UNHCR Technical Workshop: Predictive Analytics in Humanitarian Contexts

Online Workshop – CLIFDEW GRID

March, 27th

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CLIFDEW-GRID: Early Warning Grid-Based Risk Modelling of Climate Induced Forced Displacement

Technical workshop: 27 March 2025

Data Science Team
Statistics, Data Science, and Survey Section
Global Data Service

Background

Background: project overview

Aims and Goals

Aim

Risk index for forced displacement

- Subnational (grid cell) level
- Monthly frequency

Case area

East, Central, and West Africa

Goal

Early Warning Model and Insights

- Provide UNHCR and other humanitarian agencies and stakeholders with a tool for anticipatory action relating to forced migration, taking climate change into account.
- Create deeper insights into the nexus between climate change and forced displacement.

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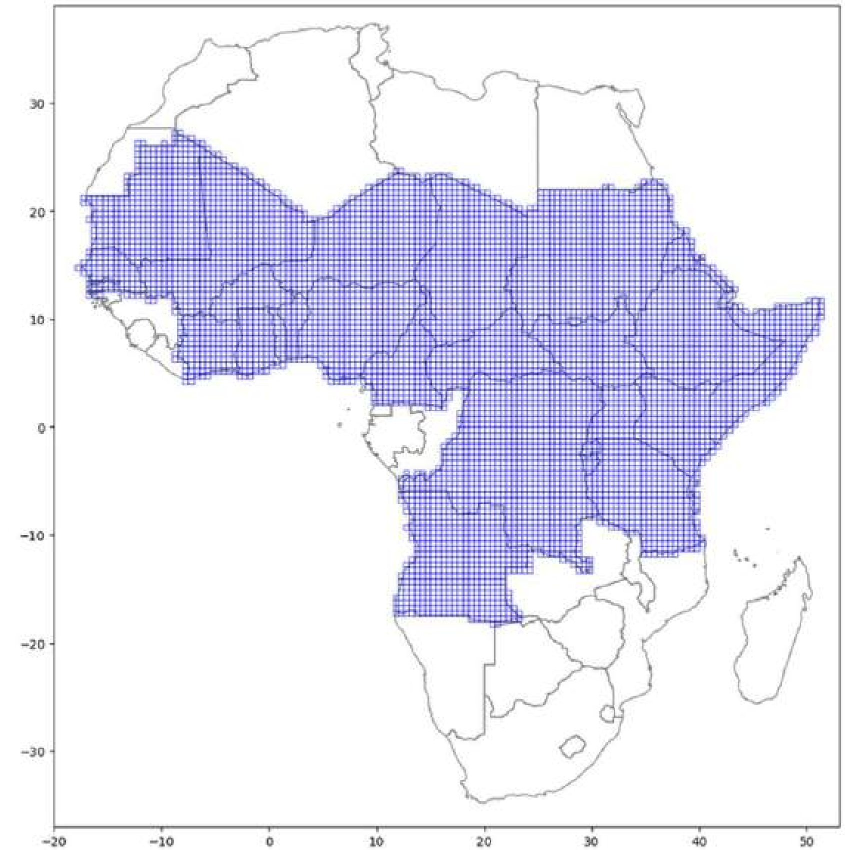
Geographical focus

- East, Central and West Africa
- 0.5° grid-cells (approx. 55 km x 55km)
- Approx. 6220 grid-cells



Geographical focus

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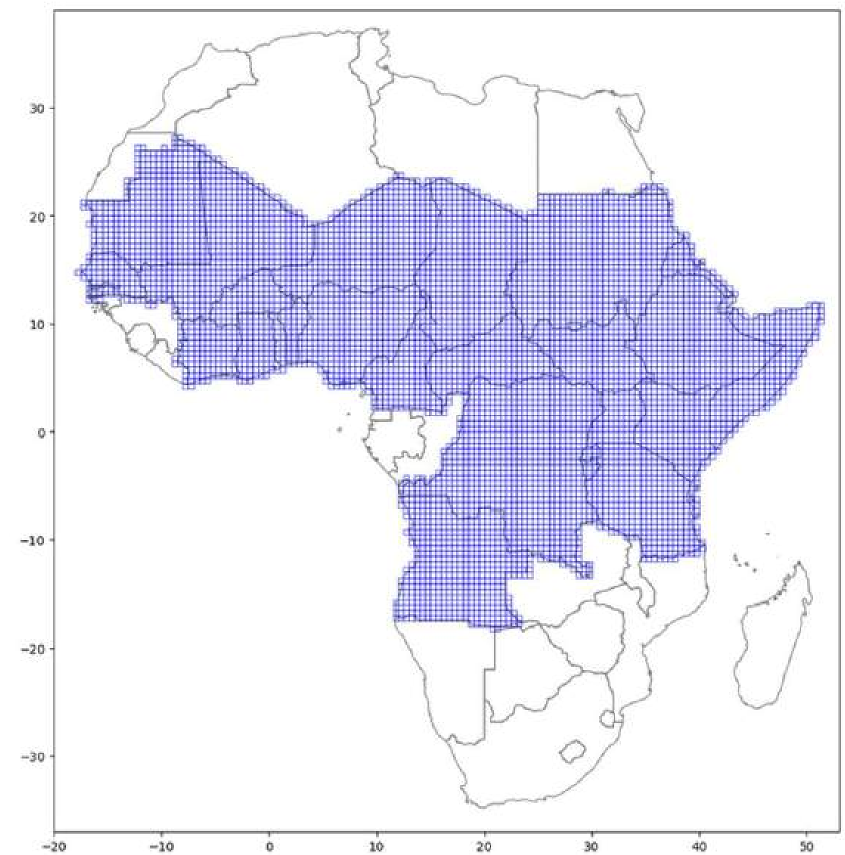
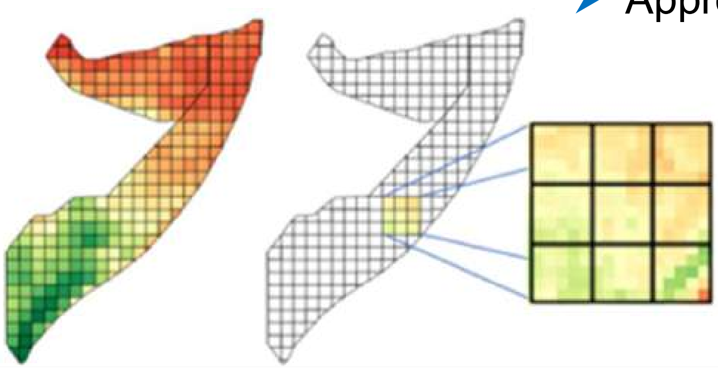


- Feature variable data collected at the 0.1° grid-cell level to account for variance
- Approx. 150,000 grid cells



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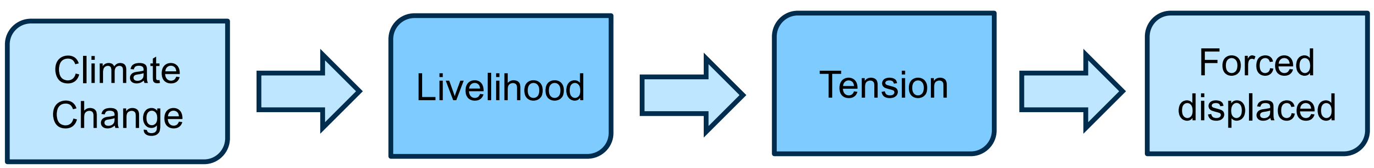
Project structure

Hypothesis

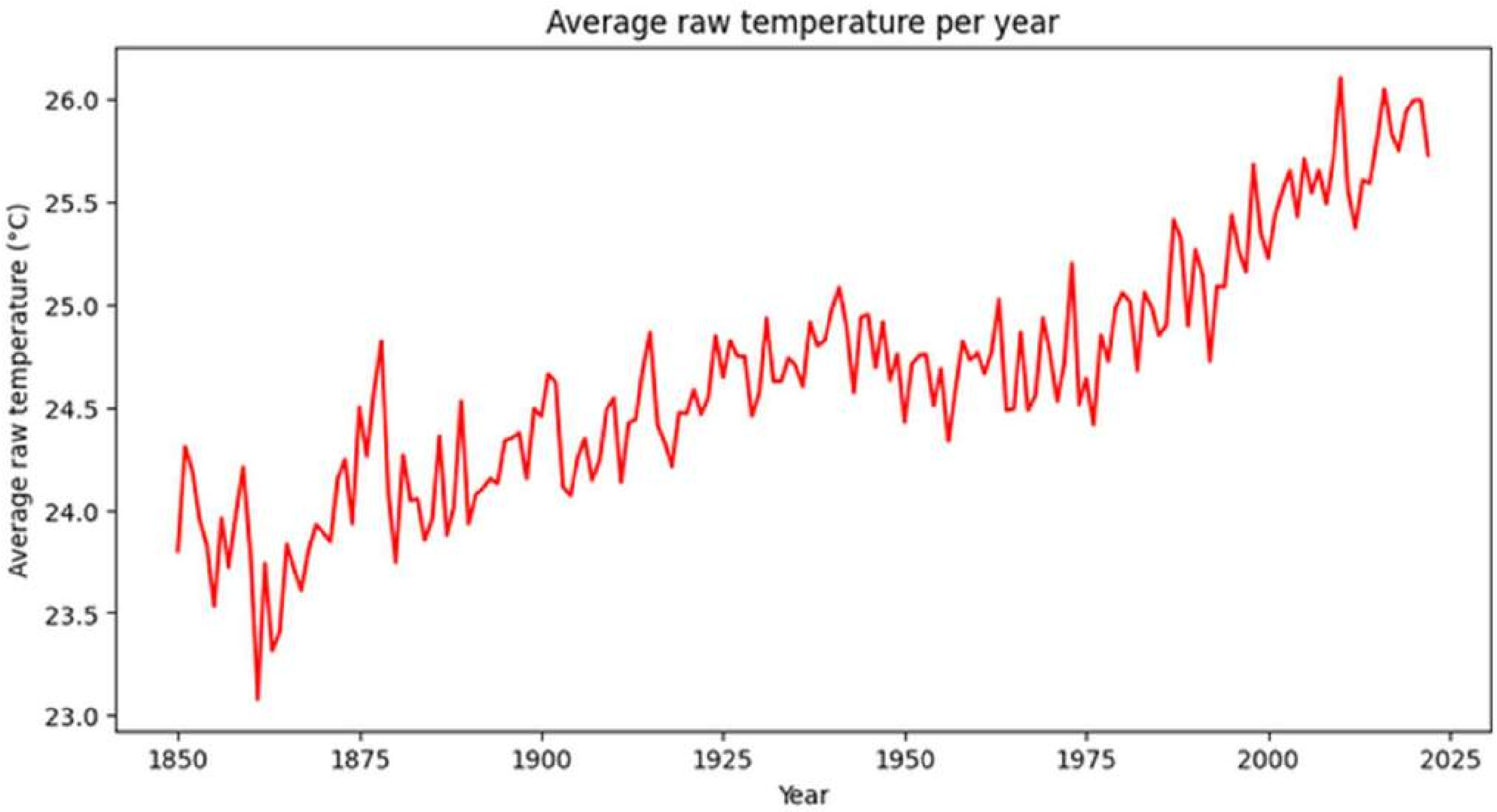
Modelling structure

- Slow on-set climate change generates loss of livelihood.
- Loss of livelihood can lead to competition over diminishing resources, resulting in political tension.
- Conflict contributing to forced displacement.

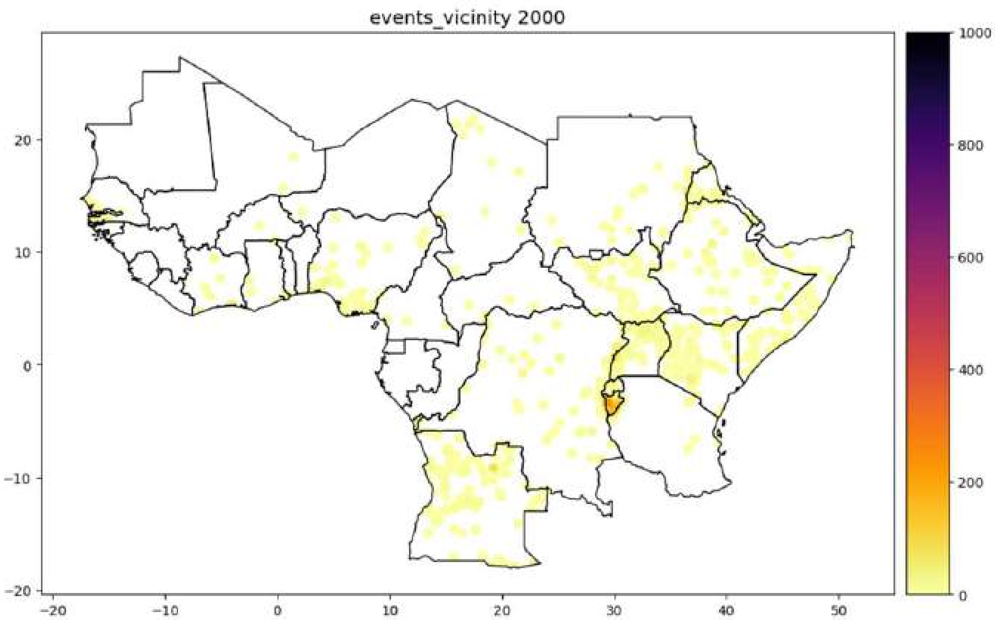


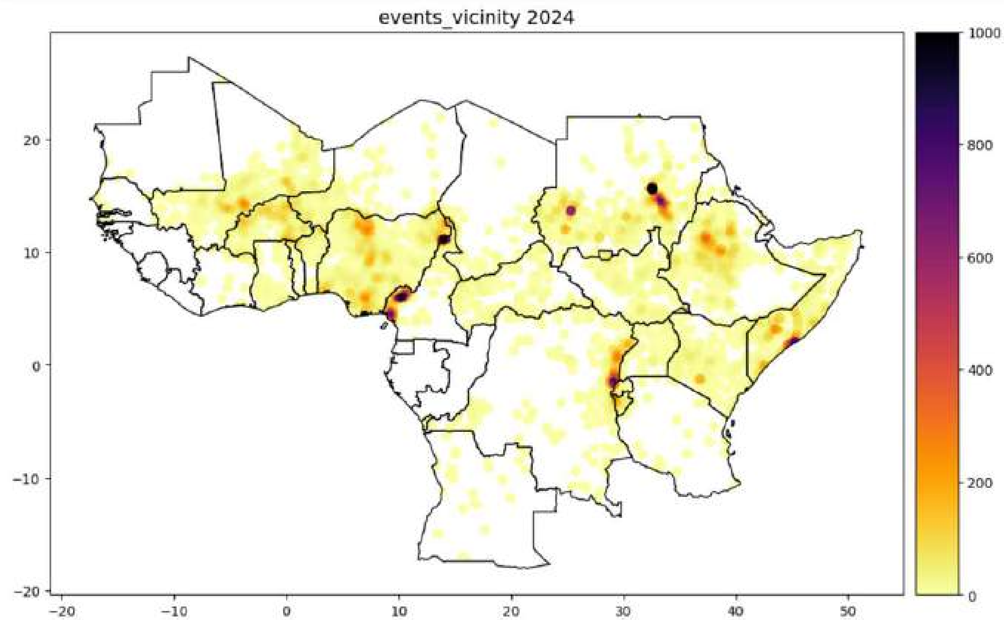
Feature variables

Climate conditions: temperature over time



Tension: conflict



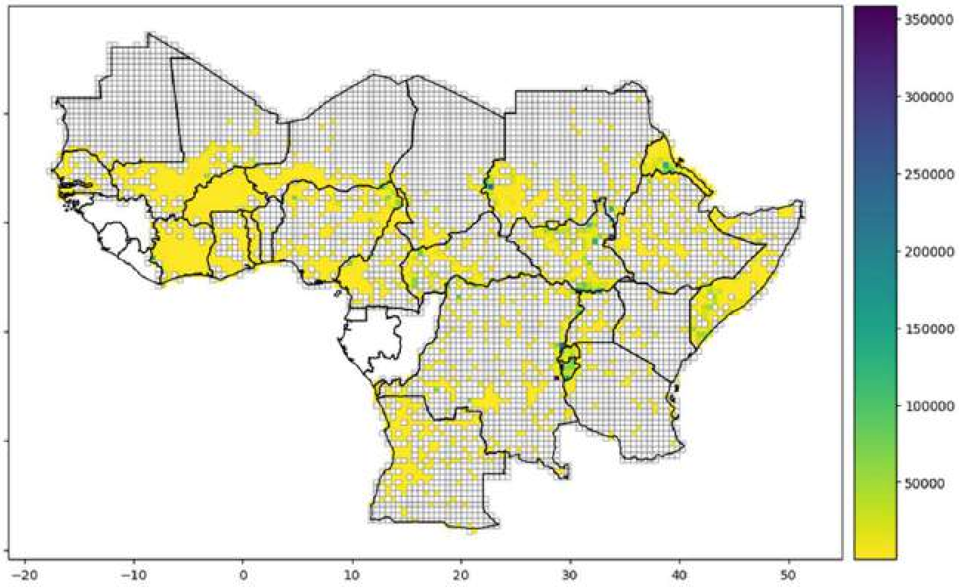


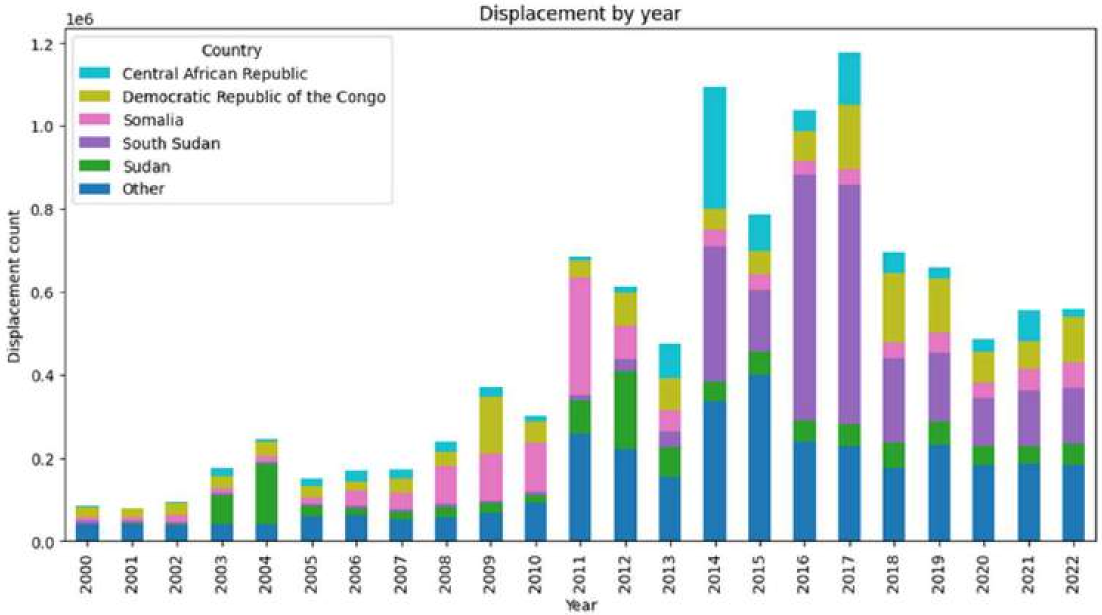
Conflict variables

- Event types: events, new event, social tension
- Severity: fatalities
- Groups: state violence, political militia, extremist, separatist, identity militia, rebel group
- Targets: civilian targeting

Target variable

Target: displacement





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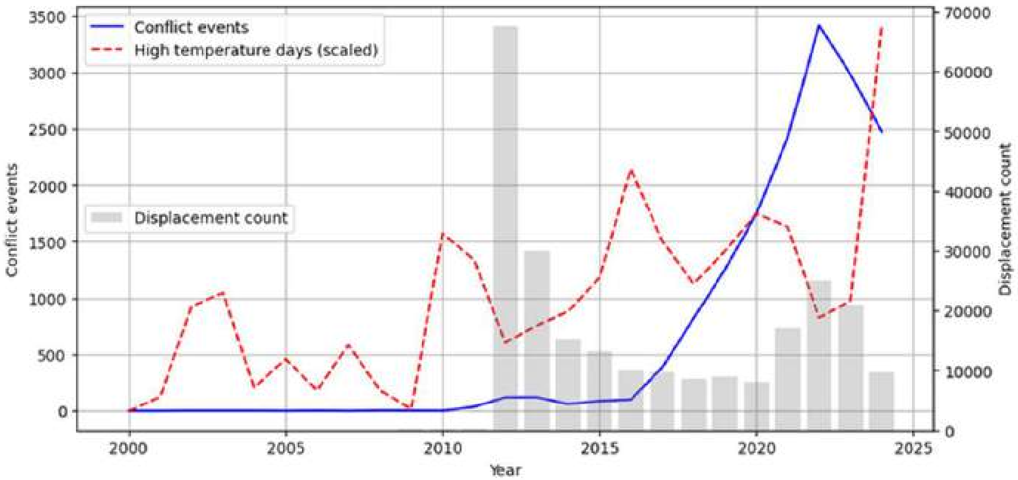
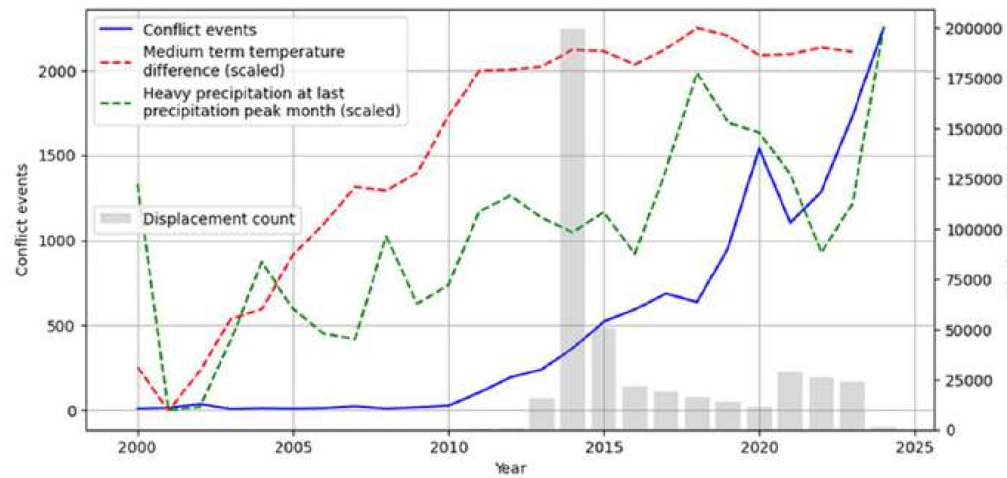
Target: displacement

Liptako-Gourma (Mali, Burkina Faso, Niger)



Lake Chad



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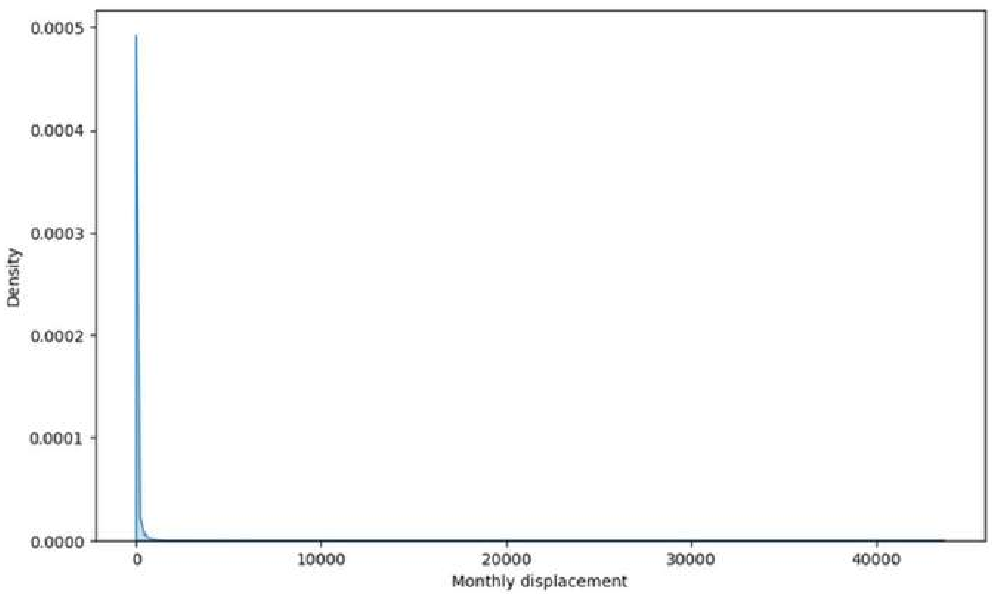
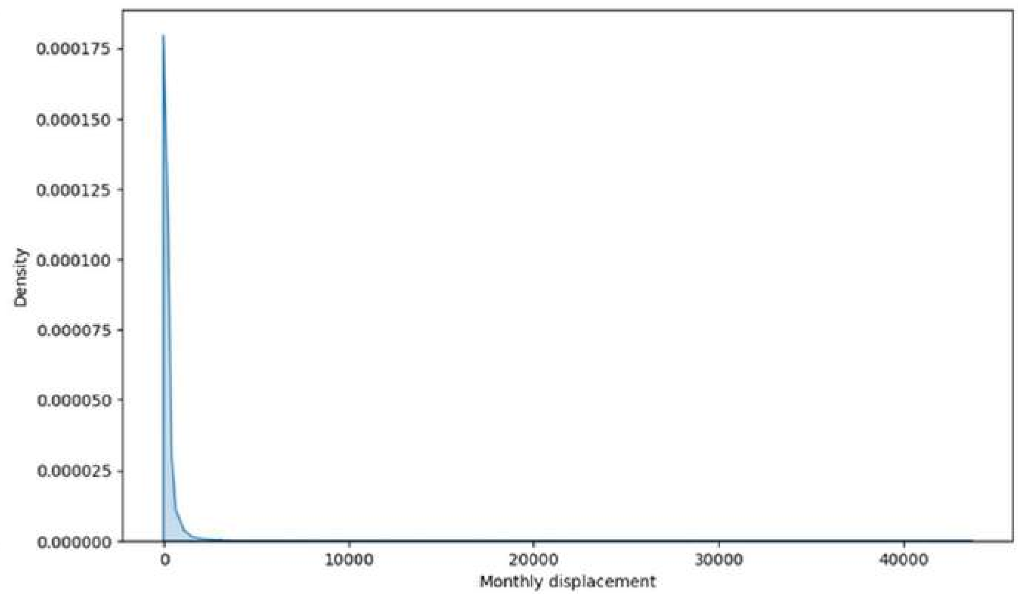
Target: displacement

- Goal: predict the risk of displacement up to 6 months in advance
- Limit data to only grid cells that have historically experienced at least some displacement
    - 1785 of 6221 grid cells

Kernel density monthly displacement, all observations



Kernel density monthly displacement, reduced observations



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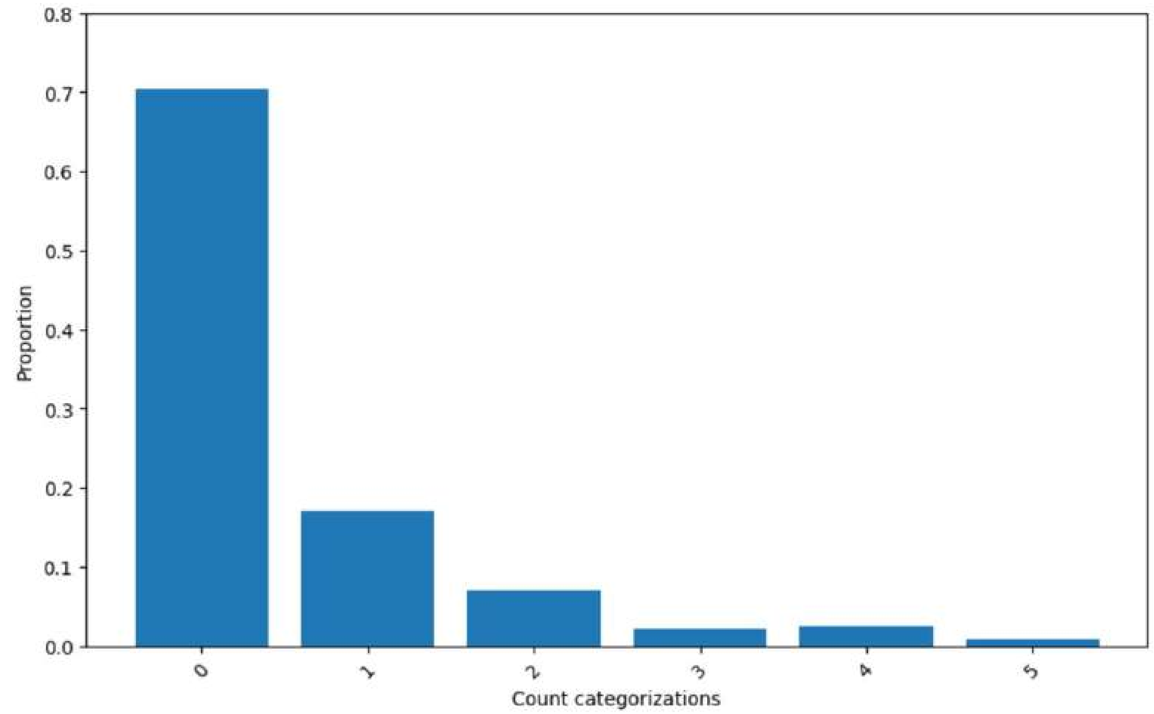
Target variable

- Goal: predict the risk of displacement up to 6 months in advance
- Limit data to only grid cells that have historically experienced at least some displacement
  - 1785 of 6221 grid cells

- Target variable:
  - Categorization of monthly displacement counts:
    - 0: 0
    - 1: 1-10
    - 2: 11-50
    - 3: 51-100
    - 4: 101-500
    - 5: >500



Predicting Forced Displacement Risk

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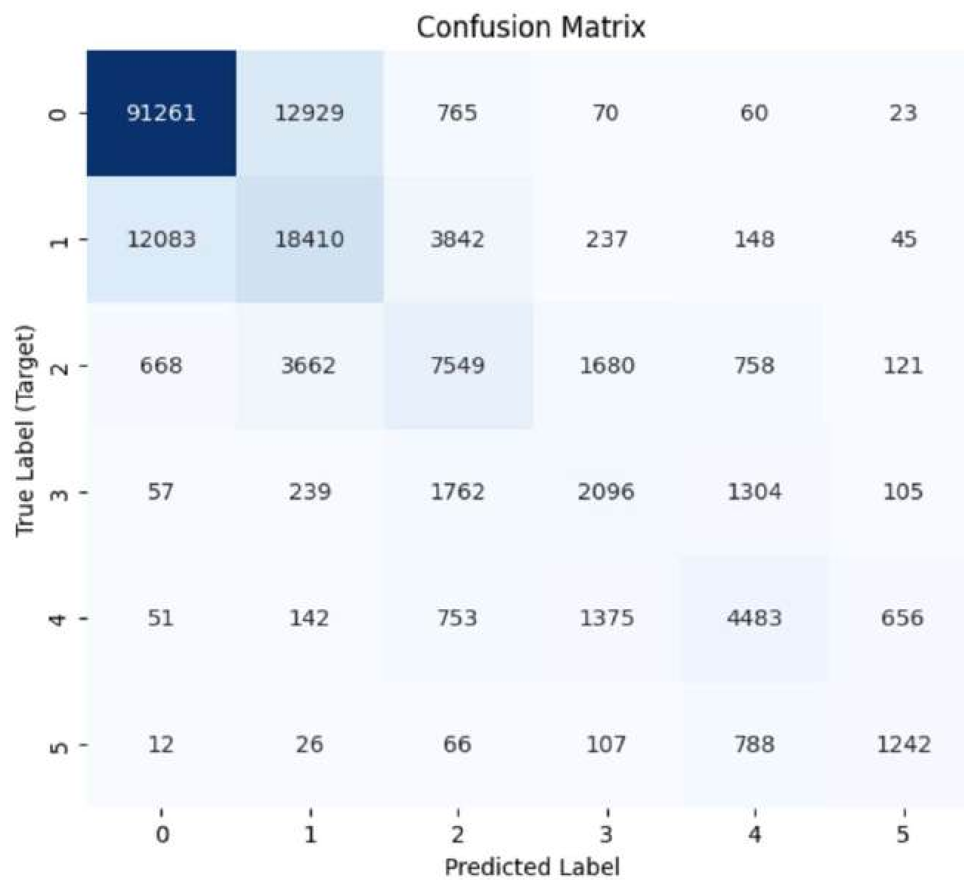
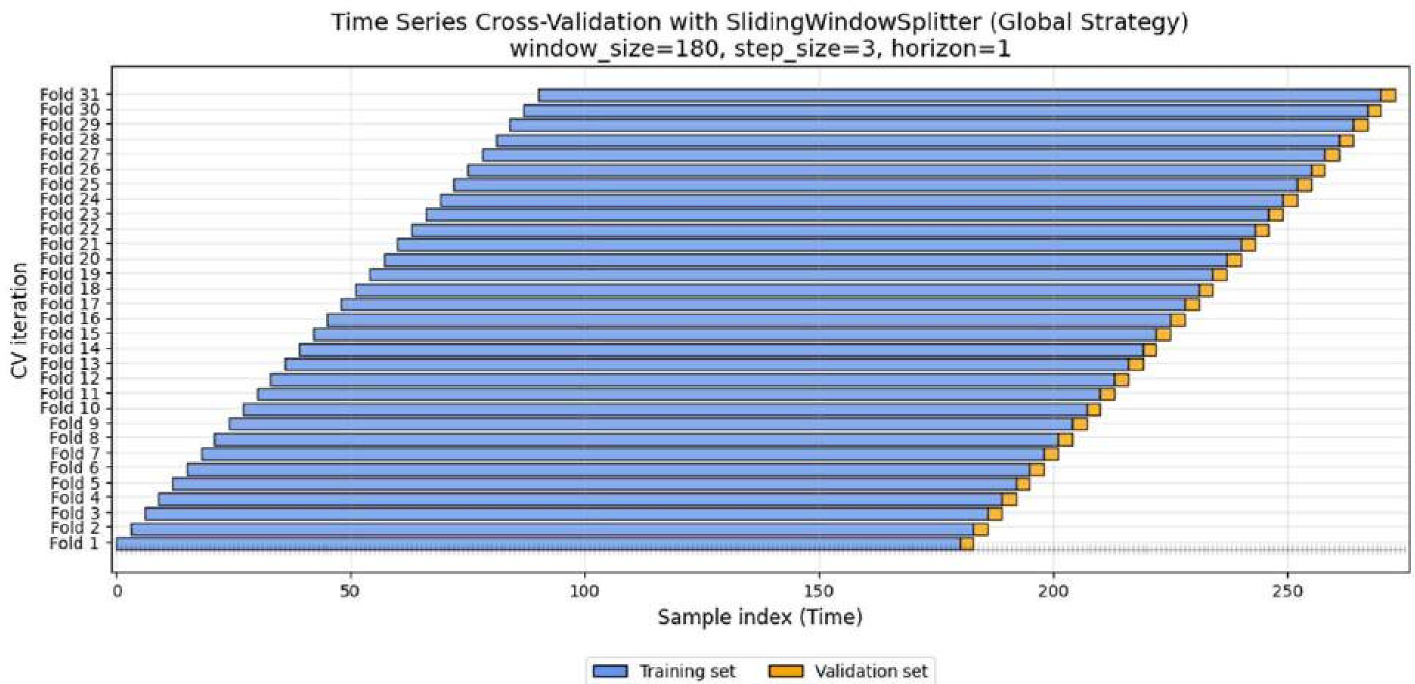
Baseline model

- Last observation carried forward (LOCF)

- Ability of current count categorization to predict count categorization in 6 months
- Performance:
    - Accuracy: 0.7374
    - Precision: 0.7354
    - Recall: 0.7374
    - **F1: 0.7364**

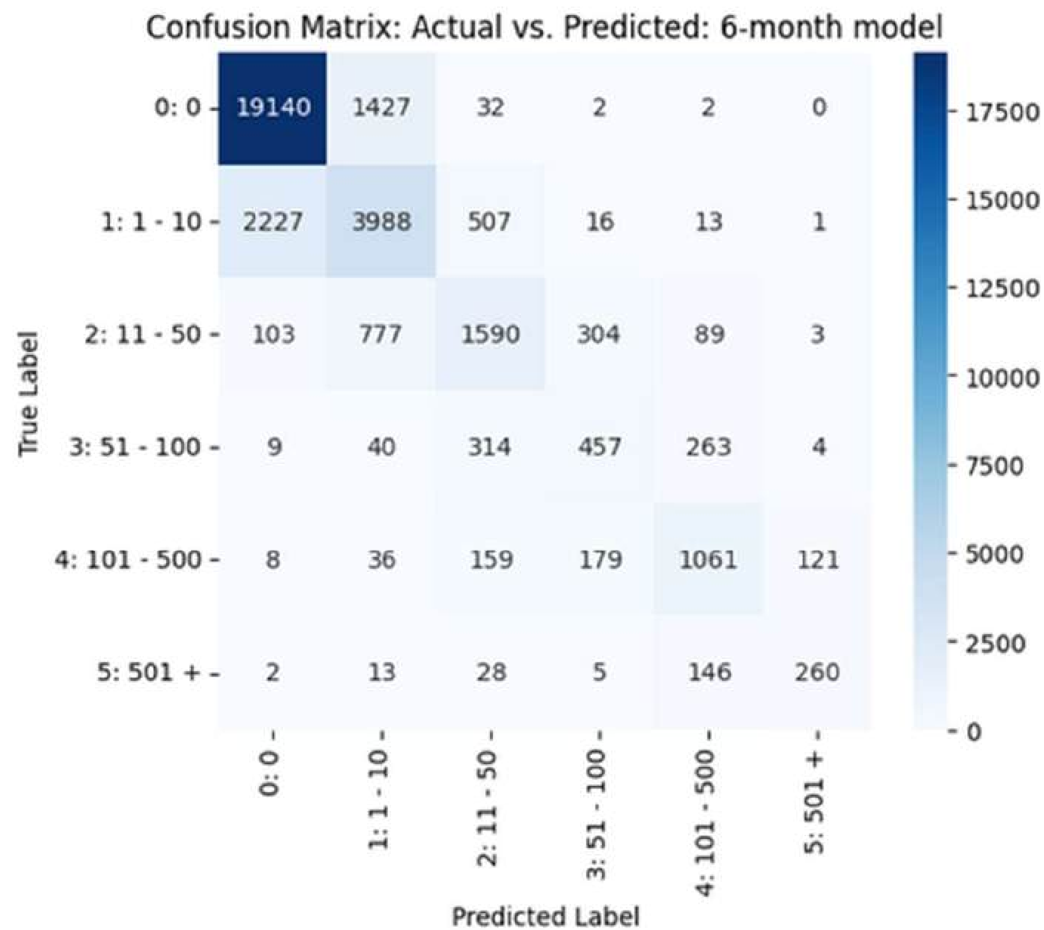


Cross-validation technique



Forecasting model

- Include climate, conflict and demographic variables
- Light Gradient-Boosting Machine (GBM)
  - Tree-based forecasting
  - Training period: 2001/06 – 2020/12
  - 15-year window
  - Fold every 3 months
- Performance:
  - Accuracy: 0.7951
  - **Precision: 0.7875**
  - **Recall: 0.7951**
  - **F1: 0.7917**



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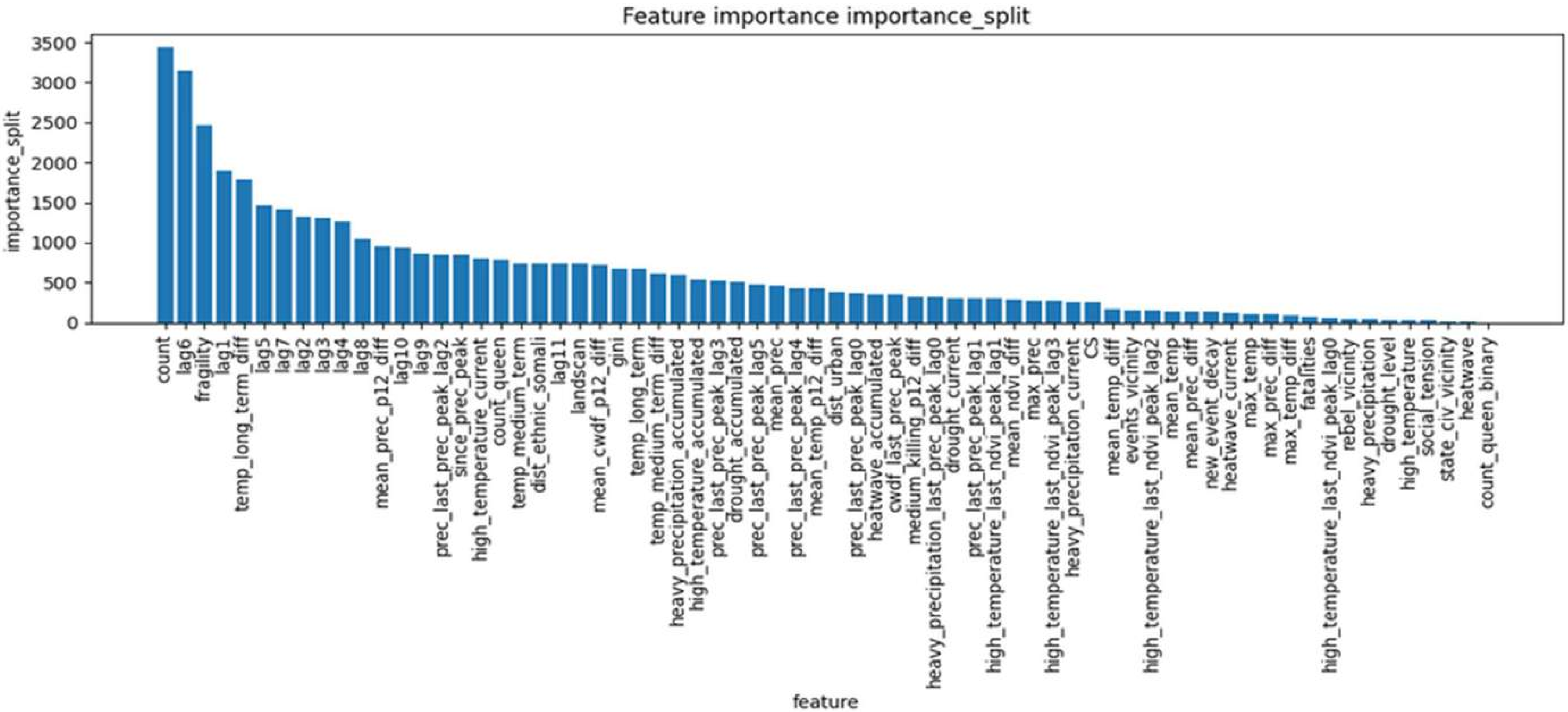

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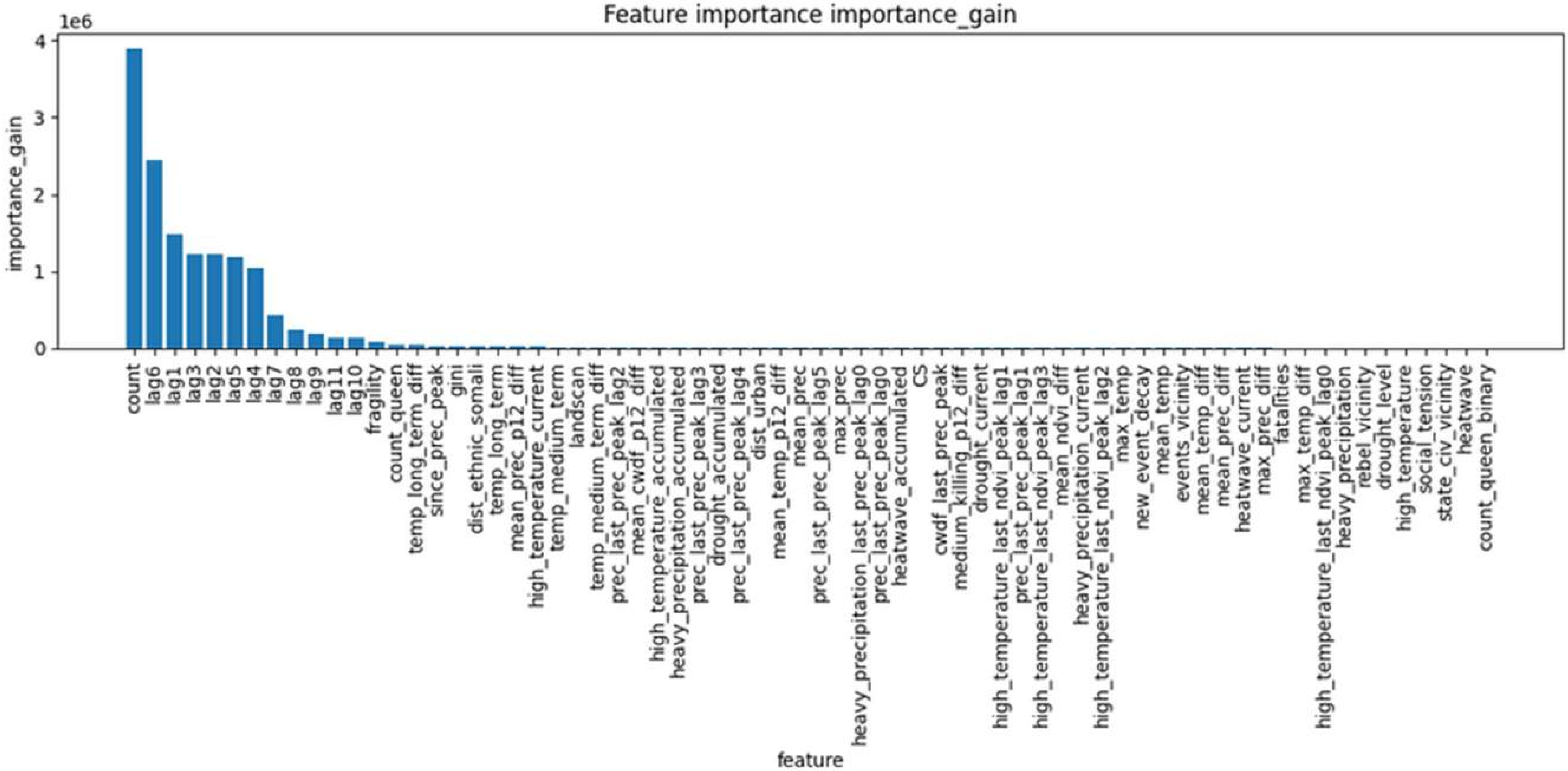
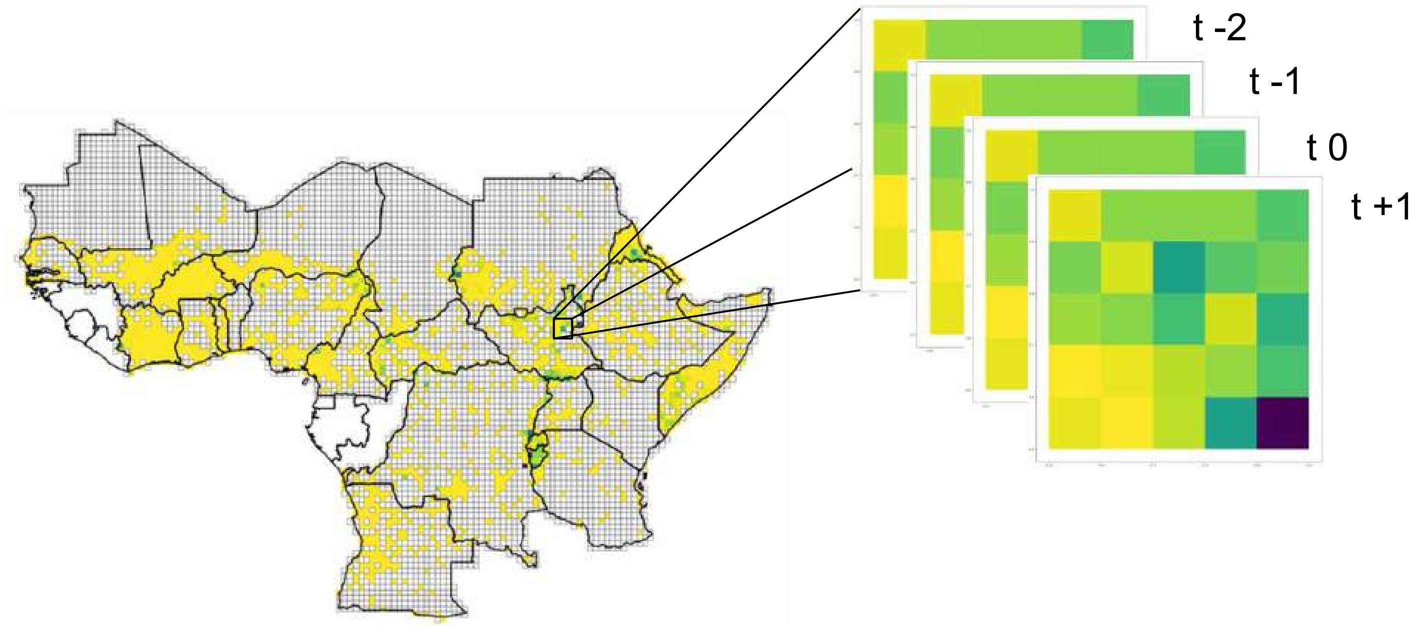
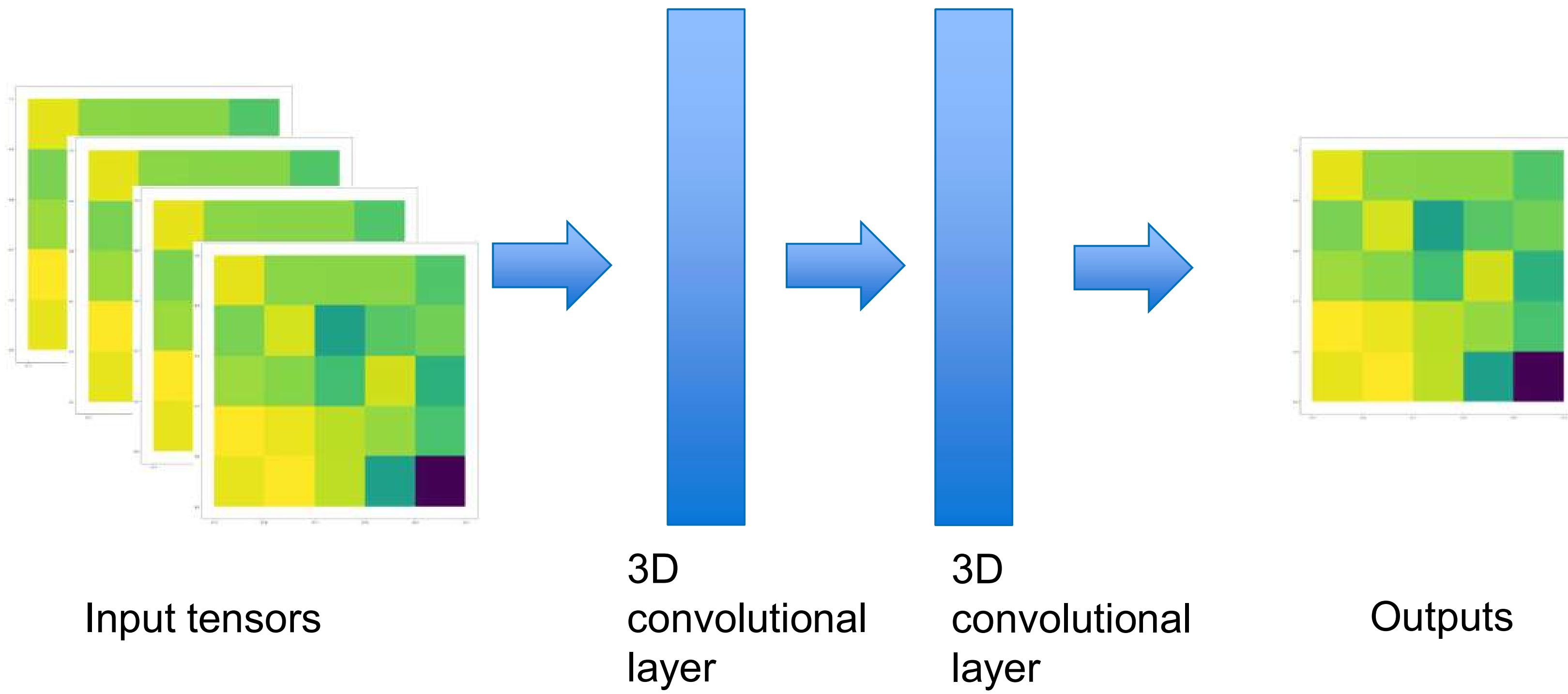


Feature importance importance_gain
1e6
importance_gain
feature
count
lag6
lag1
lag3
lag2
lag5
lag4
lag7
lag8
lag9
lag11
lag10
fragility
count_queen
temp_long_term_diff
since_prec_peak
gini
dist_ethnic_somali
temp_long_term
mean_prec_p12_diff
high_temperature_current
temp_medium_term
landscan
temp_medium_term_diff
prec_last_prec_peak_lag2
mean_cwdf_p12_diff
high_temperature_accumulated
heavy_precipitation_accumulated
prec_last_prec_peak_lag3
drought_accumulated
prec_last_prec_peak_lag4
dist_urban
mean_temp_p12_diff
mean_prec
prec_last_prec_peak_lag5
max_prec
heavy_precipitation_last_prec_peak_lag0
prec_last_prec_peak_lag0
heatwave_accumulated
CS
cwdf_last_prec_peak
medium_killing_p12_diff
drought_current
high_temperature_last_ndvi_peak_lag1
prec_last_prec_peak_lag1
high_temperature_last_ndvi_peak_lag3
mean_ndvi_diff
heavy_precipitation_current
high_temperature_last_ndvi_peak_lag2
max_temp
new_event_decay
mean_temp
events_vicinity
mean_temp_diff
mean_prec_diff
heatwave_current
max_prec_diff
fatalities
max_temp_diff
high_temperature_last_ndvi_peak_lag0
heavy_precipitation
rebel_vicinity
drought_level
high_temperature
social_tension
state_civ_vicinity
heatwave
count_queen_binary

Data structure



Convolutional neural network (CNN)

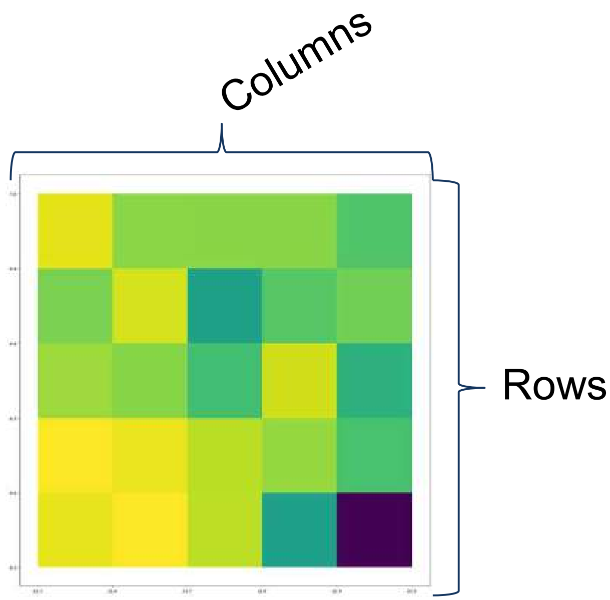


Convolutional long short-term memory (ConvLSTM)

Tensor set-up

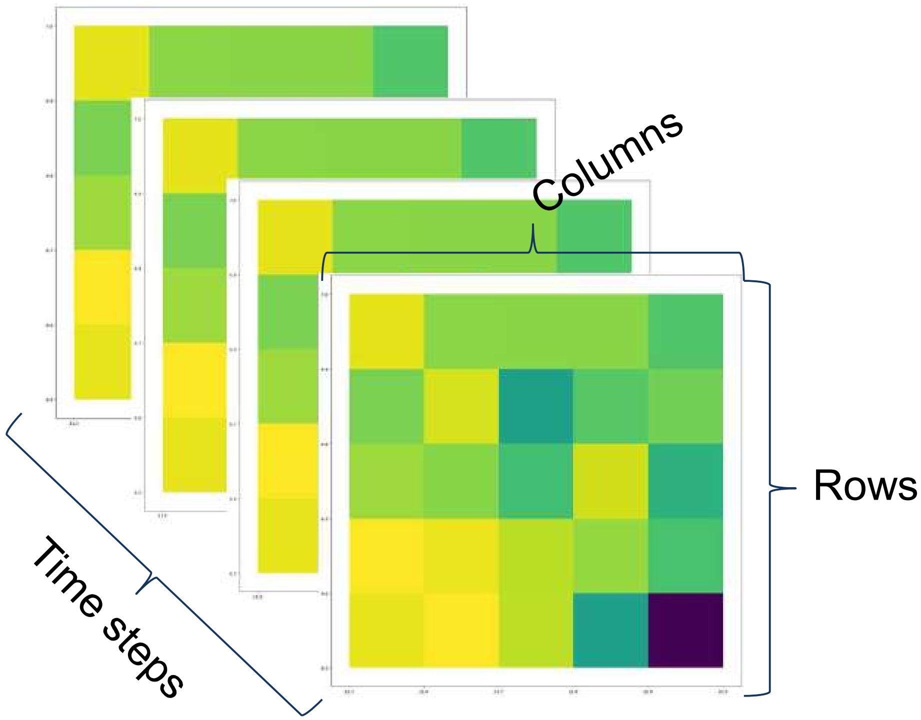
Tensors for ConvLSTMs are 5-dimensional:

1. Rows
2. Columns



Convolutional long short-term memory (ConvLSTM)
Tensor set-up

Tensors for ConvLSTMs are 5-dimensional:
1. Rows
2. Columns
3. Time steps



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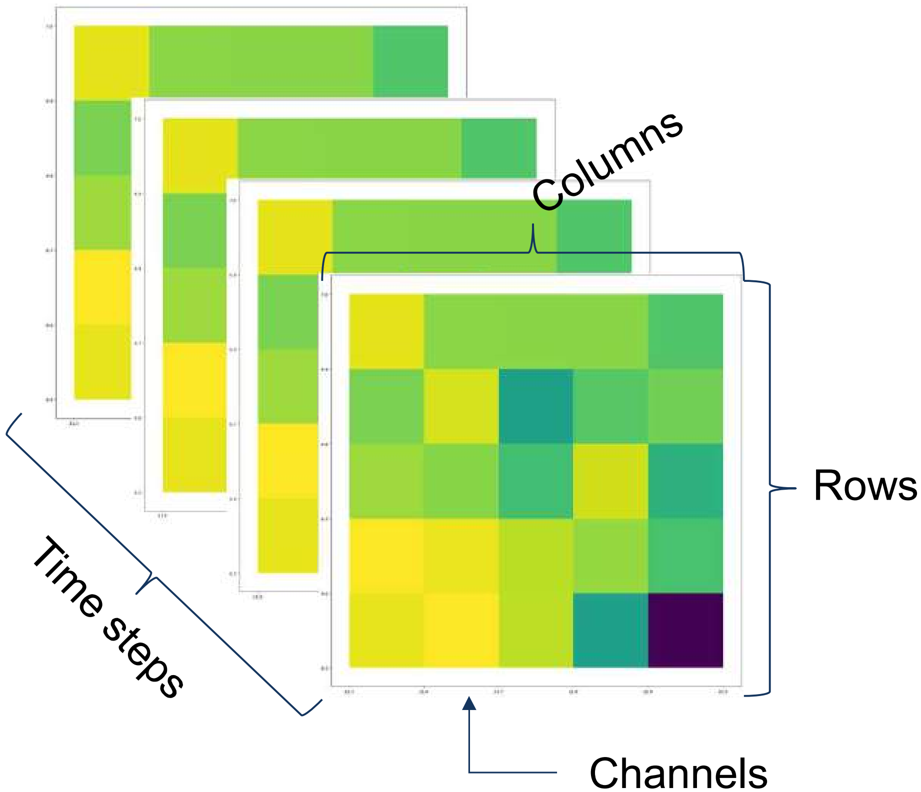
Convolutional long short-term memory (ConvLSTM)

Tensor set-up

Tensors for ConvLSTMs are 5-dimensional:

1. Rows
2. Columns
3. Time steps
4. Channels (features)
5. Batch size



Convolutional long short-term memory (ConvLSTM)

- ConvLSTM is a type of recurrent neural network for spatio-temporal prediction
- Convolutional structures in both the input-to-state and state-to-state transitions.
- The ConvLSTM determines the future state of a certain cell in the grid by the inputs and past states of its local neighbors.

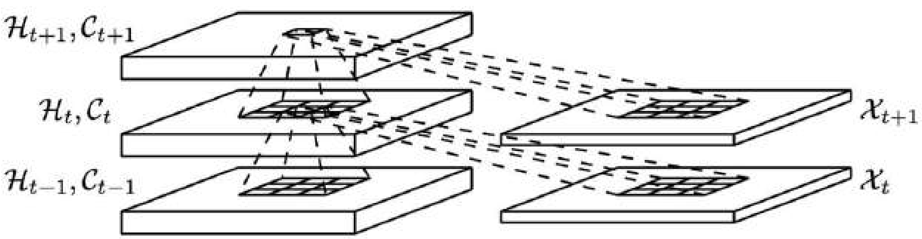
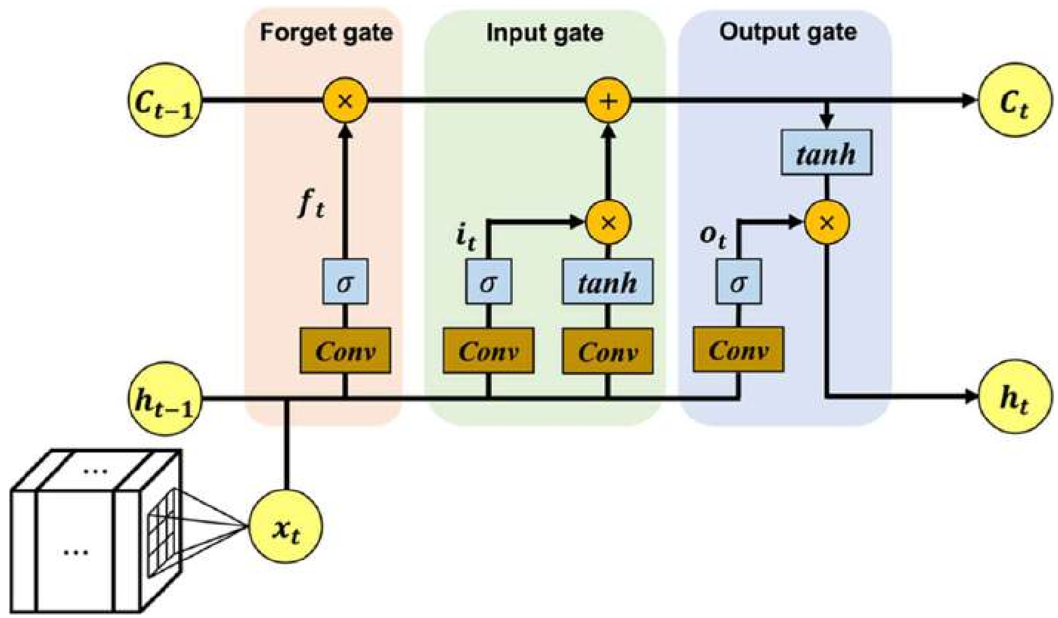
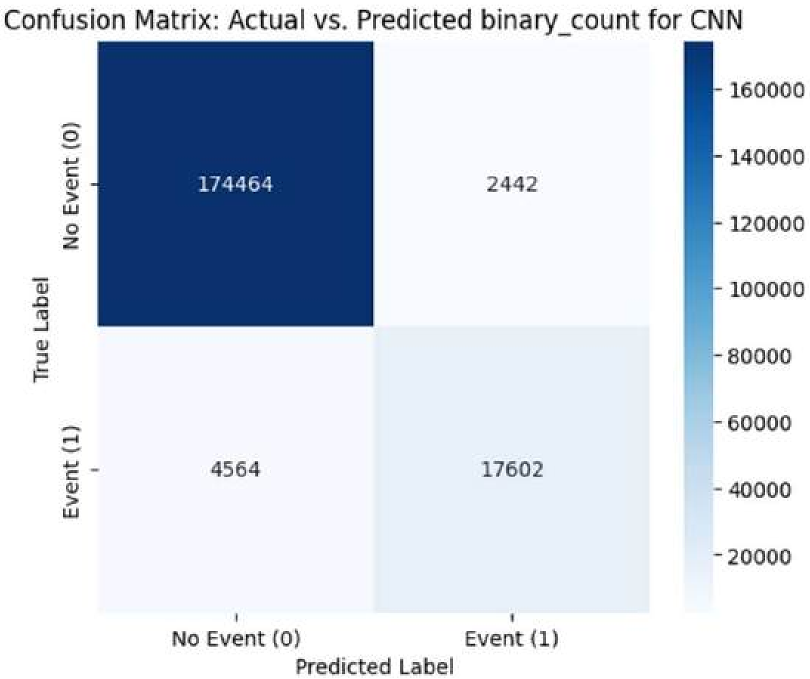


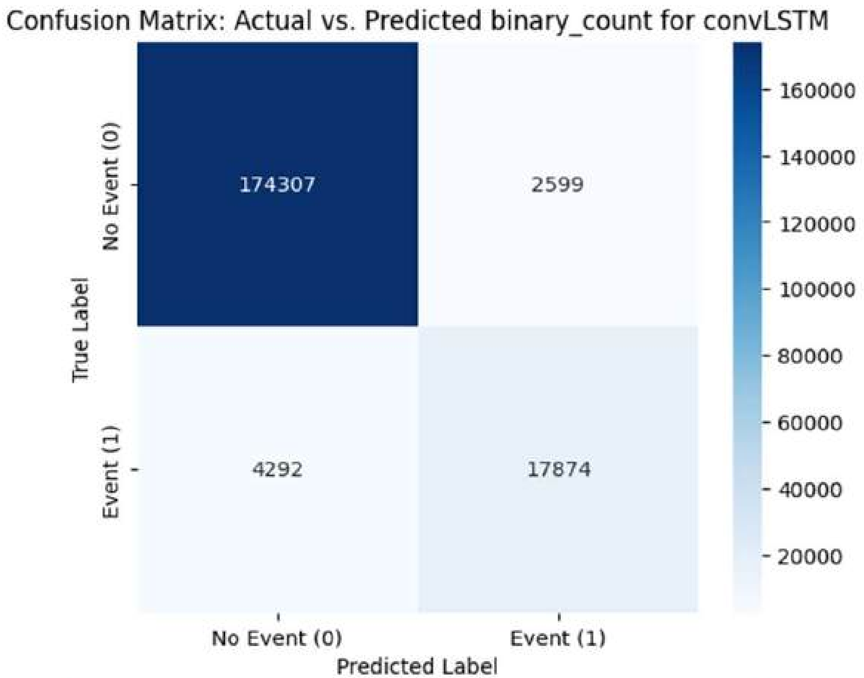
Figure 2: Inner structure of ConvLSTM



Preliminary results



Zero grids	Accuracy	Precision	Recall
True	0.999993	0	1
False	0.87016	0.8782	0.7940



Zero grids	Accuracy	Precision	Recall
True	0.999912	0	1
False	0.8723	0.8731	0.8063

Forecasting forced displacement

27th March 2025

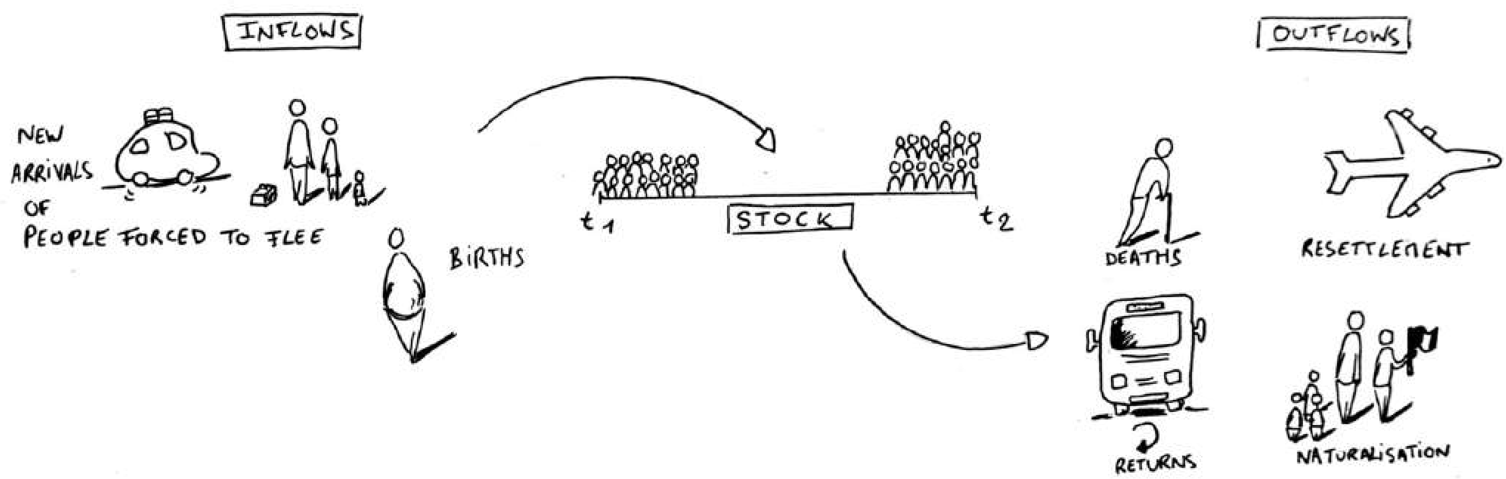
EconAI team (funded by GFFO)

Hannes Mueller, Christopher Rauh, Ben Seimon, Ramón Talvi Robledo

(1)Data overview and objectives

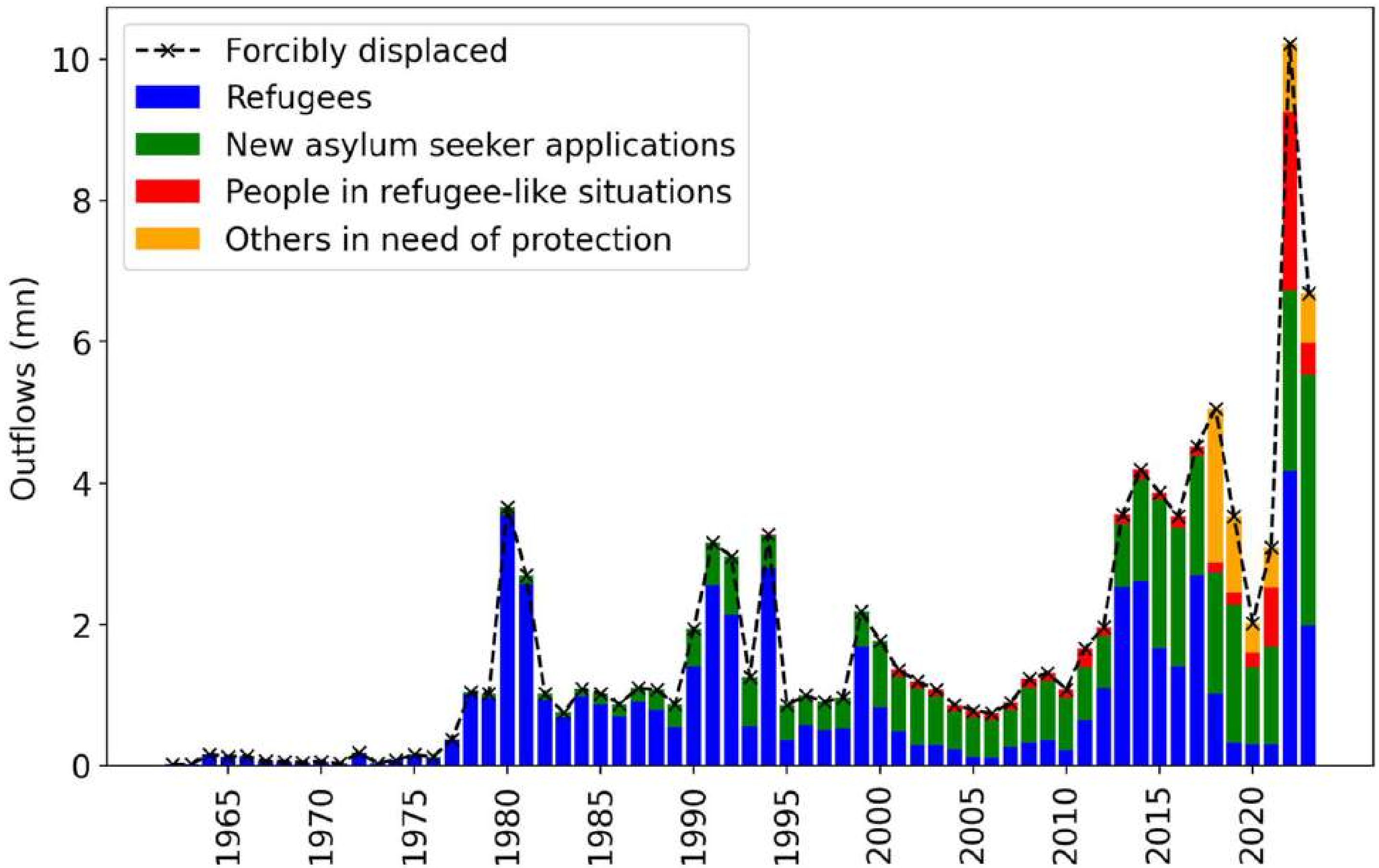
Context and data

- Units of analysis: origin and dyad.
- **Stocks:** Snapshot of number of forcibly displaced.
- **Flows:** Movement of forcibly displaced between two points in time.
- We choose the yearly flows dataset to study movements of forcibly displaced people.

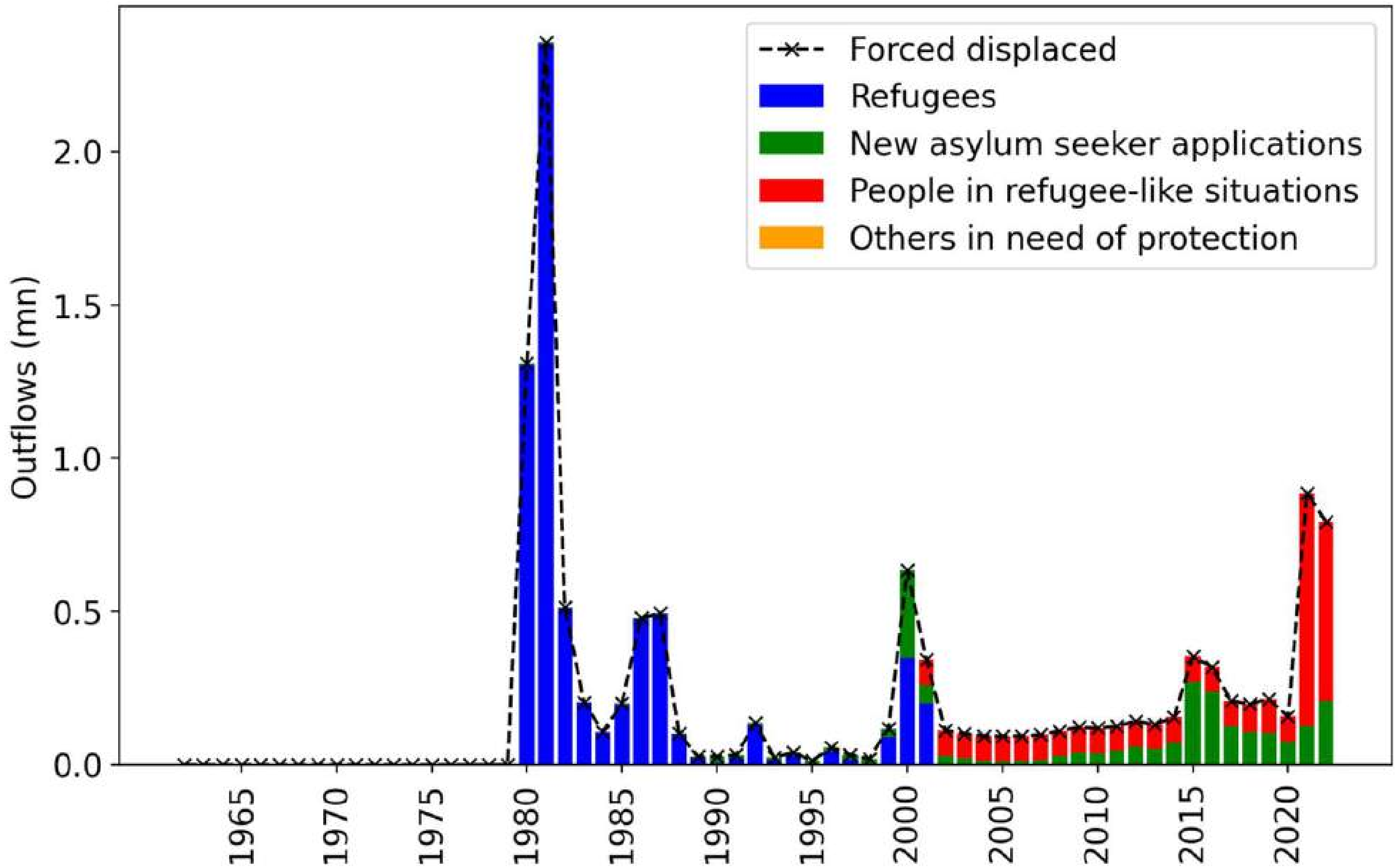


Source: UNHCR, https://www.unhcr.org/refugee-statistics/insights/explainers/common-mistakes-forcibly-displaced-data.html

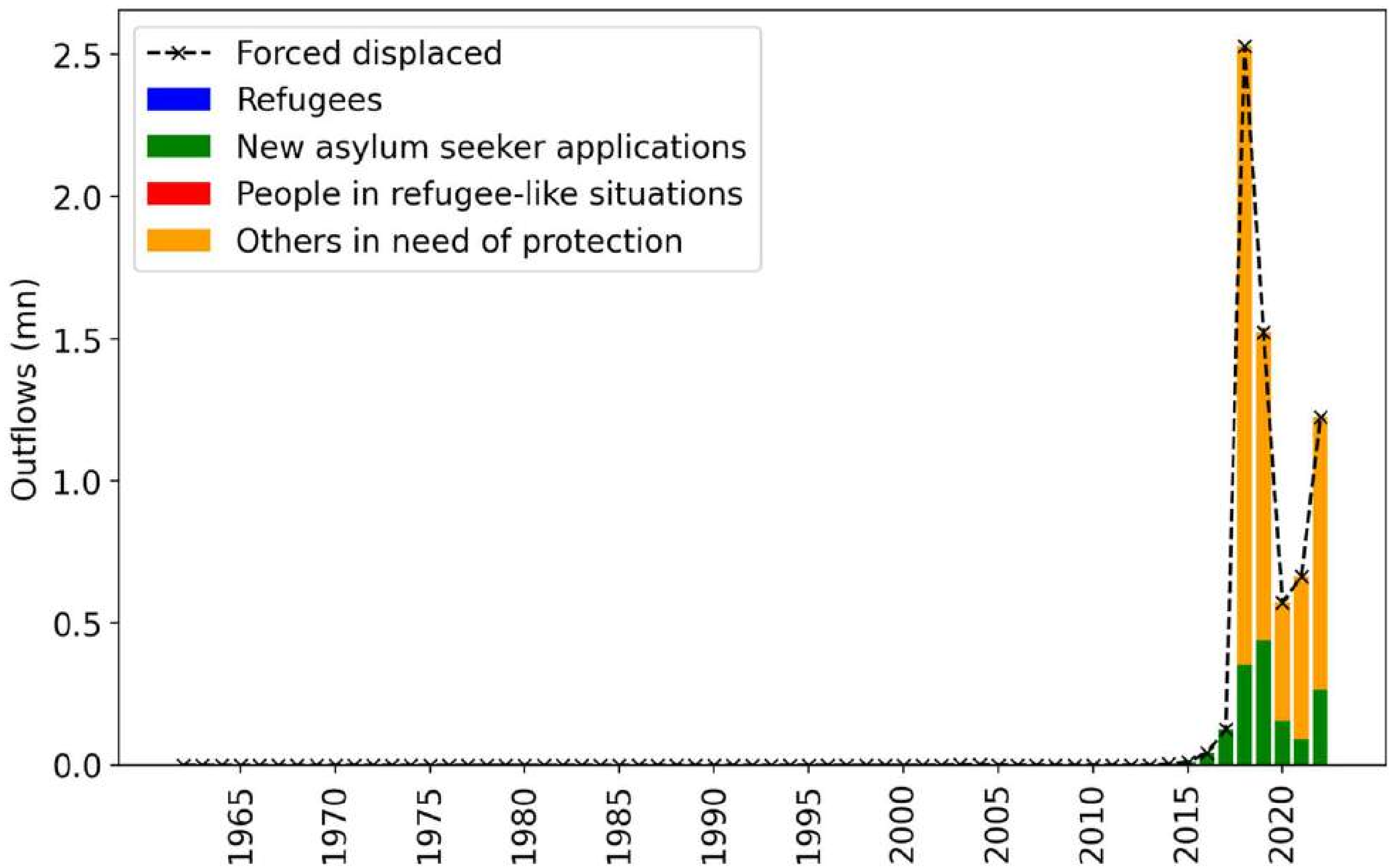
Forced displacement over time



Case study: Afghanistan



Case study: Venezuela



Objectives

- Forecasting should inform a policy responses to address humanitarian demand.
- Target total forced displacement i.e. sum across UNHCR categories.

1. **Outflows classifier: raise alerts for possible future crises - origin/year**

2. **Dyadic regression: bilateral forecast of future flows - dyad/year**

Features

	Data	Source
	Historical flows	UNHCR
Violence	Conflict fatalities	UCDP
Text-based	Text topics	Conflict Forecast
	Google Trends Index	Google Trends
Socio-economic	Economic indicators	World Bank/IMF
	Democracy indices	VDEM
Dyad only	Dyadic relationship	CEPII

Text data:

Newspaper articles

- 6mn+ newspaper articles from various sources. 1989 to present.
- Improves forecasts of conflict risk in countries with a long history of peace.

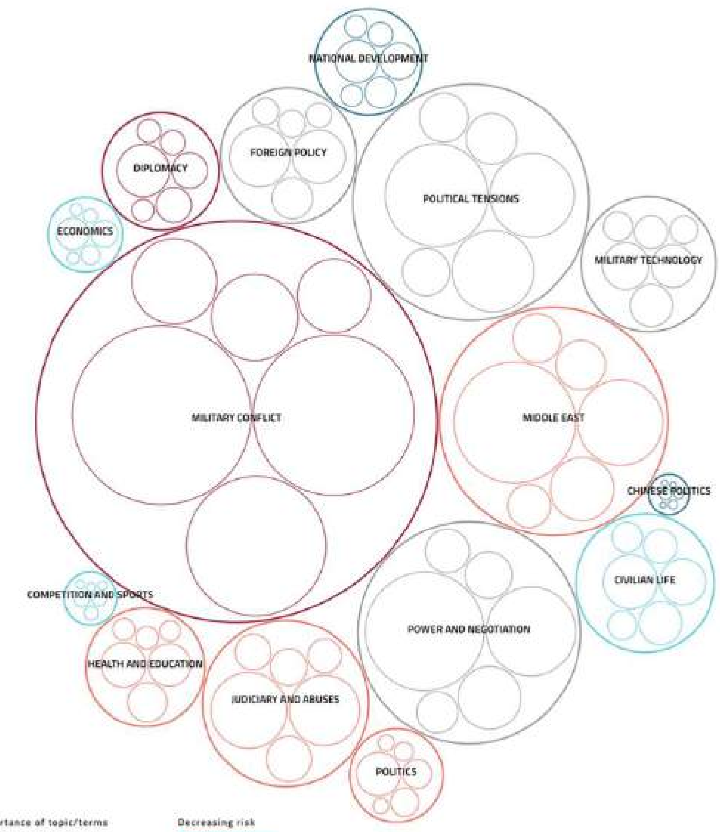
Google Trends Index

- 400+ keywords in 197 languages. 2004 - present.
- Query 1: embassy, …, visa + visas
- Query 2: Afghanistan, …, Zimbabwe

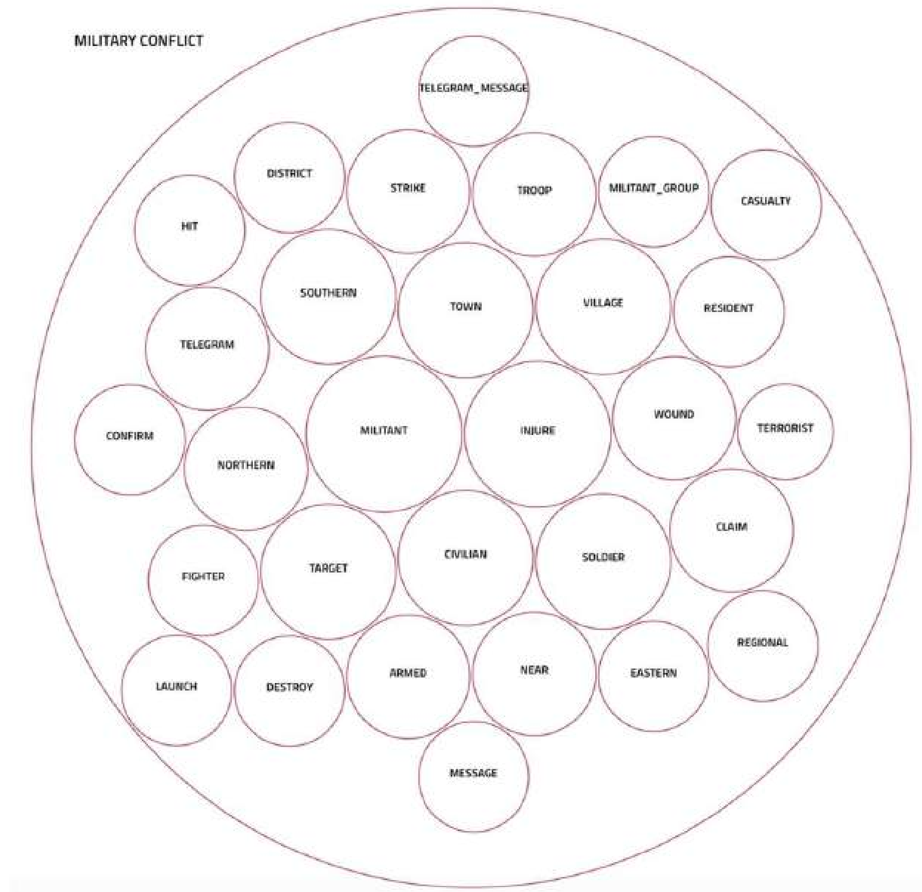
LDA topic model

- Topics are represented by words.
- Categorises the text data for any country/year according to topic "shares".

Text data: Conflict Forecast



Syria, Nov 2024



Text data: Google Trends index, “outflows” topics

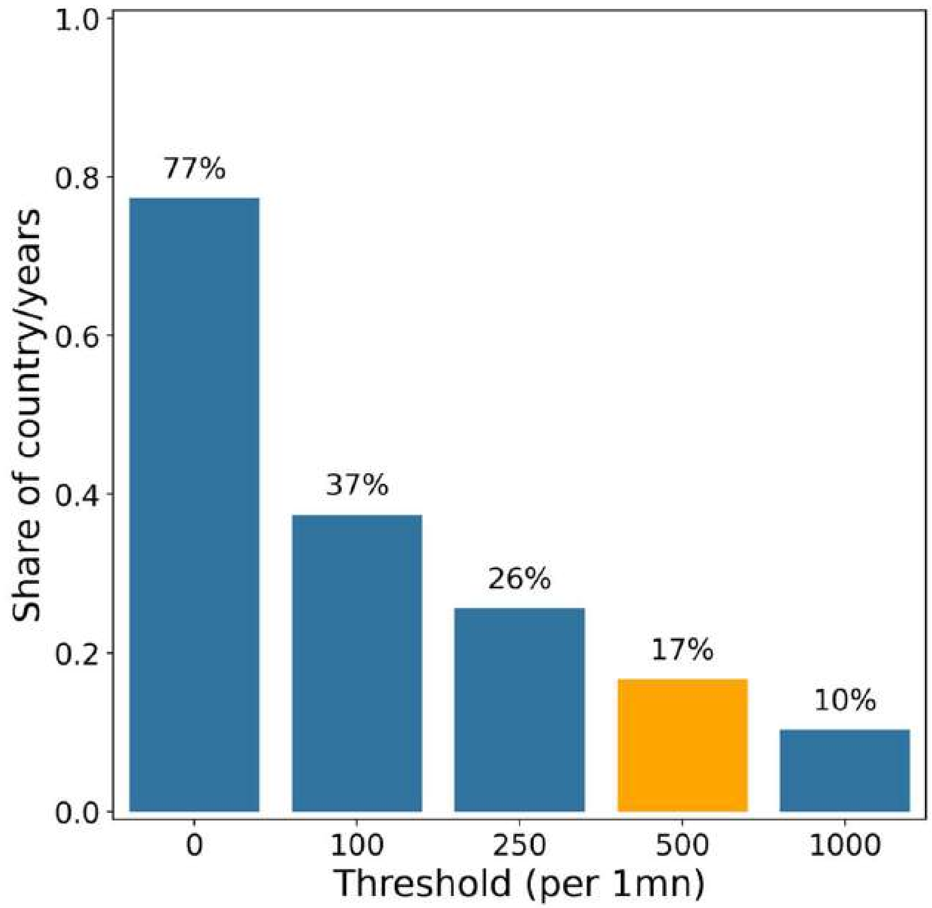
Topic 1: migration risk

Topic 2: legal status

(2)Outflows classifier: raise alerts

Model overview

- Binary classification task.
- We need a definition for a crisis:
  - Per capita measure
  - Threshold: 500 outflows per 1mn inhabitants.
- Chart shows the share of country/years since 2000 that exceed a given threshold.



Target overview

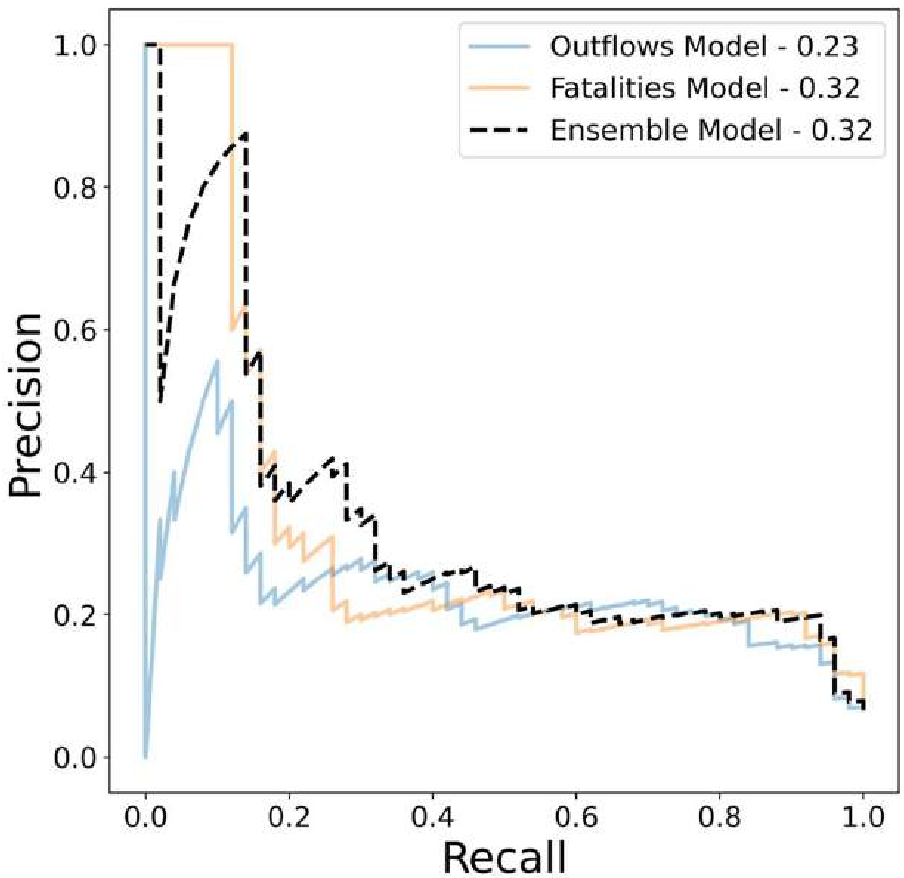
- Total of 190 countries. Table shows the number of countries experiencing:
  - Incidence (more than 500 forced displacements per 1 million inhabitants)
  - Onset (below threshold in previous year)
  - **Hard onset (below threshold in previous 3 years)**

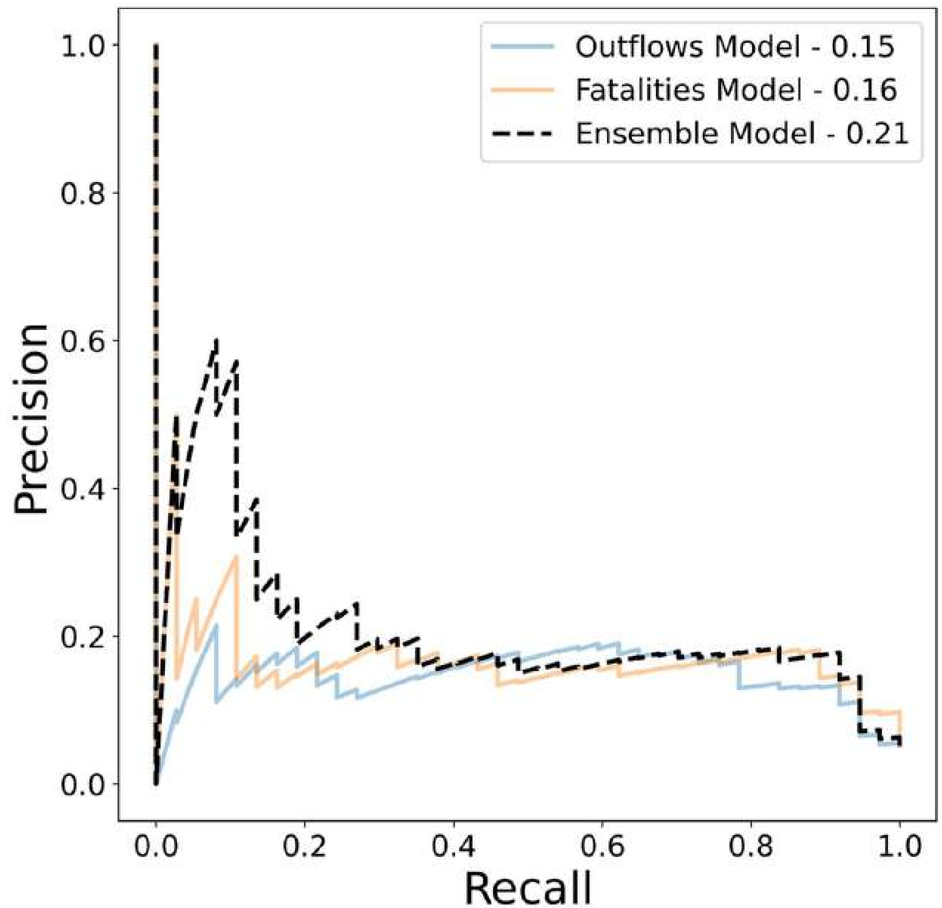
	2019	*2020*	*2021*	*2022*	*2023*
Incidence	38	38	35	55	73
Onset	1	5	6	22	18
Hard onset	0	3	3	16	16

Overall model evaluation

- Evaluate on onsets & hard onsets.
- **Onset:** Country/year that experiences a crisis, with at least 1 years of no crisis.
- **Hard onset:** Country/year that experiences a crisis, with at least 3 years of no crisis.
- Challenge: class imbalance, particularly few onsets/hard onsets.
- Assess model performance using precision-recall curves.

Best model performance (onsets & hard onsets)





Model as an early-warning system (onsets)

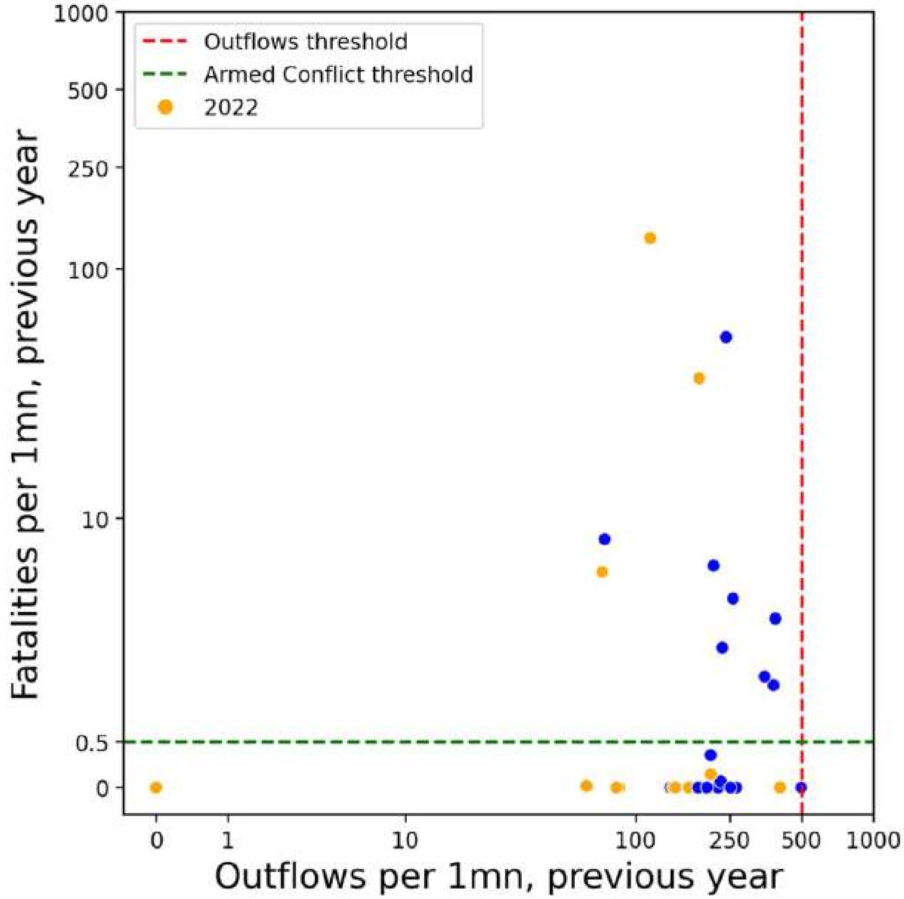
Maximize precision: th = 0.6

	False warnings	*Correct warnings*	*Missed crises*
2019	0	0	1
2020	1	0	5
2021	0	1	5
2022	0	4	18
2023	0	2	16

Maximize recall: th = 0.02

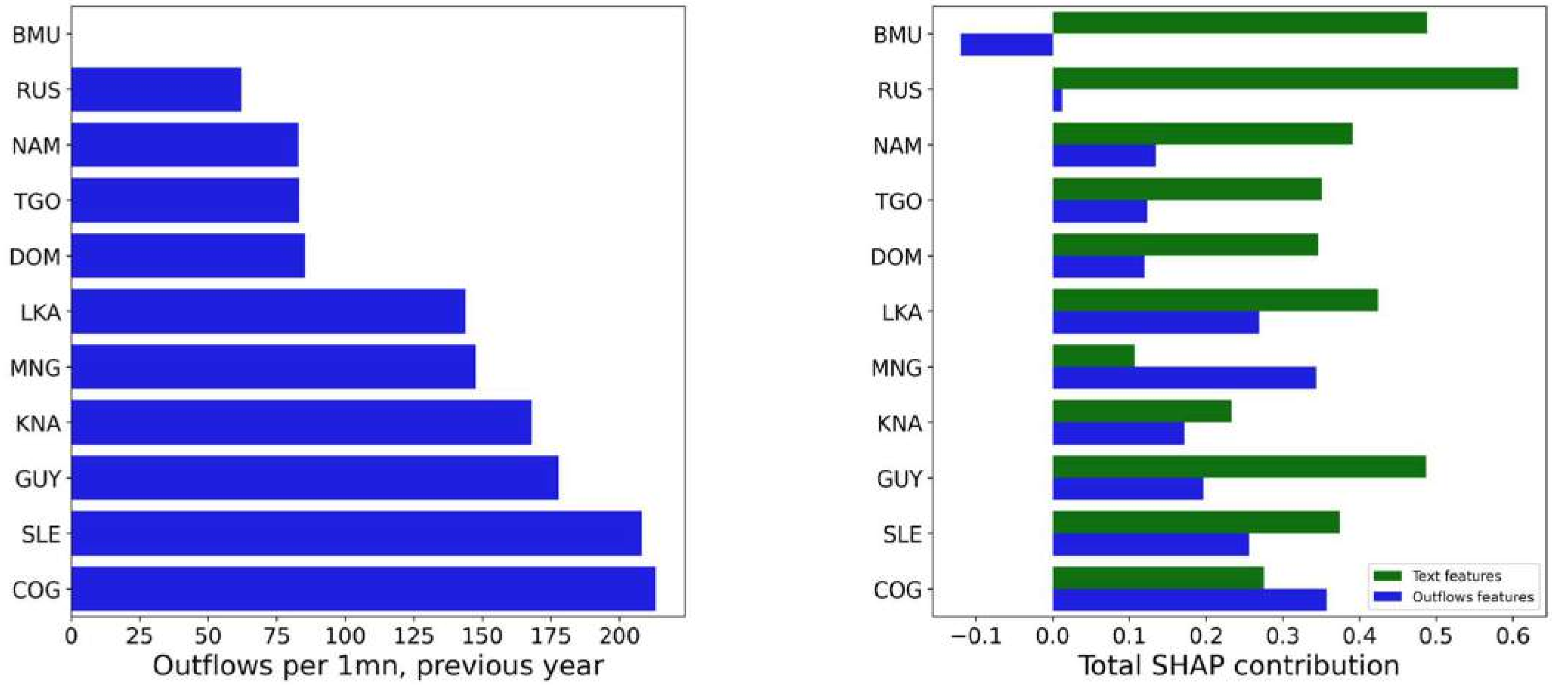
	False warnings	*Correct warnings*	*Missed crises*
2019	44	1	0
2020	42	3	2
2021	43	6	0
2022	23	18	4
2023	15	11	7

Hard onsets cases



- Hard onsets are usually preceded by outflows close to threshold and/or high fatalities.
- Crises without outflows/violence in the previous year are much harder to forecast.
- How does text drive risk in these cases?

Text features as a predictor (2022)

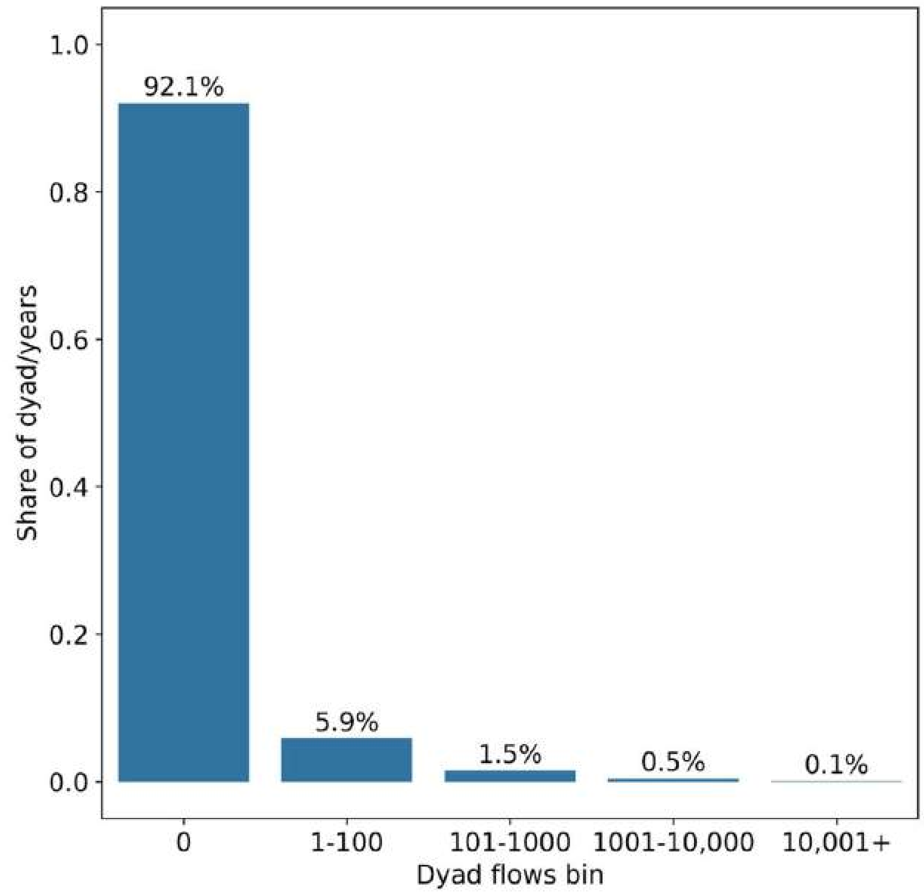


- Filter only for hard onsets with low fatalities/outflows in the previous year (2021)
- Text features driving risk in these situations

(3) Dyadic regression model: Bilateral flows

Model overview

- Forecasts of origin-destination forced displacement flows.
- Regression task.
- Chart shows the share of dyad/years since 2000 that fall into a given bin.
- Less than 1% of observations in two highest bins.



Results relative to naive

	Target bin				
	0	**1-100**	**101-1,000**	**1,001-10,000**	**10,001+**
Ensemble, relative MAE	0.11	0.57	0.64	0.63	0.94

- Naive forecast mimics most simple forecasting strategy → flows next year will be the same as last observed year.
- Relative MAE < 1 indicates improvement over the naive.
- Decreasing performance as bin increases.

Regression forecasting and uncertainty intervals

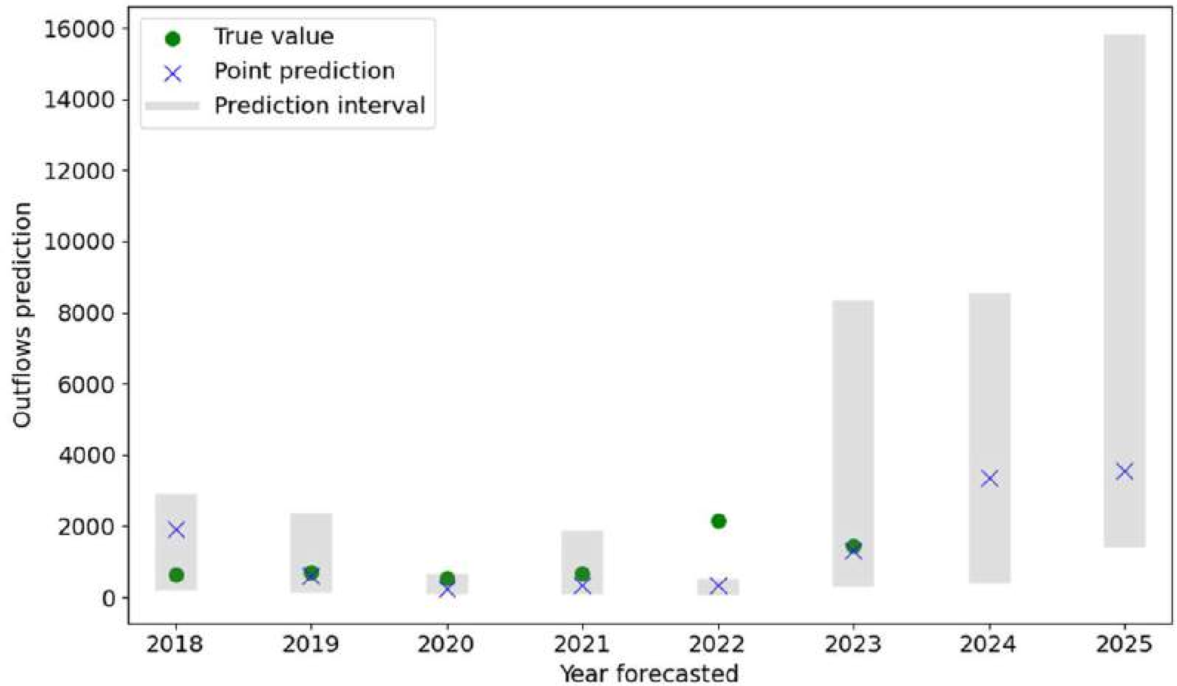
- **LPCI:** Conformal prediction algorithm for panel data.

Key definitions

Prediction interval: The range of possible values for a 90% confidence level.

Coverage: The share of times the true value falls within the prediction interval.

Case studies: Lebanon-Germany (90% confidence level)

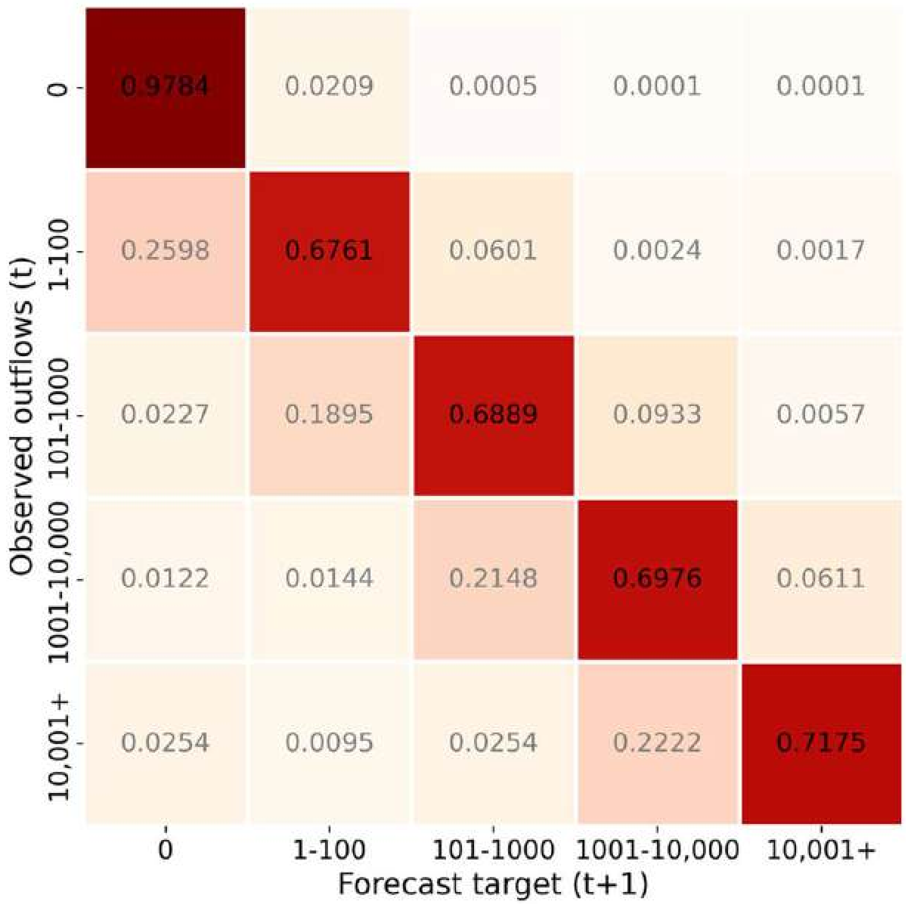


- True value falls outside of the prediction interval for 2022.
- Intervals become wider (more uncertainty) after shock year.

Uncertainty quantification: the trade-off

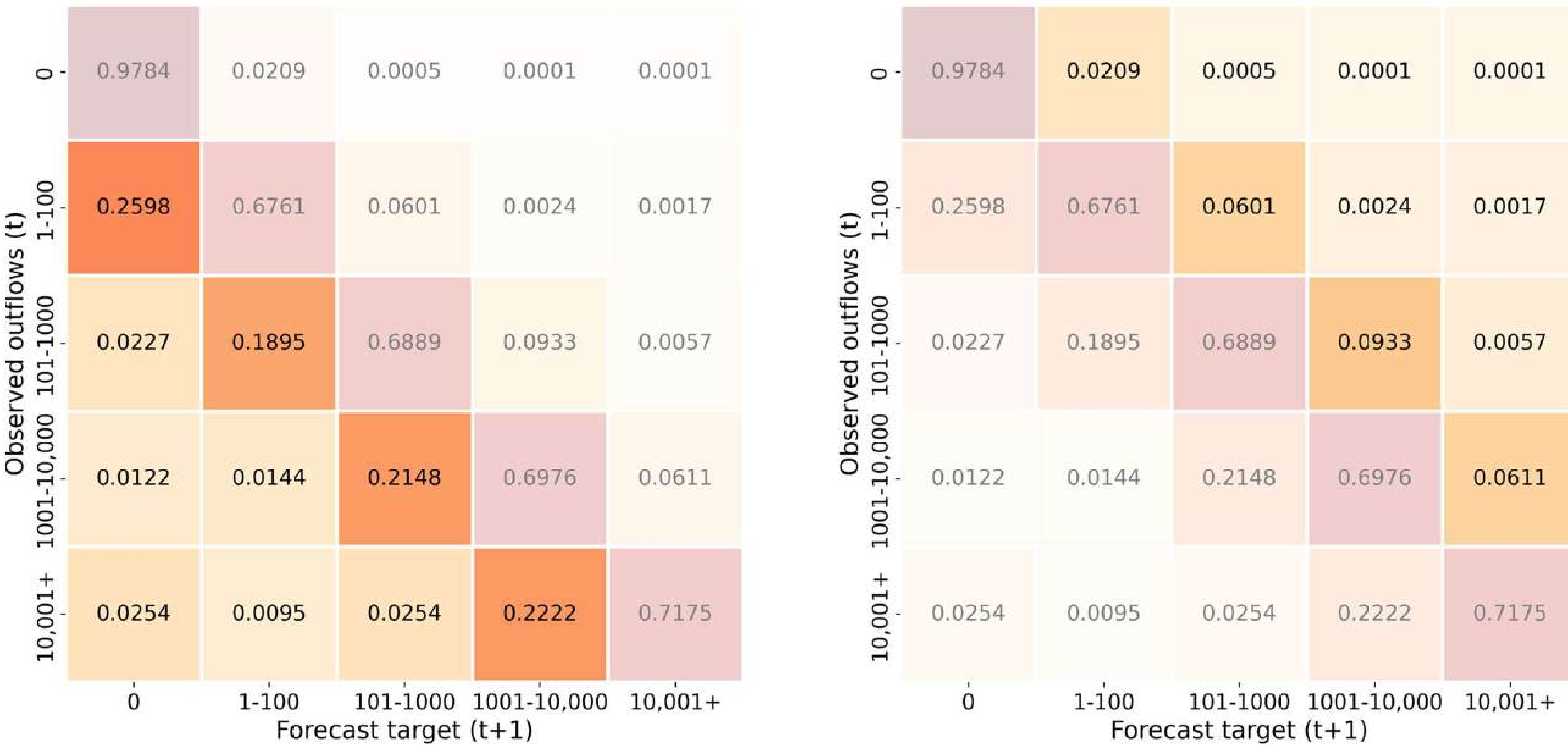
- We can artificially achieve perfect coverage by increasing interval widths.
- But this is impractical for policy purposes.
- The objective is to achieve the best coverage for the narrowest interval widths.
- This is dictated by the confidence level.
- Higher confidence level leads to better coverage, but wider intervals.

Flows are sticky

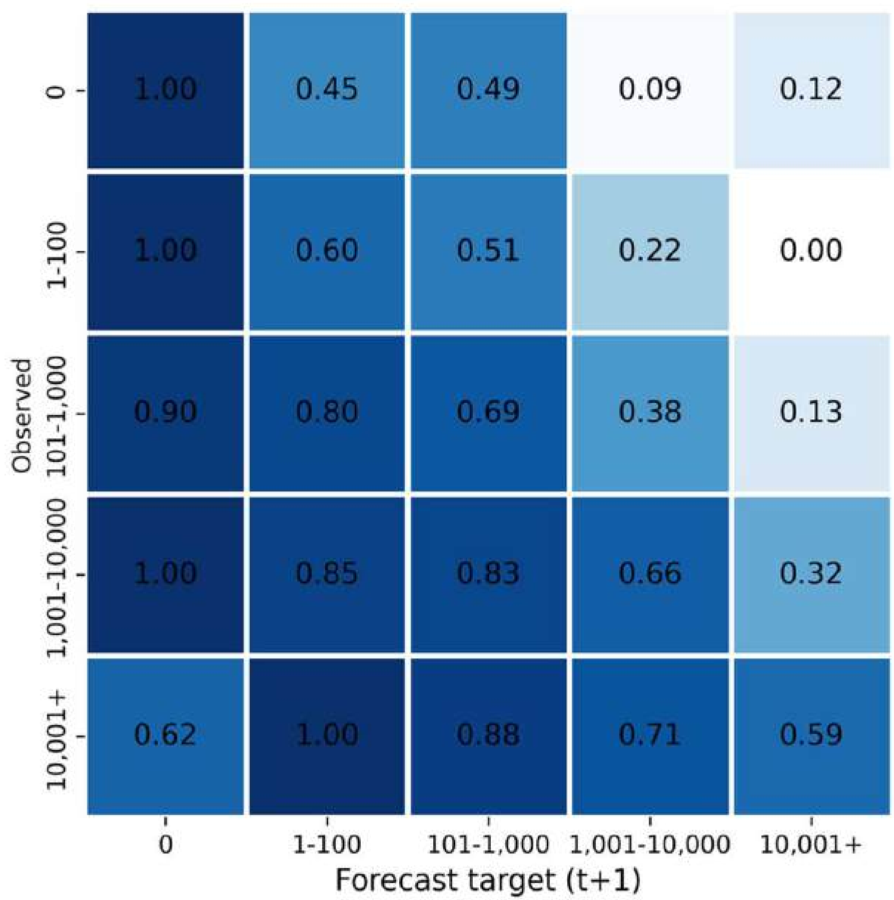


- Flows observed in the previous year are a strong predictor of flows next year.

De-escalations and escalations are relatively rare



Coverage for escalations and de-escalations



- Poor coverage for extreme escalations (0 to 10,001+).
- This is not a spike model: it does not capture acute sudden spikes.
- Conditional coverage on escalations and de-escalations for neighbouring bins high.

(4) Next steps

Next steps

- Put forecasts into “production” i.e. generate regular updates
- Explore other techniques e.g. hierarchical forecasting
- Develop forecasting model for internal displacement

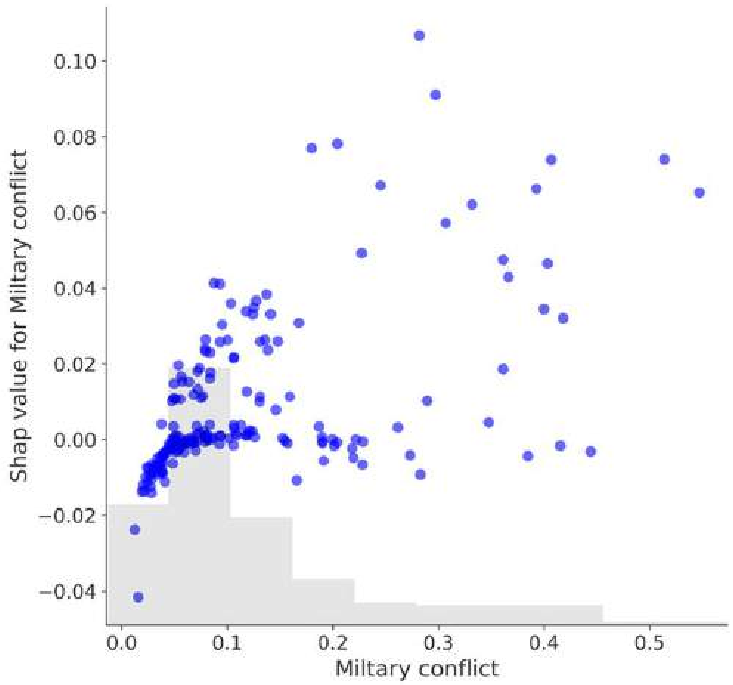
Appendix

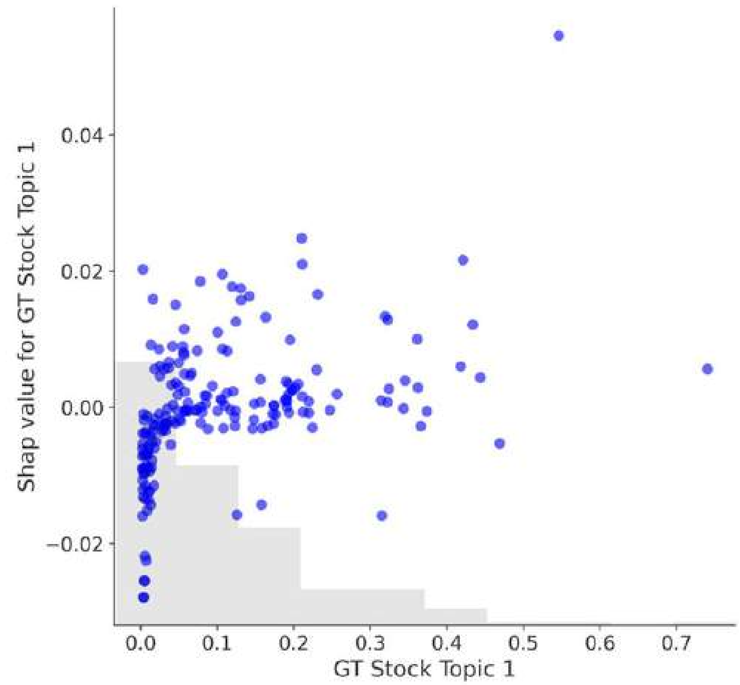
Why a threshold of 500?

Forced displacement outflows per 1mn inhabitants

Country	*Year prior to crisis*	*Year of crisis*	*Year after crisis*	*Average in years after crisis*
Rwanda	*1993:* 439	*1994:* 343,286	*1995:* 6,358	*1996 - 2000:* 19,680
Syria	*2010:* 354	*2011:* 559	*2012:* 105,400	*2014 - 2022:* 33,855
Yemen	*2014:* 61	*2015:* 760	*2016:* 472	*2017 - 2022:* 371

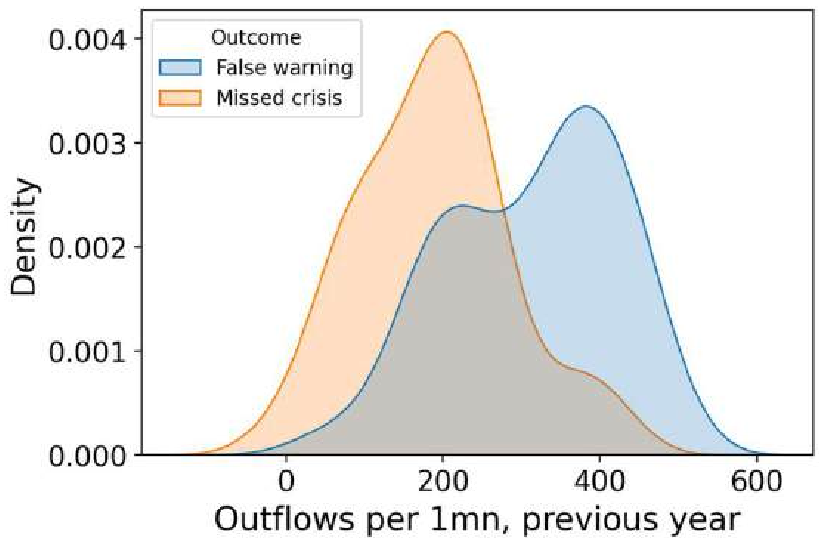
Text features as a predictor (hard onsets)

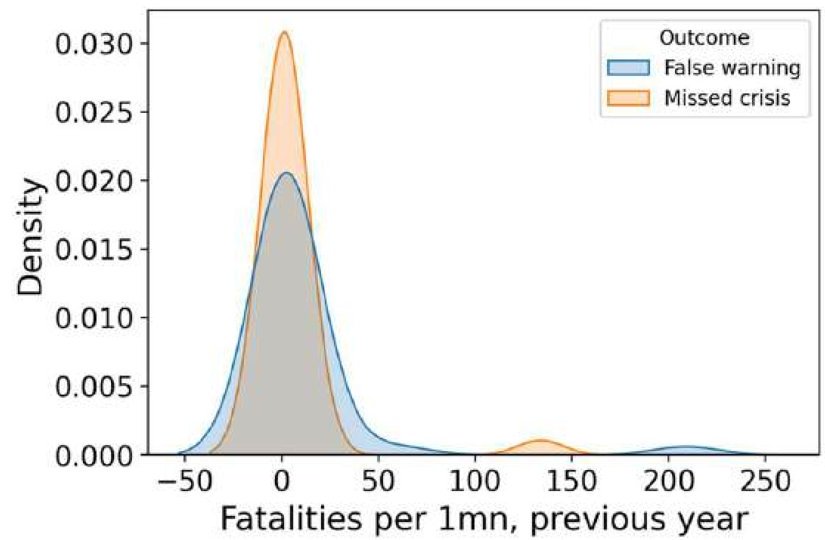




- Charts show Shap values for 2023 predictions.
- Both CF and Google Trends topics contribute to increase risk.

False warnings vs missed crises





- Generate false warnings in the presence of outflows and/or violence in the previous year.
- Crises without outflows/violence in the previous year are much harder to forecast.

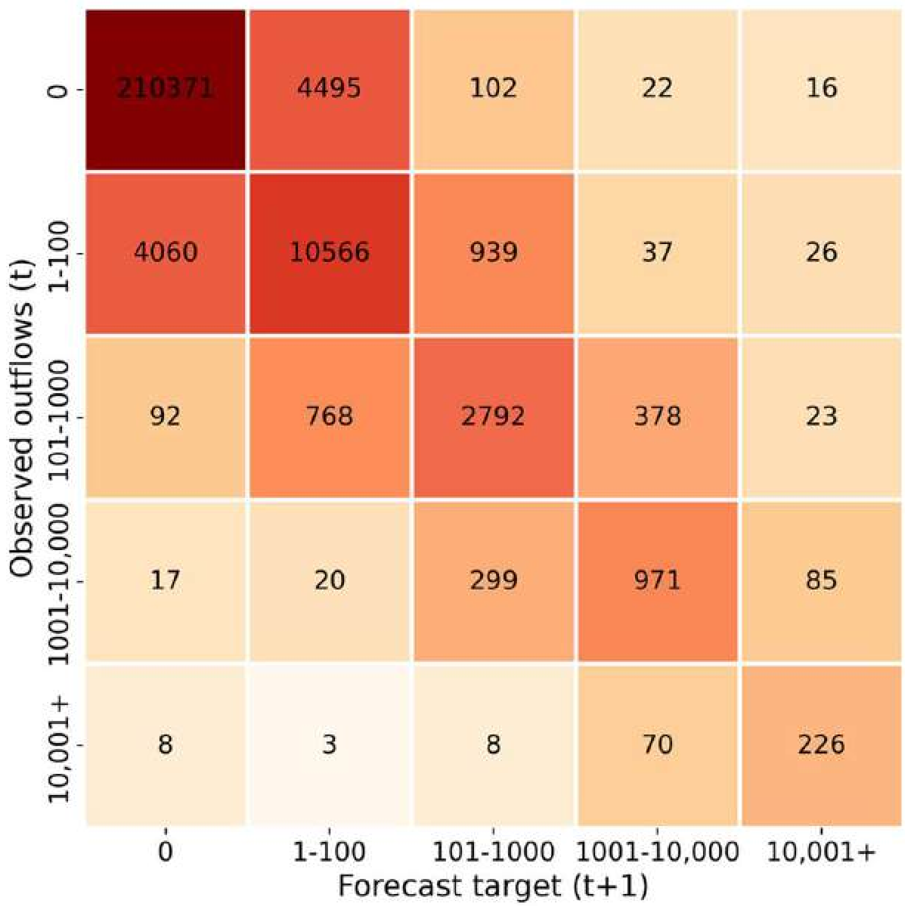
Uncertainty quantification: dyadic coverage (99% confidence level)

	Year forecasted				
	2019	**2020**	**2021**	**2022**	**2023**
Coverage by time	0.95	0.98	0.98	0.98	0.91

	Target bin				
	0	**1-100**	**101-1,000**	**1,001-10,000**	**10,001+**
Coverage by bin	0.99	0.57	0.66	0.57	0.44

- **Coverage by year:** high coverage across years driven by high share of 0's.
- **Coverage by bin:** coverage drops in largest bin.

Dyad flows transition matrix



- Row is latest observed outflow bin.
- Column is the target bin.
- Heatmap shows the number of dyad transitioning from one bin (row) to another (column) in our test set (2017 - 2022).

Predictive Simulation of Forced Displacement in Climate-Driven Flooding Scenarios

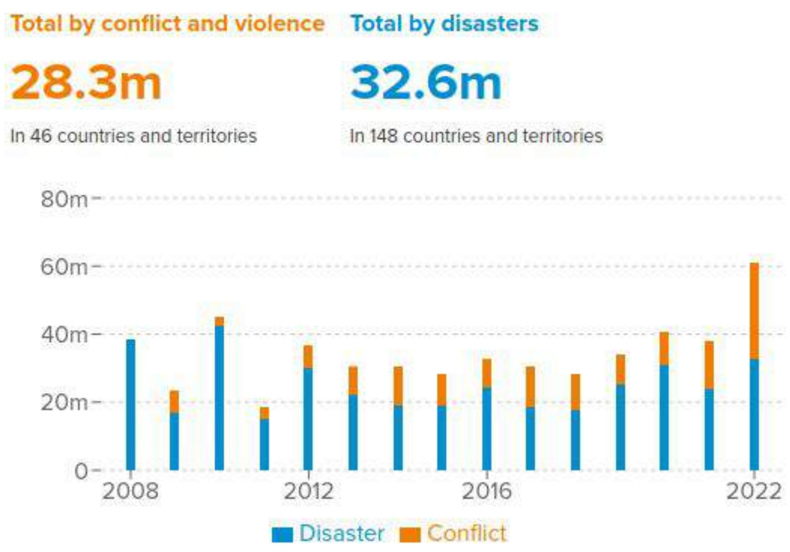
Alireza Jahani, Laura Harbach, Maziar Ghorbani, Diana Suleimenova, Yani Xue, and Derek Groen

Introduction

The resulting extreme weather events, such as droughts, floods, wildfires, hurricanes, and tornadoes, are directly linked to rising temperatures and sea levels.

Flooding is the leading cause of climate-related displacement, accounting for over 9% of natural disaster displacements.

In 2023 alone, floods accounted for 9.7 million of the 26.8 million people displaced by disasters globally, with a staggering 7.6 million remaining displaced at year's end



Research Gap

Despite the ongoing devastating effects of flooding worldwide, little research has been done to investigate the displacement of affected people and provide useful information for humanitarian organizations and governments.

Therefore, this study focuses on simulating the evacuation caused by floods and the movement of internally displaced people who are seeking a safe shelter, by using agent-based modeling:

- The individual movement
- Distribution of internally displaced persons (IDPs)
- Evacuation destinations.

DFlee

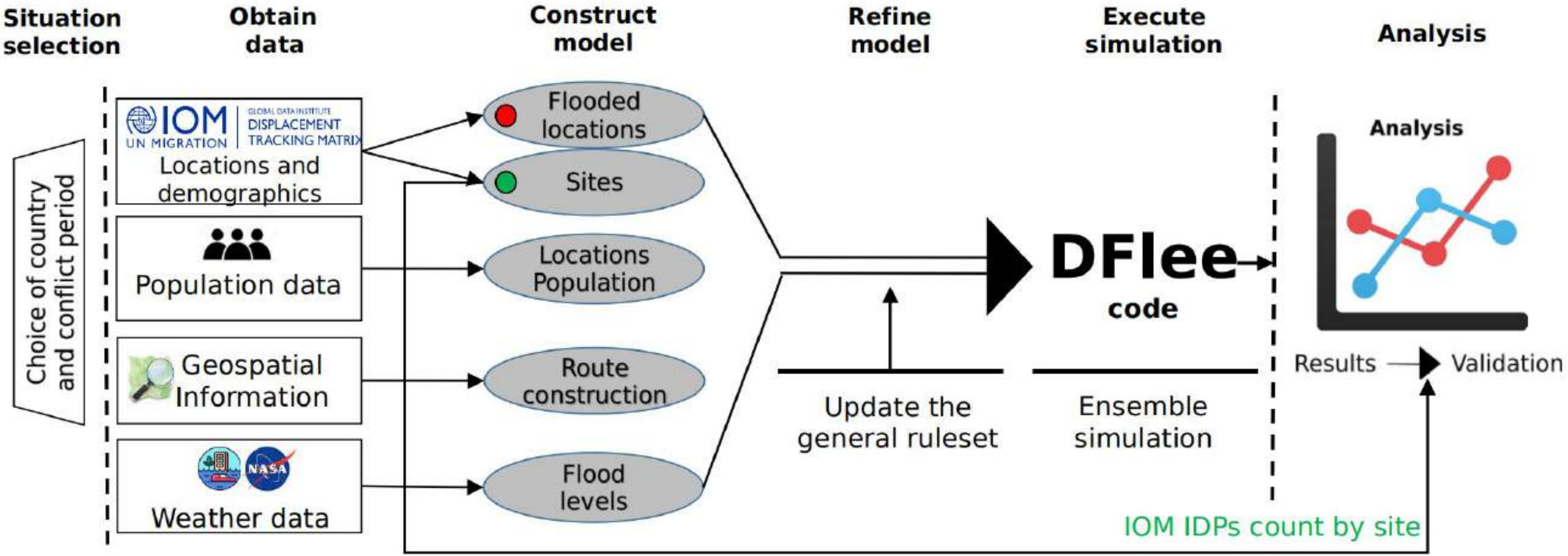
We employed and extended the Flee agent-based modelling toolkit to simulate flood-induced evacuation.

Flee is used to simulate the geographical movement of people fleeing from conflict and violence.

Despite similarities, between conflicts and disasters, there are some differences in terms of shelters and camps between the two events.

Moreover, Flee has not been used to model a small region instead of an entire country or state, but this study aimed to repurpose the model to investigate the movement of IDPs during a flood event in small regions.

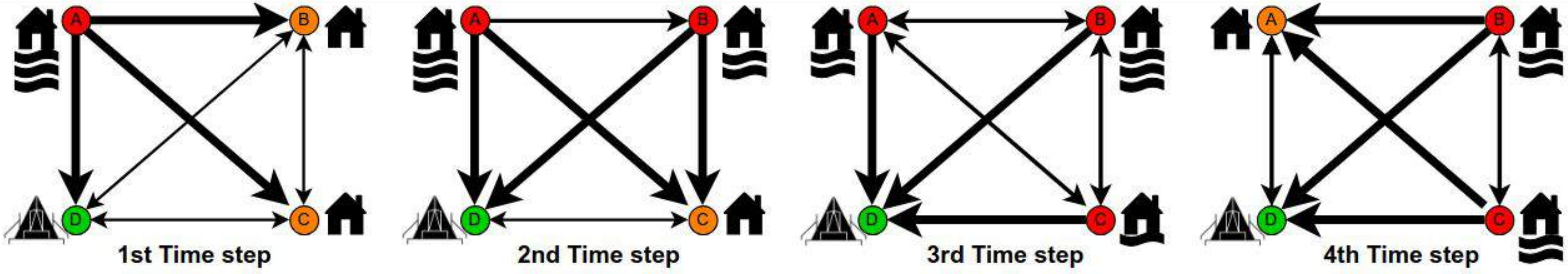
Development Approach



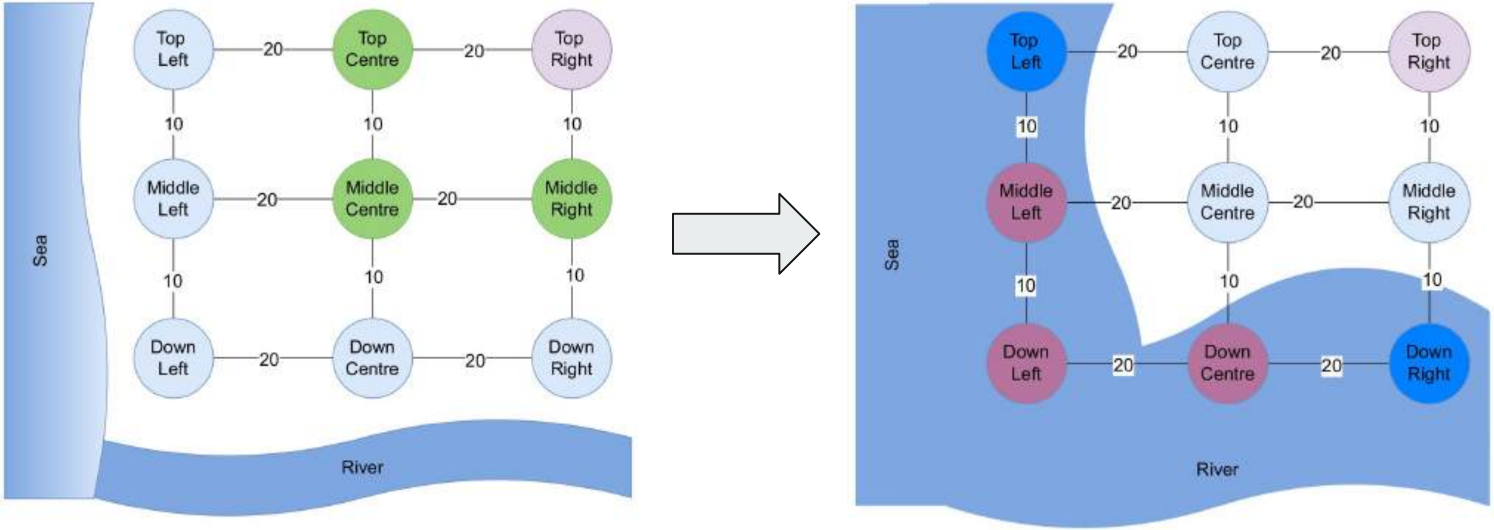
Assumptions

1. Floods cause internal displacement
2. Floods need immediate response and evacuation
3. People might use various ways of transportation (i.e., walking, driving, and river crossing)
4. People might want to return to their homes after the flood recession
5. The evacuation decision includes when, how, and where to go questions
6. Some forms of shelters include higher grounds or even high buildings
7. Cities and areas can have different levels of floods

Initial Conceptual Model



Sample Scenarios

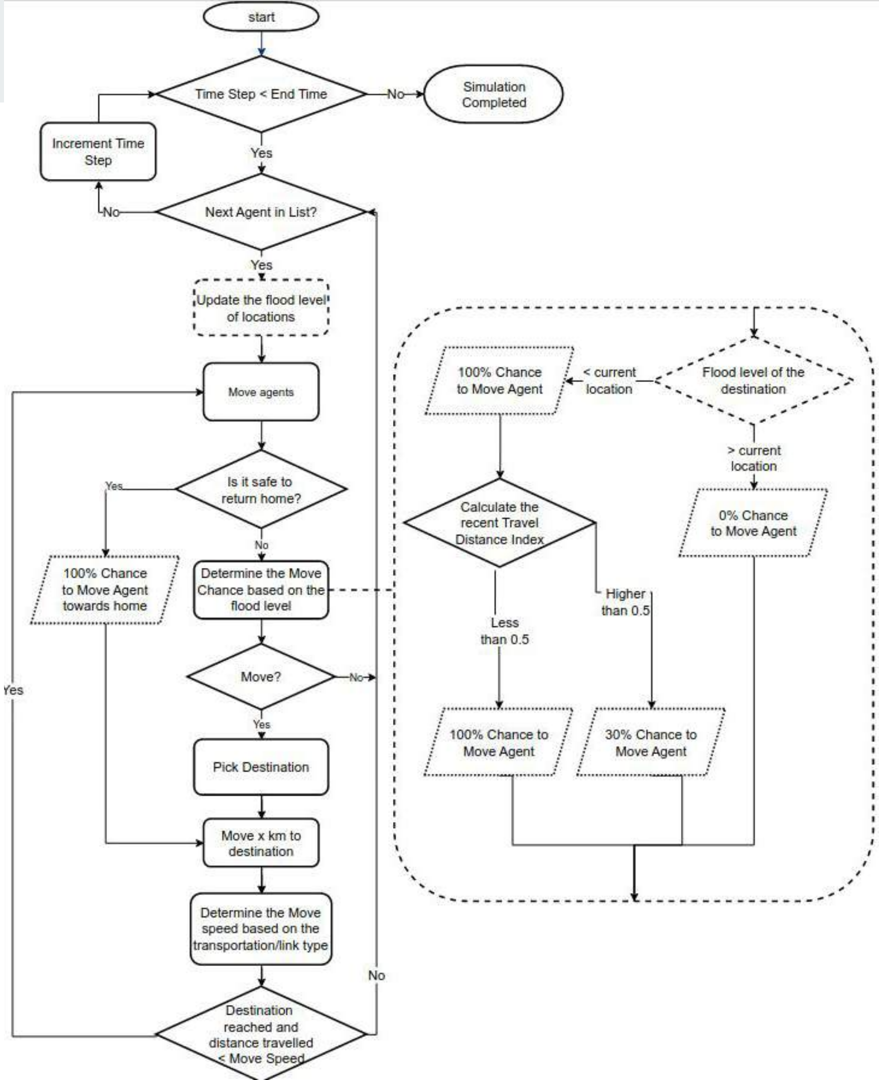


Flowchart

The agents move through routes using a weighted probability function based on route length.

The total number of displaced people is extracted from IOM reports using linear interpolation between data points.

Agents representing people move with a probability of movechance to different locations to find safety, with a chance of returning to their homes when the flood level decreases.

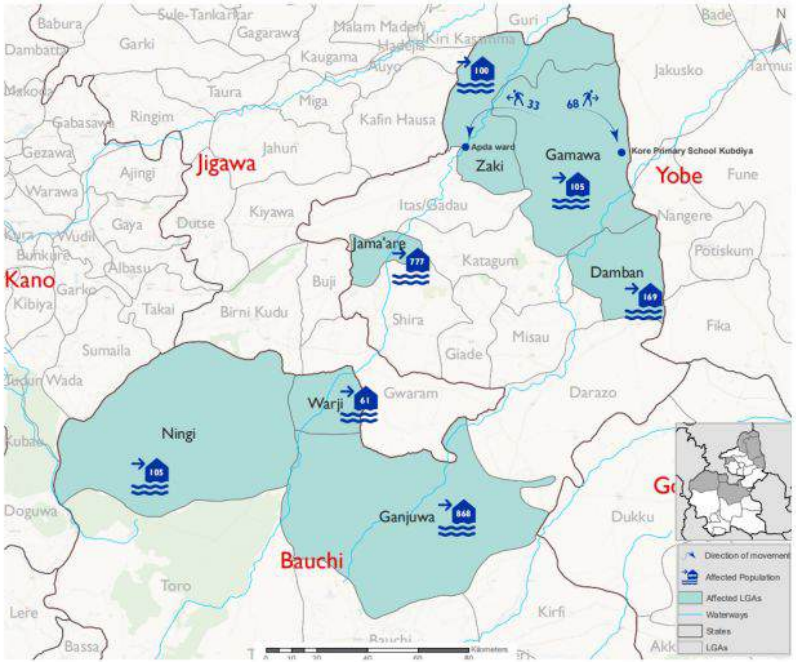


A Case Study: Nigeria, Bauchi State

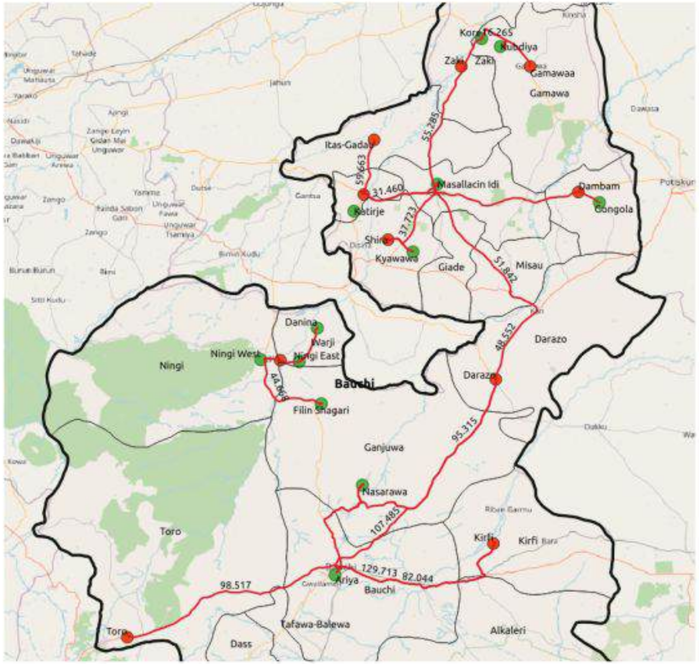
- Bauchi state, located in the northeastern part of Nigeria, experienced flooding due to heavy rainfall and strong winds.
- A total of 2,185 people were affected, 90% of them displaced to neighbouring communities in seven Local Government Areas (LGAs).
- According to IOM, the flooding affected a total of 222 houses, leaving 256 households in need of shelter, repair kits, and non-food items as most houses need re-enforcement with brick blocks.

Brunel University London

A Case Study: Nigeria, Bauchi State

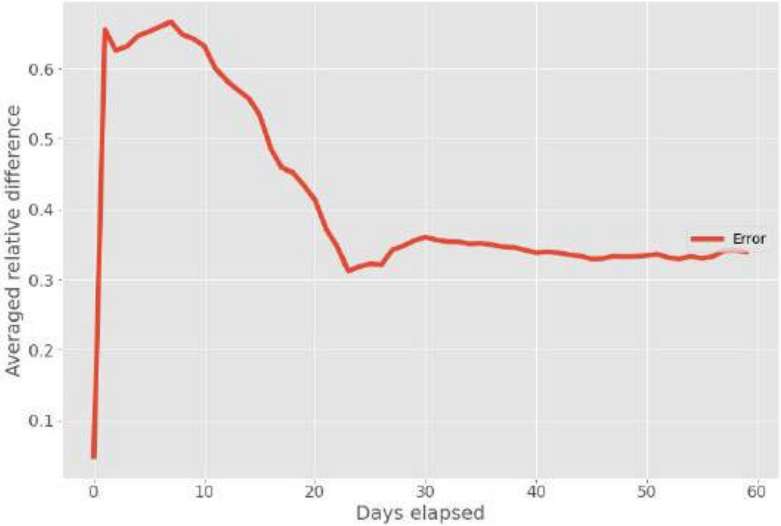


(a)



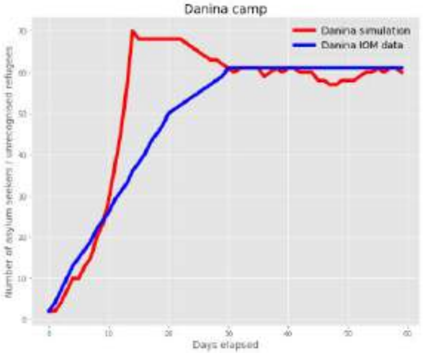
(b)

Results

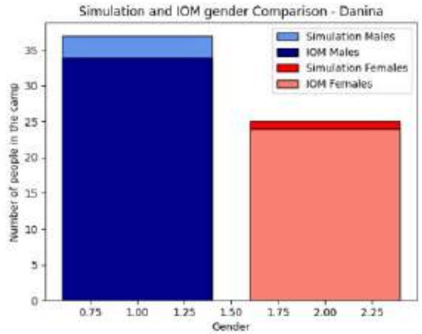


Results compared with data from the IOM's Displacement Tracking Matrix (DTM) for two sample sites:

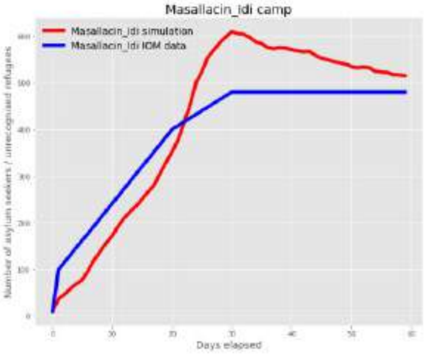
Danina (a) and Masallacin-Idi (c).



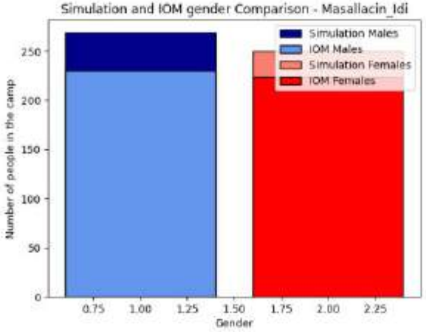
(a) Validation of registered people at a Danina site



(b) Validation of the registered people in terms of their gender (Danina)



(c) Validation of registered people at a Masallacin-Idi site



(d) Validation of the registered people in terms of their gender (Masallacin-Idi)

Q&A

From Climate to Conflict: A Multiscale Cognitive-Decision Framework for Modelling Human Mobility and Displacement

Michael J Puma
Professor of Climate
Director, Center for Climate Systems Research
March 27, 2025

UNHCR's CLIFDEW-GRID project:
Technical Workshop
Date: March 27th, 2025
Time: 13:00-19:00 CET (7:00-13:00 EST)

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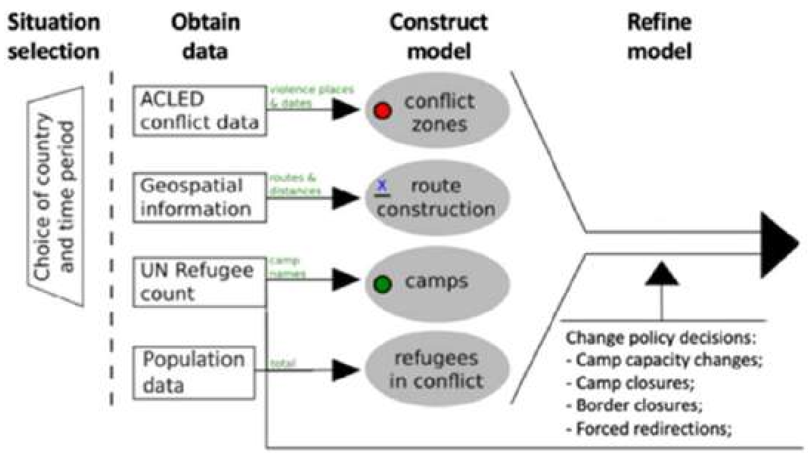
An SDA approach for an agent-based model

A simulation development approach (SDA) for rapid response – connects input and evaluation data into process.



Source: https://flee.readthedocs.io/en/latest/index.html

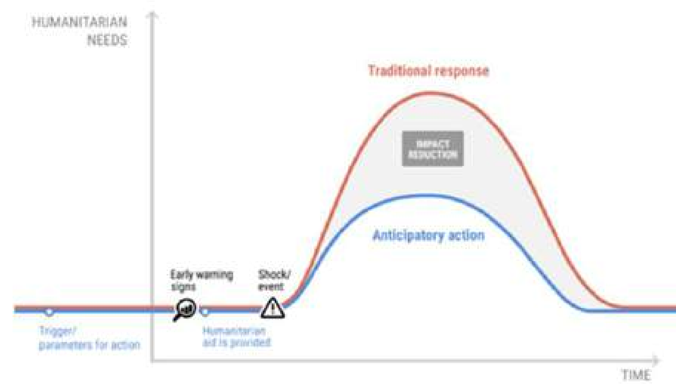
FLEE

Sensitivity-driven simulation development: a case study in forced migration (2021), D Suleimenova, H Arabnejad, WN Edeling, D Groen, Philosophical Transactions of the Royal Society

Flee is designed to simulate the movements of refugees and internally displaced persons (IDPs)

Input parameters
MaxMoveSpeed
ConflictMoveChance
CampMoveChance
DefaultMoveChance
CampWeight
ConflictWeight

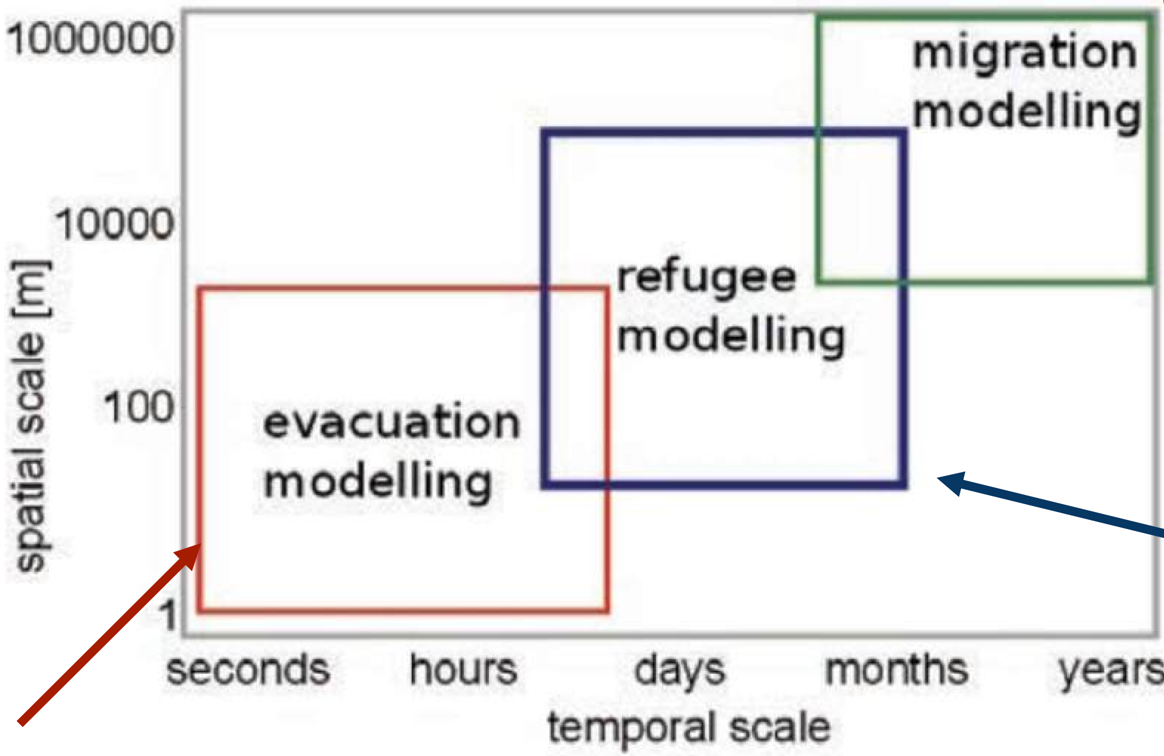
For anticipatory action



Source: https://centre.humdata.org/

Scales for modeling

Flee AC



DFlee

FLEE

Understanding migration pathways and drivers requires integrating spatial and socioeconomic data.

https://www.brunel.ac.uk/news-and-events/news/articles/Climate-refugees-why-we-cant-yet-predict-where-millions-of-displaced-people-will-go

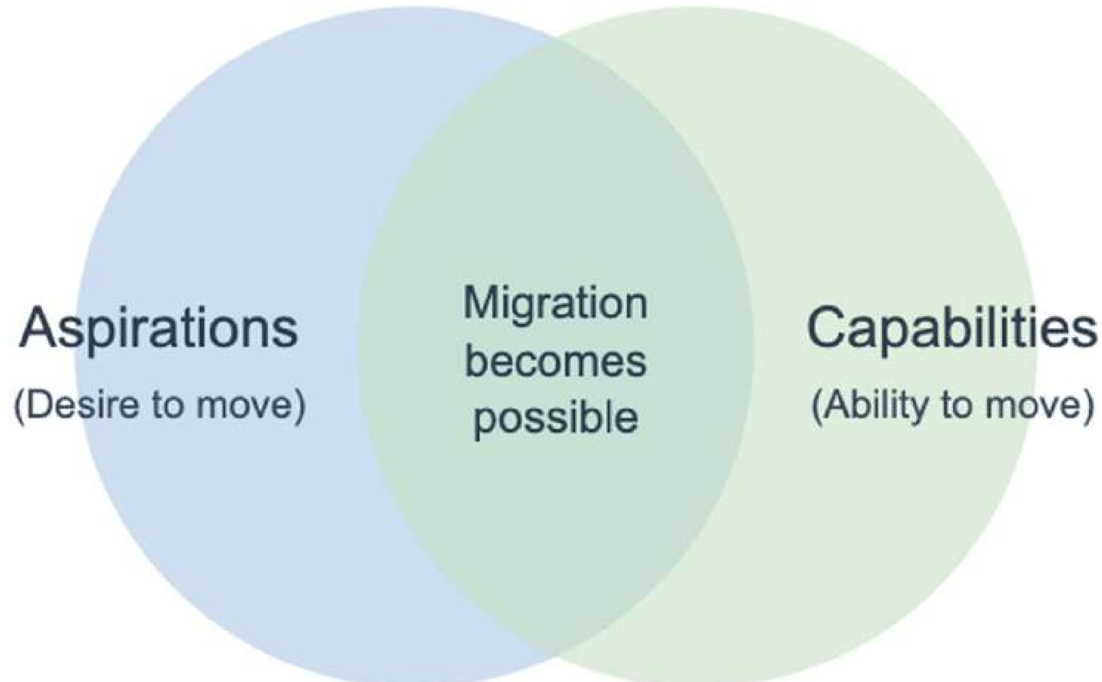
Migration: Aspirations and Capabilities (Carling, 2002; de Haas, 2021)

Aspirations (Desire to move)

- Better economic opportunities
- Education access
- Family reunification
- Safety and security
- Environmental conditions

Capabilities (Ability to move)

- Financial resources
- Social networks
- Legal pathways
- Skills/education
- Physical ability



Migration becomes possible when both aspirations to move and capabilities to do so align

Enhancing Flee 3's Agent Decision-Making

Opportunity: Building on Flee 3's successful modeling framework with cognitive science insights

Innovation: Dual process theory provides complementary framework for migration decisions

Goal: Create proof-of-concept by distinguishing System 1 vs System 2 decision processes

Focus: Conflict-induced migration as test case

Understanding Kahneman's Dual Process Theory

Sudden Displacement (System 1)

- Rapid, emotional decisions during disasters or immediate threats
- Example: Fleeing from floods or wildfires

Planned Migration (System 2)

- Carefully considered, calculated decisions
- Example: Planning relocation due to gradual environmental changes

Aspirations and capabilities get processed *differently* under various circumstances

Mapping to Migration Decision Making

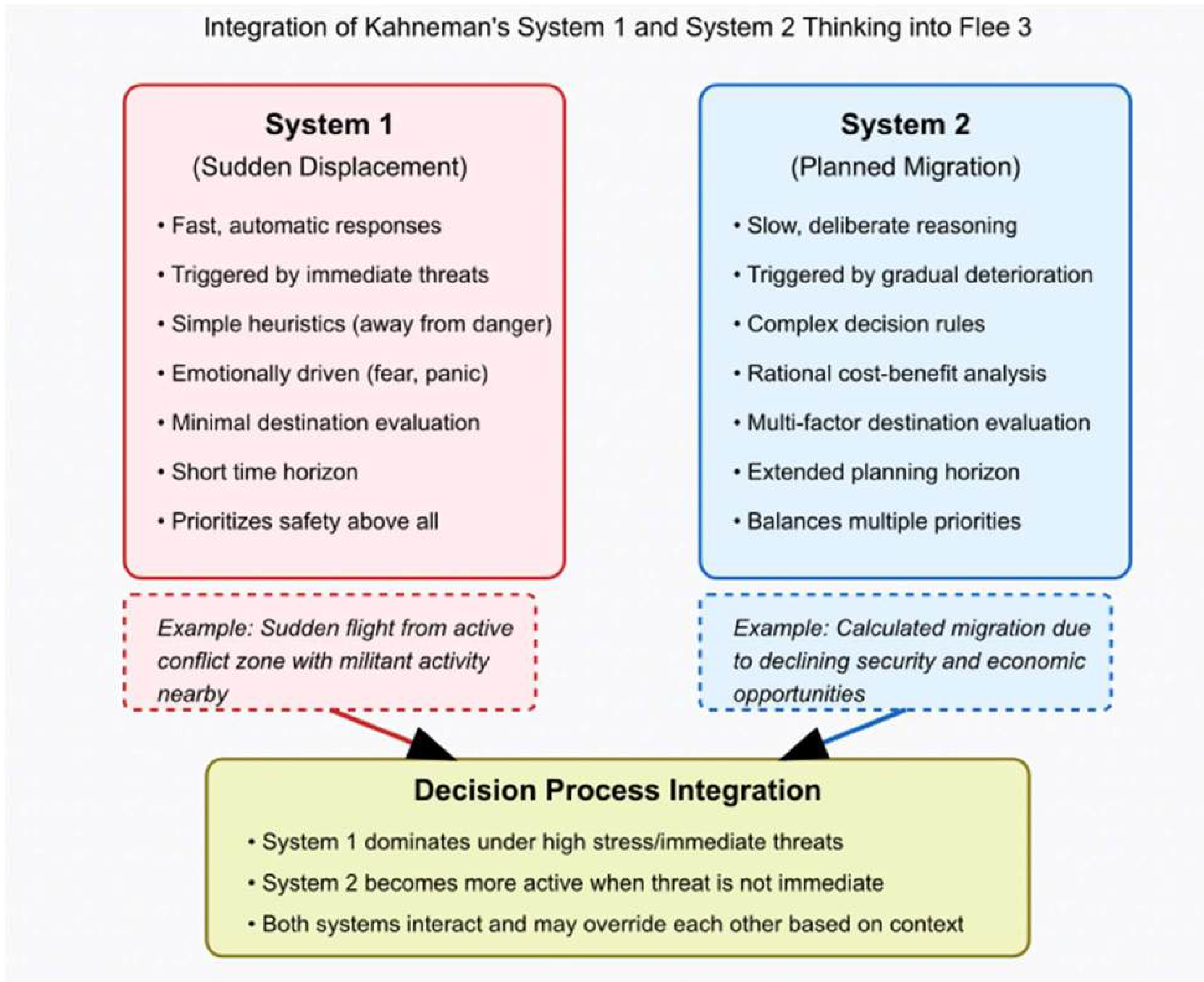
System 1 (Sudden Displacement)

- **Triggers:** Immediate threats, active conflict, violence
- **Process:** Quick emotional decisions to flee from danger
- **Example:** Rapid evacuation during armed insurgent activity
- **Characteristics:** Safety prioritization, minimal planning, nearest safe location

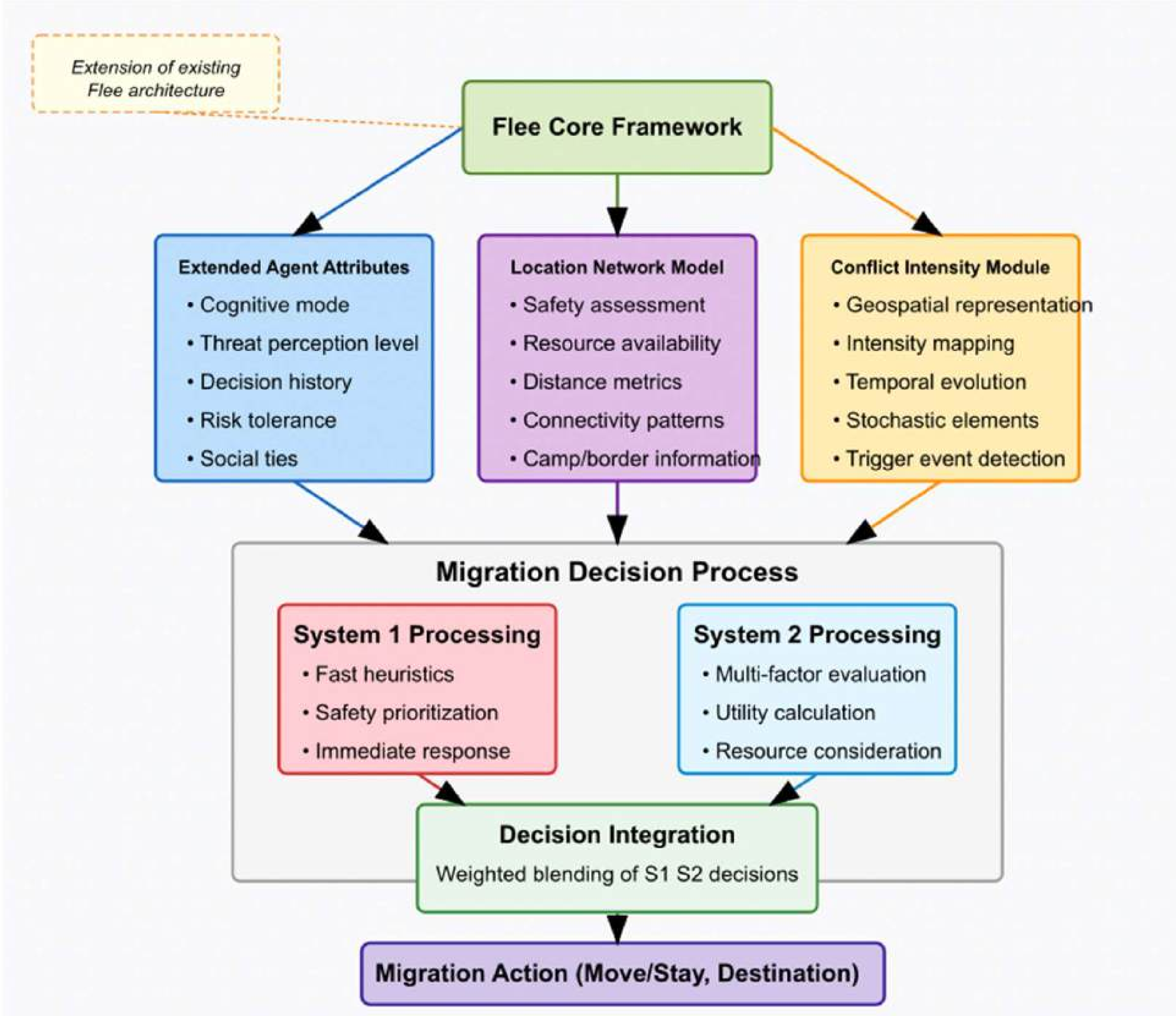
System 2 (Planned Migration)

- **Triggers:** Gradual deterioration, resource scarcity, indirect threats
- **Process:** Calculated decisions balancing multiple factors
- **Example:** Evaluating destination options based on resources and opportunities
- **Characteristics:** Multi-factor analysis, resource optimization, future planning

Conceptual Framework Visualization



Implementation Architecture



System 1 Implementation Details

Sudden Displacement Decision Logic

Core Components:

- Threat level assessment
- Safety-first heuristics
- Emotional response triggers
- Rapid decision execution

Key Parameters:

- Immediate threat threshold
- Safety improvement threshold
- System 1 activation level
- Emotional response intensity

Decision Rules:

- If threat > immediate_threshold → Activate flight response
- Choose nearest location where threat < current_threat - safety_improvement
- Minimal destination evaluation
- Immediate departure timing

System 2 Implementation Details

Planned Migration Decision Logic

Core Components:

- Multi-factor destination evaluation
- Cost-benefit analysis framework
- Resource optimization calculations
- Social network consideration

Key Parameters:

- Utility calculation weights
- Resource assessment factors
- Planning horizon length
- System 2 activation threshold

Decision Rules:

- Evaluate all potential destinations on multiple criteria
- Calculate comparative utilities of current vs potential locations
- Assess migration timing strategically
- Optimize route planning

Systems Integration

Balancing System 1 and System 2 in Decision Making

Integration Mechanisms:

- Weighted decision blending based on context
- System activation thresholds by conflict intensity
- Override protocols for extreme situations
- Dynamic adjustment based on agent experience

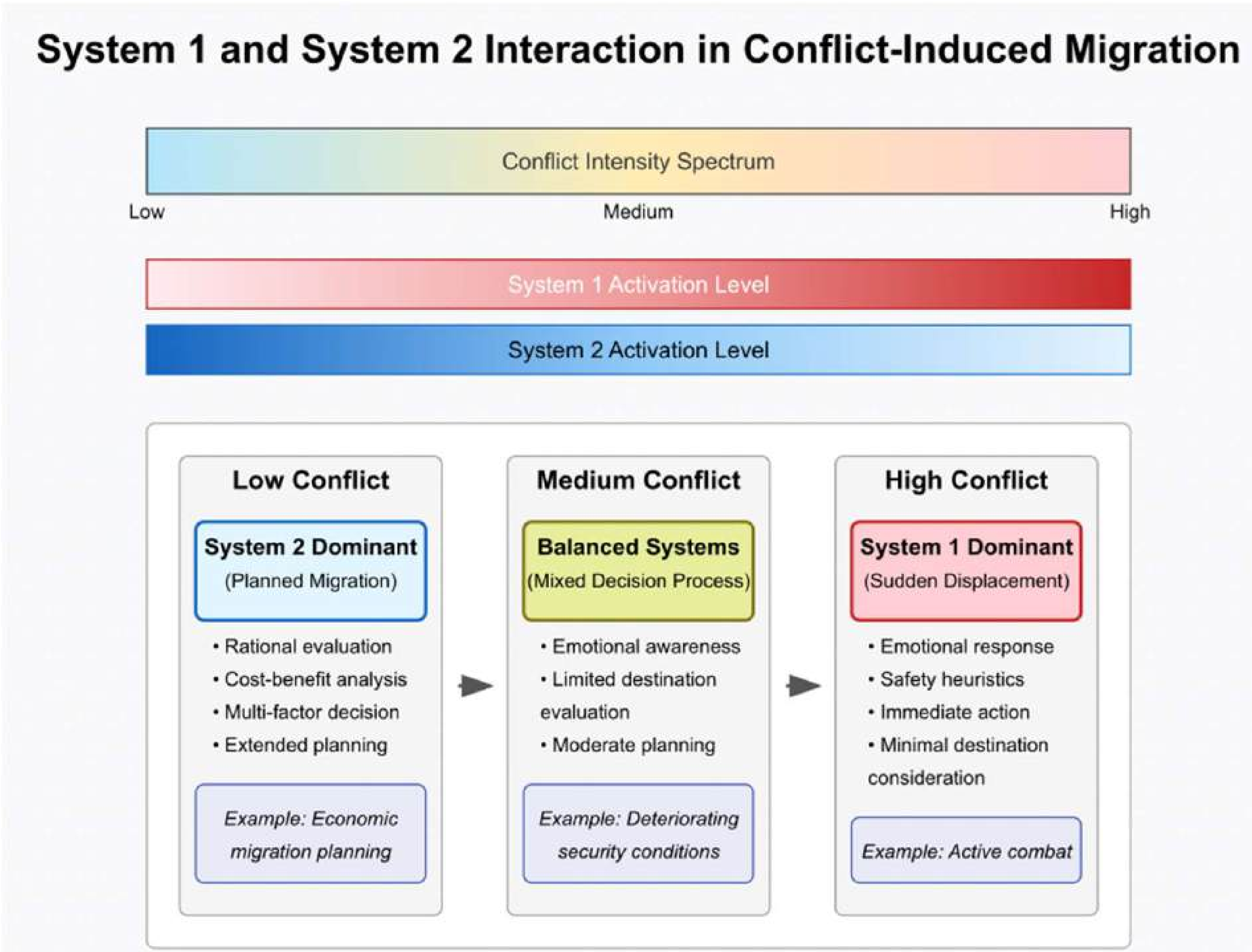
Edge Cases:

- System 1 overrides System 2 during sudden extreme threats
- System 2 can suppress System 1 when safety is adequate
- Mixed responses in uncertain or moderate threat contexts

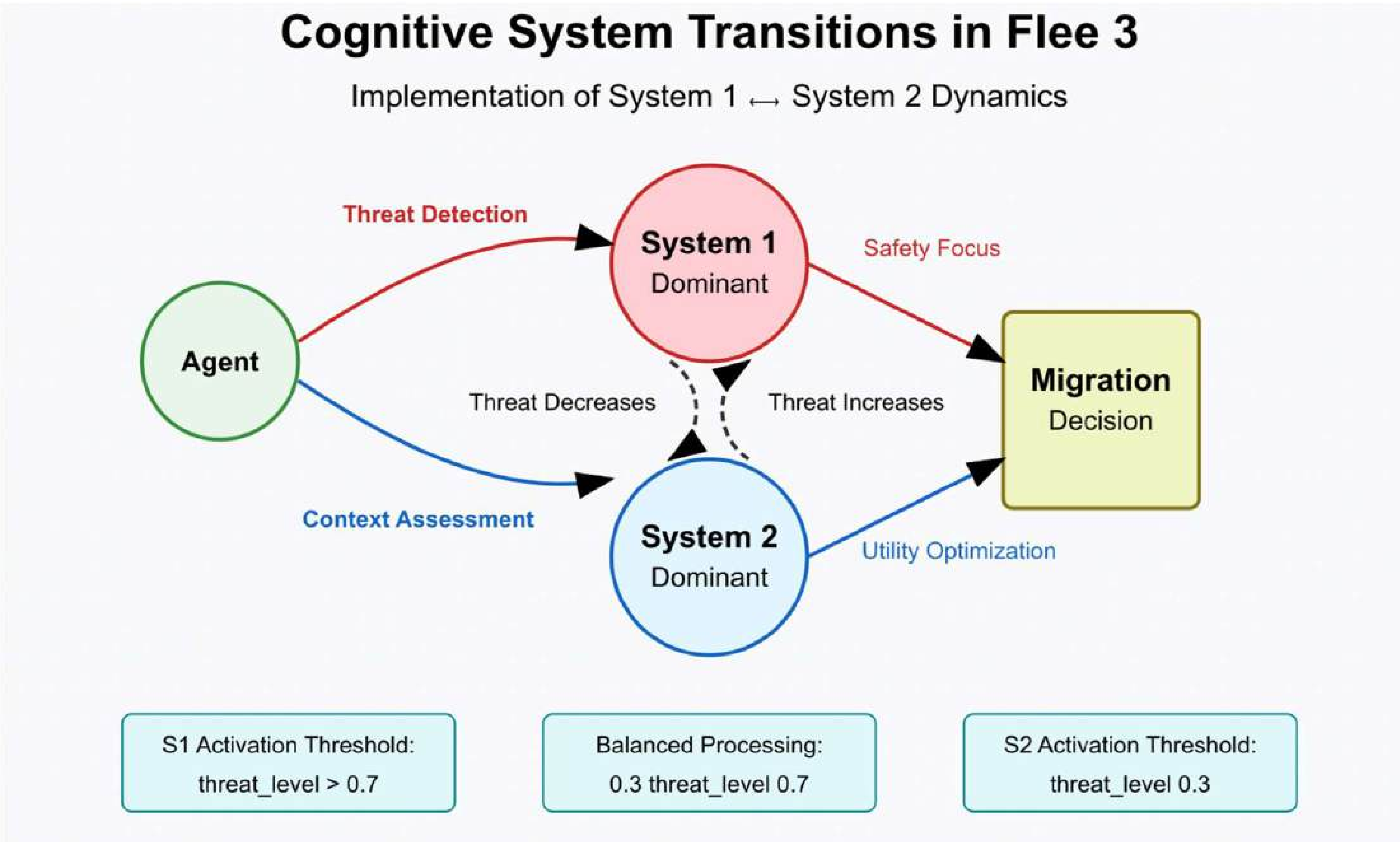
Example Scenarios:

- Low conflict → System 2 dominates (rational planning)
- Medium conflict → Balanced systems (mixed approach)
- High conflict → System 1 dominates (emotional response)

Conflict-Decision Process Interactions



Cognitive Transitions



Benefits and Challenges

Benefits of Dual Process Approach

Enhanced Realism:

- More accurate representation of human decision-making
- Differentiated response to varying conflict intensities
- Improved migration pattern prediction

Research Opportunities:

- Platform for testing cognitive theories
- Insights into psychological aspects of migration
- Better understanding of intervention effectiveness

Challenges to Address

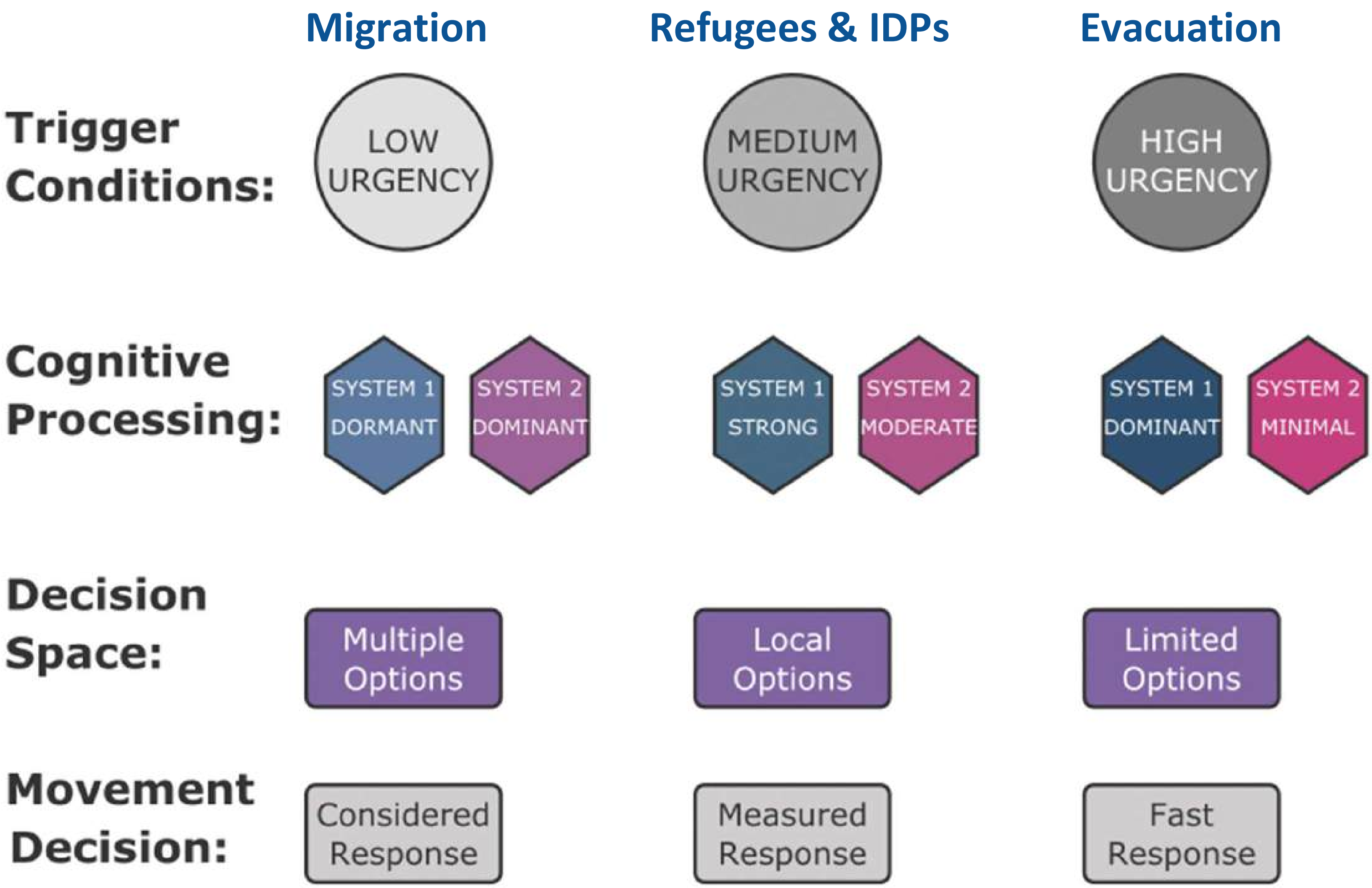
Implementation Complexity:

- Calibrating appropriate thresholds between systems
- Balancing computational complexity with realism
- Data availability for validating cognitive processes

Validation Difficulty:

- Limited empirical data on migrant decision processes
- Challenge of measuring "correctness" of cognitive model
- Need for qualitative validation approaches

A multiscale mobility framework



MINERVA RESEARCH INITIATIVE
SUPPORTING SOCIAL SCIENCE FOR A SAFER WORLD

Funding:Comparing Underlying Drivers of South-North Migration in Central America and West Africa. PI de Sherbinin, Air Force Office of Scientific Research DOD Minerva

Thanks!

mjp38@columbia.edu

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Implementation Strategy for Flee 3

Extending the Current Architecture

1. **Extended Agent Attributes:**
   - Cognitive mode (System 1 vs System 2 dominance)
   - Threat perception levels
   - Risk tolerance profiles
   - Social ties and networks
   - Decision history tracking
2. **Conflict Intensity Module:**
   - Geospatial threat representation
   - Temporal evolution of conflict
   - Trigger event detection
   - Conflict intensity thresholds
3. **Dual Process Decision Engine:**
   - System 1 processing path
   - System 2 processing path
   - Decision integration mechanism

Next Steps

Roadmap for Implementation and Refinement

1. **Phase 1: Core Implementation**
   - Extend agent attributes
   - Implement basic System 1/System 2 logic
   - Integrate with conflict data
2. **Phase 2: Validation**
   - Test against historical cases
   - Refine parameters and thresholds
   - Compare with baseline Flee performance
3. **Phase 3: Extension**
   - Add group decision dynamics
   - Incorporate social network effects
   - Implement cognitive biases (anchoring, availability, etc.)
4. **Phase 4: Documentation and Release**
   - Comprehensive documentation
   - Case study development
   - Integration into Flee 3 mainline

Validation Approach

Measuring Success of the Dual Process Implementation

Quantitative Metrics:

- Comparison with historical migration patterns
- System activation distributions across conflict scenarios
- Decision timing and destination selection accuracy

Qualitative Assessment:

- Realism of agent behaviors in different conflict contexts
- Comparison with documented migrant decision accounts
- Expert evaluation of migration patterns

Case Studies:

- Apply to historical conflict data from existing Flee validation cases
- Compare with and without dual process implementation

Leveraging Emotion & Sentiment for Displacement Prediction

Helge-Johannes Marahrens, PhD
Postdoctoral Fellow
Massive Data Institute (Georgetown University)
https://helgemarahrens.com

Research Experiences for Undergraduates (REU)

Summer 2023

Overview

- Big Data & Forced Displacement
  - Key Problem: Selecting the Right Variables
- Premise: Emotion / Sentiment
- Empirical Results
- Conclusions
- Code Examples

Premise: Emotion / Sentiment

- Differences
- Previous Work

Sentiment

- Broad Measure
  - Single Dimension (Positive/Negative)
- Easy to detect
- Computationally cheap

"Simple but Broad"

Sentiment

- Broad Measure
  - Single Dimension (Positive/Negative)
- Easy to detect
- Computationally cheap

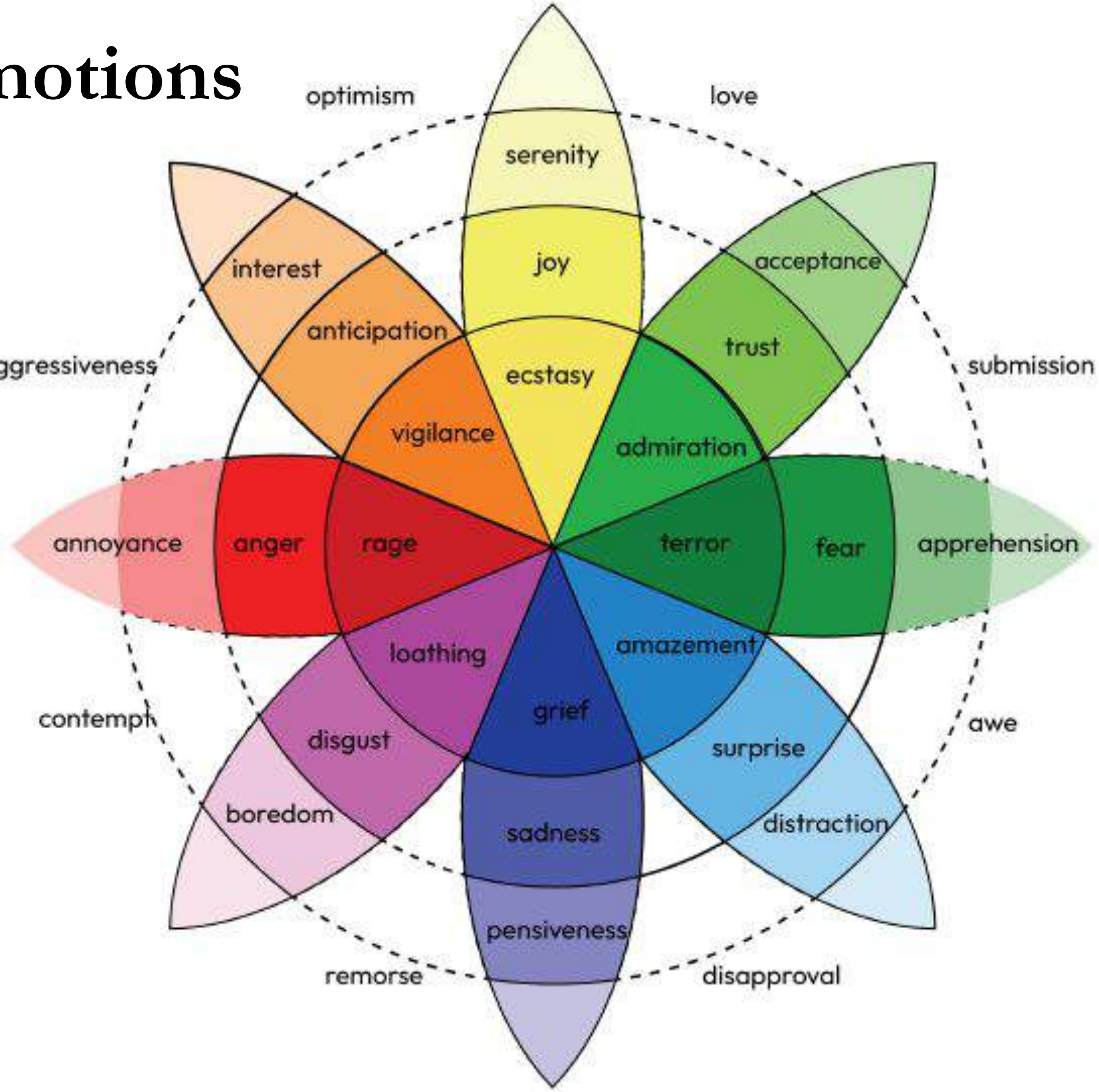
"Simple but Broad"

Emotions

- Nuanced Measure
  - Multiple Dimensions (Joy/Anger/Fear/Sadness)
- Harder to detect
- Computationally expensive

"Nuanced but Complex"

Plutchik's Wheel of Emotions



Previous Literature

- Sentiment & Stock Market, Election Outcomes, Consumer Demand
- Emotion Detection & Crisis Response

- Sentiment used to predict internal movement (e.g., in Iraq; Singh et al. 2019)
- Emotions to understand public views toward Ukraine-Russian war (Piyush et al. 2023)

Empirical Results

- Case Studies
- Measurement & Prediction

Case Studies

CONFLICT		TIMESCALE	MOVEMENT	SCALE
	**Ukraine (2022–)**	Daily, Feb 24 – October 18, 2022	External, moving to various countries	**3.7 Million internal, 6.5 Million refugees**
	**Sudan (2023–)**	Weekly, April – August, 2023	Mostly internal, or to bordering cities	**>8 Million**
	**Venezuela (2014–)**	Monthly, Jan – Dec, 2022	External, majority migrating to Colombia	**>3 Million**

Pretrained Language Models Work Best

	Ukrainian	Spanish	Arabic
Best Model	mBERT	BETO	GloVe
anger	0.86	0.83	0.82
fear	0.90	0.98	0.95
sadness	0.82	0.85	0.76
joy	0.92	0.83	0.67

TABLE V

BEST MODEL ACCURACY BY EMOTIONS & LANGUAGES

	Ukrainian			*Spanish*			*Arabic*		
Type	Accuracy	F1	Model	Accuracy	F1	Model	Accuracy	F1	Model
Lexicon	69%	70%	CombLex	50%	44%	CombLex	62%	69%	CombLex
ML	76%	73%	SVM	**81%**	**80%**	**SVM**	87%	88%	SVM
PLM	**82%**	**81%**	**mBERT**	74%	79%	BETO	**91%**	**92%**	**mBERT**

TABLE III

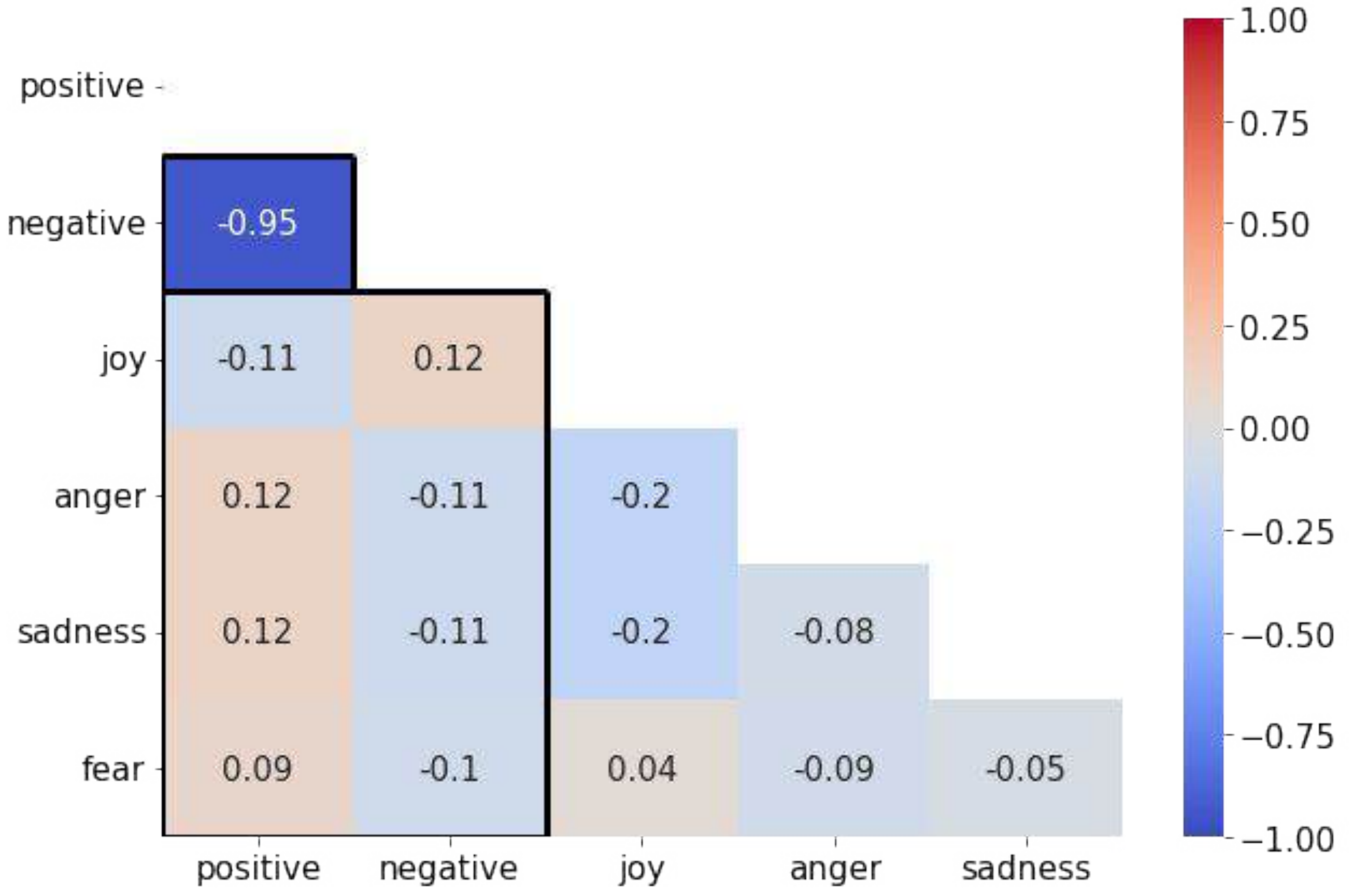
BEST PERFORMING MODELS FOR SENTIMENT DETECTION. COMBLEX MEANS THAT ALL THE AVAILABLE LEXICONS FOR THE LANGUAGE WERE COMBINED INTO A SINGLE LEXICON.

	Ukrainian			*Spanish*			*Arabic*		
Type	Accuracy	F1	Model	Accuracy	F1	Model	Accuracy	F1	Model
Lexicon	74%	23%	NRCLex	70%	18%	NRCLex	60%	24%	NRCLex
ML	55%	55%	LogitReg	75%	53%	SVM	56%	67%	NaiveBayes
PLM	**76%**	**75%**	**mBERT**	**87%**	**87%**	**BETO**	**82%**	**79%**	**GloVe**

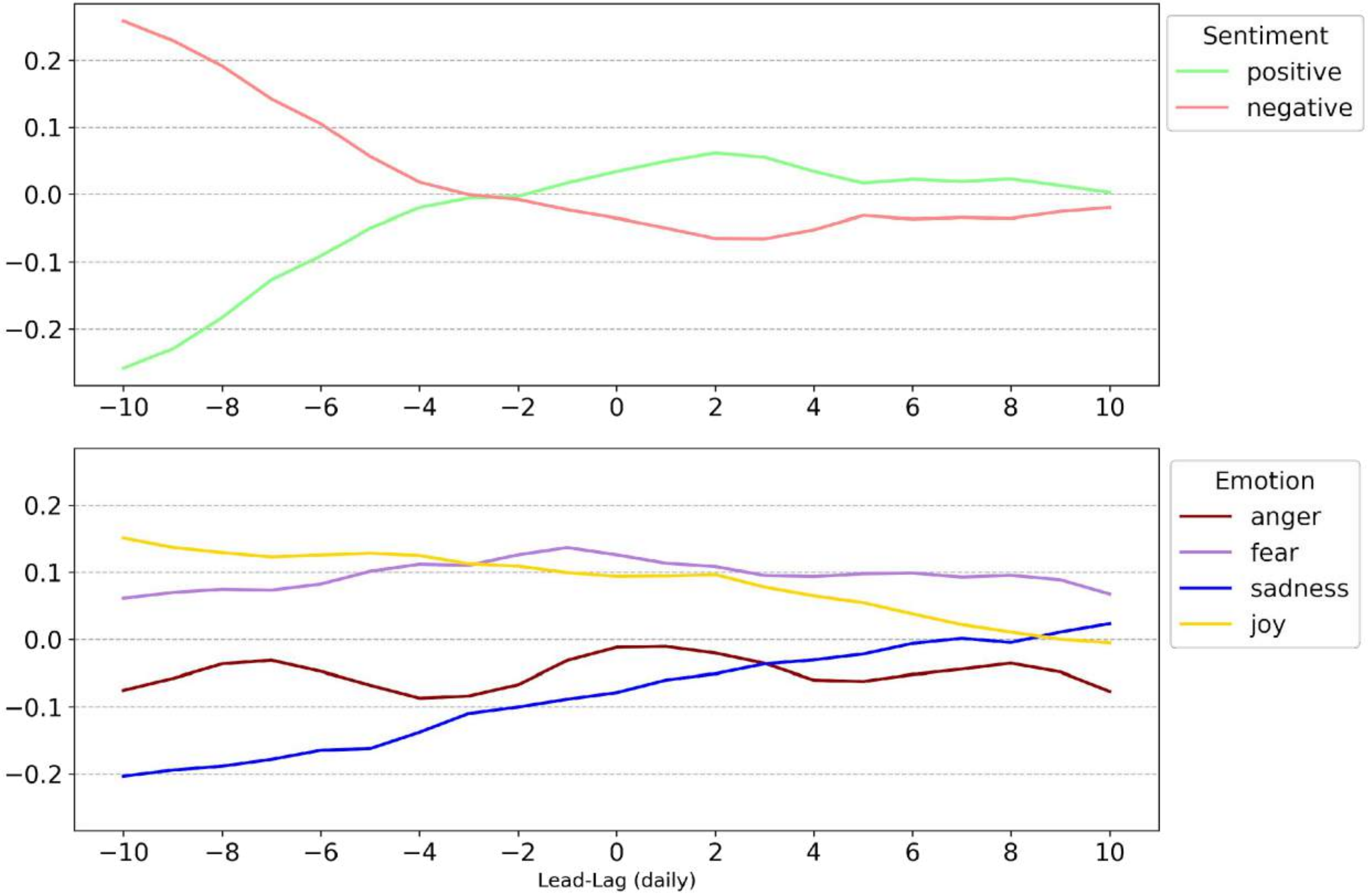
TABLE IV

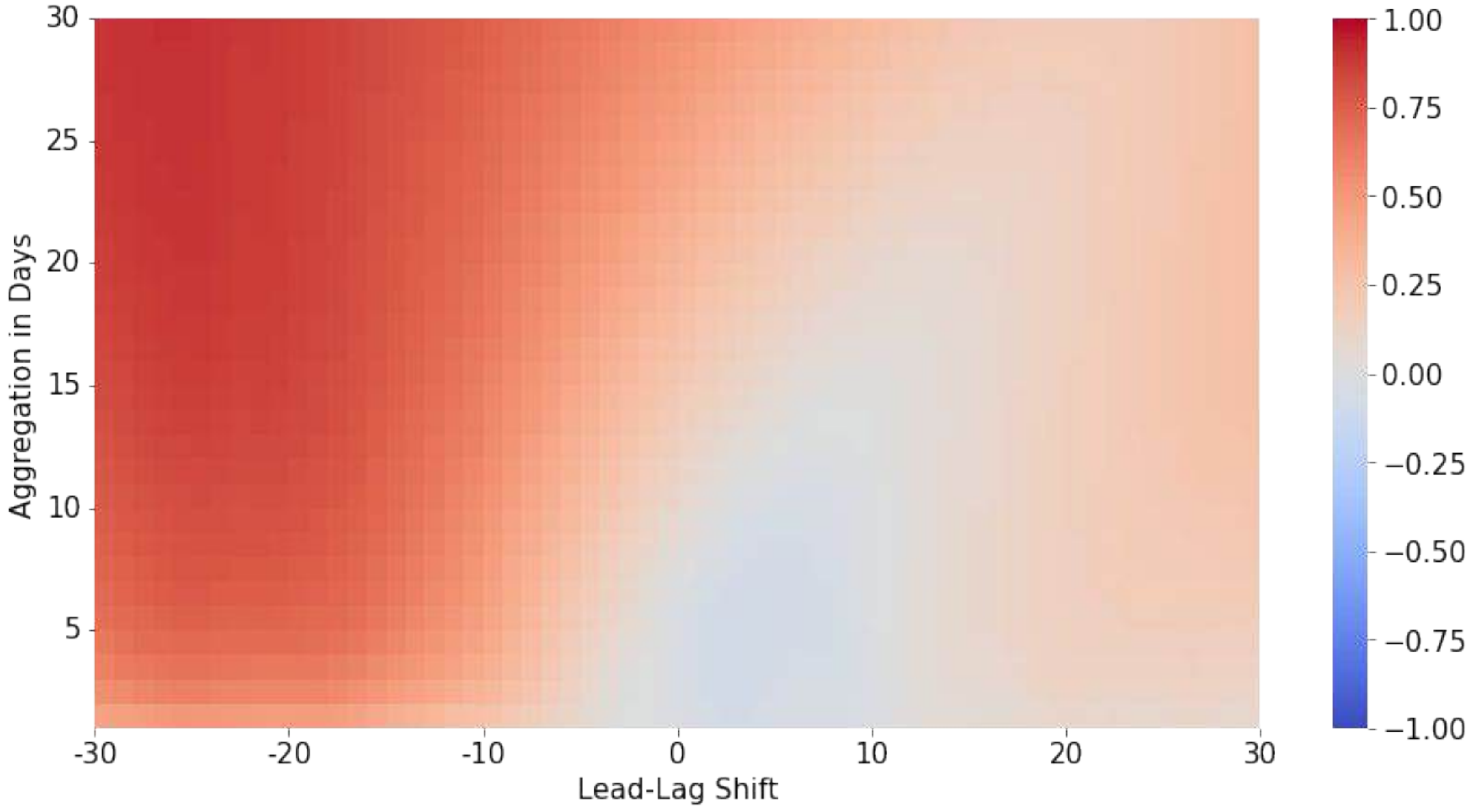
BEST PERFORMING MODELS FOR EMOTION DETECTION FOR EACH EMOTION.

Emotions Show Strange Patterns (Mismeasured?)



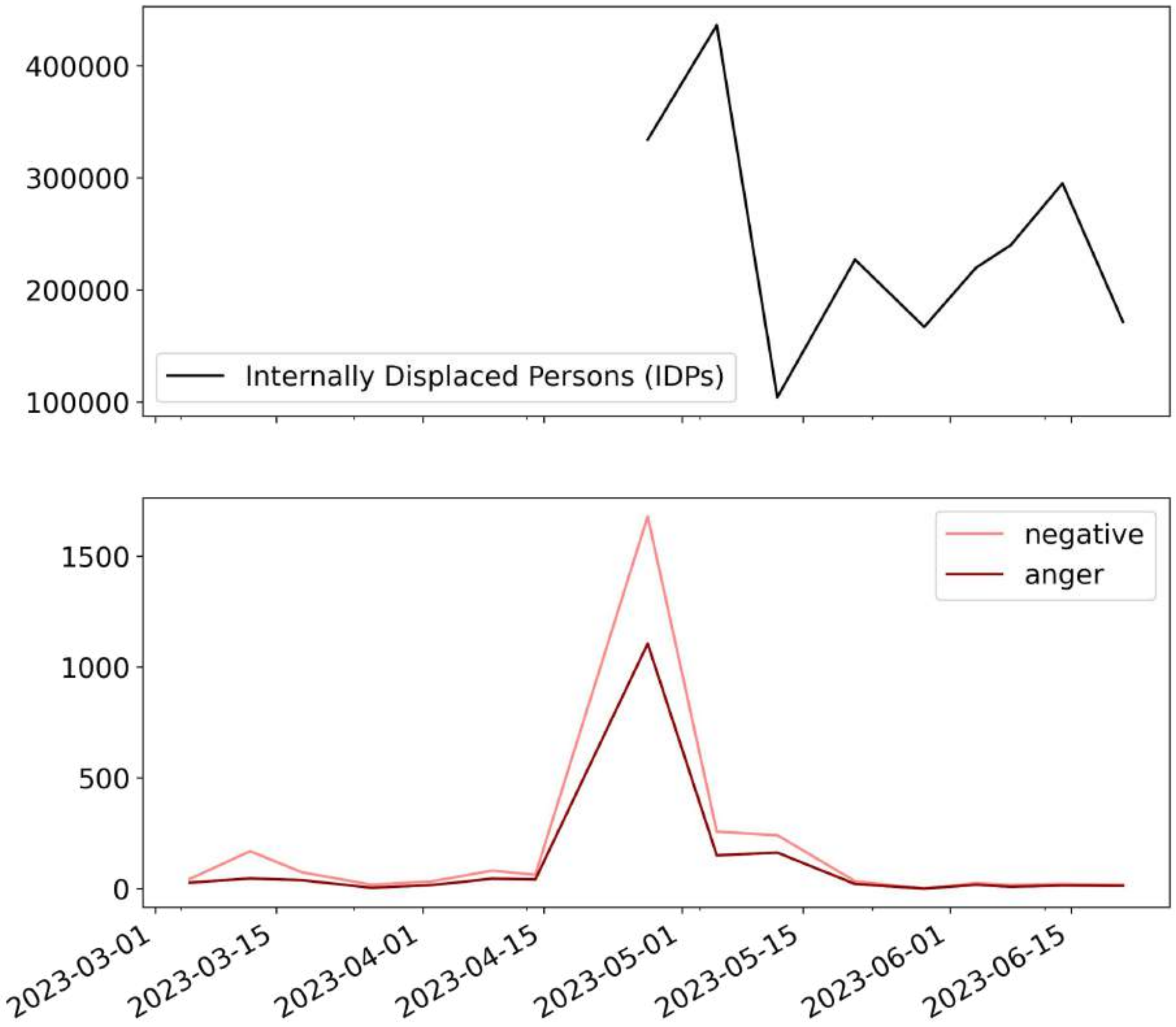
Sentiment is a Leading Indicator (Ukraine)



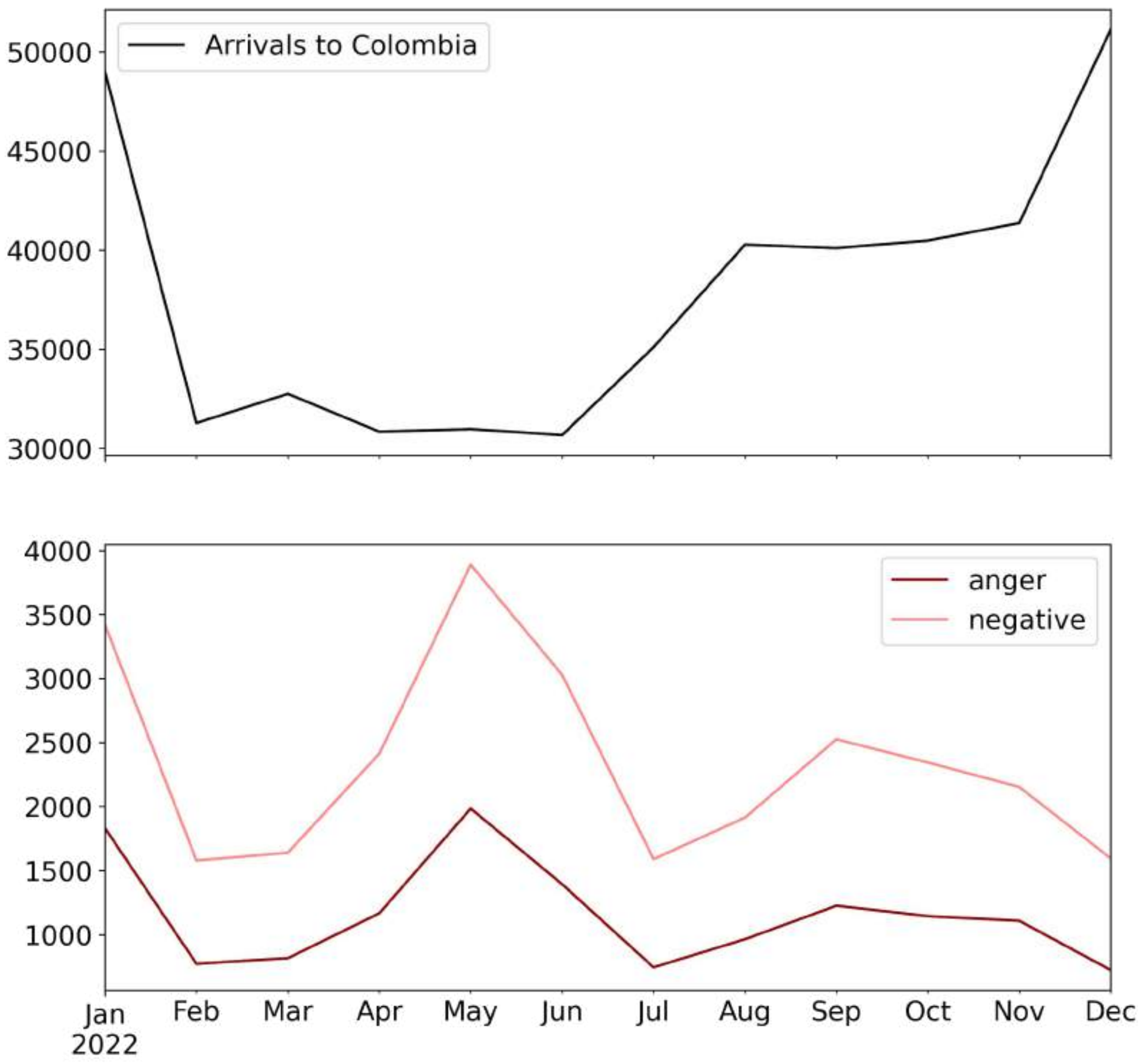


Robust to Different Aggregation and Lead Windows

In Sudan, Anger and Negative Sentiment Work Equally Well



At the Monthly Scale (Venezuela), Neither Sentiment Nor Emotion Works Well



Conclusion

- Sentiment works better than emotions (yet?)
  - Additional Nuance of Emotions provides no clear advantage
  - Difficulties in measuring emotions
- At low temporal resolutions neither work well
- Full-Model Comparison

Code Examples

- multilingual BERT (mBERT)

In [1]:
```
import torch
import numpy as np
from transformers import BertTokenizer, BertForSequenceClassification, Trainer, TrainingArguments
from datasets import load_dataset
from sklearn.metrics import accuracy_score, precision_recall_fscore_support
```

In [2]:
```
# Load the multilingual BERT tokenizer
MODEL_NAME = "bert-base-multilingual-uncased"
tokenizer = BertTokenizer.from_pretrained(MODEL_NAME)

# Load the Multilingual Sentiments Dataset
dataset = load_dataset("tyqiangz/multilingual-sentiments", "german")
```

In [3]:
```
# Tokenization Function
def tokenize_function(example):
    return tokenizer(example["text"], padding="max_length", truncation=True, max_length=128)

# Apply tokenization
tokenized_datasets = dataset.map(tokenize_function, batched=True)

# Load Pretrained mBERT Model for Sentiment Classification
model = BertForSequenceClassification.from_pretrained(MODEL_NAME, num_labels=3)
```

In [4]:
```
# Training Arguments
training_args = TrainingArguments(
    output_dir="./sentiment_results",
    eval_strategy="epoch",
    save_strategy="epoch",
    num_train_epochs=3,
    per_device_train_batch_size=8,
    per_device_eval_batch_size=8,
    logging_dir="./logs",
    logging_steps=10,
    load_best_model_at_end=True,
    use_cpu=True
)

# Compute Metrics
def compute_metrics(eval_pred):
    logits, labels = eval_pred
    predictions = np.argmax(logits, axis=-1)
    acc = accuracy_score(labels, predictions)
    precision, recall, f1, _ = precision_recall_fscore_support(labels, predictions, average="weighted")
    return {"accuracy": acc, "f1": f1, "precision": precision, "recall": recall}

# Trainer
trainer = Trainer(
    model=model,
    args=training_args,
    train_dataset=tokenized_datasets["train"],
    eval_dataset=tokenized_datasets["test"],
    compute_metrics=compute_metrics,
)
```

In [5]:
```
# Train the Model
trainer.train()

# Evaluate on Test Set
results = trainer.evaluate()
print("Test Set Results:", results)
```

[690/690 15:40, Epoch 3/3]

Epoch	Training Loss	Validation Loss	Accuracy	F1	Precision	Recall
1	0.878600	0.863428	0.597701	0.578333	0.689167	0.597701
2	0.693500	0.842189	0.670115	0.670575	0.692271	0.670115
3	0.412500	0.866347	0.686207	0.686035	0.688806	0.686207

[109/109 00:33]

```
Test Set Results: {'eval_loss': 0.842188835144043, 'eval_accuracy': 0.6701149425287356, 'eval_f1': 0.67057523808884
98, 'eval_precision': 0.6922707503152887, 'eval_recall': 0.6701149425287356, 'eval_runtime': 33.3937, 'eval_samples
_per_second': 26.053, 'eval_steps_per_second': 3.264, 'epoch': 3.0}
```

In [6]:
```
# Save Model & Tokenizer
model.save_pretrained("./multilingual_sentiment_model")
tokenizer.save_pretrained("./multilingual_sentiment_model")
```

Out[6]:
```
('./multilingual_sentiment_model/tokenizer_config.json',
 './multilingual_sentiment_model/special_tokens_map.json',
 './multilingual_sentiment_model/vocab.txt',
 './multilingual_sentiment_model/added_tokens.json')
```

```
In [7]: # Reverse label mapping for predictions
label_mapping = {0:'positive', 1:'neutral', 2:'negative'}
idx_to_label = {k: v for k, v in label_mapping.items()}
```

```
In [8]: # Prediction Function
def predict_sentiment(text):
    inputs = tokenizer(text, return_tensors="pt", padding=True, truncation=True, max_length=128)
    with torch.no_grad():
        outputs = model(**inputs)
    prediction = torch.argmax(outputs.logits, dim=1).item()
    return idx_to_label[prediction]

# Example Predictions
sample_texts = [
    '@user lmao ich lach mich kaputt',  # should be Positive
    "Stiftung Warentest: 'Zehn Staubsauger im Test.'",  # should be Neutral
    "Was labert ihr für einen Stuss?",  # should be Negative
]

for text in sample_texts:
    print(f"Input: {text} -> Predicted Sentiment: {predict_sentiment(text)}")
```

```
Input: @user lmao ich lach mich kaputt -> Predicted Sentiment: positive
Input: Stiftung Warentest: 'Zehn Staubsauger im Test.' -> Predicted Sentiment: neutral
Input: Was labert ihr für einen Stuss? -> Predicted Sentiment: negative
```

Thank you!

For questions: hm868@georgetown.edu

Helge-Johannes Marahrens, PhD
Postdoctoral Fellow
Massive Data Institute (Georgetown University)
https://helgemarahrens.com

The Digital Traces of Ukraine's 2022 Refugee Exodus

Nathan Wycoff

Department of Mathematics and Statistics
University of Massachusetts Amherst

CLIFDEW-GRID Technical Workshop

Internet Data for Migration

Social Media

- *Facebook*
  - "Direct" measurement of migration based on location updates.
  - Look at location of friends.
- *X (formerly Twitter)* (formerly *Twitter*)
  - Geotagging on twitter is problematic
  - Location mentions
  - Look at location of friends.

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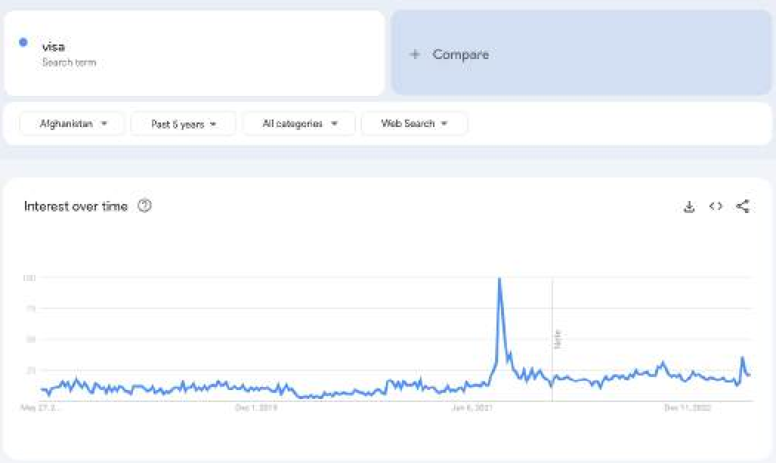
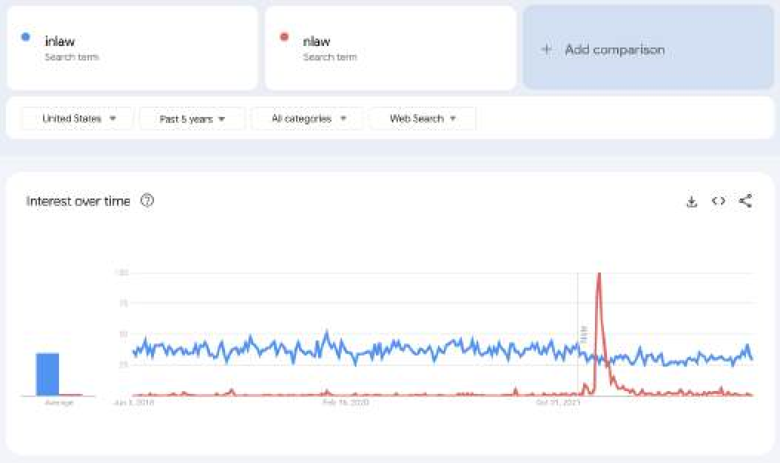
Internet Search Engine Data

Google Trends



Internet Search Engine Data

Google Trends



Google Trends

- Can look at "Interest" of search term over time and space, between 0 and 100.
- Need to manually renormalize different terms.
- Useful but difficult to reproduce [1].

[1] Wanner 2020

Others

- Local Newspaper data.
- Yahoo Emails - Zagheni and Weber 2012.

Event Aggregators

These sources estimate casualties related to violent conflict, among much else.

- Armed Conflict Location & Event Data Project (ACLED)
- Global Database of Events, Language and Tone (GDELT)

Forming Topics

For this talk, a *topic* is simply a set of words.

A search or document is said to contain a topic if it contains any of its words.

Topics are directly constructed in the target language.

2022-Present Russian Invasion of Ukraine

Background

- On February 24 ’22, Russia invaded Ukraine.
- Among largest refugee crisis since WWII.
- Ukrainians are moving to various countries throughout the world.

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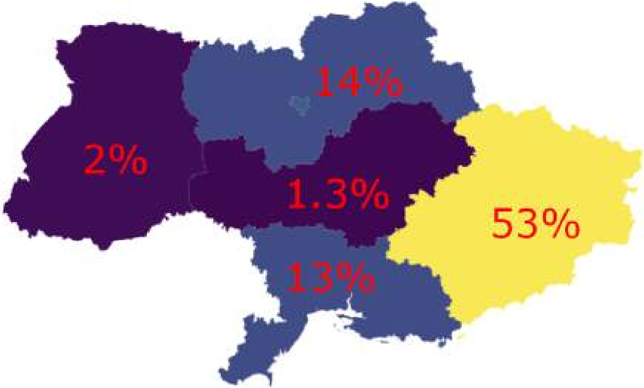
Internal Displacement



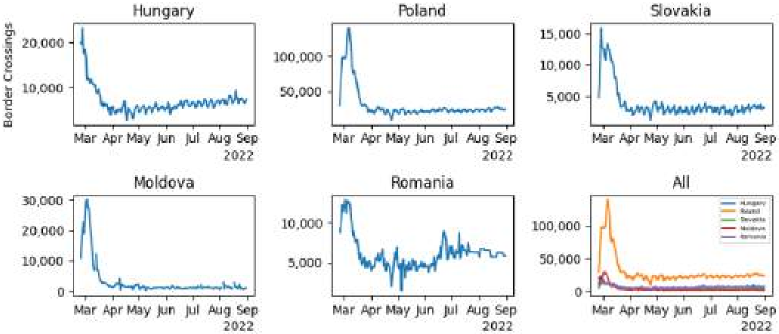
UNHCR Flow Data - Scope of Destinations

Cumulative Flows to Neighboring Countries

UNHCR Ukraine Situation Flash Update #8

Border Crossings

y_t - Hungary + Poland + Slovakia Outflow.



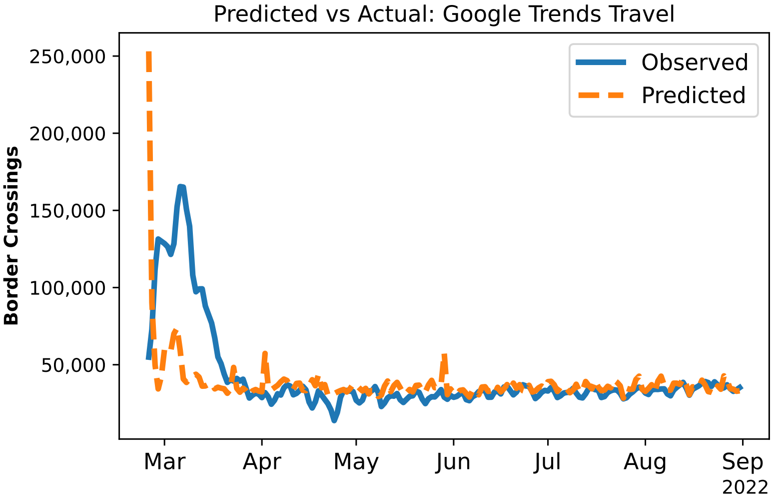
Predictors

- Twitter
- Google Trends
- Local Newspapers
- ACLED
- GDELT

Topics

- Direct Indicators:
  - flee/travel
- Insecurity Indicators:
  - Political
  - Economic
  - Physical
- Contextual Indicators:
  - Economic
  - Health

Trends - Travel Predicting Border Crossings



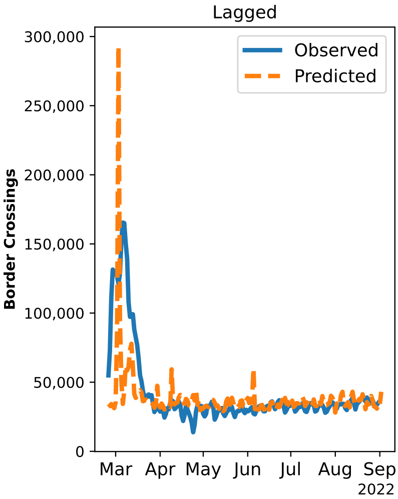
Shifted Moving Averages

$z(t) = \frac{1}{2\sigma+1} \sum_{\tau=-w}^{w} x(t - \tau - \mu)$

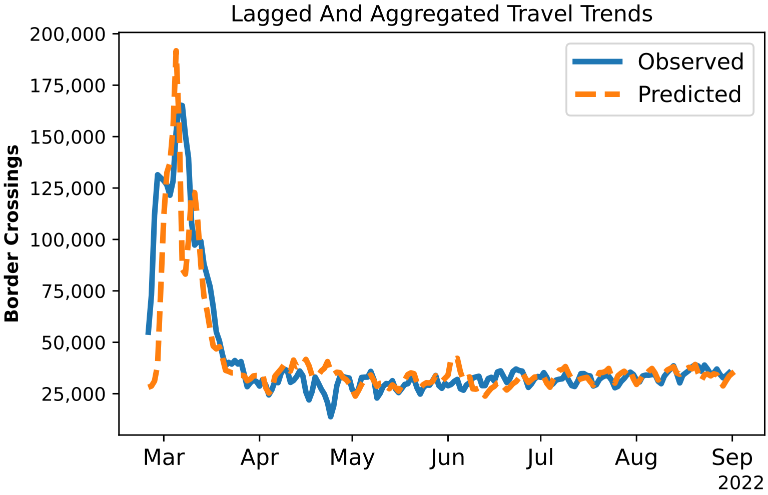
$z(t) =$ Average value of x for the 2σ days closest to day $t - \mu$ (and day $t - \mu$ itself).

If $\mu = 7, \sigma = 3$ then $z(\mathrm{Today}) =$ Average value of x from Monday the 24th to Sunday the 30th.

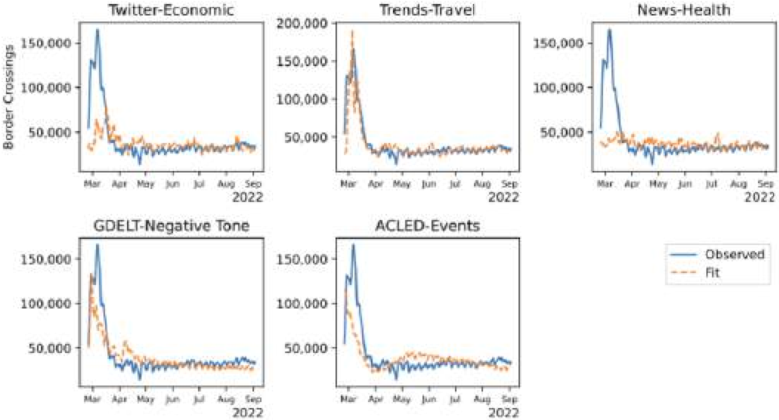
Google Trends Travel Example



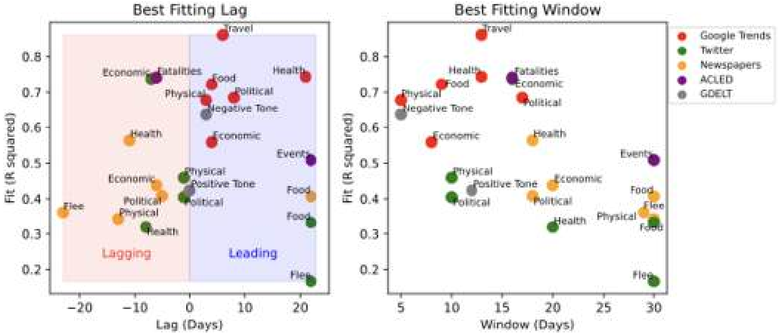
Laggregation



Fit


Twitter-Economic
Trends-Travel
News-Health
GDELT-Negative Tone
ACLED-Events
Border Crossings
200,000
150,000
100,000
50,000
Mar
Apr
May
Jun
Jul
Aug
Sep
2022
Observed
Fit

Lag-Lead



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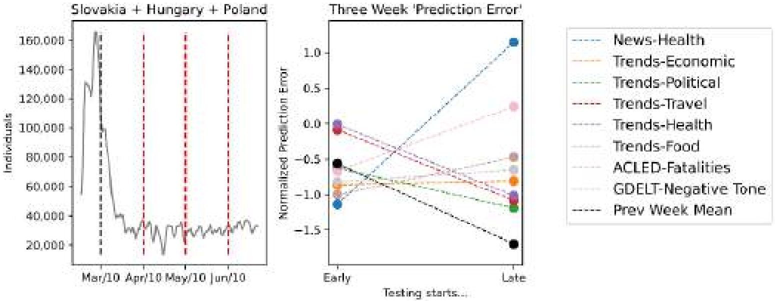
Predictions



Predictions?

How seriously should we take these predictions?

1. The transient dynamics are simple ("first up, then down").
2. In the steady state, are the predictions valuable?

Global Migration Contexts

State of the art: for each crisis, craft an appropriate model from scratch.

How can we use knowledge of prior migration patterns to predict migration in future crises?

- Can learn what types of indicators "tend" to be good.
- But we want to quantitatively leverage prior migration data.
- Focus on transfer learning.

Thanks!

Wycoff, N., Singh, L. O., Arab, A., Donato, K. M., & Marahrens, H. (2024). The digital trail of Ukraine's 2022 refugee exodus. Journal of Computational Social Science, 7(2), 2147-2193.

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Predicting Forced Displacement Patterns using Agent-based Simulations

Diana Suleimenova, Yani Xue, Alireza Jahani,

Maziar Ghorbani, Laura Harbach and Derek Groen

Brunel University of London

27 March 2025

SEAVEA

Content

- Modelling conflict-driven forced displacement
- Simulation development approach
- Flee: An agent-based simulation code
- FabFlee: An automation plugin
- Summary

Modelling conflict-driven displacement

Motivation:

- Conflict erupts, people flee
    - Where do they go?
- Can predicting their arrival help organisations to effectively allocate support in advance?
- How do humanitarian decisions affect them?
    - Border closure.
    - Camp placement.
- Better understand historical processes.
- Inform decision-making, and possibly public awareness.

1st paper: Groen, D., 2016. Simulating refugee movements: Where would you go?. *Procedia Computer Science*, *80*, pp.2251-2255.

Objective

Refugee movements matter, and it is important to be able to predict where refugees go:

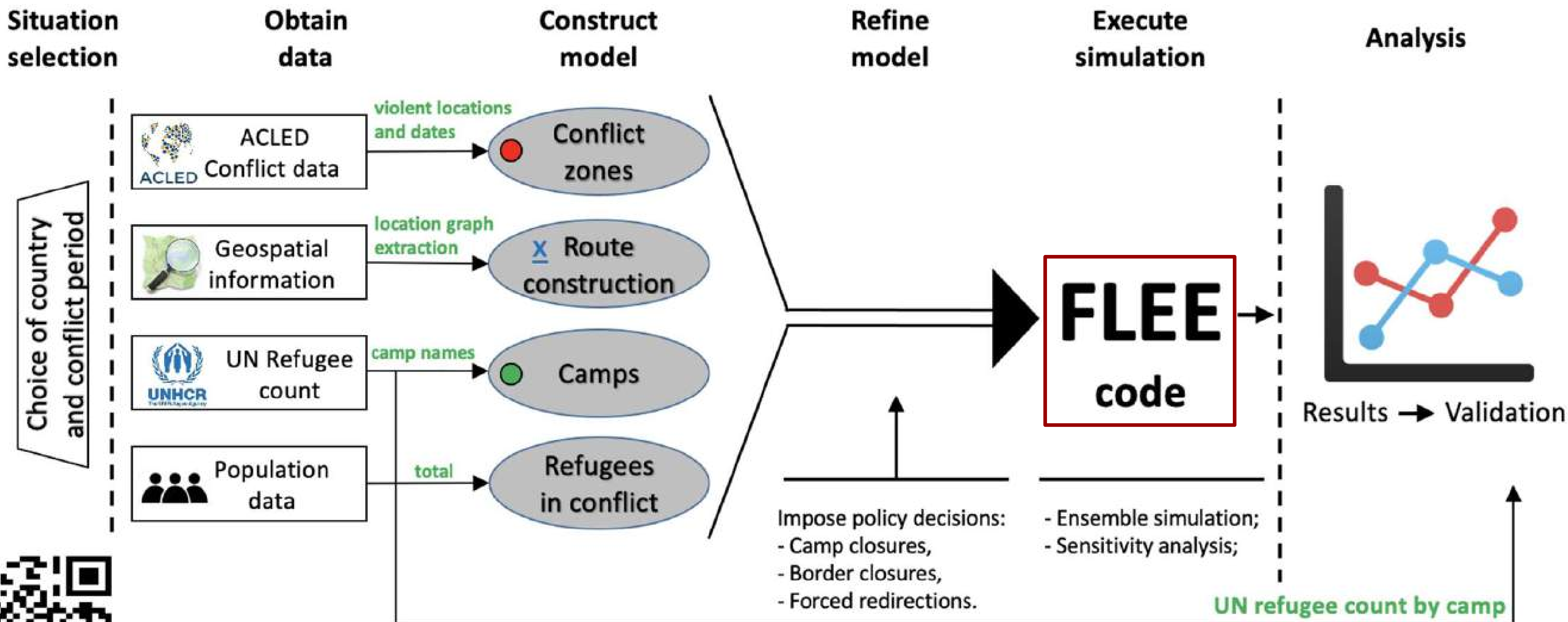
To save refugee lives, as it helps governments and NGOs to correctly allocate humanitarian resources to refugee camps

To help complete incomplete data collections on refugee movements

To investigate the consequences of a nation closing its border for refugees

Groen, D. “Simulating refugee movements: where would you go?”, International Conference on Computational Science, 2016.

Simulation Development Approach



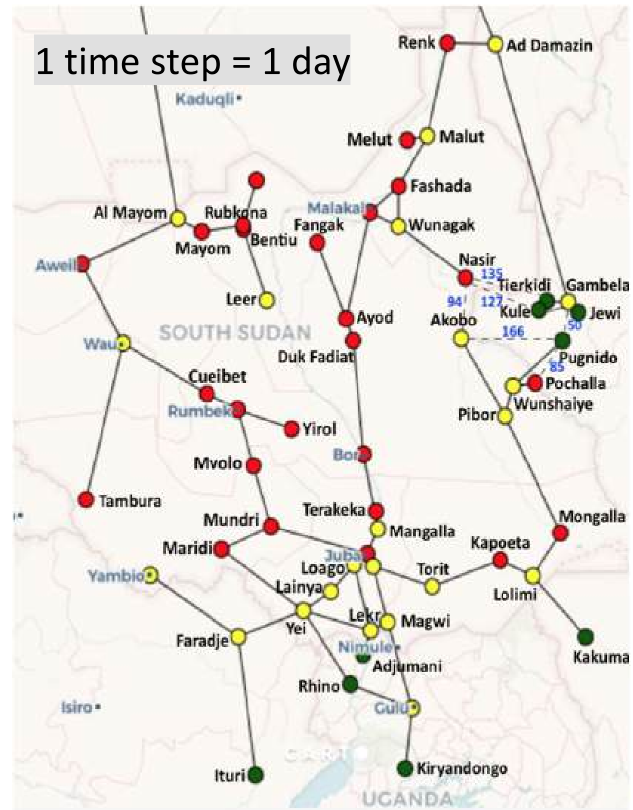
Suleimenova, D., Bell, D. & Groen, D. A generalized simulation development approach for predicting refugee destinations. Sci Rep 7, 13377 (2017)

Introducing Flee

- Agent-based model for forecasting conflict-driven displacement.
- Predicts where people may go, given a developing conflict.
- Existing models for more than 15 historical conflicts offer a starting point.
- Open source, explicit assumptions.
- https://flee.readthedocs.io

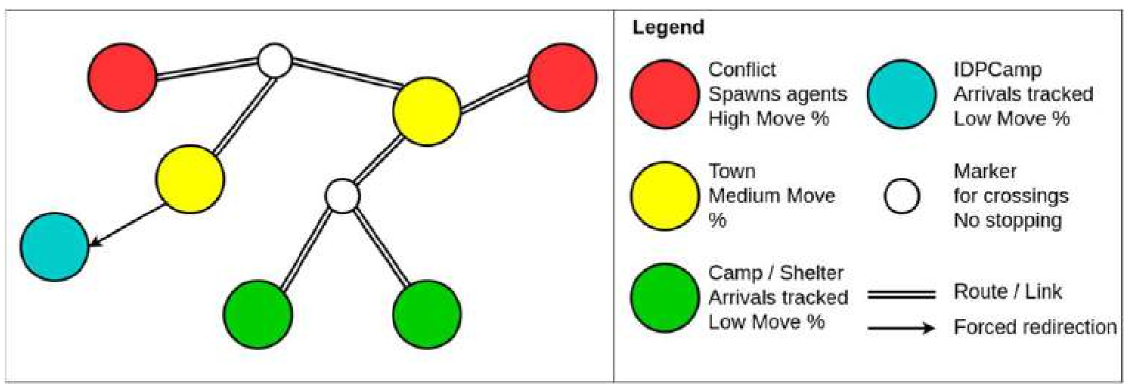
Initial Code: Suleimenova, D., Bell, D. & Groen, D. A generalized simulation development approach for predicting refugee destinations. *Sci Rep* 7, 13377 (2017).

Forecasting challenge: Groen, D., Suleimenova, D., Jahani, A. and Xue, Y. Facilitating simulation development for global challenge response and anticipation in a timely way. Journal of Computational Science, 72, p.102-107 (2023).



Basics of the logic

- Each agent = 1 displaced person.
  - Placed in a conflict zone, will move around in search of a camp.
- Each agent decides:
  - Do I stay put, or move to a neighbouring location?
  - If I move, which location shall I go to?
- Factors such as distance, perceived safety, ethnic match, distance from home can be introduced to shape the decisions.



Advances in Flee 3

- Demographic characteristics (i.e., age,gender,ethnicity,religion).
- Location and link characteristics.
- Flexible system for defining movement rules.
- Conflict-driven spawning.
- First support for IDP modelling.
- Still exploring how to best do this responsibly.
- Many objective optimisation for selecting support locations.

Ghorbani, M., Suleimenova, D., Jahani, A., Saha, A., Xue, Y., Mintram, K., Anagnostou, A., Tas, A., Low, W., Taylor, S.J., et al. Flee 3: Flexible agent-based simulation for forced migration. Journal of Computational Science 81, 102371 (2024)

Strengths and risks of using Flee

Strengths:

- Validated across many conflicts.
- Explainable logic.
- High resolution in space and time.
- Open-source.

- Not a self-learning system.
- No reliance on personal data.
- No reliance on social media sources.

Risks:

- Assumptions can contain bias.
  - Scrutiny is very important.
- Specific context of use.
  - Training is essential.
- Supports, but does not replace decision-makers.

Some things can be sensitive to forecast:

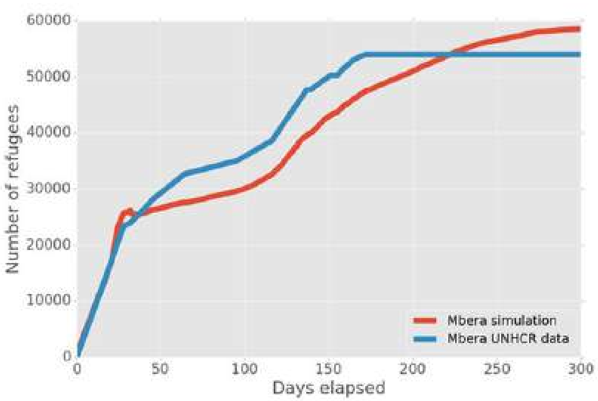
- How a conflict evolves on a fine-grained level.
- How many persons are displaced by a specific conflict event.
- What kind of interventions governments will make.

Flee does not forecast these, but provides tools for users to create scenarios covering these aspects.

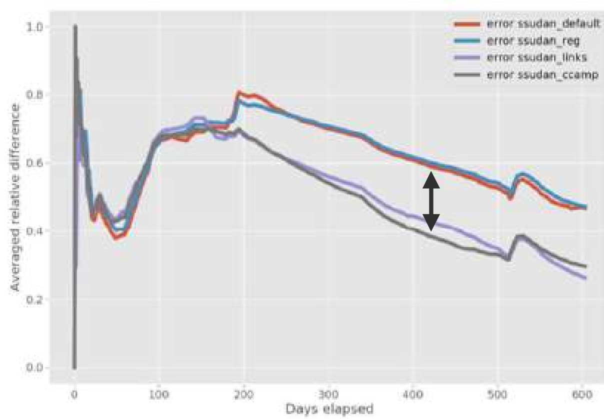
Flee simulation results

	A	B	C	D	E	F	G	H	I	J	K
1	Day	D sim	D data	D error	E sim	E data	E error	F sim	F data	F error	Total error
2	0	20	20	0	60	60	0	19	20	0.05	0.01
3	1	20	68	0.705882352941176	61	104	0.413461538461538	19	38	0.5	0.523809523809524
4	2	21	116	0.818965517241379	66	148	0.554054054054054	22	56	0.607142857142857	0.659375
5	3	26	164	0.841463414634146	69	192	0.640625	27	74	0.635135135135135	0.716279069767442
6	4	36	212	0.830188679245283	73	236	0.690677966101695	29	92	0.684782608695652	0.744444444444444
7	5	36	260	0.861538461538462	73	280	0.739285714285714	40	110	0.636363636363636	0.770769230769231
8	6	36	308	0.883116883116883	73	324	0.774691358024691	40	128	0.6875	0.803947368421053
9	7	36	356	0.898876404494382	73	368	0.801630434782608	40	146	0.726027397260274	0.828735632183908
10	8	51	404	0.873762376237624	89	412	0.783980582524272	40	164	0.75609756097561	0.816326530612245
11	9	67	452	0.851769911504425	104	456	0.771929824561403	66	182	0.637362637362637	0.78256880733945

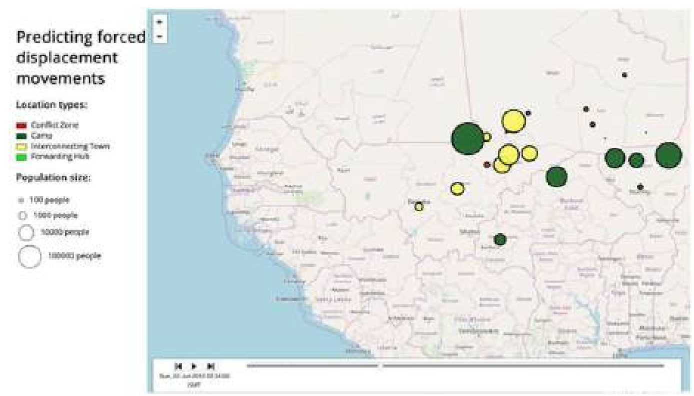
Simulation output



Camp arrivals

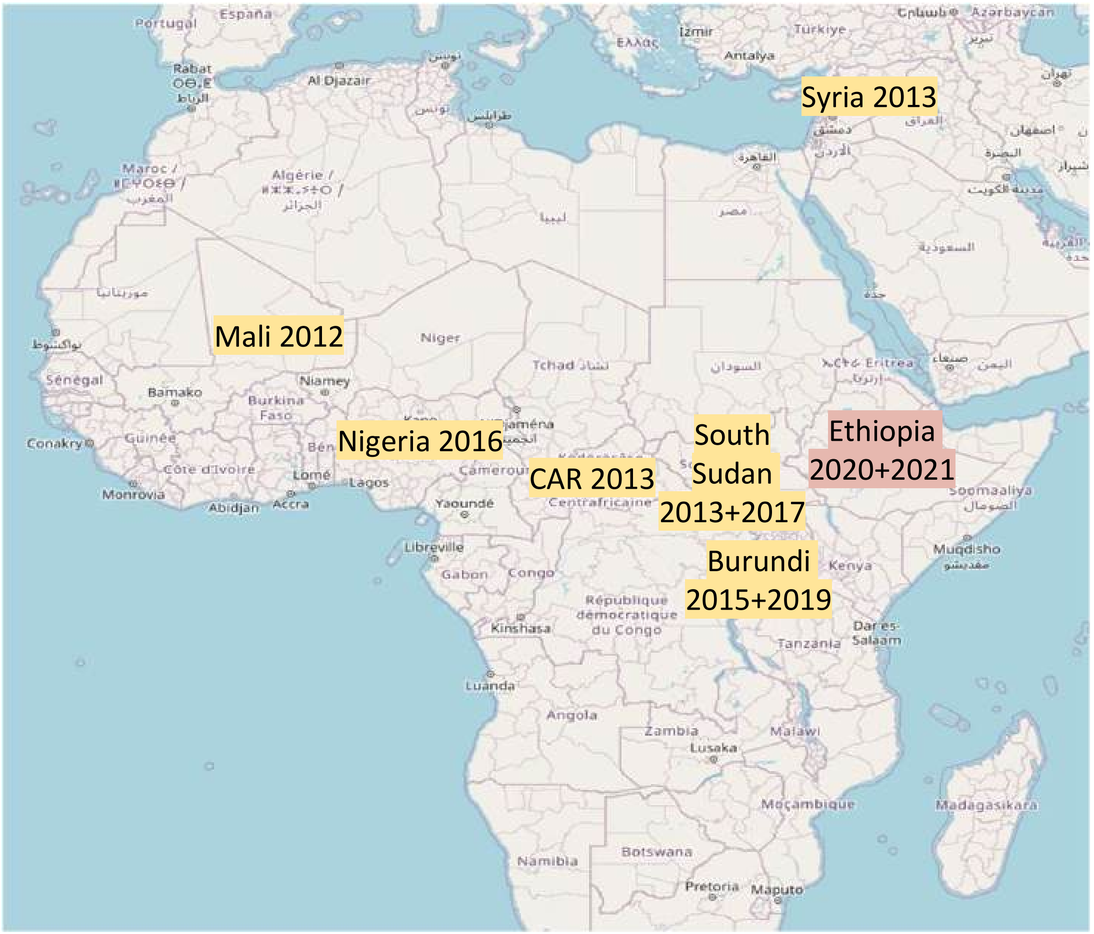


Error term validation

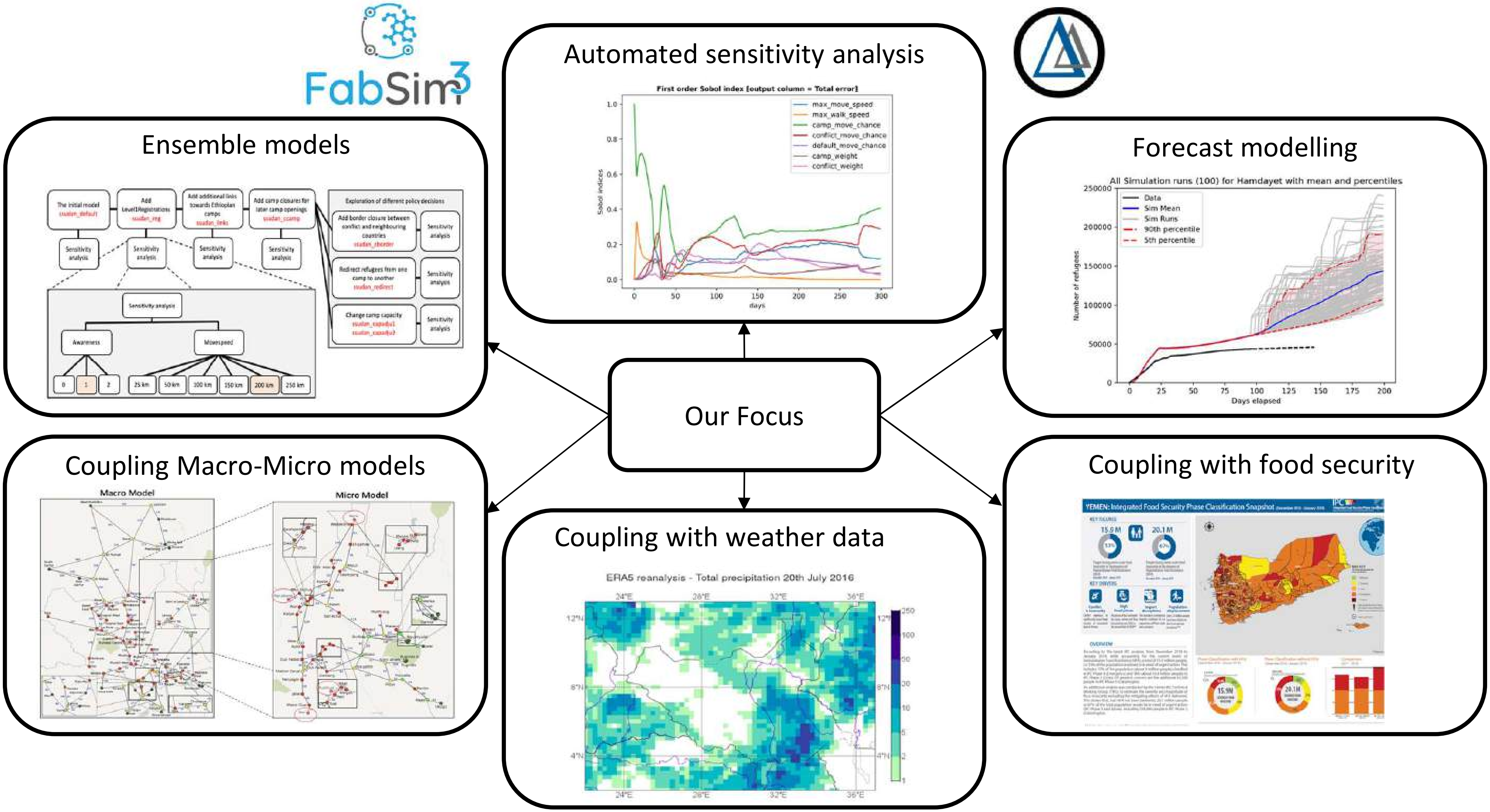


Visualisation

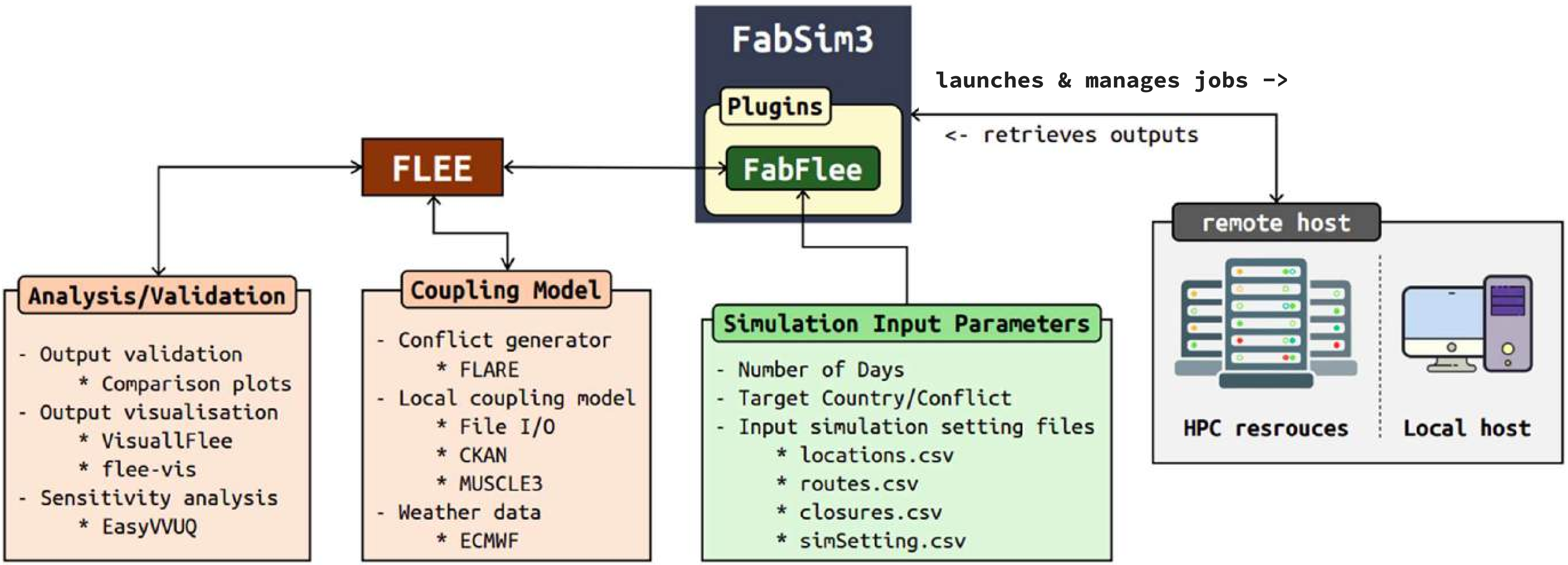
Main simulations so far



We validated our approach against refugee registration data from UNHCR, and we able to predict >75% of the arrivals correctly across four conflicts.


FabSim3
Ensemble models
Automated sensitivity analysis
First order Sobol index [output column = Total error]
max_move_speed
max_walk_speed
camp_move_chance
conflict_move_chance
default_move_chance
camp_weight
conflict_weight
Sobol indices
days
Forecast modelling
All Simulation runs (100) for Hamdayet with mean and percentiles
Data
Sim Mean
Sim Runs
90th percentile
5th percentile
Number of refugees
Days elapsed
Our Focus
Coupling Macro-Micro models
Macro Model
Micro Model
Coupling with weather data
ERA5 reanalysis - Total precipitation 20th July 2016
Coupling with food security
YEMEN: Integrated Food Security Phase Classification Snapshot

FabFlee: Forced displacement plugin



Summary

- Active modelling efforts:
  - Improving the quality of our models by validating settings.
  - Search for optimal configurations to model different scenarios.
  - Sensitivity analysis: testing which assumptions matter most.
- Collaborations and projects

SEAVEA

IOM UN MIGRATION

UNHCR The UN Refugee Agency United Kingdom for UNHCR

Georgetown University

Save the Children

Columbia University

Questions?

Diana Suleimenova

diana.suleimenova@brunel.ac.uk

Input parameters: Movement speed

Input Parameters	Description	Default Value
max_move_speed	Agents' maximum movement speed in the simulation while traversing between locations.	360 km/day
max_walk_speed	Agents' maximum walking speed in the simulation while traversing between locations.	35 km/day
max_crossing_speed	Agents' maximum crossing speed in the simulation while traversing on boat or walk to cross river.	20 km/day

Input parameters: Movement chance

Input Parameters	**Description**	**Default Value**
camp_move_chance	Probability of an agent moving from camp location where an agent resides to another location.	0.001
conflict_move_chance	Probability of an agent moving from camp location where an agent resides to another location.	1.0
default_move_chance	Probability of an agent moving from other (default) location where an agent resides to another location.	0.3
idpcamp_move_chance	**Probability of an agent moving from internally displaced camp location where an agent resides to another location.**	**0.1**

Input parameters: Location weight

Input Parameters	Description	Default Value
camp_weight	The attractiveness value for camp locations making them twice as likely to be chosen as a destination.	1.0
conflict_weight	The attractiveness value for conflict locations making them four times less likely to be chosen as a destination.	0.25
foreign_weight	The attractiveness value for foreign locations that stacks with camp multiplier.	1.0

Global Early Warning System

Strengthening preparedness and response in complex humanitarian emergencies.

Yu Li, Patrick Matgen (LIST)
Asuka Imai (UNHCR)

UNHCR The UN Refugee Agency

LUXEMBOURG AID & DEVELOPMENT

LUXEMBOURG INSTITUTE OF SCIENCE AND TECHNOLOGY | LIST

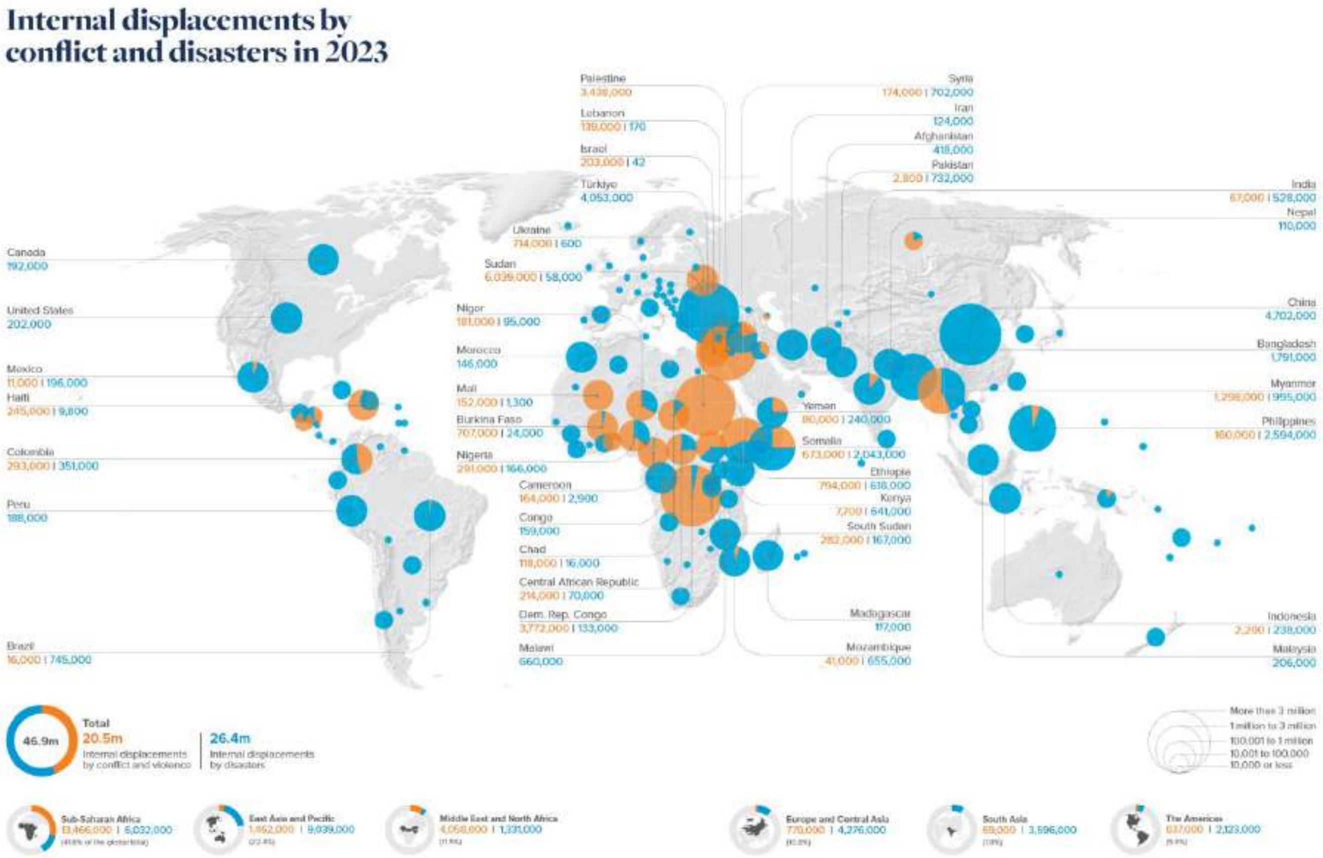
Background

- Conflict and violence triggered 20.5 million new internal displacements, across 45 countries.

- Disasters triggered 26.4 million new intern displacements across 148 countries.

▪ Funded by the Ministry of Foreign Affairs in Luxembourg.

▪ Collaboration between LIST and UNHCR.



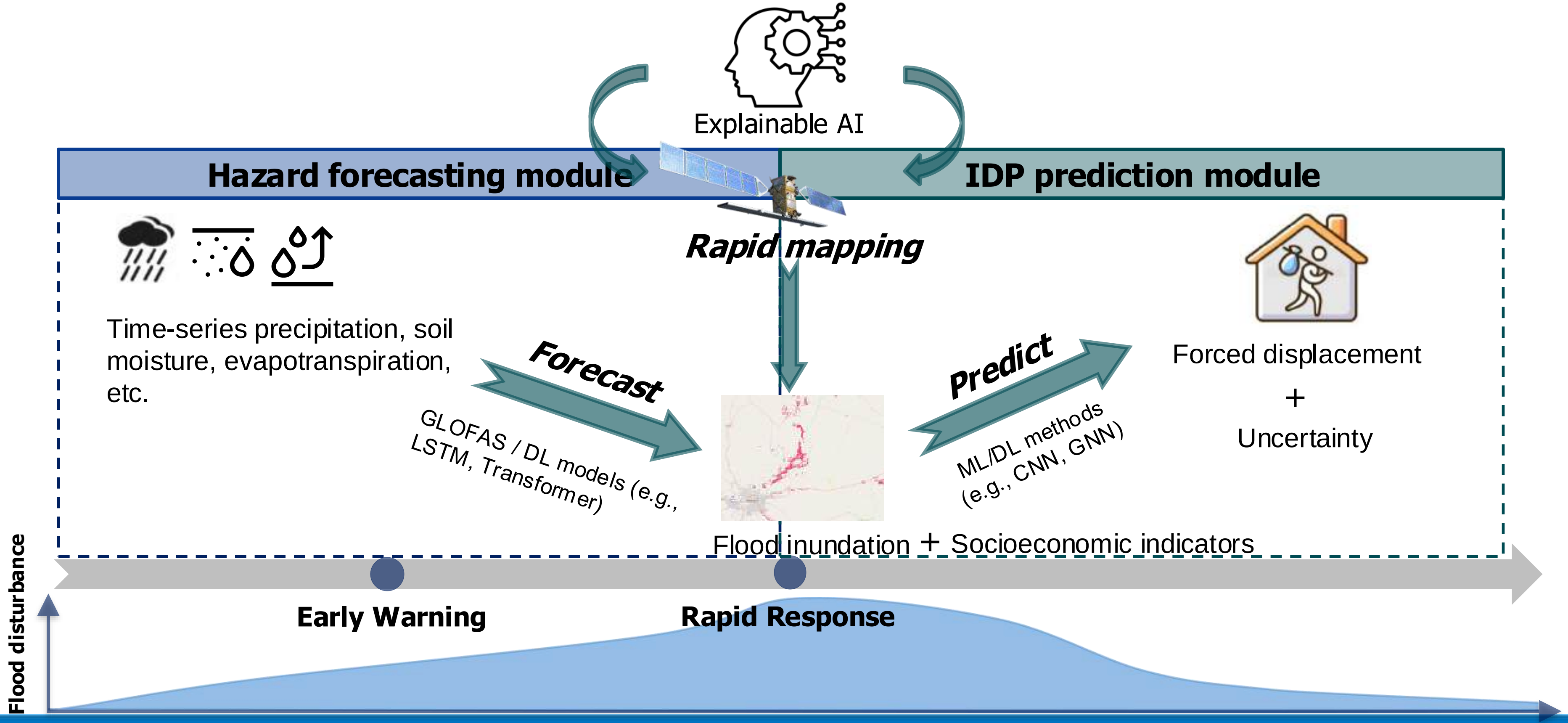
Goal | Impact - Displacement forecasting

We aim to predict **where/when/magnitude** of potential displacement 1 – 2 weeks in advance

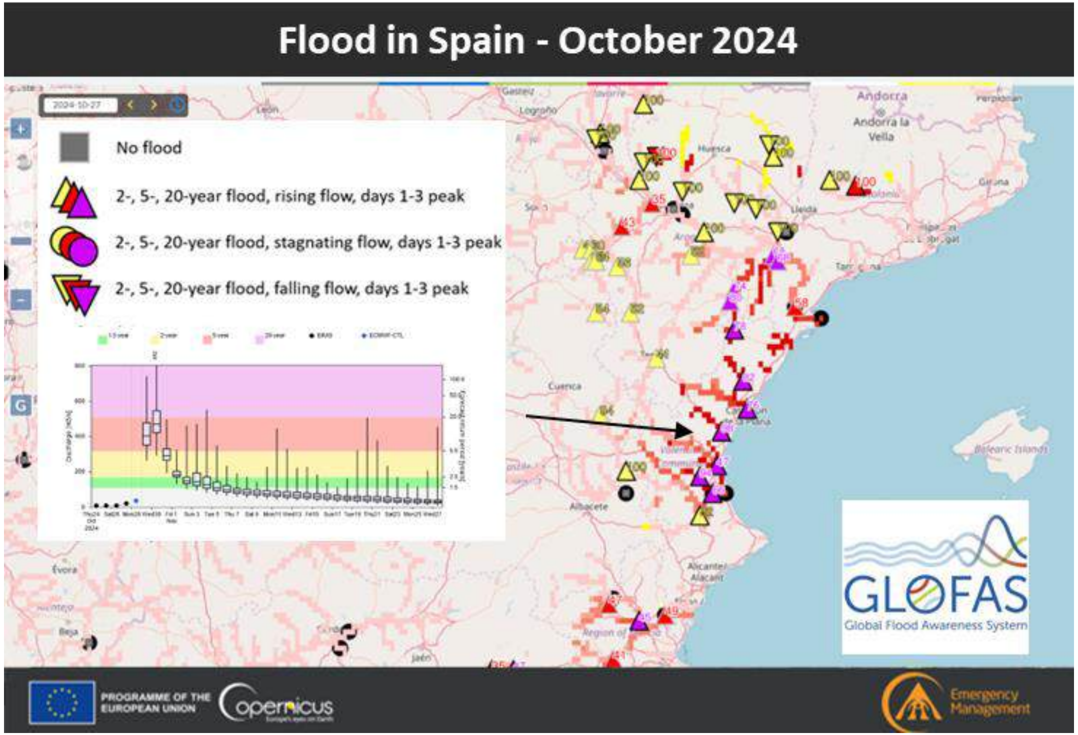
Displacement induced by floods (2025), conflict, and tropical cyclone

- ✓ Provide early warning
- ✓ Targeted preparedness actions
- ✓ Minimize response times
- ✓ Optimize supply process
- ✓ Avoid the duplication of humanitarian efforts
- ✓ Result in more life saving
- ✓ Achieve resource saving

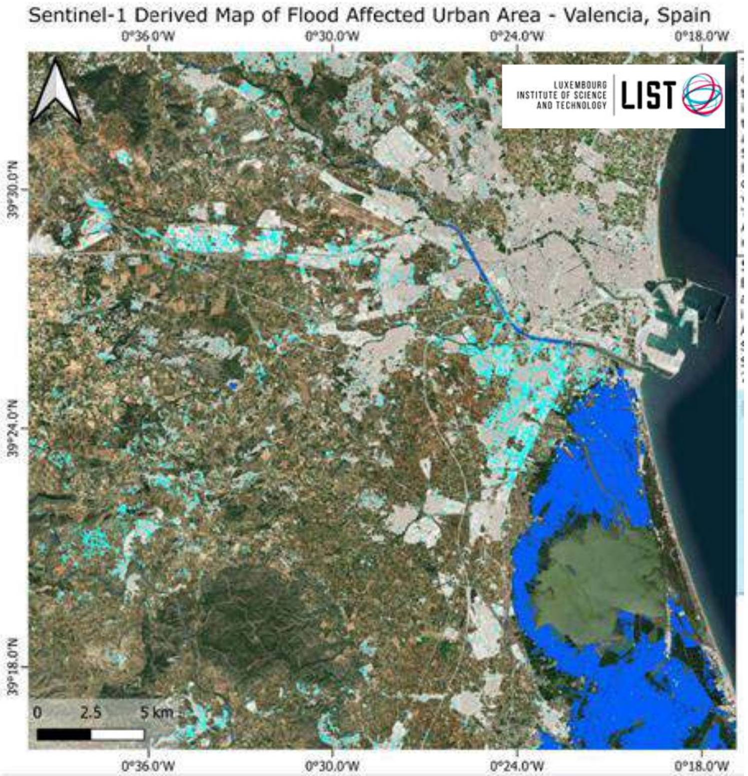
Approach: data-driven displacement forecasting



Flood monitoring & forecasting

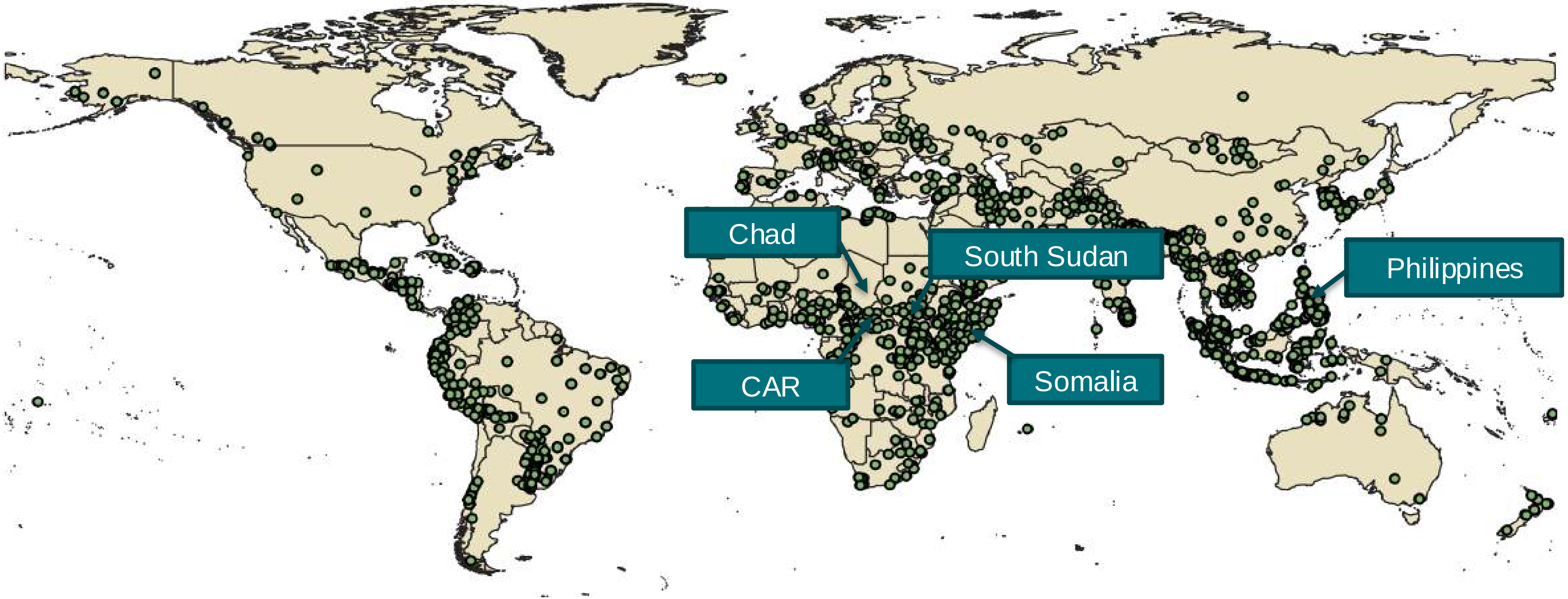


Flood prediction model



Satellite-based observation of flood extent

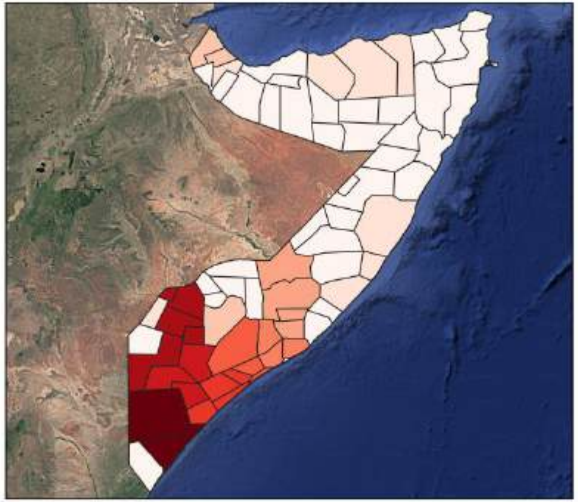
IDP dataset: IDMC Global Internal Displacement Database



IDMC GIDD disaster internal displacement (ID) in year 2023.

Flood-induced IDP in Somalia, November 2023

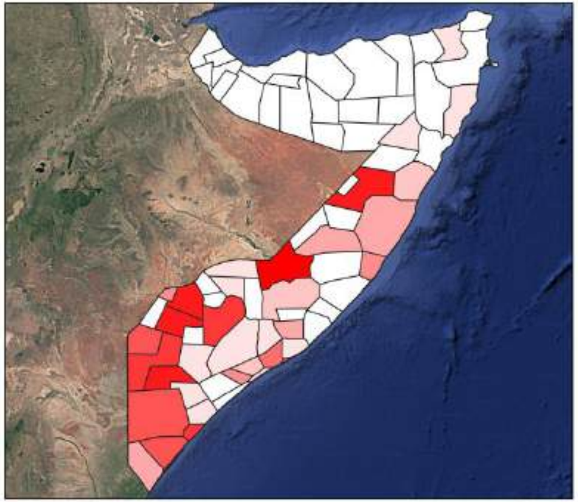
GLOFAS discharge forecast



GLOFAS 2-day leadtime forecast (cumecs)

- 0 - 1.4
- 1.4 - 5.8
- 5.8 - 163.9
- 163.9 - 573.1
- 573.1 - 589.6
- 589.6 - 636
- 636 - 2297.3
- 2297.3 - 2374.4
- 2374.4 - 2391.3
- 2391.3 - 2905

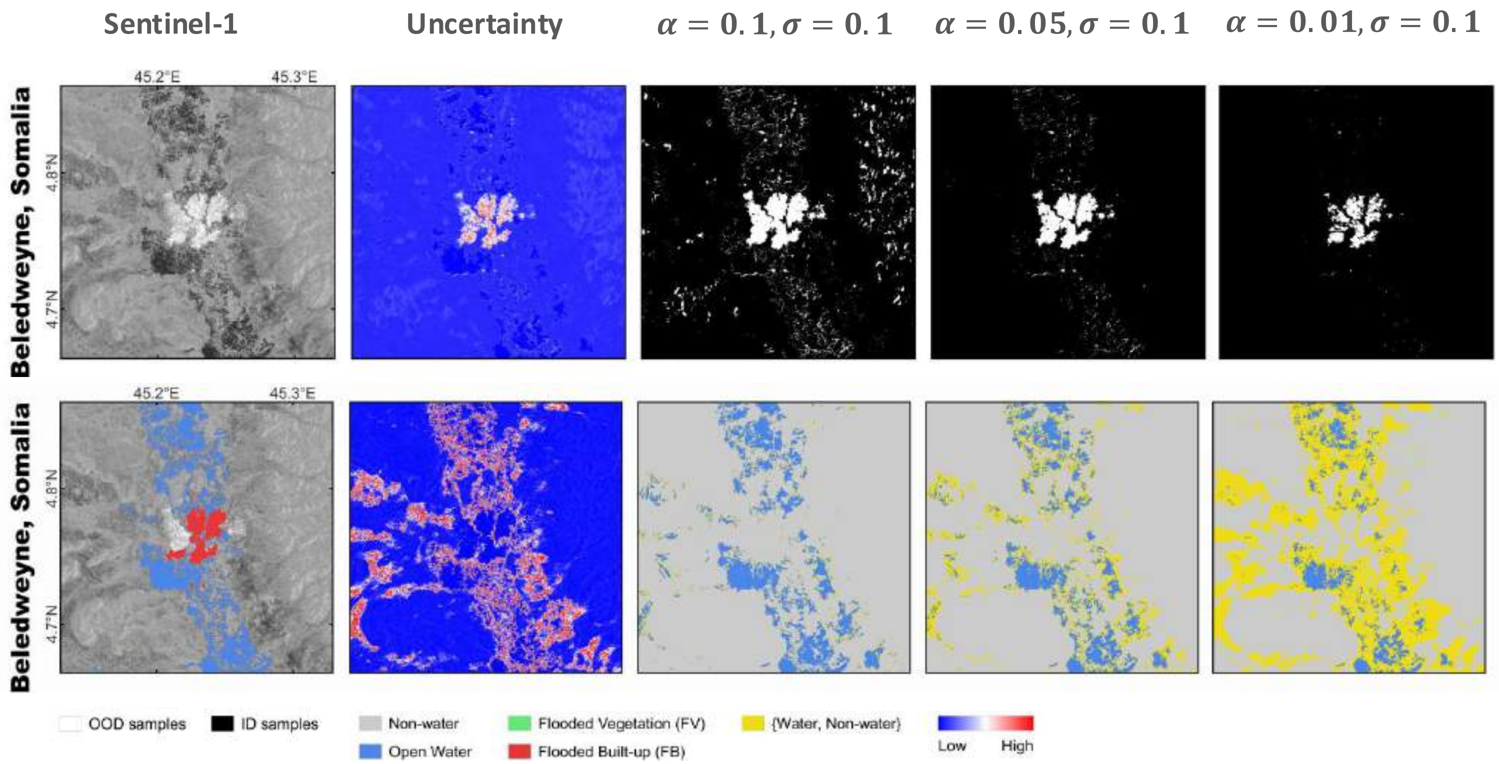
Flood-induced IDP from UNHCR-PRMN



Flood-induced IDP from UNHCR-PRMN

- 0 - 300
- 300 - 2000
- 2000 - 4000
- 4000 - 6000
- 6000 - 15000
- 15000 - 22000
- 22000 - 46000
- 46000 - 84000
- 84000 - 195000
- 195000 - 225000

Account for uncertainty: conformal risk control



Instead of a point prediction, providing a prediction set (interval) that the risk does not exceed α at probability of $1 - \sigma$.

Li, Y., Matgen, P., Chini, M., Uncertainty quantification and communication in SAR-based flood mapping through density-aware neural networks and conformal risk control. IEEE TGRS (under review)

Account for explainability: attribution and counterfactual

Attribution based:

SHAP, LIME, Gradients-based

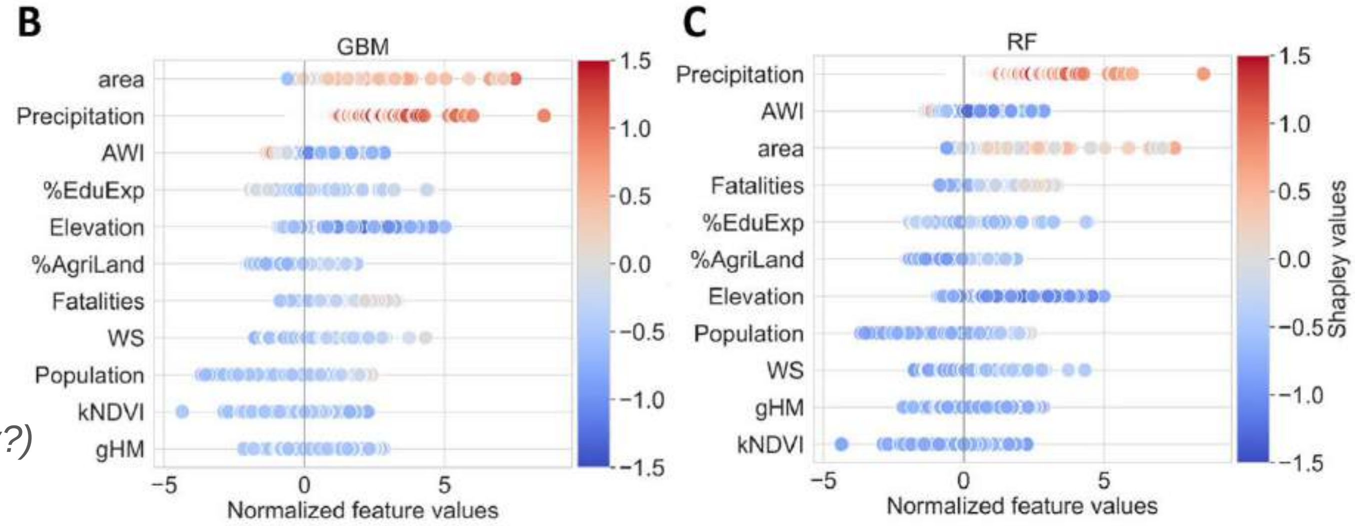
- ***Why?***

Counterfactual based:

- ***What-If?***

(as means to achieve causality?)

Sudden-onsets hazards induced IDP prediction



Ronco, M., Tárraga, J.M., Muñoz, J. *et al.* Exploring interactions between socioeconomic context and natural hazards on human population displacement. *Nat Commun* **14**, 8004 (2023). https://doi.org/10.1038/s41467-023-43809-8

Dataset challenges

❖ **Dependent variable: IDP**

IDMC GIDD:

- Multiple publishers (inconsistency)
- Spatial resolution (admin 0-3)
- Temporal granularity (week, month)

Variable	Temporal aggregation	Spatial aggregation	Granularity	Source
1. AWI	Max	Max	Polygon	Meta Data4Good[13]
2. Precipitation	Max	Sum	Polygon	ERA5-Land (GEE)[67]
3. 10m Wind Speed	Max	Max	Polygon	ERA5-Land (GEE)[67]
4. kNDVI	Mean	Mean	Polygon	MODIS TERRA (GEE)[105]
5. Population	Mean	Mean	Polygon	GPWv4[72]
6. gHM	Mean	Mean	Polygon	CSP[74]
7. Elevation	Mean	Mean	Polygon	NASA/CGIAR (GEE)[70]
8. Conflict fatalities	Sum	Sum	Polygon	ACLED[75]
9. Area	–	–	Polygon	OpenStreetMap[71]
10. Education expenditures	–	–	National	SDG API[69]
11. % Agricultural Land	–	–	National	SDG API[69]

Metric	LR (all)	GBM (all)	RF (all)	LR (no weather)	GBM (no weather)	RF (no weather)
1. R^2	0.19 ± 0.02	0.36 ± 0.02	0.37 ± 0.02	0.16 ± 0.02	0.32 ± 0.02	0.33 ± 0.02
2. RMSE	1.02 ± 0.02	0.91 ± 0.02	0.90 ± 0.02	1.04 ± 0.01	0.93 ± 0.02	0.93 ± 0.02
3. ME	−0.001 ± 1.0	−0.003 ± 0.91	−0.006 ± 0.90	−0.001 ± 1.02	−0.002 ± 0.93	−0.005 ± 0.93

❖ **Independent variables:**

- Forecasted discharge/flood
- Exposed population
- Absolute wealth index (AWI)
- Global human modification (gHM)
- Area
- Land Cover, building height, elevation
- Conflict/Violence status
- …

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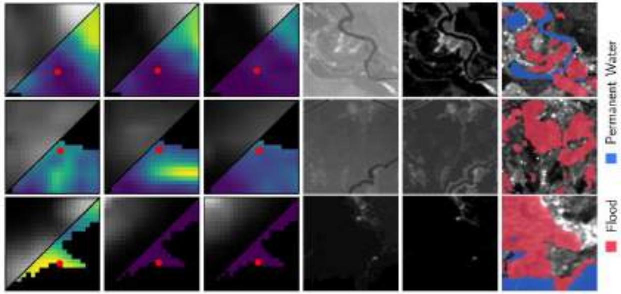
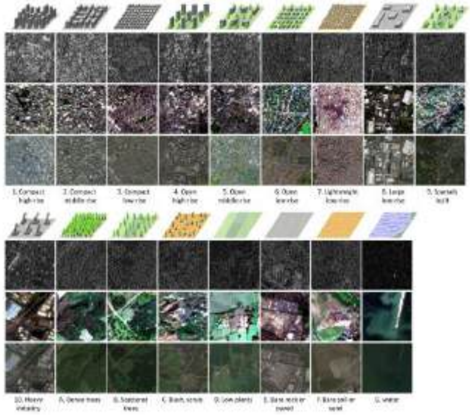
Dataset challenges

IMAGENET: image classification



Forecasting: flood mapping and forecast

Caravan: hydrology

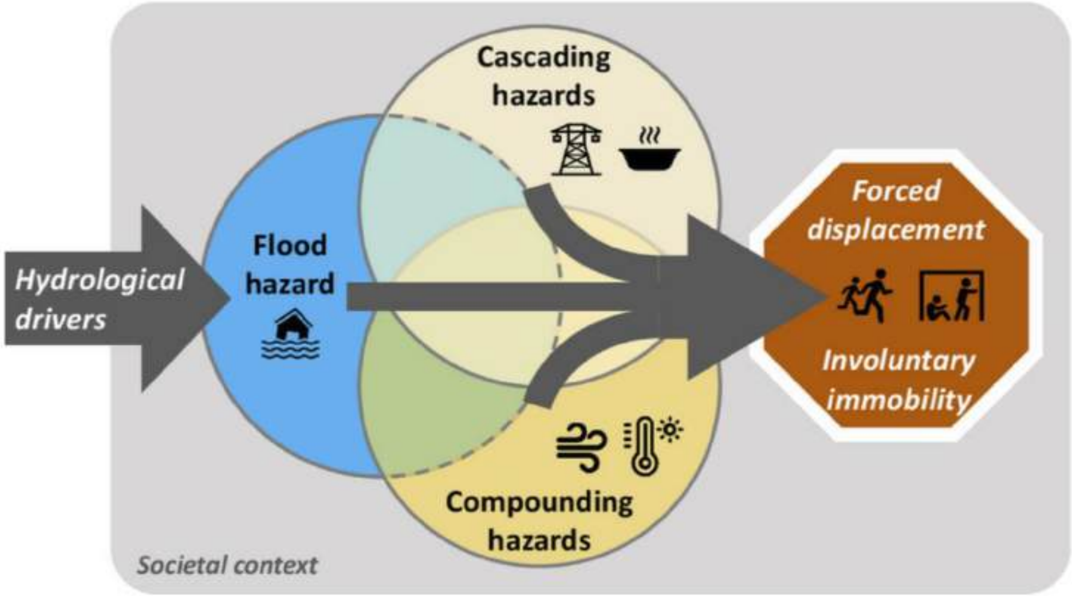


So2Sat LCZ42: LCZ classification

ShipRSImageNet: ship detection

Benchmark dataset for climate- and conflict-induced displacement?

Conceptual challenges



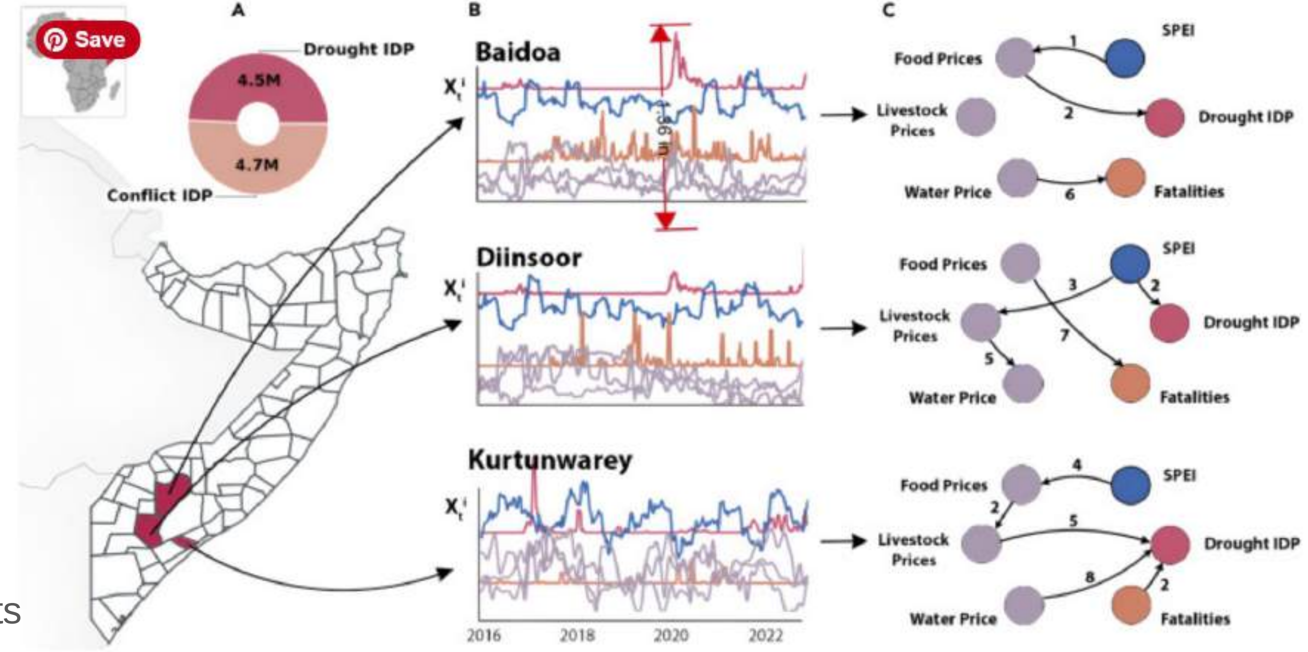
- What is the definition of flood-induced displacement?
- Would it be possible to disentangle root causes for displacement?

Modeling challenges

Association or Causality?

- Association is fragile
- Suspicious correlations
- Data shift sensitivity

- Multi-cause interactions
- Unobserved confounders
- Heterogeneous causal effects



Causal discovery for drought-induced IDP in Somalia

Jose María Tárraga, Eva Sevillano-Marco, Jordi Muñoz-Marí, María Piles, Vasileios Sitokonstantinou, Michele Ronco, María Teresa Miranda, Jordi Cerdà, Gustau Camps-Valls, Causal discovery reveals complex patterns of drought-induced displacement, iScience, Volume 27, Issue 9, (2024)

Next Steps

- IPD data collection: IDMC, local authorities
- RS- and census-based socioeconomic data collection
- Flood forecast: GLOFAS, Google flood hub
- Integration of conflict forecast
- Uncertainty quantification: combination of Bayesian (e.g., BNNs) and frequentist methods (e.g., conformal prediction)
- Model explainability: attribution and counterfactual-based methods
- Medium-size data modeling: tabular foundation model

Thank you!

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