Lux War Risk Model

Predicting Armed Conflict using Machine Learning

Navarun Jain

Actuarial Manager

Lead Model Developer

Presentation
Agenda

Introduction

Motivation

- Civil war and organised violence continue to erupt throughout the world into the 21st century

- Armed conflict appears to be more likely in some countries than in others

- Can we potentially predict armed conflicts before they occur?

- Can we use data to understand what drives armed conflict, especially in regions without current conflict?

- Can such information help guide insurance risk assessment and underwriting?
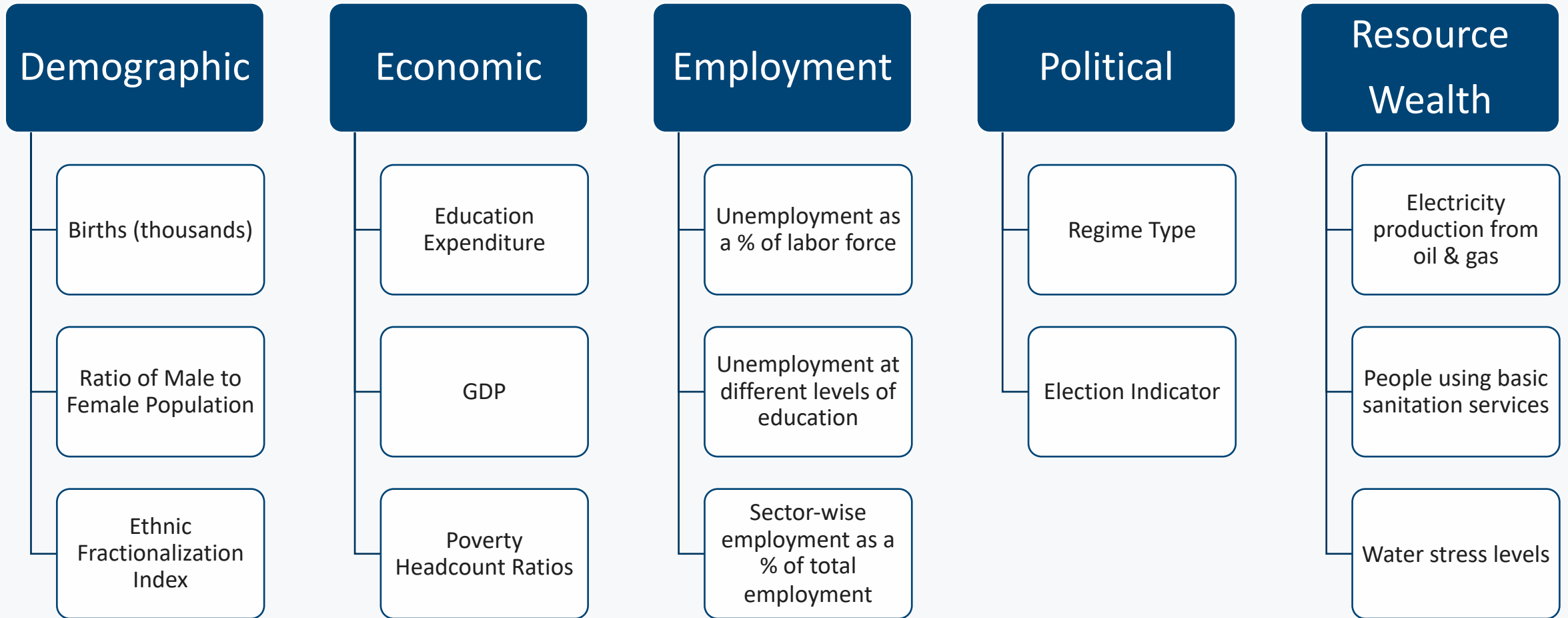
Armed Conflict

A **state-based armed conflict** is a **contested incompatibility** that concerns government and/or territory where the **use of armed force** between two parties, of **which at least one is the government of a state**, results in **at least 25 battle-related deaths** in one calendar year.

(UCDP Official Definition)

Data

Examples of Indicators

Demographic	Economic	Employment	Political	Resource Wealth
Births (thousands)	Education Expenditure	Unemployment as a % of labor force	Regime Type	Electricity production from oil & gas
Ratio of Male to Female Population	GDP	Unemployment at different levels of education	Election Indicator	People using basic sanitation services
Ethnic Fractionalization Index	Poverty Headcount Ratios	Sector-wise employment as a % of total employment		Water stress levels

Data Splits

Training Set
- Used to train War Risk Model
- 1950 - 2018

Validation Set
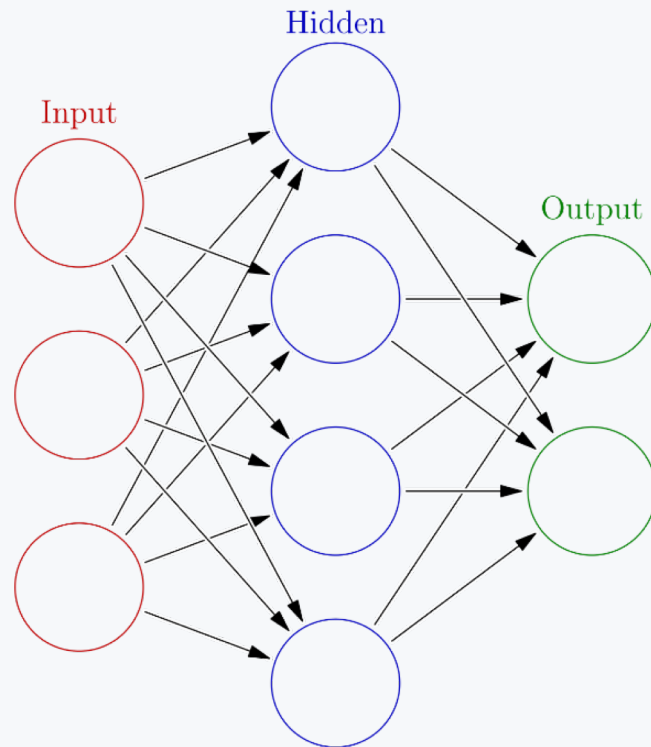- Used to evaluate Model
- 2019 - 2020

Future Set
- Based on indicator forecasts
- 2021 - 2024

Algorithm

Artificial Neural Network (ANN)

Structured Sequential Model

Structured: A Neural Network has a defined structure that consists of 3 types of layers

Sequential: Information flows in a sequence from one layer to the next, undergoing operations at each layer – almost like an assembly line

Training Process

Tuning
- Determine Hyperparameter Space – possible model configurations
- Tuning Run tests each potential candidate in limited capacity

Training
- Top candidates from Tuning step selected
- Final candidate models run on Train Set

Evaluation
- Final candidate model evaluated on Test set
- Best performing candidate selected as Final Model

Model Evaluation on Test Data – Final Candidates

Model Evaluation Statistics

Model	Accuracy	Precision	Recall	F2 Score	AUC
A1_M4	95.54	87.63	81.49	82.65	89.74
A2_M3	95.52	87.73	81.18	82.41	89.60
A1_M1	95.36	86.59	81.34	82.34	89.57
A2_M7	90.78	63.59	88.80	82.28	89.96
A1_M8	89.83	60.79	88.96	81.41	89.47
A2_M5	95.29	88.85	78.07	80.01	88.18
A1_M3	94.89	86.13	78.23	79.69	88.01
A1_M5	95.43	90.83	76.98	79.40	87.81
A1_M2	95.06	88.10	77.14	79.11	87.66
A2_M6	94.89	87.41	76.67	78.60	87.37
A2_M4	94.36	84.94	75.43	77.16	86.55
A2_M1	94.36	84.94	75.43	77.16	86.55
A2_M2	94.87	90.40	73.25	76.14	85.95
A1_M7	14.88	14.86	100.00	46.60	50.01
A1_M6	72.00	23.88	40.44	35.51	58.97
A2_M8	28.00	11.13	55.05	30.77	39.17
A1_M9	85.17	57.14	0.62	0.78	50.27

**Accuracy**: Percentage of total cases correctly identified

Recall: Percentage of actual conflicts correctly identified

Precision: Percentage of predicted conflicts correctly identified

F2 Score: Weighted average of Precision and Recall (more weight given to Recall over Precision)

AUC: Indicator of how well the model can distinguish between conflict/peace

Final Model

Confusion Matrix - Final Model
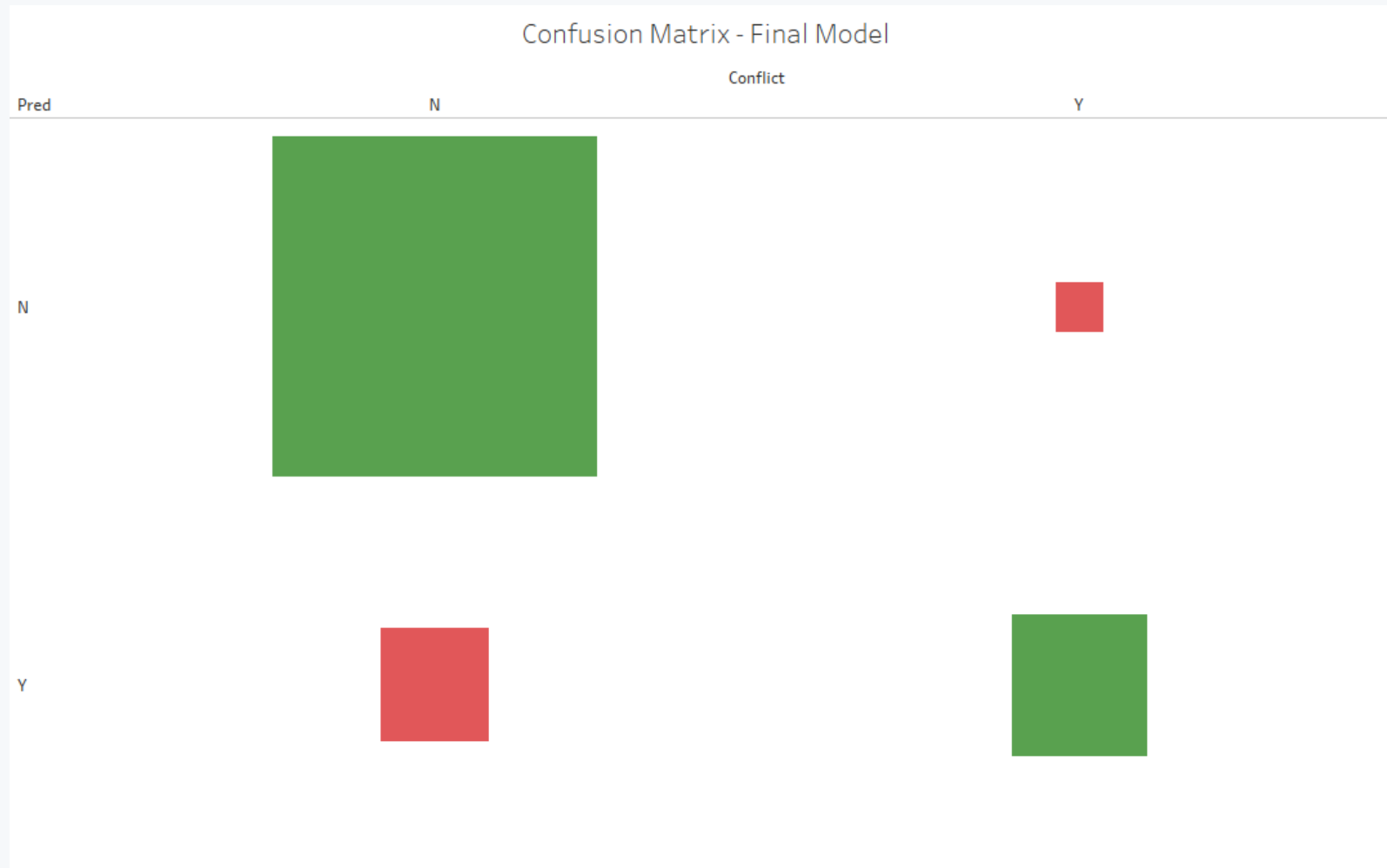
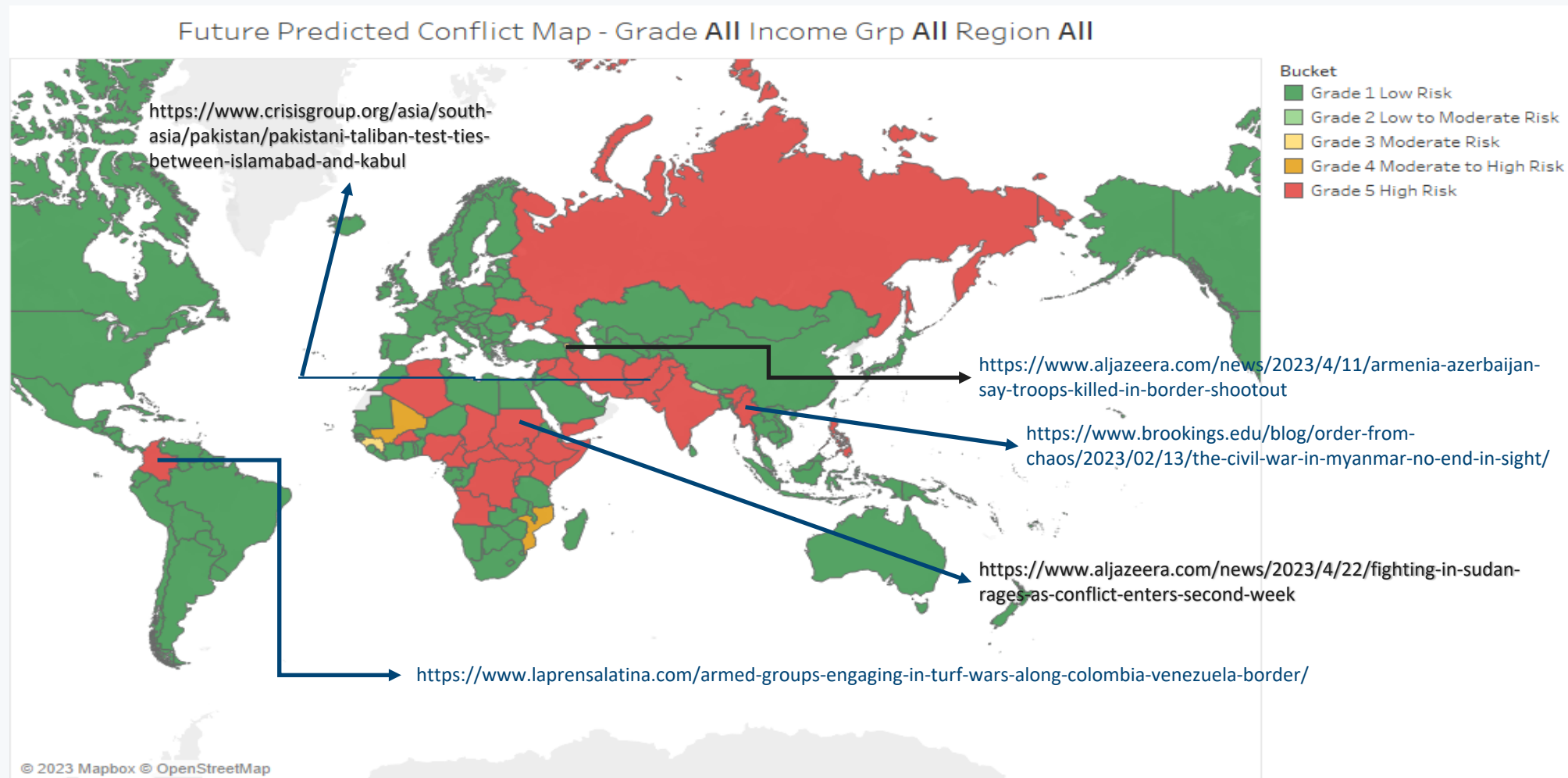A1_M8 – 89% Accuracy, 89% Recall

Model with high **Recall preferred**

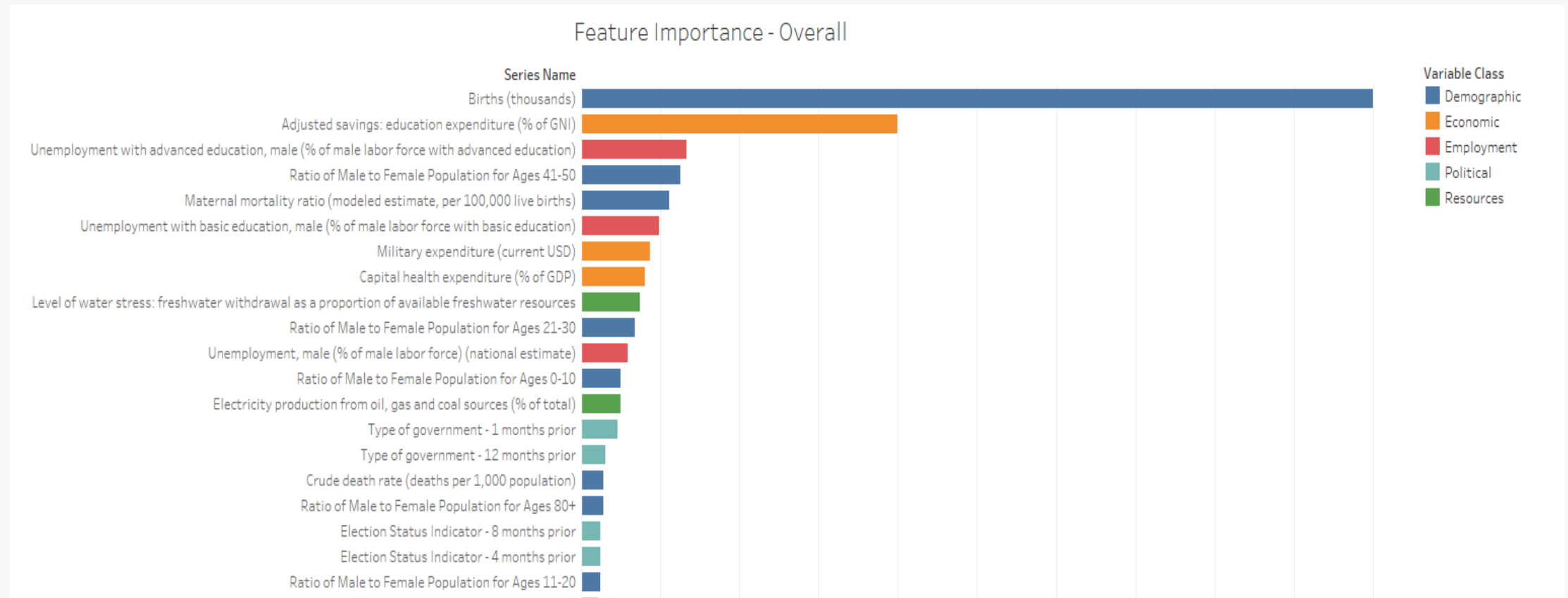This was highly effective at capturing **future armed conflicts**
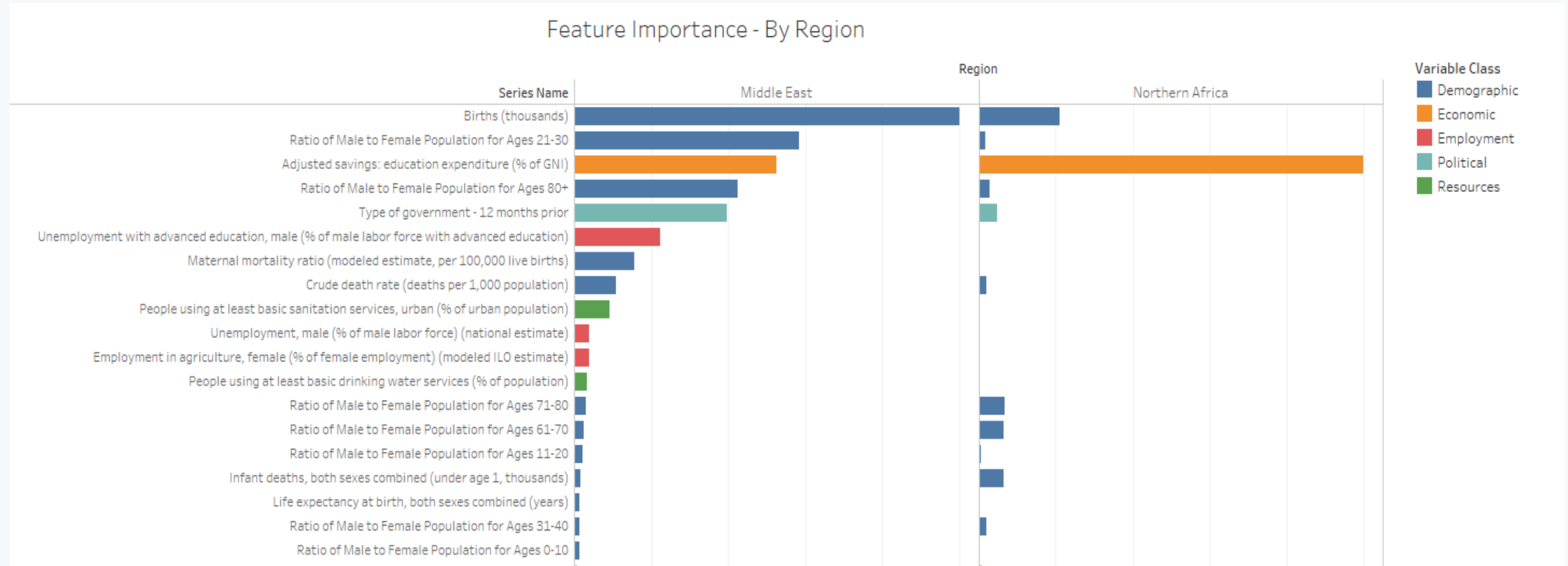
Predictions & Key Insights
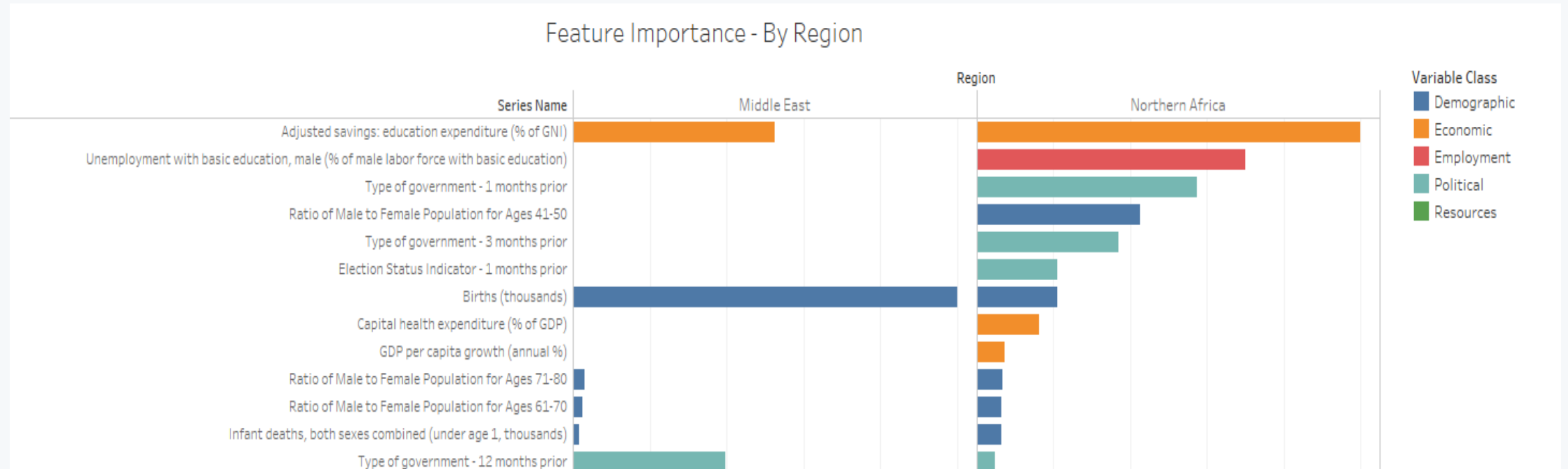
Future Predictions – 2023

Future Predicted Conflict Map - Grade **All** Income Grp **All** Region **All**

Bucket
- Grade 1 Low Risk
- Grade 2 Low to Moderate Risk
- Grade 3 Moderate Risk
- Grade 4 Moderate to High Risk
- Grade 5 High Risk

https://www.crisisgroup.org/asia/south-asia/pakistan/pakistani-taliban-test-ties-between-islamabad-and-kabul

https://www.aljazeera.com/news/2023/4/11/armenia-azerbaijan-say-troops-killed-in-border-shootout

https://www.brookings.edu/blog/order-from-chaos/2023/02/13/the-civil-war-in-myanmar-no-end-in-sight/

https://www.aljazeera.com/news/2023/4/22/fighting-in-sudan-rages-as-conflict-enters-second-week

https://www.laprensalatina.com/armed-groups-engaging-in-turf-wars-along-colombia-venezuela-border/

© 2023 Mapbox © OpenStreetMap

Exploring the Key Drivers of Conflict Risk

Feature Importance - Overall

Exploring the Key Drivers of Conflict Risk

Feature Importance - By Region

Exploring the Key Drivers of Conflict Risk

Feature Importance - By Region

Conclusions

Potential Insurance Applications

Terrorism/ Passive War Risk Insurance	Political Risk Insurance	Business Interruption Insurance
Region-based Liability Insurance	Property/Casualty Insurance	Marine/Aviation Insurance
	Cat Exposure Management/Pricing – Insurers and Reinsurers	

Future Development Roadmap

- Still quite early days in development, further testing and refinement of insights continually targeted

- Credibility of data for certain countries may be questioned, eg. China, Taiwan, Palestine, North Korea

- More enhanced data engineering process audits to be implemented – can identify potential gaps and help improve quality of existing data

- Deeper dive into key drivers of conflict risk can help understand interactions and nature of relations between national indicators and likelihoods of armed conflict – active development ongoing on this

- Availability of data at more granular (subnational) level can generate more localized predictions of armed conflict risk

- Could consider targeted region-based models instead of a global approach

Contact

Navarun Jain

Actuarial Manager, Lux UAE (Dubai)

navarun.jain@luxactuaries.com

+971 58 904 1352