Climate Variability and Conflict Risk in East Africa, 1990-2009

John O’Loughlin\textsuperscript{a1}, Frank D.W. Witmer\textsuperscript{a}, Andrew M. Linke\textsuperscript{a}, Arlene Laing\textsuperscript{b}, Andrew Gettelman\textsuperscript{b}, and Jimy Dudhia\textsuperscript{b}

\textsuperscript{a} Institute of Behavioral Science and Department of Geography, University of Colorado, Boulder, CO 80309-0483; \textsuperscript{b} National Center for Atmospheric Research, Boulder, CO 80307-3000

\textsuperscript{1}Corresponding author: E-mail: johno@colorado.edu, phone: 303-492-1619.

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Abstract: Recent studies concerning the possible relationship between climate trends and the risks of violent conflict have yielded contradictory results, partly due to choices of conflict measure, modeling design, and use of different climate indicators. In this study we look for climate-conflict relationships using a geographically-disaggregated approach. We consider the effects of climate change to be both local and national in character and we use a conflict database that contains 16,359 individual geolocated violent events for East Africa from 1990-2009. Unlike previous studies that relied exclusively on political and economic controls, we also analyze the many geographical factors that have been shown to be important in understanding the distribution and causes of violence while also considering yearly and country fixed effects. For our main climate indicators at gridded 1° resolution (~100km), wetter deviations from the precipitation norms decrease the risk of violence while drier and normal periods show no effects. The relationship between temperature and conflict shows that warmer than normal temperatures raise the risk of violence while average and cooler temperatures have no effect. These precipitation and temperature effects are small, and large variations in the climate-conflict relationships are evident between the nine countries of the study region and across time periods.

The debates surrounding a possible association between climate change and violent conflict continue without much resolution in both the academic and policy realms. The tone of the consensus emerging from politicians and the policy-making community is decidedly gloomy. U.S. President Barack Obama recently declared that climate change represents an “urgent, serious, and growing threat” (1), as the stress of frequent drought and crop failures “breed hunger and conflict” (2). Government-associated think-tanks follow closely this line with ecological stress and climate change generating a “range of security problems that will have dire global consequences,” according to a Center for Strategic and International Studies report (3). Such claims are predicated on a national security paradigm: The ability of societies in non-industrialized regions of the world to cope with ecological change can jeopardize the stability of the international system and rebound adversely to wealthy countries. Though they receive significant public and policy attention, such reports are marked by speculation and lack strong empirical support.

Two main bodies of academic research address the climate-conflict nexus. The first claims a positive link between scarcity and violence (4-8) making the case that shortages – food, water, crop...
imports – introduce stress on formal and informal social institutions. In one rendering, these associations purportedly operate through an economic mechanism, whereby rainfall deficits negatively affect earnings in predominantly agricultural societies (9). Where such changes take place, the gains associated with participation in armed expressions of grievance outweigh the costs of so doing. Proponents of this viewpoint have a receptive audience within policy-making communities. A conclusion in this research cluster suggests that both dry (slow onset) as well as wet (fast onset) precipitation extremes are associated with increased risk of social conflict (10).

Researchers who question any consistent connection between the climate change and violent conflict may be classified into two distinct groups. Relying on quantitative analysis of climate and sub-national conflict data, recent work has illustrated either a null (non-significant) or negative relationship between scarcity and conflict (11, 12). Considering the specific locations of conflicts, disaggregated analysis moves beyond crude understandings of conflict that follow the country-year unit of analysis common in international relations—where “conflict” is coded in binary (“1 or 0”) terms for the entire territory of a country and for a complete year. The coarse resolution of the country-year approach cannot capture the dramatic location-specific differences that characterize political violence across a country (13, 14); configuring statistical models to include sub-national locations has called these country-level findings into question (12).

A second set of studies that questions the climate change-conflict nexus emerges from the political ecology tradition, especially in human geography; it often adopts an ethnographic character, and is conducted with an emphasis on local-level power dynamics (15-17). In this perspective, individual communities are unique and place-specific experiences are each rooted in particular historical trajectories that cannot be easily quantified. Power relationships that distort the management of public resources are cited as the true foundation of “resource conflicts” in West Africa’s Sahel (18).

Sweeping generalizations have undermined a genuine understanding of any climate-conflict link, while cumulative results from the numerous studies of individual communities are difficult to summarize. Our work balances the quantitative approach with close attention to local and temporal differences in climate and conflict by examining nine countries in the Horn and Eastern regions of Africa between 1990 and 2009 (Fig. 1). These countries represent substantial variation across climate regimes, recent conflict experience (Fig. S2) and political systems, and these variations allows for both generalization and consideration of regional-local nuances. An example of the type of climate-conflict relationship that we are examining is found in our conflict data. On July 3, 2004 over 100 farmers’ homes in Tanzania’s Arusha District (in Themi area) were burned by herders who have been pushing
authorities for years to turn the land into grazing area. Such a link between violence and resource availability is purported to be an outcome of climate change on livelihoods in sub-Saharan Africa. The event must be analyzed in the context of political, social, economic, and geographic variables that are often ignored as key controls, thereby addressing a common complaint about the existing literature

[Fig. 1 here]

Using a 1° gridded analysis (402 grids; Fig. S4), we estimate the influence of six-month deviations in rainfall (Standard Precipitation Index, SPI6) and temperatures (Temperature Index, TI6) from long-term averages upon levels of violence. We use the Armed Conflict Location and Event Dataset (ACLED) (19) to capture the nuances of violence beyond the confines of a civil war, rebel-versus-government logic, and avoid setting a death-threshold that indicates simplistically whether a country suffers violence or not. Our estimation procedure accommodates both the known spatial interdependence of observations and possible non-linear relationship between climate measures and conflict. Through myriad robustness checks, including the use of a different disaggregated violence data set (20) and multiple climate indicators (see supporting information), our findings question the most simplistic climate-conflict narratives. The relationships between rainfall and temperature variability and violence are complex and warrant careful interpretation.

**Results**

For East Africa 1991-2009, we find no statistically significant relationship between precipitation extremes and conflict after controlling for socio-economic and physiographic factors, and country and year fixed effects (Table 1, column a). (Because we lag some variables, data for 1990 are not modeled.) When rainfall is higher by more than $1\sigma$ than the historical average for the same months, we find a reduction in the risk of conflict after controlling for influential social, geographic and political factors (Table 1, col. c). While we have a regional, rather than global or continental, focus, this finding about rainfall stands in contrast to the thrust of some existing research (10). Our overall results for temperature deviations also do not conform to other findings in the literature (6). Where temperatures are much higher than the long-term average for a given month, there is no statistically significant increase in the risk of conflict (Table 1).
Table 1, column a) shows parameter estimates for the simple GLM negative binomial model. All of the statistically significant predictors match our expectations for predicting violence; the precipitation and temperature anomalies are not statistically significant. We explore the climate anomaly effects by creating binary versions of SPI6 and TI6 using a threshold of ±1σ. Results for SPI6 (Table 1, cols. b-c) show that unusually wet periods reduce the risk of violence. TI6 results (Table 1, cols. d-e) are not statistically significant in the basic GLM binary model. To capture any possible coefficient variations over the variable range, we allow the estimates to vary in a generalized additive model (GAM) model. Both climate anomaly variables significantly affect the risk of conflict in this functional form (Table 1, col. f), but to a varying degree depending on the severity of the anomaly (Fig. 2).

Fig. 2 shows the coefficient estimates for a given weather condition; thus, for periods wetter than usual, SPI6 = 2, the coefficient estimate predicts less violent conflict by about -0.3 logged events, which corresponds to a relative risk ratio of 0.74 (values >1 indicate increase and < 1 decrease). The broad effect of SPI6 on conflict forms an inverse-U relationship, but the effect is only significant for unusually wet periods (Fig. 2a). We are particularly interested in the impact of unusually wet and dry periods on conflict compared to normal conditions, Table 2 presents the relative risk ratios with 0 (normal climate conditions) as the starting point. Compared to normal conditions, the model predicts a 30.3% decrease in violent events when recent precipitation is 2σ above the long term mean (difference for SPI6 changing from 0 to 2, all other factors constant).

[Table 1 here]
[Fig. 2 here]

For the temperature relationship to conflict, colder temperatures have no effect on the risk of conflict, while moderate increases in temperature reduce the risk of conflict and very hot temperatures increase the risk; e.g. for TI6 = 2, there is a 29.6% increase in predicted violent events compared to normal temperature conditions.

[Table 2 here]

Given the very large N (91,656) of our study, we are hesitant to rely too much on the statistical significance of our model estimates, despite using grid-clustered standard errors. As an alternative measure of significance, we calculate the predictive power for each variable based on the effect each
has on the overall prediction accuracy of the model. This area under the curve (AUC) metric is calculated based on true and false positive prediction rates for thresholds from 0.0 to 1.0. The AUC is more commonly used for logit models (21), but we apply it to our count models by truncating predicted values above 1. Fig. 3 shows the change in predictive power contributed by each variable. Population and the space-time lag for violence stand out as contributing most to the predictive power of our model. Two variables, infant mortality and crop production, slightly reduce the model’s predictive power. Because the SPI6 and TI6 climate measures have no single z value, their predictive power is plotted as a dashed line for a range of possible z values. TI6 improves the predictive power slightly (ranked seventh overall in contribution to the AUC change), whereas SPI6 is closer to 0. Despite the relationships found in Fig. 2a, the actual contribution of SPI6 and TI6 to predicting violence in the study area is minimal.

[Fig. 3 here]

We perform a variety of robustness tests that are reported in the supporting information. Examining the cell-months data by the nine countries in the region and across 5-year periods shows sizeable variations in the significance of both the control and the climate variables (Tables S5 and S8 and Figs. S6-S7, S9-S10). Both the precipitation and temperature spline plots show considerable variation in predicting violence, suggesting their effects are mediated by location and time. Recognizing that we are stressing local climatic conditions in our models, we also examine whether larger-scale effects in the form of the El Niño-Southern Oscillation (ENSO) and Indian Ocean Surface Temperatures influences modify our overall conclusions. The results (Table S8 cols. g-h, and Figs. S9g-h and S10g-h) indicate that including Indian Ocean Temperatures has little impact on the model, but that sub-setting the model based on ENSO months results in less confidence in the SPI6 spline plots and a more linear TI6 relationship, with cooler than usual temperatures associated with less violence.

We estimate several interaction terms for political rights and ethnic leadership with both climate variables. None of the interaction terms is significant or affect the climate variable spline plots. The most influential combination, TI6 and ethnic leadership, is reported in Table S11 col. g and Figs S12g and S13g. Conceptually, we might expect that the effect of climate variability on conflict may be greatest during growing seasons, but including a growing season has little effect (Table S11 col. h). We also test the effect of dropping the space-time lag variable (Table S11 col. f, Figs S12f & S13f).

Finally, we tested two alternative measures of violence and a logistic regression model functional form. We subset the ACLED events classified as “Riots/protests” and “Violence against
civilians” as a measure of lesser violence; there are some differences in coefficient standard errors, but little change to the climate spline plots (Table S11 col. a, Figs S12a & S13a). The ACLED logit model uses the full database with violent event counts truncated to one, and yield largely similar results (Table S11 col. b, Figs S12b & S13b) to the main model.

A recently released conflict data set from the Uppsala Conflict Data Program (20) that has independently geolocated African violence allows a helpful check on our results, even though the definition of conflict is much more conservative. Using these data and both a negative binomial and logit functional form, the temperature and precipitation variable splines retain statistical significance (Table S11 cols. c-d). Figures S12c-d show few differences for the estimation of precipitation using these data, but the effect of temperature differs substantially (S13c-d), with less violence predicted for warmer temperature anomalies and more violence for cooler anomalies (though this result is only statistically significant for the negative binomial version).

Discussion
While decades of research on the distribution and correlates of war have greatly increased understanding of its social, political and economic dimensions, more recent work in this genre has tackled the highly variegated nature of violence across the localities of countries experiencing war. Our study and others (11, 22, 23) question the evidence that climatic variability is driving up the risk of conflict in sub-Saharan Africa, which is the world region generally recognized as most vulnerable to such new hazards. But unlike previous skeptical studies of the climate-conflict nexus, our study of East Africa over the past two decades is more nuanced in two respects. First, we have shown that higher temperatures may increase the risk of conflict in East Africa even when precipitation trends are considered and a wide range of geographic and socio-economic-political controls, as well as yearly and country fixed effects are added to the model. Previous work (6) had attributed more influence in raising violence to temperature increases than to precipitation deviations across Africa and our study can be seen as partially vindicating this finding. Wet precipitation deviations from the long-term trends appear to dampen conflict. Second, we have shown the dramatic differences between countries and between time periods of five years in the model fit and the important precipitation and temperature coefficient splines. We provide these checks as a cautionary notice of the instability of the climate-conflict relationship whilst suggesting that fixing a model with few controls and non-specific locations of violence across a large region and a long time period hides a myriad of contextual interactions.
Methods

We aggregate all data to a common 1° grid (110 km × 110 km). Grid cells for the study area include a 100 km buffer inland to incorporate conflict spillover effects with neighboring countries, resulting in a total of 402 cells (after excluding grid cells over Lake Victoria, cells with missing climate data, and coastal cells with < 20% land area and no violence). The count distribution of grid-month violence is heavily over-dispersed; of the 91,656 grid-month units (402 grids over 19 years since a one year lag for several variables requires excluding 1990 data), 5.9% of the observations are non-zero (μ = .18, σ =1.28; Table S1). We use a negative binomial generalized linear model (GLM) to retain the full distribution of the data, preferring it over the logit model often used in conflict study and which truncates count values greater than one (though see Table S11 for logit versions). For SPI6 and TI6 indicators, initial model estimates for extreme conditions (≥1σ and ≤ −1σ; Table 1, cols. b-e) varied sufficiently to suggest that a more flexible model (with non-linear parameters) was required.

To address this non-linearity, we estimate a generalized additive model (GAM) (24) using the R package mgcv and a thin plate spline for SPI6 and TI6 (Table 1, col. f). This specification allows SPI6 and TI6 coefficients to vary over the values within their distributions, and enables us to explore the nuances of the relationship between our climate measurements and conflict across our study area. Since there is no single coefficient estimate for these splined variables, we present these coefficients graphically (Fig. 2).

For both the GLM and GAM versions of the models, we control for residual unmeasured country-scale variables by estimating country-level effects. These country-level effects are included as fixed, instead of random, effects since several of the predictor variables are reported at the country-level, and so are correlated at that spatial scale. Such country-level fixed effects are common in studies of violence (6, 11). We also include year fixed effects to account for unexplained variation over time and the possibility that media coverage of conflict in earlier years of our study period is sparse relative to later periods. The negative binomial dispersion parameter, θ in R, is estimated using maximum likelihood for both the GLM and GAM versions of the model.

The GAM version of the model has the following functional form:

\[ Y_{it} = WY_{i,t-1} + X_{it}\beta + f_1(\text{SPI6}_{it}) + f_2(\text{TI6}_{it}) + \text{Country}_{it} + \text{Year}_{it} + \epsilon_{it} \]

where \( i = \text{grid}, t = \text{time (month)}, W \) is the first order contiguity spatial weights matrix used to calculate the violent events space-time lag, \( \beta \) is a vector of coefficients associated with the matrix of independent variables \( X \), \( f_1 \) and \( f_2 \) are thin plate spline functions, Country and Year are fixed effect terms, and \( \epsilon \) is the
grid-month error term. Since much of the data for some variables are duplicated over time, we use grid-clustered standard errors for all models to assess statistical significance.

Data

Precipitation: We use SPI6 to compare the moving six-month precipitation record against the long-term (since 1949) distribution for the same six-month period. The primary data are monthly mean gridded land surface precipitation and temperature obtained from the Climate Research Unit (CRU) of the University of East Anglia. These data are the CRU TS3.10 global data on 0.5° x 0.5° grids for the period 1949-2009, which are resampled to 1° x 1° grids, thereby facilitating regression with environmental and socio-economic variables. The SPI measures the number of standard deviations that the observed cumulative precipitation departs from the long-term mean. It can be compared across markedly different climates and is calculated for each grid cell. Negative deviation in rainfall is said to be one of the primary observable effects of climate change, and one that increases the risk of civil war (25) and the likelihood of other low-intensity forms of conflict (10): other research finds an association of conflict with positive vegetation growth (26). Related measures reach similar conclusions, such as greater freshwater availability reducing the risk of civil war onset (27).

Temperature: We use a six-month TI6 to measure the deviation from the corresponding long-term monthly mean temperature (since 1949). The temperature index expresses the monthly anomaly departure as a multiple of the standard deviation, thus helping to identify anomalous warm or cold periods. While higher than normal temperatures have been linked to civil war (6), others have called this finding into question claiming that Burke et al. (6) use a poorly-specified model and only a national-level conflict measure (11). Temperature variability has important implications for agriculture (28), and has important effects on evapo-transpiration: Hsiang, Meng and Kane (7) use both climate metrics as part of their classification of areas affected by ENSO cycles (see Table S8, col. h for a test of this effect in our study region). In contrast to the claim that rising temperatures will cause violence, global (8) and regional (29) studies have uncovered an association between human insecurity and colder temperatures. In the studies with competing conclusions, however, the mechanism remains the same: colder temperatures in temperate climates resulted in crop failure just as warmer deviations introduce agricultural stress in warmer climates.

For socio-demographic and geographic controls in our regression models, we included a variety of measures. Space-time lag: At an international (30) and local level (31, 32) conflict exhibits qualities that might be described as “contagion”, “diffusion” and “clustering” patterns. We account for these kinds of
dependencies by including a space-time lagged dependent variable. Failure to account for geographic clustering may have biased the results of previous research on the climate change-conflict relationship, though authors may have controlled for temporal trends. In our models, the space-time effect is the second most influential predictor. **Population:** Within a country, conflict risk is associated with greater population densities (12) and rates of population growth (33). We use the Gridded Population of the World (v3) data from the Center for International Earth Science Information Network and Socio-Economic Data and Applications Center of Columbia University (34) to derive yearly populations for the 1° cells. Population is the most important predictor of the number of violent events in an area. **Well-being (IMR):** Cross-national studies have illustrated a link between low socio-economic status and conflict at the country (35). We use the yearly Infant Mortality Rate (IMR) (36) instead of Gross Domestic Product per capita because it serves as a broader measure of social well-being. **Political rights:** In authoritarian political climates, violent social unrest can develop because citizens have a limited ability to express their interests through formal governmental avenues (37). We use the yearly political rights score from Freedom in the World (38) to measure the extent to which a country’s government is autocratic or democratic in character. **Presidential election:** Violence may rise during campaigning or as a reaction to the outcome of an election (39) when ethnic conflict is especially likely to occur. To isolate the influence of this factor, we include a binary variable for every country coded as 1 if a presidential election occurred in a ±three-month period. **Ethnic leadership:** Clientelism or “private rule” is a known characteristic of political regimes in sub-Saharan Africa (40). Patron-client ties can result in the (usually ethnic) exclusion of certain populations from government representation and services (41). We control for the fact that certain territories within states may benefit from central government patronage ties by coding cells (excluded group or not) in a geographic representation of political leadership information from Archigos data (42) using Ethnologue spatial boundaries (43).

We add six geographic controls to the modeling. **Crop production index:** There is a risk that social unrest will follow rising food prices because of impacts on family budgets (44) and because crop shortages represent a threat to central government coffers and disbursement options (45). As a surrogate for fluctuating food prices, we include the crop production index (annual percentage change) from the Food and Agriculture Organization and the World Bank (46). **Capital city:** The capital city can be an important site of contention during certain conflicts because of its symbolic importance (claiming control of the seat of government of a state in civil war) (47). Lower-level skirmishes (riots, protests) may also concentrate in a capital city because it is the seat of government. We use a binary measure of
whether or not a grid cell includes the capital city of a country. **Distance to borders:** Because armed actors can use neighboring territory as a sanctuary, borders represent transmission points of conflict; a substantial body of work on the geography of conflict demonstrates the importance of border regions in conflict diffusion (32). We calculate the mean distance to border from the centroid of each grid cell. **Distance to roads:** As routes for transporting people and supplies, roads are often a key target for military activity (48) even though they may also serve as a tool for a central government to secure control over a country’s territory (49). We judge the road network data from the Digital Chart of the World (50) to be the most spatially consistent database, and calculate the average distance to primary and secondary roads for each grid cell. **Grassland:** Pastoralist cattle raiding activity can be a daily livelihood strategy in regions of our study area, such as northern Kenya (51). We account for the influence of this social dynamic by including a measurement of the percentage of a grid cell that is grassland in the History Database of the Global Environment HYDE (52). **Vegetation:** We include a Vegetation Condition Index (VCI) to control for variation in vegetation health over time. This weekly metric is derived from NOAA’s Advanced Very High Resolution Radiometer (AVHRR) sensor and captures changes in the Normalized Vegetation Difference Index (NDVI) compared to its historical range for each pixel (53). We elaborate on the data sources and specific metrics in the supporting material (Table S1) for this article. **Growing season:** A binary variable is used to designate each grid-month as part of the growing season. Growing seasons were calculated based on average daily temperatures above 6 °C and a ratio of actual to potential evapotranspiration exceeding 0.35 (54).

**Violent events:** The human-coded and media-based conflict data are from ACLED (19). Much of the existing research relies on country-level data (6), which can be problematic because conflict processes do not unfold uniformly within a country. ACLED data are georeferenced with latitude and longitude coordinates, allowing for the localized study of conflict within a country’s borders: the database also distinguishes between various types of violence (civil war, riots/protests, attacks on civilians), thus allowing robustness checks with different conflict measures. For Somalia, we have excluded the data in the file that are not based on the standard media sources. To assign large countries (e.g. Ethiopia or Tanzania) a single binary measure of war or peace for a given year is clearly ignoring the dynamic geographic and temporal differences evident in violence, as indicated in Fig. 1 for our 9 countries of study.
Replication code and data are available at (website anonymous for purposes of review).
References

20. Uppsala Conflict Data Program (UCDP) http://www.pcr.uu.se/research/ucdp/datasets/

**Figure Legends**

**Fig. 1.** The distribution of ACLED violent events for five-year periods in the 9 countries of the study area. The devastating civil conflicts in Rwanda (early 1990s) and Burundi (throughout the study period), the Ethiopia-Eritrea border war (1998-2000), the diffusion of violence into eastern DRC from Rwanda, the LRA (Lord’s Resistance Army) war in northern Uganda and surroundings, the Ethiopian invasion of Somalia in mid-2006 and the civil conflict in Somalia involving the Al-Shabab militias, and the Kenyan electoral violence of early 2008 are easily discernible on the maps. Border areas adjoining the 9 countries of study (in Sudan, Zambia, DRC, Malawi, Mozambique) are included in the analysis and have also seen violence. The size of the circles is proportional to the number of events at the specific locations. The number of deaths or amount of property damage associated with violence was not recorded in ACLED due to unreliable data reporting in news outlets.

**Fig. 2.** These plots show the coefficient estimate and 95% confidence interval over the range of SPI6 and TI6. Non-overlap between the confidence interval and dashed 0-line indicate a statistically significant effect. The lower dark
grey plots of Fig. 2 show the density distributions of the variable – both SPI6 and TI6 are centered right of 0, indicating our study period is wetter and warmer than the 60-year comparison period.

**Fig. 3.** Change in predictive power versus statistical significance for Table 1, col. f model. The positions of the predictors on the graph clearly indicate the relatively small contribution of the climate predictors to the model. Geographic variables (cell populations, the space-time clustering effect, capital city locations, distance to international borders, grassland ratio and distance to road) are more important in predictive power than the climate or political measures.

**Table Legends**

**Table 1.** Negative binomial regression models for number of violent events per grid cell, 1991-2009.

**Table 2.** Relative risk ratios for climate anomalies.
<table>
<thead>
<tr>
<th>Model Description</th>
<th>GLM Socio-econ, Physical, Climate</th>
<th>SP6 Binary Dry (≤ -1σ)</th>
<th>SP6 Binary Wet (≥ 1σ)</th>
<th>TI6 Binary Hot (≥ 1σ)</th>
<th>TI6 Binary Cold (≤ -1σ)</th>
<th>GAM Splines</th>
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<td><strong>Estimate</strong></td>
<td><strong>z value</strong></td>
<td><strong>Estimate</strong></td>
<td><strong>z value</strong></td>
<td><strong>Estimate</strong></td>
<td><strong>z value</strong></td>
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<td>0.525 **</td>
<td>0.530 **</td>
<td>14.857 **</td>
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<td>-0.205</td>
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<td>14.973 **</td>
<td>0.512 **</td>
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<tr>
<td>Grassland (percent)</td>
<td>0.020</td>
<td>4.131 **</td>
<td>0.020</td>
<td>4.126 **</td>
<td>0.020</td>
<td>4.112 **</td>
</tr>
<tr>
<td>Dist. to road (ln)</td>
<td>-0.040</td>
<td>-3.151 **</td>
<td>-0.040</td>
<td>-3.146 **</td>
<td>-0.040</td>
<td>-3.141 **</td>
</tr>
<tr>
<td>Crop prod. ind. (pct. Δ)</td>
<td>-0.004</td>
<td>-1.447</td>
<td>-0.004</td>
<td>-1.551</td>
<td>-0.004</td>
<td>-1.507</td>
</tr>
<tr>
<td>Veg. cond. ind. (lag)</td>
<td>-0.002</td>
<td>-0.956</td>
<td>-0.002</td>
<td>-0.971</td>
<td>-0.001</td>
<td>-0.909</td>
</tr>
</tbody>
</table>

Log-likelihood: 25150.6, 25153.0, 25146.1, 25153.9, 25155.0, 25112.0
AIC: 50395.1, 50399.9, 50386.3, 50401.9, 50404.0, 50331.7

Significance codes: ** p < 0.01, * p < 0.05 using grid-clustered standard errors. Number of observations for all models is 91,656 grid-months. Binary models b)-d) use precipitation and temperature anomalies of beyond 1 standard deviation (σ) of the long-term mean to define binary variable.
All models estimated with year and country fixed effects (not shown). AIC is the Akaike information criterion.
a) Spline estimates for SPI6 (precipitation)

b) Spline estimates for TI6 (temperature)
Table 2. Relative risk ratios for climate anomalies

<table>
<thead>
<tr>
<th>SPI6</th>
<th>From</th>
<th>To</th>
<th>Relative risk ratio</th>
<th>TI6</th>
<th>From</th>
<th>To</th>
<th>Relative risk ratio</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0</td>
<td>to -1</td>
<td>0.980</td>
<td>0</td>
<td>to -1</td>
<td>1.100</td>
<td></td>
</tr>
<tr>
<td>Drier</td>
<td>0</td>
<td>to -2</td>
<td>0.867</td>
<td>0</td>
<td>to -2</td>
<td>1.063</td>
<td></td>
</tr>
<tr>
<td></td>
<td>0</td>
<td>to -3</td>
<td>0.736</td>
<td>0</td>
<td>to -3</td>
<td>0.932</td>
<td></td>
</tr>
<tr>
<td></td>
<td>0</td>
<td>to -4</td>
<td>0.621</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Wetter</td>
<td>0</td>
<td>to 1</td>
<td>0.881 *</td>
<td>0</td>
<td>to 1</td>
<td>0.880 *</td>
<td></td>
</tr>
<tr>
<td></td>
<td>0</td>
<td>to 2</td>
<td>0.697 *</td>
<td>0</td>
<td>to 2</td>
<td>1.296 *</td>
<td></td>
</tr>
<tr>
<td></td>
<td>0</td>
<td>to 3</td>
<td>0.536 *</td>
<td>0</td>
<td>to 3</td>
<td>1.448 *</td>
<td></td>
</tr>
<tr>
<td></td>
<td>0</td>
<td>to 4</td>
<td>0.408 *</td>
<td>0</td>
<td>to 4</td>
<td>1.602</td>
<td></td>
</tr>
</tbody>
</table>

* significantly different from 0 based on a 95% confidence interval (Fig. 2)
Values in the table are for SPI6 & TI6 values.
Predictive power for variables in GAM negative binomial model.

- Population (ln)
- Grassland (percent)
- Distance to border (ln)
- Distance to road (ln)
- Presidential election buffer
- Political rights (lag)
- Well-being (IMR lag)
- Crop production index (percent change)
- Vegetation condition index (lag)

Best fit line through origin.