How well can machine learning tools for humanitarian forecasting be used in predicting the consequences of forced displacement?

Humanitarian forecasting for displacement: a survey

Lia Petrova[1]

Supervisors: Cynthia Liem[1]**, Marijn Roelvink**[1]

[1]EEMCS, Delft University of Technology, The Netherlands

A Thesis Submitted to EEMCS Faculty Delft University of Technology,
In Partial Fulfilment of the Requirements
For the Bachelor of Computer Science and Engineering
June 25, 2025

Name of the student: Lia Petrova
Final project course: CSE3000 Research Project

Thesis committee: Cynthia Liem, Marijn Roelvink, Jing Sun

Abbreviations

AI	Artificial Intelligence
ML	Machine Learning
UNHCR	United Nations High Commissioner for Refugees
IDMC	Internal Displacement Monitoring Centre
DRC	Danish Refugee Council
ECMWF	European Centre for Medium-Range Weather Forecasts
IFRC	International Federation of Red Cross and Red Crescent Societies
IOM	International Organization for Migration
HDX	Humanitarian Data Exchange
ITFLOWS	IT Tools for Migration Flows Management
GDELT	Global Database of Events, Language, and Tone
FAO	Food and Agriculture Organization
FSNAU	Food Security and Nutrition Analysis Unit
WFP	World Food Programme
EM-DAT	Emergency Events Database
UCDP	Uppsala Conflict Data Program
UN	United Nations
UN-DESA	United Nations Department of Economic and Social Affairs
OCHA	Office for the Coordination of Humanitarian Affairs
ACLED	Armed Conflict Location and Event Data
WHO	World Health Organisation
EPS	Early Warning and Preparedness System
LSTM	Long-Term Short-Term Memory
MAPE	Mean Absolute Percentage Error
EMT	European Union Migration Tool
ARD	Averaged Relative Difference
UI/UX	User Interface and User Experience

Abstract

Displacement is a focal point of humanitarian aid efforts, since it affects millions of people globally. Mitigating the consequences of forced migration is important for reducing suffering and one way of doing so is through predicting displacement to prioritise resources in advance. To achieve this, machine learning can be used for its ability to analyse larger amounts of data and identify latent structures more efficiently than human experts. Through a systematized literature review, this research evaluates thoroughly six machine learning tools: UNHCR's Jetson, DRC's Foresight and AHEAD, the EU's EUMigraTool and EPS-Forecasting, and the agent-based simulation Flee, in order to assess their suitability to that end. The analysis compares these tools across several criteria, including the way they use data, algorithmic characteristics, and operational use cases. Finally, it makes recommendations about what should be considered and how to choose amongst the tools for displacement prediction.

1 Introduction

1.1 Human Migration

In our world, torn by conflict and endangered by environmental and anthropological catastrophes, every day thousands of people are displaced. Many particular reasons, including persecution, conflict, violence, human rights violations, or other events that seriously disturb public order, as well as natural disasters and climate change [121], can be pointed out as the cause of forced migration of people, which has intensified in recent years (esp. during the 2015-2016 European refugee crisis [8, 14, 20, 67]). Migration is asymmetric and usually unexpectable, predominant in the EU as destination and the Global South as the origin location. To further hinder the process of predicting and managing displacement, funds for humanitarian causes are inherently unevenly distributed and their allocation often depends on different factors, such as the country of origin and upbringing of the donors [15], political biases of the participating governments, or ideological preferences [95].

1.2 Motivation

As the need for humanitarian help is growing, but funding is limited, it is vital to prioritise causes and people that need it the most. Achieving this requires thorough budget planning and reliable forecasting of displacement crises by humanitarian organisations and governments, but these crises can often be predicted only a few weeks, days, or even hours in advance due to limited, uncertain, and/or biased information [4, 70]. To mitigate crises before they have scaled is cheaper, more effective for the humanitarian parties involved [23], and more humane for victims of forced displacement, whose suffering will be reduced early.

Currently, many displacement forecasting systems use statistical analysis and expert knowledge to predict and manage crises. However, these approaches suffer from the fact that human analysts tend to make predictions based on a small number of strong signals that were relevant in the past [48], limiting the effectiveness of detection and the ability to act early during unseen crises. In contrast, ML methods excel at combining a large number of weak signals [48], thus being often better at identifying latent structures of the data and unnoticed dependencies. These are recurring reasons that advocate for the improvement of migration prediction, for which the use of previous data, pattern recognition, and ML methods is worth analysing and researching further [102].

While multiple tools for displacement forecasting that utilise ML methods have been developed, they are rarely compared systematically. In addition, it can be overwhelming for outsiders to utilise this knowledge, partially due to the large amount of associated works, numerous versions, and the lack of an organised view even for one tool. This literature review aims to reduce this knowledge gap by compiling and analysing different tools developed or used by popular organisations, and serve as a starting point in understanding their capabilities in technical and operational context.

1.3 Research Question

No tool will ever be universally useful for displacement forecasting, due to the different underlying causes and consequences of forced migration in the different parts of the world. What this research aims to answer instead is what predictive ML systems are most effective in terms of accuracy of predictions, countries assisted, and ease of implementation, and under what circumstances they are useful. The following subquestions will guide the course of the review: 1) what ML tools for predicting displacement exist/are currently in use, 2) how do they work, what can they achieve, and 3) how well can they be used in predicting the consequences of displacement.

1.4 Data Challenges and Ethical Constraints

Several recurring challenges are highlighted in the literature on displacement forecasting relating to the availability and quality of data, as well as ethical and operational considerations. Predicting irregular migration is usually hindered by the poor quality and overall scarcity of data available - often the regions in which displacement is the most severe lack appropriate ways of measuring it and even if they do not, data can be withheld deliberately by the respective totalitarian governments to remain in charge [8]. As discussed further in [8], migration movements are usually not caused "by slow structural changes but by sudden events" and are strongly contextual, therefore, it is nearly impossible (and frankly undesirable) to come up with a one-size-fits-all framework. Instead, the focus should be on choosing the right system with respect to the scenario and available resources.

Applying ML in humanitarian contexts also has a number of specific requirements for safe and practical use, for example the need for a clearly defined problem, addressing bias and discrimination in the data and algorithms, the localisation of the problem and the respective regulations, accountability and transparency in the humanitarian context, safety and sustainability, and maintenance needs [97]. Whenever coming up with a new model or choosing an existing one for predicting displacement, explainability of the system and accountability of the decisions made should be of high priority for the actors involved, since human lives and political stability are often at stake. Another ethical concern is the risk to data privacy and security, both in terms of the protection of personal data and the potential for gross misuse of results. The latter includes preventive closure of borders, danger of human trafficking, racism or deliberate attacks on aid convoys, political instrumentalisation, commercialisation of data gathering, lack of democratic control (especially when funding is concerned), and new pressures to act, leading to loss of the bigger picture of priorities [8]. These constraints are important to acknowledge when dealing with humanitarian issues, but mitigating them is a convoluted topic and out of the scope of this work.

1.5 Report Overview

The paper will extensively discuss previous related research in the Background section. The Methodology section includes how papers were gathered and tools compared. The Results section contains the assessment of the chosen tools with respect to the evaluation criteria. The Discussion and Conclusion section presents a synthesis of the results and an analysis of the tools' suitability under different conditions. The Responsible Research section describes the ethical implications of this research and what measures were taken in order to mitigate potential concerns. Finally, the Limitations and Future Research section will determine remaining questions.

2 Background

2.1 Related Humanitarian Work

A thorough review on factors, effects, types of people and host countries affected, governmental planning and integration, and legal and technological point of view is presented in the Joint Data Centre's Literature review of forced displacement, but there are little papers on actual predicting mechanisms using ML and big data [61]. In practice, many organisations have taken it upon themselves to collect data, research and develop a relevant displacement prediction tool, and/or make policies to manage resources for the actual crises. These include humanitarian agencies, multilateral organisations, private companies, academic institutions, non-governmental and intergovernmental organisations, and national and local governments [48]. A significant amount of documented models for predicting, early action, responding, and recovery of humanitarian disasters (including displacement) were gathered in [48]. The review is broad and does not focus on the technical predictive qualities of the models, but is a relevant starting point for further research.

Another work that provides insights into the overall situation of disaplacement forecasting models is [8]. It discusses the concerned organisations by dividing them into European initiatives (e.g. the EU Agency for Asylum, Frontex, the EU Commission, and funding organisations) and international actors (e.g. the UNHCR, IDMC, the World Bank). It briefly mentions the technical capabilities of eight models (some of which included in this research) and pays more detailed attention to the political functions and risks and ethical implications of predicting displacement with ML.

2.2 Older Approaches

Before delving deeper into the technical capabilities of ML models, previous ways of predicting displacement should be noted. Besides AI, the most popular ways of predicting forced migration are expert reviews on basic statistical analysis of the current situation and driving factors (e.g. manually looking through past trends and assuming similar results), push-pull models, and gravity models. Push-pull models take into account "push" (i.e., repulsing) factors from the origin country and "pull" (i.e., appealing) factors from the destination country and can therefore be used to come up with an affinity function and predict the probability of migration [2]. Gravity models are based on the idea that displacement flows between two areas are proportional to the population sizes of the origin and destination areas and inversely proportional to the distance between them.

However, all of these approaches have their downsides and fail to capture the complex nature and many underlying factors of human displacement (or do it properly fast enough). Therefore, as mentioned in 1.2, ML methods are preferable for their ability to automatically process large volumes of data while taking all variables into account, and training and validation possibilities before producing results. Of course, the underlying assumptions of push-pull (e.g. importance of the economy) and gravity (e.g. distance between origin and destination country) models are often implemented in the form of input variables for modern ML approaches.

3 Methodology

To answer the question how well ML tools can be used for predicting consequences of forced displacement, a systematised review of recent literature on ML methods and models used for displacement forecasting was conducted. It was aimed to include both primary and secondary sources of information in order to arrive at a maximally transparent evaluation. Primary sources were included to gather the tools' characteristics as specifically described by their authors and secondary sources were incorporated to gain critical assessments and comparisons, since authors sometimes tend to emphasise on the positive, rather than the negative or challenging features of their work.

3.1 Databases and Search Criteria

The search queries consisted of the terms "machine learning", "displacement", and "forecast" and synonyms. The full queries per search engine and the corresponding results can be found in A.1. It should be noted that all engines produced a significant amount of papers that may be considered in a review with a broader scope (e.g. nowcasting, trends in movement, predicting and learning behaviour of displaced people) and some papers connected to the topic that had ambiguous or non-explanatory titles and abstracts might have been excluded accidentally.

Two humanitarian databases, the Centre for Humanitarian Data (Humdata) database [21] and the UK Humanitarian Innovation Hub [9], were surveyed as starting points for practical tools as recommended in the research proposal. They did not produce enough results for the intended scope of the review (filtering resulted in 5 and 0 models for displacement respectively), so popular scientific engines were also used. The primary engines surveyed were Scopus, Web of Science, and IEEExplore. Inspiration from Google Scholar and Research Gate was also taken for suplementary and enhancing materials. Grey literature considered was limited to websites of humanitarian organisations, supplementary reports by authors of the applicable papers, and several Master's theses.

As the primary focus of the survey was prediction and early warning of forced displacement, a large amount of the results yielded by the search queries were not included due to inapplicability. Papers using non-ML methods, predicting or assessing non-forced (i.e. voluntary and regulated) or non-human (e.g. animal, platform, cell) migration were discarded, as well as papers not in English. After removing irrelevant results, filtering by abstract and title, and deduplication, the final set of papers that fully corresponded to the search was 113. Due to time constraints and the desired depth of the analysis, this number was reduced to 19 (excluding gray literature) by picking the most relevant models first. The resources given priority were: (in this order) 1) tools developed by or for world humanitarian organisations and applied in practice with corresponding scientific papers, 2) influential papers with high citation count, and 3) papers that discussed the largest number of metrics from the evaluation criteria below. The final set of academic papers surveyed can be found in A.2.

Due to time limitations, only resources relating to 1) were included in the review. The tools evaluated are the Jetson model [120] by UNHCR, the Foresight [26] and AHEAD [25] models by DRC, the IDETECT model [54] by IDMC, the EPS-Forecasting model [20] by the European Union Agency for Asylum, the EUMigraTool [59] by the ITFLOWS (funded by the European Commission), and the agent-based model Flee [42] developed at Brunel University.

3.2 Comparison Criteria

Part of the assessment criteria to compare the models and their suitability was based on Pham and Luengo-Oroz's research on developing a framework for predictive modelling [86], since it highlights the important steps of development of such a model. These metrics are the time horizon, the target and feature variables, treatment of missing data and data quality, the modeling approach, the model performance (error metrics and benchmarks), and how/if the resulting models are deployed. In addition, the assessment is enhanced with information about the categories of data used, usability and user interface, security, availability, and countries/regions for which these tools have been tested. These criteria were chosen because they summarise how the tools operate, what they can achieve, how they can be adopted by governments, organisations, and individuals. Understanding how data is handled and used is also important for addressing the data challenges mentioned in 1.4. To analyse the tools' suitability for displacement forecasting, information about each metric per tool from corresponding papers will be shown in the Results section.

4 Results and Findings

4.1 History of the Examined Tools

Almost all models picked for analysis in this paper are a result of iterative work, several prototypes, and continuous improvements. Jetson [86] was preceded by UNHCR's Winter Cell established to research the challenges associated with population flows from Turkey to Europe during the 2015-2016 winter [28]. It was UNHCR's first operational support initiative that combined non-traditional and traditional sources of data for predictive purposes [28]. Project Jetson "builds on the Winter Cell's predictive model" and "uses open data sharing and innovative approaches" [119]. It was one of the first open source ML tools developed and used by a humanitarian organisation in 2019 and other authors mention taking inspiration and/or acknowledge the efforts of Jetson [13, 14, 37, 82].

The Foresight tool is based on two subsequent prototypes: a framework for internal use by Ahmed et al. [2] and the actually implemented in use MM4Sight model [81] with which it shares a large amount of data sources, input variables, and ML algorithms. Its most recent version discussed in [82] will be the focus of the evaluation. Furthermore, the AHEAD tool, developed by the same authors, is also a reaction to some of Foresight's limitations "to develop a more operational model that could be used to inform direct humanitarian responses" [67]. However, [67] also discusses some additional specifications and limitations (e.g. higher error rate, bias) of Foresight that remained undisclosed before they were improved.

The EMT's iterations and improvements to reach its current state have been documented in the form of reports, which can be found on the European Commission website [31] (although some resources are not specific to EMT). The grey sources used in this paper are the final report [40] and the report focused on modelling and simulation [60], and the peer reviewed papers - [13, 107]. A review of three other tools discussed in this work (Jetson, Foresight, and EPS-Forecasting) was partially done by a member of ITFLOWS (Casagran) [14], so the EMT was further improved from that level in terms of data, algorithms, and usability [40]. It consists of a large-scale model (LSM) which uses textual and quantitative data sources for prediction of migration across the EU, and a small-scale model (SSM) used for country-specific predictions, which utilises the Flee model [60].

The Flee model, an agent-based simulation tool, has several documented versions and applications. The paper describing the first version of Flee [112] and the first supporting instrument for automation of some steps are from [111]. A sensitivity-driven analysis and adjustment of parameters (the second version) was conducted in [110], followed by a case study application [113]. The most recent version, Flee 3 [37], has the main difference that it discusses the inclusion of more external factors connected to displacement than just conflict outbursts (as was the case for the first version). Again, the most recent paper will be used to derive information when inconsistencies arise.

The last tool, IDETECT, does not appear to have an associated academic paper, but is actively in use by IDMC [54] and was presented in a 2019 conference alongside the centre's Global Disaster Displacement Risk model [123]. Its main purpose is automatic data gathering and is for internal use, therefore, information about some of its characteristics is limited.

4.2 Overview of Data Used

The first set of criteria to compare the methods is the data-related characteristics. A comparison of the data categories (Table 1) and data sources (Table 2) used by each model, and an overview of the feature and target variables (Table 3) will be provided. The comparison aims to reveal patterns in data selection across models, while highlighting the distinct variables chosen in each case.

4.2.1 Data Categories

The different categories of input variables are presented in Table 1. Socio-demographic factors refer to age, gender, religion and economic factors to jobs, market prices, development indices, and availability of basic commodities. Of course, these categories do not encompass all possible input variables, but serve as an overview of which data classes are recurring in predicting forced migration. This is a valuable insight since different data categories correspond to different drivers of migration and are suitable for prediction along different time horizons.

All models consider conflict as a cause of displacement under one form or another and natural disasters are a close second, with only the Flee model missing data on climate by default. However, as mentioned in the latest version of the Flee tool, this is a limitation which "led to spin-off developments for instance to develop support for migration driven by food insecurity or strongly affected by weather factors" [37]. Economic factors are another important aspect influencing migration. The specific variables differ per model and importance for the prediction, but for example commodity prices, and more specifically goat prices, are one of the interesting indications discovered in the Jetson model, since goats require food and water and cannot be on the move long [86].

What draws further attention is that the EMT considers almost all categories of data under one form or another (except for travelling differences and social unrest). This, alongside with the fact that it has the most findable intermediary reports issued, can be a testimony that it is reliable and thorough in using information effectively. However, it also shows that the system's performance is heavily dependent on different data categories and can be disturbed more easily. The Flee model examines the least number of factors and is hindered by this in some aspects (as stated by the authors), but it is an agent-based modelling system whose purpose is to be able to simulate the outcomes of (in this case) conflicts, instead of largely relying on previous data.

Data Category	**Jetson**	**Foresight**	**EPS**	**IDETECT**	**AHEAD**	**EMT**	**Flee**
Internet Search Keywords			✓	✓		✓	
Diseases and Healthcare	✓				✓	✓	
Socio-demographics		✓				✓	✓
Food Security		✓			✓	✓	
Political Events/Governance		✓	✓			✓	
Violence/Conflict	✓	✓	✓	✓	✓	✓	✓
Economy	✓	✓	✓			✓	
Travelling Distances	✓						✓
Natural Disasters/Climate	✓	✓		✓	✓	✓	
Social Unrest			✓				

Table 1: Data Categories Across Models

4.2.2 Data Sources

Table 2 examines how the different models use popular data sources (humanitarian organisations datasets, open-source websites, own surveys and data collections). A big fraction of the data sources are upkept by popular organisations and open to the public. On the one hand, this is important for reproducibility and verification of the results, but on the other hand, publicly accessible information is often incomplete and/or heavily aggregated to reduce privacy concerns, which can reduce its descriptive capacity. Furthermore, most of these data sources have more than one dataset, but no information about the specific datasets could be obtained, which is a limitation for reproducibility (an exception is the Jetson model, for which the PRMN dataset from UNHCR and the SWALIM dataset for FAO are quoted [86]).

As can be seen in the Table 2, the data sources used by all models are the UNHCR refugee database and ACLED for data on conflict events. The UHNCR database is used for displacement data and numbers of refugees per region and ACLED is utilised for numbers of killings, bombings, locations of conflicts and other documented violent events. The only two models that do not use ACLED data are the IDETECT model (which works with linguistic sources) and the EPS-Forecasting tool (where conflict events were examined through GDELT data).

The other sources are used on a more case-by-case basis. Internet search keywords and trends are usually sourced by GDELT [116], Google Trends [41], and online news sources. Information about diseases and healthcare was taken from WHO [131] and can be found in IFRC [55]. Data on food security and availability is derived from FAO [33], WFP [130], FSNAU (Somalia) [34], and Cadre Harmonisé (West African countries) [24]. Political events and governance specifics were obtained partially from ACLED [10], GDELT, and Frontex (border crossings) [35]. Data on conflict was also sourced from UCDP [126] and economy data - at the World Bank, UN-DESA [122], EUROSTAT [32], and FSNAU. Travelling distances and geospatial data were derived from Bing [80] and OpenStreetMaps [85]. Finally, information about natural disaster, extreme weather and climate events was sourced at EM-DAT [22], ECMWF [30], FSNAU, and FAO. Additional data about migration figures, trends and specifics was collected at IOM [56], OCHA [124], and HDX [50].

Model	**Data Sources Used**
Jetson	ACLED, FAO, FSNAU, IOM, OpenStreetMap, UNHCR, WFP, WHO
EPS-Forecasting	ECMWF, EPS (own) data, EUROSTAT, FAO, Frontex, GDELT, Google Trends, News, UN-DESA, WHO, World Bank
Foresight	ACLED, Cadre Harmonisé, ECMWF, FAO, Frontex, GDELT, Google Trends, HDX, IFRC, IOM, News, OpenStreetMap, Social Media, UN/NGO Reports, UNHCR, WFP, WHO, World Bank
AHEAD	ACLED, Cadre Harmonisé, FAO, P21 (own) data, UNHCR, WFP, WHO
IDETECT	ACLED, GDELT, Google Trends, IOM, IFRC, News, OCHA, Social Media, UN/NGO Reports, UNHCR
EUMigraTool	ACLED, ECMWF, EM-DAT, EUROSTAT, FAO, Frontex, GDELT, Google Trends, HDX, IOM, News, OpenStreetMap, Social Media, UN/NGO Reports, UNHCR, WHO, World Bank
Flee	ACLED, Bing Maps, IOM, OpenStreetMap, UNHCR

Table 2: Forecasting Tools and Associated Data Sources

4.2.3 Time Horizon

In terms of how far in the future data is predicted, there are 4 main milestones as depicted in Figure 1. Nowcasting is not examined thoroughly in this work, but the IDETECT tool collects information in real time from different sources and the Flee model can technically be used to assess the consequences of conflicts in terms of displacement as soon as they happen and information about them is available. However, the Flee model can also be used to predict how events will unfold as long as one year in the future, which is another benefit of using agent-based modelling, given enough time, computational power and correct underlying assumptions (which is another limitation).

As can be seen, all models' predictions can be adjusted a little bit - the Jetson model started as 1 month in advance predictor due to most data being available on a per-month basis, but it was soon extended to predict 3 months into the future. The EMT also supports both time frames for different purposes (short-term and mid-term predictions, respectively) [13]. The AHEAD model supports predictions of 3-4 months in advance and "is constructed to work with the outcome data being available at irregular intervals" due to the irregular nature of displacement data [67]. The EPS-Forecasting tool is designated for even shorter-term predictions, of between 1 and 4 weeks, and the Foresight tool, in contrast, supports long-term predictions of 1 to 3 years in advance.

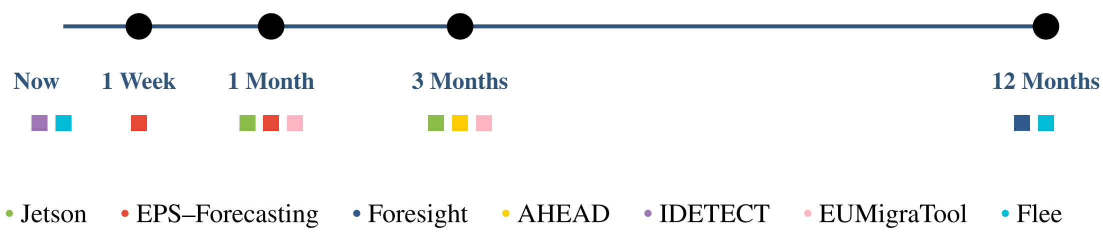

Figure 1: Time Horizon

4.2.4 Variables and Data Handling

Table 3 summarises how data is used across the models. Output variables differ, as some tools focus on predicting the exact number of displaced people (Jetson, Foresight, AHEAD), others on asylum applications (EPS-Forecasting, EMT), and the Flee model - on the actual distribution, trends, and demographic details of the refugees across camps and given routes. These dependent variables, in combination, can be used to produce valuable forecasts and informed decisions.

There is a variety of exact feature variables each model uses, even though a number of the data sources used are the same. For the Jetson model the feature variables discussed are from the Somalia case study [86] (the only case study for which data has been used) and for the EMT the variables - from the Syria-Greece migration case study of the earlier applications of the tool [107]. For Foresight, the most recent set of variables has a total size of 120 [82]. EPS-Forecasting's and EMT's authors discuss that the final set of variables used is dynamically determined out of a larger group by the models during training based on most significant correlation [20, 107].

Handling of missing values is important when dealing with sparse and biased data of uncertain quality like migration and third-world countries data. Not all of the papers discuss exactly what they perform (e.g. the Foresight tool mentions regression and heuristic approaches in its earlier version, but not exactly what these consist of), which can be a problem for the reproducibility of the results. Some authors also opt for dropping missing values of the analysis to not bias the model's predictions.

Moving on to data preprocessing techniques, Foresight uses autoregressive features for past data in order to decrease the importance of scores happened far in the past [82]. The EPS-Forecasting tool computes event indices from GDELT data based on GDELT code and topic, the sign, denoting a potential to generate (+) or constrain (-) displacements; the grouping factor used to aggregate selected events into the five macrocategories: conflict, economic events, social unrest, governance events, and political events, and the strength of the potential displacement-generation effect associated with single events [19]. The Flee model authors have worked on improving the automatisation of data preprocessing in order to cut the time for transforming the data into the desired input [112].

Name	Feature variables	Output	Missing data	Data Processing
Jetson (Somalia case study)	Departure and current regions, number of incidents and fatalities, prices of basic food items, goats, and fuels, daily wage and shilling-USD rate, river levels, NDVI, disease hospitalisations and deaths, distances between regions, time since 2010.	The number of arrivals per region and month.	Missing feature variables indicated by binary flags and replaced by propagating the last recorded value; missing values with no preceding data filled with a 0.	Missing values of the target variable were dropped in training
Foresight	Public services, Corruption index, total unemployment, GDP per capita, population growth, battle-related deaths, civilian fatalities, State legitimacy, GINI Index, freedom from political killings, dietary energy supply adequacy, occurrence and effect of natural disasters, Human Rights Score Mean.	Total forced displacement per 100k population per country + confidence intervals.	Regression and heuristic approaches are used to treat data gaps. Data from other Sub-Saharan countries with similar relationships between the drivers and migration is also leveraged.	Domain-specific transformations of the features based on subject matter expert input, past features projected using an auto-regressive model till the current year.
AHE-AD	Violent events, kidnappings/ lootings, attacks from extremist groups, deaths from violence, share of people in classification 3+, food prices, Vegetation Health Index, mortality rate among small children, index of safety.	Number of displaced people at Admin levels 1 and 2.	Months with missing or overabundant displacement data treated as parameters to be inferred.	Not specified
IDE-TECT	Type of displacement, cause, location, number of people, reporting units and terms.	Incidents of internal displacement	Not specified	Only keep articles likely relating to internal displacement, analyse and extract key information.
EPS-Forecasting	Daily event indices, clusters of keywords related to migration, asylum seeking, and countries of transit and destination, monthly detections of illegal border-crossing with the EU, monthly asylum decisions	Early warning alerts and asylum applications	Data with insufficient variability (too low or too many missing values) are dropped from the analysis.	Compute event indices; apply normalisation, data cleaning, filtering, clock-alignment
EU-Migra-Tool (Syria-Greece case study)	Civilian violence, total fatalities, asylum applications during the year, number of natural disasters, number of battles, explosions, or remote violence, deaths and people affected, last month's arrivals, net official development assistance and official aid received, female population 20-24	Asylum applications in the EU+, attitudes towards immigration	Categorical and numerical imputation methods are applied and the data of the least value are removed.	GDELT data (Large-Scale Model): elimination of stop words, removing everything but nouns, verbs and adjectives, lemmatization, and tokenization.
Flee	Conflict locations, camps and intermediate towns and capacity, population size, distances between locations, movement speed and probability	Distribution and demographics of refugees across the camps or on given routes	Not specified	Select conflict(s), put conflict attributes in CSV files, interpolate linearly between data points and calculate the total refugee count by aggregating the registrations.

Table 3: Comparison of Data Use

4.3 Algorithms and Accuracy

Table 3 summarises the technical details of the models, more specifically the ML algorithms for prediction they employ, performance metrics and accuracy as reported in the papers, and the benchmark(s) against which they are compared. All authors report exceeding their chosen benchmark's performance, but for models that are only compared to one simple benchmark (like an assumption of a constant level of displacement), this may not be as explanatory as intended. The IDETECT model has not been evaluated, since it is not accompanied by a dedicated academic paper and specific algorithms and performance metrics are not discussed.

Name	Models and Alogithms	Performance Metrics	Benchmark
Jetson (case study Somalia)	Ridge and lasso regressions Multi-layer perceptrons, XGBoost, Adaboost, Decision trees, Random forests Support vector machines, LSTM neural network	Root Mean Square Error (RMSE) between 6288 and 7361 for mean number of arrivals 3,255, with a standard deviation of 7,700 and a maximum of 76,267	Lagged values (assume arrivals will be equal to the observed value from n periods ago), expanding mean, exponentially weighted mean, historical mean
Foresight	A set of gradient boosted trees; a gradient boosting ensemble (xgboost), random forest, a linear regression, and a support vector regression (MM4Sight)	MAPE for the first year was 6.9 and 8.1% increasing to 7.6%–20.0% by year 3 for Afghanistan and Myanmar, respectively.	Humanitarian Response Plans (HRP) estimates, current flows
EPS-Forecasting	DynENet (includes Ridge and Lasso regressions), vector autoregression model for future values of covariates, random forest for variable importance ranking	Confidence bands of ± 2 standard errors; for Syrian refugees in Germany, the average and median relative errors are 7% and 4%, respectively.	Autoregressive Integrated Moving Average - ARIMA(1,0,1)
AHEAD	Bayesian state-space model for the stock number of internally displaced people in a given area for monthly time steps	Burkina Faso - MAPE of 15%; for classification - 69% accuracy of action taken for threshold of 1200 increase.	Constant (no change) and level of displacement in each province evolving with a rate like the previous 24m.
EUMigraTool	Support Vector, Lasso, Ridge, and linear regression, Random Forests, Decision Tree, and LSTM + LDA and MLP for text analysis, VGG16 for feature extraction (LSM); Flee model (SSM)	(LSM) Median Relative Error - ca. 80% accuracy, (rescaled) average absolute error also used; (SSM) absolute relative difference - between 0.19 and 0.84 (for big and sudden outliers)	Tested against true labels from IOM and UNHCR, no immediate benchmark mentioned
Flee	Agent-based modelling, automated ensemble forecasting for the final results	ARD for all countries - between 0.377 and 0.446	Flat extrapolation, sloped (linear) extrapolation from day 0, and fraction extrapolation of a given camp, assuming that it remains constant, of month day 7 or 30

Table 4: Technical Specifications

While most models combine several algorithms to produce the results, many of them are recurrent - for example Lasso, Ridge and linear regressions, random forests, and different neural networks. On the one hand, this is a reason to compare performance since a trend can be identified in the choice of standardized algorithms and data sources. On the other hand, however, reported accuracy metrics differ across models (besides the Foresight and AHEAD models, which both use MAPE) and, more importantly, target variables are different and require a different level of precision.

What could be discussed instead are the actual error metrics. The Jetson authors chose RMSE for its ability to give real values which directly correspond to the number of mispredicted people and are easier for reporting and understanding by organisations [86]. The Foresight and AHEAD tools' authors, which are almost the same, chose MAPE, but do not elaborate why they preferred this method. The latest paper on Foresight also shows the mean absolute percentage error and its comparison to the benchmarking expert forecasts [82] and in its previous version, MM4Sight, MAE of the results about displacement in Ethiopia was discussed [81]. A more interesting error measure is discussed for the EPS model where errors are presented as a confidence band around the moving average for time series, besides the usual metrics for relative and absolute error [20]. The EMT has two parallel error measurements for its two models - the LSM achieves up to 80% accuracy using the median relative error (MdRE) (the median is used instead of the mean to reduce the impact of outliers in the performance validation) [13] and the SSM achieves quite a large variation of the error rate, proving to be sensitive to outliers. Finally, the latest reported errors of the Flee model are stabilised around 0.4 for the ARD [37], but previously the error metric preferred by the authors was Mean Absolute Scaled Error [111].

4.4 Operational Specifications

The final topic for analysis concerns operational specifications and the overall applicability of the tools in Table 5. The UI/UX column covers the process around the development of the user interface and the user experience. Whether the tool is open source is also highlighted, since this is important both for the reproducibility of the results and to faciliate the use by other organisations. Security of the tool and privacy of the data used are not delved into in most cases, but are important to consider in order to prevent misuse of results (an ethical consideration discussed in 1.4). Finally, which countries each tool is applied or at least tested for is important for identifying how useful it is truly.

There is a variety in how much effort and research has been put into the user experience depending on the target audience for the tool. IDETECT is again not included, since it is neither open-source nor does it have a designated public UI. The EPS-Forecasting tool also mentions a general UI for customising some of the input variables, but probably because the tool is not directly open-sourced, implementation of visualisation and security capabilities are not referenced.

The other tools put significant effort into making the results available and presenting the necessary information well. Jetson's authors mention that developing an interactive dashboard for use by humanitarian teams with design choices like different sets of input features, different transformations of the target variable, and different strategies for handling missing data is planned in the near future [86] to improve on the existing website, which is a bit cumbersome [117]. The Foresigh tool has a corresponding academic paper that explains the process behind the UX development [7] and EMT was undergoing iterative validation sessions with a User Board of NGOs, which helped shape the UX with the tool [13]. The AHEAD model authors do not mention processes of developing the tool, except for including data from their Project21, which consisted of conducting interviews with people of concern in West and Central Africa [67]. Finally, the authors of the Flee model talk about the current visualisation capabilities of the tool, including migration routes and agent concentrations, density variations, and quantitative trends, but also acknowledge that "a major challenge remains to establish a generic, sophisticated and open source visualisation platform" [37].

In terms of security and privacy measures implemented, not many papers talk about them explicitly, likely since they use open-source data and the liability for it is transferred to the owners of the platforms/databases. However, the purpose of these tools is to be used for humanitarian purposes and

Name	UI/UX	Open	Countries Tested
Jetson (case study Somalia)	Interactive website for results, includes storytelling and maps, current version is 4.0.0 [117]; an interactive dashboard for use by humanitarian teams is planned;	Yes [118]	Somalia
Foresight	Utilised expert-in-the-loop knowledge and conducted interviews with field officers, availability of projections and scenario generations and analysis; uses 4MI data which conducts in-depth surveys with thousands of refugees and migrants on the move.	Yes [52]	Afghanistan, Burkina Faso, Burundi, Cameroon, CAR, Chad, Colombia, DR Congo, El Salvador, Ethiopia, Guatemala, Honduras, Iraq, Libya, Mali, Mozambique, Myanmar, Niger, Nigeria, Palestine, Somalia, Sudan, South Sudan, Syria, Ukraine, Venezuela, Yemen
EPS-Forecasting	General User Interface of our system permits to easily customise the topic searches to include in the analysis of single countries (not linked)	Research and non-commercial use.	70 flows between seven origins (Afghanistan, Eritrea, Iraq, Nigeria, Syria, Turkey and Venezuela) and ten destinations (Austria, Belgium, Germany, Greece, Spain, France, Italy, The Netherlands, Sweden and the EU)
AHEAD	No particular information about the development, existing dashboard of results in Somalia and a prototype for West Africa (currently only for Burkina Faso) [25]	Yes [100]	Burkina Faso, Niger, Mali, Somalia, South Sudan
EMT	17 NGOs were involved as part of the Users Board (UB) in the design and validation of the tool through online surveys and questionnaires; suggestions for improvement of features (e.g. disaggregation of results, interface improvements)	Only for humanitarian purposes	Syria, Nigeria, Mali, and Venezuela
Flee	Visualisations of agent trajectories, population distributions, location attributes, and temporal changes using geographic maps, heat maps, graphs and charts, but still no universal visualisation tool.	Yes [43]	Nigeria, Mali, Syria, South Sudan, Burundi, CAR, Ethiopia (Tigray), currently testing for Mozambique

Table 5: Overview of Model Interfaces, Access, Security, and Usage

people's well-being may depend on them, therefore, it is important to ensure security of the results and privacy of personal data. A student thesis has examined available grey resources between 2019 and 2022 for the Jetson tool and discusses anonymised and aggregated data [49]. Flee is explicitly designed to not use personal data [37]. The EMT discusses the security side more thoroughly. The platform is only available for organisations and individuals with explicitly ethical and humanitarian purposes [13]. This is ensured by requiring personal identification to log in, which is granted on a case-by-case basis. Personal data is minimised, protected, and collected after consent [13].

Finally, an important consideration is how widely these tools have been applied. Looking at Table 5, there is quite a variety of the scope for which the models have been tried - the Jetson model has only been applied in Somalia and the EPS-Forecasting tool has reported experiments in as many as 70 country-to-country flows. Some of the tools are only for internal displacement or predicting movements to/from a country, while others (like the EPS and EMT) consider both countries of origin and destination. How useful a tool will be, therefore, depends on what the use case is - bilateral flows, internal displacement, overall migration per country, etc.

5 Responsible Research

5.1 Reproducibility

As this work is intended as a literature review, no new or proprietary datasets have been collected or used. Papers are sourced as explained in the Methodology section from popular scientific databases either with open access or using TU Delft's standard institutional login. Generative AI has not been used in writing the report or extracting information to be used in it, except for creating Figure 1 (given the models and the respective input times) and styling the tables.

5.2 Ethical Implications

Although sensitive data have not been used in the report, I acknowledge the possibility of misuse of the results, since the models reviewed are for humanitarian purposes and may create harm if operated by parties who want to prevent instead of provide humanitarian help. Many authors whose work has been used in the review also acknowledge the possibility of ethical misconduct, which is why some of the models and data are proprietary or at least available on demand. An overview of risks and ethics of forecasting humanitarian crises with ML in general is presented in [48]: change is constant and not everything can be predicted, explainability and replicability limitations are ever-present and data is often biased.

Furthermore, malicious use of the tools acquired from this review can lead to "preventive closure of border crossings to asylum-seekers, the growing danger of physical attack and exploitation in the context of people trafficking, and encouragement of racism", deliberate attacks on aid convoys in humanitarian context and political instrumentalisation (parties using the forecasts "to stoke fears and propagate an often xenophobic agenda"), commercialisation of data gathering and lack of democratic control (especially when funding is concerned), and, new pressures to act, leading to loss of the bigger picture of priorities in societal context [8].

5.3 Bias and Reliability of the Results

Despite the numerous efforts to improve the data quality, iterations of developing the models, and validation techniques applied to the algorithm results, the outcomes are neither bias-free nor completely reliable to follow yet. In addition, racist biases may be amplified when looking at the most commonly surveyed countries of origin of refugees, although specific numbers are not reported. However, in the event of radicalised opinions, we should remember that these are forcibly displaced people who did not have much of a choice whether to stay in their home country or region or not.

Almost all authors explicitly classify their work as a tool to help policy makers in displacement management in allocating resources and preparing for crises, rather than a means of eliminating humans in the loop in humanitarian decision making. Accountability is vital when dealing with sensitive groups such as refugees and internally displaced people and black box approaches can be dehumanising and even dangerous when followed blindly. Humanitarian organisations also acknowledge this - "the Centre for Humanitarian Data have reminded practitioners of the value of keeping 'humans in the loop' and cautioned that predictive analytic models should be seen as tools rather than solutions – which require the involvement of human decision-makers from the beginning in order to be successful" [48].

6 Discussion and Conclusion

This paper has conducted a systematised review of ML models designed for forecasting forced displacement, namely UNHCR's Jetson, DRC's Foresight and AHEAD, IDMC's IDETECT, the EU's EPS-Forecasting and EUMigraTool, and the agent-based model Flee. As expected, there is no one-size-fits-all solution for predicting forced displacement due to different data requirements, desired outputs and performance, and operational characteristics.

6.1 Synthesis of Results

A clear trend is the use of a common set of data categories. This is not coincidental: conflict, economic declines, food insecurity, and natural disasters are historically main drivers of migration as mentioned in the Introduction; previous refugee statistics and socio-demographics are important for identifying and learning trends; and the importance of real-time (textual) data for short-term predictions and quick action becomes clearer with every model.

Another observation is that models designed for short- and mid-term forecasting, up to a few months, tend to rely on data that captures sudden triggers and is updated regularly (e.g. GDELT, ACLED, news, food prices and recent countries transitions). In contrast, models that focus on long-term predictions (in particular Foresight) use variables classified by slow and structural changes that need a longer time of monitoring and update (e.g. GDP per capita, Gini index, and overall human rights score). Furthermore, underlying causes that influence migration in the long term, e.g. caused by climate change, are easier to track than others, e.g. conflicts and internal political unrest, which are notorious for arising unexpectedly and having consequences of unpredictable scope.

The main focuses are prediction of the number of refugees per country and/or region, asylum applications (specifically in the EU), and distribution of refugees in camps, depending on what purpose the tools serve: preparation of the destination country for arrivals, allocation of humanitarian aid for internally displaced people, or forecasting and equip for the situation in the camps.

Popular ML models and algorithms are regressions, random forests, neural networks, and agent-based modelling. Regression models make more sense when data is of lower dimensionality and dependencies are clearer, while ensemble methods are better suited for non-linear dependencies or missing data. Neural networks are more suitable for larger datasets and may be more tempting for their performance, but are less interpretable, which is a problem for humanitarian purposes. Agent-based models are good for when data is unavailable, since they are not data-heavy (but are computationally heavier), however, they may lack information on important drivers and require more computational power, which can negatively influence their performance.

Accuracy metrics are diverse and error rates are hard to compare, but all models report exceeding their corresponding benchmarks. RMSE, MAPE, and the MdRE are used when an absolute number is predicted, since they are easy to understand and incorporate in reports, but RMSE and MdRE penalise outliers more harshly (and displacement data is rarely without such). RMSE also has the advantage for interpretability, as it is evaluated in the same unit as the predicted variable. For agent-based modelling, the average and absolute relative difference is discussed, but for comparing the overall accuracy for longer periods, the averaged is more suitable.

In terms of operational specifications, different amount of effort is put into developing a user interface, depending on who it is intended for. The development of user-friendly interfaces and open-source models signifies a positive movement towards transparency, reproducibility, and accessibility for more humanitarian organisations and NGOs. Finally, the models also differ in the scope for which they have been tested, from just one case study (Jetson) to 27 countries (Foresight).

The field of humanitarian forecasting is constantly evolving. The tools reviewed demonstrate significant potential to improve the effectiveness of humanitarian action. However, their practical application requires careful consideration of the context, intended use case, and inherent limitations.

6.2 Choosing a Suitable Model

Figure 2 summarises the recommendations that could be derived from the review if an existing tool from the examined 6 is to be chosen for displacement forecasting. The main choices that have to be made is what data is available or preferred, what is the desired time horizon of the predictions, what is being predicted, the purpose of the implementation (experimental - for in-house use and more open to changes, or practical and already in use), and/or the level to which the UI is developed (note that EMT is only for proved humanitarian organisations and EPS code is available on demand).

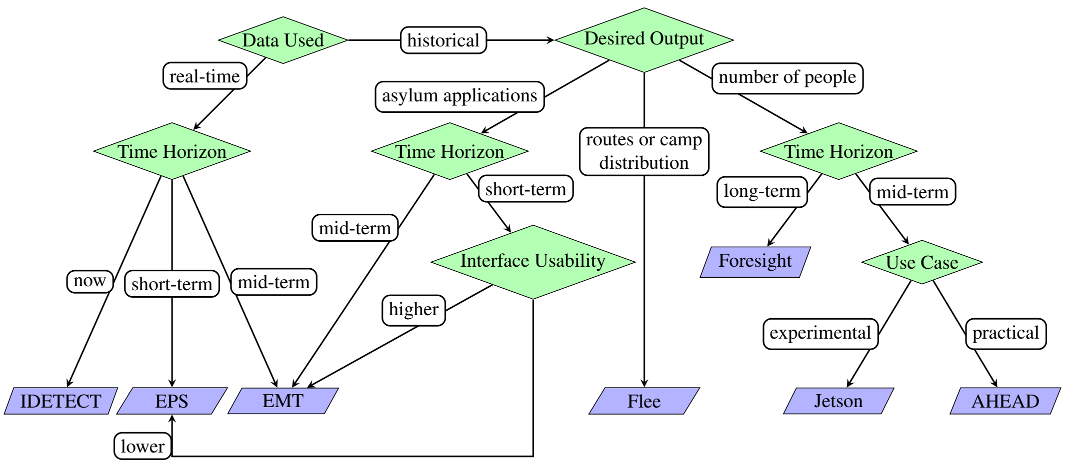

Figure 2: Tool Choice

7 Limitations and Future Work

This literature review spanned 10 weeks and was therefore subjected to time constraints. In case of more time, the span of the review would be bigger, with more individual academic papers (e.g., models not explicitly in use by organisations) included. Unsurveyed but collected articles can be found in A.3 for reference and future research. The depth of the survey was also adjusted to correspond to the time constraints - the characteristics discussed were mostly factual and summarising of the results reported in the papers. Additionally, the tools could be surveyed from an ethical perspective to address the issues from 1.4, data and results bias could be evaluated, and replicability could be tested with new data. The last one is an important limitation and future research on the topic could be accompanied by experiments in order to further support or oppose the claims made in this work.

Viability of the discussion and recommendations made about the suitability of models is constrained by two factors. First, they are based on the criteria mentioned in the Methodology section and the results as reported by the models' authors. As standardised way of comparing models for predicting displacement was not found (this was also not the focus of the review), the criteria were a hybrid of what characteristics were often discussed in the examined works and some relevant features may have been omitted. Second, models examined in this review are all quite new (the most recent academic paper of each model dated between 2021 and 2024) and are likely still under development. Since humanitarian forecasting and displacement prediction in particular are rapidly evolving fields, some results and recommendations may not be as applicable in the future.

A Appendix

A.1 Queries per Search Engine

Scopus: (“machine learning" OR "artificial intelligence") AND ("forced displacement" OR "refugee*" OR "migrat*”) AND ("forecast*" OR "predict*" OR "early warning" OR "anticipatory action") AND NOT ("cell migration" OR "species migration" OR "gene migration" OR "data migration" OR "server migration" OR "cloud migration") + limiting the area to computer science, engineering, and mathematics - 944 results in total.

Web of Sciences - ("machine learning" OR "artificial intelligence" OR "neural network" OR "deep learning") AND ("forced displacement" OR "refugee*" OR "human migration" OR "population displacement" OR "involuntary migration") NOT ("cell migration" OR "species migration" OR "gene migration" OR "data migration" OR "server migration" OR "cloud migration") - 331 results in total.

IEEEXplore: ("machine learning" OR "artificial intelligence") AND ("forced displacement" OR "refugee*" OR "migrat*") AND (forecast* OR predict* OR "early warning" OR "anticipatory action”) - 524 results in total.

Google Scholar: machine learning forced displacement prediction - the first 20 pages were loaded.

A.2 Final Set of Papers Included

Name	Year	Topic	Cit.
"A Multi-Scale Approach to Data-Driven Mass Migration Analysis"	2016	An early prototype of Foresight, examines a population diffusion model and a machine learning migration analysis	[2]
"Forecasting in humanitarian operations: Literature review and research needs"	2020 (jour. 2022)	A literature review of papers between 1990-2018 and aggregation of what is (not) discussed	[4]
"Scenario-based XAI for Humanitarian Aid Forecasting"	2020	A paper on which the user-centered design of Foresight is based	[7]
"Predicting irregular migration: high hopes, meagre result"	2023	A literature review of models predicting displacement with a focus on their limitations	[8]
"Developing AI predictive migration tools to enhance humanitarian support: The case of EUMigraTool"	2024	A review and summary of reports of EMT’s LSM	[13]
"The Role of Emerging Predictive IT Tools in Effective Migration Governance"	2021	A review and summary of 3 displacement prediction models’ current versions (Jetson, Foresight, and EPS-Forecasting)	[14]

"Forecasting asylum-related migration flows with machine learning and data at scale"	2022	EPS-Forecasting's main academic paper, discusses most of the evaluation criteria	[20]
"Pioneering Predictive Analytics for Decision-Making in Forced Displacement Contexts"	2019	Background on Jetson and its predecessor Winter Cell	[28]
"Flee 3: Flexible agent-based simulation for forced migration"	2024	Flee's last version and improvements	[37]
"Predictive Analytics in Humanitarian Action: A Preliminary Mapping and Analysis"	2020	A literature review on humanitarian forecasting and 49 models used for it	[48]
"Pushing the boundaries of anticipatory action using machine learning"	2024	The main paper of the AHEAD tool	[67]
"A machine learning approach to scenario analysis and forecasting of mixed migration"	2020	The second version of the Foresight tool (MM4Sight)	[81]
"An explainable forecasting system for humanitarian needs assessment"	2023	The newest version of the Foresight tool	[82]
"Predictive modeling of movements of refugees and internally displaced people: Towards a computational framework"	2022	A paper on the Jetson tool and a generalised framework for assessing such systems	[86]
"A Novel Migration Simulation and Prediction Tool"	2022	A case study of the EMT with a focus on Syria-Greece migration	[107]
"Sensitivity-driven simulation development: a case study in forced migration"	2021	The second version of the Flee tool with sensitivity analysis of the parameters	[110]
"A generalized simulation development approach for predicting refugee destinations"	2017	The first version of the Flee tool, a pioneering work at that time	[111]
"Towards an automated framework for agent-based simulation of refugee movement"	2017	An attempt to automatise some feature extraction approaches of the Flee model	[112]
"An Agent-Based Forced Displacement Simulation: A Case Study of the Tigray Crisis"	2022	An application of the Flee model to refugee camps in Tigray	[113]

Table 6: Summary of Academic Literature Used

A.3 Future Research

The following papers were not included in the research due to time limitations. Nevertheless, I believe they could provide valuable insights into displacement forecasting and humanitarian action with machine learning.

Unread or not included papers about machine learning for humanitarian forecasting, overall displacement prediction, evaluation criteria and ethical considerations are [23, 57, 61, 66, 68, 91, 95, 99, 108, 115].

Migration specifically caused by one driver (conflict/climate) was discussed in [63, 64, 89, 98, 101]. The focus of this paper was predicting overall displacement, so such driver-specific works were of lower priority. Same goes for displacement models using probabilistic models [114, 132] Nevertheless, they may be useful to some.

Nowcasting is another useful method for managing displacement. It may not be as efficient for long-term planning, but can be crucial for quick action and short-term decision making. The most popular approaches are through remote sensing. Paper gathered from the search are [3, 29, 36, 38, 44, 45, 83, 87, 90, 94, 103, 127, 129].

Two humanitarian organisations are also actively considering

Finally, the following papers could not be included in the review, even though they corresponded to the search due to time limitations and lower priority (models currently in use by humanitarian organisations were of higher priority): [1, 5, 6, 11, 12, 16, 17, 18, 27, 39, 46, 47, 51, 53, 58, 62, 65, 69, 71, 72, 73, 74, 75, 76, 77, 78, 79, 84, 88, 92, 93, 96, 104, 105, 106, 109, 125, 128].

References

[1] S. Abrishamkar and F. Khonsari. "Mining Large-scale News Articles For Predicting Forced Migration". en. In: (2018).

[2] M. N. Ahmed et al. "A Multi-Scale Approach to Data-Driven Mass Migration Analysis". en. In: (2016). URL: https://ceur-ws.org/Vol-1831/paper_4.pdf.

[3] N. Ahmed et al. "Artificial Neural Network and Machine Learning Based Methods for Population Estimation of Rohingya Refugees: Comparing Data-Driven and Satellite Image-Driven Approaches". en. In: *Vietnam Journal of Computer Science* 06.04 (Nov. 2019), pp. 439–455. ISSN: 2196-8888, 2196-8896. DOI: 10.1142/S2196888819500246. URL: https://www.worldscientific.com/doi/abs/10.1142/S2196888819500246 (visited on 05/05/2025).

[4] N. Altay and A. Narayanan. "Forecasting in humanitarian operations: Literature review and research needs". en. In: *International Journal of Forecasting* 38.3 (July 2022), pp. 1234–1244. ISSN: 01692070. DOI: 10.1016/j.ijforecast.2020.08.001. URL: https://linkinghub.elsevier.com/retrieve/pii/S0169207020301151 (visited on 04/23/2025).

[5] S. Anakal et al. "Predictive Analytics and Machine Learning in Assessing Migration Patterns: A Comparative Study". en. In: 21 (2024), pp. 1557–1564. ISSN: 1741-8984. URL: www.migrationletters.com.

[6] P. Anastasiadis et al. "P-Flee: An Efficient Parallel Algorithm for Simulating Human Migration". In: *2021 IEEE International Parallel and Distributed Processing Symposium Workshops (IPDPSW)*. Portland, OR, USA: IEEE, June 2021, pp. 1008–1011. ISBN: 978-1-6654-3577-2. DOI: 10.1109/IPDPSW52791.2021.00159. URL: https://ieeexplore.ieee.org/document/9460661/ (visited on 04/25/2025).

[7] J. Andres et al. "Scenario-based XAI for Humanitarian Aid Forecasting". In: *Extended Abstracts of the 2020 CHI Conference on Human Factors in Computing Systems*. Honolulu HI USA: ACM, Apr. 2020, pp. 1–8. DOI: 10.1145/3334480.3382903. URL: https://dl.acm.org/doi/10.1145/3334480.3382903 (visited on 05/23/2025).

[8] S. Angenendt, A. Koch, and J. Tjaden. "Predicting irregular migration: high hopes, meagre results". en. In: *SWP Research Paper* (2023). Publisher: Stiftung Wissenschaft und Politik (SWP), German Institute for International and Security Affairs Version Number: 1, pp. 11/2023. DOI: 10.18449/2023RP11. URL: https://www.swp-berlin.org/10.18449/2023RP11/ (visited on 05/02/2025).

[9] Anticipation Hub. *Trigger List – Anticipation Hub*. https://www.anticipation-hub.org/experience/triggers/trigger-database/trigger-list/page-2#c2871. Accessed: 2025-06-04. 2023.

[10] Armed Conflict Location & Event Data Project. *ACLED Data*. https://acleddata.com/. Accessed: 2025-06-06. 2025.

[11] J. Ashmore et al. "Urgent Decisions, Lasting Challenges: Enhancing Data-driven Planning for Humanitarian Shelter and Settlements during Urban Crises". In: vol. 2. 2024, pp. 97–98. URL: https://www.scopus.com/inward/record.uri?eid=2-s2.0-105001500823&partnerID=40&md5=bfafa690e578bda0beaf7cd12edb8cb8.

[12] B. Aydoğdu et al. "Mobile phone data for anticipating displacements: practices, opportunities, and challenges". en. In: *Data & Policy* 7 (2025), e5. ISSN: 2632-3249. DOI: 10.1017/dap.2024.94. URL: https://www.cambridge.org/core/product/identifier/S2632324924000944/type/journal_article (visited on 05/05/2025).

[13] C. Blasi Casagran and G. Stavropoulos. “Developing AI predictive migration tools to enhance humanitarian support: The case of EUMigraTool”. en. In: *Data & Policy* 6 (2024), e64. ISSN: 2632-3249. DOI: 10.1017/dap.2024.76. URL: https://www.cambridge.org/core/product/identifier/S2632324924000762/type/journal_article (visited on 05/07/2025).

[14] C. Blasi Casagran et al. “The Role of Emerging Predictive IT Tools in Effective Migration Governance”. In: *Politics and Governance* 9.4 (Oct. 2021), pp. 133–145. ISSN: 2183-2463. DOI: 10.17645/pag.v9i4.4436. URL: https://www.cogitatiopress.com/politicsandgovernance/article/view/4436 (visited on 05/13/2025).

[15] C. Bommer, A. Dreher, and M. Perez-Alvarez. “Home bias in humanitarian aid: The role of regional favoritism in the allocation of international disaster relief”. en. In: *Journal of Public Economics* 208 (Apr. 2022), p. 104604. ISSN: 00472727. DOI: 10.1016/j.jpubeco.2022.104604. URL: https://linkinghub.elsevier.com/retrieve/pii/S0047272722000068 (visited on 04/23/2025).

[16] C. Bosco et al. “A Machine Learning architecture to forecast Irregular Border Crossings and Asylum requests for policy support in Europe: a case study”. en. In: *Data & Policy* 6 (2024), e81. ISSN: 2632-3249. DOI: 10.1017/dap.2024.48. URL: https://www.cambridge.org/core/product/identifier/S2632324924000488/type/journal_article (visited on 05/06/2025).

[17] K. Boss et al. “Forecasting bilateral asylum seeker flows with high-dimensional data and machine learning techniques”. en. In: *Journal of Economic Geography* 25.1 (Jan. 2025), pp. 3–19. ISSN: 1468-2702, 1468-2710. DOI: 10.1093/jeg/lbae023. URL: https://academic.oup.com/joeg/article/25/1/3/7731436 (visited on 06/22/2025).

[18] M. H. Böhme, A. Gröger, and T. Stöhr. “Searching for a better life: Predicting international migration with online search keywords”. en. In: *Journal of Development Economics* 142 (Jan. 2020), p. 102347. ISSN: 03043878. DOI: 10.1016/j.jdeveco.2019.04.002. URL: https://linkinghub.elsevier.com/retrieve/pii/S0304387819304900 (visited on 04/30/2025).

[19] M. Carammia, S. Iacus, and T. Wilkin. “Supplementary information for “Forecasting asylum-related migration flows with machine learning and data at scale””. en. In: (2022). URL: https://static-content.springer.com/esm/art%3A10.1038%2Fs41598-022-05241-8/MediaObjects/41598_2022_5241_MOESM1_ESM.pdf.

[20] M. Carammia, S. M. Iacus, and T. Wilkin. “Forecasting asylum-related migration flows with machine learning and data at scale”. en. In: *Scientific Reports* 12.1 (Jan. 2022), p. 1457. ISSN: 2045-2322. DOI: 10.1038/s41598-022-05241-8. URL: https://www.nature.com/articles/s41598-022-05241-8 (visited on 04/29/2025).

[21] Centre for Humanitarian Data. *Catalogue for Predictive Models in the Humanitarian Sector*. https://centre.humdata.org/catalogue-for-predictive-models-in-the-humanitarian-sector/. Accessed: 2025-06-04. 2023.

[22] Centre for Research on the Epidemiology of Disasters. *The Emergency Events Database (EM-DAT)*. https://www.emdat.be/. Accessed: 2025-06-06. 2025.

[23] P. G. S. Coletti, R. E. Mays, and A. Widera. “Bringing technology and humanitarian values together: A framework to design and assess humanitarian information systems”. In: *2017 4th International Conference on Information and Communication Technologies for Disaster Management (ICT-DM)*. Münster: IEEE, Dec. 2017, pp. 1–9. ISBN: 978-1-5386-2553-8. DOI: 10.1109/ICT-DM.2017.8275687. URL: http://ieeexplore.ieee.org/document/8275687/ (visited on 04/25/2025).

[24] Comité permanent Inter-Etats de Lutte contre la Sécheresse dans le Sahel. *Cadre Harmonisé for the Identification of Risk Areas and Vulnerable Populations in the Sahel and West Africa*. https://www.food-security.net/en/topic/cadre-harmonise/. Accessed: 2025-06-06. 2025.

[25] Danish Refugee Council. *Anticipatory Humanitarian Action for Displacement (AHEAD)*. Accessed: 2025-05-21. 2025. URL: https://drc.ngo/what-we-do/innovation/anticipatory-action/ahead/.

[26] Danish Refugee Council. *Foresight: Displacement Forecasts*. 2025. URL: https://drc.ngo/what-we-do/innovation/digital-innovation/foresight-displacement-forecasts/.

[27] G. Dupuis-Mc Donald. "Downward Causation in Complex Systems of Migration. Challenges for Prediction and Intervention". en. In: *Human Migration and Complex Systems Science*. Series Title: SpringerBriefs in Population Studies. Cham: Springer Nature Switzerland, 2024, pp. 29–61. ISBN: 978-3-031-65056-7 978-3-031-65057-4. DOI: 10.1007/978-3-031-65057-4_2. URL: https://link.springer.com/10.1007/978-3-031-65057-4_2 (visited on 04/29/2025).

[28] C. Earney and R. Moreno Jimenez. "Pioneering Predictive Analytics for Decision-Making in Forced Displacement Contexts". en. In: *Guide to Mobile Data Analytics in Refugee Scenarios*. Ed. by A. A. Salah et al. Cham: Springer International Publishing, 2019, pp. 101–119. ISBN: 978-3-030-12553-0 978-3-030-12554-7. DOI: 10.1007/978-3-030-12554-7_6. URL: http://link.springer.com/10.1007/978-3-030-12554-7_6 (visited on 05/05/2025).

[29] T. M. Elebe and S. Kurnaz. "Efficient detection of refugees and migrants in Turkey using convolutional neural network". en. In: *Physical Communication* 59 (Aug. 2023), p. 102078. ISSN: 18744907. DOI: 10.1016/j.phycom.2023.102078. URL: https://linkinghub.elsevier.com/retrieve/pii/S1874490723000812 (visited on 05/06/2025).

[30] European Centre for Medium-Range Weather Forecasts. *ECMWF Datasets*. https://www.ecmwf.int/en/forecasts/datasets. Accessed: 2025-06-06. 2025.

[31] European Commission. *ITFLOWS Project Results*. https://cordis.europa.eu/project/id/882986/results. Accessed: 2025-05-27.

[32] Eurostat. *Eurostat - Your key to European statistics*. https://ec.europa.eu/eurostat/. Accessed: 2025-06-06. 2025.

[33] Food and Agriculture Organization of the United Nations. *FAOSTAT*. http://www.fao.org/faostat/. Accessed: 2025-06-06. 2025.

[34] Food Security and Nutrition Analysis Unit - Somalia. *FSNAU Data and Analysis*. https://www.fsnau.org/. Accessed: 2025-06-06. 2025.

[35] Frontex. *Risk Analysis*. https://frontex.europa.eu/what-we-do/risk-analysis/. Accessed: 2025-06-06. 2025.

[36] Y. Gao et al. "Comparing the robustness of U-Net, LinkNet, and FPN towards label noise for refugee dwelling extraction from satellite imagery". In: *2022 IEEE Global Humanitarian Technology Conference (GHTC)*. Santa Clara, CA, USA: IEEE, Sept. 2022, pp. 88–94. ISBN: 978-1-6654-5097-3. DOI: 10.1109/GHTC55712.2022.9911036. URL: https://ieeexplore.ieee.org/document/9911036/ (visited on 05/02/2025).

[37] M. Ghorbani et al. "Flee 3: Flexible agent-based simulation for forced migration". en. In: *Journal of Computational Science* 81 (Sept. 2024), p. 102371. ISSN: 18777503. DOI: 10.1016/j.jocs.2024.102371. URL: https://linkinghub.elsevier.com/retrieve/pii/S1877750324001649 (visited on 04/25/2025).

[38] O. Ghorbanzadeh et al. “DWELLING EXTRACTION IN REFUGEE CAMPS USING CNN – FIRST EXPERIENCES AND LESSONS LEARNT”. en. In: *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences* XLII-1 (Sept. 2018), pp. 161–166. ISSN: 2194-9034. DOI: 10.5194/isprs-archives-XLII-1-161-2018. URL: https://isprs-archives.copernicus.org/articles/XLII-1/161/2018/ (visited on 05/01/2025).

[39] N. Golenvaux et al. *An LSTM approach to Forecast Migration using Google Trends*. Version Number: 2. 2020. DOI: 10.48550/ARXIV.2005.09902. URL: https://arxiv.org/abs/2005.09902 (visited on 05/01/2025).

[40] D. M. González et al. “Final EMT Analysis Report”. en. In: (Aug. 2023). URL: https://ec.europa.eu/research/participants/documents/downloadPublic?documentIds=080166e500c00f61&appId=PPGMS.

[41] Google. *Google Trends*. https://trends.google.com/. Accessed: 2025-06-06. 2025.

[42] D. Groen. *FLEE: Simulation Toolkit for the Movement of Individuals*. Accessed: 2025-05-21. 2025. URL: https://flee.readthedocs.io/en/master/.

[43] D. Groen. *Flee v3.1*. Accessed: 2025-06-04. 2021. URL: https://github.com/djgroen/flee/releases/tag/v3.1.

[44] A. Hadzic et al. “Estimating Displaced Populations from Overhead”. In: *IGARSS 2020 - 2020 IEEE International Geoscience and Remote Sensing Symposium*. Waikoloa, HI, USA: IEEE, Sept. 2020, pp. 1121–1124. ISBN: 978-1-7281-6374-1. DOI: 10.1109/IGARSS39084.2020.9324617. URL: https://ieeexplore.ieee.org/document/9324617/ (visited on 04/26/2025).

[45] C. Havas et al. “Spatio-Temporal Machine Learning Analysis of Social Media Data and Refugee Movement Statistics”. en. In: *ISPRS International Journal of Geo-Information* 10.8 (July 2021), p. 498. ISSN: 2220-9964. DOI: 10.3390/ijgi10080498. URL: https://www.mdpi.com/2220-9964/10/8/498 (visited on 05/02/2025).

[46] G. Henningsen. “Big Data for the Prediction of Forced Displacement”. en. In: *International Migration Review* 59.1 (Mar. 2025), pp. 141–164. ISSN: 0197-9183, 1747-7379. DOI: 10.1177/01979183231195296. URL: https://journals.sagepub.com/doi/10.1177/01979183231195296 (visited on 04/26/2025).

[47] G. Henningsen and G. D. Panta. “Early Warning for Forced Displacement”. en. In: ().

[48] K. Hernandez and T. Roberts. *Predictive Analytics in Humanitarian Action: A Preliminary Mapping and Analysis*. K4D Emerging Issues Report 33. Brighton, UK: Institute of Development Studies, 2020.

[49] A. Holmstrom. *Project Jetson: Predicting Migration Patterns During the Somali Conflict*. Accessed: 2025-06-04. URL: https://aegai.nd.edu/latest/project-jetson-predicting-migration-patterns-during-the-somali-conflict/.

[50] Humanitarian Data Exchange. *Humanitarian Data Exchange*. https://data.humdata.org/. Accessed: 2025-06-06. 2025.

[51] B. Q. Huynh and S. Basu. “Forecasting Internally Displaced Population Migration Patterns in Syria and Yemen”. In: *Disaster Medicine and Public Health Preparedness* 14.3 (June 2020). arXiv:1806.08819 [stat], pp. 302–307. ISSN: 1935-7893, 1938-744X. DOI: 10.1017/dmp.2019.73. URL: http://arxiv.org/abs/1806.08819 (visited on 04/26/2025).

[52] IBM Research. *Mixed Migration Forecasting*. Accessed: 2025-06-04. 2020. URL: https://github.com/IBM/mixed-migration-forecasting/tree/master.

[53] I. Iliopoulos et al. “National press monitoring using Natural Language Processing as an early warning signal for prediction of asylum applications flows in Europe”. In: *2022 IEEE International Conference on Big Data (Big Data)*. Osaka, Japan: IEEE, Dec. 2022, pp. 4802–4806. ISBN: 978-1-6654-8045-1. DOI: 10.1109/BigData55660.2022.10020278. URL: https://ieeexplore.ieee.org/document/10020278/ (visited on 05/27/2025).

[54] Internal Displacement Monitoring Centre. *Monitoring Platform: How IDMC Monitors*. Accessed: 2025-05-21. 2025. URL: https://www.internal-displacement.org/monitoring-tools/monitoring-platform/.

[55] International Federation of Red Cross and Red Crescent Societies. *IFRC GO*. https://go.ifrc.org/. Accessed: 2025-06-06. 2025.

[56] International Organization for Migration. *Migration Data Portal*. https://www.migrationdataportal.org/. Accessed: 2025-06-06. 2025.

[57] International Organization for Migration (IOM). *State-of-the-Art Displacement Indicators for Disaster Risk Reduction: Analysis of Existing Methodologies, Research and Datasets*. Report. Geneva: International Organization for Migration, 2024. URL: https://environmentalmigration.iom.int/sites/g/files/tmzbdl1411/files/documents/2024-03/iom_state-of-the-art_displacement-indicators-for-disaster-risk-reduction-analysis-of-existing-methodologies-research-and-datasets.pdf (visited on 06/17/2025).

[58] M. S. Islam et al. “Prediction of Irregular Bangladesh-EU Migration Trends Using Machine Learning Techniques”. In: *2024 3rd International Conference on Advancement in Electrical and Electronic Engineering (ICAEEE)*. Gazipur, Bangladesh: IEEE, Apr. 2024, pp. 1–6. ISBN: 979-8-3503-8828-2. DOI: 10.1109/ICAEEE62219.2024.10561697. URL: https://ieeexplore.ieee.org/document/10561697/ (visited on 04/30/2025).

[59] ITFLOWS Project. *Introducing the EUMigraTool (EMT)*. Accessed: 2025-05-21. 2025. URL: https://www.itflows.eu/eumigratool/.

[60] A. Jahani, D. Suleimenova, and D. Groen. “Report of migration modelling and simulation”. en. In: (June 2022). URL: https://ec.europa.eu/research/participants/documents/downloadPublic?documentIds=080166e5029bd107&appId=PPGMS.

[61] Joint Data Center on Forced Displacement. *Forced Displacement Literature Review 2019–2021*. Accessed: 2025-05-25. 2021. URL: https://www.jointdatacenter.org/wp-content/uploads/2021/05/JDC-Forced-Displacement-Literature-Review-2019-2021.pdf.

[62] T. Jurić. *Predicting refugee flows from Ukraine with an approach to Big (Crisis) Data: a new opportunity for refugee and humanitarian studies (preprint)*. en. Mar. 2022. DOI: 10.1101/2022.03.15.22272428. URL: http://medrxiv.org/lookup/doi/10.1101/2022.03.15.22272428 (visited on 04/26/2025).

[63] Justin Ginnetti and Travis Franck. *Assessing drought displacement risk for Kenyan, Ethiopian and Somali pastoralists*. en. Institution: Koninklijke Brill NV. Apr. 2014. DOI: 10.1163/2210-7975_HRD-9806-2014039. URL: https://primarysources.brillonline.com/browse/human-rights-documents-online/assessing-drought-displacement-risk-for-kenyan-ethiopian-and-somali-pastoralists;hrdhrd98062014039 (visited on 05/14/2025).

[64] P. M. Kam et al. “Impact-based forecasting of tropical cyclone-related human displacement to support anticipatory action”. en. In: *Nature Communications* 15.1 (Oct. 2024), p. 8795. ISSN: 2041-1723. DOI: 10.1038/s41467-024-53200-w. URL: https://www.nature.com/articles/s41467-024-53200-w (visited on 05/13/2025).

[65] F. D. Khangahi and F. Kiani. "Social Mobilization and Migration Predictions by Machine Learning Methods: A study case on Lake Urmia". In: *International Journal of Innovative Technology and Exploring Engineering* 10.6 (Apr. 2021), pp. 123–127. ISSN: 22783075. DOI: 10.35940/ijitee.F8833.0410621. URL: https://www.ijitee.org/portfolio-item/F88330410621/ (visited on 04/29/2025).

[66] N. Kinchin. "Technology, displaced?: The risks and potential of artificial intelligence for fair, effective, and efficient refugee status determination". en. In: (Sept. 2021).

[67] A. Kjærum and B. S. Madsen. "Pushing the boundaries of anticipatory action using machine learning". en. In: *Data & Policy* 7 (Nov. 2024), e8. ISSN: 2632-3249. DOI: 10.1017/dap.2024.88. URL: https://www.cambridge.org/core/product/identifier/S2632324924000889/type/journal_article (visited on 04/26/2025).

[68] A. Kondraganti. *Big Data Analytics in Humanitarian and Disaster Operations: A Systematic Review*. Issue: arXiv:2108.09800 arXiv:2108.09800 [cs]. Sept. 2021. DOI: 10.48550/arXiv.2108.09800. URL: http://arxiv.org/abs/2108.09800 (visited on 04/28/2025).

[69] P. Kulkarni and L. Jeon. "Quantitative Feasibility of Predictive Machine-Learning Optimization Algorithms for Refugee Routing". In: *2023 IEEE MIT Undergraduate Research Technology Conference (URTC)*. Cambridge, MA, USA: IEEE, Oct. 2023, pp. 1–4. ISBN: 979-8-3503-0965-2. DOI: 10.1109/URTC60662.2023.10535008. URL: https://ieeexplore.ieee.org/document/10535008/ (visited on 05/02/2025).

[70] E. C. Lentz and D. Maxwell. "How Do Information Problems Constrain Anticipating, Mitigating, and Responding to Crises?" In: *International Journal of Disaster Risk Reduction* 81 (2022), p. 103242. DOI: 10.1016/j.ijdrr.2022.103242.

[71] A. Lyons et al. "A Machine Learning Approach to Targeting Humanitarian Assistance Among Forcibly Displaced Populations". en. In: *SSRN Electronic Journal* (2023). ISSN: 1556-5068. DOI: 10.2139/ssrn.4404113. URL: https://www.ssrn.com/abstract=4404113 (visited on 05/05/2025).

[72] M. Maritsch and K. Winter. "Mining Call Detail Records to understand Cross-border Refugee Movements". en. In: (Apr. 2019).

[73] S. Martin et al. *Dynamic Model of Displacement*. Mar. 2021. DOI: 10.31234/osf.io/mb9zt. URL: https://osf.io/mb9zt (visited on 05/12/2025).

[74] S. F. Martin and L. Singh. "Data Analytics and Displacement: Using Big Data to Forecast Mass Movements of People". en. In: *Digital Lifeline?* Ed. by C. Maitland. The MIT Press, May 2018, pp. 185–206. ISBN: 978-0-262-34619-1. DOI: 10.7551/mitpress/10843.003.0015. URL: https://direct.mit.edu/books/book/3590/chapter/120343/Data-Analytics-and-Displacement-Using-Big-Data-to (visited on 04/29/2025).

[75] E. Mead, K. T. Islam, and N. Agarwal. "EXPERIMENTATION WITH DATA IMPUTATION METHODS TO IMPROVE REFUGEE REGRESSION AND CLASSIFICATION PREDICTION MODELS". en. In: *Selected Papers* (2022).

[76] E. Mead et al. "Proposing Location-based Predictive Features for Modeling Refugee Counts". In: *Transnational Education Review* 1.1 (May 2023), pp. 3–16. ISSN: 2753-8664, 2753-8656. DOI: 10.33182/ter.v1i1.2883. URL: https://journals.tplondon.com/ter/article/view/2883 (visited on 05/05/2025).

[77] V. Mebelli, M. Drakaki, and P. Tzionas. “An Investigation of Time Series Models for Forecasting Mixed Migration Flows: Focusing in Germany”. en. In: *Operations Research Forum* 4.2 (Apr. 2023), p. 34. ISSN: 2662-2556. DOI: 10.1007/s43069-023-00212-9. URL: https://link.springer.com/10.1007/s43069-023-00212-9 (visited on 05/02/2025).

[78] Z. Mehrab et al. “An agent-based framework to study forced migration: A case study of Ukraine”. en. In: *PNAS Nexus* 3.3 (Feb. 2024). Ed. by M. Muthukrishna, pgae080. ISSN: 2752-6542. DOI: 10.1093/pnasnexus/pgae080. URL: https://academic.oup.com/pnasnexus/article/doi/10.1093/pnasnexus/pgae080/7624910 (visited on 04/26/2025).

[79] M. Micevska. “Revisiting forced migration: A machine learning perspective”. en. In: *European Journal of Political Economy* 70 (Dec. 2021), p. 102044. ISSN: 01762680. DOI: 10.1016/j.ejpoleco.2021.102044. URL: https://linkinghub.elsevier.com/retrieve/pii/S0176268021000446 (visited on 05/01/2025).

[80] Microsoft. *Bing Maps Platform*. https://www.microsoft.com/en-us/maps/. Accessed: 2025-06-06. 2025.

[81] R. Nair et al. “A machine learning approach to scenario analysis and forecasting of mixed migration”. In: *IBM Journal of Research and Development* 64.1/2 (Jan. 2020), 7:1–7:7. ISSN: 0018-8646, 0018-8646. DOI: 10.1147/JRD.2019.2948824. URL: https://ieeexplore.ieee.org/document/8880487/ (visited on 04/25/2025).

[82] R. Nair, B. Madsen, and A. Kjærum. “An explainable forecasting system for humanitarian needs assessment”. en. In: *AI Magazine* 44.4 (Dec. 2023), pp. 354–362. ISSN: 0738-4602, 2371-9621. DOI: 10.1002/aaai.12133. URL: https://onlinelibrary.wiley.com/doi/10.1002/aaai.12133 (visited on 04/25/2025).

[83] M. Nasir et al. *Dwelling Type Classification for Disaster Risk Assessment Using Satellite Imagery*. Version Number: 1. 2022. DOI: 10.48550/ARXIV.2211.11636. URL: https://arxiv.org/abs/2211.11636 (visited on 05/01/2025).

[84] A. Oishi et al. “Forecasting Internally Displaced People’s Movements with Artificial Intelligence”. en. In: *Digital Innovations, Business and Society in Africa*. Ed. by R. Boateng et al. Series Title: Advances in Theory and Practice of Emerging Markets. Cham: Springer International Publishing, 2022, pp. 311–339. ISBN: 978-3-030-77986-3 978-3-030-77987-0. DOI: 10.1007/978-3-030-77987-0_14. URL: https://link.springer.com/10.1007/978-3-030-77987-0_14 (visited on 04/29/2025).

[85] OpenStreetMap contributors. *OpenStreetMap*. https://www.openstreetmap.org/. Accessed: 2025-06-06. 2025.

[86] K. H. Pham and M. Luengo-Oroz. *Predictive modeling of movements of refugees and internally displaced people: Towards a computational framework*. arXiv:2201.08006 [cs]. Jan. 2022. DOI: 10.48550/arXiv.2201.08006. URL: http://arxiv.org/abs/2201.08006 (visited on 04/23/2025).

[87] F. Poletto et al. “Developing Annotated Resources for Internal Displacement Monitoring”. en. In: *Companion Proceedings of the Web Conference 2021*. Ljubljana Slovenia: ACM, Apr. 2021, pp. 136–144. ISBN: 978-1-4503-8313-4. DOI: 10.1145/3442442.3453455. URL: https://dl.acm.org/doi/10.1145/3442442.3453455 (visited on 05/02/2025).

[88] H. Qi and T. Bircan. “Modelling and predicting forced migration”. en. In: *PLOS ONE* 18.4 (Apr. 2023). Ed. by L. De Benedictis, e0284416. ISSN: 1932-6203. DOI: 10.1371/journal.pone.0284416. URL: https://dx.plos.org/10.1371/journal.pone.0284416 (visited on 05/01/2025).

[89] H. Qi et al. *Modeling Climate-Induced Refugee Migration: An Explainable Machine Learning Approach*. Oct. 2024. DOI: 10.21203/rs.3.rs-4931065/v1. URL: https://www.researchsquare.com/article/rs-4931065/v1 (visited on 05/05/2025).

[90] J. A. Quinn et al. "Humanitarian applications of machine learning with remote-sensing data: review and case study in refugee settlement mapping". en. In: *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences* 376.2128 (Sept. 2018), p. 20170363. ISSN: 1364-503X, 1471-2962. DOI: 10.1098/rsta.2017.0363. URL: https://royalsocietypublishing.org/doi/10.1098/rsta.2017.0363 (visited on 04/25/2025).

[91] R. Read, B. Taithe, and R. Mac Ginty. "Data hubris? Humanitarian information systems and the mirage of technology". en. In: *Third World Quarterly* 37.8 (Aug. 2016), pp. 1314–1331. ISSN: 0143-6597, 1360-2241. DOI: 10.1080/01436597.2015.1136208. URL: http://www.tandfonline.com/doi/full/10.1080/01436597.2015.1136208 (visited on 04/23/2025).

[92] F. Rowe. *Using Twitter Data to Monitor Immigration Sentiment*. en. Apr. 2021. DOI: 10.31219/osf.io/sf7u4. URL: https://osf.io/sf7u4 (visited on 05/13/2025).

[93] A. d. N. G. d. Rubalcava et al. *Modeling Population Movements under Uncertainty at the Border in Humanitarian Crises: A Situational Analysis Tool*. arXiv:2303.15614 [cs]. Mar. 2023. DOI: 10.48550/arXiv.2303.15614. URL: http://arxiv.org/abs/2303.15614 (visited on 04/26/2025).

[94] M.-C. Rufener et al. "Estimation of internal displacement in Ukraine from satellite-based car detections". en. In: *Scientific Reports* 14.1 (Dec. 2024), p. 31638. ISSN: 2045-2322. DOI: 10.1038/s41598-024-80035-8. URL: https://www.nature.com/articles/s41598-024-80035-8 (visited on 05/01/2025).

[95] S. A. Rustad et al. *Political Exclusion, Group Inequality and Aid Distribution*. Conflict Trends, Issue 9. 2018. URL: https://www.prio.org/publications/11087.

[96] A. A. Salah et al., eds. *Guide to Mobile Data Analytics in Refugee Scenarios: The 'Data for Refugees Challenge' Study*. en. Cham: Springer International Publishing, 2019. ISBN: 978-3-030-12553-0 978-3-030-12554-7. DOI: 10.1007/978-3-030-12554-7. URL: http://link.springer.com/10.1007/978-3-030-12554-7 (visited on 05/23/2025).

[97] Sarah W. Spencer. "Humanitarian AI: the hype, the hope and the future". en. In: (Nov. 2021).

[98] K. Schewel et al. "How well can we predict climate migration? A review of forecasting models". en. In: *Frontiers in Climate* 5 (Jan. 2024), p. 1189125. ISSN: 2624-9553. DOI: 10.3389/fclim.2023.1189125. URL: https://www.frontiersin.org/articles/10.3389/fclim.2023.1189125/full (visited on 04/25/2025).

[99] S. Schneider. "Anticipatory humanitarian action". en. In: *An Introduction to Humanitarian Action*. 1st ed. London: Routledge, Jan. 2025, pp. 343–362. ISBN: 978-1-003-35027-9. DOI: 10.4324/9781003350279-19. URL: https://www.taylorfrancis.com/books/9781003350279/chapters/10.4324/9781003350279-19 (visited on 04/29/2025).

[100] B. Schwartz. *Sub-national Forecasting*. Accessed: 2025-06-04. 2021. URL: https://github.com/boschwartz/sub-nat-forecasting.

[101] C. Searle and J. Van Vuuren. "Modelling forced migration: A framework for conflict-induced forced migration modelling according to an agent-based approach". en. In: *Computers, Environment and Urban Systems* 85 (Jan. 2021), p. 101568. ISSN: 01989715. DOI: 10.1016/j.compenvurbsys.2020.101568. URL: https://linkinghub.elsevier.com/retrieve/pii/S019897152030301X (visited on 05/02/2025).

[102] V. Sekara et al. "THE OPPORTUNITIES, LIMITATIONS, AND CHALLENGES IN USING MACHINE LEARNING TECHNOLOGIES FOR HUMANITARIAN WORK AND DEVELOPMENT". en. In: *Advances in Complex Systems* 27.03 (May 2024), p. 2440002. ISSN: 0219-5259, 1793-6802. DOI: 10.1142/S0219525924400022. URL: https://www.worldscientific.com/doi/10.1142/S0219525924400022 (visited on 04/23/2025).

[103] R. Sharma and A. Kaur. "A review of technology in supervising the migration management for refugees with special reference to Artificial intelligence and Fog Computing". In: *2024 International Conference on Emerging Innovations and Advanced Computing (INNOCOMP)*. Sonipat, India: IEEE, May 2024, pp. 469–472. ISBN: 979-8-3503-7647-0. DOI: 10.1109/INNOCOMP63224.2024.00082. URL: https://ieeexplore.ieee.org/document/10664063/ (visited on 05/02/2025).

[104] S. Sharmin. "Refugee Resettlement & AI-Powered Resource Allocation Optimizing social services for displaced populations". en. In: ().

[105] L. Singh et al. "Blending Noisy Social Media Signals with Traditional Movement Variables to Predict Forced Migration". en. In: *Proceedings of the 25th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining*. Anchorage AK USA: ACM, July 2019, pp. 1975–1983. ISBN: 978-1-4503-6201-6. DOI: 10.1145/3292500.3330774. URL: https://dl.acm.org/doi/10.1145/3292500.3330774 (visited on 05/05/2025).

[106] Smit Dipeshkumar Khatri. "Deep Learning for Refugee Crisis Management". en. In: (2024). Publisher: Unpublished. DOI: 10.13140/RG.2.2.15706.96967. URL: https://rgdoi.net/10.13140/RG.2.2.15706.96967 (visited on 05/06/2025).

[107] G. Stavropoulos et al. "A Novel Migration Simulation and Prediction Tool". en. In: *Intelligent Technologies and Applications*. Ed. by F. Sanfilippo et al. Vol. 1616. Series Title: Communications in Computer and Information Science. Cham: Springer International Publishing, 2022, pp. 81–92. ISBN: 978-3-031-10524-1 978-3-031-10525-8. DOI: 10.1007/978-3-031-10525-8_7. URL: https://link.springer.com/10.1007/978-3-031-10525-8_7 (visited on 04/25/2025).

[108] Steffen Angenendt and Anne Koch. "Migration forecasting: expectations, limitations and political functions - Forced Migration Review". en. In: (May 2024). URL: https://www.fmreview.org/digital-disruption/#flipbook-fmr-73-digital-disruption-and-displacement/101/.

[109] S. Sulaiman, U. I. Ali, and M. S. Hossen. "A Predictive Model for the Population Growth of Refugees in Asia: A Multiple Linear Regression Approach". en. In: *Journal of Computational and Theoretical Nanoscience* 16.3 (Mar. 2019), pp. 1196–1202. ISSN: 1546-1955. DOI: 10.1166/jctn.2019.8016. URL: https://www.ingentaconnect.com/content/10.1166/jctn.2019.8016 (visited on 05/05/2025).

[110] D. Suleimenova et al. "Sensitivity-driven simulation development: a case study in forced migration". en. In: *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences* 379.2197 (May 2021), rsta.2020.0077, 20200077. ISSN: 1364-503X, 1471-2962. DOI: 10.1098/rsta.2020.0077. URL: https://royalsocietypublishing.org/doi/10.1098/rsta.2020.0077 (visited on 05/24/2025).

[111] D. Suleimenova, D. Bell, and D. Groen. "A generalized simulation development approach for predicting refugee destinations". en. In: *Scientific Reports* 7.1 (Oct. 2017), p. 13377. ISSN: 2045-2322. DOI: 10.1038/s41598-017-13828-9. URL: https://www.nature.com/articles/s41598-017-13828-9 (visited on 04/25/2025).

[112] D. Suleimenova, D. Bell, and D. Groen. “Towards an automated framework for agent-based simulation of refugee movements”. In: *2017 Winter Simulation Conference (WSC)*. Las Vegas, NV: IEEE, Dec. 2017, pp. 1240–1251. ISBN: 978-1-5386-3428-8. DOI: 10.1109/WSC.2017.8247870. URL: http://ieeexplore.ieee.org/document/8247870/ (visited on 05/02/2025).

[113] D. Suleimenova, W. Low, and D. Groen. “An Agent-Based Forced Displacement Simulation: A Case Study of the Tigray Crisis”. en. In: *Computational Science – ICCS 2022*. Ed. by D. Groen et al. Vol. 13353. Series Title: Lecture Notes in Computer Science. Cham: Springer International Publishing, 2022, pp. 83–89. ISBN: 978-3-031-08759-2 978-3-031-08760-8. DOI: 10.1007/978-3-031-08760-8_7. URL: https://link.springer.com/10.1007/978-3-031-08760-8_7 (visited on 05/21/2025).

[114] H. Susmann and A. E. Raftery. *Bayesian Projection of Refugee and Asylum Seeker Populations*. Version Number: 1. 2024. DOI: 10.48550/ARXIV.2405.06857. URL: https://arxiv.org/abs/2405.06857 (visited on 05/08/2025).

[115] L. Thalheimer, E. Simperingham, and E. W. Jjemba. “The role of anticipatory humanitarian action to reduce disaster displacement”. In: *Environmental Research Letters* 17.1 (Jan. 2022), p. 014043. ISSN: 1748-9326. DOI: 10.1088/1748-9326/ac4292. URL: https://iopscience.iop.org/article/10.1088/1748-9326/ac4292 (visited on 04/29/2025).

[116] The GDELT Project. *The GDELT Project*. https://www.gdeltproject.org/. Accessed: 2025-06-06. 2025.

[117] UNHCR. *Jetson Interactive Website*. Accessed: 2025-06-04. 2024. URL: https://jetson.unhcr.org/index.html.

[118] UNHCR. *Jetson Wiki*. Accessed: 2025-06-04. 2020. URL: https://github.com/unhcr/Jetson/wiki.

[119] UNHCR Innovation Service. *Innovation at UNHCR 2019*. Accessed: 2025-05-24. 2019. URL: https://www.unhcr.org/innovation/wp-content/uploads/2019/07/Innovation-at-UNHCR-2019-Web.pdf.

[120] UNHCR Innovation Service. *Project Jetson*. 2019. URL: https://www.unhcr.org/innovation/project-jetson/.

[121] United Nations. *Refugees*. Accessed: 2025-06-09. United Nations. 2024. URL: https://www.un.org/en/global-issues/refugees.

[122] United Nations Department of Economic and Social Affairs. *UN Data*. https://data.un.org/. Accessed: 2025-06-06. 2025.

[123] United Nations Office for Disaster Risk Reduction. *Unveiling the true magnitude of disaster displacement: new tools, more evidence, better policies*. Session at the Global Platform for Disaster Risk Reduction 2019. Geneva, Switzerland, 15–17 May 2019. Organized by the Internal Displacement Monitoring Centre (IDMC). 2019. URL: https://www.unisdr.org/conference/2019/globalplatform/programme/platform/view?id=962.html.

[124] United Nations Office for the Coordination of Humanitarian Affairs. *Humanitarian Data Exchange (HDX)*. https://data.humdata.org/. Accessed: 2025-06-06. 2025.

[125] H. A. Unver. “Using Social Media to Monitor Conflict-Related Migration: A Review of Implications for A.I. Forecasting”. en. In: *Social Sciences* 11.9 (Sept. 2022), p. 395. ISSN: 2076-0760. DOI: 10.3390/socsci11090395. URL: https://www.mdpi.com/2076-0760/11/9/395 (visited on 05/02/2025).

[126] Uppsala Conflict Data Program. *UCDP Data*. https://ucdp.uu.se/. Accessed: 2025-06-06. 2025.

[127] J. Van Den Hoek and H. K. Friedrich. "Satellite-Based Human Settlement Datasets Inadequately Detect Refugee Settlements: A Critical Assessment at Thirty Refugee Settlements in Uganda". en. In: *Remote Sensing* 13.18 (Sept. 2021), p. 3574. ISSN: 2072-4292. DOI: 10.3390/rs13183574. URL: https://www.mdpi.com/2072-4292/13/18/3574 (visited on 05/13/2025).

[128] E. Walk, K. Garimella, and F. Christia. "Displacement and return in the internet Era: Social media for monitoring migration decisions in Northern Syria". en. In: *World Development* 168 (Aug. 2023), p. 106268. ISSN: 0305750X. DOI: 10.1016/j.worlddev.2023.106268. URL: https://linkinghub.elsevier.com/retrieve/pii/S0305750X23000864 (visited on 05/12/2025).

[129] L. Wickert, M. Bogen, and M. Richter. "SUPPORTING THE MANAGEMENT OF HUMANITARIAN OPERATIONS CONCERNING MIGRATION MOVEMENTS WITH REMOTE SENSING". en. In: *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences* XLIII-B3-2020 (Aug. 2020), pp. 233–240. ISSN: 2194-9034. DOI: 10.5194/isprs-archives-XLIII-B3-2020-233-2020. URL: https://isprs-archives.copernicus.org/articles/XLIII-B3-2020/233/2020/ (visited on 04/26/2025).

[130] World Food Programme. *WFP GeoSpatial Data*. https://dataviz.wfp.org/. Accessed: 2025-06-06. 2025.

[131] World Health Organization. *The Global Health Observatory*. https://www.who.int/data/gho. Accessed: 2025-06-06. 2025.

[132] N. Wycoff et al. "Forecasting Ukrainian Refugee Flows With Organic Data Sources". en. In: *International Migration Review* 59.1 (Oct. 2023), pp. 37–60. ISSN: 0197-9183, 1747-7379. DOI: 10.1177/01979183231203931. URL: https://journals.sagepub.com/doi/10.1177/01979183231203931 (visited on 04/30/2025).