Pre-Interview Assessment – Global Water Security Center
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Kenya has been experiencing pronounced climate anomalies, leading to recurrent droughts that adversely affect agricultural productivity, water resources, and rural livelihoods. There is a growing number of political violence and protests in Kenya, including events related to environmental and agricultural issues (see Fig. 1). Given the dominance of rainfed crop production, these social unrests potentially stem from water-related conflicts arising from drought conditions. To examine the relationship between drought and conflict in Kenya, and to assess the risk of future conflicts under potential climate anomalies, I begin by analyzing[1] historical climate anomalies, focusing on temperature and precipitation patterns across the country. As visually depicted in Fig. 2 and Fig. 3, there are notable anomalies in both precipitation and temperature in recent years compared to the early 2000s. These figures also reveal a clear spatial heterogeneity, with clustering in areas experiencing higher degrees of climate anomalies. Fig. 4 illustrates areas with changes in land use patterns, highlighting regions where land use conflicts could potentially emerge. Fig. 5 depicts the total rainfed harvested area in 2000 across Kenya, which helps to identify regions dominated by rainfed production. These initial visual assessments help to identify patterns of climate anomalies and the spatial relationships between conflicts, climate variation, and land conversion events. In particular, it appears that regions with higher conflict densities tend to coincide with areas experiencing climate anomalies and changes in land use patterns

Next, I implement a formal empirical approach to analyze drought-conflict patterns in Kenya and predict conflict risk using climate anomalies. A fixed-effects logistic regression model is used to examine whether historical precipitation and temperature anomalies are associated with the occurrence of conflict events (Equation 1). Logistic regression is used because the i^{th} conflict event at time t^{th} is modeled as a binary variable (Conflict_{it}) within each location, where each location is defined as a $0.25° \times 0.25°$ pixel across Kenya. In this model, the occurrence of conflict events is analyzed as a function of current and lagged anomalies in temperature (TempAnom_{it}, $\text{TempAnom}_{i,t-1}$, $\text{TempAnom}_{i,t-2}$) and precipitation (PrcpAnom_{it}, $\text{PrcpAnom}_{i,t-1}$, $\text{PrcpAnom}_{i,t-2}$) (up to two months) to capture both immediate and delayed effects. Several other location- and time-specific factors that may influence the occurrence of conflict are not explicitly accounted for in this model (e.g., static geographic features or annual policy changes); thus, to control for unobserved heterogeneity across space and time, spatial fixed effects (α_i) at the pixel level and temporal fixed effects for year (γ_t) and month (δ_m) are included.

$$
\begin{aligned}
\text{Conflict}_{it} = {} & \beta_1 * \text{TempAnom}_{it} + \beta_2 * \text{TempAnom}_{i,t-1} + \beta_3 * \text{TempAnom}_{i,t-2} \\
& + \beta_4 * \text{PrcpAnom}_{it} + \beta_5 * \text{PrcpAnom}_{i,t-1} + \beta_6 * \text{PrcpAnom}_{i,t-2} \\
& + \alpha_i + \gamma_t + \delta_m + \epsilon_{it}
\end{aligned} \tag{1}
$$

The estimation results of the empirical model are summarized in Table 1. Warmer temperature anomalies (values $>$ °C above historical averages) are associated with increased conflict incidence, with each 1°C increment corresponding to a 6.5% rise in conflict odds[2] ($\beta_1 = 0.063$, Odds Ratio $= 1.065$). However, the lagged effects of temperature anomalies do not display statistically significant delayed impacts. This finding may be attributed to the fact that elevated temperatures can reduce agricultural yields and intensify competition for water. By contrast, the negative coefficient on precipitation anomalies suggests reduced conflict risk during wetter periods - aligning with expectations that increased precipitation alleviates water resource competition, thereby lowering conflict likelihood. The lagged effects of precipitation demonstrate stronger impacts: a 1 mm increase in precipitation reduces the odds of conflict by 0.06% after one month, and by 0.09% after two months, with both effects being statistically significant. This modeling approach quantifies historical relationships between climate anomalies and conflict patterns across Kenya's diverse regions, providing decision-makers with spatially explicit evidence of how climatic changes may influence future conflict risks. Furthermore, by employing logistic regression—a well-established method for modeling binary outcomes—I develop an empirical framework to assess how future

[1] I completed the entire analysis using R, and the reproducible code can be found at GitHub.

[2] Both temperature and precipitation anomalies are modeled as continuous linear predictors, representing deviations from historical averages. Positive values indicate warmer/wetter-than-average conditions, while negative values indicate cooler/drier-than-average conditions. This specification does not test for potential asymmetric effects of positive vs. negative anomalies. All reported effects should be interpreted as average linear associations across the full range of observed anomalies.

temperature and precipitation anomalies could influence conflict risk. This approach enables the identification of high-risk zones. Fig. 6 shows the spatial distribution of the predicted probability of a conflict event during 2021, under a +1°C temperature anomaly and a +10 mm precipitation anomaly across Kenya. This illustrative approach demonstrates how the empirical model can be applied in a practical scenario. When more accurate projected weather anomaly data become available, this model can be used to derive more actionable insights on conflicts, helping policymakers and decision-makers mitigate the risk of humanitarian crises.

Table 1: Estimation results for the primary model specifications using a mixed logit model.

Variable	Coeff.	S.E.	Odds Ratio
Temperature Anomaly (t)	0.0631*	0.034	1.065
Temperature Anomaly (t-1)	0.0080	0.039	1.008
Temperature Anomaly (t-2)	0.0000	0.042	1.000
Precipitation Anomaly (t)	-0.0003	0.000	1.000
Precipitation Anomaly (t-1)	-0.0005**	0.000	0.999
Precipitation Anomaly (t-2)	-0.0009 **	0.000	0.999
Fixed Effect	Pixel ID + Year + Month		
Observations	95,000		
R^2	0.25		
Log-Likelihood	-12,512		

Notes: This table summarizes the results of the logistic regression model described in Equation 1. We use historical temperature and precipitation anomalies from year 2000 to 2020, along with conflict events summarized at a 0.25° × 0.25° resolution across Kenya. Multicollinearity diagnostics confirm all climate variables and their lags are within acceptable ranges (VIFs < 2), ensuring reliable estimates of their independent effects on farmer-herder conflict risk in Kenya.

If I had more time and data available, I would:

- Incorporate additional explanatory variables into the model. While I currently use spatial fixed effects to control for time-invariant characteristics affecting conflict incidents, many other factors (e.g., distance to water bodies or rivers, ethnic composition, and the presence of irrigation infrastructure) likely contribute to these conflicts and could be explicitly included.
- Extend the analysis beyond binary outcomes by modeling conflict intensity. Although the current binary logit model effectively captures conflict occurrence, future work could adopt count-based models (e.g., Poisson or Negative Binomial regression) to differentiate between frequent and low-intensity clashes, providing a more nuanced understanding of violence dynamics.
- Disaggregate conflict types to focus specifically on farmer–rancher conflicts. The current analysis includes all types of conflicts without distinction, but narrowing the scope to conflicts most closely linked to climate anomalies would yield more accurate estimates of the climate–conflict relationship.
- Explore alternative modeling frameworks. The current use of a fixed-effects model is driven by limited access to additional covariates. While random-effects models could enable predictions for all pixels, they would risk biased estimates due to the violation of the exogeneity assumption (i.e., climate anomalies must be uncorrelated with all unobserved factors). With fixed effects, estimates are restricted to within-pixel variation and predictions for pixels with observed conflict events.
- Incorporate land cover change data more effectively into the modeling framework (e.g., annual grassland-to-cropland conversions) to better capture human–environment interactions. Fixed-effects models require temporal variation in land cover to retain these variables, whereas random-effects models could estimate their effects if land cover changes are plausibly exogenous to omitted factors (e.g., unobserved policy changes).
- Integrate the Irrigated and Rainfed Crop Areas to examine whether climate–conflict relationships differ by agricultural system (irrigated vs. rainfed). Since this dataset is static (available only for the year 2000), it would need to be combined with temporal land-use trend data to reflect changes over time.

Supplementary Images

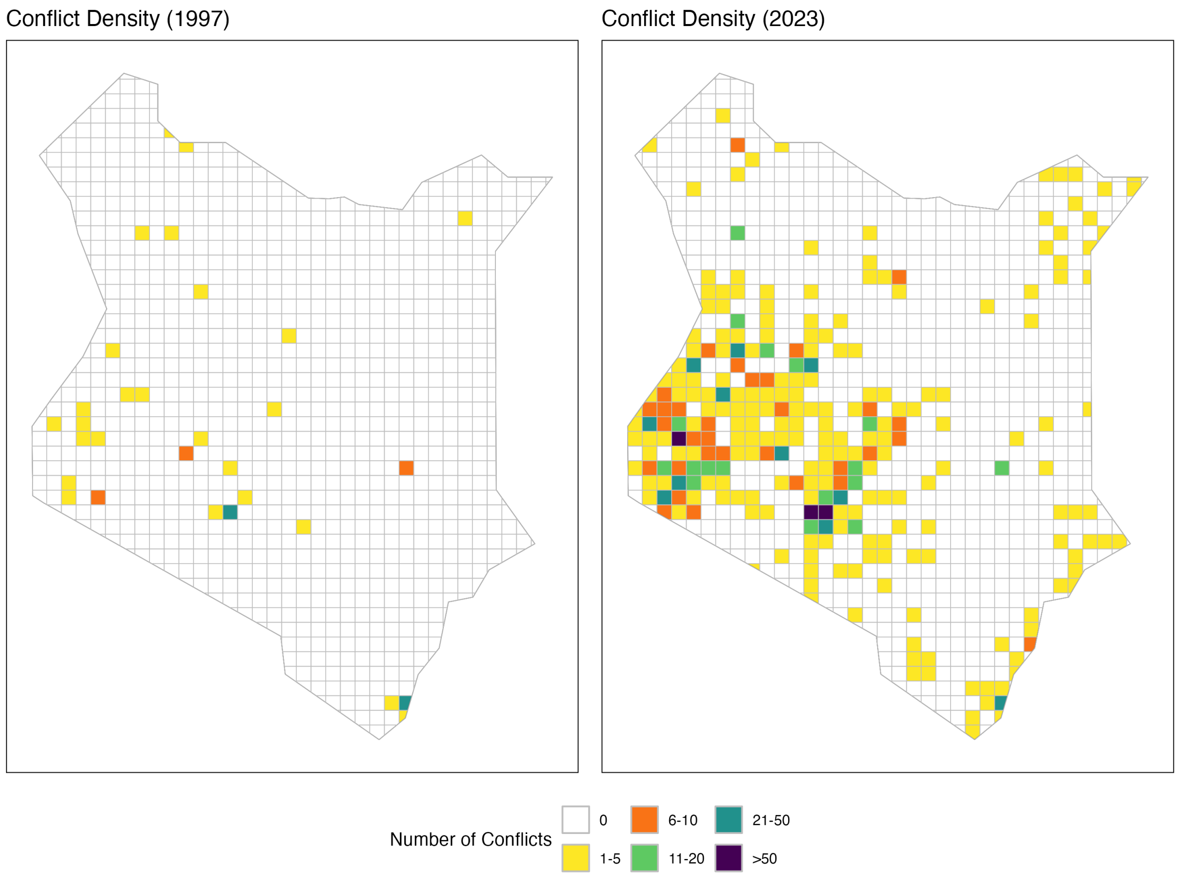
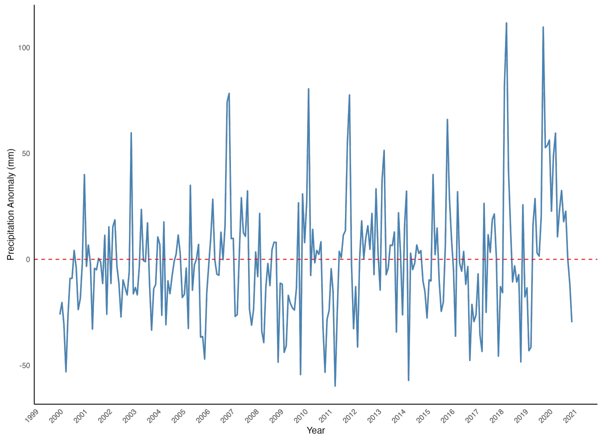
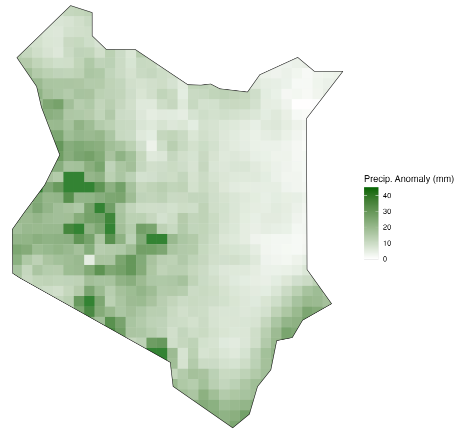


Figure 1: Density of political violence and protests in Kenya, including events related to environmental and agricultural issues.

Notes: This image shows the density of political violence and protests in Kenya, including events related to environmental and agricultural issues, for year 1997 and year 2023. The data are based on the ACLED dataset, summarized at a 0.25° × 0.25° resolution.



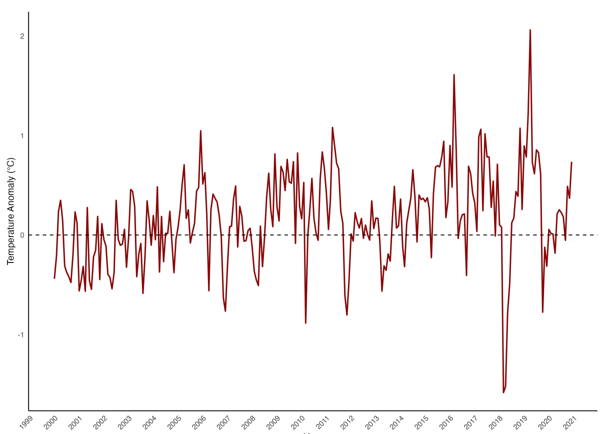
(a) Precipitation anomalies (mm) in Kenya from 2000 to 2020.



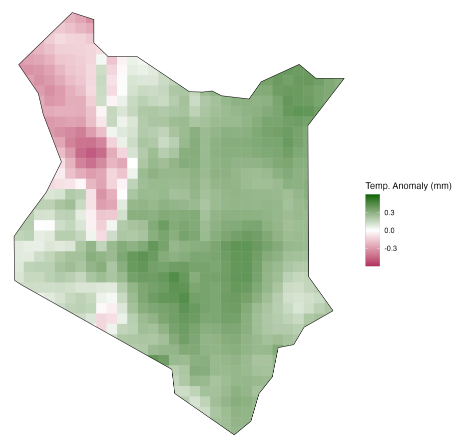
(b) Spatial distribution of precipitation anomalies (mm) in Kenya from year 2018 to the year 2020.

Figure 2: Precipitation anomalies across Kenya (a) temporal patterns and (b) spatial distribution

Notes: These anomalies are calculated based on global monthly rasters, at a resolution of 0.25°× 0.25°, for the years 2000–2020, representing temperature anomalies measured in °C.



(a) Temperature anomalies (°C) in Kenya from 2000 to 2020.



(b) Spatial distribution of temperature anomalies (°C) in Kenya from 2018 to 2020.

Figure 3: Temperature anomalies across across Kenya (a) temporal patterns and (b) spatial distribution

Notes: These anomalies are calculated based Global monthly rasters at the resolution of 0.25°X 0.25°forthe years 2000-2020 representing temperature anomalies measured in °C.

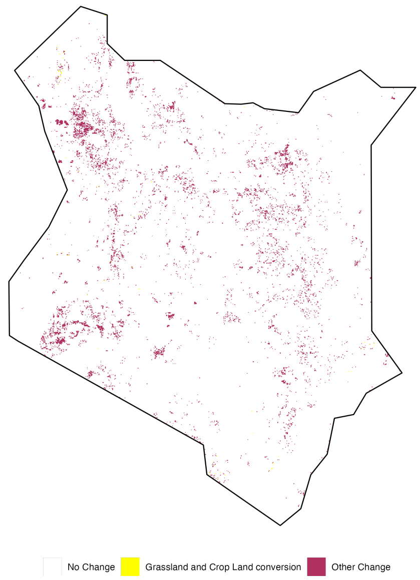


Figure 4: Areas with changes in land classification between 2000 and 2015.

Notes: This map shows the areas where land classification changed in year 2015 compared to year 2000, based on high-resolution satellite observations. The highlighted pixels represent areas that converted from grassland to cropland (or vice versa), as well as other forms of land classification shifts.

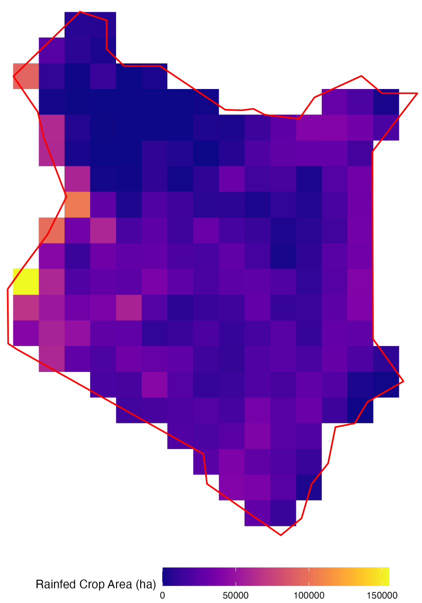


Figure 5: Rainfed Crop Production Area (All Crops, 2000)

Notes: This map shows the total rainfed harvested area in 2000 at a spatial resolution of 0.5° $\times$ 0.5° across Kenya, based on the Global Dataset of Monthly Irrigated and Rainfed Crop Areas.

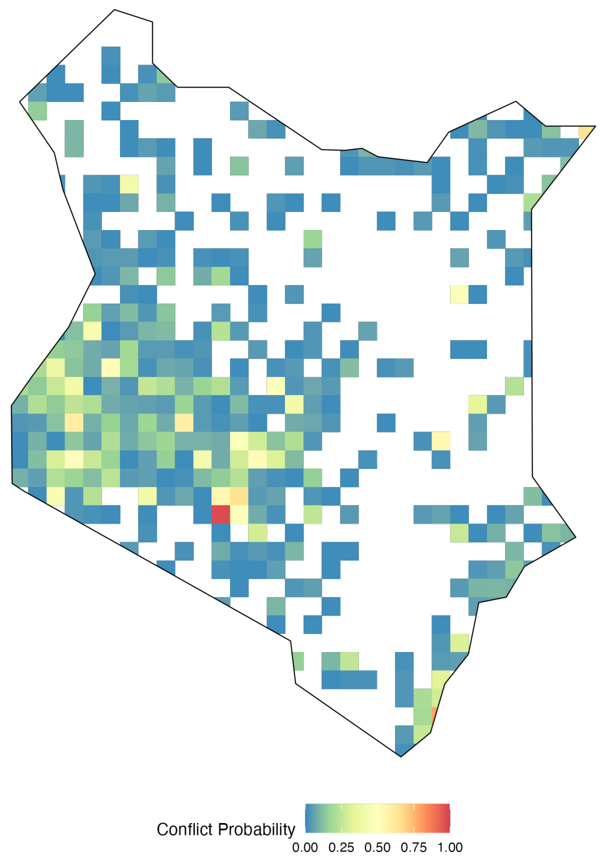


Figure 6: Probability of conflict under temperature and precipitation anomalies.

Notes: Based on the logistic regression model, this image shows the spatial distribution of the estimated probability of a conflict event at a $0.25° \times 0.25°$ resolution in 2021, under a $+1$°C temperature anomaly and a $+10$ mm precipitation anomaly. Because the model incorporates lag effects, historical data from 2018–2020 are used to generate the 2021 conflict probability estimates.