AI-enhanced agent-based modelling approach for forced displacement predictions

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Abstract. The increasing occurrence and complexity of forced displacement require robust predictive models to aid humanitarian responses. However, existing predictive models for forced displacement lack accurate and timely data, have gaps in existing datasets, struggle with the unpredictability of human behaviour, do not account for rapidly evolving political and environmental factors and introduce methodological uncertainties. Hence, this paper proposes a theoretical discussion of an artificial intelligence (AI)-enhanced agent-based modelling (ABM) approach to assist effective humanitarian planning and efficient resource allocation. This novel approach aims to predict the movements of internally displaced people and the arrival of forcibly displaced individuals in neighbouring countries. Importantly, it introduces a combination of quantitative models and qualitative insights from expert knowledge, along with humanitarian reports. Our AI-enhanced ABM approach (i) uses an agent-based simulation tool, Flee, incorporating behavioural assumptions and customisable rulesets for scenario modelling, (ii) explores innovative near real-time data sources from geospatial data and social media activity to satellite imagery with AI techniques, and (iii) discusses the ABM model with AI-generated inputs to enhance the granularity, accuracy, and reliability of predictions.

Keywords: Agent-based modelling · Artificial intelligence · Predictive models · Forced displacement

1 Introduction

The global forced displacement crisis has reached unprecedented levels, with over 120 million people forcibly displaced worldwide [1]. This includes refugees, asylum seekers, internally displaced persons (IDPs) and others forced to flee their homes due to conflict, persecution, human rights violations, natural disasters, and climate change. The scale, occurrence and complexity of these movements present significant challenges for humanitarian organisations, hosting countries, and policymakers. Existing predictive approaches, such as traditional statistical methods, simulation models or artificial intelligence (AI) techniques, for

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forced displacement suffer from several critical limitations, such as data gaps, delayed access to timely information, difficulties in modelling human behaviour and decision-making processes, inability to incorporate rapidly evolving political and environmental factors, and methodological uncertainties that undermine prediction accuracy.

This paper addresses these challenges by introducing a theoretical foundation for integrating artificial intelligence (AI)-enhanced agent-based modelling (ABM) to predict forced displacement patterns. Our approach aims to predict both internal and cross-border displacement movements by integrating quantitative data with qualitative insights from expert knowledge and humanitarian reports. Moreover, it will (i) use the Flee agent-based simulation tool [2,3,4], incorporating behavioural assumptions and customisable rulesets for scenario modelling, (ii) examine innovative near real-time data from diverse sources including geospatial information, social media activity, and satellite imagery using AI techniques, and (iii) discuss Flee using AI-generated inputs to improve the granularity, accuracy, and reliability of displacement predictions. The following sections explore existing predictive models, introduce the Flee simulation tool, propose AI techniques for innovative data sources, and present an implementation strategy for refining ABM using AI-generated inputs.

2 Related Work

Statistical models of forced displacement typically use regression analysis to identify correlations between displacement flows and explanatory variables, grounded in migration theories emphasising "push" and "pull" factors [5]. Models like the Displacement Tracking Matrix by the International Organization for Migration [6] forecast displacement based on conflict events and migration drivers. While offering interpretability, they face limitations [7]. Many rely on linearity assumptions that do not reflect complex dynamics of displacement patterns. Their dependence on historical patterns makes them vulnerable when confronted with novel crises, and data quality issues present major challenges as displacement data from conflict zones often suffer from missing values [8], reporting biases, and inconsistent collection methodologies.

Agent-based models simulate interactions of autonomous agents operating within a defined environment. In forced displacement contexts, ABMs typically model how people make decisions based on perceived threats, available resources, social networks, and information flows. They capture micro-level dynamics driving displacement decisions [9], revealing emergent patterns that arise from micro-level interactions [10]. ABMs offer scenario testing capabilities, allowing analysts to explore "what-if" scenarios in virtual environments [11]. Their spatial explicitness enables incorporation of geographical information and movement constraints. However, ABMs present significant challenges, requiring extensive data for parameterisation and validation, heavy computational requirements, calibration challenges [12], validation difficulties, and scalability issues [13]. Several ABMs exist in the forced displacement field, including the Flee simulation

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tool [2,3,4], the MASON Refugee model [14], the Burundi Population Model [15], and SimMigration [16].

AI techniques are increasingly deployed to predict forced displacement trends. Machine learning (ML) techniques identify patterns in data without explicit programming, including supervised learning, unsupervised learning, and deep learning. Unlike traditional statistical methods, ML models can capture complex, non-linear relationships between variables and integrate diverse data types [17,18]. Their adaptability enables continuous learning and adjustment to new patterns, and they can use non-traditional data streams offering potential for early warning [19]. Challenges include limited interpretability, data biases, substantial data requirements, overfitting concerns, and high computational needs [20,21]. Examples include UNHCR's Jetson Project [22], IDMC's Disaster Displacement Risk Model [23], IBM's Refugee and Migration Predictive Analytics [24], and DRC's Mixed Migration Foresight model [25].

Statistical models, ABMs and AI techniques offer distinct advantages while introducing significant limitations. Thus, there is a compelling case for using the interpretability and theoretical foundations of statistical models, the granular decision-making insights of ABMs, and the pattern recognition capabilities of AI, to produce more robust and comprehensive predictions for understanding and responding to forced displacement crises.

3 Methodology

3.1 The Flee Agent-based Simulation Tool

The foundation of our approach is the Flee agent-based simulation tool [2,3,4], which is supported by a generalised simulation development approach (SDA) and developed to predict the distribution of incoming forced displacement, who fled because of war, persecution and/or political instability, across destination camps in neighbouring countries [26,27]. In Flee, forcibly displaced people (i.e., agents) make movement decisions based on a combination of factors, including conflict intensity, geographical distance, border constraints, and the presence of designated camps or safe locations. It implements a network-based representation of the geographical information where displacement occurs. The model comprises several interconnected core components forming a comprehensive simulation environment, including locations (nodes representing conflict locations, interconnecting towns, camps in neighbouring countries, and border crossings), routes (edges with attributes like distance and speed), agents (individuals making displacement decisions), and temporal and spatial conflict data.

Agents in the Flee code operate according to a set of behavioural rules that determine their movement decisions across the network defined from statistical analysis of displacement data. Safety-seeking behaviour forms the foundation of agent decision-making, as individuals prioritise movement away from conflict locations. When multiple safe destinations are available, agents use distance optimisation strategies, generally preferring shorter routes to minimise travel

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risks and resource expenditure. The model accounts for the significant pull factor of established camps and safe locations, and international borders are modelled with nuanced border effects that may either impede or facilitate cross-border movement.

3.2 AI Techniques for Innovative Data Sources

Our proposed approach includes AI techniques to analyse innovative near real-time data from diverse sources, addressing critical limitations regarding data availability and comprehensiveness. We suggest using multiple complementary data streams to overcome data limitations. Geospatial data forms a critical foundation, including satellite imagery for infrastructure status monitoring, population density changes, and identification of displacement camps. Social media activity provides valuable near real-time insights through text, images, and location data indicating emerging crises and movement patterns (i.e., a "digital footprint" of displacement [17]). Structured and unstructured information from news reports contributes essential context about conflict events, policy changes, and humanitarian responses. When available and ethically sourced, anonymised mobile phone data through call detail records offers insights into population movements [18]. Remote sensing expands the framework's capabilities by incorporating environmental data including weather patterns, flooding, drought conditions, and other natural hazards.

AI techniques to process these data sources include computer vision with deep learning for satellite imagery analysis, natural language processing for textual data analysis, unsupervised learning for anomaly detection, spatiotemporal pattern mining using RNNs and temporal convolutional networks, and integration of multiple data streams through attention-based architectures.

3.3 Integration of AI Techniques with ABM

Our AI-enhanced ABM approach introduces in the integration of AI-generated insights with the Flee agent-based code to enhance prediction granularity, accuracy, and reliability. It operates as a cyclical process that continuously refines displacement predictions through iterative improvement. The process begins with initial ABM parameterisation, where the Flee model is configured using historical data and expert knowledge about the region of interest, establishing a baseline that incorporates known displacement patterns and contextual factors. This foundation is then enhanced through continuous statistical and AI analysis, with ongoing processing of near real-time data sources generating insights about emerging patterns that might not be captured in historical data or expert assumptions. These insights feed into dynamic parameter updating, where AI-derived information updates the ABM parameters, including conflict intensity, route accessibility, and border permeability (i.e., a "learning system" that adapts to changing circumstances [9]). The updated ABM then generates refined predictions at multiple geographical scales, providing decision-makers with improved predictions that incorporate both structural understanding and emerging

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insights (see a potential implementation strategy of AI-enhanced Flee integration in Table 1).

Table 1. AI-enhanced Flee integration pathways

AI component	Data sources	AI techniques	Integration with Flee	Expected impact
Conflict intensity mapping	ACLED database, news reports, social media	NLP, temporal trend analysis	Updates conflict intensity parameters at locations	Improves push factors in agent decision-making, more accurate conflict behaviour
Route accessibility analysis	Satellite imagery, infrastructure reports	CNN for damage detection, change detection algorithms	Updates route traversability parameters between locations	More realistic movement constraints, better prediction of movements
Border permeability assessment	Border policy documents, news reports, social media	NLP for policy extraction, sentiment analysis	Updates border crossing parameters	More accurate cross-border movement predictions
Behavioural rule adjustment	Historical movement data, survey data	Reinforcement learning, pattern mining	Updates agent decision-making rules	More realistic agent behaviour and patterns

3.4 Potential application to the Ukraine Conflict

Our approach offers significant potential for modelling displacement patterns in the Ukraine conflict, which presents unique characteristics: rapidly changing conflict lines, seasonal patterns related to weather conditions, complex border policies across multiple neighbouring countries, and high digital connectivity among the affected population.

The high rate of smartphone ownership and social media usage in Ukraine provides rich data streams for the AI component, while the European context offers comprehensive satellite coverage and weather data (see Figure 1). Specific data sources identified for the Ukrainian conflict include the International NGO Safety Organisation (INSO) [29], Humanitarian Data Exchange (HDX) platform [30], Climate Change AI repository [31], Copernicus Emergency Management Service [32], Google Trends [33], GDELT Project [34], Facebook's Data for Good initiative [35], and Ushahidi crowdsourcing [36].

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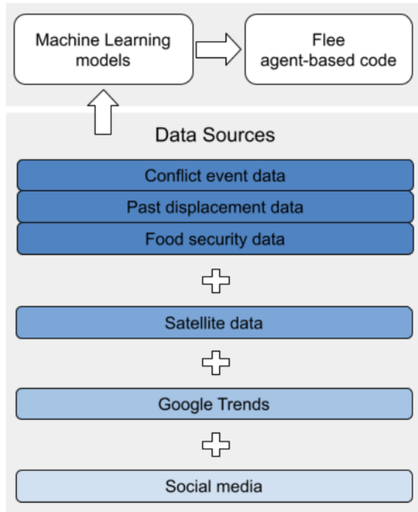

Fig. 1. An overview of the proposed AI-enhanced Flee approach for the Ukrainian conflict.

4 Conclusions

Our theoretical integration of AI with ABMs offers a promising approach for forced displacement prediction, addressing critical limitations of existing methods. This approach enhances behavioural complexity modelling by capturing nuanced individual decision-making while using AI-derived insights to continuously refine behavioural rules. The dynamic adaptation capabilities enable response to evolving situations rather than relying solely on historical patterns, particularly valuable in novel crisis contexts.

For humanitarian organisations, our approach offers practical benefits addressing operational challenges, such as resource allocation optimisation through more accurate predictions, early warning system enhancement via diverse data integration, scenario planning capabilities supporting evidence-based decision-making, improved cross-border coordination through transnational movement predictions, and micro-level predictions informing critical infrastructure decisions. This optimisation is particularly critical given the chronic funding shortfalls facing humanitarian operations worldwide [37].

While representing significant advancement, several research avenues remain including developing more interpretable AI components to increase practitioner trust [20], emphasising participatory modelling approaches incorporating perspectives of displaced people, and enhancing ethical protocols for responsible AI use in humanitarian contexts, particularly regarding privacy, consent, and data governance in crisis settings [38].

As forced displacement continues to affect millions worldwide, the need for accurate, timely, and granular predictive tools becomes increasingly urgent. Our

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AI-enhanced ABM approach provides a promising path forward, enabling humanitarian organisations to anticipate needs, allocate resources efficiently, and ultimately provide better protection and assistance to displaced populations.

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