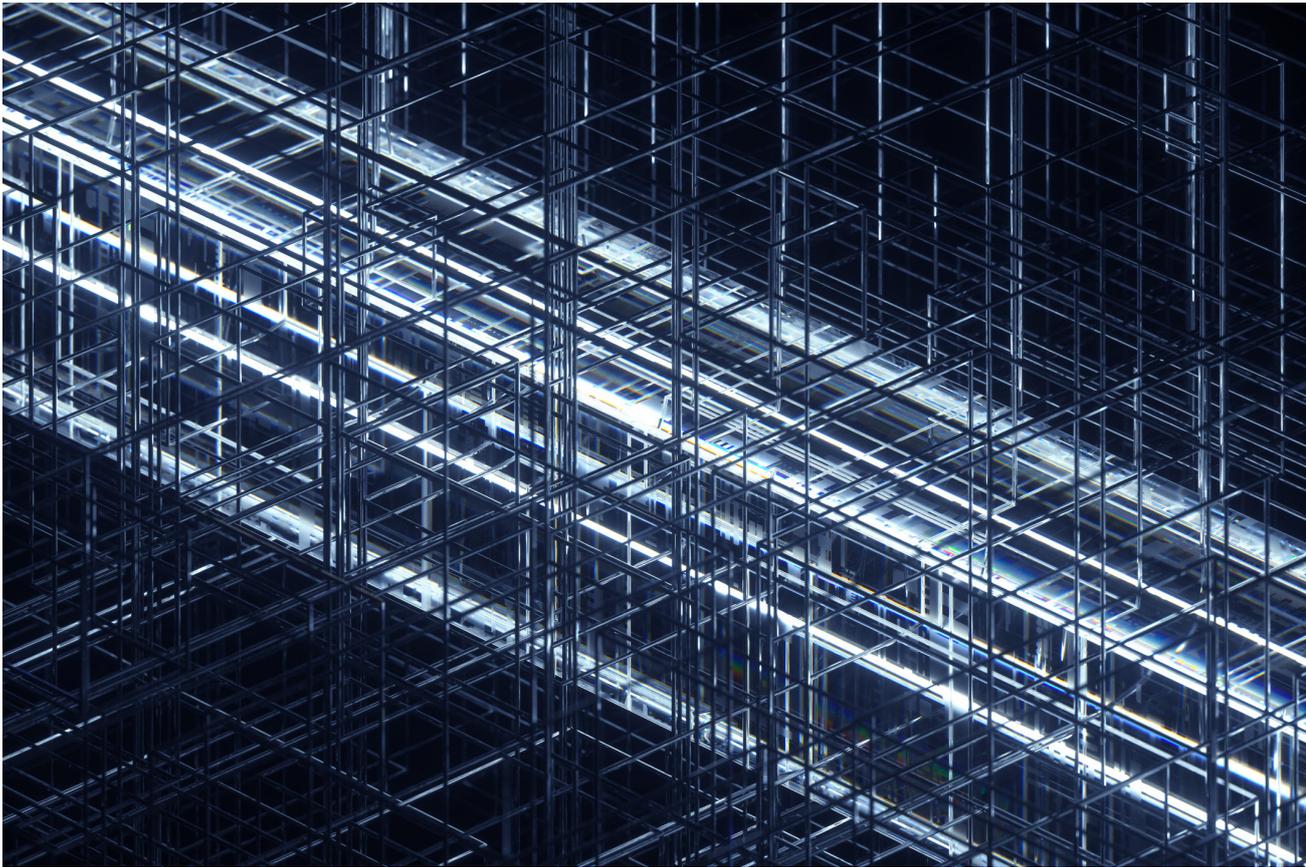


How artificial intelligence can support peace

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1. AI and the benefits of peace

Armed conflict has been on the rise over the past 15 years. Figure 1 shows the number of fatalities in state-based armed conflict – armed conflict involving at least one state as an actor – over time, according to the Uppsala Conflict Data Program (UCDP) (Davies et al., 2024). The first decade of this century was the least violent for as long as reliable data exist, but then the world changed. Beginning with the conflicts in Syria and Yemen, and then in Ukraine, Ethiopia, Gaza and other places, several hundreds of thousands of soldiers and civilians have lost their lives in violent clashes. Figure 2 shows the geographical distribution of violence in 2023. State-based violence (blue circles) is the most lethal form, but one-sided violence – where a government or an armed group targets civilians – and non-state violence – where non-state armed groups fight each other – are also on the rise.

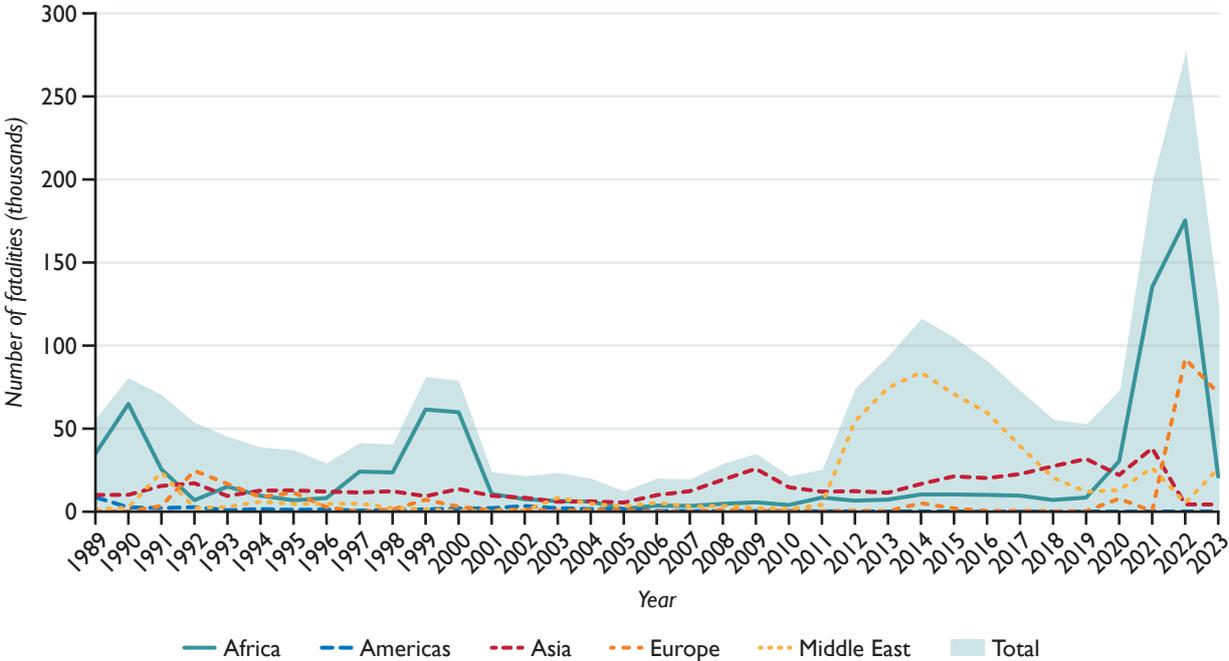


Figure 1: Fatalities in state-based conflict 1989–2023, by region Source: Based on UCDP 24.1 data

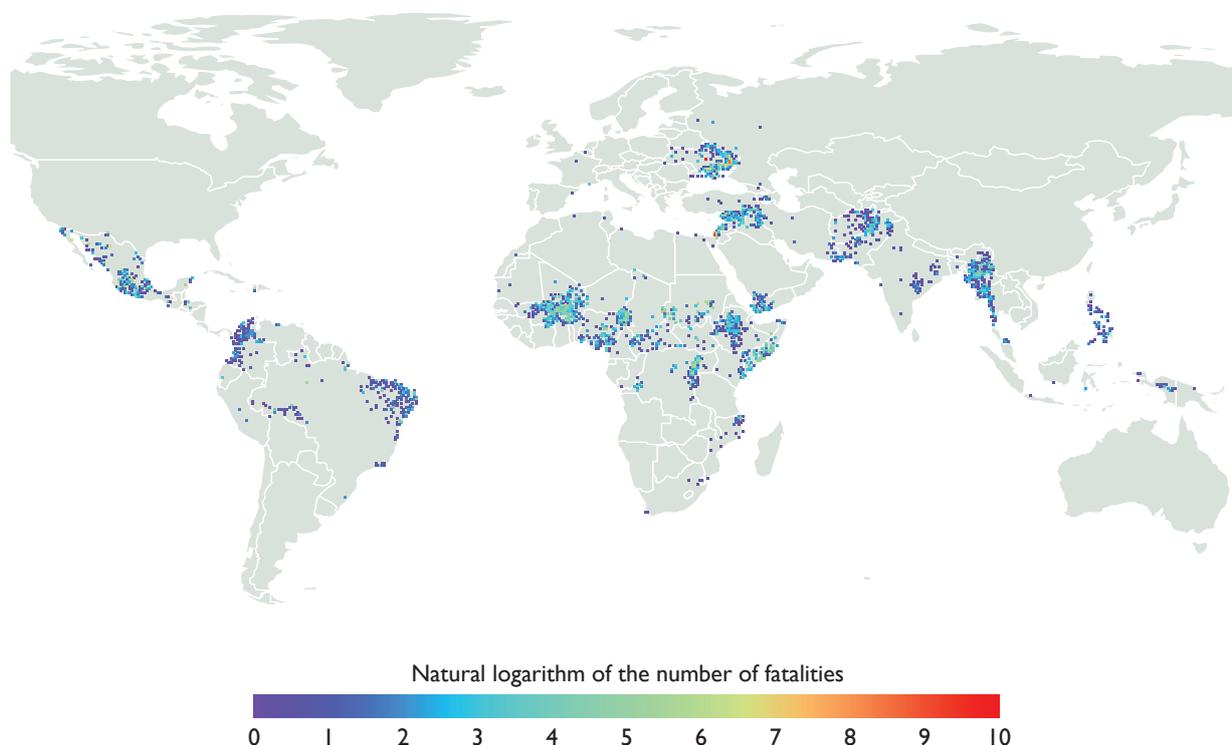


Figure 2: Three forms of organized violence in 2023 (state-based, one-sided, non-state)

Source: UCDP Georeferenced Event Dataset version 24.1

Direct fatalities from armed conflict are only the tip of the iceberg, as conflict also destroys health, food security, education, gender equality and other aspects of human welfare (Dahlum & Wig, 2020; Vesco et al., 2025; Martin-Shields & Stojetz, 2019; Garry & Checchi, 2019). When considering long-term effects, indirect excess mortality and morbidity due to armed conflict are at least as high as the direct impact. Conflict is ‘development in reverse’ (Collier et al., 2003).

Global welfare could improve immensely if the world succeeded in preventing armed conflicts, or reducing their intensities and alleviating their indirect effects (Mueller & Rauh, 2022). When leading actors agree to such goals, this is possible: the first decade of our century was peaceful because there was widespread consensus about these goals, and the UN was empowered to take forceful action (Hegre; Hultman & Nygård, 2019). Provided that such a consensus commitment to human welfare can be refound, artificial intelligence – if applied wisely – can help in attaining such goals. Here, I will suggest some ways AI can help to strengthen the information basis for decision-making, provide useful risk analysis and support decision-making through scenario analysis.

2. Monitoring conflict

Good decisions can only be made when information is adequate. To reduce the suffering due to armed conflict, we need to know where, when, why and how wars are fought and monitor the most important consequences that conflicts have. Providing such information is feasible in most places, but requires lots of resources. Since conflicts are political phenomena where powerful actors have incentives to misrepresent the situation, the leading conflict data providers (UCDP and ACLED: Davies et al., 2024; Raleigh et al., 2010) use human coders to analyse news reports, reports, local sources and other available information, screening them and synthesizing them into consistent data adhering to clear, uniform definitions. The best providers are neutral, academic entities shielded from political manoeuvring within intergovernmental organizations (IGOs), entities that tend to rely on limited and uncertain funding streams. These constraints mean that there are insufficient resources to collect data, limiting the scope, coverage and precision of the data and leaving gaps in information.

Several AI tools can be employed to improve the quantity and quality of conflict data without increasing the costs of data collection (Brandt & Sianan, 2025; Radford et al., 2023). Given the importance of information in text sources, large language models (LLMs) are particularly valuable. LLMs can efficiently and accurately process large volumes of text with unprecedented efficiency and accuracy. They need, however, clear guidance from human coders that understand political complexities and misrepresentations. A promising pilot has supplemented Uppsala Conflict Data Program (UCDP) datasets with richer information (see www.prio.org/projects/1998). Relatedly, Croicu (2024) leverages active learning to extract additional information from the sources used by the UCDP. Here, a machine-learning classifier is improved in an iterative loop where the algorithm requests human input on the news items it finds most hard to classify. By applying such methods in close collaboration with conflict experts but economizing on their time, it becomes possible to expand conflict data systematically to provide information about targets, objectives, actor characteristics and motivations, and modes of engagement (Croicu, 2025).

Satellite imagery is another source of information that AI tools such as convolutional neural net models can harness to improve available information (Mueller et al., 2021). Satellite and radar imagery can thus be linked to labelled data from the leading conflict data providers and domain knowledge about local weaponry and tactics to identify patterns of destruction. With such data, many instances of fires and demolitions due to fighting can be identified well before news sources are able to pick them up, in particular in areas where reporters and other observers are unable to move and report freely due to intense violence or harsh repression (Williams, 2025).

Modelling of uncertainty is another area where machine learning and statistical modelling can strengthen the quality, usefulness and credibility of conflict data. Human coders have to relate to many sources that provide only partial information. For instance, news reports may leave out the exact date or location of a violent event, and the coder must assign a placeholder time and location for it. Statistical modelling and machine-learning methods can be used to leverage

associated information to provide a more useful, albeit probabilistic, representation of when and where the event happened. Croicu (2025) makes use of information on which actors were fighting and where they had fought in the past to construct a useful approximation of events with partial information that, for a large set of cases, observers otherwise would have been forced to disregard. Relatedly, Vesco et al. (2024) use statistical modelling and expert elicitation to approximate the number of fatalities in events where the reported numbers are unclear. In these situations, human coders often feel compelled to choose a conservative estimate, and the true intensity of fighting is under-reported. Chadeaux (2023) proposes an algorithm to detect patterns in fighting that indicate when significant changes in the situation are developing.

Another constraint is that news sources and other observers often need time to record events, and human coders require further time to process these records. As a consequence, it can take a year or even much longer before high-quality, carefully vetted datasets reach the desired level of completeness. Nowcasting models overcome lags in data availability by estimating the current intensity of fighting given historical data on how data providers gradually revise and improve their datasets. This provides users access to a probabilistic representation of the world.

3. Anticipation: forecasting conflict

Employing AI tools to expand and improve data with as little delay as possible will help actors mandated to reduce suffering from conflict to monitor situations and understand what is going on. In addition, better data will strengthen these actors' ability to anticipate crises at early stages of escalation. Conflict forecasting has advanced substantially over the past decade, increasingly enabling the prediction of the likelihood, location and intensity of future conflict events (Hegre et al., 2019; Mueller & Rauh, 2018; Rød; Gässte & Hegre, 2023; Hegre et al., 2022; Chadeaux, 2023). Several forecasting projects provide open-source online demonstration systems that showcase their usefulness – most notably the VIEWS project, ConflictForecast, and the US Holocaust Memorial Museum early warning project.

Conflict forecasting is still a field in early stages of development, and some expectation management is necessary (Cederman & Weidmann, 2017). Forecasting truly new armed conflicts is hard. In most cases, political conflicts are settled without overt use of violence, in 'the shadow of power' (Powell, 1999). Theoretical models suggest that wars tend to occur when rational bargaining breaks down because of misunderstandings, inadequate military intelligence, and other sources of incomplete information. Only then, when actors misunderstand or miscalculate, is there a need to carry out a threat to use violence. According to this argument, 'war is in the error term' (Gartzke, 1999), and as such is very hard to predict.

Given that we rarely observe bargaining between political leaders and lack reliable ways to assess decision-makers' private perceptions of situations, adequate data to forecast new armed conflict with certainty do not exist. Still, 'structural' factors such as political systems, economic structures and poverty are useful to sort locations well in terms of latent risk. Although such models could not suggest precisely the timing of violence, Ethiopia was at the top of the list of future war countries long before the Tigray conflict (Hegre et al., 2013).

Forecasting new armed conflict is an exceedingly difficult problem, but forecasting the trajectories of conflicts after the first couple of months is much more manageable (Hegre et al., 2022). Many conflicts – and in particular civil wars, the most common conflict type – last for a long time, typically many years and sometimes several decades. A systematically quantified estimate of the long-range trajectory of an incipient or established conflict is useful, in particular to assess the long-term costs of fighting and the relative benefits of intervention, as discussed below.

Conflict forecasting models are developing rapidly along with the entire machine-learning and AI field. Early models used various decision tree-based models (Mueller & Rauh, 2018; Hegre et al., 2019), whereas neural nets, transformers and other deep learning architectures promise new advances (Radford, 2022; Malone, 2022; Walterskirchen et al., 2024; von der Maase, 2023). The data-enhancing possibilities described above will further strengthen the performance of forecasting models. In particular, automatized extraction of information from news sources has proved

highly effective (Chadefaux, 2014; Mueller & Rauh, 2018), and the revolution in LLM modelling will certainly accelerate conflict forecasting models.

Also in line with how machine-learning models are evolving in general, conflict forecasting is increasingly attentive to the uncertainty of the forecasts (Hegre et al., 2025). This is important beyond the obvious need to provide honest representations of the precision of the forecasts: since war often results from a long, unobserved process of bargaining that sometimes abruptly erupts into extreme violence, we need models that can tell us that even if the most likely outcome over the next months is the continued absence of violence, there is also a low but significant probability of extreme escalation. Such uncertainty models that capture the full probability distribution across a wide range of possible outcomes will greatly increase the usefulness of conflict forecasting models (Hegre et al., 2025). They are also well suited to make use of the probabilistic modelling of input data discussed above. Technically, the models use various methods such as bootstrapping, Bayesian modelling, Monte Carlo drop-out, ensembling, and ‘conformal prediction’ (Randahl; Williams & Hegre, 2024) to extract probability distributions from machine-learning models.

4. Anticipatory action

AI-supported models to develop the monitoring and anticipation of armed conflict are naturally supplemented by models to support ‘anticipatory action’ – actions to prevent armed conflict or at least to minimize the negative impact of fighting on local populations.

One way to use these approaches is scenario modelling – estimating the projected intensity of conflict globally or in a region under various assumptions about the investment in conflict prevention and its efficacy, and then estimating the likely benefits of the changes in global conflict. Such modelling exercises show that the possible benefits from prevention – even under conservative assumptions – are staggeringly high (Mueller & Rauh, 2022; Petrova et al., 2023). Scenario simulation also shows that peacekeeping operations that mainly work through containing the intensity of violence have massive beneficial effects (Hegre; Hultman & Nygård, 2019).

Scenario modelling could be made even more forceful with more advanced modelling of the humanitarian impacts themselves, and in particular by modelling the conflict shocks and the impacts jointly. Again, a major constraint is the availability of data – we have more precise data on the location, time and lethality of violent conflict events than on the more diffuse impacts, such as migration flows, deterioration of local health services, changes to food availability, and other economic effects at the village level (Vesco et al., 2025). The AI-based data-enhancing tools described above will also increase our ability to monitor and model these effects.

Advanced machine-learning models will also help scenario models, as well as the simulation of interventions and their impacts relative to the counterfactuals. The forecasting models described above can be adapted to such simulations. In combination with good models for the costs and benefits of intervention, these can provide excellent tools to support anticipatory action decisions. In turn, incorporating the effects of policy interventions in forecasting models is also necessary to counter the risk of self-fulfilling or self-defeating prophecies (King & Mertens, 2023): if effective intervention is initiated based on a highly precise conflict forecast, the forecast will be wrong unless the intervention is adequately captured in the prediction model itself.

AI models designed to monitor and forecast armed conflicts and their impacts can also be used in ‘parametric insurance’ mechanisms, through which funding for humanitarian assistance is paid out immediately after a destructive event without waiting for exact loss estimation. If an earthquake with magnitude 7.5 on the Richter scale is observed in a heavily populated location, a parametric insurance mechanism would automatically trigger a predefined outpayment to assist the affected population. Such mechanisms can also be designed for armed conflict, which are equally as destructive as earthquakes, although the cost estimation is more complex. The UN Food and Agriculture Organization (FAO) are developing such models for a variety of shocks affecting food security, including conflict, using UCDP data and VIEWS forecasting models.

5. Conclusion

AI comes with risks on its own. In particular, AI technologies can be used to surveil and repress dissent, spread disinformation, and undermine well-informed public debate that takes facts and alternative points of view into account. Used in such a way, AI technologies can thereby gradually weaken democratic institutions and strengthen powerful elites that can benefit from armed conflict (Goldstein et al., 2023; Monteith et al., 2024; Coeckelbergh, 2024). Research on these urgent challenges remains nascent.

Still, AI is a powerful tool that can be harnessed for a common good. I have sketched a set of approaches through which AI can help reduce the unnecessary human costs of armed conflict, through improving monitoring, anticipation, and ultimately anticipatory action. Any effective action requires a willingness to invest resources to make any difference, of course, but research on these methods and demonstration of their usefulness also highlights the need and promises of costly action. In addition to these benefits themselves, by using and developing the tools for good purposes, the UN, governments and other actors with a humanitarian agenda will also increase their competence in countering the adverse effects of malign use of new technologies.

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How artificial intelligence can support peace

Armed conflict is a global problem that threatens human life and the safety of human beings. In order to reduce the suffering due to armed conflict, we need to know where, when, why and how wars are fought and monitor the most important consequences that conflicts have. Artificial intelligence (AI) is able to perform complex tasks such as visual perception, recognition of meaning in text and decision making. The paper suggests some ways AI can help to

strengthen the information basis for decision making, provide useful risk analysis and support decision making through scenario analysis. In particular, it gives a brief overview of AI's use in conflict forecasting and scenario modelling. These approaches will help to improve the monitoring, anticipation and ultimately anticipatory action of armed conflicts.