

Disaster displacement risk in Kenya

Overview of the risk of future displacement by riverine floods, storm surges, cyclonic winds and droughts at the national and sub-national levels



Acknowledgements

Lead authors:

Sylvain Ponserre

Vicente Anzellini

Other contributing organizations include:

CIMA foundation

United Nations University

Institute for Environmental Decisions – ETH Zurich

Nanyang Technological University

Potsdam Institute for Climate Impact Research.

IDMC's report was made possible thanks to the generous funding of the European Union and the German Federal Foreign Office.

Graphic design, cartography and layout: Stéphane Kluser (Komplo).



**Co-funded by
the European Union**



Federal Foreign Office

Cover photo: A woman tending to crops on a farm in Taita-Taveta County, Kenya, in 2023. The owner of the farm has already adapted agricultural practices to cope with the impacts of climate change. © NRC/ Ingebjørg Kårstad



Flooded houses in an IDP camp in Busia County, Kenya, in 2024. Heavy rains during the May-to-April rainy season triggered over 293,000 movements across the country. © UNOCHA/Jane Kiiru



Table of contents

6

Introduction

8

**Disaster displacement
in Kenya: historical
trends (2008-2024)**

10

**Displacement risk
concepts**



**12****Disaster displacement
risk in Kenya: results
by hazard type****20****Conclusion****22****Annexes**

A truck submerged by a flash flood in Garissa, Kenya in May 2024. Kenya has seen a significant increase in the number of internal displacements by disasters since 2008, mostly driven by drought and floods.

© Luis Tato/AFP via Getty Images

Introduction

Every year, floods, droughts, storms, earthquakes and other natural hazards force millions of people to leave their homes. Latest data from the Internal Displacement Monitoring Centre (IDMC) shows that 45.8 million of internal displacements, or movements, associated with disasters were reported in 2024, the highest figure on record and far above the decadal average of 26.5 million.

Fleeing can be the first of many further disruptions to people's lives, however. Not only their livelihoods are affected, but it can take weeks or even months before they are able to return. Those who do return often face unsafe conditions and the prospect of being displaced again by the next disaster.

While understanding historical trends is key, looking at the past is not enough. Producing information and analysis on the risk of future disaster displacement can help reducing risk and build resilience before hazards strike, thereby minimising the impacts of disasters, including displacement. In 2017, IDMC began a unique probabilistic modelling exercise for disaster displacement, assessing the likelihood of population movements in the future at a global level. The model used a state-of-the-art probabilistic approach, like that applied by catastrophe modellers and the insurance industry over the past few decades. It built on a risk analysis developed by the UN Office for Disaster Risk Reduction (UNDRR), which considered a wide range of hazard scenarios, their likelihood, and their potential to cause housing damage, which was used as a proxy to assess the likelihood of people getting displaced.

The model provided disaster displacement risk data at the national level (Admin 0), and defined vulnerability from a purely physical perspective -e.g structural vulnerability of buildings being severely damaged or destroyed by different hazard intensities-, without taking into account other socioeconomic factors including poverty, inequality and access to services, nor how global warming could affect the frequency and intensity of certain weather-related hazards.

Understanding physical impacts alone is not sufficient to fully capture displacement risk, however. Given that people's level of vulnerability and exposure to hazards does much to determine the severity of a hazard, it is important to assess how these aspects may change over space and time, and to unpack the economic, social and environmental factors that affect disaster risk, including optimistic and pessimistic climate change scenarios.

To refine further the granularity and comprehensiveness of its model, IDMC collaborated with several partners to develop an updated version that incorporates the latest hazard scenarios, both optimistic and pessimistic climate change projections affecting their frequency and intensity, new exposure layers, and an enhanced vulnerability component that goes beyond structural building fragility. The model assesses the risk of severe housing damage or destruction, as well as the loss of livelihoods for certain hazards, to estimate the probability of displacement. In essence, it focuses on the risk of medium- to long-term displacement and does not account for or model pre-emptive evacuations. Compared to the previous model, data is provided at Admin 1.

While still work in progress, the first results at a global level were obtained in early 2025, allowing to have a more detailed picture of global disaster displacement risk. As part of a series of papers on disaster displacement risk at a national level, the objective of this report is to advance our collective understanding of the current interlinkages between disasters, displacement and climate change, and better anticipate their future evolution. Given that "riskscapes" are constantly evolving, we need to better understand population and socioeconomic patterns, as well as fluctuations in the frequency and intensity of climate-related hazards in order to act more efficiently and ensure that no one is left behind.



Two women carry firewood in Turkana County, Kenya, in 2022. Between 2020 and 2023, the country experienced its worst drought since the 1980s, triggering internal displacement and leaving affected communities in need of humanitarian assistance. © UNOCHA/Jane Kiiru

Disaster displacement in Kenya: historical trends (2008-2024)

Kenya is located in East Africa. From the Indian Ocean coast, the land gradually rises into central highlands, split by the Great Rift Valley. On both sides of the valley, there are fertile plateaus, especially around Lake Victoria and further east.¹ Kenya has a population of over 55 million people, nearly 10% of which lives in the capital Nairobi.²

The country lies across the equator and covers an area of over 582,000 km². It shares borders with Tanzania to the south, Uganda to the west, South Sudan to the northwest, Ethiopia to the north, and Somalia to the northeast. It has a 536 km coastline along the Indian Ocean.³

Kenya's diverse topography gives rise to a wide range of climates. The coastal region is typically hot and humid, while inland areas tend to be more temperate. The northern and northeastern parts of the country are generally very hot and arid. In contrast, the central highlands are cooler, with tropical highland conditions that become increasingly arid toward the interior. Kenya's climate is strongly influenced by the Intertropical Convergence Zone, which plays a key role in driving rainfall patterns across the country.^{4,5}

Kenya's economy relies heavily on rainfed agriculture, but natural resources face growing pressure from population growth, coastal erosion, deforestation, and climate change. These challenges threaten the country's unique biodiversity, local livelihoods, and long-term food security for much of the population.⁶

IDMC has identified a total of 2.7 million disaster displacements between 2008 and 2024, triggered by 90 events. Over this period, movements have gradually increased year after year (see Figure 1).

The overwhelming majority have been triggered by weather-related hazards, mainly floods (see Figure 2).

In 2018, around 336,000 displacements were recorded as heavy rains led to flooding in all of the country's 47 counties. Thousands of hectares of farmland were inundated and livestock killed, threatening the livelihoods of pastoralists and farmers alike. At least six dams burst, triggering around 12,000 movements.⁷

In 2020, four back-to-back below average rainy seasons led to the longest drought in at least 40 years, leaving 4.2 million people in need of humanitarian assistance.^{8,9} Figures for Kenya were hard to come by, but data from the counties of Garissa, Isiolo, Marsabit and Turkana yielded a total of 316,000 movements.¹⁰

Kenya has seen a significant increase in the number of internal displacements by disasters since 2008, mostly driven by drought and floods. In 2023, 649,000 internal displacements were reported, the near totality of which were triggered by floods. This is the highest figure since data first became available for the country in 2008 and more than three times higher than the annual average of the past decade.

The country experienced severe floods, particularly in the last quarter of the year, fuelled in large part by the onset of El Niño. The floods were preceded by six consecutive failed rainy seasons and drought as a result of La Niña, which affected pastoral and agricultural livelihoods.

Most displacements were reported in the north-eastern counties of Mandera and Wajir and the eastern county of Garissa. Significant flooding also took place in the north-western county of Turkana, where refugees living in the Kakuma camp were affected.

Figure 1: Internal displacements by disasters in Kenya, 2008-2024

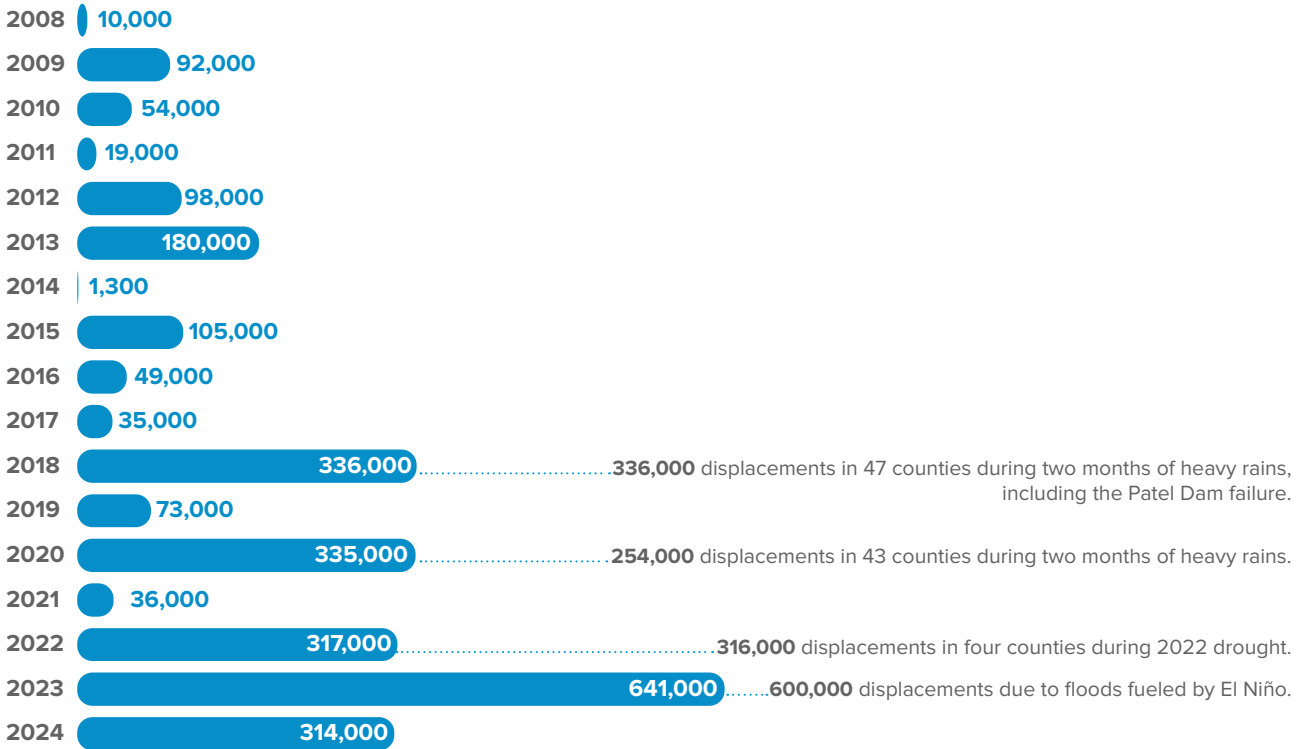
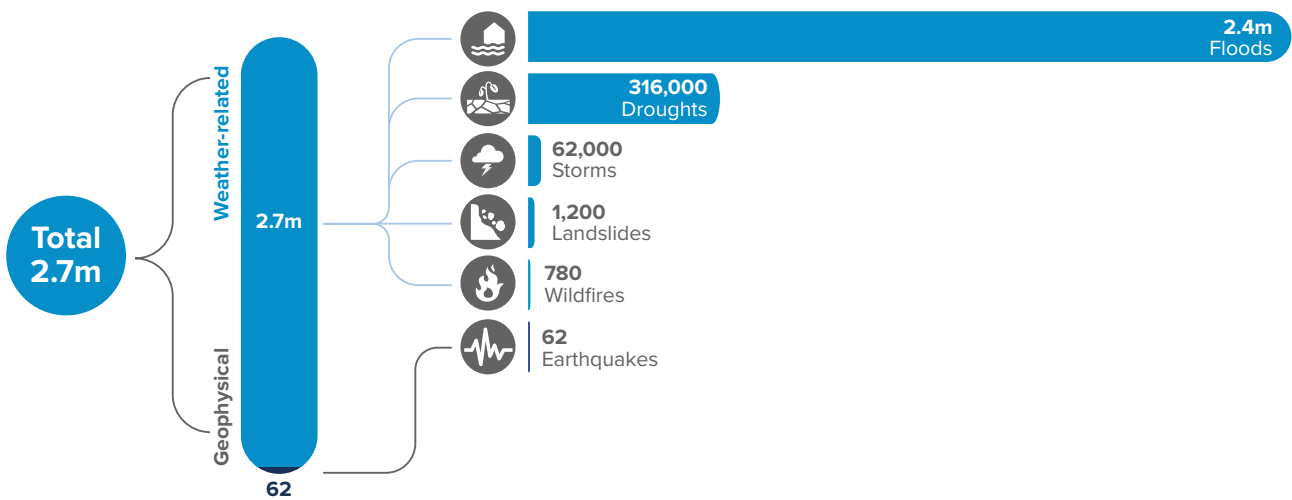


Figure 2: Breakdown by hazard in Kenya



Displacement risk concepts

The need for a broader approach, using probabilistic risk assessment

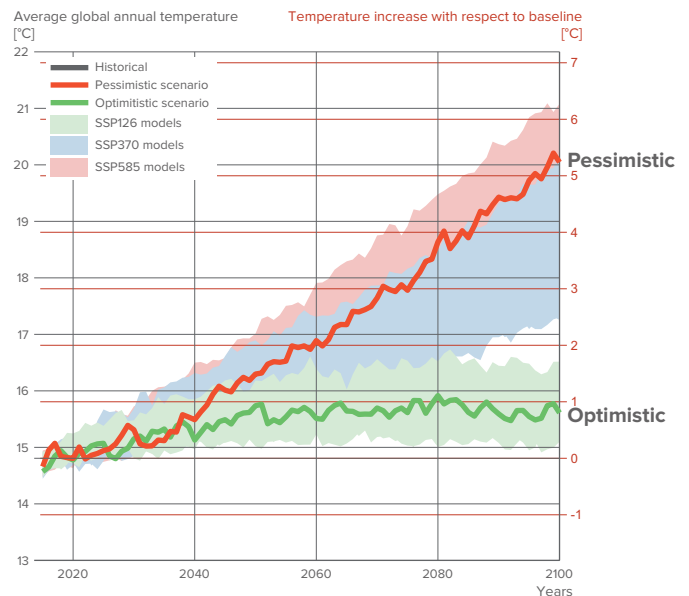
Before diving into the results of the displacement risk model, it is important to first understand key concepts underpinning the modeling approach and how it integrates diverse climate scenarios. These elements are essential to better interpret the outputs.

The baseline established by our new global disaster displacement risk model presents results at the national level downscaled at admin 1 resolution, and provides insight into future displacement situations in a changing climate in Kenya.

It uses a probabilistic approach, applying statistical methods to estimate the likelihood and potential impact of different hazard scenarios. It accounts for uncertainty by analyzing a range of possible outcomes rather than a single deterministic prediction, and evaluates the risk of severe housing damage or destruction, along with livelihood loss for certain hazards, to estimate the likelihood of displacement. It primarily focuses on the risk of medium, to long-term displacement and does not include or model pre-emptive evacuations which means its estimates are inherently conservative.

The outputs are presented using two key metrics: Average Annual Displacement (AAD) and Probable Maximum Displacement (PMD), disaggregated by hazard type and downscaled to the administrative level 1 resolution.

Figure 3: Illustration of different climate scenarios



The new generation of the Global Displacement Risk Model integrates the potential impact of climate change on the future frequency and intensity of extreme events (see Methodology). To facilitate interpretation of the outputs, we have consolidated the results under three different scenarios:

- Under the **current** climate condition
- “**Optimistic**”, corresponding approximately to an average temperature rise of about +1°C by 2100
- “**Pessimistic**”, corresponding approximately to an average temperature rise of over +5°C by 2100

Displacement risk metrics

To represent how many people are at risk of displacement in a given country, the commonly used and comparable metric is **Average Annual Displacement (AAD)**, which measures the expected magnitude of future displacement by hazard type that a country is likely to experience. It does not indicate the actual number of displacements that will occur each year, but rather the average annual number projected over a long time period, taking into account all potential events. (See methodology section for more details.)

AAD represents the annualized, accumulated effect of all events in the hazard catalogue. It is a compact metric that captures the expected displacement from both medium and extreme events. The model estimates that under the current climate conditions, 81,000 people could be displaced by droughts in Kenya in any given year in the future, on average.

While AAD is useful for conveying the scale of displacement risk on an annual basis, it tends to mask potential outliers. High-intensity but low-frequency events, such as a Category 5 cyclone or a magnitude 7 earthquake, could cause mass displacement, even if they occur only rarely.

To better account for such extremes, we also use a second metric: **Probable Maximum Displacement (PMD)**. PMD represents the maximum number of displacements expected within a given return period, capturing the outlier scenarios mentioned above. It is especially useful for preparedness planning, such as determining the size and scope of shelters, infrastructure, and emergency response assets a government may need.

The likelihood or probability of displacement is usually expressed in terms of a return period, which is often misunderstood. A return period is the average time interval in years that separates two consecutive events equal to or exceeding the given magnitude. The most common misconception is that an event with a 100-year return period will only occur once a century. In fact, it means that it has an exceedance probability of 1/100, so events of the same or greater intensity happen once every 100 years on average. It does not preclude more than one event with a 100-year return period happening within a century or even the very small probability of back-to-back events one year after another. Nor does it rule out a century passing without such an event occurring.

AAD

Average Annual Displacement (AAD)

is a measure of the magnitude of future displacement by hazard type that a country is likely to experience. It does not reflect the number of displacements it will face each year, but the number it can expect per year considering all the events that could occur over a long timeframe. AAD is a compact metric with low sensitivity to uncertainty.

PMD

Probable Maximum Displacement (PMD)

is the maximum displacement expected within a given time period. It answers the question: What is the maximum expected displacement within a range of X years? It represents the outlier event that could occur during a specific time frame. PMD can be used to determine the size of shelters and other assets that a government needs to provide to cope with the potential magnitude of displacement.

Disaster displacement risk in Kenya: results by hazard type

Looking only to the past is not a reliable guide for understanding what may occur in the future or how best to prepare for it. As climate patterns shift and hazards evolve, it becomes increasingly important to use forward-looking tools such as probabilistic modelling to anticipate future displacement risks and inform proactive planning and preparedness efforts.

Riverine floods

The analysis of flood displacement risk at a country level shows an Annual Average Displacement (AAD) value of more than 37,000 people under current climate conditions. When looking at the results under optimistic and the pessimistic climate change scenarios, the model points at an increase in AAD values, which may more than double in the optimistic scenario and triple in the pessimistic one.

When downscaling the analysis at the county level, several notable trends emerge regarding how risk evolves under the two scenarios.

Except for Vihiga, Nyamira and Nyandarua, all counties in Kenya may face a risk of displacement linked to riverine floods. Under current climate conditions, Mandera and Turkana are the highest at risk, with an Annual Average Displacement (AAD) of approximately 10,000 and 15,000 people, respectively (see Figure 4).

In Mandera, the risk of displacement may double under the optimistic scenario and triple under the pessimistic one, reaching an Annual Average Displacement (AAD) of 32,000 people.

In Turkana, the situation is slightly different: the risk of displacement may be worse under the optimistic scenario than under the pessimistic one. In fact, the Annual Average Displacement (AAD) may reach 36,000 under the optimistic scenario, compared to 27,000 under the pessimistic.

Aside from Mandera and Turkana, our modeling approach highlights that only a few families to a few hundred people may be at risk of displacement in any given year. However, in all counties, the risk of displacement due to riverine flooding is projected to increase under both the optimistic and pessimistic scenarios.

While the Annual Average Displacement (AAD) reflects the average number of flood-induced displacements over a long-time frame, it tends to mask potential outliers. Understanding the impacts of these outliers and estimating the number of people potentially displaced during frequent (low return period) or rare (high return period) events, is essential. It is evident that the number of people at risk of displacement increases significantly with higher return periods. Understanding the potential impact of such events is crucial for preparedness planning, such as determining the size and scope of shelters, infrastructure, and emergency response assets that a government may require.

For instance, under current climate conditions across the country, displacement figures more than double from frequent events (e.g., a 5-year return period) to rare events (e.g., a 100-year return period).

This trend is also observed when analyzing the Probable Maximum Displacement (PMD) under long-term optimistic and pessimistic climate scenarios. At the national level, a 100-year event may result in displacement figures that triple under both scenarios (see Figure 10 in Figure Annex).

Under current climate conditions, a 50-year return period event, meaning a 2% chance of occurring in any given year, a 33% chance over the next 20 years, and a 64% chance over the next 50 years, could displace approximately 47,500 people in Turkana, 38,000 in Mandera and around 20,000 in Tana Rivers.



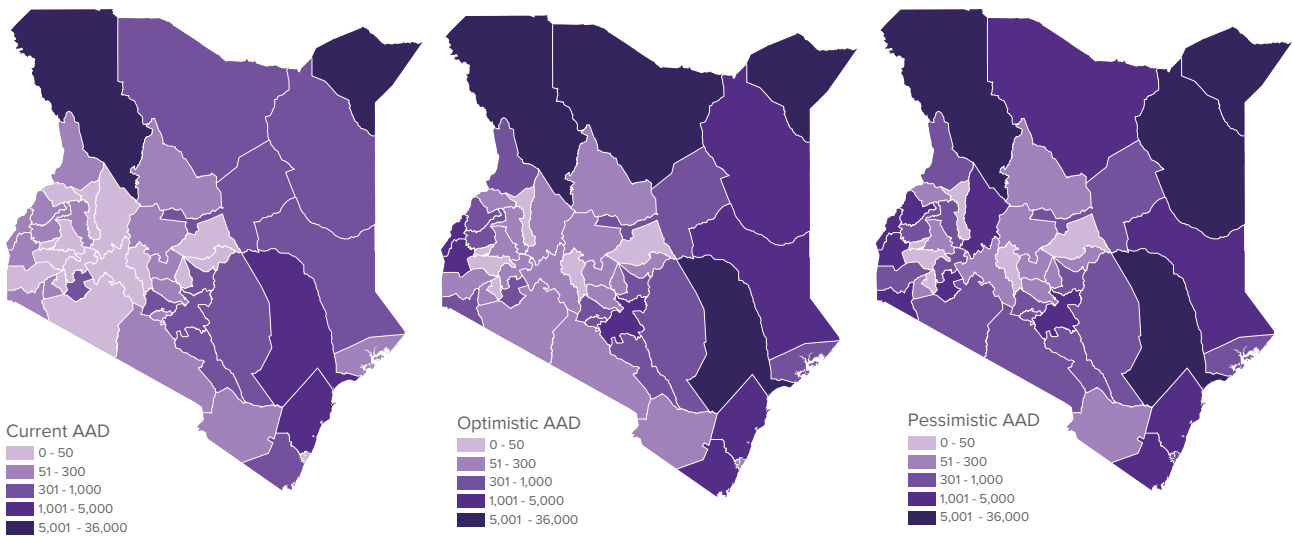
In the three counties, and assuming the population remains constant, the risk may increase by 57% in Turkana, double in Tana River, and nearly triple in Mandera.

Mombasa County may experience the largest increase in displacement risk. While the current risk is nearly zero, approximately 2,000 people could be displaced by a 50-year return period event, rising to 6,000 if a 100-year event occurs. Under the pessimistic scenario, the risk in Mandera remains approximately the same for a 50-year return period event. In contrast, in Tana River, the risk may

double, reaching 86,000 people at risk of displacement. Garissa County shows a similar trend, with the risk doubling from the optimistic to the pessimistic scenario, reaching 42,000 people at risk.

Still under a pessimistic scenario, a 100-year return period flood event, meaning a 1% chance of occurring in any given year and a 39% chance over the next 50 years, could displace almost 112,000 people in Mandera and 91,000 in Tana River.

Figure 4: Average Annual Displacement risk by riverine floods in Kenya under different climate scenarios



Storm surges

Storm surge is the abnormal rise in seawater level during a storm. The surge is caused primarily by a storm's winds pushing water onshore. The amplitude of the storm surge at any given location depends on the orientation of the coastline with the storm track; the intensity, size, and speed of the storm; and the local bathymetry. Our model assesses the risk from storm surges, taking into account how sea-level rise in a changing climate could affect potential run-up in coastal areas.

The analysis of storm surge displacement risk at the national level shows an Annual Average Displacement (AAD) of approximately 280 people. Results under different climate scenarios highlight the significant influence of climate change and sea-level rise (see Figure 5). In both optimistic and pessimistic scenarios, AAD values increase, multiplying by a factor of 10 in the optimistic case and by a factor of almost 20 in the worst-case scenario.

When downscaling the analysis to the county level, several notable trends emerge regarding how risk evolves under the two scenarios. In most of the 5 counties at risk of storm surges, the risk of displacement is projected to increase under the optimistic and significantly increase under pessimistic scenario.

Kilifi county is the most exposed under current climate conditions. Kilifi may experience a significant increase in displacement risk under the optimistic climate scenario, where the risk could increase tenfold, and double again under the pessimistic scenario.

In three counties, Kwale, Lamu, and Tana River, where displacement risk is absent or negligible, the combination of sea-level rise and storm surge introduces new risks under optimistic scenario that are projected to grow under the pessimistic one.

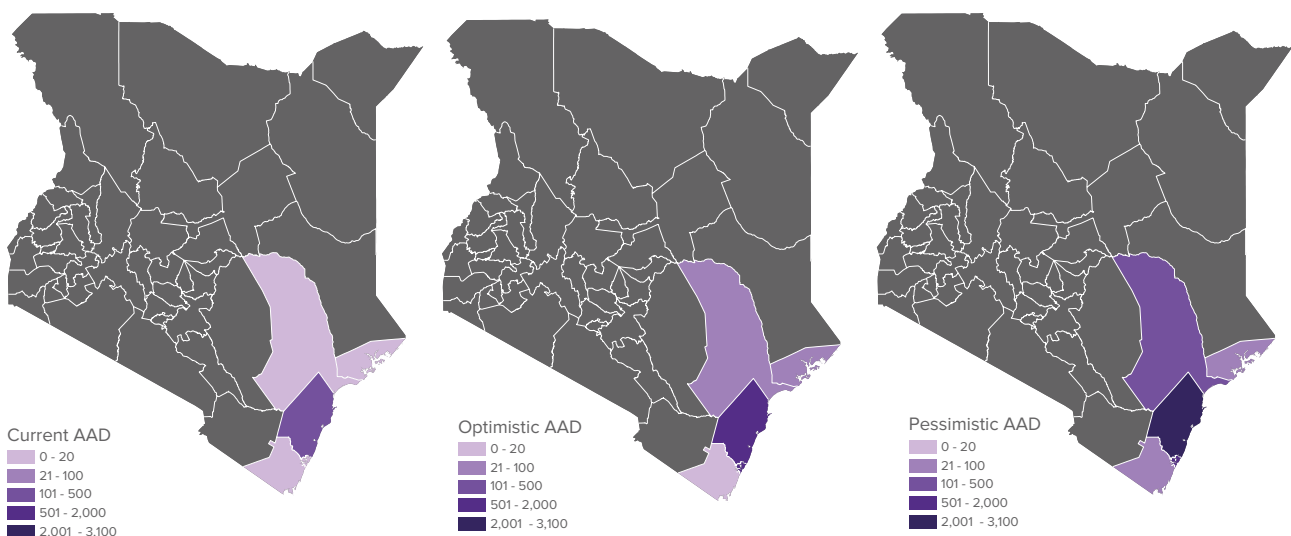
As highlighted in riverine floods risk section, while the Annual Average Displacement (AAD) reflects the average number of displacements over a long-time frame, it tends to mask potential outliers.

Under current climate conditions, a 50-year return period storm surge event, meaning a 2% chance of occurring in any given year, an 18% chance over the next 20 years, and a 39% chance over the next 50 years, could displace approximately 280 people in Kilifi (see Figure 9 in Figure Annex).

In more pessimistic scenarios, these numbers could multiply by 10-fold, reaching almost 2,800 in Delta, 35,000 in Rivers, and 1,000 in Mombasa County.

In Kwale, where our modeling did not detect any displacement risk under current climate conditions, a significant increase may occur if a 100-year return period event, which has an 18% probability of occurring over the next 20 years, affects the county's coastline. While the risk under optimistic scenarios may be limited to a few families, it could increase more than twentyfold under pessimistic conditions.

Figure 5: Average Annual Displacement risk by storm surges in Kenya under different climate scenarios





A traditional weather forecaster and farmer stands by a road in Taita-Taveta County, Kenya, in 2023. Growing impacts of climate change and environmental degradation are making his work more challenging. © NRC/Ingebjörg Kårstad

Cyclonic winds

Due to its location along the Indian Ocean coast, Kenya is also exposed to cyclonic winds.

High winds can directly damage or destroy buildings and infrastructure, rendering homes uninhabitable and disrupting essential services like power and water. Even though evidence is limited, wind damage alone does not appear to be one of the primary triggers of displacement during cyclones. Roofs may be damaged, but the structural integrity of buildings often remains intact—though this depends on the type of construction and the severity of the impact in the affected area.

The analysis of displacement risk due to cyclonic winds in Kenya shows that three counties may be affected. Kilifi, Kwale, and Mombasa counties could have average annual displacement (AAD) estimates of approximately 250, 300, and 435, respectively under current climate conditions (see Figure 6).

Although cyclones are currently rare in Kenya, a changing climate may lead to less frequent and less intense events, potentially decreasing the risk of medium- to long-term displacement along the coastline.

Under both optimistic and pessimistic scenarios, the risk of displacement due to cyclonic winds in Kenya may decrease and remain at similar levels across the two scenarios.

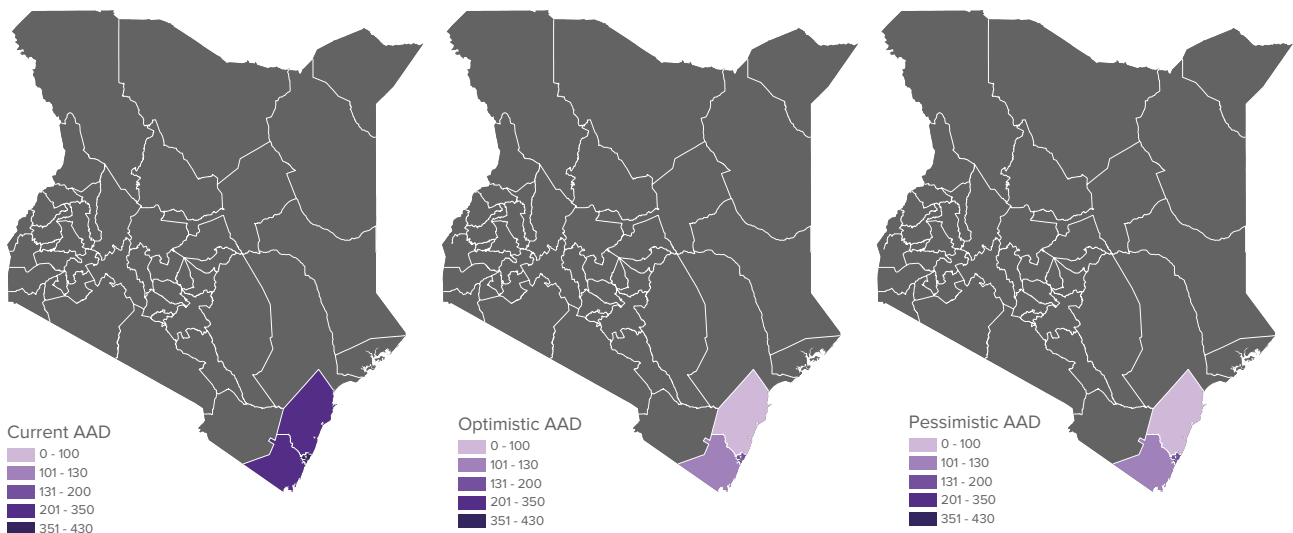
In Kilifi, Kwale, and Mombasa counties, the estimated Annual Average Displacement (AAD) is approximately 80, 120, and 145 people, respectively, representing a decrease of around 60% in both scenarios compared to the current risk.

As highlighted in the riverine flood risk section, the Annual Average Displacement (AAD) provides a long-term average of cyclonic winds-induced displacements. However, this metric can underrepresent the impact of rare but extreme events.

Our modeling framework includes the capacity to assess risks associated with high-return period events, such as a 250-year cyclone, representing an exceptionally intense storm well beyond typical conditions.

Due to data and modeling constraints, we were not able to estimate displacement figures for such rare events in the three coastal counties. Nevertheless, acknowledging this limitation is important, as it highlights the need for further research and investment in modeling rare but high-impact hazards to inform long-term resilience planning.

Figure 6: Average Annual Displacement risk by cyclonic winds in Kenya under different climate scenarios





People cross a bridge over a dry riverbed in Turkana County, Kenya, in 2024. The region was severely affected by the historic drought in the Horn of Africa, displacing people in search of food, water and pasture.
© NRC/ Ingebjørg Kårstad

Drought

Droughts are one of the most complex disasters, causing severe damage to agriculture, which is a key sector of Kenya's economy, contributing for more than 30 per cent of its Gross Domestic Product (GDP). The sector employs more than 40 per cent of the total population and more than 70 per cent of the country's rural communities.

Shifting weather patterns associated with ENSO oscillations affect rainfall patterns in Kenya, bringing either exceptionally heavy and prolonged rains or extended dry seasons, both of which have significant consequences, including displacement.

Drought displacement data is still hard to come by in Kenya, with a few data points for some years, mostly since 2017, which does not allow to use a solid historical baseline to calibrate the model. To bridge this gap, our model incorporates economic, social, and environmental factors to refine risk estimates. The analysis of drought displacement risk at the country level reveals an Annual Average Displacement (AAD) of approximately 81,000 people (see Figure 7). However, results under different climate scenarios highlight the significant influence of climate change. Notably, the risk more than quadruples under the optimistic scenario and increases sevenfold under the pessimistic one, reaching over 600,000 displaced individuals in any given year.

When downscaling the analysis to the county level, a key finding emerges: almost all counties in Kenya are at risk of drought-related displacement, with the exception of Nyamira and Mombasa. Many counties have thousands of people at risk. Under current climate conditions, the Annual Average Displacement (AAD) ranges from around 100 people in Lamu and 370 in Nairobi, to over 6,000 in Mandera County.

Except Lamu and Tana River, where the risk may decrease under optimistic scenarios, all other counties may experience either a minor or, in some cases, a major increase in displacement risk. Notably, in Bungoma, Kericho, Nakuru, and Uasin Gishu, the Annual Average Displacement (AAD) could reach approximately 28,000, 19,000, 33,000, and 17,000 people, respectively. In these areas, the risk could increase by 7 to 9 times compared to current climate conditions.

Under the pessimistic scenario, a similar trend is observed: with the exception of Kilifi, Kwale, Lamu, where the risk may slightly decline under pessimistic conditions, all other counties are likely to experience either modest or, in some cases, substantial increases in displacement risk.

In Baringo, Nakuru, and Uasin Gishu, the risk of displacement is projected to increase drastically under pessimistic climate scenarios, rising by 15 to 18 times compared to current climate conditions. In the worst-case scenario, up to 28,000 people in Baringo, 51,000 in Nakuru, and 29,000 in Uasin Gishu could be displaced in any given year.

It is also important to note that Bungoma County may experience a significant increase in displacement risk, with the Annual Average Displacement (AAD) potentially reaching approximately 42,000 people per year.

Looking at PMD, under current climate conditions, a 100-year return period drought event with a 1% chance of occurring in any given year and a 39% chance over the next 50 years could displace around 100,000 in Mandera (see Figure 11 in Figure Annex).

In the optimistic scenario for Nakuru, a similar event could displace 237,000 people, almost four times the displacement risk of a similar event under current climate conditions.

Under pessimistic scenarios, Bungoma and Nakuru may face the highest populations at risk of drought displacement. In both counties, more than 300,000 people could be displaced if a 100-year return period drought event takes place.

It is also important to note that a 50-year return period event, with a 33% probability of occurring in the next 20 years, could displace more than 100,000 people in Mandera under current climate conditions. This number may rise to 152,000 under the optimistic scenario and double under the pessimistic scenario, reaching 206,000.

Kakamega County may experience a similar increase, where a 50-year return period event could displace 31,000 people under current conditions. This number could rise fourfold to 122,000 under the optimistic scenario, with a further increase to 152,000 under the pessimistic scenario.

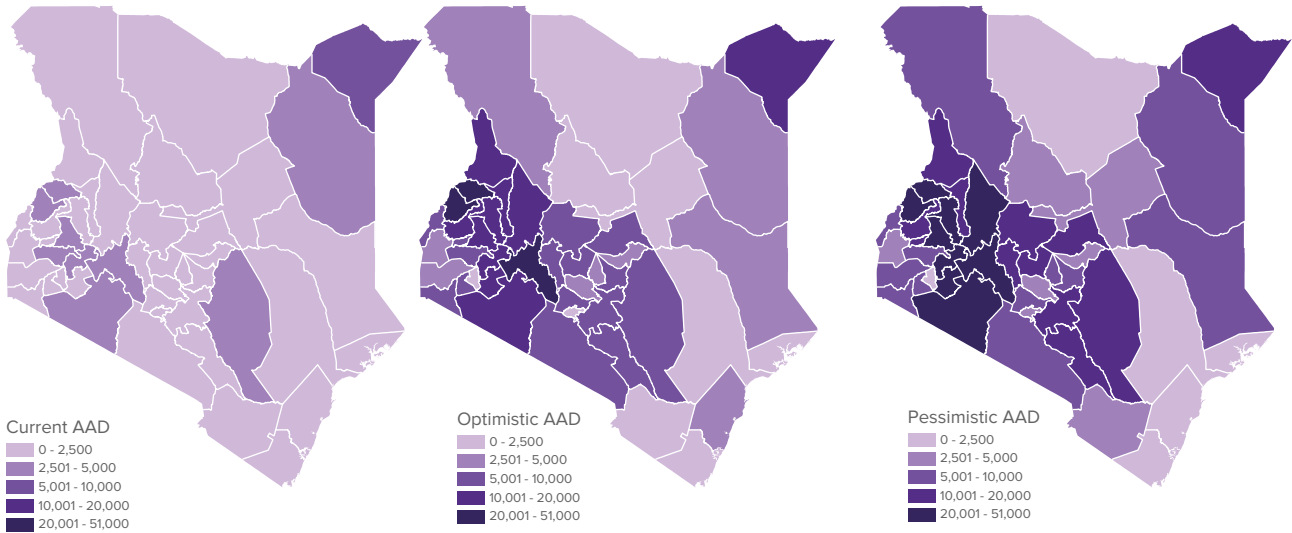
Disaster displacement is one of the most significant humanitarian and development challenges we face in the 21st century.



The insights from probabilistic risk models underscore the need for proactive policy interventions to prevent and manage future displacement driven by natural hazards in a changing climate. They also provide insights into how and where that displacement may occur. To minimise the risk of displacement and its most adverse impacts, the

government in Kenya and all actors managing disaster risk reduction can use this information to move beyond reactive responses to displacement events and adopt forward-thinking strategies that anticipate risks and build resilience in vulnerable communities.

Figure 7: Average Annual Displacement risk by drought in Kenya under different climate scenarios



Conclusion

Our study outlines an effort to create and apply a multi-hazards displacement risk model that utilizes novel methods for vulnerability assessment. The methodology gauges the potential displacement of individuals due to riverine floods, storm surges, cyclonic winds and drought.

The quantification of risk is expressed in terms of Average Annual Displacement (AAD) and Probable Maximum Displacement, calculated under current climate conditions as well as long-term projections based on both optimistic and pessimistic scenarios. This methodology, first applied in two small Pacific islands, Fiji and Vanuatu, was later scaled up to the regional level in the Horn of Africa before being implemented globally. The resulting outputs provide valuable insights into the proportion of housing rendered uninhabitable and the loss of livelihoods caused by floods and droughts, both of which can trigger displacement. We present outputs at Admin level 1 highlighting where the spatial risk pattern increases under projected conditions influenced by climate change, considering optimistic and pessimistic scenarios.

The model's results can be used to inform national and subnational disaster risk reduction measures, identify areas where large numbers of people could be made homeless by floods, and calculate evacuation centre capacities and the amount of investment needed to support displaced people. Through this report, we present some recommendations that can serve as a foundation for developing comprehensive policies and strategies to mitigate displacement risks associated with hazards highlighted in this report floods and protect the rights and wellbeing of affected populations.

Tangible steps must be reinforced to identify and target vulnerable populations who are at higher risk of displacement. Tailored strategies should be developed to protect their rights and well-being. Additionally, investment in flood-resistant infrastructure (riverine and storm surges) and improved building standards is essential to reduce displacement and property damage. Finally, continued advocacy for and implementation of climate mitigation measures remains crucial.

Data availability, technological advances and growing international recognition of the scale and increasing risk of disaster displacement mean the time is right for more and better-coordinated action to build on good practices and address the challenge of designing effective displacement risk models.

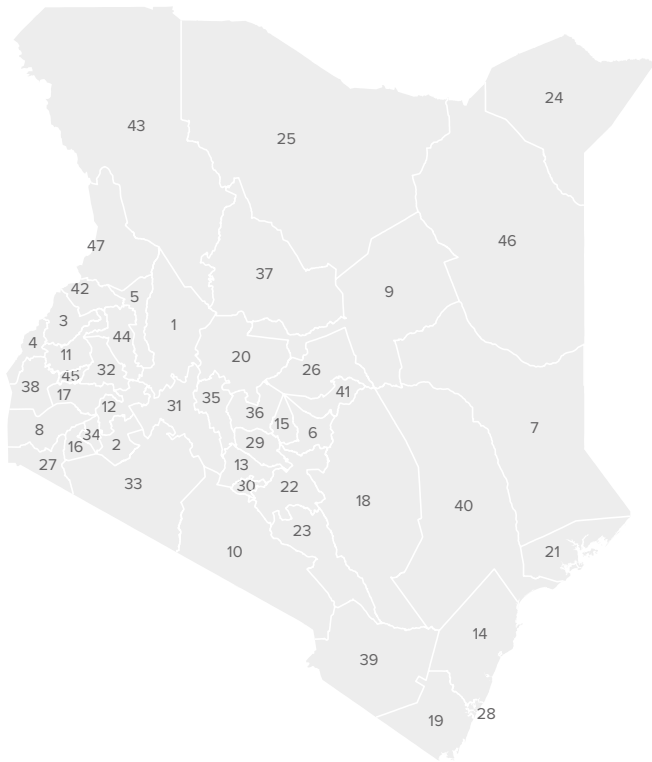
Further efforts are required to effectively quantify future hazard risks, especially with the dynamic background of evolving "riskscapes" in Kenya. The effectiveness of our efforts will naturally improve with the availability of additional data to refine and calibrate our models. This necessitates a comprehensive understanding of population and socioeconomic patterns, along with fluctuations in the frequency and intensity of hazards associated with climate change. To achieve this, we must leverage open-access data, refine terrain models for greater accuracy and acquire more hydrometeorological, and meteorological data. The risk of disaster-induced displacement is a global reality, present in every country. Now is the opportune time to demonstrate our collective commitment to the principle of leaving no one behind, particularly those already enduring the challenges of protracted and repeated displacement.



Tomato plants destroyed by the severe 2023 drought in Taita-Taveta County, Kenya, reflecting the severe impact of prolonged drought on food security and livelihoods. © NRC/ Ingebjørg Kårstad

Figure Annex

Figure 8: Map of Kenya by county



Counties

- 1 Baringo
- 2 Bomet
- 3 Bungoma
- 4 Busia
- 5 Elgeyo-Marakwet
- 6 Embu
- 7 Garissa
- 8 Homa Bay
- 9 Isiolo
- 10 Kajiado
- 11 Kakamega
- 12 Kericho
- 13 Kiambu
- 14 Kilifi
- 15 Kirinyaga
- 16 Kisii
- 17 Kisumu
- 18 Kitui
- 19 Kwale
- 20 Laikipia
- 21 Lamu
- 22 Machakos
- 23 Makueni
- 24 Mandera
- 25 Marsabit
- 26 Meru
- 27 Migori
- 28 Mombasa
- 29 Murang'a
- 30 Nairobi
- 31 Nakuru
- 32 Nandi
- 33 Narok
- 34 Nyamira
- 35 Nyandarua
- 36 Nyeri
- 37 Samburu
- 38 Siaya
- 39 Taita Taveta
- 40 Tana River
- 41 Tharaka-Nithi
- 42 Trans Nzoia
- 43 Turkana
- 44 Uasin Gishu
- 45 Vihiga
- 46 Wajir
- 47 West Pokot

Figure 9: Probable Maximum Displacement per county for storm surges

Legend



By Counties	Current PMD50	Optimistic PMD50	Pessimistic PMD50
14 Kilifi	280	1,700	2,800
19 Kwale	0	15	93
21 Lamu	0	66	110
28 Mombasa	0	940	970
40 Tana River	0	20	380

By Counties	Current PMD100	Optimistic PMD100	Pessimistic PMD100
14 Kilifi	280	1,700	2,900
19 Kwale	0	42	920
21 Lamu	0	66	110
28 Mombasa	480	950	1,100
40 Tana River	0	20	470



Figure 10: Probable Maximum Displacement per county for riverine floods

By Counties		Current PMD50	Optimistic PMD50	Pessimistic PMD50	By Counties		Current PMD100	Optimistic PMD100	Pessimistic PMD100
1	Baringo	100	190	1,300	1	Baringo	130		1,400
2	Bomet	420	840	2,800	2	Bomet	470		2,900
3	Bungoma	620	2,300	3,200	3	Bungoma	750		3,300
4	Busia	410	5,700	8,200	4	Busia	490		8,400
	Elgeyo-Marakwet	60	150	160		Elgeyo-Marakwet	81		200
6	Embu	2,200	2,900	2,900	6	Embu	2,300		2,900
7	Garissa	2,500	28,000	42,000	7	Garissa	11,000		48,000
8	Homa Bay	52	1,600	3,100	8	Homa Bay	86		3,300
9	Isiolo	2,000	3,100	4,700	9	Isiolo	2,400		5,500
10	Kajiado	200	630	870	10	Kajiado	220		900
11	Kakamega	1,300	4,100	3,400	11	Kakamega	1,700		3,400
12	Kericho	1,200	1,600	1,600	12	Kericho	1,200		1,600
13	Kiambu	2,100	3,400	4,200	13	Kiambu	2,700		4,600
14	Kilifi	6,400	20,000	28,000	14	Kilifi	6,700		30,000
15	Kirinyaga	390	560	650	15	Kirinyaga	410		790
16	Kisii	1,000	1,700	2,500	16	Kisii	1,200		2,500
17	Kisumu	27	230	390	17	Kisumu	38		470
18	Kitui	1,300	3,100	2,600	18	Kitui	1,400		2,700
19	Kwale	1,500	6,800	7,100	19	Kwale	1,600		7,400
20	Laikipia	680	1,200	1,200	20	Laikipia	730		1,300
21	Lamu	330	1,600	2,700	21	Lamu	380		2,900
22	Machakos	2,800	5,100	5,400	22	Machakos	3,100		5,800
23	Makueni	1,400	2,800	2,900	23	Makueni	1,700		3,000
24	Mandera	38,000	109,000	108,000	24	Mandera	42,000		112,000
25	Marsabit	2,000	4,600	3,500	25	Marsabit	2,000		7600
26	Meru	200	380	390	26	Meru	260		430
27	Migori	2,000	5,600	7,300	27	Migori	2,800		8,000
28	Mombasa	2	2,100	6,900	28	Mombasa	69		8,600
29	Murang'a	660	990	1,000	29	Murang'a	700		1,100
30	Nairobi	1,300	2,700	2,700	30	Nairobi	1,500		2,900
31	Nakuru	31	200	270	31	Nakuru	38		270
32	Nandi	240	660	870	32	Nandi	310		900
33	Narok	58	180	1,100	33	Narok	63		1,100
34	Nyamira	0	4	0	34	Nyamira	6		0
35	Nyandarua	0	0	0	35	Nyandarua	0		0
36	Nyeri	920	1,400	1,300	36	Nyeri	1,000		1,500
37	Samburu	220	380	440	37	Samburu	230		470
38	Siaya	2,800	8,700	14,000	38	Siaya	3,100		14,000
39	Taita Taveta	260	1,200	1,000	39	Taita Taveta	290		1,100
40	Tana River	21,000	49,000	87,000	40	Tana River	23,000		91,000
41	Tharaka-Nithi	220	550	380	41	Tharaka-Nithi	240		460
42	Trans Nzoia	11	420	600	42	Trans Nzoia	12		650
43	Turkana	47,000	73,000	79,000	43	Turkana	50,000		80,000
44	Uasin Gishu	380	730	1,300	44	Uasin Gishu	420		1,500
45	Vihiga	0	0	0	45	Vihiga	0		0
46	Wajir	2,300	14,000	21,000	46	Wajir	2,700		27,000
47	West Pokot	170	440	590	47	West Pokot	190		600

Figure 11: Probable Maximum Displacement per county for drought

By Counties		Current PMD50	Optimistic PMD50	Pessimistic PMD50	By Counties		Current PMD100	Optimistic PMD100	Pessimistic PMD100
1	Baringo	33,000	116,000	176,000	1	Baringo	47,000	117,000	177,000
2	Bomet	35,000	122,000	197,000	2	Bomet	50,000	132,000	213,000
3	Bungoma	77,000	232,000	304,000	3	Bungoma	112,000	253,000	32,000
4	Busia	38,000	61,000	67,000	4	Busia	55,000	72,000	79,000
	Elgeyo-Marakwet	25,000	86,000	138,000		Elgeyo-Marakwet	35,000	95,000	147,000
6	Embu	23,000	72,000	97,000	6	Embu	33,000	84,000	113,000
7	Garissa	32,000	41,000	54,000	7	Garissa	46,000	58,000	70,000
8	Homa Bay	43,000	57,000	71,000	8	Homa Bay	62,000	77,000	93,000
9	Isiolo	3,700	12,000	20,000	9	Isiolo	5,300	13,000	21,000
10	Kajiado	16,000	46,000	78,000	10	Kajiado	23,000	52,000	86,000
11	Kakamega	31,000	123,000	152,000	11	Kakamega	64,000	146,000	185,000
12	Kericho	43,000	162,000	251,000	12	Kericho	62,000	174,000	276,000
13	Kiambu	11,000	40,000	64,000	13	Kiambu	16,000	4,000	64,000
14	Kilifi	39,000	37,000	24,000	14	Kilifi	59,000	67,000	50,000
15	Kirinyaga	13,000	49,000	83,000	15	Kirinyaga	19,000	54,000	83,000
16	Kisii	12,000	48,000	76,000	16	Kisii	17,000	51,000	76,000
17	Kisumu	50,000	92,000	101,000	17	Kisumu	72,000	113,000	123,000
18	Kitui	48,000	87,000	123,000	18	Kitui	69,000	108,000	147,000
19	Kwale	21,000	34,000	6,000	19	Kwale	35,000	48,000	26,000
20	Laikipia	17,000	62,000	98,000	20	Laikipia	24,000	66,000	99,000
21	Lamu	1,800	870	1,400	21	Lamu	2,600	2,300	2,300
22	Machakos	42,000	103,000	146,000	22	Machakos	61,000	122,000	160,000
23	Makueni	45,000	74,000	114,000	23	Makueni	64,000	95,000	153,000
24	Mandera	108,000	152,000	206,000	24	Mandera	155,000	208,000	256,000
25	Marsabit	5,800	8,000	18,000	25	Marsabit	8,400	12,000	20,000
26	Meru	37,000	82,000	111,000	26	Meru	53,000	93,000	120,000
27	Migori	36,000	70,000	80,000	27	Migori	52,000	84,000	94,000
28	Mombasa	0	0	0	28	Mombasa	0	0	0
29	Murang'a	18,000	37,000	42,000	29	Murang'a	27,000	46,000	50,000
30	Nairobi	6,800	21,000	26,000	30	Nairobi	9,700	23,000	26,000
31	Nakuru	62,000	236,000	363,000	31	Nakuru	88,000	237,000	363,000
32	Nandi	45,000	165,000	264,000	32	Nandi	65,000	176,000	267,000
33	Narok	44,000	154,000	237,000	33	Narok	64,000	168,000	259,000
34	Nyamira	0	0	0	34	Nyamira	0	0	0
35	Nyandarua	22,000	82,000	136,000	35	Nyandarua	31,000	86,000	141,000
36	Nyeri	16,000	56,000	102,000	36	Nyeri	23,000	62,000	102,000
37	Samburu	5,600	18,000	30,000	37	Samburu	8,000	19,000	30,000
38	Siaya	38,000	58,000	58,000	38	Siaya	54,000	71,000	72,000
39	Taita Taveta	14,000	30,000	37,000	39	Taita Taveta	21,000	38,000	46,000
40	Tana River	12,000	8,800	11,000	40	Tana River	17,000	18,000	22,000
41	Tharaka-Nithi	12,000	3,000	34,000	41	Tharaka-Nithi	18,000	35,000	43,000
42	Trans Nzoia	49,000	183,000	281,000	42	Trans Nzoia	70,000	184,000	281,000
43	Turkana	21,000	46,000	74,000	43	Turkana	30,000	53,000	83,000
44	Uasin Gishu	27,000	118,000	182,000	44	Uasin Gishu	40,000	119,000	182,000
45	Vihiga	12,000	68,000	92,000	45	Vihiga	30,000	78,000	151,000
46	Wajir	47,000	42,000	70,000	46	Wajir	68,000	68,000	94,000
47	West Pokot	33,000	118,000	163,000	47	West Pokot	48,000	128,000	196,000

Methodological Annex

The true benefits of a probabilistic risk assessment are frequently misconstrued because it is regarded as a complex and challenging method to implement and follow, with a communication hurdle when presenting outcomes. A probabilistic disaster displacement risk profile must be seen as a diagnostic tool, because it offers insights into potential hazard occurrences and their consequences.

Such profiles cover all possible risk scenarios in a certain geographical area. Both low-frequency, high-impact events and high-frequency, low-impact events are considered. Their probability of occurrence, all elements of the risk equation (risk = hazard X exposure X vulnerability), and their variability and uncertainty ranges are all included (see Figure 12).

Events that have rarely been recorded but might occur more often under climate projections are thus also considered. This feature is particularly useful because climate change is increasing uncertainty about future hazard patterns. To be prepared, societies need to calculate the worst possible impact. Viewed through this lens, there is no valid alternative to a probabilistic analysis to address such uncertainty in a usable, quantitative way.

Displacement risk information, expressed in average annual displacement (AAD) and probable maximum displacement (PMD), is calculated at the subnational regions and aggregated at country level, allowing for a geographic and quantitative comparison within and between countries. These analyses and comparison exercises are an important step in risk awareness processes and key to pushing for risk reduction, adaptation and management mechanisms to be put in place.

The PMD curve illustrates the probability of a specific scenario leading to an estimated number of displacements. This likelihood is usually measured in terms of return period, which is often misunderstood. A return period is the average time interval in years that separates two consecutive events equal to or exceeding the given magnitude. The most common misconception is that an event with

a 100-year return period will only occur once a century, when instead it means that it has an exceedance probability of 1 in 100, so events of the same or greater intensity happen once every 100 years on average. This does not preclude the possibility of several events with a 100-year return period happening within a century, or even the rare chance of consecutive events transpiring in consecutive years. Neither does it eliminate the possibility of an entire century passing without such an event occurring.

Our model assesses the risk of severe housing damage or destruction, as well as the loss of livelihoods for certain hazards such as droughts and floods, to estimate the likelihood of displacement. In essence, it focuses on the risk of medium- to long-term displacement and does not account for or model pre-emptive evacuations. This means the figures presented here are highly conservative. Our approach looks at people who may suffer the consequences of their homes becoming uninhabitable and who are forced to be displaced for weeks, months, or even years.

Using the similar approach of “catastrophe Modeling” CAT assessing economic losses associated with disasters (Average Annual Loss -AAL- and Probable Maximum Loss -PML-), we “humanised” the approach by looking, instead of the monetary value of residential building, how many people lives in it, **to estimate the probability of people getting displaced**. Our outputs are presented under two main metrics: Average Annual Displacement (AAD) and Probable Maximum Displacement (PMD) for each hazard type and downscaled at admin 1 resolution (see section - *Making sense of displacement risk metrics*).

Displacement risk from the four hazards is estimated using two distinct risk modeling framework, one from CIMA foundation for riverine floods and CLIMADA for the other hazards, each of which estimates human displacement resulting from the interplay of the hazard, exposure, and vulnerability data. This consistency allows for a comparative analysis of outputs across models.



Figure 12: The displacement risk equation



Displacement risk from **riverine floods** is assessed using the risk model developed by [CIMA foundation](#), while displacement from **tropical cyclones** (winds) and **coastal floods** (storm surge and sea level rise) is calculated using the Python implementation of CLIMADA under the [Weather and Climate Risks at ETH Zürich](#). Drought-related displacement is modeled using an earlier version of CLIMADA, implemented in Matlab, by [United Nations Universities - Institute for Environment and Human Security](#).

Hazards

River flood hazard maps were generated using a climate-hydrology-inundation framework with bias-corrected CMIP6 projections from 15 global climate models. The Continuum hydrological model simulated river discharge, which was processed through the REFLEX inundation model to produce flood hazard maps. A synthetic 3,000-year event catalogue was created to improve risk estimates. ([CIMA foundation](#))

To capture the spread of possible climate scenarios, we compared 15 models from the Inter-Sectoral Impact Model Intercomparison Project (ISIMIP3b), which provides bias-corrected Coupled Model Intercomparison Project Phase 6 (CMIP6) climate scenarios for pre-industrial, historical, SSP1-RCP2.6, SSP3-RCP7.0 and SSP5-RCP8.5 conditions, in terms of temperature and precipitation rise in 2016. Temperature and precipitation trends proved to be highly correlated in the models considered, so we referred only to temperature trends to define representative scenarios, from which we selected, optimistic and pessimistic.

Coastal flood hazard maps were developed based on storm surges and sea-level rise (SLR) projections, considering future scenarios for 2050 and 2100 under SSP1-2.6

and SSP5-8.5. ([Disaster Analytics for Society Lab](#) - Nanyang Technological University - NTU Singapore)

Drought hazard conditions were analysed using the Standardized Precipitation Index (SPI₁₂), which measures long-term precipitation anomalies. Data from the Cordex dataset at a 0.22° resolution were used, incorporating RCP2.6 and RCP8.5 scenarios. Drought intensity and frequency were assessed for return periods of 10 to 100 years. (UNU-EHS – Climate Risk Analytics)

Tropical cyclone wind hazards. We used synthetic tropical cyclone event sets from the MIT model, downscaled from ERA-5 reanalysis data for historical periods and from nine GCMs for future climate scenarios (SSP2-4.5 and SSP5-8.5) for 2041–2060 and 2081–2100. Wind-driven impacts were modelled using the Holland (2008) parametric wind model, with maximum sustained wind speeds serving as the hazard intensity variable. Storm surge effects were categorized under coastal flooding, while rainfall impacts were excluded. (MIT - [Weather and Climate Risks at ETH Zürich](#))

Exposure

We use the Global Building Exposure Model at 1km resolution globally to assess how different hazards impact communities and infrastructure. This model helps us understand which buildings and populations are most at risk from disasters like cyclones, floods, and droughts. By integrating high-resolution data on population, land use, and economic activity, we can better estimate potential displacement and improve disaster response planning. (The GIRI global building exposure model (BEM) - UNEP-GRID-Geneva-CDRI-IDMC).

Vulnerability

In hazard risk modelling, vulnerability is represented through impact functions, which estimate structural damage and displacement risk from hazards like tropical cyclones, floods, and droughts. We use CAPRA impact functions to assess building damage based on wind speed and flood depth, while a separate function estimates livelihood loss due to flooding in agricultural areas. (CAPRA - [Comprehensive Approach to Probabilistic Risk Assessment: international initiative for risk management effectiveness](#) and Rossi and al. [A new methodology for probabilistic flood displacement risk assessment](#))

For drought-related displacement, our model considers economic, social, and environmental factors to refine risk estimates at national and subnational levels. This approach ensures a comprehensive understanding of displacement drivers and informs more effective resilience planning.

This risk assessment considers a large number of possible scenarios, their likelihood, and the resulting damage to housing, while also accounting for livelihood damages, mainly from medium- to large-scale events. Small and recurrent events still require daily monitoring of empirical information to understand and capture the true scale of displacement risk by different triggers.

For this iteration, we did not account for changes in exposure between current and future scenarios, although factors such as population growth and distribution—such as rapid urban sprawl reducing natural areas that absorb floodwater—may significantly alter the future “riskscape.” However, for drought-related displacement, we explore potential changes in population distribution and dynamics over time using United Nations population projections for 2050 and 2100.

It is important to note that the results exclude individuals involved in pre-emptive evacuations. Our outputs focus on people at risk of medium- to long-term displacement,

primarily due to severe damage to homes. For floods, we also explore the risk of loss of livelihoods, incorporating a complex process to avoid double-counting individuals who may experience both housing and livelihood loss in the same scenario. However, since droughts rarely damage built environments, we focus on how they impact agriculture, undermining livelihoods and forcing communities into displacement situation in search of alternatives.

Lastly, even with the use of more accurate exposure layers at a 1 km x 1 km resolution, the resolution of certain hazard datasets did not allow for proper subnational displacement risk assessments. The outputs should be viewed as tools to raise awareness and guide further discussions on disaster risk reduction investments centered on internal displacement. The model and its current resolution are not suitable for informing land use or urban planning decisions. Additional efforts are needed to develop more accurate and higher-resolution data on hazards and exposure, as well as customized vulnerability assessments that incorporate coping mechanisms from different regions within the country. This would enable the design of more detailed and effective measures to actively reduce displacement risk at the local level. Currently, the outputs are intended to support discussions at the national level.

IDMC has been working with numerous partners since the mid-2010s to put our data to use in estimating disaster displacement risk. Collaborating with diverse and respected partners allows us to use the most up-to-date data and methodologies for various components of displacement risk and apply strict scientific rigour and quality assurance in our models.

Our current consortium of partners includes the [CIMA Foundation](#), [ETH-Zurich's Weather and climate risk group](#), the [Nanyang Technological University - NTU Singapore](#), the [Potsdam Institute for Climate Impact Research \(PIK\)](#), The United Nations University's Institute for Environment and Human Security ([UNU-EHS](#)).

Houses submerged by floodwaters caused by heavy rains in Kisumu County, Kenya, in 2024. Kenya has seen a significant increase in the number of disaster displacements since 2008, with floods and droughts as the main drivers. © UNOCHA/Milka Ndungu



Endnotes

- 1 <https://link.springer.com/book/10.1007/978-981-10-3241-7> accessed on 26.06.2025
- 2 <https://data.worldbank.org/indicator/SP.POP.TOTL?locations=KE> accessed on 26.06.2025 ; <https://www.ebsco.com/research-starters/geography-and-cartography/nairobi-kenya> accessed on 26.06.2025
- 3 <https://kenyaembassybrazil.com.br/about-kenya/country-profile/> accessed on 26.06.2025
- 4 https://www.afdb.org/sites/default/files/documents/publications/kenya_39_4.pdf accessed on 26.06.2025
- 5 https://climateknowledgeportal.worldbank.org/sites/default/files/2021-05/15724-WB_Kenya%20Country%20Profile-WEB.pdf accessed on 26.06.2025
- 6 Ibid
- 7 <https://www.internal-displacement.org/publications/2019-global-report-on-internal-displacement-grid/> accessed 26.06.2025
- 8 <https://www.asalrd.go.ke/> accessed on 27.06.2025
- 9 <https://www.unocha.org/publications/report/kenya/kenya-drought-response-dashboard-may-2022> accessed on 27.06.2025
- 10 <https://www.internal-displacement.org/publications/2023-global-report-on-internal-displacement-grid/> accessed on 27.06.2025



A farmer in Taita-Taveta County holds green grams affected by the 2023 drought in Kenya. © NRC/ Ingebjørg Kårstad

Every day, people flee conflict and disasters and become displaced inside their own countries. IDMC provides data and analysis and supports partners to identify and implement solutions to internal displacement.

Join us as we work to make real and lasting change for internally displaced people in the decade ahead.



The Internal Displacement Monitoring Centre

La Voie Creuse 16, 1202 Geneva, Switzerland

+41 22 552 3600 | info@idmc.ch



[internal-displacement.org](https://www.internal-displacement.org)



x.com/IDMC_Geneva



youtube.com/c/InternalDisplacementMonitoringCentreIDMC



linkedin.com/company/idmc-geneva