cell in a given year.
- *I(Type: Battles)*: Indicator variable equal to one if at least one battle event occurs in a given year and cell. Battles are events where armed groups engage in combat. Examples include armed clashes and situations where the government regains territory.

- *I(Type: Protests)*: Indicator variable equal to one if at least one protest event occurs in a given year and cell. This includes events where civilians publicly demonstrate against policies, actions, or situations. This category includes peaceful protests and instances where excessive force is used against protesters.

- *I(Type: Riot)*: Indicator variable equal to one if at least one riot event occurs in a given year and cell. Riots are violent disturbances caused by large groups of people. Examples include mob violence and violent demonstrations.

- *I(Type: Strategic deployment)*: Indicator variable equal to one if at least one strategic deployment occurs in a given year and cell. Those are events related to strategic changes or significant occurrences that affect conflict dynamics, looting/property destruction, and other significant developments.

- *I(Type: Violence civilians)*: Indicator variable equal to one if at least one event with violence against civilians occurs in a given year and cell. Violence against civilians is defined as deliberate violent acts targeting non-combatants. Examples include abductions/forced disappearances and attacks on civilians.

- *I(Type: Explosion)*: Indicator variable equal to one if at least one explosion event occurs in a given year and cell. This includes events involving explosive devices or remotely detonated attacks, such as suicide bombs and remote explosive/landmine/IED incidents.

- *I(Type: Battles, riots, violence civilians)*: Indicator variable equal to one if at least one battle, riots, or violence against civilians event occurs in a given year and cell.

- *I(Type: 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(Type: Government)*: Indicator variable equal to one if at least one conflict involving the state occurs in a given year and cell. Incidents are included if **any** of the two primary actors (actor1 or actor2) are identified as government-related entities. Keywords: "Government", "Police", "Military" are used for this identification.

- *I(Type: Non-government)*: Indicator variable equal to one if at least one conflict that does not involve the state occurs in a given year and cell. Incidents included are those in which **neither** of the two (actor1 or actor2) are identified as government-related entities. Keywords: "Government", "Police", "Military" are used for this identification.

- *I(Type: Interstate violence)*: Indicator variable equal to one if at least one conflict involving only state actors occurs in a given year and cell. Incidents are included if **both** of the two primary actors (actor1 or actor2) are identified as government-related entities. Keywords such as "Government", "Police", "Military" are used for this identification.

Source: ACLED (Raleigh, Kishi, and Linke 2023)

A-2. Conflict involving pastoralists

Pastoralists are not listed as primary conflict actors in ACLED. However, they appear as an "associated" actor in a subset of the events. Pastoralists are mentioned in 118 of the cases as *Associated Actor One* and 112 of the cases as *Associated Actor Two*. The overall frequency of events involving pastoralist groups as associated actors is 7.03% for *assoc actor one* and 4.86 for *assoc actor two*. The ten actors with the highest share of pastoralists as their associated actors are reported in Table A-3. Moreover, some notes indicate conflict among pastoralists or between pastoralists and other land users.

In the absence of a precise classification, we leverage the actor and associated actor relations, as well as the notes, to classify incidents as events plausible involving "pastoralists". When using notes, we leverage both dictionary-based and LLM classification with GPT-4O.

Measures of pastoralist conflict

- *I(Pastoral: Actor)*: Indicator variable equal to one if at least one conflict event involving an actor that has a share of pastoralists as associated actors of 10% or more (excluding civilians and unidentified armed groups), occurs in a cell during a period and zero otherwise (see Table A-3 for details).

- *I(Pastoral: Associated actor)*: Indicator variable equal to one if at least one conflict event occurs in a cell during a period where one of the associated actors is labeled "Pastoralists" by ACLED, and zero otherwise.

- *I(Pastoral: Associated tribes)*: Indicator variable equal to one if at least one conflict event occurs in a cell during a period where one of the actors belongs to one of the ethnic groups in which pastoralism is common (see List A-1 for details), and zero otherwise.

- *I(Pastoral: Notes + GPT)*: Indicator variable equal to one, if at least one conflict event occurs in a cell during a period, is classified by GPT-4o as likely involving pastoralists based on the event notes, and zero otherwise.

- *I(Livestock: Notes + dictionary)*: Indicator variable equal to one if at least one conflict event occurs in a cell during a period where the note of the event matches our dictionary terms of livestock events and zero otherwise. Our dictionary terms are: "animals", "herding", "herders", "graze", "grazing", "cattle", "sheep", "goat", "livestock", "camel", "pastoral", "herder", "herdsman", "cow".

- *I(Livestock: Notes + GPT)*: Indicator variable equal to one if at least one conflict event occurs in a cell during a period classified by GPT-4o as likely involving livestock based on the event notes, and zero otherwise.

- *I(Pastoral: Associated actor ∪ Livestock: Notes + dictionary)*: Indicator variable equal to one if at least one conflict event occurs in a cell during a period where one of the associated actors is labeled "pastoralists" by ACLED or whose notes match our livestock dictionary (see *I(Livestock: Notes + dictionary)* above), and zero otherwise.

- *I(Pastoral: Associated tribe ∪ Livestock: Notes + dictionary)*: Indicator variable equal to one if at least one conflict event occurs in a cell during a period where one of the actors belongs to one of the ethnic groups in which pastoralism is common (see List A-1 for details) or whose notes match our livestock dictionary (see *I(Livestock: Notes + dictionary)* above), and zero otherwise.

- *I(Pastoral: Notes + GPT ∪ Livestock: Notes + dictionary)*: Indicator variable equal to one if at least one conflict event occurs in a cell during a period is classified by GPT-4o as likely involving livestock, based on the event notes or whose notes match our livestock dictionary (see *I(Livestock: Notes + dictionary)* above), and zero otherwise.

- *I(Pastoral: Associated actor ∪ Livestock: Notes + GPT)*: Indicator variable equal to one if at least one conflict event occurs in a cell during a period where one of the associated actors is labeled "pastoralists" by ACLED or is classified as a livestock event by GPT-4o based on its notes (see *I(Livestock: Notes + GPT* above), and zero otherwise.

- *I(Pastoral: Associated tribes ∪ Livestock: Notes + GPT)*: Indicator variable equal to one if at least one conflict event occurs in a cell during a period where one of the actors belongs to one of the ethnic groups in which pastoralism is common (see List A-1 for details) or is classified as a livestock event by GPT-4o based on its notes (see *I(Livestock: Notes + GPT*above), and zero otherwise.

- *I(Pastoral: Notes + GPT ∪ Livestock: Notes + GPT)*: Indicator variable equal to one, if at least one conflict event occurs in a cell during a period, is classified by GPT-4o as likely involving pastoralists based on the event notes, or is classified as a livestock event by GPT-4o based on its notes (see *I(Livestock: Notes + GPT*above), and zero otherwise.

Source: ACLED (Raleigh, Kishi, and Linke 2023)

A-3. Index-Based Livestock Insurance (IBLI) variables

- *IBLI coverage*: Indicator variable equal to one if the centroid of a cell is located within an insurance unit that offers the Index-Based Livestock Insurance (IBLI) in a given year.
- *IBLI*: Indicator variable equal to one if the cell is located in an insurance unit where IBLI is available during the period.
- *IBLI coverage, ever*: Indicator variable equal to one if the centroid of a cell is located within an insurance unit that received or will receive the Index-Based Livestock Insurance (IBLI) at some point between 2010 and 2020.
- *IBLI eligible*: Indicator variable equal to one if the centroid of a cell is located within an insurance unit that is eligible to the Index-Based Livestock Insurance (IBLI) in a given year.
- *IBLI not eligible*: Indicator variable equal to one if the centroid of a cell is not located within an insurance unit 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 equal to one if the centroid of a cell is located within an insurance unit that received payouts from the Index-Based Livestock Insurance (IBLI) in a given year. The payout information is only available for selected years and has been shared with us by the International Livestock Research Institute.
- $IBLI^{Homeland}$: Indicator variable equal to 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 equal to one if an insurance unit 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)

A-4. 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 period level. World Atlas Desertification (Cherlet et al. 2018), TerraClimate (Abatzoglou et al. 2018)

- *AI deficit*: Continuous variable constructed ny multiplying the *Log AI* by minus one.

- *Rainfall*: Continuous variable indicating the mean precipitation in millimeters per period for a given period and cell. NASA's GPM product (Huffman et al. 2022).

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

- *Rain deficit*: Continuous variable constructed by multiplying the logarithm of (*Rainfall*) by minus one for a given period 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. 2022). 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 period and cell. The DMP is a continuous variable indicating the overall growth rate or dry biomass (phytomass) increase of the vegetation (kg/ha/period). Copernicus Global Land Service (2019).

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

A-5. Other variables

- *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).
- *Rangeland share*: Continuous variable indicating the rangeland share for a given cell (in %) built following the Climate Change Initiative Land Cover (CCI CL) classification of the 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, Velthuizen, and Verelst 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, Velthuizen, and Verelst 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, Velthuizen, and Verelst 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, Velthuizen, and Verelst 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, Velthuizen, and Verelst 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, Velthuizen, and Verelst 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, Velthuizen, and Verelst 2009).
- *Log pop*: Continuous variables constructed taking the logarithm of population estimates from the GHSL population raster data (2000 estimates) for a given cell.
- *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 Safety Net Programme (HSNP) for a given period.
- *Aid*: Is the number of active World Bank projects in the agricultural sector in a cell during a period, based on the geocoded data and sector codes from AidData (2017).
- *World Bank: No aid projects*: Is the number of active World Bank projects in a cell during a period, based on the geocoded data from AidData (2017).
- *World Bank: Log aid commitments*: Is the log sum of aid commitments allocated to projects within a cell and period, based on active geocoded World Bank projects from AidData (2017).
- *Bilateral and multilateral aid: No aid projects*: Is the number of active development aid projects in a cell during a period, based on the geocoded data from Bomprezzi et al. (2024). The data includes the following aid donors: 18 European donors (1973-2020), the United States (1973-2020), the World Bank (1995-2023), India (2007-2014), and China (2000-2021). We only use projects with a precision code of 8 or below, which corresponds to the precision categories in the World Bank data.
- *Bilateral and multilateral aid: Log aid commitments*: Is the log sum of aid commitments allocated to projects within a cell and period, based on active geocoded aid projects from Bomprezzi et al. (2024). The data includes the following aid donors: 18 European donors (1973-2020), the United States (1973-2020), the World Bank (1995-2023), India (2007-2014), and China (2000-2021). We only use projects with a precision code of 8 or below, which corresponds to the precision categories in the World Bank data.
- *Mixed land use area*: Indicator variable that takes the 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).

- *Mixed settlement*: Indicator variable equal to 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).

- *Agricultural-pastoral suitability*: Indicator variable equal to one if the suitability difference between pastoral and agricultural suitability based on Becker (2025) is within the 1st quartile. Becker (2025) defines pastoral suitability broadly as the maximum suitability value for pastoralism or sedentary animal husbandry based on Beck and Sieber (2010). We derive the suitability measures for pastoralism, sedentary animal husbandry, and agriculture from (Beck and Sieber 2010).

- *Grassland to cropland transition*: Indicator variable equal to one if the grassland share of a cell declines between 2000 and 2020 and the cropland share of a cell increases between 2000 and 2020. Grassland and cropland shares of cell in 2000 and 2020 are derived from (Copernicus Climate Change Service 2019).

- *Log distance*^{Homeland}: Continuous variable indicating the geographic distance between the geolocation of a conflict event (Raleigh, Kishi, and Linke 2023) involving an actor matched to an ethnic homeland from Murdock's Geographic Atlas (Murdock 1967).

- *Dist. border*: Continuous variable indicating the minimum 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.

- *Cellphone coverage*: Is an indicator variable equal to one if the cumulative sum of cellphone towers sampled in a PRIO gridcell in a given period is more than a 100 based on OpenCELLID data, and zero otherwise (as in Ackermann, Churchill, and Smyth 2021). Data has kindly been shared by Ackermann, Churchill, and Smyth (2021).

- *Dist. market (agriculture)*: Continuous variable indicating the geographic distance between a cell's centroid and the closest agricultural goods market. Agricultural goods market data has been obtained from (Kenya Ministry of Agriculture and Livestock Development 2024) and georeferenced by us.

- *Dist. market (livestock)*: Continuous variable indicating the geographic distance between a cell's centroid and the closest livestock market. Livestock market data has been obtained from Kenya Livestock Market Information System (2024) and georeferenced by us.

- *Dist. least-cost path*: Continuous variable indicating the travel distance between any two cells in Kenya. The travel distance is calculated using Tobler's off-path hiking function (Tobler 1993) and based on the elevation raster provided by open tiles (Amazon Web Services 2024).

- *Value of statistical life*:

  - *WHO VSL estimate*: 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× the GDP per capita, 167 US$ in 2017.

  - *WB VSL estimate*: 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).

A-6. Livestock data (county populations and market prices)

We use data from the KilimoSTAT (https://statistics.kilimo.go.ke/en/cd_s_livestock/) from the Kenyan Ministry of Agriculture and Livestock Development for the number of cattle across counties. The cattle numbers are based on data from the agricultural censuses and surveys, and can be downloaded in Excel format.

- $All\ cattle_{c,t}$: is the sum of dairy and beef of cattle numbers in county c during year t provided by KilimoSTAT. KilimoSTAT gathered cattle numbers based on agricultural census and survey data to provide time series information on the county level.

- $Beef\ cattle_{c,t}$: is the sum of beef cattle numbers in county c during year t provided by KilimoSTAT. KilimoSTAT gathered cattle numbers based on agricultural census and survey data to provide time series information on the county level.

- $Dairy\ cattle_{c,t}$: is the sum of dairy cattle numbers in county c during year t provided by KilimoSTAT. KilimoSTAT gathered cattle numbers based on agricultural census and survey data to provide time series information on the county level.

- $Cattle_{m,i,t}$: is the log of the livestock, the average price for cattle at market m, located in cell i during our 12-month periods based on monthly prices provided by the Kenzan Livestock Market Information System. Note that the data includes many missing values; therefore, the 12-month averages for different markets may be based on a varying number of monthly prices.

Livestock prices at livestock markets are obtained from the Kenyan National Livestock Market Information System (LMIS) (http://www.lmiske.go.ke/lmis/home.htm?action=getData). The LMIS trains individuals who report local prices via cell phone. Research assistants manually tabulate the price data from the charts posted on their homepage.

- $Camel_{m,i,t}$: is the log of the livestock, the average price for camel at market m, located in cell i during our 12-month periods based on monthly prices provided by the Kenya Livestock Market Information System. Note that the data includes many missing values; therefore, the 12-month averages for different markets may be based on a varying number of monthly prices.

- $Sheep_{m,i,t}$: is the log of the livestock, the average price for sheep at market m, located in cell i during our 12-month periods based on monthly prices provided by the Kenya Livestock Market Information System. Note that the data includes many missing values; therefore, the 12-month averages for different markets may be based on a varying number of monthly prices.

- $Goats_{m,i,t}$: is the log of the livestock, the average price for goats at market m, located in cell i during our 12-month periods based on monthly prices provided by the Kenya Livestock Market Information System. Note that the data includes many missing values; therefore, the 12-month averages for different markets may be based on a varying number of monthly prices.

A-7. Afrobarometer

We use data from the geocoded Afrobarometer survey rounds 3 to 8 for Kenya. 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.

- $Hunger_{r,t}$: Indicator variable for whether a respondent r surveyed on gridcell g during wave w has experienced hunger during the last 12 months. The indicator equals 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”, “Several times”, or “Once or twice” and zero otherwise.

- *No cash income*$_{r,t}$: Indicator variable for whether a respondent r surveyed on gridcell g during wave w has experienced no cash income during the last 12 months. The indicator equals one if the respondent answers the question "Over the past year, how often, if ever, have you or anyone in your family gone without cash income?" with either "Always", "Many times", "Several times", or "Once or twice" 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.

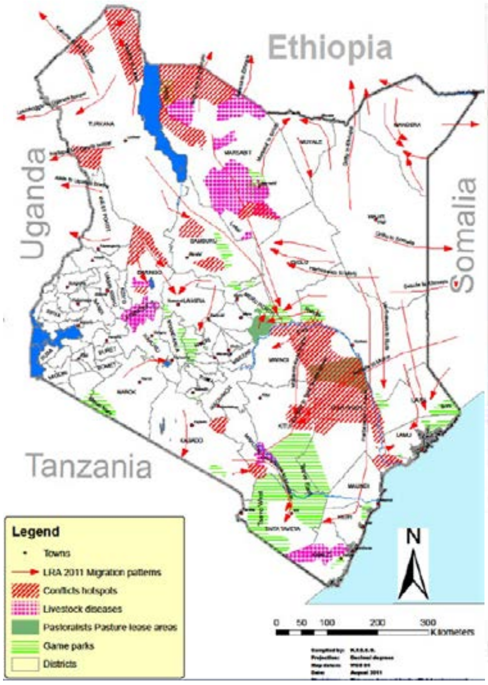
- *Some secondary education*: Indicator variable equal to one if the respondent indicates to have completed primary education and taken some secondary education, and zero otherwise. Based on self-reported education level.

- *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.

A-8. Data visualization and summary statistics

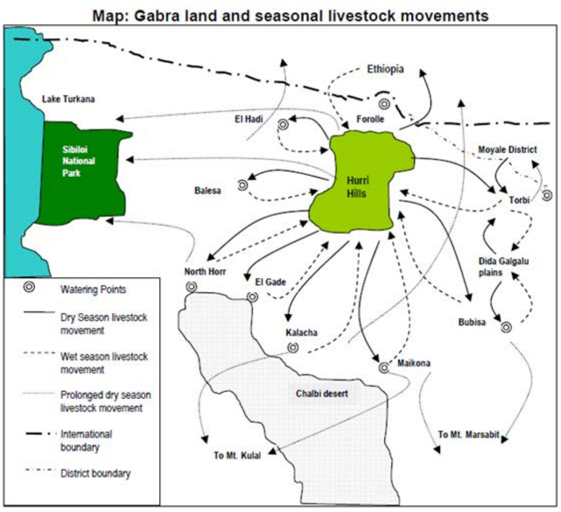
FIGURE A-1
Pastoral migration route estimates for all Kenya

(A) 2011



(B) 2013

(C) Gabra (northern Kenya)

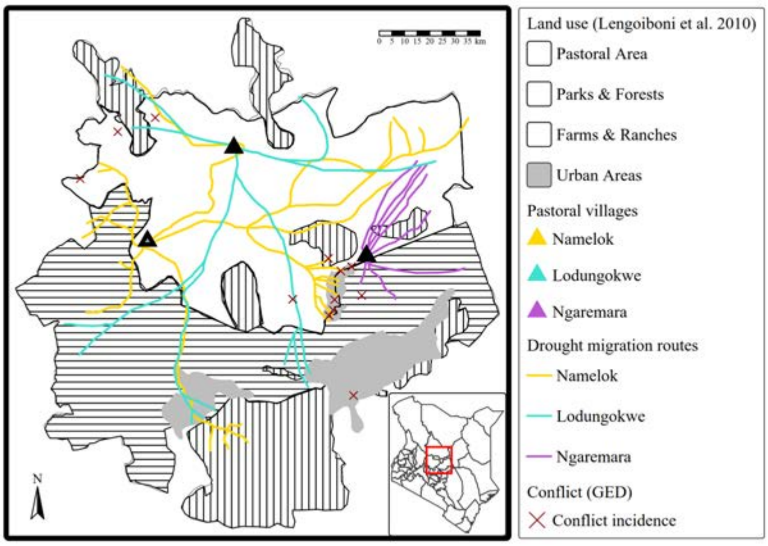


Source: Adapted from the Global Environmental Facility – Indigenous Vegetation Project (GEF – IVP) Livestock migration routes map

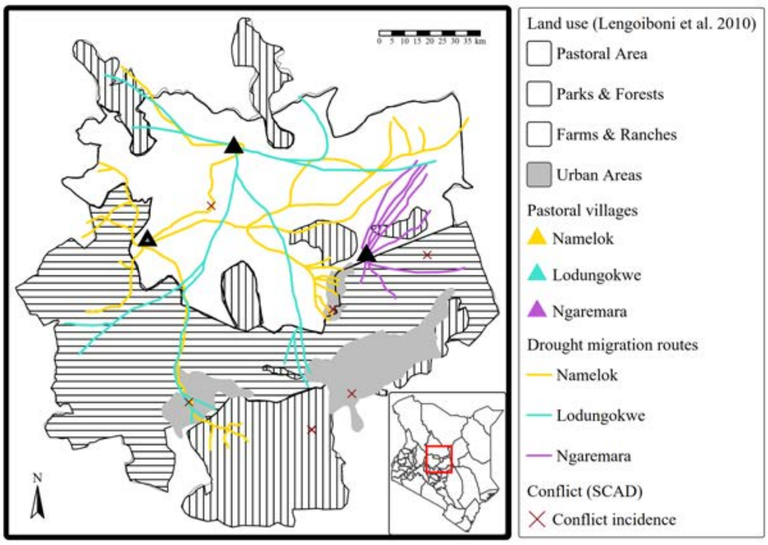
Notes: The figures show estimates of pastoralist migration routes by different authors. The variation across panels A to C likely reflects regional variation, changes in migration routes between years, and differences in assessment methods. Comparing the panels to Figure II reveals that those estimates 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, Behnke, and Neely (2013). Panel C depicts seasonal migration routes from Munyao and Barrett (2007) in northern Kenya.

Figure A-2
Recoded conflict events in the Samburu-Laikipia-Isiolo-Meru counties

(a) Pastoralist migration routes
and conflict (GED)



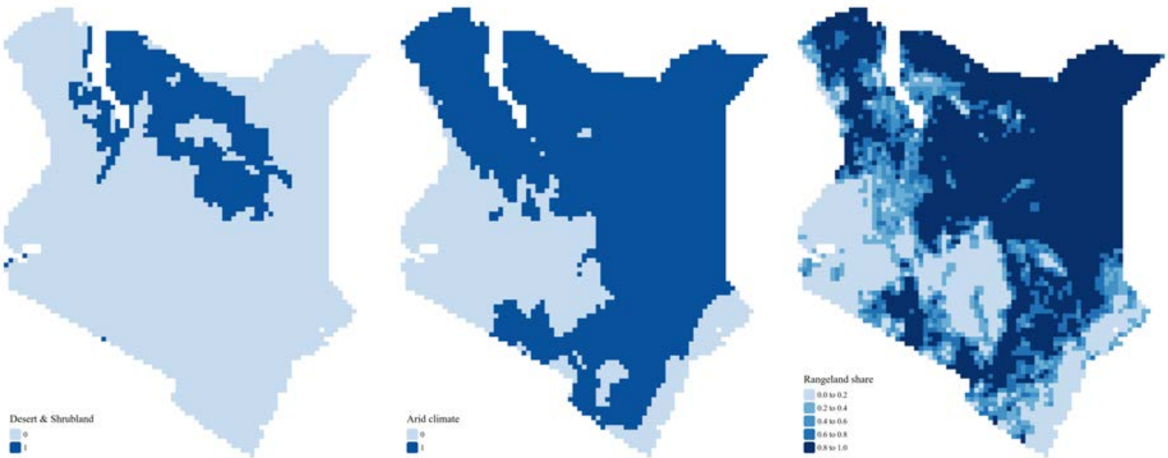
(b) Pastoralist migration routes and conflict (SCAD)



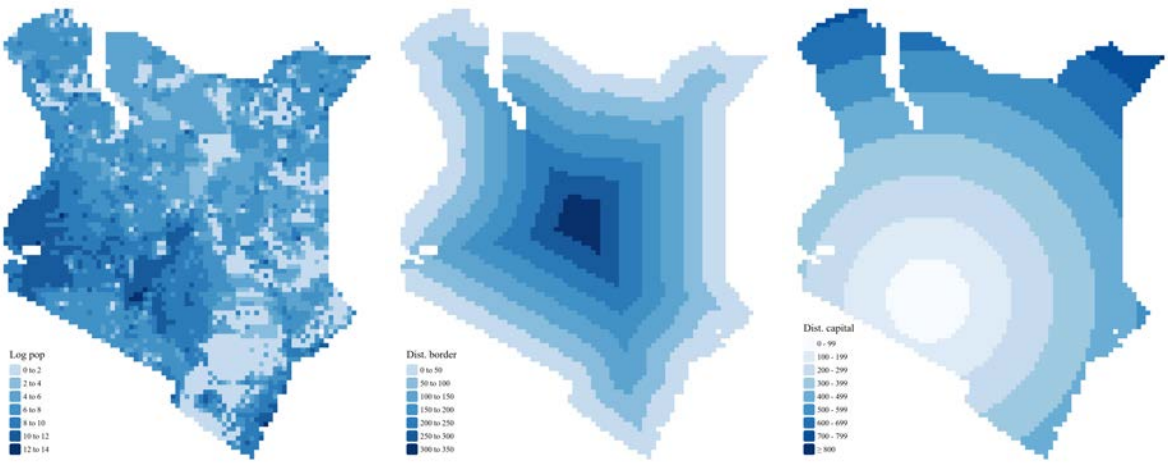
Notes: Panel A shows the digitized map from Lengoiboni, Bregt, and van der Molen (2010) with the different land use types for the Samburu-Laikipia-Isiolo-Meru region and the drought migration routes and villages for the Namelok, the Lodungokwe, and the Ngaremara pastoral groups, and conflict incidents from ACLED (Raleigh, Kishi, and Linke 2023). Panel B replaces the conflict incidents from ACLED with conflict incidents from the UCDP Georeferenced Event Dataset (GED) Global version 24.1 (Sundberg and Melander 2013; Davies et al. 2024), and Panel C replaces them with conflict incidents from the Social Conflict Analysis Database (SCAD) (Salehyan et al. 2012).

FIGURE A-3
Land cover, population and distances

(A) Desert & Shrubland (B) Arid climate (C) Rangeland share



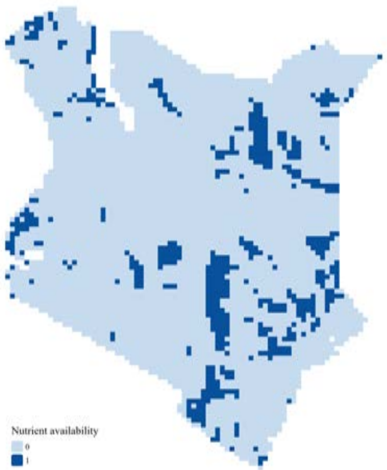
(D) Log pop (E) Dist. border (F) Dist. capital



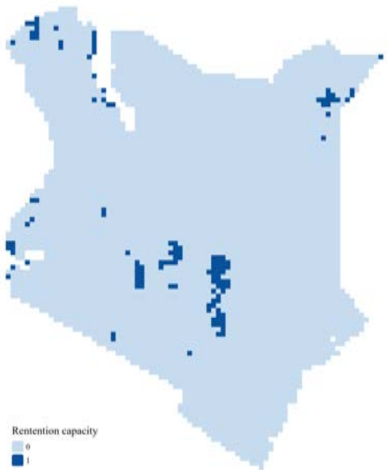
Notes: Panels A and B show the desert & shrubland and the arid climate zone indicator variable that takes value one for cells predominantly located in these climate zones following the Köppen-Geiger climate classification from Beck et al. (2018). The share of rangeland in panel C is built following the Climate Change Initiative Land Cover (CCI CL) classification from the 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 $0.1^\circ \times 0.1^\circ$ grid-cell level.

FIGURE A-4
Soil characteristics

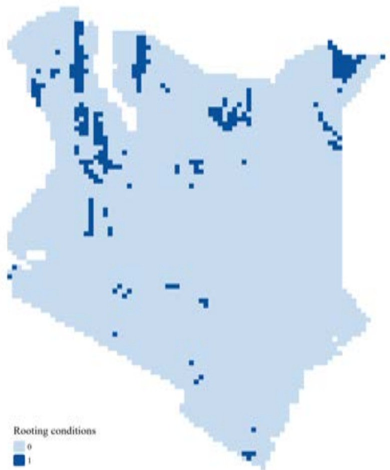
(A) Nutrient availability



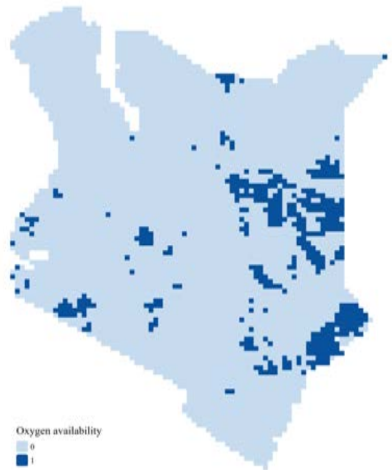
(B) Nutrient retention cap.



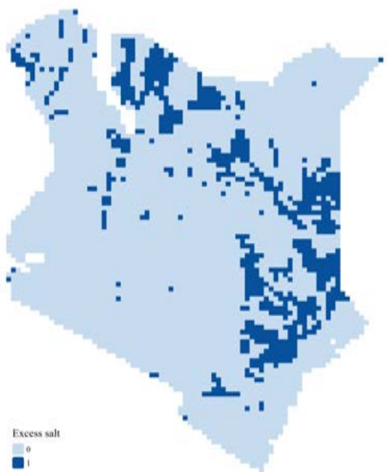
(C) Rooting conditions



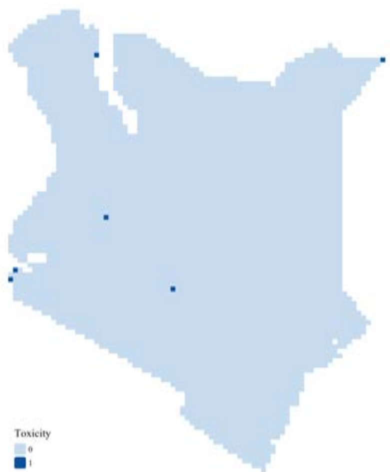
(D) Oxygen availability



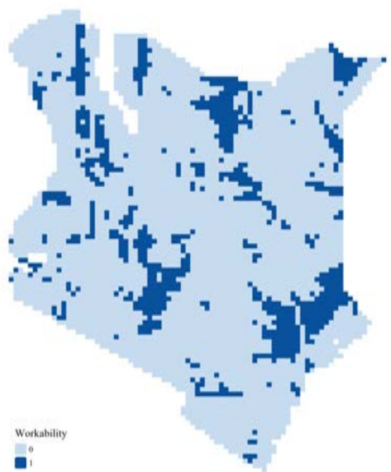
(E) Excess salts



(F) Toxicity



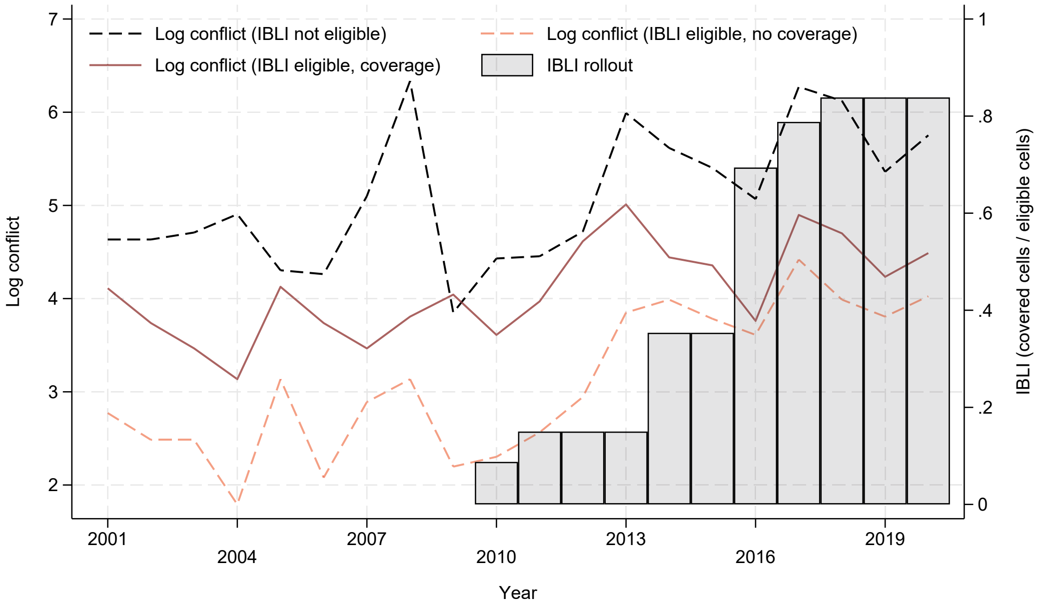
(G) Workability



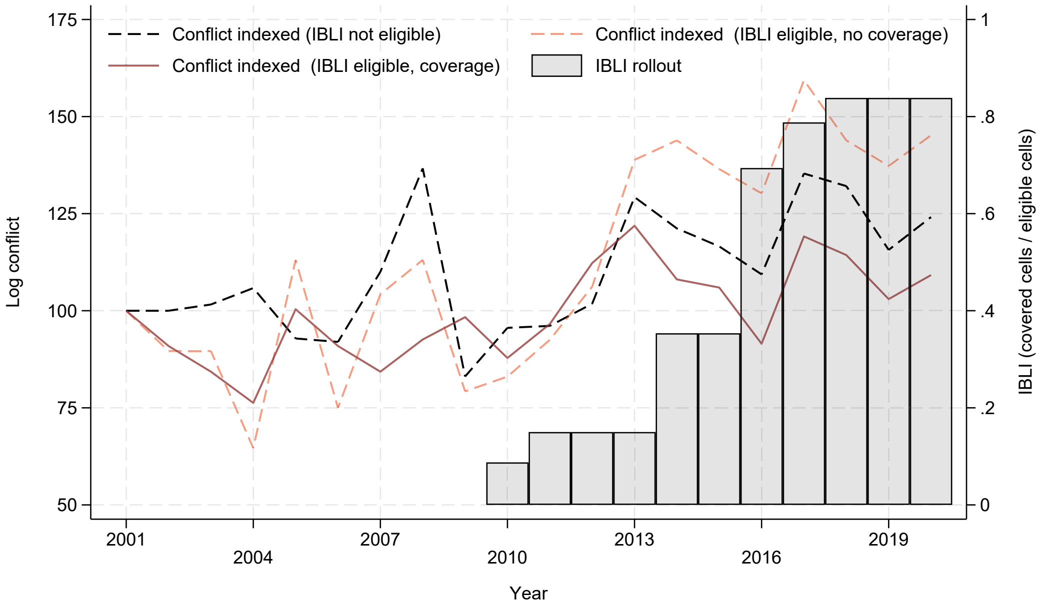
Notes: The soil characteristics are indicator variables taking value 1 (poor soil quality) if a cell's location is associated with class 3, 4, or 5 (severe limitations, very severe limitations, and mainly non-soil). Harmonized World Soil Database (Nachtergaele, Velthuizen, and Verelst 2009). All variable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

FIGURE A-5
Conflict trends across IBLI eligible and non-eligible areas

(A) Conflict levels



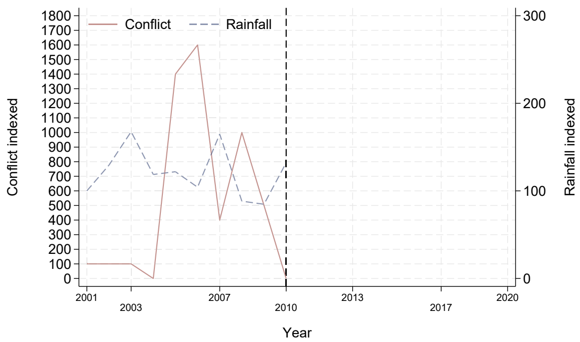
(B) Conflict levels (indexed)



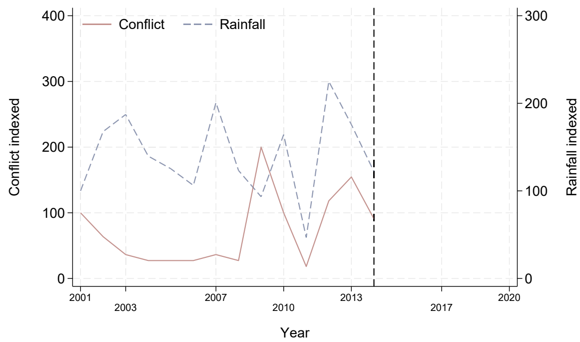
Notes: Panel A of the figure plots the log of conflict incidents for areas that are never eligible for IBLI (black dashed line), eligible areas (bright red dashed line), and areas that receive IBLI coverage (dark red line) over our sample period. In addition, we plot as bar charts the share of cells that receive IBLI over the share of cells eligible for IBLI over time. Panel B of the figure replicated panel A but indexes each conflict time series by its initial value.

FIGURE A-6
Conflict and rainfall trends across IBLI rollout cluster

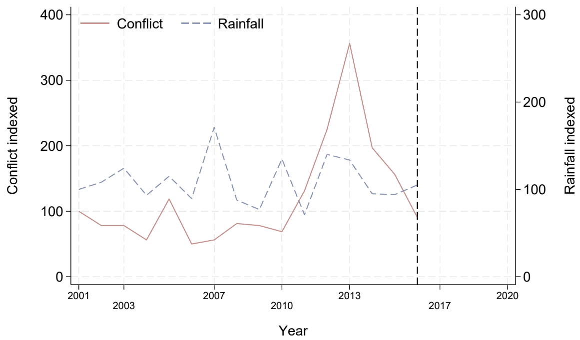
(A) Cluster 1



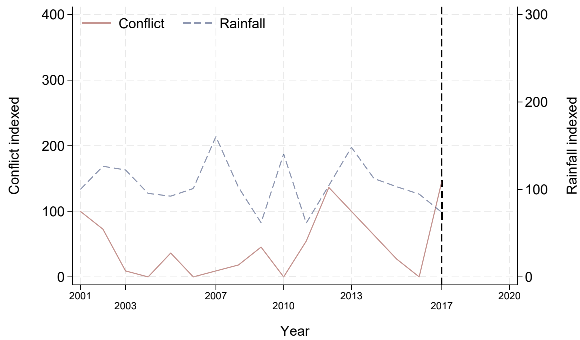
(B) Cluster 2



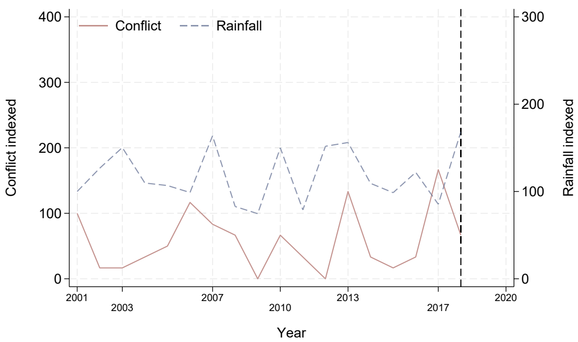
(C) Cluster 3



(D) Cluster 4

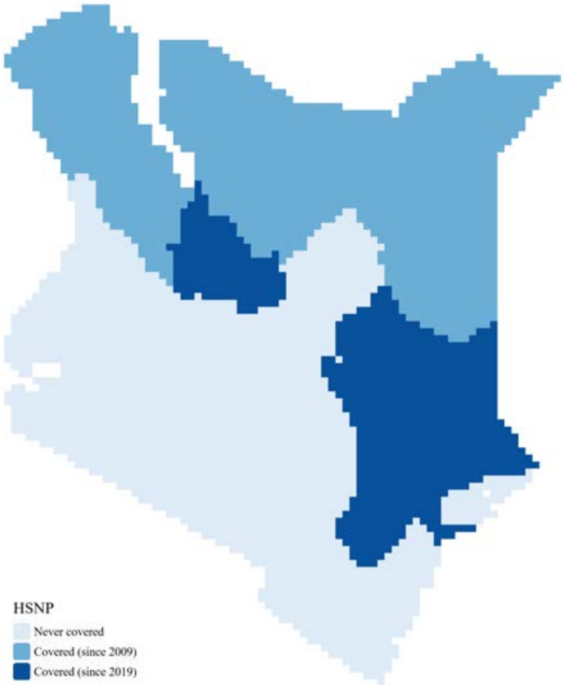


(E) Cluster 5



Notes: Panel A to E of the figure plot the pre-rollout indexed conflict incidents (dark red line) and rainfall (blue dashed line) within the five rollout clusters that receive IBLI during our sample period. The vertical lines indicate the period in which the respective rollout cluster receives IBLI.

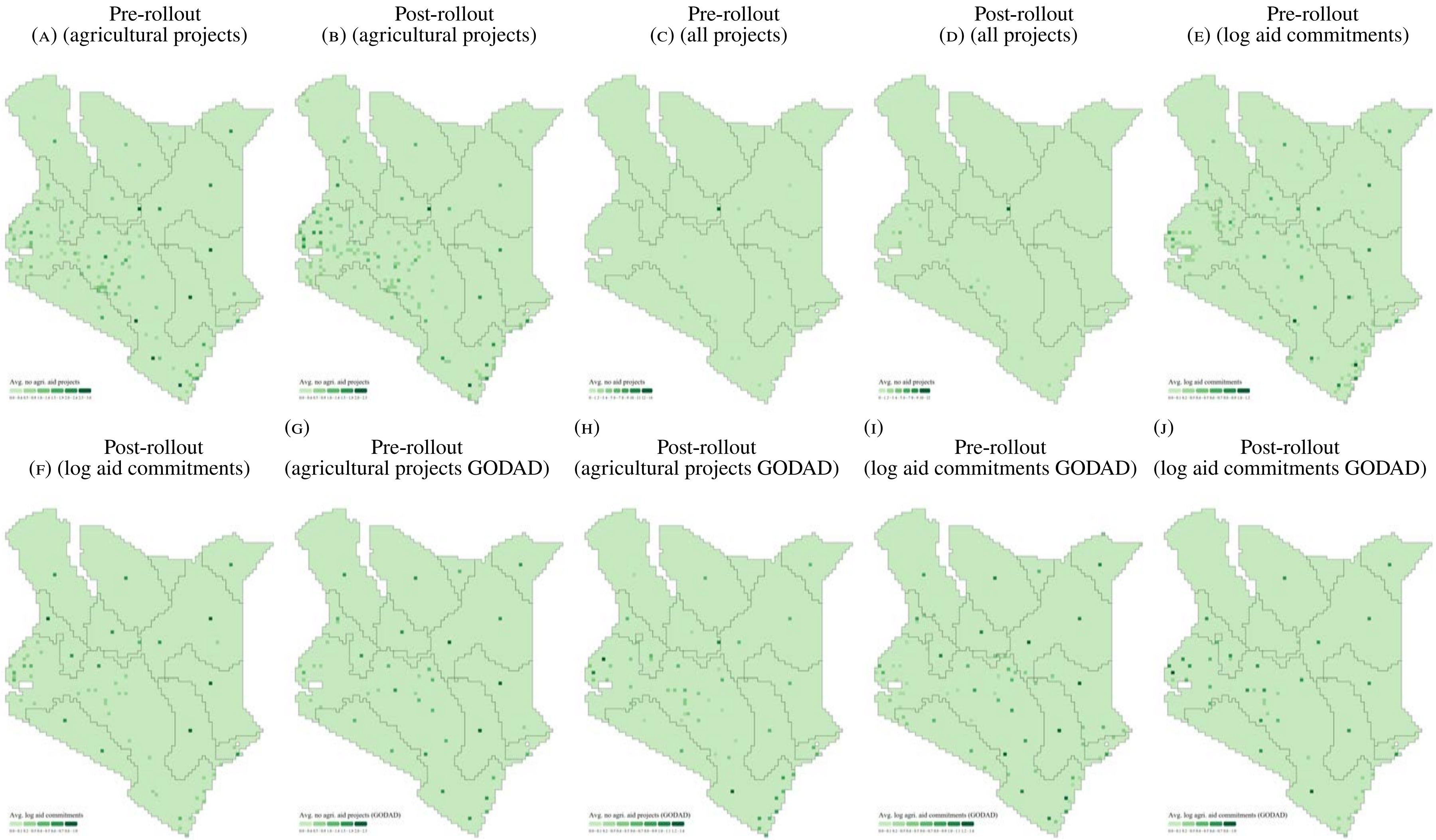
Figure A-7
Hunger Safety Net Program (HSNP) rollout



Notes: The figure represents the area eligible to receive payouts from the Hunger Safety Net Program (HSNP), first in 2009 and then in 2019. The variable is processed at a $0.1° \times 0.1°$ grid-cell level.

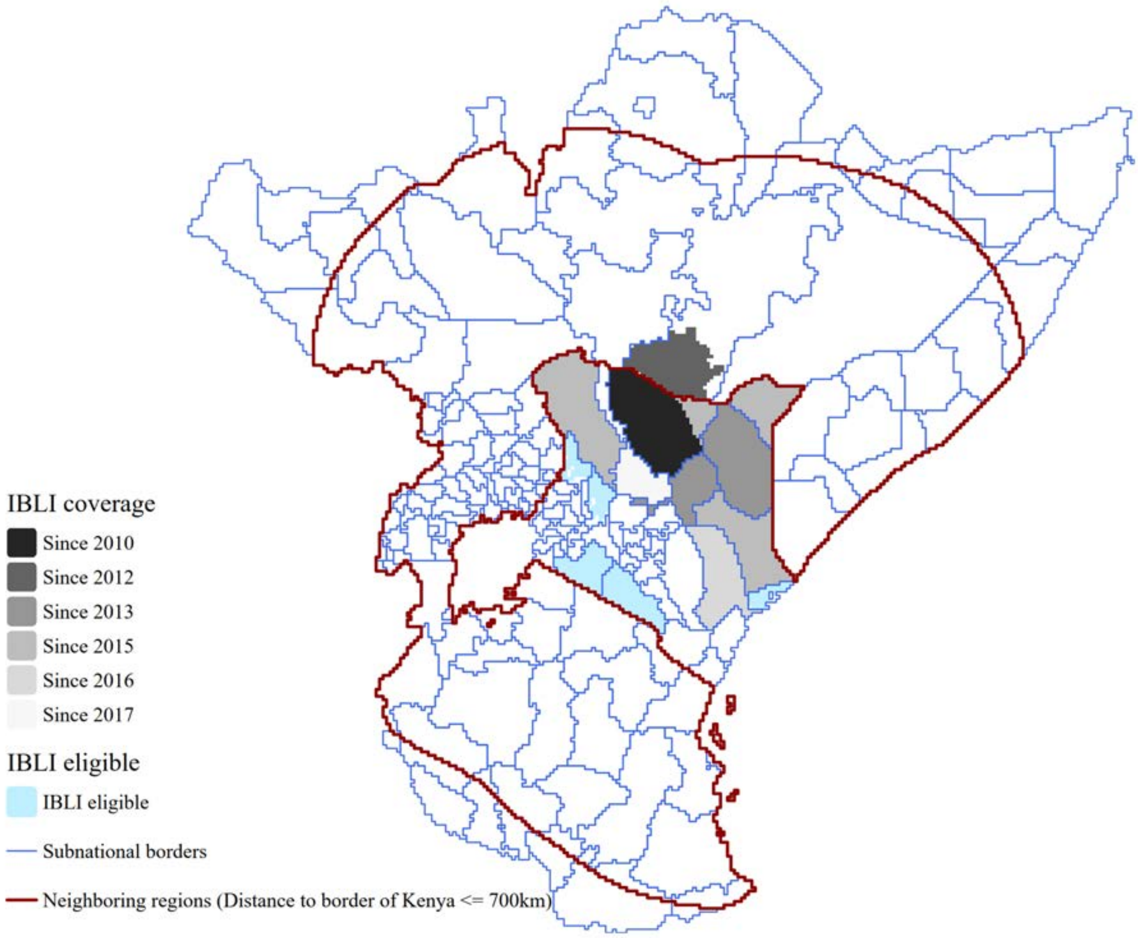
FIGURE A-8

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



Notes: Panel A of the figure plots the average number of development aid projects (classified as agricultural aid) running in the pre-rollout period (2000-2009). 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 World Bank aid projects. Panels E and F report the corresponding distributions for log aid commitments from the World Bank. Panels G and H report the distributions of agricultural aid projects from bilateral and multilateral donors. Panels I and J report the distributions of log aid commitments from multilateral and bilateral donors. Variables are processed at a $0.1° \times 0.1°$ grid-cell level. World Bank aid projects and commitments are obtained from AidData (2017). Multilateral and bilateral agricultural aid projects and commitments are obtained from Bomprezzi et al. (2024).

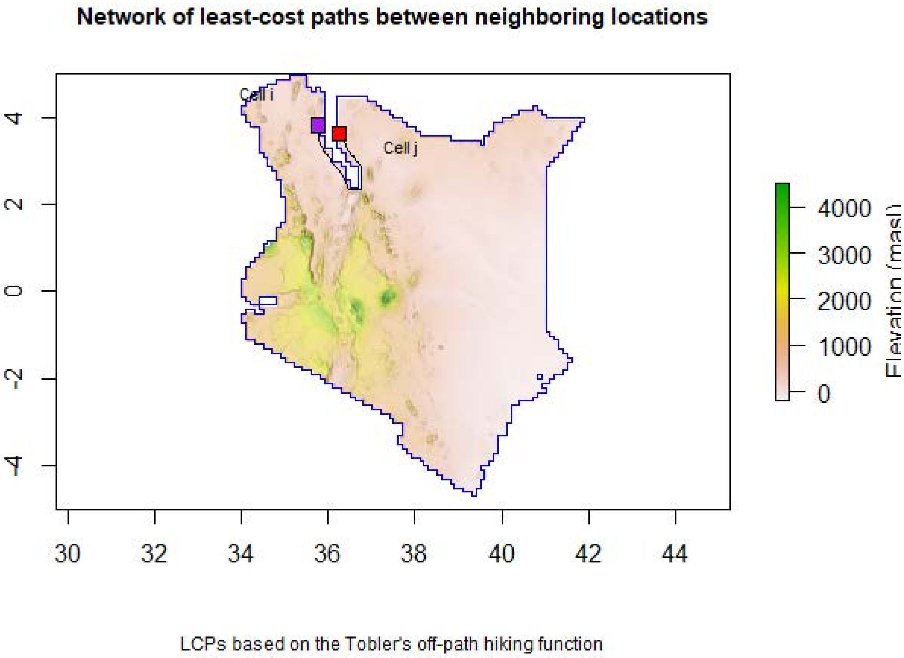
FIGURE A-9
Spillovers from abroad: Kenya neighborhood



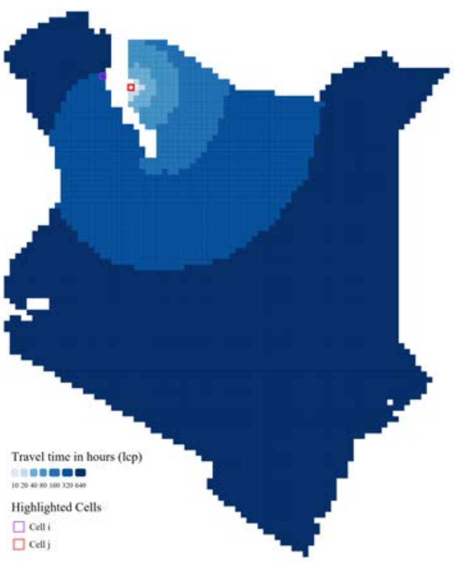
Notes: The figure plots the rollout of IBLI coverage across Kenya and Ethiopia (based on Johnson et al. 2019; Fava et al. 2021). Blue lines highlight subnational borders. The white areas highlight ineligible locations in East Africa as of 2022. The red line indicates the neighborhood of Kenya (cells within 700 km of Kenya's national border) that are used in Figure VII to estimate the potential spillovers into Kenya. The variable is processed at a $0.1° \times 0.1°$ grid-cell level.

Figure A-10
Least-cost path (LCP) distance comparison

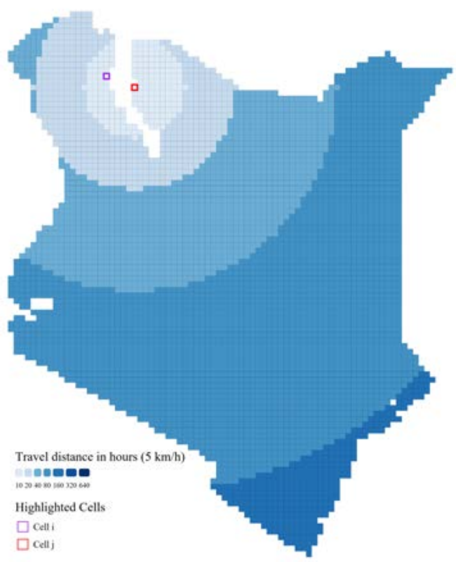
(a) Least-cost path example (cell i to j)



(b) Distance form example cell i (LCP)



(c) Distance form example cell i (geographic)

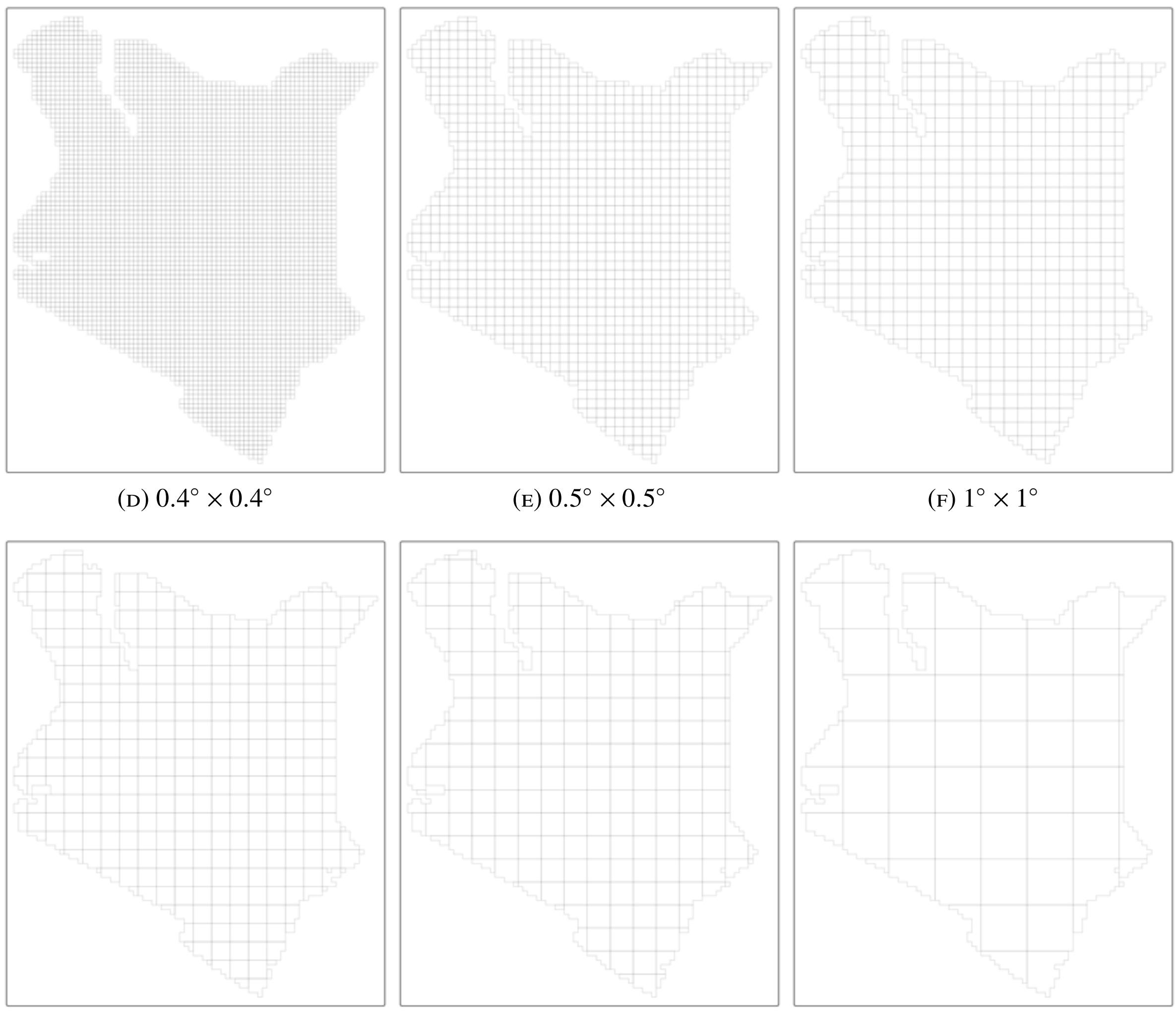


Notes: Panel A of the figure depicts the topography of Kenya based on Amazon web tiles (Amazon Web Services 2024), as well as an example least-cost path from cell i to cell j based on Tobler's off-path hiking function (Tobler 1993). Panel B of the figure plots the distances to all other cells from example cell i using the least-cost path. Panel C plots the distance to all other cells from cell i based on simple geographic distance. All variable are processed at a $0.1° \times 0.1°$ grid-cell level.

FIGURE A-11
Different cell sizes

(A) $0.1° \times 0.1°$ (B) $0.2° \times 0.2°$ (C) $0.3° \times 0.3°$

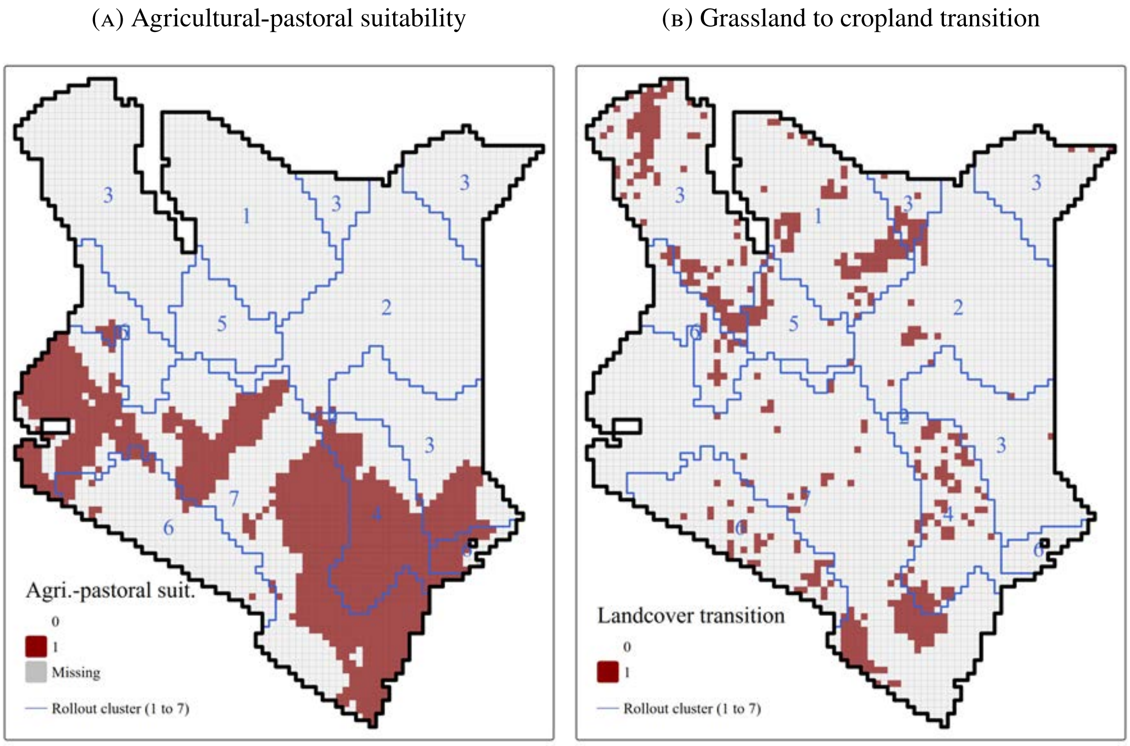
(D) $0.4° \times 0.4°$ (E) $0.5° \times 0.5°$ (F) $1° \times 1°$



Notes: The figure plots different cell sizes across Kenya.

FIGURE A-12

Contested land use: Agricultural-pastoral suitability and land cover transition



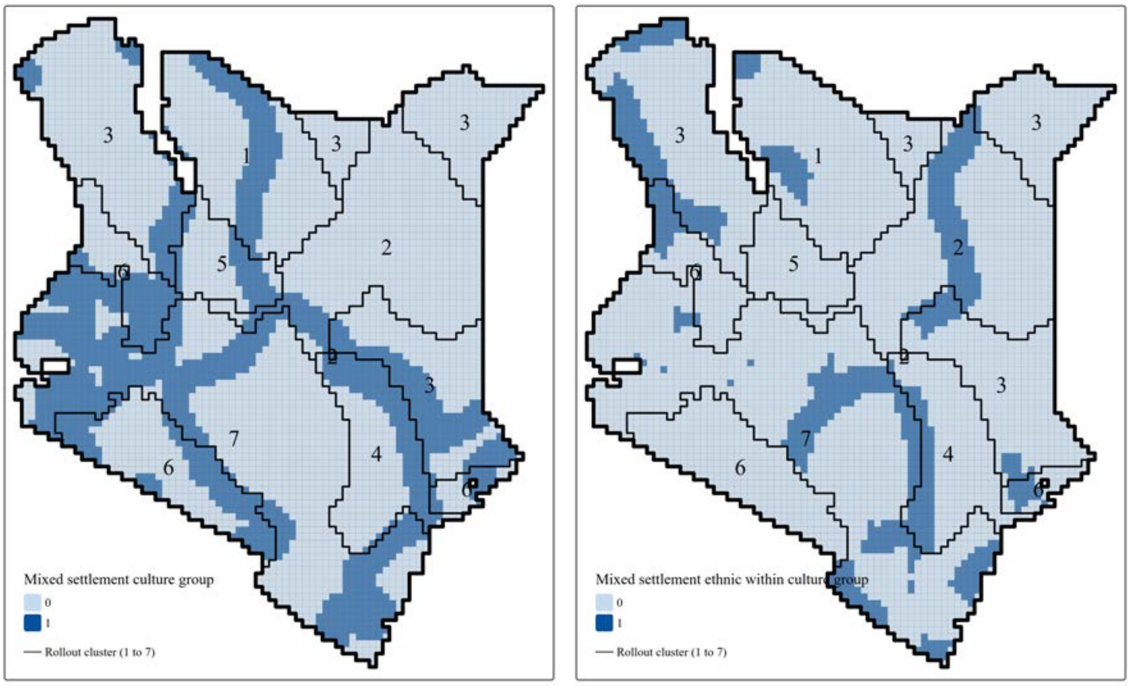
Notes: Panel A plots our Agricultural-pastoral suitability indicator, which is unity for all cells that fall within the 1st quartile of the pastoral-agricultural suitability difference measures, based on Becker (2025). Panel B plots our grassland to cropland transition indicator, that is unity if a cell has a reduction in grassland and an increase in cropland between 2000 and 2020 based on the Copernicus Climate Change Service (2019) landcover data. Blue lines indicate the borders of the insurance rollout clusters. The numbers within the cluster indicate the order in which the insurance clusters received IBLI. The variables are processed at a $0.1° \times 0.1°$ grid-cell level.

Figure A-13

Contested land use: Mixed settlement heterogeneity

(a) Mixed settlement culture group (Murdock)

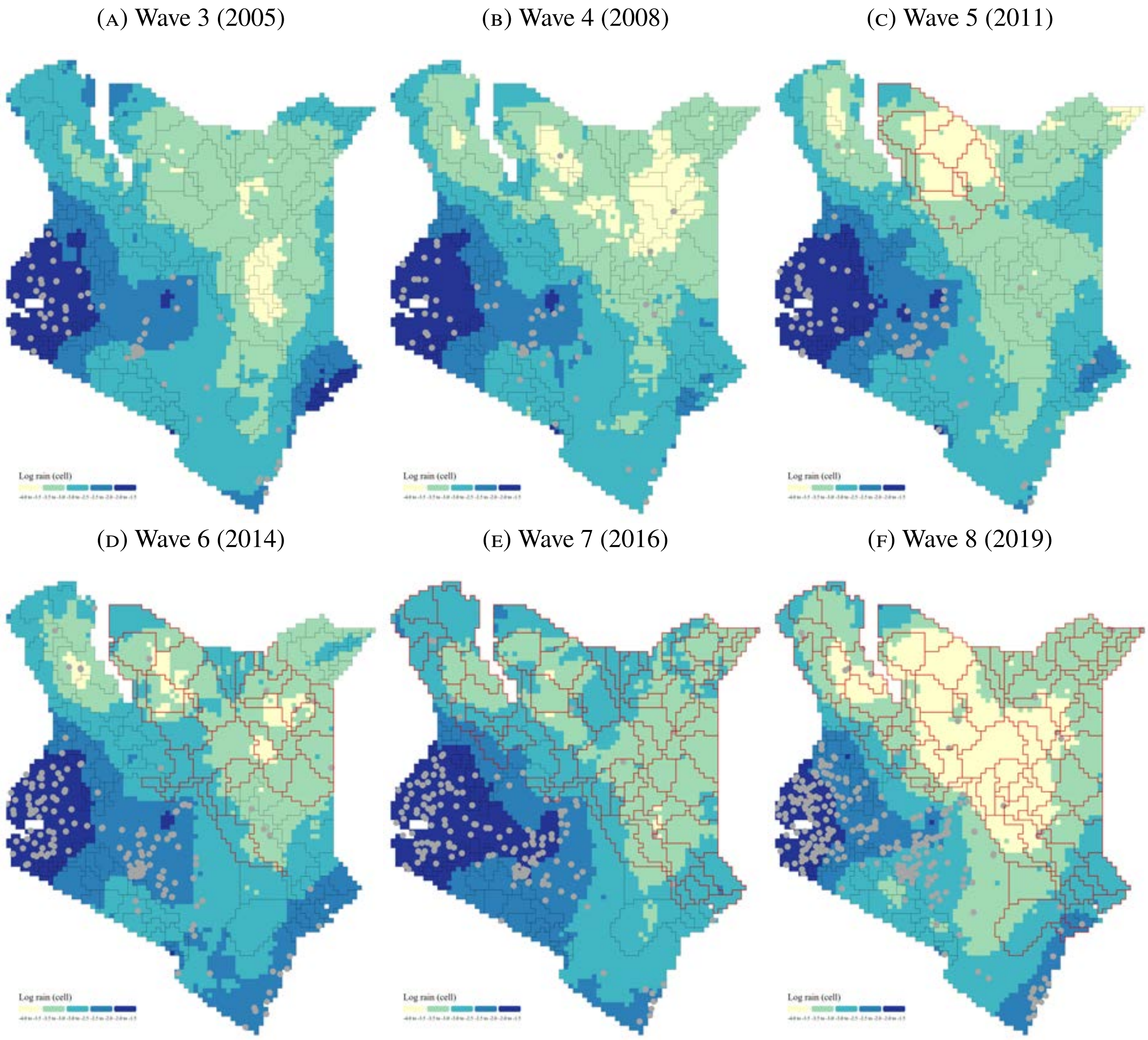
(b) Mixed settlement ethnic group within culture group (Murdock)



Notes: Panel A subsets the mixed settlement indicator (see panel A of Figure IX) to the cells that are in proximity to a culture group border (based on Murdock's Geographic Atlas Murdock (1967)). Panel B subsets the mixed settlement indicator to the cells near ethnic borders within culture groups. Black lines indicate the borders of the insurance rollout cluster. The numbers within the cluster indicate the ordering in which the insurance clusters received IBLI. The variables are processed at a $0.1° \times 0.1°$ grid-cell level.

Figure A-14

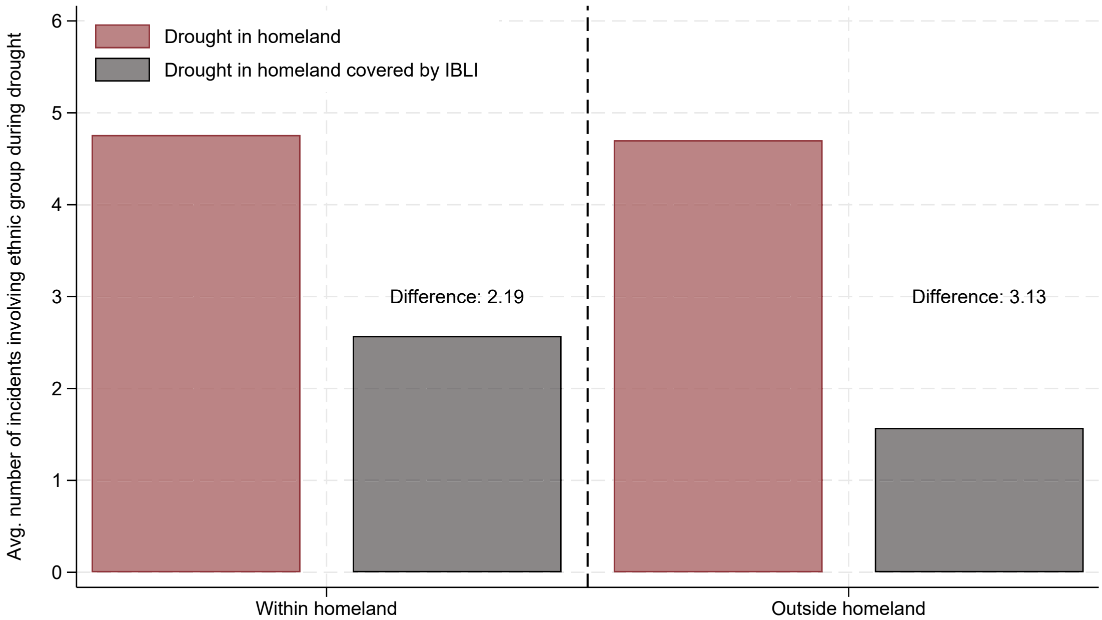
Afrobarometer clusters, avg. log precipitation and IBLI coverage over cells



Notes: Panels A to F of the figure plot the Afrobarometer survey locations over the different waves across Kenya. We also plot the log rainfall averaged across the 12 months preceding the respective Afrobarometer survey for each cell. Black lines are IBLI insurance units. Red lines indicate IBLI insurance units with IBLI coverage during the 12 months preceding 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. 2022). The geospatial variables are processed at a $0.1° \times 0.1°$ grid-cell level.

FIGURE A-15

Conflicts involving members of an ethnic group within and outside of their homelands during droughts



Notes: The figure plots the average number of conflict incidents involving members of an ethnic group both within and outside of their homeland (following Murdock 1967) during drought periods (defined as below median rainfall in the homeland). “Within homeland” refers to the conflict incidents occurring on the homeland of a group and involving its members. “Outside homeland refers to” conflict incidents occurring outside of the homeland of an ethnic group but involving members of that ethnic group. involving ethnic group members of a homeland. For each case, we distinguish periods where the homeland is fully covered by IBLI (defined as above 90% coverage) versus those that are not . All variables are processed at the homeland level.

TABLE A-1
Summary statistics

Variable	Mean	SD	Min	Max	N
Cell sample					
Outcomes					
$\text{Conflict}_{i,t}$	0.02	0.15	0.00	1.00	93,400
Log(incident+0.1)	-2.23	0.46	-2.30	4.65	93,400
Log(incident+0.01)	-4.48	0.80	-4.61	4.64	93,400
Incidents (asinh)	0.03	0.23	0.00	5.34	93,400
Log(fatalities+0.1)	-2.26	0.41	-2.30	5.06	93,400
Log(fatalities+0.01)	-4.53	0.66	-4.61	5.06	93,400
Fatalities (asinh)	0.02	0.25	0.00	5.76	93,400
I(Type: Government)	0.01	0.10	0.00	1.00	93,400
I(Type: Non-Government)	0.02	0.14	0.00	1.00	93,400
I(Type: Outside metropolis)	0.02	0.15	0.00	1.00	93,400
I(Type: Battles, riots, violence civilians)	0.02	0.14	0.00	1.00	93,400
I(Type: Battle)	0.01	0.08	0.00	1.00	93,400
I(Type: Riot)	0.01	0.09	0.00	1.00	93,400
I(Type: Violence civilians)	0.01	0.10	0.00	1.00	93,400
I(Type: Protests)	0.01	0.09	0.00	1.00	93,400
I(Type: Explosions)	0.00	0.03	0.00	1.00	93,400
I(Type: Strategic deployments)	0.00	0.04	0.00	1.00	93,400
I(Type: Interstate)	0.00	0.02	0.00	1.00	93,400
I(Non-pastoral other conflcit types)	0.01	0.11	0.00	1.00	93,400
I(Pastoral: Actor)	0.02	0.15	0.00	1.00	93,400
I(Pastoral: Associated actor)	0.00	0.03	0.00	1.00	93,400
I(Pastoral: Associated tribes)	0.00	0.06	0.00	1.00	93,400
I(Pastoral: Notes + GPT)	0.01	0.07	0.00	1.00	93,400
I(Livestock: Notes + dictionary)	0.00	0.06	0.00	1.00	93,400
I(Livestock: Notes + GPT)	0.01	0.07	0.00	1.00	93,400
I(Pastoral: Associated actor ∪ Livestock: Notes + dictionary)	0.00	0.06	0.00	1.00	93,400
I(Pastoral: Associated tribe ∪ Livestock: Notes + dictionary)	0.01	0.08	0.00	1.00	93,400
I(Pastoral: Notes + GPT $\cup : Notes + dictionary$)	0.01	0.08	0.00	1.00	93,400
I(Pastoral: Associated actor $\cup : Notes + GPT$)	0.01	0.07	0.00	1.00	93,400
I(Pastoral: Associated tribes $\cup : Notes + GPT$)	0.01	0.08	0.00	1.00	93,400
I(Pastoral: Notes + GPT $\cup : Notes + GPT$)	0.01	0.08	0.00	1.00	93,400
Treatments (cell level)					
Log rain deficit	2.71	0.57	1.10	5.05	93,400
Log aridity index deficit	3.38	0.69	0.74	5.28	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	0.19	0.39	0.00	1.00	93,400
Log rain deficit * IBLI coverage	0.56	1.18	0.00	4.99	93,400
Log aridity index deficit * IBLI coverage	0.69	1.45	0.00	5.28	93,400
Log dry matter productivity deficit * IBLI coverage	-0.47	1.04	-4.77	0.08	93,000
Mixed landuse (farmland and pastoral)	0.06	0.24	0.00	1.00	93,400
Mixed settlement area	0.47	0.50	0.00	1.00	93,400
Mixed settlement area (within culture group)	0.17	0.37	0.00	1.00	93,400
Mixed settlement area (across culture group)	0.31	0.46	0.00	1.00	93,400
Pastoral-agricultural suitability	0.25	0.43	0.00	1.00	93,400
Grassland-cropland transition	0.10	0.30	0.00	1.00	93,400
Controls (cell level)					
HSNP coverage	0.24	0.43	0.00	1.00	93,400
No. of aid projects (agriculture)	0.03	0.21	0.00	4.00	93,400

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Table A-1 – *Continued from previous page*

Variable	Mean	SD	Min	Max	N
No. of aid projects (all)	0.04	0.36	0.00	19.00	93,400
Log aid commitments (World Bank)	0.03	0.19	0.00	3.59	93,400
No of aid projects (agriculture GODAD)	0.01	0.12	0.00	3.00	93,400
Log aid commitments (agriculture GODAD)	0.01	0.10	0.00	3.40	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
Distance border	111.62	81.20	0.03	347.94	93,400
Distance capital	362.70	167.50	4.55	806.10	93,400
Distance livestock market	58.16	34.42	0.98	179.68	93,400
Distance agricultural market	54.45	40.23	0.28	212.46	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	-0.26	0.33	-1.19	0.95	93,400
Log aridity index deficit	0.35	0.39	-0.81	1.56	93,400
Log dry matter productivity deficit	-1.55	0.36	-2.32	-0.13	93,400
IBLI coverage	-0.10	0.93	-0.78	2.42	93,400
IBLI payouts	0.06	1.06	-0.38	5.23	93,400
Log rain deficit * IBLI coverage	0.01	0.41	-2.15	0.78	93,400
Log aridity index deficit * IBLI coverage	-0.09	0.49	-1.13	2.26	93,400
Log dry matter productivity deficit * IBLI coverage	0.22	1.38	-4.45	1.73	93,400
Controls (neighborhood level)					
HSNP coverage	-0.08	0.93	-1.00	2.17	93,400
No. of aid projects	0.21	0.90	-1.37	4.80	93,400
No. of aid agricultural projects	0.19	0.93	-1.25	6.59	93,400
Log aid commitments (World Bank)	0.61	0.33	0.03	2.14	93,400
No of aid projects (agriculture GODAD)	0.16	0.12	0.02	1.21	93,400
Log aid commitments (agriculture GODAD)	0.18	0.17	0.01	1.38	93,400
County panel sample					
Cattle in 1000s	351.68	345.49	0.00	2,883.16	423
Cattle in 1000s (beef production)	254.08	348.04	0.00	2,883.15	423
Cattle in 1000s (dairy production)	97.60	106.77	0.00	451.71	423
IBLI cover (county)	0.11	0.31	0.00	1.00	423
Market panel sample					
Log cattle price	9.98	0.48	7.13	10.79	196
Log goat price	8.20	0.37	7.36	9.08	137
Log sheep price	8.08	0.40	7.10	8.99	120
Log rain deficit (neighborhood)	-0.24	1.09	-2.28	3.28	196
IBLI coverage (neighborhood)	-0.08	1.05	-1.11	2.22	196
Log rain deficit * IBLI coverage (neighborhood)	-0.12	1.18	-3.51	2.78	196
Afrobarometer respondent sample					
$Hunger_{r,g,w}$	0.51	0.50	0.00	1.00	8,172
$No\ cash\ income_{r,g,w}$	0.82	0.38	0.00	1.00	8,172
Rain deficit cell (Respondent cell)	2.20	0.50	1.34	3.99	8,172
IBLI coverage cell (Respondent cell)	0.05	0.22	0.00	1.00	8,172
Pastoral group identification (Respondent)	0.20	0.40	0.00	1.00	8,172

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Table A-1 – *Continued from previous page*

Variable	Mean	SD	Min	Max	N
Female indicator (Respondent)	0.50	0.50	0.00	1.00	8,172
Age in years (Respondent)	35.96	13.78	18.00	99.00	8,171
Urban indicator (Respondent)	0.37	0.48	0.00	1.00	8,172
Completed primary education (Respondent)	0.20	0.40	0.00	1.00	8,142
Some secondary education (Respondent)	0.13	0.34	0.00	1.00	8,142
Secondary education or more (Respondent)	0.44	0.50	0.00	1.00	8,142
Actor-homeland (Murdock) sample					
Ln distance Actor-location to homeland (Conflict)	4.74	0.91	1.55	6.58	719
Avg. log rain deficit (Homeland)	2.56	0.57	1.30	4.27	719
IBLI coverage (Homeland)	-0.04	0.94	-0.41	2.95	719
Avg. log rain deficit × IBLI coverage (Homeland)	0.07	2.78	-1.60	10.58	719
Pastoral group (Homeland)	0.71	0.45	0.00	1.00	719

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
Event types and example sub-event types

Event type	**Sub-event types**
Battles	Armed clash, Government regains territory
Explosions/remote violence	Suicide bomb, Remote explosive/landmine/IED
Protests	Peaceful protest, Excessive force against protesters
Riots	Mob violence, Violent demonstration
Strategic developments	Looting/property destruction, Other
Violence against civilians	Abduction/forced disappearance, Attack

Notes: The table reports the different event types in recorded in ACLED (Raleigh, Kishi, and Linke 2023), as well as selected sub-event types as reported in the ACLED codebook.

Table A-3
Top ten actors with the highest share of pastoralists

Actor	Frequency	Share of Assoc. Actors	Share of Assoc. Actors Pastoralists
Unidentified Communal Militia (Kenya)	91	0.19	0.94
Unidentified Armed Group (Kenya)	919	0.01	0.78
Pokot Ethnic Militia (Kenya)	166	0.10	0.76
Turkana Ethnic Militia (Kenya)	101	0.07	0.71
Samburu Ethnic Militia (Kenya)	40	0.20	0.62
Unidentified Ethnic Militia (Kenya)	207	0.08	0.62
Borana Ethnic Militia (Kenya)	26	0.38	0.60
Maasai Ethnic Militia (Kenya)	103	0.12	0.50
Garre Ethnic Militia (Kenya)	44	0.30	0.08
Civilians (Kenya)	2145	0.38	0.05

Notes: The table reports the 10 actors recorded in the ACLED event database (Raleigh, Kishi, and Linke 2023) with the highest share of pastoralists as their associated actors within Kenya. Given that associated actors are often unknown we limits the sample to actors that have at least 5 events with a known associated actor.

Table A-4

Pastoralist incident classification: Cross-correlations

Indicator:	Conflict indicator: Pastoral				Livestock		Pastoral					
	Actor	Assoc. actor	Assoc. tribes	Notes + GPT	Notes + dictionary	Notes + GPT	Assoc. actor ∪ Notes + dictionary	Assoc. tribe ∪ Notes + dictionary	Notes + GPT ∪ Notes + dictionary	Assoc. actor ∪ Notes + GPT	Assoc. tribes ∪ Notes + GPT	Notes + GPT ∪ Notes + GPT
Pastoral: Actor	1											
Pastoral: Assoc. actor	0.250	1										
Pastoral: Assoc. tribes	0.412	0.572	1									
Pastoral: Notes + GPT	0.477	0.504	0.662	1								
Livestock: Notes + dictionary	0.406	0.520	0.487	0.774	1							
Livestock: Notes + GPT	0.473	0.481	0.590	0.883	0.831	1						
Pastoral: Assoc. actor ∪ Notes + dictionary	0.416	0.581	0.518	0.792	0.979	0.833	1					
Pastoral: Assoc. tribe ∪ Notes + dictionary	0.498	0.473	0.827	0.826	0.798	0.807	0.815	1				
Pastoral: Notes + GPT ∪ Notes + dictionary	0.495	0.487	0.646	0.967	0.827	0.909	0.843	0.862	1			
Pastoral: Assoc. actor ∪ Notes + GPT	0.477	0.505	0.602	0.889	0.825	0.993	0.844	0.814	0.915	1		
Pastoral: Assoc. tribes ∪ Notes + GPT	0.519	0.452	0.790	0.856	0.740	0.888	0.757	0.937	0.877	0.895	1	
Pastoral: Notes + GPT ∪ Notes + GPT	0.501	0.477	0.643	0.947	0.797	0.945	0.813	0.841	0.968	0.950	0.907	1

Notes: The table reports the cross-correlations for different proxies for conflict incidents involving pastoralists (see Section A-2 for details on the indicators).

Table A-5
Correlation of drought proxies

	Log rain deficit	Log AI	Log DMP
Log rain deficit	1		
Log aridity index (AI)	-0.839	1	
Log dry matter productivity (DMP)	-0.814	0.807	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. 2022). 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-6
Match: ACLED actors with Murdock groups

Murdock group	Actor	Actor type
Bararetta	Ajuran Ethnic Militia	Semi-organized
Bararetta	Auliyan Clan Militia	Semi-organized
Bararetta	Auliyan Ethnic Militia	Semi-organized
Bararetta	Degodia Ethnic Militia	Semi-organized
Bararetta	Galwina Ethnic Militia	Semi-organized
Bararetta	Garre Clan Militia	Semi-organized
Bararetta	Garre Ethnic Militia	Semi-organized
Bararetta	Jibril Clan Militia	Semi-organized
Bararetta	Marehan Clan Militia	Semi-organized
Bararetta	Matan Clan Militia	Semi-organized
Bararetta	Ogaden-Absame-Bah Geri Sub-Clan Militia	Semi-organized
Bararetta	Police Forces Of Kenya	Semi-organized
Bararetta	Somali Ethnic Militia	Semi-organized
Bararetta	Unorganized Group Members	Unorganized
Bararetta	Wardei Ethnic Militia	Semi-organized
Boni	Abduwak Ethnic Militia	Semi-organized
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	Police Forces Of Kenya	Semi-organized
Boran	Unorganized Group Members	Unorganized
Dorobo	Kapshoi Clan Militia	Semi-organized
Dorobo	Ndorobo Ethnic Militia	Semi-organized
Dorobo	Ogiek Ethnic Militia	Semi-organized
Dorobo	Unorganized Group Members	Unorganized
Gusii	Kisii Communal Militia	Semi-organized
Gusii	Kisii Ethnic Militia	Semi-organized
Gusii	Unorganized Group Members	Unorganized
Gyriama	Unorganized Group Members	Unorganized
Jie	Jie Ethnic Militia	Semi-organized
Karamojong	Dodoth Ethnic Militia	Semi-organized
Karamojong	Dongiro Ethnic Militia	Semi-organized
Karamojong	Karamajong Ethnic Militia	Semi-organized
Karamojong	Matheniko Ethnic Militia	Semi-organized
Kikuyu	Akorino Sect Militia	Semi-organized
Kikuyu	Kiambu Ethnic Militia	Semi-organized
Kikuyu	Kikuyu Ethnic Militia	Semi-organized
Kikuyu	Mau Mau War Veterans	Semi-organized
Kikuyu	Mungiki Militia	Mungiki Militia
Kikuyu	Unorganized Group Members	Unorganized
Kipsigi	Kipsigi Ethnic Militia	Semi-organized
Kipsigi	Unorganized Group Members	Unorganized
Luo	Luo Ethnic Militia	Semi-organized
Luo	Unorganized Group Members	Unorganized
Masai	Erwasingishu Clan Militia	Semi-organized
Masai	Isiria Clan Militia	Semi-organized
Masai	Maasai Ethnic Militia	Semi-organized
Masai	Moran Ethnic Militia	Semi-organized
Masai	Siria Clan Militia	Semi-organized
Masai	Unorganized Group Members	Unorganized

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Table A-6 – *Continued from previous page*

Murdock group	Actor	Actor type
Meru	Imenti Ethnic Militia	Semi-organized
Meru	Meru Ethnic Militia	Semi-organized
Meru	Tharaka Ethnic Militia	Semi-organized
Meru	Unorganized Group Members	Unorganized
Nandi	Marakwet Ethnic Militia	Semi-organized
Nandi	Nandi Ethnic Militia	Semi-organized
Nandi	Unorganized Group Members	Unorganized
Pokomo	Pokomo Ethnic Militia	Semi-organized
Pokomo	Unorganized Group Members	Unorganized
Samburu	Isiolo Communal Militia	Semi-organized
Samburu	Pokot Ethnic Militia	Semi-organized
Samburu	Samburu Ethnic Militia	Semi-organized
Samburu	Unorganized Group Members	Unorganized
Sonjo	Sonjo Ethnic Militia	Semi-organized
Suk	Unorganized Group Members	Unorganized
Topotha	Toposa Ethnic Militia	Semi-organized
Turkana	Merrile Ethnic Militia	Semi-organized
Turkana	Police Forces Of Kenya	Semi-organized
Turkana	Turkana Ethnic Militia	Semi-organized
Turkana	Unorganized Group Members	Unorganized
Wanga	Kabasiran Clan Militia	Semi-organized
Wanga	Luhya Ethnic Militia	Semi-organized
Wanga	Unorganized Group Members	Unorganized

Notes: The table reports the Murdock groups in our sample (Murdock 1967), the actors reported in ACLED (Raleigh, Kishi, and Linke 2023) 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 (P), Boran (P), Chaga, Didinga (P), Digo, Dorobo (P), Duruma, Gusii, Gyriama, Jie (P), Kamba, Karamojong (P), Keyu, Kikuyu, Kipsigi (P), Luo, Masai (P), Meru, Nandi, Pare, Pokomo (P), Rendile (P), Reshiat, Sabei, Samburu (P), Sanye, Segeju, Shambala, Shashi, Sonjo, Suk (P), Teita, Topotha (P), 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, Rohner, and Thoenig 2025), roughly a transhumant pastoralists value of 0.5 and higher in McGuirk and Nunn (2025)

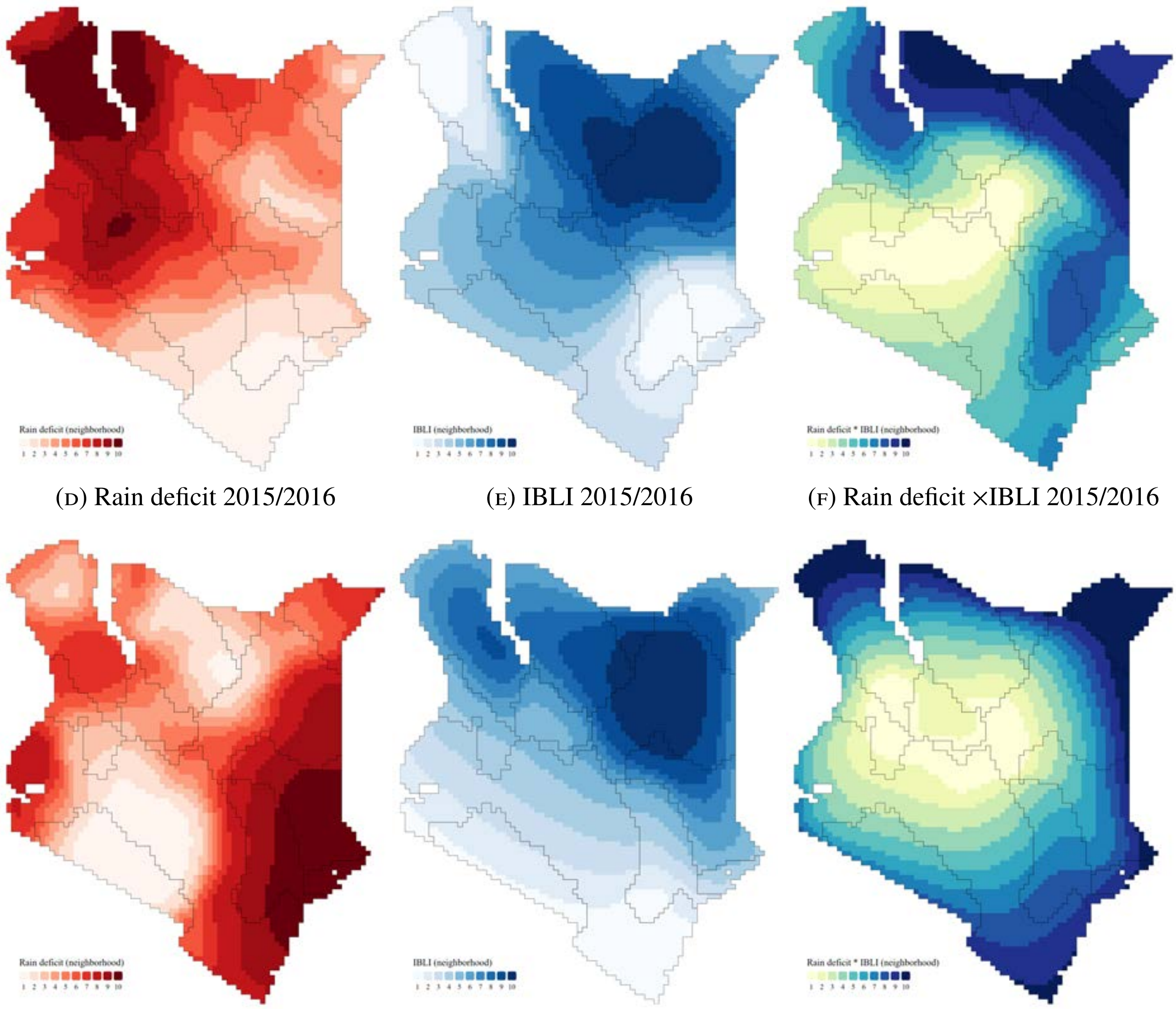
B. Additional results

B-1. Additional figures

Figure B-1
Variation of variables of interest (neighborhood)

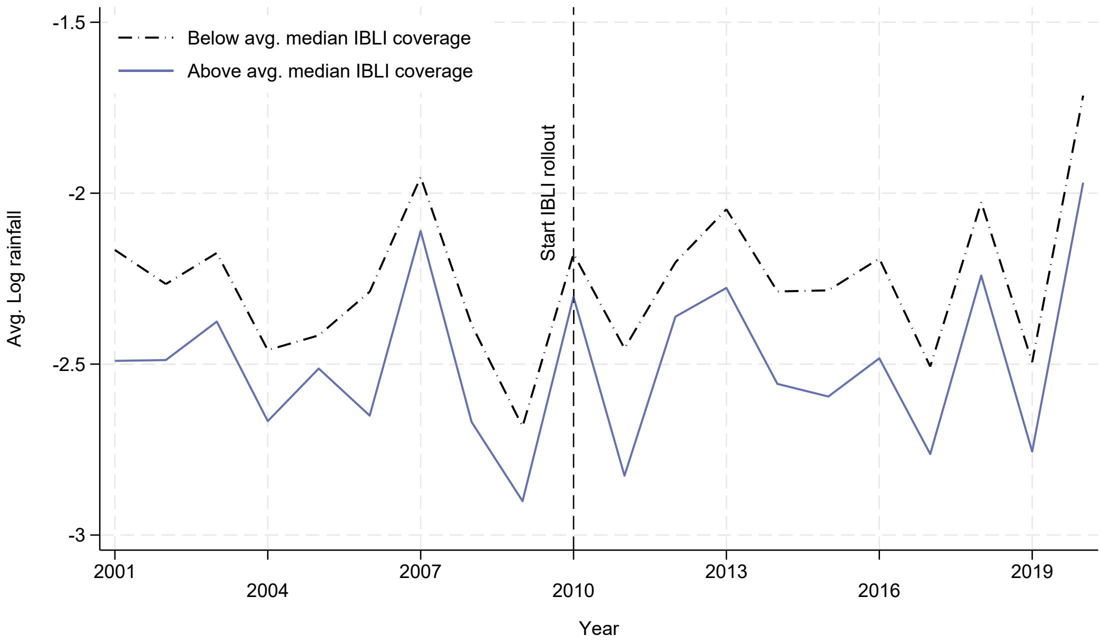
(a) Rain deficit 2014/2015 (b) IBLI 2014/2015 (c) Rain deficit ×IBLI 2014/2015

(d) Rain deficit 2015/2016 (e) IBLI 2015/2016 (f) Rain deficit ×IBLI 2015/2016



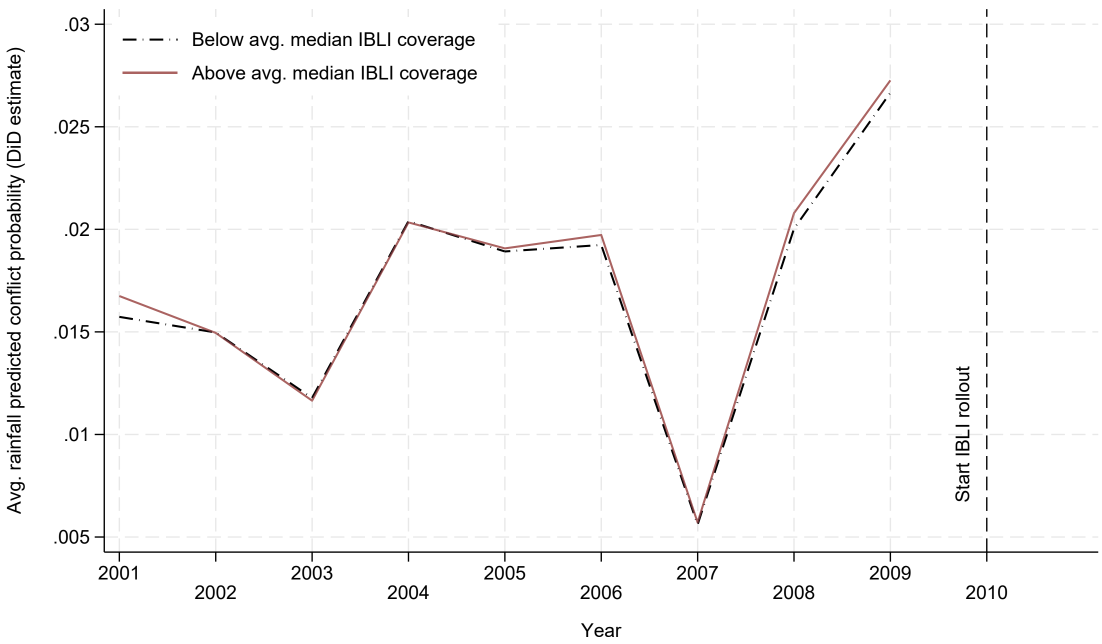
Notes: The figure plots the identifying variation used in our main specification, specifically our neighborhood variables of interest net of cell and period fixed effects. Panel A of the figure plots the average neighborhood version of the rain deficit (log (rainfall) ×-1) between October 2014 and September 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



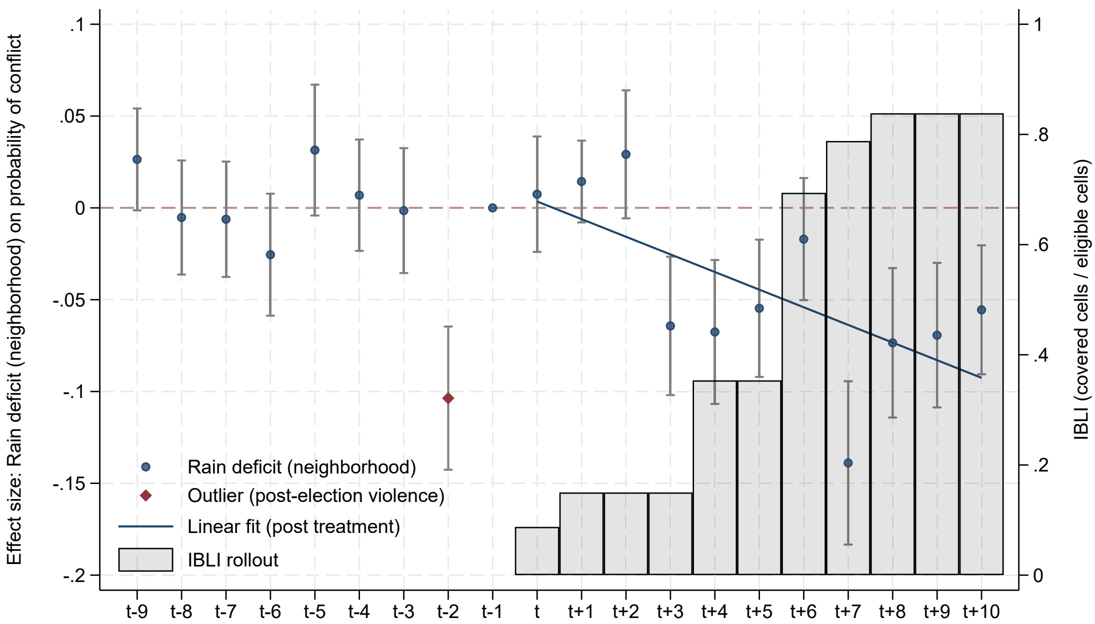
Notes: The figure plots the average neighborhood rainfall for cells with below and above time-averaged IBLI coverage in Kenya over our study period.

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



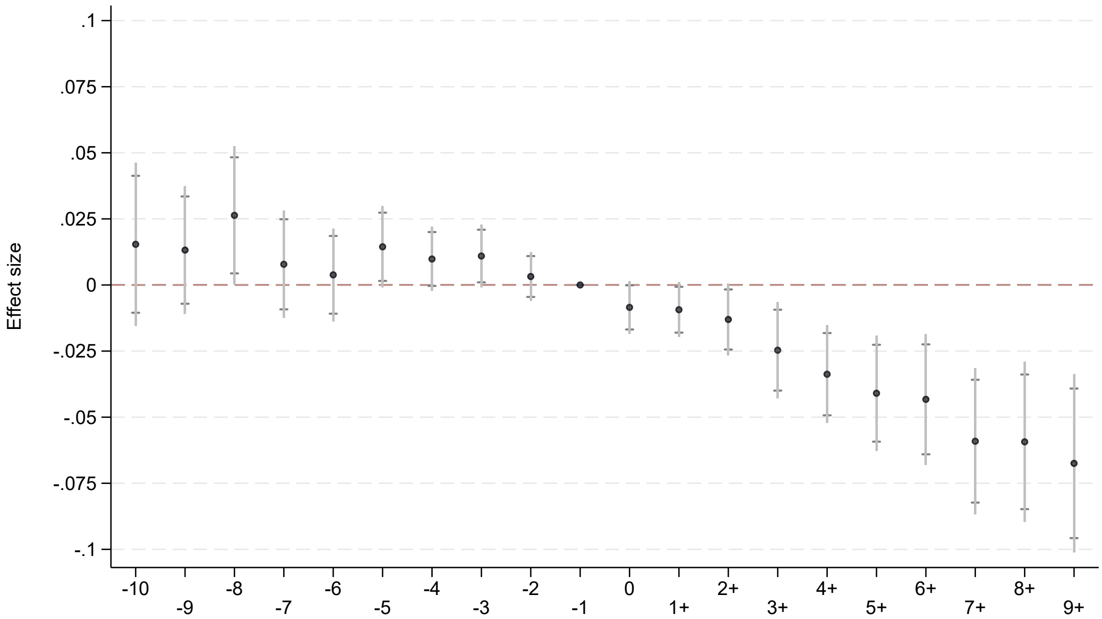
Notes: The figure plots the conflict predicted by the rain deficit in the cell and neighborhood (based on column 1 of Table I) for cells that have above (below) median IBLI coverage in the neighborhood over the pre-rollout period of IBLI.

FIGURE B-4
Conflict differences by IBLI and drought impact over time



Notes: The figure plots the relative impact of the neighborhood rain deficit on the probability of cell-level conflict in each period compared to the last pre-IBLI period. Specifically we plot the event study estimates based on the following specification Specifically, we estimate $Conflict_{it} = \sum_{j=\underline{j}}^{\bar{j}} \beta^{j}_{Rain\ deficit\ neighborhood} + \eta_{it} + \lambda_t + epsilpon_{it}$, where the $\beta^{j}_{I_{Rain\ deficit\ neighborhood}}$ are year specific effects. Confidence intervals are 90% CI and constructed based on Conley standard errors, implemented using the acreg package in Stata (Colella et al. 2019), with a distance cutoff of 200km. The figure also plots the IBLI rollout as a share of cells covered over the cells eligible. The outlier in the pre-treatment period is highlighted in red. This period includes the post-election violence of 2007/2008, which occurred primarily in Nairobi, and the Western Highlands are characterized by high levels of rainfall both at the cell and neighborhood level. The overall pattern documents that the effect of the neighborhood rain deficit falls on average as IBLI coverage is expanded in Kenya.

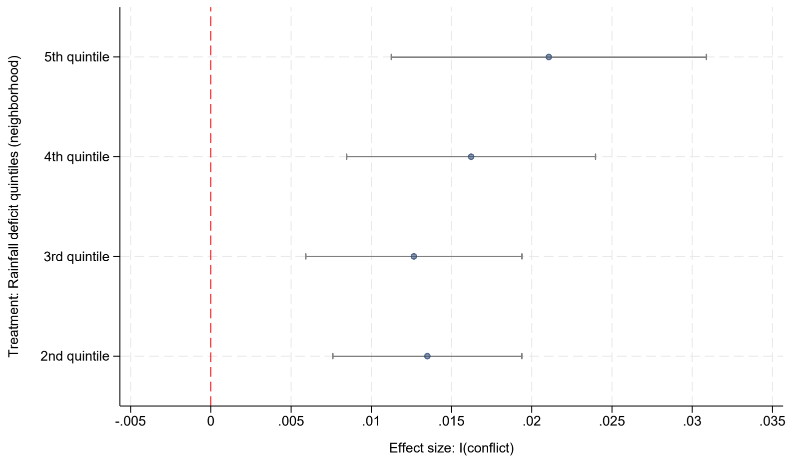
Figure B-5
Event study: IBLI neighborhood coverage



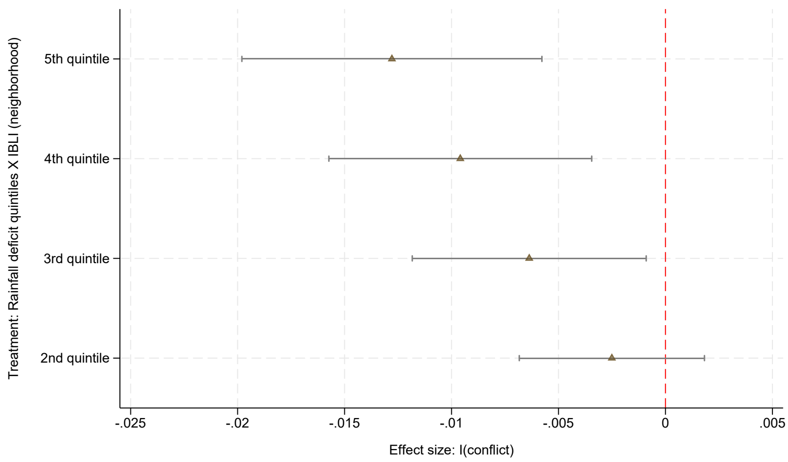
Notes: The figure plots the event study estimates and the corresponding 90 and 95% confidence intervals from regressing the conflict indicator on above median IBLI neighborhood coverage indicators. Specifically, we estimate $Conflict_{it} = \sum_{j=\underline{j}}^{\overline{j}} \beta^{j}_{I_{IBLI\ neighborhood}} + \eta_{it} + \lambda_t + epsilpon_{it}$, where the $\beta^{j}_{I_{IBLI\ neighborhood}}$ are treatment indicators for the cell with above median IBLI neighborhood coverage. Confidence intervals are 90% CI and constructed 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: Rainfall deficit and IBLI bins

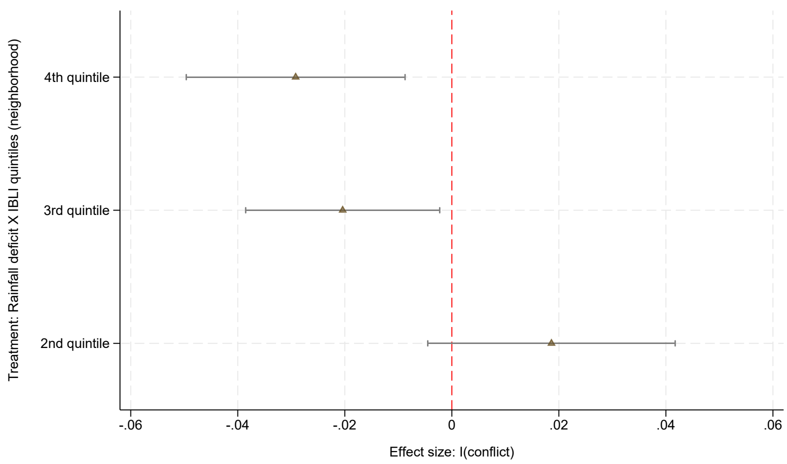
(A) Rain deficit bins (δ_1)



(B) Rain deficit bins × IBLI (δ_3)

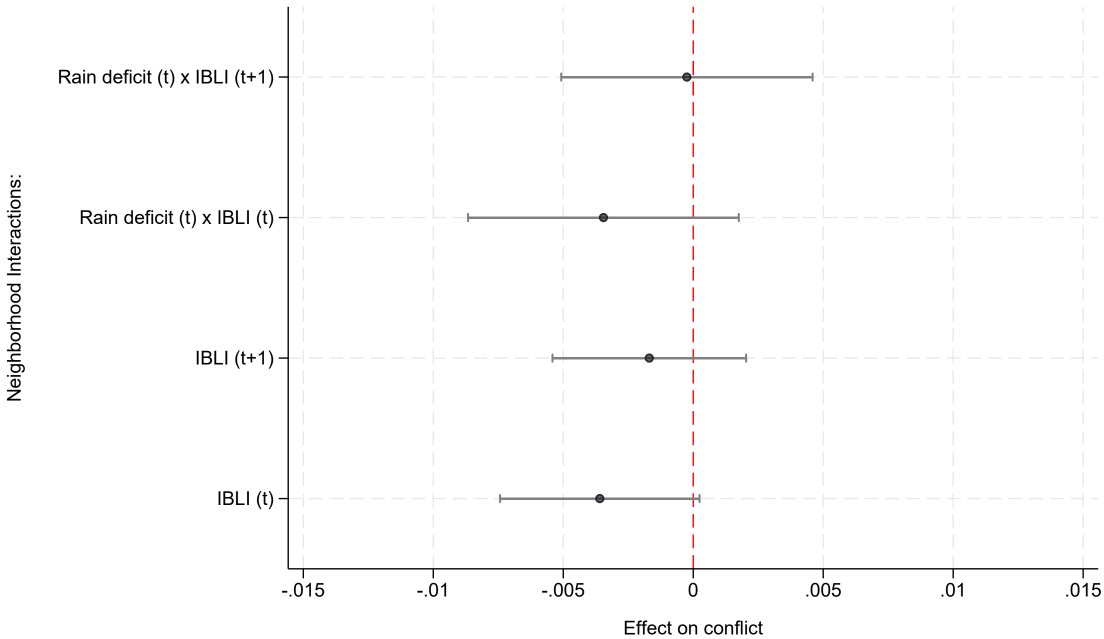


(C) Rain deficit × IBLI bins (δ_3)



Notes: Panels A and B of the figure report our point estimates of interest (δ_1 and δ_3) and 90% 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. Panel C reports the interaction coefficient of interest (δ_3) for our baseline specification, where we bin neighborhood IBLI coverage. The 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.

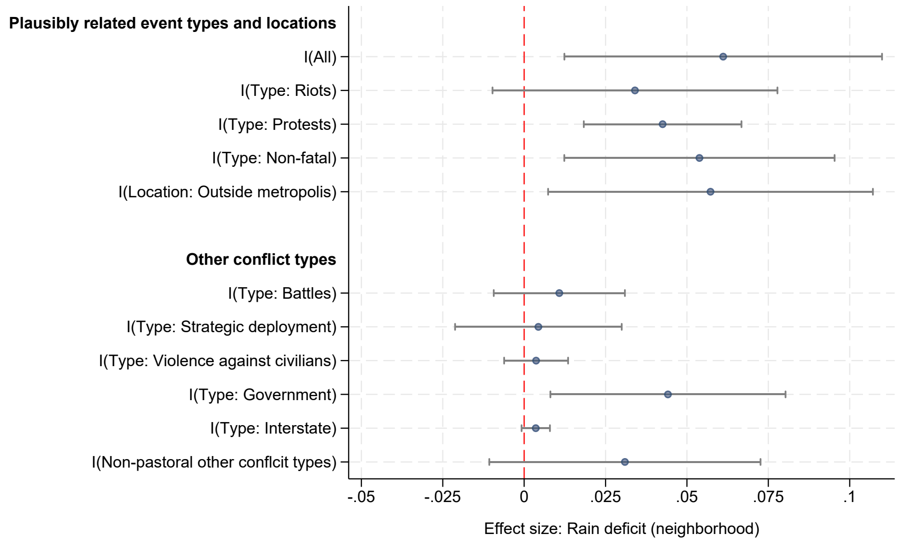
FIGURE B-7
Controlling for next periods IBLI coverage



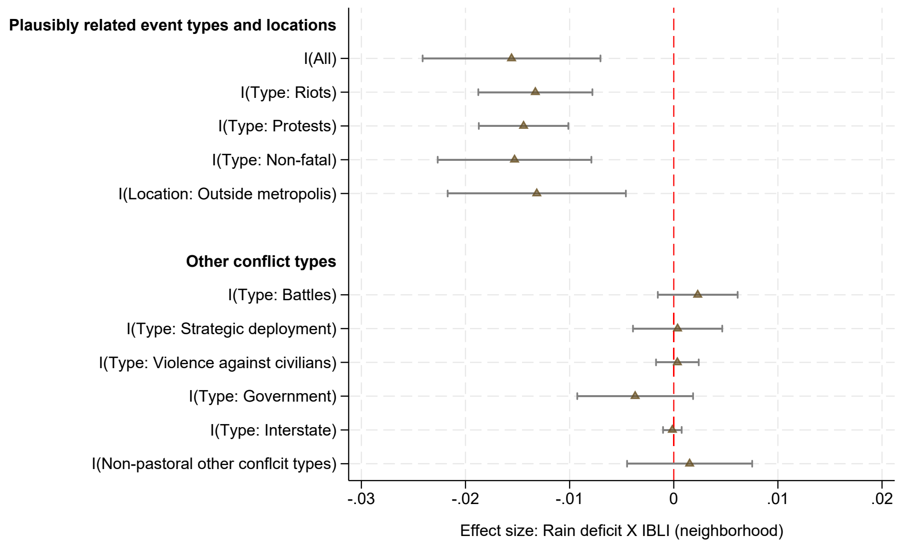
Notes: The figure plots the coefficients of interest for adding a lead in the IBLI coverage and the interaction with current rainfall to our main specification reported in column 3 of Table I. The 90% confidence intervals are based on Conley standard errors, implemented using the acreg package in Stata (Colella et al. 2019), with a distance cutoff of 200km.

Figure B-8
Main results: Alternative conflict measures

(a) Rain deficit (neighborhood)



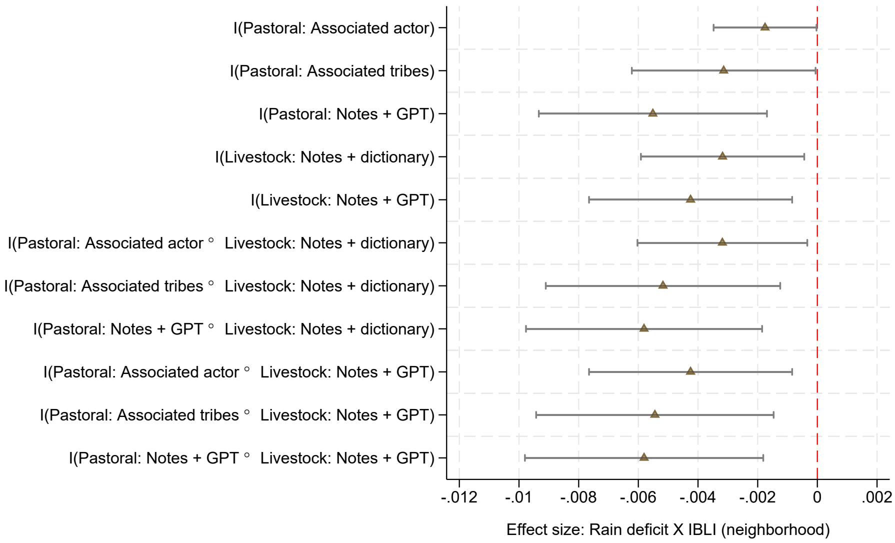
(b) Rain deficit × IBLI (neighborhood)



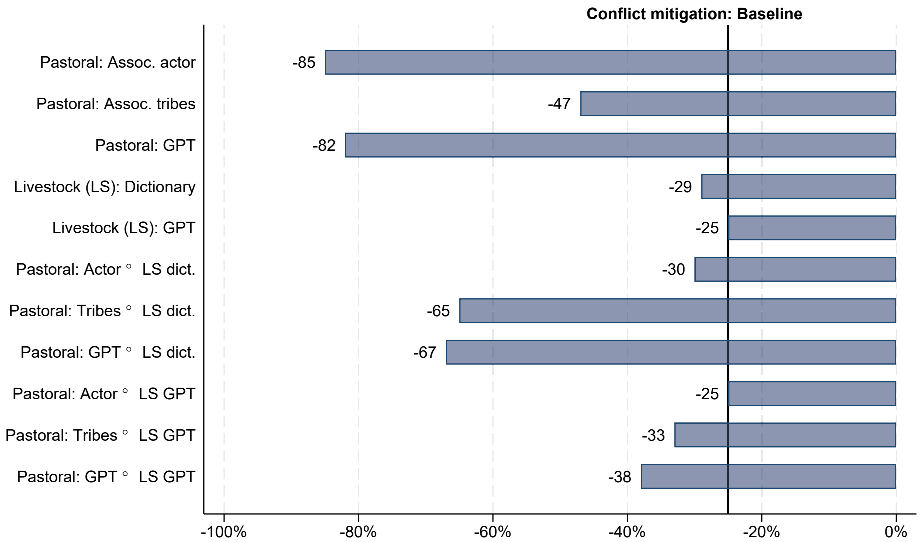
Notes: The figure reports our point estimates of interest δ_1 (panel A) and δ_3 (panel B) and 90% confidence intervals for alternative conflict measures from the ACLED dataset (Raleigh, Kishi, and Linke 2023) regressed on the specification in column 3 of Table I. *I(All)* is our baseline indicator based on all incidents in ACLED. *I(Type: Riots)* and *I(Type: Protests)* only consider incidents classified as riots or protests in constructing the indicator.*I(Type: Non-fatal)* is based only on non-fatal incidents. *I(Location: Outside metropolis)* is based only on incidents outside the major cities. *I(Type: Battles)*, *I(Type: Strategic deployment)*, and *I(Type: Violence against civilians)*, are based only on events classified as "battles", "strategic deployments", or "Violence against civilians" respectively. *I(Type: Government)* is based only on events in which the government is a primary actor. *I(Type: Interstate)* is based only on events in which exclusively the government entities are primary actors. *I(Non-pastoral other conflict types)* is all of the cells that experience any of the other conflict types but no pastoral or livestock violence during a period. The 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-9
Conflicts involving pastoralists

(A) Rain deficit × IBLI (Neighborhood)



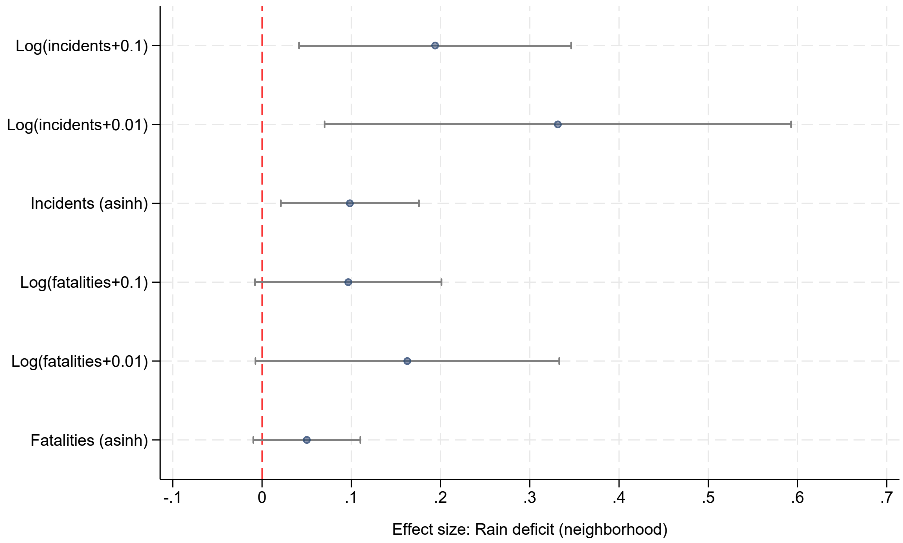
(B) Mitigation



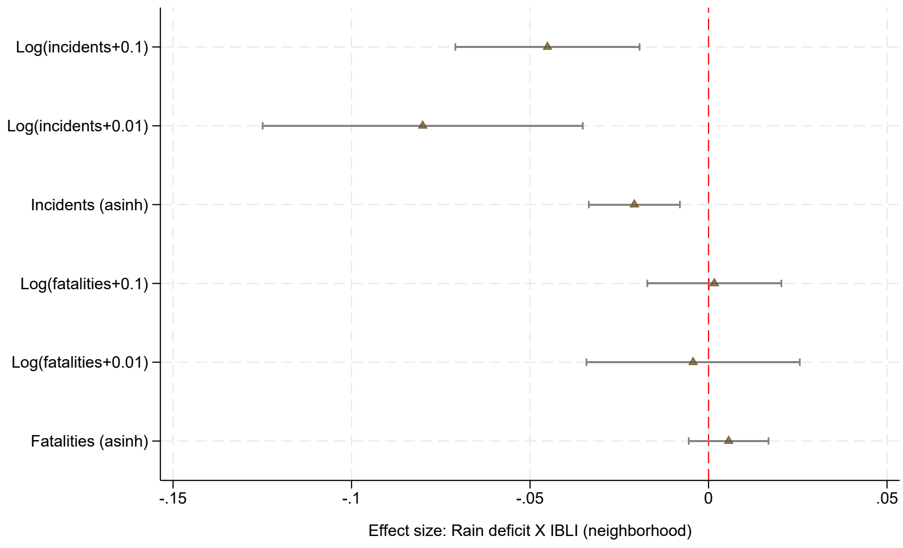
Notes: Panel A of the figure reports our point estimates of interest δ_3 and 90% confidence intervals for alternative conflict measures proxying for conflict involving pastoralists, based on the specification in column 3 of Table I. Panel B plots the corresponding conflict mitigation. *I(Pastoral: Associated actor)*, *I(Pastoral: Associated tribes)*, *I(Pastoral: Notes + GPT)* are events based on different actor classifications. Specifically "associated actor", "associated tribes" or based on notes using "GPT4". *I(Livestock: Notes + dictionary)* and *I(Livestock: Notes + GPT)* are based on events classified as conflict events involving livestock either based on a dictionary approach or GPT. *I(Pastoral: Associated actor ∪ Livestock: Notes + dictionary)*, *I(Pastoral: Associated tribe ∪ Livestock: Notes + dictionary)*, and *I(Pastoral: Notes + GPT ∪ Livestock: Notes + dictionary)* are based on events that are either classified via the actor or are classified as a livestock event based on the dictionary approach. *I(Pastoral: Associated actor ∪ Livestock: Notes + GPT)*, *I(Pastoral: Associated tribes ∪ Livestock: Notes + GPT)*, and *I(Pastoral: Notes + GPT ∪ Livestock: Notes + GPT)* are based only on events that are classified based on pastoralist actors or livestock events identified via GPT. Details on all variables are provided in Section A-2. Descriptive patterns on the locations of the events are provided in Online Appendix C. The 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-10
Main results: Conflict intensive margin

(A) Rain deficit (neighborhood)



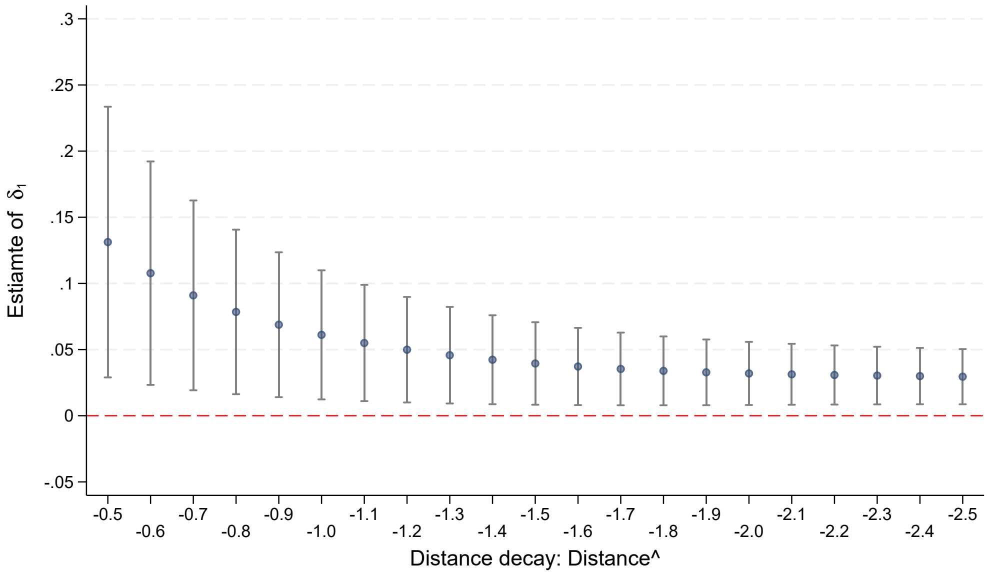
(B) Rain deficit × IBLI (neighborhood)



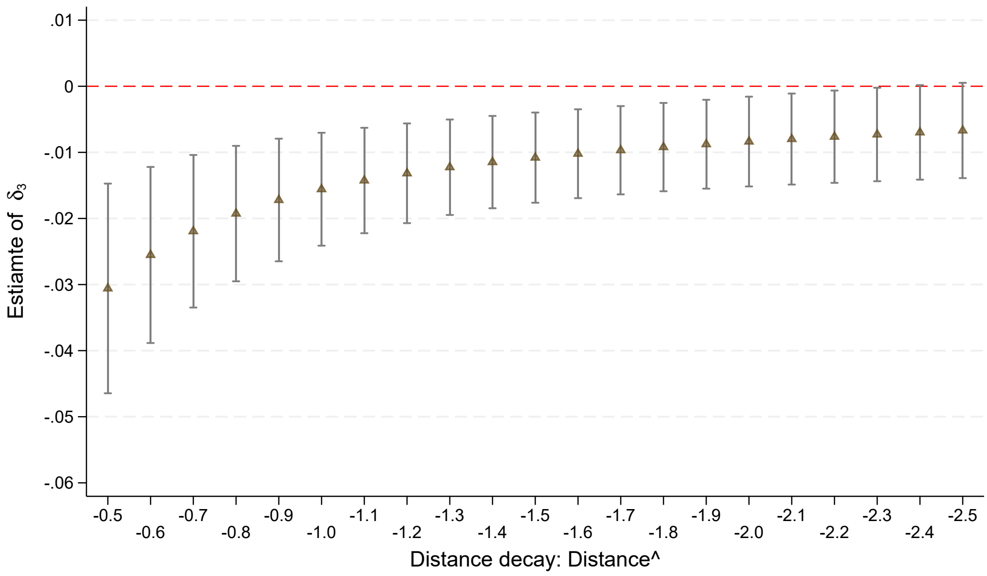
Notes: The figure reports our point estimates of interest δ_1 (panel A) and δ_3 (panel B) and 90% confidence intervals for alternative conflict measures from the ACLED dataset (Raleigh, Kishi, and Linke 2023) regressed on the specification in column 3 of Table I. *Log(incidents+0.1* is the log number of conflict events in a cell during a period plus 0.1. *Log(incidents+0.01* is the log number of conflict events in a cell during a period plus 0.1. *Incidents (asinh)* is the inverse hyperbolic sine transformation of the number of conflict events in a cell during a period. *Log(fatalities+0.1*, *Log(fatalities+0.01*, and *Fatalities (asinh)* are the corresponding measures based on the number of fatalities in a cell during a period. The 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-11
Main results: Alternative distance decay

(A) Decay: Rain deficit (Neighborhood)



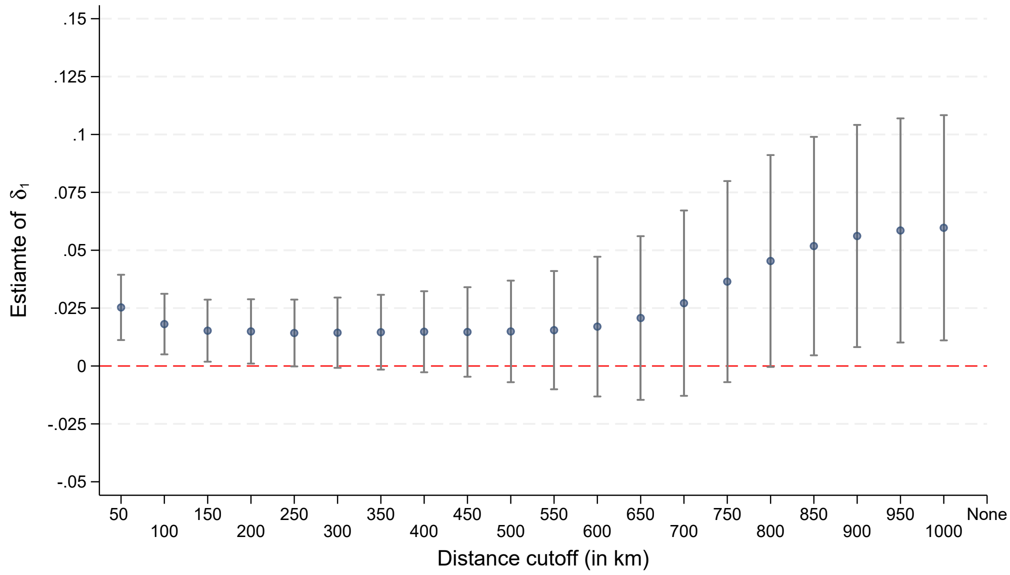
(B) Decay: Rain deficit × IBLI (Neighborhood)



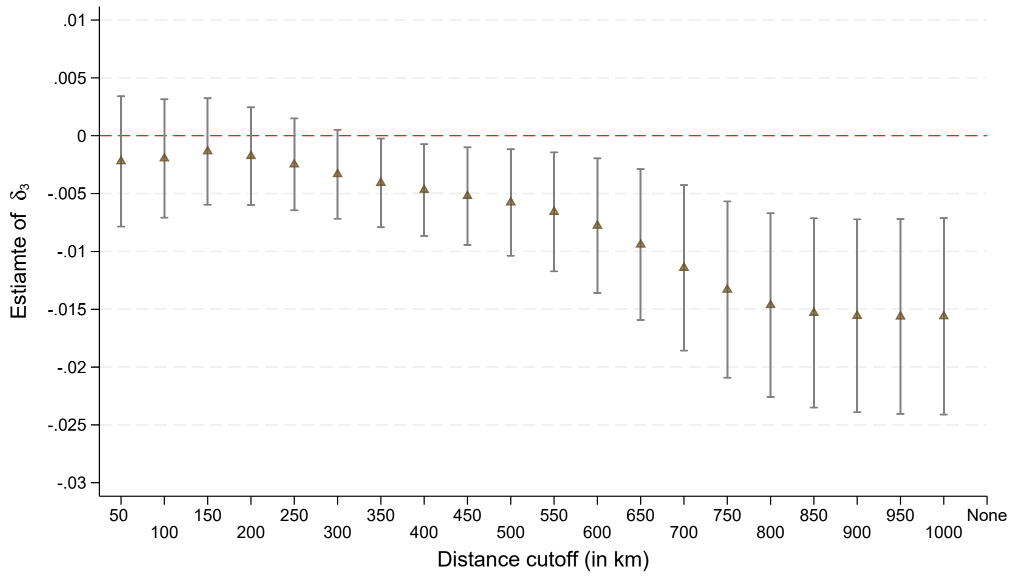
Notes: Panel A of the figure plots the point estimates and 90% confidence intervals of the log of neighborhood rainfall deficit (log(rainfall) $\times -1$) for varying distance decays (based on our main specification column 3 of Table I). Panel B plots the point estimates and 90% confidence intervals of the corresponding interaction with the standardized neighborhood IBLI coverage. 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-12
Main results: Neighborhood measures with distance cutoff

(A) Cutoff: Rain deficit (Neighborhood)

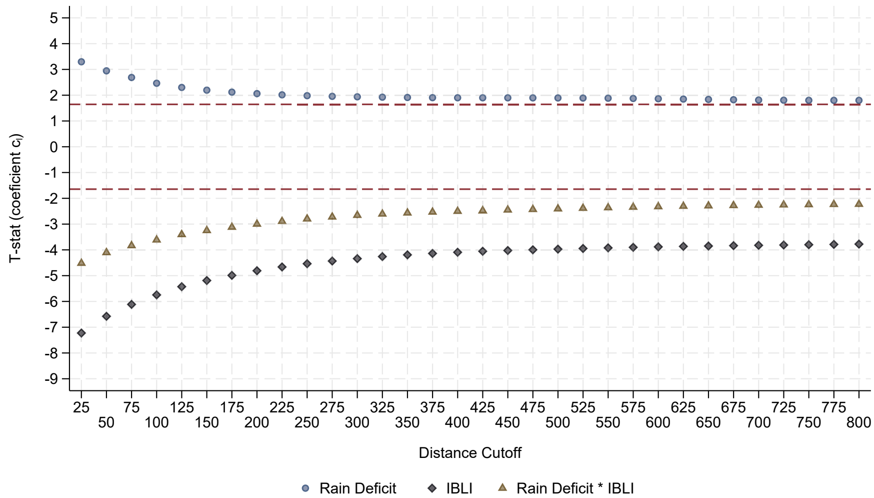


(B) Cutoff: Rain deficit × IBLI (Neighborhood)



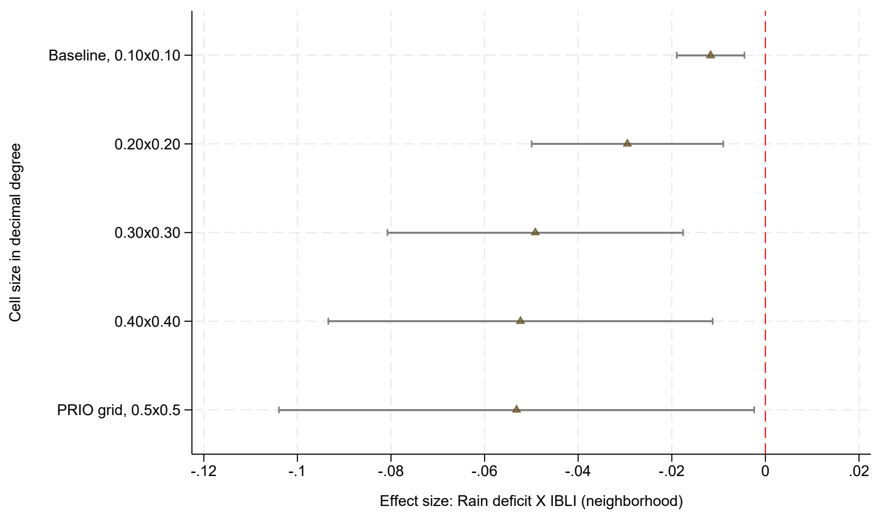
Notes: Panel A of the figure plots the point estimates and 90% confidence intervals of the log of neighborhood rainfall deficit (log(rainfall) $\times -1$) for varying distance cutoffs, after which cells are no longer used to calculate the neighborhood measures (based on our main specification column 3 of Table I). Panel B plots the point estimates and 90% confidence intervals of the corresponding interaction with the standardized neighborhood IBLI coverage (panel B). 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-13
Main results: Standard errors spatial cutoffs



Notes: 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.

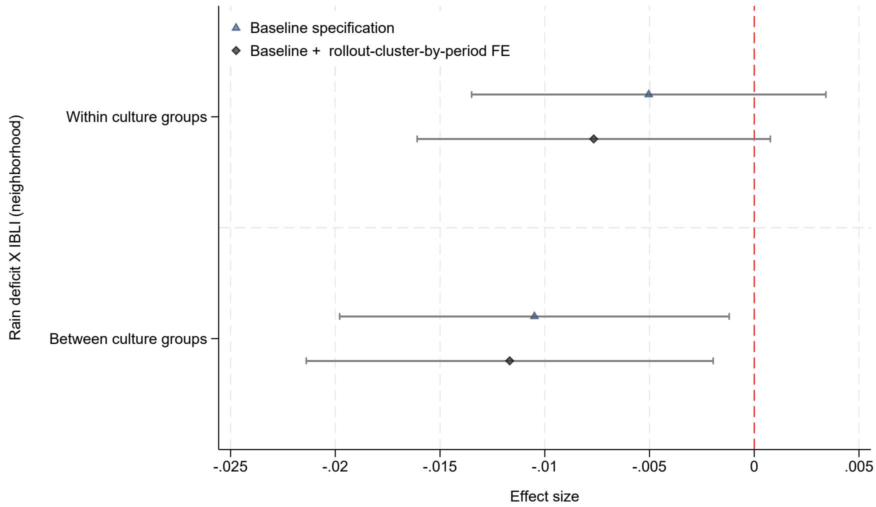
FIGURE B-14
Main results: Grid cell sizes



Notes: The figure plots the point estimates and 90% confidence intervals of the log of neighborhood rainfall deficit (log(rainfall) $\times -1$) interacted with the standardized neighborhood IBLI coverage (δ_3) for different grid cell sizes, based on column 3 of Table I excluding the cell-level terms (due to higher aggregation). 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-15

Triple interaction results: Mixed settlement (ethnic & culture groups)



Notes: The figure plots the point estimates and 90% confidence intervals of the triple-interaction of the log of neighborhood rainfall deficit (log(rainfall) $\times -1$) with the standardized neighborhood IBLI coverage and two different mixed settlement indicators. The first is based on proximity to homeland borders within broader culture group homeland, and the second is exclusively based on the proximity to borders of those larger culture group homelands. Blue triangles represent a specification similar to column 3 of Table III and black diamonds to column 4 of Table III (adding rollout-cluster-by-time fixed effects). Cell-level coefficients are omitted, and the IBLI neighborhood coefficients are not reported to conserve space. 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.

B-2. Additional tables

TABLE B-1
Sensitivity: Serial correlation

Dependent variables:	Cell			Neighborhood	
	Conflict	Rain deficit	IBLI coverage	Rain deficit	IBLI coverage
	(1)	(2)	(3)	(4)	(5)
Conflict (t-1)	0.0643				
	(0.0144)				
Rain deficit cell (t-1)		-0.1018			
		(0.0403)			
IBLI coverage cell (t-1)			0.8498		
			(0.0325)		
Rain deficit neighborhood (t-1)				-0.1610	
				(0.0418)	
IBLI coverage neighborhood (t-1)					0.9476
					(0.0193)
Cell FE	✓	✓	✓	✓	✓
Period FE	✓	✓	✓	✓	✓
Adj. R2	0.00397	0.0109	0.667	0.0274	0.827
Obs	88730	88730	88730	88730	88730
Breitung unit root test: 1 lag, linear trend, demeaned					
Lambda	-1.2e+02	-88.5953	-8.1667	-89.0208	-14.7161
P-value	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Breitung unit root test: 2 lags, linear trend, demeaned					
Lambda	-91.2274	-67.5975	-16.0487	-76.4201	-20.7342
P-value	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)

Notes: The table reports the results of regressing our core variables of interest on their lagged values. Moreover, we report the Breitung test statistic for a unit root (Breitung and Das 2005). Conley standard errors are implemented using the acreg package in Stata (Colella et al. 2019), with a distance cutoff of 200km.

TABLE B-2

Baseline results (full)

	Dependent variable: Conflict$_{i,t}$			
	(1)	(2)	(3)	(4)
CELL				
$Rain\ deficit$	-0.0069		-0.0088	-0.0071
	(0.0059)		(0.0059)	(0.0054)
$IBLI$		-0.0077	-0.0381	-0.0254
		(0.0045)	(0.0146)	(0.0144)
$Rain\ deficit \times IBLI$			0.0135	0.0086
			(0.0049)	(0.0048)
NEIGHBORHOOD				
$Rain\ deficit\ (\delta_1)$	0.0708		0.0611	0.0579
	(0.0335)		(0.0297)	(0.0268)
$IBLI\ (\delta_2)$		-0.0167	-0.0252	-0.0136
		(0.0043)	(0.0052)	(0.0069)
$Rain\ deficit \times IBLI\ (\delta_3)$			-0.0156	-0.0096
			(0.0052)	(0.0057)
Dep. var. mean	0.0246	0.0246	0.0246	0.0246
Conflict mitigation	–	–	-25.48 %	-16.66%
Cell-level controls	✓	✓	✓	✓
Cell fixed effects	✓	✓	✓	✓
Time fixed effects	✓	✓	✓	✓
Macro-cell time trends	–	–	–	✓
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)×-1), the standardized Index-Based Livestock Insurance (IBLI) coverage, and their respective interaction at both 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. Macro-cell time trends are linear trends on 1-degree by 1-degree grid cells, in which our 0.1-degree by 0.1-degree cells are nested. If fewer than 55 cells are within a macro cell (5% of the sample at the national borders) we group them into a common border-specific macro cell. Conley standard errors are implemented using the acreg package in Stata (Colella et al. 2019), with a distance cutoff of 200km.

TABLE B-3

Baseline: Further controls (Neighborhood level)

	Dependent variable: $Conflict_{i,t}$									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
NEIGHBORHOOD										
Rain deficit (δ_1)	0.0548	0.0591	0.0632	0.0552	0.0524	0.0601	0.0650	0.0560	0.0482	0.0520
	(0.0317)	(0.0292)	(0.0303)	(0.0294)	(0.0293)	(0.0297)	(0.0297)	(0.0302)	(0.0293)	(0.0284)
	(0.0317)	(0.0292)	(0.0303)	(0.0294)	(0.0293)	(0.0297)	(0.0297)	(0.0302)	(0.0293)	(0.0285)
IBLI (δ_2)	-0.0251	-0.0256	-0.0253	-0.0254	-0.0254	-0.0251	-0.0256	-0.0252	-0.0223	-0.0236
	(0.0053)	(0.0053)	(0.0052)	(0.0053)	(0.0053)	(0.0052)	(0.0053)	(0.0052)	(0.0052)	(0.0053)
Rain deficit × *IBLI* (δ_3)	-0.0156	-0.0188	-0.0156	-0.0180	-0.0180	-0.0172	-0.0176	-0.0172	-0.0096	-0.0127
	(0.0052)	(0.0057)	(0.0052)	(0.0058)	(0.0057)	(0.0054)	(0.0056)	(0.0056)	(0.0049)	(0.0056)
Cellphone cover									-0.0049	-0.0077
									(0.0056)	(0.0060)
Rain deficit neighborhood × **NEIGHBORHOOD CHARACTERISTICS**										
Avg. conflict (00–09)	-0.0030									-0.0149
	(0.0066)									(0.0187)
Avg. Rain deficit (00–09)		0.0074								0.0438
		(0.0035)								(0.0266)
Log pop			0.0008							0.0032
			(0.0049)							(0.0251)
Rangeland share				0.0058						-0.0054
				(0.0038)						(0.0159)
Arid climate					0.0063					-0.0273
					(0.0043)					(0.0245)
Desert & shrubland						0.0050				0.0061
						(0.0028)				(0.0042)
Dist. border							0.0053			-0.0106
							(0.0033)			(0.0090)
Dist. capital								0.0045		-0.0059
								(0.0037)		(0.0103)
Cellphone cover									-0.0147	-0.0172
									(0.0067)	(0.0073)
Cell fixed effects	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Time fixed effects	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Obs	93400	93400	93400	93400	93400	93400	93400	93400	93400	93400

Notes: The table reports the results of regressing the probability of conflict at the cell level 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-4
Baseline: Soil quality controls (cell level)

	Dependent variable: Conflict$_{i,t}$						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Neighborhood							
$Rain\ deficit\ (\delta_1)$	0.0602	0.0610	0.0616	0.0626	0.0603	0.0612	0.0652
	(0.0298)	(0.0297)	(0.0297)	(0.0298)	(0.0298)	(0.0296)	(0.0298)
$IBLI\ (\delta_2)$	-0.0252	-0.0252	-0.0252	-0.0252	-0.0252	-0.0252	-0.0252
	(0.0052)	(0.0052)	(0.0052)	(0.0052)	(0.0052)	(0.0052)	(0.0052)
$Rain\ deficit \times IBLI\ (\delta_3)$	-0.0156	-0.0156	-0.0156	-0.0155	-0.0156	-0.0156	-0.0156
	(0.0052)	(0.0052)	(0.0052)	(0.0052)	(0.0052)	(0.0052)	(0.0052)
$Rain\ deficit\ neighborhood \times$ **poor soil cell characteristics**							
Nutrient availability	0.0041						
	(0.0052)						
Nutrient retention capacity		0.0065					
		(0.0125)					
Rooting condition			-0.0064				
			(0.0082)				
Oxygen availability				-0.0067			
				(0.0066)			
Excess salts					0.0018		
					(0.0039)		
Toxicity						0.0267	
						(0.1047)	
Workability							-0.0122
							(0.0073)
Cell fixed effects	✓	✓	✓	✓	✓	✓	✓
Time fixed effects	✓	✓	✓	✓	✓	✓	✓
Obs	93400	93400	93400	93400	93400	93400	93400

Notes: The table reports the results of regressing the probability of conflict at the cell level 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, Velthuizen, and Verelst 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-5

Baseline: Soil quality controls (neighborhood level)

	Dependent variable: Conflict$_{i,t}$						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
NEIGHBORHOOD							
$Rain\ deficit\ (\delta_1)$	0.0576	0.0618	0.0614	0.0609	0.0530	0.0620	0.0598
	(0.0294)	(0.0298)	(0.0296)	(0.0296)	(0.0296)	(0.0287)	(0.0295)
$IBLI\ (\delta_2)$	-0.0254	-0.0253	-0.0252	-0.0252	-0.0252	-0.0252	-0.0253
	(0.0053)	(0.0053)	(0.0052)	(0.0052)	(0.0053)	(0.0052)	(0.0052)
$Rain\ deficit \times IBLI\ (\delta_3)$	-0.0161	-0.0157	-0.0157	-0.0156	-0.0169	-0.0156	-0.0163
	(0.0052)	(0.0052)	(0.0052)	(0.0053)	(0.0053)	(0.0052)	(0.0054)
NEIGHBORHOOD $Rain\ deficit \times$ **POOR SOIL NEIGHBORHOOD CHARACTERISTICS**							
Nutrient availability	0.0030						
	(0.0024)						
Nutrient retention capacity		0.0013					
		(0.0030)					
Rooting condition			0.0008				
			(0.0030)				
Oxygen availability				0.0002			
				(0.0025)			
Excess salts					0.0049		
					(0.0030)		
Toxicity						0.0005	
						(0.0047)	
Workability							0.0025
							(0.0038)
Cell fixed effects	✓	✓	✓	✓	✓	✓	✓
Time fixed effects	✓	✓	✓	✓	✓	✓	✓
Obs	93400	93400	93400	93400	93400	93400	93400

Notes: The table reports the results of regressing the probability of conflict at the cell level 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, Velthuizen, and Verelst 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-6
Relief results (full)

	Dependent variable: $\text{Conflict}_{i,t}$				
		Controlling for relief variable:			
		HSNP		Aid	
	(1)	(2)	(3)	(4)	(5)
Cell					
Rain deficit	-0.0088	-0.0085	-0.0064	-0.0110	-0.0125
	(0.0059)	(0.0061)	(0.0061)	(0.0060)	(0.0060)
IBLI	-0.0381	-0.0390	-0.0451	-0.0490	-0.0519
	(0.0146)	(0.0144)	(0.0164)	(0.0152)	(0.0152)
Rain deficit × *IBLI*	0.0135	0.0135	0.0161	0.0169	0.0177
	(0.0049)	(0.0049)	(0.0056)	(0.0051)	(0.0051)
Cell relief controls					
Relief		0.0014	0.0182	-0.0067	0.0290
		(0.0042)	(0.0133)	(0.0108)	(0.0335)
Rain deficit × *Relief*			-0.0071		-0.0158
			(0.0046)		(0.0141)
Neighborhood					
Rain deficit (δ_1)	0.0611	0.0600	0.0508	0.0710	0.0844
	(0.0297)	(0.0302)	(0.0318)	(0.0303)	(0.0304)
IBLI (δ_2)	-0.0252	-0.0237	-0.0252	-0.0264	-0.0260
	(0.0052)	(0.0068)	(0.0069)	(0.0053)	(0.0052)
Rain deficit × *IBLI* (δ_3)	-0.0156	-0.0154	-0.0232	-0.0179	-0.0164
	(0.0052)	(0.0054)	(0.0072)	(0.0053)	(0.0053)
Neighborhood relief controls					
Relief		-0.0021	0.0011	0.0076	0.0153
		(0.0043)	(0.0046)	(0.0039)	(0.0057)
Rain deficit × *Relief*			0.0113		0.0112
			(0.0062)		(0.0065)
Dep. var. mean	0.0245	0.0245	0.0245	0.0245	0.0245
Conflict mitigation	-25.48%	-25.74%	-45.68%	-25.16%	-19.39%
Cell-level 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. 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.

Table B-7
Accounting for development aid

	Dependent variable: Conflict$_{i,t}$			
	Controlling for:			
	World Bank aid		*Bilateral and multilateral aid*	
	Number aid projects	*Log aid commitments*	*Number aid projects (agriculture)*	*Log aid commitments*
	(1)	(2)	(3)	(4)
Neighborhood				
$Rain\ deficit\ (\delta_1)$	0.0712	0.0626	0.0518	0.0308
	(0.0298)	(0.0298)	(0.0293)	(0.0305)
$IBLI\ (\delta_2)$	-0.0245	-0.0255	-0.0239	-0.0187
	(0.0052)	(0.0053)	(0.0051)	(0.0051)
$Rain\ deficit \times IBLI\ (\delta_3)$	-0.0171	-0.0160	-0.0153	-0.0112
	(0.0052)	(0.0053)	(0.0051)	(0.0051)
Neighborhood Controls				
Aid	0.0014	0.0076	0.1293	0.0340
	(0.0166)	(0.0128)	(0.0361)	(0.0063)
$Rain\ deficit \times Aid$	0.0101	-0.0009	0.1026	-0.0054
	(0.0077)	(0.0028)	(0.0402)	(0.0032)
Cell Controls				
$Rain\ deficit$	-0.0165	-0.0092	-0.0099	-0.0050
	(0.0076)	(0.0061)	(0.0059)	(0.0059)
$IBLI$	-0.0503	-0.0409	-0.0460	-0.0293
	(0.0152)	(0.0152)	(0.0149)	(0.0145)
$Rain\ deficit \times IBLI$	0.0171	0.0143	0.0156	0.0094
	(0.0051)	(0.0051)	(0.0050)	(0.0048)
Aid	0.0200	0.0513	0.0543	0.0760
	(0.0144)	(0.0395)	(0.0486)	(0.0523)
$Rain\ deficit \times Aid$	-0.0080	-0.0208	-0.0294	-0.0402
	(0.0062)	(0.0177)	(0.0191)	(0.0207)
Dep. var. mean	0.0245	0.0245	0.0245	0.0245
Conflict mitigation	-24.03%	-25.53%	-29.49%	-36.25%
Cell-level 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)×-1), Index-Based Livestock Insurance (IBLI) coverage, and the interaction of the two at the cell and neighborhood level. In addition, we control for the number of aid projects (columns 1 and 2) and the log value of aid commitments in US$ (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 for the World Bank is obtained from AidData (2017). The bilateral and multilateral aid data is obtained from GODAD (Bomprezzi et al. 2024). Conley standard errors are implemented using the acreg package in Stata (Colella et al. 2019), with a distance cutoff of 200km.

TABLE B-8

Alternative drought proxies

	Dependent variable: Conflict$_{i,t}$	
	(1)	(2)
NEIGHBORHOOD		
$DMP\ deficit\ (\delta_1)$	0.0182	
	(0.0307)	
$DMP\ deficit \times IBLI\ (\delta_3)$	-0.0119	
	(0.0042)	
$AI\ deficit\ (\delta_1)$		0.0932
		(0.0314)
$AI\ deficit \times$ IBLI (δ_3)		-0.0126
		(0.0041)
$IBLI\ (\delta_2)$	-0.0895	-0.0187
	(0.0263)	(0.0045)
CELL		
$DMP\ deficit$	0.0030	
	(0.0038)	
$DMP\ deficit \times IBLI$	-0.0009	
	(0.0028)	
$AI\ deficit\ (\delta_1)$	-0.0211	
		(0.0081)
$AI\ deficit \times$ IBLI (δ_3)		0.0166
		(0.0050)
$IBLI$	-0.0028	-0.0585
	(0.0081)	(0.0174)
Dep. var. mean	0.0245	0.0245
Cell fixed effects	✓	✓
Time fixed effects	✓	✓
Obs	93000	93400

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-9
2SLS results using insurance payouts for selected years

	OLS	2SLS 1st stage	2SLS 2nd stage
	Dependent variable:		
	$\text{Conflict}_{i,t}$	IBLI payout	$\text{Conflict}_{i,t}$
	(1)	(2)	(3)
CELL			
$Rain\ deficit$	-0.0067	-0.0916	-0.0119
	(0.0058)	(0.0637)	(0.0065)
$IBLI$	-0.0249	-1.0891	-0.0742
	(0.0140)	(0.3015)	(0.0245)
$Rain\ deficit \times IBLI$	0.0056	0.1988	0.0201
	(0.0043)	(0.1071)	(0.0071)
NEIGHBORHOOD			
$Rain\ deficit\ (\delta_1)$	0.0617	0.7837	0.0871
	(0.0298)	(0.2824)	(0.0318)
$IBLI\ (\delta_2)$	-0.0146	0.9007	0.0046
	(0.0045)	(0.0819)	(0.0085)
$Rain\ deficit \times IBLI\ (\delta_3)$		0.4706	
		(0.0597)	
$IBLI\ payouts\ (\delta_4)$	-0.0036		-0.0331
	(0.0040)		(0.0108)
F-stat 1st stage		61.56	
Cell fixed effects	✓	✓	✓
Time fixed effects	✓	✓	✓
Obs	93400	93400	93400

Notes: The table report results from regressing the probability of conflict at the cell level on IBLI payouts in the neighborhood of a cell and our standard set of cell and neighborhood variables in OLS (column 1) and 2SLS (column 3). Column 2 reports the first stage of column 3. IBLI payouts are (z standardized, with mean zero and standard deviation of one), see Online Appendix A for details. We drop the interaction between the neighborhood weighted rainfall deficit and IBLI coverage because it is our instrument for the IBLI payouts in the neighborhood. The 1st age F-stat reported in columns 2 and 3 is the Kleinberg-Papp F-stat. Conley standard errors are implemented using the acreg package in Stata (Colella et al. 2019), with a distance cutoff of 200km.

TABLE B-10

Differential pastoral neighborhood evidence for Kenya post IBLI: Replication McGuirk and Nunn 2025

	Dependent variable:			
	ACLED I(Any)	UCDP I(Any)	UCDP (Wet season) Incidence Year Equiv.	UCDP (Dry season) Incidence Year Equiv.
	(1)	(2)	(3)	(4)
TP neighbor $\times post_{2009}$	-0.0366	-0.0126	0.0443	0.0284
	(0.0102)	(0.0079)	(0.0378)	(0.0469)
TP neighbor $\times post_{2009} \times$ Kenya	-0.1130	-0.0381	-0.1520	-0.0550
	(0.0389)	(0.0310)	(0.0813)	(0.0766)
Cell fixed effects	✓	✓	✓	✓
Country-by-year fixed effects	✓	✓	✓	✓
Obs	203511	184129	127414	107730

Notes: This table reports the results from adding a Kenya indicator for cells located within Kenya and a post-2009 indicator (to proxy for the IBLI rollout period) to the regression specification of Table 6 in McGuirk and Nunn (2025). Note that we drop the rain treatment for simplicity. Our goal is to test if the effect of neighboring pastoral (transhumant) homelands (TP Neighbors) on conflict in 0.5 × 0.5 degree grid cell is declining in Kenya relative to other countries following the introduction and consecutive rollout of IBLI.Specifically, we estimate: $Conflict_{i,t} = \beta(THP\ neighbor_i \times post_{2009}) + \delta(TP\ neighbor_i \times post_{2009} \times Kenya_i) + \alpha_i + \gamma_{c,t} + i, c, t$ The conflict proxy indicates at least one conflict event reported by ACLED during a year within a cell (column 1), a similar indicator using the UCDP dataset (column 2). Columns 3 and 4 use count variables for UCDP incidents in the wet season (column 3) or dry season (column 4). All columns include cell and country-by-year fixed effects. The data is taken from the replication package of McGuirk and Nunn (2025). Standard errors are clustered two-way at the PRIO-grid-cell and country-year level.

Interpretation: We take the negative and statistically significant coefficient of $TP\ neighbor \times post_{2009} \times Kenya$ as suggestive evidence that pastoralist neighboring homelands are less linked to conflict in cells in Kenya post-IBLI rollout compared to cells in other countries in the post-IBLI rollout period in Kenya.

TABLE B-11

East Africa

	Dependent variable: Conflict$_{i,t}$								
	ACLED			Livestock (ACLED)			UCDP		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: *Dependent variable:* Conflict$_{i,t}$ *(ACLED)*									
NEIGHBORHOOD									
Rain deficit	0.1590	0.1570	0.2118	0.0596	0.0589	0.0794	0.0613	0.0632	0.0864
	(0.0193)	(0.0189)	(0.0221)	(0.0086)	(0.0084)	(0.0101)	(0.0081)	(0.0080)	(0.0097)
IBLI (δ_2)	-0.0027	-0.0121	-0.0120	-0.0025	-0.0043	-0.0042	0.0010	-0.0040	-0.0027
	(0.0034)	(0.0030)	(0.0036)	(0.0010)	(0.0010)	(0.0013)	(0.0016)	(0.0015)	(0.0018)
Rain deficit $\times$ *IBLI* (δ_3)	-0.0001	-0.0078	-0.0053	-0.0013	-0.0030	-0.0029	0.0007	-0.0037	-0.0029
	(0.0025)	(0.0023)	(0.0029)	(0.0007)	(0.0008)	(0.0011)	(0.0011)	(0.0012)	(0.0014)
CELL									
Rain deficit	-0.0573	-0.0606	-0.0552	-0.0214	-0.0218	-0.0199	-0.0217	-0.0230	-0.0207
	(0.0061)	(0.0063)	(0.0052)	(0.0031)	(0.0031)	(0.0025)	(0.0028)	(0.0028)	(0.0023)
IBLI	-0.0094	-0.0622	-0.0613	-0.0081	-0.0215	-0.0236	0.0020	-0.0277	-0.0341
	(0.0235)	(0.0155)	(0.0145)	(0.0067)	(0.0059)	(0.0058)	(0.0111)	(0.0080)	(0.0085)
Rain deficit $\times$ *IBLI*	0.0024	0.0248	0.0274	0.0041	0.0090	0.0096	-0.0015	0.0095	0.0103
	(0.0088)	(0.0054)	(0.0051)	(0.0024)	(0.0021)	(0.0021)	(0.0041)	(0.0028)	(0.0028)
Dep. var. mean	0.0184	0.0184	0.0184	0.0025	0.0025	0.0025	0.0041	0.0041	0.0041
Cell FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Time FE	✓	✓	–	✓	✓	–	✓	✓	–
Macro-cell time trends	–	✓	✓	–	✓	✓	–	✓	✓
Country-period-FE	–	–	✓	–	–	✓	–	–	✓
Obs	662648	662648	662648	662648	662648	662648	662648	662648	662648

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. Columns 1 to 3 construct the conflict indicator based on all conflicts included in ACLED. Columns 4 to 6 construct the conflict indicator based on all incidents that are associated with livestock violence based on our dictionary approach. Columns 7 to 9 construct the conflict indicator based on the UCDP (GED) events with a precision code of 2 or below (geographic precision is a location). The neighborhood variables are based on the 1/distance weighting scheme and leverage a cutoff of 700km, i.e., after 700km distance, cells j do not contribute to the neighborhood measure of cell i. Macro-cell time trends are linear trends on 1-degree by 1-degree grid cells, in which our 0.1-degree by 0.1-degree cells are nested. If fewer then 55 cells are within a macro cell (5% of the sample at the national borders) we group them into a common border specific macro cell. Standard errors are clustered two-way at the PRIO-grid-cell and country-year level.

Table B-12

East Africa: IBLI neighborhood dummy

	Dependent variable: $\text{Conflict}_{i,t}$								
	ACLED			Livestock (ACLED)			UCDP		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: *Dependent variable:* $\text{Conflict}_{i,t}$ *(ACLED)*									
Neighborhood									
$Rain\ deficit$	0.1592	0.1582	0.2128	0.0598	0.0593	0.0799	0.0613	0.0637	0.0869
	(0.0194)	(0.0190)	(0.0222)	(0.0087)	(0.0084)	(0.0102)	(0.0081)	(0.0081)	(0.0097)
$IBLI$ (δ_2)	-0.0218	-0.0440	-0.0327	-0.0114	-0.0172	-0.0142	-0.0030	-0.0171	-0.0104
	(0.0132)	(0.0127)	(0.0119)	(0.0043)	(0.0040)	(0.0045)	(0.0051)	(0.0048)	(0.0052)
$Rain\ deficit \times IBLI$ (δ_3)	-0.0081	-0.0349	-0.0222	-0.0073	-0.0136	-0.0109	-0.0012	-0.0147	-0.0091
	(0.0117)	(0.0109)	(0.0105)	(0.0031)	(0.0035)	(0.0037)	(0.0041)	(0.0047)	(0.0050)
	(0.0117)	(0.0109)	(0.0105)	(0.0031)	(0.0035)	(0.0037)	(0.0041)	(0.0047)	(0.0050)
Cell									
$Rain\ deficit$	-0.0573	-0.0607	-0.0551	-0.0214	-0.0219	-0.0199	-0.0217	-0.0231	-0.0207
	(0.0061)	(0.0063)	(0.0053)	(0.0031)	(0.0031)	(0.0025)	(0.0028)	(0.0028)	(0.0023)
$IBLI$	-0.0181	-0.0585	-0.0664	-0.0097	-0.0189	-0.0209	-0.0008	-0.0196	-0.0275
	(0.0248)	(0.0173)	(0.0136)	(0.0065)	(0.0052)	(0.0048)	(0.0111)	(0.0079)	(0.0078)
$Rain\ deficit \times IBLI$	0.0052	0.0203	0.0236	0.0038	0.0075	0.0079	0.0006	0.0070	0.0086
	(0.0088)	(0.0062)	(0.0051)	(0.0024)	(0.0019)	(0.0017)	(0.0037)	(0.0025)	(0.0024)
Dep. var. mean	0.0184	0.0184	0.0184	0.0025	0.0025	0.0025	0.0041	0.0041	0.0041
Conflict mitigation	-5.11%	-22.07%	-10.43%	-12.18%	-22.97%	-13.63%	-1.90%	-23.08%	-10.47%
Cell FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Time FE	✓	✓	–	✓	✓	–	✓	✓	–
Macro-cell time trends	–	✓	✓	–	✓	✓	–	✓	✓
Country-period-FE	–	–	✓	–	–	✓	–	–	✓
Obs	662648	662648	662648	662648	662648	662648	662648	662648	662648

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. Columns 1 to 3 construct the conflict indicator based on all conflicts included in ACLED. Columns 4 to 6 construct the conflict indicator based on all incidents that are associated with livestock violence based on our dictionary approach. Columns 7 to 9 construct the conflict indicator based on the UCDP (GED) events with a precision code of 2 or below (geographic precision is a location). The neighborhood variables are based on the 1/distance weighting scheme and leverage a cutoff of 700km, i.e., after 700km distance, cells j do not contribute to the neighborhood measure of cell i. The IBLI neighborhood variable is not z-standardized but turned into an indicator that takes unity if a cell's neighborhood coverage corresponds to an above-standard deviation coverage in Kenya. Macro-cell time trends are linear trends on 1-degree by 1-degree grid cells, in which our 0.1-degree by 0.1-degree cells are nested. If fewer then 55 cells are within a macro cell (5% of the sample at the national borders) we group them into a common border specific macro cell. Standard errors are clustered two-way at the PRIO-grid-cell and country-year level.

Table B-13
Triple-interaction results: Competing land use

Contested land use proxies:	*Dependent variable:* Conflict$_{i,t}$		
	Main: Murdock ethnographic atlas		*Alternative:* Historical land use map
	(1)	(2)	(3)
Cell			
$Rain\ deficit$	-0.0072	-0.0047	-0.0068
	(0.0066)	(0.0066)	(0.0061)
$Rain\ deficit \times contested\ land\ use$	-0.0014	-0.0019	0.0185
	(0.0071)	(0.0065)	(0.0287)
$IBLI$	-0.0147	0.0000	0.0000
	(0.0166)	(0.0000)	(0.0000)
$IBLI \times contested\ land\ use$	-0.0485	-0.0484	0.0000
	(0.0245)	(0.0246)	(0.0000)
$Rain\ deficit \times IBLI$	0.0064	-0.0103	-0.0018
	(0.0053)	(0.0066)	(0.0067)
$Rain\ deficit \times IBLI \times contested\ land\ use$	0.0155	0.0171	0.0000
	(0.0076)	(0.0078)	(0.0000)
Neighborhood			
$Rain\ deficit\ (\delta_1)$	0.0587	0.0867	0.0899
	(0.0299)	(0.0338)	(0.0339)
$Rain\ deficit \times contested\ land\ use\ (\psi_1)$	0.0039	0.0057	-0.0194
	(0.0105)	(0.0095)	(0.0360)
$IBLI\ (\delta_2)$	-0.0251	-0.0146	-0.0145
	(0.0053)	(0.0068)	(0.0067)
$IBLI \times contested\ land\ use\ (\psi_2)$	-0.0030	-0.0048	-0.0223
	(0.0031)	(0.0033)	(0.0086)
$Rain\ deficit \times IBLI\ (\delta_3)$	-0.0122	-0.0059	-0.0097
	(0.0051)	(0.0057)	(0.0059)
Neighborhood mitigation heterogeneity			
$Rain\ deficit \times IBLI \times contested\ land\ use\ (\psi_3)$	-0.0095	-0.0114	-0.0274
	(0.0043)	(0.0044)	(0.0141)
Dep. var. (non-contested)	0.0186	0.0186	0.0226
Dep. var. (contested)	0.0312	0.0312	0.0543
Conflict mitigation (non-contested)	-20.87%	-6.84%	-10.83%
Conflict mitigation (contested)	-34.72%	-18.75%	-52.73%
Cell-level controls	✓	✓	✓
Cell fixed effects	✓	✓	✓
Time fixed effects	✓	–	–
Rollout-cluster-time-fixed effects	–	✓	✓
Obs	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 a cell located within a contested land use area. Our main proxy is based on an indicator for all cells closer to their homeland border than the median cell in their homeland, based on Murdock's ethnographic atlas (Murdock 1967). The alternative proxy indicates areas where agriculture, ranging, and pastoral land use are practiced, based on a historical land use map from the Kenyan government (1984). 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). Conflict mitigation in the contested land use is defined as $((\delta_3 + \psi_3)/(\delta_1 + \delta_3))$. 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.

TABLE B-14

Triple-interaction results: Competing land use (current land use)

	Dependent variable: $\text{Conflict}_{i,t}$			
	Contested land use proxies:			
	Agricultural-pastoral suitability		Grassland to cropland transition	
	(1)	(2)	(3)	(4)
CELL				
$Rain\ deficit$	-0.0105	-0.0111	-0.0079	-0.0056
	(0.0061)	(0.0062)	(0.0059)	(0.0061)
$Rain\ deficit \times contested\ land\ use$	0.0237	0.0289	-0.0124	-0.0146
	(0.0139)	(0.0136)	(0.0091)	(0.0091)
$IBLI$	-0.0180	0.0000	-0.0336	0.0000
	(0.0150)	(0.0000)	(0.0154)	(0.0000)
$IBLI \times contested\ land\ use$	-0.0638	-0.0654	-0.0332	-0.0378
	(0.0385)	(0.0422)	(0.0371)	(0.0376)
$Rain\ deficit \times IBLI$	0.0090	-0.0002	0.0114	-0.0038
	(0.0049)	(0.0068)	(0.0051)	(0.0068)
$Rain\ deficit \times IBLI \times contested\ land\ use$	0.0106	0.0203	0.0168	0.0180
	(0.0132)	(0.0147)	(0.0118)	(0.0120)
NEIGHBORHOOD				
$Rain\ deficit\ (\delta_1)$	0.0573	0.0844	0.0600	0.0887
	(0.0281)	(0.0322)	(0.0291)	(0.0334)
$Rain\ deficit \times contested\ land\ use\ (\psi_1)$	-0.0302	-0.0365	0.0172	0.0212
	(0.0185)	(0.0175)	(0.0103)	(0.0103)
$IBLI\ (\delta_2)$	-0.0254	-0.0170	-0.0240	-0.0141
	(0.0054)	(0.0065)	(0.0052)	(0.0068)
$IBLI \times contested\ land\ use\ (\psi_2)$	0.0089	0.0020	-0.0138	-0.0131
	(0.0050)	(0.0063)	(0.0035)	(0.0037)
$Rain\ deficit \times IBLI\ (\delta_3)$	-0.0146	-0.0091	-0.0141	-0.0085
	(0.0053)	(0.0054)	(0.0052)	(0.0058)
NEIGHBORHOOD MITIGATION HETEROGENEITY				
$Rain\ deficit \times IBLI \times contested\ land\ use\ (\psi_3)$	-0.0076	-0.0157	-0.0146	-0.0175
	(0.0082)	(0.0094)	(0.0062)	(0.0062)
Dep. var. (non-contested)	0.0181	0.0181	0.0260	0.0260
Dep. var. (contested)	0.0439	0.0439	0.0115	0.0115
Conflict mitigation (non-contested)	-25.50%	-10.74%	-23.53%	-9.58%
Conflict mitigation (contested)	-81.91%	-51.63%	-37.23%	-23.65%
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 a cell located within a contested land use area. Our first proxy is based on an indicator that is unity if a cell's relative suitability for pastoralism relative to the agricultural suitability is in the 1st quartile, i.e., a cell is generally more suitable for agriculture compared to pastoralism. The relative suitability measure is based on Becker (2025) using the data from Beck and Sieber (2010). The second proxy indicates cells that have transitioned from grassland to cropland. Specifically, cells that have a negative change in the grassland share and a positive change in their cropland share between 2000 and 2020 based on land use raster data from Copernicus Climate Change Service (2019). 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). Conflict mitigation in the contested land use is defined as $((\delta_3+\psi_3)/(\delta_1+\delta_3))$. The neighborhood variables are based on the 1/distance weighting. The contested land use proxies are depicted in Figure A-12. Conley standard errors are implemented using the acreg package in Stata (Colella et al. 2019), with a distance cutoff of 200km.

Table B-15

County-level results: Herd sizes

	Dependent variable: Cattle numbers		
	All	*Beef*	*Dairy*
	(1)	(2)	(3)
IBLI coverage	-0.4647	-0.4464	-0.0487
	(0.1493)	(0.1504)	(0.0536)
County fixed effects	✓	✓	✓
Time fixed effects	✓	✓	✓
Observations	423	423	423

Notes: The table reports the results from regressing the z-standardized number of cattle (all cattle, and those kept specifically for beef or dairy) on county-averaged IBLI coverage. All specifications include county and time fixed effects. Standard errors are clustered at the county level.

Table B-16

Market-level results: Stabilizing returns to livestock

	Dependent variable: Log livestock price							
	$\text{Cattle}_{m,i,t}$		$\text{Camels}_{m,i,t}$		$\text{Sheep}_{m,i,t}$		$\text{Goats}_{m,i,t}$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Rain\ deficit$	-0.1396	-0.2697	-0.0487	-0.2203	-0.1273	-0.3110	-0.0649	-0.1237
	(0.0288)	(0.1212)	(0.0561)	(0.2918)	(0.0393)	(0.1269)	(0.0322)	(0.1155)
$IBLI$	0.1903	0.1408	0.0838	-0.0324	0.2176	-0.1197	0.2396	-0.0117
	(0.0320)	(0.1020)	(0.0460)	(0.1009)	(0.0327)	(0.0658)	(0.0316)	(0.0673)
$Rain\ deficit \times IBLI$	0.0437	0.0702	0.0110	0.0696	0.0100	-0.0057	0.0097	0.0106
	(0.0221)	(0.0349)	(0.0319)	(0.0434)	(0.0291)	(0.0219)	(0.0214)	(0.0250)
Market FE	–	✓	–	✓	–	✓	–	✓
Time FE	–	✓	–	✓	–	✓	–	✓
Observations	196	196	39	39	152	152	173	173

Notes: The table reports the results from regressing the log of livestock price on the market level on the rain deficit (log(rainfall)×-1), Index-Based Livestock Insurance (IBLI) coverage, and the respective interaction at the cell and neighborhood level. Columns 1 and 2 report cattle prices, columns 3 and 4 camel prices, columns 5 and 6 sheep prices, and columns 7 and 8 goat prices. 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.

Interpretation: Cattle are by far the most important assets for pastoralists, but we do report all results for transparency. Camels are relevant in particular in the Northern regions. The mitigating effect for camels points in the same direction, but the results are generally noisy as the number of observations is too low. Sheep and goats are more often kept in the village with the rest of the family, and should thus be less affected by IBLI coverage. In line with this, there is also a negative effect of droughts on prices, but less of a mitigating effect of IBLI.

TABLE B-17
Individual-level results: Cushioning economic shocks

	Dependent variable:			
	Hunger$_{i,t}$		No cash income$_{i,t}$	
	All respondents	*Pastoralist group members*	*All respondents*	*Pastoralist group members*
	(1)	(2)	(3)	(4)
$Rain\ deficit$	0.3196	0.3671	0.0440	0.1911
	(0.0036)	(0.0087)	(0.0095)	(0.0120)
$Rain\ deficit \times IBLI$	-0.2270	-0.2890	-0.0034	-0.1958
	(0.0668)	(0.0791)	(0.0465)	(0.0188)
Dep. var. mean	0.5143	0.5362	0.8214	0.8502
Individual level controls	✓	✓	✓	✓
IBLI-unit-county-by-time FE	✓	✓	✓	✓
Ethnic-group FE	✓	✓	✓	✓
Respondents	8141	2904	8141	2904

Notes: The table reports the results from regressing the probability of going hungry (columns 1 to 2) and the probability of having no cash income (columns 3 to 4) on the cell level rain deficit and its interaction with the cell-level insurance cover, averaged across the 12 months preceding the respective Afrobarometer survey round t. The dependent variables are based on the Afrobarometer questions: "Over the past year, how often, if ever, have you or your family gone without:" either "Enough food to eat" or "A cash income". They are coded as 0 if the answer is "never", and 1 if the answer is "once, or twice" or "several times" or "many times" or "always". In columns 1 and 3, we use all survey respondents. In columns 2 and 4, we only include survey respondents in the regression that identify with an ethnic group in which pastoralism is a common practice (the Boran, Gabra, Kalenjin, Kipsigis, Rendile, Maasai, Samburu, Somali, Sabaot, Tugen, and Turkana) or people who work in the agricultural sector (broadly defined). 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-unit-county-by-time and ethnic-group fixed effects. Standard errors are clustered at the IBLI-unit-by-county level.

Table B-18
Conflict-location-homeland results: Migratory distance

	Dependent variable: Log distance$_{k,i,e,t}$			
Sample:	*All*		*Pastoralist*	
	(1)	(2)	(3)	(4)
$Rain\ deficit$	0.2588	0.3228	0.2835	0.3274
	(0.1546)	(0.1863)	(0.0858)	(0.1086)
$IBLI\ coverage$	0.4519	0.4094	0.5200	0.4644
	(0.1962)	(0.1967)	(0.2257)	(0.2303)
$Rain\ deficit \times IBLI\ coverage$	-0.1393	-0.1223	-0.1478	-0.1285
	(0.0642)	(0.0640)	(0.0681)	(0.0697)
Avg. outcome	4.7355	4.7367	5.0006	5.0020
Ethnic-group fixed effects	✓	–	✓	–
Ethnic-group-by-actor-type fixed effects	–	✓	–	✓
Time fixed effects	✓	✓	✓	✓
Obs.	716	714	509	508

Notes: The table reports the results from regressing the geographic distance of conflict locations involving members of a group associated with an ethnic homeland (based on Murdock 1967) on the homeland averaged cell-level rain deficit, insurance coverage and the interaction of the two. Columns 1 and 2 report results for all ethnic groups. Columns 3 and 4 report results for the subset of ethnic groups in which pastoralism is a common practice. All specifications include time fixed effects and Ethnic-group-FE or Ethnic-group-actor-type-FE. See Table A-6 for details on Actor-Type-Ethnic association and List A-1 for the pastoral classification of ethnic groups.

TABLE B-19
Spillovers to neighboring countries

	Dependent variable: $\text{Conflict}_{i,t}$				
Country:	Ethiopia	South Sudan	Somalia	Tanzania	Uganda
	(1)	(2)	(3)	(4)	(5)
NEIGHBORHOOD					
Rain deficit (δ_1)	0.2887***	0.3396***	0.1069***	0.0090	0.3051***
	(0.0438)	(0.0431)	(0.0208)	(0.0082)	(0.0657)
IBLI (δ_2)	-0.0354***	0.0501	-0.0073	-0.0178	-0.1414***
	(0.0116)	(0.1008)	(0.0081)	(0.0306)	(0.0444)
Rain deficit × *IBLI* (δ_3)	-0.0224**	0.0363	-0.0173*	-0.0037	-0.0876**
	(0.0084)	(0.0728)	(0.0091)	(0.0210)	(0.0327)
CELL					
Rain deficit	-0.0768***	-0.0639***	-0.0357***	-0.0036*	-0.0456*
	(0.0100)	(0.0096)	(0.0061)	(0.0018)	(0.0260)
IBLI	-0.0468				
	(0.0548)				
Rain deficit × *IBL*	0.0282				
	(0.0212)				
Avg. outcome	0.0100	0.0202	0.0279	0.0019	0.0375
Conflict mitigation	-7.74%	–	-16.19%	–	-28.73%
Cell level treatment controls	✓	✓	✓	✓	✓
Cell fixed effects	✓	✓	✓	✓	✓
Time fixed effects	✓	✓	✓	✓	✓
Macro-cell time trends	✓	✓	✓	✓	✓
Obs	184968	103025	102980	145661	33522

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 for the neighboring countries of Kenya. The neighborhood variables are based on the 1/distance weighting scheme and leverage a cutoff of 700km, i.e., after 700km distance, cells j do not contribute to the neighborhood measure of cell i. Macro-cell time trends are linear trends on 1-degree by 1-degree grid cells, in which our 0.1-degree by 0.1-degree cells are nested. If fewer then 55 cells are within a macro cell (5% of the sample at the national borders) we group them into a common border specific macro cell. Conley standard errors are implemented using the acreg package in Stata (Colella et al. 2019), with a distance cutoff of 200km.

C. Conflict patterns and actors: Descriptive analysis

This appendix provides further background on the conflict data we employ, details on the most active conflict actors in Kenya, their geographical area of operation, and the likelihood that they respond to droughts. Moreover, we show the locations for our pastoral violence indicators.

C-1. Conflict indicators: Actors

The ACLED dataset (Raleigh, Kishi, and Linke 2023), our primary conflict data source, records conflict events from open sources, mostly media. For each event, ACLED provides information on the type of violence (see Online Appendix A), the locations of the event, and defines two main actors (the main conflict parties), referred to as actor1 and actor2. These actors are always specified and never missing. The dataset also includes information on associated actors, which represent more detailed descriptions of the actors. These are recorded in the columns *assoc_actor_1* and *assoc_actor_2*, but these columns are not always filled. Specifically, *assoc_actor_1* is missing in 62.44% of cases, and *assoc_actor_2* is missing in 73.62% of cases.

Table C-1
Top 15 Actors in Kenya and their Associated Actors

Actor	Frequency	Share with Assoc Actors	Distinct Assoc Actors
Civilians (Kenya)	2145	0.38	158
Police Forces of Kenya	1825	0.02	25
Rioters (Kenya)	1806	0.59	91
Protesters (Kenya)	1488	0.41	93
Unidentified Armed Group (Kenya)	919	0.01	4
Al Shabaab	481	0.00	2
Unidentified Ethnic Militia (Kenya)	207	0.08	6
Military Forces of Kenya	173	0.11	4
Pokot Ethnic Militia (Kenya)	166	0.10	4
Mungiki Militia	161	0.01	2
Maasai Ethnic Militia (Kenya)	103	0.12	6
Turkana Ethnic Militia (Kenya)	101	0.07	4
Unidentified Communal Militia (Kenya)	91	0.19	3
Garre Ethnic Militia (Kenya)	44	0.30	3
Kikuyu Ethnic Militia (Kenya)	44	0.05	3
Marakwet Ethnic Militia (Kenya)	7	0.14	2

Notes: The table reports the 15 most frequent actors operating in Kenya during our study period, based on ACLED (Raleigh, Kishi, and Linke 2023).

Most important actors: Table C-1 provides a summary of the top 15 actors in terms of their frequency of appearance in either *actor1* or *actor2*. Those actors are involved in 93% of all incidents occurring during our study period within Kenya. For each actor, we also show the share of entries where associated actors are identified by ACLED, and the count of distinct associated actors linked to each group. There are 99 distinct actors in the dataset that are involved in conflict events in Kenya. The share of entries with associated actors varies significantly among these groups but is always rather high. Due to the high variation in associated actors, it is not sufficient to know an actor to directly infer the actor involved in an event. Moreover, six of the most frequent actors are "civilians", "rioters", "protesters", "unidentified armed group", "unidentified ethnic militia", and "unidentified communal militia", all of which also frequently appear as an associated actor. This highlights the general challenge to identify events that concern our actors of interest. Hence, we conduct several approaches to classify events likely involving pastoralists (see Section A-2).

The majority of the most frequent actors can easily be assigned to known non-state actors (e.g., Al Shabaab), the government, or different ethnic groups. Table C-1 highlights that the government as an actor is mostly represented in terms of the police forces and, to a much lesser degree, by the military. We observe six ethnic militias among the most frequent actors. All of these belong to ethnic groups in which pastoralism is a common occupation, suggesting the important role of pastoralism for conflict in Kenya.

Distribution of violence: There is a large variation in the spatial distribution of events involving the different actors. Figure C-1 depicts the distribution of conflict incidents during our sample, by either red dots or blue dots (in case an actor belongs to the top 10 actors with the highest frequency of pastoralist as an associated actor, see Table A-3). Protesters and rioters are predominantly involved in areas of Kenya characterized by higher population density. The military, in turn, mainly operates in close proximity to Kenya's borders, while Al Shabaab operates in proximity to Somalia. Civilians and the police are represented everywhere in Kenya. The same is true for unidentified armed groups, unidentified ethnic militias, or unidentified communal militias, which likely reflects the fact that they encompass many different actual actors. For the ethnic groups for which a name is provided ("named ethnic groups"), the pattern is very different.

Named ethnic groups are primarily involved in conflict events either within or close to their ancestral homeland (as classified by Murdock 1967)). Moreover, we can observe that conflict events involving the named ethnic groups characterized by pastoralism (highlighted by the blue conflict incidents in Figure C-

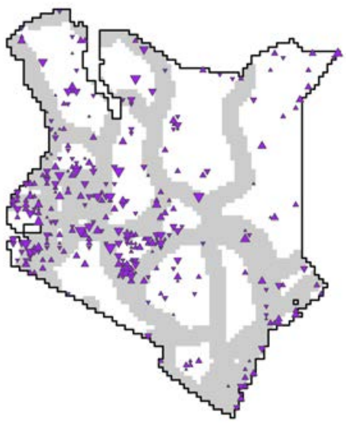
1) are overrepresented in contested land use areas. This is in line with the patterns and hypothesis that we explore in section 5.3.

Impact of drought on violence: If we investigate the conflict patterns of the top 15 actors with respect to rainfall, we can observe that most of the "non-pastoral" actors have a similar spatial pattern during years in which Kenya has above median rainfall (triangles) compared to years that feature below median rainfall (inverted triangles) (see Figure C-1). Moreover, the share of incidents is relatively equal between years with above vs. below median rainfall (50.9% vs. 49.1%). The breakdown in numbers is quite different for the actors with a high share of pastoralists in Figure C-1, where 57.4% of incidents occur during years with below median rainfall and only 42.6% occur in years with above median rainfall. In addition, for the actors that we can actually match to pastoral ethnic homelands, we observe that during years with below median rainfalls, the incidents tend to occur further away from the ancestral homeland and grazing grounds of those groups. Both patterns suggest that incidents of groups that feature pastoralists as associated actors follow the pattern that we expect, and that could be mitigated by IBLI, much more likely compared to the other actors.

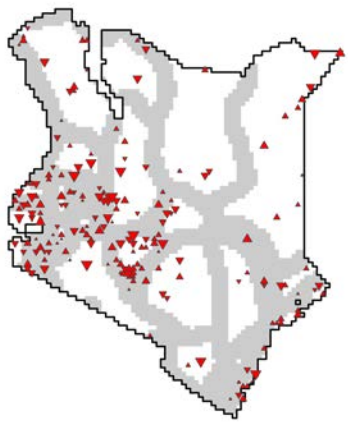
Distribution of pastoralist violence: Panels A to F of Figure C-2 depict the average conflict probabilities over the 2000 to 2020 period across cells for different pastoral violence proxies we employ. Panel A shows that our primary measure, leveraging the most frequent actors that have events involving pastoralists, except civilians and unidentified armed groups (see Table A-4), has broad spatial coverage. Coverage is narrower if we exclusively rely on ACLED events that code pastoralists as an associate actor. It becomes broader once we leverage the ethnicity match of actors (panels B and C). The most striking difference is that the more narrow indicators shift the distribution toward Kenya's semi-arid and arid regions. This is less the case if we classify based on the conflict notes with our dictionary approach for livestock (see panel D). Finally, our assignments employing GPT to classify based on associated actors or notes provide similar distributions (panels E and F) compared to the primary measure, although with fewer events. A common feature across all the different proxies for conflict involving pastoralists is that most events in the IBLI eligible areas (mainly the north and the east) occur during periods with below median rainfall. Finally, the breakdown in events between below vs. above median rainfall periods is similar to the actors with a high frequency of pastoralists as associated actors, with around 54.5% of conflict incidents occurring during periods with below median rainfall.

Figure C-1
Conflict pattern most frequent actors in Kenya

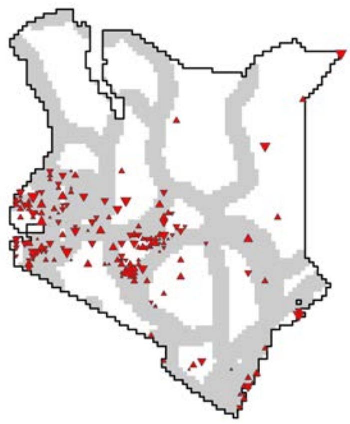
(A) Civilians



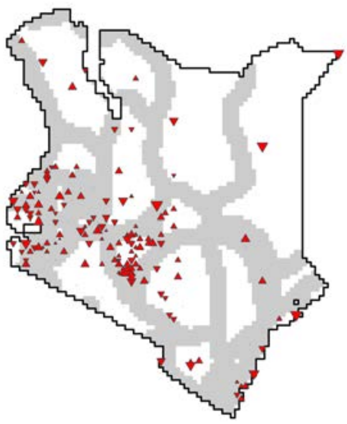
(B) Police forces



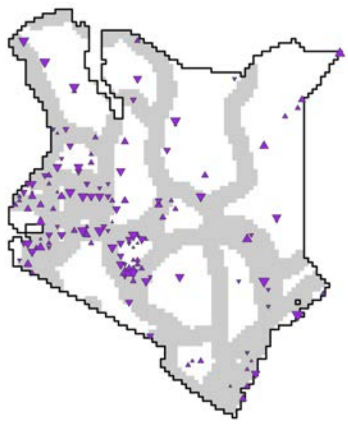
(C) Rioters



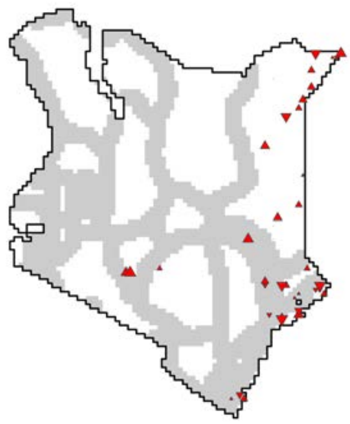
(D) Protesters



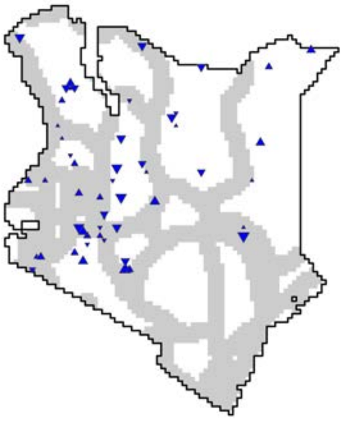
(E) Unidentified armed group



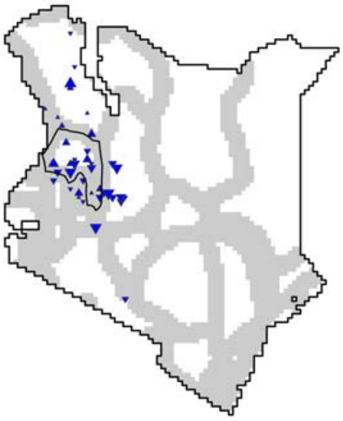
(F) Al Shabaab



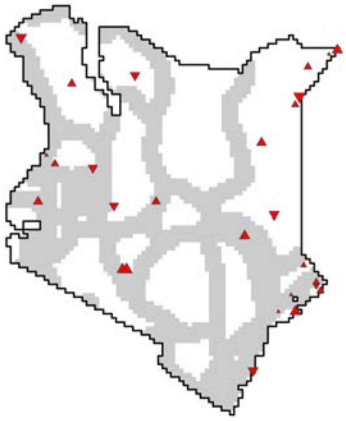
(G) Unidentified ethnic militia



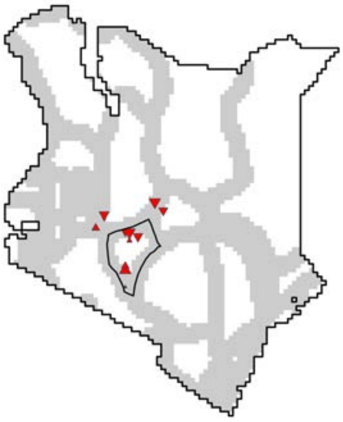
(H) Pokot ethnic militia



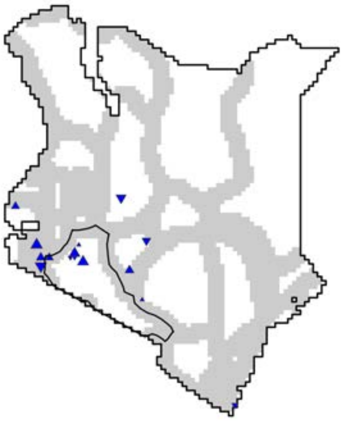
(I) Military forces



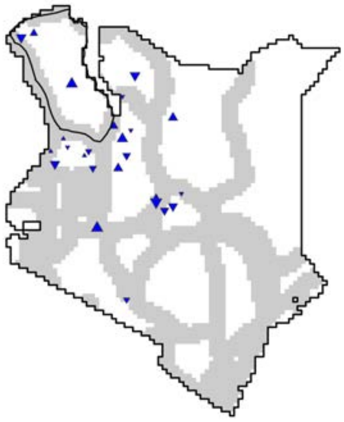
(J) Mungiki militia



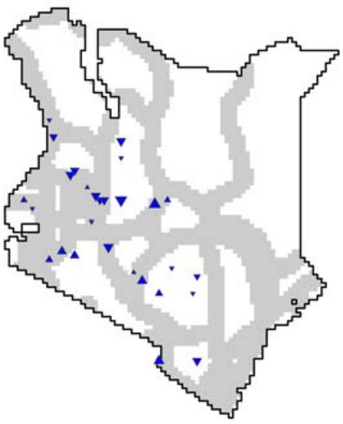
(K) Masaai ethnic militia



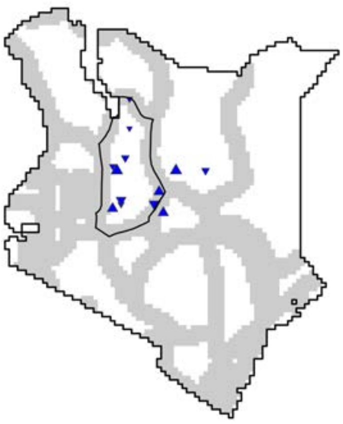
(L) Turkana ethnic militia



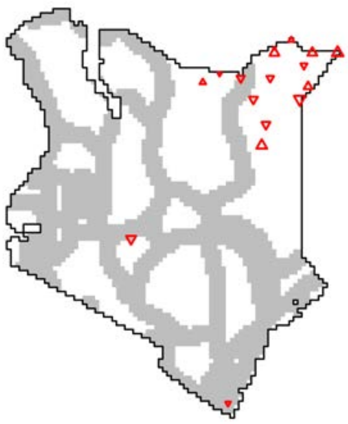
(M) Unidentified communal militia



(N) Samburu ethnic militia

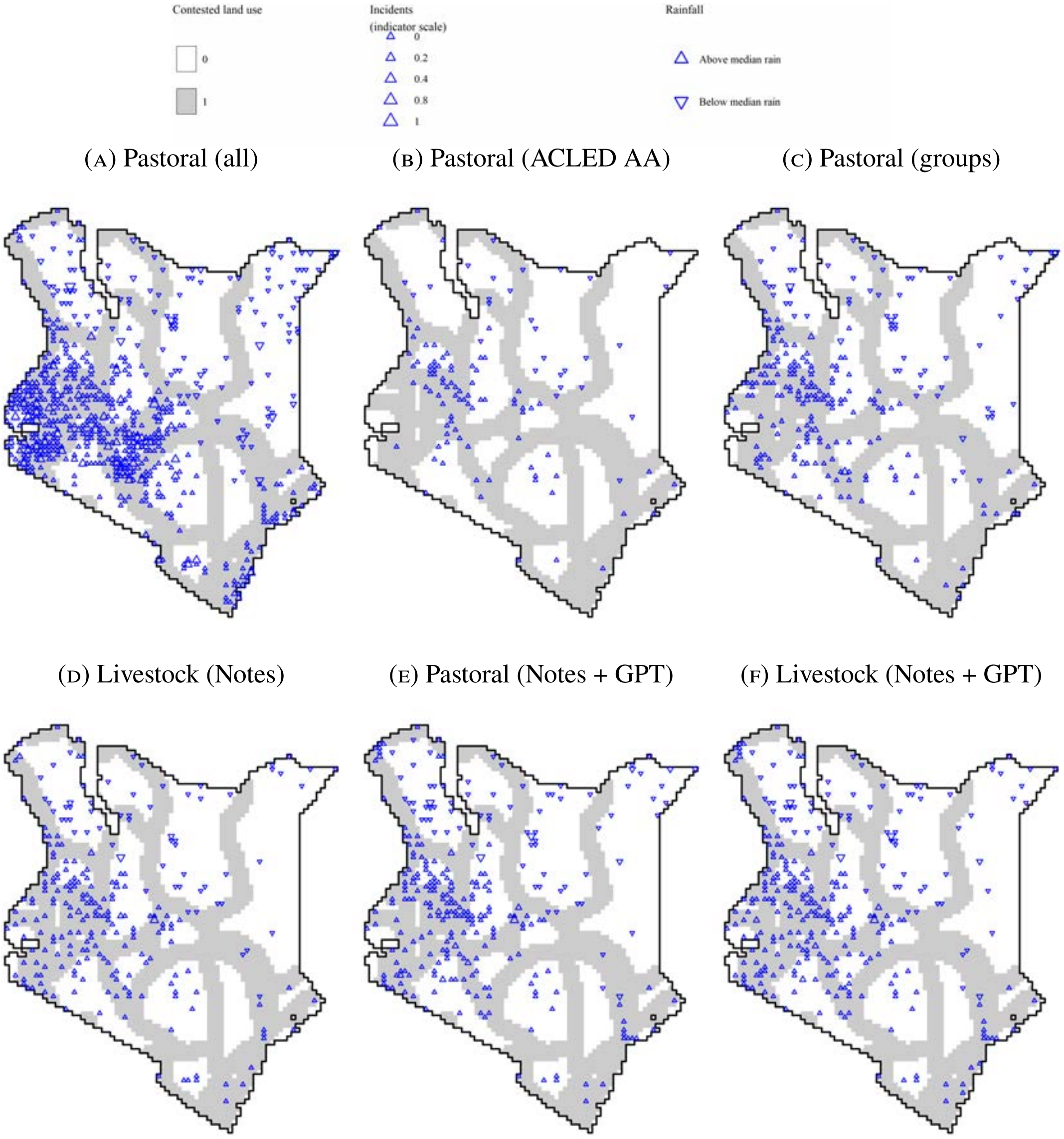


(O) Garre ethnic militia



Notes: Panels A to O plot the conflict distribution of the 15th most frequent actors in Kenya, which are reported in Table C-1, and the Marakwet ethnic militia in panel (P). Triangles indicate incidents occurring during years with above median rainfall; inverted triangles indicate incidents occurring during years with below median rainfall. Incidents of actors that belong to the set of groups with the highest share of pastoralists as associated actors (see Table A-3) are depicted in blue, apart from civilians and unidentified armed groups (depicted in purple). We depict civilians and unidentified armed groups separately because we do not use those actor types to identify conflict events likely involving pastoralists. Contested land use areas are highlighted in grey. Murdock homeland borders are depicted as solid black lines for the actors that we can match to Murdock ethnic groups (Murdock 1967). All variables are processed at a $0.1° \times 0.1°$ grid-cell level.

FIGURE C-2
Conflict patterns of pastoral conflict in Kenya, using alternative proxies



(A) Pastoral (all) (B) Pastoral (ACLED AA) (C) Pastoral (groups)

(D) Livestock (Notes) (E) Pastoral (Notes + GPT) (F) Livestock (Notes + GPT)

Notes: Panels A to F plot in blue dots the average probability of pastoralist conflict events between 2000 and 2020 over our cells for the different pastoral conflict proxies, define in Section A-2. Triangles indicate incidents occurring during years with above median rainfall; inverted triangles indicate incidents occurring during years with below median rainfall. Contested land use areas are highlighted in grey. Murdock homeland borders are depicted as solid black lines for the actors that we can match to Murdock ethnic groups (Murdock 1967). All variables are processed at a $0.1^{\circ} \times 0.1^{\circ}$ grid-cell level.

D. Quantification

D-1. Magnitude of mitigation effect (coverage and take-up)

How big is the overall potential of IBLI to further reduce drought-related conflict in Kenya and beyond? Our analysis focuses on the intention-to-treat effect, with treatment defined as IBLI coverage, ignoring differences in take-up rates. In 2020, the last year of our analysis, 84% of the eligible areas were already covered. Hence, spatial coverage can be increased by the remaining 16%. These 16% do roughly correspond to an additional half a standard deviation increase in IBLI neighborhood coverage. We can use a back-of-the-envelope calculation to quantify the remaining potential of increasing spatial coverage, assuming linearity and the same take-up in newly covered areas. This calculation suggests that increasing IBLI coverage from 84% to full coverage of all eligible cells would reduce the sensitivity to a 100% increase in the rain deficit from roughly a 3.44 percentage points increase in the likelihood of conflict to a minimum of a 2.70 percentage points increase.

Another approach is to increase take-up rates. One limitation of our analysis in this regard is the lack of comprehensive take-up data, but we can use the average take-up rate of 16% documented by Jensen, Barrett, and Mude (2017) as a basis for further considerations. 16% leaves ample room for improvement, and indeed, fostering take-up is one of the key goals of the World Bank's current DRIVE initiative (as of 2024). It might seem at first surprising that we find a conflict-mitigation effect of 25% with take-up rates that are potentially lower than 25%. There could be different explanations for this overall very stable mitigation effect, which also helps us to think about the remaining conflict-reduction potential from increasing take-up. While we can support some arguments with direct evidence, others rest on plausible assumptions about individual behavior and systemic spillovers.

It is plausible and rational for those households most negatively affected by droughts to adopt IBLI first. This can help explain why the conflict-mitigating effect is relatively large, i.e., a stronger percent reduction than the share of households with an IBLI contract. However, it also suggests a potentially decreasing marginal effect of increasing take-up as less vulnerable households would start adopting more broadly. Assuming there would indeed be a decreasing marginal effect, would this necessarily mean increasing take-up would lower efficiency? Not necessarily. Jensen, Barrett, and Mude (2017) points out that social insurance schemes tend to have high initial fixed costs but low marginal costs of adding additional users. Hence, IBLI could remain cost-efficient even with declining marginal benefits for additional users.

Further explanations for the over-proportional conflict-mitigation effect we observe at current take-up rates are provided by the prior evidence on mechanisms. Recall that conflict arises from competing resource demands, which drought exacerbates by forcing pastoralists to migrate to areas occupied by other pastoralists and, more importantly, other land users. IBLI directly reduces this pressure on insured households by stabilizing their incomes and allowing the purchase of feed, both of which help to explain why we see less migration to areas further away that have a higher risk of conflict. Most of these conflicts neither constitute large-scale war nor carefully planned crime but instead, in many cases, result from unplanned encounters of pastoralists with other groups in highly stressful circumstances. Takahashi, Barrett, and Ikegami (2019) provide evidence that IBLI also enhances informal risk sharing mechanisms among pastoral households. Besides the monetary effects and the reduction in travel distance, IBLI payouts can also reduce mental and physical stress and thus ease tensions in such stressful situations or simply provide funds to compensate the marginally affected land user, all of which increase the likelihood of finding peaceful solutions.

Moreover, it is possible that IBLI households create a positive externality by easing the pressure on others, as each insured pastoralist traveling less far reduces congestion on migration routes and on contested grazing grounds. Conflict escalation often follows a nonlinear path, where small tensions can cascade into larger disputes and, in the worst case, due to cascading dynamics, into outright fights. At the same time, even the best traditional conflict-resolution mechanisms necessarily operate within finite boundaries and may reach a tipping point where they struggle to resolve disputes. The more interactions occur, the higher the chance that some will escalate due to unresolved tensions, misunderstandings, or competing interests. Removing some participants from the potential pool of conflict actors can thus make it more likely that the remaining actors will find peaceful solutions with the existing conflict-resolution mechanisms that exist in Kenya. While we have no direct evidence of this plausible channel, we saw that IBLI has a positive externality by easing pressure via its stabilizing effect on livestock prices.

D-2. Quantifying benefits in terms of value of life

IBLI benefits include both the direct benefits to the well-being of pastoralists and the indirect benefits due to mitigating conflict. We can think of the latter 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 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 bounds of the 90% confidence intervals to sum up these probabilities over cells to approximate the number of drought-induced conflict events within a year. 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. Although ACLED fatality estimates should be treated as approximations and not as precise data, this computation suggests that IBLI can help reduce conflict-related deaths to a meaningful extent.

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 values, obtaining a range between 103 and 219 fatalities. Multiplying the obtained fatalities by 0.2548 results in an estimated number of lives saved, ranging from 27 to 57.

Recall that the 25% reduction is estimated based on a counterfactual rainfall shock with a one standard deviation higher coverage of IBLI in the neighborhood, which corresponds to the aggregate IBLI coverage in 2017 compared to 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). Instead of choosing a specific VSL for Kenya in 2017, we compute this ROI of the conflict externality for a whole range of VSL ranging from 0 to 20.000 US$. The return to investment is calculated by dividing the costs (1.2 million) from the estimated "saved" fatalities valued between 0 and 40.000 US$ each, which yields the estimated return per dollar for differing VSL.

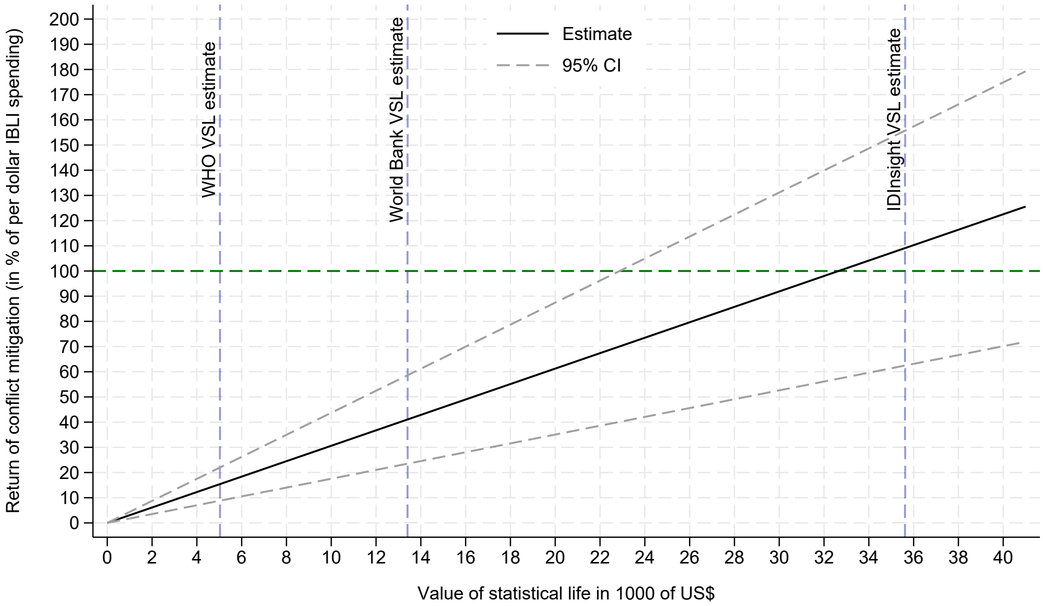
Panel A of Figure D-1 presents the results. The black line plots the return to investment based on saved VSL over our range of VSL. The horizontal green line depicts the size of the conflict externality that would equal the total costs of IBLI for the Government of Kenya. This is reached for a VSL of roughly 22000 US$ 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 0.10 and 0.22 US$ for each dollar spent under the VSL of the WHO and between 0.25 and 0.58 US$ for each dollar spent for the World Bank VSL estimate.[1] Results are essentially the same if we focus only on pastoral conflict and related conflict mitigation thereof (see panel B of Figure D-1).

Another approach to assess effectiveness is to compare the costs of saving a life to those of other interventions. A useful comparison here are cash transfers, which share some features but are not as responsive to needs as an insurance. For example, the charity GiveDirectly assesses the cost of their cash transfer program in Kenya to be around $100,000 per life saved (based on Egger et al. 2022; Wiebe 2022). Our own back-of-the-envelope calculations suggest IBLI public spending for IBLI to be between roughly $21,000 and $45,000 per life saved. While such a simple comparison is at best suggestive, the numbers are in line with Jensen, Barrett, and Mude (2017), who highlight the efficiency of social insurance compared to social protection programs.

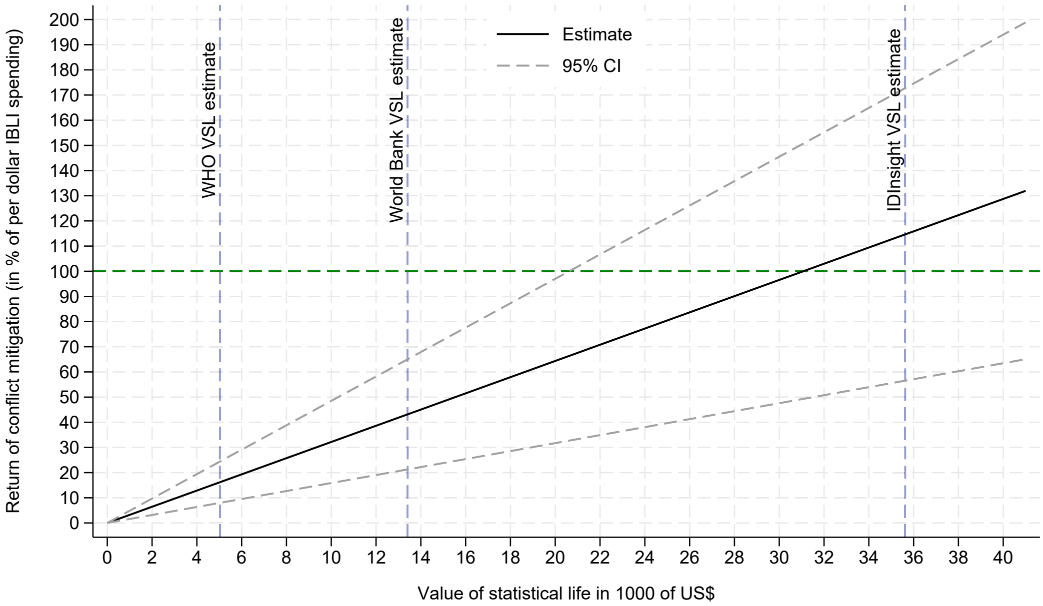
[1]This estimate is also conservative as it ignores any conflict-mitigating effect of IBLI by limiting the migration of Kenyan pastoralists into neighboring countries that could result in conflict. Additional estimates in Table B-19 suggest that there is a significant conflict-mitigating effect of IBLI in three of its neighboring countries, Ethiopia, Somalia, and Uganda, which are also plausibly most affected by pastoralist out-migration and relatively close to areas with extensive IBLI coverage.

Figure D-1
Conflict mitigation return per IBLI dollar spent in 2017 (for VSF)

(a) Based on all incidents



(b) Based on pastoral incidents



Notes: The solid black line depicts the return to 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)). The third blue vertical line depicts a VSL based on a transfer function from a study conducted by Li (2020), which is 35.624$. Panel A is based on all incidents, and panel B is based on pastoral incidents only.

Additional references

Abatzoglou, John T, Solomon Z Dobrowski, Sean A Parks, and Katherine C Hegewisch, "TerraClimate, a high-resolution global dataset of monthly climate and climatic water balance from 1958–2015", *Scientific Data*, 5 (2018), 1–12

Ackermann, Klaus, Sefa Awaworyi Churchill, and Russell Smyth, "Mobile phone coverage and violent conflict", *Journal of Economic Behavior & Organization*, 188 (2021), 269–287

AidData, "WorldBank Geocoded Research Release Level1 v1.4.2 geocoded dataset", 2017

Amazon Web Services, "Amazon Web Services Terrain Tiles", Amazon Web Services Terrain Tiles Dataset. Accessed on August 9, 2024. Available at https://registry.opendata.aws/terrain-tiles/, 2024

Beck, Hylke E, Niklaus E Zimmermann, Tim R McVicar, Noemi Vergopolan, Alexis Berg, and Eric F Wood, "Present and future Köppen-Geiger climate classification maps at 1-km resolution", *Scientific Data*, 5 (2018), 1–12

Beck, Jan, and Andrea Sieber, "Is the spatial distribution of mankind's most basic economic traits determined by climate and soil alone?", *PloS one*, 5 (2010), e10416

Becker, Anke, "On the economic origins of concerns over women's chastity", *Review of Economic Studies*, 92 (2025), 2303–2309

BenYishay, A., R. Rotberg, J. Wells, Z. Lv, S. Goodman, L. Kovacevic, and D Runfola, "Geocoding Afrobarometer Rounds 1–6: Methodology and Data Quality", 2017

Bomprezzi, Pietro, Axel Dreher, Andreas Fuchs, Teresa Hailer, Andreas Kammerlander, Lennart C Kaplan, Silvia Marchesi, Tania Masi, Charlotte Robert, and Kerstin Unfried, "Wedded to Prosperity? Informal Influence and Regional Favoritism", CESifo Working Paper No. 10969, CESifo, 2024

Breitung, Jörg, and Samarjit Das, "Panel unit root tests under cross-sectional dependence", *Statistica Neerlandica*, 59 (2005), 414–433

Carleton, Tamma et al., "Valuing the global mortality consequences of climate change accounting for adaptation costs and benefits", *Quarterly Journal of Economics*, 137 (2022), 2037–2105

Cherlet, Michael, Charles Hutchinson, James Reynolds, Joachim Hill, Stefan Sommer, and Graham von Maltitz, *World Atlas of Desertification*, (Publication Office of the European Union, Luxembourg, 2018)

Colella, Fabrizio, Rafael Lalive, Seyhun Orcan Sakalli, and Mathias Thoenig, "Inference with arbitrary clustering", Discussion Paper No. 12584, IZA Institute of Labor Economics, 2019

Copernicus Climate Change Service, Climate Data Store, "Land cover classification gridded maps from 1992 to present derived from satellite observation", 2019

Davies, Shawn, Garoun Engström, Therese Pettersson, and Magnus Öberg, "Organized violence 1989–2023, and the prevalence of organized crime groups", *Journal of Peace Research*, 61 (2024), 673–693

Eberle, Ulrich J., Dominic Rohner, and Mathias Thoenig, "Heat and Hate: Climate Security and Farmer-Herder Conflicts in Africa", *Review of Economics and Statistics* (2025), 1–47 https://doi.org/10.1162/rest_a_01546

Edejer, Tessa Tan-Torres, Rob Baltussen, T Adam, Arnab Acharya, R Hutubessy, D Evans, and CJL Murray, *Making choices in health: WHO guide to cost-effectiveness analysis*, (World Health Organization, 2003)

Egger, Dennis, Johannes Haushofer, Edward Miguel, Paul Niehaus, and Michael Walker, "General Equilibrium Effects of Cash Transfers: Experimental Evidence from Kenya", *Econometrica*, 90 (2022), 2603–2643

Fava, Francesco, Nathaniel Jensen, James Sina, Andrew Mude, and Barry Maher, *Building financial resilience in pastoral communities in Africa: Lessons learned from implementing the Kenya Livestock Insurance Program (KLIP)*, (World Bank, Washington, D.C., 2021)

Flintan, Fiona E, Roy H Behnke, and Constance Neely, "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* (2013), 1–44

Huffman, George J., Erich F. Stocker, David T. Bolvin, Eric J. Nelkin, and Jackson Tan, "GPM IMERG Final Precipitation L3 1 month 0.1 degree x 0.1 degree V06", 2022

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

Johnson, Leigh, Brenda Wandera, Nathan Jensen, and Rupsha Banerjee, "Competing expectations in an index-based livestock insurance project", *Journal of Development Studies*, 55 (2019), 1221–1239

Kenya Livestock Market Information System, "Livestock Paramaters", Livestock Market Information System Kenya (LMISKE) Dataset. Accessed on November 4, 2024. Available at http://www.lmiske.go.ke/lmis/livestock.htm?action=getLivestockParameters, 2024

Kenya Ministry of Agriculture, and Livestock Development, "Market Prices", Kenya Agricultural Market Information System (KAMIS) Dataset. Accessed on November 4, 2024. Available at https://amis.co.ke/site/market, 2024

Kenya Rangeland Ecological Monitoring Unit, "Land Use Map of Kenya", 1983

(KFSSG), Kenya Food Security Steering Group, "The 2011 long rain season assessment report", 2012

Lengoiboni, Monica, Arnold K Bregt, and Paul van der Molen, "Pastoralism within land administration in Kenya—The missing link", *Land Use Policy*, 27 (2010), 579–588

Li, Sindy, "How we measured the value of a statistical life in Kenya and Ghana", 2020

Macmillan, Susan, "Record payouts being made by Kenya Government and insurers to protect herders facing historic drought", 2017

McGuirk, Eoin F, and Nathan Nunn, "Transhumant Pastoralism, Climate Change, and Conflict in Africa", *Review of Economic Studies*, 92 (2025), 404–441

Milligan, Craig, Andreas Kopp, Said Dahdah, and Jeannette Montufar, "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 (2014), 236–247 https://doi.org/https://doi.org/10.1016/j.aap.2014.05.026

Munyao, Kioko, and Christopher B Barrett, "Decentralization of pastoral resources management and its effects on environmental degradation and poverty: Experience from Northern Kenya.", in *Decentralization of pastoral resources management and its effects on environmental degradation and poverty: Experience from Northern Kenya.*, (CABI Wallingford UK, 2007), 97–110

Murdock, George Peter, "Ethnographic Atlas: A Summary", *Ethnology*, 6 (1967), 109–236 http://www.jstor.org/stable/3772751

Nachtergaele, Freddy, Harrij van Velthuizen, and Luc Verelst, "Harmonized World Soil Database (HWSD)", 2009

OECD/SWAC, "Africapolis (database)", 2020

Raleigh, Clionadh, Roudabeh Kishi, and Andrew Linke, "Political instability patterns are obscured by conflict dataset scope conditions, sources, and coding choices", *Humanities and Social Sciences Communications*, 10 (2023), 1–17

Salehyan, Idean, Cullen S Hendrix, Jesse Hamner, Christina Case, Christopher Linebarger, Emily Stull, and Jennifer Williams, "Social conflict in Africa: A new database", *International Interactions*, 38 (2012), 503–511

Sundberg, Ralph, and Erik Melander, "Introducing the UCDP Georeferenced Event Dataset", *Journal of Peace Research*, 50 (2013), 523–532

Takahashi, Kazushi, Christopher B Barrett, and Munenobu Ikegami, "Does index insurance crowd in or crowd out informal risk sharing? Evidence from rural Ethiopia", *American Journal of Agricultural Economics*, 101 (2019), 672–691

Tobler, Waldo, "Three presentations on geographical analysis and modeling: non-isotropic geographic modeling; speculations on the geometry of geography; and global spatial analysis (93-1)", Technical report 93-1, National Center for Geographic Information Analysis, 1993

Wiebe, Michael, "Reanalysis of Egger et al. (2022)", 2022