The Violence & Impacts Early-Warning System (VIEWS)

‘Prediction, Prevention and Preparedness’ workshop at IAE

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Speakers

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Overview

1. What is VIEWS?
2. Using the VIEWS forecasts
3. How does the model work?
4. Explainable AI?
5. What's next?

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Violence & Impacts Early Warning System (VIEWS)

An academic consortium of research projects that leverage AI to enhance conflict prediction and anticipatory action → the VIEWS early-warning system

VIEWS: The Core Team

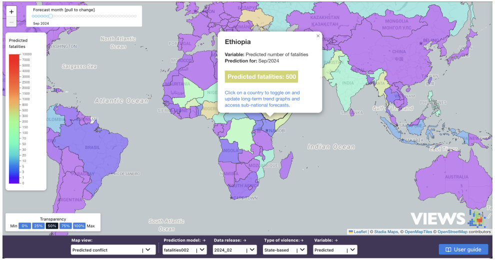
The Oslo and Uppsala teams, working across:
Research & Development | *Model Deployment* | *Data Infrastructure* | *Outreach and User Engagement*

... And about 15 Research Associates across the globe

The VIEWS Early-Warning System (EWS)

We offer a live **conflict early-warning system** – informed by the findings from our R&D efforts – to assist policymakers and practitioners in preventing and mitigating armed conflict and its adverse impact on society.

- *Forecasting horizon:* 1–36 months
- *Temporal resolution:* Monthly
- *Geographic coverage:*
  - Global (country level)
  - Africa and the Middle East (grid level)
- *Updates:* Every month



The VIEWS data dashboard (beta version, 2024-05)

Freely accessible on our website, API, and (soon) data dashboard.

Conflict Definitions

We currently predict state-based armed conflict:
Armed conflict over government and/or territory that involves at least one government-affiliated actor (UCDP definition).

Possible actors: the national army, armed wings of political parties, or individual soldiers/police/politicians.

Set to expand to non-state conflict and one-sided violence by the end of the year.

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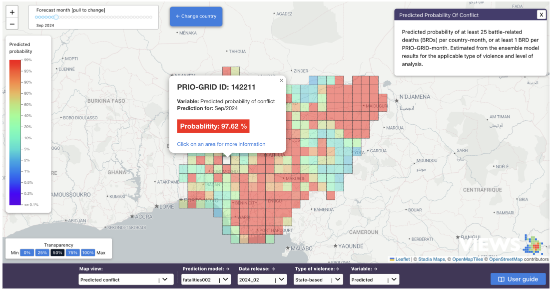
The VIEWS Data Dashboard: Predicted Conflict View

Forecasts displayed as:

- Predicted number of fatalities
- Predicted probability of observing given conflict thresholds per month
    - 25+ deaths per country
    - 1+ death per grid cell (55 sq.km.)

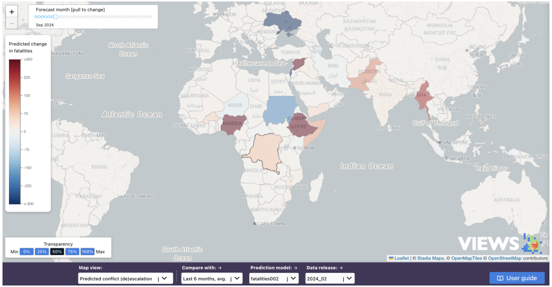


The VIEWS data dashboard. Beta version as of May 2024.

The VIEWS Data Dashboard: Predicted (De)escalation View

Forecasts displayed as:

- Predicted change in fatalities, as compared to historic averages of recorded fatalities (UCDP)
    - Last month
    - Last 3 months, avg.
    - Last 6 months, avg.
    - Last 12 months, avg.



(De)escalation view, VIEWS data dashboard.
Beta version as of May 2024.

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What data informs the model?

Input Data

High-quality data from a dozen renowned data providers

- Regularly updated (at least yearly, some monthly) and well maintained
- Broad coverage across time and space (many back to 1990)

200+ unique indicators at the country level; 100+ at the grid level

UCDP, ACLED: Conflict history

V-DEM: Governance, Democracy, Political institutions

WDI: Development

MAPSPAM, MIRCA, SPEI, FAO: Climate and societal vulnerability

PRIO-GRID: Natural and social geography

Mueller & Rauh 2018 (conflictforecast.org): Trending topics in news articles

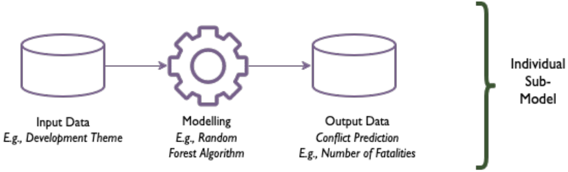
Full list of indicators on the VIEWS website.

How do we generate our predictions?

Modelling: Sub-models

First: estimate 10–20 (pgm/cm) individual machine learning **sub-models**, made up of:

- Grouped input data (conflict history, development, governance, etc.)
- Statistical and machine learning algorithms (random forest, gradient boosting, hurdle models, markov models, etc.)



No model is perfect, and the sub-models are tailored to address the prediction problem from different angles. So, we combine them.

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How do we generate our predictions?

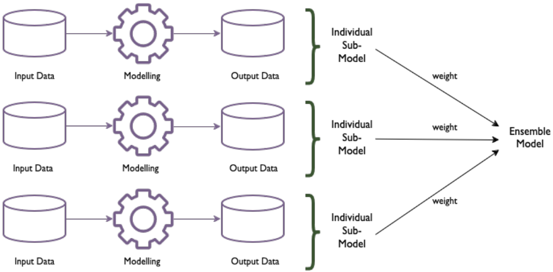
Modelling: Ensemble models

Wisdom of the Crowd:
Individual sub-models are combined into our core product, **ensemble models**, for more accurate and robust predictions.

One ensemble per LoA, by means of:

- Genetic algorithm at country level
- Unweighted average at grid level

Predictions for the two LoAs are reconciled: the country-level prediction(s) is roughly the same as the sum of the grid-level predictions.



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"We Need to Talk"

The Why, What, When, and How of Explainable AI

AI technology in conflict forecasting offers a transformative potential for enhancing preparedness, crisis response, and anticipatory action.

Yet, substantial challenges remain → call for EWS that are *interpretable*, *explainable*, and capable of generating *actionable insights*.

What does that mean? Highly ambiguous.

We Need to Talk.

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Surrogate Models to Peek into the 'Black Box'

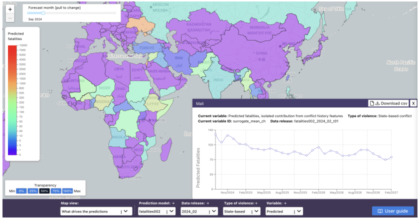
The Early Practical Approach

- Dynamic tool to peek into the model's 'black box'
- Show the isolated contribution to the forecasts from selected predictors – in each data release
- Easy to map and compare to the main predictions

- Correlation, not causation
- Still at risk of misleading

  E.g conflict history as a proxy for all causal mechanisms

- Only a handful of predictors, but can be expanded
- Limited to country level



'What drives the forecasts?', VIEWS data dashboard. Beta version, May 2024.

Learn more on our website: Main menu → Early-Warning System → User Guide for Practitioners

The Next Steps Towards Explainable AI

The next few months: Short-term projects pending confirmed funding

- Scenario/what-if simulations
- Ablation studies

The next few years: Ongoing research

- Forecasting drivers of conflict

  E.g. infant mortality rate, child growth, education levels – disaggregated across demography and geography
  - Can help identify and prioritise key areas at risk of deterioration
  - An alternative to deducing similar insights from the conflict forecasts
- Forecasting impacts of conflict on human development and humanitarian outcomes

  E.g. conflict-induced food shortages, and migration flows

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What's Next?

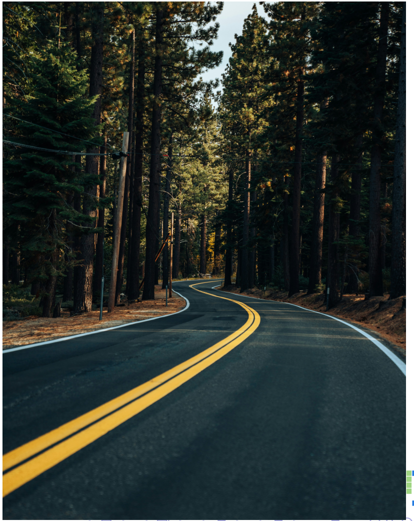
EconAI guiding question #2:
How should the early warning systems be designed to help in practice?

How to make VIEWS predictions more useful for practitioners?

- Modeling uncertainty of the predictions
- Evaluating at multiple scales and conditions
- Forecasting the impacts of armed conflict

Other extensions:

- New prediction models
  HYDRA-NET
- Towards an industry-grade pipeline
- AI centre application – Looking for operational partners!



Uncertainty Modeling – Why?

Valuable in itself

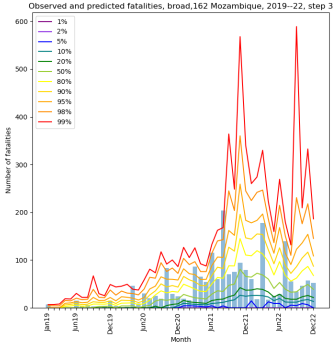
- An honest prediction quantifies uncertainty

Allows asking more questions

- What is the probability of more than 100 fatalities in the month three months from now?
- What is the likely number of fatalities in that month (with confidence intervals)?

Helps specifying the model

- Models that are optimized to forecast number of fatalities (point predictions) tend to be either **unstable** or **overly conservative** in our context
- Modeling the full probability distribution predicting low-probability, high-intensity cases



Sample forecasting model for Mozambique, three-months forward.

2023/24 VIEWS prediction competition

Challenge:

- Predict the number of fatalities in armed conflict
- With an estimate of the uncertainty of the predictions
- Rewarding those that do well both in terms of point prediction and uncertainty

For the true future and for selected historical periods

- Funded by the German FFO/PREVIEW
- 15 teams
- Socring committee: Thomas Mayer, Seth Caldwell, Philip Schrodt, Céline Cunen
- Metrics: CRPS, MIS, Log score
- Live forecasting window July 2024–June 2025
- Forecasts will be made public 30 June 2024 in a dashboard at https://viewsforecasting.org
- Evaluation article in 2025

How to Model Uncertainty

Aim:

- To produce VIEWS forecasts as *n* draws from the probability distributions over possible fatality counts

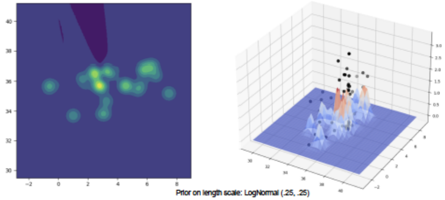
Solution:

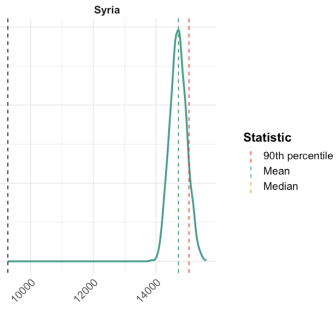
- Formulating models of:
  - uncertainty of input data
  - uncertainty about model specification
  - sample variation/statistical uncertainty
- Possibly adding the estimated residual prediction error
- Extract draws from the probability distributions these imply
- Pool predictions from these models into an ensemble

Uncertainty of Input Data

Three projects to handle known uncertainty in the UCDP data:

- Models for 'known geographical imprecision'
- Model for true number of fatalities given news report
- Model to nowcast final UCDP coding based on UCDP candidate data





How to Promote a Useful Forecasting System

Problem:

- In most cases, violence is similar from one month to the other
- We are most interested in the cases where they change
- How to avoid that the many no-change observations crowd out the change observations?

Solutions:

- Modeling with uncertainty
- Favoring models that forecast well over an extended period and over space
- Favoring models that do well for the risk of onset cases

A weighted set of evaluation metrics to balance different qualities

Weighting evaluation metrics, costs of misclassification

We will work towards a system that minimizes misclassification costs, but what are the relative costs of different errors?

- False calm is worse than false alarms, so $\alpha_4 > \alpha_3$ and $\alpha_2 > \alpha_1$?
- Onsets are more important to predict than continuation, so $\alpha_2 > \alpha_4$?

		Predicted state			
		At risk of onset		Not at risk of onset	
		Positive	Negative	Positive	Negative
Actual	conflict	True positive $c = 0$	False negative $c = \alpha_2$	True positive $c = 0$	False negative $c = \alpha_4$
State	not conflict	False positive $c = \alpha_1$	True negative $c = 0$	False positive $c = \alpha_3$	True negative $c = 0$

Table: Costs of classification; onset vs continuation cases

Modeling the impact of armed conflict

EconAI guiding question #1:

What are concrete policy actions that could be taken differently with better early warning?

- We are as concerned about the indirect consequences of conflict as the fighting itself
- And the negative side effects may be easier to contain than the fighting itself

Forecast the impact of armed conflict on adverse outcomes such as:

- Displacement
- Food insecurity/hunger
- Health

As a function of:

- Exposure to violence, in the past and as forecasts
- Vulnerability to conflict-driven impact

Challenge: Impact data

Thank you for listening!

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