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ASSESSING THE LINK BETWEEN CLIMATE, MIGRATION, CONFLICT AND VIOLENCE IN IGAD STATES

A COMPLETE ASSESSMENT REPORT

AUTHOR: ORE KOREN

DEPARTMENT OF POLITICAL SCIENCE, INDIANA UNIVERSITY, BLOOMINGTON, USA

Email: okoren@iu.edu

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DISCLAIMER

The maps used in this report do not reflect the official position of all parties included in the document.

1. EXECUTIVE SUMMARY

OVERVIEW

This report geospatially assesses the relationship between environmental and socioeconomic indicators and a host of conflict and violence measures by different actors in countries that are members of the Intergovernmental Authority on Development (IGAD), which is intended to facilitate development and environmental control in member states.[1] Accordingly, the report emphasizes the role of environmental stressors, agricultural productivities, and migration as potential drivers.

Three key advantages of this report are:

1. Looking at **monthly rather than annual** changes in conflict and violence rates, environmental health, weather, etc.
2. Focusing on **local conflict events** rather than the general incidence (yes/no) at the country level.
3. Identifying the efficacy of each determinant in **improving our ability to forecast** conflict type in question based on its impact on the forecasting model *as a* **whole.**

METHODS

This report relies on ***predictive forecasting*** to assess these impacts. It employs an original, newly released, high resolution geographic dataset, AfroGrid, ***specifically designed for studying how climate and the environment impact conflict and political violence in Africa (Schon & Koren 2022)***. Empirically, logistic regression, a "workhorse" model in conflict prediction (Goldstone et al. 2010), is used in combination with forecasting techniques designed to assess how well the explanation of conflict included in each model improve our ability to predict conflict and violence one-year and, separately, five-years forward in time.

HIGHLIGHTS

- The strongest conflict and violence ***risk factors*** are a history of conflict over the last month and year, and whether nearby locations were experiencing conflict during the same month.
- ***Separately, environmental and/or climate predictors*** show, on average, little noticeable impact on whether a given area will experience greater conflict risk in a given month in most cases.
- ***Combined, environmental and climate predictors*** emerge as a relatively strong risk factor for when and where the risk of conflict and violence against civilians by rebels will increase**.** However, these results are sensitive, and do not mean that in most cases these indicators have a clear and robust effect on most conflict and violence risk indicators.
- ***Cash/food crops and cash/food productivity indicators*** show, generally, little-to-no effect on improving the predictive strength of the models.
- The role of internally displaced persons (IDPs) as a risk factor in South Sudan is weak. ***In Ethiopia, a greater number of environmental IDPs is linked to conflict risk, while IDPs displaced due to conflict and other reasons is not.*** However, the exact reason for this relationship cannot be clearly determined.
- ***Areas with more population and slightly improved development*** are associated with a greater risk of conflict and violence, although their impact on this risk is relatively small.
- On average, ***general country-level measures*** (e.g., country area, the degree of its land that is mountainous) do not emerge as a clear conflict and violence risk factor.
- In IGAD states, ***areas in Somalia, Kenya, Uganda, and Ethiopia*** show the highest predicted risk of conflict.

[1] These countries are Djibouti, Eritrea, Ethiopia, Kenya, Somalia (including Somaliland), South Sudan, Sudan, and Uganda.

PART A. CONTINENTAL BASELINE REPORT

2. OVERVIEW

Researchers and policymakers are concerned that climate change can influence conflict dynamics by generating intensified competition over resources and inducing migration, especially in African states (e.g., Raleigh et al. 2008; Theisen et al. 2013; Gleick 2014; Bellemare 2015; Ide 2016; Von Uexkull & Buhaug 2021; Schon & Koren 2022). There are several relationships that could exist between climate, migration/displacement, and conflict. For instance, climate change can trigger conflict that then triggers migration. This report focuses on exploring one specific link of policy concern (e.g., Gleick 2014): that climate disasters can induce displacement, and that displaced persons are more likely to be involved in conflict, either as participants (for instance, joining a rebel group) or as victims (for example, if armed forces attack a refugee camp).

More specifically, this stage of the report focuses on first testing whether there is a systematic relationship between climate and environmental factors on the one hand, and conflict and violence on the other, without evaluating the role of migration specifically.

To this end, this stage quantifies the links between climate, agricultural resource variability, and seven types of social conflict in IGAD states:

(i) Battle events initiated by state forces from the Armed Conflict Location and Event Dataset (ACLED) (Raleigh et al. 2021);

(ii) Battle events fought as part of a war between governments and rebel groups recorded by the Geolocated Event Dataset (GED) (Sunderg & Melander 2013);

(iii) Battle events initiated by rebels from ACLED;

(iv) Battle events fought between two or more nonstate actors (including farmer-herder conflicts) from GED; violence against civilians incidents perpetrated by;

(v) State actors,

(vi) Rebels

(vii) Militias from ACLED

(viii) Riots (ACLED).

While there are many resources that could be considered, because these resources are especially vulnerable to climate change, are more likely to cause migration if depleted, and due to data availability, ***the focus here is specifically on environmental health and agricultural commodities such as cereals (wheat, maize, rice, etc.), fruits (bananas, mangoes, etc.), and cash crops (tobacco, coffee, etc.).***

To this end, this assessment stage leverages a recently-released data framework on climate-conflict in Africa (Schon & Koren 2022), with the ultimate aim of calibrating the relevant models and identifying the role of general climate proxies (temperature, rainfall, drought), environmental health, and agricultural resources (crop and food crops) as predictors of these conflict types within IGAD countries over the 2003-2018 period, forecasting locations that are especially vulnerable to resource-driven conflict and violence (as defined above), and producing predictions for where climate variations over the next five years (2022-2027) might lead to increased (or decreased) risk of conflict, rioting, and violence. A map of all IGAD countries is provided in **Figure 1** below.

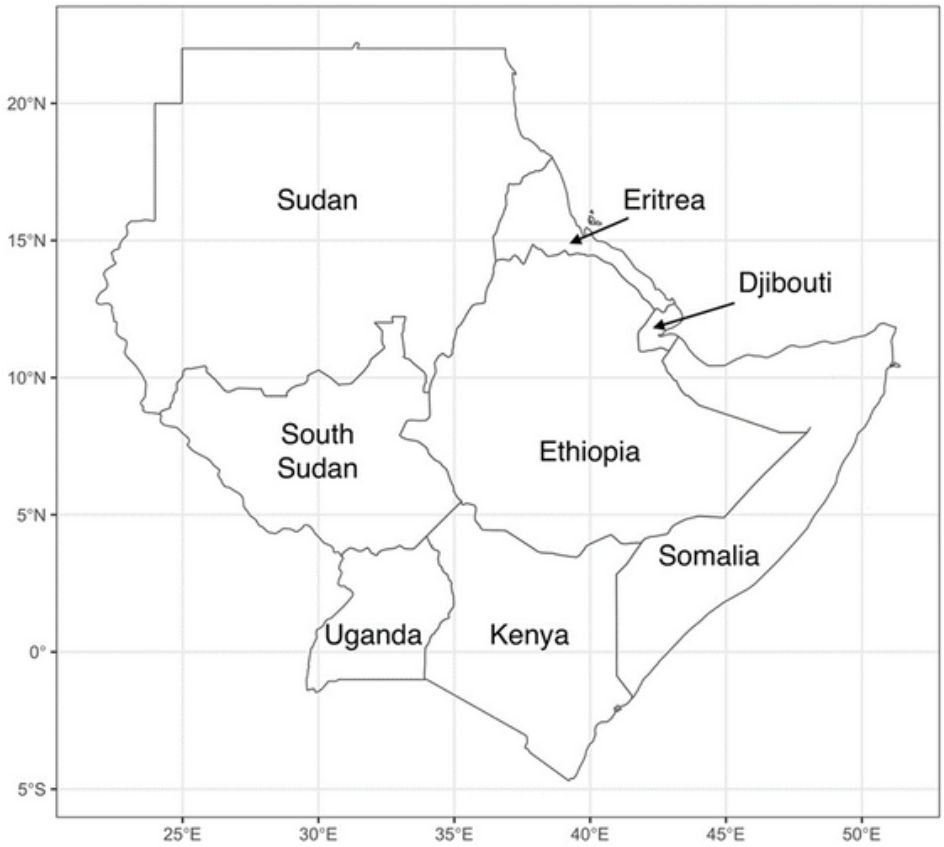


Figure 1. A map of IGAD States

LIST OF ABBREVIATIONS USED IN THE GRAPHS

Hist.

Conflict history (including one-, two-, and twelve-month lags).

Spl.

Spatial lags, namely whether there was a conflict in a nearby location/cell.

TZ.

Sahara transition zone.

NDVI.

Environmental health.

Drt.

Drought/SPEI.

Temp.

Temperature

Prec.

Precipitation/rainfall.

Env.

All climate and environmental health predictors (tz., NDVI, drt., temp., and prec.)

Food.

Cash and food crop and cash and food crop productivity indicators.

NTL.

Night-time light emissions.

POP.

Local population density

Count.

Country fixed effects

3. DATA

UNIT OF ANALYSIS

For analysis, the area of all the states plotted in **Figure 1** is divided into a grid consisting of 1,730 squares measured at the 0.5 decimal degree resolution cell – or squares of about 55km x 55km at the equator. I refer to these squares as "locations" throughout this report. For each location, the data include monthly information. The unit of analysis here is therefore the 0.5-degree cell-month, and is a major improvement on past analyses, which usually only analyse such localized information for every year, meaning they are unable to identify potentially crucial determinants such as the impact of seasonal changes or harvests on conflict and violence.

CONFLICT AND POLITICAL VIOLENCE INDICATORS

The political violence phenomena analysed in this report are as follows: (i) battle events initiated by state forces from the Armed Conflict Location and Event Dataset (ACLED) (Raleigh et al. 2021); (ii) battle events fought as part of a war between governments and rebel groups recorded by the Geolocated Event Dataset (GED) (Sunderg & Melander 2013); (iii) battle events initiated by rebels from ACLED; (iv) battle events fought between two or more nonstate actors (including farmer-herder conflicts) from GED; violence against civilians incidents perpetrated by (v) state actors, (vi) rebels and (vii) militias from ACLED and (viii) riots (ACLED). Due to the overall rarity of conflict events in the sample and the need to evaluate predictive strength of the different models, each of these indicators is defined based on ***whether a given location experienced at least one event during a given month*** (=1) or not (=0).

CONFLICT DETERMINANTS

I considered a variety of potential indicators used in conflict and environmental/climate security research. Considering missingness issues and having tested a wide range of variable choices, the indicators chosen should capture the entire range of conflict explanations discussed in the TOR without "overfitting" the relevant models, that is hurting the models' applicability to future events. The explanatory indicators included in the models are as follows:

1. HISTORICAL AND SPATIAL CONFLICT TRENDS:

a. **One-month lags** of each conflict phenomena, i.e., whether or not at least one conflict event happened in the same location ***one month prior.***
b. **Two-month lags** of each conflict phenomena, i.e., whether or not at least one conflict event happened in the same location ***two months prior.***
c. **One-year lags** of each conflict phenomena, i.e., whether or not at least one conflict event happened in the same location ***one year prior***.
d. **A spatial lag**, i.e., whether at least one conflict event happened in a ***neighboring (contiguous) location*** during the same month.

2. ENVIRONMENTAL AND FOOD INDICATORS:

a. **Sahara Desert transition zone**, which measures whether a given location was within the ***Sahara expansion boundaries*** (experiencing low levels of greenery and less than 200mm precipitation) during a given year, a region that scholars and policymakers argue is especially susceptible to both conflict and harsh conditions (e.g., Hendrix and Salehyan, 2012; Raleigh and Kniveton, 2012). For instance, these regions may experience from greater period of agricultural scarcity, inducing greater competition over agricultural resources, especially during and after the harvest (e.g., Schon et al., forthcoming).
b. **Environmental health**, which measures the range (in precents) of a given location that had ***"green" coverage*** during a given month (officially, this variable is known as the Normalized Difference Vegetation Index, or NDVI).
c. **Drought severity** measured using the Standardized Precipitation Evapotranspiration Index (SPEI). Unlike other drought indicators, SPEI accounts not only for rainfall but also potential evapotranspiration by incorporating the impacts of both precipitation and temperature. The SPEI indicator can hence be conceived as ***a measure of water deficit*** in a given location during a given month.
d. **Temperature**, i.e., the ***average temperature in a given location*** during a given month (as often done in research, this measure was logarithmically transformed to a continuous linear measure to account for wide-range biases).
e. **Precipitation**, i.e., the ***average rainfall (in mm)*** measured in a given location during a given month (as often done in research, this measure was logarithmically transformed to a continuous linear measure to account for wide-range biases).

3. AGRICULTURAL AND FOOD PRODUCTIVITY:

a. **Cash crops,** namely whether the main crop produced in a given location (if any) was a ***cash crop (oil, cotton, and sugarcane)***. Locations with N/As were converted to =0 (i.e., no production). Values are for 2003.
b. **Cereals and grains**, namely whether the main crop produced in a given location was a cereal crop or a grain (wheat, maize, rice and millet, sorghum). Locations with N/As were converted to =0 (i.e., no production). Values are for 2003.
c. **Fruit**, namely whether the main crop produced in a given location was a fruit (e.g., mangos, bananas). Locations with N/As were converted to =0 (i.e., no production). Values are for 2003.
d. **Cash crop productivity**, namely the level of vegetation health within areas that primary produce cash crops as defined in (a).
e. **Cereal and grain productivity**, namely the level of vegetation health within areas that primary produce cereals and grains as defined in (b).
f. **Fruit productivity**, namely the level of vegetation health within areas that primary produce fruits as defined in ©.

4. SOCIOECONOMICS:

a. **Nighttime light emissions** measured as the total level of lights observed within a given region during a given year – the most often used measure of local development and economic activity (Chen and Nordhaus 2011; Koren and Sarbahi 2018). Unlike the measures usually used in these regards, this indicator is more sensitive and captures local development levels even in largely rural areas, which other measures often miss (as is often done in research, this measure was logarithmically transformed to a continuous linear measure to account for wide-range biases).
b. **Population density,** measured as the total number of people residing within a given location during a given year (as often done in research, this measure was logarithmically transformed to a continuous linear measure to account for wide-range biases).

5. OTHER EMPIRICAL "CONTROLS" (NO SUBSTANTIVE INTERPRETATION):

a. **Country "fixed effect**" indicators, which account for all general country-specific factors (e.g., GDP, Gini). This is a set of indicators, one for each country included in the sample (minus one which is used as reference), which in essence "fix" the effect of each country. For every month and year in the sample, all locations within – say – Ethiopia get a value of 1, and all locations outside of Ethiopia a value of zero. The next indicator then does the same for, say, Sudan, and so forth. These indicators accordingly have no substantive interpretations.
b. **Temporal indicators** capture the possibility that the risk of conflict changes during factors related to specific months or over time due to reasons other by the variables discussed in 1-4.
c. **Clustering by location** to adjust the estimates for the possibility that some indicators include similar information recorded over time.

4. METHODS, ESTIMATION, AND MEASURING PREDICTIVE PERFORMANCE

The sample relies on a location-month framework for all IGAD countries, where a "location" is defined geographically as a 0.5-degree cells, or squares of approximately 55km x 55km, which increase in size as one moves toward to poles. Note that the dataset I used to construct the agricultural and food productivity indicators – the Spatial Production Allocation Model (SPAM) dataset – did not include locations located in many desert areas due to the lack of availability of relevant information. As discussed in "Limitations," because we can be fairly certain that no value crops are being produced in these missing information locations, I changed these missing information areas from "no information available" to "0" without the fear of introducing bias.

In line with major conflict forecasting efforts such as the Presidential Instability Task Force (PITF), the underlying statistical model used is logistic regression, or logit (Goldstone et al. 2010). A major advantage of this method is that – unlike some machine learning based approaches (e.g., random forests, support vector machines) – allows for a substantive interpretation of each determinant, while providing (in most cases) similar to or better performance than such computational methods (Schrodt 2017). Once adjusted for temporal dependencies and "clustering" as mentioned in part 5 of the previous section, these models should provide an effective and powerful tool for assessing the predictive impacts of different local-level impacts, once the following assessment protocols are employed:

1. **General validation:** The full model with all determinants listed in steps 1-5 is estimated to ensure that there are no convergence, monotone likelihood, or other statistical problems.
2. **Creating a training and test framework:** The dataset is divided into two segments. The first, ***or "training" segment***, will be used to re-estimate the model from 1 as well as the reduced form models (discussed below), and the resulting estimates will be then used to evaluate the predictive effectiveness of each model ***based on the "test" dataset.***

- There are two thresholds for separating the training and test datasets:

1

i) one-year forward (i.e., using the last year in the data as a test subset) and

5

(ii. five-year forward (i.e., using the last five years in the data as a test subset).

- The predictive strength of each model is evaluated using a tool called **"precision-recall (PR) curves."** The use of PR curves is recommended in extent research for situations where the researcher is interested in rare events such as conflict (Beger 2016). The metric of interest is the area under the curves (AUC), which measures how many of the conflict events analyzed could be effectively predicted by the model. Because this tool is designed to be less sensitive to avoid risk of overprediction, an AUC of 0.3-0.5 (i.e., a model that successfully predicts 30%-50% of events) is considered a good fitting model (Ward & Beger 2017). However, because the data used here is far sparser than usual conflict data (that is, the ratio between conflict to non-conflict events is very small), I treat **a model with an AUC of over 0.2 as calibrated** and assess the predictive contribution of each determinant therein accordingly.

3. **Evaluating predictors**: Having established an effective specification for the full model and identified an effective threshold of accepting predictive performance, I then turn to evaluate the individual impact of each determinant/predictor on the model as a whole. This approach works better than using other measures (e.g., statistical significance, marginal effects) because it;

(i) Tests how this determinant improves the predictive out-of-sample performance of

(ii) The model as a whole (rather than based on some unrealistic "all else equal" scenario).

Note that an indicator that reduces the risk of conflict (e.g., greater levels of development) can still has a positive impact on improving prediction – it tells us where conflict is less likely, which is important information for the model to predict conflict. The process of estimation and evaluation is as follows:

a. The full model is estimated on the training data with the predictor in question (e.g., droughts, country indicators) removed.

b. The model estimates are used to predict conflict in the test (one or five year forward) data.

c. The precision-recall curve of the model based on this prediction exercise is plotted and the area under the curve (AUC) is calculated.

d. The difference between the AUC of this reduced model and the full model is calculated and normalized as percent change of reduced form model.[**2**]

e. Having done this for all predictors mentioned in the Conflict Determinants section, as well as combination of specific categories (e.g., all environmental indicators), which means estimating 11 separate model in addition to the full model (a total of 12 models for each conflict measure), I plot these predictive impacts in one summary plot.

4. **Using different lengths of future data:** I repeat the exercises in parts 2 and 3 twice, once for one-year in the future as a test dataset and again for a five-year in the future test dataset.

[**2**] This calculation was done as follows: [(AUCfull model – AUCreduced model)/AUCfull model]*100

5. LIMITATIONS

This report relies on some of the best relevant data available and widely used methods for assessing predictive fit. However, there are several limitations the reader should bear in mind.

1

The analysis and evaluation of each predictor's impacts are focused on localized conflict events. In other words, the emphasis is on how each indicator improves our ability to predict whether a particular event – an attack, atrocity, demonstration – will happen in a particular location during a given month. These models are not intended to predict if a major campaign (civil war, mass killing) will arise at the country level, although the results can inform such efforts by identifying where such campaigns may onset locally.

2

While the event datasets used here are considered among the best in existence, they are subject to the risk of reporting biases. Generally, incidents data are generally regarded as more accurate the fatality data (e.g., Weidmann 2015), which is why researchers focus on incident events almost exclusively. Nevertheless, it is important to bear in mind that the science of localized conflict forecasting is still at its early stages (Hegre et al. 2021).

3

The approach used here does not account for the possibility that just like environmental, climatic, and socioeconomic factors could affect conflict, protracted violence could impact environmental stability. This problem is called endogeneity. To some extent, the climatic and environmental measures used here are "plausibly exogenous," namely, they are highly unlikely to be affected by conflict. Moreover, for predictive purposes, endogeneity is not necessarily a concern (see, e.g., Koren 2017). However, it does mean that one cannot claim these effects cause conflict, only that their presence and variability affects our ability to make accurate conflict forecasts.

4

In the crop data, areas where no information on production was available (and would hence would have been omitted from analysis) were converted to zeros (there is, included in the analysis as areas where none of the crops of interest were grown). This is an assumption that could be problematic seeing that we do not know for sure no crops are being produced there, *we just do not have information on whether this is the case*.

Considering that the crop indicators used to assess the impact of agricultural commodities on conflict and violence (tobacco, tea, bananas, wheat, maize, etc.) all require generally climate that is more hospitable than what desert conditions have to offer, while most locations with missing information on production are located in desert areas, we can be fairly certain that no value crops are being produced in these missing information locations. From this perspective, changing these areas from "no information available" to "0" should not introduced much bias. Nevertheless, this is an issue that the reader should bear in mind when interpreting the results. There are also concerns related to the potential impacts of climate change on these data, e.g., because people shift to more drought resistant crops. Note, however, that an informal assessment of data (including updated reports from more recent years) suggests that the biggest contributor to whether a given location will shift from one crop to another is ongoing conflict, not climate. Nevertheless, this is another issue the reader should bear in mind.

5

With respect to "natural resources," the report focuses on agricultural and environmental resources. Other natural resources – gold, diamonds, gems – have been potentially linked to conflict incidence (e.g., Lujala et al. 2005). However, as **Figure 5** below illustrates, the data reports very few areas where such resources are available. As a result – and considering the possibility that the inclusion of such a zero (i.e., no resources) indicators might bias the models – I did not include those indicators in the models. As the **Figure 6** below additionally show, conflict risk predictions rarely overlap with these locations, suggestions this decision should not bias the models.

6

While the models all include general country indicators, they do not include measures for specific country indicators (e.g., democracy, GDP). The reason was that World Bank indicators – which provide the most comprehensive coverage of such factors – did not have information for most period of interests on two IGAD countries (South Sudan and Eritrea). Moreover, when I estimated the predictive performance of models that did include such measures, they tended – on average – to harm model performance, potentially due to overfitting the models. Accordingly, I decided to use the more general indicators, which account for such issues without inducing missingness.

7

The forecasts made here are for one-year and five years into the future. Considering the possibility of unknown events happening over longer periods of time, this report makes no claims as to each predictor's impacts beyond this five-year window.

8

On a related note, it is important to emphasize that due to the inherent complex and unpredictable nature of climate change, we fail to identify effect for the environmental and agricultural predictors simply because we are measuring them over a long period of stasis. It is possible that at some point—maybe when we reach a certain threshold of rising temperatures—we will enter a new period of much faster and more extreme changes in local habitable environments and agricultural productivity and access due to, e.g., massive increases in the frequency of flooding, droughts, and heatwaves. In other words, the relationship between climate change and conflict might experience a tipping point, after which we shift from experiencing conflicts whose primary reasons are sociopolitical and economic – for instance, the civil wars of post-World War II and post-Cold War (Fearon and Laitin 2003) – to experiencing conflicts that are primarily driven by environmental motivations (see, e.g., Koren 2022). Unlike slow and linear effects, such 'punctuated equilibrium' shifts and their resulting impacts are impossible to predict, although the results of this report can assist in preparations.

6. AN ASSESSMENT OF CONFLICT DETERMINANTS IN IGAD COUNTRIES

Figures 2-5 below report how each predictor (or category of predictors) discussed in Section 3 impacts conflict risk, which is operationalized here as our ability to predict conflict and violence. Additionally, Table 1 report all statistical estimates for the model, explaining whether each improvement is due to a positive association with conflict (i.e., higher conflict risk) or the opposite relationship (reducing the risk of conflict and violence).

Figure 2 shows examines how each predictor impacts our ability to predict conflict and violence from the ACLED dataset one year into the future. Beginning with the top-left plot, focuses on conflict events initiated by state forces, we can see that the best improvement (24%) in our ability to predict conflict is provided by accounting for a history of such conflicts, namely whether an attack occurred in the same location in the past month, two months, and year. The next best predictor is whether a nearby location experienced a similar conflict during the same month (6%), followed by areas that are more densely populated (5%). As **Table 1** shows, statistically, the coefficients on all these variables are positive and mostly significant, suggesting that in each case, the risk of state-initiated conflict increases when values on these indicators also increase. The rest of the indicators – including environmental ones – show no effect, or even harm model performance, suggesting that they do not provide a good explanation for state led conflicts. It is important to note that the overall performance (AUC) of the model is relatively high (0.326), suggesting calibration and specification are valid.

Moving to the top-right plot, which examines conflict events initiated by rebels, we see more variability. While a history of conflict, conflict in nearby locations the same months, and greater population densities are still the predictors, climate and environmental factors (combined) now emerge as a relevant explanation for rebel attacks (8%). Country-level factors, crop productivity, and temperature (separately from all environmental factors in the aggerate) also provide modest explanations for rebel attacks.

As **Table 1** shows, statistically, these environmental impacts appear to be the result of environmental degradation – the risk of conflict increases in warmer periods, times of drought, and during months of decreased rainfall. This suggests that rebel attacks are potentially more likely to be motivated by environmental concerns or and/or incentives for rapacity and looting of agricultural resources. Overall model performance is above the 0.2 threshold we defined for a model to be considered calibrated, i.e., for the determinants included in the model to provide – together – an effective explanation for rebel-initiated conflicts in the region.

The center-left plot focuses on violent riots and their predictors. Again, the strongest predictor is a history of riots, followed by population densities and local development levels (both unsurprising considering riots generally happen in cities and towns) and whether nearby locations also experienced riots the same month. As **Table 1** shows, statistically, greater/positive values on each of these indicators is associated with an increase in conflict risk. Environmental and crop indicators do not seem to matter in this case, although it is important to remember that this may be the result of the fact that environmental degradation impacts primarily rural areas. While this can indirectly contribute to riots in urban areas, e.g., by affecting food prices or possibly inducing migration, these are not local level effects that the modeling approach here can capture. This may also explain why model performance is relatively weak (below the 0.2 threshold), which suggests these predictors do not provide a very good explanation for riots.

> **Rebel attacks are potentially more likely to be motivated by environmental concerns or and/or incentives for rapacity and looting of agricultural resources.**

The last three plots then assess the impact of each predictor on violence against civilians initiated by state forces (bottom-left), rebels (center-right), and pro-government and nonaligned militias (bottom-right). In the case of state violence against civilians, we generally see each factor making the same impact as it did on conflict risk, although model performance is slightly lower (0.237), but still above the calibration threshold.

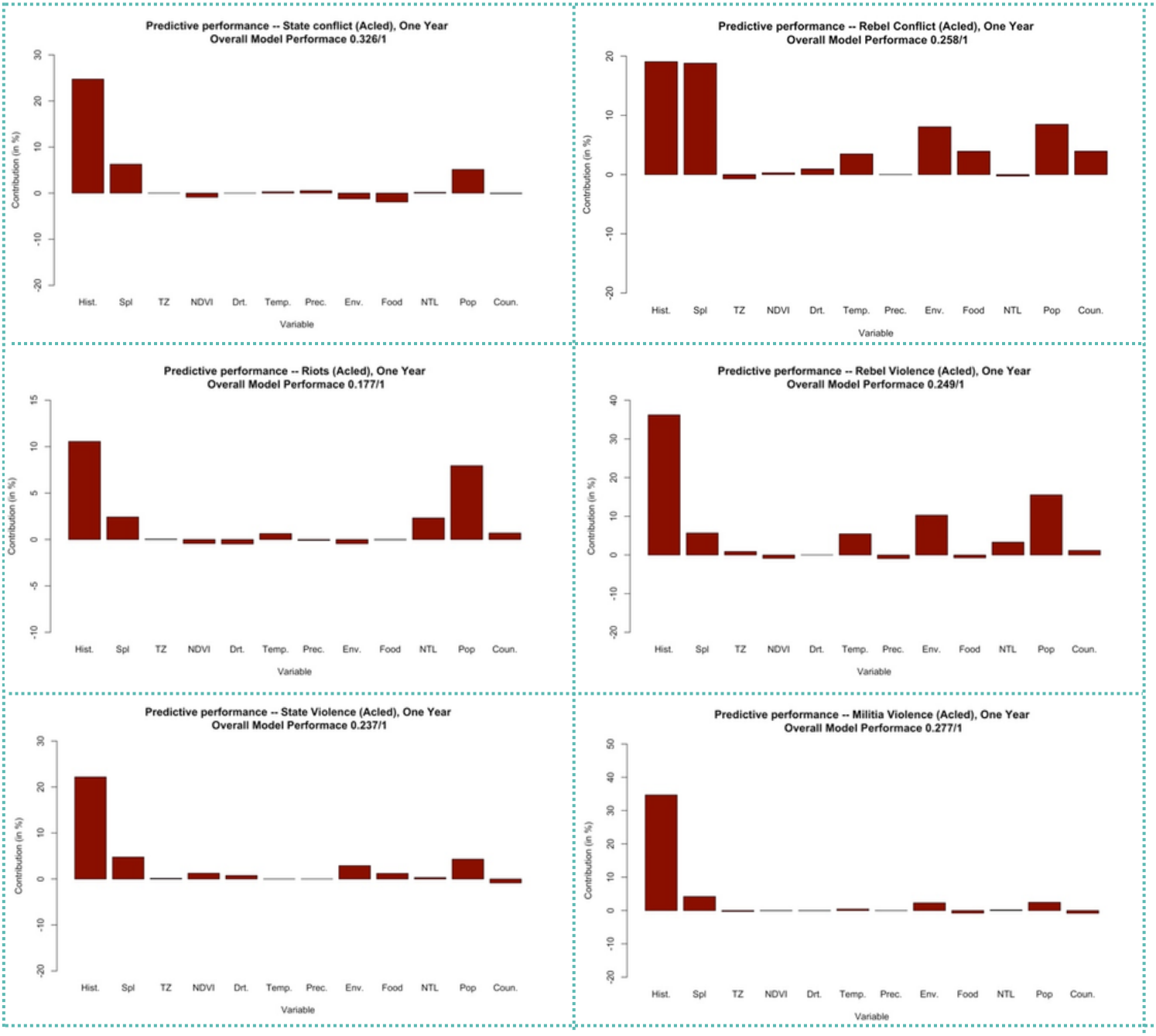


Figure 2. Predictor contribution for one-year-ahead data, ACLED indicators.

In the case of rebel violence against civilians, a history of rebel attacks emerges as an even more important risk factor of violence compared with conflict events (contributing to nearly 40% of the model's performance). Population densities, environmental and climate indicators, and – separately – temperature are still the next most important risk factors. As Table 1 shows, statistically, the statistically significant coefficients of each environmental and climate indicator is in line with the environmental degradation logic. One exception is that violence rebel violence seems to be decreasing in Sahara Desert transition zones, which is in line with new research (Schon et al., forthcoming). Generally, model calibration values are similar to the rebel-initiated conflict model and above the calibration threshold.

Finally, researchers have long been concerned with the potential role of militias as a threat to civilian wellbeing (e.g., Koren 2017). To this end, the bottom-right figure shows that the strongest – and already clearly relevant – risk factor of violence against civilians by militias is a history of such attacks. Again, the model's AUC is above calibration threshold.

Figure 3 plots the role of each determinant in predicting conflict from the GED datasets. A key difference between GED and ACLED is that the former codes only incidents that (i) involved at least one casualty and (ii) occurred as part of a broader conflict with at least 25 deaths. This makes these indicators more likely to capture "true" civil war incidents compared with ACLED data, which are more focused on lower level attacks that may occur both during but also independently of an ongoing civil war.

Turning to the figure on the left, which analyzes state-initiated conflicts (GED), we can see that the same general relationship as identified in the ACLED state-initiated data holds. The strongest risk factors (in ascending order) are a history of state conflicts (22%), greater population densities (6%), and whether a state conflict occurred in a nearby location the same month (4%). As Table 1 shows, statistically, the sign of these coefficients is in the expected (positive) direction, and they are significant in most cases. Overall, the model's AUC is 0.291, which is above our 0.2 calibration threshold, suggesting the indicators included provide a relatively effective explanation for state conflicts in this case.

The figure on the left focuses on conflict initiated by nonstate actors. ***This category includes farmer-herder conflicts, attacks involving crime and banditry, etc***. The strongest risk factor is whether such attacks occurred in a nearby location during the same (~50%) followed by a history of conflict (9%). ***Most importantly, in contrast to the ACLED rebel models, environmental health and cash and food crops harm our ability to predict nonstate conflict, suggesting deadly attacks may arise due to different incentives than those underlying violent attacks more generally.*** However, considering the model AUC is 0.07, which is well below our 0.2 calibration threshold, it does not seem that the predictors included therein provide a sufficiently good explanation for nonstate conflict, suggesting other explanations – which we do not analyze here – are more important.

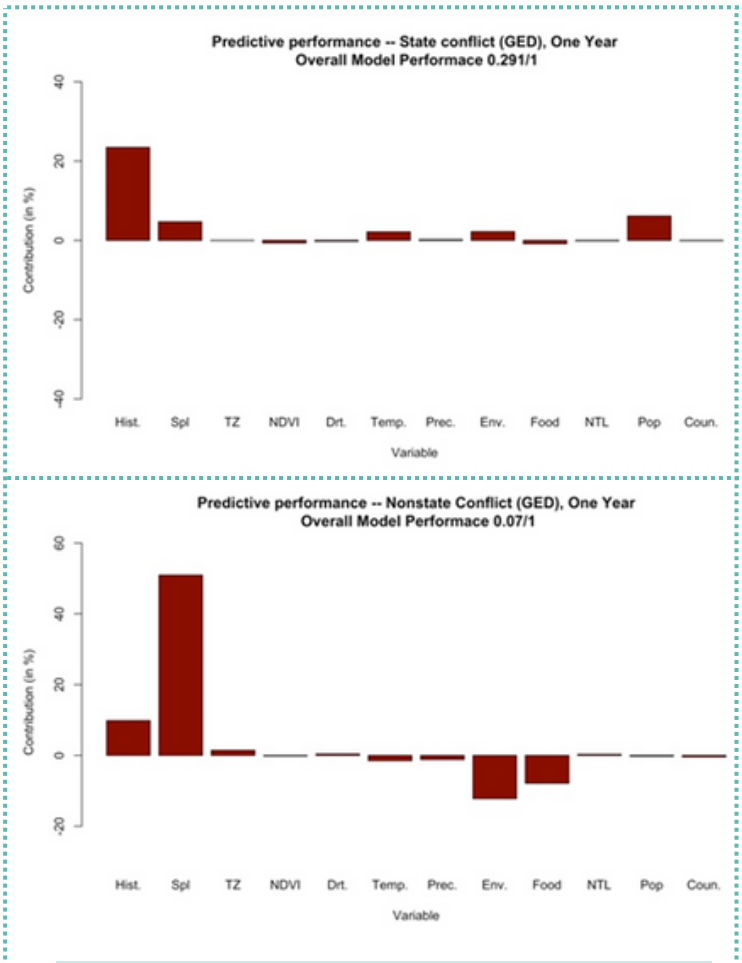


Figure 3. Predictor contribution for one-year-ahead data, GED indicators.

Figures 4 and **5** repeat the analyses from **Figures 2** and **3** (respectively), only this time evaluating how each predictor contributes to our ability to explain and forecast conflict and violence five years into the future. The results generally hold for state-forces-initiated conflict and violence in both the ACLED and GED datasets, suggesting the same risk factors highlighted for predicting violence one year into the future are valid when we try to forecast conflict and violence five year into the future. The models lose some of their overall predictive power, which is not surprising due to the expansion of the time window for forecasting, but they are still well above the 0.2 calibration threshold.

Similarly, the militia-initiated attack against civilians models are generally in line with the one-year-forward model, with two important exceptions:

(i) Many of the predictors that had no effect on the latter actually harm performance in this case, and

(ii) The model now falls below the 0.2 calibration threshold, suggesting any risk factors should be considered with caution.

In the case of the riot models, both predictor contributors and model performance are somewhat improved, moving from below the calibration threshold to slightly above it.

The biggest differences between the one-year and five-years forward forecasting exercises occurs in the rebel-initiated conflict and violence data. Conflict history and nearby conflicts the same month are still the strongest predictors in the five-year forward models. ***However, climate, environmental, and food and cash crop indicators now harm our ability to predict violence and conflict by rebels.*** This is perhaps best exemplified by the case of temperature, which contributed about 5-6% to the predicting conflict risk in the one-year forward conflict and violence models (**Figure 2**) but are harming its performance by the same rate in the five-year forward models (**Figure 4**). Additionally, as a whole, the five-year forward rebel-initiated conflict and violence models now fall below calibration threshold of 0.2, suggesting that the predictors included therein do a subpar job in explaining why rebels will engage in conflict and violence five years from now.

“The results generally hold for state-forces-initiated conflict and violence in both the ACLED and GED datasets, suggesting the same risk factors highlighted for predicting violence one year into the future are valid when we try to forecast conflict and violence five year into the future

These different issues highlight the potential limitations of using medium- and long-term climate and environmental variability trends for predicting conflict. In line with points 6 and 7 under “Limitations,” this suggest that any attempts to quantify or incorporate the effects of climate changes on conflict and violence trends should interpret medium- and long-term impacts very cautiously, highlighting the sensitivity of such interpretations and the variability of the impacts.

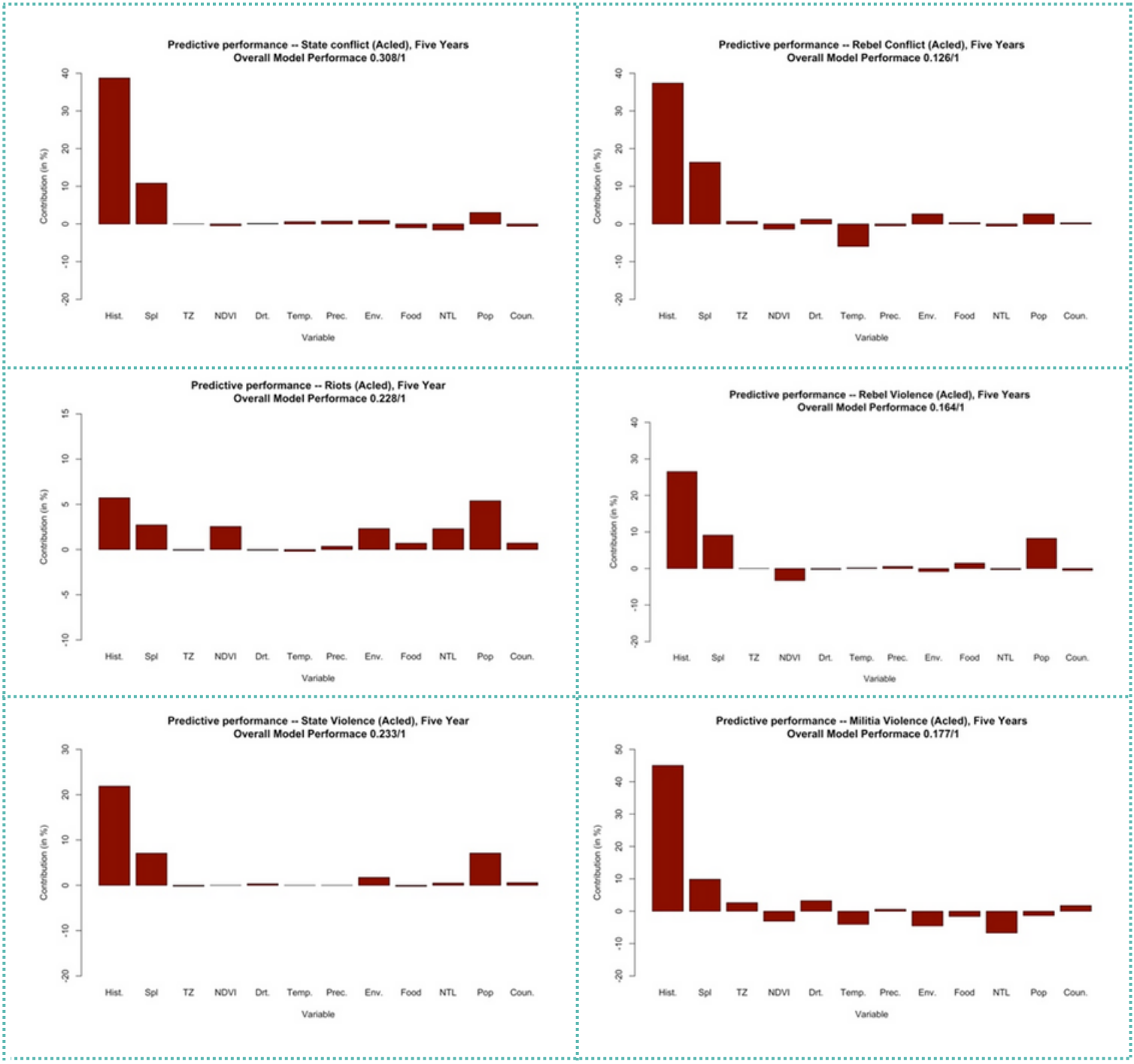


Figure 4. Predictor contribution for five-years-ahead data, ACLED indicators.

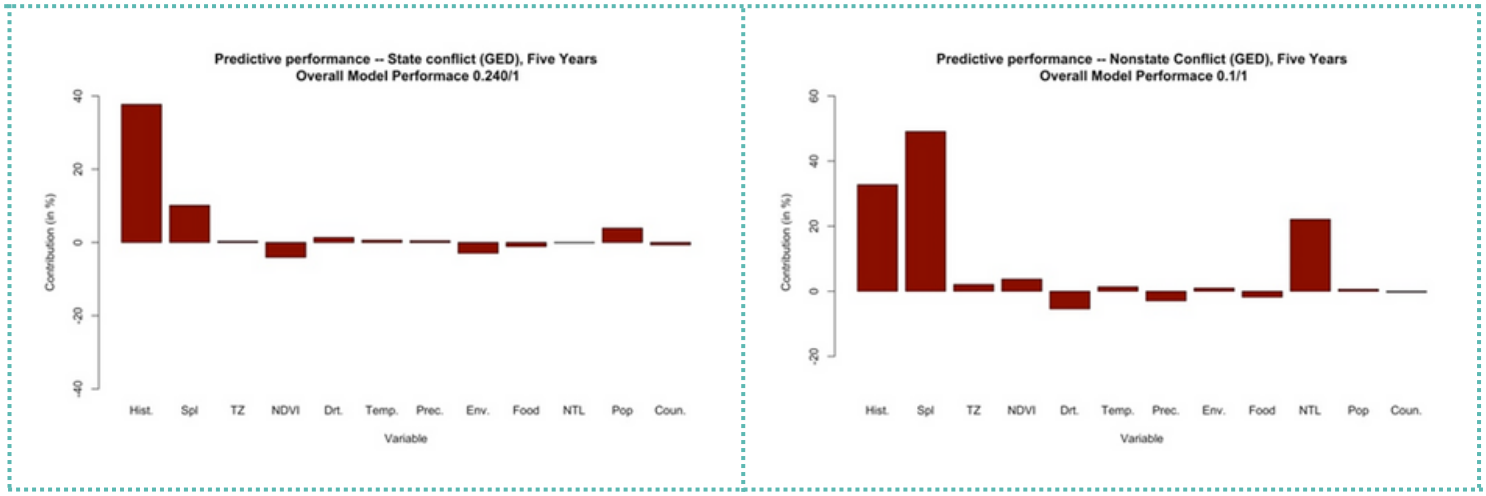


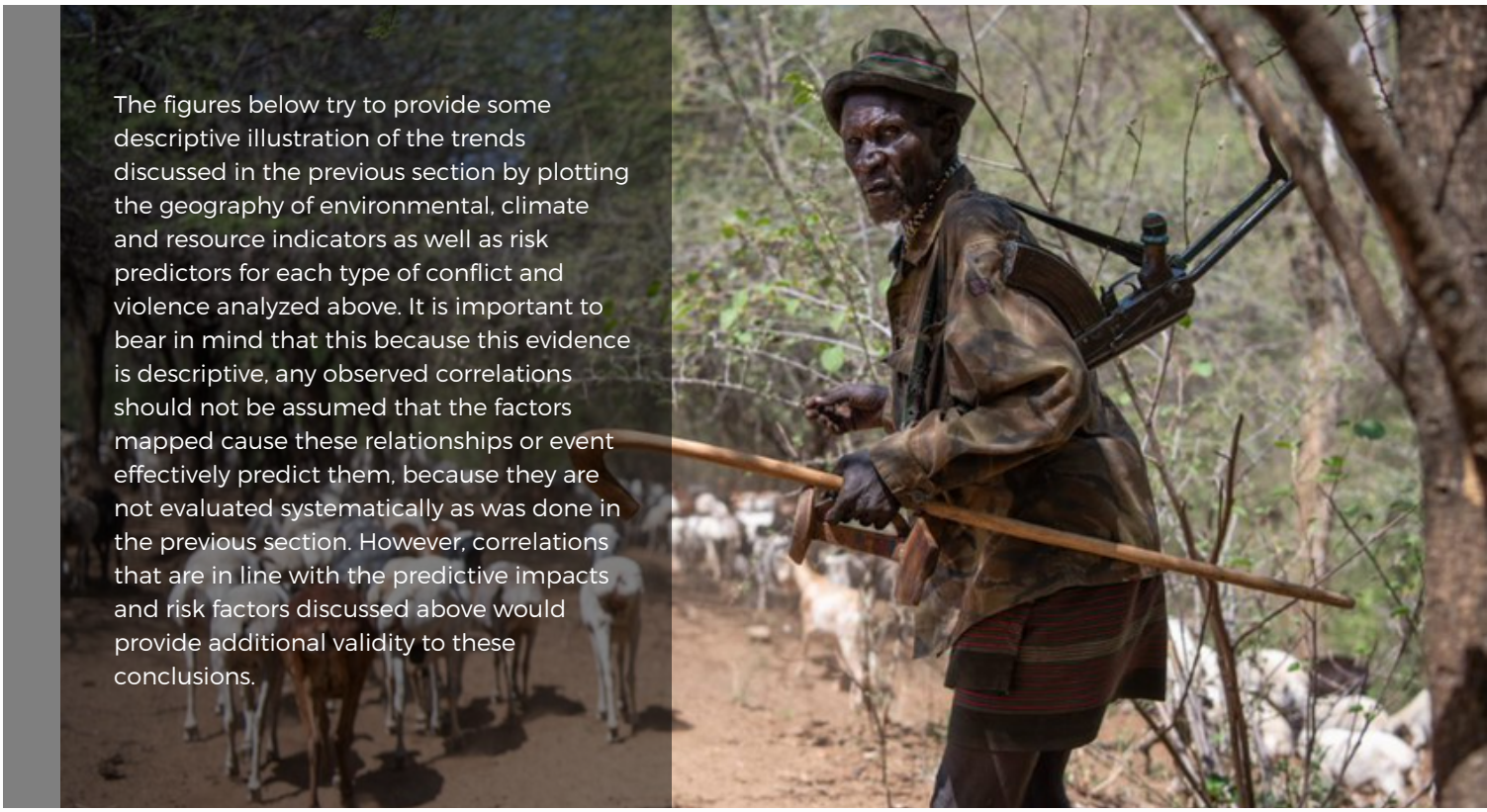
Figure 5. Predictor contribution for five-years-ahead data, GED indicators.

Table 1: Logit Estimates of Conflict Predictors in IGAD States

	State (ACLED) (1)	Rebel (ACLED) (2)	State (GED) (3)	Nonstate (GED) (4)	Riots (ACLED) (5)	State viol. (ACLED) (6)	Rebel viol. (ACLED) (7)	Militia viol. (ACLED) (8)
$Conflict_{it-1}$	0.235***	0.175	0.132	−0.117	0.138	0.154	0.213*	0.259***
	(0.063)	(0.116)	(0.095)	(0.200)	(0.103)	(0.102)	(0.112)	(0.060)
$Conflict_{it-2}$	1.525***	1.982***	1.976***	1.996***	0.851***	1.591***	1.527***	1.566***
	(0.053)	(0.098)	(0.078)	(0.196)	(0.081)	(0.081)	(0.095)	(0.047)
$Conflict_{it-12}$	1.229***	1.406***	1.393***	1.502***	0.643***	1.102***	1.364***	1.244***
	(0.058)	(0.097)	(0.089)	(0.259)	(0.088)	(0.094)	(0.101)	(0.051)
$Nearby\ conflict_{it}$	2.577***	2.955***	2.896***	3.886***	1.244***	2.193***	2.678***	2.180***
	(0.056)	(0.097)	(0.082)	(0.157)	(0.088)	(0.086)	(0.099)	(0.053)
TZ_{it}	−0.030	0.103	0.021	−0.306	−0.119	0.153**	−0.434***	0.338***
	(0.066)	(0.092)	(0.091)	(0.190)	(0.112)	(0.076)	(0.136)	(0.053)
$NDVI_{it}$	0.398**	−0.095	0.028	−0.752*	−2.120***	−0.837***	2.174***	−1.390***
	(0.171)	(0.285)	(0.236)	(0.438)	(0.281)	(0.278)	(0.287)	(0.180)
$Drought_{it}$	0.013	0.127***	0.061**	0.070	−0.058*	0.109***	0.033	0.080***
	(0.021)	(0.033)	(0.029)	(0.055)	(0.030)	(0.030)	(0.036)	(0.020)
$Log\ temp._{it}$	1.676***	1.762***	1.505***	2.020***	−0.298	0.544***	4.612***	0.788***
	(0.153)	(0.244)	(0.209)	(0.391)	(0.184)	(0.192)	(0.331)	(0.133)
$Log\ prec._{it}$	−0.068***	−0.064***	−0.047**	−0.030	0.042*	−0.010	−0.117***	−0.007
	(0.015)	(0.022)	(0.020)	(0.037)	(0.024)	(0.020)	(0.025)	(0.013)
$Cash\ crops_{it}$	0.551***	0.620***	0.907***	0.816**	0.754***	0.462**	1.792***	0.285**
	(0.128)	(0.193)	(0.162)	(0.329)	(0.182)	(0.190)	(0.192)	(0.111)
$Cereals_{it}$	0.469***	0.816***	0.691***	0.373	0.032	0.585***	1.134***	0.504***
	(0.094)	(0.148)	(0.128)	(0.240)	(0.170)	(0.144)	(0.176)	(0.088)
$Fruits_{it}$	−0.464**	−0.956**	−1.583***	−0.261	0.452**	0.429	−0.916**	−0.026
	(0.225)	(0.443)	(0.409)	(0.565)	(0.214)	(0.295)	(0.391)	(0.184)
$NDVI_{it} \times Cash\ crops_{it}$	−2.108***	−1.365**	−2.493***	−2.982***	−0.770**	−1.849***	−3.734***	−0.619**
	(0.376)	(0.533)	(0.482)	(1.042)	(0.368)	(0.515)	(0.514)	(0.297)
$NDVI_{it} \times Cereals_{it}$	−0.643***	−0.906***	−0.956***	−0.035	0.015	−0.423	−1.987***	−0.269
	(0.217)	(0.346)	(0.308)	(0.573)	(0.349)	(0.312)	(0.402)	(0.209)
$NDVI_{it} \times Fruits_{it}$	0.044	0.628	1.495**	−0.855	−0.384	−1.076**	1.021	−0.152
	(0.393)	(0.745)	(0.682)	(1.103)	(0.405)	(0.541)	(0.627)	(0.341)
$Log\ NTL_{it}$	0.038***	0.041***	−0.003	0.063***	0.289***	0.167***	−0.037***	0.103***
	(0.006)	(0.010)	(0.009)	(0.017)	(0.015)	(0.012)	(0.010)	(0.007)
$Log\ pop.\ dens._{it}$	0.270***	0.248***	0.233***	0.194***	0.456***	0.404***	0.412***	0.202***
	(0.018)	(0.028)	(0.025)	(0.043)	(0.029)	(0.026)	(0.030)	(0.017)
Constant	16.467***	−1.082	2.742	−20.887***	10.784***	1.597	15.448***	5.371**
	(2.580)	(4.278)	(3.493)	(6.203)	(4.067)	(4.102)	(4.123)	(2.494)
Observations	331,168	331,168	331,168	331,168	331,168	331,168	331,168	331,168
Log Likelihood	−15,875.980	−7,500.075	−9,572.895	−3,351.895	−8,007.640	−8,498.754	−6,658.396	−17,936.820
Akaike Inf. Crit.	31,799.960	15,048.150	19,193.790	6,751.790	16,063.280	17,045.510	13,364.790	35,921.640

Standard errors clustered by grid cell in parentheses; logging was done in natural base; fixed effects by month and time trend controls where included in each model, although none is reported here.
*** p<0.01, ** p<0.05, * p<0.1. t stands for month, i stands for cell/location, and j stands for country.

7. DESCRIPTIVE VISUAL EVIDENCE



The figures below try to provide some descriptive illustration of the trends discussed in the previous section by plotting the geography of environmental, climate and resource indicators as well as risk predictors for each type of conflict and violence analyzed above. It is important to bear in mind that this because this evidence is descriptive, any observed correlations should not be assumed that the factors mapped cause these relationships or event effectively predict them, because they are not evaluated systematically as was done in the previous section. However, correlations that are in line with the predictive impacts and risk factors discussed above would provide additional validity to these conclusions.

Figure 6 plots the values of six determinants of interest – (i) temperature, (ii) precipitation, (iii) drought, (iv) environmental health (NDVI) – averaged over 12 months for one specific year (2018) – in addition to (v) crop coverage, and (vi) valuable resources (diamonds, gems, and gold). **Figure 7** then plots the one-year foreword conflict risk predictions – i.e., the estimated probability of a conflict happening according to the fully specified model, averaged for all months in one specific year (2018).

Overall, the maps reveal some interesting information. Looking at the temperature map (upper-left) may explain why this variable may overpredict conflict – most locations exhibit relatively similar levels of average temperature. Other factors – cash and food crops, rainfall, and environmental health – show greater variability across different locations. Additionally, as the bottom-right figure illustrates, the availability of valuable natural resources (diamonds, gems, and gold) in the region is very limited – only 9 locations (cells) are recorded to contain resources, and they are all located in Kenya, suggesting their role as a predictor of conflict is very limited, and providing support for not including them in the prediction models.

Turning to **Figure 7,** several interesting trends emerge. First, more areas appear to be at a risk of experiencing some state-initiated conflicts according to ACLED compared with the GED, where conflict risk is concentrated heavily in Somalia. This is likely the results of the different standards used by GED which – as mentioned above – only capture events that involved at least one death and occur as part of a civil war. The same spread relates to political violence by state forces. Additionally, it appears that violence against civilians by militias is the trend that most closely overlaps with environmental health trends in **Figure 5**, potentially because many of these militias represent local communities of farmers and herders.

Turning to examine riots, the risk appears to be highest in Kenya and Uganda, and specifically in regions that are more densely populated, which is in line with the relevant predictors identified above. Additionally, it appears that Somalia is at the higher risk of experiencing both conflicts and political violence events initiated by rebels.

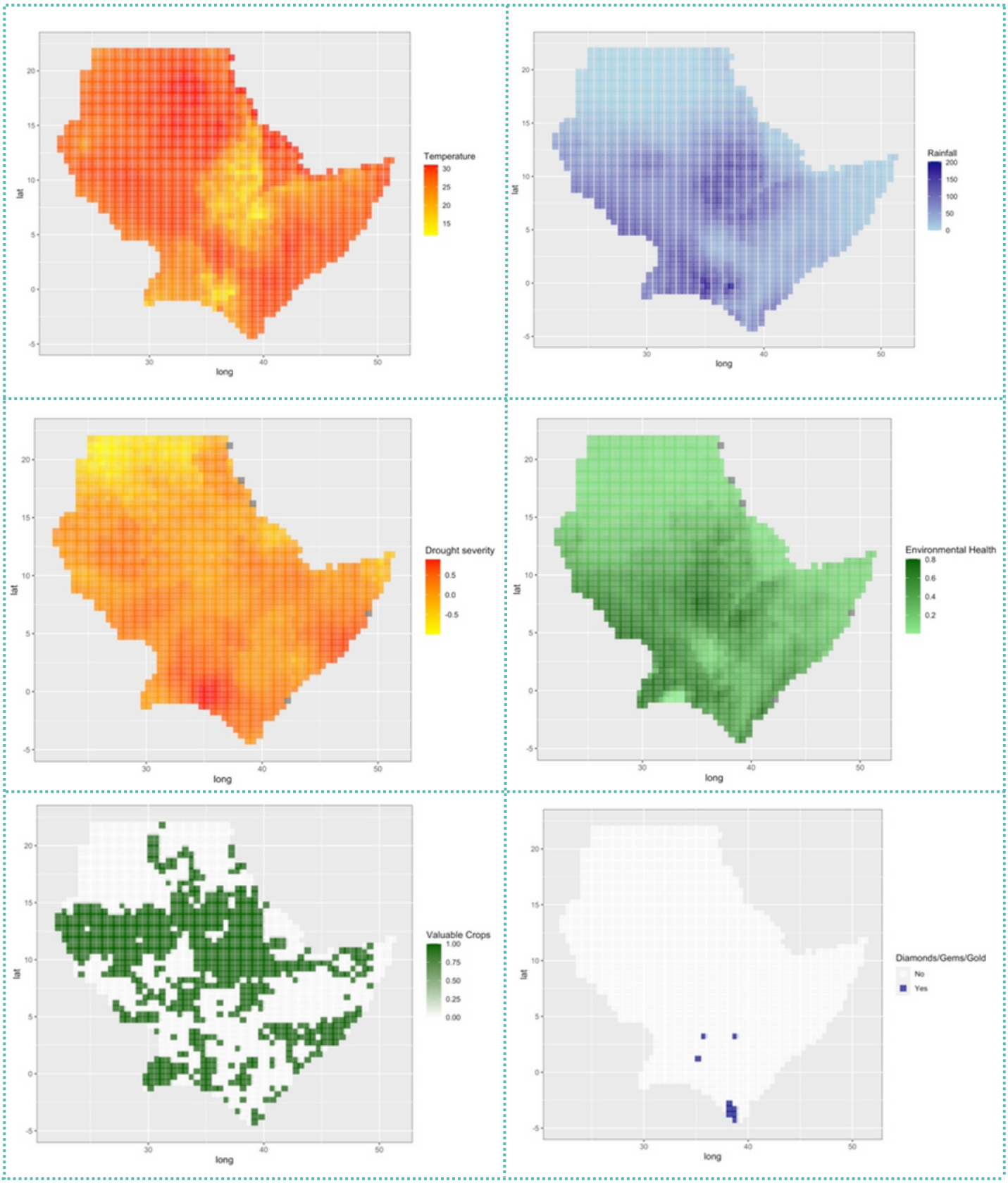


Figure 6. Maps of key environmental and natural resources predictors (2018 average)

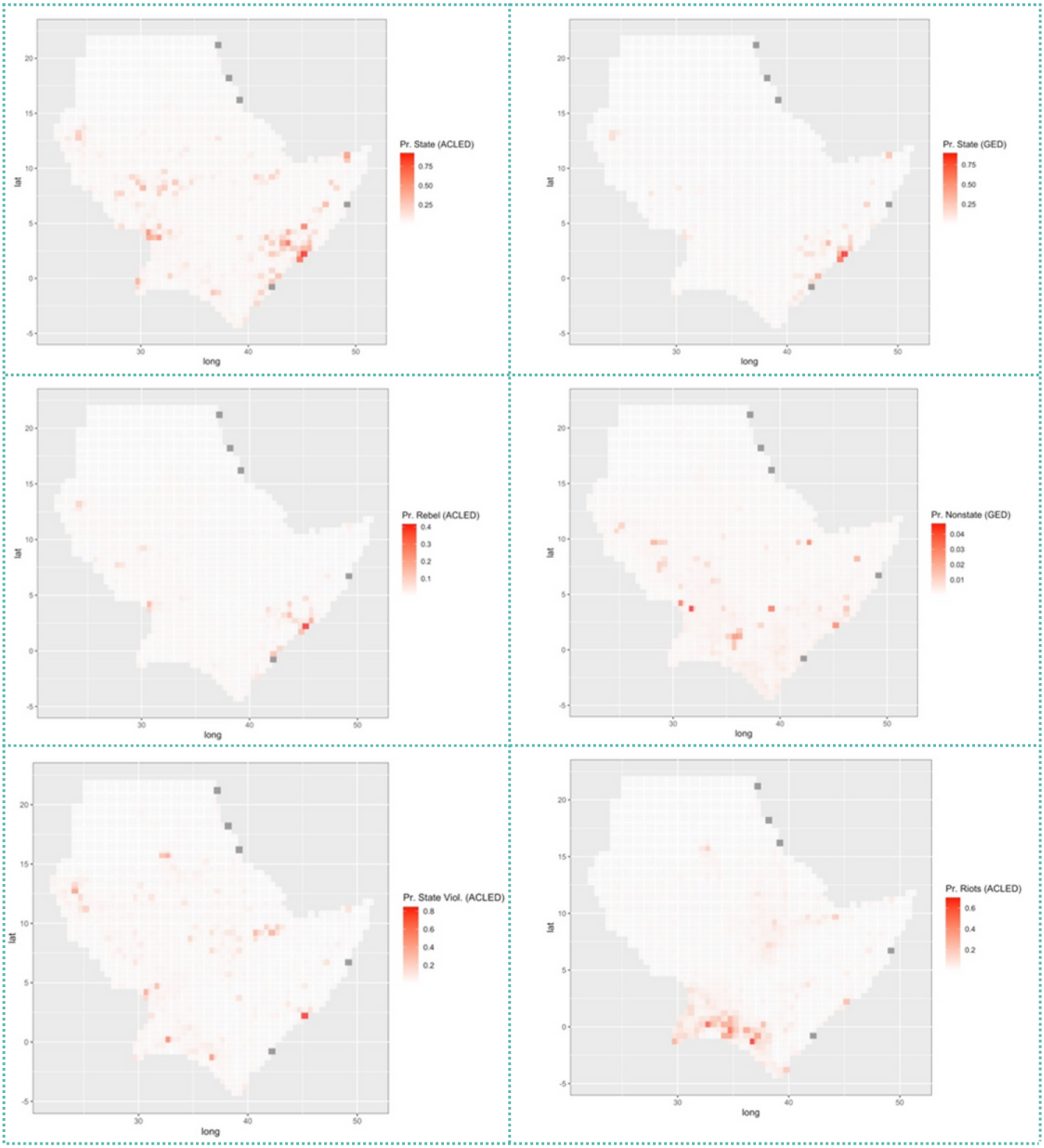

Pr. State (ACLED)
0.75
0.50
0.25
Pr. State (GED)
0.75
0.50
0.25
Pr. Rebel (ACLED)
0.4
0.3
0.2
0.1
Pr. Nonstate (GED)
0.04
0.03
0.02
0.01
Pr. State Viol. (ACLED)
0.8
0.6
0.4
0.2
Pr. Riots (ACLED)
0.6
0.4
0.2
lat
long

Figure 7. One-year-forward conflict prediction maps (annual average)

8. PREDICTING ENVIRONMENTAL AND CONFLICT TRENDS, 2022-2027

Figure 8 plots climate trend predictions based on historical values for the period 2022 – 2027. ***Each plot reports the predicted change in environmental and climate conditions for the 2022-2027 period based on monthly linear trends calculated for the region as a whole***. Accordingly, ***these predicted effects likely overestimate true trends in most locations***, especially on the margins (i.e., in areas where values are closer to zero, so even small changes appear larger in comparison to other locations): variations in temperature, precipitation and drought severity are likely over/under predicted, although in most cases, the expected changes are generally small. The results overall suggest some light fluctuations in predicted indicator values ("noise"), but not much intensification beyond the trends observed over the past period.

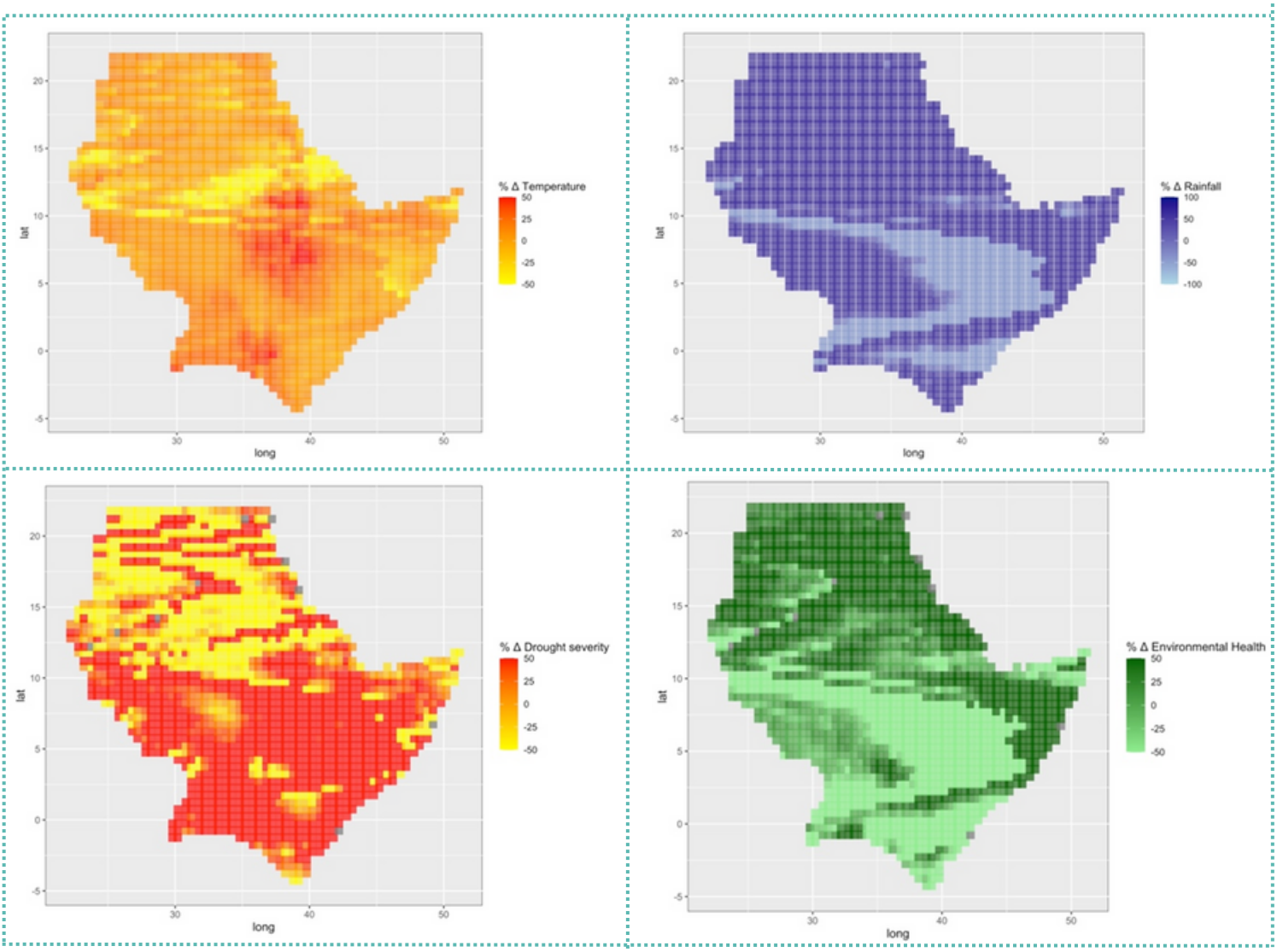
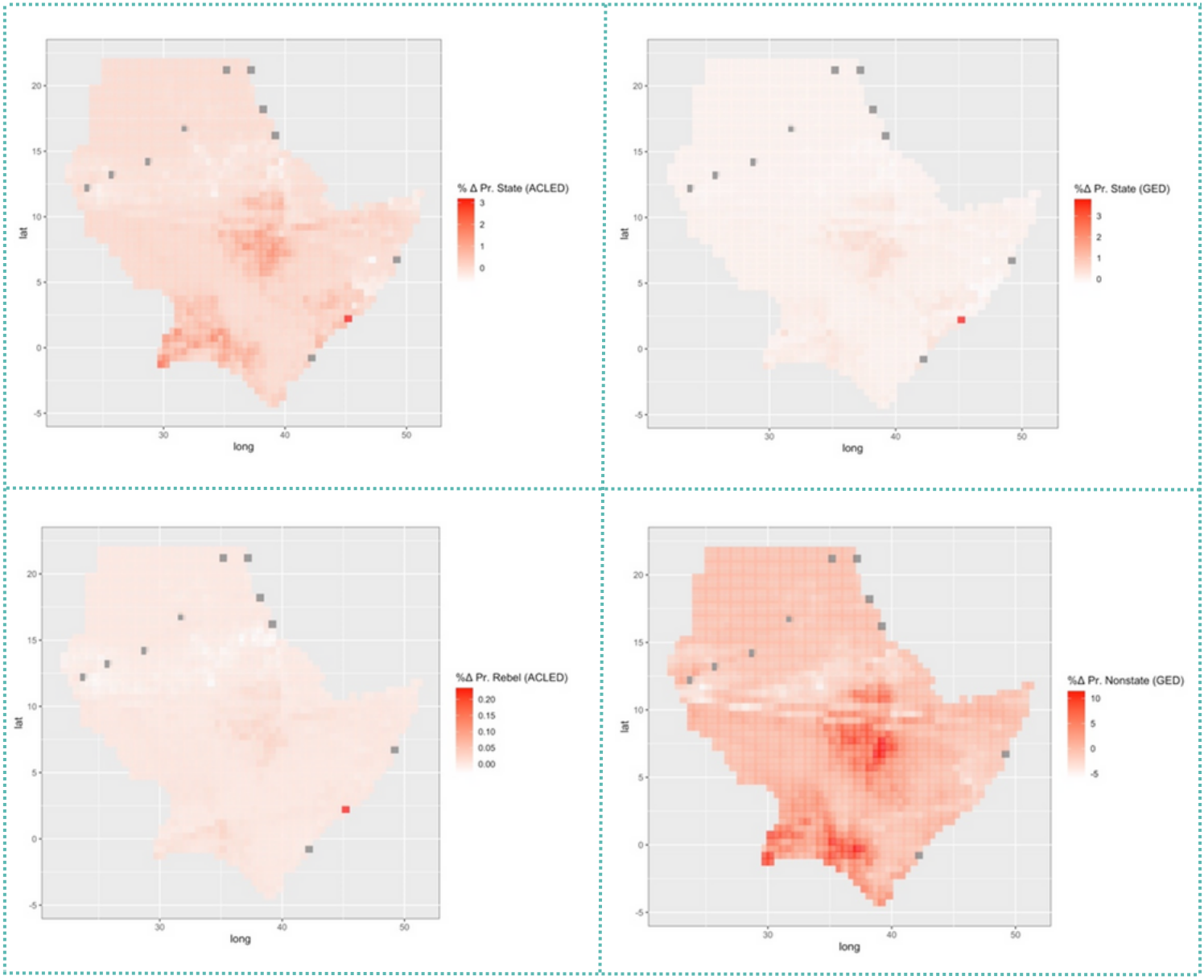


Figure 8. Maps of environmental change predictions, 2022-2027 average.

These simulated data are used to predict the percent change in conflict risk for the same 2022-2027 period compared with a case where climate features were held in their 2003-2018 means in Figure 9. Note that ***the average predictions for each country as well as the region as a whole do not change*** when these variables are set to follow the climate trends calculated in Figure 8 vs. when these indicators are held at their 2003-2018 means, ***suggesting climate change is unlikely to lead to noticeable intensified conflict over the coming five years.*** However, the predictive models also show that for violence against civilian by state forces, rebels, and militias (all from ACLED), ***variability will increase***, where some locations are expected to have a slightly increased rates for violence, while other areas are expected to experience a slight decrease in the risk of violence (~ -15% ó ~ +15%, depending on the location and types of violence). Here, Ethiopia in particular appears to be at a risk of experiencing intensified state- and rebel-based conflicts due to these shifted climate trends, followed by Kenya and Uganda, which – presumably due to their generally greater rates of urbanization – are at a higher risk of experiencing more riots over the next half a decade.



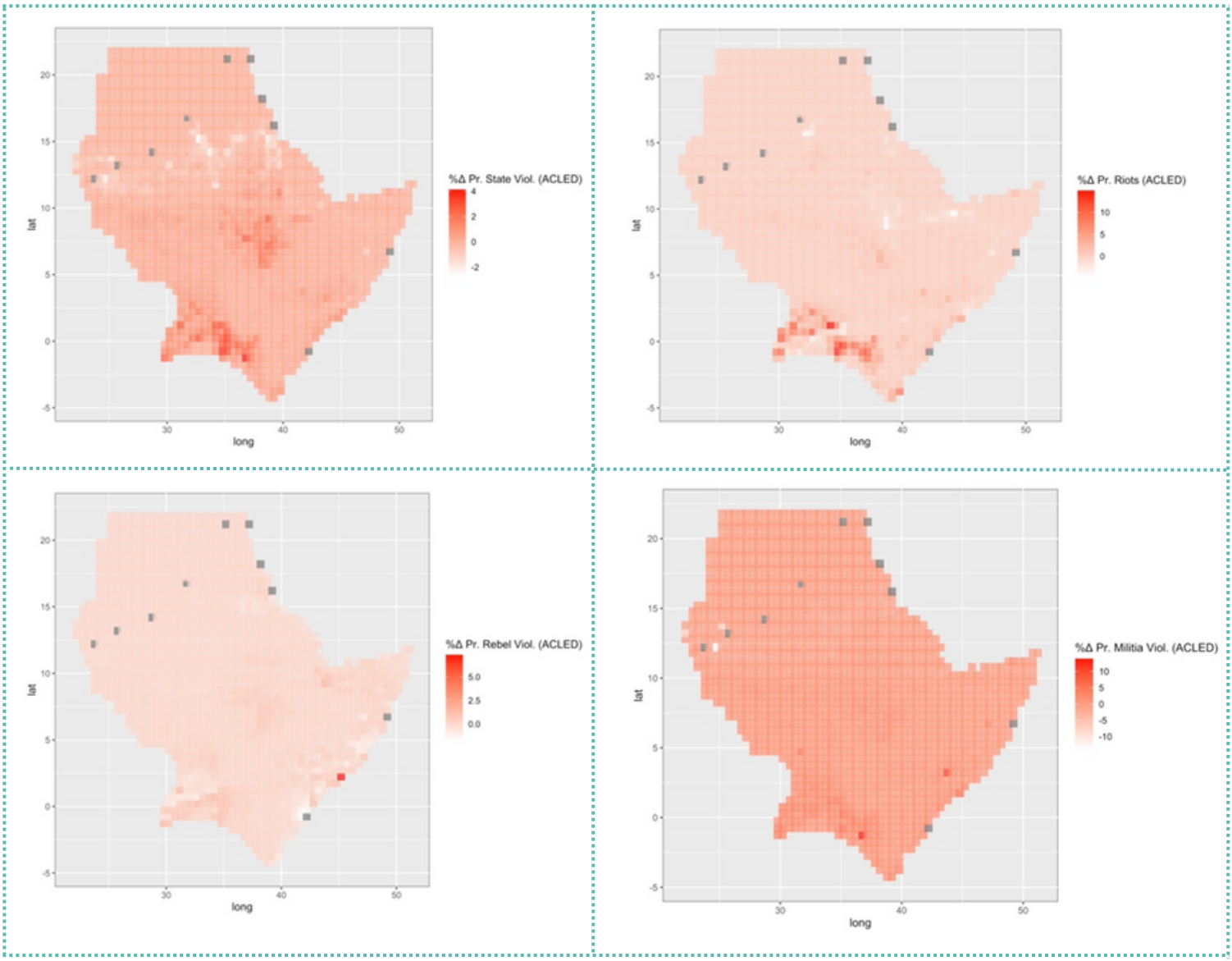


Figure 9. Maps of conflict risk predictions based on estimated linear environmental trends, 2022-2027 average.

PART B. ASSESSING THE ROLE OF INTERNAL MIGRATION AND DISPLACEMENT

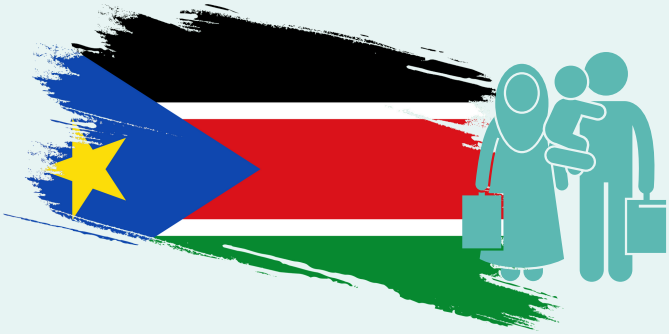
9. OVERVIEW

Comparable geolocated data on internal migration across the entire region that could be aggregated into AfroGrid effectively were unfortunately unavailable. In consultation with an IOM expert (Laura Nistri), two countries where sufficient geolocated data on internally displaced persons – i.e., individuals and households forced to relocate due to an external factor such as an attack, a natural disaster, etc. – are available were identified: South Sudan and Ethiopia. Even here, there were several limitations (discussed in each specific report below). Only in one case – Ethiopia – it was possible to systematically separate internally displaced persons (IDPs) that were displaced due to climate shocks from those who were displaced due to conflict or other reasons.

Another concern relates to the impact of *endogeneity* into the models – IDPs might be both displaced due to and increase the risk of conflict and violence. For predictive purposes endogeneity is not necessarily a concern (see, e.g., Koren 2017), but it does ***preclude identifying a clear causal relationship***. This means that – practically – any role of IDPs as a risk factor does not mean that IDPs *cause* these effects, only that their presence improves our ability to predict their occurrence.

> **Any role of IDPs as a risk factor does not mean that IDPs cause these effects, only that their presence improves our ability to predict their occurrence.**

10. ASSESSING THE IMPACT OF INTERNAL MIGRATION ON CONFLICT IN SOUTH SUDAN



The present analysis uses localized data on internally displaced persons (IDPs) – which is generally available for South Sudan in a much better level and specificity than for other countries analyzed as part of this project (excluding Ethiopia) – to analyze whether taking the location and densities of IDPs (displaced due to different reasons) can help us to better predict conflict and violence. Despite the availability of these data, however, there are several issues that should be taken into consideration when interpreting the results:

- **Data coverage varies greatly across periods:** one IOM report assesses the 2016-2017 period and focuses only on refugee/IDP camps; there is no clear coverage for 2018; for 2019-2020, there were multiple report assessing the number of refugees in a large number of communities across the country (**see Figure 10**). [3] Accordingly, the analysis deploys separate models that are analyzed over several periods.

- **As a result, I had to modify model specification to accommodate these issues:** (i) for the 2016-2017 period, with the exclusion of country level indicators (lack of sufficient variability biased the models) and the time controls (unnecessary over a two-year period), although monthly fixed effects were retained to account for seasonality. (ii) for the 2019-2020 period, I was additionally forced to remove the environmental, climate, food, nighttime light, and food indicators, considering they were not available after 2018. Accordingly, these models include (in addition to IDPs), conflict/violence lags, monthly fixed effects, and petroleum. Accordingly, I reduced the window time for forecasting assessment to six months (instead of one year).

- **Based on the information in the IOM reports and data sheets, the vast majority of IDPs were displaced due to conflict,** not environmental shocks. As was mentioned in the overview to the report, this stage of analysis examines one of several possible relationships between climate change, displacement, conflict: that natural disasters lead to displacement, which can – in turn – contribute to greater conflict risk in different ways. To this end, I compare the impact of environmental IDPs to that of IDPs displaced due to other reasons. Yet, the fact that most IDPs were displaced due to conflict introduces endogeneity into the models – IDPs might be both be impacted by and impact the risk of conflict and violence. For predictive purposes this is not necessarily a concern (see, e.g., Koren 2017), but it does preclude identifying a clear causal relationship – it must not be assumed that IDPs cause conflict or violence, only that they are one of several risk factors.

[3] These are too numerous to include, but these reports are available at: https://displacement.iom.int under "Datasets" when "South Sudan" is inserted as a search term.

Figure 10 maps the distribution of IDPs in South Sudan based on information for the 2016-2017 (left) and 2019-2020 (right) periods. As is clearly illustrated (and was mentioned above), the 2016-2017 period only included reports on IDP centers, whereas during 2019-2020 coverage was extended to all communities hosting IDPs. In both maps, the locations (cells) with the greatest concentrations of IDPs are generally in the northern part of the state. The direction and statistical significance of each coefficient are reported in Table 2.

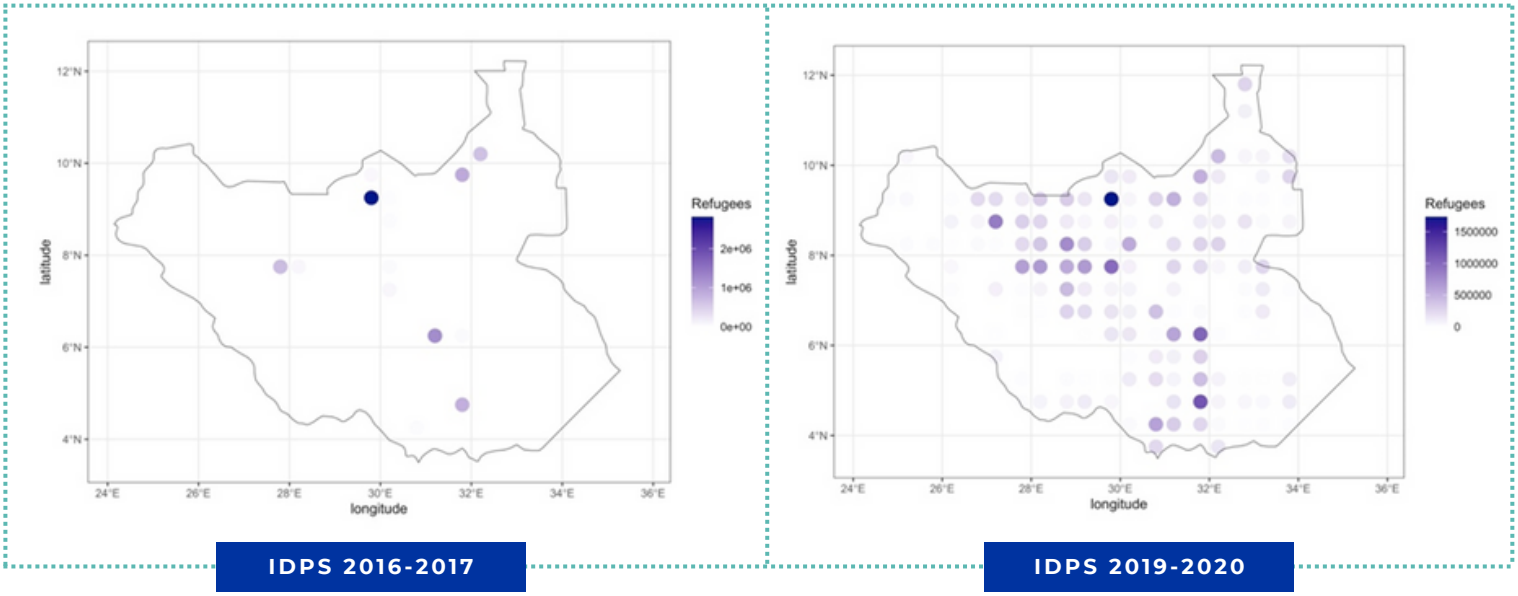


Figure 10. South Sudan IDPs by number and location, 2016-2017 and 2019-2020 (Source: IOM 2022).

- **Figures 11** then reports the percentage of model improvement provided by including IDPs [4] for the 2016-2017 and 2019-2020 period based on the specifications discussed in 10B. This is followed by **Figure 12**, which reports the impact of a history of conflict – generally a strong predictor – on the same models. For each conflict type, the numeric values below the labels report the models' performance – recall that a calibrated model should have a value greater than 0.2.

- Interestingly, despite the issues mentioned above, the degree to which IDPs serve as a risk factor in both models is generally similar. Here, we see this role is most important in the case of rebel violence against civilians, followed by the state conflict (from the GED data), both for the 2019-2020 period. The former example is hardly surprising. Researchers have shown that rebels and other nonstate actors often attack such targets (Hultman 2007). Refugee camps can also provide manpower for rebel groups, which can result with higher rates of violence (Salehyan 2007).

However, it is also important to bear in mind that, in terms of overall performance, both the rebel violence models (0.05 in the 2016-2017 sample and 0.02 in the 2019-2020 period) and the state GED model (0.01 in the 2016-2017 sample and 0.06 in the 2019-2020 period) are well below the 0.2 calibration threshold, suggesting that the predictors we use to predict these types of conflicts do not provide a strong explanation for their incidence.

[4] Note that – like other indicators with a wide range of values – this indicator was log-transformed prior to being entered into the models.

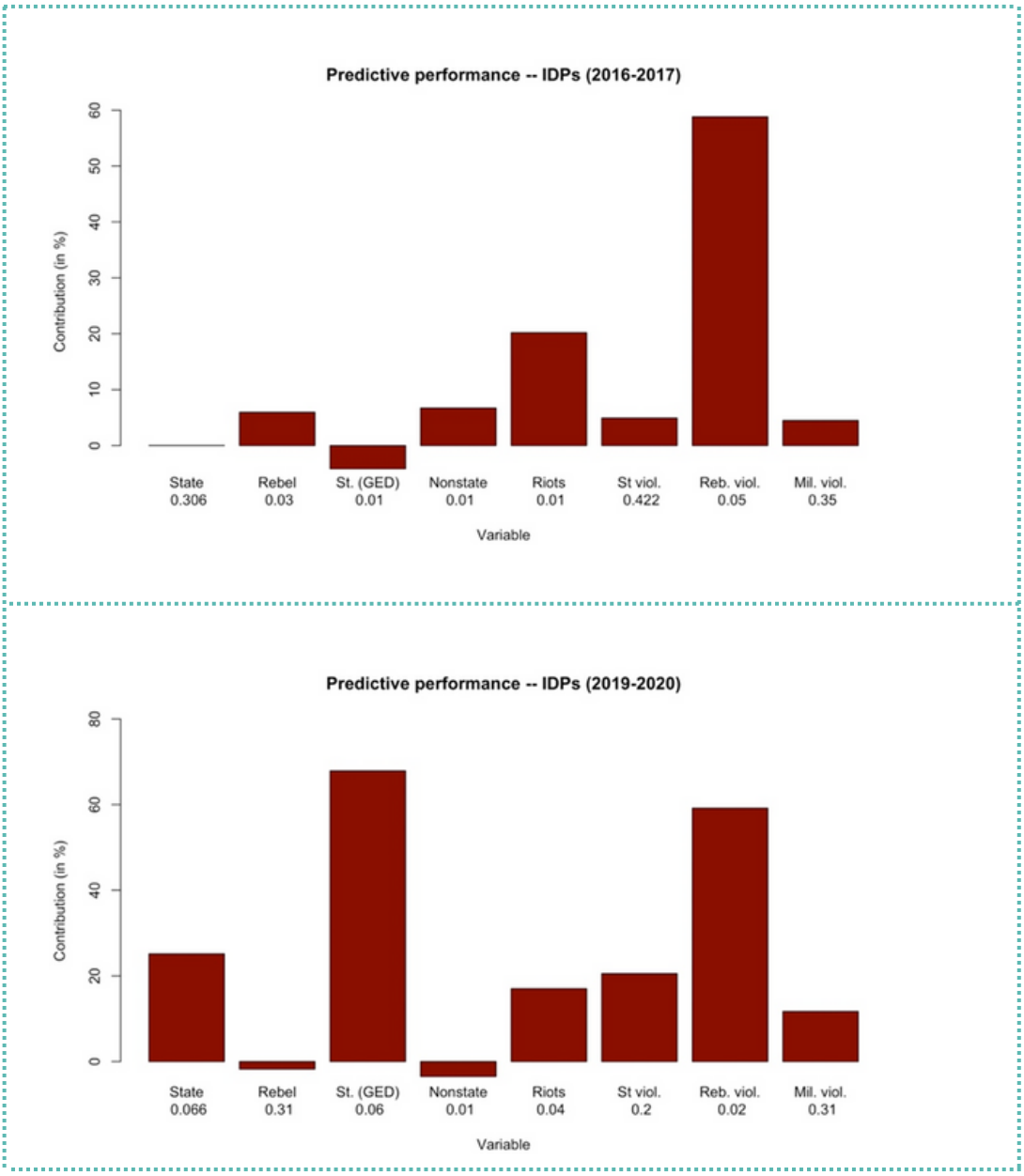


Figure 11. IDPs contribution for six-months-ahead data in South Sudan, 2016-2017 (upper plot) and 2019-2020 (bottom plot)

Turning to other conflict types, IDPs also emerge as a reasonably relevant risk factors in the case of riots in both periods of analysis, improving our ability to predict a riot in a given location during a given six month period by about 20%. IDPs also help us predict violence by state forces (improving model performance by 10% - 20%) and militia violence (5% - 15%) (both of these trends follow a similar logic to rebel violence discussed above). ***Statistically, the effect of IDPs on the risk of conflict is positive in every case but one (nonstate GED 2016-2017) and mostly significant, suggesting that the predictive performance is the result of higher number of IDPs.***

Statistically, the effect of IDPs on the risk of conflict is positive in every case but one (nonstate GED 2016-2017) and mostly significant, suggesting that the predictive performance is the result of higher number of IDPs

For comparison, **Figure 12** shows the impact of history of conflict, a major explanation for conflict in Section 6, in both samples. For rebel violence ACLED and state GED, ***the role of history of conflict as a risk factor is substantively comparable to that of IDPs***; in fact, for rebel violence over the 2019-2020 period, a history of conflict harms model performance, whereas IDPs improve performance. Generally, it seems that IDPs are a less important risk factor, but on average their contribution to the models' predictive performance is positive. In contrast, history of conflict emerges as a relevant risk factor in some cases but harms the models' predictive performance much more that IDPs in others. This suggests the role of a history of violence identified in Section 6 is heavily dependent on the inclusion of other determinates alongside these indicators.

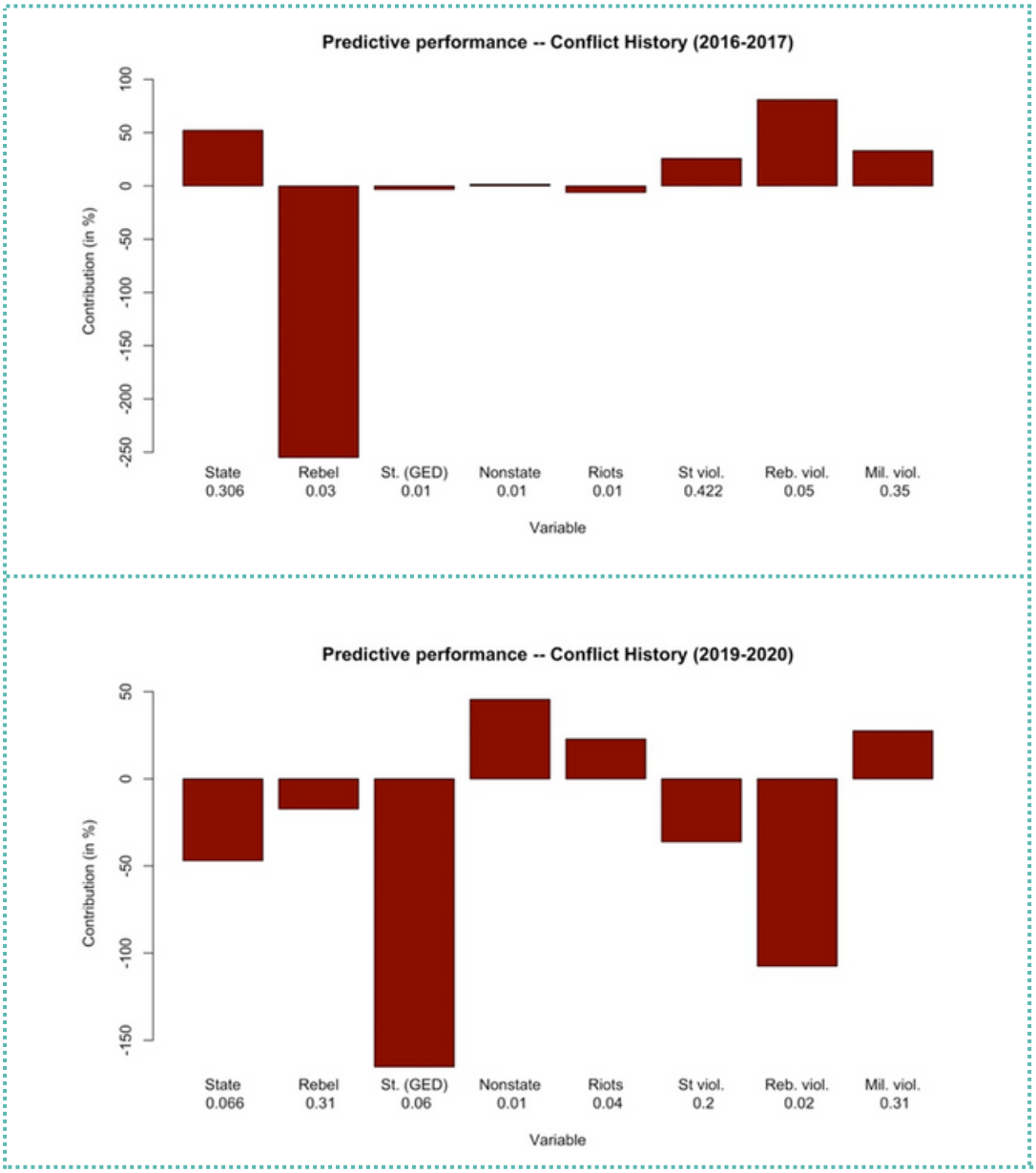


Figure 12. Conflict history contribution for six-months-ahead data in South Sudan, 2016-2017 (upper plot) and 2019-2020 (bottom plot)

Overall, then, it does not appear that more IDPs increase the risk of conflict and violence, excluding – perhaps – violence by rebels. Again, it is important to ***bear in mind that due to endogeneity, this does not imply that even in this case, IDPs cause more violence***, only that their presence reflects different factors – most likely the ability of rebels to recruit or a higher density of rebel "targets" – that increase the probability the risk of civilian killings. Considering that these survey data do not distinguish between IDPs displaced due to environmental causes from other IDPs (primarily from conflict), it is impossible to tell whether environmental vulnerability and climate shocks are directly related to this risk. Nevertheless, it is possible that – by increasing the number of IDPs – such shocks could indirectly contribute to increased risk of rebel attacks due to the same causes (easing recruitment and providing greater density of potential targets). Therefore, for individuals seeking to identify emerging 'host spots' of violence and victimization locally within South Sudan, this information allows projecting potential locations of such attacks and devise preventing solutions – e.g., by increasing civilian protection or providing alternatives to reduce the appeal of joining the rebels.

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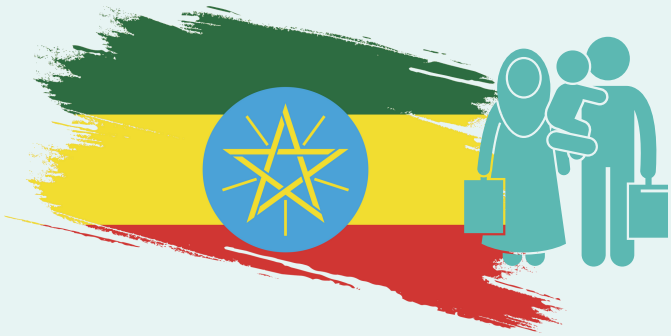
For individuals seeking to identify emerging 'host spots' of violence and victimization locally within South Sudan, this information allows projecting potential locations of such attacks and devise preventing solutions.

Table 2: Logit Estimates of IDPs Impact on Conflict in South Sudan

	State (ACLED)	Rebel (ACLED)	State (GED)	Nonstate (GED)	Riots (ACLED)	State viol. (ACLED)	Rebel viol. (ACLED)	Militia viol. (ACLED)
IDPs (2016-2017)$_{it}$	0.014	0.054	0.131*	−2.329	0.171***	0.112***	0.151**	0.087***
	(0.030)	(0.043)	(0.074)	(832.383)	(0.066)	(0.039)	(0.061)	(0.027)
IDPs (2019-2020)$_{it}$	0.141***	0.133***	0.313**	0.110*	0.557***	0.214***	0.333***	0.160***
	(0.045)	(0.044)	(0.126)	(0.067)	(0.184)	(0.059)	(0.090)	(0.023)

*** p<0.01, ** p<0.05, * p<0.1. t stands for month, i stands for cell/location, and j stands for country. The IDP indicator was log transformed based on base 10 to account for outliers.

11. ASSESSING THE IMPACT OF INTERNAL MIGRATION ON CONFLICT IN ETHIOPIA



In this analysis I leverage localized data on internally displaced persons (IDPs) from Ethiopia to assess their impact on conflict and political violence. Despite the availability of these data, however, there are several issues that should be taken into consideration:

- ***Data coverage overlaps with AfroGrid for a limited period:*** Data reports were detailed, but they are not available until November 2017. The last month for which there is data availability of conflict in AfroGrid is December 2020. Accordingly, I only focus on the period from November 2017 to December 2020 period. Moreover, most other indicators are only available until December 2018. [**5**] To deal with this I calculated average values on these indicators for each location during each month between January 2017 and December 2018 and used these values to extrapolate average values for the same months and locations in 2019 and 2020.

- ***Surveys occur, on average, every quarter***: To deal with this, rather using a grid cell month as my unit of analysis, I now use the grid cell quarter – where quarters are defined as follows: the first quarter includes January, February, and March; the second quarter includes April, May, and June; the third quarter includes July, August, and September; and the fourth quarter includes October, November, and December. For these quarters, I averaged AfroGrid values over these three months to calculate risk predictions.

- ***As a result, I had to modify model specification to accommodate these issues***: Accordingly, the models used to assess the role of IDPs as a conflict and violence risk factor include the following indicators/indicator categories discussed in Section 3: (i) all three conflict lags and (ii) whether a conflict or violence event was recorded in a nearby location during the same month; (iii) environmental health, (iv) temperature, (v) precipitation, (vi) and drought; crop indicators for (vii) cash crops, (viii) cereals, and (ix) fruit, but *no crop productivity indicators*, due to lack of variation across different months, only location; socioeconomic indicators for (x) nighttime light and (xi) local population densities; (xii) fixed effects by year; and (xiii) the different IDP indicators.

- ***Based on the information in the IOM reports and data sheets, the vast majority of IDPs migrated due to conflict,*** not environmental shocks. As mentioned above, this introduces endogeneity into the models but for predictive purposes this is not necessarily a concern (see, e.g., Koren 2017). Note that unlike in the South Sudan case, I was able to distinguish here between IDPs displaced by conflict, environmental issues, and other reasons, and use this distinction to assess the tripartite association leading from climate disasters, through displacement, to conflict.

[**5**] These are too numerous to include, but these reports are available at: https://displacement.iom.int under "Datasets" when "Ethiopia" is inserted as a search term.

Figure 13 maps the distribution of IDPs in Ethiopia, starting with all IDPs (top left), then only those displaced by conflict, environmental reasons, and other causes according to the reports (top right, bottom left, and bottom right, respectively). As **Figure 14** – which plots the number of quarters during the Nov. 2017 – Dec. 2020 period that experienced one or more violent events in each location – illustrates, it does not appear that a clear overlap emerges.

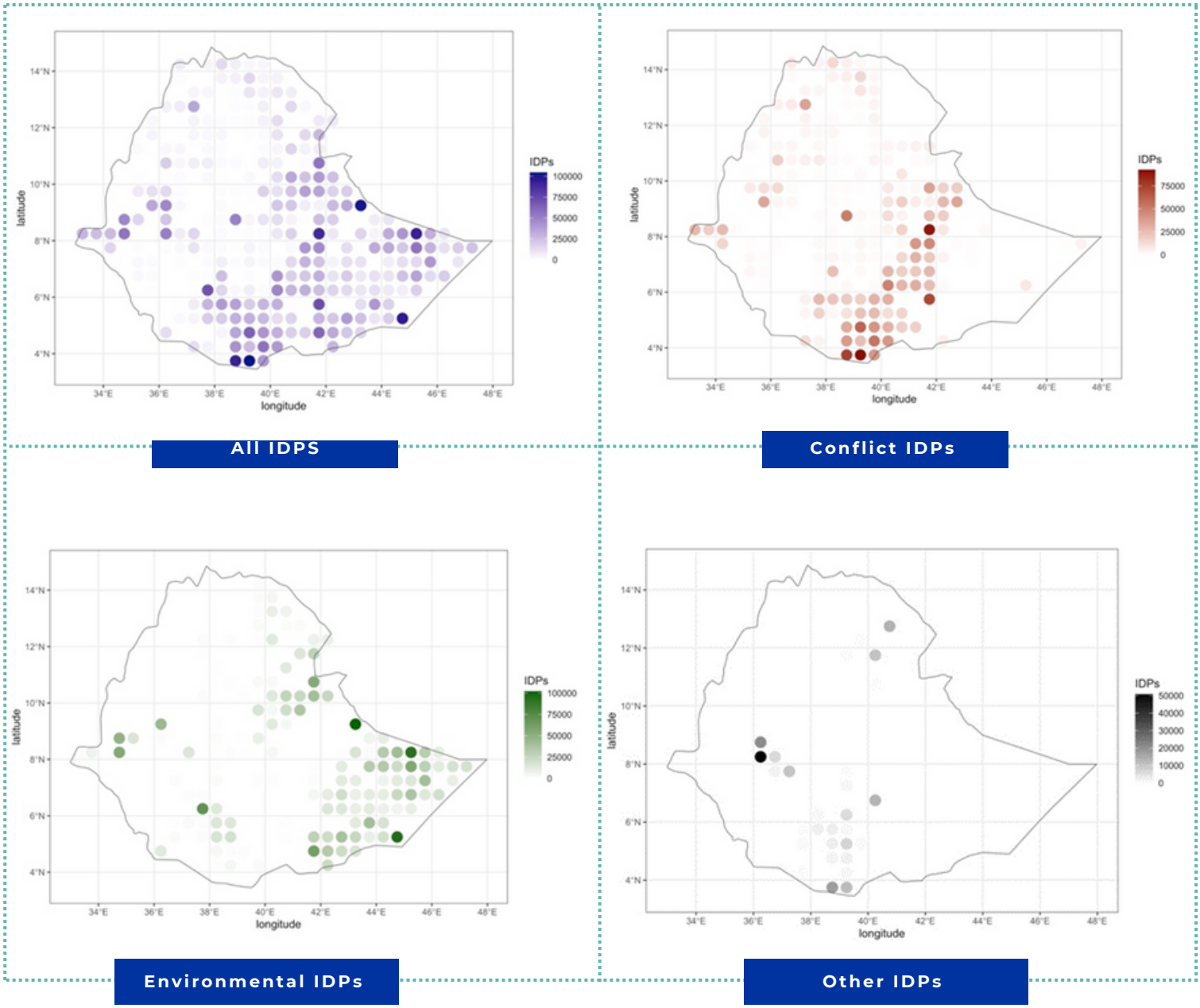
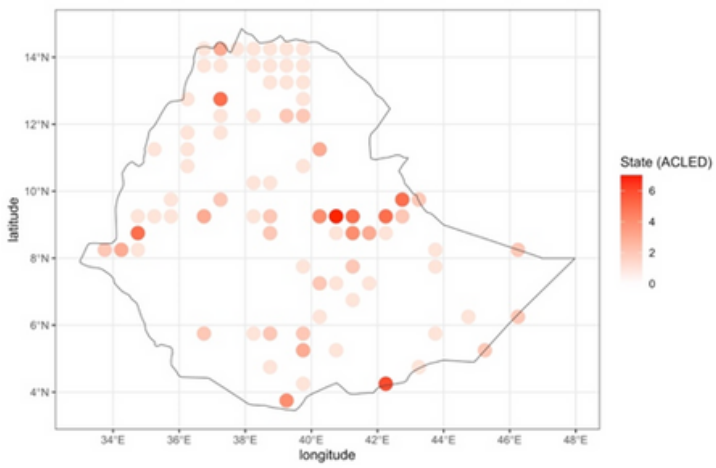
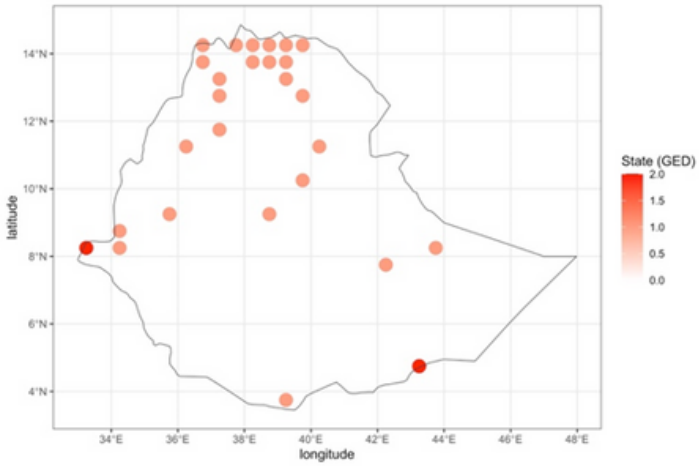
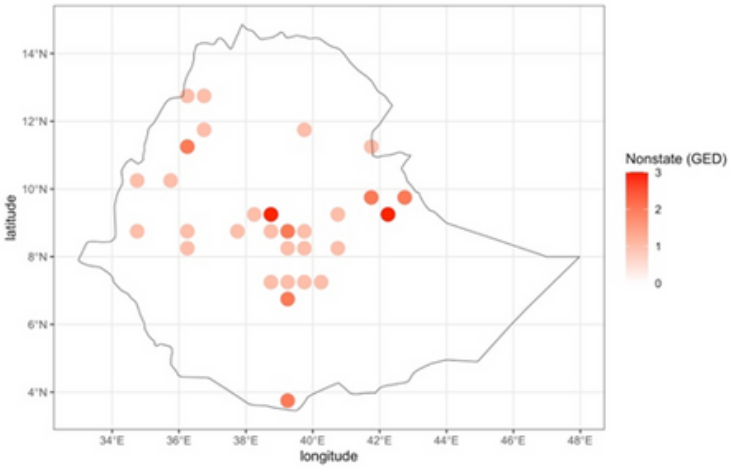


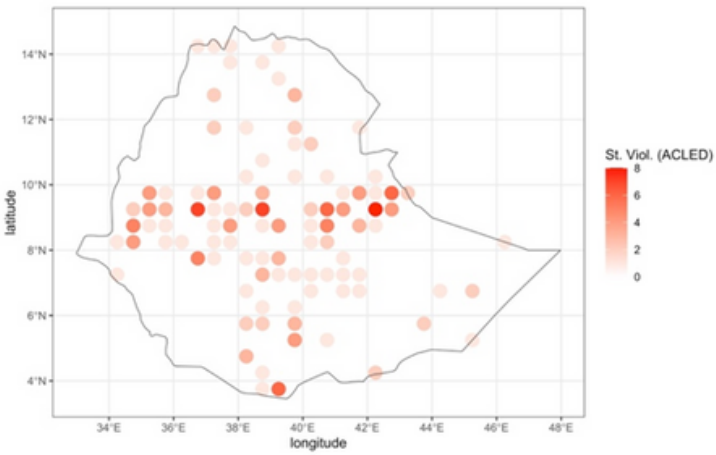
Figure 13. Ethiopia IDPs by number and location, Nov. 2017- Dec. 2020 (Source: IOM 2022).


State (ACLED)
6
4
2
0
latitude
longitude
14°N
12°N
10°N
8°N
6°N
4°N
34°E
36°E
38°E
40°E
42°E
44°E
46°E
48°E


State (GED)
2.0
1.5
1.0
0.5
0.0
latitude
longitude
14°N
12°N
10°N
8°N
6°N
4°N
34°E
36°E
38°E
40°E
42°E
44°E
46°E
48°E


Rebel (ACLED)
2.0
1.5
1.0
0.5
0.0
latitude
longitude
14°N
12°N
10°N
8°N
6°N
4°N
34°E
36°E
38°E
40°E
42°E
44°E
46°E
48°E


Nonstate (GED)
3
2
1
0
latitude
longitude
14°N
12°N
10°N
8°N
6°N
4°N
34°E
36°E
38°E
40°E
42°E
44°E
46°E
48°E


St. Viol. (ACLED)
8
6
4
2
0
latitude
longitude
14°N
12°N
10°N
8°N
6°N
4°N
34°E
36°E
38°E
40°E
42°E
44°E
46°E
48°E


Riots (ACLED)
8
6
4
2
0
latitude
longitude
14°N
12°N
10°N
8°N
6°N
4°N
34°E
36°E
38°E
40°E
42°E
44°E
46°E
48°E

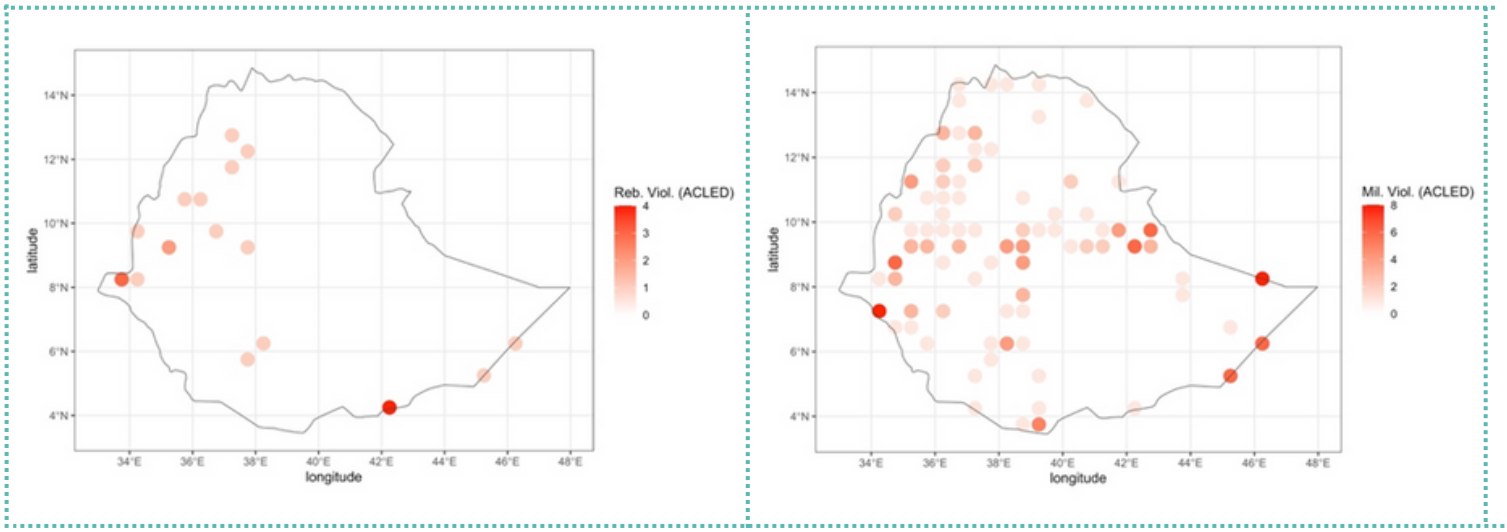


Figure 14. The number of quarters between Nov. 2017 and Dec. 2020 where a location experienced each conflict type in Ethiopia.

- **Figure 15** attempts a more systematic assessment of IDPs'[**6**] impact as a conflict and violence risk factor. Table 3 then reports the coefficient estimates for each of the IDP indicators across each of the models. **Figure 16** then compares these effects to the impact of a history of conflict – generally an important risk factor. For each conflict type, the numeric values below the labels report the models' performance – recall that a calibrated model has a value greater than 0.2.

- Turning to examine the impact of IDPs at the aggregate, the top-left plot in **Figure 15** suggests that IDPs generally do not emerge as a clear risk factor; they may even harm predictive model performance. The results here appear weaker than in **Figure 11** above, which evaluated IDPs' impact as a conflict risk factor in South Sudan. The one exception in the case of Ethiopia is that IDPs provide about 27% improvement in our ability to predict nonstate conflicts from the GED dataset, although considering that this model's performance is below the calibration threshold (0.2), these results are far from employing a clear and strong relationship. ***As Table 3 shows, this improvement is due to a negative relationship between IDPs and nonstate GED, namely that conflict intensifies where there are less – not more – IDPs.*** This means that IDPs might be a risk factor, because not because of their direct impact on rebellion via pathways such as rebel recruitment or attacks.

[**6**] Note that – like other indicators with a wide range of values – this indicator was log-transformed prior to being entered into the models.

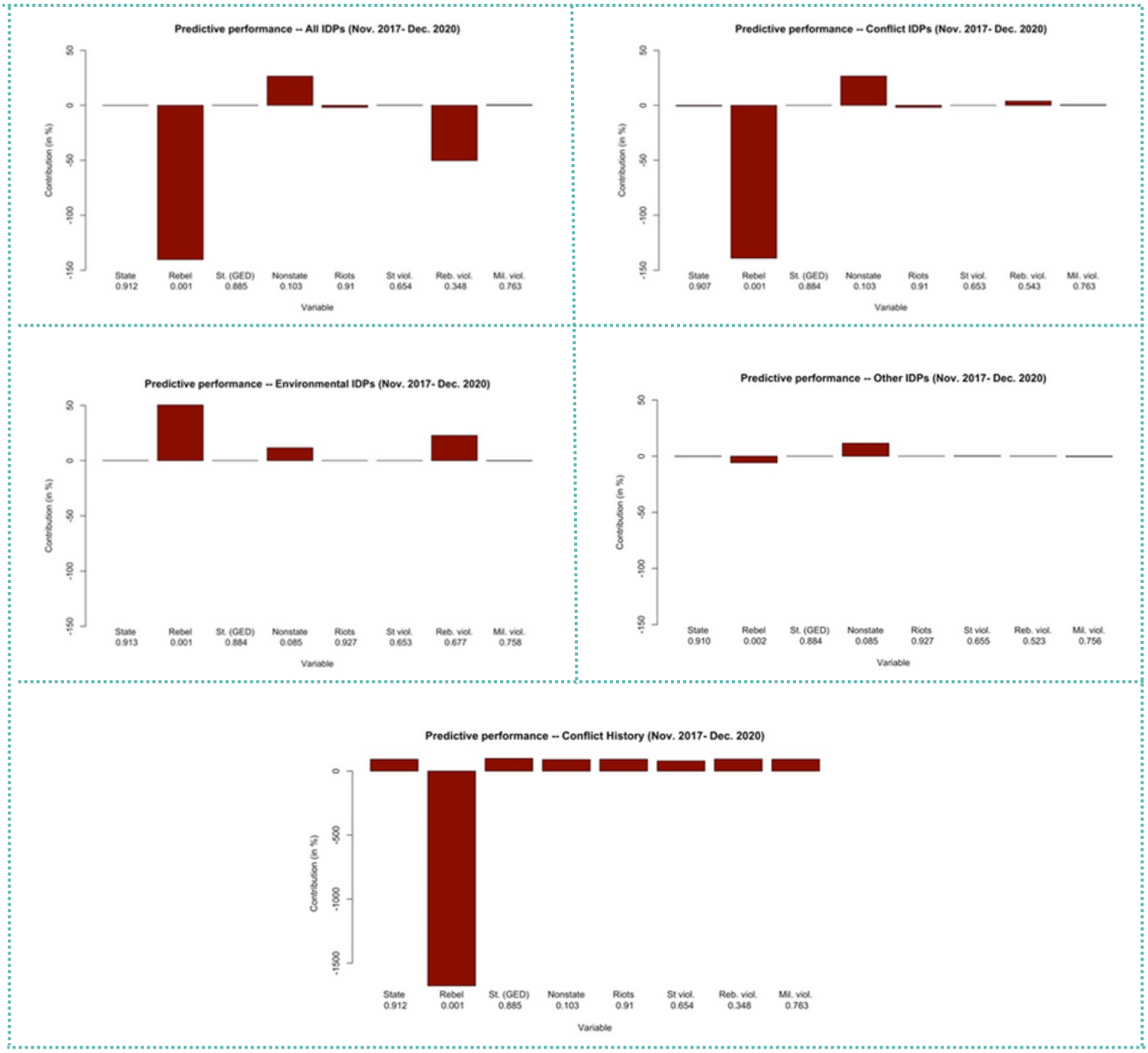


Figure 15. IDP and conflict history predictor contribution for six-months-ahead models in Ethiopia, Nov. 2017- Dec. 2020.

Turning to examine the role of IDPs displaced due to conflict as a risk factor, specifically (top-right plot in **Figure 15** and second row in **Table 3**), the results remain largely unchanged. Note the large coefficient in the rebel violence column in **Table 3**, which suggests that IDPs are perfectly correlated with incidents of rebel violence, namely that such attacks concentrate almost exclusively in locations where IDPs due to conflict reside. Again, this suggests strong endogeneity issues, which explains why this correlation does not improve prediction – IDPs contribute to model *overfit* in this case.

The center-left plot in **Figure 15** reports the impact of environmentally displaced IDPs (i.e., those recorded as such in the IOM surveys). Here, environmental IDPs emerge as a relevant risk factor, leading to overall improvement in forecasting rebel conflict incidents (ACLED data), nonstate conflict incidents (GED data), and rebel violence incidents (ACLED data). Note that model performance values as a whole in the two rebel conflict models (ACLED and GED) are well below the calibration threshold, suggesting that the indicators in the model do not provide an effectively sizable explanation for these conflicts. However, the rebel violence (ACLED data) model has a very high-performance rank (=0.67), suggesting environmental IDPs are an important explanation for such violence. ***This plot suggests that environmental IDPs are an important rebel violence risk factor, in contrast to IDP displaced due to conflict or other reasons.***

Interestingly, the lower left plot in **Figure 15** suggests that there is little overlap between where rebel violence attacks happen and where environmental IDPs are concentrated. Most environmental IDPs in Ethiopia over the Nov. 2017 to Dec. 2020 period were located in the eastern part of the country, whereas conflict over the same period is concentrated mostly in the central and western parts. This is supported by Table 3, which shows that the coefficient estimates for environmental IDPs are not robust is sign and are never significant, suggesting there is no statistical relationship between environmental IDPs and conflict risk. Combined, then, ***this suggests that the contribution of environmental IDPs to our ability to predict conflict risk six months into the future is caused not by their direct link to rebellion, either as participants or as targets of victimization, but due to other reasons.*** For instance, the local densities of environmental migrants might reflect weakness and vulnerabilities in local and regional environmental and state capacity that are also related to rebel behaviors.

Table 3: Logit Estimates of IDPs Impact on Conflict in Ethiopia

	State (ACLED)	Rebel (ACLED)	State (GED)	Nonstate (GED)	Riots (ACLED)	State viol. (ACLED)	Rebel viol. (ACLED)	Militia viol. (ACLED)
$IDPs\ (all)_{it}$	−0.015	−0.539*	−0.442	−0.073	0.095	0.044	46.825	0.013
	(0.057)	(0.313)	(0.394)	(0.164)	(0.061)	(0.063)	(846.360)	(0.044)
$IDPs\ (conflict)_{it}$	−0.047	−0.496*	−0.278	−0.180	0.104	0.011	33,268,373,670,713.000***	0.003
	(0.062)	(0.290)	(0.292)	(0.172)	(0.066)	(0.062)	(345,758.900)	(0.050)
$IDPs\ (environmental)_{it}$	−0.016	−0.199	0.005	−0.182	0.001	0.019	3.634	0.033
	(0.075)	(0.262)	(0.332)	(0.741)	(0.075)	(0.070)	(5.655)	(0.058)
$IDPs\ (other)_{it}$	−0.155	0.408	−0.132	0.230	0.164	−0.056	−0.581	−0.057
	(0.175)	(3,057.528)	(0.727)	(0.336)	(0.269)	(0.161)	(2,760.134)	(0.101)

*** p<0.01, ** p<0.05, * p<0.1. t stands for month, i stands for cell/location, and j stands for country.
The IDP indicator was log transformed based on base 10 to account for outliers.

Turning to examine whether IDPs displaced due to reasons other than conflict and environmental disasters are a risk factor (center-left plot of **Figure 15** and bottom row in **Table 3**), the results suggest that this is not the case, either in terms of substantive impacts (as illustrated by **Figure 15**) or statistically (as illustrated by **Table 3**).

For comparison, the bottom plot in **Figure 15** shows the role of history of conflict, a major explanation, as a risk factor of conflict in Ethiopia. Here, we observe that – excluding the rebel conflict (ACLED data) model – ***history of conflict overtakes all IDP indicators as an important conflict and violent risk factor in every case, with an average improvement of about 92% in each model's predictive performance.*** This is directly in line with the IGAD baseline analysis reported in Part A of this report, which similarly shows that conflict history is by far the most robust predictor of conflict (see, for example, in **Figures 2 – 5**). The one exception when rebel conflicts from the ACLED data are concerned, where including a history of conflict reduces predictive performance a factor of 16. However, the very low overall performance value of this model (=0.001) suggests that it is extremely sensitive to specification choices (see discussion in Section 4) – they should not necessarily mean that accounting for conflict history is irrelevant due to the model's overall weakness.

Overall, then, the analysis of Ethiopia suggests that (i) (conflict) IDPs are heavily and likely endogenously associated with conflict and violence, especially on the part of rebels, and (ii) that environmental IDPs emerge as a risk factor of rebel conflict and violence, although not due to the reasons that might be expected. More specifically, it suggests that more displacement – especially due to environmental reasons – can indirectly increase the risk of rebel violence. While we cannot say that more environmental IDPs cause more rebel violence, environmentally displaced camps allow rebels to recruit more easily or facilitate their ability to kill civilians as a means of hurting the government (as we might have observed in South Sudan). More environmental IDPs might also reside in areas where environmental is generally lower, meaning climate shocks cause greater damage, and where the government is weaker, which allow rebels to more easily operate, making them a predictive proxy, but not necessarily the cause, of such violence.

Therefore, accounting for IDPs allows us to identify emerging '***host spots' of violence and victimization locally within Ethiopia and devise preventive policies***. Such policy improvements may involve, for instance, more effectively allocating protection for civilians against attacks in high risk locations, or incorporating aid measures that can ofset the benefits individuals may gain from joining rebels. They will also point to increasing environmental resilience – and government capacity broadly – will most effectively assist in preempting their impact on rebel mobilization and violence.

12. CONCLUSION

The analyses reported in both stages of this analysis shed new light on the role of climate and environmental stress as direct generators of conflict in IGAD countries, and how they can contribute to conflict and violence by inducing migration. More generally, these results suggest several relevant implications that might become relevant over the coming half a decade.

ELITE COMPETITION

The strongest risk factors of state-initiated conflict and violence against civilians identified here are historical conflict trends and whether a nearby location experienced a conflict event during the same month. Several countries in the region have been marred by violence induced by repeated elite competition and its potential impacts (e.g., South Sudan). These predictors suggest the risk will proceed, especially where competition over natural resource revenues may 'lock in' intensives to fight rather than negotiate.

REBEL CONFLICT AND VIOLENCE

Reductions in environmental health, lower precipitation, and warming are associated with greater risk of rebel conflict and violence, at least in some of the one-year-forward predictions. Extrapolation of climate trends over the next five years suggests that changes in these indicators across most of the region are not expected to be severe, excluding in Ethiopia, which is predicted to experience more warming and where several conflicts are ongoing. However, precipitation predictions – which are likely to be (highly) exaggerated – suggest that rainfall may increase, on average, which may serve to lower conflict rates. Accordingly, based on the data it is unclear as to whether climate change will increase or decrease rebel conflict and violence over the next five years.

REPRESSION AND STATE VIOLENCE

The greatest predicted risk of state violence/repression arise in and around big cities such Mogadishu, Nairobi, Addis Ababa, and Kampala, as well as the border areas of Uganda. Considering population and urbanization trends, the risk of both riots and – correspondingly – state repression in capitals and other large cities may increase over the next half a decade. This is especially likely during election years, considering past research finds electoral politics to be an important driver of violence and political repression (Bhasin and Gandhi 2013).

INTERETHNIC/CLAN RIVALRIES

As illustrated in **Figures 3** and **5**, the different indicators discussed in Section 3 do a poor job at explaining and forecasting conflict incidents involving nonstate actors in the GED data. While drought and temperature forecasts in **Figure 8** are likely overestimating the risk, there is a possibility that interclan rivalries may intensify with climate change. Specific areas where this risk might intensify suggest that central Ethiopia and the border areas of Kenya and Uganda may be more susceptible to nonstate actor conflict risk due to changing climate trends (**see Figure 9**), although these results are far from conclusive.

RIOTS AND CIVILIAN MOBILIZATION

Especially considering ongoing population and urbanization trends, and a history political turmoil in some cities, large urban centers in Kenya and Uganda show may be at a highest predicted risk of riots over the next five years.

DISPLACEMENT AND CONFLICT

Results from the second part of this report suggest that internal displacement generally is not a strong risk factor of intensified conflict and violence. However, environmental displacement seems to be related to higher rebel conflict and violence risk. Considering that this risk appears to increase where there are less environmental IDPs, it is not clear that – if climate change increases the number of environmental IDPs over the coming half a decade – this will directly contribute to conflict. However, the findings suggest that there might be an indirect relationship between a country's environmental resilience and local capacity on the one hand, and the risk of rebel attacks on the other. Without being able to assess the exact causes underlying this relationship, it is practically impossible to suggest clear policy remedies. However, it is possible to use this information to identify emerging 'host spots' of violence and victimization. Accordingly, based on available data, Ethiopia might be susceptible to rebel violence resulting from low environmental resilience, an impact that might intensify in the future due to climate change.

REFERENCES

- Beger, Andreas. "**Precision-recall curves**." (2016). https://www.andybeger.com/papers/Beger_2016_PrecisionRecallCurves.pdf.
- Bellemare, Marc F. 2015. "**Rising food prices, food price volatility, and social unrest**." American Journal of agricultural economics 97(1): 1-21.
- Bhasin, Tavishi, and Jennifer Gandhi. "**Timing and targeting of state repression in authoritarian elections**." Electoral Studies32, no. 4 (2013): 620-631.
- Chen, Xi, and William D. Nordhaus. "**Using luminosity data as a proxy for economic statistics**." Proceedings of the National Academy of Sciences 108, no. 21 (2011): 8589-8594.
- Englebert, Pierre, and James Ron. "**Primary commodities and war: Congo-Brazzaville's ambivalent resource curse**." Comparative Politics (2004): 61-81.
- Fearon, J.D. and Laitin, D.D., 2003. **Ethnicity, insurgency, and civil war. American political science review**, 97(1), pp.75-90.
- Gleick, Peter H. "**Water, drought, climate change, and conflict in Syria**." Weather, climate, and society 6, no. 3 (2014): 331-340.
- Goldstone, Jack A., Robert H. Bates, David L. Epstein, Ted Robert Gurr, Michael B. Lustik, Monty G. Marshall, Jay Ulfelder, and Mark Woodward. "**A global model for forecasting political instability**." American Journal of Political Science 54, no. 1 (2010): 190-208.
- Hegre, Håvard, Curtis Bell, Michael Colaresi, Mihai Croicu, Frederick Hoyles, Remco Jansen, Maxine Ria Leis et al. "**ViEWS2020: revising and evaluating the ViEWS political violence early-warning system**." Journal of peace research 58, no. 3 (2021): 599-611.
- Hendrix, Cullen S, and Idean Salehyan. "**Climate change, rainfall, and social conflict in Africa**." Journal of peace research 49 no. 2 (2012): 35-50.
- Hultman, Lisa. "**Battle losses and rebel violence: Raising the costs for fighting**." Terrorism and Political Violence 19, no. 2 (2007): 205-222.
- Ide, Tobias. 2016. "**Toward a constructivist understanding of socio-environmental conflicts**." Civil wars 18(1): 69-90.
- International Organization for Migration (IOM). "**Datasets**." Accessed May 20, 2022. https://displacement.iom.int.
- Koren, Ore. "**Food, Climate Change, and War in the 21st Century**." Georgetown Journal of International Affairs, March 7, 2022. https://gjia.georgetown.edu/2022/03/07/food-climate-change-and-war-in-the-21st-century/.
- Koren, Ore. "**Means to an end: Pro-government militias as a predictive indicator of strategic mass killing**." Conflict Management and Peace Science 34, no. 5 (2017): 461-484.
- Koren, Ore, and Anoop K. Sarbahi. "**State capacity, insurgency, and civil war: A disaggregated analysis**." International Studies Quarterly 62, no. 2 (2018): 274-288.
- Raleigh, Clionadh, Andrew Linke, Håvard Hegre, and Joakim Karlsen. "**Introducing ACLED: an armed conflict location and event dataset: special data feature**." Journal of peace research 47, no. 5 (2010): 651-660.

REFERENCES

- Raleigh, Clionadh, and Dominic Kniveton. "**Come rain or shine: An analysis of conflict and climate variability in East Africa**." Journal of peace research 49 no. 1 (2012): 51-64.

- Raleigh, Clionadh, Lisa Jordan, and Idean Salehyan. "**Assessing the impact of climate change on migration and conflict**." In paper commissioned by the World Bank Group for the Social Dimensions of Climate Change workshop, Washington, DC, pp. 5-6. 2008.

- Salehyan, I., 2007. **Transnational rebels: Neighboring states as sanctuary for rebel groups**. World Politics, 59(2), pp.217-242.

- Schon, Justin, and Ore Koren. "**Introducing AfroGrid, a unified framework for environmental conflict research in Africa**." Scientific data 9, no. 1 (2022): 1-11.

- Schon, Justin, Britt Koehnlein (G), and Ore Koren. "**The need for willingness and opportunity: Analyzing where and when climate influences conflict in the Sahel**." Forthcoming in Population and Environment.

- Schrodt, Philip A. "**A Practical Guide to Current Developments in Event Data**." International Methods Collqium (2017).

- Sundberg, Ralph, and Erik Melander. "**Introducing the UCDP georeferenced event dataset**." Journal of Peace Research 50, no. 4 (2013): 523-532.

- Theisen, Ole Magnus, Nils Petter Gleditsch, and Halvard Buhaug. "**Is climate change a driver of armed conflict?** " Climatic change 117, no. 3 (2013): 613-625.

- Ward, Michael D., and Andreas Beger. "**Lessons from near real-time forecasting of irregular leadership changes**." Journal of Peace Research 54, no. 2 (2017): 141-156.

- Weidmann, Nils B. "**On the accuracy of media-based conflict event data**." Journal of Conflict Resolution 59, no. 6 (2015): 1129-1149.

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