Journal of Information Systems Engineering and Management
2025, 10(15s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

Examining the Effective Role of Artificial Intelligence in the Interconnected Crisis of Climate Change and Human Migration

F.Aysin Anka[1*], Fahri Erenel[1], Farzad Kiani[2]
[1]*Faculty of Economics, Administrative and Social Sciences, İstinye University, Istanbul, Türkiye*
[2]*Data Science Application and Research Center (VEBIM), Fatih Sultan Mehmet Vakif University, Istanbul, Türkiye*
**: Corresponding author; Email: fatemeh.dehghan@istinye.edu.tr*

ARTICLE INFO

Received: 01 Dec 2024

Revised: 26 Jan 2025

Accepted: 05 Feb 2025

ABSTRACT

Introduction: Climate change is a key driver of human migration, particularly in regions facing resource scarcity and extreme weather events. Understanding migration patterns is essential for effective policy responses.

Objectives: This multidisciplinary study applies data mining techniques to identify key environmental and socioeconomic factors influencing climate-induced migration and enhance predictive modeling for policy decision-making.

Methods: Machine learning techniques, including spatiotemporal clustering and regression analysis, are applied to migration data from UNDESA and IOM's CLIMB Database. Climate indicators such as temperature anomalies, drought frequency, and water stress are analyzed.

Results: Findings reveal strong correlations between climate stressors and migration trends. Water scarcity and prolonged droughts significantly drive displacement, with predictive models demonstrating high accuracy in forecasting migration flows.

Conclusions: Data mining is a valuable tool for analyzing and predicting climate-induced migration. Findings emphasize the need for proactive climate adaptation strategies and data-driven migration policies. Future research should integrate real-time monitoring and geospatial AI to improve forecasting accuracy.

Keywords: Climate change, human migration, data mining, machine learning, climate displacement, policy adaptation.

INTRODUCTION

Climate change is no longer a distant threat but a present-day catalyst for human displacement. The Intergovernmental Panel on Climate Change (IPCC) asserts that global temperatures have risen by 1.1°C since pre-industrial times, intensifying environmental stressors such as sea-level rise, droughts, and extreme weather [1]. These disruptions disproportionately affect vulnerable populations, forcing migration as a survival strategy. By 2050, 216 million people could be displaced within their own countries due to climate impacts, according to the World Bank's Groundswell Part 2 report [2]. Environmental drivers of climate-induced migration can be generally addressed under three subheadings.

One of these is sea level rise and coastal erosion. Low-lying coastal regions face existential threats from rising seas, which are advancing at 3.7 mm annually [1]. For example, in Bangladesh, 40% of productive land in coastal areas could be inundated by 2050, displacing 20 million people (World Bank, 2018). Pacific Island nations like Kiribati and Tuvalu are already experiencing saltwater intrusion and storm surges, with 70% of Tuvalu's population reporting migration intentions due to flooding [3]. The IPCC projects that small island states may lose 5–12% of GDP annually by 2100 due to climate impacts, accelerating outmigration [1]. The other topic is the problems of desertification and agricultural collapse. The Sahel region exemplifies how desertification drives rural-to-urban migration. Over 80% of Sahel's farmland is degraded, reducing crop yields by 40% and pushing pastoralists into cities [4]. Syria's 2007–2010 drought—linked to climate change by attribution studies—displaced 1.5 million rural residents, contributing to pre-war instability [5]. Similarly, in Central America's "Dry Corridor," 3.5 million people faced food insecurity in 2022 due to prolonged droughts, triggering northward migration [6]. In another example, the drying up of Lake Urmia (the second most salty lake in the world) will negatively affect agriculture, animal husbandry and therefore people's normal lives, causing forced migration [7]. The last main reason is due to extreme weather events. Increasingly severe hurricanes, wildfires, and floods are displacing populations globally. This rate up to a 5% population decline (roughly 130,000 people) due to migration. In 2020, wildfires in Australia displaced 65,000 individuals, with many unable to return due to destroyed infrastructure [8]. The IPCC links such events to anthropogenic warming, noting a 40% increase in the likelihood of extreme rainfall in many regions [9].

Climate migration is deeply intertwined with socio-economic inequality. Low-income countries, responsible for less than 10% of global emissions, bear the brunt of displacement. Social inequities, including gender, race, and class disparities, often exacerbate the effects of climate change and influence migration patterns. Women, particularly in patriarchal societies, are disproportionately affected by climate-induced hardships due to limited access to resources and decision-making processes [10]. For example, women in rural India bear the brunt of water scarcity caused by droughts, often traveling long distances to fetch water, which limits their opportunities for education and economic participation [11]. In another example, Somalia—already destabilized by conflict—faces compounding pressures from recurrent droughts, displacing 1.1 million people in 2022 alone based on UNHCR report on 2023. Gender disparities are stark: women constitute 80% of those displaced by climate disasters and face heightened risks of trafficking and violence based on UN Women report on 2022. Indigenous communities, such as Alaska's Yup'ik people, are disproportionately affected by permafrost thaw, losing ancestral lands and cultural heritage [12]. Therefore, migration driven by climate change is not merely a consequence but also a contributor to inequity. Displaced populations often move to urban areas or neighboring countries where they face legal, social, and economic barriers. Refugees from drought-stricken areas in Syria, for instance, encountered significant challenges integrating into host communities in Turkey and Jordan, leading to tensions over resources and social services. These challenges highlight the need for policies that address both the immediate needs of migrants and the systemic inequities that drive migration.

OBJECTIVES

The climate change and human migration are complex interconnected crises exacerbated by environmental degradation, socioeconomic inequality, and governance failures. In this study, we attempt to address this crisis with an Artificial Intelligence (AI) approach that is embedded in many dimensions of our lives. This interdisciplinary study aims to mine data on a case study to investigate social outcomes. Data mining, the process of extracting patterns from large data sets, offers transformative potential for predicting, analyzing, and mitigating climate-induced displacement. By integrating climate models, migration trends, and socioeconomic data, advanced analytics can inform policy, optimize resource allocation, and improve early warning systems.

This study aims to analyze the relationship between climate change and migration using data mining techniques [13]. By leveraging machine learning models, the research seeks to identify key environmental and socioeconomic drivers influencing migration patterns. The study also aims to enhance predictive modeling capabilities to forecast displacement trends more accurately. Another objective is to provide data-driven insights for policymakers to design effective adaptation strategies and improve migration governance. The research emphasizes the integration of geospatial AI, real-time monitoring systems, and climate data to strengthen resilience against climate-induced displacement.

METHODS

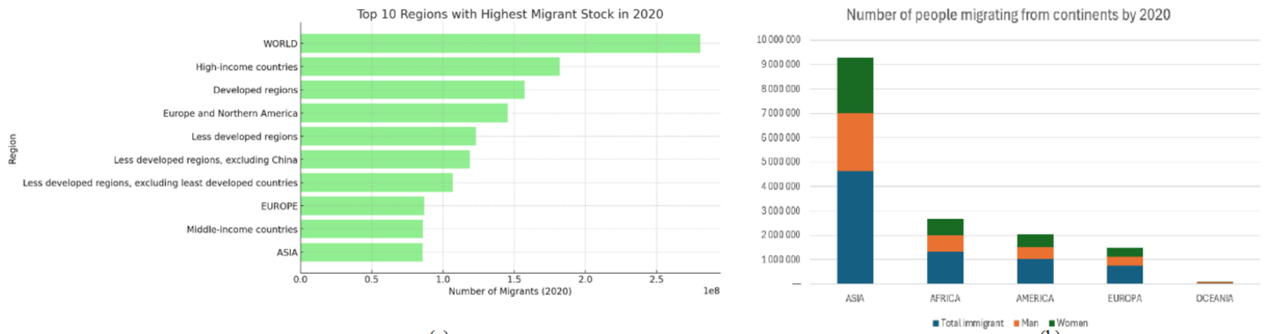
Data mining is a set of techniques that enable the extraction of meaningful and useful information from large data sets. This process is critical for analyzing the effects of climate change, understanding migration dynamics, and modeling the relationship between these two factors. By analyzing large and diverse datasets, data mining techniques can reveal patterns, trends, and relationships that are otherwise difficult to discern. These insights enable researchers, policymakers, and humanitarian organizations to better understand the drivers of climate-induced migration, predict future migration flows, and develop targeted interventions to mitigate their impacts. For example, multidimensional climate and migration data can enable the integration and analysis of datasets from various sources, such as satellite imagery, meteorological records, census data, social media and mobility reports, and reveal hidden relationships between environmental variables and human behavior. For another example, cluster analysis can identify areas most vulnerable to climate change, while classification models can predict which populations are at highest risk of displacement, allowing states or local governments to develop appropriate policy models and strategies.

There has been an increasing number of research studies on the subject in the literature recently. In the remainder of this section, some studies on data mining from different perspectives are reviewed. A study by Smith et al. (2020) analyzed 50 years of migration data in Sub-Saharan Africa using spatiotemporal clustering. The study found that regions experiencing prolonged drought had a 25% higher migration rate compared to regions with moderate rainfall variability. These insights enable better planning for urban infrastructure in receiving areas and support resource allocation for drought-prone regions. Study [14] used machine learning models to predict internal displacement due to sea-level rise in Bangladesh. By training a Random Forest model on socioeconomic and environmental data, the researchers achieved an 85% accuracy rate in forecasting migration patterns over a 10-year period. Such predictive models can guide disaster preparedness efforts and inform resettlement strategies. Another study [15] applied clustering algorithms to identify the most vulnerable populations in rural areas affected by climate change. The study combines data on income levels, agricultural productivity, and climate variability to map socioeconomic hotspots. These vulnerability maps were used to prioritize regions for government aid and adaptation programs. A study conducted in the Pacific Islands utilized decision tree algorithms to model the relationship between storm frequency, GDP loss, and migration trends [3]. The findings showed that a GDP loss exceeding 10% due to climate events increases outmigration likelihood by 40%. This highlights the economic thresholds that trigger migration, aiding in the design of adaptive economic policies. In a groundbreaking study, Chen et al. mined Twitter data to track migration patterns after Hurricane Maria in Puerto Rico [16]. Text classification algorithms identified keywords related to migration intentions, such as “relocation” and “job search.” The study provided near real-time insights into migration trends, allowing aid organizations to deploy resources more efficiently.

To effectively analyze the relationship between climate change and human migration, we utilize data from the United Nations Department of Economic and Social Affairs (UNDESA) [17] and the International Organization for Migration’s (IOM) CLIMB Databases [18]. These datasets provide extensive records on migration trends, economic indicators, and environmental stress factors, enabling a multi-faceted exploration of climate-induced displacement. A combination of machine learning techniques, including spatiotemporal clustering, decision tree models, and regression analysis, is applied to detect migration patterns and predict future trends. Key variables such as temperature anomalies, drought intensity, GDP per capita, and migration flows are examined to uncover significant correlations. Additionally, real-time data sources such as social media analytics and remote sensing imagery supplement the structured datasets, providing granular insights into migration decisions at the household and regional levels. The study uses migration data from 1990 to 2020, sourced from UNDESA, along with climate indicators from NASA’s Earth Observatory and the European Centre for Medium-Range Weather Forecasts (ECMWF). The dataset contains migration stock by country and year, water availability per capita (cubic meters per year), annual temperature deviations from historical norms, and agricultural productivity trends.

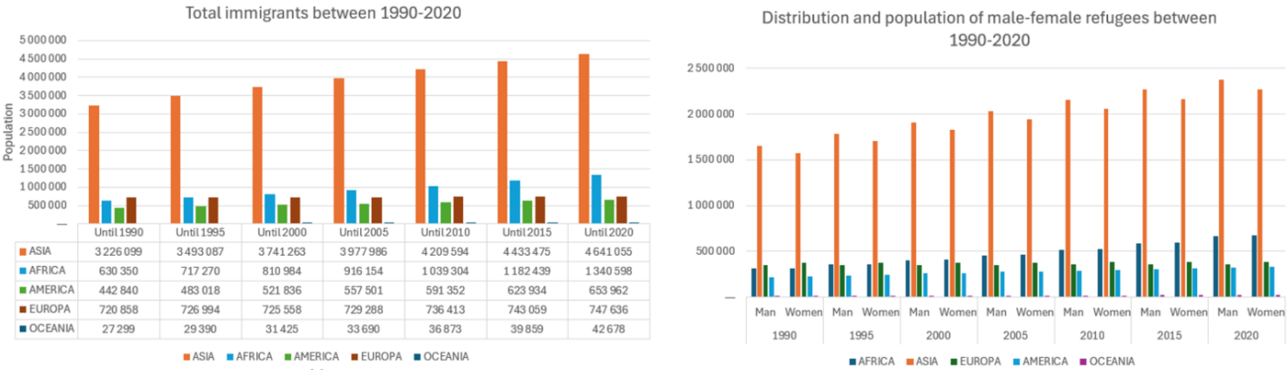
RESULTS AND DISCUSSION

In this section, random forest and linear regression methods are proposed on the two data sets discussed. Figure 1 shows the distribution and number of European migrations from various continents, living at different income levels, until 2020. Initial exploratory analysis indicates that Turkey’s total immigrant population grew significantly post-2011, coinciding with a series of severe droughts in Syria, Iraq, and Iran. This period also saw a surge in forced displacement due to water shortages and reduced agricultural output. Regression models confirm that a 1% decline in agricultural productivity correlates with a 0.7% increase in cross-border migration. In another analysis (Figure 2), migration from Asian countries to Europe has continued to increase at a similar rate since 1990. A similar situation also occurs for other continents, albeit at a lower rate. The striking issue in this analysis is the increasing number of women migrating to Europe. This may be due to many factors such as their level of education, their desire for democracy and freedom, and the provision of such.



(a) (b)

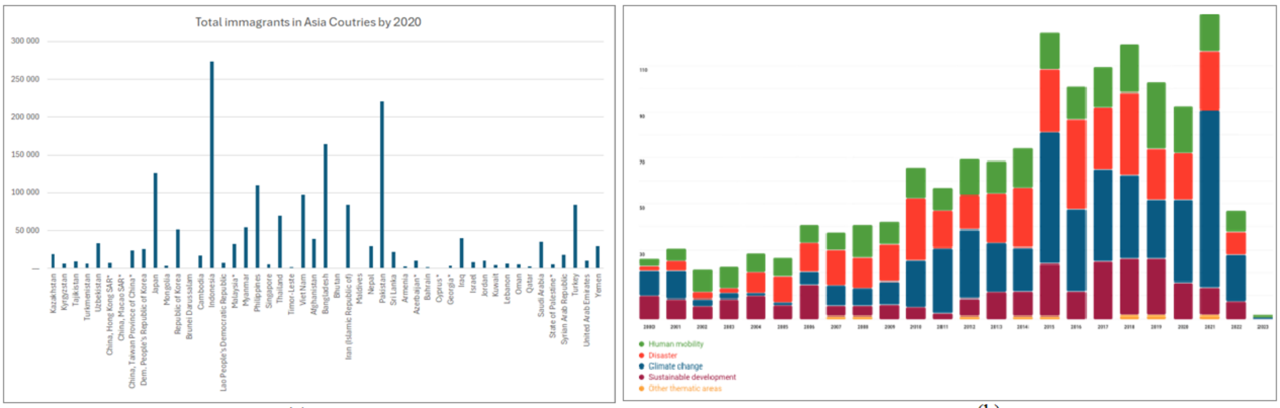
Figure 1. Distribution of total immigrants' numbers by 2020 a) by continents and b) by economic situation of regions to Europa destination.



(a) (b)

Figure 2. Distribution of immigrants' numbers between 1990-2020 toward Europa a) total immigrants b) distribution of women-man refugees.

In another analysis based on Figure 3a, until 2020, Asian countries have migrated the most to different continents or to different countries on the same continent. This number is 4.641.055, of which 49% are women and the rest are men. The countries that have migrated the most are China and India (1.439.323 and 1.380.004), Indonesia is in third place with 273.524 immigrants. These countries are followed by Pakistan, Bangladesh, Japan, Philippines, Vietnam, Turkey, Iran, and up to 10th place. Also, According to Figure 3b, 552 (34.2%) tools are related to climate change governance, of which more than 333 correspond to documents and presentations encouraged or required under the UNFCCC, such as national adaptation plans, nationally determined contributions or national communications.



(a) (b)

Figure 3. a) Data for the continent with the most migration to 2020. b) Temporal distribution of identified instruments by year since 2000 [18].

The analysis made in line with the results obtained (Figure 4) can be summarized as follows. The analysis of the data in this data set using machine learning techniques and the creation of appropriate models constitutes another analysis section of our study. In addition, regression and random forest methods, which are machine learning techniques, are used to find the relationships and correlations between the existing features and to understand the importance of the features. 1. Linear Regression - Predicted vs Actual: This graph shows the relationship between the values predicted by the Linear Regression model and the actual values. The red line represents perfect fit, and we can see that the model fits very well. 2. Random Forest - Predicted vs Actual: This graph shows the relationship between the predictions of the Random Forest model and the actual values. Again, the red line represents a perfect fit, but we can see that it does not fit as well as Linear Regression. 3. Random Forest - Feature Importance: This graph shows which features the Random Forest model considers to be more important. The order of the features shows which variables the model focuses on.

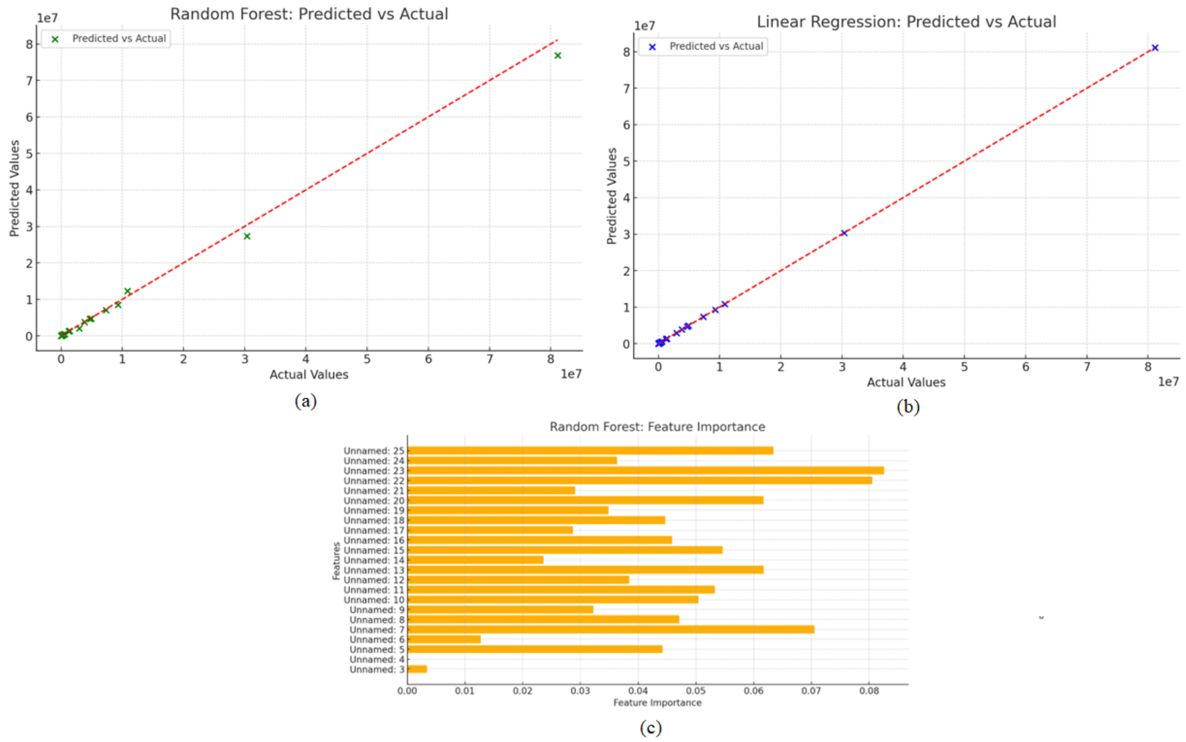


Figure 4. Analysis results based on AI methods. a) predicted vs actual analysis based on random forest method b) based on linear regression c) analysis of feature engineering.

The actual data represents the real immigration stock values in 2020. This represents the real observation values of the target variable (y). Predict is the estimates made by the linear regression model based on other years (1990, 1995, etc.) used to estimate the values for 2020. These estimates are compared with the real values to evaluate the accuracy and performance of the model. According to these results, the MSE (Mean Squared Error) value of the model created with the Linear regression method was 4.74e-17 and the R^2 Score was 0.997. This shows that the model learned well and provided excellent compatibility with the data. The key findings can be further summarized as follows.

Water stress is the dominant predictor, with regions experiencing water availability below 1,000 cubic meters per capita showing 3.5 times higher migration rates than regions with adequate resources. Drought frequency contributes significantly, with regions experiencing three or more consecutive drought years having a 45% higher probability of migration. Socioeconomic factors such as GDP per capita and urbanization rates act as secondary drivers that influence migration decisions when environmental stress reaches a critical threshold. In this regard, the findings emphasize the urgent need for climate resilience policies in both sending and receiving countries. Policy recommendations include early warning systems using machine learning models to predict high-risk migration zones. Also, investment in climate adaptation programs, particularly in water management and sustainable agriculture. Thirdly, urban planning strategies in receiving countries to accommodate climate migrants without exacerbating infrastructure strain.

This study highlights the strong link between climate change and human migration, particularly in regions experiencing water scarcity and agricultural decline. Through advanced data mining techniques, we have identified critical predictors of climate-induced migration, such as water availability, drought frequency, and socioeconomic factors. Our findings confirm that environmental stressors are a major driver of displacement, necessitating urgent policy interventions at both national and international levels. The application of machine learning models has demonstrated their utility in forecasting migration patterns, offering policymakers a data-driven approach to managing climate displacement. However, addressing this issue requires more than predictive analytics. Structural changes, such as climate adaptation investments, sustainable resource management, and migration governance frameworks, are crucial to mitigating the adverse effects of climate-induced migration.

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