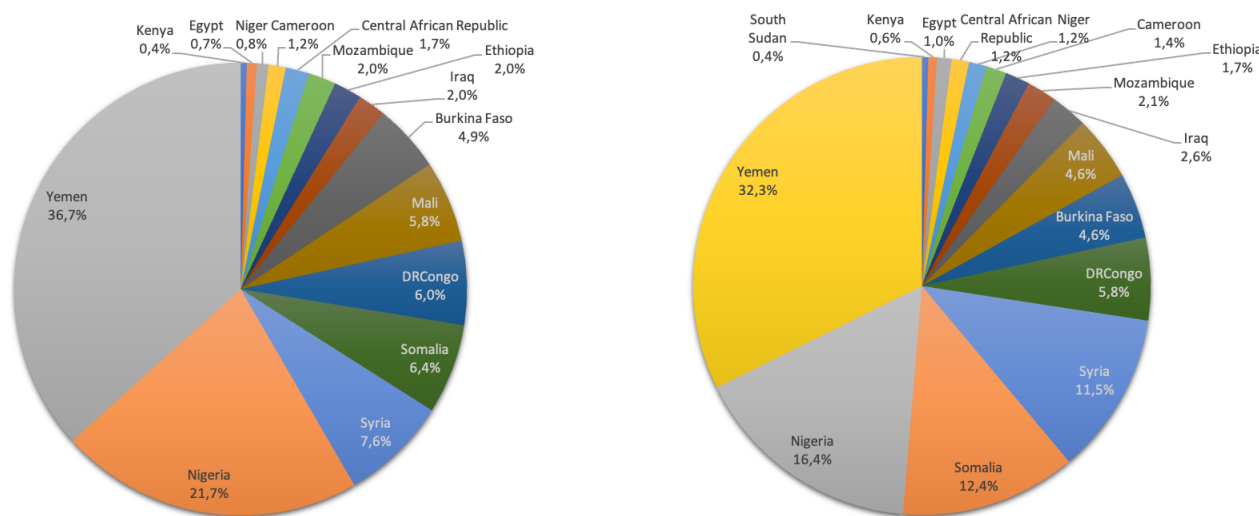


Forecasting fatalities in armed conflict

Forecasts for April 2022–March 2025

Figure 1. Distribution of predicted fatalities over the next 12 (left) and 36 (right) months amongst countries with ≥ 100 and ≥ 300 fatalities during this time.



Note: Forecasts for the next 12 and 36 months from March 2022, the last month of input data informing these figures.

Source: ViEWS, May 2022

INTRODUCTION

Knowing the dire consequences of armed conflict, preventing and containing future conflicts are high on policy-makers' agenda. Early action, however, requires early warning (World Bank Group and United Nations, 2017). With an objective understanding of when, where, and for how long future conflicts will last, as well as how lethal they will be, the international community can come together to make timely and evidence-based strategic decisions to prevent or mitigate future conflicts, engage in diplomacy efforts, and allocate resources where most needed. This is what the political Violence Early-Warning System (ViEWS) (Hegre et al., 2021,) offers.

THE VIEWS SYSTEM

ViEWS is an early-warning system at the frontier of research that provides monthly forecasts for the number of battle-related deaths expected in impending political violence dur-

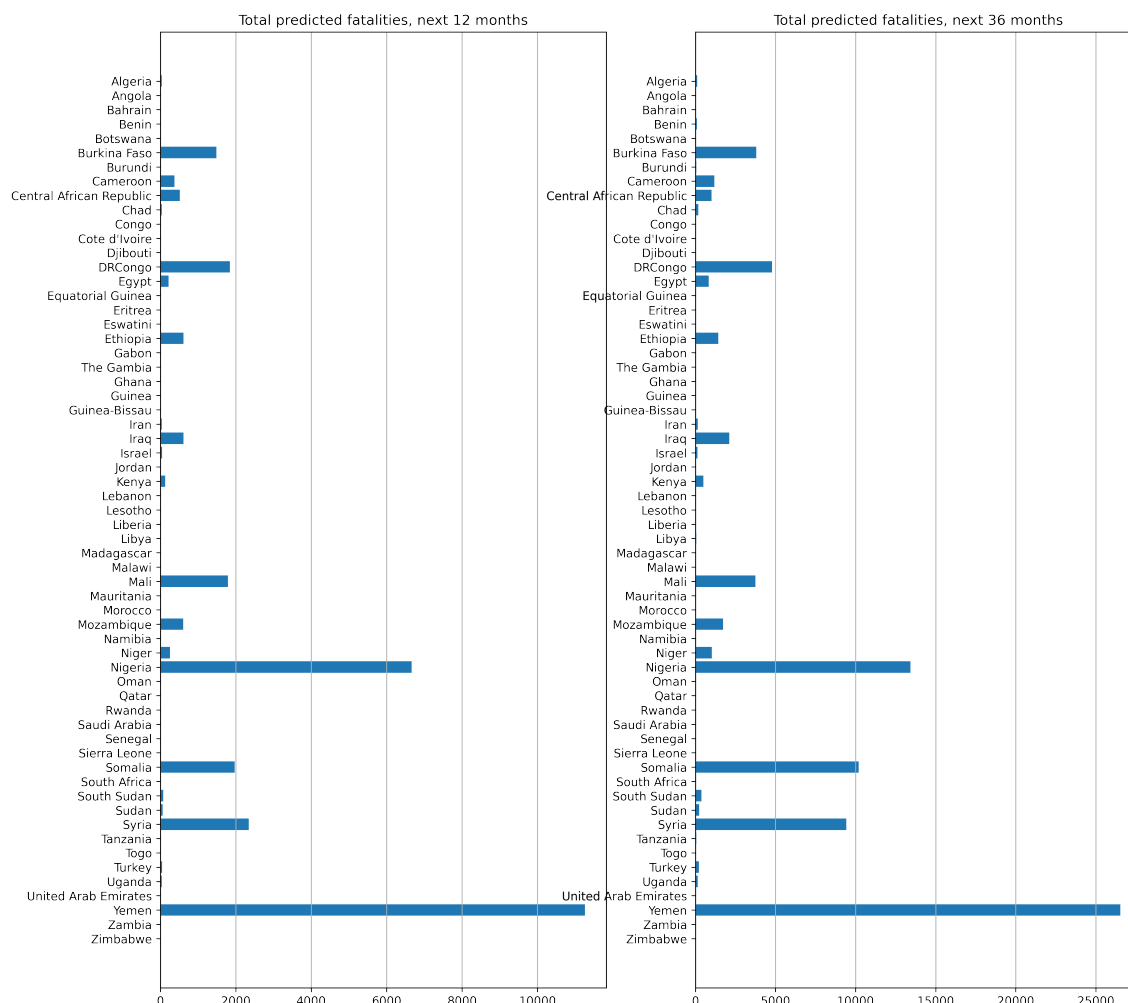
ing each of the next 36 months in Africa and the Middle East. The forecasts are generated at two levels of analysis: for countries and sub-national locations spanning approximately 55x55 km.¹ They are made available for each of three different types of political violence (state-based, non-state, and one-sided violence; as defined and recorded by the Uppsala Conflict Data Program, UCDP) (UCDP, Gleditsch et al., 2002; Sundberg and Melander, 2013; Pettersson et al., 2021; Hegre et al., 2020).

The system is based on well-established academic research on the causes and correlates of conflict, drawing on a variety of predictors. Moreover, the system only makes use of publicly available data in order to allow for maximum transparency, further ensured by conducting – and publishing – continuous evaluations of its predictive performance (see e.g. Hegre et al., 2019; Hegre et al., 2021).

ViEWS has been publishing monthly updates of its forecasts since July 2018. The initial approach was however limited to dichotomous forecasts – whether or not violence will

¹The gridded pattern formed is known as the PRIO-GRID Tollefsen, Strand, and Buhaug (2012). With calendar months as the temporal units of analysis, we refer to this level as the 'PRIO-GRID-month' level, or *pgm* for short. The country-month level is shortened as *cm*.

Figure 2. Number of predicted fatalities over the next 12 (left) and 36 (right) months in Africa and the Middle East



Note: Forecasts for the next 12 and 36 months from March 2022, the last month of input data informing these figures.

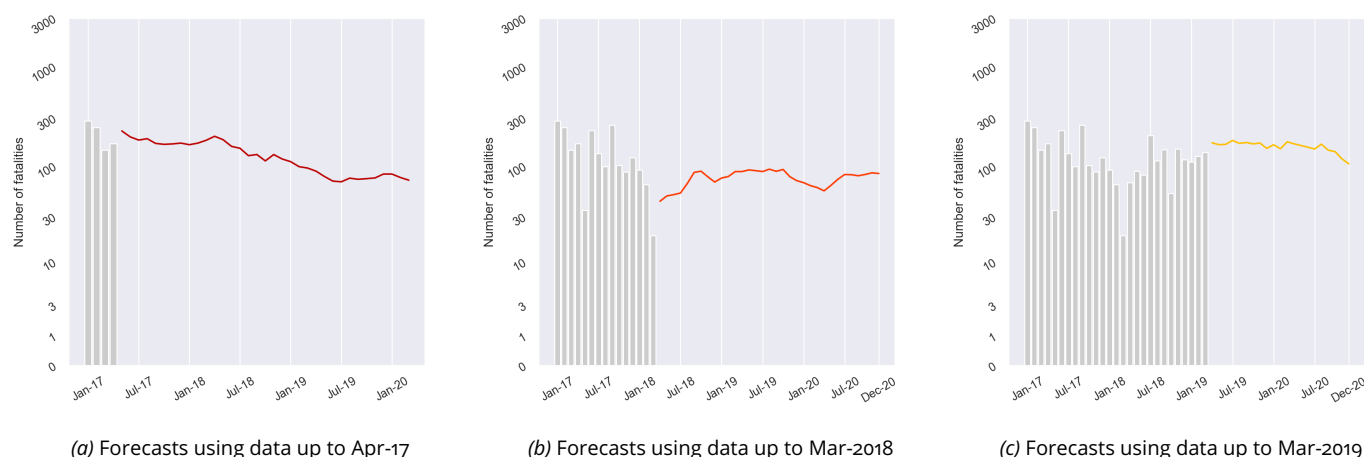
Source: ViEWS, May 2022

exceed a given threshold of fatalities each month. Such forecasts are highly valuable, but the use of an arbitrary threshold comes at a cost. A high threshold (such as 500 fatalities per month) will only alert to high-impact cases and shift focus away from less serious but non-negligible conflicts, such as those simmering in Tunisia and Kenya. A low threshold, in turn, will not distinguish between these relatively minor incidents and major conflagrations such as the Syrian civil war and the genocide in Rwanda. With funding from the Global Security Rapid Analysis Fund at the United Kingdom Foreign, Commonwealth & Development Office, ViEWS has developed a new set of models that instead predict the number of fatalities expected in impending conflicts each month in a rolling three-year window. This report presents the new model, its most recent forecasts, and a discussion of the key drivers behind them.

THE FATALITIES MODEL

The new forecasting tool is composed by a number of smaller forecasting models – sub-models – each of which is informed by data on one or more themes of conflict drivers. They are trained by means of machine-learning algorithms. Key variables in these themes include conflict and protest history (sources from UCDP (Hegre et al., 2020; Pettersson et al., 2021) and ACLED (Raleigh et al., 2010)); democracy and development indices (V-Dem (Coppedge et al., 2020) and WDI (WDI WorldBank, 2019)); drought and societal vulnerability (SPEI (Vicente-Serrano, Beguería, and López-Moreno, 2010), MIRCA (Portmann, Siebert, and Döll, 2010), Mapsdam (International Food Policy Research Institute, 2019)); as well as social and natural geography, e.g., local poverty, distance to city and international borders, exclusion of minorities

Figure 3. How the forecasts change as new data becomes available, example for Nigeria



Note: The figure illustrates how the ViEWS forecasts for Nigeria changed over selected months in 2017–2019 as new input data (here conflict data from UCDP) was made available to the forecasting system. The vertical bars show the monthly number of recorded fatalities from state-based violence in Nigeria from Jan 2017–Apr 2017, Jan 2017–March 2018, and Jan 2017–March 2019. The horizontal line in each figure shows the ViEWS forecasts as they would have been produced using these data (in addition to older data). Each figure displays a separate forecast release. While all forecasts releases contain predictions for the next 36 months, the figures have here been limited to the same time period to facilitate comparison.

Source: UCDP GED, 2021; ViEWS, 2022

from political power, terrain, and distance to key deposits of natural resources. One of the sub-models also analyses topics discussed in news media to capture changes in conflict risk Mueller and Rauh (2018), Mueller and Rauh (2020), and Mueller and Rauh (2022b).

Rather than relying on the limited perspective offered by these models individually, the forecasting system combines the input from all sub-models into ensembles or collections of models – one for each level of analysis – which produce the final forecasts. New data are fed into these models each month, upon which they update their forecasts for the next three years accordingly, illustrated by Figure 3.

The model generates forecasts for each of the three types of violence that ViEWS covers. In this report, however, we focus on results for state-based conflicts – intra- or interstate armed conflicts fought to seize or maintain control over government or territory, set between two or more actors, of which at least one is directly affiliated with a government.² This type of violence is the most frequent and deadly of the three UCDP categories, and the other two types frequently occur in the context of state-based violence. Forecasts for state-based conflict thus often function as a fore-

cast also for the other two types.

FORECASTS FOR 2022–2025

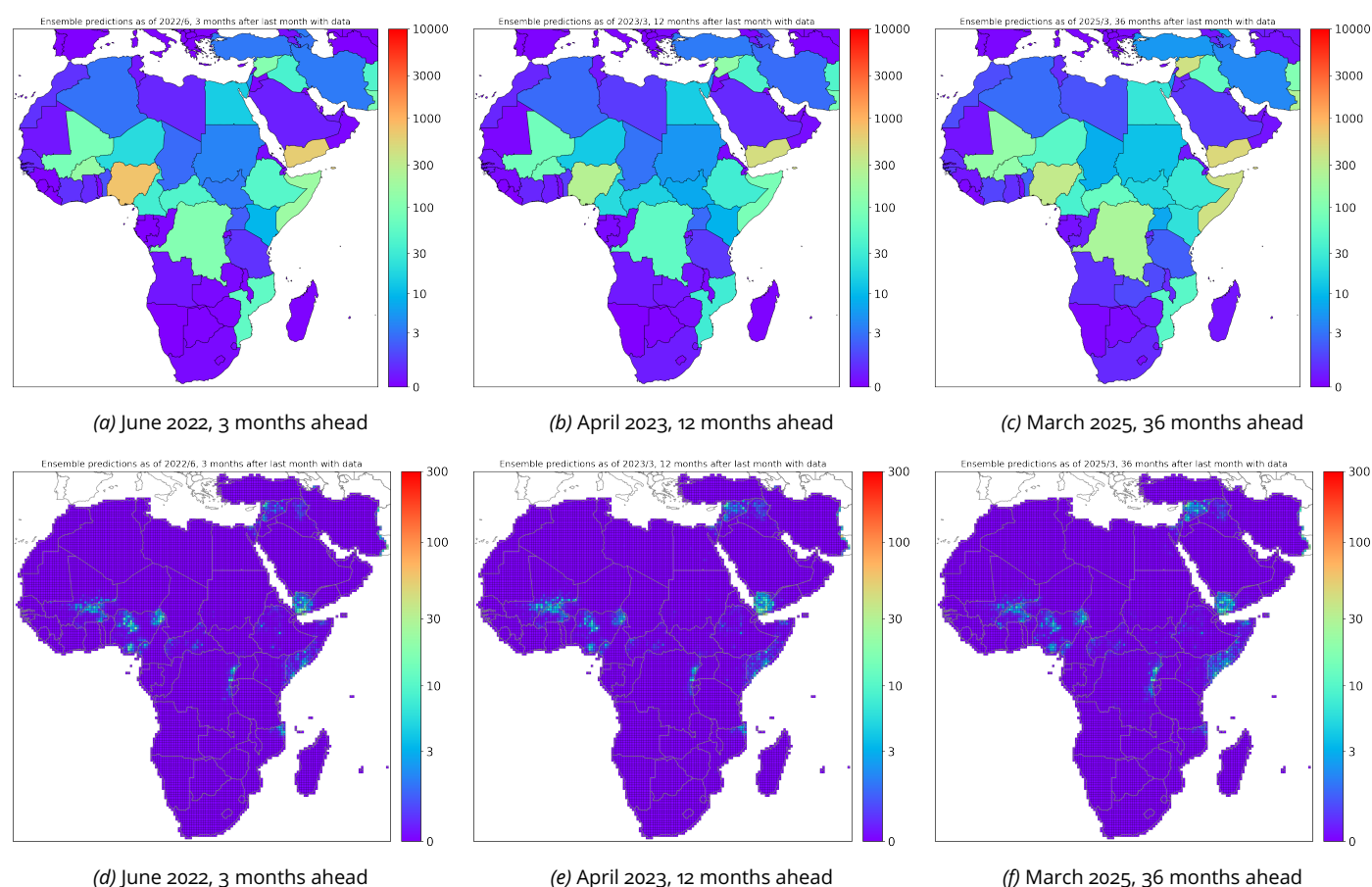
Figure 4 shows the ViEWS forecasts for state-based political violence in June 2022, April 2023, and March 2025 – 3, 12, and 36 months into the future from the last month of data informing these maps (March 2022). The top row shows the country-level predictions for each month; the bottom row displays forecasts for sub-national locations measuring approximately 55x55 km each (PRIO-GRID cells).

The forecasts suggest that the civil war in Yemen will continue to take more than 500 lives per month by June 2022 – from state-based violence alone. The conflict risks are concentrated to the Houthi-controlled northern highlands, with some locations expected to suffer as much as 30–50 fatalities per month. Also Nigeria, Somalia, Democratic Republic of Congo, Mali, Burkina Faso, and Syria, stand out in the forecasts, with country-wide fatality estimates ranging from about 100–500 per month (Figure 9e–4c).

More specifically, the model alerts to future violence in Borno and Yobe state in the Nigeria's North-East (with some spill-over to northern-most Cameroon); Katsina, Kaduna,

²E.g., attacks by armed groups and terrorist organisations against government targets such as embassy buildings, military posts, government officials, soldiers, or police officers. Conversely, it also includes military action such as airstrikes or other armed violence exercised by a government against another government or armed group.

Figure 4. Predicted fatalities, April 2022–March 2025



Note: Predicted number of fatalities per country (top row), grid cell (bottom row), and month, based on data up to and including March 2022. Forecasts for 3, 12, and 36 months into the future relative to the last month of data.

Source: ViEWS, May 2022

and Zamfara in the North-West; as well as a portion of the South-East and South-South (Figure 4d–9h). Other hot-spots include the Ituri and Kivu provinces of DRC; Cabo Delgado in Mozambique; and the broader border region between Mali, Burkina Faso and Niger – all of which have been frequent targets of militant Islamist operations in recent years. The model further alerts to continued violence in Anglophone Cameroon, portions of the Central African Republic, and the Sinai peninsula in Egypt. Last, the protracted or recurring conflicts in Syria; northern Iraq; Israel and Palestine; southern Somalia; and Ethiopia's Tigray, Oromiya, Amhara, and Benishangul-Gumuz regions are expected to remain active at varying degrees.

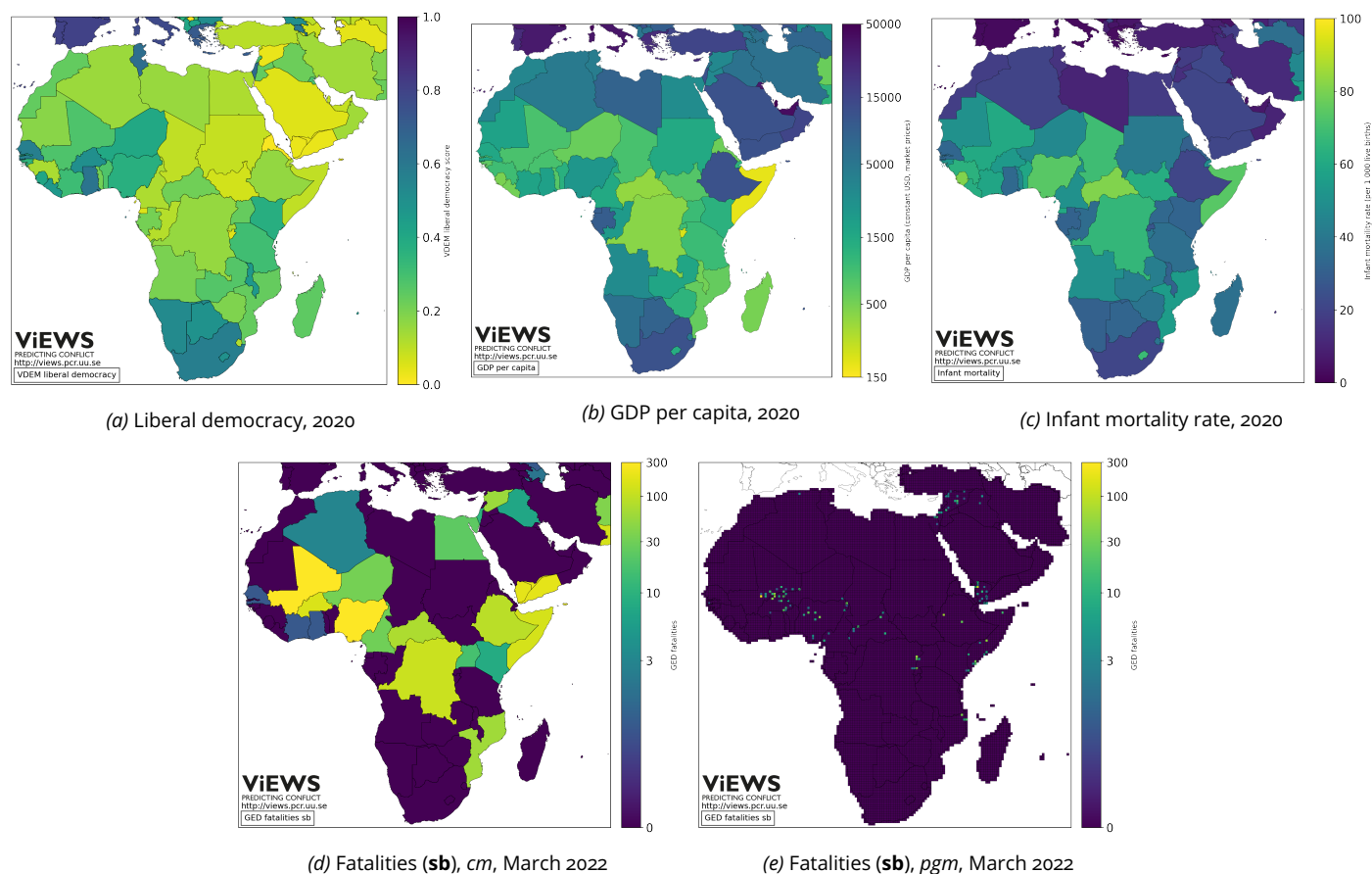
The regions and countries discussed above are highlighted by the model also when looking 12 and 36 months ahead, albeit fatality estimates are lower the further into the future we look. However, this is not necessarily a sign of de-

escalating violence, but rather an indication that the model becomes less certain of its predictions the further into the forecasting horizon it looks, further discussed below.

Key predictors of future conflict

By knowing the time, location, and intensity of past conflict, we can explain about 90% of the variance in the ViEWS model's predictions for future conflict. The reasons are manifold. First, empirically, most fatal violence occurs in – or close to – locations that have suffered such violence in the recent past. Second, violence breeds violence through a number of processes: weapons flows strengthens military organisations and increases the risk of conflict escalation and prolongation; human and financial capital may flee the scene, reducing incentives for a speedy resolution; and state capacity is often reduced during conflict, opening up for rebel group in-fighting, criminal networks, and

Figure 5. Key predictors of conflict



Note: Latest input data on five key predictors of conflict in Africa and the Middle East. From top left to bottom right: democratic freedom, low (0) to high (1); GDP per capita; infant mortality rate per 1,000 live births; recorded fatalities in March 2022, country level; recorded fatalities in March 2022, sub-national level.

Source: V-Dem, 2020; WDI, 2020; UCDP-Candidate, 2022.

widespread violence against civilians. Moreover, conflicts continue to inflict damage long after the fighting ends, aggravating pre-existing issues and grievances, and forming new ones. The affected countries and regions are thus placed at risk of falling into a 'Conflict Trap' (Collier et al., 2003). Third, past violence serves as a powerful proxy for the underlying causes of conflict – from local grievances to societal vulnerability and more fundamental structural factors such as governance and development.

As an indicator, conflict history is thus somewhat limited in its explanatory power, but it remains the – by far – most important predictor of future violence, and the patterns thereof. This is illustrated by the similarities between the conflict history maps for March 2022 (the last month of input data informing the forecasts in this report) in Figure

5d–5e, and the forecasts for June 2022 in Figure 4.³

As a key predictor of future conflict, the monthly updates of conflict data that inform the ViEWS forecasts are crucial for model performance, with some implications for interpretation of the forecasts. When the model generates predictions using data that are only one or a couple of months old, the forecasts are quite sharp (see, e.g., the conflict forecasts for Nigeria and Yemen in June 2022, Figure 4d). However, when forecasting 12 or 36 months ahead, the model can no longer rely as heavily on recent data and instead places greater emphasis on longer historic conflict trends, as well as on structural and slow-moving features. This includes for example the quality of governance, development indices, natural and social geography. These are all important predictors of future conflict, but repre-

³The topic model developed by Mueller and Rauh is another important predictor of future conflict in the ViEWS forecasts. It generates predictions using a topic analysis of news articles. It is however best discussed on a country-by-country basis and therefore not further elaborated on here. Please see Hegre et al. (2022) or Mueller and Rauh (2022a) to learn more.

sent more long-term and static risk, which on average predict a fairly small portion of the predicted fatalities. Since they also represent more general predictors of conflict, the long-term forecasts that are more reliant upon these predictors tend to be less 'sharp' or geographically precise, as compared to the short-term forecasts that place greater weight on the most recent history of conflict. Moreover, most structural indicators are only updated once a year. As a result, the model becomes less certain of its predictions when forecasting further into the future. In high-risk countries, this uncertainty leads to lower fatality estimates. This can be observed from comparing the forecasts for June 2022 (3 months ahead relative to the last month of input data) with the forecasts for April 2023 and March 2025 (12 and 36 months ahead, respectively) in Figure 4.

In Figure 5a–5c, we show the latest data on the most important structural drivers of the ViEWS forecasts: liberal democracy (one of several governance indicators); GDP per capita, and infant mortality rate per 1,000 live births (key indicators of the level of development). Yellow and green colors in the figures indicate a negative (risk-increasing) influence on the conflict predictions; dark colors a positive influence.⁴ The indicators' relative importance for the ViEWS forecasts is readily apparent from a comparison with the country-level forecast maps in Figure 4.

Strengths and weaknesses of the model

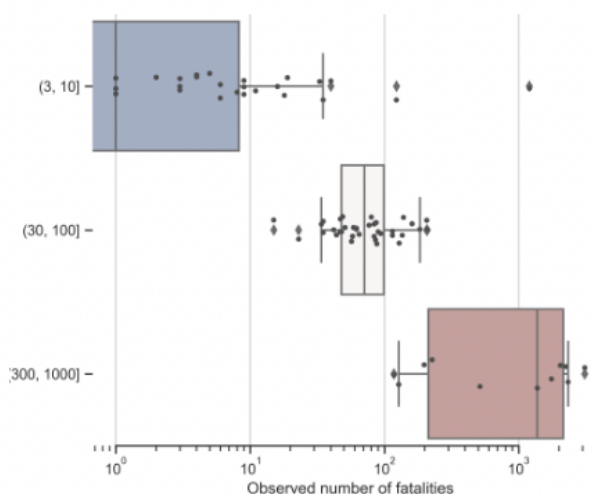
Figure 6 illustrates the confidence we can have in the ViEWS forecasts. It is based on a test run of the ViEWS model for the years 2018–2020, where we predict 12 months into the future. When the model predicted between 3 and 10 fatalities at the country level over this period (the topmost, blue box), more than half of the observations were 1 or higher.

Only a small number of cases saw more than 100 fatalities in these cases. When the model predicted between 30 and 100 deaths (light grey box), the UCDP recorded more than 10 deaths in all cases, and a quarter of cases saw more than 100 deaths. If we predicted more than 300 deaths, most cases saw 200 deaths or more.

These results suggest how precise the model is, and indicates some weaknesses. A clear strength is that predictions of serious violence are very accurate, particularly when intense violence has been recorded for a long period of time.

⁴While we use a linear scale on the color bar in these figures to facilitate comparison between locations at risk, the correlation between the different predictors and their respective contribution to the risk of conflict is not always linear; for example, previous studies show that the level of democracy in a country exhibits an inverted-U relationship with the risk of onset of internal political violence – conflict risks are at higher in semi-democracies than in autocracies and full-fledged democracies (Boswell and Dixon, 1990; Muller and Weede, 1990; Hegre et al., 2001; Fearon and Laitin, 2003)

Figure 6. Prediction uncertainty

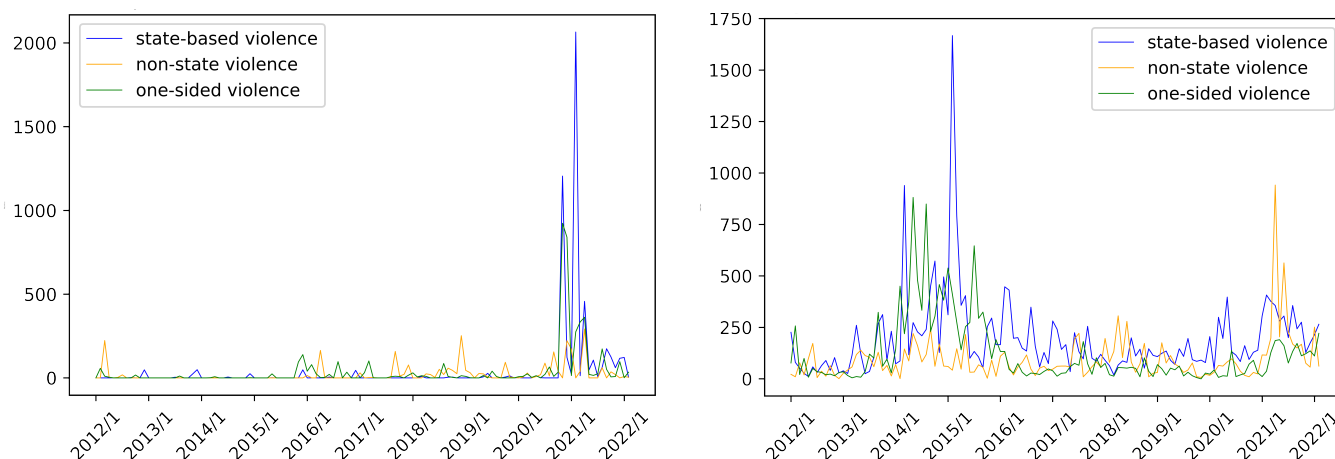


Source: ViEWS, 2022

When we predict more than 300 deaths in Yemen in April 2023, or in Nigeria in June 2022 (Figure 4), for example, the chance that there will be less than 100 is very small.

For Yemen, the high fatality estimate is based on the protracted civil war that now has entered its eight year. Also Nigeria has a long history of both state-based, non-state, and one-sided violence (Figure 7). In the state-based violence category alone, the UCDP has recorded a monthly number of fatalities in Nigeria that reaches or exceeds 100 for the greater part of the last decade (with several spikes over 300 deaths per month), most of which the ViEWS model has captured very well. In Figure 8, we show some examples of these results, illustrating the prediction errors for a selection of forecasts for 2018–2020, generated using data up to and including December 2017. The forecasts for 3, 6, and 12 months into the future (relative to the last month of input data, December 2017) shows very few 'misses' – overall, Nigeria actually observed fewer fatalities (blue colors) than predicted in all three cases. Only a few grid cells in the North-East observed more fatalities than anticipated. When forecasting 36 months into the future, the model expectantly performed less well; one grid cell is filled with a bright red color, indicating a notable 'miss', and Nigeria overall observed more fatalities than expected. It should however be noted that Nigeria observed a steep peak in fatalities in December 2020 with nearly 400 recorded deaths, while the

Figure 7. History of violence in Ethiopia (left) and Nigeria (right), 2012–2022



Note: Recorded fatalities per month from state-based, non-state, and one-sided violence in Ethiopia and Nigeria over the past 10 years.
Source: UCDP, 2022

model – forecasting 36 months into the future – was uninformed of developments in Nigeria since December 2017.

The issue above is an inevitable limitation of data-driven forecasts, which should be kept in mind when interpreting results from models like ViEWS. They offer great benefits in their rigorous, systematic, and objective assessments of conflict risks across all areas at potential risk and can thus help eliminate blind spots in conflict analysis and inform timely and evidence-based strategic decisions for conflict mitigation and prevention. They are however best used as a complement to traditional expert assessments and conflict analyses, as one tool in the analytical toolbox.

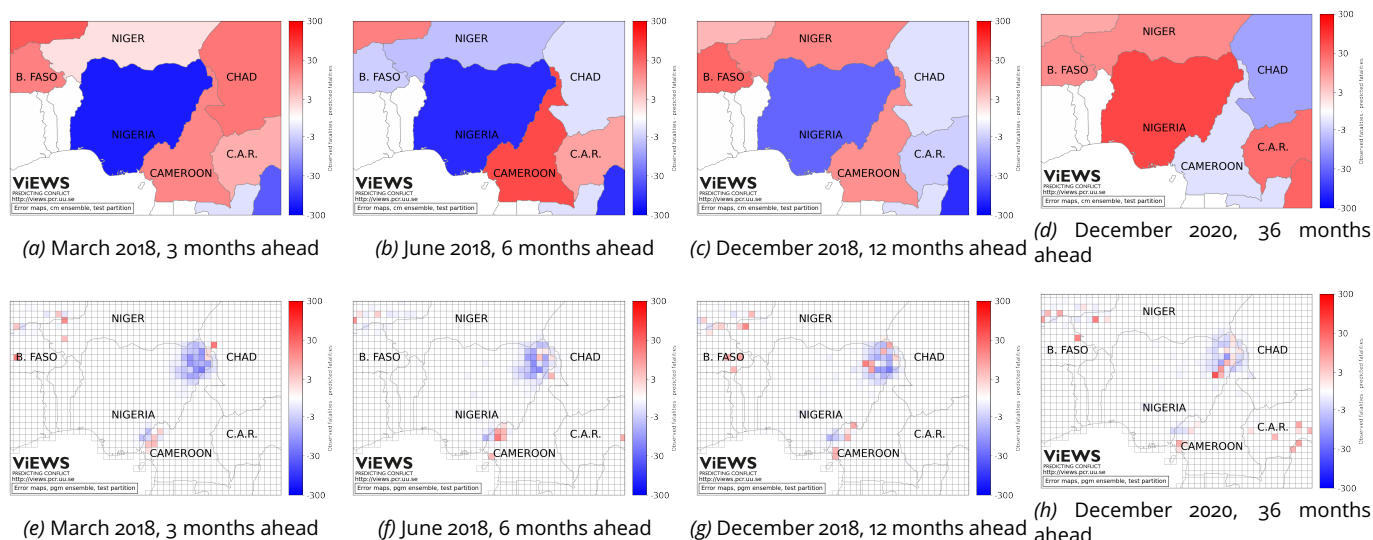
That the model's uncertainty increases when forecasting further into the forecasting window is also illustrated by the error maps for Ethiopia in Figure 9. While bouts of communal or non-state violence have been recorded every few months over the past few years in Ethiopia, as well as cases of one-sided violence against civilians, state-based violence has – until the Tigray war – been a relatively rare occurrence in Ethiopia over the past decade. Most months, the country observed less than 25 deaths per month, often less than 10 (see the conflict history map in Figure 7). When limited to data up to December 2017 (the last month of data informing the forecasts evaluated in the error maps), the model therefore expected the same trends to be followed over the near future. For the first year, this was also predominantly the case. Only one grid cell observed more violence than predicted in March 2018 (a difference by less than 10 fatalities). In June and December 2018, Ethiopia observed less violence

than predicted at both levels of analysis. By December 2020, at the height of the Tigray war and 36 months into the forecasting horizon evaluated in Figure 9, the model however heavily under-predicted the level of violence in the country. Still only informed by data up to December 2017 with no signs of escalating violence at the time, this is of course expected.

The Ethiopian case however raises another inherent weakness of data-driven models: they can only be as good as the data informing them. Even if we had looked at short-term forecasts generated using the data that was available by November 2020, the prediction errors for the December 2020 forecasts would have been substantial. In this case, it would not have been due to model uncertainty, but to the media blackout imposed over the first months of the Tigray war. While UCDP and other conflict data providers did pick up rising fatalities in the country at the time, the numbers reported by media and IGOs in the early months of the war were only a fraction of the numbers we recognise today. The ViEWS model would thus have alerted to rising tensions and escalating violence, but the full extent of the Tigray war would not have been accurately predicted until several months into the conflict, when conflict data better reflected the reality on the ground.

Last, returning to the illustration in Figure ??, it should be noted that less serious cases of violence tend to be more uncertain than high-intensity cases. For example, the current ViEWS predictions for Chad (about 10 deaths in March 2023) means that there is about a 20% chance that there will

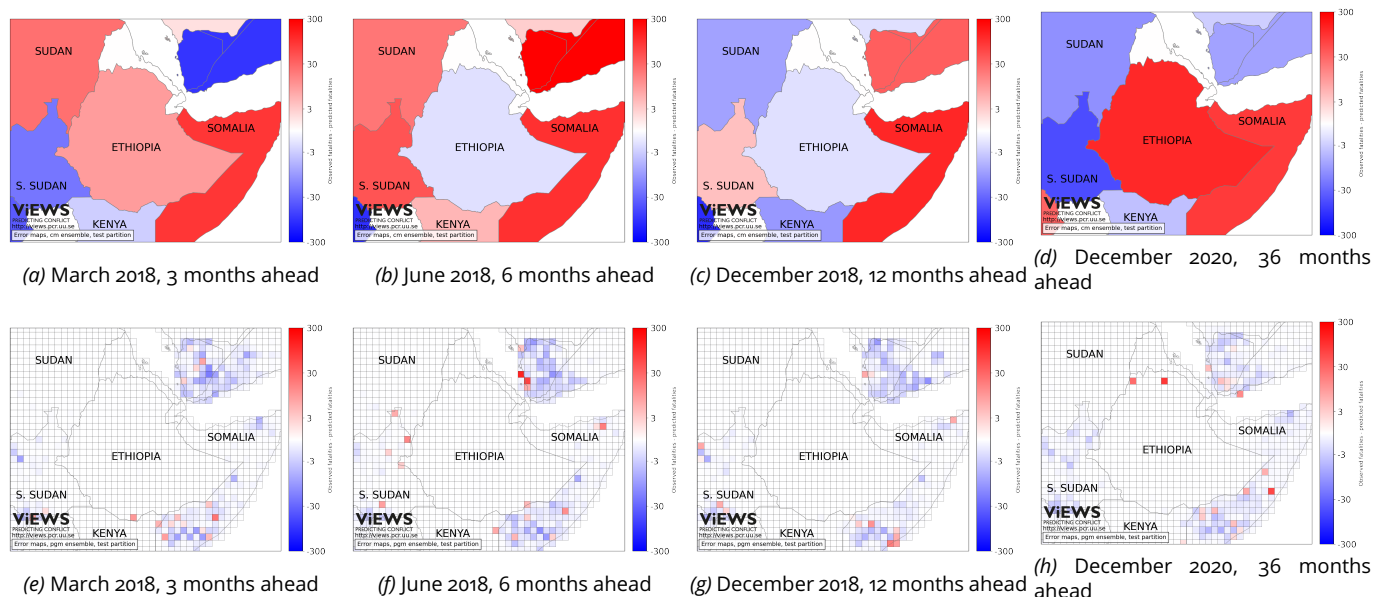
Figure 8. Prediction errors, Nigeria 2018–2020



Note: Error maps showing the difference between the ViEWS predictions and the observed number of fatalities from state-based armed conflict in a test set of data, country-level (top) and sub-national level (bottom). Forecasts for 3, 6, 12, and 36 months into the future from December 2017, the last month of data informing these figures. Red shows a higher number of fatalities than predicted; blue a lower number of fatalities than predicted.

Source: ViEWS, 2022

Figure 9. Prediction errors, Ethiopia 2018–2020



Note: Error maps showing the difference between the ViEWS predictions and the observed number of fatalities from state-based armed conflict in a test set of data, country-level (top) and sub-national level (bottom). Forecasts for 3, 6, 12, and 36 months into the future from December 2017, the last month of data informing these figures. Red shows a higher number of fatalities than predicted; blue a lower number of fatalities than predicted.

Source: ViEWS, 2022

more than 10 deaths, and a non-negligible chance that they will be counted in the hundreds. Also this reflects the difficulty of the prediction problem that the ViEWS model sets out to solve. Countries like Chad are clearly at risk of

escalating into serious conflict, but it is challenging to predict exactly when this will happen.

CONCLUSION

This report has presented a new prediction model developed by the ViEWS team at Uppsala University. The model generates monthly predictions of the number of fatalities expected in impending violence over the next 1–36 months, for each country and sub-national approximately 55x55 km location in Africa and the Middle East.

The model alerts to risks of continued high-intensity violence in the near future in Yemen, Nigeria, Somalia, Democratic Republic of Congo, Mali, Burkina Faso, Syria, and Iraq, with low- to medium-intensity violence expected in several other countries. The forecasts are primarily driven by records of past violence in these countries, complemented by vulnerabilities from structural factors such as the quality of governance, development, social- and natural geography.

While the data-driven early-warning system ViEWS offers great benefits to the international community in providing rigorous, systematic, and objective predictions of impending conflict, there are several limitations to the model. It does well at predicting serious cases of armed conflict, but is less certain about low-scale violence. Model uncertainty also increases when looking further into the forecasting horizon. The early-warning system should therefore be used as one tool in the predictive analytics toolbox, for example as a first assessment or a complement to traditional expert assessments.

To learn more about the new model, its uses, and its limitations, please see Hegre et al. (2022).

ACKNOWLEDGEMENTS

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Descriptions of the methodology behind the forecasts in this report, including the data informing the them, can

be found in Hegre et al. (2022). To learn more about the main ViEWS system, see Hegre et al. (2019) and Hegre et al. (2021).



HOW TO ACCESS THE FORECASTS

The forecasts presented in this report will along with future updates become readily available through the ViEWS API at <https://api.viewsforecasting.org>. over the spring of 2022. Documentation of the models informing this report can be found in the public GitHub repository https://github.com/prio-data/FCDO_predicting_fatalities. Future developments of the models will be published in the main ViEWS repository <https://github.com/prio-data/viewsforecasting>. Further questions are directed to views@pcr.uu.se.

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