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RESEARCH ARTICLE

Understanding Climate-Driven Migration: A Nonlinear Machine Learning Approach

SABRINA DE NARDI [1], CLAUDIO CARNEVALE [1], (Member, IEEE), GABRIELE PICCOLI [1], SARA RACCAGNI [1], AND LUCIA SANGIORGI [2]

[1]Department of Mechanical and Industrial Engineering, University of Brescia, 25123 Brescia, Italy
[2]DATINNOVA Srl, 25124 Brescia, Italy

Corresponding author: Sabrina De Nardi (sabrina.denardi@unibs.it)

ABSTRACT The relationship between climate change and migration has gained significant attention in recent years, particularly regarding its impact on vulnerable regions. This study proposes a novel modeling approach to climate-induced migration by systematically comparing traditional statistical models and machine learning techniques. While most existing research in this field relies on linear models or case-specific analyses, our work explicitly models complex non-linear and multidimensional relationships among environmental and socio-economic drivers of migration. By comparing autoregressive, polynomial, and logarithmic models with a Random Forest model, we demonstrate the added value of machine learning in capturing complex patterns that conventional models often fail to detect. Furthermore, we analyze how variables such as temperature anomalies, the Human Development Index (HDI), water stress, and the agricultural sector's contribution to the Gross Domestic Product influence migration. This framework is applied to data-scarce and climate-sensitive regions, namely North Africa, Sub-Saharan Africa, and Southeast Asia, where robust modeling remains both challenging and urgently needed. Model performance was systematically evaluated through multiple metrics, including correlation, Mean Error (ME), Mean Absolute Error (MAE), and their normalized forms (NME and NMAE). Results show that while simpler models exhibit limited explanatory power, the Random Forest model substantially improves predictive accuracy, achieving correlation = 0.81, MAE = 0.95, NME = –0.009, and NMAE = 0.25. These findings demonstrate the model's effectiveness in capturing migration dynamics, and also provides a replicable methodology that can support targeted adaptation strategies, effective migration management, and climate policies, particularly relevant for data-scarce regions of the Global South.

INDEX TERMS Climate change, migration, climate-driven displacement, nonlinear models, random forest.

I. INTRODUCTION

Environmental degradation and climate change pose severe risks to human well-being and livelihoods, also reshaping human mobility patterns [1], [2], [3], [4]. The growing number of climate-related displacement cases confirms that climate change has become a major and accelerating determinant of human mobility [5]. Recent reports indicate a persistent rise in climate-related displacement, from tens of millions annually in recent years to a projected 44–216 million by 2050 [6], [7], [8]. This trend poses major challenges to the achievement of Sustainable Development Goal (SDG) 10, which focuses on reducing inequalities both within and among countries, and on promoting safe, orderly, and well-governed migration (Target 7) [9]. As extreme weather events, rising sea levels, prolonged droughts, and other environmental disruptions become increasingly frequent and severe, more communities face growing challenges in sustaining livelihoods in their places of origin [10], [11], [12]. Consequently, there is an urgent need for policies that address not only the environmental aspects of migration, but also the broader socio-economic and political determinants that influence adaptive capacity and mobility choices [13], [14]. Understanding and modeling climate-induced migration

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TABLE 1. Comparative overview of migration theories and their linkage to climate change.

Theory	Focus	Key Authors	Link to Climate Change
Push–Pull Theory	Migration results from negative push factors at origin and positive pull factors at destination	Lee (1966)	Climate change acts as a strong push factor (e.g., droughts, floods, sea-level rise), while safer and economically attractive destinations serve as pull factors
New Economics of Labor Migration (NELM)	Household-level migration decisions to diversify income and manage risk	Stark & Bloom (1985)	Climate variability and extreme events increase livelihood risks, prompting households to send members to migrate and secure alternative income or remittances
Sustainable Livelihoods Approach	Strategies to maintain well-being by combining different capitals (natural, financial, social, human)	Chambers & Conway (1992); Scoones (1998)	Climate change threatens multiple forms of capital (agriculture, water, health), making migration one adaptation strategy; highlights immobility for resource-poor households (trapped populations)
Migration Systems Theory	Migration flows shaped by historical, social, economic, and institutional networks	Mabogunje (1970); de Haas (2010)	Environmental shocks increase migration pressure, but flows follow pre-existing networks and pathways rather than creating entirely new ones
Capabilities and Aspirations Framework	Migration depends on both aspiration and capability to move	de Haas (2014)	Climate change can increase the desire to migrate while constraining actual mobility due to poverty, lack of networks, or restrictive policies; explains trapped populations

require interdisciplinary and integrative approaches capable of capturing these multifaceted and nonlinear dynamics. Despite growing research on this topic, most existing modeling approaches continue to depend upon linear assumptions that fail to represent the nonlinear interactions among environmental, socio-economic, and political variables. This study addresses this gap by developing and testing a comparative modeling framework that systematically compares traditional statistical models with nonlinear machine learning techniques to identify the key environmental and socio-economic drivers of migration under climatic stress and improve predictive accuracy. Methodologically, the study:

- systematically compares traditional statistical regressions and nonlinear machine learning algorithms within a consistent comparative framework;
- assesses the performance of autoregressive, polynomial, and logarithmic regressions against Random Forest (RF) models, demonstrating the latter's ability to capture nonlinearity and higher-order interactions;
- explicitly incorporates multifactorial and nonlinear relationships often overlooked in conventional econometric models; and
- proposes a scalable, data-driven modeling pipeline designed to handle heterogeneous variables and non-stationary migration patterns associated with climatic stress.

In terms of application, the framework:

- focuses on climate-sensitive and data-scarce regions (North Africa, Sub-Saharan Africa, and Southeast Asia) where model robustness is often limited;
- significantly improves predictive accuracy, indicating the potential of RF models for operational early warning systems and evidence-based migration policymaking.

Addressing the pressing challenge of climate-driven migration in highly vulnerable regions, this study demonstrates that nonlinear and machine learning models can effectively capture complex migration dynamics. The proposed comparative framework enhances predictive accuracy while offering a replicable foundation for evidence-based adaptation and migration policy design. Beyond its empirical applications, the study advances quantitative methodologies for analyzing the multifactorial drivers of human mobility under climate change.

II. BACKGROUND AND STATE OF ART

The vast majority of econometric models conceptualize migration flows as a linear function of various demographic, economic, social, political, and environmental factors [4], [15], [16], [17], [18], [19], [20]. While these models provide valuable insights into migration dynamics, they fail to capture nonlinear interactions and dynamic feedback loops, especially under climatic stress, where environmental and socio-economic variables interact in complex ways. Their simplifying assumptions make them inadequate for analyzing migration dynamics in the context of climate variability. First, they assume proportional and constant relationships between independent variables and migration flows, making them incapable of identifying tipping points. In reality, these relationships are often nonlinear; for instance, increased economic opportunities in a region may not proportionally increase migration and may trigger a sudden surge once a threshold is crossed. Second, migration results from multiple socio-economic and environmental processes that intersect in patterns that linear models cannot represent accurately. Climate change, political instability, poverty, social inequalities, and historical dynamics interact in ways that linear models cannot represent. Social networks, family ties, and cultural identities further shape migration decisions and are often neglected in linear models. Third, linear models cannot account for sudden shocks like disasters, conflicts, pandemics, or abrupt policy changes, which can drastically alter migration dynamics. Finally, they tend to emphasize direct causes but overlook indirect effects, such as climate change impacting agriculture, public health, education, and resource competition, which influence migration in multiple, interrelated ways. Given these limitations, advanced modeling approaches are required to better capture the complexity of migration dynamics [18], [21]. Nonlinear models, including logarithmic transformations, polynomial regressions, and ensemble algorithms such as Random Forests, provide a more flexible powerful framework to analyze migration [22], [23], [24]. These models can capture nonlinear relationships, thresholds, behaviors, and multi-variable interactions that linear models cannot, thus enhancing the accuracy of migration forecasting and yielding insights that can inform more adaptive, evidence-based policies. While existing literature extensively examines climate-induced migration, a significant gap remains in understanding how climate stressors interact with socio-economic factors [25]. The present study addresses this gap by analyzing the combined impact of temperature anomalies, water stress, the Human Development Index (HDI), and the agriculture sector's share of GDP on migration patterns in selected areas of the Global South. Using machine learning techniques, this study aims to uncover mechanisms driving voluntary and forced migration, offering a comprehensive perspective on the multidimensional nature of climate-induced displacement and providing insights to guide effective policy interventions.

A. A THEORETICAL FRAMEWORK TO UNDERSTAND CLIMATE CHANGE INDUCED MIGRATION

While migration has long been studied through multiple theoretical lenses, five frameworks are particularly relevant for examining how climate change influences migration decisions. They suggest that climate change rarely acts as a sole cause of migration. Rather, it interacts with economic, social, and political drivers to shape migration decisions at multiple levels.

1) PUSH–PULL THEORY

The push–pull framework is a foundational concept in migration studies [19]. It conceptualizes migration as a decision-making process driven by a combination of negative factors at the origin (*push factors*), such as economic hardship or environmental degradation, and positive factors at the destination (*pull factors*), such as higher wages or improved services. In the context of climate-induced migration, climate change acts primarily as a push factor, as extreme weather events and long-term degradation undermine livelihood security. At the same time, resilient destination areas with better economic and institutional conditions may act as pull factors, encouraging mobility [26], [27].

2) NEW ECONOMICS OF LABOR MIGRATION (NELM)

The New Economics of Labor Migration (NELM) framework reconceptualizes migration as a household-level risk management strategy rather than merely an individual choice [28]. Households use migration to diversify income sources, reduce vulnerability, and manage economic risk, particularly under environmental uncertainty. Climate variability, droughts, floods, and storms increase livelihood instability, prompting households to adopt migration as an adaptive response [29], [30], [31]. Migration thus becomes part of a broader adaptive portfolio, complementing other resilience strategies such as remittances and diversification.

3) SUSTAINABLE LIVELIHOODS APPROACH

The Sustainable Livelihoods Approach (SLA), proposed by Chambers and Conway [32] and later expanded by Scoones [33], emphasizes how households draw on multiple capitals (natural, human, social, financial, and physical) to sustain well-being. Climate change threatens these capitals by undermining agricultural productivity, water access, and health security, thereby increasing vulnerability. Migration often emerges as a component of adaptive livelihood diversification [34], [35], [36], [37] [38], [39]. However, the SLA also highlights "immobility," where poverty or legal barriers prevent migration, producing trapped populations. This results in populations unable to migrate, thus remaining exposed to intensifying climate risks.

4) MIGRATION SYSTEMS THEORY

Migration Systems Theory, pioneered by Mabogunje [40] and developed by de Haas [41] identifies migration as part of interconnected systems of flows, institutions, and networks. Environmental shocks, such as droughts or floods, can increase migration pressure, but these flows typically occur along pre-existing pathways shaped by labor markets and social linkages [42], [43].

5) CAPABILITIES AND ASPIRATIONS FRAMEWORK

The Aspirations–Capabilities Framework, articulated by de Haas posits that migration depends on both the aspiration to move and the capability to do so [44]. Climate change may heighten aspirations to migrate by threatening livelihoods, yet simultaneously reduce capabilities through poverty or restrictive policies, resulting in trapped populations [45], [46]. This framework complements the SLA by linking immobility to structural constraints rather than household choice.

Table 1 offers a comparative overview of migration theories and their linkage to climate change.

B. ENVIRONMENTAL MIGRANTS, CLIMATE MIGRANTS, CLIMATE REFUGEES, INTERNALLY DISPLACED PERSONS AND TRAPPED POPULATIONS

The terminology surrounding climate-related human mobility lacks consistency across disciplines and policy debates, and no universally accepted legal definition exists. To ensure conceptual clarity, this study adopts terminology from widely cited institutional sources. The International Organization for Migration (IOM) defines *environmental migrants* a persons who, for compelling reasons of environmental change, are obliged or choose to leave their habitual homes temporarily or permanently, within or across borders [47], [48]. Within this category, *climate migrants* are those whose movement is primarily driven by climate change impacts such as sea-level rise or desertification [9]. Although the term lacks legal status, it is referenced in the UNFCCC's Cancun Agreements [49], which distinguish it from forced climate-induced displacement, thereby implying a narrower interpretation referring only to voluntary movements [50]. The expression *climate refugees*, introduced by El Hinnawi [51], underscores the severity of environmental displacement but remains legally unrecognized, as the 1951 Geneva Convention defines refugees only in relation to persecution based on race, religion, nationality, membership of a particular social group, or political opinion [8], [11], [52], [53]. For this reason, the present study avoids this term. A distinct but related group are the *internally displaced persons* (IDPs), defined in the UN Guiding Principles on Internal Displacement as individuals or groups forced to flee their homes due to armed conflict, generalized violence, human rights violations, or natural disasters, without crossing an international border [54]. Finally, the concept of *trapped populations* refers to those who wish or need to migrate but lack the resources, networks, or political support to do so [55], [56]. It thus describes situations of involuntary immobility, where vulnerability persists without mobility opportunities [57].

Clarifying these distinctions is crucial to framing policy responses and analytical models that accurately represent the complexity of climate-induced mobility.

III. METHODOLOGY

While the frameworks reviewed in Section II are conceptually capable of including climate forcing among the drivers of migration, this link is frequently underrepresented in practice, largely due to the methodological and conceptual challenges of embedding climate processes into comprehensive migration frameworks. This study introduces a novel, comprehensive and data-driven framework for modeling climate-induced migration, that addresses the nonlinear and multifactorial nature of migration drivers. To overcome the traditional limitations of the linear models, the proposed framework compares conventional statistical approaches, such as autoregressive, polynomial, and logarithmic regressions, with advanced machine learning techniques, particularly Random Forests (RF). This combination allows for a systematic comparison between linear and nonlinear models and highlights the capacity of machine learning methods to capture high-order interactions and nonlinear relationships that shape migration patterns. Previous research on climate-induced migration has relied heavily on linear or panel regression models, which have provided important evidence of significant associations between climatic shocks and migration flows [22], [58] [59], [60]. For example, Feng et al. showed that drought-induced yield declines in Mexico were linearly associated with emigration to the United States [61]; Marchiori et al. [62], Missirian and Schlenker [63], and Nawrotzki and DeWaard [27], similarly reported that deviations in temperature and precipitation systematically increase out-migration rates, particularly in agriculture-dependent economies. Chen and Mueller [64] and Davis et al. [65] employed linear regression frameworks to quantify the effects of coastal climate change and sea-level rise on human mobility in Bangladesh. Even analyses in higher-income contexts, such as Partridge et al. [66], demonstrated the effectiveness of linear models in capturing regional migration responses to climatic variability in the United States. Despite their contributions, later research has emphasized how linear models tend to smooth out nonlinear dynamics and regional heterogeneity [67], limiting their explanatory capacity. Recent work therefore emphasizes the importance of considering nonlinear dynamics, threshold effects, and regional heterogeneity to better understand migration patterns. In 2021 Hoffmann et al. underscored that linear models often fail to account for the highly nonlinear dynamics of climate change, which can significantly alter migration patterns [15]. Similarly, Beyer et al. advocated for the adoption of nonlinear machine learning methods to replace overly simplistic linear frameworks [18], and Thiede and Gray found that climate effects exhibit threshold responses that linear models fail to capture [68]. This literature reinforces that linear regressions are insufficient to capture the multifaceted relationship between climate and migration and advocates for the adoption of nonlinear approaches that can accommodate regional variability and interaction effects. Building on these insights, the present study develops a Random Forest-based framework capable of capturing complex, nonlinear interactions that linear models overlook. The framework is applied to a multi-regional dataset covering North Africa, Sub-Saharan Africa, and Southeast Asia, enhancing model generalizability and robustness across diverse socio-economic contexts. The modeling pipeline is designed to be scalable, modular, and adaptable even in data-scarce environments, and its performance is evaluated using multiple accuracy metrics.

A. THE AREA UNDER STUDY

The impact of environmental factors varies significantly across regions and countries, and may play a greater role in areas already facing political instability, economic hardship, demographic pressures, or social inequalities [69]. The impacts of climate change have been particularly severe in the Global South, home to the majority of the world's population. Many of these nations already experience rapid population growth, exerts increasing pressure on natural resources, infrastructure, and social systems. As climate-induced hazards become more frequent and intense, climate change acts as a threat multiplier, exacerbating existing vulnerabilities and intensifying migration trends [11], [21], [69], [70] [71], [72], [73]. Projections suggest that between

800 million and 3 billion people could face varying degrees of water scarcity with a 2°C increase in global temperatures, and up to 4 billion people could be affected under a 4°C warming scenario, resulting in severely increased water insecurity [8]. Over the coming decades, the combined effects of climate stressors and socio-economic pressures are expected to drive large-scale internal and cross-border migration, with profound implications for domestic and international security, economic development, human rights, and global justice. People with limited adaptive resources are disproportionately affected by these stressors. With fewer financial and social assets, they face greater challenges in coping with the impacts of climate change, such as extreme weather events, sea-level rise, and prolonged droughts [11], [74], [75]. Vulnerability is not determined by poverty alone, but is shaped by social, political, and economic inequalities, such as gender, ethnicity, disability, and social status [8]. For instance, women often bear a disproportionate burden due to their role in managing household resources such as water, food, and energy, particularly in low-income contexts [76], [77], [78]. Similarly, people with disabilities or those from marginalized groups may face barriers in accessing shelters, information, or evacuation routes, limiting their ability to respond effectively. As a result, they may be left behind in emergencies or compelled to take dangerous or difficult decisions, such as migrating under unsafe conditions [79], [80]. Climate change exacerbates these inequalities, deepening existing disadvantages and limiting adaptive capacity [81]. Yet migration, when well-governed, can serve as a form of adaptation, helping communities access new opportunities and build resilience [21]. By facilitating access to opportunities, fostering economic resilience, and supporting sustainable urbanization, migration can contribute to poverty reduction, livelihood strengthening, and the improvement of overall living conditions.

This study covers 25 countries across three regions of the Global South: South-East Asia (Bangladesh, the People's Republic of Cambodia, Indonesia, the Lao People's Democratic Republic, Myanmar, Nepal, the Philippines, Thailand, and Vietnam), North Africa (Algeria, Egypt, Libya, Morocco, Sudan, and Tunisia), and Sub-Saharan Africa, including countries from the East (Ethiopia, Kenya, Tanzania, Uganda, and South Sudan), West (Ivory Coast, Senegal, Burkina Faso, and Guinea), and Southern Africa (South Africa).

These regions were selected as comparative analysis, as they exemplify particularly well the complex interplay between climate vulnerability, socio-economic pressures, and migration dynamics. They are characterized by high exposure to climate stressors such as droughts, flooding, and agricultural disruptions, while also facing challenges including rapid population growth, social inequalities, and varying governance capacities. This combination of environmental and socio-political factors provides an analytical basis for understanding how climate-induced hazards influence migration pressures. By encompassing diverse climatic and geographic contexts, the sample captures both common and region-specific mechanisms through which climate change drives migration, offering insights that are relevant across much of the Global South.

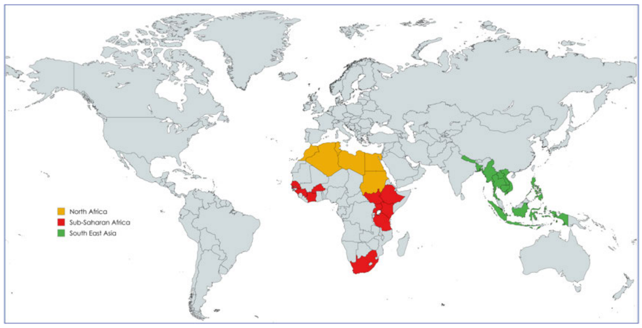

FIGURE 1. Countries selected for the study.

1) SOUTH-EAST ASIA

South-East Asia is among the most vulnerable regions to climate change, facing intensifying river flooding, sea-level rise, and extreme weather events. These impacts not only threaten local communities but also exacerbate both internal and cross-border migration [82]. Between 2010 and 2021, the Asia-Pacific region experienced 225.3 million disaster-related internal displacements, 95% of which were caused by extreme weather events such as floods and storms. The highest displacement figures were recorded in the Philippines (5.68 million), Vietnam (780,000), Indonesia (749,000), and Myanmar (158,000) [83]. This evidence underscores the scale and persistence of climate-induced mobility across South-East Asia, highlighting how extreme weather has become a primary migration driver. Looking ahead, the World Bank's Groundswell report projects that by 2050, up to 49 million people in East Asia and the Pacific could become internal climate migrants. In the Lower Mekong region alone, between 3.3 and 6.3 million people may be displaced, representing 1.4–2.7% of the population [84], [85]. Within this broader regional context, Bangladesh emerges as one of the most climate-vulnerable countries: projections suggest that sea-level rise could displace 0.9–2.1 million people by mid-century [86], [87], creating significant economic and infrastructural pressures, including the demand for nearly 600,000 new jobs and 200,000 housing units [9], [88], [89]. Other studies suggest that the number may reach 19.9 million internal climate migrants by 2050, nearly half of all projected climate-related displacements across South Asia [8], [90], [91]. The cascading effects of climate stressors and socio-economic feedbacks are expected to be profound. Rising sea levels, recurrant flooding, and extreme weather events are projected to render vast low-lying coastal zones increasingly, forcing millions to relocate inland. Such large-scale displacements are likely to undermine food security, degrade agricultural land, reduce livestock, and intensify competition for scarce resources.

As food shortages and urban congestion worsen, affected populations may increasingly migrate in search of stability, placing additional pressure on both origin communities and destination regions [92]. These dynamics highlight the broader regional implications of climate-driven mobility, affecting both rural sending areas and urban or cross-border destinations [93].

2) NORTH AFRICA

North Africa is one of the world's most climate-vulnerable regions, facing severe stressors such as water scarcity, desertification, and sea-level rise. These processes are reshaping livelihoods and migration dynamics by undermining agricultural productivity, degrading arable land, and increasing soil salinity through saltwater intrusion into aquifers [94], [95]. The resulting decline in food security is forcing many communities to migrate in search of more stable living conditions, and these pressures are expected to worsen in the coming decades [69], [72], [96] [97]. Rural-urban displacement is accelerating as desertification and reduced crop yields push people out of farming areas, while rapid urban growth continues to overwhelm fragile urban infrastructure [98]. At the same time, high youth unemployment, social insecurity, and governance challenges amplify migration pressures [99]. North Africa is projected to experience the highest proportion of internal climate migrants relative to total population. [8]. Between 2020 and 2050, at least 750,000 people are expected to be displaced along East and North African coastlines due to sea-level rise [9], [100], [101]. The population living in low-elevation coastal zones (LECZs) across Africa is projected to increase from around 54 million in 2000 to 110 million by 2030, and further to 185–230 million by 2060, placing North Africa among the most exposed subregions [102], [103], [104], [105]. An assessment of 12 major African coastal cities (including Alexandria, Algiers, and Cairo) estimates cumulative damages of USD 65 billion under a moderate emissions pathway (RCP4.5) by 2050, with losses potentially rising to USD 187–397 billion under extreme scenarios (RCP8.5). Notably, Alexandria alone could account for nearly half of these damages [106]. Climate risks also intersect with deep-seated socio-economic and political drivers. Migration in North Africa is not only a developmental issue but also a security concern. Since the early 2000s, shifting migration patterns have altered departure, transit, and destination dynamics across the region [107]. The Arab uprisings of 2011 further transformed the migration landscape, particularly with the destabilization of Libya, which triggered large-scale displacement and had spillover effects across the Sahel [108]. This highlighted the growing interdependence between North African and Sahel migration systems. Climate change acts as a risk multiplier, intertwining environmental, social, and political crises [98]. These overlapping pressures underscore the urgent need for comprehensive policy responses that address both the environmental drivers of displacement and the structural socio-economic challenges of the region. Without such measures, North Africa risks entering a self-reinforcing cycle in which climate stress, food insecurity, and political instability reinforce one another, making sustainable development and regional stability increasingly difficult to achieve.

3) SUB-SAHARAN AFRICA

Sub-Saharan Africa has long experienced high climate variability, with recurrent droughts, floods, erratic rainfall, and storms shaping environmental and social systems [71], [109]. Yet, the accelerating impacts of climate change are severely undermining food security, water availability, public health, and socio-economic development [9], [110], [111], [112] [113], [114], [115], [116]. The vulnerability of the region is amplified by the fact that a large share of its population depends on rainfed agriculture for livelihoods [117], [118], [119]. As crop failures and yields decline, the impact on staple food becomes increasingly severe [120], [121]. The World Bank's Groundswell Report projects that Sub-Saharan Africa will bear a disproportionately high share of global internal climate migration. By 2050, as many as 86 million people could be forced to move within their own countries due to climate impacts, nearly 60% of projected global climate migrants (216 million) [8]. The Lake Victoria Basin is projected to be a major hotspot, with up to 38.5 million people displaced, including 16.6 million in Tanzania and 12 million in Uganda by mid-century [122]. Recent climate disasters underscore the immediacy of these projections. In Somalia, prolonged drought displaced nearly 1.1 million people in a single year [123], [124], while in Madagascar, cyclones displaced more than 290,000 people [125]. In Burundi, flooding has affected over 10% of the national population, forcing tens of thousands to move [126], [127]. These events highlight how acute shocks compound long-term climate stressors. Demographic and geographic trends further exacerbate exposure [128]. Coastal populations in Sub-Saharan Africa's low-elevation coastal zones are projected to grow from 24 million in 2000 to 66 million in 2030, and to 174 million by 2060, with particularly rapid urban expansion across West and East Africa [129], [130]. These demographic pressures, coupled with environmental stressors, are driving migration as both an adaptation strategy and a survival mechanism. Many smallholder farmers rely on circular and seasonal migration to diversify incomes, reduce vulnerability, and enhance resilience amid agricultural decline [56], [131]. However, many of those most affected lack the resources to migrate, creating "trapped populations", who remain unable to move away from high-risk areas, thus enduring prolonged exposure to food and water insecurity [46], [56], [110], [132]. This immobility reinforces cycles of poverty and social marginalization. Climate pressures intersect with fragile governance and conflict dynamics, intensifying existing vulnerabilities [99], [114], [116], [133], [134],, [135]. These environmental stressors, particularly water scarcity and competition over natural resources, further exacerbate political tensions and trigger cycles of displacement and insecurity [110], [117], [136], [137], [138], [139], [140]. These converging pressures make Sub-Saharan Africa a critical case study in climate-driven migration, where environmental fragility, rapid demographic expansion, and socio-political instability intertwine to produce some of the most acute migration pressures globally.

B. THE DATASET

Four key variables were chosen as inputs for this study: temperature anomalies, water stress, the Human Development Index (HDI), and the agricultural sector's contribution to Gross Domestic Product (GDP). These variables are widely recognized in the literature as robust proxies for environmental stressors and adaptive capacity [63], [141], [142], [143], [144]. Their inclusion was guided both by the availability of high-quality, temporally and geographically consistent data across the 25 analyzed countries and by their demonstrated relevance in shaping migration dynamics, particularly in climate-sensitive regions of the Global South. By analyzing these four variables, the study aims to capture both gradual climatic pressures (temperature anomalies and water stress), thereby focusing on slow-onset climate processes rather than abrupt hazard events [13], and broader socio-economic conditions (HDI and agricultural dependence) that influence migration decisions. This approach allows us to examine how climate-related and socio-economic factors are associated with migration flows, with special attention to nonlinear relationships. While additional climatic indicators (e.g., extreme weather events, seasonal variability, drought indices) and socio-political drivers (e.g., conflict, political instability, pre-existing social networks) are important determinants of migration, their integration was not included in this initial analysis due to data limitations [136], [145], [146], [147]. Instead, the present study concentrates on climate-related and socio-economic variables consistently available across all study countries. Some missing values were addressed via temporal interpolation, although this procedure cannot be reliably applied to other potential drivers, such as conflict, political instability, or social networks, without introducing bias or distorting the underlying dynamics [12], [15], [67]. Therefore, the inclusion of such variables requires further methodological development and the availability of comparable, high-quality datasets, to be pursued in future research. This approach ensured methodological rigor and consistency, enabling the detection of nonlinear and multidimensional relationships between climate-related stressors and migration flows.

- Temperature anomalies (TA) are a key driver of environmental and economic stress. Rising temperatures, heatwaves, and prolonged periods of extreme heat have led to severe consequences for human well-being and economic stability [9]. These effects are especially pronounced in regions where agriculture constitutes the main livelihood, as excessive heat reduces crop yields, disrupts planting and harvesting cycles, and increases evapotranspiration, causing soil degradation [92], [148], [149] [150]. Beyond agricultural losses, extreme heat also increases mortality and morbidity, particularly among vulnerable groups such as children, the elderly, and low-income communities [151]. Furthermore, sustained temperature increases exacerbate water scarcity, reduce labor productivity, and strain infrastructure. These pressures may compel populations to migrate in search of more habitable and economically viable regions [4]. Data on annual temperature anomalies were obtained from Our World in Data, based on the Copernicus Climate Change Service (ERA5) reanalysis dataset [152]. The dataset covers 1980–2021, with values expressed in degrees Celsius (°C), calculated over both land and ocean surfaces. Monthly data were averaged to annual means, missing values were linearly interpolated, and all values are expressed as deviations relative to the 1981–2010 baseline, ensuring consistent cross-country comparison of long-term climatic trends.
- Water stress (WS) represents the imbalance between water demand and available supply and has become one of the most critical challenges intensified by climate change [117]. Water scarcity threatens food security, public health, energy production, and economic stability [153]. Many regions in the Global South have already experienced significant declines in freshwater availability due to erratic rainfall, prolonged droughts, and depletion of groundwater reserves [37], [39], [154], [155], [156]. Water stress affects migration through two principal channels: first, by directly reducing agricultural productivity and income; and second, by intensifying competition for scarce water resources, potentially fueling local conflicts [37], [117]. Water stress data were obtained from the Food and Agriculture Organization (FAO), AQUASTAT Database [157]. The dataset covers 1980–2021 with annual national-level observations. Missing values were linearly interpolated and harmonized for cross-country comparison. According to UN-Water SDG 6, water stress is classified as: No stress (<25% of renewable freshwater withdrawn), Low (25–50%), Medium (50–75%), High (75–100%), and Critical (>100%). This classification was used to assess thresholds of migration vulnerability.
- The Human Development Index (HDI) is a composite indicator capturing well-being through life expectancy, education, and income. It served as a critical socio-economic variable for understanding populations' responses to climate stressors. Regions with low HDI were more vulnerable to climate-induced migration due to limited infrastructure, weak governance, and dependence on rainfed agriculture. Paradoxically, extreme poverty can also constrain migration, producing "trapped populations" unable to relocate despite worsening conditions [110]. Conversely, higher HDI levels corresponded to greater resilience, although

migration may still occur among rural and marginalized groups [158], [159]. Data were obtained from the United Nations Development Programme (UNDP) Human Development Reports Data Center [160]. The dataset covers 1990–2021, includes all countries globally, and provides annual national-level HDI scores. Missing data were linearly interpolated to ensure temporal continuity and comparability.

- The agricultural sector's share of GDP (AGRI) was an essential indicator of economic dependence on climate-sensitive activities. In economies where agriculture dominates, climate-related shocks, such as droughts, floods, and heatwaves, have triggered cascading economic consequences, raising food prices and destabilizing national markets [74], [161], [162], [163]. These disruptions often lead to increased migration pressures, especially in rural communities. Data on agriculture's value added as a percentage of GDP were obtained from the World Bank's World Development Indicators [164]. The dataset spans 1980–2021 and provides annual national-level data. Missing values were linearly interpolated to ensure completeness and comparability across countries.

Data on human mobility were considered as the output variable in this study. Reliable migration data remain scarce due to inconsistent reporting and the multi-causal nature of human mobility [165], especially in countries with limited resources or where conflicts are ongoing. Until recent years, migration data has often been fragmented, inconsistent, or limited to specific case studies. This limitation is particularly evident for slow-onset environmental processes, such as desertification and gradual climatic shifts [166]. Migration data were obtained from the United Nations Department of Economic and Social Affairs (UN DESA), Population Division – International Migrant Stock [167]. The dataset covers 1990–2024, providing five-year interval estimates for 233 countries and territories. Data include total international migrants, disaggregated by sex, with information on country of origin and country of destination. Missing values for specific years were linearly interpolated to ensure continuity over the time series. The dataset primarily captures long-term migration patterns rather than short-term or temporary movements; nonetheless, it provides systematic global coverage for comparative analyses. The migrant fraction (migrant stock divided by total population) was derived as the output variable. Population statistics (1980–2021) were obtained from Our World in Data, based on the UN World Population Prospects 2024 [168]. The dataset provides annual national-level population estimates for all countries globally. Missing population values were interpolated linearly to ensure consistency across the time series. Table 2 summarizes the main features of the dataset.

Although the methodology was applied to a specific dataset encompassing environmental and socio-economic variables across selected regions, the modeling framework was designed to be generalizable. Its modular structure, combining standardized preprocessing, comparative linear and nonlinear modeling, and robust evaluation metrics, enabled its application to other regions or temporal scales, provided that relevant predictor variables are available.

C. MODELS

In this work, we explored different models to investigate the relationship between climatic variables and migration patterns. The models evolved in complexity, starting from a basic linear approach and progressing towards more sophisticated machine learning methods. The modeling pipeline was executed on a standard desktop computer, given the relatively low computational demand of the models used. All models were tested and validated using the Python libraries. We implemented and evaluated the models to efficiently compare their predictive capabilities across the three regions under study. In identifying our models, we limited the climate-related explanatory variables to the current year and the immediately preceding year. This decision was motivated by practical and conceptual considerations. From a methodological standpoint, longer temporal lags were limited by data availability and quality and could have compromised model robustness. On a conceptual level, empirical evidence suggests that migration responses to acute climate-related stressors, such as temperature anomalies, water scarcity, or crop failures, tend to manifest within short time frames [169], particularly in regions where adaptive capacity is limited. Focusing on a two-year window captures immediate responses while avoiding signal dilution. For model training and validation, the dataset was randomly split: 80% for model training, while the remaining 20% for validation, ensuring balanced representation across both sets. Based on these premises, four different modeling approaches were tested and compared.

1) ARX LINEAR DYNAMIC MODEL

The first model tested was an Autoregressive Exogenous (ARX) Linear Dynamic Model, which is commonly used for modeling time series data. This model includes both past values of the dependent variable (migration rate as percentage of the total population, M) and external explanatory variables (HDI, WS, TA, AGRI) to predict future migration patterns. The model can be expressed as:

$$\begin{aligned} M_t = \alpha &+ \beta_1 TA_t + \beta_2 TA_{t-1} \\ &+ \beta_3 HDI_t + \beta_4 HDI_{t-1} + \beta_5 WS_t + \beta_6 WS_{t-1} \\ &+ \beta_7 AGRI_t + \beta_8 AGRI_{t-1} \end{aligned} \tag{1}$$

where:

- M_t is the migration rate (% of population) at year t (dependent variable);
- TA_t, TA_{t-1} are the current and previous year temperature anomaly values;
- HDI_t, HDI_{t-1} are the current and previous year Human Development Index values;

TABLE 2. Summary of dataset variables, sources, period, coverage, and extraction methods.

Variable	Role	Source	Period	Coverage	Extraction / Notes
Temperature Anomalies (TA)	Climate & economic stress; affects agriculture, health, water, migration	Our World in Data (Copernicus ERA5) [56]	1980–2021	Gbl, land & ocean	Annual °C; missing values interpolated
Water Stress (WS)	Water demand vs supply; impacts agriculture, health, conflicts, migration	FAO AQUASTAT [63]; UN-Water SDG6	1980–2021	Gbl, Nat.	Annual % freshwater withdrawal; missing values interpolated; No/Low/Med/High/Critical
HDI	Socio-economic well-being; affects vulnerability & adaptive capacity	UNDP HDR [64][65]	1990–2021	Gbl, Nat.	Annual; low HDI → trapped populations
Agriculture GDP (%)	Economic vulnerability; high dependence leads to stronger migration pressures	FAO AQUASTAT [63]	1980–2021	160+ countries	Annual %; missing data interpolated
Human Mobility	Fraction of migrant stock / total population; measures migration trends	UNPD IMS [71]	1990–2024, 5y int.	233 countries	Long-term migration; disaggregated by sex, origin, destination; missing values interpolated
Population	Total population for migration fraction calculations	Our World in Data (UN WPP 2024) [72]	1980–2021	Gbl, Nat.	Annual estimates; missing values interpolated

- WS_t, WS_{t-1} are the current and previous year Water Stress values;
- $AGRI_t, AGRI_{t-1}$ are the current and previous year agricultural sector contribution to GDP values;
- α is the model intercept;
- $\beta_1, \beta_2, \ldots, \beta_8$ are the coefficients measuring the influence of each variable.

Although the ARX model provided an initial understanding of the relationships between climate variables and migration, its linear structure cannot fully capture potential nonlinear interactions and complex dependencies; therefore, more complex models were explored.

2) POLYNOMIAL QUADRATIC DYNAMIC MODEL

To capture nonlinear relationships, polynomial quadratic terms were introduced for the explanatory variables:

$$\begin{aligned}M_t = \alpha &+ \beta_1 \cdot TA_t + \beta_2 \cdot TA_{t-1}\\ &+ \beta_3 \cdot HDI_t + \beta_4 \cdot HDI_{t-1}\\ &+ \beta_5 \cdot WS_t + \beta_6 \cdot WS_{t-1}\\ &+ \beta_7 \cdot AGRI_t + \beta_8 \cdot AGRI_{t-1}\\ &+ \beta_9 \cdot (TA_t)^2 + \beta_{10} \cdot (TA_{t-1})^2\\ &+ \beta_{11} \cdot (HDI_t)^2 + \beta_{12} \cdot (HDI_{t-1})^2\\ &+ \beta_{13} \cdot (WS_t)^2 + \beta_{14} \cdot (WS_{t-1})^2\\ &+ \beta_{15} \cdot (AGRI_t)^2 + \beta_{16} \cdot (AGRI_{t-1})^2 \end{aligned} \tag{2}$$

where:

- M_t is the migration rate (% of population) at time t (dependent variable);
- TA_t, TA_{t-1} are the current and previous year temperature anomaly values;
- HDI_t, HDI_{t-1} are the current and previous year Human Development Index values;
- WS_t, WS_{t-1} are the current and previous year Water Stress values;
- $AGRI_t, AGRI_{t-1}$ are the current and previous year agricultural sector contribution to GDP values;
- α is the model intercept;
- $\beta_1, \beta_2, \ldots, \beta_{16}$ are the coefficients that measure the influence of each variable and its squared terms.

This extension captured more complex patterns, but some variables remained statistically non-significant, motivating further model refinements.

3) LOGARITHMIC DYNAMIC MODEL

Recognizing the need for more complex nonlinear relationships, we turned to the logarithmic dynamic model. By applying logarithmic transformations to the variables, we aimed to better capture diminishing returns and other nonlinear interactions. The model can be expressed as:

$$\begin{aligned}M_t = \alpha &+ \beta_1 \cdot \log(TA_t) + \beta_2 \cdot \log(TA_{t-1})\\ &+ \beta_3 \cdot \log(HDI_t) + \beta_4 \cdot \log(HDI_{t-1})\\ &+ \beta_5 \cdot \log(WS_t) + \beta_6 \cdot \log(WS_{t-1})\\ &+ \beta_7 \cdot \log(AGRI_t) + \beta_8 \cdot \log(AGRI_{t-1})\end{aligned} \tag{3}$$

where:

- M_t is the migration rate (% of population) at time t (dependent variable);
- $\log(TA_t), \log(TA_{t-1})$ are the current and previous year temperature anomaly values (log-transformed);
- $\log(HDI_t), \log(HDI_{t-1})$ are the current and previous year Human Development Index values (log-transformed);
- $\log(WS_t), \log(WS_{t-1})$ are the current and previous year water stress values (log-transformed);
- $\log(AGRI_t), \log(AGRI_{t-1})$ are the current and previous year agriculture share of GDP values (log-transformed);
- α is the intercept of the model;
- $\beta_1, \beta_2, \ldots, \beta_8$ are the coefficients that measure the influence of each variable.

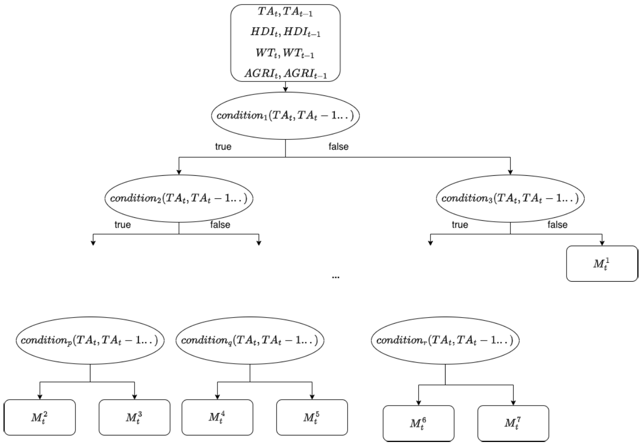

FIGURE 2. **Regression tree structure.**

This model improved predictive performance, with all variables becoming statistically significant predictors of migration.

4) RANDOM FOREST DYNAMIC MODEL

Finally, advanced machine learning methods, specifically Random Forests (RF), were applied. RF models capture complex nonlinear interactions without requiring explicit functional assumptions. They are ensemble methods based on regression trees, where each tree splits the input space recursively to minimize the variance of the target variable within each region (Figure 2).

Let $T_1, T_2, \ldots, T_k$ represent the set of decision trees in the random forest model. For each decision tree, the prediction for migration at year t is: $\hat{M}_t = f(T_i, X_t)$ where $X_t = (TA_t, HDI_t, WS_t, AGRI_t)$. The final prediction is the average over all trees: $\hat{M}_t = \frac{1}{k}\sum_{i=1}^{k} f(T_i, X_t)$.

where:

- M_t is the migration rate (% of population) at time t (dependent variable);
- $\{T_1, T_2, \ldots, T_k\}$ is the set of decision trees in the Random Forest model;
- $f(T_i, X_t)$ is the prediction from the decision tree i based on the input variables X_t;
- $X_t = (\mathrm{TA}_t, \mathrm{HDI}_t, \mathrm{WS}_t, \mathrm{AGRI}_t)$ are the input features at time t, which are TA, HDI, WS, and AGRI;
- k is the number of decision trees in the Random Forest;
- $\hat{M}_t$ is the final prediction of migration at time t, which is the average of the individual tree predictions.

While Random Forests are not inherently dynamic models, temporal relationships are indirectly captured through the inclusion of lagged explanatory variables. Figure 3 presents a scheme of the overall random forest.

RF method effectively improved predictive accuracy and outperformed all previous models. For this work, a hyper-parameter tuning procedure was used to define the number of trees in the forest and the depth of each single tree. The tuning results set the number of to 100, with a depth equal to

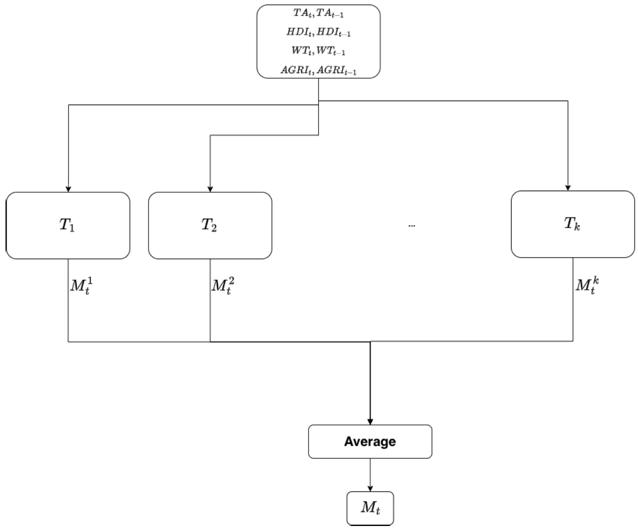

FIGURE 3. **Random forest structure.**

max(5,N/100) where N is the number of observations, for the implemented forest. Although Random Forests offer lower interpretability than the other models tested, they remain among the most explainable machine learning methods due to the relative ease of understanding their decision-tree structure. This approach therefore balances predictive performance with a reasonable degree of interpretability, as each variable's contribution can be traced through the model's tree-based logic [170], [171], [172].

D. EVALUATION METRICS

To assess the performance of the models, several accuracy indicators were employed, including correlation, Mean Error (ME), Mean Absolute Error (MAE), and Normalized Mean Absolute Error (NMAE). Correlation quantifies the strength and direction of the linear relationship between observed (actual) and predicted values. The correlation coefficient (usually denoted as r) ranges from -1 to +1. Values near +1 or -1 indicate a strong linear relationship, showing that observed and predicted values co-vary closely. A positive correlation ($r > 0$) indicates that as one variable increases, the other tends to increase as well; a negative correlation ($r < 0$) indicates that as one variable increases, the other tends to decrease; a correlation of 0 (or close to 0) indicates a weak or no linear relationship [173]. ME quantifies the average bias by indicating whether predictions tend to overestimate or underestimate the observations. A positive ME indicates systematic overestimation, while a negative ME indicates systematic underestimation. When predicted and observed values coincide on average, the ME approaches zero [174]. MAE represents the average magnitude of the errors, regardless of their direction, providing an intuitive measure of overall accuracy. It is computed as the mean of the absolute differences between predicted and observed values across all data points. NMAE normalizes MAE by the mean of observed values in this study, allowing

TABLE 3. Performance comparison of different models.

Model	Corr.	ME	MAE	NME	NMAE
ARX	0.38	-0.27	1.94	-0.07	0.52
Polynomial	0.42	-0.21	1.91	-0.05	0.51
Logarithmic	0.46	-0.23	1.87	-0.06	0.50
Random Forest	0.81	-0.03	0.95	-0.009	0.25

for meaningful comparisons across datasets with different scales. This normalization makes NMAE a unitless, scale-independent indicator, particularly useful for cross-dataset comparison [174]. These metrics collectively provide a comprehensive evaluation of model performance by quantifying the deviation between observed and predicted values. Details of the computation and results for each metric are presented in the following section.

E. VALIDATION AND ROBUSTNESS TESTING

To assess the robustness of the models, a train–test split approach was employed, where 80% of the dataset was used for model training and 20% for model validation. This method provides an independent evaluation of model performance, allowing the assessment of the model's generalization capability on unseen data.

IV. RESULTS AND DISCUSSION

The evaluation of four prediction models - ARX linear, polynomial, logarithmic, and Random Forest (RF) - showed considerable differences in their ability to forecast migration trends in North Africa, Sub-Saharan Africa, and Southeast Asia. Table 3 summarizes the evaluation metrics obtained for each model across the three regions:

Overall, the Random Forest model outperformed all others, achieving a correlation of 0.81 with observed migration patterns and the lowest Mean Absolute Error (MAE) of 0.95. These results confirm that the RF model effectively captures the nonlinear interactions between climate and socio-economic variables that influence migration. In contrast, linear and polynomial models achieved only moderate correlations (0.38 and 0.42, respectively) and high MAE values (1.94 and 1.91), confirming their limited capacity to capture complex, nonlinear relationships. The logarithmic model improved slightly (correlation 0.46, MAE 1.87) but still did not provide an accurate representation of migration dynamics. In terms of computational efficiency, all models exhibited low processing times, with execution on the validation dataset completed in less than one second. The Random Forest model required slightly longer training (approximately one minute) due to its ensemble structure, yet overall computational complexity remained limited, confirming that the proposed modeling framework is suitable for practical and scalable applications. The strong differences in performance between the RF model and all the others, together with its relatively higher complexity compared to the dataset size, may suggest a possible overfitting issue. To investigate this, a robustness check was conducted through a Monte Carlo

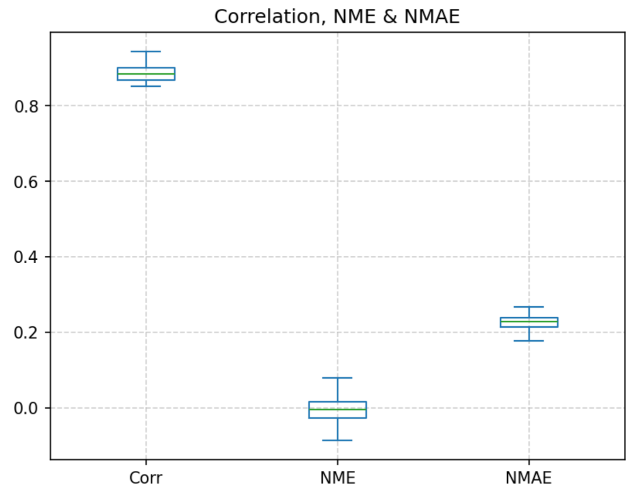

FIGURE 4. Correlation, NME and NMAE Boxplot of the 250 performed identification test for the Random Forest model.

analysis, generating 250 different Random Forest models by randomly selecting 20% of the validation dataset in each run. Figure 4 presents the boxplots of correlation, Normalized Mean Error (NME), and Normalized Mean Absolute Error (NMAE). The boxplots show that the 25th, 50th, and 75th percentiles are very close to one another, resulting in a narrow interquartile range and indicating that the metrics are highly concentrated around the median, with only slight inter-trial deviations. To visually assess the performance of the Random Forest model, we compared the predicted migration rates (as a percentage of the total population) M values with actual observations for 2019-2021 across the three regions under consideration. Performance remained robust across all regional datasets, supporting the model's generalizability and stability, except for South Sudan, where results were affected by uncertainty and limitations in the quality and availability of data. These results suggest that the Random Forest model effectively captures both interregional variation and temporal dynamics of climate-induced migration.

A Leave-One-Out feature importance analysis identified the key drivers of migration within the Random Forest model. Water stress (WS) emerged as the most critical factor: its removal reduced the correlation from 0.81 to 0.62 and increased MAE from 0.95 to 1.57, highlighting that hydrological variability acts as a critical migration driver. The Human Development Index (HDI) also significantly influenced predictions, with a correlation drop of 18.5% and an MAE increase of 25.3% when excluded. These findings underscore that populations in water-stressed and socioeconomically vulnerable regions are particularly prone to climate-induced migration. In contrast, removing Temperature Anomalies (TA) caused only a minor decrease in correlation and a slight improvement in MAE, suggesting that temperature extremes alone are less predictive than when combined with other stressors. The agricultural contribution to GDP (AGRI) had a limited impact on model performance,

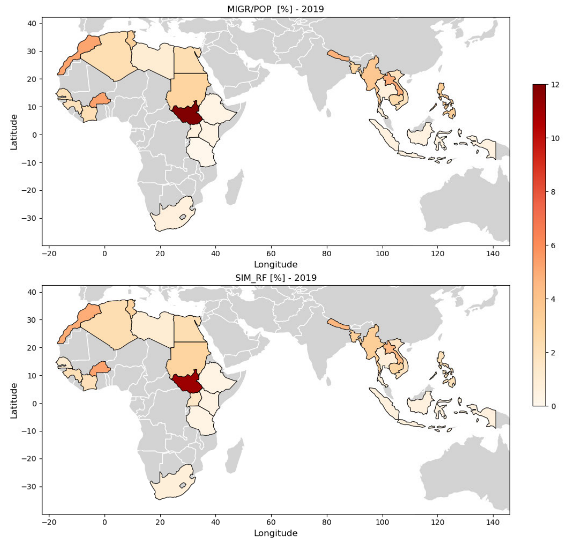

FIGURE 5. **Comparison between observed and predicted migration rates (% of population) for the year 2019, across North Africa, Sub-Saharan Africa, and Southeast Asia.**

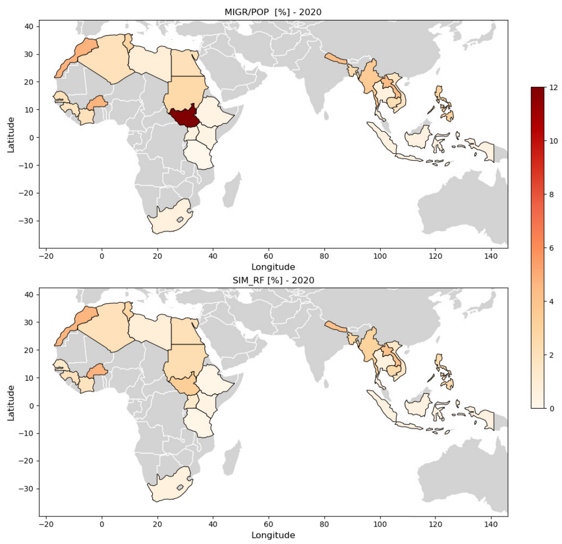

FIGURE 6. **Comparison between observed and predicted migration rates (% of population) for the year 2020, across North Africa, Sub-Saharan Africa, and Southeast Asia.**

indicating that, although relevant, agricultural dependency is a contextual driver compared to water stress and socio-economic vulnerability. The results are summarized in Table 4, where the impact on correlation and Mean Absolute Error (MAE) is reported along with percentage variation compared to the complete model.

Overall, the findings confirm that migration is not solely driven by climatic variables but emerges from complex interactions between environmental, social, and economic conditions. The superior performance of the Random Forest model highlights the importance of capturing these interactions to accurately predict climate-induced population

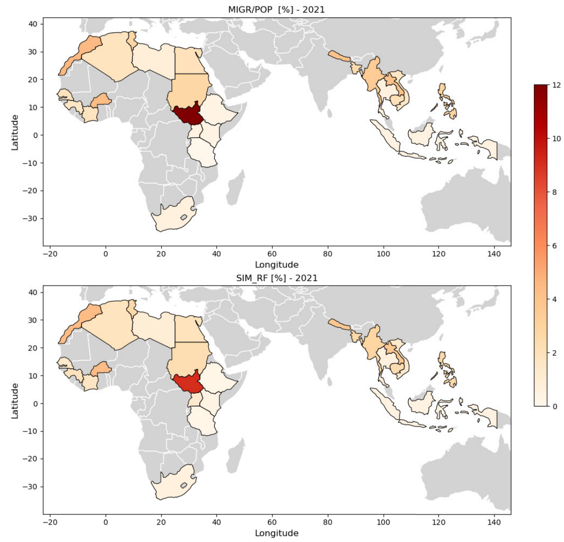

FIGURE 7. **Comparison between observed and predicted migration rates (% of population) for the year 2021, across North Africa, Sub-Saharan Africa, and Southeast Asia.**

TABLE 4. **Performance metrics after removing one variable.**

Removed Variable	Corr.	ΔCorr (%)	MAE	Δ MAE (%)
Complete Model	**0.81**	-	**0.95**	-
TA removed	0.80	-1.2	0.88	-7.4
WS removed	0.62	-23.5	1.57	+65.3
HDI removed	0.66	-18.5	1.19	+25.3
AGRI removed	0.78	-3.7	0.98	+3.2

movements. Water scarcity and socioeconomic vulnerability emerge as the main drivers, while temperature extremes and agricultural dependence act mainly as amplifiers or modulators of migration only in conjunction with other factors [4], especially in rural areas [69].

A. THE SOUTH SUDAN ANOMALY

South Sudan represents a notable outlier in our model results, exhibiting a significant deviation between predicted and observed migration values. This discrepancy is largely attributable to severe weaknesses in the quality and availability of official migration data, mainly due to prolonged conflict and political instability. This finding underscores the importance of integrating institutional and political variables into future models. Incorporating such variables would help disentangle the effects of climatic and political stressors, improving both model realism and explanatory power. The 2008 national census [175], [176], the latest comprehensive demographic source, remains the only complete survey conducted for both Sudan and the then-autonomous Southern Sudan prior to the 2011 secession. However, it was widely contested and ultimately rejected by South Sudanese authorities due to a lack of data transparency that prevented independent verification. Allegations of political manipulation were common, suggesting deliberate undercounting in conflict-affected and remote areas such as Southern Kordofan, Blue Nile, and the Abyei Area [177]. No subsequent national census has been successfully conducted in either Sudan or South Sudan, resulting in a persistent data vacuum with critical implications for political representation, resource allocation, and development planning. Second, ongoing conflict, intercommunal violence, and recent natural disasters, including severe flooding in 2024 [178], [179], [180], have triggered frequent, large-scale population displacements, further complicating data collection and reporting. Third, the main displacement data source, the International Organization for Migration's Displacement Tracking Matrix (DTM) [181], relies heavily on key-informant interviews and rapid field assessments. In conflict-affected zones, access restrictions and population fluidity produce irregular update frequencies and significant temporal gaps. As a result, demographic estimates often lag behind actual dynamics, limiting their longitudinal reliability. Moreover, uneven coverage reduces the comparability of regional figures, undermining their usefulness for national aggregation. The combined effects of environmental disasters and conflict-induced displacement have rendered traditional census and survey methods impracticable, forcing agencies such as UNHCR, IOM, and national bureaus to depend on fragmented sources, including rapid assessments, registration datasets, and satellite imagery. Consequently, population estimates show large discrepancies across agencies, undermining demographic credibility and complicating planning. To address data gaps, in this study, missing values in the time series were managed using simple linear interpolation between adjacent points. More complex imputation techniques were intentionally avoided to limit the introduction of assumptions or bias. These factors indicate that deviations in South Sudan reflect deficiencies in underlying data rather than model errors. Reliable, timely data remain essential for identifying needs, targeting interventions, and supporting evidence-based policymaking. Future research should prioritize integrating alternative data sources, such as anonymized aggregated mobile phone call detail records (CDRs), satellite imagery and biometric registration data [182], [183]. Rapid emergency surveys conducted by UNHCR and IOM can also enhance migration monitoring in complex humanitarian settings. Finally, enhanced collaboration among national authorities, international organizations, and local communities is essential to achieve more comprehensive and accurate data collection.

V. CONCLUSION

This study introduces key methodological and conceptual innovations to the analysis of climate-induced migration. By systematically comparing traditional regression models with nonlinear machine learning algorithms, it demonstrates the limitations of linear approaches in capturing the multifactorial and interactive nature of migration drivers. The superior performance of the Random Forest model (correlation = 0.81, MAE = 0.95) highlights its capacity to model complex relationships and detect higher-order interactions often obscured in conventional frameworks. The proposed pipeline provides a scalable and transferable framework for data-scarce and climate-sensitive regions such as North Africa, Sub-Saharan Africa, and Southeast Asia. By integrating climatic stressors (temperature anomalies, water stress) with socio-economic indicators (HDI and agricultural dependence), the model enhances predictive accuracy and enables a more comprehensive assessment of vulnerability dynamics. This demonstrates the feasibility of implementing advanced, data-driven methods in regions traditionally constrained by limited data availability, thereby expanding both the geographical scope and policy relevance of migration modeling. Beyond methodological advances, the study underscores the practical utility of machine learning for evidence-based decision-making, als offering actionable insights to policy makers. Random Forest models can be integrated into operational early warning systems to anticipate climate-related migration flows and inform adaptive policy design. Although the model aggregates data across macro-regions and thus does not yield local-scale predictions, it provides a robust regional overview that can guide adaptation and resilience planning. Known vulnerabilities, such as water scarcity in North Africa, agricultural dependence in Sub-Saharan Africa, and coastal exposure in Southeast Asia, can inform localized applications of these findings. Human mobility will increasingly shape climate adaptation in the coming decades. If global average temperatures exceed 1.5 °C above pre-industrial levels, pressures on societies, economies, and ecosystems will intensify. Integrating human mobility into climate strategies is therefore essential to protect vulnerable populations, strengthen adaptive capacity, and promote sustainable livelihoods. A data-driven and coordinated policy approach, combining climate adaptation, economic resilience, and international cooperation, is required [25], [184], [185]. This includes investments in climate-resilient infrastructure, the promotion of alternative livelihoods, and the establishment of safe and legal migration pathways through multilateral agreements. Machine learning approaches, such as the Random Forest framework applied here, offer valuable support for these objectives by providing empirical forecasts and identifying priority areas for intervention.

A. LIMITATIONS AND FUTURE RESEARCH DIRECTIONS

This study provides valuable insights into the relationship between climate change and migration, yet several inherent limitations must be acknowledged. As with most large-scale, cross-regional analyses, some data gaps required interpolation. While this ensured continuity, it may have introduced minor uncertainties. Similarly, reliance on aggregate indicators such as HDI and agricultural GDP share offers a robust yet simplified representation of complex socio- economic realities. The UNPD migration stock dataset provides reliable long-term global coverage, though it does not capture short-term or internal displacements, which are especially relevant in climate contexts. Finally, while Random Forest models handle nonlinear relationships effectively, they capture correlations rather than causal mechanism. These aspects do not undermine the validity of our findings, but rather highlight areas where future research can further refine the analysis through more granular data and complementary methodological approaches. Another major limitation is the scarcity of high-quality socio-economic and migration data, especially in many countries of the Global South, even at the national level [186]. To address this, our analysis adopted a regional-level perspective, enabling identification of broad patterns, vulnerabilities, and risk factors, and providing a comparative framework valuable for policy discussions. However, finer-grained analyses at the household or subnational level would allow a more nuanced understanding of how specific communities respond to climate stressors through migration. Future research should focus on acquiring detailed migration data, household surveys, administrative records, and disaggregated socio-economic datasets, ideally integrated with geospatial information. Ensuring compatibility and consistency across different data sources is essential, highlighting the need for increased collaboration between social and natural sciences to develop comprehensive, comparable databases. Due to data limitations, this study could not fully exploit advanced machine learning techniques such as deep learning or ensemble models, nor develop region-specific models that capture localized migration dynamics. Socio-political factors, including political instability, conflict, governance quality, and migration policies, were not included due to limited data availability. Future work could integrate available indicators such as World Bank Governance Indicators, UCDP conflict events, country-level migration policies, and proxies for migrant social networks to better capture socio-political drivers of migration. Finally, the study primarily captures short- to medium-term effects and focuses on climate stressors influencing migration in a one-directional framework. Long-term environmental changes (e.g., persistent droughts, gradual climate shifts) and feedback effects, where migration itself reshapes local adaptation capacity, labor markets, and environmental stress, should be explored through longitudinal and dynamic modeling approaches, such as system-dynamics or agent-based models, for a more holistic understanding of the climate–migration nexus.

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SABRINA DE NARDI received the M.S. degree in international relations from the University of Milan, Milan, Italy, in 2007. She is currently pursuing the Ph.D. degree with the Department of Mechanical and Industrial Engineering, University of Brescia. She is the Research Manager with the Research and Innovation Office, University of Brescia. Her main research interests include data analysis and modeling and the evaluation of the socio-economic impacts of climate change to support decision-makers.

CLAUDIO CARNEVALE (Member, IEEE) received the M.S. degree in electronic engineering and the Ph.D. degree in information engineering from the University of Brescia, Brescia, Italy, in 2001 and 2005, respectively. He is currently an Associate Professor with the Department of Mechanical and Industrial Engineering, University of Brescia. His main research interests include modeling and control of deterministic nonlinear systems, online and offline data assimilation techniques, identification of nonlinear systems, and nonlinear optimization problems.

GABRIELE PICCOLI received the bachelor's and master's degrees in computer science and engineering from the University of Brescia, Brescia, Italy, in 2022 and 2024, respectively, where he is currently pursuing the Ph.D. degree in mechanical and industrial engineering. His research interests include the modeling and control of nonlinear complex systems, employing deep learning and optimal control methods.

SARA RACCAGNI received the B.S. and M.S. degrees in computer science and engineering from the University of Brescia, Brescia, Italy, in 2021 and 2023, respectively, where she is currently pursuing the Ph.D. degree in mechanical and industrial engineering. Her research interests include modeling and control of nonlinear complex systems, using deep learning models and optimal control techniques.

LUCIA SANGIORGI received the B.S. and M.S. degrees in industrial engineering from the University of Brescia, Brescia, Italy, in 2019 and 2021, respectively, where she is currently pursuing the Ph.D. degree in mechanical and industrial engineering. Her research interests include modeling and control of deterministic nonlinear systems, identification of nonlinear systems, and nonlinear optimization problems.