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TRANSLATIONAL ARTICLE

Pushing the boundaries of anticipatory action using machine learning

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Abbreviations: AHEAD, Anticipatory Humanitarian Action for Displacement; DRC, Danish Refugee Council

Abstract

Displacement continues to increase at a global scale and is increasingly happening in complex, multicrisis settings, leading to more complex and deeper humanitarian needs. Humanitarian needs are therefore increasingly outgrowing the available humanitarian funding. Thus, responding to vulnerabilities before disaster strikes is crucial but anticipatory action is contingent on the ability to accurately forecast what will happen in the future. Forecasting and contingency planning are not new in the humanitarian sector, where scenario-building continues to be an exercise conducted in most humanitarian operations to strategically plan for coming events. However, the accuracy of these exercises remains limited. To address this challenge and work with the objective of providing the humanitarian sector with more accurate forecasts to enhance the protection of vulnerable groups, the Danish Refugee Council has already developed several machine learning models. The Anticipatory Humanitarian Action for Displacement uses machine learning to forecast displacement in subdistricts in the Liptako-Gourma region in Sahel, covering Burkina Faso, Mali, and Niger. The model is mainly built on data related to conflict, food insecurity, vegetation health, and the prevalence of underweight to forecast displacement. In this article, we will detail how the model works, the accuracy and limitations of the model, and how we are translating the forecasts into action by using them for anticipatory action in South Sudan and Burkina Faso, including concrete examples of activities that can be implemented ahead of displacement in the place of origin, along routes and in place of destination.

Policy Significance Statement

There have been many advancements on doing anticipatory action in the humanitarian sector. Most of this work has been done in the domain of responding to climate hazards such as floods, typhoons and droughts. When it comes to responding to climate hazards in conflict settings, the number of actors and activities becomes limited, as this is seen as complex and sensitive. When it comes to anticipatory action in response to conflict and its impact, there is currently no active work in this domain. With this article, we therefore want to show how

This research article was awarded Open Data and Open Materials badges for transparent practices. See the Data Availability Statement for details.

policymakers and practitioners can expand the domain of anticipatory action from climate hazards to conflict hazards based on accurate displacement forecasting tools.

1. Introduction

The world is faced with an increasing number of forcibly displaced persons. Ten years ago, around 37 million people were displaced from their homes—eight countries were the origin of major displacement crises, having more than 1 million people displaced. Today, the total number of displaced people has tripled and now 18 countries have more than 1 million of their nationals displaced (UNHCR, 2023). These numbers continue to grow as existing crises are not being resolved and new ones are emerging. In 2013, there were 35 situations of protracted displacement, while this number has grown to 57 in 2022.

With growing displacement, humanitarian needs are also increasing at an unprecedented pace. In 2015, 78 million people needed humanitarian aid worldwide (OCHA, 2015). This number increased to 339 million in 2023 (OCHA, 2023).

While displacement is not alone in driving up these numbers, as other crises such as COVID-19, climatic changes and economic deterioration have also contributed, it is a major driver of humanitarian needs. Displacement limits people's access to their lands, income-generating activities, assets and social support structures. This drives up food insecurity and poverty (Reynaud and Falkowitz, 2023). Displaced people also face challenges in accessing services which can have a severe negative impact on aspects related to health and education. Furthermore, people living in displacement often face protection challenges as they live in precarious situations often in fragile settings, which can expose displaced people to, for example, violence, forced recruitment into armed groups and forced labour. Lastly, the mental stress that displacement puts on households can lead to issues not only related to mental health but also an increase in domestic abuse, Sexual- and Gender-Based Violence (SGBV) and violence against children. Research has also found that women and girls tend to disproportionally suffer during displacement, as being displaced reinforces harmful pre-existing gender norms (Cazabat, 2020).

As the development shows, there is a need to reverse this trend and new approaches are needed. One such way is to get ahead of crises to prevent and mitigate the impact and humanitarian needs. Rather than watching crises unfold and then reacting, planning for crises ahead allows for a swifter response that can help to prevent needs from arising in the first place and respond to suffering faster when they arise. This can take the form of anticipatory action, which can be defined as anticipatory action "actions taken to reduce the impacts of a forecast hazard before it occurs, or before its most acute impacts are felt (Anticipation Hub, n.d.)."

The ability to plan and act ahead of crises requires the ability to accurately forecast where future shocks—for example, conflict or natural hazards—are going to materialize. This is not new in the humanitarian sector and calls have been made for effective early warning systems in response to displacement as far back as 1989 (Druke, 1989). Today, scenario-building continues to be an exercise conducted in most humanitarian operations to strategically plan for coming events. However, the accuracy of these exercises remains limited. Analysis of 140 humanitarian response plans shows that in ~70% of the plans, the projected number of displaced persons was underestimated. The plans were on average 22% off the actual number—a significant variation when translated to the actual numbers of people who missed out. When planning processes fail to accurately assess risks and build scenarios, actions fail. An evaluation of UNICEF's response to the Rohingya crisis noted that "Given the history of the Rohingya, further refugee arrivals were predictable […] UNICEF's March 2017 two-year strategy does not refer to scenarios or contingency plans for new influxes – a clear gap. The strategy hardly refers to any preparedness activities at all. […] it should be noted that when the August 2017 refugee influx began, few systems, if any, were in place to respond in an adequate manner (UNICEF, 2018)." Similarly, an evaluation of UNHCR's response to the Rohingya crisis noted that "UNHCR has an emergency preparedness tool, whereby situations are monitored on an ongoing basis and ranked as either low, medium or high risk. In early August 2017 (just 3 weeks before the mass influx), the Bangladesh operation

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was ranked as a medium risk of experiencing an emergency." The lack of preparedness meant that "when the Rohingya started crossing in late August 2017, UNHCR had little emergency stock and a small team dealing with a stable caseload of 34,000 (registered) long-term refugees. This meant that UNHCR was effectively responding from a 'standing start' – it had to import emergency supplies and deploy emergency specialists, all of which takes time even when it is done very rapidly" (UNHCR, 2018).

One reason for the inaccuracy is the fact that the current planning and scenario-building processes often use limited data sources, resulting in a fragmented view of current events and lack rich details as well about the complex network of events that ultimately drive displacement and needs. Work on anticipatory action has thereby mainly gained prominence in areas where reliable forecasting models have been available: weather forecasts. Anticipatory action has therefore made great advances in response to droughts, floods, typhoons and so forth. The approach has recently gained further momentum with the UN Secretary General launching the Early Warning for All action plan in 2022, which aims to ensure that every person in the world is covered by early warning systems by 2027. With the presence of such systems, anticipatory action responses can further be enabled across more countries.

The evidence so far suggests that anticipatory action can have several positive effects including lowering psychosocial stress, decreasing food insecurity and increasing asset protection and recovery (Weingärtner et al., 2020). Food and Agriculture Organization of the United Nations (FAO) has shown that for every USD 1 invested in anticipatory action for farming families, more than USD 7 in avoided losses and added benefits is provided in return.

In 2022, there were an estimated 70 anticipatory action frameworks in place across 35 different countries, with USD 138 million committed through these frameworks, and 47 of the frameworks were activated reaching 3.6 million people (Anticipation Hub, 2023). These frameworks have been developed to respond to issues such as floods, droughts, cold/heat waves, typhoons, disease outbreaks and so forth. However, much of the anticipatory action work being done in response to climate hazards is being done in more stable settings with less than one-third of the countries with active frameworks being conflict- and fragility-affected (World Bank, 2023). Only half of the countries that are the most vulnerable (ND-Gain, n.d.) to the impacts of climate change and in situations of conflict/fragility have anticipatory action frameworks in place.

When it comes to responding to conflict hazards—such as conflict-induced displacement—progress on anticipatory action has so far been meagre, due to both the challenging contexts and the lack of forecasting tools to accurately predict future shocks. The Anticipation Hub's Global Overview Report 2023 showed that there was only one active anticipation action framework to respond to population movement out of 47 reported globally (Anticipation Hub, 2024). As such, the expected benefits of anticipatory action are only to a limited extent being extended to conflict- and displacement-affected populations. To address this issue, the Danish Refugee Council has sought to develop innovative displacement forecasting models and approaches to anticipatory action to conflict-induced displacement, to expand the domain of anticipatory action to the benefit of these target groups.

2. Using machine learning to enable anticipatory action to conflict-induced displacement

Systems and tools are needed to enable the integration of more data into these strategic planning and scenario-building exercises to make them more accurate. A lack of data in the humanitarian system is often highlighted (e.g., UNICEF, UNHCR, IOM, Eurostat and OECD, 2018, Gillsäter, 2021) and "expanding anticipatory action to new Humanitarian Response Plans (HRP) locations will be challenging without improvements to the data landscape" (Centre for Humanitarian Data, 2022). The ability to integrate and use the existing data to its full potential is a first step in becoming more data-driven and exposing where the critical data gaps exist.

Danish Refugee Council (DRC) has explored the use of predictive analytics for improving accuracy in strategic planning and operational response since 2017. The initial modelling work focused on developing a prediction model to forecast displacement at the national level 1–3 years into the future. This initial model—Foresight—uses more than 140 indicators from open-source data, to predict future displacement. The machine-learning model employed is an ensemble. The ensemble model works by leveraging several constituent models to generate independent forecasts that are then averaged. The model employs an ensemble of gradient-boosted trees and linear models to generate the point forecasts. The model hyperparameters were determined using a grid search. Each year-ahead forecast has a separate model. The evaluation of this model showed that based on 214 historical forecasts across 26 different countries, the model had a mean absolute margin of error of 19% and a median absolute margin of error of 11%. The absolute margin of error is defined as the absolute difference between the forecasted value of displacement and the actual historical figure. One of the reasons for using this metric is that it is simple and is already used in a humanitarian context to evaluate differences between planning figures and outcomes.

The output of the forecasts can only be evaluated against the official figures on displacement, which also means that the models are trained on historical official numbers. These numbers exist with some uncertainty but it is beyond the scope of these models to estimate and evaluate figures that are outside the official numbers.

The aim of the Foresight is to be used for yearly, strategic planning purposes and, therefore, it is relevant to benchmark the tool up against existing practices of developing planning figures in the sector. In the humanitarian sector, joint humanitarian response plans are developed each year for a humanitarian crisis in a joint effort between the different humanitarian actors present in the country. Those reports often include figures on the number of displaced people in the country, as this is a relevant planning figure. There is no consistent practice in the different countries how this figure is developed, but it is sometimes based on a scenario or expectations of future developments. As highlighted in the introduction, the average margin of error of 140 plans analysed is 22%. In the 123 plans where a forecast was also developed using the Foresight tool, the average margin of error is 23%, while it is 19% for this subset of the Foresight predictions. The median is 17% and 12%, respectively.

Based on these initial findings, a subsequent modelling exercise was undertaken, to develop a more operational model that could be used to inform direct humanitarian responses. In 2020, a project was initiated to develop the Anticipatory Humanitarian Action for Displacement (AHEAD) model. The purpose of this model is to support operational response by predicting displacement at the Admin 1 and Admin 2 level 3–4 months into the future.

Since the data on displacement at the subnational level is often sparse and sporadic with no reliable frequency of publication, the standard methods for working with regular-spaced time series are not feasible. To forecast displacement at a sub-yearly frequency, the model is constructed to work with the outcome data being available at irregular intervals. The basis of the model is the Bayesian state-space model for the stock number of internally displaced people $\mathbf{D}$ at time t in area s, where the time steps are monthly, and the areas are the relevant administrative levels of the country.

$$D_{s,t} = D_{s,t-1} + \boldsymbol{\beta} \boldsymbol{x}_t + \varepsilon_t.$$

The evolution of the state is determined by several external covariates $\mathbf{x}_t$, which describe the conditions in the area s and the neighbouring areas at time t with the assumption being that most internal displacement is within the same area or between neighbouring areas. The list of covariates includes indicators of conflict, food security, climatic conditions, development, protection and so forth, which have been selected in concert with experts on displacement and the local context. We assume that the functional relationship between the covariates and the outcome variable of displacement is constant in time and space, which allows us to infer this relationship fitting the model to historical data. The model structure treats the months with missing displacement data as additional parameters to be inferred and this allows us to work with data sets on displacement that contain gaps and missing information. In many of the displacement data sets, there is an overabundance of constant values, where we can suspect that the previous amount was recorded again without any new measurement having taken place. While we cannot say so for certain, the model is constructed as a hurdle model to take this overabundance into account.

Based on 315 historical forecasts in Burkina Faso, the model has shown that the mean absolute percentage error is 15%. The hindcasts are constructed by setting a past now at a historical date, training

Indicators	Theme	Source
Violent events, kidnappings/lootings, attacks from extremist groups, deaths from violence against civilians	Conflict	ACLED
Share of people in classification 3+	Food security	Cadre Harmonisé
Food prices	Food security	WFP
Vegetation Health Index	Climate	FAO
Mortality rate among small children	Development	WHO
Survey index of safety	Protection	Project21

the model on all previous historical data and attempting to forecast displacement 4 months into the "future," where we have historical records to compare to. This is repeated at seven different time points for each of the 45 provinces in Burkina Faso. We benchmark the model against two simple approaches: The first is forecasting a constant level of displacement with no change and the second model is forecasting that displacement in each province will evolve with a rate of displacement per month as it has in the previous 24 months. Both approaches have a mean average percentage error of 21%.

The results also show that predicting the onset or unprecedented escalation in displacement due to conflict is difficult for the model. This mirrors similar results found in the evaluation of conflict forecasting models (Caldwell, 2022). The correlation between the relative, absolute increase in displacement and the absolute margin of error is 0.74. In the situations where displacement has increased by more than 4,759 (fourth quartile) over a 3-month period, the absolute average margin of error increases to 21%. When the relative, absolute increase is more than 35.4% (fourth quartile), the average absolute margin of error on the forecasts is 34%. This mirrors the results found in the initial Foresight model, albeit this error comes out even stronger in the Foresight model. Whereas the Foresight model has a slight conservative bias, that is, 60% of the forecasts have underestimated the level of displacement for the coming year, the AHEAD model does not have the same bias (52% of forecasts underestimate).

Using the AHEAD for classification, which is relevant when applying it for anticipatory action, the results in the historical forecasts reveal that it would correctly classify future displacement in ~70% of the time. If a threshold is set for anticipatory action to be taken when the model predicts future displacement to increase by 1,200 people, the model would lead to correct actions being taken 69% of the time, that is, action being taken and >1,200 people become displaced as predicted or inaction and <1,200 people are displaced 3 months later. The remaining would include 17% false negatives and 14% false positives.

Where to place the exact threshold depends largely on the capacity to respond (i.e., a lower threshold would entail actions being triggered more often) and the risks associated with the activities to be triggered,

		Actual displacement (>1,200 people)	
		Negative	Positive
Predicted displacement (>1,200 people)	Negative	116 (37%)	53 (17%)
	Positive	44 (14%)	102 (32%)

which would largely drive the preference for having either few false positive or few false negatives. If the threshold instead of 1,200 was set at 10,000, then actions would only be taken 12% of the time, but 90% of the time action/inaction would be correct.

3. Combining prediction data with community data

Turning the displacement prediction into actions is not straightforward, nor necessarily desirable. While a prediction model can be perceived as offering a more objective and scientific means of decision-making

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and allocation of support and resources, this would ignore the fact that "existing flaws in accountability and epistemic processes can be also found in the mathematical and statistical formulas and in the algorithms used for automation, artificial intelligence, predictive analytics, and other efficiency-gaining-related processes" (Coppi et al., 2021). Basing decision-making solely on predictive models, where the black-box nature means that the causal link between the prediction and resulting humanitarian action is obscured, thus entails both ethical and practical concerns, for example, the challenges these models have in predicting major crises (Coppi et al., 2021).

To address these issues and enhance ownership in affected communities, the trigger of actions can be based on a combination of the model predictions and community-level data. This would also serve as a means for the inclusion of communities' voices and perspectives in the design, development and use of AI systems and would serve to empower the communities in the decision-making process (Wright and Verity, 2020).

In South Sudan, The Protection Monitoring System (PMS) of the Protection Cluster was rolled out as a pilot in October 2022. The PMS contains data collected by humanitarian agencies with key informants on the occurrence of protection violations, their scale and their impact on communities (UNHCR, 2023). In the Sahel region, the DRC is a part of the interagency project, Project 21, which is a regional PMS initiated in 2020, to address gaps in protection data and analysis in West and Central Africa. In 2022, P21 monitors conducted almost 15,000 interviews with key informants and heads of households in 2,500 localities on the protection situation, risks and trends (Project 21, n.d.).

To analyse the links between the P21 data and future conflict, a data set was developed based on cases defined as admin–week–year. Cases draw on the interviews conducted in the preceding 4 weeks to make the data more robust. Cases were only included if they were able to draw upon at least 30 interviews. The total data set ended up consisting of 246 cases.

Based on the analysis of this data, some clear correlations between the protection situation and future conflict can be identified as shown in figure 1. Insecurity during movement on the outskirts of towns/villages appears to be a particularly good indicator of future conflict. When people feel unsafe going to the field, collecting water and/or firewood, or for other reasons have to travel far away from the community, they can encounter armed groups or see movement or signs of these groups. Based on interviews in South Sudan, where the protection monitoring data does not have enough interviews to enable a more robust statistical analysis, some of the same indicators were highlighted: when people feel unsafe in the communities on the outskirts of towns or when killings, abductions and cattle raiding start to occur in the outskirts, it is typically a strong indicator of future escalation of conflict/attacks in the community. Other strong indicators of future conflict based on the P21 data are aspects such as a feeling of safety, children's ability to access schools and the safety of the school environment.

For example, using the freedom of movement indicator as a trigger for anticipatory action, analysis of the data suggests that it could correctly classify future conflict in ~80% of the time. Unfortunately, the overlap between the displacement data and P21 data does not allow to compare the ability of the P21 to predict displacement but can be compared to levels of violence, that is, if the P21 data can predict if an Admin 2 area will experience a level of monthly violence in the highest quartile (>29.25 conflict events). If a threshold is set for anticipatory action to be taken when 40% or less feel they can move around freely inside and outside the community, this would lead to correct action being taken 81% of the time, that is, action being taken and >29.25 conflict events happen in the next month or inaction and <29.25 conflict events occur the following month. Due to the inability to combine the P21 data with displacement data, it is not possible to analyse to what extent the combination of the prediction model and a P21 indicator as triggers for anticipatory action would lead to correct action/inaction.

4. Turning data into action: anticipatory action in response to conflict-induced displacement

Even with a system for reliably forecasting conflict-induced displacement, there are still several challenges and considerations for turning this information into action. Acting ahead of conflict-induced displacement can bring into question political neutrality and do no harm aspects for humanitarian actors. As such, it raises concerns that "immediate response to predicted conflict could be (too) political and thus counterproductive to humanitarian goals" (Wagner and Jaime, 2020). Providing early warning

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Correlations

Variable	Variable2	Statistic Correlation	Count	Lower C.I.	Upper C.I.	Notes
Access_school	Violence_events_t4_weeks	-.066	246	-.190	.059	
	Violence_events_t8_weeks	-.093	246	-.216	.032	
	Violence_events_t12_weeks	-.056	246	-.180	.069	
Feeling_safe	Violence_events_t4_weeks	-.650	246	-.717	-.572	
	Violence_events_t8_weeks	-.611	246	-.684	-.527	
	Violence_events_t12_weeks	-.561	246	-.641	-.469	
Freedom_movement	Violence_events_t4_weeks	-.751	246	-.800	-.690	
	Violence_events_t8_weeks	-.673	246	-.736	-.598	
	Violence_events_t12_weeks	-.606	246	-.680	-.520	
Having_documents	Violence_events_t4_weeks	.455	246	.350	.549	
	Violence_events_t8_weeks	.416	246	.307	.514	
	Violence_events_t12_weeks	.378	246	.265	.480	
Protection_incidence_school	Violence_events_t4_weeks	-.112	246	-.234	.013	
	Violence_events_t8_weeks	-.094	246	-.216	.032	
	Violence_events_t12_weeks	-.072	246	-.195	.054	
Safe_school_environment	Violence_events_t4_weeks	-.725	246	-.779	-.659	
	Violence_events_t8_weeks	-.658	246	-.724	-.581	
	Violence_events_t12_weeks	-.592	246	-.667	-.504	
Share_children_armed_group_recruitment	Violence_events_t4_weeks	.459	246	.354	.552	
	Violence_events_t8_weeks	.476	246	.373	.567	
	Violence_events_t12_weeks	.337	246	.221	.443	
Share_children_domestic_violence	Violence_events_t4_weeks	-.561	246	-.641	-.469	
	Violence_events_t8_weeks	-.522	246	-.608	-.425	
	Violence_events_t12_weeks	-.465	246	-.557	-.360	
Share_children_extremism	Violence_events_t4_weeks	.484	246	.382	.574	
	Violence_events_t8_weeks	.420	246	.311	.518	
	Violence_events_t12_weeks	.374	246	.261	.477	
Share_children_illegal_activities	Violence_events_t4_weeks	-.056	246	-.180	.070	
	Violence_events_t8_weeks	-.054	246	-.178	.071	
	Violence_events_t12_weeks	-.087	246	-.210	.038	
Share_children_labor	Violence_events_t4_weeks	.114	246	-.012	.235	
	Violence_events_t8_weeks	.089	246	-.037	.211	
	Violence_events_t12_weeks	.083	246	-.043	.205	
Share_children_marriage	Violence_events_t4_weeks	.557	246	.465	.638	
	Violence_events_t8_weeks	.462	246	.357	.555	
	Violence_events_t12_weeks	.403	246	.293	.503	
Share_children_unable_school	Violence_events_t4_weeks	.575	246	.484	.653	
	Violence_events_t8_weeks	.544	246	.449	.626	
	Violence_events_t12_weeks	.500	246	.400	.588	
Share_feeling_unsafe_certain_routes	Violence_events_t4_weeks	.582	246	.493	.659	
	Violence_events_t8_weeks	.523	246	.425	.608	
	Violence_events_t12_weeks	.466	246	.362	.558	
Share_feeling_unsafe_far_away	Violence_events_t4_weeks	.693	246	.622	.753	
	Violence_events_t8_weeks	.626	246	.543	.696	
	Violence_events_t12_weeks	.579	246	.489	.657	
Share_feeling_unsafe_fields	Violence_events_t4_weeks	.687	246	.615	.748	
	Violence_events_t8_weeks	.638	246	.557	.707	
	Violence_events_t12_weeks	.570	246	.480	.649	
Share_feeling_unsafe_getting_water_wood	Violence_events_t4_weeks	.740	246	.678	.792	
	Violence_events_t8_weeks	.713	246	.645	.769	
	Violence_events_t12_weeks	.628	246	.546	.698	

Missing value handling: PAIRWISE, EXCLUDE. C.I. Level: 95.0

Figure 1. *Correlation between protection indicators and future violence incidents.*

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information to potentially affected communities could lead to a perception among local authorities and local actors that humanitarian organisations are actively promoting or encouraging (pre-emptive) displacement. It could also be seen as questioning the authorities' capacity to manage conflicts and keep civilians safe, as the predictions in certain contexts would entail a failure of the authorities to do so. One way to mitigate this would be by working with local authorities and sharing the forecasts with them so they can take early actions, but this would again be problematic in areas where authorities are an active part of a conflict. Furthermore, there is a risk that if information on predictions of future conflict-induced displacement gets into the hands of one side in a conflict, they take pre-emptive, violent measures against the other side in the conflict to minimize the future risk of attacks from that side. As such, careful considerations need to be taken when turning displacement forecasting into anticipatory action. Approaches need to be contextualized and built on a strong conflict analysis and conflict sensitivity.

With a strong understanding of the local contexts, working actors across the triple actions—humanitarian, development and peacebuilding—can provide an avenue for anticipatory action in response to conflict-induced displacement. Local communities and actors, such as local nongovernmental organizations (NGOs), peace committees, early warning committees, religious organisations and charities, can play a strong role as an intermediary for providing and sharing information on upcoming risks and help diffuse or mitigate tensions to avoid conflict. Collaborating with these actors is key to developing relevant community action plans for the type of support needed by communities ahead of a displacement crisis. This approach also empowers local communities and affected populations and gives them a central role in aid delivery. As such, acting ahead of crises cannot only work to reduce humanitarian needs but the longer lead time also enables better inclusion and accountability to displacement-affected communities.

The specific action plans and activities can be developed both in the place of origin (conflict location) when people are on the move and in the place of destination (host communities). These plans can include several activities that can help to reduce the humanitarian impacts of conflict and displacement.

When significant displacement is predicted 3–4 months into the future, actors can support communities in the place of origin. A key first step is to implement proper needs assessments, identify and select the vulnerable households. Rather than collecting this information when people arrive in host communities following displacement, this information can be gathered beforehand, to help ensure that access to proper support is readily available in host communities upon arrival. Furthermore, vulnerable individuals and households can be provided with protection assistance, such as support to having proper documentation, which is often a barrier to accessing services during displacement and a hindrance to return. Another type of support is to provide awareness raising on the potential protection risks that can arise during displacement, the availability of services and safe spaces and routes to take if having to flee the area. Actors working on peacebuilding and mediation can use the forecasts to initiate dialogue, to diffuse tensions between parties in the conflict with the aim of de-escalating and averting the displacement. Actors can furthermore seek to engage with armed actors, to ensure humanitarian access and protection of civilians.

Humanitarian actors can furthermore use the predictions to better support people as they flee from conflict to places of safety. Humanitarian actors can prepare and pre-position support along the key safe routes that displaced people will take, to ensure that they have access to food and water. Actors can also prepare cash assistance to people on the move, to help facilitate their access to services and transportation to reach the place of destination. Organizing mobile health clinics can ensure immediate access to basic health support as people move. Setting up hotspots with internet and phone connectivity can provide people on the move with the ability to connect with relatives and family members, and get information to be used for onward movement, which can help to decrease instances of family separation. Such service hotspots can be organized as part of establishing interim, transition sites where people fleeing can stay for a short period of time before moving on to the place of destination.

Anticipatory action activities in host communities, where there will be a predicted influx of displaced people can similarly have several benefits to reduce the humanitarian needs. When predicting an influx of displaced people, it will be relevant to sensitize communities to this potential influx, explaining in more detail the support that will be provided, to whom, and so forth, to try to mitigate potential social tensions that could arise between host communities and displaced people. Furthermore,

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a key aspect in host communities is to pre-position supplies and staff, and as such ensure that when the displaced people arrive in the communities, they can immediately get the required support and services. This will help to decrease a deepening of humanitarian needs and decrease the resource constraints on host communities as well.

A key element when taking action is to sequence the activities according to the probability of the impending shock. Activities that are either (a) low cost, (b) with minimal risks and/or (c) with benefit regardless of whether the shock materializes can be taken when only the forecast indicates a significant increase in future displacement. Such activities—also known as "no-regret activities"—depend on the contexts, but for activities that need assessment, raising awareness for protection would, in many contexts, typically fall into this category. When both displacement forecasts and community monitoring data point in the same direction, the activities with higher costs, higher risks and benefits depending on shock are taken. This would typically be activities such as pre-positioning of stocks, which comes at a high cost and can be a waste of resources, and not be beneficial if the shock does not materialize. Sharing information with communities about potential upcoming displacement risks also entails significant reputational risks for humanitarian actors, puts unnecessary stress on communities and may lead to people taking actions (e.g., pre-emptive fleeing and selling household assets), which has a negative impact on their well-being if the predicted shock does not materialize. Such activities therefore should only be conducted when there is a high degree of probability of an impending displacement and would require that both forecasts and the various community indicators are triggered.

4.1. Case: acting ahead of conflict in South Sudan

In Akobo town on the border with Ethiopia, the community is plagued by a number of different conflicts. The major driver of displacement is inter-ethnic conflict primarily between the Lou Nuer and the Murle ethnic groups. This conflict is underpinned by a perception of cultural and ethnic differences, and tends to escalate due to incidents of cattle raiding, abductions of women and children, and revenge killings (Meraki Labs, 2021). Peace dialogue between the communities led to a cessation of conflict, which lasted for about 1 year. In late 2022, violence remerged between the communities. In December 2022, Murle and Nuer clashes killed 56 people during 4 days of fighting after youth from the Nuer community began attacking the Murle community. Twenty-four people were killed in Gumuruk County and Likuangole County. The conflicts led to several protection concerns including the safety and security of the community members. Attackers often target women and children who are either killed, raped and/or abducted. When people are displaced, they often find it hard to find shelter, which again can expose them to abductions by attackers, in addition to dangers of sexual harassment, rains and related sicknesses, theft and hunger.

Working with local peace committees, the DRC set up community action plans to act ahead of displacement. The triggers for the activities were based on the displacement prediction model and community-level indicators identified together with the peace committees. The peace committees highlighted indicators such as feeling insecure in the outskirts of town or increased cattle raiding, abductions and killings in the outskirts of the town as relevant indicators, as such events typically lead to a spiral of violence that ends up causing significant displacement. Anticipatory displacement, where communities on the outskirts of town started moving into town, was another good indicator of increased insecurity and potential future conflict and displacement. Lastly, the mobilization of youths and the related absence of youths in the markets or public spaces was also a good indicator of future conflict.

The initial trigger of activities is the prediction model and, based on the analysis of historical displacement data, the trigger level was set at the forecasted increase in number of displaced people by 1,000. This initial trigger would be used to mobilize DRC staff and conduct initial needs assessment, baselines and beneficiary identification. When community level triggers such as anticipatory displacement and feeling insecure on the outskirts of town are triggered, community dialogue between the peace committees in the different communities will be initiated, to attempt to diffuse tensions. If this fails and community triggers, such as increased cattle raiding, abductions and killings, as well as a mobilization of youth, are witnessed, then actions such as the community dialogue will be intensified, information sharing

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and protection awareness sessions will be conducted with potentially affected communities and host communities, information will be shared with other humanitarian actors in the communities and relevant relief items based on the needs assessment will be pre-positioned.

5. Conclusions and lessons learned

Getting ahead of displacement crises entails working with uncertainty, needly summarized by Bijak and Czaika (2020) as “black swans (aleatory, low-probability and high-impact events, the consequences of which can be severe)” and “grey rhinos—events that are also very consequential in terms of their high impact, but more predictable, yet “hiding in plain sight,” leading to neglect and inaction” (Bijak and Czaika, 2020). While the issue of black swan events remains an issue, new and innovative ways of addressing grey rhinos have been identified in this article.

DRC has since 2017 leveraged machine learning to forecast displacement at the national and sub-national levels. These models have proven to be able to accurately predict conflict-induced displacement both 3–6 months and 1–3 years into the future. The forecasting models, despite generally performing well and outperforming benchmarks, are not able to fully capture unprecedented surges in displacement or the onset of displacement crises. Further research and efforts are needed to identify ways of improving model performances to predict displacement surges. A potential opportunity would be to make a focus exclusively trained on data from situations of displacement surges, to assess whether such a focused model could better predict future surges in displacement. Another option could be to explore models predicting displacement above certain thresholds, for example, situations where displacement increases by more than 500,000 people.

While these advanced data models and further developments in that space can provide a good starting point for anticipatory action, they cannot stand alone and need ground truthing. DRC leverage our wide access to community data through existing community-based protection networks and joint protection monitoring exercises. This data is used both in the displacement modelling, as well as to validate and confirm the forecasting. The combination of these different data sources provides a solid foundation for triggering anticipatory action. In terms of addressing the limitations of existing displacement forecasting models, further research using methods from anthropology and sociology could explore the ability to predict displacement surges based on direct information from communities. Another opportunity could be to explore the use of the Delphi method, where a panel of experts through several rounds of inquiry are used to forecast. Such experts could be drawn from the field staff from NGOs or local partners. Such methods have, for example, been used to forecast future immigration to the European Union (Acostamadiedo et al., 2020).

Yet, even if the accuracy and level of confidence can be enhanced by combining these different data sources, acting ahead of conflict-induced displacement still entails risks and ethical considerations. One way to mitigate these risks is by working closely with local communities and actors. This also helps to increase sustainability, ownership and accountability of the actions.

Further evidence is now needed on the different outcomes and impact of the approaches and anticipatory action activities, to prevent and mitigate the impact of conflict-induced displacement. Based on the evidence from anticipatory action in response to climate shocks, it is likely that these approaches can help to reduce upward pressure on humanitarian needs due to conflict-induced displacement, as an expansion of anticipatory action to this domain enables a more timely, dignified, efficient and sustainable humanitarian response.

Data availability statement. Replication data and code can be found on GitHub: https://github.com/boschwartz/sub-nat-forecasting.

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