A multidimensional approach to predictive migration modelling in the European Union

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Group: El Equipo

Members: Simon Karumbi (s3455453), Verity Miles (s3644459), Christopher LeMarshall (s3482127)

Introduction

2019 has seen an estimated 272 million people migrate internationally (UN 2019a) a figure that has increased by 51 million in the last 10 years. Forced migration (refugees/ asylum seekers) increased by 13 million in seven years up until 2017. This is at a much faster rate than those who chose to migrate voluntarily. Of the 272 million people who migrated in 2019, 82.3 million of them migrated to European countries. 740,000 applications for asylum were lodged within the EU, the highest number of applications since the migration crisis of 2016/17 (EASO 2021). Some countries including the UK, Spain and Germany received their highest number of applications in recorded history. Migration within and into the EU is driven by many of the factors that impact global migration including climate change, food security, natural disasters, conflict and extreme violence (IOM 2021b).

A quarter of all applications for migrations were made from three countries; Syria (80,000), Afghanistan (61,000) and Venezuela (46,000) (EASO 2021). There are a number of different ways that migrants enter Europe. The major routes by sea are shown in Figure 1. Migrants from Syria and Afghanistan would travel the east African sea migration route as shown below. Afghani migrants may also arrive in Europe over the Balkan route that enters Europe over land through Croatia/ Slovenia (Tondo 2021). Venezuelan migrants would come from the sea and generally enter Spain through the western migration route.

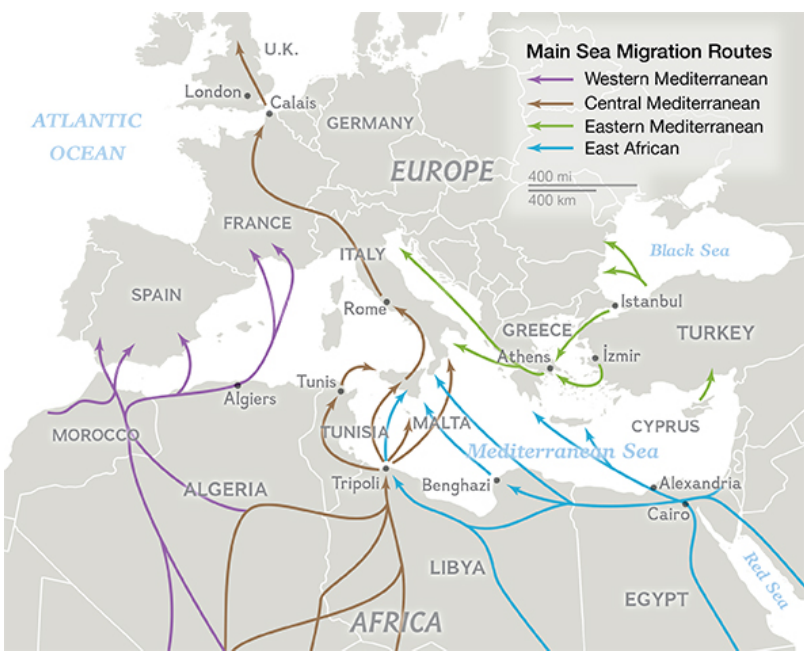

Figure 1: Main sea migration routes into Europe (NG 2015)

There are a number of different reasons why a person chooses to migrate from their place of birth as summarised in Figure 2 below.

Figure 2: Cause of migration (adapted from figure 12, Rahmati & Tularam 2017)

These factors are split into two groups when it comes to migration modelling, push factors (those impacting the decision to leave) and pull factors (those impacting the decision of where to go) and the obstacles for the movement between the two locations (Lee 1966). This is a very simplistic model for migration that helps visualise the decisions that individuals make about whether to migrate or not. Existing frameworks that dictate the long-term development of immogration policy in the EU use political theory and frame the problem using the push and pull factor theory (EASO 2016).

General patterns see younger people more likely to migrate (Sandefur & Scott 1981) while other studies have shown that people tend to migrate as family or household groups (Sandell 1977). The decision to migrate an entire household will depend if there is a net positive gain for the household (Bigsten 1988) - this may be due to better economic, educational or employment opportunities or less danger from political uncertainty or natural disaster events.

Climate change, especially the increased variability of extreme climate events is a very important factor to consider when looking at predicting migration patterns on a regional scale. In the push/pull framework migration as a result of climate change is often categorised as a 'soft' push factor despite a growing consensus that it will be a main driver of migration by the middle of the century (EASO 2017, Kent & Behrman 2018). Prolonged environmental phenomena such as desertification and rising ocean levels are causing issues such as food insecurity, and the increase in ferocity and frequency of natural disasters as a result of climate change is causing mass displacement. Human mobility as a result of these events needs to be addressed in order to support vulnerable populations that will be most affected, while adequately preparing the EU for the predicted influx of migrants over the next several years (Kent & Behrman 2018).

Figure 3 depicts the main areas in which Europe is likely to be impacted by the changing climate. The areas where migrants by sea tend to originally arrive in Europe (as shown in Figure 1) are also areas where there are climate change hotspots, less precipitation, increased risk of bushfires and negative agricultural changes.

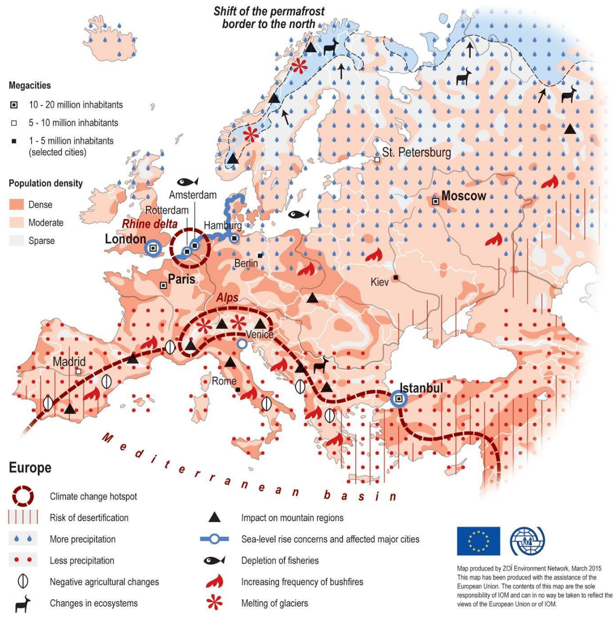

Figure 3: The predicted impact of climate change on land use in Europe (ZOI 2015)

When considering the impact of climate change on migration into Europe, it is also important to consider the impact of climate change where migrants are beginning their journey. Figure 4 highlights some of the predicted change to Africa and Asia including some of the top destinations for migrants. Climate hotspots, desertification, less precipitation and negative agricultural impacts potentially meaning that there will be higher demand to migrate.

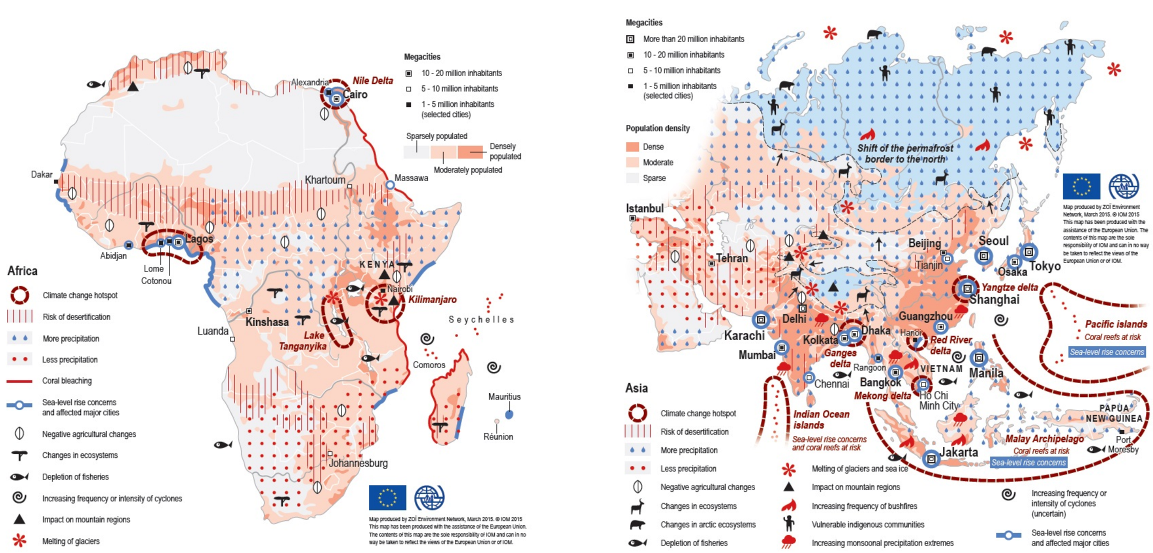

Figure 4: The predicted impact of climate change on land use in a) Africa and b) Asia (ZOI 2015)

Problem definition

As the largest host of migrants in the world, the EU and surrounding observer states face the challenge of collating a huge amount of structured and unstructured quantitative and qualitative data from different countries, agencies and organisations in order to make accurate predictions on the future of migration flow into european countries and allocate resources accordingly (EASO 2016, EASO 2017, EASO 2018, Kent & Behrman 2018).

Existing solutions used by the EU to predict migration flows use the data mentioned, and are separated into three main categories, Early Warning Systems, Modelling and Risk Analysis and Foresight. Foresight is a method used in the long-term development of policy and involves scenario building that tests alternate futures in order to predict the long-term effects of policies to migration patterns (EASO 2018). Although this is a good exercise in building consensus on long term challenges and objectives, it often excludes a broad number of stakeholders and doesn't lend itself well to a data-driven approach (EASO 2017).

Early Warning and Alert Systems (EWS) typically utilise real time systems to monitor migration flow through the utilisation of sensors, surveys at migration corridors and expert opinion to provide a quick alert to meet the evolving needs of migrants (EASO 2018). The Displacement Tracking Matrix System is an EWS that monitors migration flow through the systematic capturing, processing and distribution of data at specific migration corridors (IOM 2021). Weaknesses of EWS is that it doesn't provide the ability to analyse changing pull and push factors, and only provides a very short-term outlook. They also need to be configured with a threshold that ensures false positives and false negatives are minimised, resulting in missed signals (EASO 2017).

Data-driven Modelling and Risk Analysis solutions provide a longer outlook, although their accuracy starts to degrade quite quickly due to quality and complexity issues. A fragmented understanding of theoretical frameworks of migration also leads to a discount of the importance of some factors including demographics, historical proximity and climate change (EASO 2017). One recent improvement in modelling has been the adoption of bayesian modelling utilising expert opinion as well as data (EASO 2018). The accuracy of data driven modelling is heavily reliant on the accuracy of the data input into it. There has been a plethora of research in the field of climate modelling and forecasting.

Data-driven approaches to modelling migration flow into the EU cannot be reliably used for political decision making as existing models are based on complex, and often inaccurate data that results in an insensitivity to potential migration surges. These models don't consider climate change as a 'strong' push factor and provide an overly optimistic outlook on the future of migration into Europe.

Despite this, there exists a wide range of valuable data sources that aren't being used that could improve upon existing mechanisms and provide a better foundation for decision-making over the next several years. The compilation of these data sources will not only serve an analytical purpose, but also provide individuals with an awareness of the increasing severity of the issue.

The opportunity for improvement of existing predictive mechanisms used by the EU is in the availability of Big Data such as social media, improvements in the collaborative efforts of national statistics agencies of member countries, and the formalised processes of the labour market and asylum and will help to position the EU as a leader in migration flow modelling (EASO 2018).

Significance

There is a need to predict existing and future migration volumes and pathways for the EU and its member states to adequately plan and resource for new migrants. This will enable policy makers to have the data to make informed decisions about international governance, foreign emergency aid, resource allocation and areas for resettlement (IOM 2021b). These decisions may have a chance to offset the figure of 200 million climate refugees expected by the year 2050 (Myers 2002), and improve the quality of life for both host and migrant residents.

The European Union plus observer states include 27 countries, with different data collection and administrative processes in each country. Over the past several years, the goal of a harmonised effort in the tracking of migration data has been realised, in order to reduce complexity and drive better decision making within the EU. However, one of the biggest challenges with existing predictive methods is that the historic data collected by national statistics agencies and the UN suffer from quality issues. Since 1951, the UNHCR has maintained the most complete database on migration, yet historically there were motivations for the data to be overstated in order to receive additional funding, as well as political pressure that affected data integrity. Additionally, national statistics agencies record inconsistencies between individual agencies, with different countries exhibiting significant differences in reporting certain concepts. For example, migrants may not be recorded in some transit countries (EASO 2017).

Existing frameworks that dictate the long-term development of immigration policy in the EU use political theory and frame the problem using push and pull factors of origin and destination countries (EASO 2016). Monitoring systems such as Early Warning Systems (EWS) are used to provide real time analysis on flows of migration (EASO 2018). Other data-driven approaches are used with mixed success, where issues of data quality and complexity due to multidimensionality lead to the deployment of models with little practicality (EASO 2017). Challenges arise in the case of unprecedented surges in migration flow, where these existing mechanisms lead to a lack of preparedness and adequate policy response causing a large strain on stakeholders in particular migration corridors (EASO 2018).

Migration can have a significant impact on destination countries. In Germany, the total expenditure for refugees and asylum seekers across 2018-2023 is expected to be €117.2 billion (Statista 2020). Migration also forces governments of destination countries to face further complexity in domestic policy decision making, since migration can necessarily lead to changes in the dynamics of social welfare systems, employment, infrastructure, cultural and ethnic diversity, and taxation (Rahmati & Tularam 2017). While the question of whether destination countries ultimately benefit or are harmed by migration over the long term has not been solved empirically, it is nonetheless important for governments of destination countries to be able to make informed policy decisions with regards to probable future migration volumes (OECD 2014).

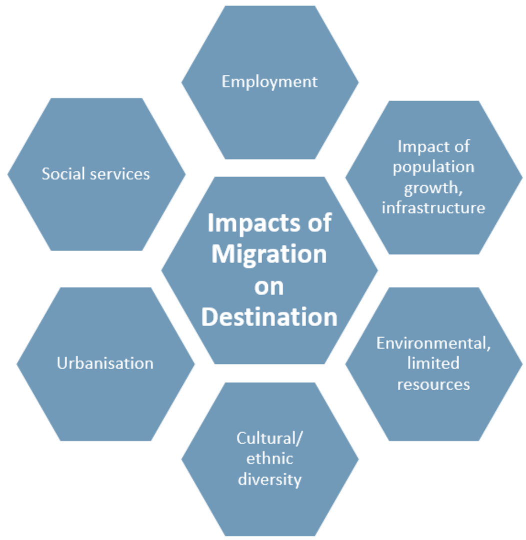

Figure 5: Impacts of migrant on destination (adapted from figure 13, Rahmati & Tularam 2017)

Proposed Solution

To assist the EU in defining effective policy and preparing for increases in migration flows, we propose to develop an easy-to-understand visual dashboard that will show current European migration flows on a map, along with predictions on how these will change over time after accounting for expected increases in severity of migration push factors.

The map will display current migration routes between origin and destination countries, and include a time-series slider to allow users to scan forward into the future to observe incremental changes to migration flows. The map will be overlaid to show current push factors contributing to displacement and migration based on real-time data, for example war or political turmoil. As the dashboard slider progresses further into the future, it will show push factors that are likely to contribute to displacement and migration, for example with predicted climatological disasters such as flooding, rising sea levels, desertification, wildfires, and other events.

The data behind this dashboard will leverage multiple machine learning algorithms in a composite model through ensemble learning, with the goal of achieving a richer, more informed view of migration risk that notably considers the impact of climate change. Near-term predictions will include real-time data sources such as news, social media, and aerial imaging to enable emergency reactivity and humanitarian aid. The system will also enable alerts to be issued to relevant humanitarian and government organisations when real-time data indicates an impending surge in migration.

Conceptually, this dashboard will be similar to IOM's European Flow Monitoring tool as shown in Figure X; however, where IOM's tool provides historical data, our solution proposes to predict future migration, and will include additional information on the causes of migration. This tool will be designed to be used by policy-makers for internal decision making, as well as for public education and consultation. There are multiple expected benefits to this approach.

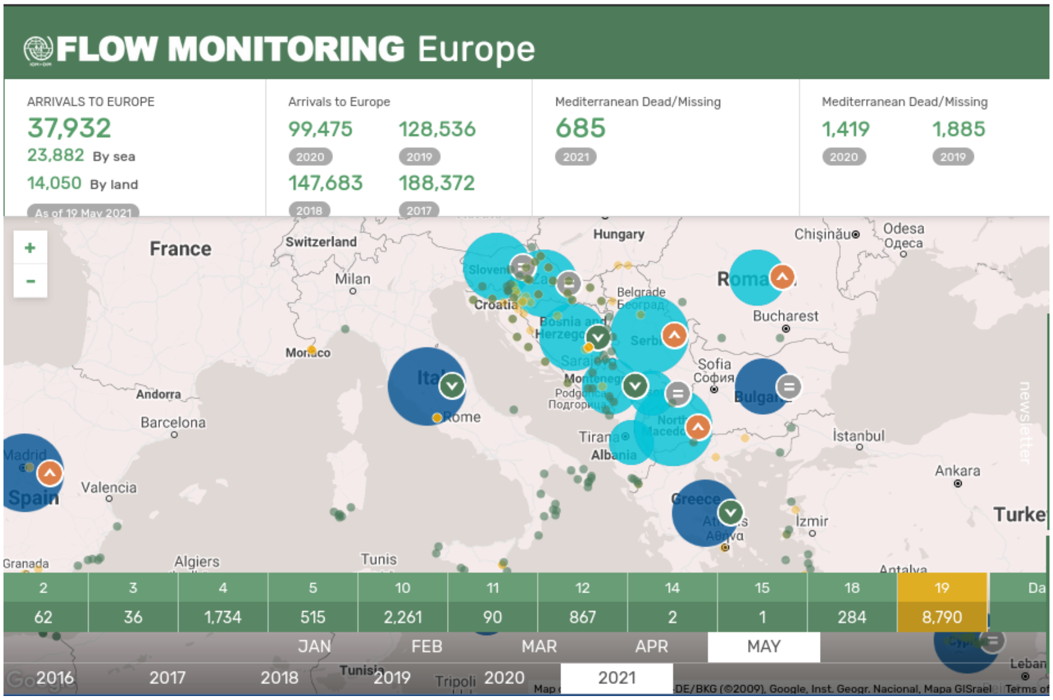

Figure 6: A map of historic migration into European countries (IOM 2021c)

Through the use of a composite model we aim to improve the accuracy of predictions by taking advantage of a more diverse range of data sources, overcoming some noted issues with historical data integrity and bias, as well as providing a view into real-time developments, which will enable reactivity to unprecedented migration flows that may not be captured in historical data.

By taking abstract figures and displaying them as visual increases in migration flows relative to past migration flows on a dashboard, it is hoped that the scale of the problem will be communicated more effectively. People may not necessarily know how to react to the idea of 200 million climate refugees by the year 2050 (Myers 2002). Whilst this probably sounds like a large figure to most people, it may also seem like the distant future, and does not explain what intermediate states towards this future will look like. Similarly, people may not easily appreciate the true consequences of abstract figures. For example, a 7% recurring annual increase in migration flows may sound innocuous, but the compounding effect would lead to a doubling in the initial figure over a ten year period. By allowing people to slide forward incrementally into the future, it is hoped they will understand the dramatic implications of climate change on migration and the need for present day policy action to mitigate it.

Another expected benefit is that by overlaying push factors onto the map, it will more clearly demonstrate a causal relationship and assist policy makers with triage. For example, there may be multiple approaches to mitigating the impact of future migration pressures, such as supporting origin countries with preventative aid to reduce the rise in push factors from occurring in the first place. There may also be strong financial incentives for destination countries to attempt this rather than to deal with the consequences of migration after it has already occurred. It is hoped that access to high-level causality will serve as a good starting point for mitigation cost-benefit analysis.

Ethical considerations

While collating a variety of different data sources to predict future migration patterns provides a great source of information for policy makers and Non-Government Organisations (NGOs), it may be exploited by those who wish to take advantage of vulnerable migrants or discriminate against them (ECRI 2020). People smugglers may use predictions about migration hotspots to help target locations to scout for business. People who wish to limit immigration to their region or country may also use predictions of hotspots as places to target discrimination or provide tips to local authorities about potential illegal immigrants. To ensure that this does not occur, the dashboard will contain generalised data with more detailed analysis only available to those you sign up to the service. The dashboard will only contain datasets that have been analysed and generalised with raw and detailed datasets not available online. The dashboard will also be restricted to the extent that you can zoom into so that the exact location of hotspots is not identifiable and that more generalised areas are shown. This is particularly important as people often assume that something on a map is highly accurate without understanding the scale and accuracy of the data being shown.

As with any data source used, it is important to consider the accuracy or bias of the data. The accuracy of the data collected by national statistics agencies cannot be guaranteed, where there is still some disparity on data collection practices and definitions of migration. As a vulnerable and often desperate population, migrants may also feel coerced by government agencies to provide more data than necessary as part of the asylum process, where data protection rights are still a fairly recent development (van der Aalst et al. 2017). Collecting any data from those who are migrating outside the law has its own set of ethical implications as they are vulnerable people and may be suspicious of anyone collecting information about them or their journey (Duvall et al 2019, van Liempt & Bilger 2018). This then raises ethical concerns on how governments and data collection agencies may use and store this data to target and surveile individuals in the future for political motivations, where the securitisation of migration will empower data collection agencies and reduce the human/ data protection rights of these individuals (Franco 2020). Any model that uses historic data from the United Nations High Commissioner for Refugees (UNHCR) or EU member states must consider that inferences made based on this data is susceptible to data integrity issues, with the exaggerated number of migrants directly correlating to the amount of funding allocated to the UNHCR an example of a model that may overly predict migrant flow and not necessarily reflect the truth (van der Aalst et al. 2017). Migrants whose data are collected at multiple points in the journey may not be an accurate representation of where they started and completed their migration journeys. Frontex may collect data on a migrant that makes multiple detected crossings during one journey, with some borders more difficult to police than others. This may result in different points at the border receiving a higher proportion of resourcing, while some migrant crossings may go completely undetected (EASO 2018).

This dashboard/ analysis will be using social media and aerial imaging as detailed in the methodology section below. It will be very important to have transparency about exactly what social media is being used and how it is incorporated into the analysis. The use of aerial imagery in the analysis also raises privacy issues. The spatial accuracy of this data will be at a level in which individuals are not identifiable and none of the raw data will be accessible.

Methodology

The most challenging aspect of developing and fine tuning this predictive migration model will be the collection of a wide range of quality data, that are easily accessible and fall under re-usable categories for the purpose of re-implementing and scaling this solution in different geolocations. Many of the data sources proposed in this solution are global, with location specific data sources able to be substituted depending on the intended deployment of this solution.

Data collection will be separated into 5 categories, that can be further divided by push and pull factors. This data will then be ingested into a composite Machine Learning pipeline that will output key predictive metrics to be displayed on the Dashboard to aid in policy decision making. The collection of a wide range of data sources and the utilisation of an ensemble of Machine Learning and Deep Learning techniques will be the point of difference when compared to other solutions.

Category 1: Origin Country Data

In this category, data collected will focus on an origin country's push factors, ranging from historical data collected by national statistics agencies, migration policy and real time social media and broadcast data, sourced from the Global Database of Events, Language and Tone (GDELT) as well as Google Trends and Twitter. GDELT 2.0 is updated every 15 minutes and could be utilised to provide real time sentiment analysis of the push factors contributing to emigration from origin countries. These push factors will include a set of predefined historical, political, environmental and social factors defined in existing migration literature that could potentially lead an individual to make a decision to emigrate from their origin country (EASO 2017, Kent & Behrman 2018). Each of these factors will be weighted, with more weight being lent to climate change related features. GDELT is already utilised by EASO as part of the Push Factor Index (PFI) to measure real time sentiment and correlates well with counted migrant applications and arrivals (EASO 2019)

Category 2: Destination Country Data

Destination regions or countries, such as the European Union and its member states collect many forms of data on migration that can be used, as well as providing features that could be used as target variables in other models such as migrant applications and migrant arrivals. Eurostat compiles a list of each member state's national statistics agencies, which collect data on migration, including number of asylum applications and arrivals.

Category 3: External Data

Frontex is the main authority in the European Union responsible for collecting and aggregating data from their external borders. They collect information from member states of the European Union on detected border crossings, aggregating and updating this information on a monthly basis.

Organisations such as the International Organisation for Migration (IOM), a related organisation to the United Nations collect data in the form of surveys at several border crossing areas, known as Flow Monitoring Points. Data collected from these surveys includes a migrants origin country, next intended destination and final intended destination. Data also collected include demographic information such as sex and nationality. Data from these surveys, as well as other sensors used by the IOM form an existing solution called the Displacement Tracking Matrix (DTM) that is publicly accessible.

Category 4: Satellite Data

Satellite imaging has recently been successful in detecting human activity using thermal activity and night-time light tracking in Uighur camps in China (Robinson & Mann 2021). In addition to this, the UN already employs a web based tool called PulseSatellite to monitor population displacement, settlement mapping, damage and flood assessment using a neural network (Logar et. al 2020).

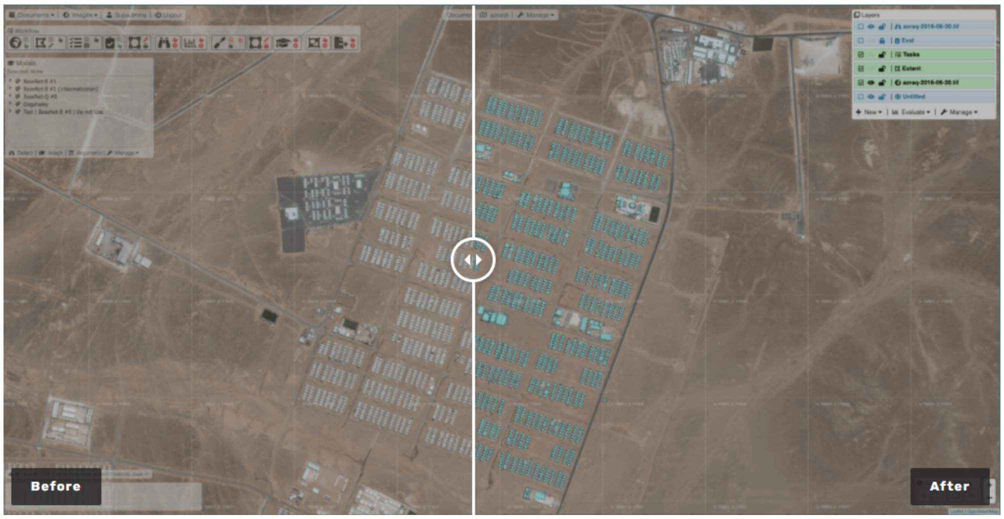

Figure 7: PulseSatellite being used to identify settlement camps (UN Global Pulse 2021)

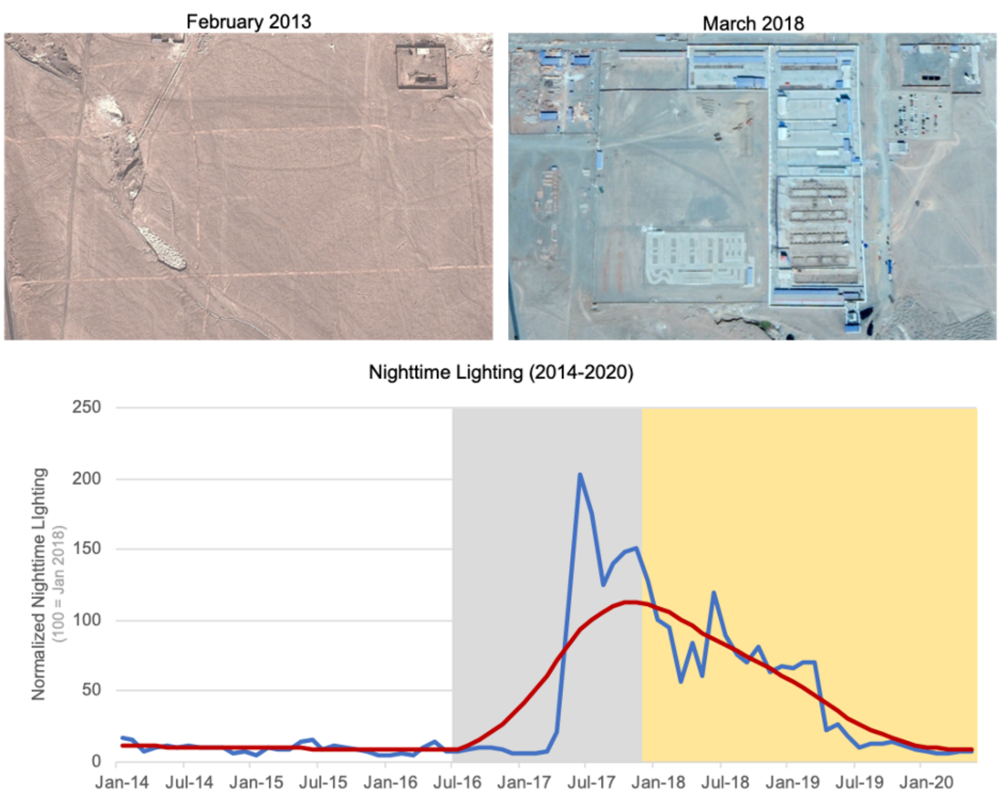

Figure 8: Increases in night-time lighting in Uighur camps indicate heightened activity (Robinson & Mann 2021)

These examples demonstrate the application of a neural network trained on satellite imagery already has viability in order to address similar problems. Data from the NOAA VIIRS will be utilised at a predefined set of known locations such as border crossing points and origin countries to detect increases and decreases in activity through the utilisation of thermal and night-time imaging.

Category 5: Climate Change Data

Most importantly, to address the effects of Climate Change, data will be collected from several sources and be manually weighted to have a greater impact on the compilation model. Data sources will include publicly available global weather station data collated by the NOAA at the Global Historical Climatology Network Daily (NOAA 2021), the EM-DAT International Database from the Centre for Research on the Epidemiology of Disasters (EM-DAT 2021) and existing simulation models from the International Panel for Climate Change (IPCC 2014). Climate data collected from weather stations will be trained to predict extreme weather events, and then we propose to use data from a range of projects from multiple general circulation models at two different time periods (2050 and 2080) under a moderate emissions scenario as part of the IPCC (Intergovernmental Panel for Climate Change) 5th Assessment process (IPCC 2014).

The Composite Model

Utilising all the data sources mentioned above, a composite model utilising different Machine Learning and Neural Network techniques will be utilised, to generate a multilayered artificial neural network that will output key metrics to be used by our Dashboard. Each layer of this network will produce a range of outputs that will propagate forward and be utilised in subsequent models. At a high level, utilising a structure like this enables human interaction throughout the process, facilitating strengths of the model including the manual weighting of climate data. What this also achieves is a high level of transparency, where it will be possible to query certain aspects of the Dashboard when drilling down into certain alerts and metrics.

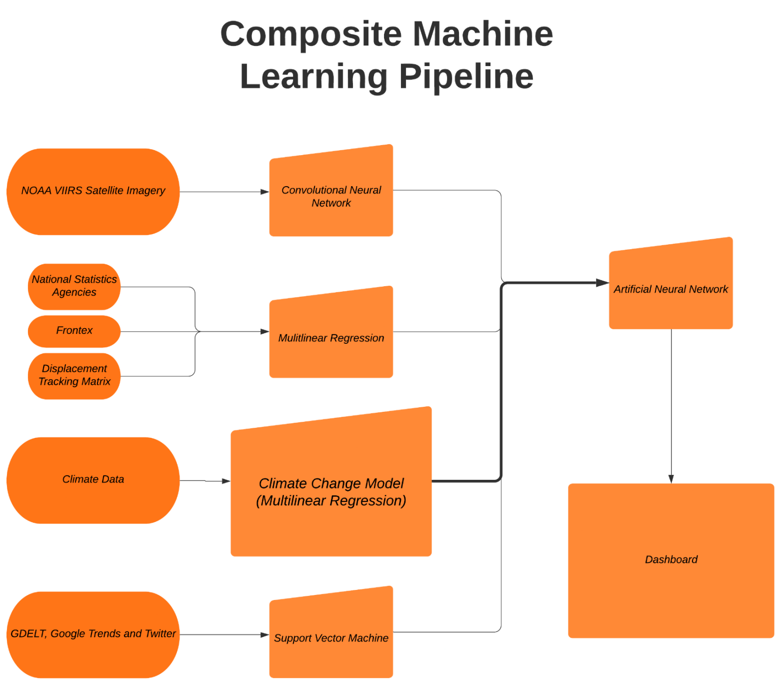

Figure 9: The proposed structure of the composite machine learning model

Conclusion

Migration is set to significantly increase over the next several years, and governments across the world are starting to realise the importance that data driven strategies will have on mitigating the effects that climate change will have. Current political strategies address specific push and pull factors of migration, however, there are few that use a multidimensional approach across a broad range of data sources, including the utilisation of big data from social media and other internet sources to assist in decision making. Our solution proposes a methodology to contribute to a composite model structure, with a heavier weight on climate data to account for future climate scenarios and to address potential concept drift that may occur when attempting to fit historical data on future predictions, therefore improving reliability and usability in policy making situations. This will be supported through an easy to digest dashboard, which will summarise key metrics, and assist in the decision making process. Ethical considerations will be addressed to increase positive impact on vulnerable people in the migration, such as aggregating data to ensure the safety of individuals who could be potentially discriminated against, and an understanding that data from certain data sources may lack credibility and therefore need to be excluded.

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Contribution Sheet

For each member in your team, please write your name, student number, contribution percentage to the assignment and your signature. Marks are awarded to the individual team members, according to the contributions made towards the final work. Please submit what percentage each team member made to this assignment and submit this sheet in your submission.

The contributions of your group should add up to 100%.

Name	Student Number	Contribution Percentage	Signature
Simon Karumbi	s3455453	33.33%	
Verity Miles	s3644459	33.33%	VMiles
Christopher LeMarshall	s3482127	33.33%	