

# An Explainable Forecasting System for Humanitarian Needs Assessment

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## Abstract

We present a machine learning system for forecasting forced displacement populations deployed at the Danish Refugee Council (DRC). The system, named Foresight, supports long term forecasts aimed at humanitarian response planning. It is explainable, providing evidence and context supporting the forecast. Additionally, it supports scenarios, whereby analysts are able to generate forecasts under alternative conditions. The system has been in deployment since early 2020 and powers several downstream business functions within DRC. It is central to our annual Global Displacement Report which informs our response planning. We describe the system, key outcomes, lessons learnt, along with technical limitations and challenges in deploying machine learning systems in the humanitarian sector.

## Problem Setting

The ‘*decade of displacement*’ is how UNHCR, the United Nations’ Refugee Agency has called the past ten years. Close to 90 million people are forcibly displaced from their homes due to a variety of reasons including conflict, violence, and climate. This is the highest ever recorded and more than double from ten years ago (UNHCR 2021a). This has put a severe strain on responding organisations and governments who have precious few resources to address the challenge.

Several initiatives have been undertaken for a more coordinated and considered approach. For instance, the Global Compact for Migration ratified in 2018 seeks to use ‘accurate and disaggregated data as a basis for evidence-based policies’. More broadly, the humanitarian sector is undergoing a transformation towards more proactive response. The sector is traditionally been organised to react to crisis. While local humanitarian staff have deep expertise in local context, forecasting of displacement futures remains a challenge. For instance, the community has largely missed warning signs for major crises in recent years, notably Syria and Myanmar.

Understanding displacement dynamics and drivers is inherently complex. Displacement occurs in fluid contexts and generally it can be difficult to assess ‘root causes’. Circumstances differ from person to person. The question ‘why did you decide to move?’ is not straightforward for people to

answer. However, to the extent that individual decisions reflect structural societal factors, the dynamics can be partially explained by aggregate measures. For instance, economic drivers for movement can be expected to be related to employment opportunities and therefore macro indicators on employment.

This project aimed to bring machine learning methodologies to provide forecasts of displacement futures. Our system deployed at the Danish Refugee Council (DRC) since 2020, gathers over 120 societal indicators from several institutional providers to capture a broad range of displacement drivers including those on the labour economy, conflict, food, education, socio-demographics, infrastructure, strength of institutions, and governance. Models then learn structural patterns and at inference time predict likely displacement futures.

In this setting, the understanding of societal dynamics leading to displacement, be it ethnic violence or lack of employment or climate change, is just as critical as the forecasts. The system additionally estimates the sensitivity of the forecast to specific driver categories to generate supporting evidence.

## System Description

The deployed system consists of several components for situational awareness on displacement globally, including system for exploration of published sources of news, analyst reporting tools, and data exploration interfaces. We focus on the core ML components shown at a high-level in Figure 1.

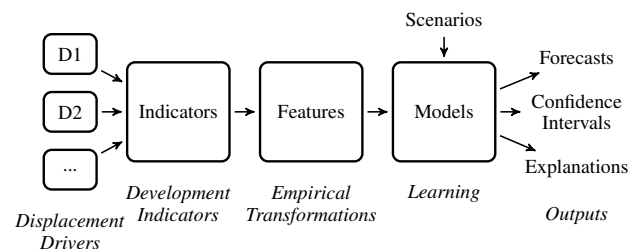


Figure 1: Overview of overall pipeline

We leverage the 4MI monitoring programme<sup>1</sup> which con-

<sup>1</sup><https://mixedmigration.org/4mi/>

ducts field interviews with thousands of people on the move. Analysis of survey data reveals high-level clusters of drivers for displacement. These clusters ranged from lack of rights and other social services, to economic necessity and conflict. These drivers are then mapped to quantitative indicators sources from a wide range of institutional providers. Features derived from these indicators are used during a learning step where a suite of models are built. These models generate forecasts along with confidence intervals, and estimates of drivers contributing to the forecast.

An earlier prototype of this system was reported in Ahmed et al. (2016) and a subsequent version in Nair et al. (2019) with an evaluation in two countries. The models are available in open-source<sup>2</sup>. The suite of constituent methods are briefly described.

**Forecast Models** To generate point forecasts of forced displacement volumes for future years, the system employs a set of Gradient Boosted Trees (GBTs) for each forecast year. Specifically, we learn a function  $f_h$  for each prediction horizon  $h = (0, \dots, 3)$ , i.e.  $\hat{y}_h = f_h(x)$ , where  $x$  is a feature vector based on all available indicators for a specific country. The feature vector included domain-specific transformations based on subject matter expert input. Often, there is considerable time lag before these indicators are available. For these cases, individual features were projected using an auto-regressive model till the current year.

To arrive at the deployed pipelines, we iterated over several candidate pipelines using a range of model classes and feature engineering steps to determine best performing pipelines for the task. Error rates were measured on test data for years where displacement figures were known. Model forecasts were also compared to a naive forecast which assumed future displacement to be the same as current displacement. For several countries with long-term displacement crisis like Afghanistan, the naive forecast is very competitive. Overall, in this offline evaluation GBTs provided the best performance and were selected for deployment.

The associated confidence intervals were generated by learning Quantile Regressors for the 25<sup>th</sup> and 75<sup>th</sup> quantile on the same features. We tried to generate intervals based on the empirical bootstrap method (where the source error distribution was generated based on a retrospective analysis of all countries), but found the error distributions to be very different across countries. Given data limitations, we were unable to evaluate the quality of the confidence intervals. The point forecasts and intervals were shown on a per-country basis in the dashboard (Figure 2).

**Scenario “What-If” Analysis** The system supports what-if analysis for selected dimensions of economy, conflict, natural environment, governance, and population. For a user-specified scenario (usually expressed as a quantum of change in that sector), the projections are updated based on estimated *elasticities* for each cluster for that country.

To derive this, we fit a simple linear model on a subset of features for each theme. We then use statistically significant

coefficients to get country-specific estimates. Figure 2 shows selected features for each theme.

The elasticity describes the percentage change in the target variable for a percentage change of input variables. To compute scenario forecasts, these elasticities are applied directly to the point forecast generated by the Gradient Boosted Tree and Quantile Regressors.

A user-scenario here is defined as a percentage change in sector, e.g. a 5% increase in conflict, or a 2% decrease in economy. A natural approach to generate forecasts here would be to perturb the feature vector appropriately and generate a forecast. However, in this case the training data is sparse and the point forecast models were not robust under these perturbations. The simpler methods via estimated elasticities provided a principled and deterministic mechanism to model scenarios.

This approach constitutes a explainable forecast, as analysts can view changes to the outcome based on changes to certain thematic elements within a country. This type of prospective or exploratory analysis where users are involved have been advocated in the literature (Shneiderman 2020).

**Graphical Models** While point forecasts indicate the likely severity of displacement, the actual response plans depend on an understanding of drivers. To better intuit drivers, we additionally developed graphical models aimed at capturing dependencies between socio-economic factors and displacement. In this step, we factored in subject matter expertise on displacement drivers and used structure learning to learn graphical models.

Specifically, given a training dataset  $X$  with observations  $(\mathbf{x}_i, y_i)$  denoting features and labels, we aim to learn a graphical model denoted by a graph  $G(V, E)$ . Using structure learning methods and treating both features  $\mathbf{x}_i$  and labels  $\hat{y}_i$  as random variables, we learn conditional probabilities that relate all inputs. In workshops involving several subject matter experts, we sought to determine a graph  $G'$  that contained a superset of all likely influences.  $G'$  is then used to constrain the learning algorithm.

To make the graphical model accessible to non-experts, we developed interactive mechanisms<sup>3</sup> for analysts at inference time. Users can provide arbitrary feature values on a thematic feature dashboard (Figure 2), and the marginal distribution of displacement outcomes estimated using the formula

$$\begin{aligned} & P(\overbrace{x_1 = a_1, x_2 = a_2, \dots, x_k = a_k}^{\text{user provided scenario}}, y = y_1) \\ &= \prod_{v=1}^n P(x_v = a_v \mid x_j = a_j \forall j \in pa(v)), \end{aligned}$$

where  $pa(v)$  denotes all parents of a node  $v$  in  $G$ . The outcome distributions can be updated very quickly as inference is fast. This allows for interactive exploration.

Several challenges needed to be addressed to realise these models. Chief among them was the issue of data availability. For some countries there was insufficient historical data

<sup>2</sup><https://github.com/IBM/mixed-migration-forecasting>

<sup>3</sup>A demo version can be viewed here: <https://foresight-bn.eu-gb.mybluemix.net/ui/explorer/index.html>

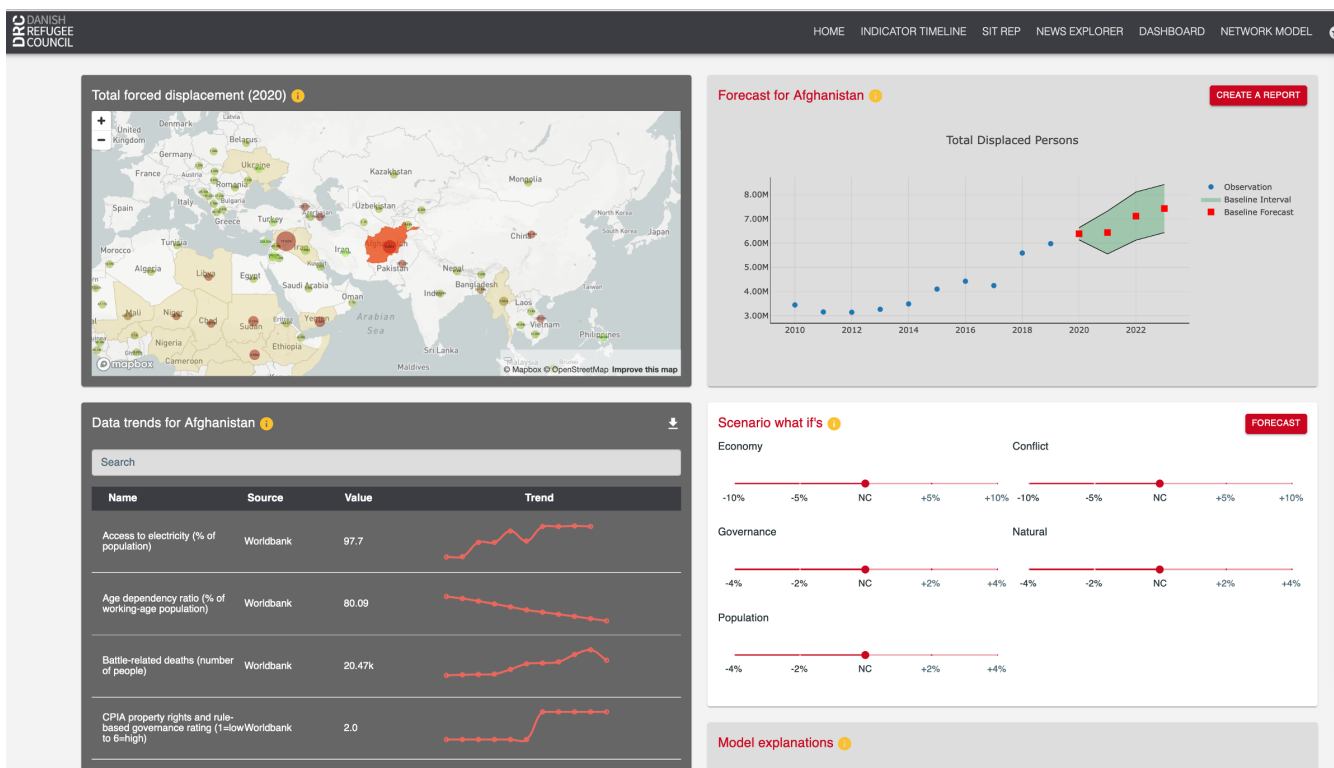


Figure 2: Main dashboard view of country forecasts

to generate reliable forecasts or elasticities. The quality and coverage of the data also varied considerably across countries. In these cases the system makes appropriate assumptions and generates a ‘best-effort’ forecast. For example, in the case of Myanmar, where data coverage is low and the elasticity estimates not statistically significant, we rely on a basket of 25 countries with displacement to provide an estimate.

For graphical models, we discretised continuous features (including the outcome variable of forced displacement volumes). This avoids the need of end-users to inspect continuous probability distributions, eases scenario building, and makes the structure learning task easier. The requirement for the graphical model  $G$  to be acyclic is restrictive for this application. During solicitation of the expert-specified graph  $G'$ , we sought links between clusters of indicators (e.g. governance, economy, demographics, etc.). Several cycles were present as there are many feedback loops between societal aspects, some direct and many indirect. We remove cycle inducing links, by dropping the least influencing edges.

**User-Centric Design** The design of the model pipelines and overall user experience was driven by extensive interviews with end-users. We conducted semi-structured interviews with 13 field offices to better understand their needs. Using a scenario based design method we identified the key themes that shape humanitarian aid planning: (a) surfacing causality, (b) multifaceted trust and lack of data quality, (c) balancing risky situations. Users wanted information backed

by solid analysis with timely insights and upfront on limitations. The full user study is reported in Andres et al. (2020). We focused on *expert-in-the-loop* knowledge co-creation as a means to address some of these challenges.

## Evaluation

Empirical evaluation of the system was done in three phases. First, at the pilot stage, forecast accuracy for two countries were assessed based retrospective data using five-fold cross validation. Mean Absolute Percentage Error (MAPE) for the first year were 6.9% and 8.1% increasing to 7.6% to 20.0% by year 3 for Afghanistan and Myanmar respectively. The forecasts for Myanmar were worse partially on account of data quality and availability.

Second, the system underwent model peer review by Centre for Humanitarian Data (2020) run by U.N. Office for Coordination of Humanitarian Affairs. The review uses a model card - a summary of salient features of the model - to assess intended uses, operational readiness, technical rigour, and ethical concerns. For this assessment, we documented performance of the system in Afghanistan and Myanmar.

Third, in the post-deployment phase, forecasts for 20 countries were compared to displacement numbers from the Humanitarian Response Plans (HRP). HRP estimates are displacement projections based on cross-sectoral experts on the ground. Projections can also be qualitative and provide a description of anticipated changes in the region. HRP estimates are also generally not analysed retrospectively so it can be difficult to assess their correctness over time. Never-



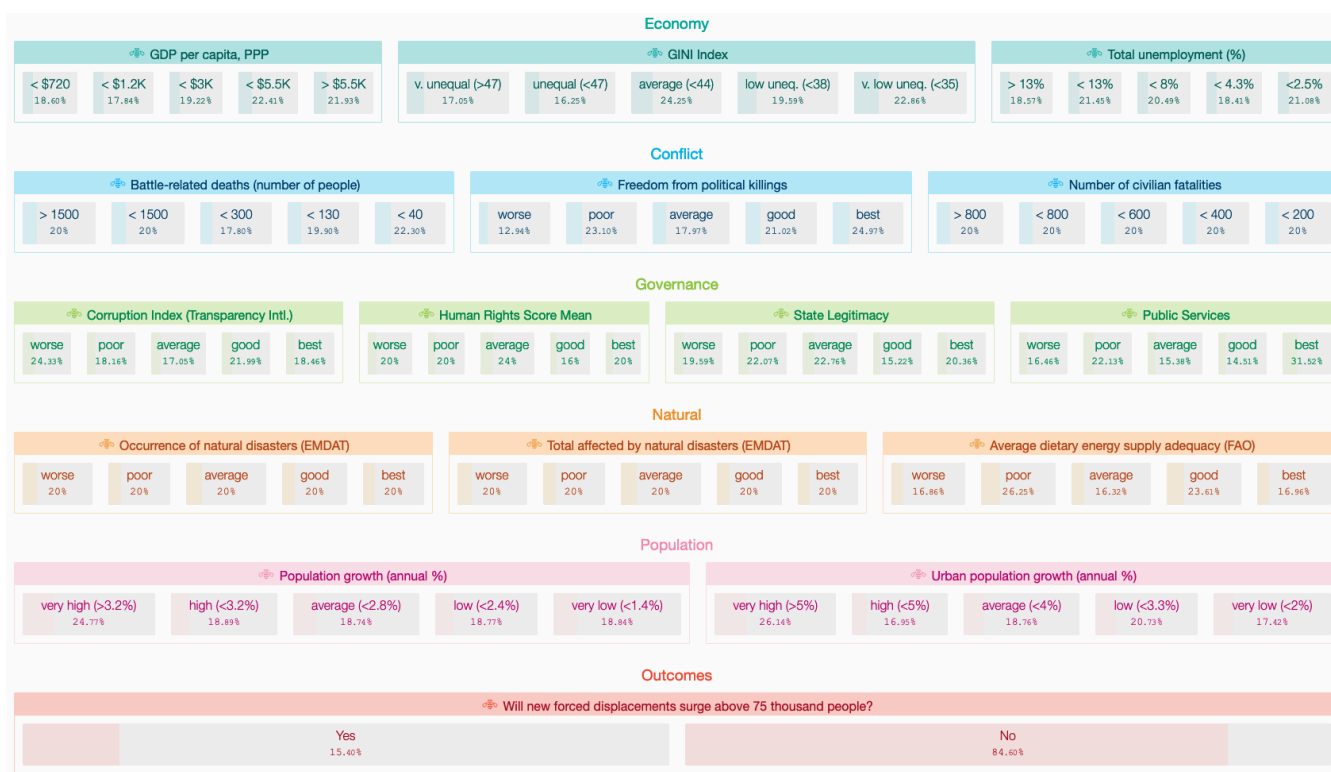


Figure 4: Interactive risk explorer to build scenarios

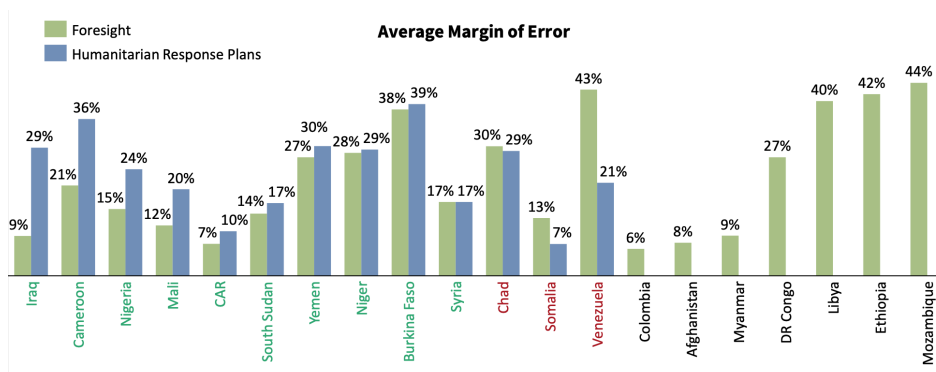


Figure 5: Error rates of Foresight system compared to expert assessments in Humanitarian Response Plans

efforts. The Foresight system directly supports this recipe by providing forecasts and supporting analysis for planning purposes.

Since its deployment the system has informed the annual strategic review in key displacement regions in Asia and West Africa, both at a regional level and at seven country-level operations. These reviews are critical in developing our response plans, quantifying our resource requirements and deciding local staffing. Scenario-displacement forecasts for 2021 and displacement risk scenarios for 2025 for five countries in West Africa were developed based on workshops with local staff, who provided contextual development and aided in defining scenarios for 2025. Climate-induced dis-

placement analysis for Myanmar and Afghanistan were developed based on a workshop with staff from the two country operations for building climate change induced displacement scenarios and forecasts using the Foresight system.

**Displacement Reporting** The system forms the basis for DRC's annual Global Displacement Report which provides analysis and summary of anticipated displacement futures. The reports (Danish Refugee Council 2021, 2022) for the past two years have documented the increase in displacement in several displacement hotspots. The analysis highlights the funding gaps particularly in areas where displacement is anticipated to grow. This provides strategic guid-

ance for our organisation as a whole and helps in prioritising longer term initiatives.

**Impact of COVID-19** The system served as the basis for several scenario-forecasts in various countries. The system was used in the first, and to our knowledge the only, analysis of the impact of COVID-19 on forced displacement. To do so, risk scenarios based on secondary impact of COVID on economy, violence, governance were constructed and displacement forecasts generated. The risk analysis and forecast were disseminated internally in combination with an overall analysis of COVID-19 impact on people of concern to guide DRC's contextual and strategic understanding of the immediate and future effects of the pandemic. The risk analysis and forecast was disseminated to donors and relevant stakeholders. In Syria, the system was used to assess displacement should ISIS re-emerge and the US military withdrew.

**Broaden Awareness** This initiative showcased the use of predictive analytics in this sector. The work was reported on in The Guardian<sup>4</sup>, BBC World<sup>5</sup>, Der Spiegel<sup>6</sup> and several other outlets broadening the awareness of the role of AI in humanitarian assessment. The work has been influential within the humanitarian community through sector specific articles and engagement with several international organisations.

These outcomes provide a flavour for how the system has shifted our organisations' thinking and operations on proactive response, proactive planning, and needs assessments. Ongoing workstreams are aimed at contributing more evidence-based analysis and tailor-made planning tools for the sector. The vision is to ease the integration of AI within our field and provide tangible outcomes.

We additionally continue to explore additional avenues where forecasting can be transformative. One example is in anticipatory financing. The response to humanitarian crisis needs to be operational in very short time frames. If the nature of future needs can be quantified then resource requirements become clearer and funding can be put in place ahead of time for faster and more effective responses.

## Lessons Learnt

**Human-Centered AI** AI systems in this sector will complement - not replace - existing practices. The main value-add of AI systems is in complementing decision making through better integration of data and tooling. Displacement situations evolve rapidly and context is often very fluid. Relevant and timely data on such situations is seldom available to monitors, let alone predictive models like ours. So contextualizing data-driven forecasts and formulating response plans will require an *expert-in-the-loop* paradigm (Andres

et al. 2020). Tools, such as the 'what-if' scenario capability that combine expert priors with available data therefore become valuable.

**Application challenges** Building the model is secondary to applying it in practice. Significant effort is needed to integrate models and ensure that they are used to inform humanitarian action. In our experience, this needs three elements. (a) Clear use cases in terms of who, when, and where the models are going to be used, (b) Community building and fostering use of the model through appropriate policies, and (c) Training and capacity building of staff in using model, to understanding opportunities and also limitations. These are difficult challenges to address and require considerable organisational buy-in and resources.

This reflects a familiar pattern found in technology for global development (Donner et al. 2008). Initial stages of problem formulation and exuberance at devising a technical solution give way to a realisation of ground realities and adaptation to address real organisational needs.

**Technical maturity** Dealing with data in the humanitarian and allied areas is time consuming. Organisations that publish data follow ad hoc data models. We spent considerable time in data transformation steps that aim to standardise such data for our use. Further, data updates and model maintenance need to be manually managed as data is seldom programmatically available. This limits scope for automation.

On the other end, system outputs are intended for non-technical audiences who may need substantial guidance to interpret forecasts and confidence intervals. For instance, communicating error rates as a percentage was preferred to other metrics such as mean-squared error. Our user interviews indicated that information products need to be simplified and be upfront with limitations of methods. Specific details on methodology can be relegated and accessed when needed.

## Related Works

In this paper we have aimed to reflect on the development and deployment of the Foresight system. Few previous works have described, in greater technical details, various aspects. An early prototype of the system that used population diffusion models was presented in Ahmed et al. (2016). The first version of the current system aimed at estimating flows was described in Nair et al. (2019) with user experience studies reported in Andres et al. (2020).

Broadly, the problem of forecasting in the humanitarian sector has received considerable attention. For practice-oriented systems, the aims, methods, and intended uses vary widely. Hernandez and Roberts (2020) provide a review recent initiatives around predictive analytics in the humanitarian sector. Beduschi (2022) identify various stages at which AI systems can support (and pose risks) for humanitarian actions. They also discuss salient attributes and limitations of the various approaches. Pham and Luengo-Oroz (2022) reflect on their experience building forecasting models in Somalia and provide a general framework to guide forecasting efforts. In this setting, Bijak (2010) have proposed Bayesian methods for forecasting.

<sup>4</sup><https://www.theguardian.com/global-development/2020/aug/11/covid-to-displace-more-than-a-million-across-the-sahel-new-tool-predicts>

<sup>5</sup><https://www.bbc.co.uk/sounds/play/w172x2wcfccc76r>

<sup>6</sup><https://www.spiegel.de/ausland/kuenstliche-intelligenz-als-krisenhelfer-software-die-fluchtbewegungen-vorhersieht-a-a8b6f194-cc33-4284-bac9-4f0326c0e47f> (in German)

Forecasting aimed at supporting a humanitarian response can be viewed broadly in two categories. *Operational forecasts* in the order of weeks aimed at an operational response (e.g. staffing, resourcing, monitoring), and *longer term forecasts* useful for planning, prioritization, and policy setting. In current state of practice, Jetson (UNHCR 2021b) would be an example of operational forecasts at the sub-national level.

Longer term assessments are typically expert-driven in practice, where experienced staff provide inputs on likely scenarios that lead to projections and likely evolution. There are specific domains where AI systems have been positioned to help in longer term assessments. For instance in Forecast-based financing (IFRC 2021) aims at anticipating financial needs during crises based on forecasts. Topical forecasts have also been made for conflict (Hegre et al. 2019) and food insecurity<sup>7</sup>. Comparable tools to Foresight, that provide longer term displacement assessments, have previously not been used in practice.

Additionally, organisations such as the European Commission have sought to buttress experts with quantitative tools such as the broad risk assessment tools like the Global Risk Index European Commission (2022) and associated early warning systems.

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<sup>7</sup><https://hungermap.wfp.org>