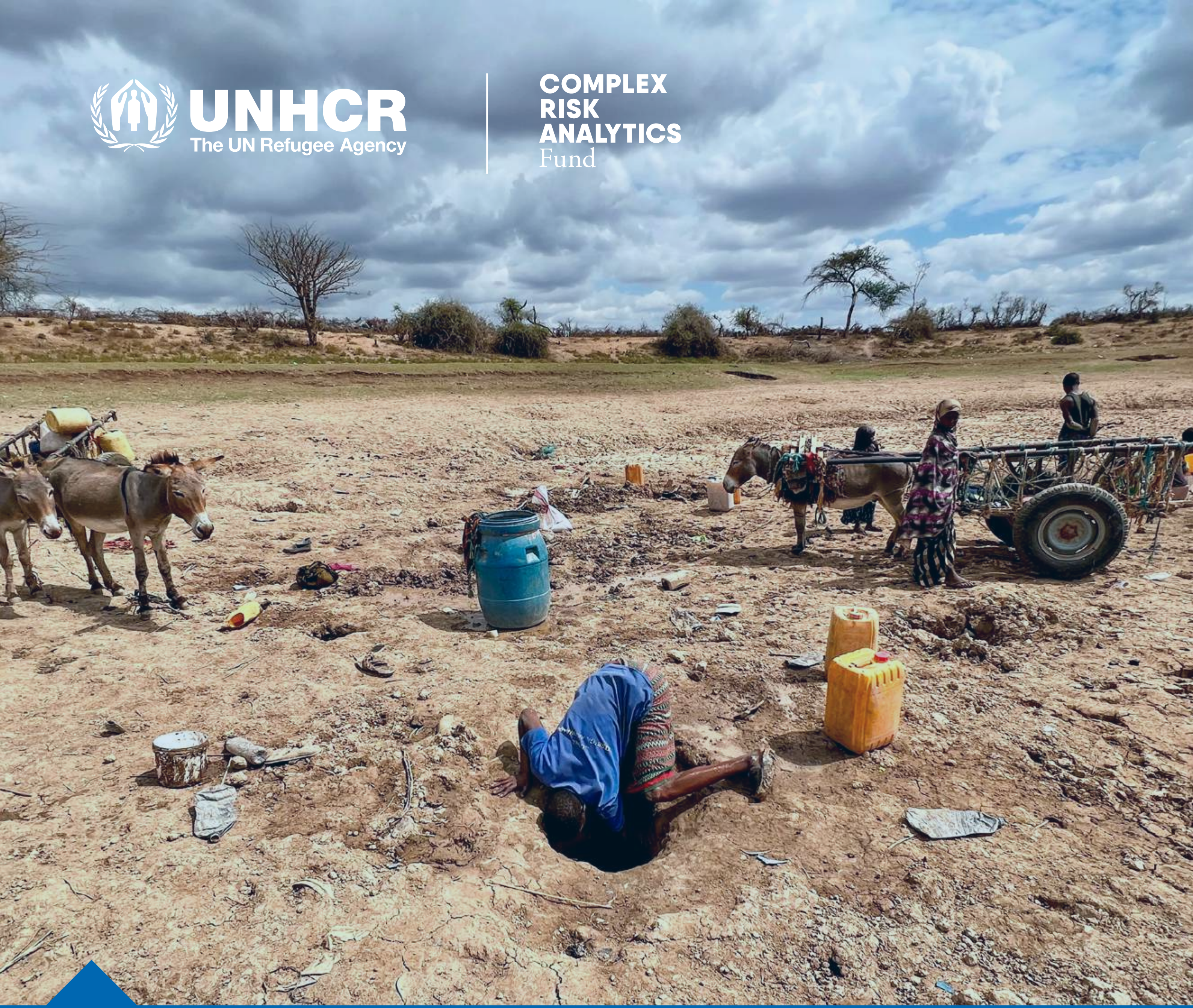

Predicting forced displacement in the context of climate change

Table of Contents

Executive Summary

We live in a world confronted with the impacts of interacting climate change and forced displacement crises. Millions of people are being forced to flee because of conflicts, violence, and persecution, and many of them have simultaneously been impacted by slow-onset or sudden-onset weather events, exacerbated by climate change. Given the likely scenario of an average global increase in temperature of more than 2°C compared to pre-industrial temperatures by the end of the century, the potential impact on livelihoods will be significant and likely to result in greater numbers of people being forced to flee. Estimates ranging between 200 million to 1 billion people are regularly cited in the media and academic literature.[1] However, empirical evidence for such severe scenarios remains sparse. Instead, as climate change incrementally progresses, the evidence points towards more nuanced changes in human mobility patterns.[2]

The potential impact of climate change on forced displacement occurs through both rapid and slow-onset events, each operating in distinct ways. While rapid-onset disasters like storms and floods typically generate immediate and often temporary displacement, slow-onset changes such as rising temperatures, drought, desertification, and sea-level rise have the potential to create more systematic and long-term displacement patterns, depending on the context in which they occur. These gradual climate shifts can contribute to economic instability, food insecurity, competition for resources, and political instability over extended periods, with the impact felt

1 "Climate Migrants Might Reach One Billion by 2050," *Inter Press Service*, August 21, 2017, https://www.ipsnews.net/2017/08/climate-migrants-might-reach-one-billion-by-2050/

2 See, S., Opdyke, A., & Banki, S. (2025). A review of the climate change-disaster-conflict nexus and humanitarian framing of complex displacement contexts. *Climate and Development*, 1-14. doi:https://doi.org/10.1080/17565529.2025.2514027

Figure 1: Map of project region embedded in map of Africa. The countries outlined in black are included.

most by already vulnerable populations. However, those engaging in climate-related mobility due to slow-onset climate events remain largely overlooked in statistical analyses, as clearly establishing a link between climate change and displacement remains very challenging.

To shed more light on the climate-displacement nexus, UNHCR developed a machine learning (ML) model to anticipate and prepare for slow-onset climate-induced displacement across East, Central, and West Africa.[3] The climate crisis is particularly acute in these regions, where many states lack the necessary resources for adaptation. The model uses individual data on refugees and asylum-seekers registered by UNHCR after crossing a national border as the main dependent variable for analysis and modelling. The target variable being predicted in this work is therefore cross-border displacement. While internally displaced people (IDPs) generally outnumber those displaced across an international border,[4] internal displacement data was not available at the temporal and geo-spatial granularity sought after for this project and therefore were not included. As the individuals in UNHCR's registration database are refugees and asylum-seekers, forcibly displaced people in this report refers to those forcibly displaced across an international border due to persecution, conflict, violence, human rights violations and events seriously disturbing the public order.[5]

The novelty of this project lies in the temporal and geospatial precision of the data, from which predictions of forced displacement are made. Temporally, the project focuses on monthly time intervals. The geospatial focus of the analysis are 0.5° grid cells, which are approximately 55 km^2.[6] This geospatial precision is more granular than national and even subnational analyses and predictions that are typically made regarding forced displacement. Additionally, feature variables used for predicting the cross-border forced displacement such as climate, food security, socio-demographic, and conflict are aggregated to the 0.1° grid cell unit, approximately 11 km^2, which allows for even more granular analysis.

In this project, the predictions are generated by an AI model that combines tree-based models and different types of neural network architectures to handle the spatial dependencies and temporal dynamics inherent in displacement events to predict forced displacement outflows for each 0.5° grid cell. The AI model enables monthly displacement predictions up to six months ahead across three magnitude levels: small-scale movements (0-10 people), medium-scale events (11-500 people), and large-scale crises (>500 people).

Overall, the predictive accuracy is reasonably high, decreasing slightly with longer forecast horizons. On the test dataset, the accuracy of the predictions is around 99 per cent and 85 per cent for small-scale and medium-scale displacement, respectively, while the AI model manages to correctly predict more than

3 The 25 countries of focus include: Angola, Benin, Burkina Faso, Burundi, Cameroon, Central African Republic, Chad, Côte d'Ivoire, Democratic Republic of the Congo, Eritrea, Ethiopia, Ghana, Kenya, Mali, Mauritania, Niger, Nigeria, Rwanda, Senegal, Somalia, South Sudan, Sudan, Togo, Uganda, and United Republic of Tanzania. Certain countries in this region are left out due to a lack of displacement data, these include Equatorial Guinea, Gabon, The Gambia, Guinea, Guinea-Bissau, Liberia, Republic of the Congo, and Sierra Leone. The small island countries of Cabo Verde, Comoros, São Tomé and Príncipe and Seychelles are also not included due to their small size.

4 Based on conflict-induced IDP data from the Internal Displacement Monitoring Centre (IDMC), 89.1 million people were internally displaced within the 25 countries that this project focuses on between 2009 and 2024. Over this same period, there were 10.4 million individuals registered in UNHCR PRIMES for these countries.

5 It is noteworthy that in 2020 UNHCR developed a document containing legal considerations concerning the applicability of international and regional refugee and human rights law to claims for international protection when cross-border displacement occurs in the context of the adverse effects of climate change and disasters. The document clarifies that "the assessment of claims for international protection made in the context of the adverse effects of climate change and disasters should not focus narrowly on the climate change event or disaster as solely or primarily natural hazards. Such a narrow focus might fail to recognize the social and political characteristics of the effects of climate change or the impacts of disasters or their interaction with other drivers of displacement. More broadly, climate change and disasters may have significant adverse effects on State and societal structures and individual well-being and the enjoyment of human right." (https://www.refworld.org/policy/legalguidance/unhcr/2020/en/123356)

6 There are 6,225 grid cells within the project region of interest.

53 per cent of large-scale displacement events up to six months in advance. However, large-scale crises remain more difficult to predict, and the AI model tends to generate more false negatives for large-scale events than false positives, reflecting a tendency to underpredict these events.

These results highlight the potential of this approach to provide relatively reliable forecasts of forced displacement up to six months beyond the timeframe of the source dataset. By providing spatially and temporally granular predictions, the framework offers humanitarian organizations a tool to strengthen early warning systems and support anticipatory action. Ultimately, these predictions can enhance preparedness and resilience in regions that are most vulnerable to the risks of climate change and forced displacement.

This report consists of four chapters. Chapter 1 discusses the theoretical linkages between climate change, migration, and forced displacement, and the findings of previous research investigating these linkages. Chapter 2 offers an analysis of the climate conditions within the region this project is focused on, as well as historical forced displacement trends. Chapter 3 details the modelling approaches used for the intermediate models used to grid the displacement data and predict the population and food security within the grid cells at monthly intervals. The chapter also describes the AI model for predicting forced displacement outflows from the grid cells in the future. Chapter 4 sets out how this research can be applied in practice, explaining how this project and the findings generated from it can be used by UNHCR and other humanitarian and development organizations for better targeting investments in resilience and preparedness.

Key terms

Anthropogenic climate change — Climate change driven primarily by human activities such as greenhouse gas emissions and industrial processes.[7]

Artificial Intelligence (AI) — A branch of computer science using hardware, algorithms, and data to create "intelligence" to do things like make decisions, discover patterns, and perform some sort of action.[8]

Climate change — A change in the state of the climate that can be identified (such as by using statistical tests) by changes in the mean and/or the variability of its properties and that persists for an extended period, typically decades or longer. Climate change may be due to natural internal processes or external forces such as modulations of the solar cycles, volcanic eruptions and persistent anthropogenic changes in the composition of the atmosphere or land use.[9]

Climate-related mobility — Human movement (voluntary or forced) influenced partly or entirely by climate or environmental change.[10]

Deep learning — A subset of machine learning using multilayer neural networks capable of learning complex, hierarchical representations.[11]

Disaster displacement — Refers to situations where people are forced or obliged to leave their homes or places of habitual residence as a result of a disaster or in order to avoid the impact of an immediate and foreseeable natural hazard.[12]

Displacement — The movement of persons who have been forced or obliged to flee or to leave their homes or places of habitual residence (whether within their own country or across an international border), in particular as a result of or in order to avoid the effects of armed conflict, situations of generalized violence, violations of human rights or natural or human-made disasters.[13]

Ecosystem services — The benefits people obtain from ecosystems, such as fertile land and precipitation.[14]

Ensemble model — A machine learning approach that combines multiple models to improve predictive accuracy and robustness.[15]

Forced displacement — The involuntary movement of people from their homes due to persecution, conflict, generalized violence, human rights violations or the adverse effects of climate change, environmental degradation, or disasters.[16]

7 United Nations Framework Convention on Climate Change (UNFCCC). (2024). *Technical guide on integrating human mobility and climate change linkages into relevant national climate change planning processes.* UNFCCC. https://unfccc.int/sites/default/files/resource/WIM_ExCom_human-mobility_TFD_2024.pdf

8 Center for Integrative Research in Computing and Learning Sciences (CIRCLS). (2024). *Glossary of Artificial Intelligence Terms for Educators.* https://circls.org/educatorcircls/ai-glossary

9 United Nations Framework Convention on Climate Change (UNFCCC). (2024). *Technical guide on integrating human mobility and climate change linkages into relevant national climate change planning processes. UNFCCC.* https://unfccc.int/sites/default/files/resource/WIM_ExCom_human-mobility_TFD_2024.pdf

10 Carnegie Council for Ethics in International Affairs. (2025). *Climate mobility*. Carnegie Council. https://www.carnegiecouncil.org/explore-engage/key-terms/climate-mobility?utm_source=chatgpt.com

11 Center for Integrative Research in Computing and Learning Sciences (CIRCLS). 2024. *Glossary of Artificial Intelligence Terms for Educators.* https://circls.org/educatorcircls/ai-glossary

12 United Nations Framework Convention on Climate Change (UNFCCC). (2024). *Technical guide on integrating human mobility and climate change linkages into relevant national climate change planning processes.*

13 United Nations High Commissioner for Refugees (UNHCR). (n.d.). Master Glossary of Terms. Retrieved from https://www.unhcr.org/glossary

14 United Nations (UN). (n.d.). System of Environmental-Economic Accounting. Retrieved from https://seea.un.org/ecosystem-accounting

15 Brown, D. W. (2023). A Unified Theory of Diversity in Ensemble Learning. *Journal of Machine Learning Research* 24, 1-49.

16 United Nations High Commissioner for Refugees (UNHCR). (n.d.). Master Glossary of Terms. Retrieved from https://www.unhcr.org/glossary

Grain formation — The phase in crop development during which grains (such as wheat or rice kernels) develop and fill, determining yield.

Hydroclimatic whiplash — Rapid shifts between extreme dry and extreme wet conditions within a short timeframe.[17]

Integrated Food Security Phase Classification (IPC) — A global, evidence-based system that categorizes the severity of food insecurity into standardized phases to guide humanitarian action.[18]

Internally displaced people — A person who has been forced or obliged to flee from their home or place of habitual residence, in particular as a result of or in order to avoid the effects of armed conflicts, situations of generalized violence, violations of human rights or natural or human-made disasters, and who has not crossed an internationally recognized State border.[19]

Liptako-Gourma — Area along the borders between the countries Burkina Faso, Mali, and Niger.

Neural network model — A computational model composed of interconnected layers of nodes ("neurons") that learn patterns from data.[20]

Phenological analysis — The study and interpretation of the timing of recurring biological events (such as flowering, leaf-out, or migration) and how they are influenced by environmental conditions, especially climate.[21]

Population Registration and Identity Management Eco-System (PRIMES) — UNHCR's registration of refugees and asylum-seekers.[22]

Rapid (sudden)-onset climate events — Short-timescale hazard events such as floods, storms, or heatwaves that occur abruptly and cause immediate impacts.[23]

Slow-onset climate events — Gradual environmental changes like sea-level rise, desertification, or increasing drought that unfold over long periods.[24]

Transhumance corridors (routes) — Seasonal migration pathways used by pastoralists to move livestock between grazing areas and water sources.[25]

Tree-based model — A machine learning method that makes predictions by recursively splitting data into decision "branches" using features.[26]

---

17 Swain, D. L., Prein, A. F., Abatzoglou, J. T., Albano, C. M., Brunner, M., Diffenbaugh, N. S., . . . Touma, D. (2025). Hydroclimate volatility on a warming Earth. *Nat Rev Earth Environ, 6*, 35-50. doi:https://doi.org/10.1038/s43017-024-00624-z

18 *IPC Famine Fact Sheet.* (2025). Retrieved from Integrated Food Security Phase Classification: https://www.ipcinfo.org/famine-facts/

19 United Nations High Commission for Refugees (UNHCR). (n.d.). Master Glossary of Terms. Retrieved from https://www.unhcr.org/glossary

20 Center for Integrative Research in Computing and Learning Sciences (CIRCLS). 2024. *Glossary of Artificial Intelligence Terms for Educators.* https://circls.org/educatorcircls/ai-glossary

21 USA National Phenology Network (USANPN). (n.d.). Glossary. Retrieved from https://www.usanpn.org/nn/glossary

22 United Nations High Commission for Refugees (UNHCR). (n.d.). *Registration and identity management*. Retrieved from https://www.unhcr.org/what-we-do/protect-human-rights/protection/registration-and-identity-management

23 United Nations Framework Convention on Climate Change (UNFCCC). (2024). *Technical guide on integrating human mobility and climate change linkages into relevant national climate change planning processes.* UNFCCC. https://unfccc.int/sites/default/files/resource/WIM_ExCom_human-mobility_TFD_2024.pdf

24 Ibid.

25 IGAD Centre for Pastoral Areas and Livestock Development (ICPALD). (2020). *IGAD Protocol on Transhumance. Intergovernmental Authority on Development (IGAD).* https://icpald.org/wp-content/uploads/2021/06/IGAD-PROTOCOL-ON-TRANSHUMANCE-Final-Endorsed-Version.pdf

26 Pedregosa, F., Varoquaux, G., Gramfort, A., Michel, V., Thirion, B., Grisel, O., ... Duchesnay, É. (2011). *Scikit-learn: Machine learning in Python. Journal of Machine Learning Research, 12,* 2825–2830. https://jmlr.org/papers/v12/pedregosa11a.html

© UNHCR/Charity Nzomo

CHAPTER 1:

The Big Picture

1.1 Overview of climate trends in Africa

Africa has experienced some of the most pronounced warming trends globally, with temperatures increasing at approximately 1.5 times the global rate.[27] Current climate models show that as global temperatures keep increasing, there will be a profound redistribution of ecosystem services across the world. These changes in ecosystem services hold potential disadvantages, and in some cases

27 He, C., Zhu, Y., Guo, Y., Bachwenkizi, J., Chen, R., Kan, H., & Fawzi, W. W. (2025). Escalated heatwave mortality risk in sub-Saharan Africa under recent warming trend. *Science Advances*, 11(48).

advantages, for local populations depending on the many, often non-linear, relationships between climatic variables and other factors, particularly factors in the primary sector such as agriculture and fishing. For example, per-hectare yields for most grains follow an inverted U-shaped relationship with climate variables such as temperature and precipitation. A similar relationship exists between temperature and dairy production, with productivity starting to decrease once temperatures pass an optimal threshold. Rising sea temperatures also impact the movements of migratory fish, which, for many coastal populations, are both an essential staple food and a primary source of income. Whilst some regions may benefit from increasing temperatures and precipitation, most regions will experience a considerable decline in agricultural and fishery productivity as the local ecosystem services decline.

The impact of climate change on human mobility is complex, but it manifests itself mainly through two broad channels: an increase in the frequency and intensity of sudden-onset events, like storms, floods, and wildfires, and a higher risk for slow-onset events, like droughts, changes in precipitation patterns, loss of ecosystems, and salinisation of coastal areas due to rising sea levels. Both types of events can lead to changes in human mobility by aggravating multiple causes of forced displacement both within and across borders, especially where the ability to adapt is low and vulnerability is high.

Natural hazards from rapid-onset climate events usually lead to a displacement of short duration and limited geographic scope, but more intense and frequent natural hazard events can deplete a household's capital assets over time, reducing its general resilience and adaptability to more gradual environmental changes. At the same time, slow-onset events may lead to ecosystem degradation, particularly impacting households that depend on rain-fed agriculture. Technology solutions can replace many deteriorating ecosystem services (e.g., flood protection, irrigation systems, crop rotation systems, drought-resistant varieties, storm shelters, and others), though often at considerable financial costs. Consequently, given the considerable resources needed to implement these solutions, poor and marginalized population segments will experience a loss of livelihood and quickly reach their coping limits in the face of deteriorating ecosystems. As discussed in the following sections, the loss of livelihoods due to slow-onset climate change events is a potential factor contributing to mobility and forced displacement.

BOX 1: What are slow-onset climate events?

What are slow-onset climate events? Unlike sudden onset disasters (floods, storms, landslides, wildfires), that generally lead to sudden and usually short-term displacement within a limited geographic area, slow-onset events develop gradually over months, years, or decades. Examples include:

- Rising average temperatures
- Changing precipitation patterns
- Increases in the occurrences of drought and desertification
- Land and forest degradation
- Sea level rise and coastal erosion
- Glacial retreat

These gradual changes often have little noticeable impact until they cross critical thresholds, at which point entire areas can become uninhabitable or livelihoods can be impacted. Unlike sudden-onset events that immediately force people from their homes, slow-onset events progress at a speed that can allow households to adapt to changing circumstances. Adaptation can happen in situ, however when climate conditions pass a certain threshold, migration may be the only solution.

1.2 When people are forced to move

Cross-border forced displacement in Africa stems from multiple interconnected causes. While conflict and violence generally remain the primary drivers, they may be exacerbated by slow-onset climate events, which increasingly act as multipliers that intensify existing vulnerabilities and contribute to events that trigger displacement.

The primary drivers of forced displacement include:

- **Conflict and violence:** Armed conflicts, including extremist insurgencies, inter-communal violence, and civil wars, constitute the largest displacement driver. The Lake Chad Basin, the Sahel region, and Horn of Africa have experienced particularly high conflict-driven displacement.
- **Political persecution and human rights violations:** Authoritarian governance, ethnic discrimination, and targeted persecution force populations to seek safety across borders.

Additional indirect causes of forced displacement include:

» **Economic collapse:** Livelihood failure, particularly in agricultural communities, leads to further stressors when households exhaust coping mechanisms.

» **Resource competition:** Disputes over land, water, and grazing rights between different user groups, particularly farmers and pastoralists, trigger localized tensions.

Given these drivers of forced displacement, slow-onset climate events do not typically cause displacement in isolation. Instead, they interact with and intensify these existing drivers in multiple ways.[28] Communities can often adapt to slow-onset changes through technical solutions such as planting drought resistant crops, improved water management, or adjusting the timing of planting and harvesting cycles. But, when slow-onset climate change impacts areas where people are already subject to high level of poverty and underlying group tensions, resource scarcity induced by changing precipitation patterns and rising temperatures have a potential to heighten tensions between groups that compete for these resources. These developments can amplify preexisting tensions that might otherwise remain manageable.[29] In the Liptako-Gourma region along the borders of Mali, Burkina Faso and Niger, for example, decreased rainfall and vegetation loss have potentially been a factor in intensified farmer-herder conflicts, contributing to some of the over 233,000 displaced persons who have fled their homes as refugees between 2000 and 2025 (see box 2).

Figure 2 shows the theoretical linkage between slow-onset climate events and conditions and human mobility, which can materialize in several phases, potentially leading to forced displacement:

- **Immediate impacts:** Extreme heat and significant changes in precipitation patterns directly threaten agricultural yields and livestock survival. When crops fail repeatedly or pastures become unusable, households lose their primary source of income and may become food insecure. Rural families, who depend entirely on rain-fed agriculture or vegetation and dependable water for their livestock, find themselves with diminishing options as each failed season depletes their resources further.
- **Cascading effects:** Temperature increases, prolonged drought, or heavily concentrated rainfall may force people to change their behaviour. As water sources dry up, herders must travel further distances to find water and pasture for their animals. Meanwhile, traditional coping mechanisms that once helped communities weather difficult periods, such as selling livestock assets or relying on extended family support, become exhausted when entire

28 See, Opdyke, and Banki, "A Review of the Climate Change-Disaster-Conflict Nexus and Humanitarian Framing of Complex Displacement Contexts."

29 Intergovernmental Panel on Climate Change (IPCC). (2022). *Climate Change 2022: Impacts, Adaptation and Vulnerabilities*. Intergovernmental Panel on Climate Change.

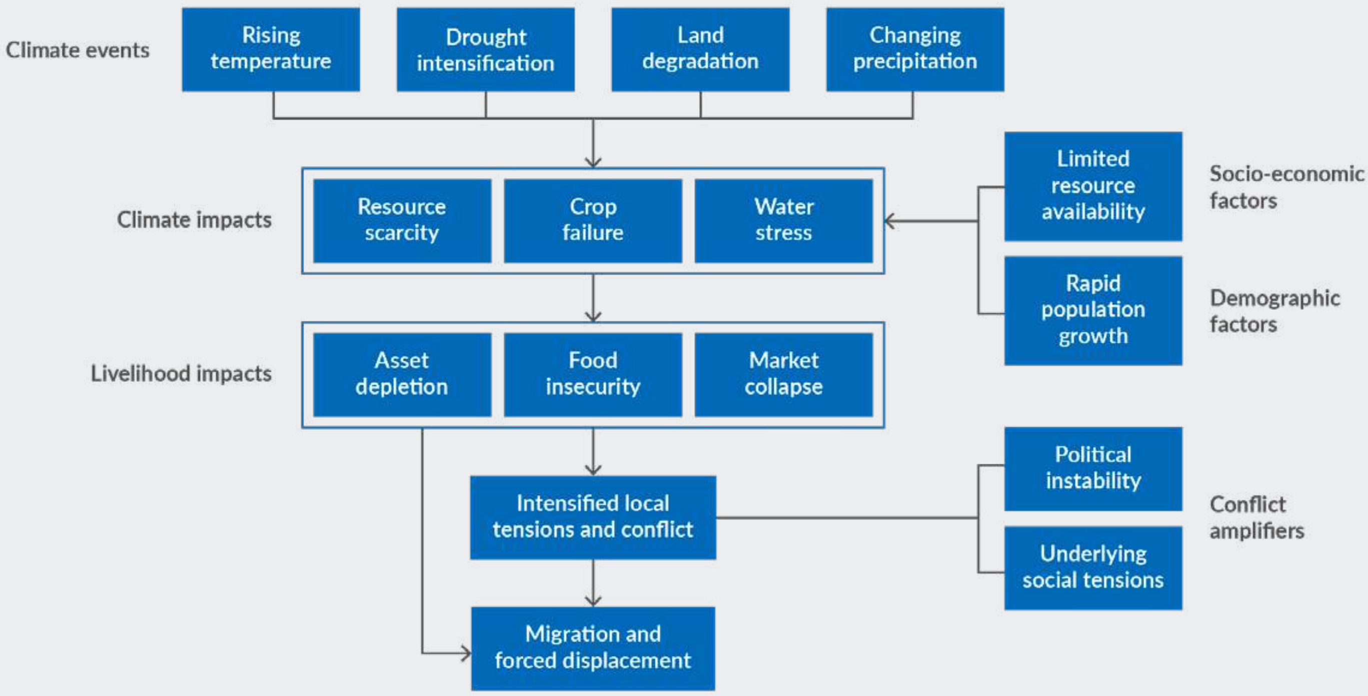

Figure 2: Connection of slow-onset climate change events with primary migration displacement drivers.

regions face the same pressures simultaneously. Those that can may send some members of the family to urban centres to find other forms of work.

- **Tipping points:** Herders who engage in extended movements, taking their livestock outside their traditional territories, possibly and into more agricultural areas, increase the risk of conflict with farming communities. If these conflicts occur along group or ethnic lines, where tensions and prejudices pre-existed, they may boil over into violence. These risks radicalizing people further and creating cycles of violence and reciprocal violence. Meanwhile, mass movements of people from rural to urban areas may strain limited resources in cities. Combined with limited food supplies because of decreased productivity in agricultural areas, this risks creating grievances among people against others and public institutions, and escalating violence, both in rural and urban settings, possibly forcing people to become displaced. Climate change may also create challenges to durable solutions and increase the vulnerability of already displaced communities, leading to further onwards movements and protracted displacement situations.[30]

30 United Nations High Commissioner for Refugees (UNHCR). (2025). *No Escape II: The Way Forward. Bringing climate solutions to the frontlines of conflict and displacement. United Nations High Commissioner for Refugees.*

BOX 2: Liptako-Gourma: Climate stress and rising tensions

As in much of Africa, temperatures in the Sahel, which lies south of the arid Sahara Desert, are climbing faster than the global average. Additionally, the region is experiencing increasingly erratic rainfall patterns. While overall precipitation across the Sahel may be increasing due to climate change,[31] it is now often in the form of sudden, heavy rainfalls that causes soil erosion rather than replenishing groundwater. Precipitation of this kind delays and disrupts traditional planting cycles instead of nurturing vegetation. Additionally, localized land degradation occurs in heavily used areas, particularly around water points and along constrained transhumance corridors. These traditional transhumance routes that long sustained pastoral communities are becoming unviable as water points dry up and pastures degrade.

The Sahel region has also experienced heightened levels of conflict in recent years. One area within the Sahel of particular concern is the Liptako-Gourma region, which is the border area of Mali, Niger, and Burkina Faso. UNHCR registered over 233,000 refugees and asylum-seekers from the Liptako-Gourma region between 2000 and 2025.[32]

As traditional grazing areas deteriorated, many pastoralists have been forced to move their herds to new grazing areas, bringing them into direct conflict with farming communities. At the same time, amid a reality of a lack of formalized land registration and land titles[33], farmers have taken over grazing areas in response to soil depletion and the demand for land amid rapid population growth. These factors have all contributed to disrupting traditional resource-sharing arrangements. As a result, some farmers saw herders as a nuisance or even a threat. Meanwhile, many pastoralists saw the farms as encroaching on their traditional land. These overlapping claims have created flashpoints for violence in the Liptako-Gourma region.

Resource competition alone, however, does not explain the scale of violence that has been observed over recent years. Many of these conflicts take an ethnic dimension, particularly between Fulani pastoralist communities and farming groups like the Dogon and Bambara in Mali. In recent years, many Fulani pastoralists have felt marginalized and accused of supporting criminal activities, further inflaming tensions.[34] Armed groups, made up, at least partially, of disgruntled Fulani youths, have engaged in activities targeting both farmers and other pastoral communities. ACLED reports 16,000 conflict events in the Liptako-Gourma region from 2000 to 2024, with 900 conflict events featuring people of Fulani ethnicity, either as civilians under attack or as ethnic militias.

The bar plot in Figure 3 shows the annual cross-border displacement from the Liptako-Gourma region. The grey bars show almost no displacement up to 2012, and then a sudden rise in displacement to over 37,000 people, corresponding with the outbreak of the civil war in Mali in 2012. The level of cross-border displacement decreased after 2012, but has steadily been rising in the years since, reaching its highest levels in 2024 with over 44,000 refugees from the region, most of them coming from Burkina Faso. The number of conflict fatalities and high temperature days over the previous 12 months, shown in the blue and red lines respectively have also trended upward over time. Between 2000 and 2011 there were a total of 117 conflict fatalities, climbing to almost 5,000 in 2020 and peaking at over 8,800 in 2023. The average number of high temperature days over the previous 12 months for all grid cells in the year 2000 was just under 7, but this figure rose to an average of 14.2 high temperature days in 2012 and 42.1 in 2024.

31 United Nations High Commissioner for Refugees (UNHCR) and Potsdam Institute for Climate Impact Research (PIK). (2021). *Climate Risk Profile: Sahel.* https://www.unhcr.org/61a49df44.pdf

32 Through September 2025.

33 Due to the lack of land registration/land titles/tenure, farmers are not willing to invest in infrastructure or expanding their land parcels to make them more efficient. Consequently, small plots of land are over exploited, and the combined effect of population growth and climate change makes the competition over the shrinking available arable land areas even fiercer.

34 Modibo Ghaly Cissé, "Understanding Fulani Perspectives on the Sahel Crisis," *Africa Center for Strategic Studies*, April 22, 2020, https://africacenter.org/spotlight/understanding-fulani-perspectives-sahel-crisis/

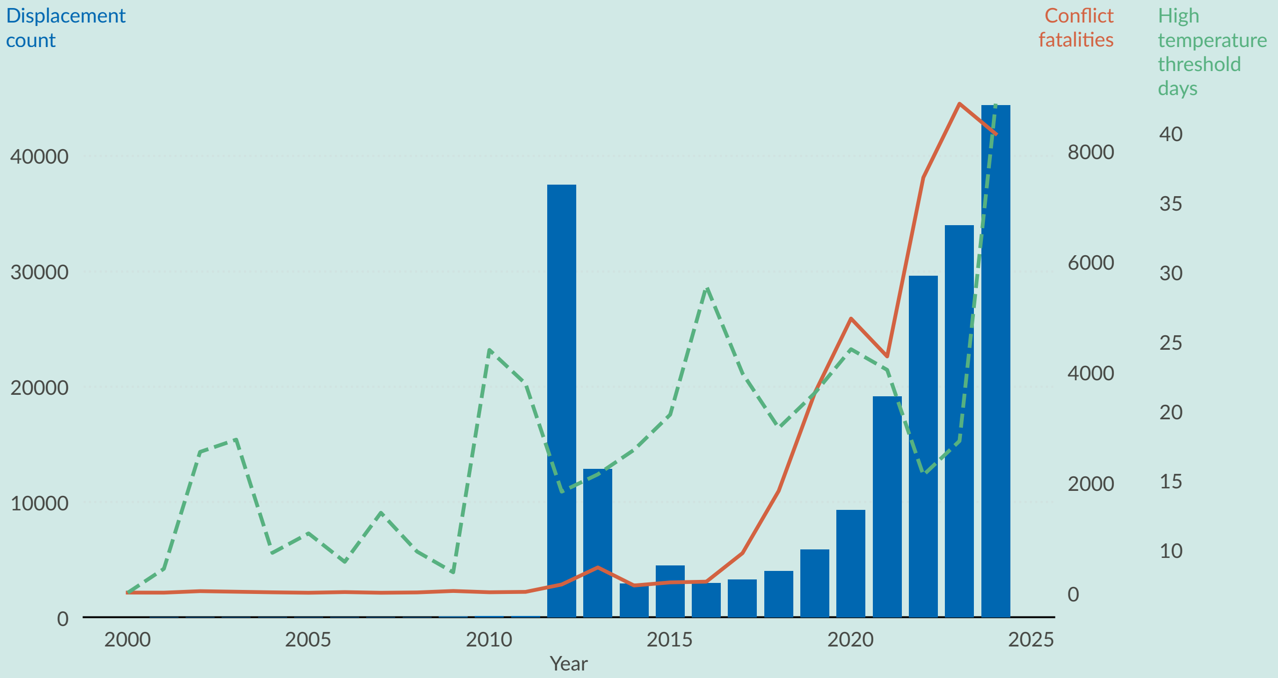

Figure 3: Number of yearly high temperature days (green), number of conflict fatalities (red), and displacement counts (blue) for the Liptako-Gourma region from 2000 to 2024.

CHAPTER 2:
Slow Changes, Big Impacts

2.1 Rising temperatures

Temperature data across our study region reveal a general warming pattern over the past two decades. Analysis of temperature data[35] reveals a linear trend averaging 0.03°C per year from 2000 to 2024, which translates to approximately 0.3°C per decade of warming. This is higher than the global average

35 Temperature data from the Climate Hazards Center InfraRed Temperature with Stations (CHIRTS).

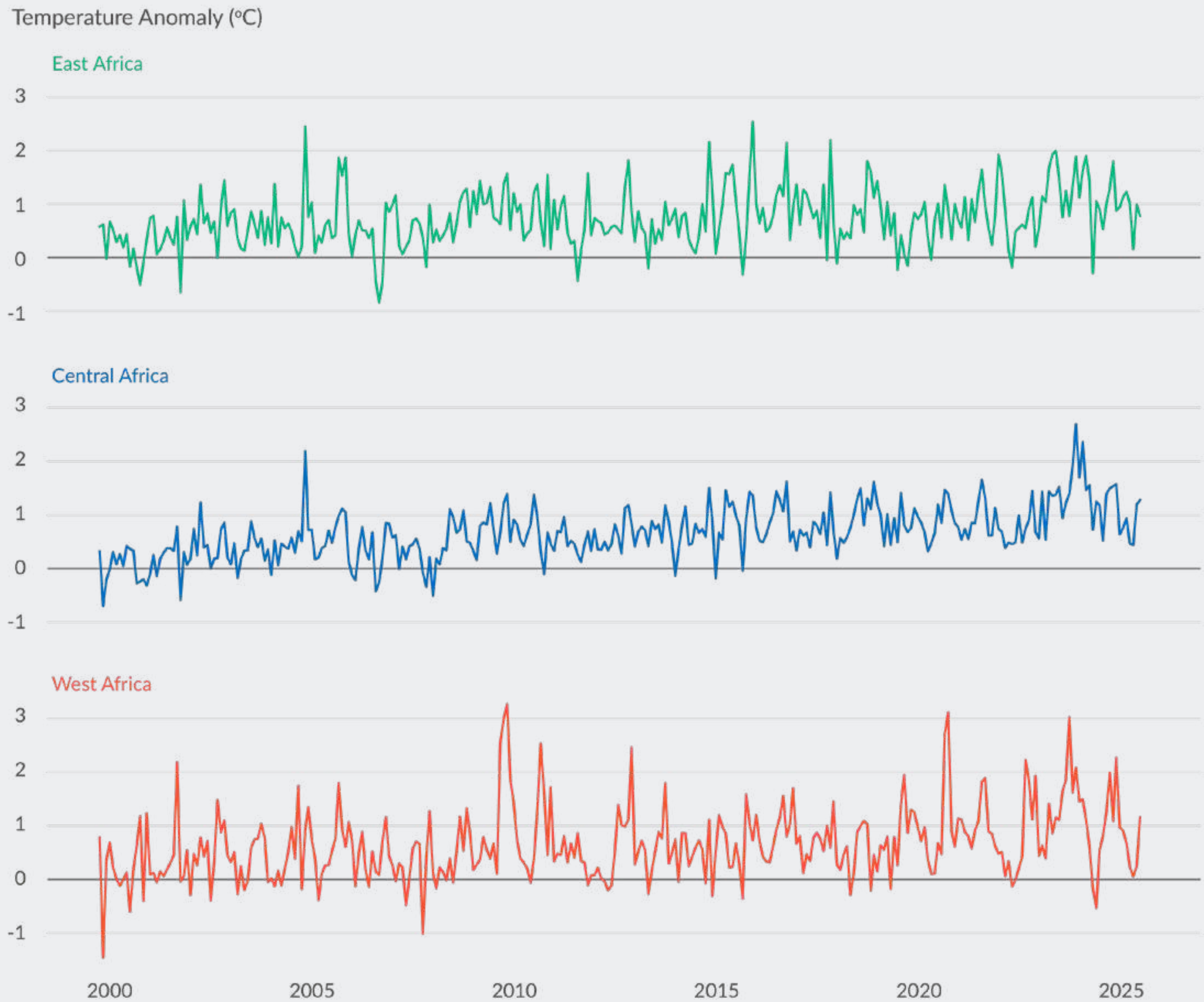

Figure 4: Average monthly temperature anomalies over East, Central, and West Africa regions over baseline – average monthly temperature between 1980 and 1990.

rate of warming, which has been 0.15 to 0.2°C per decade since 1975.[36] The increase in temperature is not uniform across the region, though. Some areas experienced significantly higher temperature increases than others depending on the geographic location and with seasonal variations. Figure 4 plots the monthly average temperature against the baseline temperature from the years 1980 – 1990 for the same location and month, for countries in East[37], Central[38], and West[39] Africa. In East Africa, the average difference in

36 NASA. *World of Change: Global Temperatures.* Retrieved from https://science.nasa.gov/earth/earth-observatory/world-of-change/global-temperatures/

37 Countries classified as East African include Burundi, Ethiopia, Eritrea, Kenya, Rwanda, Somalia, Sudan, South Sudan, United Republic of Tanzania, and Uganda.

38 Countries classified as Central African include Chad, Central African Republic, Cameroon, Democratic Republic of the Congo, and Angola.

39 Countries classified as West African include Benin, Burkina Faso, Côte d'Ivoire, Ghana, Mali, Mauritania, Niger, Nigeria, Senegal, and Togo.

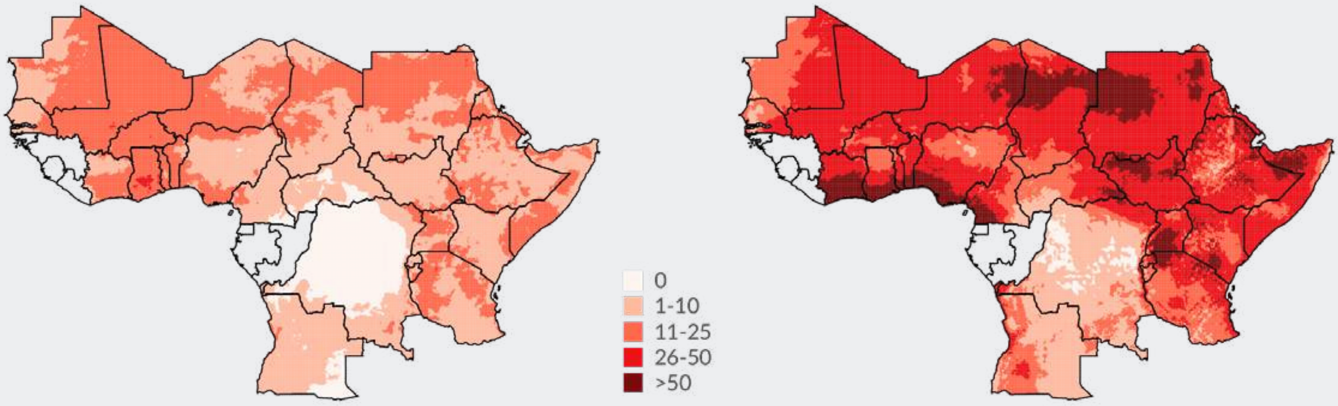

Figure 5: 3-year averages of the yearly number of high temperature days in study region – comparison of the period of 2000 to 2002 (left) and the period of 2022 to 2024 (right).

temperature from the baseline among all months in the years 2000-2004 was +0.47°C and by 2020-2024, this rose to +0.88°C. These figures were +0.24°C and +1.00°C in Central Africa, and +0.33°C and +0.96°C in West Africa, respectively, for the same years. The three regions therefore all experienced an average rise in monthly temperature from the baseline averages when comparing earlier and later periods of the project timeline, with the largest increase in Central African countries.

In addition to generally rising temperature trends, the frequency of extreme heat events has increased dramatically across the region over the past two decades. Figure 5 shows the average number of high temperature days,[40] for each 0.1° grid cell for the years 2000-2002 (left) and 2022-2024 (right). As high temperature days are above the 99th percentile for a given location, stable conditions would yield 3-4 high temperature days annually. In the years 2000-2002, the annual average number of high temperature days was 8.47, during the 2022-2024 period, this had jumped to 30.63 days.

Between 2000 and 2002, 48.6 per cent of grid cells saw 1-10 annual high temperature on average, 40.3 per cent experienced 11-25 annual high temperature days, and 10.9 per cent experienced 0 annual high temperature days. The number of grid cells with 26 or more high temperature days on average was negligible. Between 2022 and 2024, 51.0 per cent of grid cells saw 26-50 annual high temperature days and 12.3 per cent saw more than 50 annual high temperature days on average. The percentage of grid cells experiencing 0 high temperature days was 1.5 per cent. The maps and underlying statistics demonstrate that in recent years, large swaths of the continent have experienced 26 or more high temperature days annually. Some regions, particularly the highly populated areas of coastal West Africa and around Lake Victoria in Uganda and the United Republic of Tanzania,, have endured more than 50 such days.

Periods of anomalously high temperatures risk coinciding with critical agricultural periods, such as the beginning of the growing season when crops need stable conditions to grow,[41] and when pastoralists traditionally move their herds to established grazing areas. Extreme heat during these sensitive periods can damage vegetation

40 High temperature day defined as a day with temperature high above the 99th percentile of high temperature among all days from 1950-1980 for a given location.

41 Shukla, Shraddhanand, Gregory Husak, William Turner, Frank Davenport, Chris Funk, Laura Harrison, et al. (2021). "A Slow Rainy Season Onset Is a Reliable Harbinger of Drought in Most Food Insecure Regions in Sub-Saharan Africa." *PLoS ONE* 16, no. 1: e0242883. https://doi.org/10.1371/journal.pone.0242883

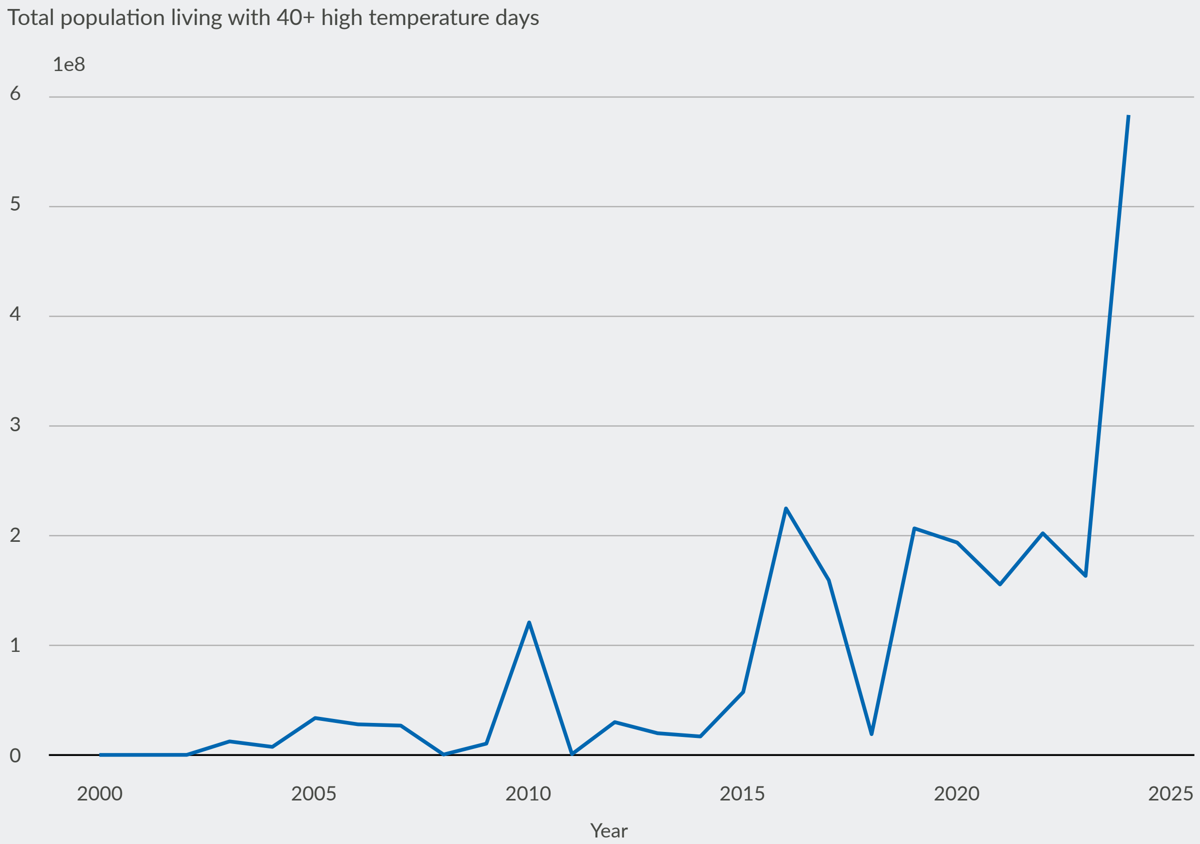

Figure 6: Estimated number of people living in area with 40 or more high temperature days per year.

and decrease water supplies through increased evaporation. These conditions can therefore disrupt agricultural and pastoral calendars that communities rely upon, adding additional stress on communities, especially those with fewer resources.

As discussed above, rising temperatures can strain agricultural systems by impacting crop and vegetation yields, lowering the supply of available food and water supplies. Such vulnerabilities are of particular concern in Sub-Saharan Africa, which has the fastest population growth rate in the world. So, the strained supply of vegetation and water is met with increased demand due to a rapidly growing population. According to the population data,[42] the estimated population of the region of focus was approximately 520 million in 2000. In 2024, the estimated population was around 1 billion, an almost doubling of the population in less than 25 years. The rising temperatures and increased population mean that many more people are being exposed to temperatures that would be considered anomalous on a frequent basis. Figure 6 shows the estimated number of people experiencing 40 or more high temperature days in each year. In a normal situation, an area would only experience 1 per cent of days being high temperature (3 – 4 days a year). So, 40 high temperature days represents a huge deviation from this norm.

The number of people experiencing 40 or more high temperature days in 2000 remained relatively low until 2015, but exploded since 2023, reaching almost 600 million in 2024.

Although long-term predictions are beyond the scope of this project, temperature and population trends in the region clearly indicate an upward trajectory in the coming years. Figure 7 illustrates the potential impact of these trends on the number of people exposed

42 LandScan data of modelled annual population at 1 km resolution from 2000 – 2024.

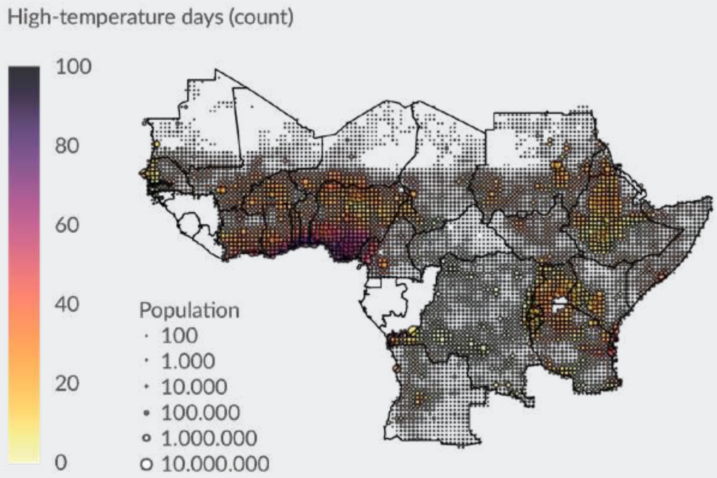

Figure 7: High temperature days (coloured) and population size (bubble size) by grid cell in 2010 (left) and expected figures in 2040 (right).

to high temperature days per 0.5° grid cell in 2040, assuming a linear continuation of the trends observed between 2000 and 2025. The bubble sizes in Figure 7 represent the population of each 0.5° grid cell in 2010 (left) and the projected population in 2040 (right) based on simple linear trends. The colours of the bubbles indicate the number of high temperature days in the respective year. In 2010, the region of interest had a population of 680 million people, of which approximately 122 million were exposed to 40 or more high temperature days. Our simple linear extrapolation suggests that the region's population will reach around 1.5 billion by 2040[43]. Based on our analysis, 887 million of this total population are expected to be exposed to 40 or more high temperature days in that year.

A significant number of the grid cells are expected to experience 60 and more high temperature days in 2040 , particularly in the regions of coastal West Africa, South Sudan, northern Somalia, and the Lake Victoria. According to UN population estimates, countries in Sub-Saharan Africa are projected to increase in population by 79 per cent by the mid-2050s, reaching 2.2 billion. Three countries within the focus of this project, Angola, the Democratic Republic of the Congo, and Niger, are likely to double in size between 2024 and 2054.[44] This population growth is evident in Figure 7, where many of the bubbles in 2040 are larger than their 2010 counterparts, especially in urban and para-urban areas. It should be noted that the 2040 map appears to have more empty grids, indicating a population below zero. This is a result of negative population trends in these grid cells, which are interpreted in our simple model. However, as climate and population predictions are beyond the scope of this project, these figures should be understood as rough estimates of the converging trends of rising temperatures and populations rather than precise projections.

As discussed in Chapter 3, the rising temperatures and populations along with a myriad of other triggers will potentially contribute to forced displacement, especially from unstable areas experiencing conflict. The movements of large number of people will put further strain on the areas that they settle, such as urban areas and refugee camps, which may already be experiencing environmental and population stress. This additional pressure on resources and infrastructure in these receiving areas could exacerbate existing challenges and potentially lead to new conflicts or humanitarian crises.

43 This closely match the UN Population Division medium variant prediction for the same countries of 1.48 billion in 2040 (retrieved from: https://population.un.org/wpp/)

44 United Nations. "Population." United Nations – Global Issues. https://www.un.org/en/global-issues/population

2.2 Unpredictable precipitation

In the 1980s, parts of Africa, particularly the Sahel and Ethiopia, experienced some of the most devastating droughts of the 20th century. Since then, there has been a recovery in seasonal rainfall amounts. But the recovery in rainfall quantity masks important changes in disruptions to the timing, intensity, and geographic distribution of the precipitation that many livelihoods depend upon. Three notable characteristics relating to precipitation in the region since 2000 have been increasing drought levels, especially in certain areas, increased levels of very high precipitation, periodically creating flood conditions, and shifts in the seasonal timing of vegetation peaks, which pose a challenge to farmers and pastoralists.

Increasing drought

Although drought conditions have improved since the mid-1980s, they have increased overall since the early-2000s. Examining accumulated drought, which measures the sum of inverted drought index[45] over the previous 72 months (6 years), Figure 8 shows the average accumulated drought in each grid cell in the periods 2000-2006 (left) and 2018-2024 (middle), as well as the change in drought levels between the 2018-2024 average and the 2000-2006 average (right). The average accumulated drought among all grid cells in the period 2000-2006 was 22.81, as compared to 49.15 in 2018-2024, representing a more than doubling of average drought levels between the two periods.

Some notable sub-regions that have seen an increase in average drought levels are the Liptako-Gourma region, which experienced an average increase of 24.0; central Nigeria, which experienced an average increase of 35.4; northeast South Sudan with an increase of 52.5, and Somalia with an increase of 76.9 average accumulated drought levels between the period 2000-2006 and 2018-2024. As discussed later in the chapter, these are also areas that have experienced high levels of forced displacement since 2000. Extended periods of drought risk causing desertification, which is a permanent transition towards desert conditions. The process of desertification affect about 46 per cent of Africa and approximately 500 million people.[46]

45 Drought levels measured through the Standardized Precipitation Evapotranspiration Index (SPEI). Higher drought levels have a more negative SPEI, so we invert SPEI values for our analysis.

46 Reich, P., Numbem, S. T., Almaraz, R., & Eswaran, H. (2001). Land resource stresses and desertification in Africa. In E. Bridges, *Responses to Land Degradation.* Boca Raton: CRC Press.

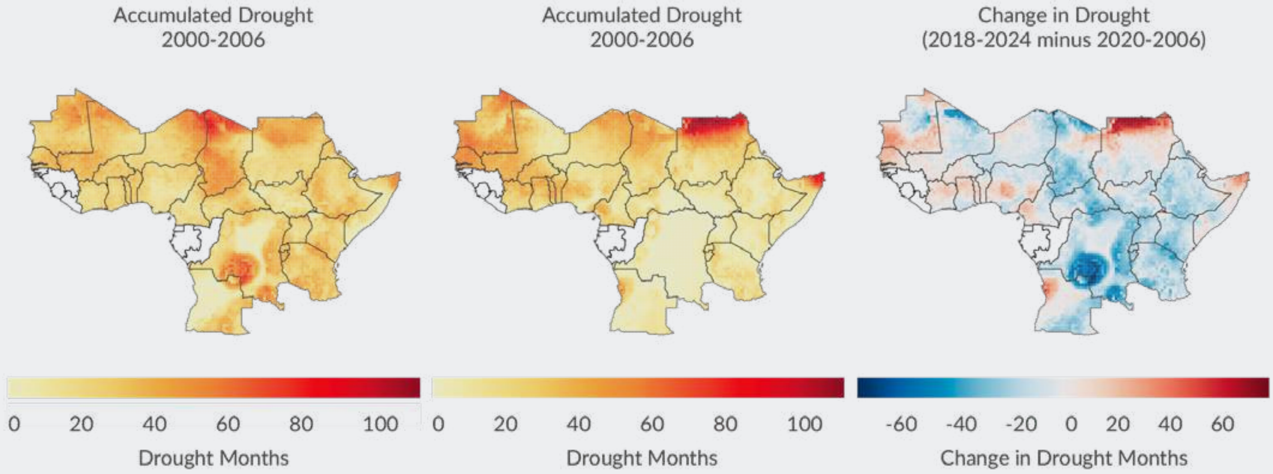

Figure 8: Accumulated number of drought months over the periods of 2000 to 2006 (left) and 2018 to 2024 (middle) as well as comparison between both periods (right). Drought months are defined as those with an SPEI of -1 or less.

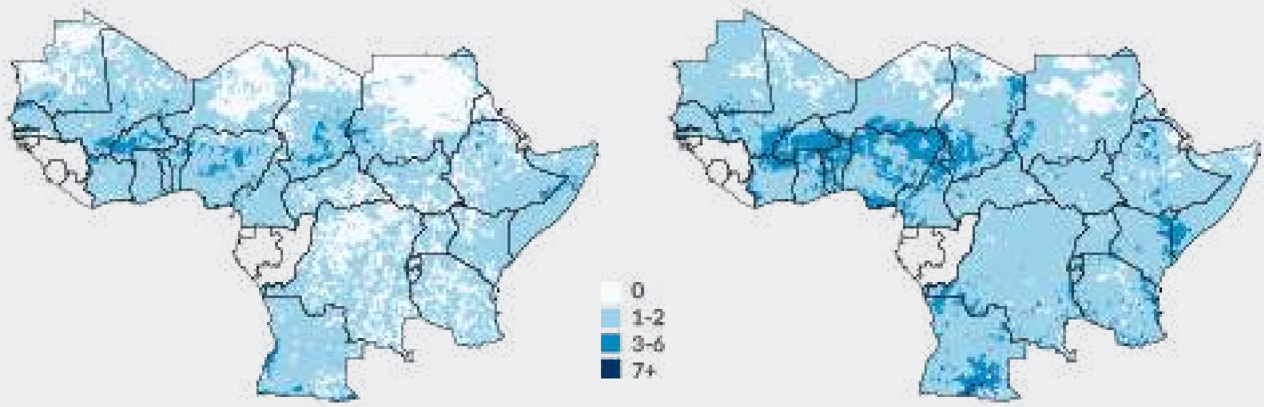

Figure 9: Average number of heavy precipitation days during peak precipitation month in the years 2000-2002 and 2022-2024.

Communities in these persistently arid regions are confronted with a new reality: drought conditions are no longer temporary events requiring short-term coping strategies and have become semi-permanent environmental conditions requiring either a complete shift in livelihoods or permanent migration. Traditional resilience mechanisms including livestock sales, kinship support networks, and inter-annual resource buffering become ineffective in the absence of recovery periods.

Concentrated precipitation

As the region has experienced increasing levels of drought, many areas also receive annual precipitation matching or exceeding historical averages, but this rainfall is concentrated in high-intensity events. Precipitation that previously occurred steadily, over multiple days, allowing for soil infiltration and aquifer recharge, now occurs as intense storms delivering the equivalent of previous total monthly rainfall within hours. Figure 9 documents this intensification, showing the number of average heavy precipitation days. in the high precipitation month between the years 2000 and 2002 (left) and between the years 2022 and 2024 (right). Areas that experienced a normal amount of heavy precipitation events in the earlier period now face them much more frequently.

Some noticeable changes in the number of heavy precipitation days during the high precipitation months are Burkina Faso, which experienced an average of 1.78 heavy precipitation days during the period 2000-2002 and 2.34 days during the period 2022-2024; the area around Lake Chad, which averaged 0.49 heavy precipitation days in the earlier period and 1.76 in the later period; and southern Somalia, which experienced 1.03 heavy precipitation days in the earlier period and 1.29 in the later period.

The increase in concentrated rainfall disrupts traditional agricultural practices that depend on predictability. For agricultural systems, the intense, heavy rainfall can lead to seeds being washed away or damaged. Pastoral systems also face flooding within pastures, followed by rapid desiccation.

As much of the region has experienced both increased drought during certain times of the year and extremely high precipitation during other times of the year, these areas with alternating extremes risk can experience “hydroclimatic whiplash,” a phenomenon characterized by an extended dry period that leads to soil hardening, followed by intense precipitation events. When rain falls on hardened soil, it tends to generate surface runoff rather than infiltrating the ground, which can lead to increased erosion, flash flooding, and reduced groundwater recharge.[47]

Changing vegetation

Despite conditions of increased drought and extreme precipitation, much of the region has seen an increase in average annual vegetation,[48] in recent years. Figure 10 shows the percentage change in NDVI in the peak NDVI months for each 0.1° grid cell in years 2018-2024 as compared to 2000-2006 average levels. Overall, the average NDVI in peak NDVI months during the period 2018-2024 was 4.48 per cent higher than during the 2000-2006 period. In the Liptako-Gourma region, which encompasses the border area between Mali, Niger, and Burkina Faso, NDVI in the 2018-2024 period was 17.42 per cent higher than in the 2000-2006 period. In northeast South Sudan, NDVI was 4.85 per cent higher in the later period. Conversely, central Nigeria and southern Somalia have experienced a decrease in average NDVI between the two periods of 4.20 per cent and 2.54 per cent, respectively.

Although the region has experienced an increase in NDVI in the peak NDVI months in recent years, Figure 11's phenological analysis reveals that peak vegetation is now out of sync with traditional agricultural and pastoral calendars in certain areas. This increases the risk of agricultural and/or pastoral activities being implemented at the wrong time. For instance, if farmers plant a certain crop at the same time each year, changing precipitation patterns may mean that their crops will face too much or too little precipitation at key stages in the development of the vegetation process, damaging the crops and lowering yields. Similarly, pastoralists may travel to a certain area during a particular period, expecting there to be vegetation and water for their livestock, but upon arriving find that these vital resources are insufficient, posing a risk to their animals, and thereby, their livelihoods. While Figure 10 indicates vegetation increases in the region, phenological shifts documented in Figure 11 may reflect multiple

47 Swain, D. L., Prein, A. F., Abatzoglou, J. T., Albano, C. M., Brunner, M., Diffenbaugh, N. S., . . . Touma, D. (2025). Hydroclimate volatility on a warming Earth. *Nat Rev Earth Environ,* 6, 35-50. doi:https://doi.org/10.1038/s43017-024-00624-z

48 As measured by the Normalized Difference Vegetation Index (NDVI).

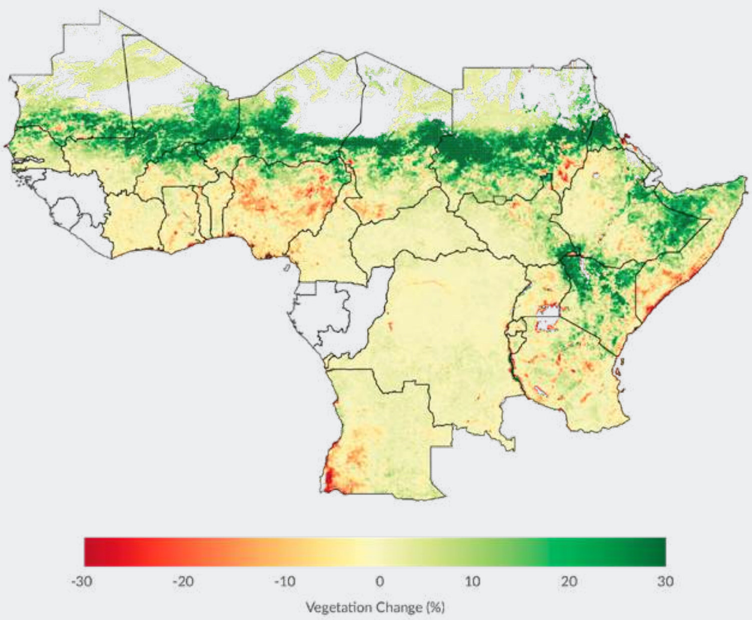

Figure 10: Differences in average NDVI indices over the periods of 2018 to 2024 and of 2000 to 2006.

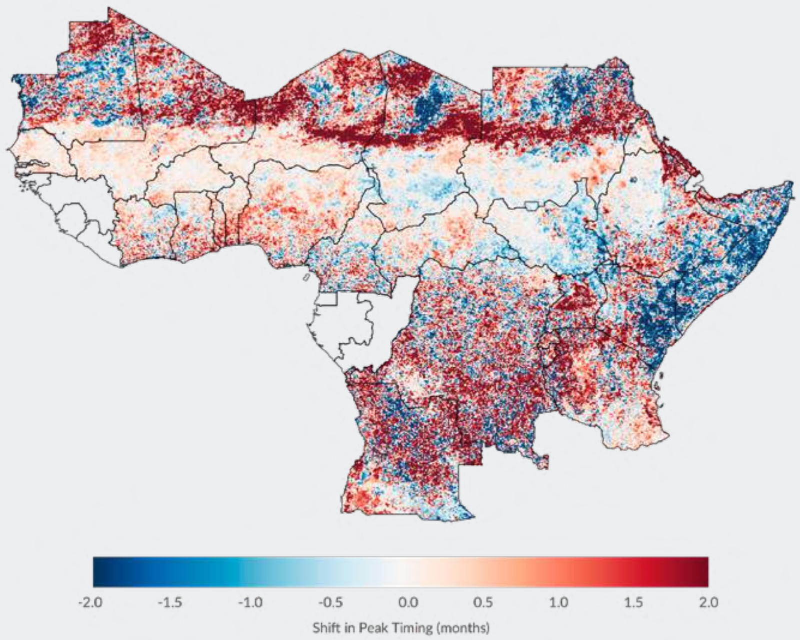

Figure 11: Phenological shift - change in peak vegetation timing (2018-2024 vs 2000-2006).

factors beyond precipitation changes. Agricultural expansion, changing crop varieties, urbanization, and shifts from pastoral to agricultural land use could all alter peak vegetation timing. For instance, replacing natural vegetation with crops would lead to peaks in vegetation cover aligning with cropping seasons rather than natural rainfall patterns. Areas showing dramatic changes over time may indicate land use conversion rather than, or in addition to, climate-driven ecosystem changes.

BOX 3: Lake Chad: Conflict in a changing environment

The Lake Chad region, encompassing parts of Nigeria, Chad, Niger, and Cameroon, has become a hotspot for violence and instability. The crisis in this area is driven by a combination of factors, including the rise of extremist groups such as Boko Haram and the Islamic State West Africa Province (ISWAP), ethnic tensions, poor resource management, and environmental changes.

The origins of Boko Haram can be traced back to the early 2000s when it emerged as an Islamist sect in northeastern Nigeria. Boko Haram has drawn much of its membership from Kanuri fishermen and traders, many of whom lost their traditional livelihoods as Lake Chad shrank due to climate change and water mismanagement. Economic hardship and political marginalization made these communities particularly vulnerable to Boko Haram's recruitment efforts. The group exploited local grievances, promising financial incentives and a sense of purpose to disillusioned youths. This is exemplified by 16 per cent of survey respondents in northeast Nigeria reporting that they knew someone who joined Boko Haram because of challenges relating to climate change.[49]

In 2016, Boko Haram splintered following leadership disputes, leading to the emergence of the Islamic State West Africa Province (ISWAP). While Boko Haram continued its brutal tactics, ISWAP sought to portray itself as a more strategic and governance-oriented group. ISWAP initially gained support by presenting itself as less indiscriminate in its violence. However, as both factions competed for control over resources, recruitment, and territory, they began engaging in direct conflict. Clashes between Boko Haram and ISWAP have further deepened the region's insecurity.

49 United Nations Institute for Disarmament Research. (2024). *Climate Change is Driving People into Armed Groups*. United Nations Institute for Disarmament Research.

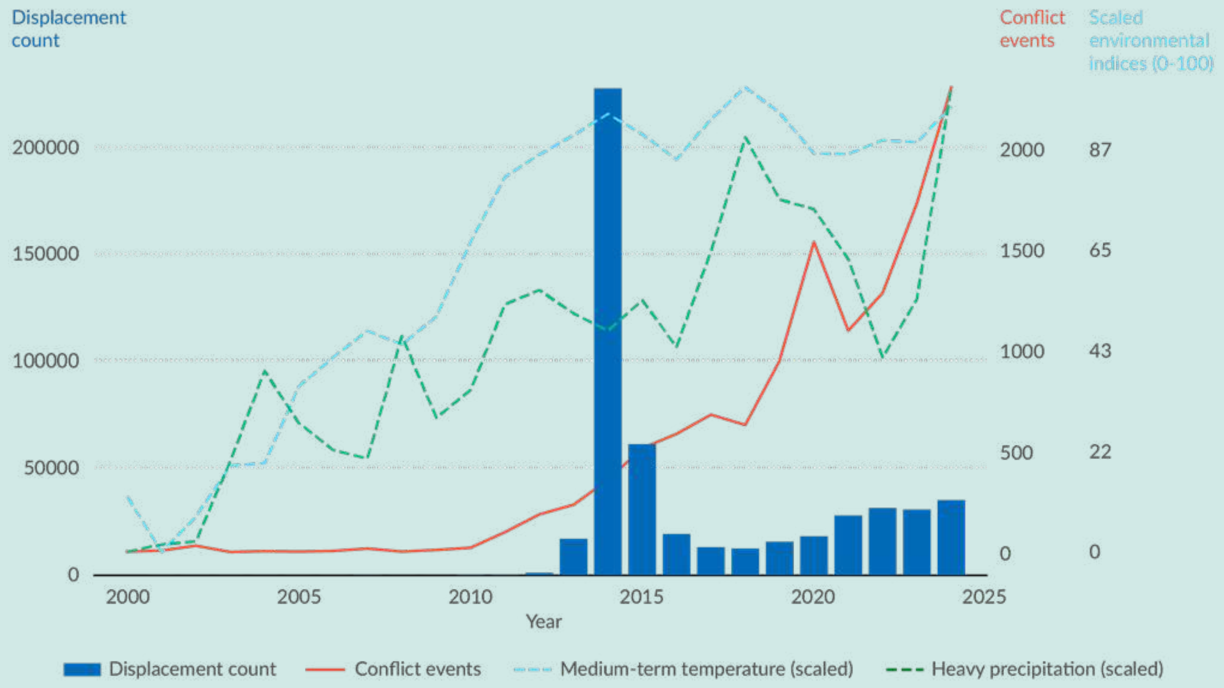

Figure 12: Number of conflict events (red), medium temperature (light blue), heavy precipitation (green) and forced displacement counts (blue bar chart) for the lake Chad region from 2000 to 2024.

In Figure 12, the bar plot below shows the annual levels of cross-border displacement, while the levels of conflict events, medium-term temperature and heavy precipitation days are depicted in the blue, red and green lines respectively. The grey bars show that there was very little cross-border displacement prior to 2013, but this increased to over 200,000 people in 2014, coinciding with the expansion of Boko Haram. Cross-border displacement has dropped since then but has risen slightly in recent years. Since 2000, the levels of conflict events, medium-term temperature and heavy precipitation have all trended upward.

2.3 Interlinkages between environmental stressors

The temperature and precipitation changes detailed in the two previous sections affect populations through various channels. Especially in regions where livelihoods depend heavily on rain-fed agriculture, as is the case in most of our study region, environmental stressors can trigger sequential impacts that subsequently contribute to displacement.

Most rural households in the region practice smallholder farming and pastoralism. These systems have historically adapted to variable conditions, but the magnitude of current changes, as documented in Chapters 2.1 and 2.2, increasingly exceeds traditional coping capacities. Nearby urban populations depend on rural production through market chains that connect rural producers to urban consumers.

As explained above, rising temperatures and shifting precipitation patterns affect agricultural output. Crop yields decrease when temperatures exceed optimal ranges for photosynthesis and grain formation. Altered rainfall timing disrupts traditional planting and harvesting cycles which normally follow the rainy season. Particularly, in the early stages of the planting season, high temperatures and the lack of precipitation, or abnormally high precipitation, have a lasting impact on the plants and later yields.

For pastoral systems, these changes are observed in reduced pasture quality and changes in water availability, as well as reduced dairy production. Traditional routes taken by pastoralists become less viable when the expected resources fail to materialize consistently over time and in known locations.

Reduced agricultural productivity affects food security in several ways. Rural households face direct shortfalls in their consumption when yields decline. Market systems experience disruptions as reduced volumes lead to higher transaction costs per unit and increased price volatility, making trade less predictable and profitable. As a consequence, urban consumers face reduced availability and higher prices for basic food items. When production shortfalls occur across multiple areas simultaneously, they can overwhelm traditional support mechanisms such as family assistance and local food sharing arrangements.

Sustained climate-induced stress can intensify competition for resources between different traditional user groups. Farmers and herders may find themselves competing for the same land and water resources as environmental conditions shift. Historical resource-sharing arrangements come under pressure when the availability of resources declines below critical thresholds. In areas with weak governance or pre-existing social divisions, such competition for resources can lead to escalating tensions.

Therefore, climate risks and conflict dynamics reinforce one another, with flooding, drought and desertification contributing to competition over land and water, exacerbating existing livelihood stresses, and intensifying conflict over scarce resources. In turn, insecurity and the presence of non-state armed groups restrict safe access to farmlands, grazing areas and markets, limiting households' ability to recover from climate shocks. In many conflict-affected areas, people already displaced by violence are repeatedly exposed to floods and heatwaves, further undermining their resilience and complicating efforts to support safe returns or local integration, often leading to cross-border displacement.

2.4 Displacement trends across the region

This report uses forced displacement data from UNHCR's Population Registration and Identity Management Eco-System (PRIMES) database. PRIMES records each individual who has been registered as a refugee or an asylum-seeker by UNHCR after crossing an international border. The report therefore focuses on people displaced beyond their own country. Data limitations curtail the opportunity to include internally displaced people (IDPs), granular data is rarely available for such populations and the population estimates are often based on relatively infrequent surveys which do not allow the production of monthly figures at the sub-national geo-spatial resolution required to place individuals into specific grid cells by their place of origin.

Displacement over time

Between January 2000 and September 2025, the region saw a number of monthly peaks in forced displacement levels corresponding to major events as depicted in Figure 13.

The intensity of these surges has increased in more recent years and the geographical distribution of displacement has undergone a substantial transformation between the earlier and later years of the study period. Through 2010, cross-border displacement was relatively low. There were only a few outbreaks of conflict events including the crisis in Darfur in 2003, the civil war in Somalia in 2009, and the civil war in Côte d'Ivoire in 2010, which contributed to spikes in forced displacement. Notably, this decade saw lasting peace resolutions to long-running conflicts in Angola in 2002, where a civil war

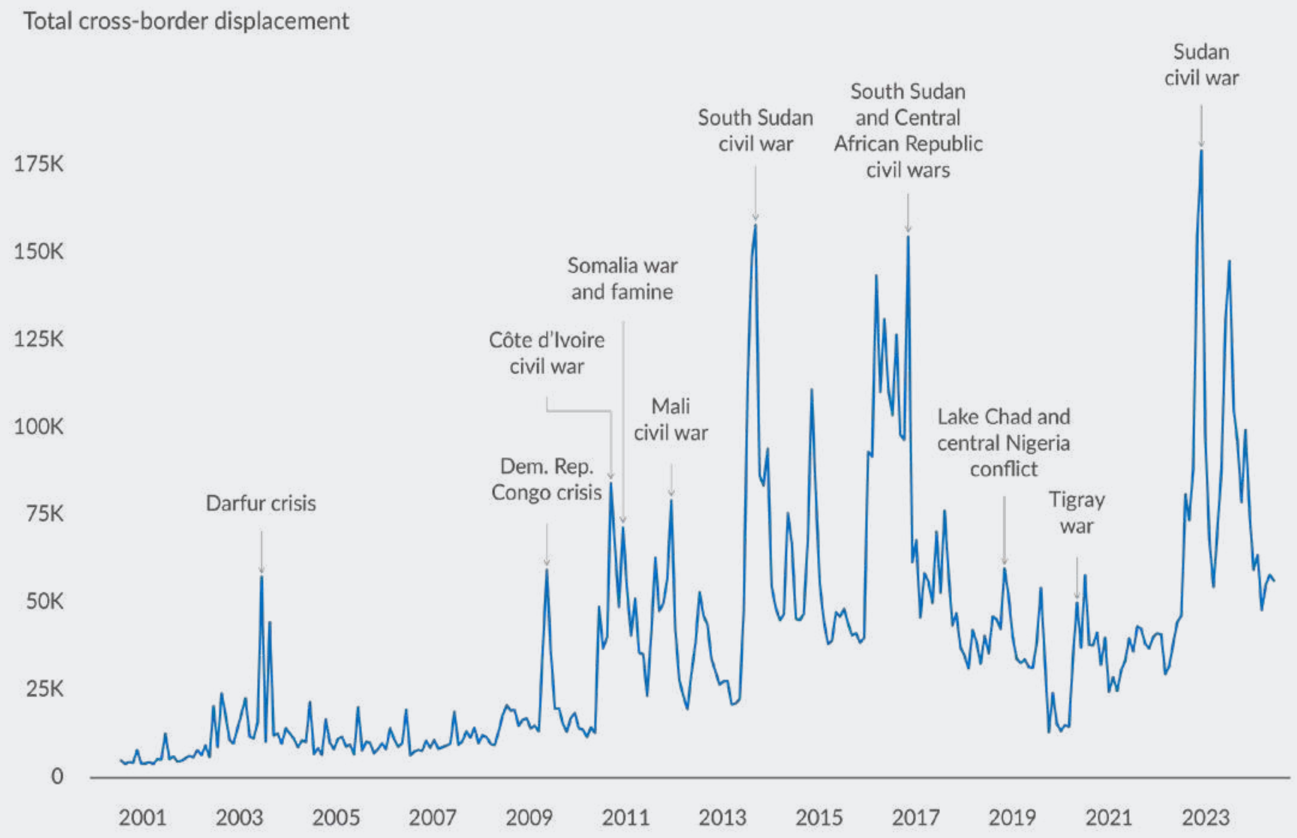

Figure 13: Total monthly cross-border displacement from East-, Central-, and West-African countries, January 2000 to September 2025. Figure 13 presents the stark reality of escalating cross-border forced displacement across East, Central, and West Africa. The figure shows a rising trend in cross-border forced displacement with many sudden surges, mainly triggered by the outbreak of conflict events.

was fought since 1975, and in Burundi in 2005, where a civil war was fought since 1993. Additionally, the Second Ivoirian Civil War, which broke out in late-2010, was resolved by mid-2011. Since 2011, there has been an escalation of conflicts across much of this region, which have led to large-scale surges in cross-border displacement. In addition to the continuation of civil war in Somalia, civil wars broke out in Mali and the Central African Republic in 2012, and southwest Cameroon in 2016, all of which continue to the present. Civil wars in Ethiopia (2020 – 2022) and South Sudan (2014 – 2020) ended in peace deals, but there is still a risk of conflict flaring up again in these countries. Extremist groups such as Al Shabaab in Somalia, Jama'at Nasr al-Islam wal-Muslimin (JNIM) in the Sahel, and Boko Haram and ISIS in the Lake Chad area continue to exploit weak public institutions and cause conflict in the region. Finally, the outbreak of conflict in Sudan in 2023 and the rising intensity of conflict in the Democratic Republic of the Congo in 2025 have also led to significant cross-border displacement.

Figure 14 shows the intensity of displacement from grid cells between the earlier years of our analysis, 2000 to 2006, and the later years, 2018 to 2024. There are small clusters of grid cells that experienced higher displacement in the earlier period than the later period; these include the Casamance area of

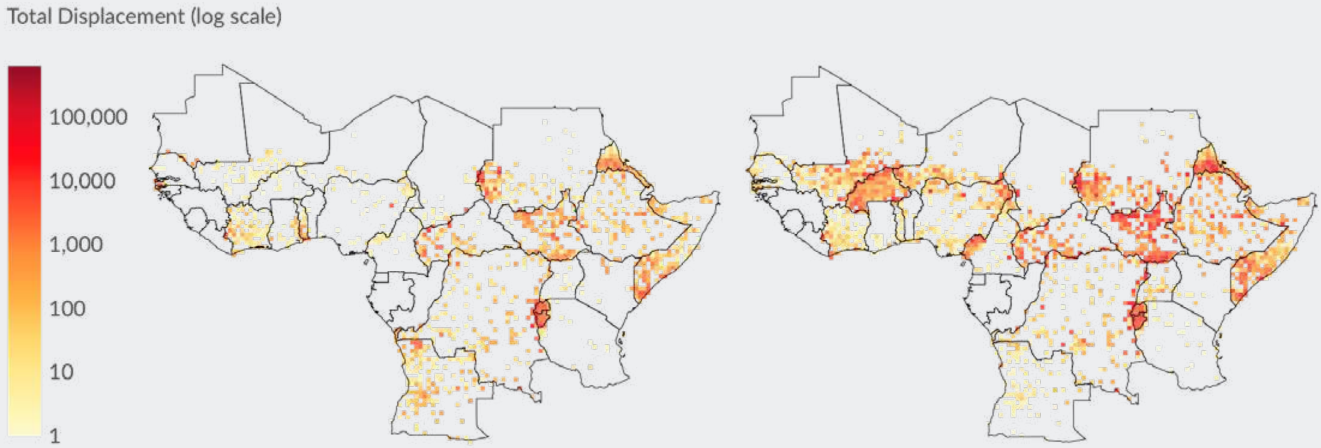

Figure 14: Cumulative cross-border displacement at the 0.5-degree grid level for the periods 2000 to 2006 and 2018 to 2024 (log scale) by area of origin.

southern Senegal, southern Togo, and Angola. But in general, the grid cells which have experienced displacement are a darker colour in the 2018-2024 map, demonstrating higher levels of displacement in the later period owing to the development of conflicts detailed above. Interestingly, areas with high displacement in the later period, such as Liptako-Gourma, southwest Cameroon, Lake Chad, western Central African Republic, eastern South Sudan, Eritrea, and southern Somalia, all experienced some displacement in the earlier period. This suggests high levels of displacement often occur in areas where at least some displacement had previously occurred.

2.5 Climate trends and displacement

In light of the changing climate conditions and the increased incidence of forced displacement in recent years, we examined the relationship between these two trends. As discussed in Chapter 1, the linkage between slow-onset climate change and displacement is indirect and complex. As this project focuses on a large geographical area, it would be impossible to find a single statistic which measures the uniform relationship between a climate variable and displacement. For instance, rising temperatures in one area might have no impact on livelihoods and the risk of people becoming displaced, but may have a significant impact in another areas. Therefore, the following sections focus on the localized relationship between temperature change and displacement and drought and displacement. We also observed increased seasonal variation in displacement in recent years, which may indicate increased displacement due to climate conditions at certain times of the year, such as displacement at the end of the dry season due to diminishing crop stocks resulting from poor yields during the growing season. However, these trends require further analysis to establish a more definitive relationship between climate change and displacement patterns.

Displacement and temperature

There is some spatial correspondence between temperature change and significant humanitarian crises in some areas, though this relationship is not universal. The circles in Figure 15 represent the level of displacement from the grid cells that have experienced any displacement outflows since 2000. The colour scale shows the average 2020-2024 monthly temperatures change by grid cell against

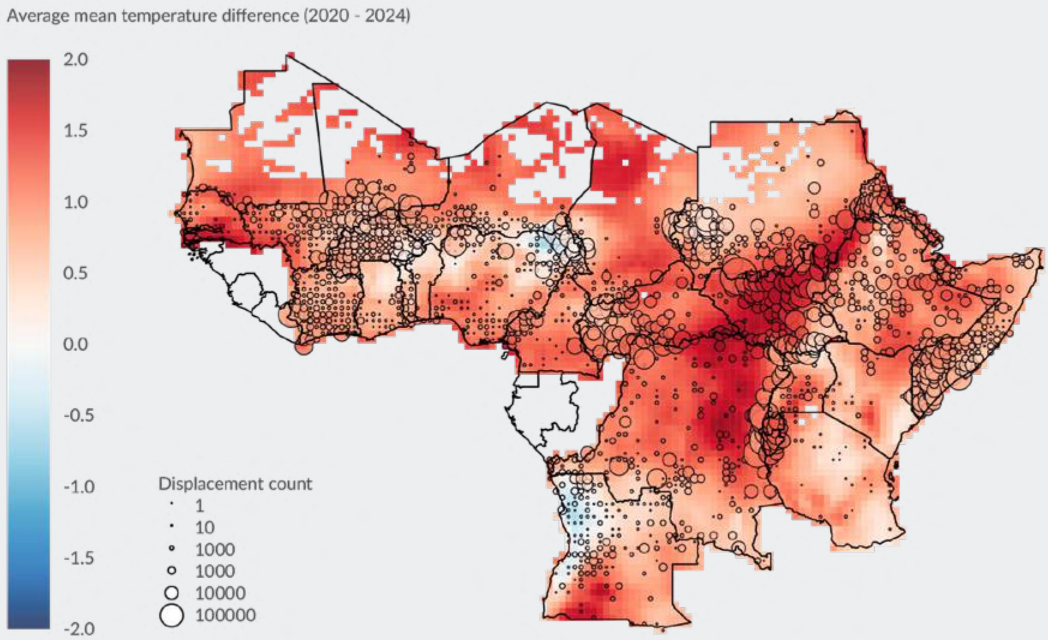

Figure 15: Geographical distribution of temperature anomalies and displacement across the study region – comparison of 2020-2024 average temperatures with baseline period (1980-1990) and cross-border displacement between 2000 and 2024. Only grids with at least a population of 50 people are colored.

the average temperatures during the baseline period of 1980-1990. The average monthly temperature difference from the baseline for each grid cell in the 2020-2024 period was +0.95°C. The border between Sudan and South Sudan, which appears prominently in the warmest zones of our temperature mapping, with an average temperature difference of +1.37°C, has been among the largest sources of forced displacement in our study region, producing 2.5 million refugees since 2000. Some other areas of notice in terms of temperature rise and forced displacement are Eritrea, which has experienced an average temperature difference of +1.04°C and over 600,000 refugee outflows; and Central African Republic, which has experienced an average temperature difference of +1.13°C and almost 1 million refugee outflows.

Interestingly, the Liptako-Gourma region, Lake Chad and Darfur region in western Sudan have all experienced significant displacement but did not experience particularly high temperatures during the period of 2000 to 2024 as compared to the baseline. The average monthly temperature differences in these areas were +0.79°C, +0.44°C, and +0.51°C, respectively. These areas, which have experienced high levels of forced displacement, have therefore seen temperatures that are higher than the baseline, but less than the average temperature increase for the whole project region. This finding suggests that while temperature change may contribute to displacement, other factors such as political instability, conflict, and socio-economic conditions likely play a more direct role in driving forced displacement in these specific regions.

Displacement and drought

As mentioned in Chapter 2.2, the region of study has experienced a general increase in drought conditions since 2000. Figure 16 below shows the correlation index of accumulated drought[50] with logged monthly displacement for each grid cell over the period January 2000 to September 2025. Similar to Figure 15 above, the bubble size represents the total displacement from each grid cell since 2000.

Overall, the average correlation between accumulated drought and monthly logged displacement among the grid cells that have experienced some displacement is 0.12, indicating a weak signal. But certain clusters of grid cells show a high correlation between the drought measurements and logged displacement. For instance, grid cells in the Liptako-Gourma region have an average correlation of 0.38 between accumulated drought and monthly logged displacement. When weighting this correlation average by total displacement from the grid cells in Liptako-Gourma, the coefficient increases to 0.44, demonstrating that grid cells with higher displacement have generally experienced more severe drought conditions. Similarly, in southwest Cameroon, where a civil war has been ongoing since 2016, the correlation between accumulated drought and logged monthly displacement is 0.28. When weighted by displacement, the coefficient rises to 0.55. In the Lake Chad region, grid cells have a correlation of 0.31 between accumulated drought and logged displacement, and weighting by displacement yields a coefficient of 0.68. These findings suggest that while the overall correlation between drought and displacement may be weak across the entire study area, specific regions experiencing high levels of displacement tend to show a stronger relationship between drought severity and forced displacement. It is important to note that some areas with high displacement have a negative correlation between drought and logged displacement. The most notable example is western Sudan, where the Darfur region has experienced waves of conflict, particularly during the crisis in 2003-2004 and since the civil war broke out in 2023. The blue grid cells in Darfur indicate a negative correlation between drought and logged displacement, with an average correlation of -0.11 in this area. This finding suggests that the relatively

50 Accumulated drought measures the sum of inversed drought index, SPEI, over the previous 72 months (6 years).

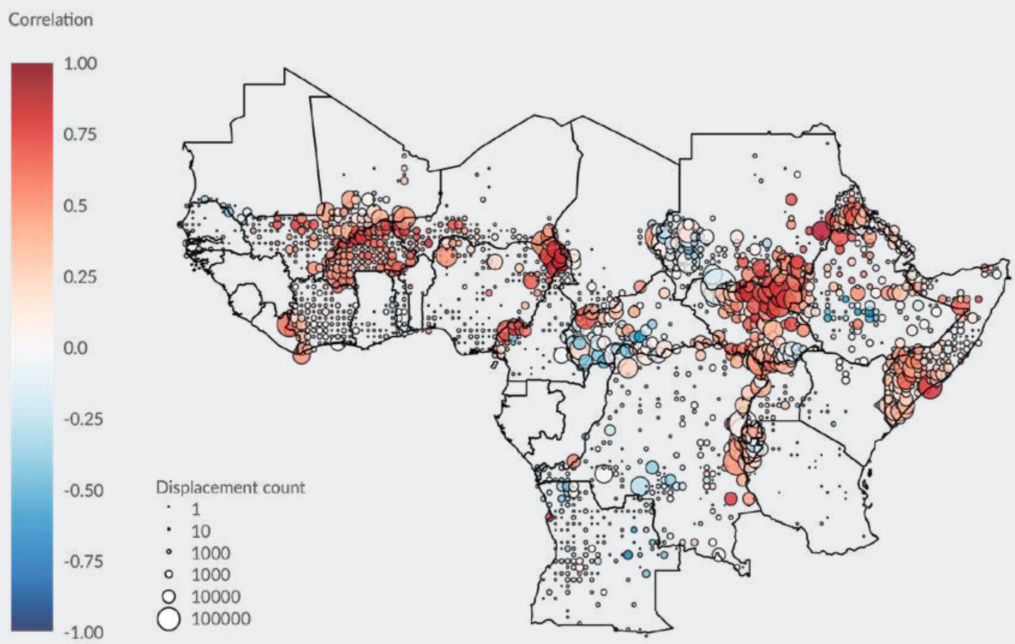

Figure 16: Correlation coefficient of accumulated drought and logged monthly displacement by grid cell.

favorable climate conditions in Darfur may actually be a source of conflict, as people compete over fertile lands.[51]

Seasonality

Figure 17 illustrates the average monthly displacement from all grid cells, grouped into 5-year periods, showing the seasonal dynamics that underlie cross-border displacement. Based on the increased intensity of displacement events since 2010, it is unsurprising that the lines for the 5-year periods 2000-2004 and 2005-2009 have lower average monthly displacement than the lines for the later periods. It is interesting that not only has displacement increased in the recent periods, but that the seasonal variation of displacement has also increased. In the early periods, there was very little difference in average displacement between peak and low months. However, starting from the period 2010-2014, there have been large seasonal swings in the average number of displaced persons. As discussed above, most spikes in displacement are triggered by conflict events, which may be influenced by seasonal factors. It is possible that these conflict events are partially driven by increased competition for resources due to the impacts of climate change, which can be amplified at certain times of the year. For instance, reduced crop yields resulting from rising temperatures, drought conditions, and/or erratic precipitation can lower food stocks and trigger tensions or conflicts, particularly during the late dry season when food scarcity is at its peak. Such dynamics may increase the likelihood of displacement during specific periods of the year, leading to seasonally concentrated displacement patterns. Further investigation into the growing seasonality of displacement trends could provide greater insight into the complex relationship between climate change and forced displacement, making it an area that warrants additional research.

51 Olsson, O., & Siba, E. (2013). Ethnic cleansing or resource struggle in Darfur? An empirical analysis. *Journal of Development Economics*, 103, 299-312. doi:https://doi.org/10.1016/j.jdeveco.2013.02.004

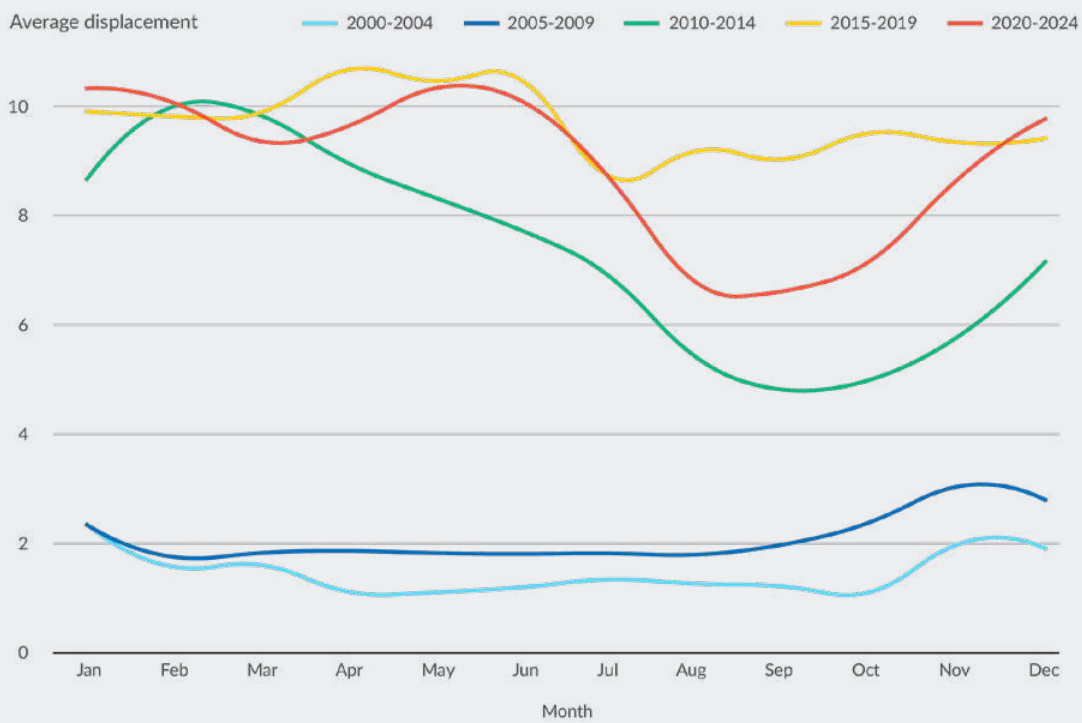

Figure 17: Seasonality patterns in mean displacement over five-year increments.

© UNHCR/Eugene Sibomana

CHAPTER 3: Understanding the patterns

This chapter presents the methodological framework underpinning the CLIFDEW-GRID displacement prediction model. Acknowledging the complex relationship between climate change and forced displacement, we have developed a systematic approach to capture these interactions through intermediate modelling steps. These steps involve predicting specific feature variables that contribute to estimating the risk of forced displacement from individual grid cells. By breaking down the modelling process into smaller, interconnected components, the CLIFDEW-GRID model aims to provide a more nuanced understanding of the various factors that influence displacement patterns in the context of a changing climate.

Although previous sections focused on potential interplay between climate change and displacement, we avoid drawing direct causal links between climate conditions and forced displacement. Instead, our approach recognizes that slow-onset climate events potentially contribute to displacement through indirect pathways, interacting with social, economic, and political factors. For instance, climate stress affects agricultural yields and pastoral systems, which impacts food security, which in turn increases population vulnerability. This vulnerability, when combined with pre-existing tensions along ethnic lines or other grievances, can escalate into conflict and ultimately forced displacement.

To model this indirect linkage, we require data to serve as indicators at each stage. Climate data, such as historical temperature, precipitation, drought, and vegetation index measurements, are readily accessible. These datasets provide essential information on the changing environmental conditions that may influence factors like resource availability and agricultural productivity. In addition to climate data, we utilize geo-coded point locations of conflict events from the Armed Conflict Location & Event Data Project (ACLED). This dataset offers valuable insights into the spatial distribution and intensity of conflicts, which can be a significant driver of forced displacement. By combining climate and conflict data, we can better understand the complex interplay between environmental factors, resource scarcity, and political instability, and how these elements contribute to displacement risk. The integration of these diverse datasets enables the CLIFDEW-GRID model to capture the multi-faceted nature of the climate-displacement relationship and provides more accurate predictions of forced displacement patterns.

However, there were no readily useable data for certain steps in our theoretical structure. Levels of forced displacement from a specific location are influenced by the population present in that location. As historical population data are only available annually, we developed a model to predict the monthly population in each grid cell. As an indicator of livelihoods, we chose food security as a key variable. Although historical data on food security is available through sources such as the Famine Early Warning Systems Network (FEWS NET), these data do not cover our entire region and do not extend far enough back in time for the timeline on which we train our models. To address this limitation, we developed a model to predict the food security classification for each location, starting from the initial point of our model training. Finally, the raw cross-border refugee data used for this project were not allocated to the desired grid cells. Therefore, we developed a model to assign the refugee observations to the appropriate grid cells. By creating these intermediate models, we

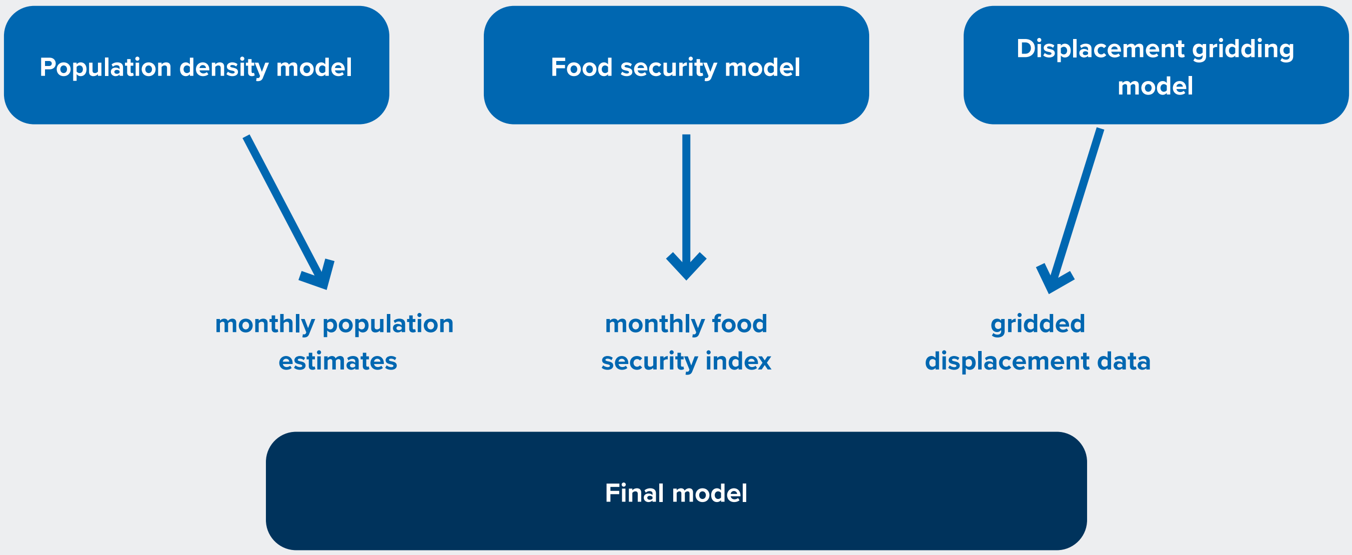

Figure 18. Overview of intermediate models and how they feed into the final model.

were able to fill critical data gaps and ensure that the CLIFDEW-GRID model has access to the necessary inputs to accurately predict forced displacement patterns in response to climate change and other relevant factors. In summary, to capture these complex pathways, we developed three intermediate models that provide monthly inputs to our final displacement prediction model:

- **Population Density Model:** This model predicts the monthly population in each grid cell, addressing the limitation of historical population data being available only annually. By estimating population at a higher temporal resolution, we can better account for the influence of population dynamics on forced displacement levels.
- **Food Security Model:** To incorporate livelihoods as a key factor in displacement risk, this model predicts the food security classification for each location. It extends the historical food security data from sources like FEWS NET, enabling us to cover our entire region of interest and the full timeline required for training our displacement prediction model.
- **Displacement Gridding Model:** As the raw cross-border refugee data were not initially allocated to the desired grid cells, this model assigns refugee observations to the appropriate grid cells. This intermediate model ensures that the displacement data is spatially aligned with the other input variables, facilitating the accurate prediction of forced displacement patterns.
  These intermediate models play a crucial role in the CLIFDEW-GRID framework by filling data gaps, increasing the temporal and spatial resolution of key variables, and ensuring the consistency and compatibility of the input data.

The population density, food security, and gridded cross-border displacement variables produced through the intermediate models, along with additional variables measuring climate, geography, demographics, wellbeing, governance, and conflict[53] are used as inputs to the model that predicts cross-border displacement from the 0.5° grid cells. The model generates predictions for 1, 3, and 6 months into the future, providing valuable information for early warning and preparedness efforts.

To address the challenge of covering such a wide area with diverse dynamics, ranging from regions experiencing minimal displacement to those facing highly complex interactions between slow-onset climate change, conflict, and economic shocks, we employ an ensemble modeling approach. Using granular 0.5° grid-level data allows the ensemble to identify fine-scale dynamics that analysis with country-level or regional data might overlook.

The ensemble incorporates several models, including tree-based methods, which are able to capture non-linear relationships and deep neural networks, designed for complex spatiotemporal dependencies. By combining these methods, we leverage the strengths of each. The simpler models provide insights into common patterns, while deep learning architectures identify more intricate localized dynamics.

3.1 Population model

Overview

Predicting forced displacement outflows from a geographical area requires knowing the number of people exposed to conditions that lead to forced displacement. While modelled population estimates at very high resolution (100 - 1000 meters) are freely available through sources such as WorldPop and LandScan, these data only estimate the annual population at these geographical points. As this project is making monthly predictions, monthly population estimates are required for each of the

53 See list of variables in annex/website

grid cells. Research has shown the viability of using nighttime lights to predict population changes.[54] [55] Therefore, we use monthly nightlight radiance data to enhance our estimations of monthly population trends between known annual population figures.

Data

Annual population data

The population data used for this project are LandScan modelled population count data, which has a resolution of 1000 meters, and are available from 2000 to 2024.

Nightlight data

The nightlight data used for this model are satellite data from two sources, the Defense Meteorological Satellite Program (DMSP) – Operational Linescan System (OLS) Nighttime Lights Time Series[56] and the Visible Infrared Imaging Radiometer Suite (VIIRS), specifically VIIRS/NPP Gap-Filled Lunar BRDF-Adjusted Nighttime Lights Daily L3 Global 500m Linear.[57] The DMSP – OLS Nighttime Lights offers monthly data at a resolution 30 arc seconds (approximately 1000 meters) from a series of different satellites from 1992 through 2014. This project uses data from the F18 satellite for the years 2010 – 2013. Monthly data were extracted from VIIRS at native resolution of 500 meters for nightlight data from 2014 to near present.

Processes

First, the point locations of the population and nightlight data, are placed within the grids defined by the project. The annual population figures from points within each grid cell are then summed to find the total annual population within each individual 0.1° grid cell for 2000 to 2024. The monthly nightlight data from points within each grid cell are averaged to find the aggregate monthly nightlight for each grid cell from 2000 to near present. This gives each of the grid cells annual population values from 2000 to 2024 and monthly values of nightlight radiance from January 2000 to near present.

54 Archila Bustos MF, Hall O, Andersson M. Nighttime lights and population changes in Europe 1992-2012. Ambio. 2015 Nov;44(7):653-65. doi: 10.1007/s13280-015-0646-8. Epub 2015 Mar 14. PMID: 25773533; PMCID: PMC4591227.

55 Nawaj Sarif and Archana K. Roy, "Measuring Urban Shrinkage in India Using Night-Light Data from DMSP-OLS and VIIRS-NPP Satellite Sensors," *Cities* 152 (2024): 105176, https://doi.org/10.1016/j.cities.2024.105176

56 Image and data processing by Earth Observation Group, Payne Institute for Public Policy, Colorado School of Mines. DMSP data collected by US Air Force Weather Agency.

57 C. D. Elvidge, M. Zhizhin, T. Ghosh, F-C. Hsu, "Annual time series of global VIIRS nighttime lights derived from monthly averages: 2012 to 2019", *Remote Sensing*, 2021, 13(5), 922.

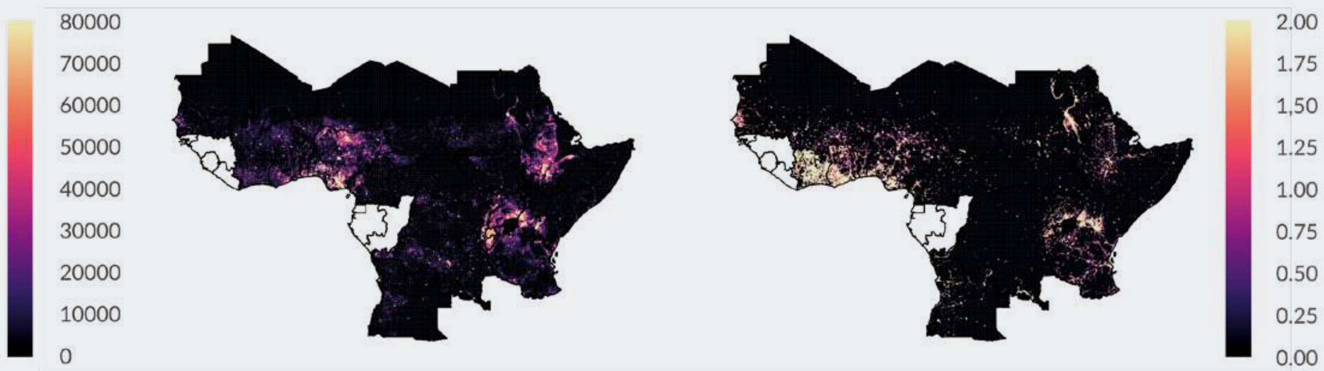

Figure 19: Gridding LandScan population figures in year 2020 (left), gridded VIIRS nightlight radiance in May 2020 (right).

The gridded LandScan population data have two issues; firstly, they only offer population estimates up to 2024, and secondly, there are no monthly indicators to build the estimates on. To estimate the data beyond 2024, recent trends in the population figure of each grid cell are projected forwards. Each grid cell uses the most recent years of data to fit a linear trend for each cell calculating a best-fit line to predict the population in each cell for 2025.

The LandScan annual population value for each grid cell is then assigned to December of the corresponding year, on the assumption that the annual estimate represents the end-of-year population. A smoothing technique was then applied to interpolate monthly population values between these December anchor points. This smoothing produces monthly estimates for each grid cell that follow gradual trends and avoid abrupt jumps in the rate of population change from one December to the next.

Once we have the smoothed population data, which gives the monthly population predictions for each grid cell, we calculated the average population and nightlight radiance for each grid cell in each year. After calculating each grid cell's annual average nightlight and the average of the smoothed monthly population predictions, the deviation for each monthly nightlight radiance value from the annual mean was calculated by dividing each monthly nightlight value by the mean nightlight radiance for that year (1). Similarly, the deviation for each monthly population value from the annual mean was calculated by dividing each monthly smoothed population value by the mean of the population values for that year (2). These deviation ratios showed how much brighter and more populated a given month is relative to that year's average level for the grid cell.

(1) $$monthly\ nighlight\ deviation = \frac{monthly\ nighlight\ deviation}{average\ nightlight\ for\ that\ year}$$

(2) $$monthly\ population\ deviation = \frac{smoothed\ LandScan\ value\ in\ month}{average\ population\ value\ for\ that\ year}$$

Next, for each monthly record, the difference is found between the nightlight deviation from the population deviation (3).

(3) $$difference\ in\ deviation = monthly\ nightlight\ deviation - monthly\ population\ deviation$$

The difference in deviation measures how much the monthly nightlight signal changed relative to its annual mean compared to how much the smoothed monthly population changed relative to the annual population mean, for the same month.

The population difference was then calculated, which is the difference between the smoothed monthly population value and the average population value for that year (4). Multiplying the difference in deviation and the population difference (5) produced a correction term, which indicates how much the smoothed population should be adjusted based on nightlight signals. Finally, this correction was added to the smoothed population (6) to yield a predicted population value that reflects monthly changes informed by relative nightlight changes.

(4) $$population\ difference = smoothed\ monthly\ LandScan - average\ population\ value\ for\ that\ year$$

(5) $$corrected\ difference = difference\ in\ deviation \times population\ difference$$

(6) $$predicted\ population = smoothed\ monthly\ LandScan + corrected\ difference$$

3.2 Food security model

Overview

Adverse climate conditions can contribute to situations of food insecurity along with other factors, such as poor governance, food prices and conflict. If the food insecurity situation does not improve, it can be a factor in people's decision to leave their homes. Food security can therefore indicate which people have been affected by adverse climate conditions caused by slow-onset climate change and those that may then subsequently be forced to flee. By using food security as a proxy for estimates of climate conditions, the power of climate variables in predicting forced displacement is improved as they would otherwise be less significant than other variables such as conflict and state fragility if they were used directly as feature variables in a model predicting forced displacement. Regularly updated food security data are available from sources such as the Famine Early Warning Systems Network (FEWS NET) for larger geographical zones from 2011 onwards in 3–4-months intervals. To improve the granularity of the data and make it useable as a variable for predicting force displacement, a model was developed to predict the food security situation in each of the 0.1° grid cells on a monthly basis from January 2009 to near present.

Data

Food security data

Through its analysis of current situations and predictions of future food security situations, FEWS NET offers historical food security data every 3 or 4 months from 2011 to the near present for certain sub-national areas, with predictions up to 6 months ahead. The FEWS NET data are compliant with the Integrated Food Security Phase Classification (IPC) system of classifying the food security situation within an area. The classifications rank from 1 (minimal risk) to 5 (famine). These data are available for all areas within the focus countries except for Senegal, Côte d'Ivoire, Ghana, Togo, Benin, United Republic of Tanzania, and Eritrea. Figure 20 below shows the geographical distribution of food security classes in July 2024.[58]

58 IPC classifications, or phases, in order of severity: 1, minimal/ generally food secure; 2, stressed/ borderline food insecure; 3, crisis/ acute food and livelihood crisis; 4, emergency; 5, catastrophe/ famine.

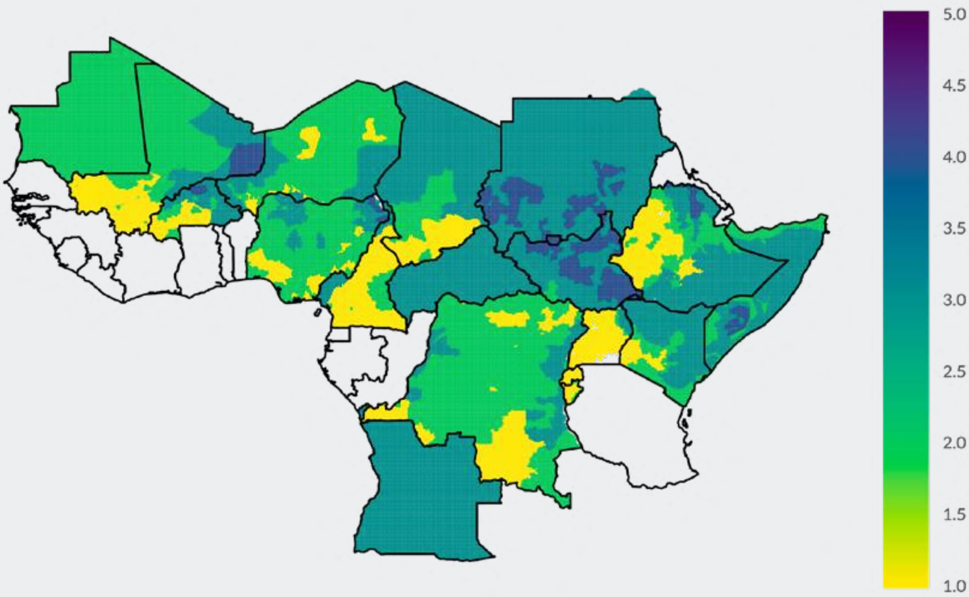

Figure 20: FEWS NET classifications for July 2024 within the project region.

Climate data

Appropriate climatic conditions are necessary for the development of crops and vegetation for pastoralism. Less appropriate climate conditions, such as those induced through climate change, can compromise the growth of crops and pastoral vegetation, which may lead to food insecurity among the local population. We therefore use several climate variables to develop a predictive model for the IPC food security classification of each grid cell in each month.[59]

Conflict data

To account for the potential link between armed conflict and food insecurity,[60] certain conflict variables were used, based on ACLED data as feature variables in this model predicting food security.[61]

Land use classification

Variables on the proportion of each grid cell's area which is of the different land-use classification based on Copernicus data. These variables are the proportion of each grid cell which are: bare area, cover flooded, cropland, grassland, shrubland, tree cover, urban, and water.

State fragility

To account for the fact that food insecurity may be a function of public mismanagement, instability, and even coordinated state repression, the fragility index from the Fragile States Index was included as a variable in predicting food security.

Child health

Food security classifications as classified by the IPC focus particular attention on child health and malnutrition.[62] In order to account for this, variables for infant mortality rate and prevalence of malnutrition are included in the model. Infant mortality rate counts the number of children per 10,000 which die before reaching their first birthday. Prevalence of malnutrition is the percentage of children under 5 that are malnourished. Both of these variables are extracted from the PRIO dataset, which offers data at the 0.5° grid cell level.

Processes

Because detailed food security data are only available from 2011 onward, a method was needed to estimate conditions for earlier years. A backcasting model was developed for this purpose. Instead of predicting the future, this model works backward to fill in earlier months. To prepare the data, the time order was reversed so that the most recent month came first, and earlier months followed. This reversal allowed a forecasting approach to be used in reverse, effectively estimating past conditions.

The data were then split into two sets:

- Training set – February 2014 to January 2024, used for the model to learn patterns.

59 Climate variables include: mean temperature difference, mean temperature difference over previous 12 months, low killing days, medium killing days, medium killing day difference over previous 12 months, medium term temperature difference, heatwave, heatwave current, mean precipitation difference over previous 12 months, heavy precipitation current, heavy precipitation accumulated, drought current, drought accumulated, heavy precipitation days in the last precipitation peak month, precipitation in the last precipitation peak month, precipitation in the month, as well as, 2, 3, 4 and 5 months preceding the last precipitation peak month, precipitation in the month three months preceding the last precipitation peak month, precipitation in the month four months preceding the last precipitation peak month, precipitation in the month five months preceding the last precipitation peak month, high temperature days in the last NDVI peak month, high temperature days in the month proceding the last NDVI peak month, high temperature days in the month two months preceding the last NDVI peak month, high temperature days in the month three months preceding the last NDVI peak month, high temperature days in the month four months preceding the last NDVI peak month, high temperature days in the month five months preceding, as well as, 2, 3, 4 and 5 months preceding the last NDVI peak month.

60 Cohen, M. J., & Pinstrup-Andersen, P. (1999). Food Security and Conflict. *Food, Nature and Culture,* 66(1), 375-416.

61 Conflict variables include: number of conflict events, number of conflict events in 50 km radius, number of conflict events involving a rebel group in 50 km radius, number of conflict events featuring state force against civilians in 50 km radius, number of conflict fatalities within 50 km radius, level of social tension.

62 *IPC Famine Fact Sheet.* (2025). Retrieved from Integrated Food Security Phase Classification: https://www.ipcinfo.org/famine-facts/

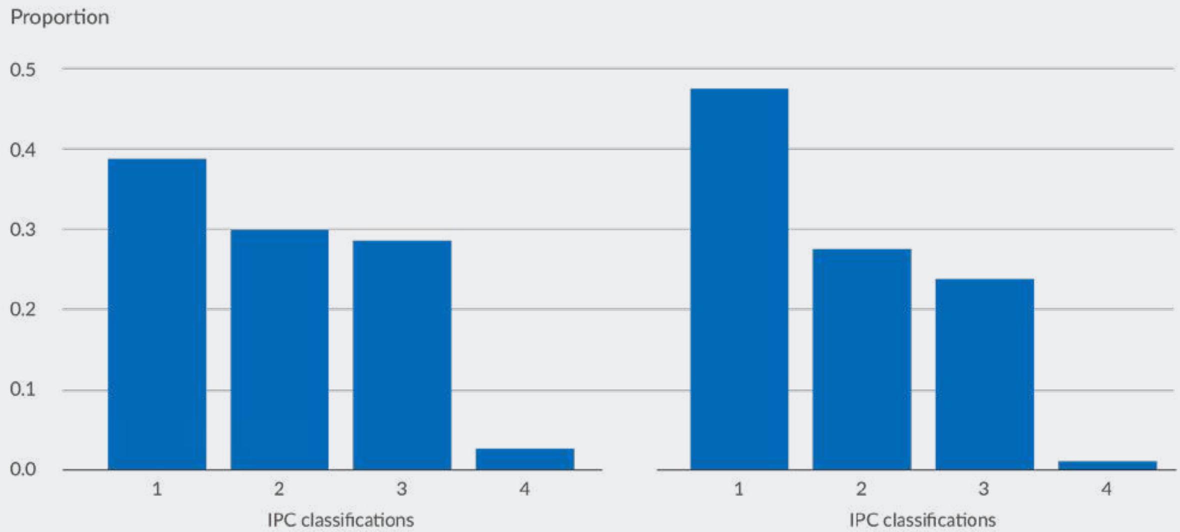

Figure 21: Distribution of food security classifications for training set (left) and test set (right)

- Test set – January 2011 to January 2014, used to check the model's accuracy.

Figure 21 shows the distribution of food security classes among the observations in the training and testing datasets used for developing the model. The plots show that there is an imbalance, with more instances having a classification of 1 (minimal/ no food security risk) and relatively few instances of classifications of 4 (emergency/ catastrophe/ famine). IPC classifies food security situations into 5 categories. But as the threshold for an area to be classified as experiencing famine, IPC classification of 5, is very high, we group categories 4 and 5 together. Both represent situations of extreme food insecurity.

To classify food security levels for earlier periods, a LightGBM machine-learning model was applied. This approach is well suited to identifying patterns and assigning each area to one of several food security categories. LightGBM is particularly effective because it can handle large, complex datasets, manage uneven data, and capture complex relationships between the feature variables used to predict our target variable, food security classification in this case, and the feature variable and target variable itself.

Results

The overall accuracy of the model in predicting values on the testing dataset was 0.94. By food security class, the model has an accuracy of 0.97 at predicting category 1 (minimal risk), an accuracy of 0.90 at predicting category 2 (stressed), 0.95 at predicting category 3 (emergency), and 0.86 at predicting category 4 (combined with category 5) (emergency/ famine/ catastrophe).

The model also allows us to see the features which have the most overall importance in predicting the food security classifications. The LightGBM algorithm is a tree-based ensemble method, so feature importance is calculated based on how often and how effectively a feature is used to split data across all trees in the ensemble—features that lead to larger reductions in loss (or higher information gain) are considered more important.

The feature importance analysis presented in figure 22 provides valuable insights into the key factors influencing food security in the study region. The findings highlight the complex interplay between socio-economic, environmental, and temporal factors in determining the vulnerability of populations to food insecurity. The high importance of the fragility index suggests that areas with weak governance, social instability, and limited institutional capacity are

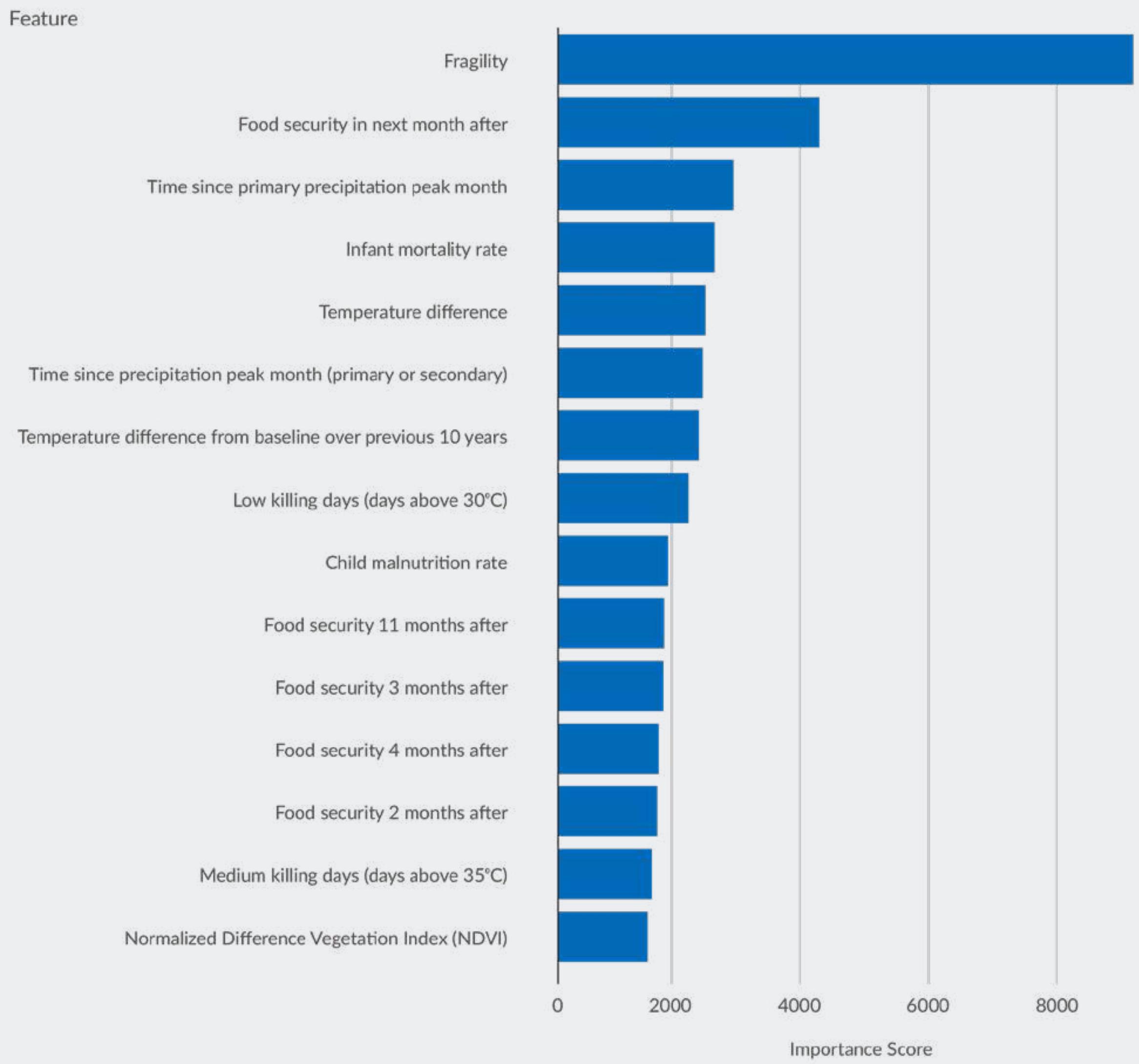

Figure 22: Importance of top 15 features

more susceptible to food insecurity. This underscores the need for targeted interventions and support in fragile contexts to build resilience and improve food security outcomes.

The strong influence of the previous month's food security classification on the current month's prediction is consistent with the persistent nature of food insecurity. This temporal dependency indicates that food insecurity tends to be a chronic issue rather than a transient one, requiring sustained efforts to address the underlying drivers and break the cycle of vulnerability.

The significance of the time since the primary precipitation peak month highlights the crucial role of seasonal climate patterns in shaping food security. As the months progress further away from the peak rainfall and vegetation growth period, food supplies may become increasingly strained, leading to a higher risk of food insecurity. This finding emphasizes the importance of climate-sensitive agricultural practices, such as improved water management and drought-resistant crops, to mitigate the impact of seasonal variability on food security.

These models produce two critical outputs: predicted population and predicted food security, each mapped to small grid cells and updated every month. This fine level of detail makes it possible to detect local changes and short-term trends that might otherwise be hidden. The integration of the population and food security models into the overall forced displacement prediction framework is a crucial step in capturing the complex pathways through which climate change and other factors influence displacement risk. By providing high-resolution, monthly estimates of population and food security conditions, these models enable a more granular and dynamic analysis of the drivers of forced displacement.

3.3 Displacement Gridding Model

Overview

The objective of this final intermediate model was to place the observations from the PRIMES dataset into 0.5° grid cells within our region of interest. Only a third of UNHCR registration records contain data disaggregated by origin at the administrative 3 level or higher, which prevents undertaking a comprehensive analysis needed to understand more localized displacement trends. To estimate the geographical location of refugee outflows at a more granular level, we utilize a semi-supervised learning approach that disaggregates country and regional refugee counts by 0.5° grid cell resolution. The approach integrates data from UNHCR's PRIMES database with satellite-derived information from Google Open Buildings[63] and location coordinates from OpenStreetMap Populated Places.[64]

Data

Displacement data

UNHCR's PRIMES registry represents this study's primary source of cross-border displacement information. Developed in 2002 as a comprehensive case management tool, PRIMES is a centralized repository containing information on approximately 18 million registered refugees and asylum-seekers across more than 130 countries. Each registry entry contains detailed individual-level data, including asylum country, arrival date, demographic characteristics (age, gender, ethnic group), and, critically, hierarchical place of origin information spanning administrative levels from the country (admin0) to country/town/village (admin3).

Building data

Building footprint data from Google Open Buildings provides information on settlement patterns that inform the spatial disaggregation process. This dataset delivers building footprint information derived from high-resolution satellite imagery processed through deep learning models. Our methodology utilizes the centroid point location of each building footprint to assign structures to corresponding 0.5° grid cells and to administrative districts. This assignment process enables the approximation of population distribution patterns within administrative units and overlapping 0.5° grid cells, thereby creating the weighting surface necessary for disaggregating refugee counts from the administrative level to the grid cell resolution.

Location data

OpenStreetMap Populated Places data complements the building footprint information by providing specific geographic coordinates for named settlements. This dataset offers precise point locations for towns, villages, and cities across the study region. These settlement coordinates serve as spatial anchors for admin3-level place names appearing in the PRIMES registry. Through a spatial joining process, we use these data to match available admin3 entries from refugee records in PRIMES with corresponding settlement locations, thereby placing these observations within 0.5° grid cells even when higher-level administrative boundaries span multiple grid cells.

Processes

To estimate refugee counts at a fine spatial scale, we first use building footprint data from Google Open Buildings as a proxy for population distribution. Each building footprint is assigned to both an administrative district (admin level 2) and a 0.5° grid cell based on its geographic coordinates. This dual assignment allows us to see how buildings, and therefore people, are spread across both administrative boundaries and grid cells. We then group buildings by each unique

63 Google Research. (2022). Open Buildings. Retrieved from https://sites.research.google/open-buildings/

64 Humanitarian OpenStreetMap Team. (2022). OpenStreetMap Populated Places. Retrieved from https://www.hotosm.org/

admin level 2–grid cell combination and calculate what share of an admin level 2's buildings fall into each cell. These percentages become weights for redistributing refugee counts from administrative areas to grid cells.

In parallel, we clean and validate refugee records from the PRIMES database to ensure accurate location information. We keep only records with at least admin 2-level origin data and match their names to official boundaries, correcting spelling and naming differences with fuzzy matching (Levenshtein similarity ≥70 per cent). Records that still don't match are checked against OpenStreetMap populated place names to assign coordinates and administrative units. Where all buildings in an admin level 2 area fall within one grid cell, refugees are directly assigned to that grid cell. Otherwise, the proportional weights from the building data guide their distribution. This process yields two datasets: one where refugee locations are assigned with certainty, and another where locations are proportionally modelled across multiple grid cells. A semi-supervised learning process then assigns refugee records to 0.5° grid cells within each administrative area (level 2). For every admin level 2 area, we first identify the grid cells it overlaps and calculate how many buildings fall in each, representing the likely population distribution. Refugee records are split into two groups: labelled (with known grid cells) and unlabelled (without). Labelled records are then combined with the unlabelled data for modelling.

Using a label-spreading algorithm, known locations from the training set guide the assignment of unknown ones. The model spreads location labels across similar records, using building distributions and other variables in the PRIMES data to refine predictions. Over repeated iterations, grid-cell assignments stabilize, balancing known data with building-based probabilities.

Figure 23 shows the total amount of displacement by grid cell among all of the grid cells within the project region of focus. Of the 6,225 grid cells, 1,777 (28.5 per cent) have actually experienced any displacement. This is unsurprising as many grid cells lie within unpopulated areas of the Sahara Desert and Congo Basin Rainforests. But some grid cells, such as those in the Darfur region of Sudan, eastern Democratic

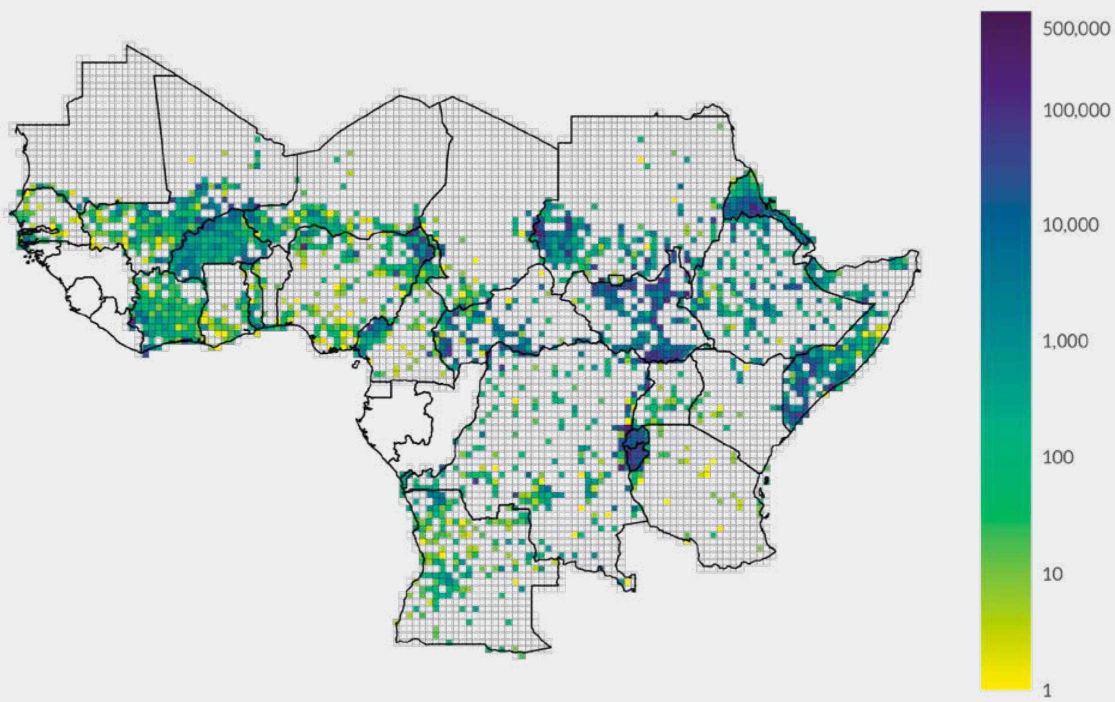

Figure 23: Total level of displacement by grid cell

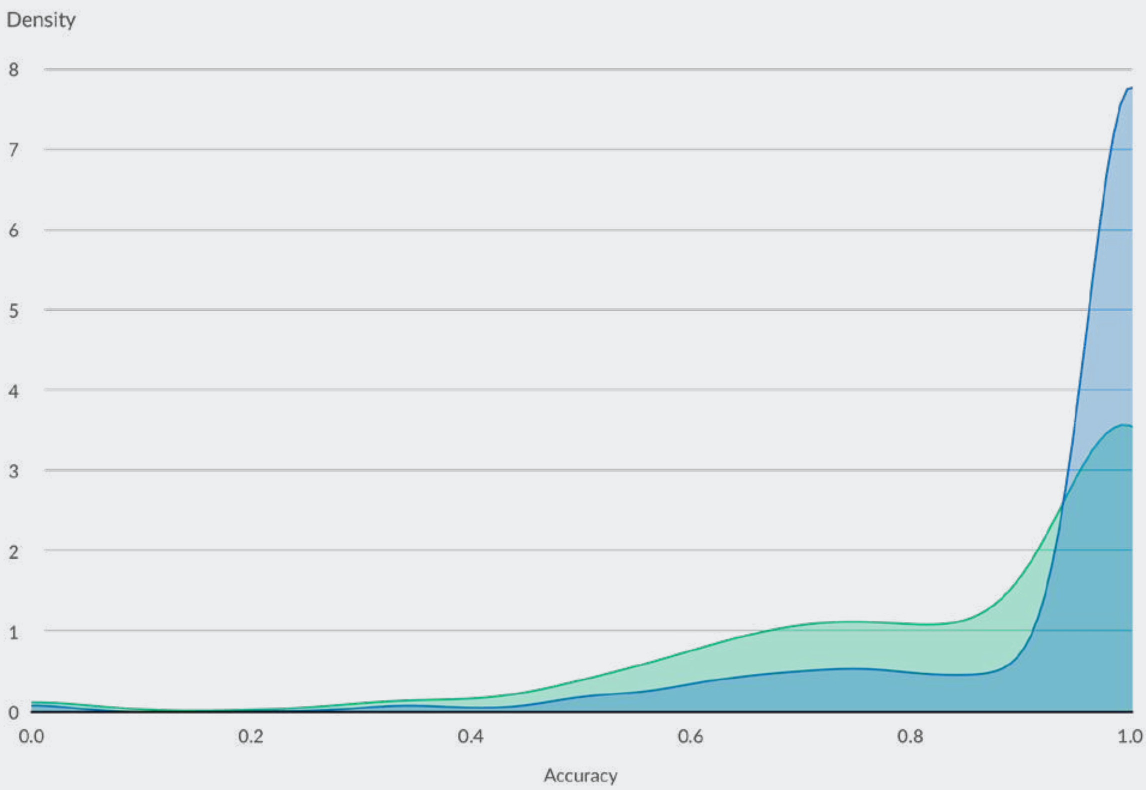

Figure 24: Density plot of gridding model accuracy: admin level 2 areas subject to modelling in green, all admin level 2 areas in blue

Republic of the Congo and Burundi, Lake Chad, southern Somalia, Burkina Faso, and Eritrea have experienced significant displacement.

Results

Table 1 demonstrates that our approach achieves strong predictive performance across multiple statistical metrics, demonstrating the ability of the cleaning and modelling processes to place observations into grid cells. Figure 24 illustrates the distribution of accuracy across all admin level 2 units in the sample. While accuracy varies among admin level 2 units, the majority achieve high levels of predictive accuracy. Moreover, when the model is combined with deterministically placed observations, overall performance improves substantially across all evaluation metrics. This gain highlights the complementary roles of the deterministic and semi-supervised components of the methodology.

Metric	Semi-supervised Modelling Only	Combined (Modelled + Deterministic)
Accuracy	0.845	0.929
F1 Score	0.837	0.925
Precision	0.842	0.928
Recall	0.845	0.929

Table 1: Performance results of gridding model

3.4 Predicting displacement

Humanitarian organizations face an increasingly complex challenge: how to prepare and respond to situations of forced displacement before they escalate into crises, amid progressively dwindling resources. Traditionally, responses have been largely reactive, with resources mobilized and allocated once a crisis has already escalated. This approach often results in higher costs and missed opportunities to prevent or mitigate worse impacts. To address this issue, humanitarian organizations need reliable tools to anticipate, plan, and prepare for forced displacement events.

To give countries a tool for anticipatory action, we have developed a predictive model which allows us to understand localized risks of forced displacement up to six months in advance. This model is not intended to work in isolation or to replace human judgement and expertise. It is meant to serve as a decision-support tool that can complement the expertise of field staff and regional institutions. By specifying areas of high potential displacement up to six months ahead, the model aims to give additional information and time to organize resources and plan interventions to respond effectively.

However, forced displacement is inherently difficult to predict. The same situations and escalations may lead to forced displacement in one area and little to no movement in another. Human decision-making is not only shaped by immediate risk but also by cultural ties, social networks, and access to support which is difficult to capture in quantitative datasets. Furthermore, the complex interactions between different factors such as environmental degradation and conflict can differ from region to region and are therefore hard to measure in a single model, no matter how sophisticated. There is also the challenge of data limitations. Datasets may be incomplete, biased, or inconsistent across different regions. Situations can change very rapidly which might not be reflected in every dataset, leading to additional gaps and uncertainty.

Data and method

The model draws on more than 180 different variables, capturing different aspects of the environment, economic conditions, and conflict. Climate data includes measures of precipitation, temperature anomalies and changes, drought indices, and vegetation health. Geographic variables include market access, and proximity to borders, which can influence the scale of refugee movements. Conflict data contains information on the type, severity, and frequency of conflict events, including the associated fatalities. In addition, we also incorporate the variables from the food security and population density models, which are described in Chapters 3.1 and 3.2. We use the predicted food security classification resulting from the food security model, which predicts the food security classification in each 0.1° grid cell from January 2009 to the present and we include the predicted population from the population density model which obtains gridded predicted population data through annual population figures and monthly nightlight radiance. The main dataset variable categories used and respective sources are presented in Table 2.

Variable name	Unit	Source
Dependent variable		
Displacement	Monthly, 0.50° grid cell	UNHCR's PRIMES Database
Climate variables		
Temperature	Daily, 0.05° Daily, 0.10° Monthly, 0.25°	CHIRTS Copernicus ERA-5 Berkeley Earth

Variable name	Unit	Source
Precipitation	Daily, 0.05° Daily, 0.10°	CHIRPS Copernicus ERA-5
Normalized Difference Vegetation Index	Monthly, 0.05°	NASA
Standardized Precipitation Evapotranspiration Index	Monthly, 1.00°	SPEI Global Drought Monitor
Resource and geographic variables		
Landcover	Constant, 0.05°	Copernicus
Agro-ecological zone	Constant, defined regions	International Food Policy Research Institute
Elevation	Constant, 0.10°	HarvestChoice CELL5M
River	Constant, defined regions	Natural Earth
Road	Constant, defined regions	Humanitarian OpenStreetMap
Market access	Constant, 0.10°	International Food Policy Research Institute
Subsistence Index	Constant, 0.10°	International Food Policy Research Institute, Harvard Dataverse
Demographic variables		
Population density	Monthly, 0.10°	LandScan, DMSP, VIIRS
Ethnicity	Constant, 0.10°	ETH Zurich
Food security		
Predicted food security	Monthly, 0.10°	FEWS NET
Socio-economic and wellbeing variables		
Child health	Constant, 0.50°	PRIO
Gini	Constant, 0.10°	WorldPop, VIIRS
Political variables		
Fragility	Annual, national	Fragile States Index
Conflict variables		
Conflict	Daily, geo-point locations	ACLED

Table 2: Key variable categories used

The model predicts the risk and scale of forced displacement from each grid cell at one, three, and six months into the future. To simplify the interpretation of risk for humanitarian workers, we implement a three-category classification scheme that aligns with operational humanitarian response frameworks:

- **Small-scale movements (0-10 persons):**
  Captures background displacement and minor population movements
- **Medium-scale events (11-500 persons):**
  Represents significant displacement events requiring humanitarian attention
- **Large-scale crises (>500 persons):**
  Identifies major displacement emergencies demanding immediate large-scale response

We use a combination of different models to leverage their individual strengths and predict the risk of each displacement level. Our framework includes a tree-based method as well as several neural networks with different architectures. Each model is designed to capture different aspects of displacement patterns at local and subregional levels.

The tree-based method we have selected is effective at modelling non-linear temporal relationships and identifying subtle patterns in complex data. It has been selected for its computational efficiency and low memory usage which is particularly important given the scale of our dataset. One of its strengths is also its built-in ability to automatically identify the most relevant variables and filter out less useful information, allowing us to input all 180 feature variables and not worry about collinearity and/or multilinearity negatively impacting model results. In practice, this makes it a reliable method that performs especially well when predicting the most common forced displacement outcomes which are the small-and medium-scale movements.

Alongside this method, we have developed three neural network architectures, each designed to capture both spatial and temporal patterns in the data. These models analyze how conditions in specific areas change over time and influence neighbouring areas, revealing complex patterns that span across space and time.

The first neural networks, also known as a convolutional neural network (CNN), uses different layers which are able to detect short-term changes as well as longer-term patterns while focusing on local neighbourhoods within regions.

The other two neural networks are convolutional long short-term memory models (ConvLSTM), which combine the two strengths of the CNN with a memory mechanism that allows them to decide which past information is important to remember and which one to discard, basically only remembering the most relevant information. This makes them well suited to track displacement risks that build gradually over time while also capturing sudden events that matter.

The most advanced network of the two is designed to look at patterns on two levels. At the first level, it captures local changes such as sudden changes within a subregion. At the second level, it identifies larger patterns across larger regions. By combining these perspectives into one prediction, the model can account for both more granular detail and the broader picture which can lead to more reliable predictions.

For the last model we develop an Ensemble model that combines the individual predictions of these models into a single forecast. This is done by evaluating the performance of each individual model on the test dataset and assigns weights to their contribution based on their relative accuracy. Ensemble modelling is a well-established method which allows us to take advantage of each model's strengths.[65] This is particularly important given the

65 Brown, D. W. (2023). A Unified Theory of Diversity in Ensemble Learning. *Journal of Machine Learning Research 24* , 1-49.

nature of our dataset which ranges from areas with no or minimal displacement to areas experiencing highly volatile and complex displacement dynamics.

Finally, all models are evaluated and tested separately to compare their performance and to identify the best model for each displacement class and forecast horizon.[66] It is important to note that there is no single model that performs best across all scales and horizons. For example, the tree-based model performs particularly well across all horizons for areas with low or occasional displacement, where relationships are more stable and less complex. In contrast, the Ensemble model is better at capturing higher levels of displacement over all horizons, while the neural networks are good at capturing escalations from medium to higher levels of displacements. This suggests that when large-scale displacement occurs, more complex interactions are happening and the model's ability to model these becomes more important. The inclusion of neural network models in the ensemble model greatly improves its accuracy by enabling it to capture such non-linear relationships and escalations. Based on these results, the final model was selected as the tree-based model for low and medium displacement while the Ensemble model was selected for the higher displacement class as its ability to integrate various modelling approaches allows it to better capture different interactions. By combining the tree-based method with neural networks of increasing complexity, our framework balances efficiency with predictive power.

To ensure that forecasts remain accurate and reliable, models are re-trained every three months, incorporating the latest data and trends. This regular updating allows the system to adapt to changing conditions on the ground and maintain its usefulness in humanitarian planning.

What forecasts show

Forecasts generated for February 2025 are displayed on a map in Figure 20 as an example, with each grid coloured according to the relative displacement risk. This visualization allows humanitarian teams to quickly identify areas where displacement is expected to be higher, providing an intuitive overview of potential hotspots. The forecasts are also integrated

66 Further details of the modelling methodology are provided in Clifdew's second technical report.

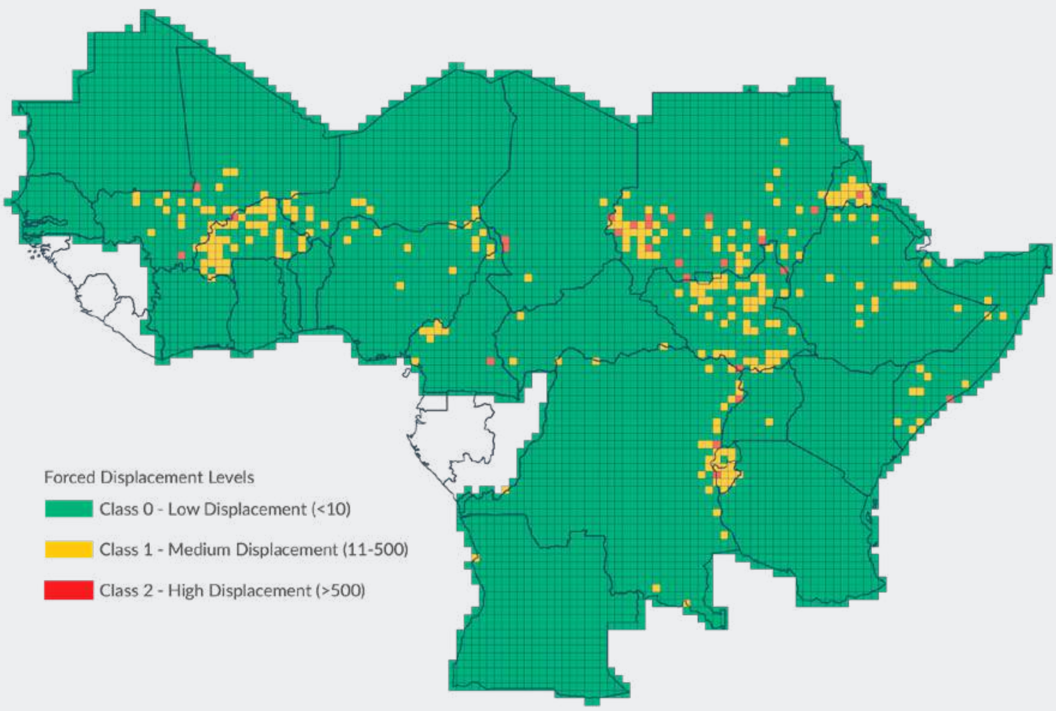

Figure 25: Most likely displacement levels for 6 months ahead for February 2025, made in August 2024.

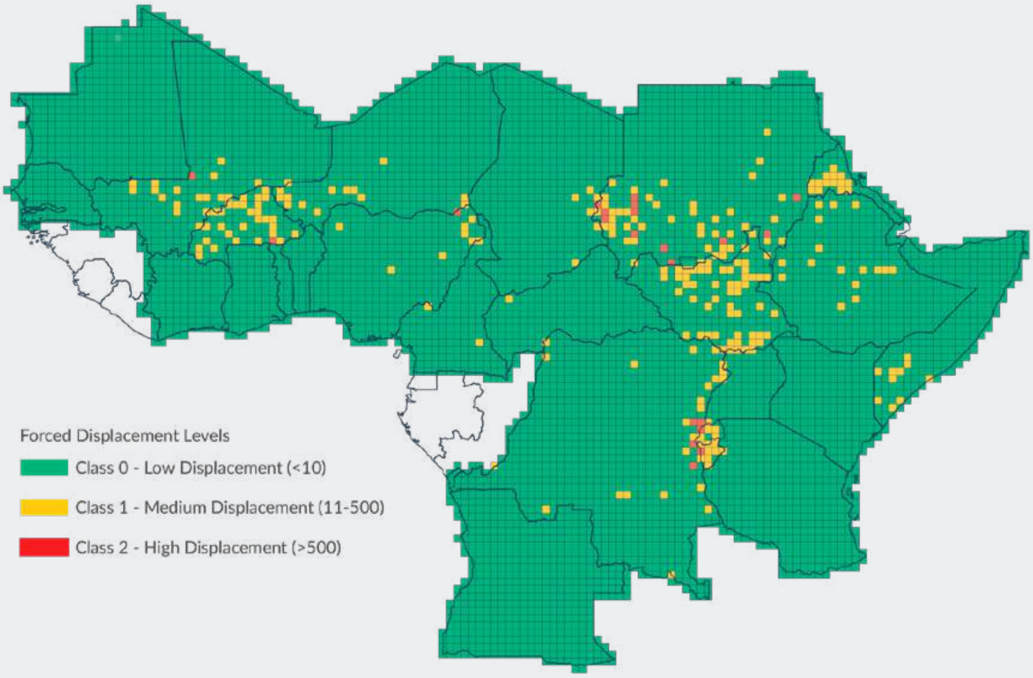

Figure 26: Actual displacement levels for February 2025.

into an internal dashboard, developed in consultation with regional teams to ensure clarity and usability for operational planning.

For example, the predictions for February 2025, generated in August 2024, show that the highest levels of displacement risk are concentrated in specific regions. In Sudan, the Darfur region stands out, while Burkina Faso is also prominent. Parts of eastern Democratic Republic of the Congo (DRC) and the Lake Chad Basin also show elevated risk. These predictions closely match with actual displacement reported in the same month (Figure 25), demonstrating the model's ability to identify high-risk areas well in advance.

To further analyze the accuracy of the predictions, we calculate a range of performance metrics to understand where predictions are more, or less reliable. For the testing period from 2024 to 2025, we visualized the quality of our predictions by grid for the 3- and 6-months horizons in Figures 25 and 26. In these maps, the accuracy of predictions is colour coded in red, orange, and red, for high, medium, and low accuracy, respectively. Different shades of colours indicate displacement levels, with lighter colours corresponding to grids with lower displacement, darker colours to higher levels of displacement, and grids with dark colour and thick border representing areas of very high displacement, which are the most critical for humanitarian planning.

The results show that the final model was able to accurately predict risk for high displacement areas such as eastern DRC, Burundi, and Eritrea where conflict and environmental stressors are major drivers of movement. Predictions in South Sudan were also largely accurate. We can also see that the model performs best in regions with concentrated displacement patterns, where multiple grids show similar levels of risk. Isolated high displacement areas are more difficult to predict, which is expected given the complex interactions of local drivers. The model is also correctly predicting areas of very low forced displacement, avoiding false positive warnings in those areas as can be seen in Table 3.

Displacement level	Accuracy level	Number of grids
No displacement	Low	0
	Medium	0
	High	5,320
Medium displacement	Low	26
	Medium	90
	High	583
High displacement	Low	8
	Medium	45
	High	149

Table 3: Grid accuracy level by displacement level over the testing period 2024-2025 for horizon 3. The accuracy is defined as the PR AUC, with 0-0.5, 0.5-0.7, 0.7-1, defined as low, medium and high accuracy respectively.

Overall, the forecasts demonstrate the final model's ability to anticipate the three levels of displacement. Even though the highest displacement level can at times be challenging to predict, especially in isolated areas or in parts of Eastern Africa, it generally performs well in anticipating medium and high displacement risks up to six months in advance.

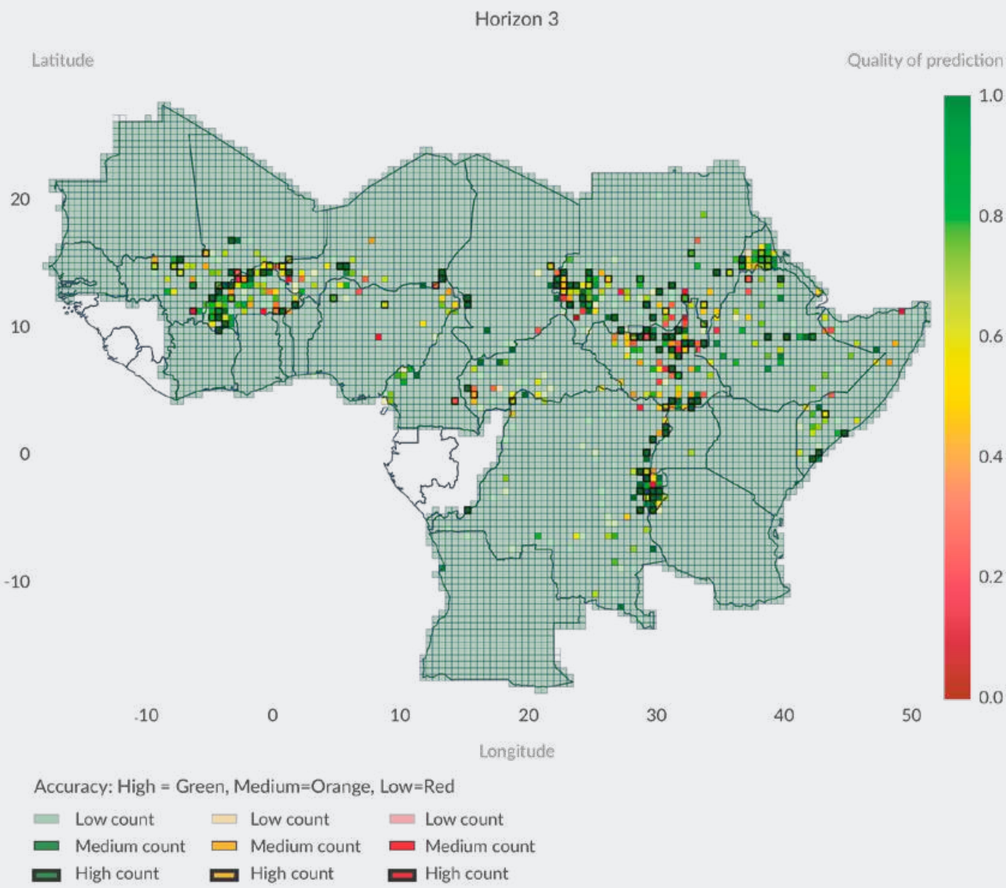

Figure 27: Average prediction quality by grid for horizon 3, 3 months into the future. Colour hue shows average precision-recall AUC; colour depth shows actual displacement levels

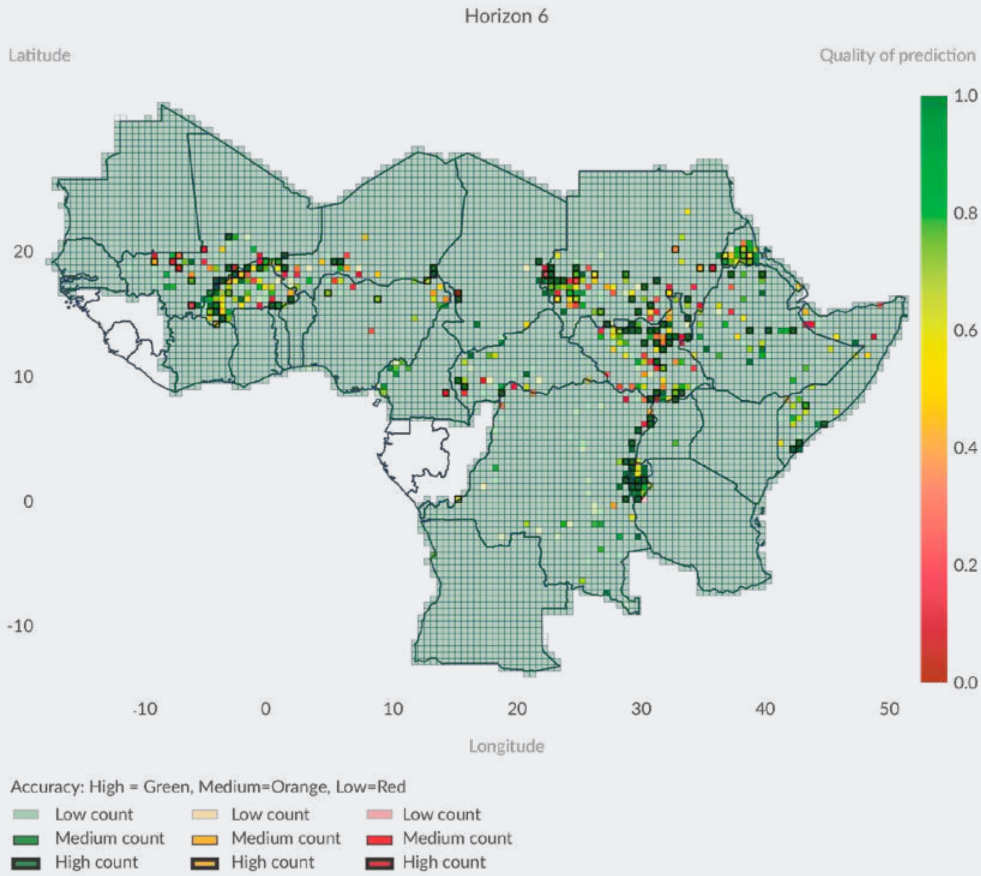

Figure 28: Average prediction quality by grid for horizon 6, 6 months into the future. Colour hue shows average precision-recall AUC; colour depth shows actual displacement levels

Figure 29 offers a zoomed-in view of the grid cells along the border between Northeast South Sudan and Southeast Sudan, coloured based on the actual displacement category and quality of prediction. This area has seen high levels of displacement, especially since the outbreak of the South Sudanese Civil War in late 2013, which lasted until 2020. Even though a peace deal was reached in 2020, escalating violence risks throwing the country back into civil war.[67] Ethnic Dinka and Nuer communities border each other in this area and have suffered high levels of violence and unrest as the civil war is fought largely between these two ethnic groups.

The majority of the dark green grid cells that have a bold border, those with high displacement, are green, meaning that the model more accurately predicts the high displacement grid cells. There are only a handful of bordered grid cells, those with high actual displacement, that are yellow or red, representing lower accuracy. The grid cells that are lighter coloured and not bordered which represent those with lower displacement levels are more mixed, meaning the model either accurately predicts low displacement or overpredicts it.

By accommodating indirect pathways rather than drawing direct causal lines between climate conditions and displacement, the modelling assesses the influence of slow-onset climate events on displacement indirectly. Intermediate models convert raw data into indicators theoretically linked to displacement risk. Monthly population estimates indicate how many people are present in each grid

67 United Nations, "South Sudan at 'Turning Point' Amid Worsening Violence," *UN Press (August 18, 2025)*, https://press.un.org/en/2025/sc16146.doc.htm

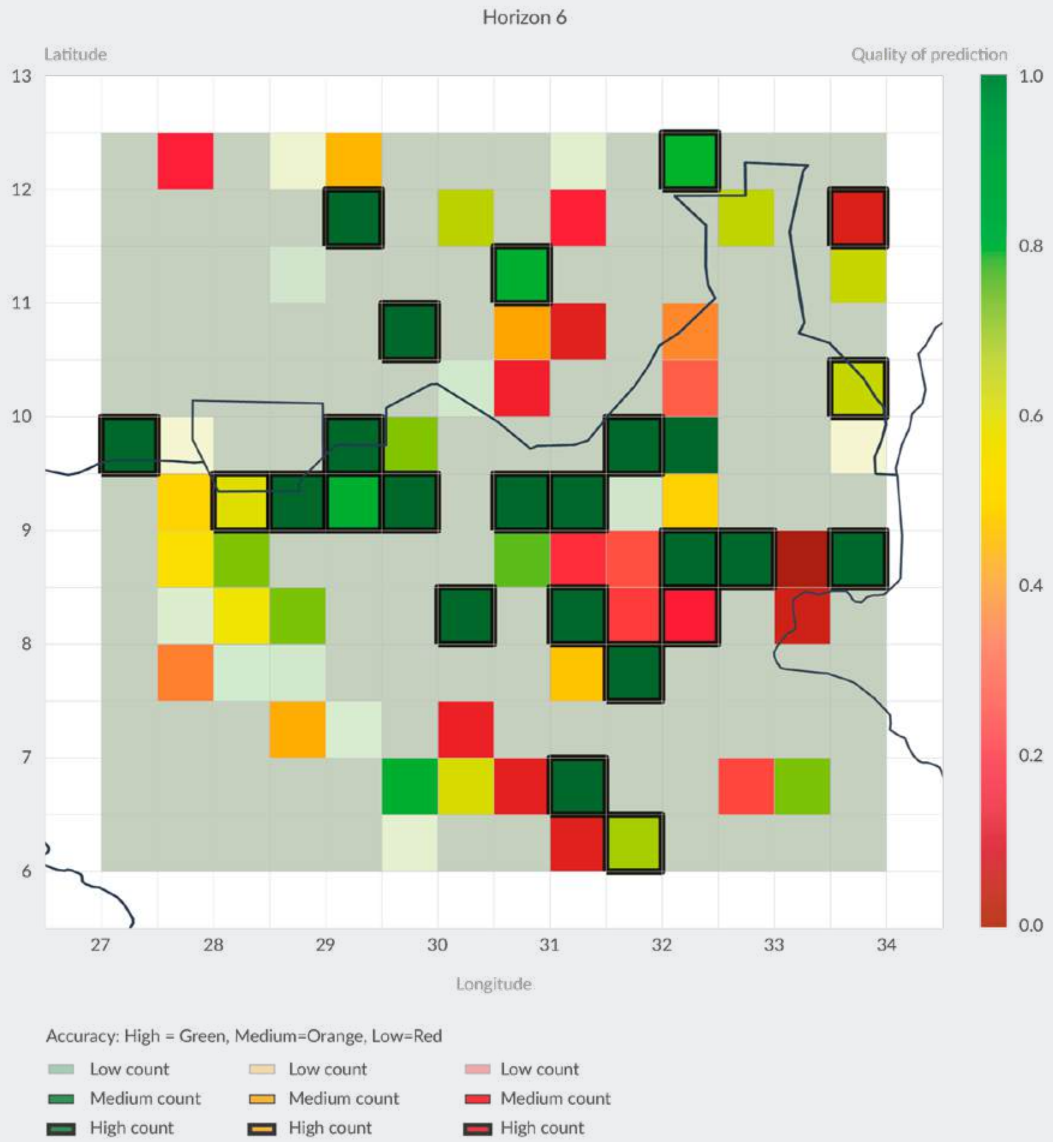

Figure 29: Average prediction accuracy across northern South Sudan and southern Sudan (6-month forecasts)

cell, offering insights into the levels of exposure and the potential scale of displacement when risk factors emerge. Food security is incorporated into the model as it is influenced by climate change and poor food security undermines livelihoods, potentially triggering population movements.

Drawing on population density and food security indicators—alongside data on climate, geography, demographics, well-being, governance, and conflict—the final 0.5° grid models produced forecasts up to six months ahead. This fine spatial resolution, coupled with an ensemble of complementary methods, proved essential for capturing the nuanced interplay of environmental change, conflict, and economic shocks that shape displacement patterns across diverse contexts.

Taken together, the results highlight the value of integrating tree-based and deep-learning approaches to balance interpretability with the ability to detect subtle spatiotemporal dynamics. The high-resolution predictions generated through this framework provide not only an empirical basis for anticipating displacement but also a practical tool for directing humanitarian resources with greater precision. In doing so, the modelling approach offers a pathway for early action and risk reduction as climate-related pressures continue to intensify.

CHAPTER 4:

How data can inform humanitarian action

4.1 the cost of slow-onset events

Voluntary returns to the places of origin are often the preferred solution to forced displacement once the threat from conflict, violence, or a rapid-onset disaster disappears. However, slow-onset environmental degradation operates on timescales that exceed human life spans. The temperature increases documented in Chapter 2.1 represent changes that are not reversable on any timeline relevant to humanitarian planning. Therefore, the climatic changes described in this report establish new permanent baselines rather than temporary deviations which may make return a less viable option.

When environmental degradation catalyses conflict, as documented in the farmer-herder tensions across the Sahel,[68] the underlying climatic drivers persist even after violence subsides. The Liptako-Gourma region exemplifies this dynamic: even if the threat from extremist groups was eliminated, the degraded pastures and disrupted rainfall patterns that potentially contributed to the competition for resources would remain and create stressors that potentially lead to new tensions when populations return. The vegetation shifts shown in Figures 10 and 11, particularly the phenological changes disrupting traditional agricultural calendars, represent ecological transformations that cannot be reversed through peace agreements alone.

This creates a fundamentally different displacement typology. Populations fleeing the impact of environmental stress and conflict cannot simply wait for “post-conflict” conditions because the resource base that previously supported their livelihoods will remain degraded even after the conflict has abated. Many of the millions of refugees that have fled from, among other areas, the Liptako-Gourma and Lake Chad regions, southwest Cameroon, South Sudan and Somalia since 2000 may face more permanent relocation, as the ecological foundation for both pastoralism and farming in their areas of origin continues to degrade.

Conflicts that emerge from elite political competition, military coups, or ideological movements, are often geographically contained and potentially resolvable through political settlements. The climate-catalysed tensions documented in this report operate differently: they emerge from the bottom up as thousands of localized resource disputes. Individually, each dispute is too small to trigger international attention, but collectively all disputes are contributing to a reshaping of the continent’s stability map. The data revealed this transformation starkly.

Another important factor in understanding displacement is population size and growth rate. This project’s geography covers large regions, which have very low populations such as parts of the Sahara Desert and the Congo Basin Rainforest. Of the 6,225 grid cells, 497 have a population of 100 or less.[69] These low population grid cells have not yielded any displacement. Another important trend is the increasing population in the region, which has coincided with general displacement trends. Based on the LandScan annual population estimates for 2020, the 1,777 grid cells that have experienced some displacement had an average population of 320,000 compared to the grid cells that never experienced displacement, which had an average population of 90,000 in the same year. So, displacement has tended to occur in more populated grid cells on average. As discussed in Chapter 2.1, this project’s countries of focus have experienced high population growth. Overall, the grid cells that have experienced at least some displacement have an average annual population growth rate of 7.3 per cent between 2001 and 2024. The average annual displacement change rate during this period was 142.8 per cent. As discussed above, there have been more displacement in recent years; of the 1,777 grid cells experiencing displacement, 47 per cent recorded their highest monthly displacement level since 2018, with 33 per cent recording the highest monthly level between 2021 and 2025. But the average annual growth rate among the grid cells which have experienced some displacement was 5.0 per cent prior to 2018 and 3.1 per cent since 2018, and 3.0 per cent since 2021. So, the increase in displacement does not seem fully a function of rapid population growth within these grid cells.

As degraded areas expand, the number of potential flashpoints increases. Each failed growing season, each disrupted pastoral route, and each depleted water source represent not just local hardship but also potential displacement that then further strains receiving areas, potentially triggering secondary displacement as the host communities’ resilience erodes because of over population.

68 United Nations Office of the Special Coordinator for Development in the Sahel (OSCDS) and United Nations High Commissioner for Refugees (UNHCR). (2022). *Moving from Reaction to Action - Anticipating Vulnerability Hotspots in the Sahel.*

69 Based on average annual populations from LandScan data between 2000 and 2024.

The convergence of permanent environmental degradation with conflict and local tensions fundamentally challenges humanitarian operating assumptions. The traditional humanitarian cycle, emergency response, early recovery, and development, assumes an eventual return to stability. When slow-onset events drive displacement, this cycle breaks down. There is no “post-emergency” phase when temperatures will cool, or rainfall patterns will stabilise. There is no “early recovery” when degraded rangelands will restore themselves or aquifers will refill.

In such a scenario, investment in resilience and prevention is critical. The seasonal patterns showing February-May peaks align with pre-planting periods when interventions could be most effective. Yet humanitarian funding remains predominantly reactive, with resources released only after displacement has commenced.

The evidence presented throughout this report highlights that mitigating the impacts of slow-onset environmental changes require short-term humanitarian support, but longer-term development funding is equally critical. This includes prioritizing prevention and anticipatory action. Some population movements are likely to be permanent and will require initiatives in hosting locations to minimize the need for people to move onwards.

4.2 How can humanitarian and development organizations use the model’s outputs

The evidence from this project shows that slow-onset environmental changes are presenting increasing challenges in many locations within the study region, potentially driving social unrest, conflict and forced displacement. There are risks that the population movements may become more permanent. Given the longer time horizons over which these changes occur, shorter-term humanitarian support should be complemented by longer-term development support. The predictive model developed through this project (see Chapter 3), although not a standalone solution, provides such organizations with a tool to guide their operations. By providing risk levels at 1, 3, and 6-month intervals for 0.5° grid cells, the model transforms the patterns documented in this report into figures that can be incorporated in operational planning.

One-month prediction horizon

The one-month predictions serve traditional emergency responses whereby organizations can gain more precise geographic information for immediate preparedness. This allows agencies to identify specific 0.5° ($55km^2$) grid cells from which the risk of displacement is highest and where displacement would exceed current operational thresholds. This would support pre-positioning emergency supplies, water treatment units, shelter materials, medical supplies, close to population centres in those 0.5° specific grid cells or along routes that lead from those grid cells.

Three-month prediction horizon

The three-month timeframe allows organizations to establish and plan operations with a longer lead time. This could include negotiating access agreements with local authorities, recruiting and training local staff, and establishing local partnerships, including building their capacity to respond and support. A relevant scenario could be to plan food support activities in likely destination areas before a harvest, knowing that there is a high risk that the harvest would not be sufficient for the local population. This presents the opportunity to minimize the need for onwards movements, which then place additional pressure within the host locations.

Six-month prediction horizon

The six-month timeframe enables longer-term programming decisions. This can include the identification of areas where prevention still remains possible. Grid cells showing moderate but increasing risk might benefit from resilience investments, such as borehole rehabilitation, drought-resistant seed distribution and conflict mediation programmes that would be much less viable after conflict and/or population movements have already commenced. An analysis of the risks in specific areas six months into the future can inform whether to prioritize programming that includes prevention in origin areas or integration support in destination areas. The longer timelines and evidence base produced from the outputs of this project can inform discussions with donors.

Importantly, the model supplements rather than replaces existing assessment tools. Organizations should integrate model predictions with:

- Community feedback mechanisms or direct observations that validate the risk model generated within this project.
- Operational data and knowledge, including return intention surveys. This should include data from other relevant actors.
- Other analytical projects, e.g. those developed through inter-agency coordination efforts.

Updates to the model on a monthly basis enables adaptive management of situations. If 6-, and 3-month predictions prove accurate for certain regions but not others, organizations can adjust their confidence levels or the model parameters accordingly. This iterative learning improves both the utility of the model as well as the operational response.

Anticipating rather than reacting to forced displacement events will require operational adaptations. The outputs from the model will help to improve planning the release of funds, better ensuring the required budgets for responses are available. Field activities can be planned based on the predictions in addition to current needs, and indicators of successful interventions should include displacements that was prevented as well as those that have been assisted. The convergence of growing areas of permanent environmental degradation and increasing numbers of local-level conflicts and disputes, will likely lead to forced displacement levels rising over the longer term in the study region. Predictive tools such as the one presented here are likely to become much more widely used, with organizations cognizant of such tool limitations as well as recognizing the potential of the insights that can be derived from their use.

4.3 The path forward

The evidence presented throughout this report reveals that the impact of climate change is not uniform. As shown in Chapter 2, the western Sahel zone faces the risk of both increased drought and extremely high precipitation patterns, with different areas experiencing these issues to various degrees. Meanwhile, much of the Sahel shows improvement in several metrics such as an increase in vegetation, partly due to successful interventions such as farmer-managed natural regeneration. The Horn of Africa exhibits a pattern of extreme variability, which creates cycles of drought and flooding that defy traditional seasonal patterns. These spatial variations require differentiated responses; rather than treating the entire region as equally vulnerable, responses should be calibrated to specific local conditions.

Of the 6,225 grid cells in our study region, only 1,777 have experienced forced displacement since 2000. Slow-onset climate-induced displacement is not an automatic consequence of environmental change but emerges when climate stress converge with other drivers such as weak governance, resource competition, and/or pre-existing conflict. The variation in levels of displacement could reflect differences in the environment, governance capacity, economic resources, social cohesion, and traditional adaptation mechanisms. Identifying the specific drivers enables targeted interventions where the risk of displacement is especially high.

This report documents an acceleration in displacement - 47 per cent of cells reaching peak displacement after 2018, the widening of the period within years during which forced displacement typically occurs and the growing geographic extent of the displacement. Yet there is also an opportunity to apply the approach set out in this model to better assess, how, where and when to respond.

The output of the model supports a differentiated response and can be used to assess areas requiring an emergency response, areas where prevention remains possible, areas that require longer-term development support and areas that are successfully adapting without external support. In all cases, the model output also helps to assess when these responses would be required, including e.g. potential support in specific seasons if harvest are likely to be insufficient.

These distinctions are made possible through systematic data analysis of the outputs of the predictive model developed through the CLIFDEW-GRID project, which has the potential to transform these insights into operational data. By providing displacement risk level at 1-, 3-, and 6-month intervals for each 0.5° grid cell, the model outputs can guide humanitarian and development responses. The outputs include specific predictions on which cells face imminent risks, and when the displacement is most likely to occur. The outputs can be quickly refined to improve subsequent monthly updates. Organizations using the model outputs can help refine the accuracy of the predictions through ground truthing during planning phases and while responding. The model itself attempts also to improve the accuracy of the outputs by learning from each cycle. The model outputs are certainly not perfect but are grounded with remote sensing data and other reliable sources.

CLIFDEW-GRID enables humanitarian and development organizations to optimise how they utilise their resources in order to better address the challenges presented throughout this report. For cells showing high risks within one month, organizations can pre-position emergency supplies in predicted destination areas. Three-month predictions allow the establishment of operational infrastructure—partnerships, personnel recruitment and organizing coordination mechanisms—before displacement occurs. The six-month outlooks help to identify where investment in prevention might mitigate the need for people to move onwards or that the investment would be more effective in likely areas of destination. By identifying cells with the highest displacement risk, the model highlights where prevention remains possible, and by showing sustained risk in origin areas, it indicates where to best target assistance. Through using this tool, organizations need no longer wait for displacement to occur and can instead anticipate when and where to respond and plan the most effective approach.

Climate change will continue reshaping Africa's environmental landscape. Temperatures will continue to rise, rainfall patterns will shift, and environmental stresses will intensify in many areas. But as the CLIFFDEW-GRID model outputs show, displacement is not an inevitable consequence. The tool helps to identify those areas with high risks of forced displacement, informing less reactive, more anticipatory responses. As displacement patterns grow more complex and widespread, driven in part through climate change, tools that transform data into foresight will become increasingly essential to protect and support vulnerable populations.

Bibliography

Archila Bustos, M. F., Hall, O., & Andersson, M. (2015). Nighttime lights and population changes in Europe 1992-2012. *Ambio*, 653-665. doi:doi: 10.1007/s13280-015-0646-8

Brown, D. W. (2023). A Unified Theory of Diversity in Ensemble Learning. *Journal of Machine Learning Research 24* , 1-49.

Carnegie Council for Ethics in International Affairs. (2025). *Climate Mobility*. Retrieved from https://www.carnegiecouncil.org/explore-engage/key-terms/climate-mobility

Center for Integrative Research in Computing and Learning Sciences (CIRCLS). (2024). *Glossary of Artificial Intelligence Terms for Educators*. Retrieved from https://circls.org/educatorcircls/ai-glossary

Cheng, H., Zhu, Y., Guo, Y., Bachwenkizi, J., Chen, R., Kan, H., & Fawzi, W. W. (2025). Escalated heatwave mortality risk in sub-Saharan Africa under recent warming trend. *Science Advances, 11*(48).

Cissé, M. G. (2020). Understanding Fulani Perspectives on the Sahel Crisis. *Africa Center for Strategic Studies*. Retrieved from https://africacenter.org/spotlight/understanding-fulani-perspectives-sahel-crisis/

Cohen, M. J., & Pinstrup-Andersen, P. (1999). Food Security and Conflict. *Food, Nature and Culture, 66*(1), 375-416.

Elvidge, C. D., Zhizhin, M., Ghosh, T., Hsu, F.-C., & Taneja, J. (2021). Annual Time Series of Global VIIRS Nighttime Lights Derived from Monthly Averages: 2012 to 2019. *Remote Sensing, 13*(5). doi:https://doi.org/10.3390/rs13050922

Google Research. (2022). Open Buildings. Retrieved from https://sites.research.google/open-buildings/

Humanitarian OpenStreetMap Team. (2022). OpenStreetMap Populated Places. Retrieved from https://www.hotosm.org/

IGAD Centre for Pastoral Areas and Livestock Development (ICPALD). (2020). *IGAD Protocol on Transhumance*. Intergovernmental Authority on Development (IGAD).

Intergovernmental Panel on Climate Change (IPCC). (2022). *Climate Change 2022: Impacts, Adaptation and Vulnerabilities*. Intergovernmental Panel on Climate Change.

IPC Famine Fact Sheet. (2025). Retrieved from Integrated Food Security Phase Classification: https://www.ipcinfo.org/famine-facts/

Kamal, B. (2017). *Climate Migrants Might Reach One Billion by 2050*. Retrieved from Inter Press Service: https://www.ipsnews.net/2017/08/climate-migrants-might-reach-one-billion-by-2050/

NASA. (n.d.). *World of Change: Global Temperatures*. Retrieved from https://science.nasa.gov/earth/earth-observatory/world-of-change/global-temperatures/

Olsson, O., & Siba, E. (2013). Ethnic cleansing or resource struggle in Darfur? An empirical analysis. *Journal of Development Economics, 103*, 299-312. doi:https://doi.org/10.1016/j.jdeveco.2013.02.004

Pedregosa, F., Varoquaux, G., Gramfort, A., Michel, V., Thirion, B., Grisel, O., . . . P. (2011). Scikit-learn: Machine learning in Python. *Journal of Machine Learning Research, 12*, 2825-2830. Retrieved from http://jmlr.org/papers/v12/pedregosa11a.html

Reich, P., Numbem, S. T., Almaraz, R., & Eswaran, H. (2001). Land resource stresses and desertification in Africa . In E. Bridges, *Responses to Land Degradation*. Boca Raton: CRC Press.

Sarif, N., & Roy, A. K. (2024). Measuring urban shrinkage in India using night-light data from DMSP-OLS and VIIRS-NPP satellite sensors. *Cities, 152*, 105176. doi:https://doi.org/10.1016/j.cities.2024.105176

Schäfer, L., Jorks, P., Seck, E., Koulibaly, O., & Diouf, A. (2021). *Slow-onset Processes and Resulting Loss and Damage - An introduction.* German Watch.

See, S., Opdyke, A., & Banki, S. (2025). A review of the climate change-disaster-conflict nexus and humanitarian framing of complex displacement contexts. *Climate and Development*, 1-14. doi:https://doi.org/10.1080/17565529.2025.2514027

Shraddhanand, S., Husak, G., Turner, W., Davenport, F., Funk, C., Harrison, L., & Krell, N. (2021). A Slow Rainy Season Onset Is a Reliable Harbinger of Drought in Most Food Insecure Regions in Sub-Saharan Africa. *PLOS ONE*. doi:https://doi.org/10.1371/journal.pone.0242883

Swain, D. L., Prein, A. F., Abatzoglou, J. T., Albano, C. M., Brunner, M., Diffenbaugh, N. S., . . . Touma, D. (2025). Hydroclimate volatility on a warming Earth. *Nat Rev Earth Environ, 6*, 35-50. doi:https://doi.org/10.1038/s43017-024-00624-z

UN Framework Convention on Climate Change (UNFCCC). (2012). *Slow Onset Events Technical Paper.* UN Framework Convention on Climate Change.

United Nations (UN). (n.d.). *System of Environmental-Economic Accounting*. Retrieved from https://seea.un.org/ecosystem-accounting

United Nations. (2025). Population. United Nations - Global Issues. Retrieved from https://www.un.org/en/global-issues/population

United Nations Framework Convention on Climate Change (UNFCCC). (2024). *Technical guide on integrating human mobility and climate change linkages into relevant national climate change planning processes.* UNFCCC.

United Nations High Commissioner for Refugees (UNHCR). (n.d.). *Registration and identity management* . Retrieved from https://www.unhcr.org/what-we-do/protect-human-rights/protection/registration-and-identity-management

United Nations High Commissioner for Refugees. (2025). *No Escape II: The Way Forward. Bringing climate solutions to the frontlines of conflict and displacement.* United Nations High Commissioner for Refugees.

United Nations High Commissioner for Refugees and Potsdam Institute for Climate Impact Research. (2021). *Climate Risk Profile: Sahel.*

United Nations High Commissioner for Refugees (UNHCR). (n.d.). *Master Glossary of Terms*. Retrieved from https://www.unhcr.org/glossary

United Nations Institute for Disarmament Research. (2024). *Climate Change is Driving People into Armed Groups.* United Nations Institute for Disarmament Research.

United Nations Office of the Special Coordinator for Development in the Sahel (OSCDS) and United Nations High Commissioner for Refugees (UNHCR). (2022). *Moving from Reaction to Action - Anticipating Vulnerability Hotspots in the Sahel.*

USA National Phenology Network (USANPN). (n.d.). *Glossary*. Retrieved from https://www.usanpn.org/nn/glossary

Statistics, Data Science and Survey Section
UNHCR Global Data Service
UN City, Marmorvej 51
2100 Copenhagen, Denmark
stats@unhcr.org

Further information on the CLIFDEW-GRID project is available on UNHCR's statistics website: https://www.unhcr.org/what-we-do/data-and-publications/data-and-statistics/clifdew-grid.