Forecasting armed conflict in the Sahel

Forecasts for November 2021–October 2024

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Abstract

Preventing armed conflict is key to promoting development and well-being in the Sahel. To strengthen its work to promote peace globally, the United Nations have recently stressed the importance of early action and early warning about impending conflict. This report presents the ViEWS system, a systematic, data-driven conflict early-warning system developed for Africa and the Middle East. Designed to complement expert assessments drawing on qualitative methods, the system produces estimates of the probability that armed conflict events will occur in countries and sub-national locations during each of the next 1–36 months. The report outlines the main features of the system, discusses the uncertainties involved and how well the system handles these, and presents the latest forecasts for the UNISS countries of the Sahel. The ViEWS forecasts are updated on a monthly basis and made available in full through an API, and in summarised form on the ViEWS website. The report also outlines some possible future developments and improvements of the system.

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1 Introduction

Armed conflicts destroy the hopes and ambitions of entire generations to live in peace and with dignity. Beyond the immediate mortality and morbidity that results from war, conflict leads to profound long-term consequences that impede the full realization of sustainable development. It is estimated that, on average, war costs a country an accumulated loss of 15% of GDP growth, reduces life expectancy by about one year, increases infant mortality rates by 10% and undernourishment by 3.3%, and deprives an additional 1.8% of the population of access to potable water.[1] Conflicts also reduce local and national resilience to natural disasters, climate change, and health crises, rendering the immediate and secondary impacts of these crises even more severe.

The dynamics above are particularly alarming in the semi-arid Sahel region, which already suffers from below-average resilience to climate change.[2] Further exacerbating the situation, temperatures in the region are expected to rise to twice the global average by the turn of the century, the population is set to double by 2050, demands on food are projected to increase as crop production declines, and both Chad and Niger are at risk of losing their entire rain-fed agriculture by 2100.[3]

The Sahel is nevertheless a region of both great opportunity and great challenges. Comprised by Burkina Faso, Cameroon, the Gambia, Guinea, Mali, Mauritania, Niger, Nigeria, Senegal, and Chad,[4] the region is one of the richest in non-renewable deposits such as gold, oil, and uranium, home to significant renewable resources like surface water and aquifers, and a location of great potential for future renewable energy sources such as solar and wind energy.[5] In combination with increased urbanization, this presents a powerful opportunity for economic and humanitarian development.[6] Over the past decade, the region has however also faced continued and persistent issues with armed conflict and violence, resulting in 1.5 million internally displaced persons.[7] This is further compounded by a 49.7% poverty headcount ratio (making it one of the poorest regions in Africa), a consistently low ranking on the World Bank Human Capital Index, low trust in government, low life satisfaction, and difficulties in providing sufficient livelihoods, health, education, social infrastructure, governance, human security, and resilience to both endogenous and exogenous shocks.[8] These are vulnerabilities that the region will be hard-pressed to address in the absence of peace and security.

Political violence thus represents a major obstacle for the Sahel in fostering the peaceful, just, inclusive, and prosperous societies envisioned in global frameworks such as Agenda 2030 and Agenda 2063, underlining the urgent need for the international community to invest in

[1] Gates and others (2012) and World Bank (2011)

[2] ND-GAIN (*ND-GAIN Country Index*)

[3] World Bank (2019), Searchinger (2018), Ministry of Foreign Affairs of the Netherlands (2018), and Sultan, Defrance, and Iizumi (2019)

[4] UN (2019)

[5] UN (2018)

[6] UN (2018)

[7] UNHCR (2020)

[8] Andrews and others (2021), Tham Lindell and Mattsson (2014), Helliwell and others (2020), World Food Programme (2020), May, Guengant, and Barras (2017), Maiga (2019), Boyd and others (2013), and Hamro-Drotz, Dennis and United Nations Environment Programme (2011)

a "portfolio of prevention".[9]

1.1 The Sahel Predictive Analytics (Sahel PA) project

Doubling down on the special challenges facing the Sahel across the triple nexus of humanitarian aid, peace-building and development, twenty-three United Nations entities with partners at a number of prominent international research institutions have come together into an inter-agency, inter-pillar predictive analytics (PA) project for the Sahel.

Answering the call for increased support for capacity-building and strengthened data collection in Member States, the project – spearheaded by UNHCR, on behalf of the UN High-level Committee on Programmes (HLCP) and further endorsed by the UN Chief Executive Board (CEB) – sets out to assist the international community in moving from a reactive to proactive/anticipatory mode, break down silos, ensure an integrated approach to secure common outcomes, and seek opportunities for transformation and innovation in a region of enormous potential.

The project has been developed in response to the United Nations reform initiated in 2017 to strengthen global conflict prevention capacities,[10] further supporting the implementation of Sahel 2043, the United Nations Integrated Strategy for the Sahel (UNISS) and the support plan thereof, the Agenda for the Protection of Cross-Border Displaced Persons in the Context of Disasters and Climate Change, as well as the Secretary General's Data Strategy, and the work of the Special Coordinator for the Development in the Sahel.

Aspiring for the Sahel to become a region of peace, the project has five key objectives:

1. To form an expert consortium consisting of academic research groups, experts based in the region, regional governmental institutions, and United Nations staff;

2. To set new standards for high-quality data across the Sahel, as recommended by the expert consortium;

3. To create a regional data hub that fosters collaboration over competition;

4. To develop three predictive models informed by new, high-quality and disaggregated data from the regional data hub, covering challenges in the triple nexus:

    (a) A Sahel-specific forecasting model predicting the likelihood of political violence up to 36 months into the future at a country and approximately 55 km resolution;

    (b) A forecasting model predicting future crop production and suitability in the Sahel up to 2050;

    (c) A forecasting model predicting the geographic distribution of population up to 2050 in five-year intervals at a 1 km resolution;

[9] The joint United Nations-World Bank report on Pathways for Peace showed that there is a high return of prevention: for each 1 USD that is invested in prevention-related activities, 2–7 USD would be saved over the medium to long term, respectively. See Mueller (2017).

[10] See the 2020 twin resolutions on peace-building and sustaining peace (A/RES/75/201-S/RES/2558 (2020)) which builds on the earlier 2016 twin resolutions (A/70/262-S/RES/2282(2016)).

5. To strengthen national-, regional-, and local capacity-building for anticipatory action by means of the deliverable above and ultimately enhance cooperation in the Sahel

This report presents the contribution to the Predictive Analytics project from Uppsala University: a conflict risk analysis for the Sahel over November 2021–October 2024, as generated by the Violence Early-Warning System (https://views.pcr.uu.se). Following the introductory remarks, it outlines the main features of the ViEWS system as of December 2021, presents the suite of forecasting models informing the ViEWS system, and provides a guide to reading and interpreting its results. Section 5 presents the ViEWS forecasts for political violence in the Sahel over November 2021–October 2024 and discusses the key drivers of conflict in the region. Section 6, in turn, discusses the predictive performance of the ViEWS system – how accurate and reliable the forecasts are, and Section 7 presents some preliminary findings from an exploratory model that makes use of an extended set of climate extremes indices. The report concludes with some final remarks and recommendations to advance future work on conflict prevention in the Sahel.

2 Overview of the ViEWS system

The Violence Early-Warning System (ViEWS) is a data-driven early-warning system (EWS), based at the Department of Peace and Conflict Research (DPCR, https://pcr.uu.se) at Uppsala University, and the Peace Research Institute Oslo (PRIO, https://prio.org). The Africa-wide pilot of the system has been developed over the course of an ongoing research project funded by the European Research Council (ERC-AdG 694640) and Uppsala University,[11] computed on resources provided by the Swedish National Infrastructure for Computing (SNIC) at Uppsala Multidisciplinary Center for Advanced Computational Science (UPPMAX). The system has been extended and expanded to the Middle East with funding from UN ESCWA.[12]

2.1 Coverage, scope, and levels of analysis

ViEWS generates monthly probabilistic assessments of the risk of fatal political violence across Africa and the Middle East during each month in a rolling three-year forecasting horizon. The forecasts are produced separately for three different types of political violence, as defined by the Uppsala Conflict Data Program (UCDP, https://ucdp.uu.se):[13]

- State-based violence (**sb**) involving at least one government of a state, such as fighting between the government of Syria and ISIS;
- Non-state violence (**ns**) between armed groups, neither of which is a government of a state, such as the PKK and PUK in Turkey and Iraq; and

[11] Hegre and others (2019) and Hegre and others (2021b)

[12] UNESCWA (forthcoming)

[13] Full definitions are available at https://www.pcr.uu.se/research/ucdp/definitions/. Please see https://ucdp.uu.se and Gleditsch and others (2002), Sundberg and Melander (2013), and Pettersson and Öberg (2020) for more information about the UCDP dataset.

- One-sided violence (**os**) exerted by armed actors against unarmed civilians, for example terror attacks targeted at civilians.

The predictions are presented at two spatial resolutions, both using the calendar month as the temporal unit of analysis:

- The country level, separately forecasting the probability that 25 or more people will lose their lives to each type of violence per country and month (henceforth referred to as the country-month, *cm* level); and
- The sub-national level, separately forecasting the probability that at least one life will be lost to each type of violence per approximately 55x55 km location and month (henceforth referred to as the PRIO-grid-month, *pgm* level).

The spatial coverage of each country conforms with the latest version of the CShapes dataset, while the sub-national level is delimited by the PRIO-GRID, a grid structure that divides the world into squared cells corresponding to an area of approximately 55x55 kilometers at the equator, or 0.5x0.5 decimal degrees.[14]

2.2 Input data

The ViEWS system draws upon decades of peace research on the complex and inter-connected causes of conflict and – conversely – the causes of peace. It is informed by historical time-series data on an extensive suite of conflict predictors that have been assembled from this research, covering the time from 1989 up until and including two months prior to each monthly release of the ViEWS forecasts.[15] The conflict predictors pertain to themes including – but not limited to – conflict history, the strength of political institutions and measures of democracy, socio-economic conditions, food prices and food security, climate variability, societal vulnerability, natural and social geography, and social and political unrest.

All input data informing the ViEWS system is publicly available, uniform, and updated at least annually, allowing for a systematic assessment of future conflict risks. The most important data – the conflict history datasets on the outcomes of interest from UCDP – are even made available on a monthly basis. The latter is made possible by the release of so-called 'candidate' conflict events, which are later revised as part of the annual updates and quality-assurance processes of the UCDP.[16] At the country level, the forecasting system is informed by and trained on global data, while at the sub-national level, it is trained on the African continent and the Middle East. This means that forecasts for the Sahel region are informed by patterns learnt also from other places. This not only guarantees more data availability for the forecasts and thus an increase in their accuracy, but also teaches the system to infer patterns and trends that are observed broadly across space and can be usefully applied to predict violence in the region of interest.

[14] The CShapes dataset is presented in Weidmann, Kuse, and Gleditsch (2010). The list of countries included in the dataset is in turn determined in Gleditsch and Ward (1999), with subsequent updates. The PRIO-GRID system is presented at https://grid.prio.org/ and in Tollefsen, Strand, and Buhaug (2012).

[15] The December 2021 forecasts are for example informed by data covering the time up until and including October 2021 (using data released up until and including July 2021).

[16] For details on the UCDP-Candidate dataset, see Hegre and others (2020).

2.3 Algorithms and the modeling set-up

The collected data are split into three subsets: a 'training' set used to train the forecasting models on the historical data to infer the conditions and patterns that are conducive of conflict, a 'calibration' set used to re-adjust the forecasts in a such a way that the mean predicted value matches the average of the real observations, and a 'test'/'forecasting' set for which the forecasts are produced.[17]

Once split into the three subsets, the data are fed into a number of so-called random forest algorithms that learn from historical observations in order to forecast future conflict. Random forest is a machine-learning algorithm based on multiple 'decision trees', and it has been shown to be performing very well for forecasting tasks of the type discussed here. When 'training' a model, the random forest uses some data points to identify combinations of a handful of predictors that are particularly good at predicting armed conflict for another set of data points. It repeats this many times, and votes up predictors that always produce good predictions. It is therefore very useful for identifying the most promising predictors from a very large number of candidate features. Also, it works well when the relationship between a predictor and the outcome is non-linear, or when the effect of a predictor varies in association with the value of another, which may often be the case when trying to predict conflict.

A number of different sub-models are trained, calibrated, and tested by means of the procedure above, each based on data pertaining to a relevant theme or group of conflict predictors that existing literature has deemed important in explaining conflict (see Section 3). Each of these thematic sub-models allow the forecasting system to address the forecasting problem from a different angle. Sub-models informed by a theme related to water, for example, reflect the effect of availability of – and access to – water on the risk of conflict in the location at hand, while sub-models informed by a theme of natural and social geography offer insights into the role of terrain or the proximity to natural resources in setting the scene for the onset, or continuation of, conflict in the same location.[18]

As a final step, the outputs from each of the thematic sub-models are combined into two composite main models that produce the final forecasts: one model that is trained to generate predictions at the country-month level, and one that is trained to produce the sub-national PRIO-GRID-month conflict forecasts. This procedure of combining broad collections of sub-models is known as 'ensemble modeling' and is one of the main pillars of the ViEWS system.[19] Much like a crowd is wiser than the single individuals composing it, overarching models that collect forecasts from a suite of smaller thematic sub-models are known to achieve more accurate predictions. This aspect of the system not only improves how well the prediction system performs, but also helps in understanding how individual predictors contribute to the risk assessments described below.[20]

[17]When evaluating how well the system performs, a historical period is used as the test set. When forecasting into the future, this is the same as the forecasting window described above. See Hegre and others (2021b) for more details.

[18]Please note that the forecasting models are however not able to offer insights into the causal inference between the predictors and observed violence – they can point to a relationship between the two, but cannot confirm the direction of this relationship, i.e. which causes which.

[19]The two main models are therefore also known as 'ensembles', or 'ensemble models'.

[20]See Page (2007), Montgomery, Hollenbach, and Ward (2012), Ward and Beger (2017), and Hegre and others (2019) for a discussion.

Another feature of the modeling set-up is that each thematic sub-model is optimized for a different number of months into the forecasting horizon – the system produces different predictions when predicting three months into the future than when predicting three years ahead. Generally, structural conditions such as institutional characteristics and development factors are more useful in predicting conflict in the long term, while rapidly changing conditions or shocks such as food price peaks might prove more relevant to predict violence in the short term. Through a sophisticated system of weights, sub-models that for example include data on recent conflict events are therefore given more emphasis in short-term predictions, whereas structural sub-models informed by institutional factors that change slowly over time are premiered when forecasting several years into the future. As such, also analyses of forecasts for different periods into the future can serve as a valuable resource in designing policy interventions with varying targets, e.g. short-term relief or remedies, as compared to long-term investments in infrastructure or strengthening of political institutions.

To learn more about the methodology behind the ViEWS forecasts, please consult Hegre and others (2021b) and Hegre and others (2021a).

3 The forecasting models

3.1 Country-level models

The main forecasting model that is used to generate predictions at the country-month level is composed of the thematic sub-models that follow:

Macro theme: Peace and Security

The conflict history model A conflict history model capturing different aspects of each country's conflict history, as defined and sourced from the Uppsala Conflict Data Program (UCDP), including the time since the last fatal conflict event, which type of violence occurred, and which fatality thresholds were reached each month and year (at least 1, 25, 100, or 500 deaths).

The conflict onset model A model drawing upon key features from all sub-models informing the country-level forecasts, trained specifically to predict onset of conflict as recorded by the UCDP. Onset is defined as the first month that a country reaches or exceeds 25 battle-related deaths (BRDs) after a period of at least 24 months with less than 25 deaths per month.

Macro theme: Governance

The political institutions model A model that describes the political institutions of a country. From the Varieties of Democracy (V-Dem) dataset,[21], this includes the level of democracy, the degree of enforcement of civil and political rights, physical integrity as a proxy for freedom from political killings and torture by the government, freedom of domestic movement, and indicators for rule of law

[21] V-Dem institute (2020)

and access to justice. The model is also informed by data from the CoupCast project.[22]

Macro theme: Development

The WDI model A development model broadly capturing the level of development by country, including the quality of infrastructure and basic facilities, socio-economic development, national debt, education, unemployment, gender equality, health care, prevalence of malnutrition and poverty, agricultural dependence, migration flows, age structure of the population, and country size. Sourced from the World Bank's World Development Indicators.[23]

The growth forecasts model An economic growth forecasts model informed by the IMF World Economic Outlook (WEO) growth forecasts,[24] transformed to the country-month level of analysis used by the ViEWS system. The WEO data are published twice per year (in April and October) with values for each metric and country by year – retrospective data for the previous year, and forecasts for the current and next two years.

The food prices model A food prices model informed by country-level monthly market price averages for wheat, sugar, milk and meat commodities in local currencies, as well as in prices adjusted to current USD. The data are sourced from the UN Food and Agriculture Organisation (FAO)[25] and the World Food Program's (WFP) Food Price Forecasting and Alert for Price Spikes tool.[26]

The food security model A food (in)security model informed by all FAOSTAT[27] indices on consumer prices, food price inflation, and food insecurity indicators. The latter range from access to food and prevalence of malnutrition, to the average calories intake and nutritional values contained in the average individual diet. The indices are transformed to the country-month level of analysis used in ViEWS, with imputation of missing data.

Macro theme: Climate

The water management model A water management model informed by a set of country-level indicators from FAO AQUASTAT[28] on access to and management of water resources (disaggregated water conditions are captured by sub-national models). The selected indicators are based on current hydro-conflict literature and Sustainable Development Goals (SDG) reporting on water scarcity measures. These include total internal renewable water resources (IRWR), total renewable water resources (TRWR), groundwater flowing to other countries which is not

[22] CoupCast is based on REIGN data (Bell, Besaw, and Frank, 2021).
[23] WorldBank (2019)
[24] IMF (2020).
[25] FAO (2021)
[26] See https://data.humdata.org/dataset/wfp-food-prices.
[27] FAO (2021)
[28] FAO (2021)

covered by bilateral or multilateral agreements, total dam storage capacity per capita, and all indicators included in FAO's monitoring of SGD 6.4 (reducing water scarcity). FAO AQUASTAT is available for 5-year intervals (the last of which cover 2013-2017) and missing values are imputed.

Macro theme: Interactions

The global multi-feature model A global model drawing upon key features from all sub-models informing the country-level forecasts, capturing interactions and non-linearities between the different predictors.

3.2 Sub-national models

The main forecasting model that is used to generate predictions at the sub-national PRIO-GRID-month level, in turn, is composed of the thematic sub-models that follow:

Macro theme: Conflict history

The space-time model A conflict history model capturing both time and space proximity to past conflict, using conflict data at the sub-national level sourced from the UCDP-GED, the geographically disaggregated version of UCDP (Croicu and Sundberg, 2015).

Macro theme: Human and natural geography

The natural and social geography model A model built on characteristics of the local terrain, such as cultivated areas, barren lands, forest, mountains, savanna, shrub, pasture, or urban areas, and social geography features proxying the profitability of each location and its centrality, e.g. the spatial distance to exploitable resources such as diamonds and petroleum deposits, distance to the capital, the nearest urban center, and the national border. The model is further informed by some demographic, socio-economic, and socio-political features, namely population density, development variables such as local GDP and infant mortality rates, and the share of excluded ethnic groups in each location.

Macro theme: Climate and vulnerability

The agro-climatic model An agro-climatic model informed by drought and agricultural features, most importantly the SPEI index of water availability as a measure of drought (Vicente-Serrano, Beguería, and López-Moreno, 2010), information from the MIRCA calendar on the growing season of the main crops, and Mapspam data on crop harvest and yield. The indicators thus capture not only the frequency and intensity of droughts but also their impact on the main crops harvests. It excludes information on vulnerability.

The vulnerability model A model capturing communities' vulnerability to exogenous shocks, such as climate extremes. It includes information on the main drivers of societal vulnerability acknowledged by the existing empirical literature: the share of people employed in agriculture as a proxy of agricultural dependence, the number of excluded ethnic groups as defined in the GeoEPR data (Wucherpfennig and others, 2011), and the average nighttime light emissions as a proxy for economic activity. The model excludes the climatic indicators instead captured by the agro-climatic models below.

The combined agro-climatic vulnerability model A model informed by the feature sets from both the agro-climatic model and the vulnerability model in order to capture how resilience to shocks moderates or exacerbates the negative impact of climate factors on security. Key features include the SPEI index of water availability as a measure of drought, information from the MIRCA calendar on the growing season of the main crops, Mapspam data on crop harvest and yield, and variables capturing local vulnerability to climate-related impacts, such as socio-economic and political conditions and the ground, agricultural dependence, and adaptive capacity in agriculture. Adaptive capacity is a function of how communities have been exposed to past climate shocks: the higher the variance in climate conditions in the past, the higher the probability that communities have learnt how to cope with climate shocks and developed tools/practices to adapt to their negative impacts.

The combined agro-climatic, natural and social geography model A model combining the feature sets from the natural and social geography model with those from the agro-climatic model. Informed also by an extensive set of conflict history features, this model places less emphasis on drought than the other models that incorporate such variables. Key variables for this combined model are instead population size and terrain features, particularly the proportions of the given areas that are cultivated, and the distance to diamond deposits.

Macro theme: Interactions

The cross-level model A cross-level model that interacts features from the sub-national level with variables at the country level, ensuring that the forecasts at the sub-national level are informed by those at the country level, and vice versa.

4 Reading and interpreting the forecasts

The ViEWS system draws on hundreds of input variables, all of which contribute to the forecasts to varying degrees. To arrive at the explanations of the various forecasts like those presented below, ViEWS makes use of a combination of approaches.

First, the ViEWS system is built on two ensembles of thematic sub-models, each sub-model drawing on its own related set of conflict predictors. The relative weighting of the thematic sub-models into the ensembles is determined by two main approaches: a so-called

EBMA (Ensemble Bayesian Model Averaging)[29] approach at the country-month level, and a simple unweighted average at the PRIO-GRID-month level. Looking at the predictions from each of these sub-models into the ensembles indicates which variable groups are most important for a given geographic location or country.

Second, within each of these sub-models, the team inspects which individual variables are particularly important, as well as how these variables are related to conflict. For instance, results from the ViEWS forecasts have shown that risk of conflict tends to decrease somewhat when the rule of law variable increases from a very low level, and decrease strongly when rule of law improves from a moderate level to a fairly high level.

Third, the ViEWS system is complex – many of the input variables are related to each other, and sometimes the technical results are ambiguous. To guide the overall interpretation, the ViEWS team also looks to the general academic literature on the causes of armed conflict when interpreting new forecasts.[30]

Last, all predictions come with an uncertainty, or an associated variability around estimates. Uncertainty stems from two main sources: input data and modelling. Input data capture not only the true, unbiased signal of the actual event but also some random noise; this is especially the case for data on conflict events that are prone to errors in data coding. The construction of forecasting models, in turn, depend on a number of choices ranging from computational considerations to selection of predictors. Each of these choices can be difficult, and some decisions and adaptions to past events may drive a forecasting model away from what constitutes the best predictions of outcomes in the future, contributing to the prediction uncertainty.[31] The uncertainties above should be kept in mind when interpreting results from forecasting systems overall. For a brief evaluation of the how well the ViEWS system performs, please see Section 6.

5 Forecasts for the UNISS countries of the Sahel, November 2021–October 2024, as of December 2021

5.1 The country-month (*cm*) level

12-month forecasts

The left-hand column of Figure 1 shows the ViEWS forecasts for 25 or more battle-related deaths per month per UNISS country, for each type of violence. The forecasts were generated in December 2021 and are based on data up to and including October 2021. The figure shows

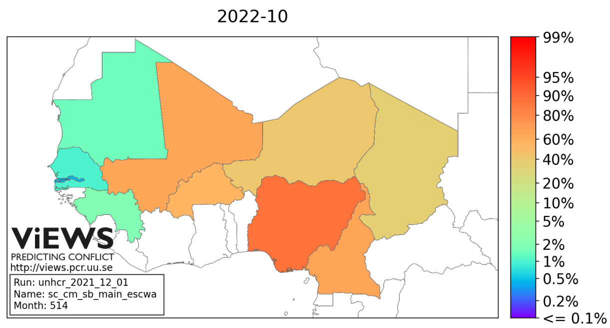
[29]Montgomery, Hollenbach, and Ward (2012)

[30]Overall, the results from the ViEWS system are consistent with major conclusions from this literature, and the interpretation of the predictions are in line with what these studies suggest drive armed conflict. See Hegre and others (2019) for a discussion of the relationship to the academic literature.

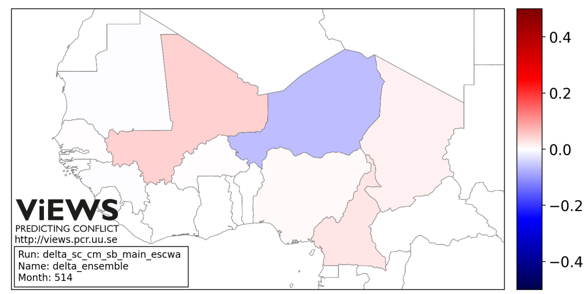
[31]For this reason, thorough evaluations of a forecasting system benefit strongly from looking not only at the overall performance of the system as a whole, but also at the performance of the many sub-models that inform it. The ViEWS system has undergone a number of such rigorous evaluations, with subsequent alterations and improvements to the modeling set-up, presented in e.g. Hegre and others (2021a) and Hegre and others (2019).

Figure 1.

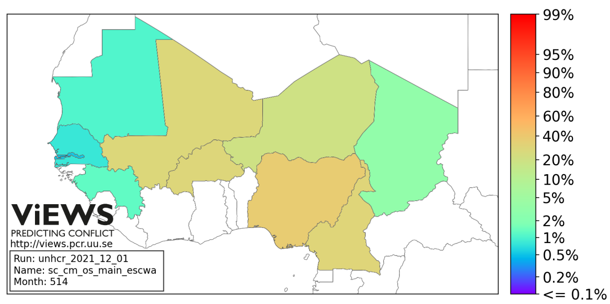
Forecasts for October 2022 at the country-month (*cm*) level, 12 months into the future relative to last month of data, and changes to the forecasts over the past three months



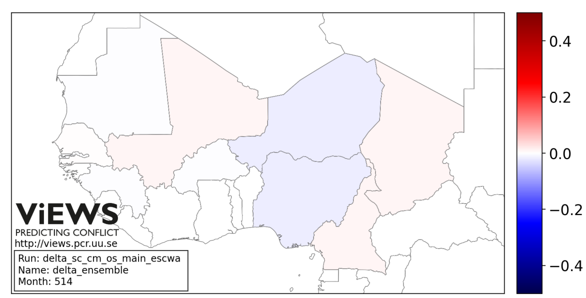
(a) State-based violence **(sb)**, *cm* level



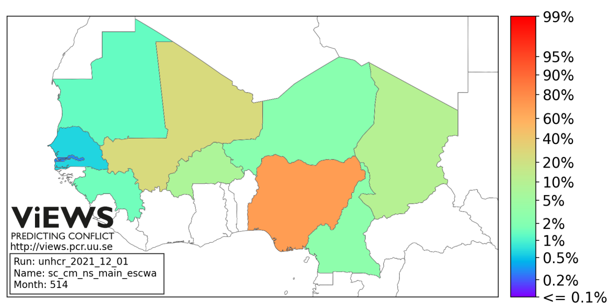
(b) State-based violence **(sb)**, *cm* level



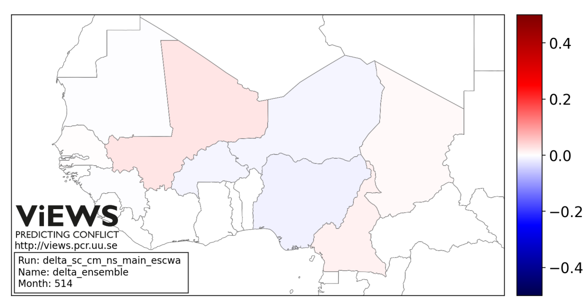
(c) One-sided violence **(os)**, *cm* level



(d) One-sided violence **(os)**, *cm* level



(e) Non-state violence **(ns)**, *cm* level



(f) Non-state violence **(ns)**, *cm* level

Note: Predicted probability of at least 25 fatalities per country, month, and type of violence (left column), and changes to the 12-month forecasts as compared to those produced in September 2021 (right column). Red colors in the change maps point to heightened risks, whereas blue colors indicate that risks are reducing. The severity of each risk alteration (by percentage points, *pp*) is illustrated by the color saturation; white indicating no change.
Source: ViEWS, December 2021

forecasts for October 2022, 12 months after the date of the last available data, but forecasts look fairly similar for all other months (see Section 5.3).

From the bright red or orange colors in the figure, we find that the risks of reaching such levels of violence from conflict between governments and armed groups (state-based violence) are very high in Nigeria, Mali, Burkina Faso, Cameroon, and Niger. In all of these, the main model suggests that the 25-deaths threshold will be crossed in more than every second month. For all five of these, such monthly levels of state-based violence have occurred frequently in recent years (see Figure 2a).[32] Conflict is also likely in Chad.

The forecasts for fatal violence inflicted by a government or an armed group against unarmed civilians (one-sided violence) resemble the results above (see Figure 1c). While risks of 25 deaths per month in one-sided violence are generally lower than for state-based conflicts, the highest probabilities (about 30–50%) are once more found in Nigeria, Mali, Burkina Faso, Cameroon, and Niger (Figure 1c). These countries have been the most prone to experience also one-sided violence in the region over the past 5 years (Figure 2b). This correlation between the two conflict categories is not a coincidence – most of the attacks against civilians occur in conflict contexts.[33] Armed actors that deliberately attack civilians are largely the same actors involved in state-based conflicts.

Non-state conflicts are rarely as violent as conflicts involving governments. Consequently, the predicted probabilities of 25 or more fatalities per month in such conflicts are lower (Figure 1e). Risks nevertheless remain very high in Nigeria, and notable in Mali. The rest of the region however observes a relatively low probability of reaching this level of non-state violence over the next year (green or blue colors in the figure).

Changes to the 12-month forecasts over the past three months

The right-hand column of Figure 1 shows how the 12-month forecasts for the UNISS countries of the Sahel have changed over the past three months – the difference between the predicted probabilities generated in December 2021 as compared to those generated in September 2021. Red colors point to heightened conflict risks, whereas blue colors indicate that risks have decreased.[34]

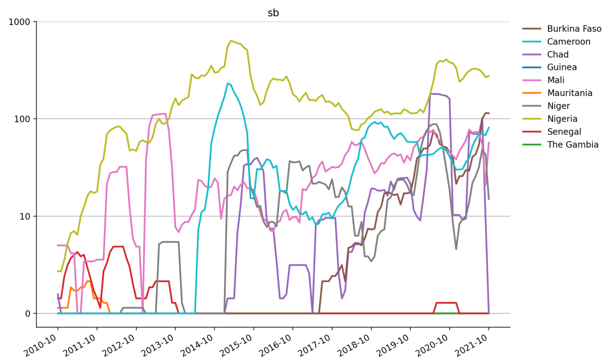
The risk assessment for state-based violence has changed notably for Mali, Cameroon, and Niger over this time, as seen in Figure 1b. Most of this change of outlook is due to changes in recorded violence between July and October 2021 (the last months of data informing the September and December productions of the ViEWS forecasts, respectively). This is illustrated by Figure 2, which shows the trends in the monthly fatalities from each type of political violence in the Sahel over the past decade up to October 2021, as recorded by the Uppsala Conflict Data Program (UCDP). Seen from the figure, Mali (pink) saw a

[32] Unless otherwise stated, all fatality counts and details on conflict events in this report are derived from the database on UCDP Candidate Events (Pettersson, Högbladh, and Öberg, 2019; Sundberg and Melander, 2013; Hegre and others, 2020) Fatality counts listed correspond to the ‘best estimate’ records.

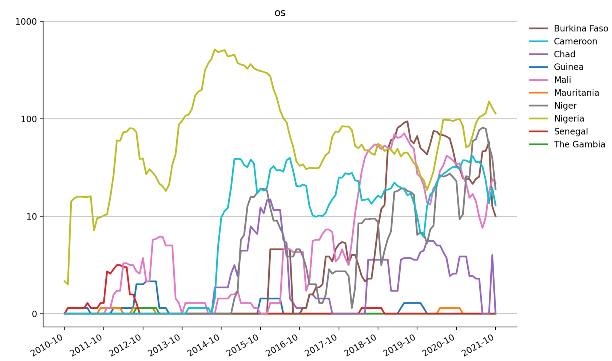
[33] The correlation is not given by definition, though. One-sided violence, according to UCDP’s definitions, does not necessarily take place in countries where armed conflict is ongoing. For a discussion of the determinants of one-sided violence, see Eck and Hultman (2007).

[34] Please note that data are only shown in the figure for UNISS countries; surrounding countries are colored white by default and are only displayed for geographic context. For UNISS countries, a white fill color indicates a lack of change in the predicted probability of conflict.

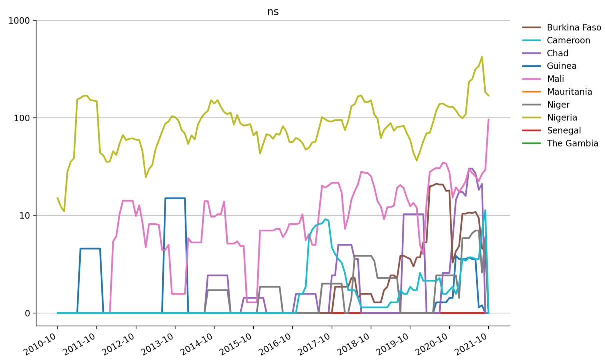
Figure 2.
Input data: conflict and protest history by number of fatalities and protest events, 2010–2021



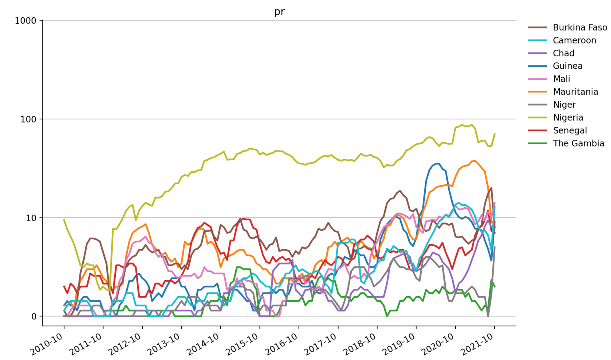
(a) State-based violence



(b) One-sided violence



(c) Non-state violence



(d) Protests (violent and non-violent)

Note: Trends in monthly fatalities due to organized political violence, and trends in monthly number of protest event (violent and non-violent) over 2010–2021, log scales. The lines have been smoothed for legibility.
Source: Source: UCDP Candidate Events Dataset (UCDP Candidate) version 21.0.3 (global), and the Armed Conflict Location & Event Data Project (ACLED) (both publicly available), adapted for the report by the ViEWS team.

sudden drop followed by a steep increase in fatalities over the late summer and fall of 2021, while Cameroon (light blue) has seen a steady increase throughout 2021 due to renewed activity from the Ambazonia separatist movement in the Anglophone regions. Niger (grey), in turn, observed a decline in fatalities over this period. These developments are reflected as heightened conflict risks in the change map for Mali and Cameroon (red color in Figure 1b), and a reduced conflict risk for Niger (blue color in Figure 1b).

In the one-sided violence category results are less pronounced. A mild risk increase is detected in Mali, Chad, and Cameroon, all of which saw a rise in fatalities over the late summer and fall of 2021, relative to the months prior, while reducing risks prevail in Niger and Nigeria (Figure 1d]).

Finally, the change map in Figure 1f shows an increased risk of non-state conflict in Mali after repeated clashes between Dozos and JNIM late summer and early fall 2021. A moderate risk elevation is also detected in Cameroon, where three non-state incidences involving Ambazonia separatists took place over the same period, coupled with an ethnic clash between fishers from the Mousgoum ethnic group and Arab herders. The rest of the Sahel remains at an equal – or even lower – risk of non-state violence over the next year than it did by the early fall of 2021.

Key predictors of conflict at the country level

The methodologies used to produce the ViEWS forecasts hold the capacity to infer what individual predictors best explain a given forecast. This is done by the ViEWS team on an annual basis as part of an extensive in-house evaluation of the forecasting system. The discussion below is based on the most recent evaluation, showcasing the main drivers of the conflict forecasts for all of Africa and the Middle East (the geographic scope of the models presented in this report).

Further supported by the forecasts presented above, the key drivers of the ViEWS forecasts at the country level can be grouped into four broad categories: conflict history, demography, economic factors, and governance issues.

Conflict history As observers familiar with existing conflict patterns in the region will notice, past conflict prevails as the most important factor in explaining large differences between conflict predictions, especially for a short forecasting horizon. For the Sahel region, this is illustrated by Figure 2.[35] It is readily apparent from the figure that the Sahelian countries differ significantly in terms of recent history of violence. Nigeria, Mali, Burkina Faso, Niger, Cameroon and Chad, which have observed the most violence in recent years across all three categories of violence, also emerge at the highest risk of future conflict in the region, whereas Senegal, Guinea, Mauritania, and the Gambia, which have been relatively peaceful over the past few years or even decade, remain at a significantly lower conflict risk

[35] Note that the UCDP only includes fatalities that are reported in news or IGO reports in their monthly reporting (the UCDP-Candidate Events Dataset), but include various other reports in their final, annual, dataset (the UCDP-GED). It should also be noted that the strict documentation standards of the UCDP result in the number of deaths often being under-estimated. See Pettersson and Öberg (2020) and Hegre and others (2020) for a detailed description of the data, and https://ucdp.uu.se for more information on the project.

(compare to the forecasts in Figure 1). The same generally applies to recent changes to the number of conflict-related fatalities; when the death toll rises, risks generally rise, and vice versa.

Demography A number of other factors also contribute to high risks of conflict at the country level. First, conflicts tend to be more lethal when occurring in large populations, so large countries are more likely to see at least 25 deaths per month than smaller ones.[36] Relative to the population, the risk of conflict in e.g. Nigeria is thus not as high as it seems from Figure 1.[37]

Socio-economic factors Socio-economic factors are another important predictor of armed conflict. In a global comparison, the vast majority of armed conflicts occur in low-income countries.[38] This is partly because low-income countries tend to have poor governance, further discussed below. Governments in low-income countries also tend to have weak military organizations. In addition, low-income economies that often rely on natural resources are more likely to attract violent competition for their control, since the assets cannot be moved and the costs of capital flight are lower. Poverty, in turn, increases markedly when conflict erupts. Accordingly, poverty indicators such as rate of undernourishment and financial insecurity are associated with high risks of conflict, as is heavy economic reliance on natural resource extraction including agriculture. The ViEWS system also picks up on increasing unemployment as a risk factor, either as a cause of unrest in itself or as a signal of a deteriorating political-economic situation.

Governance Poor governance and lack of freedom is a final category that drives the results. Figure 3 shows four governance and freedom predictors from the Variety of Democracy dataset that the system has identified as particularly important.[39] Yellow color signifies good performance; blue and blue-green poor governance.

Seen from Figure 3a, countries in which citizens enjoy extensive civil liberties (upper left) run much lower risk of armed conflict than where these rights are restricted.[40] In the Sahel region, Chad, Guinea, and to some extent Cameroon, score low on civil liberties.

Rule of law, the extent to which countries' laws are enforced effectively and impartially, is another indicator of conflict risk (see Figure 3b).[41] Again, Chad and Guinea score very

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[36]Population size is captured by the WDI sub-model. Due to the high number of other important variables informing this model, effects from population size alone is however less apparent from the sub-model forecasts.

[37]The ViEWS team is currently developing an alternative measure of conflict risk in response to this conundrum, adjusted for population size, made possible by related developments funded by the UK FCDO and UN ESCWA.

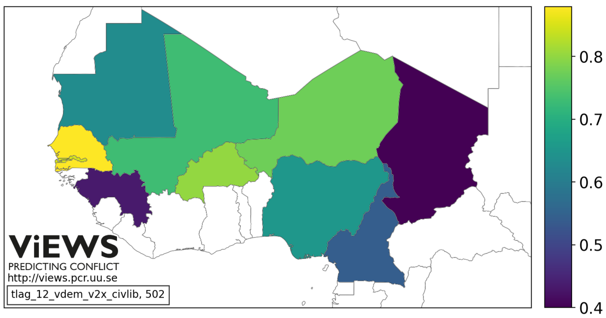
[38]For studies on poverty and conflict, see Fearon and Laitin (2003), Collier and Hoeffler (2004), Collier and others (2003), and Boix (2008), and Hegre (2018) for a review of the literature.

[39]More details on the Varieties of Democracy dataset can be found at https://www.v-dem.net/en/ and Coppedge and others (2020).

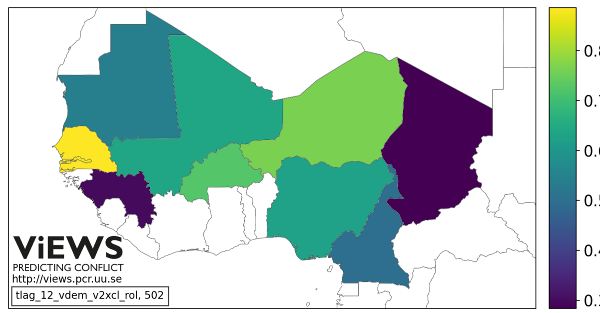
[40]Civil liberty is defined as the absence of physical violence committed by government agents, and the absence of government constraints on private and political liberties.

[41]Rule of law is defined by the V-Dem project as the extent to which laws are transparent and rigorously enforced and public administration impartial, and to what extent citizens enjoy access to justice, secure property rights, freedom from forced labor, freedom of movement, physical integrity rights, and freedom of

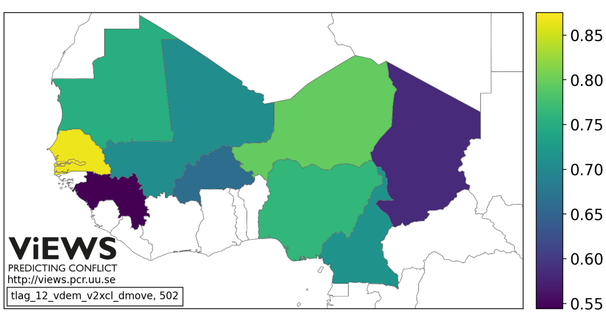
Figure 3.
Input data: Levels of governance



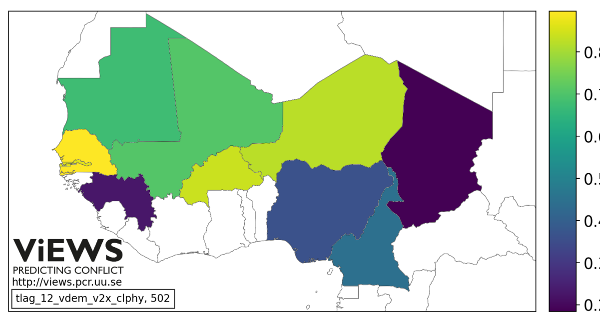
(a) V-Dem civil liberties



(b) V-Dem rule of law



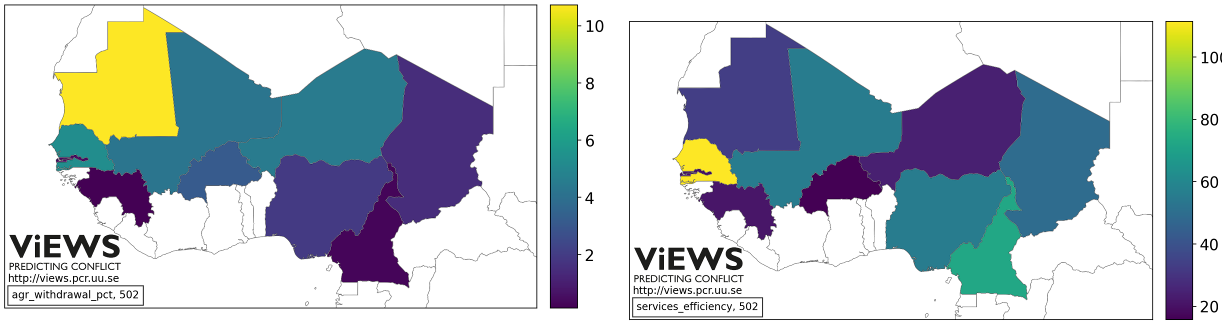
(c) V-Dem freedom of movement



(d) V-Dem physical integrity index

Note: Input data from some of the best performing indicators of levels of governance in the ViEWS system – measures of civil liberties, the rule of law, freedom of movement, and physical security, all with a 12-month lag. The December 2021 forecasts are informed by data up until and including October 2021, why the 12-month lagged data in the figures above show the level of governance as of October 2020. Indices range from 0 (no rights) to 1 (full rights).
Source: Varieties of Democracy (Coppedge and others, 2020), adapted for the report by the ViEWS team.

Figure 4.
Input data: Water resources and their use



(a) Available water used for agriculture

(b) Water services efficiency

Note: Input data from the best performing indicators of available water resources and their use in the ViEWS system – the most recent AQUASTAT data on agricultural water withdrawal as % of total renewable water resources (left), and services sector value added per unit of water (USD/m3, right). AQUASTAT releases compilations of annual data every five years, the most recent of which cover the years of 2013-2017, here showing data for 2017.
Source: FAO (2021), adapted for the report by the ViEWS team.

poorly on this risk indicator, and Mauritania and Cameroon also display poor rule of law compared to other countries in the region.

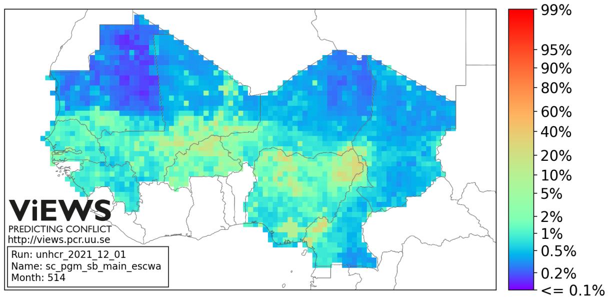
The two final governance indicators that are important for the system are the extent to which citizens enjoy freedom of movement and physical integrity – freedom from political killings and torture by the government. These freedoms also decline during war and protracted conflicts, and reinforce the expectation of continued violence in countries already suffering from such. Weak freedom of movement, however, also contributes to the risk score for Chad and Guinea (Figure 3c), and poor protection of physical integrity increases the risk of conflict not only in the two latter, but also in Nigeria and Cameroon (Figure 3d).

Two UNISS countries that have been relatively peaceful over the past decade score very well on these governance indicators – Senegal and the Gambia. Good governance and civil liberties contribute to the low predicted risk of conflict in both of these countries.

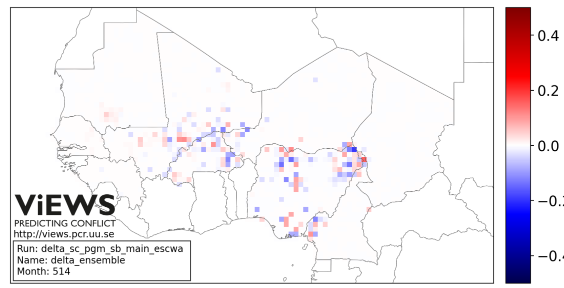
Last, the ViEWS system includes a set of water management governance variables that also contribute to the forecasts. Figure 4 shows the share of available water withdrawn from agriculture to the left and the general water services efficiency to the right.[42] High water withdrawal rates contribute to a somewhat higher risk of conflict in Mauritania, whereas efficient water services reduce the risk in Senegal.

Figure 5.

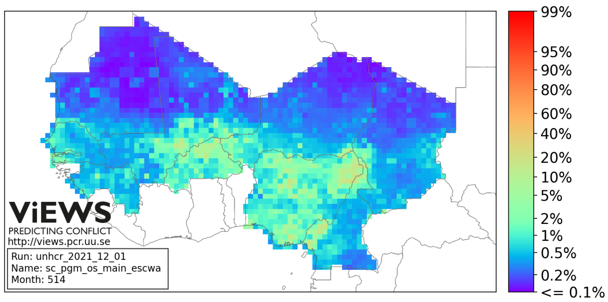
12-month forecasts for October 2022 at the PRIO-GRID-month (*pgm*), and changes to the forecasts over the past three months



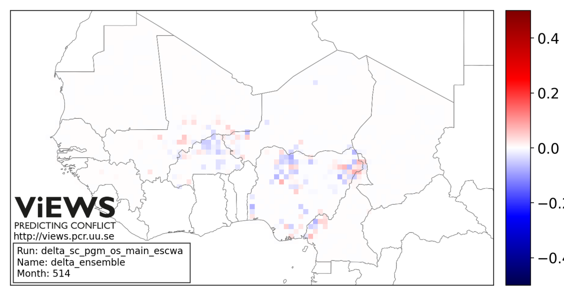
(a) State-based violence **(sb)**, *pgm* level



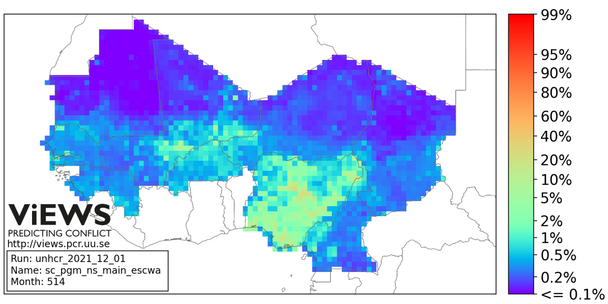
(b) State-based violence **(sb)**, *pgm* level



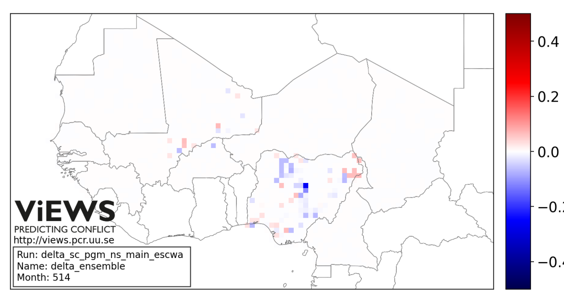
(c) One-sided violence **(os)**, *pgm* level



(d) One-sided violence **(os)**, *pgm* level



(e) Non-state violence **(ns)**, *pgm* level



(f) Non-state violence **(ns)**, *pgm* level

Note: Predicted probability of at least one fatality per sub-national (approx. 55x55 km) location and month per type of violence (left column), and changes to the 12-month forecasts as compared to those produced in September 2021 (right column). Red colors in the change maps point to heightened risks, whereas blue colors indicate that risks are reducing. The severity of each risk alteration (by percentage points, *pp*) is illustrated by the color saturation; white indicating no change.
Source: ViEWS, December 2021

5.2 The PRIO-GRID-month (*pgm*) level

12-month forecasts

The left-hand column of 5 shows the forecasts for fatal political violence per sub-national location 12 months into the future, based on data up to and including October 2021. They correspond to the country-level forecasts presented above, and show close resemblances between the state-based and one-sided categories also at this level of analysis.

For the state-based and one-sided categories, the ViEWS system alerts to particularly high risks of fatal violence in regions that have suffered such violence in the recent past. More specifically, we find the border region between Mali, Burkina Faso, and Niger, as well as north-eastern Nigeria and northernmost Cameroon – in all of which a number of militant Islamist groups operate – at particular risk over the next year. Also the Zamfara, Katsina, and Kaduna states of Nigeria, as well as the Anglophone regions of Cameroon, stand out in the 12-month forecasts for both categories of violence. The Nigerian states have been prone to banditry, whereas the Anglophone region of Cameroon has seen a recent escalation of the Ambazonia insurgency.

While past conflict remains the key driver of future conflict, some locations that have not been highly affected by conflict over the past decades are also flagged by the system (Figure 5). Currently stable countries like Senegal, Guinea, and the Gambia, all show non-negligible probabilities of state-based violence, and partially also of one-sided violence (Figure 5a–5c). In all three cases, the assessment is instead driven by a combination of drought occurrence during the growing season, heavy dependence on agriculture, and poor efficiency in water management. Although the cross-level sub-model that incorporates results from the country-level forecasts plays a role in these forecasts too, the influence of good governance and a peaceful history is relatively weak in the sub-national model.[43] Similarly, droughts and societal vulnerability, along with geography-related factors, contribute also to the forecasts for violence continuation in central Mali, northern Burkina Faso, and south-western Niger.

Last, the forecasts for non-state violence once more highlight Nigeria as the most at-risk country also sub-nationally. These forecasts are driven by recurring cultist, farmer-herder, and communal violence.

Changes to the 12-month forecasts over the past three months

Changes to the 12-month forecasts generated in December 2021 relative to those produced three months prior predominantly concern the high-risk areas identified above. Closely connected to recent patterns of conflict history (see the geographic distribution in Figure 6a), we see localities at both heightened and reduced risk in Nigeria's North-East and the extended border area between Burkina Faso, Mali, and Niger, in which militant Islamist groups continue to operate (Figure 5b). The same patterns are found in Nigeria's North-West and

religion.

[42] Data for water management are taken from FAO Aquastat, FAO (2021).

[43] This is to a considerable extent due to the sub-national model predicting the probability of at least one death in every location. With the relatively low predicted probabilities for Senegal and the Gambia, the risk of 25 deaths per month (the threshold for the country-level model) is quite low, despite the danger of some violence across the territory.

South-East (informed by arbitrary episodes of banditry and attacks by gunmen in the former, and clashes between government forces and IPOB in the latter), and in Anglophone Cameroon (where the Ambazonia insurgency persists).

The same regions are highlighted in the change map for violence exerted by armed actors against unarmed civilians (Figure 5d). Changes are however more distinct in the one-sided category – while a combination of increased and reduced risks are found in North-Eastern Nigeria and Anglophone Cameroon, reduced risks take precedence in the rest of the conflict-prone regions of Nigeria, as well as in Burkina Faso. The red grid cells in Mali relate to fatal attacks attributed to IS and JNIM.

In the non-state category, changes are yet more distinct (Figure 5f). Reducing risks are detected in North-Western Nigeria, while heightened tensions are picked up by the model in the North-East following recurrent episodes of infighting between jihadist groups, and ISWAP attacks on local militias. The aforementioned clashes between Dozos and JNIM in Mali are also demonstrated by red grid cells at heightened risk in the the Mopti and Segou regions.

Key predictors of conflict at the sub-national level

Three main groups of factors explain the evolution and distribution of forecasts at the sub-national level: conflict legacy, development levels, and the degree of societal vulnerability to climate extremes (particularly how droughts affect agricultural production and households' livelihood).

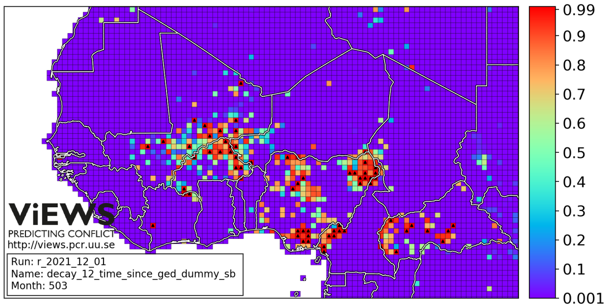
Conflict history As mentioned above, future conflict is predominantly expected in, or in close proximity to, locations with a recent history of violence. This is particularly clear from the resemblance between the sub-national forecasts and the conflict history map in Figure 6. Applying the spatial resolution that the sub-national forecasts are generated for, red cells in Figure 6a–6c show that fatal political violence has occurred as late as October 2021 (distinguished by a black marker) or September 2021, whereas purple cells have not experienced such violence for many years.

Levels of development Similar to the country-level forecasts, also the sub-national forecasts emphasize the contribution of the socio-economic themes of conflict predictors on future conflict risk. More specifically, the system highlights the effects of indicators of under-development, most importantly that of infant mortality rates. The high-risk countries of Mali and Niger, for example, present among the highest rates of infant mortality on the African continent. Clearly, the prevalence of conflict in these areas hinder development and increase infant mortality rates, contributing to 'development in reverse'.[44]

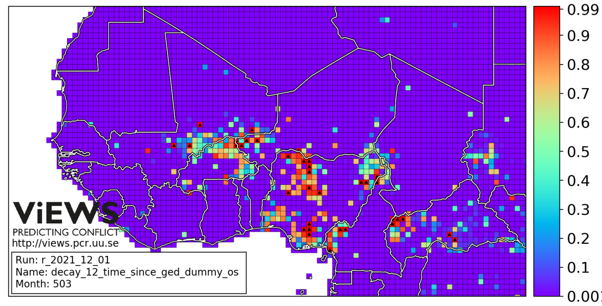
Societal vulnerability to climate extremes The final category of key sub-national drivers of conflict relate to societal vulnerability to environmental changes and other exogenous shocks, especially driven by dependence on agriculture. Locations that are strongly dependent on agriculture are more vulnerable to climate shocks and related crop failures,

[44] Collier and others (2003)

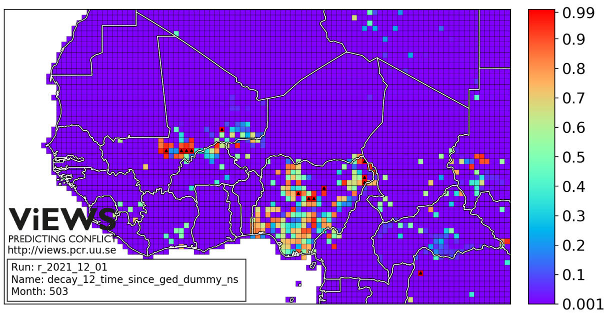
Figure 6.
Input data: Conflict and protest history by location and time since the last event



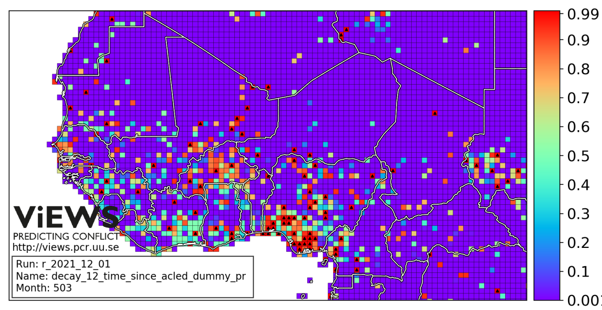
(a) State-based violence



(b) One-sided violence



(c) Non-state violence



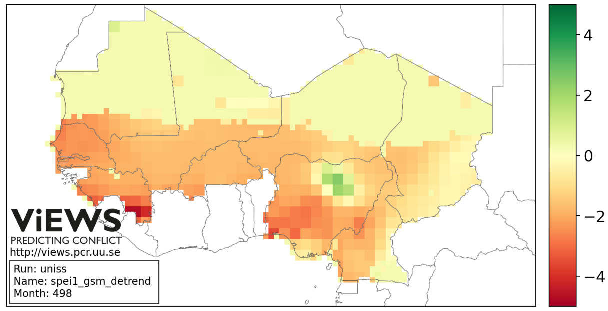
(d) Protests (violent and non-violent)

Note: The recent history of fatal political violence as well as protests (violent and non-violent). Red cells observed such incidents in October 2021 (distinguished by a black marker) or September 2021. Purple cells have not experienced such incidents for many years. Based on data up until and including October 2021.
Source: UCDP Candidate Events Dataset (UCDP Candidate) version 21.0.3 (global), and the Armed Conflict Location & Event Data Project (ACLED) (both publicly available), adapted for the report by the ViEWS team.

as households' income primarily rely on crop production. Consistently, the system assign a higher probability of conflict to locations that have a relatively high share of cultivated land, and a high percentage of people employed in agriculture. Nigeria, which presents the highest share of agricultural employment in the region, is flagged by the climate sub-models as particularly vulnerable. Broadly, the south of Nigeria, the area straddling between Senegal and Guinea, as well as the border region between Senegal and Mauritania, the districts of Niamey and Tillabéri in Niger, and the central area of Burkina Faso, which are more intensively cultivated compared to the rest of the Sahel, all have a relatively high probability of conflict according to these models.

Illustrating the effects of climate-related shocks to agriculturally dependent areas, Figure 7 shows the occurrence of drought during the growing season in June 2021. Red and orange values in the figure indicate droughts, whereas dark green shades represent the occurrence of intense rainfall during the main crops' growing season. Seen from the figure, the central-north

Figure 7.
Input data: Drought occurrence during the growing season



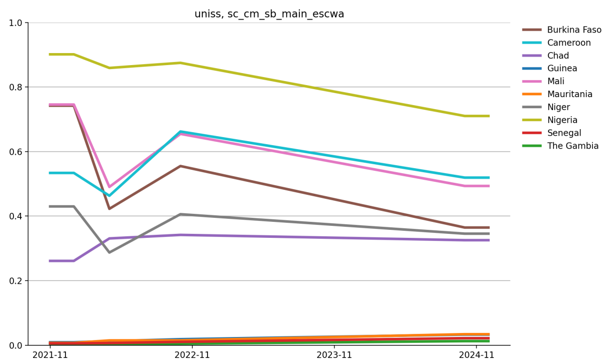
Note: Red and orange colors indicate the occurrence of a severe drought during the main crops' growing season. Yellow corresponds to average conditions; green shades correspond to intense rainfall and floods during the growing season. Values are based on the SPEI Index, an indicator of soil moisture that combines temperature and precipitation data on the ground. Data as of June 2021. *Source:* SPEI Index (Vicente-Serrano, Beguería, and López-Moreno, 2010), adapted for this report by the ViEWS team.

of Nigeria was the only area that experienced abundant rainfall in June 2021, while the rest of the UNISS countries of the Sahel were affected by very dry conditions. Extremely intense droughts in turn hit the south-east of Guinea and the south of Nigeria, particularly the area of Lagos and Ibadan. A higher probability of future conflict was consequently assigned to the affected areas in these countries by the drought-informed sub-models (compare to Figure 20c, 20e, 20f and corresponding maps for **os** and **ns** in Appendix A).

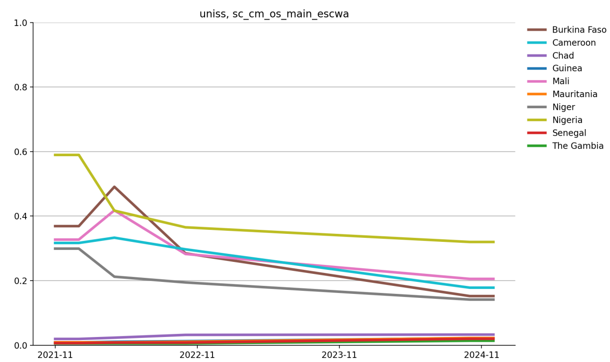
Comparing the occurrence of droughts with the results from the drought-informed forecasting sub-models reveal some additional interesting patterns. First, many of the drought-hit areas, such as Nigeria and Guinea, do get assigned a moderate to high probability of conflict by these sub-models, but not in the areas that were affected by the most intense drought; rather, high levels of violence are predicted to occur in neighboring locations. This is consistent with studies finding that droughts may trigger out-migration from affected areas, as deprived people move in a quest for better livelihood conditions. In turn, inflows of migrants can change the ethnic and socio-economic dynamics in receiving areas, trigger competition for scarce resources, and increase the likelihood of violent outbreaks.

Second, as follows from the above, it is clear that the effect of a dry growing season is not as important as conflict legacy or socio-economic conditions in predicting conflict risk. Although the system assigns quite a considerable conflict risk to drought-affected locations, it also forecasts the highest probability of conflict in those sub-national areas that experience ongoing violence, such as the area at the border between Nigeria, Chad and Cameroon, the south-west area of Cameroon, the north region of Burkina Faso, and the central and north area of Mali crossed by RN19, the country's main road. This is particularly evident when looking at the results from the combined agro-climatic, natural and social geography sub-model, which includes indicators of past conflict as a measure of vulnerability to exogenous shocks.

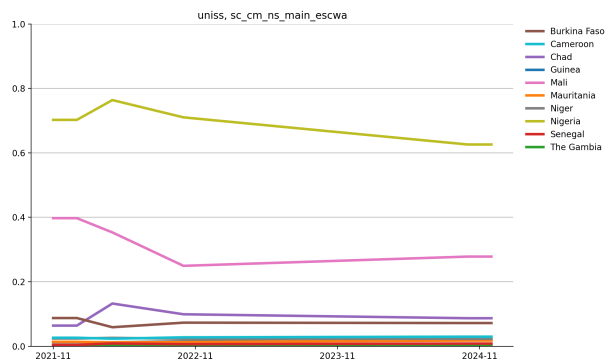
Figure 8.
Three-year forecasts, November 2021–October 2024



(a) State-based violence **(sb)**, *cm* level



(b) One-sided violence **(os)**, *cm* level



(c) Non-state violence **(ns)**, *cm* level

Note: Country-level forecasts for the Sahel region over the period November 2021–October 2024. The figure shows the predicted probability (0-1) of 25 or more fatalities per country and month, from each type of violence. Forecasts as of December 2021, based on data up to and including October 2021.
Source: ViEWS, December 2021

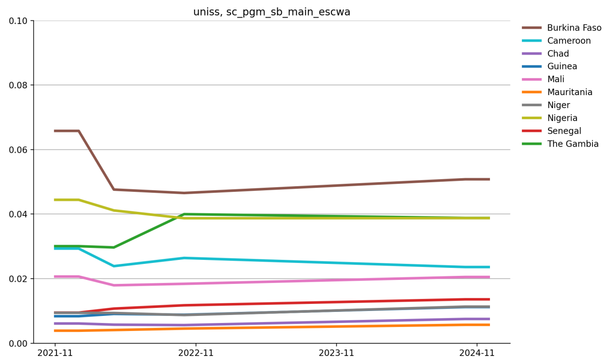
5.3 Three-year trends

Looking further into the forecasting horizon for the UNISS countries of the Sahel, little to no changes are expected. While the country level forecasts, illustrated by the line graphs in Figure 8a–8c, show some reducing conflict risks over time, these trends are not indicative of expected changes on the ground but rather a result of increasing prediction uncertainty when forecasting further into time.

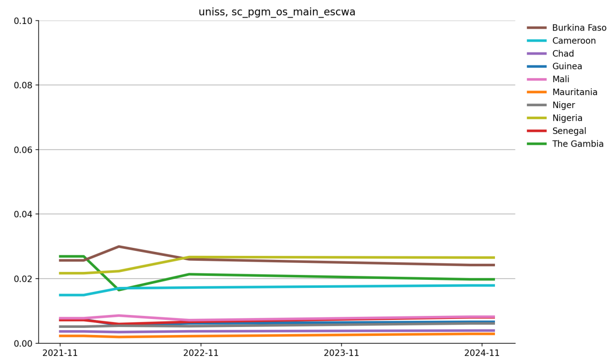
The system assumes that the global average rate of deaths in armed conflict will be constant as long as all the risk factors remain constant, but when forecasting three years into the future, it becomes less certain about where violence will occur, and distributes the expected risk more evenly. The forecasting system thus produces less geographically precise predictions (more visible from long-term forecast maps at the sub-national level), spreading the risk across a vaster area and thus somewhat reduces the risk for high- and medium risk countries or locations, while moderately increasing the predicted risk for locations otherwise

Figure 9.

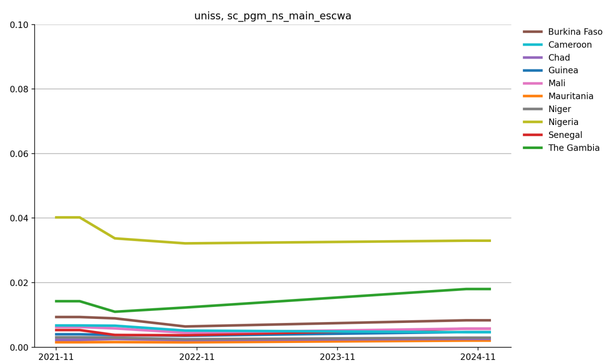
Mean forecasted share of sub-national locations to observe fatal violence, November 2021–October 2024



(a) State-based violence **(sb)**, *pgm* level



(b) One-sided violence **(os)**, *pgm* level



(c) Non-state violence **(ns)**, *pgm* level

Note: Mean forecasts share of sub-national locations expected to observe at least one battle-related death per month over the period November 2021–October 2024. Forecasts as of December 2021, based on data up to and including October 2021.
Source: ViEWS, December 2021

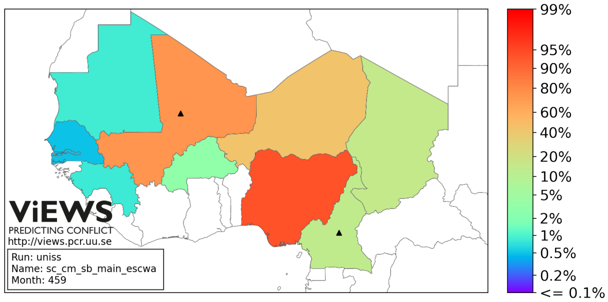
considered to be low-risk countries.

Also at the sub-national level is the three-year trend one of stability: the average risks of fatal violence at sub-national locations (Figure 9), equally the mean forecasted share of approximately 55x55 km locations to experience such violence, remain at near constant levels for almost all countries throughout the three-year forecasting horizon (with the exception of the uncertainty-induced alterations), further supporting the discussion above.

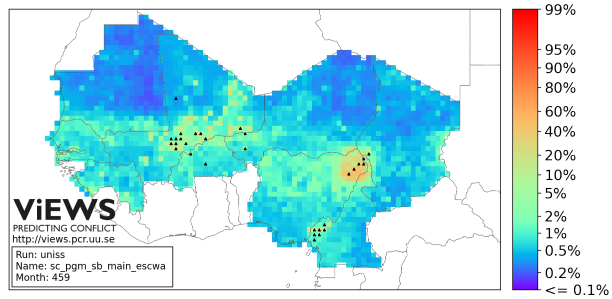
6 Predictive performance of the ViEWS models

In what follows, we present an overview of the predictive performance of the ViEWS system for the 36-month period spanning January 2018–December 2020, using examples from the 3, 12, and 36-month forecasts. A more thorough evaluation of the Africa pilot of the forecasting system is presented in Hegre and others (2021b). The Middle East expansion is in turn evaluated in a forthcoming publication co-authored with PRIO and UN ESCWA.

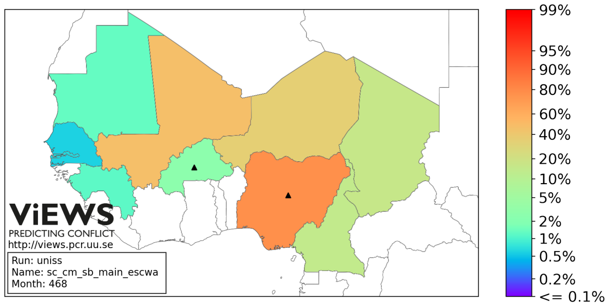
Figure 10.
Predictive performance over 2018–2020, state-based violence



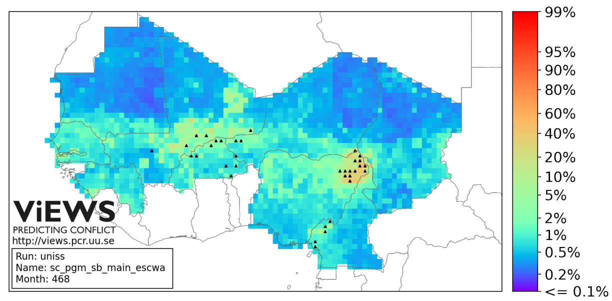
(a) Predictions for March 2018, *cm*



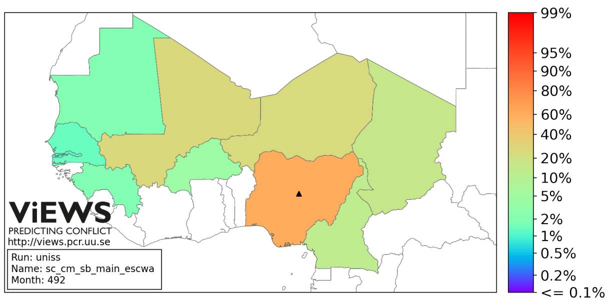
(b) Predictions for March 2018, *pgm*



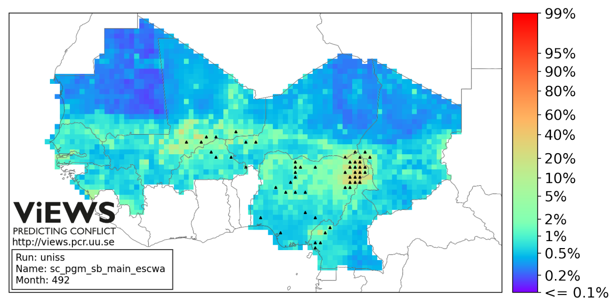
(c) Predictions for December 2018, *cm*



(d) Predictions for December 2018, *pgm*



(e) Predictions for December 2020, *cm*



(f) Predictions for December 2020, *pgm*

Note: The maps show the predicted probabilities of non-state violence generated in a retrospective run of the ViEWS system for selected months in the 2018–2020 period, as well as the violence that was observed over the same months. Red color denotes a high predicted probability of conflict, whereas purple/blue color indicates a low probability. Actual conflicts are shown with triangles; one per country that observed such in the top row of maps, and one per applicable grid cell in the bottom row. The predictioos were based on the data that were available in January 2018, up to and including December 2017. Results for one-sided and non-state violence are found in Section B.1 of Appendix B.
Source: ViEWS, December 2021

Figure 10 presents a snapshot of how well the ViEWS system performed in a test run based on data up to and including December 2017 – the data we would have had in a February

2018 update. The maps show predictions of state-based violence for March 2018, December 2018, and December 2020 – 3, 12, and 36 months into the forecasting window. The left-hand column in Figure 10 presents the country-level predictions for 25 or more conflict-related deaths from state-based violence per country in the respective months, and the right-hand column shows the corresponding predictions for at least one such death per approximately 55x55 km location and month. Forecasts are represented with colors, and actual conflict observations with triangles (one per country that observed 25 or more fatalities in the given month in the left-hand column, and one per grid cell that experienced at least one death in the given month in the right-hand column).

The right-hand column of maps suggests that the system did quite well in identifying sub-national locations in which conflict would take place – observed violence predominantly occurred in locations with a notable risk thereof, particularly with regards to north-eastern Nigeria in December 2018 and 2020, when violence was wide-spread across the region. March 2018 is the exception in terms of the number of false alarms in northern-eastern Nigeria, further discussed below.

The country-level results (left-hand column), surprisingly, proved less accurate in the near future than when forecasting one or more years into the future. Despite high expectations thereof, neither Nigeria nor Niger observed 25 fatalities in March 2018, while Mali (correctly predicted) and Cameroon (predicted at a relatively low probability) did. When forecasting 12 and 36 months into the future, the system accurately predicted conflict in Nigeria, albeit it assigned a relatively low probability to Burkina Faso which saw the 25-fatality threshold crossed in December 2018.

While this type of visual snap-shot performance mapping enables a straight-forward evaluation for individual months, it also runs a high risk of misrepresenting the true predictive performance of the system, if the months presented include major abnormalities. This was also the case for the March 2018 forecasts. The ViEWS system is trained to predict cases in which at least 25 fatalities will occur in a given country and month. Nigeria has observed more than 100 fatalities from state-based violence almost every month since mid-2013 (see Figure 2a), which is why the system assigned a very high probability of this happening also in March 2018. That specific month, however, 'only' 19 fatalities were recorded in the state-based violence category, heavily contradicting this trend. [45] To this day, March 2018 remains the only month not to have reached this threshold since early 2013, and likewise the only month for which the ViEWS system has made an incorrect prediction for Nigeria in this category of violence since the system was launched.[46] Seen from Figure 2a, also Cameroon saw a sudden change in the number of monthly fatalities around March 2018; after a nearly two-year long decline in conflict-related deaths, the numbers spiked over 2018 after the government had declared war on the Ambazonia separatists and sent its army into the Anglophone region. The fatality counts have remained at higher levels ever since also for Cameroon.

[45] By the time of the cut-off date for the retrospective run of the system presented here (November 2017), the somewhat lower levels of violence recorded in January and February 2018 had not yet been fed into the system, rendering the temporary dip in fatalities in March 2018 yet more unexpected.

[46] The monthly death toll in Nigeria declined to 90-64-19-67-87-80 fatalities over the first half of 2018 – still well over the 25-fatality threshold for the ViEWS forecasts – and then jumped back up to the hundreds by July 2018.

Results are similar also for the one-sided and non-state violence categories. Maps for these two categories can be found in Section B.1 of Appendix B. In the former category, the system generated high alerts for both Nigeria and Cameroon in both March and December 2018, neither of which crossed the 25-fatality threshold for one-sided violence in either month. The system also signalled a low probability in Mali, where the threshold was surpassed in both March 2018 and December 2018. Fatalities were however mostly concentrated to the areas that the sub-national forecasts pin-pointed as high- or medium-risk locations, the exception of north-eastern Nigeria in March 2018 excluded.

In the non-state violence category, the system performed significantly better in identifying the countries in which 25 or more fatalities would occur in the three selected months – high risks were assigned to Nigeria throughout this period, and the fatality threshold was reached all three times. Only in December 2020 was the threshold exceeded in other countries in the region; this time correctly predicted in Mali, but missed (only a low probability) in Chad. The sub-national forecasts, in turn, did relatively well in identifying future conflict locations (avoiding misses), albeit false alarms were common.

As follows from the abnormalities discussed above, evaluation metrics that incorporate the full amount of data are preferred in order to form a complete picture of the forecasting system's performance. A simple but far more telling approach to this is found in so-called confusion matrices – tables that, in this case, show the number of observed and unobserved incidences of violence against the predictions thereof. More specifically, they show how *relevant* and *accurate* the predictions were over the full forecasting window – how often the system issued an 'alarm' that correctly indicated that a conflict would occur, and vice versa.

Tables 5–8 help answer these questions. They tabulate the performance of the average 3, 12, and 36-months-ahead predictions for state-based violence in the UNISS countries of the Sahel, at both levels of analysis, over the course of 2018–2020. For this particular demonstration, the retroactive evaluation was repeated 36 times – observed values were compared to forecasts for January 2018, produced using data up and including November 2017; to forecasts for February 2018, using data up to and including December 2017, etc. At the country level, a binary alarm was issued if the system assigned a probability of conflict higher than 20%. When predictions were lower than that, they were recorded as if no conflict would occur. At the sub-national level, the threshold was set to 10%.[47] The results were then averaged across all 36 months in order to produce mean results per month, displayed in the confusion matrices.

In a perfect prediction, all values above null would line up in the diagonal from the top left to the bottom right corner of the tables; all positive warnings issued would correspond to an actual occurrence of conflict, and all cases when a warning was not issued would match a peaceful instance. A 'false positive' stands for the case when the system predicts a conflict that does not occur in reality; a 'false negative' is the opposite situation, when the system fails to capture the conflict risk.

When forecasting three months into the future, the main country-level model performed quite well for the ten countries: the majority of observations lay on the top-left to bottom-right diagonal in Table 5a. However, when setting 20% as the threshold for warnings, the

[47] The system allows setting freely the threshold generating an alarm – this choice is for demonstration only.

Table 1.
Predictive performance over 2018–2020, forecasts for state-based violence at the country-month level

(a) 3-month forecasts

	Observed		
Predicted	Pos	Neg	Sum
Pos	3.0	1.8	4.8
Neg	0.4	4.8	5.2
Sum	3.4	6.6	10.0

Note. Threshold = 0.2, accuracy = 0.783, precision = 0.632,
recall = 0.878, brier = 0.217, f1 = 0.735

(b) 12-month forecasts

	Observed		
Predicted	Pos	Neg	Sum
Pos	2.4	1.2	3.6
Neg	1.0	5.4	6.4
Sum	3.4	6.6	10.0

Note. Threshold = 0.2, accuracy = 0.778, precision = 0.664, recall = 0.707, brier = 0.222, f1 = 0.685

(c) 36-month forecasts

	Observed		
Predicted	Pos	Neg	Sum
Pos	2.1	1.1	3.1
Neg	1.4	5.5	6.9
Sum	3.4	6.6	10.0

Note. Threshold = 0.2, accuracy = 0.758, precision = 0.661, recall = 0.602, brier = 0.242, f1 = 0.63

Note: Performance of the ViEWS system when forecasting state-based violence in the UNISS countries of the Sahel 3, 12, and 36 months ahead at the country-month level, averaged over January 2018–December 2020. Results for one-sided and non-state violence are found in Section B.2 of Appendix B.
Source: ViEWS, December 2021

system has a tendency to 'over-alert', or issue warnings even when a conflict did not end up occurring. Specifically, out of the ten country-month predictions generated each month (one for each country), there were on average 4.8 warnings that a country would observe 25 or more fatalities from state-based violence. 3.0 of these were correct predictions, while 1.8 were false alarms. For an average of 4.8 out of 5.2, the model also correctly predicted that such conflict would not occur in the given month – missing 0.4. In other words, when the system predicts no conflict in a country, the prediction tends to be correct.

The selection of a warning threshold of 20% risk is arbitrary but likely to be useful: conflicts are disastrous and have extremely negative implications for the society as a whole. Such a threshold ensures the warning system prefers a 'false positive' to a 'false negative' or to prioritize the correct identification of positive cases over the null ones. For this threshold, the model yields an accuracy of 78%, a precision of about 63%, and a recall of 88%.[48] In other words, with a threshold designed to produce more than 78% correct predictions (conflict and

[48] Accuracy is calculated as the sum of correct predictions (True Positives and True Negatives) divided by the total number of predictions. Precision indicates how many conflict warnings were relevant, or the share of correctly identified positive cases out of the sum of the True Positives and the False Positives. Recall measures how many relevant warnings were correctly selected and how many conflicts were missed by the model, i.e. the number of True Positives divided by the sum of True Positives and False Negatives.

no conflict), 63% of the country-months that the system generated a conflict alert for also saw conflict that month, while the remaining cases would be false alarms. If a higher threshold was to be used, alerts would become more precise, but there would be more 'misses' (a lower recall).

When forecasting one year into the future, and the abnormality of March 2018 is no longer part of the equation, the system shows a marginally higher precision (less false alarms), but a somewhat lower recall (more misses). Accuracy remains about the same. That precision increases over time is somewhat rare – as discussed above, the system generally becomes less certain of its predictions the further into the forecasting window we come. This further emphasizes how much of an outlier the month of March 2018 was. Three years into the forecasting window, accuracy and precision show only minor declines, but we note a dip in recall from 71–60%. This is well in line with expectations. Other than being a sign of the good performance of the system, it emphasises the protracted nature of conflicts in several of the UNISS countries. While recent history of conflict becomes less relevant when forecasting far ahead into the future, and structural features such as the level of development instead gain importance, these features are still heavily affected by ongoing conflicts. For example, violence can impinge on development and lower educational attainment, which in turn are some of the strongest predictors of conflict. The country-level model, which is trained on global data, learns to infer these somber patterns of 'conflict traps' and stagnation, such as those characterising Syria, Afghanistan, and Iraq.

The accuracy of the forecasts for one-sided violence are very similar to those above: about 78% when forecasting both 3 and 12 months ahead, and 77% when forecasting 36 months into the future (Table 6). Precision and particularly recall however drops notably for this category of violence, to be expected given the arbitrary nature of many incidences classified as one-sided violence (e.g. terror attacks against civilians).

Results from the non-state category, in turn, which captures e.g. farmer-herder violence and clashes between various armed groups, show a significantly lower precision for the 3-month-ahead forecasts, than for both the 12 and 36-month predictions. They however show an accuracy rate ranging from 90-94% over the course of the whole forecasting horizon, and only a slight decline in performance when forecasting three years into the future (Table 7). Non-state conflicts are also often less sporadic than one-sided attacks, and thus more likely to re-occur or continue in locations that have been hit by this type of violence in the past, which makes them easier to predict relative to one-sided violence. The Sahel region has a strong legacy of non-state violence, such as the conflict between Boko Haram and the CMA in Mali. Another factor that can explain the higher forecasting performance for the non-state type of violence relative to the state-based one is the inclusion of water and food-related variables in the ensemble. Many non-state violence events, involving herders and pastoralists, are related to land issues, the governance of water, and competition over scarce food resources. The conflict between the Nigerien Fulani (Peulh) herders and the Malian nomadic Touareg communities, for example, originated in 1997 around the ownership of a water well. The inclusion of features to proxy the governance and access to water and food resources may contribute to increasing the system's ability to correctly predict non-state conflicts as compared to other types of violence.

At the sub-national level (Table 8), the main model on average issued more false warnings. This is due to the difficulty in predicting the accurate location of conflict events as compared

Table 2.

Predictive performance over 2018–2020, forecasts for state-based violence at the PRIO-GRID-month level

(a) 3-month forecasts

	Observed		
Predicted	Pos	Neg	Sum
Pos	18.0	34.5	52.5
Neg	18.8	2233.7	2252.5
Sum	36.8	2268.2	2305.0

Note. Threshold = 0.1, accuracy = 0.977, precision = 0.342,
recall = 0.488, brier = 0.023, f1 = 0.402

(b) 12-month forecasts

	Observed		
Predicted	Pos	Neg	Sum
Pos	14.9	25.2	40.0
Neg	21.9	2243.0	2265.0
Sum	36.8	2268.2	2305.0

Note. Threshold = 0.1, accuracy = 0.98, precision = 0.371, recall = 0.404, brier = 0.02, f1 = 0.387

(c) 36-month forecasts

	Observed		
Predicted	Pos	Neg	Sum
Pos	10.4	18.7	29.1
Neg	26.4	2249.5	2275.9
Sum	36.8	2268.2	2305.0

Note. Threshold = 0.1, accuracy = 0.98, precision = 0.357, recall = 0.282, brier = 0.02, f1 = 0.315

Note: Performance of the ViEWS system when forecasting state-based violence in the UNISS countries of the Sahel 3, 12, and 36 months ahead at the PRIO-GRID-month level, averaged over January 2018–December 2020. Results for one-sided and non-state violence are found in Section B.2 of Appendix B.
Source: ViEWS, December 2021

to which country they will happen in. At the sub-national level, the bar for including observed events as conflict is set to also a lower threshold – 10%. Considering these difficulties, the main *pgm* model trained to predict state-based violence performed quite well. When forecasting 3, 12, and 36 months into the future with a warning threshold of 10%, it generated correct predictions 98% of the time (up from 75–78% at the country level). It nevertheless issued a higher proportion of false alarms, a number of which are inevitable with a threshold of 10%. Precision is about 34–37% over the course of the forecasting window, considerably lower than for the country-level predictions. Recall declines the farther into the future the system tried to predict, dropping from about 49% to 28%. The greater uncertainty that comes with forecasting several years into the future is thus somewhat more pronounced at this level of analysis. A lower recall indicates that the model tends to miss out on an important share of conflicts. As the dataset at the sub-national level is even more imbalanced towards zeros (non-conflict) relative to the country level, this is not surprising; the model learns from the data that there are many more grid-cells without conflicts compared to those experiencing violence, and predicts accordingly.

Similar to the country-level forecasts, the predictive performance declined notably for the one-sided and non-state categories of violence further into the forecasting horizon. While accuracy remained over 98% at all three points in time for both types of violence, precision dropped from 30% (12 months ahead) to 23% (36 months ahead) when forecasting one-sided violence, and from 37 to 12% when forecasting non-state violence. With a 55x55 km resolution and a much lower level of violence to predict, the main model trained to predict one-sided violence thus significantly outperformed the main model for non-state violence further into the forecasting window.

The generally lower predictive performance at this level of analysis is mostly driven by the model's inability to identify the *exact* grid-cells where conflict will occur. For example, the ViEWS system correctly assigned a high probability of one-sided and non-state conflicts in central Mali and north-eastern Nigeria, but also attributed a widespread risk of violence to neighboring locations, which drags the precision down. Moreover, the system incorrectly flags the north of Senegal and the southern region of the Gambia as vulnerable to conflict risks. These false alarms, which lowers the recall, were driven by the agro-climatic and vulnerability sub-models, as seen from the sub-model forecasts in Appendix A.

7 Exploratory models

Maintaining an early-warning system at the frontier of research requires iterative development. Behind the scenes of the public forecasting system, there are a myriad of new sub-projects, collaborations, model developments and infrastructure improvements underway, generally released only at the end of a lengthy testing cycle. In the section below, we offer a sneak-peak into one of these developments given its importance for understanding the complex risks that the Sahel faces: preliminary results from the exploratory phase of a new sub-model, the *climate_ extremes model*.[49]

Climate change in the Sahel

The Intergovernmental Panel on Climate Change (IPCC) has identified the Sahel region of Africa as a climate hot spot due to observed hot extreme and heatwaves, a more rapid increase in surface temperature than the global average, frequent heavy precipitation events and floods, and high rate of sea level rise.[50] Extreme natural events are projected to continue throughout the 21st century with additional global warming, while relative sea-level rise is likely to lead to more frequent and severe coastal floods in low-lying areas.

Such adverse effects of climate impedes socio-economic development and impairs the enjoyment of human rights including access to freshwater and sanitation, food security, adequate housing and health. Crucially, climate extremes interact with socio-economic and political factors on the ground to increase the vulnerability of local communities and may push people to migrate or modify traditional patterns of migration.[51]

[49] Please note that the model, due to its exploratory status, has not yet been incorporated into the ViEWS ensembles. The discussion and results below should therefore be seen as preliminary and subject to change as the iterative model development process proceeds.

[50] IPCC, 2021.

[51] *Human Rights Climate Change and Migration in the Sahel*.

Among such factors, dependence on agriculture plays a major role. Droughts and climate anomalies decrease agricultural productivity and shape the distribution of crop yields across space.[52] If no adaptation takes place, global yields are expected to decrease at a global pace of 1.5% per decade.[53] and low latitudes are projected to bear the brunt of these adverse effects.[54] In turn, crop failures are associated with spikes in food prices, negative impacts to the agricultural labor market, and an overall deterioration of food security.[55] By increasing the vulnerability of local communities, climate extremes can enhance societal grievances that people are willing to act upon, trigger competition for increasingly scarce resources, ease the attractiveness of conflict actors, and overall raise the incentives of deprived individuals to join rebel groups.

Climate extremes as predictors of conflict

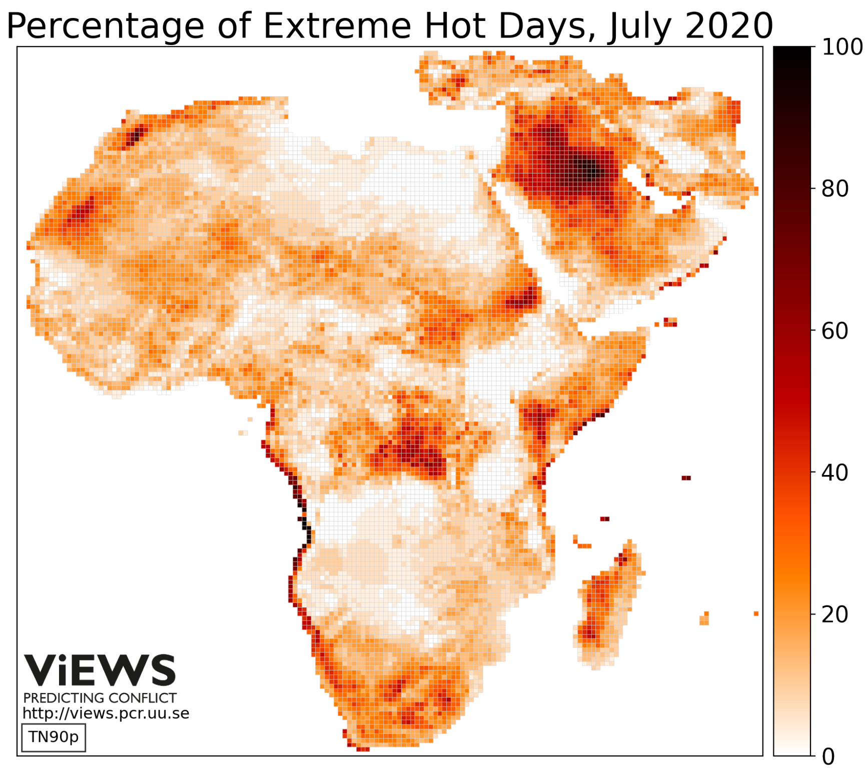
Drawing upon the findings above, we have developed a new sub-model – the *climate_ extremes model* – that is trained to predict political violence using a suite of climate extreme indices (CEIs), combined with the vulnerability indicators from *vulnerability model* in Section 3.2.

The CEIs included in the model (see Table 12 for an exhaustive list) are a standardised set of indices recommended by the Expert Team on Sector-Specific Climate Indices (ET-SCI), the standardisation of which allows results to be comparable across time periods, regions and source data. The indices were computed using the *R software climpact package* and raw hourly data on temperature and precipitation (with a resolution of 0.25x0.25 degrees) provided by ERA5,[56] using the years 1990-2010 as the baseline period. They include measures of extreme weather conditions such as droughts, warm spells and extreme hot and cold days, which are suitable metrics to capture the effect of climate on a range of socio-economic factors, such as agriculture, which can increase or decrease societal vulnerability and thereby contribute to exacerbate/mediate conflict risk. Moreover, CEIs capture both the spatial and temporal heterogeneity characterising climate extremes, which is particularly important when evaluating the future impacts of climate change. In fact, as climate conditions can vary considerably within countries, the mean climate conditions at the country level may be misrepresentative.

Figure 11 illustrates one of the CEIs informing the model: the *tx90p* index, here showing the percentage of extreme hot days in July 2020. *Tx90p* is defined as the percentage of days in a month in which the daily maximum temperature is above the 90th percentile, centred on a 5-day window. As seen from the figure, extreme heat severely affected central Mali, the area straddling the border between Chad and Libya, most of Guinea, the south of Sudan, the coastline of Egypt and the north coastal area of the Arab Peninsula.

[52]Vesco and others, 2021.
[53]Lobell and Gourdji, 2012
[54]Jägermeyr and others, 2021.
[55]Rudolfsen, 2021
[56]ECMWF, 2021)

Figure 11.
Input data: Extreme hot days (percentage), July 2020



Note: Climate extremes were computed using the *R Climpact* package, using data on temperature and precipitation from ERA-5 (ECMWF, 2021).
Source: ECMWF, 2021

Forecasts for October 2022 and October 2024

Figure 12 presents the forecasts for state-based, one-sided, and non-state violence in October 2022 and October 2024, as generated by the climate extremes model. The model assigns a medium to high risk of violence, especially *ns* violence, in the central area of Mali and north-western Burkina Faso – regions hit by severe heat spells and natural extremes, to which they are made particularly vulnerable by the gloomy legacy of conflict.

The model also predicts a high risk of violence in conflict-ridden Nigeria, especially in the north-eastern state of Borno, and along the border to Cameroon. These regions have been exposed to severe natural extremes, such as dry days, heat spells and extreme temperatures, which can contribute to increase the vulnerability of societies already weary with poverty, large populations, and heavy dependence on agriculture.

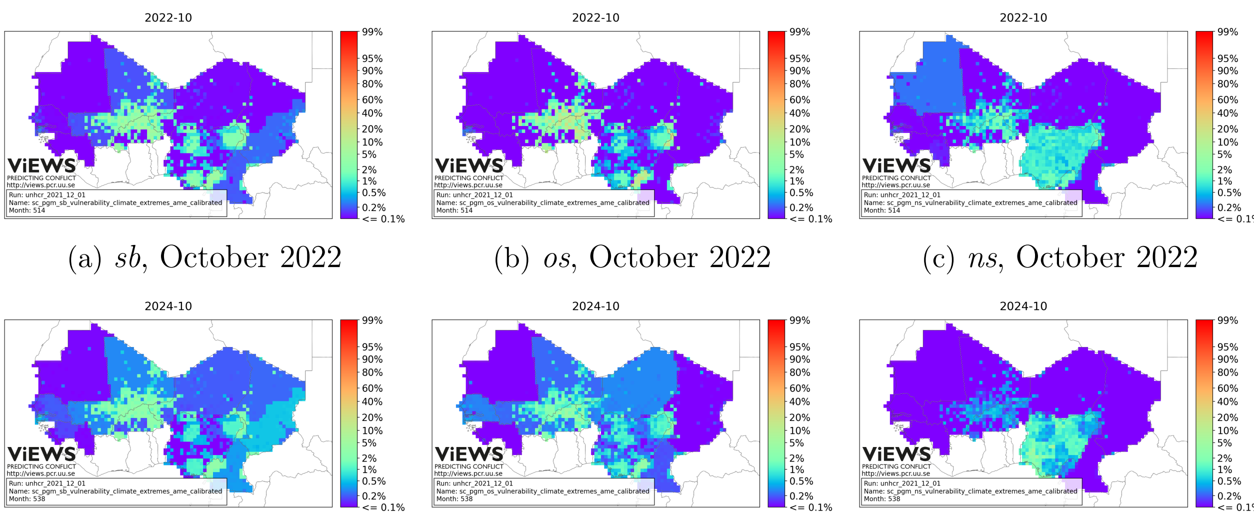
The key drivers of the forecasts above stem from the vulnerability features that the model captures. These include the history of conflict, population size, economic conditions, dependence to agriculture and ethnic exclusion. Their high importance relative to the other features included in the model can be seen from the list of feature importances for forecasts of state-based violence in Table 12 – the higher the value, the greater is the relative importance of the listed feature. Results for *os* and *ns* are found in Appendix C. While emphasis on climatic drivers are key to preventing violence, these results confirm that socio-economic factors are more important – vulnerable societies are less able to recover from the adverse impacts of climate change and may become more prone to conflict risks.

Amongst the climate extreme indices, the model flags measures of variability in precipitation patterns (*rx5day*), the daily temperature range (*dtr*), and temperature extremes (*txx, tnx, txgt50p*) as the most relevant features to predict state-based conflict, especially for the longer term (36 months ahead).

Predictive performance of the model

Table 4c presents the predictive performance of the climate extremes model for the January 2018–December 2020 period. The model presents an average precision of 0.16-0.25 across when forecasting 3, 6, 12, and 36 months ahead (or 'steps' *s* ahead). Although the performance declines along the forecasting horizon, the model performs quite well compared to the broad models in Hegre and others, 2021b, which include a number of thematic features.

Figure 12.
Sub-national forecasts from the climate extremes model



(a) *sb*, October 2022 (b) *os*, October 2022 (c) *ns*, October 2022

(d) *sb*, October 2024 (e) October 2024 (f) October 2024

Note: Predicted probability of at least one battle-related death per grid cell and month from state-based, non-state, and one-sided violence in October 2022 (12 months ahead) and October 2024 (36 months ahead), as generated by the *climate extremes* model.
Source: ViEWS, December 2021

Table 3.
Feature importances for the *climate extremes* sub-model, *sb*

feature	short description	s=3	s=6	s=12	s=36
decay_12_time_since_ged_dummy_sb	history of conflict	0.298	0.284	0.251	0.161
pgd_nlights_calib_mean	economic conditions	0.135	0.146	0.153	0.192
splag_1_1_ged_best_sb	proximity to conflict	0.086	0.077	0.067	0.050
tlag_12_wdi_nv_agr_totl_kd	dependence on agriculture	0.077	0.077	0.088	0.111
rx5day	monthly maximum consecutive 5-day precipitation	0.052	0.056	0.055	0.066
pgd_excluded	ethnic exclusion	0.020	0.019	0.021	0.026
dtr	daily temperature range	0.019	0.020	0.021	0.021
rx7day	monthly maximum consecutive 7-day precipitation	0.017	0.018	0.019	0.019
tnn	monthly minimum temperature	0.016	0.016	0.017	0.019
txn	monthly minimum value of daily maximum temperature	0.016	0.015	0.017	0.019
txx	monthly maximum temperature	0.015	0.016	0.017	0.018
tnx	monthly maximum value of daily minimum temperature	0.015	0.015	0.016	0.018
txgt50p	percentage of days with temperature above the median	0.014	0.015	0.016	0.016
spei12	spei drought index over 12 months	0.014	0.015	0.017	0.018
tnm	mean temperature	0.014	0.014	0.015	0.017
spei6	spei drought index over 6 months	0.014	0.014	0.015	0.016
txm	mean daily maximum temperature	0.014	0.015	0.016	0.017
tmm	mean daily temperature	0.014	0.015	0.015	0.017
spi12	spi drought index over 12 months	0.014	0.014	0.015	0.018
spi6	spi drought index over 6 months	0.013	0.013	0.015	0.015
spei3	spei drought index over 3 months	0.013	0.013	0.015	0.015
spi3	spi drought index over 3 months	0.012	0.013	0.015	0.015
tn90p	percentage of days when minimum temperature > 90th percentile	0.011	0.011	0.013	0.013
tx90p	percentage of days when maximum temperature > 90th percentile	0.011	0.011	0.012	0.012
tx10p	percentage of days when maximum temperature < 10th percentile	0.010	0.010	0.011	0.012
tn10p	percentage of days when minimum temperature < 10th percentile	0.010	0.010	0.010	0.012
prcptot	annual total precipitation	0.008	0.008	0.008	0.009
cdd	consecutive dry days	0.008	0.008	0.008	0.009
txge30	number of days when maximum temperature > 30°	0.007	0.007	0.007	0.008
su	number of days when maximum temperature > 25deg	0.006	0.006	0.007	0.008
tr	number of days when minimum temperature > 20°C	0.006	0.006	0.007	0.008

Note: Relative weight (on a scale from 0–1) of the features informing the sub-model when forecasting state-based conflict 3, 6, 12, and 36 months into the future. Results for **os** and **ns** are found in Appendix C. A full description of the indicators can be found at https://climpact-sci.org/indices/.
Source: ViEWS, December 2021

Table 4.
Predictive performance of the climate extremes sub-model, January 2018–December 2020

	3	6	12	36	sc
average_precision	0.245164	0.237574	0.211815	0.160621	0.215482
area_under_roc	0.954393	0.948139	0.933497	0.893019	0.923948
brier	0.008188	0.008370	0.008575	0.010188	0.008837

(a) State-based violence (*sb*)

	3	6	12	36	sc
average_precision	0.085155	0.081818	0.067438	0.041480	0.073072
area_under_roc	0.907808	0.902182	0.885848	0.837732	0.866376
brier	0.004620	0.004630	0.004757	0.005174	0.004715

(b) One-sided violence (*os*)

	3	6	12	36	sc
average_precision	0.063041	0.064048	0.066675	0.065223	0.081181
area_under_roc	0.902651	0.903295	0.900965	0.885663	0.891229
brier	0.003906	0.003939	0.003767	0.004564	0.004037

(c) Non-state violence (*ns*)

Note: Predictive performance of the climate extremes sub-model when forecasting **sb**, **os**, and **ns** violence in the UNISS countries of the Sahel 3, 6, 12, and 36 months ahead at the country-month level, and across all months, computed over January 2018–December 2020.
Source: ViEWS, December 2021

8 Conclusions

Preventing armed conflict is key to promoting development and human well-being in the Sahel. As highlighted in the UN-WB *Pathways for Peace* report,[57] conflict prevention in turn requires early warning.

This report has presented assessments for the Sahel region from the Violence Early-Warning System (ViEWS). ViEWS is a foresight tool designed to estimate not only how long ongoing conflicts will last, but also the risk that new ones will erupt. The report has laid out how the system is built and discussed the main results.

As of December 2021, the ViEWS system suggests that Nigeria, Mali, Burkina Faso, Cameroon, Niger, and Chad will be at a very high risk of 25 or more deaths per month from conflicts that involve a government of a state (state-based conflict, Figure 1a) over the next year, while Nigeria and Mali top the corresponding warning lists for violence exerted by armed groups against unarmed civilians (one-sided violence, Figure 1c) and conflicts set between non-state armed actors (non-state conflict, Figure 1e).

More specifically, the ViEWS system suggests that risks of political violence will be particularly high in areas that have suffered such violence in the recent past – conflict legacy emerges as the key driver of future conflict. Of particular note is the risk of fatal state-based and one-sided violence in the border region between Mali, Burkina Faso, and Niger, as well as in north-eastern Nigeria, all of which are home to a number of active militant Islamist groups (Figure 5a–5c). Similar patterns are seen in northernmost Cameroon. Also Zamfara, Katsina, and Kaduna states in Nigeria, and the Anglophone regions of Cameroon, are highlighted by the system. The former have been prone to banditry, whereas the Anglophone region of Cameroon has seen a recent escalation of the Ambazonia insurgency.

For non-state violence, Nigeria – particularly the southern and central states – appears as the single most at-risk country also at the geographic level (Figure 5e). These forecasts are driven by recurring cultist-, farmer-herder-, and communal violence.

Last, some geographic locations that have not been highly affected by conflict over the past decades are also flagged by the system. Currently stable countries like Senegal, Guinea, and the Gambia, all show locations of non-negligible probabilities of state-based violence, and partially also of one-sided violence (Figure 5a–5c) over the next year. In all three cases, the risk assessment is driven by a combination of drought occurrence during the growing season, heavy dependence on agriculture, and poor efficiency in water management.

Overall, the system suggests that the future risk of conflict in the Sahel will remain largely the same not only over the next 12 months but over the next three years, both nationally and sub-nationally (Figure 8–9). What drives the forecasts however changes depending on how far into the future one predicts. When forecasting a few months ahead, the immediate conflict history serves as the most important predictor of future violence, while structural and slow-moving features that tend to characterise countries over time take precedence when forecasting several years into the future. These include – but are not limited to – socio-economic grievances and low development indicators, demographic patterns, and poor governance relating to the rule of law, economic performance, and the management of crucial resources like water. The negative impact of climate variability, in turn, is another steady driver of the fore-

[57] World Bank Group and United Nations (2017)

casts: droughts combined with the level of agricultural dependence and societal vulnerability to climate extremes play an important role in predicting future conflict.

The trends identified by the system are somber: unless the compounding effects of the factors above are adequately tackled, the levels of violence in the Sahel are unlikely to change. Measures aimed at immediate conflict reduction may offer a temporary respite, but any efforts to promote a durable peace must address the structural challenges that the region faces, and invest in capacity-building for societal resilience to climate extremes.

References

Andrews, Colin and others (Jan. 2021). The State of Economic Inclusion Report 2021: The Potential to Scale. en. The World Bank. DOI: 10.1596/978-1-4648-1598-0. URL: http://elibrary.worldbank.org/doi/book/10.1596/978-1-4648-1598-0 (visited on 08/31/2021).

Bell, Curtis, Clayton Besaw, and Matthew Frank (2021). The Rulers, Elections, and Irregular Governance (REIGN) Dataset. Broomfield, CO: One Earth Future. URL: https://oefdatascience.github.io/REIGN.github.io/.

Boix, Carles (2008). Economic roots of civil wars and eevolutions in the contemporary world. In: *World Politics*, Vol. 60, pp. 390–437.

Boyd, Emily and others (July 2013). Building resilience to face recurring environmental crisis in African Sahel. In: *Nature Climate Change*, Vol. 3, No. 7, pp. 631–637. DOI: 10.1038/nclimate1856. URL: http://www.nature.com/articles/nclimate1856 (visited on 08/31/2021).

Collier, Paul and Anke Hoeffler (2004). Greed and grievance in civil war. In: *Oxford Economic Papers*, Vol. 56, No. 4, pp. 563–595.

Collier, Paul and others (2003). Breaking the Conflict Trap. Civil War and Development Policy. Oxford: Oxford University Press. URL: https://openknowledge.worldbank.org/handle/10986/13938.

Coppedge, Michael and others (2020). V-Dem Codebook v10. Varieties of Democracy (V-Dem) Project.

Croicu, Mihai and Ralph Sundberg (2015). UCDP Georeferenced Event Dataset Codebook Version 4.0. In: *Journal of Peace Research*, Vol. 50, No. 4, pp. 523–532. URL: http://www.pcr.uu.se/research/ucdp/datasets/ucdp_ged/.

Eck, Kristine and Lisa Hultman (2007). One-Sided Violence against Civilians in War: Insights from New Fatality Data. In: *Journal of Peace Research*, Vol. 44, No. 2, pp. 233–246.

ECMWF, Copernicus (2021). ERA5 hourly data on single levels from 1979 to present. URL: https://cds.climate.copernicus.eu/cdsapp#!/dataset/reanalysis-era5-single-levels?tab=overview.

FAO (2021). AQUASTAT Database. License: CC BY-NC-SA 3.0 IGO. Food and Agriculture Organization of the United Nations. URL: http://www.fao.org/nr/water/aquastat/data/ (visited on 03/25/2021).

Fearon, James D. and David D. Laitin (2003). Ethnicity, Insurgency, and Civil War. In: *American Political Science Review*, Vol. 97, No. 1, pp. 75–90.

Gates, Scott and others (2012). Development consequences of armed conflict. In: *World Development*, Vol. 40, No. 9, pp. 1713–1722. DOI: 10.1016/j.worlddev.2012.04.031.

Gleditsch, Kristian S. and Michael D. Ward (1999). A Revised List of Independent States since the Congress of Vienna. In: *International Interactions*, Vol. 25, No. 4, pp. 393–413.

Gleditsch, Nils Petter and others (2002). Armed conflict 1946-2001: A new dataset. In: *Journal of peace research*, Vol. 39, No. 5, pp. 615–637.

Hamro-Drotz, Dennis and United Nations Environment Programme, ed. (2011). Livelihood security: climate change, migration and conflict in the Sahel. OCLC: ocn768489506. Châtelaine, Geneva: United Nations Environment Programme. 108 pp.

Hegre, Håvard (2018). Civil Conflict and Development. In: *Oxford University Press Handbook on the Politics of Development*. Ed. by Nicholas van de Walle & Carol Lancaster. Oxford: Oxford University Press. URL: http://www.oxfordhandbooks.com/view/10.1093/oxfordhb/9780199845156.001.0001/oxfordhb-9780199845156-e-9.

Hegre, Håvard and others (2019). ViEWS: A political Violence Early Warning System. In: *Journal of Peace Research*, Vol. 56, No. 2, pp. 155–174. DOI: 10.1177/0022343319823860. URL: https://doi.org/10.1177/0022343319823860.

Hegre, Håvard and others (2021a). ViEWS$_{2020}$: Revising and evaluating the ViEWS political Violence Early-Warning System. In: *Journal of Peace Research*, Vol. 58 (3).

Hegre, Håvard and others (2020). Introducing the UCDP Candidate Events Dataset. In: *Research & Politics*, Vol. 7, No. 3 (3), p. 2053168020935257. DOI: 10.1177/2053168020935257. eprint: https://doi.org/10.1177/2053168020935257. URL: https://doi.org/10.1177/2053168020935257.

Hegre, Håvard and others (2021b). ViEWS$_{2020}$: Revising and evaluating the ViEWS political Violence Early-Warning System. In: *Journal of Peace Research*, Vol. 0, No. 0, p. 0022343320962157. DOI: 10.1177/0022343320962157. eprint: https://doi.org/10.1177/0022343320962157. URL: https://doi.org/10.1177/0022343320962157.

Helliwell, John F. and others (2020). World Happiness Report 2020. New York: New York: Sustainable Development Solutions Network.

IMF (2020). World Economic Outlook, April 2020: The Great Lockdown. Washington, D.C: International Monetary Fund. URL: https://www.imf.org/en/Publications/WEO/Issues/2020/04/14/weo-april-2020.

IPCC (2021). Climate Change 2021: The Physical Science Basis. URL: https://www.ipcc.ch/report/ar6/wg1/.

Jägermeyr, Jonas and others (Nov. 2021). Climate impacts on global agriculture emerge earlier in new generation of climate and crop models. In: *Nature Food*, Vol. 2, No. 11, pp. 873–885. DOI: 10.1038/s43016-021-00400-y. URL: https://www.nature.com/articles/s43016-021-00400-y (visited on 12/16/2021).

Lobell, David B. and Sharon M. Gourdji (Dec. 5, 2012). The Influence of Climate Change on Global Crop Productivity. In: *Plant Physiology*, Vol. 160, No. 4, pp. 1686–1697. DOI: 10.1104/pp.112.208298. URL: https://academic.oup.com/plphys/article/160/4/1686/6109554 (visited on 12/16/2021).

Maiga, Aliou (Oct. 4, 2019). The private sector can help transform the Sahel. World Bank Blog. World Bank. URL: https://blogs.worldbank.org/africacan/private-sector-can-help-transform-sahel (visited on 08/31/2021).

May, John F., Jean-Pierre Guengant, and Vincent Barras (2017). Demographic Challenges of the Sahel Countries. In: *Africa's Population: In Search of a Demographic Dividend*. Ed. by Hans Groth and John F. May. Cham: Springer International Publishing, pp. 165–177. DOI: 10.1007/978-3-319-46889-1_11. URL: http://link.springer.com/10.1007/978-3-319-46889-1_11 (visited on 08/31/2021).

Ministry of Foreign Affairs of the Netherlands (Apr. 2018). Climate Change Profile: West African Sahel. URL: https://www.government.nl/binaries/government/documents/publications/2019/02/05/climate-change-profiles/West+African+Sahel.pdf (visited on 08/31/2021).

Montgomery, Jacob M, Florian M Hollenbach, and Michael D Ward (2012). Improving predictions using ensemble Bayesian model averaging. In: *Political Analysis*, Vol. 20, No. 3, pp. 271–291.

Mueller, Hannes (2017). How Much Is Prevention Worth? Background paper for United Nations–World Bank Flagship Study, Pathways for Peace: Inclusive Approaches to Preventing Violent Conflict, World Bank, Washington, DC. URL: https://openknowledge.worldbank.org/handle/10986/29380.

ND-GAIN. ND-GAIN Country Index. Notre Dame Global Adaptation Initiative. URL: https://gain.nd.edu/our-work/country-index/ (visited on 08/31/2021).

Page, Scott E. (2007). The difference: how the power of diversity creaetes better groups, firms, schools, and societies. Princeton, NJ: Princeton University Press.

Pettersson, Therése, Stina Högbladh, and Magnus Öberg (2019). Organized violence, 1989–2018 and peace agreements. In: *Journal of Peace Research*, Vol. 56, No. 4, pp. 589–603. DOI: 10.1177/0022343319856046. eprint: https://doi.org/10.1177/0022343319856046. URL: https://doi.org/10.1177/0022343319856046.

Pettersson, Therése and Magnus Öberg (2020). Organized violence, 1989–2019. In: *Journal of Peace Research*, Vol. 57, No. 4, pp. 597–613. DOI: 10.1177/0022343320934986. eprint: https://doi.org/10.1177/0022343320934986. URL: https://doi.org/10.1177/0022343320934986.

Rudolfsen, Ida (2021). Food price increase and urban unrest: The role of societal organizations. In: *Journal of Peace Research*, Vol. 58, No. 2, pp. 215–230.

Searchinger, Tim (Dec. 2018). Creating a Sustainable Food Future: Synthesis Report. World Resources Institute. URL: https://www.undp.org/content/dam/undp/library/Sustainable%20Development/Creating-a-sustainable-food-future.pdf (visited on 08/31/2021).

Sultan, Benjamin, Dimitri Defrance, and Toshichika Iizumi (Dec. 2019). Evidence of crop production losses in West Africa due to historical global warming in two crop models. In: *Scientific Reports*, Vol. 9, No. 1, p. 12834. DOI: 10.1038/s41598-019-49167-0. URL: http://www.nature.com/articles/s41598-019-49167-0 (visited on 08/31/2021).

Sundberg, Ralph and Erik Melander (2013). Introducing the UCDP Georeferenced Event Dataset. In: *Journal of Peace Research*, Vol. 50, No. 4, pp. 523–532. DOI: 10.1177/0022343313484347.

Tham Lindell, Magdalena and Kim Mattsson (June 2014). Transnational Threats to Peace and Security in the Sahel. FOI-R–3881–SE. FOI - Swedish Defense Research Agency. URL: https://www.foi.se/rest-api/report/FOI-R--3881--SE (visited on 08/31/2021).

Tollefsen, Andreas Forø, Håvard Strand, and Halvard Buhaug (2012). PRIO-GRID: A unified spatial data structure. In: *Journal of Peace Research*, Vol. 49, No. 2, pp. 363–374. DOI: 10.1177/0022343311431287. eprint: http://jpr.sagepub.com/content/49/2/363.full.pdf+html.

UN (2018). UN Support Plan for the Sahel. United Nations. Tech. rep.

— (May 2019). Sahel 2043: Towards a resilient, inclusive and prosperous Sahel region. Tech. rep. Addis Ababa, Ethiopia.

UNESCWA (forthcoming). How long will the fighting last? Forecasting armed conflict for the Arab region. In:

UNHCR (June 2020). Sahel Crisis: Responding to the urgent needs of refugees, internally displaced, returnees and others of concern. Tech. rep.

United Nations High Commissioner for Human Rights (OHCHR). Human Rights Climate Change and Migration in the Sahel. Geneva, Switzerland: OHCHR. URL: https://www.ohchr.org/Documents/Issues/ClimateChange/HR-climate-change-migration-Sahel.pdf.

V-Dem institute (2020). Autocratization Surges – Resistance Grows. Democracy report 2020. Göteborg: V-Dem institute. URL: https://www.v-dem.net/media/filer_public/f0/5d/f05d46d8-626f-4b20-8e4e-53d4b134bfcb/democracy_report_2020_low.pdf.

Vesco, Paola and others (2021). Climate variability, crop and conflict: Exploring the impacts of spatial concentration in agricultural production. In: *Journal of Peace Research*, Vol. Forthcoming (XXX). DOI: 10.1177/0022343320971020.

Vicente-Serrano, Sergio M., Santiago Beguería, and Juan I. López-Moreno (2010). A Multiscalar Drought Index Sensitive to Global Warming: The Standardized Precipitation Evapotranspiration Index. In: *Journal of Climate*, Vol. 23, No. 7, pp. 1696–1718. DOI: 10.1175/2009JCLI2909.1. eprint: https://doi.org/10.1175/2009JCLI2909.1. URL: https://doi.org/10.1175/2009JCLI2909.1.

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

Weidmann, Nils B, Doreen Kuse, and Kristian Skrede Gleditsch (2010). The geography of the international system: The CShapes dataset. In: *International Interactions*, Vol. 36, No. 1, pp. 86–106.

World Bank (2011). World Development Report 2011: Conflict, Security, and Development. World Bank.

— (July 8, 2019). World's population will continue to grow and will reach nearly 10 billion by 2050. World Bank Data Blog. URL: https://blogs.worldbank.org/opendata/worlds-population-will-continue-grow-and-will-reach-nearly-10-billion-2050 (visited on 08/31/2021).

World Bank Group and United Nations (2017). Pathways for Peace: Inclusive Approaches to Preventing Violent Conflict. Main Messages and Emerging Policy Directions. International Bank for Reconstruction and Development/The World Bank.

World Food Programme (Dec. 2020). WFP's Socio-economic Response and Recovery Programme Framework. World Food Programme. URL: https://docs.wfp.org/api/documents/WFP-0000122807/download/?_ga=2.79757023.915493479.1630415585-887952700.1630415585 (visited on 08/31/2021).

WorldBank (2019). World Development Indicators. Washington DC: World Bank.

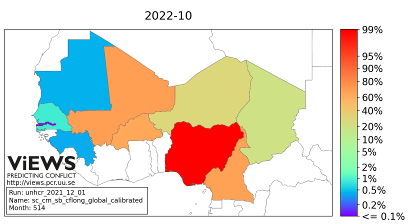
Wucherpfennig, Julian and others (2011). Politically Relevant Ethnic Groups across Space and Time: Introducing the GeoEPR Dataset. In: *Conflict Management and Peace Science*, Vol. 28, No. 5, pp. 423–437. eprint: http://cmp.sagepub.com/content/28/5/423.full.pdf+html.

Appendices

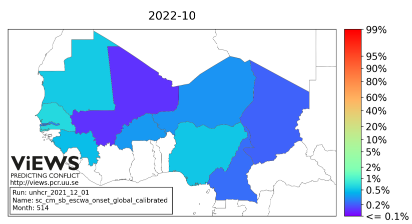
A Sub-model forecasts

A.1 Country-level forecasts

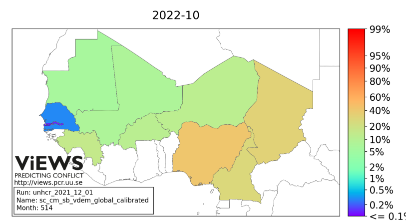
Figure 13.
Risk assessments from the sub-models informing ViEWS. 12-month *cm* forecasts for sb in October 2022.



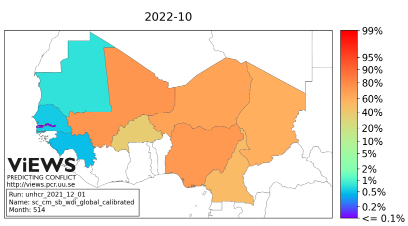
(a) Conflict history model



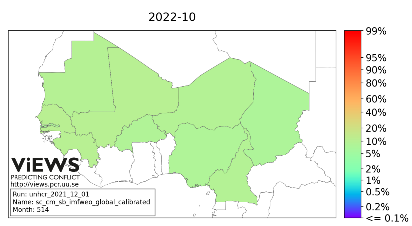
(b) Conflict onset model



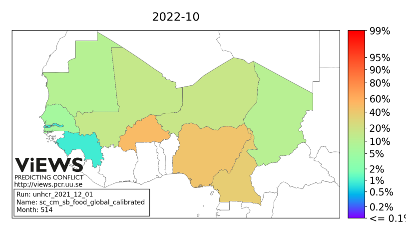
(c) Political institutions models



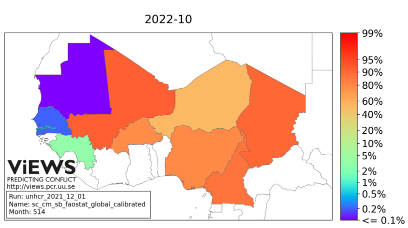
(d) WDI model



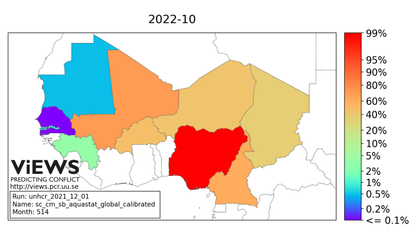
(e) Growth forecasts model



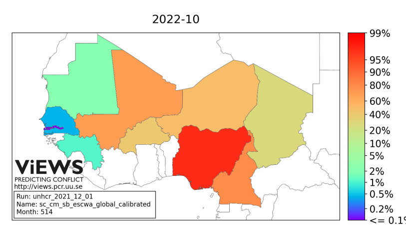
(f) Food prices model



(g) Food security model



(h) Water management model

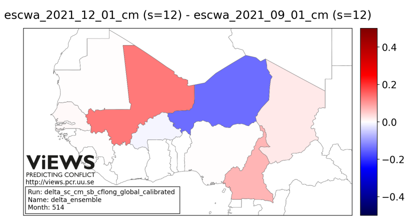


(i) Global multi-feature model

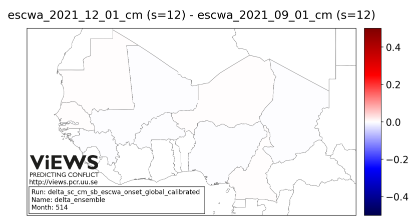
Note: Predicted probability for state-based violence as generated by each thematic group of conflict predictors—each sub-model—informing the ViEWS system. Loosely speaking, the sub-model forecasts illustrate the predictive capacity of the conflict predictors captured by the respective models. Sub-models that alert to high conflict probabilities are often informed by variables that are key to explaining conflict in that specific location, whereas sub-models pointing to low conflict probabilities instead draw upon contributing but less decisive variables for the forecast horizon at hand (in this case, a snapshot of the conflict risk 12 months ahead). The precise contribution of the thematic sub-models and the conflict predictors captured by them are determined by a sophisticated weighting mechanism documented in Hegre and others (2021b).
Source: ViEWS, December 2021.

Figure 14.

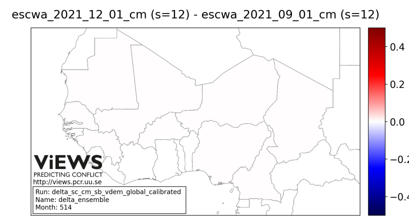
Changes to the sub-model 12-month forecasts for sb at *cm* over the past three months



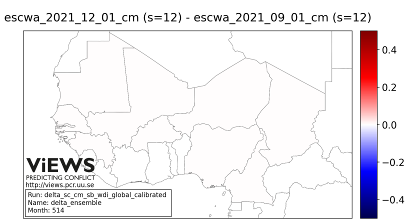
(a) Conflict history model



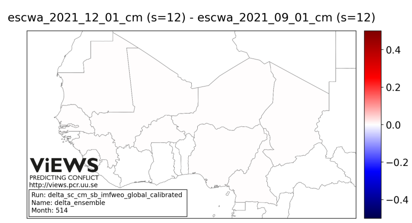
(b) Conflict onset model



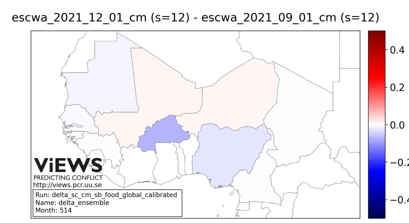
(c) Political institutions models



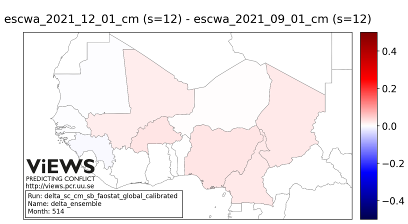
(d) WDI model



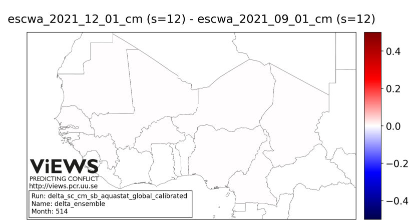
(e) Growth forecasts model



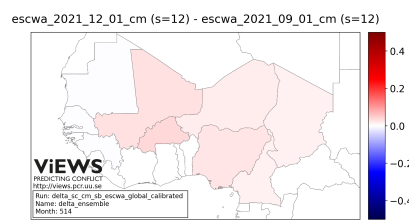
(f) Food prices model



(g) Food security model



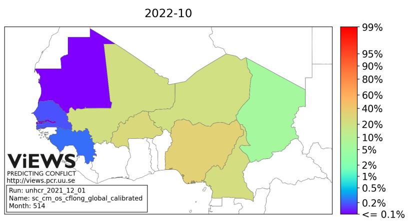
(h) Water management model



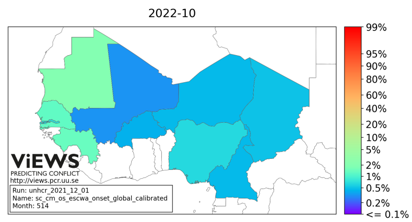
(i) Global multi-feature model

Note: Supporting material to Figure 1b in the main report, showing what happened 'under the hood' of the changes to the 12-month forecasts. The maps show the corresponding changes to each of the thematic groups of conflict predictors (each of the sub-models) informing the main forecasts. Red colors point to heightened risks, whereas blue colors indicate that risks are reducing. The severity of each risk alteration (by percentage points, *pp*) is illustrated by the color saturation; white indicating no change. Changes are indicative of updated input data, in turn illustrating what groups of conflict predictors informed any alterations to the main conflict forecasts.
Source: ViEWS, December 2021.

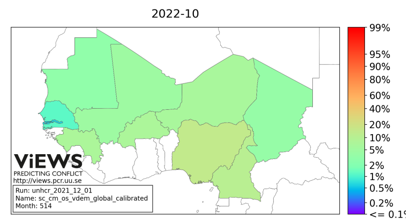
Figure 15.
Risk assessments from the sub-models informing ViEWS. 12-month *cm* forecasts for os in October 2022.



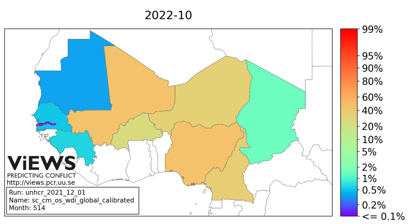
(a) Conflict history model



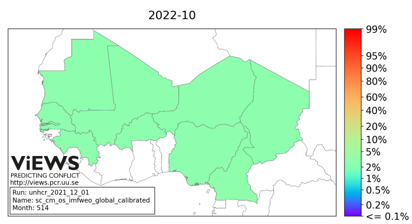
(b) Conflict onset model



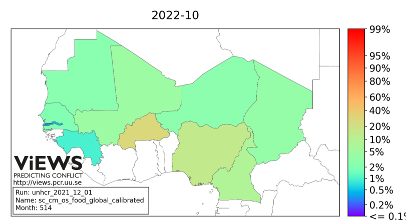
(c) Political institutions models



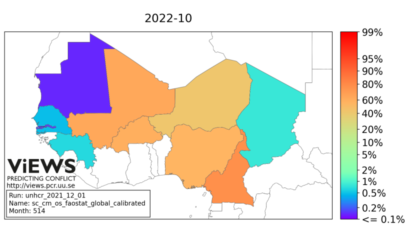
(d) WDI model



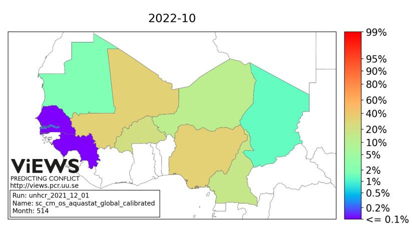
(e) Growth forecasts model



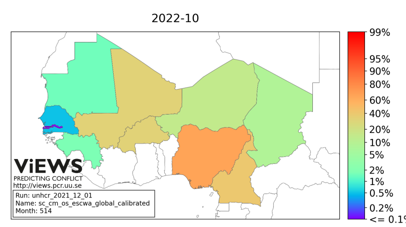
(f) Food prices model



(g) Food security model



(h) Water management model

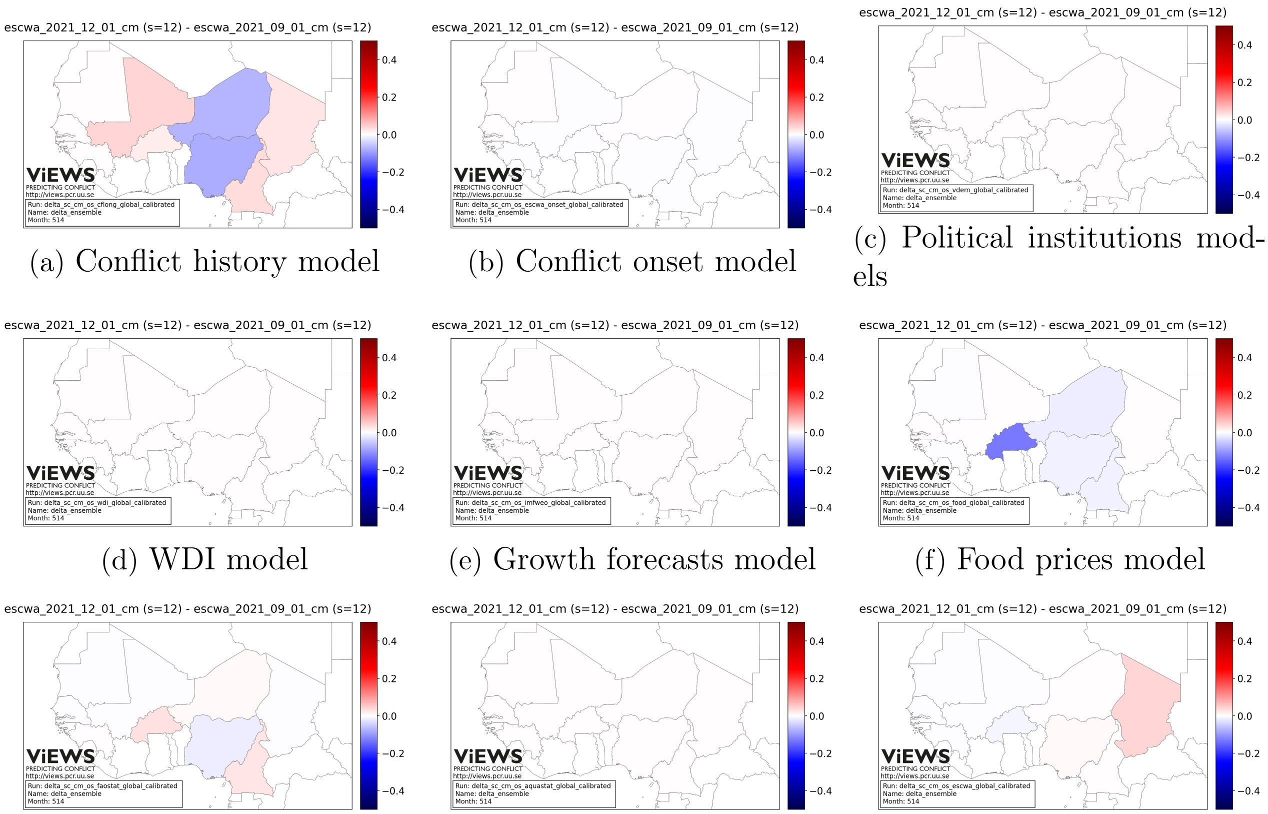


(i) Global multi-feature model

Note: Predicted probability for one-sided violence as generated by each thematic group of conflict predictors—each sub-model—informing the ViEWS system. Loosely speaking, the sub-model forecasts illustrate the predictive capacity of the conflict predictors captured by the respective models. Sub-models that alert to high conflict probabilities are often informed by variables that are key to explaining conflict in that specific location, whereas sub-models pointing to low conflict probabilities instead draw upon contributing but less decisive variables for the forecast horizon at hand (in this case, a snapshot of the conflict risk 12 months ahead). The precise contribution of the thematic sub-models and the conflict predictors captured by them are determined by a sophisticated weighting mechanism documented in Hegre and others (2021b).
Source: ViEWS, December 2021.

Figure 16.

Changes to the sub-model 12-month forecasts for os at *cm* over the past three months



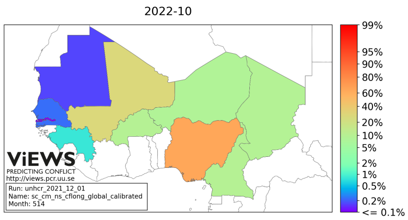
(a) Conflict history model (b) Conflict onset model (c) Political institutions models

(d) WDI model (e) Growth forecasts model (f) Food prices model

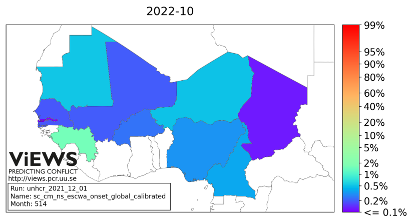
(g) Food security model (h) Water management model (i) Global multi-feature model

Note: Supporting material to Figure 1d in the main report, showing what happened 'under the hood' of the changes to the 12-month forecasts. The maps show the corresponding changes to each of the thematic groups of conflict predictors (each of the sub-models) informing the main forecasts. Red colors point to heightened risks, whereas blue colors indicate that risks are reducing. The severity of each risk alteration (by percentage points, *pp*) is illustrated by the color saturation; white indicating no change. Changes are indicative of updated input data, in turn illustrating what groups of conflict predictors informed any alterations to the main conflict forecasts.
Source: ViEWS, December 2021.

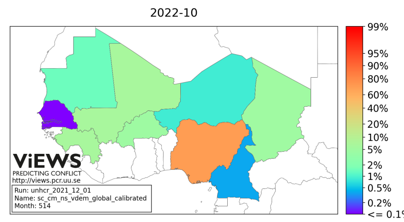
Figure 17.
Risk assessments from the sub-models informing ViEWS. 12-month *cm* forecasts for ns in October 2022.



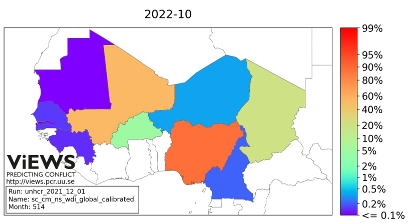
(a) Conflict history model



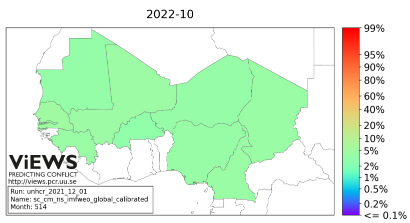
(b) Conflict onset model



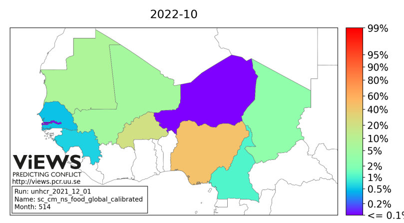
(c) Political institutions models



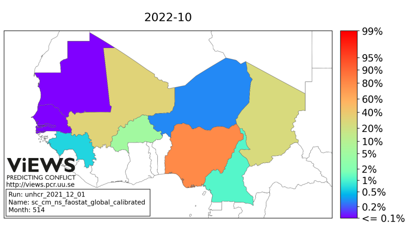
(d) WDI model



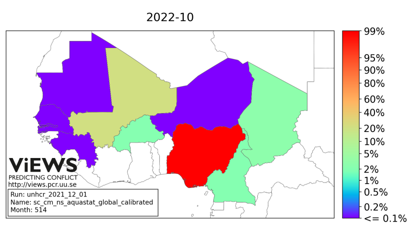
(e) Growth forecasts model



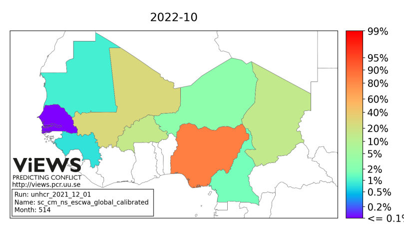
(f) Food prices model



(g) Food security model



(h) Water management model

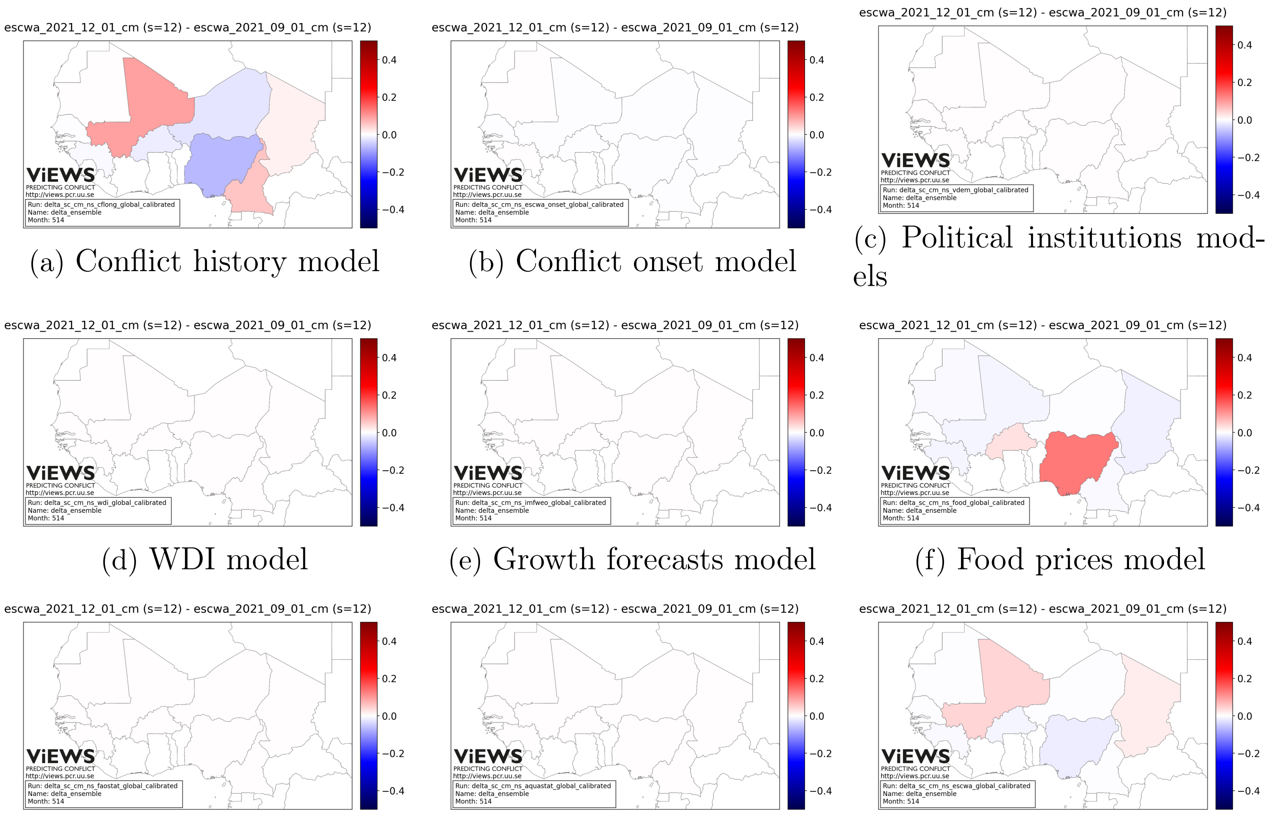


(i) Global multi-feature model

Note: Predicted probabilities for non-state violence generated by each thematic group of conflict predictors—each sub-model—informing the ViEWS system. Loosely speaking, the sub-model forecasts illustrate the predictive capacity of the conflict predictors captured by the respective models. Sub-models that alert to high conflict probabilities are often informed by variables that are key to explaining conflict in that specific location, whereas sub-models pointing to low conflict probabilities instead draw upon contributing but less decisive variables for the forecast horizon at hand (in this case, a snapshot of the conflict risk 12 months ahead). The precise contribution of the thematic sub-models and the conflict predictors captured by them are determined by a sophisticated weighting mechanism documented in Hegre and others (2021b).
Source: ViEWS, December 2021.

Figure 18.

Changes to the sub-model 12-month forecasts for ns at *cm* over the past three months



(a) Conflict history model (b) Conflict onset model (c) Political institutions models

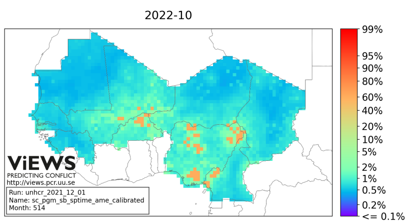
(d) WDI model (e) Growth forecasts model (f) Food prices model

(g) Food security model (h) Water management model (i) Global multi-feature model

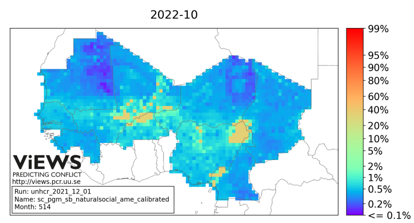
Note: Supporting material to Figure 1f in the main report, showing what happened 'under the hood' of the changes to the 12-month forecasts. The maps show the corresponding changes to each of the thematic groups of conflict predictors (each of the sub-models) informing the main forecasts. Red colors point to heightened risks, whereas blue colors indicate that risks are reducing. The severity of each risk alteration (by percentage points, *pp*) is illustrated by the color saturation; white indicating no change. Changes are indicative of updated input data, in turn illustrating what groups of conflict predictors informed any alterations to the main conflict forecasts.
Source: ViEWS, December 2021.

A.2 Sub-national forecasts

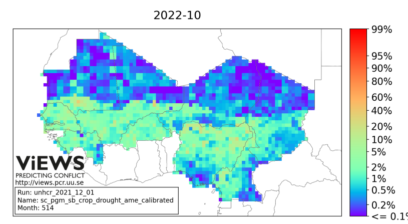
Figure 19.
Risk assessments from the sub-models informing ViEWS. 12-month *pgm* forecasts for sb in October 2022.



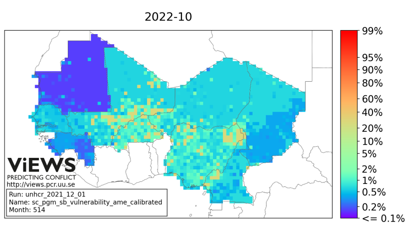
(a) Space-time model



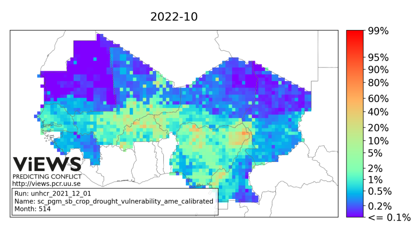
(b) Natural and social geography model



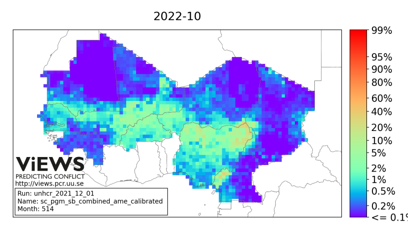
(c) Agro-climatic model



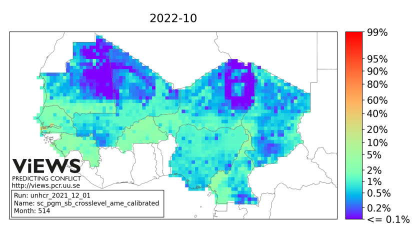
(d) Vulnerability



(e) Combined agro-climatic vulnerability model



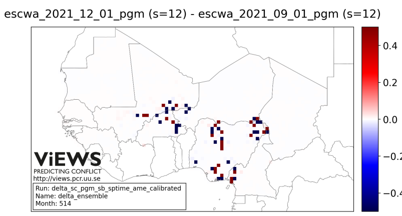
(f) Combined agro-climatic, natural and social geography model



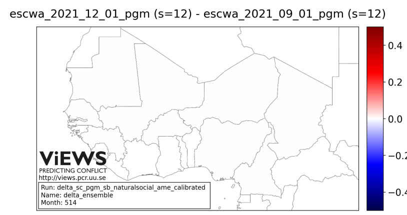
(g) Cross-level model

Note: Predicted probabilities of state-based violence as generated by each thematic group of conflict predictors—each sub-model—informing the ViEWS system. Loosely speaking, the sub-model forecasts illustrate the predictive capacity of the conflict predictors captured by the respective models. Sub-models that alert to high conflict risks are often informed by variables that are key to explaining conflict in that specific location, whereas sub-models pointing to low conflict risks instead draw upon contributing but less decisive variables for the forecast horizon at hand (in this case, a snapshot of the conflict risk 12 months ahead). The precise contribution of the thematic sub-models and the conflict predictors captured by them are determined by a sophisticated weighting mechanism documented in Hegre and others (2021b).
Source: ViEWS, December 2021.

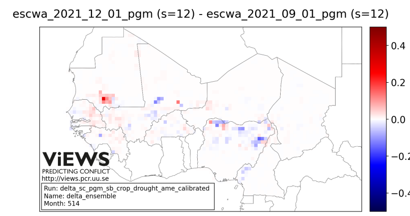
Figure 20.
Changes to the sub-model 12-month forecasts for sb at *pgm* over the past three months



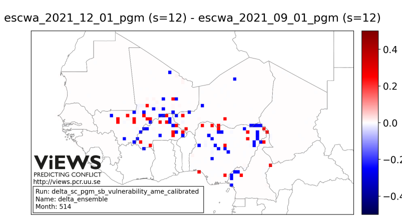
(a) Space-time model



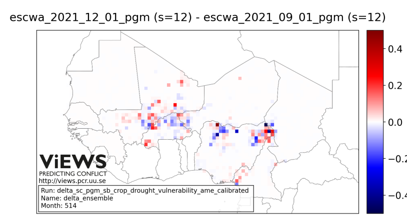
(b) Natural and social geography model



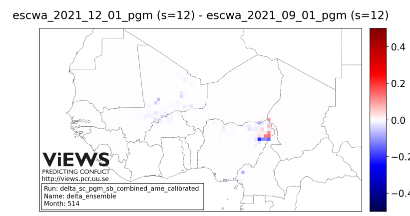
(c) Agro-climatic model



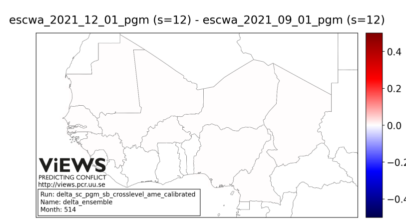
(d) Vulnerability



(e) Combined agro-climatic vulnerability model



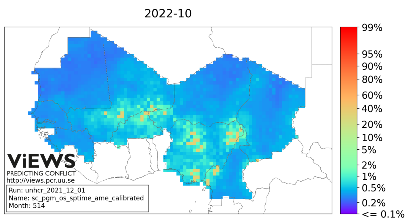
(f) Combined agro-climatic, natural and social geography model



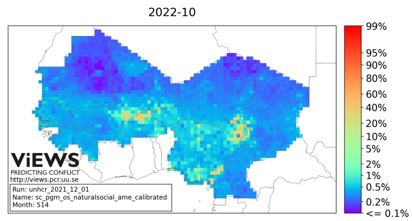
(g) Cross-level model

Note: Supporting material to Figure 5b in the main report, showing what happened 'under the hood' of the changes to the 12-month forecasts. The maps show the corresponding changes to each of the thematic groups of conflict predictors (each of the sub-models) informing the main forecasts. Red colors point to heightened risks, whereas blue colors indicate that risks are reducing. The severity of each risk alteration (by percentage points, *pp*) is illustrated by the color saturation; white indicating no change. Changes are indicative of updated input data, in turn illustrating what groups of conflict predictors informed any alterations to the main conflict forecasts.
Source: ViEWS, December 2021.

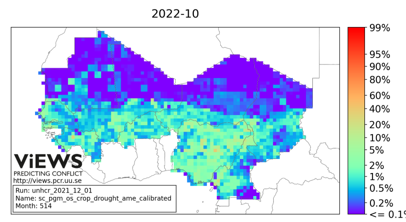
Figure 21.
Risk assessments from the sub-models informing ViEWS. 12-month *pgm* forecasts for os in October 2022.



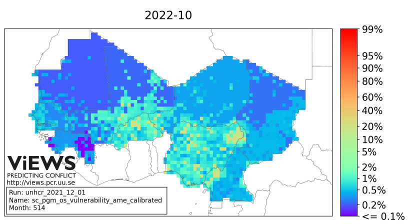
(a) Space-time model



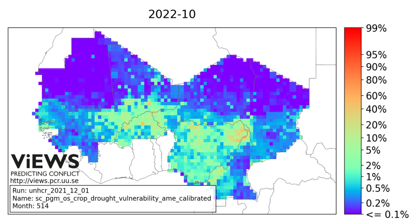
(b) Natural and social geography model



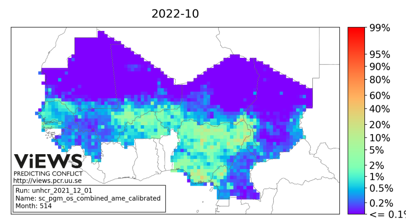
(c) Agro-climatic model



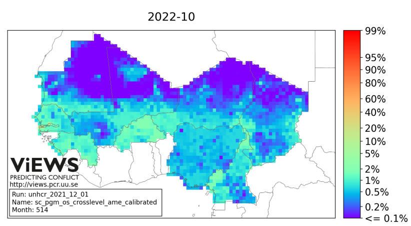
(d) Vulnerability



(e) Combined agro-climatic vulnerability model



(f) Combined agro-climatic, natural and social geography model

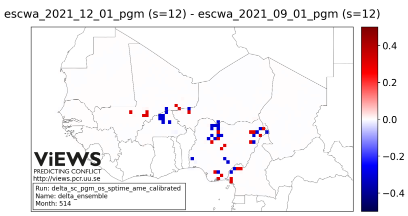


(g) Cross-level model

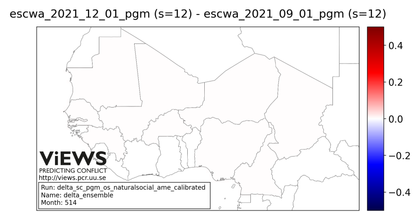
Note: Predicted probabilities of one-sided violence as generated by each thematic group of conflict predictors—each sub-model—informing the ViEWS system. Loosely speaking, the sub-model forecasts illustrate the predictive capacity of the conflict predictors captured by the respective models. Sub-models that alert to high conflict risks are often informed by variables that are key to explaining conflict in that specific location, whereas sub-models pointing to low conflict risks instead draw upon contributing but less decisive variables for the forecast horizon at hand (in this case, a snapshot of the conflict risk 12 months ahead). The precise contribution of the thematic sub-models and the conflict predictors captured by them are determined by a sophisticated weighting mechanism documented in Hegre and others (2021b).
Source: ViEWS, December 2021.

Figure 22.

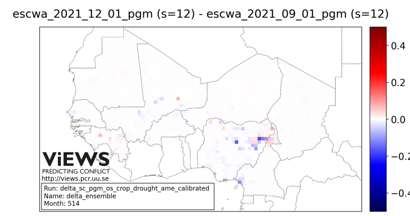
Changes to the sub-model 12-month forecasts for os at *pgm* over the past three months



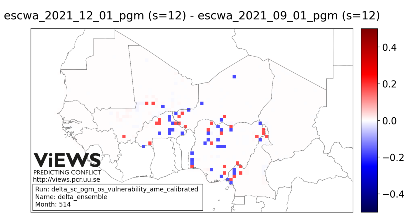
(a) Space-time model



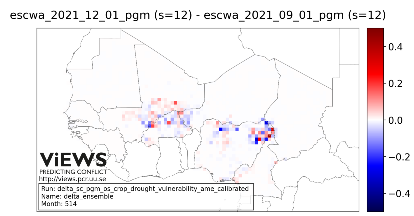
(b) Natural and social geography model



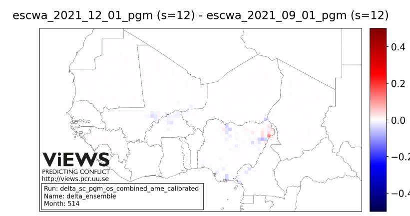
(c) Agro-climatic model



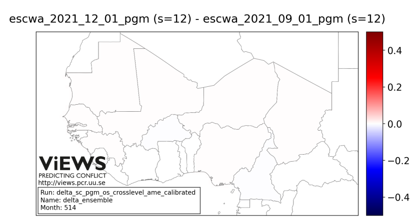
(d) Vulnerability



(e) Combined agro-climatic vulnerability model



(f) Combined agro-climatic, natural and social geography model

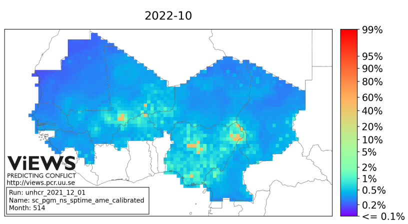


(g) Cross-level model

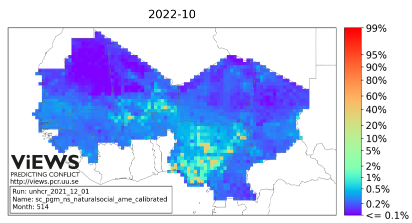
Note: Supporting material to Figure 5d in the main report, showing what happened 'under the hood' of the changes to the 12-month forecasts. The maps show the corresponding changes to each of the thematic groups of conflict predictors (each of the sub-models) informing the main forecasts. Red colors point to heightened risks, whereas blue colors indicate that risks are reducing. The severity of each risk alteration (by percentage points, *pp*) is illustrated by the color saturation; white indicating no change. Changes are indicative of updated input data, in turn illustrating what groups of conflict predictors informed any alterations to the main conflict forecasts.
Source: ViEWS, December 2021.

Figure 23.

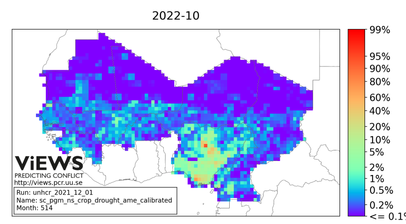
Risk assessments from the sub-models informing ViEWS. 12-month *pgm* forecasts for ns in October 2022.



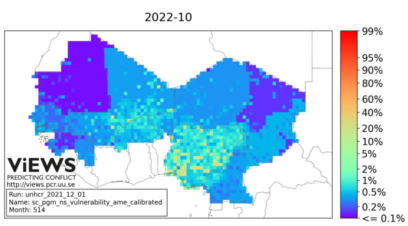
(a) Space-time model



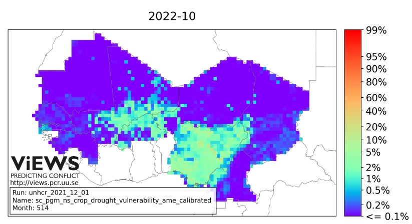
(b) Natural and social geography model



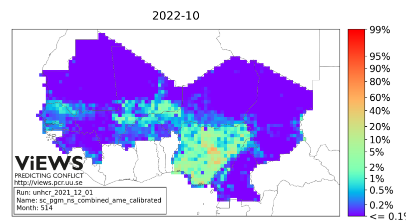
(c) Agro-climatic model



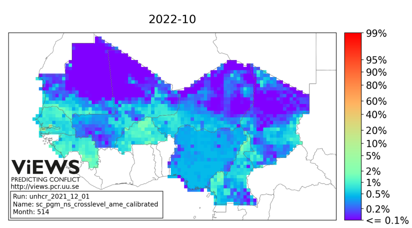
(d) Vulnerability



(e) Combined agro-climatic vulnerability model



(f) Combined agro-climatic, natural and social geography model

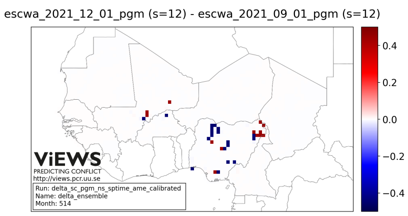


(g) Cross-level model

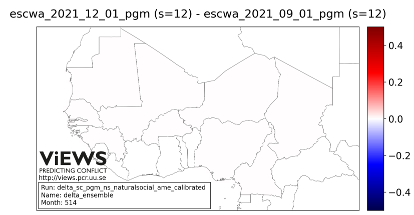
Note: Predicted probabilities of non-state violence as generated by each thematic group of conflict predictors—each sub-model—informing the ViEWS system. Lonsely speaking, the sub-model forecasts illustrate the predictive capacity of the conflict predictors captured by the respective models. Sub-models that alert to high conflict risks are often informed by variables that are key to explaining conflict in that specific location, whereas sub-models pointing to low conflict risks instead draw upon contributing but less decisive variables for the forecast horizon at hand (in this case, a snapshot of the conflict risk 12 months ahead). The precise contribution of the thematic sub-models and the conflict predictors captured by them are determined by a sophisticated weighting mechanism documented in Hegre and others (2021b).
Source: ViEWS, December 2021.

Figure 24.

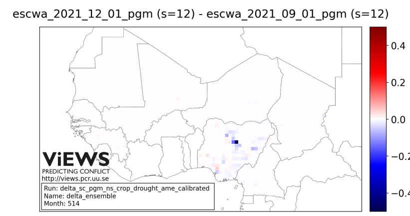
Changes to the sub-model 12-month forecasts for ns at *pgm* over the past three months



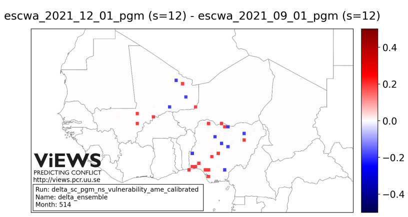
(a) Space-time model



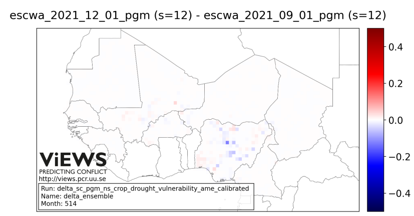
(b) Natural and social geography model



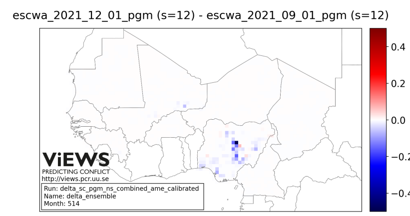
(c) Agro-climatic model



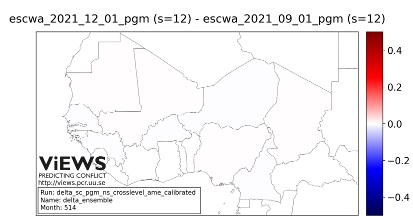
(d) Vulnerability



(e) Combined agro-climatic vulnerability model



(f) Combined agro-climatic, natural and social geography model



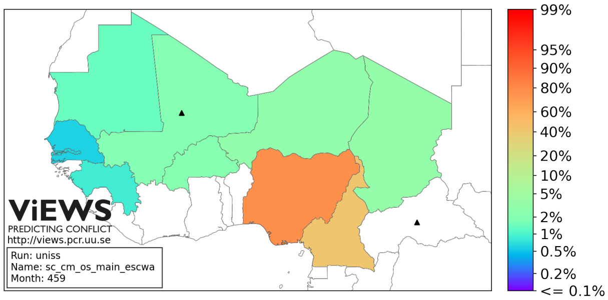
(g) Cross-level model

Note: Supporting material to Figure 5f in the main report, showing what happened 'under the hood' of the changes to the 12-month forecasts. The maps show the corresponding changes to each of the thematic groups of conflict predictors (each of the sub-models) informing the main forecasts. Red colors point to heightened risks, whereas blue colors indicate that risks are reducing. The severity of each risk alteration (by percentage points, *pp*) is illustrated by the color saturation; white indicating no change. Changes are indicative of updated input data, in turn illustrating what groups of conflict predictors informed any alterations to the main conflict forecasts.
Source: ViEWS, December 2021.

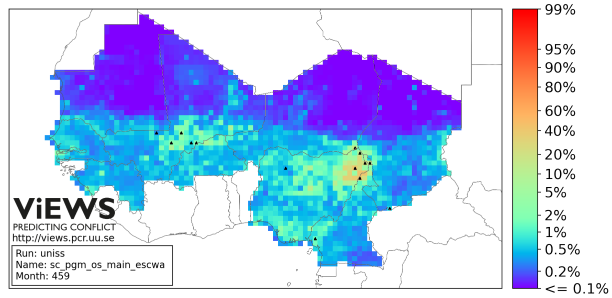
B Predictive performance

B.1 Mapping performance

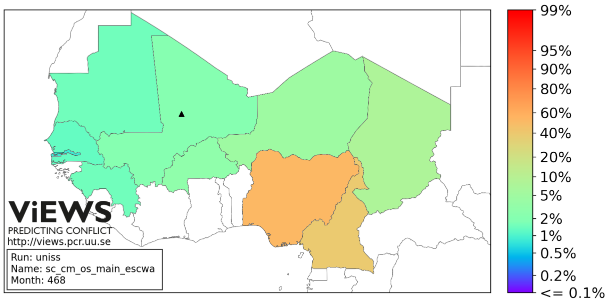
Figure 25.
Predictive performance over 2018–2020, one-sided violence



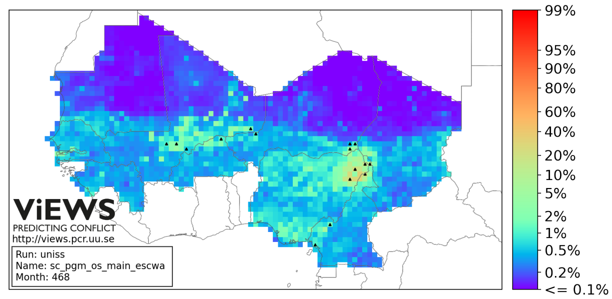
(a) Predictions for March 2018, *cm*



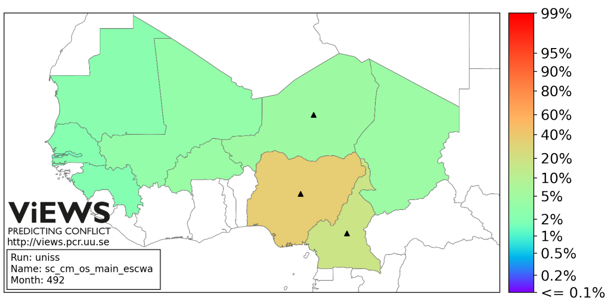
(b) Predictions for March 2018, *pgm*



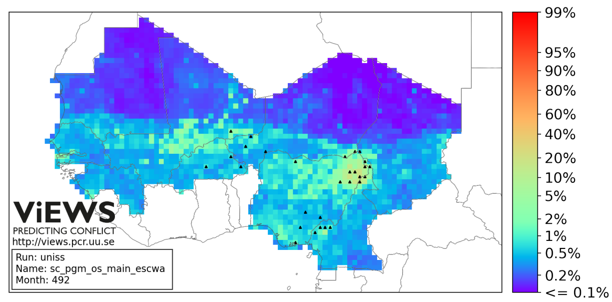
(c) Predictions for December 2018, *cm*



(d) Predictions for December 2018, *pgm*



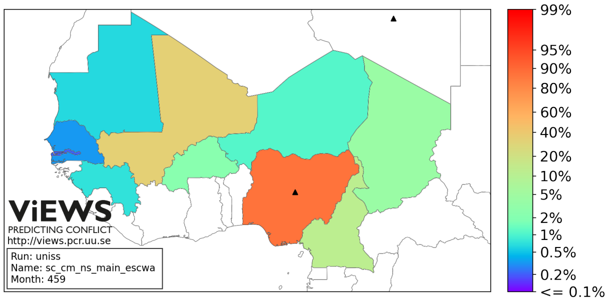
(e) Predictions for December 2020, *cm*



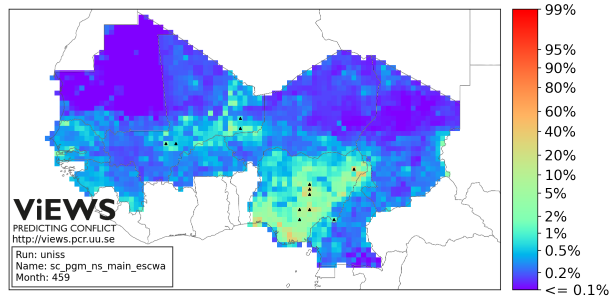
(f) Predictions for December 2020, *pgm*

Note: The maps show the predicted probabilities of non-state violence generated in a retrospective run of the ViEWS system for selected months in the 2018–2020 period, as well as the violence that was observed over the same months. Red color denotes a high predicted probability of conflict, whereas purple/blue color indicates a low probability. Actual conflicts are shown with triangles; one per country that observed such in the top row of maps, and one per applicable grid cell in the bottom row. The predictions were based on the data that were available in January 2018, up to and including December 2017. Results for state-based violence are presented in the main report.
Source: ViEWS, December 2021

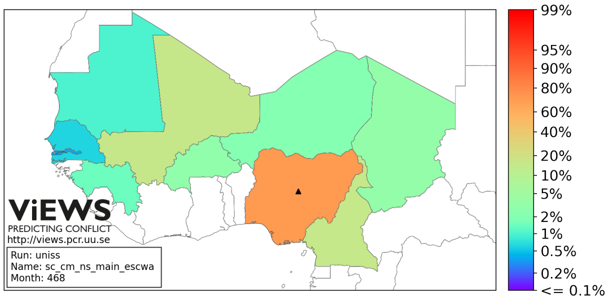
Figure 26.
Predictive performance over 2018–2020, non-state violence



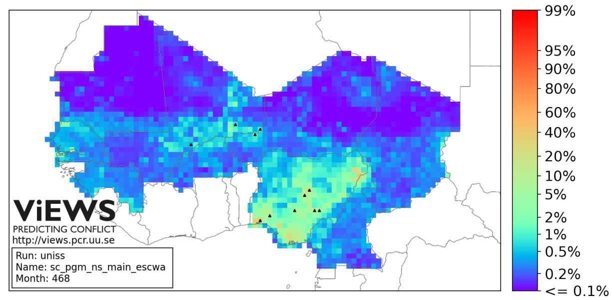
(a) Predictions for March 2018, *cm*



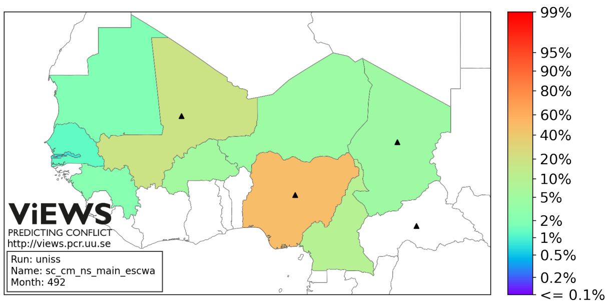
(b) Predictions for March 2018, *pgm*



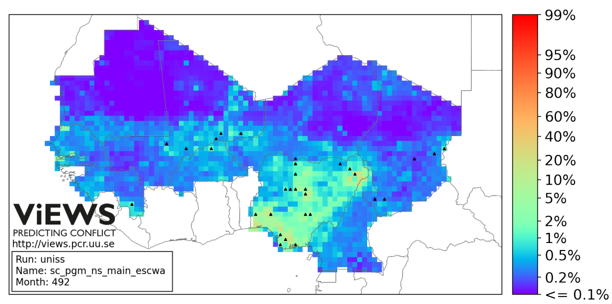
(c) Predictions for December 2018, *cm*



(d) Predictions for December 2018, *pgm*



(e) Predictions for December 2020, *cm*



(f) Predictions for December 2020, *pgm*

Note: The maps show the predicted probabilities of non-state violence generated in a retrospective run of the ViEWS system for selected months in the 2018–2020 period, as well as the violence that was observed over the same months. Red color denotes a high predicted probability of conflict, whereas purple/blue color indicates a low probability. Actual conflicts are shown with triangles; one per country that observed such in the top row of maps, and one per applicable grid cell in the bottom row. The predictions were based on the data that were available in January 2018, up to and including December 2017. Results for state-based violence are presented in the main report.
Source: ViEWS, December 2021

B.2 Tabulating performance

Table 5.

Predictive performance over 2018–2020, forecasts for state-based violence at the country-month level

(a) 3-month forecasts

	Observed		
Predicted	Pos	Neg	Sum
Pos	3.0	1.8	4.8
Neg	0.4	4.8	5.2
Sum	3.4	6.6	10.0

Note. Threshold = 0.2, accuracy = 0.783, precision = 0.632,
recall = 0.878, brier = 0.217, f1 = 0.735

(b) 12-month forecasts

	Observed		
Predicted	Pos	Neg	Sum
Pos	2.4	1.2	3.6
Neg	1.0	5.4	6.4
Sum	3.4	6.6	10.0

Note. Threshold = 0.2, accuracy = 0.778, precision = 0.664, recall = 0.707, brier = 0.222, f1 = 0.685

(c) 36-month forecasts

	Observed		
Predicted	Pos	Neg	Sum
Pos	2.1	1.1	3.1
Neg	1.4	5.5	6.9
Sum	3.4	6.6	10.0

Note. Threshold = 0.2, accuracy = 0.758, precision = 0.661, recall = 0.602, brier = 0.242, f1 = 0.63

Note: Performance of the ViEWS system when forecasting state-based violence in the UNISS countries of the Sahel 3, 12, and 36 months ahead at the country-month level, averaged over January 2018–December 2020.
Source: ViEWS, December 2021

Table 6.

Predictive performance over 2018–2020, forecasts for one-sided violence at the country-month level

(a) 3-month forecasts

	Observed		
Predicted	Pos	Neg	Sum
Pos	1.1	0.9	2.0
Neg	1.3	6.7	8.0
Sum	2.4	7.6	10.0

Note. Threshold = 0.2, accuracy = 0.775, precision = 0.528, recall = 0.447, brier = 0.225, f1 = 0.484

(b) 12-month forecasts

	Observed		
Predicted	Pos	Neg	Sum
Pos	1.1	0.9	2.0
Neg	1.3	6.7	8.0
Sum	2.4	7.6	10.0

Note. Threshold = 0.2, accuracy = 0.775, precision = 0.528, recall = 0.447, brier = 0.225, f1 = 0.484

(c) 36-month forecasts

	Observed		
Predicted	Pos	Neg	Sum
Pos	0.9	0.8	1.7
Neg	1.5	6.8	8.3
Sum	2.4	7.6	10.0

Note. Threshold = 0.2, accuracy = 0.769, precision = 0.517, recall = 0.365, brier = 0.231, f1 = 0.428

Note: Performance of the ViEWS system when forecasting one-sided violence in the UNISS countries of the Sahel 3, 12, and 36 months ahead at the country-month level, averaged over January 2018–December 2020.
Source: ViEWS, December 2021

Table 7.

Predictive performance over 2018–2020, forecasts for non-state violence at the country-month level

(a) 3-month forecasts

	Observed		
Predicted	Pos	Neg	Sum
Pos	1.1	0.9	2.0
Neg	0.1	7.9	8.0
Sum	1.2	8.8	10.0

Note. Threshold = 0.2, accuracy = 0.903, precision = 0.562, recall = 0.932, brier = 0.097, f1 = 0.701

(b) 12-month forecasts

	Observed		
Predicted	Pos	Neg	Sum
Pos	1.0	0.4	1.4
Neg	0.2	8.4	8.6
Sum	1.2	8.8	10.0

Note. Threshold = 0.2, accuracy = 0.936, precision = 0.714, recall = 0.795, brier = 0.064, f1 = 0.753

(c) 36-month forecasts

	Observed		
Predicted	Pos	Neg	Sum
Pos	1.0	0.4	1.4
Neg	0.2	8.3	8.6
Sum	1.2	8.8	10.0

Note. Threshold = 0.2, accuracy = 0.933, precision = 0.692, recall = 0.818, brier = 0.067, f1 = 0.75

Note: Performance of the ViEWS system when forecasting non-state violence in the UNISS countries of the Sahel 3, 12, and 36 months ahead at the country-month level, averaged over January 2018–December 2020. Results for state-based violence are found in the main report.
Source: ViEWS, December 2021

Table 8.

Predictive performance over 2018–2020, forecasts for state-based violence at the PRIO-GRID-month level

(a) 3-month forecasts

	Observed		
Predicted	Pos	Neg	Sum
Pos	18.0	34.5	52.5
Neg	18.8	2233.7	2252.5
Sum	36.8	2268.2	2305.0

Note. Threshold = 0.1, accuracy = 0.977, precision = 0.342,
recall = 0.488, brier = 0.023, f1 = 0.402

(b) 12-month forecasts

	Observed		
Predicted	Pos	Neg	Sum
Pos	14.9	25.2	40.0
Neg	21.9	2243.0	2265.0
Sum	36.8	2268.2	2305.0

Note. Threshold = 0.1, accuracy = 0.98, precision = 0.371, recall = 0.404, brier = 0.02, f1 = 0.387

(c) 36-month forecasts

	Observed		
Predicted	Pos	Neg	Sum
Pos	10.4	18.7	29.1
Neg	26.4	2249.5	2275.9
Sum	36.8	2268.2	2305.0

Note. Threshold = 0.1, accuracy = 0.98, precision = 0.357, recall = 0.282, brier = 0.02, f1 = 0.315

Note: Performance of the ViEWS system when forecasting state-based violence in the UNISS countries of the Sahel 3, 12, and 36 months ahead at the PRIO-GRID-month level, averaged over January 2018–December 2020.
Source: ViEWS, December 2021

Table 9.

Predictive performance over 2018–2020, forecasts for one-sided violence at the PRIO-GRID-month level

(a) 3-month forecasts

	Observed		
Predicted	Pos	Neg	Sum
Pos	4.7	14.5	19.2
Neg	17.2	2268.6	2285.8
Sum	21.9	2283.1	2305.0

Note. Threshold = 0.1, accuracy = 0.986, precision = 0.243, recall = 0.213, brier = 0.014, f1 = 0.227

(b) 12-month forecasts

	Observed		
Predicted	Pos	Neg	Sum
Pos	3.7	8.5	12.2
Neg	18.2	2274.6	2292.8
Sum	21.9	2283.1	2305.0

Note. Threshold = 0.1, accuracy = 0.988, precision = 0.304, recall = 0.169, brier = 0.012, f1 = 0.217

(c) 36-month forecasts

	Observed		
Predicted	Pos	Neg	Sum
Pos	3.6	11.9	15.6
Neg	18.3	2271.1	2289.4
Sum	21.9	2283.1	2305.0

Note. Threshold = 0.1, accuracy = 0.987, precision = 0.232, recall = 0.165, brier = 0.013, f1 = 0.193

Note: Performance of the ViEWS system when forecasting one-sided violence in the UNISS countries of the Sahel 3, 12, and 36 months ahead at the PRIO-GRID-month level, averaged over January 2018–December 2020.

Source: ViEWS, December 2021

Table 10.

Predictive performance over 2018–2020, forecasts for non-state violence at the PRIO-GRID-month level

(a) 3-month forecasts

	Observed		
Predicted	Pos	Neg	Sum
Pos	3.5	15.1	18.6
Neg	12.0	2274.4	2286.4
Sum	15.5	2289.5	2305.0

Note. Threshold = 0.1, accuracy = 0.988, precision = 0.188, recall = 0.225, brier = 0.012, f1 = 0.205

(b) 12-month forecasts

	Observed		
Predicted	Pos	Neg	Sum
Pos	14.9	25.2	40.0
Neg	21.9	2243.0	2265.0
Sum	36.8	2268.2	2305.0

Note. Threshold = 0.1, accuracy = 0.98, precision = 0.371, recall = 0.404, brier = 0.02, f1 = 0.387

(c) 36-month forecasts

	Observed		
Predicted	Pos	Neg	Sum
Pos	1.7	12.3	13.9
Neg	13.9	2277.2	2291.1
Sum	15.5	2289.5	2305.0

Note. Threshold = 0.1, accuracy = 0.989, precision = 0.12, recall = 0.107, brier = 0.011, f1 = 0.113

Note: Performance of the ViEWS system when forecasting non-state violence in the UNISS countries of the Sahel 3, 12, and 36 months ahead at the PRIO-GRID-month level, averaged over January 2018–December 2020.
Source: ViEWS, December 2021

C Supplementary material

C.1 Features importances for the *climate extremes* sub-model

Table 11.
Feature importances for the *climate extremes* sub-model, *os*

feature	s=3	s=6	s=12	s=36
decay_12_time_since_ged_dummy_sb	0.236	0.227	0.200	0.149
pgd_nlights_calib_mean	0.126	0.125	0.140	0.162
splag_1_1_ged_best_sb	0.087	0.081	0.074	0.054
tlag_12_wdi_nv_agr_totl_kd	0.080	0.080	0.087	0.102
rx5day	0.060	0.065	0.069	0.082
pgd_excluded	0.031	0.031	0.032	0.033
rx7day	0.025	0.028	0.025	0.025
tnn	0.019	0.019	0.020	0.021
dtr	0.019	0.021	0.020	0.021
txx	0.018	0.017	0.018	0.019
tnx	0.017	0.017	0.018	0.020
prcptot	0.017	0.019	0.017	0.016
txn	0.016	0.017	0.018	0.018
spei12	0.016	0.016	0.016	0.018
spi12	0.016	0.015	0.014	0.018
txgt50p	0.015	0.015	0.017	0.016
tnm	0.015	0.016	0.016	0.017
tmm	0.015	0.015	0.016	0.017
txm	0.014	0.015	0.016	0.017
spi6	0.014	0.014	0.014	0.016
spei6	0.014	0.014	0.015	0.016
spi3	0.014	0.013	0.014	0.015
spei3	0.013	0.013	0.014	0.015
tn90p	0.012	0.011	0.013	0.012
tx90p	0.012	0.012	0.012	0.012
consecutive_dry_days_index_per_time_period	0.011	0.011	0.011	0.010
tx10p	0.010	0.011	0.012	0.012
tn10p	0.010	0.011	0.011	0.012
consecutive_wet_days_index_per_time_period	0.010	0.011	0.010	0.009
txge30	0.007	0.008	0.008	0.008
su	0.007	0.007	0.007	0.008

Note: Relative weight (on a scale from 0–1) of the features informing the sub-model when forecasting one-sided violence 3, 6, 12, and 36 months into the future. Results for **sb** and **ns** are found in Section 7 in the main report. A full description of the indicators can be found at https://climpact-sci.org/indices/.
Source: ViEWS, December 2021

Table 12.
Feature importances for the *climate extremes* sub-model, *ns*

feature	s=3	s=6	s=12	s=36
pgd_nlights_calib_mean	0.145	0.150	0.146	0.166
decay_12_time_since_ged_dummy_sb	0.144	0.141	0.137	0.096
tlag_12_wdi_nv_agr_totl_kd	0.138	0.134	0.140	0.141
rx5day	0.061	0.065	0.067	0.077
splag_1_1_ged_best_sb	0.046	0.041	0.045	0.034
rx7day	0.026	0.029	0.029	0.029
tnn	0.024	0.026	0.024	0.025
txx	0.024	0.025	0.021	0.023
dtr	0.023	0.027	0.025	0.026
txn	0.022	0.021	0.020	0.022
tnx	0.021	0.019	0.020	0.021
pgd_excluded	0.021	0.021	0.021	0.024
tmm	0.020	0.019	0.019	0.020
tnm	0.020	0.020	0.020	0.020
txm	0.019	0.019	0.018	0.019
txgt50p	0.019	0.018	0.018	0.019
spei12	0.017	0.016	0.017	0.019
spi12	0.016	0.015	0.016	0.017
spei6	0.015	0.015	0.016	0.016
spei3	0.015	0.015	0.015	0.015
tn90p	0.015	0.014	0.014	0.013
spi6	0.015	0.015	0.015	0.017
spi3	0.015	0.015	0.016	0.016
tx90p	0.014	0.012	0.013	0.012
consecutive_dry_days_index_per_time_period	0.013	0.013	0.012	0.012
prcptot	0.012	0.015	0.015	0.015
tn10p	0.012	0.011	0.011	0.012
tx10p	0.012	0.011	0.012	0.012
tr	0.009	0.010	0.011	0.011
su	0.009	0.009	0.009	0.008
txge30	0.009	0.009	0.009	0.009

Note: Relative weight (on a scale from 0–1) of the features informing the sub-model when forecasting non-state conflict 3, 6, 12, and 36 months into the future. Results for **sb** and **os** are found in Section 7 in the main report. A full description of the indicators can be found at https://climpact-sci.org/indices/.
Source: ViEWS, December 2021