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TECHNICAL REPORT

# CLIMATE CHANGE AND HEALTH IN MOZAMBIQUE: IMPACTS ON DIARRHEAL DISEASE AND MALARIA



**March 2018**

This document was produced for review by the United States Agency for International Development. It was prepared by Chemonics for the ATLAS Task Order.

This document was produced for review by the United States Agency for International Development. It was prepared by Chemonics International for the Climate Change Adaptation, Thought Leadership and Assessments (ATLAS) Task Order No. AID-OAA-I-14-00013, under the Restoring the Environment through Prosperity, Livelihoods and Conserving Ecosystems (REPLACE) IDIQ.

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Cover Photo: Direct Relief, March 2016. Three boys test a new bed net provided through a partnership of the NGO Malaria Consortium and the Government of Mozambique.

# CLIMATE CHANGE AND HEALTH IN MOZAMBIQUE

## IMPACTS ON DIARRHEAL DISEASE AND MALARIA

March 2018

Prepared for:

United States Agency for International Development

Climate Change Adaptation, Thought Leadership and Assessments (ATLAS)

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# ACRONYMS

AOGCM	Atmosphere-Ocean Global Climate Model
BES	<i>Boletins Epidemiológicos Semanais</i>
CHIRPS	Climate Hazards Group InfraRed Rainfall with Stations
CI	Confidence interval
CMIP	Coupled Model Intercomparison Project
CMIP5	Coupled Model Intercomparison Project Phase 5
CRU	Climate Research Unit
CSAG	Climate System Analysis Group
DAG	Directed acyclic graph
ENSO	El Niño Southern Oscillation
GCM	Global Climate Model
GLM	Generalized linear model
GLMM	Generalized linear mixed model
INS	National Institute of Health
IPCC	Intergovernmental Panel on Climate Change
IRR	Incidence rate ratio
IRS	Indoor residual spraying
ITCZ	Intertropical Convergence Zone
LLIN	Long-lasting insecticide-treated net
MoH	Ministry of Health
RCP	Representative Concentration Pathway
SOMD	Self-Organizing Map-based Downscaling
USAID	United States Agency for International Development
WFDEI	Watch Forcing Data ERA - Interim

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# EXECUTIVE SUMMARY

This report outlines the results of a scientific study of the impacts of weather, climate variability, and climate change on health in Mozambique, with a focus on diarrheal disease and malaria. This study was financed by the United States Agency for International Development (USAID) Africa Bureau under the Climate Change Adaptation, Thought Leadership and Assessments Project (ATLAS). It was conducted in close collaboration with Mozambique's National Institute of Health (INS) by a team of leading experts in the fields of health and climate change. The work provides a country-specific lens to the growing knowledge base exploring the causal links between climate and health in sub-Saharan Africa.

Climate and health results from the 2014 Intergovernmental Panel on Climate Change's (IPCC) Fifth Assessment Report include:

- Climate change may increase the burden of a range of climate-relevant health outcomes.
- Climate change is a multiplier of existing health vulnerabilities, including insufficient access to safe water and improved sanitation, food insecurity, and limited access to health care and education.
- Detection and attribution of trends is difficult because of the complexity of disease transmission, with many drivers other than weather and climate, and short and often incomplete datasets.
- Evidence is growing that highland areas, especially in East Africa, could experience increased malaria epidemics due to climate change.
- The strong seasonality of meningococcal meningitis and associations with weather and climate variability suggest the disease burden could be negatively affected by climate change.
- Climate change is projected to increase the burden of malnutrition, with the highest toll expected in children.

As the IPCC results note, the linkages between climate change and health are often complex and indirect, making direct attribution of climate change effects on health outcomes challenging. Climate change is a stress multiplier for health, putting pressure on vulnerable systems, populations, and regions, and exacerbating existing health issues. For example, higher-than-average temperatures are associated with the incidence of diarrheal diseases that drive high rates of childhood mortality. Rising and more extreme temperatures can also change the range, seasonality, and incidence of diseases like malaria. As temperatures increase beyond the typically normal averages, these diseases are likely to become more prevalent if action is not taken.

As in many countries in Africa, the scientific knowledge describing the health risks of weather, climate variability, and climate change needs to be strengthened in Mozambique. The Mozambican National Communication to the United Nations Framework Convention on Climate

Change and the National Adaptation Program of Action recognize that climate change will bring about health impacts but do not elaborate on their nature or distribution. Similarly, the National Institute of Disaster Management published a report in 2009 investigating the effects of climate change on disaster risk in the country. The report highlighted a growing risk with little detail on the specific risks throughout the country. Although current associations between weather variables and a range of adverse health outcomes are generally understood — mostly derived from studies conducted in other countries — improved knowledge of current and projected risks in the different regions of Mozambique is needed to formulate evidence-based policies and programs. At the same time, there is an increasing call for health policy to be informed by research findings. An opportunity exists to improve the health of Mozambican communities by better understanding the role that climate and weather play in health, particularly for infectious diseases.

*“Climate change represents an inevitable, massive threat to global health that will likely eclipse the major known pandemics as the leading cause of death and disease in the 21<sup>st</sup> century. The health of the world population must be elevated in this discussion from an afterthought to a central theme around which decision-makers construct rational, well informed action-oriented climate change strategies.”*

— DANA HANSON, PRESIDENT, WORLD MEDICAL ASSOCIATION

## OBJECTIVE OF THE STUDY

The principal objective of this work is to build a scientific knowledge base to support informed investments and decision making in the health sector in Mozambique. The findings will help to shape the Ministry of Health’s (MoH) preparedness and response to emerging climate risks by working in concert with Mozambique’s new National Climate and Health Observatory, which combines weather and climate data to predict disease outbreaks, raise awareness of weather and climate impacts on health, and encourage government and public discourse on climate-sensitive health issues.

To achieve the purpose outlined above, the relationship between climate and climate-sensitive disease outbreaks was examined using existing weather, climate, and health data. A preliminary evaluation of the relative coverage and completeness of data on the climate-sensitive diseases tracked by the *Boletins Epidemiológicos Semanais* (BES) (see box to right) in Mozambique found that data on diarrheal disease and malaria offered sufficiently consistent national coverage and reporting rates to support the analysis. Furthermore, these are two of the most prevalent and devastating

### THE MINISTRY OF HEALTH’S WEEKLY EPIDEMIOLOGICAL BULLETIN

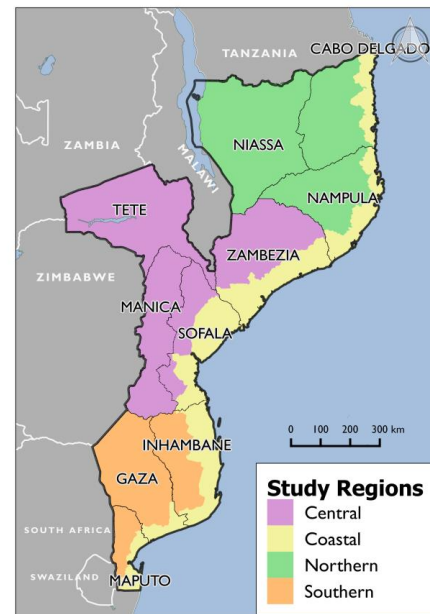
The BES (Boletins Epidemiológicos Semanais) tracks incidence information on priority diseases such as malaria, measles, meningitis, diarrhea, dysentery, cholera, poliomyelitis, rabies, plague, and neonatal tetanus. Collation of health information begins at the service/facility level and information is aggregated to the district level on a weekly basis, offering the opportunity to analyze disease incidence at a weekly scale.

diseases in Mozambique, making it key to understand how weather, climate variability, and climate change impact their occurrence.

## GEOGRAPHIC SCOPE OF STUDY




To account for Mozambique's large size and varied ecosystems, the statistical analyses of both climate and diseases were conducted at the national and regional scale. The four regions, depicted in Figure 1, include:

- **Northern** – Niassa Province and noncoastal districts of Nampula and Cabo Delgado Provinces
- **Central** – Tete and Manica Provinces, and noncoastal districts of Zambezia and Sofala Provinces
- **Southern** – Noncoastal districts of Inhambane, Gaza, and Maputo Provinces
- **Coastal** – Coastal districts of Cabo Delgado, Nampula, Zambezia, Sofala, Inhambane, Gaza, and Maputo Provinces



## HISTORICAL AND FUTURE CLIMATE IN MOZAMBIQUE

An understanding of the historical climate in Mozambique provides a baseline with which to compare climate with health risks and offers indication on the impacts of future climate change on health. The baseline analysis evaluated historical trends in temperature from 1961 to 2010 as well as the climatological differences between the periods 1981–1999 (earlier period) and 2000–2014 (later period). These dates were chosen to capture the differences between the long-term historical climate and the climate during the period for which health incidence data were available. Projected future climate change was estimated using a set of models that account for various factors to determine likely climate scenarios for 2045–2065. Available climate models include those derived from Global Climate Models (GCMs), downscaling, and Regional Climate Models. The following table summarizes the findings for both historical climate trends and climate projections.

CLIMATE TRENDS AND PROJECTIONS		
Parameter	Observed climate trends	Projected climate change
<b>Temperature</b> 	<p>A clear and statistically significant increase in mean temperatures of 1.5°–2°C occurred across the country from 1961–2010.</p>	<ul style="list-style-type: none"> <li>• Temperatures will continue to rise by approximately 1°C in the next 20 years and between 3°C and 5°C by the end of the 21st century.</li> <li>• An increase in the number of days exceeding 35°C and a decrease in the number of nights below 25°C will occur.</li> <li>• The difference between the daily maximum and minimum temperatures, called the diurnal temperature range, will also increase.</li> </ul>
<b>Rainfall</b> 	<p>Although differences in rainfall are less clear due to the large interannual variability in the rainfall records, the data suggest that:</p> <ul style="list-style-type: none"> <li>• The rainy season in the northern region and to a lesser extent in the central region is currently experiencing a delayed start and an earlier end.</li> <li>• Zambezia Province and the coastal parts of Nampula Province received lower average precipitation in the more recent period compared to the earlier period.</li> <li>• Most of the rest of the country experienced marginally higher average precipitation.</li> </ul>	<p>Rainfall will continue to vary. While no statistically significant rainfall changes are projected, the current delayed start and earlier end to the rainy season in the northern region will likely continue and the intensity of single rainfall events is likely to increase.</p>
<b>Dry Periods</b> 	<ul style="list-style-type: none"> <li>• More consecutive dry days occurred in the more recent period compared with the earlier period across Zambezia and Sofala Provinces.</li> <li>• In some areas of Zambezia Province, this difference was as high as 60 days.</li> </ul>	

## DIARRHEAL DISEASE AND CLIMATE

Diarrheal diseases are a group of climate-sensitive, serious health outcomes in Mozambique, with over 7 million cases reported from 1997 to 2014. In 2015, diarrheal disease was the fifth leading cause of death and the fourth leading cause of death and disability combined.

The causal pathways between weather and climate and diarrheal disease are complex: climate can impact transmission through heavy rains and rising temperatures, as well as floods that pollute waters with fecal matter. Although diarrheal diseases are a leading cause of morbidity and mortality in Africa, the quality of evidence linking climate and diarrheal diseases in sub-Saharan Africa is considered very low.

## HISTORICAL CLIMATE AND DIARRHEAL DISEASE ASSOCIATIONS

The burden of diarrheal disease varies regionally within Mozambique:

- The northern and central regions exhibit strong seasonality of disease outbreaks. Disease burden is about 15 to 20 cases per 100 people per week.
  - In the northern region, diarrheal disease peaks during late February–March, around the fourth week of the rainy season.
  - In the central region, diarrheal disease peaks in late March–April, around the eighth week of the rainy season.
- The coastal region has one pronounced disease peak in late February/early March and a less prominent peak later in the year. Sometimes there is no peak later in the year. Disease burden is about 15 to 20 cases per 100 people per week.
- The southern region has the least seasonality of disease outbreaks. A slight peak occurs around March, but less variability arises throughout the year and no pronounced periods without disease exist. Disease burden is about 32 cases per 100 people per week. The population in the south may be particularly sensitive to diarrheal disease because rainfall there exhibits less seasonality.

Regardless of this variation, the number of cases peaks toward the middle-to-late part of the rainy season in all regions, and incidence is lowest in the middle of the year. This corresponds with the cool, dry, winter months of June, July, and August, when the monthly mean temperature often drops below 20°C and little rain falls.

The selection of climate variables examined in relation to diarrheal disease incidence was based on a combination of previous literature and scientific understanding of causal pathways of diarrheal disease. Diarrheal incidence was related to temperature by correlating incidence with the hottest day of the week. Incidence was also correlated with rainfall using the number of wet (rainy) days as a measure.

High temperatures and the number of wet days in a week increase outbreaks of diarrheal disease in Mozambique, with significant associations in all regions for both temperature and precipitation. A statistically significant 4-week lag exists between rainfall and outbreaks, while outbreaks increase almost immediately after high temperatures. These findings are summarized below.

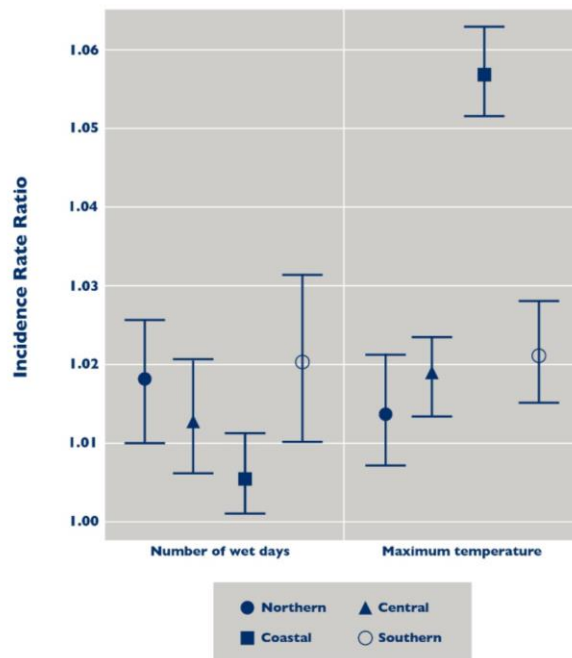
*At the national scale:*

- Each additional 1°C increase in the hottest day of the week increased diarrheal disease counts by 1.13 percent that week.
- Each additional day on which rainfall was at least 1 mm (wet day) during that week increased diarrheal disease counts by an estimated 1.04 percent per week, four weeks later.

At the regional scale:

- **Northern, central, and southern regions:** For every additional day where rainfall was at least 1 mm (wet day) per week, diarrheal disease increased 1.86 percent, 1.37 percent, and 2.09 percent in the northern, central, and southern regions, respectively.
- **Coastal region:** Patterns in this region appeared to be the least affected by precipitation; an additional day where rainfall was at least 1 mm (wet day) resulted in a 0.63 percent increase in diarrheal disease, four weeks later. For every additional 1°C increase per week in the maximum temperature, diarrheal disease counts increased by nearly 6 percent in this region.
- **All regions** exhibited a statistically significant increase in diarrheal disease for each 1°C increase in the maximum temperature. These increases are measured by incidence rate ratios (IRRs).<sup>1</sup> While the coastal region's diarrheal disease burden had the smallest association with an additional wet day, it was the most sensitive to an increase in the maximum temperature.
- **Coastal region:** The regional results are summarized in **Error! Reference source not found.** below, which demonstrates the relationship between rainfall and maximum temperature on diarrheal disease incidence by region.

Figure 1. Regional relationship between Incidence Rate Ratios and two climate variables





Note: This figure shows the regional relationship between Incidence Rate Ratios (ratio of the incidence of diarrheal disease with a one-unit increase in the climate variable compared with the baseline within the time period analyzed) and the two climate variables most significantly correlated with diarrheal disease: days with rain (number of wet days within a given week with a four-week time lag) and maximum temperature for the same week. The positive relationship shown here suggests that as the number of rain days and maximum temperatures increase, disease incidence rates increase.

<sup>1</sup> The ratio of the incidence of diarrheal disease with a one-unit increase in the climate variable compared with the baseline within the time period analyzed. IRR values were 1.45, 1.87, and 2.15 in the northern, central, and southern regions, respectively.



## DIARRHEAL DISEASE UNDER A CHANGING CLIMATE

Future risk from diarrheal disease was evaluated for the period 2046–2065, using the mean values for the worst-case climate change scenario (Representative Concentration Pathway (RCP) 8.5 emissions scenario).<sup>2</sup> This scenario provides a valuable warning against complacency in the face of climate change, assuming that the world will continue to rely on coal as the major source of power. Values were extracted from this scenario for rainfall and temperature from 11 of the 28 climate models used to derive the conclusions presented in the IPCC’s Fifth Assessment Report. Taking into consideration each climate parameter known to be significantly correlated with diarrheal disease incidence, annual minimum temperatures are projected to increase on average 2.39°C, 1.94°C, 2.17°C, and 2.09°C, respectively, across the northern, central, coastal, and southern regions. Thus, the burden of disease in the future is projected to increase as shown in the table below:

Projected increases in the burden of disease (2045–2065)				
		Northern Region	Central Region	Coastal Region
	As minimum <b>temperatures</b> rise, diarrheal disease incidence is expected to increase slightly.	3.27% per week	2.37% per week	1.84% per week
	A slight increase in diarrheal disease incidence is expected with the increase in the number of days with <b>rainfall</b> of at least 1 mm (wet days). These numbers, while fairly small, are statistically significant and represent a burden on already strained health systems, which will have to treat these additional cases.	0.91% per week	0.42% per week	0.29% per week

*“The importance of investing more in existing solutions is enhanced by the fact that diarrhea currently does not receive significant funding in Mozambique, as malaria, HIV, and TB currently are considered the top health priorities in the country. The expected increase in diarrheal incidence resulting from future climate change, coupled with the current increasing incidence and population trends in the country, make this even more of a priority.”*

— EDUARDO SAMOGUDO, DIRECTOR, MOZAMBIQUE NATIONAL INSTITUTE OF HEALTH

<sup>2</sup> RCPs are used in the IPCC’s Fifth Assessment Report to represent a set of mitigation scenarios with targets defined in terms of radiative forcing (cumulative measure of human emissions of greenhouse gases from all sources expressed in watts per square meter) of the atmosphere by 2100. The four RCPs include one mitigation scenario leading to a very low forcing level (RCP 2.6), two stabilization scenarios (RCP 4.5 and RCP 6), and one scenario with very high greenhouse gas emissions (RCP 8.5).

## MALARIA AND CLIMATE

As a result of the expected changes in climate over the next several decades, the malaria profile in Mozambique is expected to change. Preparation for these changes requires knowledge about the changes anticipated in disease incidence due to a changing climate.

The relationship between malaria transmission and climate is complex: climate can impact the transmission of malaria by affecting the parasite's and the mosquito's lifecycle, the human host, or any combination of the three. Predicting how changes in precipitation or temperature might affect transmission geographically requires detailed knowledge about all other factors involved in transmission, including number of breeding sites, vector species distribution, infection rates, and more, many of which are difficult if not impossible to measure.

Different timeframes were analyzed for malaria incidence countrywide, including periods from 2010–2012 and 2013–2014, for which malaria data were accessible. Malaria cases remained steady between 2010 and 2012, then increased rapidly between 2013 and 2014. The aim of this analysis was to uncover why malaria incidence rose between 2013 and 2014 compared with the earlier years. Incidence data were compared to several statistics across the historical climate record of 1979–2014. Rainfall measurements that help predict malaria outbreaks included rain days per week, rain days greater than 50 mm per week, and mean rainfall per rain day.

### HISTORICAL CLIMATE AND MALARIA ASSOCIATIONS

Key findings for the malaria analysis presented in this document are highlighted below. It should be noted that even considering vector control interventions, climate remained a significant predictor of incidence (see figure below):

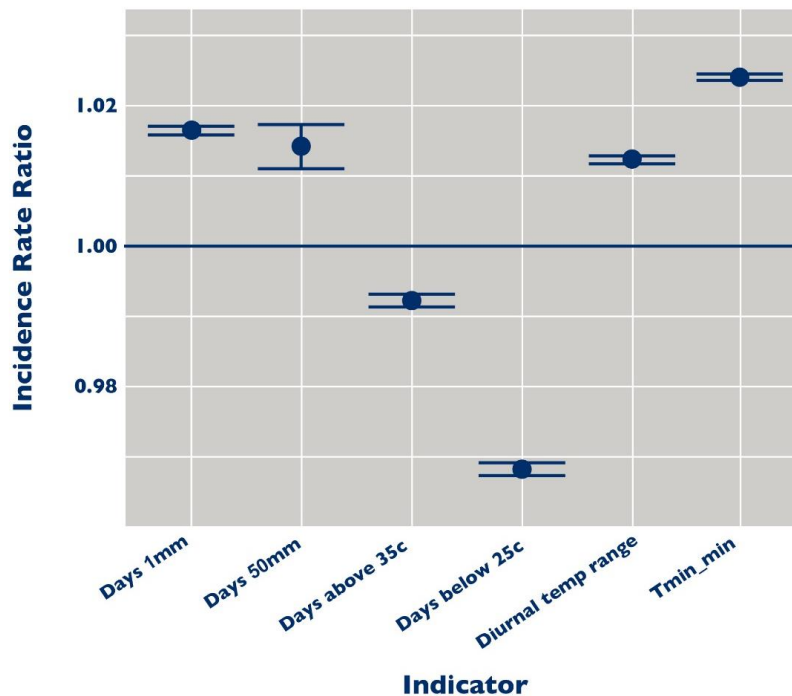
- Days with at least 50 mm precipitation had the strongest association with incidence: an increase of one day with at least 50 mm precipitation during any given week led to an 11 percent decrease in malaria incidence four weeks later.
- Days above 35°C and below 25°C, considered important thresholds of vector survival, had relatively strong relationships with the incidence of malaria. A one-day increase in number of days above 35°C during any given week led to a 6 percent decrease in malaria incidence two weeks later, while a one-day increase in number of days below 25°C during any given week led to a 7 percent decrease in malaria incidence two weeks later.
- For each 1°C increase in the weekly average minimum temperature, a 2 percent increase in malaria incidence was expected four weeks later.
- Important differences in incidence exist between the periods analyzed, specifically between 2010–2012 and 2013–2014:
  - From 2010 through 2012, a one-day increase in days with at least 50 mm precipitation in a week led to a 7 percent increase in malaria incidence four weeks later.
  - In comparison, from 2013 to 2014, number of days above 50 mm precipitation was negatively associated with malaria incidence: a one-day increase in days with at least 50 mm precipitation in a week led to a 2 percent decrease in malaria incidence four weeks later.

## MALARIA UNDER A CHANGING CLIMATE

Climate impacts are strongly associated with malaria incidence and are expected to affect the future malaria profile of the country (Figure 2).

- As temperatures continue to rise, and given the strong statistical link between the increased number of days above 25°C, **malaria incidence is expected to increase in previously unsuitable regions, such as those in the higher elevation regions of northern Tete and western Niassa Provinces near the border with Malawi.** Malaria risks are likely to remain consistent across the rest of the country.
- Since no strongly significant rainfall changes are projected for the next 20 years, precipitation variability, especially the oscillation between dry and wet periods that currently characterize rainfall patterns, will continue to contribute to malaria incidence through this time period, translating into continued malaria risks.
- The increased variability in precipitation, as well as the complicated relationship between malaria and temperature, means that **malaria transmission will likely be more variable and unpredictable in the future.**

Figure 2. Relationship between incidence rate ratios and six climate variables



Note: Relationship between incidence rate ratios (a ratio of the incidence of malaria with a one-unit increase in the climate variable compared with the baseline) and the six climate variables most significantly correlated with malaria at the weekly timescale: days 1mm – the number of days receiving at least 1 mm of rain; days 50mm – the number of days within a week when at least 50 mm of rain was received; days above 35°C – the number of days during a given week when temperatures exceeded 35°C; days below 25°C – the number of days during a given week when temperatures fell below 25°C; diurnal temp range – the difference between the daily maximum temperatures and daily minimum temperatures; and T-min – the lowest minimum temperature of the coldest night during the week. Incidence rates above 1.0 suggest a positive correlation between malaria and the variable. For example, as the number of days with rain (number of wet days) and days with at least 50 mm of rain increase, malaria incidence rates increase. The same is true for diurnal temperature range and minimum temperatures. Rates below 1.0 suggest a negative relationship between malaria and the indicator. For example, incidence decreases as the number of days above 35°C increases (i.e., as hotter temperatures occur); and incidence is reduced as the number of days below 25°C increases (as minimum temperatures increase).

## USING WEATHER AND CLIMATE INFORMATION TO IMPROVE HEALTH SYSTEM RESILIENCE

As climate change increases temperatures and alters the hydrological cycle, this study demonstrates that the burden of diarrheal disease and malaria risk in Mozambique is expected to increase without additional health system interventions. The projected additional cases of diarrheal disease and potential increase in malaria risks in higher elevation areas are potentially preventable using seasonal weather forecasts and targeted responses. For example, creating an early warning and seasonal to subseasonal forecast and response system, which warns when temperatures are expected to be higher or when weeks are expected to be wetter than normal, would provide valuable time for decision makers to put interventions in place. Developing and deploying such an early warning system would increase population resilience to outbreaks of disease over the coming decades.

Examples of interventions include:

- Diarrheal disease – modify supply chain flows to guarantee timely delivery of critical oral rehydration stocks to local health care centers and increase education on appropriate use and handling of water (such as boiling drinking water) and sanitation practices that can reduce transmission of diarrheal pathogens.
- Malaria – improve disease surveillance throughout the entire country, implement a system to detect unexpected rises in cases, and build awareness of the population and health workers in areas prone to outbreaks and where transmission is expected to be more variable due to climate change.

### THE IMPORTANCE OF CONTINUED INVESTMENT IN MALARIA

Malaria risk is expected to increase throughout the country as a result of climate change, though the complicated relationship between climate and malaria makes it difficult to predict exactly how significant and where those changes will be. The expected increase in climate variability will also result in more variability and unpredictability in malaria transmission. This has the potential to affect the acquisition of disease immunity, resulting in outbreaks with more severe disease and more deaths. There is, therefore, an impetus to ensure that surveillance systems are in place to forecast the likelihood of outbreaks before they occur, if possible, and to respond to them before they become widespread. In a larger context, climate variability reaffirms the need to continue to invest in elimination and control efforts in Mozambique, because these will likely become more challenging due to the expected changes in climate.

### NATIONAL RESPONSE

Mozambique's climate change action is guided by the country's National Climate Change Adaptation and Mitigation Strategy (ENAMMC) and Action Plan for Poverty Reduction (PARPA). These documents outline strategic priorities and specifically mention health risks and the importance of early warning, as well as strengthening the capacity to prevent and control the spread of vector-borne diseases. Tackling the challenges of understanding and responding to climate risks in the health sector means working across disciplines and organizations. Collaboration between government ministries that track key population vulnerability indicators,

health, weather, and other environmental variables is essential. Furthermore, these ministries need to continue to build partnerships with organizations outside the Government of Mozambique that work on health and climate issues.

This close collaboration is at the heart of Mozambique's climate and health observatory, established under the auspices of the INS in 2016 with the goal of providing information to aid decision making around health issues. To do this, the observatory assembles, analyzes, reviews, and synthesizes all available data (e.g., meteorological, demographic, nutritional, and health) for the country. The observatory is Mozambique's first community of practice for health professionals and reflects the importance of cross-agency and cross-departmental work and the need for evidence-based policy and decision making. By working together with other agencies, it takes advantage of existing academic and state-based public health investments. Building the capacity of the observatory is key, and many of the recommendations below focus on how this could be accomplished.

## RECOMMENDATIONS

Reducing health risks will require modifying current policies and programs and implementing new ones to explicitly consider climate variability and climate change. Adaptation actions should focus on building more resilient health systems, reducing overall vulnerability, and developing specific system capacities by investing in several entry points, including:

- 1) Information systems
- 2) Leadership and governance foundations
- 3) Risk management.

Specific actions that align with Mozambique's 2014–2019 Health Sector Strategic Plan, which prioritizes primary health care, equity, and better quality of services, are detailed below.

### 1. Information Systems

*Support research.* Mozambique will be better prepared to aid its citizens through improved understanding of past trends and future projections in climate and their relationship to health outcomes. The analysis presented here is one of a handful of studies available on the relationship between weather, climate variability and climate change, and disease incidence for Mozambique. More research is needed to understand the climate–disease relationship and identify practices that will more effectively manage risk as climate continues to change. Building on the results of this study, for example, a statistical evaluation of the relationship between El Niño Southern Oscillation (ENSO) events and disease outbreak could help to define thresholds of risk based on changing sea surface temperatures, informing the design of early warning systems, particularly in the southern region. Additionally, exploring the associations between weather and vector-borne diseases such as dengue could offer insights on improved diagnosis and response, particularly in the coastal region.

*Improve epidemic detection and response.* Exploring technological options for improving health data collection, such as SMS-based forms sent directly by health post workers, could facilitate

the timely flow of information and responses. Such systems could improve early warning specifically by detecting changes in disease incidence more quickly and in time for people to respond more promptly to an emerging outbreak. This information would be particularly useful in regions where malaria is currently not present, such those in the higher elevation regions of northern Tete and western Niassa Provinces near the border with Malawi.

*Deploy early warning systems.* Having advance (early) warning that temperatures are expected to be higher or that a week is expected to be wetter than normal — and therefore that an increase in incidence rates is likely — would provide valuable time to put interventions in place. Information on sea surface temperatures indicative of ENSO events, available four to six months in advance, could offer a window of opportunity for response efforts, particularly in areas where research indicates a strong association between events and disease outbreaks.

*Build awareness.* Communicate to the public and policy makers the risks posed by climate variability and climate change, as well as options for disease control, prevention, and treatment.

## **2. Leadership and Governance Foundations**

*Enhance cross-sectoral governance and collaboration.* Negotiate sharing agreements that could contribute to improved epidemic detection systems and ultimately support the development of early warning systems. Disease surveillance systems could benefit from being coupled with climate and weather information to build the evidence base on the links between disease and climate, information that is an essential precursor to the establishment of early warning systems.

*Develop capacity within the health system.* Mozambique's doctor–patient ratio is among the lowest in the world, and climate variability and climate change may increase local demand for services. The country already faces chronic shortages of skilled staff and low productivity stemming from poor working conditions. Health workers work long hours serving patients and may also be required to conduct additional support activities beyond administering care. Systems for tracking, motivating, and retaining staff are weak. While health service workers may recognize the links between climate extremes such as droughts and floods and health sector impacts, they often have limited access to relevant climate information to modify their treatment and diagnosis plans in response to these changes. Important areas of investment in capacity development include:

- Training professional staff on the health risks posed by weather, climate variability, and climate change.
- Training professional staff to differentially diagnose diseases based on early warning signs of health risks (using climate information).
- Building capacity to incorporate climate information into decision making. Beyond the development of the country's health information system, the ability to use data for decision making is extremely weak. The health information system and its subsystems do not produce comprehensive, timely, or quality data for policy makers. During decision making, reforms and improvements should consider the use of weather and climate information and decentralization of health service delivery.

### 3. Risk Management

*Advance integrated risk monitoring.* Well-functioning surveillance systems are crucial for effective disease control programs. The country's health information system tracks weekly and monthly reports of disease incidence, but faces recording challenges that result in important health information gaps, including improper diagnoses, as well as reporting inconsistencies. Additionally, the fact that these systems initially collect data using paper-based methods and do not report in real time means that delays across the information chain at the national level, including analysis and feedback, can limit monitoring and response options.

*Promote climate-smart health programming.* Ensure that the information available on climate and disease impacts is used in the planning of resources and supply chain management.

*Strengthen public health services and facilities.* Health care facilities are faced with many challenges. Most operate off-grid and require alternate fuel supplies to support lighting, refrigeration, and sterilization, including the collection of medical commodities from district depots if supplies are unreliable. Furthermore, many of these facilities are located long distances from district storage facilities and are only accessible via unpaved roads that are challenging to drive on, especially during the rainy season.

*Support emergency preparedness and management.* Establishing contingency plans to deploy surge support, both in staff and supplies, to areas where disease risks may rise in light of forecasts, could make supply chains more resilient to shocks.

The Government of Mozambique has demonstrated a strong commitment to addressing the needs of its population and achieving the Sustainable Development Goals (SDGs). Good governance and sound public financial management are the pillars for achieving these objectives. Carrying out these recommendations can reduce current vulnerability to weather and climate variability and help to manage future health risks from climate change. Policy and program choices made today will enable resilience in a future climate.

# BACKGROUND

Climate variability and climate change present both current and future risks to human health. Changes in temperature and rainfall not only alter the geographic range, seasonality, and survival of disease-causing pathogens, but may also increase human exposure and jeopardize the physical infrastructure necessary to prevent disease transmission. Low-income regions are expected to experience higher burdens of many diseases because these regions will, in many cases, have higher exposure and are more sensitive to climate-related hazards (such as extreme rainfall or temperature events) and because they have low capacity to respond to and manage those risks. In addition, specific knowledge of how, when, and under what circumstances climate variability and climate change impact health outcomes is limited, especially for African countries.

Given its location, Mozambique is particularly vulnerable to the effects of climate change on health. Malaria is the number one cause of illness in the country, accounting for more than 40 percent of patient consultations, 60 percent of pediatric inpatients, and a third of hospital deaths. The country is ranked among the worst in the world (180 out of 192) with respect to the public health sector's vulnerability to climate change by the ND-Gain Index, which measures the projected change in the number of deaths from climate change-induced diseases (diarrhea and malnutrition), projected change in malaria hazard, dependency on external resources for health services, slum population, medical staff, and access to improved sanitation facilities.

Also, like many countries in Africa, critical knowledge of the health risks of climate variability and climate change is lacking in Mozambique. Although there is general understanding of current associations between weather variables and a range of adverse health outcomes—generally derived from studies conducted in other countries—further knowledge of current and projected risks in the different regions of Mozambique is needed to formulate evidence-based policies and programs. Working from first principles of transmission dynamics of infectious diseases and drivers of undernutrition, and informed by the current literature, this report examines climate effects on diarrheal disease and malaria in Mozambique. The aim is to provide a knowledge base for making informed decisions about building resilience into Mozambique's health sector.

## STRUCTURE OF REPORT

**Section I** provides an overview of the climate and climate drivers of Mozambique, describing historical variability as well as current trends at a regional scale for key parameters such as rainfall and temperature. The climatological analysis presented here coincides with the period for which disease incidence data were available to ensure that the climate data used in the analysis adequately capture the climate dynamics of relevance during the same period.

**Section II** explores the causal pathways linking climate to malaria and diarrheal disease in Mozambique and examines the relationship between historical health data collected by the Ministry of Health (MoH) and satellite-derived rainfall and temperature variables. The goal is to



understand the role that historical temperature and rainfall played in disease incidence and to determine whether these relationships are robust and predictable enough to support development of an early warning system that could help the health care system respond to outbreaks faster. The section concludes by examining the potential impact of these changes on future disease risk. The analyses aim to inform future programming by predicting burden or providing early warning of increasing burden.

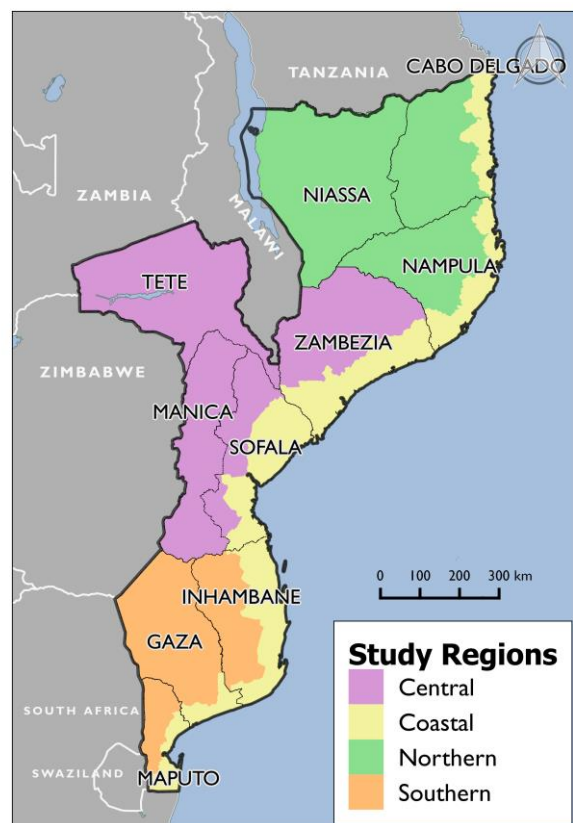
**Section III** concludes the report with a review of ongoing initiatives to address the linkages between climate and health in Mozambique. It then offers policy and programmatic guidance on the implementation of targeted approaches for disease control and prevention by building health system resilience to climate risks.

### STUDY AREA

Because of Mozambique's large and diverse geographic area, the climate varies throughout the country. To account for this, study areas were broken into the following regions (Figure 3):

- **Northern:** Niassa and noncoastal districts of Nampula and Cabo Delgado Provinces
- **Central:** Tete, Manica, and noncoastal districts of Zambezia and Sofala Provinces
- **Southern:** Noncoastal districts of Inhambane, Gaza, and Maputo Provinces
- **Coastal:** Coastal districts of Cabo Delgado, Nampula, Zambezia, Sofala, Inhambane, Gaza, and Maputo Provinces

Figure 3. Map of Mozambique showing the four regions discussed in this report



# I. WEATHER, CLIMATE VARIABILITY, AND CLIMATE CHANGE IN MOZAMBIQUE

## KEY MESSAGES

### WEATHER AND CLIMATE VARIABILITY

- Temperatures are already rising across the country.
- Due to the large interannual variability of the rainfall records, rainfall trends are less clear, but suggest that Zambezia Province and the coastal parts of Nampula Province received lower-than-average precipitation between 2000 and 2014, while most of the rest of the country experienced very marginally higher-than-average precipitation.
- More consecutive dry days occurred between 2000 and 2014 than previously across Zambezia and Sofala Provinces. In some areas of Zambezia Province, this difference is as high as 60 days.
- Fewer heavy rain days (days with rainfall above 20 mm) occurred between 2000 and 2014 than previously (1980–1999) in Zambezia Province.
- Higher rainfall intensities are occurring, with the coastal parts of Sofala and Inhambane Provinces experiencing the most pronounced difference.

### CLIMATE CHANGE

- Projected climate changes for Mozambique include:
  - Rising temperatures: Mean annual temperatures are expected to rise by approximately 1.5°C to 3.0°C, with higher values more likely based on current emissions by the 2046–2065 period. Increases will be more marked in the interior. The largest increases in temperature will likely occur from September to November, before the onset of rains over much of the country.
  - Over all regions, the likelihood of extreme maximum daily temperatures above 35°C will increase.
- No significant changes are projected in rainfall, though natural variability will continue, bringing drier and wetter years.

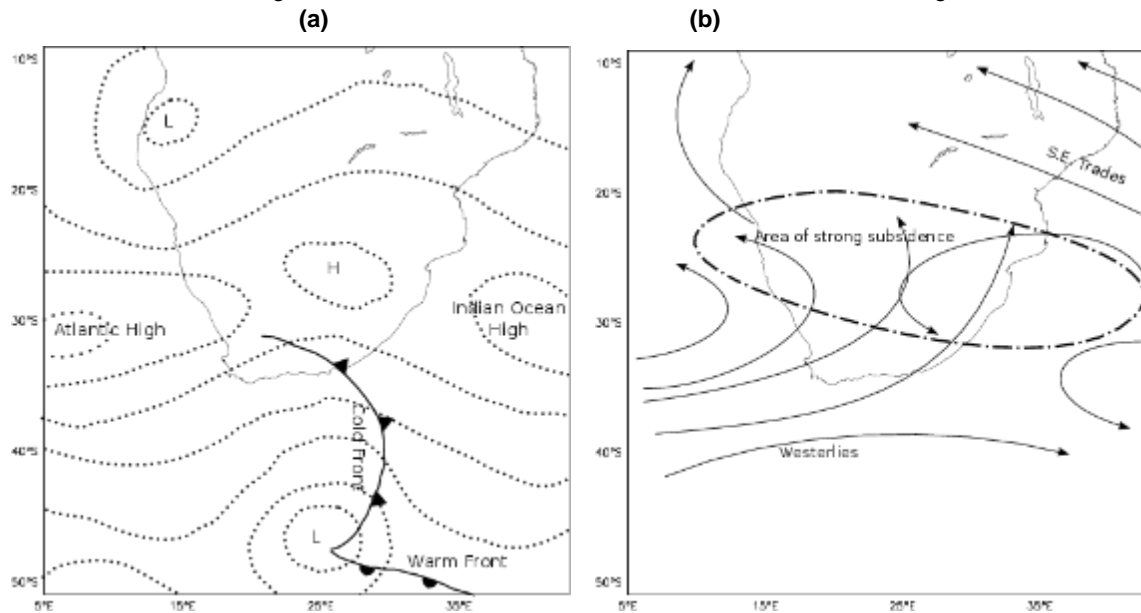
## WEATHER AND CLIMATE VARIABILITY IN MOZAMBIQUE

Mozambique is situated on the east coast of southern Africa. The majority of the country is in the intertropical zone. In summer, the climate is generally hot and rainy, with temperatures along the north coast and inland in the Zambezi Valley averaging over 35°C. Winters are cooler and drier, with nighttime average temperatures in the south reaching below 15°C. These

conditions largely result from the atmospheric systems that dominate the regional climate, the topography, and sea surface temperatures.

The basic pressure distribution and movement of air masses during winter (June, July, and August) are presented in Figure 4. During this period, anticyclones over the Atlantic and Indian Oceans and subsiding air are the prevailing atmospheric state over southern Africa. This dynamic is largely responsible for the dry conditions over Mozambique. Cold fronts, which occasionally penetrate the southern and central parts of the country, are associated with overcast conditions but little or no rainfall. Often, strong northerly winds precede the front. The central and northern parts of the country are influenced by the southeast trade winds. In the absence of the northeast monsoon, no convergence takes place and the likelihood of rainfall diminishes.

Figure 4. Pressure and air distribution over southern Africa during winter



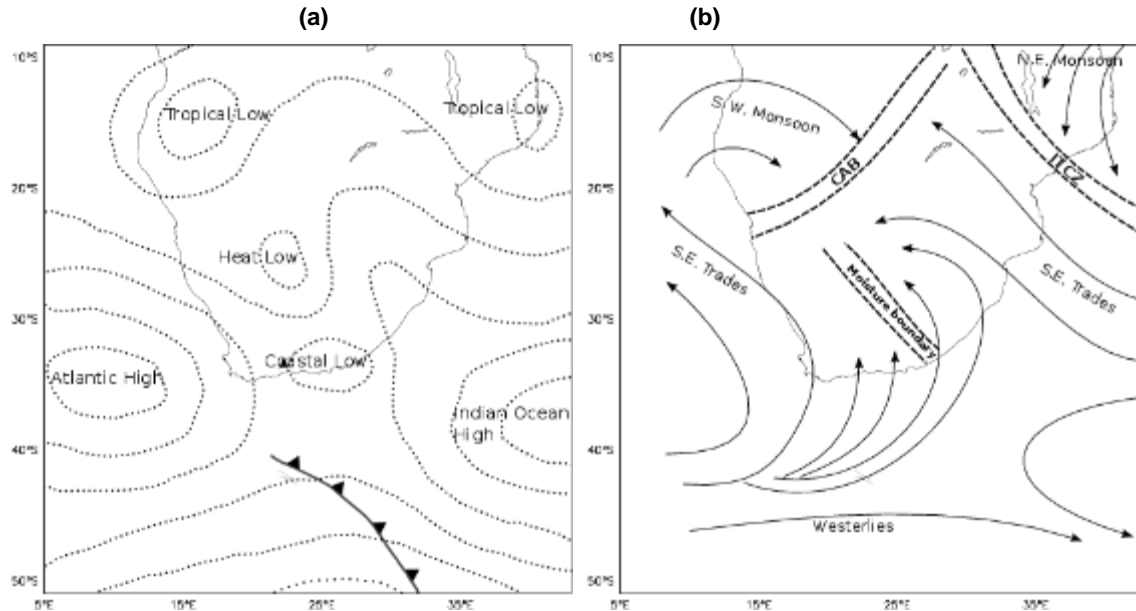
Note: (a) Pressure distribution and (b) basin movement of air masses over southern Africa during winter.

Source: Hurry and Van Heerden (1982).

During summer, due to the shift in seasonal solar radiation, the Atlantic and Indian Ocean high pressure systems move southwards by almost five degrees of latitude on both sides of the subcontinent. The basic pressure distribution and movement of air masses for summer (December, January, and February) is displayed in Figure 5. During this season, the air over southern Asia is cooler and denser than the west Indian Ocean, leading to the establishment of a stronger pressure gradient that gives rise to the northeast monsoon. The monsoon crosses the equator, converging with the southeast trade winds from the Indian Ocean and forming the Intertropical Convergence Zone (ITCZ). The ITCZ, a region of pronounced convective activity, plays a major role in southern Africa's climate variability (Tyson & Preston-White, 2000). Additionally, the summer months are associated with a semi-permanent low over southern Africa's interior, which occasionally extends east toward the Mozambique coast. This coastal low varies in strength but can enhance onshore airflow over southern and central Mozambique, resulting in thunderstorm activity. The heaviest rainfalls are, however, associated with the

passage of tropical cyclones that typically occur in summer. A list of significant tropical cyclones that made landfall in Mozambique and caused significant loss of life and damage is found in Table 1.

Figure 5. Pressure distribution and movement of air masses over southern Africa during summer



Note: (a) Pressure distribution and (b) basin movement of air masses over southern Africa during summer

Source: Hurry and Van Heerden (1982).

Table 1. Significant tropical cyclones making landfall in Mozambique, 1956–2017

Year	Month	Name	Impact
1956	April	Unknown	107 dead, Memba fishing port in ruins
1994	March	Nadia	204 dead, 1.5 million displaced, \$240 million in damages
1996	January	Bonita	11 dead
2000	February	Eline	150 dead, 1,000 casualties from flooding, 300,000 displaced, 4 ships sunk
2001	March	Dera	100 dead, 250,000 displaced, severe flooding
2003	January	Delfina	47 dead, 22,000 displaced, several days' power outage in Nampula Province, \$3.5 million in damages
2003	March	Japhet	17 dead, 23,000 displaced, 237,000 hectares of cropland destroyed, livestock losses
2007	February	Favio	10 dead, 100 injured, 33,000 displaced, \$71 million in damages
2008	March	Jokwe	16 dead, 55,000 displaced, 75% of power lines in Nampula Province destroyed
2012	January	Funso	15 dead, 56,000 displaced, 700,000 with no access to clean drinking water
2017	February	Dineo	7 dead, more than 650,000 affected, 20,000 homes destroyed, 70 health centers destroyed in Inhambane Province

Source: Fitchett & Grab (2014)

For much of Mozambique, the recent decline in reporting weather stations and unevenly distributed and erratic rain gauge observations strongly limit the reliable use of station observations to perform regional analyses. A selection of available station observations (drawn from the [Global Historical Climatology Network](#) daily station archive dataset) was used to represent historical seasonality at one station in each of the four regions of Mozambique.

However, to perform a comprehensive regional analysis, two satellite-derived gridded products were used:

- *Temperature*: The Climate Research Unit (CRU TS 3.21; Harris et al., 2014) data comprise monthly time series of various climate variables, including maximum and minimum temperature and rainfall. The data, which are based on over 4,000 global weather stations, are available for the period 1901–2012, and are gridded to a 0.5 x 0.5 degree (roughly 55 kilometers [km] on a side) spatial resolution. The CRU data are limited in accuracy by the availability of station records in a particular area at particular times. Because of this limitation, care must be taken in interpreting spatial gradients and time trends; artifacts may be present. Also, because the CRU data are monthly frequency, daily statistics such as exceedances of specific thresholds cannot be calculated.
- *Rainfall*: Climate Hazards Group InfraRed Rainfall with Stations (CHIRPS; Peterson et al., 2013) comprises daily rainfall data only. It is a combination of satellite, re-analysis, and weather station rainfall data for the period 1981–2014, gridded to a 0.05 x 0.05 degree (roughly 5 km) spatial resolution. The daily temporal resolution of this dataset makes it more suitable than the CRU TS data for the analysis of daily rainfall indices. The CHIRPS data generation algorithm was specifically designed to avoid spurious temporal trends, making it better suited to trend analysis. However, station density over Mozambique is low, which leaves the product very dependent on proxy satellite and model re-analysis data for large areas. As a result, validation over these areas is impossible. As with all such data, interpretation of results should be done with due caution.

The World Meteorological Organization Commission for Climatology and the Expert Team on Climate Change Detection and Indices developed a set of 27 indices, based on daily temperature and rainfall, that are meant to capture extreme events. Five of its daily rainfall indices were used in this analysis (Table 2).

Table 2. Indices of rainfall extremes used in this study

Name	Definition	Units
<b>Total average rainfall</b>	Total rainfall in wet days (rainfall > 1 mm)	mm
<b>Consecutive dry days</b>	Maximum length of dry spell (rainfall < 1 mm)	Days
<b>Number of very heavy rainfall days</b>	Number of days where rainfall ≥ 20 mm	Days
<b>Simple daily intensity index</b>	Mean rainfall amount on a wet day	mm/day
<b>Maximum 5-day rainfall</b>	Highest rainfall amount in 5-day period	mm

## REGIONAL CLIMATOLOGY

Although rainfall and temperature exhibit similar seasonality throughout Mozambique, monthly rainfall totals and average monthly minimum and maximum temperatures vary regionally. The northern and coastal regions tend to have higher rainfall totals while the central region has the highest maximum temperatures (Figure 6, a-d). These regional differences are described in detail in the subsections below.

Figure 6. a) Average monthly rainfall, and maximum and minimum temperatures – southern region

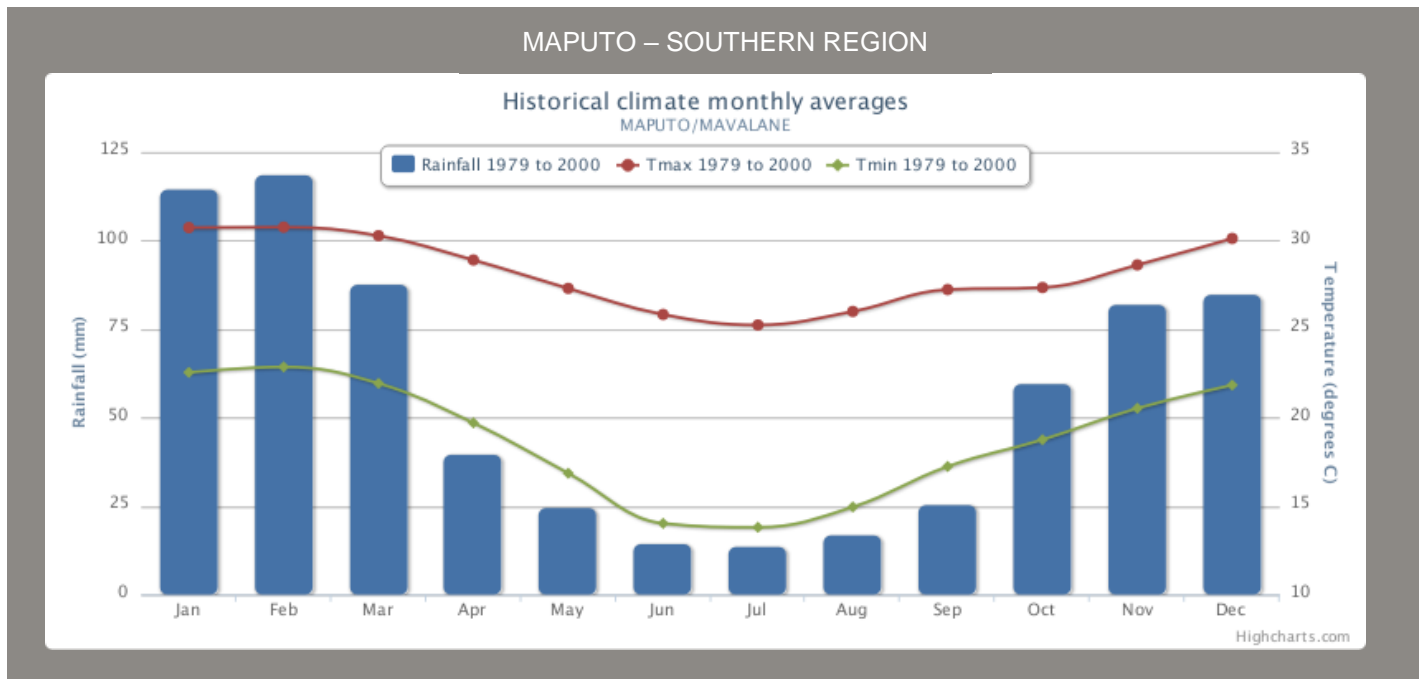
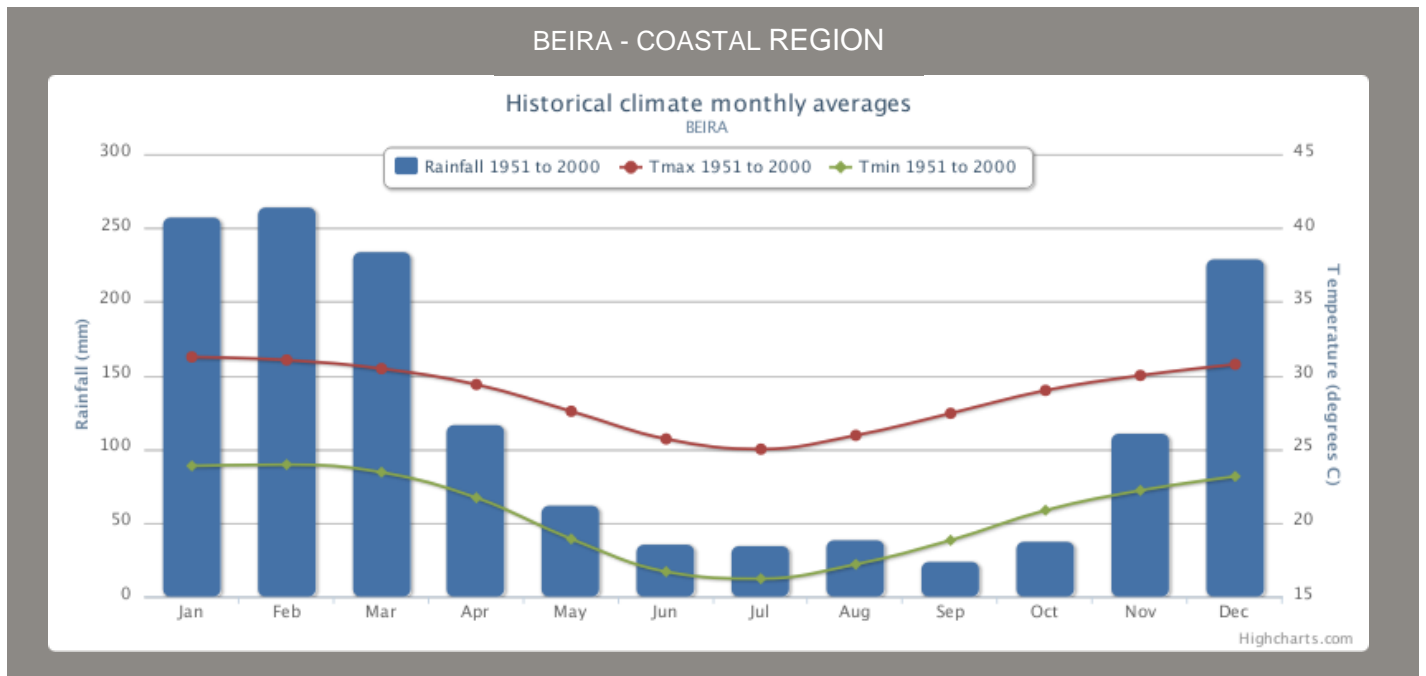


Figure 6. b) Average monthly rainfall, and maximum and minimum temperatures – coastal region



Note: Rainfall values on the y-axis are different for each plot. Blue bars: rainfall in mm; red line: maximum temperature in °C; green line: minimum temperatures in °C.

Source: CSAG Climate Information Platform, <http://cip.csag.uct.ac.za>.

Figure 6. c) Average monthly rainfall, and maximum and minimum temperatures – central region

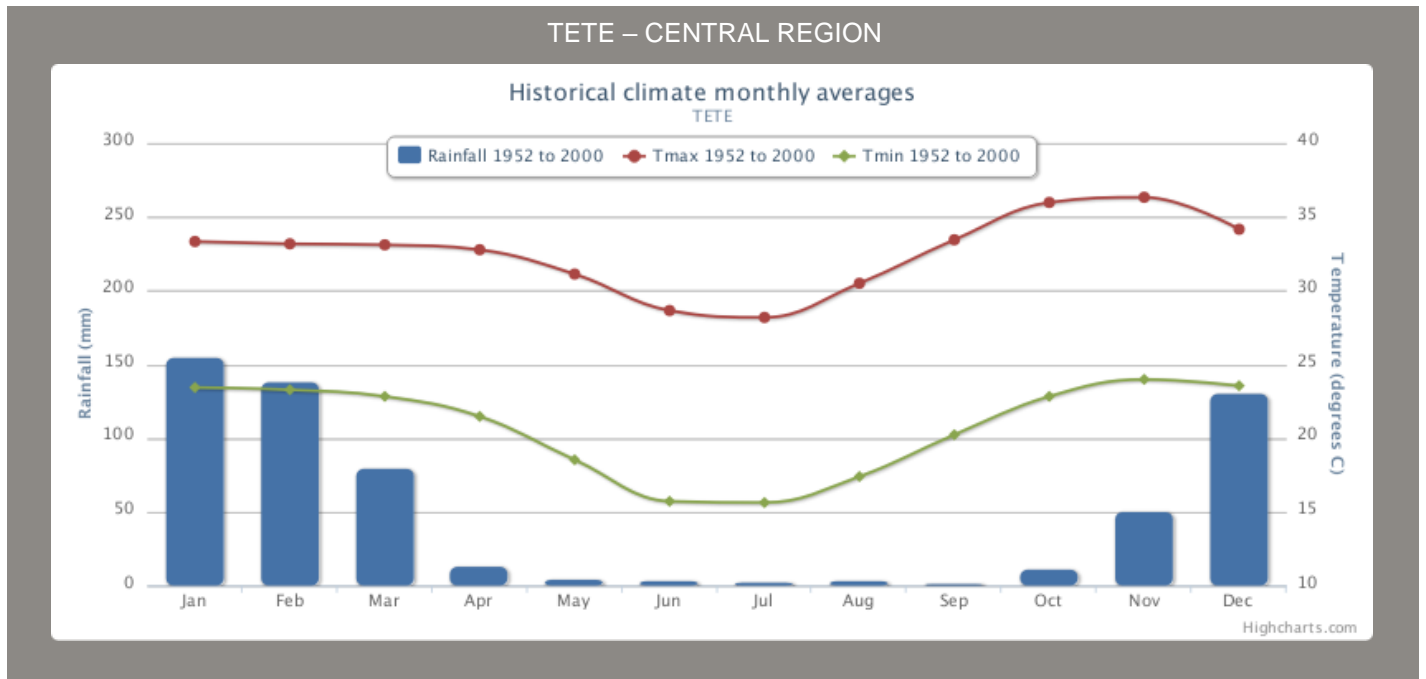
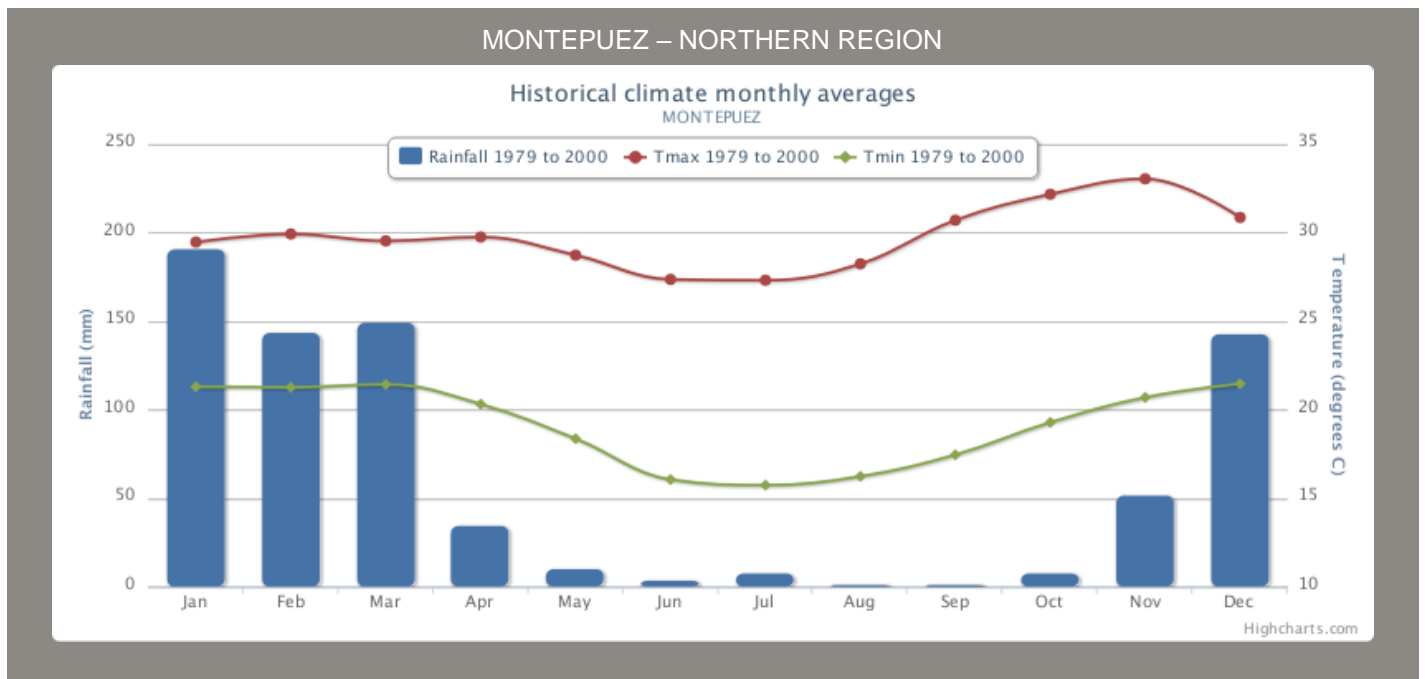


Figure 6. d) Average monthly rainfall, and maximum and minimum temperatures – northern region



Note: Rainfall values on the y-axis are different for each plot. Blue bars: rainfall in mm; red line: maximum temperature in °C; green line: minimum temperatures in °C.

Source: CSAG Climate Information Platform, <http://cip.csag.uct.ac.za>.



## RAINFALL

Rainfall is variable across the country, with totals of 1,800 mm per year near the Zambezi Delta to 300 mm per year in the lowlands of the southern interior (Figure 7). The driest areas lie in the interior of Gaza Province in the southwest. The highlands of the northern and central regions are affected by the northeast monsoon and receive 1,000 to 2,000 mm annually, except for Tete Province, which receives just 500 to 600 mm of annual rainfall. This is likely due to its position inland and in a low-lying area of the Zambezi Valley. The rainy season in Mozambique begins with the southward movement of the ITCZ in November/December, peaking in January and/or February (Figure 8).

Figure 7. Annual mean total rainfall for each grid cell, 1981-2014

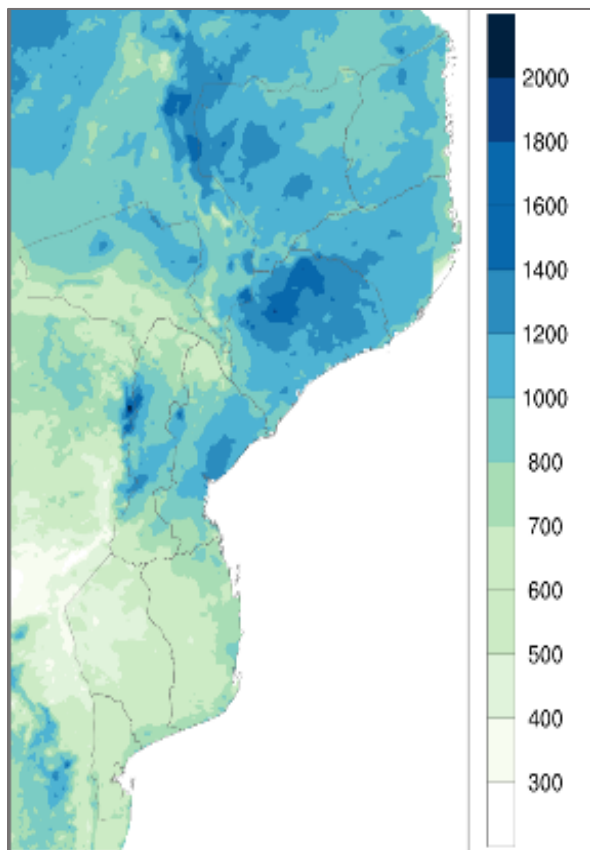
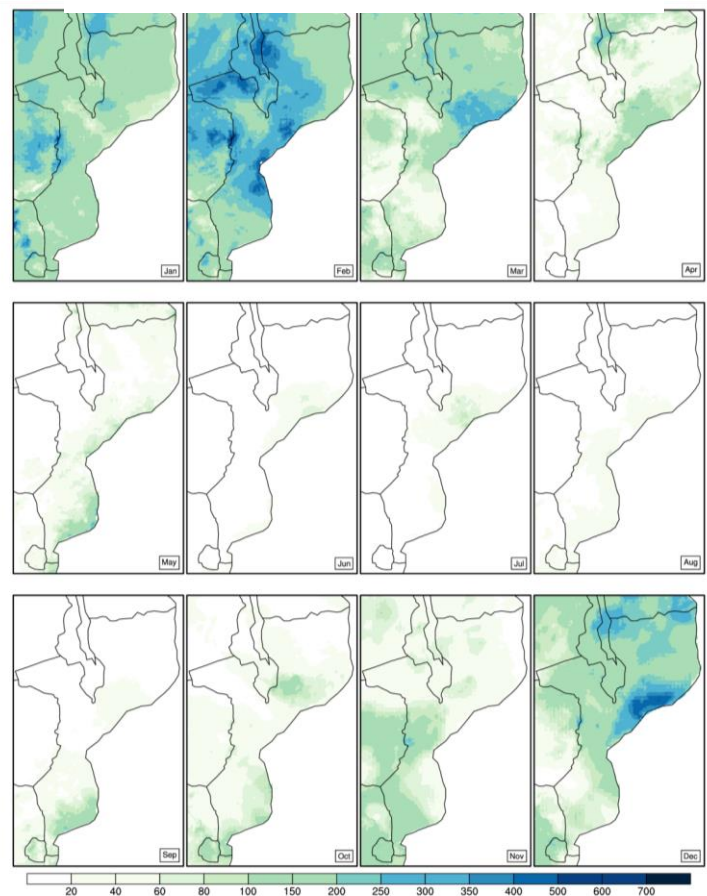


Figure 8. Average Monthly rainfall across Mozambique, 1981-2014



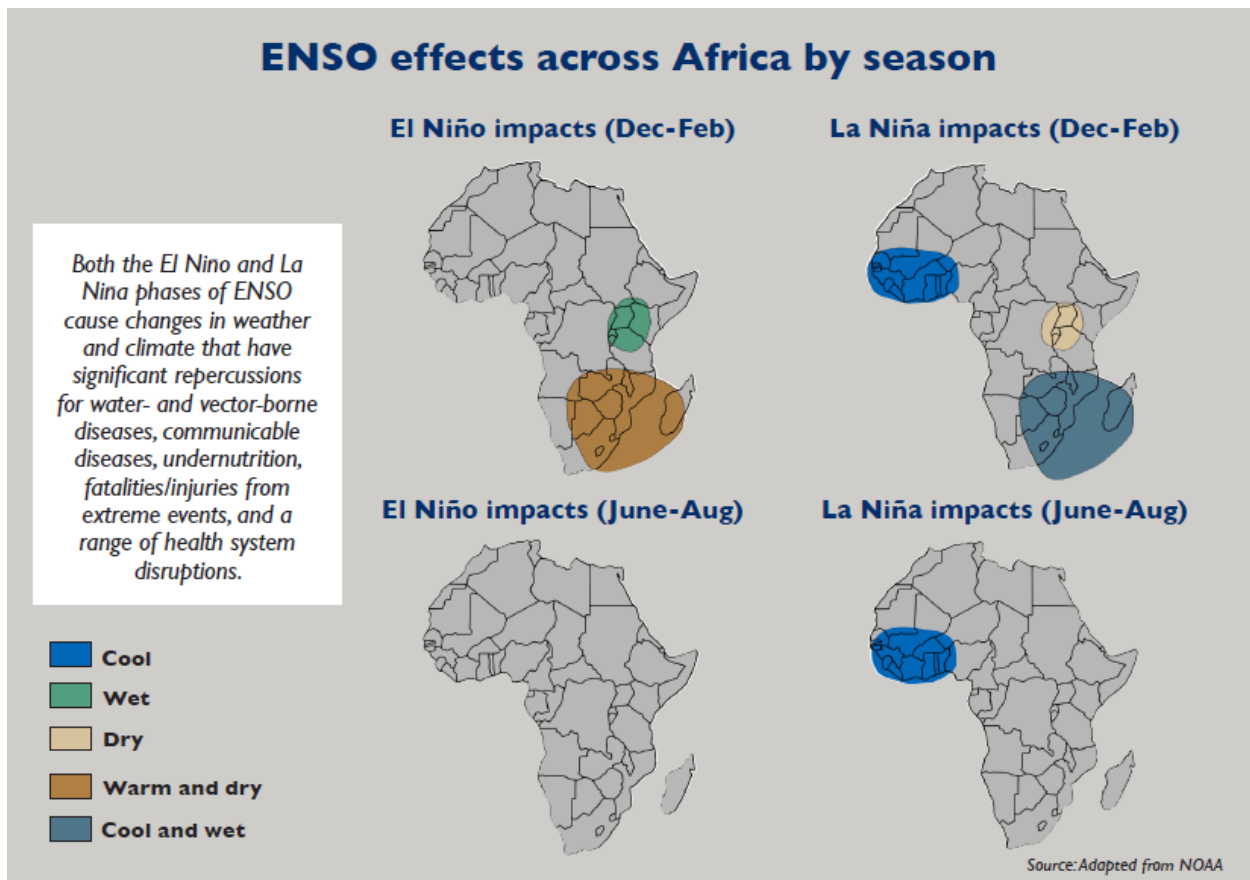
Note: Rainfall in mm. In Figure 8, the month of the year is indicated at the bottom right corner of each panel, beginning with January in the top left and ending with December in the bottom right.

Source: CHIRPS dataset.



In addition to the ITCZ, rainfall in Mozambique is influenced by sea surface temperatures in the tropical Pacific Ocean. With large-scale warming of the equatorial eastern and central Pacific, coupled with the El Niño Southern Oscillation (ENSO) over the southern Pacific, below-average rainfall is received over southern and central Mozambique (Figure 9) (Manhique et al., 2011). This below-average rainfall results from sea surface temperature anomalies that promote offshore displacement of dominant rainfall-producing systems and weaken the northern half of the South Indian Ocean high pressure cell. As a result, the easterly winds are weakened, leading to less onshore moisture transport than in normal years.

Figure 9. Effects of ENSO in Africa

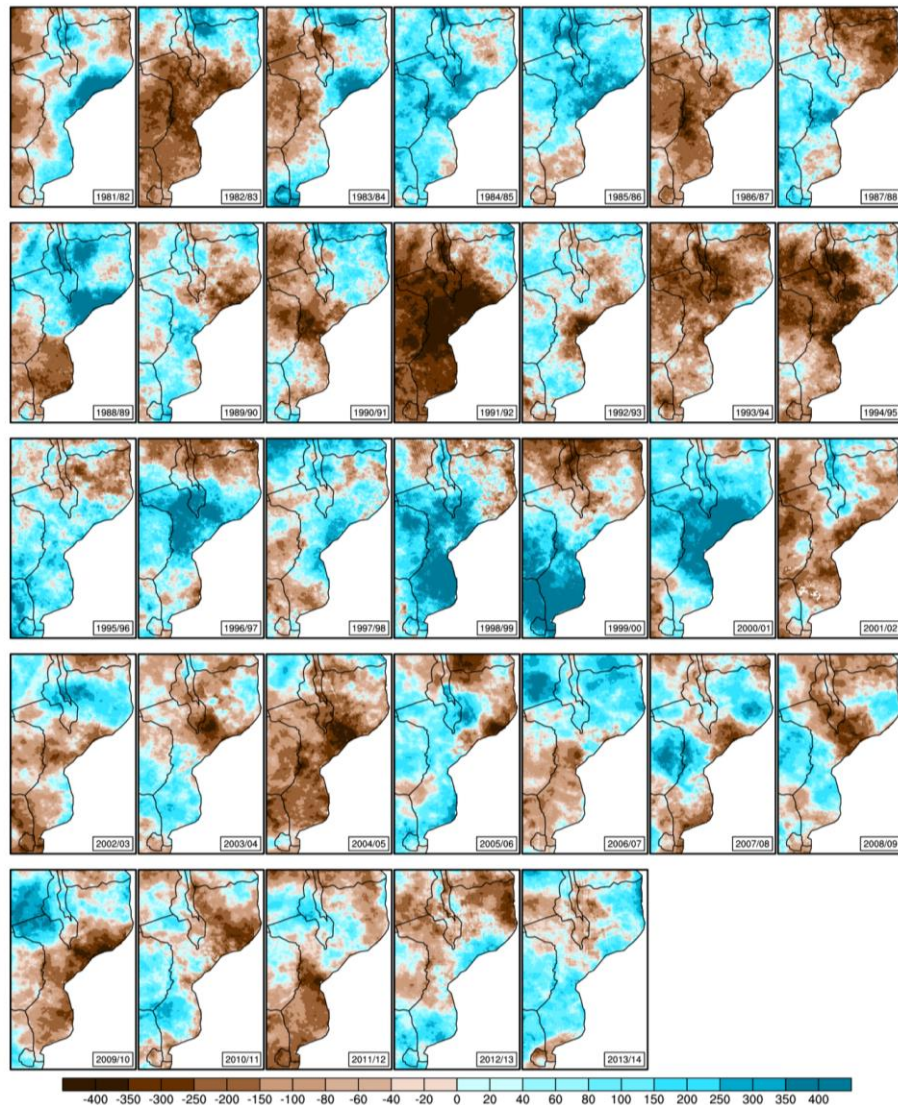


Source: USAID (2017).

Annual rainfall patterns over Mozambique exhibit considerable interannual and geographic variability as shown in Figure 10, which features the difference between each year and the climatological mean rainfall values from 1981 to 1999. This variability is more pronounced in the central and southern regions. Below-average rainfall and drought tend to occur more frequently in the south. Above-average rainfall and flooding are more frequent in the central and southern regions, mainly along the country's major river basins (e.g., Limpopo and Zambezi). Generally, droughts are cyclical and linked to high temperatures and the El Niño (warm) phase of ENSO (Meque & Abiodun, 2014). The La Niña (cold) phase of ENSO is associated with wetter conditions across southern Africa (Figure 9).

However, the strict relationship to ENSO phases (warm/cold) is not consistent. For example, while persistent drought was experienced in 1991/92, considered to be moderate El Niño years, the years 1997/98 were strong El Niño years, but the country experienced relatively normal rainfall. The floods of the 1999/2000 season were the worst recorded in Mozambique in 150 years, leaving 700 people dead and half a million homeless, destroying infrastructure and causing millions in damage (Dyson & Van Heerden, 2001). However, while 1999/2000 were moderate La Niña years, it is important to note that the 1999/2000 floods were a “perfect storm” of multiple tropical cyclones and tropical depressions that struck the region in sequence. Prediction of such complex extreme events is challenging and highly uncertain.

Figure 10. July–June rainfall anomalies between 1981–1999 and 2000–2014



Note: Maps show rainfall differences for each grid cell for July–June rainfall between 1981–1999 and 2000–2014. Considerable year-to-year rainfall variability across the country is evident. Rainfall in mm.

Source: CHIRPS dataset.

## TEMPERATURE

Figure 11 shows the annual mean temperature across Mozambique for the period 1981–2014. The south of the country experiences a mean temperature range of 22°C to 26°C. The northern and central interior regions (Zambezi Valley) generally experience higher average temperatures, with an annual mean of 24°C to 28°C. The coldest recorded temperatures were in the western mountain ranges of Manica, where frost is common during winter. Figure 12 shows the monthly mean temperature per month across Mozambique. All locations experience a peak in monthly mean temperature in the summer (November to April); January and February are the hottest months. The coldest months occur during the winter (May to August), when monthly mean minimum temperatures often drop below 20°C.

Figure 11. Annual mean temperature for each grid cell, 1981–2014

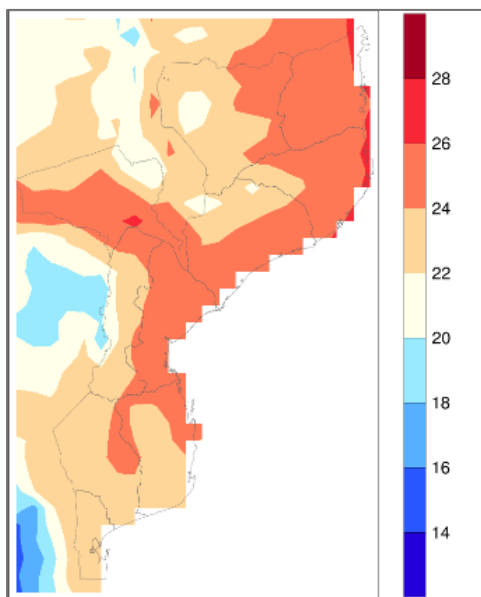
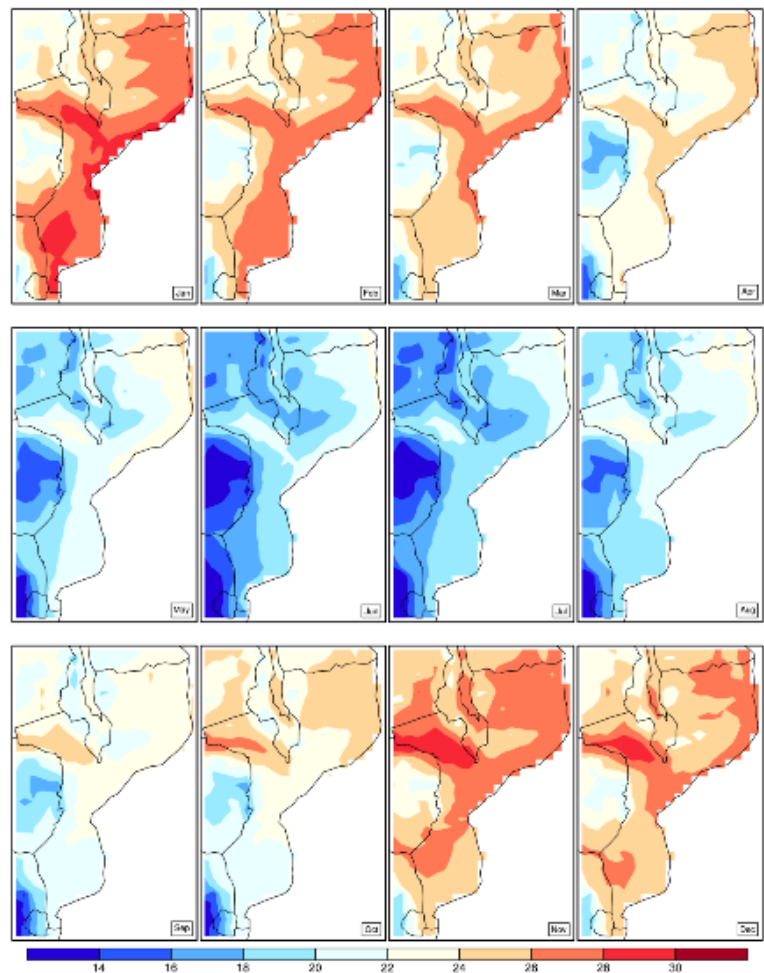


Figure 12. Seasonal cycle of monthly mean temperature, 1981-2014



Note: Temperature in °C. In Figure 11, the month is indicated in the bottom right corner of each panel, starting with January in the top left and ending in December in the bottom right.

Source for Figure 11: CHIRPS dataset.

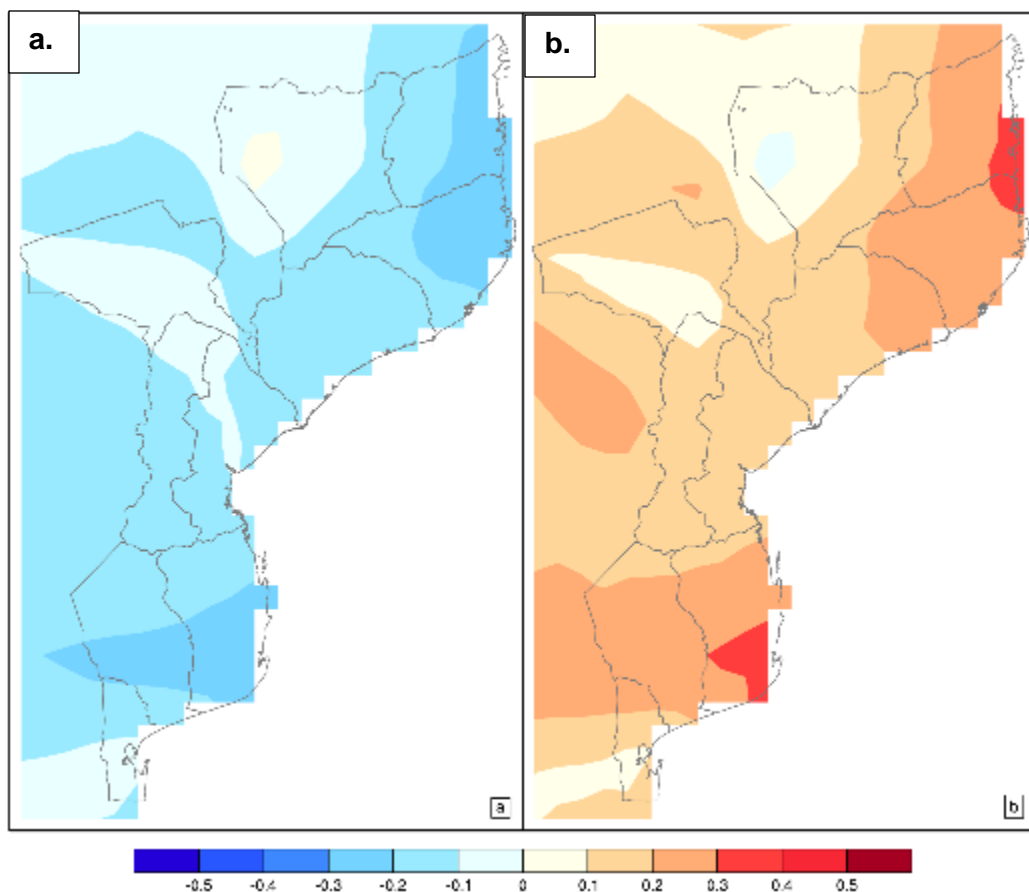
Source for Figure 12: CRU TS 3.23 dataset.

## CLIMATOLOGICAL DIFFERENCES: 1981–1999 AND 2000–2014

Malaria and diarrheal incidence data from Mozambique’s weekly epidemiological bulletin (*Boletins Epidemiológicos Semanais*, or BES) over the last 10 years were used to determine how climate and weather have impacted outbreaks. It is important to understand how the last 30 years of climatology for which we have data in Mozambique differ from the trends and dynamics of the climate in the last 10 years. The following analysis, comparing climate data from 1981–1999 to 2000–2014, offers insights on potential trends in key climate variables that coincide with the time period for which incidence data are available.

Observed anomalies in annual average near-surface temperature over Mozambique for the periods 1981–1999 and 2000–2014 compared with the long-term mean 1981–2014 are shown in Figure 13. The results indicate that temperatures have been rising over Mozambique over the past decades, with the earlier period cooler and the later period warmer than the long-term mean. Engelbrecht et al. (2015) found that Mozambique warmed at a rate of between 1.5°C and 2°C from 1961 to 2010.

Figure 13. Mean temperature differences between (a) 1981–1999 and (b) 2000–2014 relative to 1981–2014



Note: Temperature in °C.

Source: CRU TS 3.23 dataset.

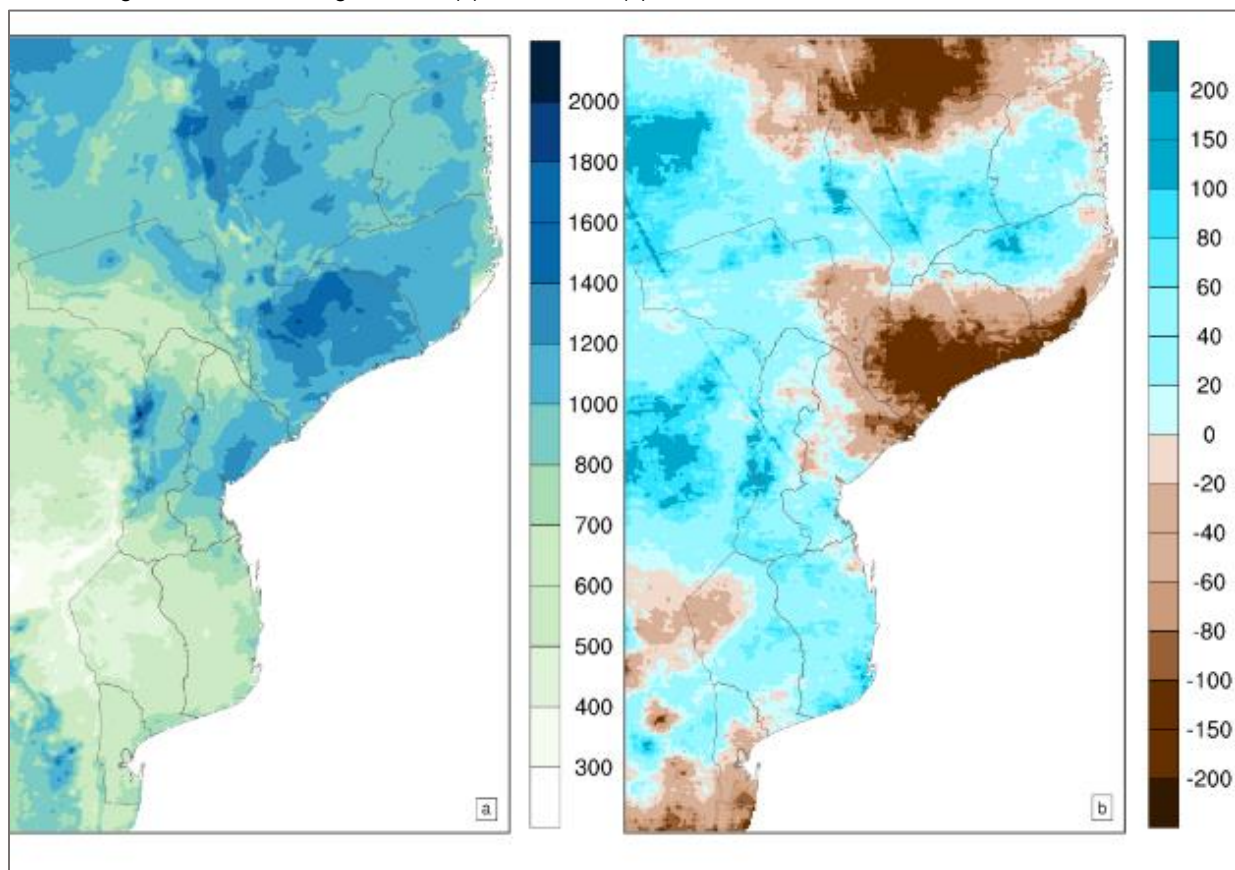


Figure 14–Figure 18 present the differences between the more recent climatological period of 2000–2014 and the earlier period of 1981–1999. In each figure, (a) shows the average for 1981–1999 and (b) shows the difference between the 2000–2014 and 1981–1999 periods. This comparison represents any differences observed between the two periods.

As noted earlier, rainfall in Mozambique, unlike temperature, is highly variable year to year. As a result, these anomalies do not necessarily represent a trend in the climatology. To understand the long-term trend better, analysis of a longer dataset would be needed to eliminate the influence of interannual and interdecadal variability.

In Figure 14, (a) shows that northern areas of Mozambique receive more rainfall on average than southern areas. This is particularly notable in Zambezia, Nampula, and Niassa Provinces. As shown in (b), Zambezia Province and the coastal areas of Nampula Province experienced lower average rainfall in the more recent period, while the majority of the rest of the country experienced higher rainfall.

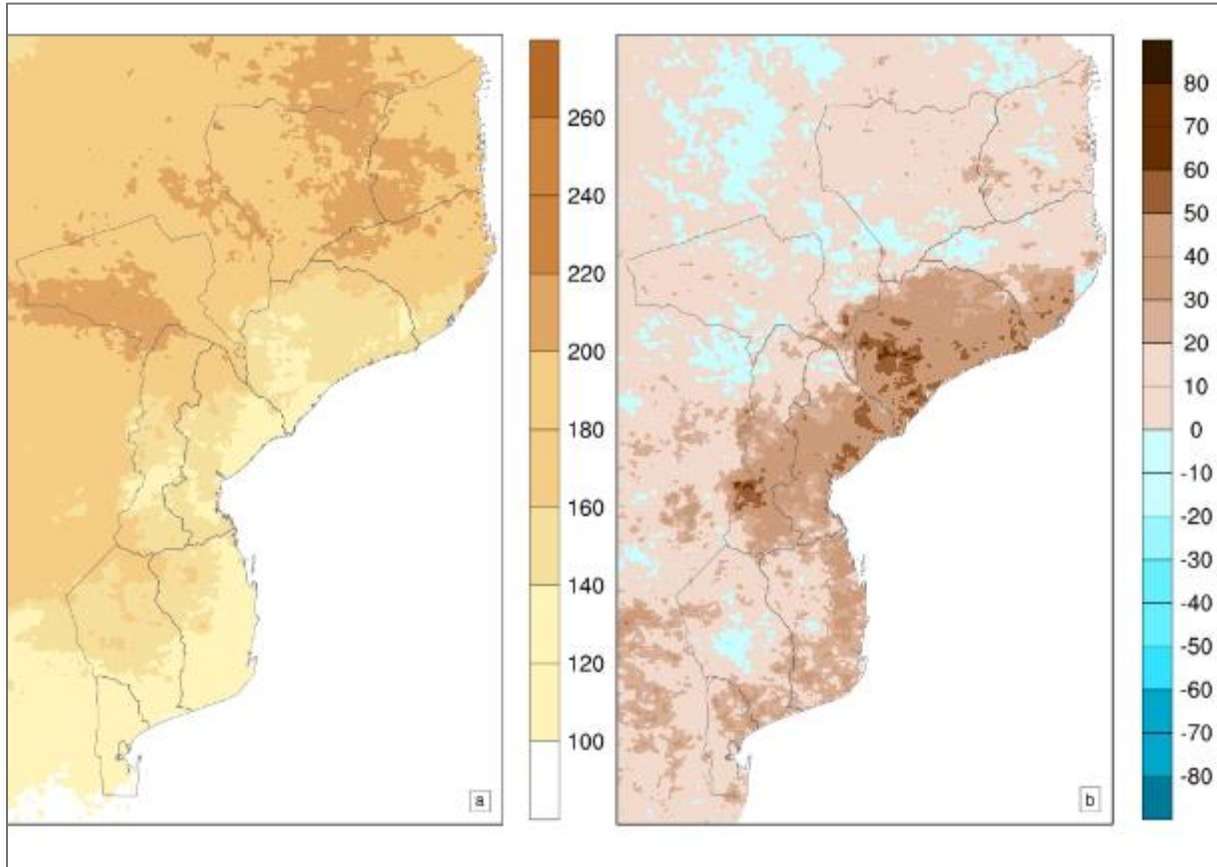
Figure 14. Total average rainfall: (a) 1981–1999; (b) Difference between 1981–1999 and 2000–2014



Note : Rainfall in mm.  
Source: CHIRPS dataset.

Figure 15 shows more consecutive dry days in the latter period (b), particularly across Zambezia and Sofala Provinces. In areas of Zambezia, the difference is as high as 60 days. This corresponds well with Figure 14, which shows lower total average rainfall in Zambezia Province for the second period. For inland and northern areas, the picture is less pronounced, with no clear differences.

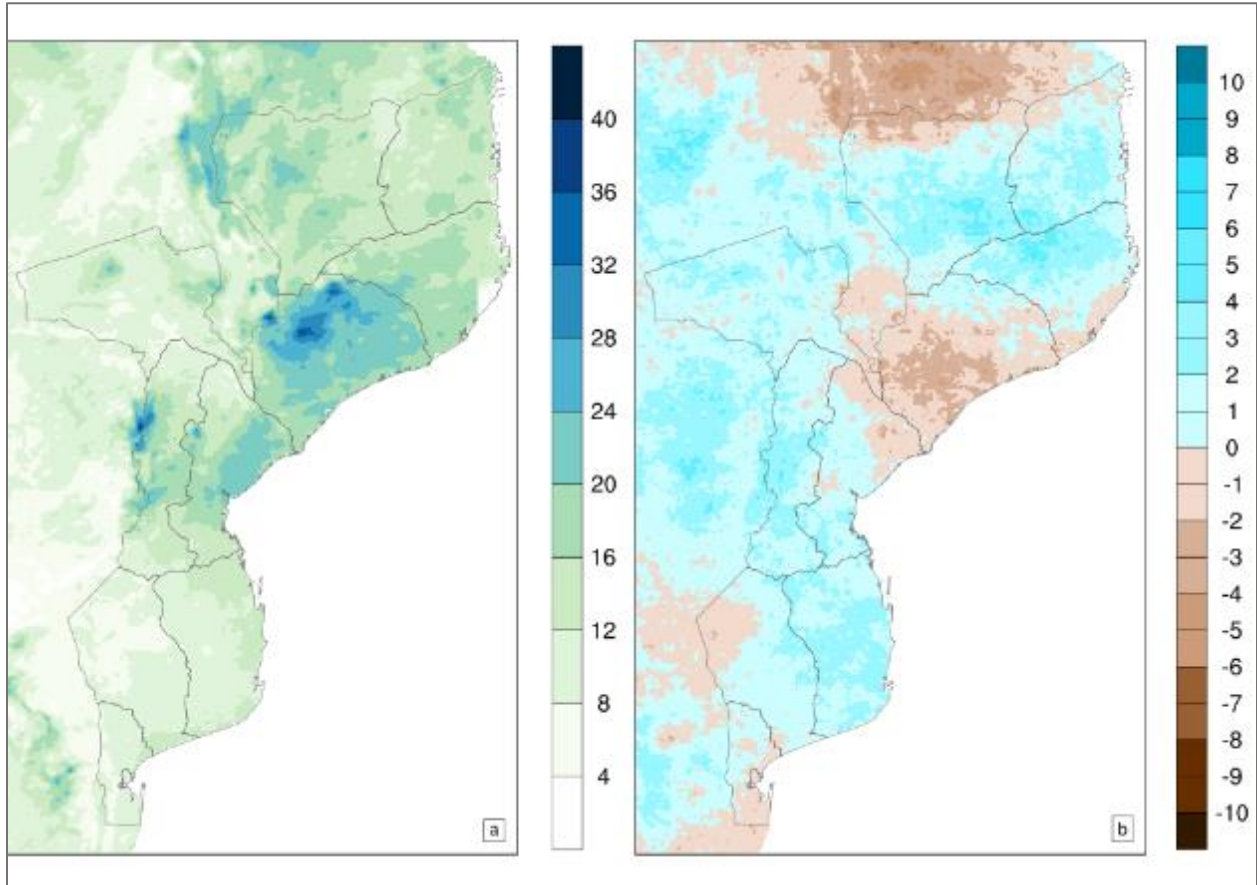
Figure 15. Average consecutive dry days: (a) 1981-1999; (b) Difference for 1981-1999 and 2000-2014



Note: Unit in days.  
Source: CHIRPS dataset.

Figure 16 shows that in the earlier period (a), parts of Zambezia and western Manica Provinces experienced the highest number of heavy rain days. In the more recent period, Zambezia shows fewer heavy rain days (more than 20 mm/day) compared with the early period. However, this decrease is minimal, between zero and three days. Again, this corresponds to the lower total average rainfall for Zambezia for the second period as shown in Figure 14. Most of the rest of the country shows slightly more heavy rainfall for the second period.

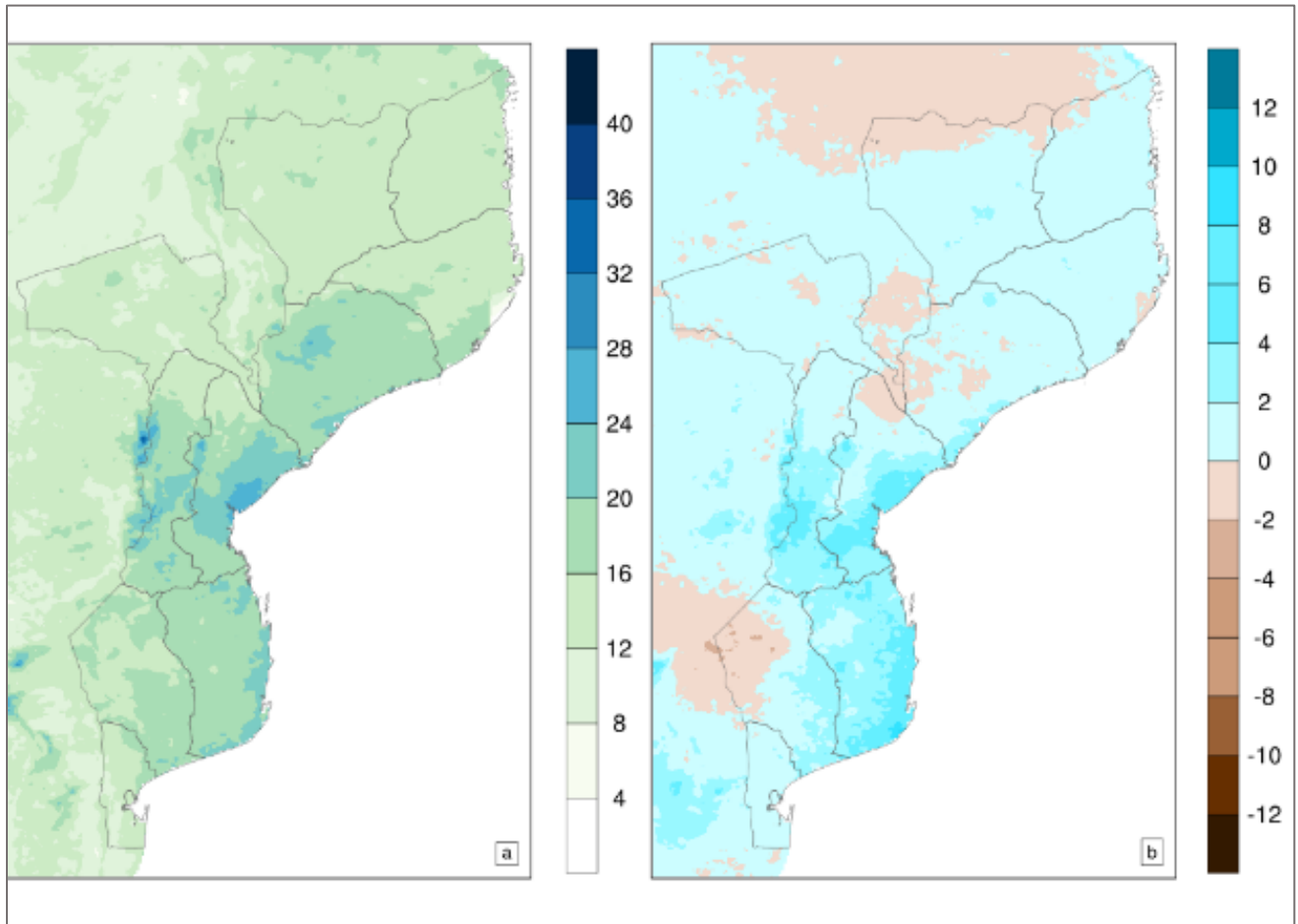
Figure 16. Average of rain days with rainfall above 20 mm: (a) 1981–1999;  
 (b) Difference between 1981–1999 and 2000–2014



Note: Unit is number of days.  
 Source: CHIRPS dataset.

Figure 17 shows the greatest rainfall intensity in the earlier period in coastal areas, particularly in Sofala and Inhambane Provinces (a). Most of the country experienced higher rainfall intensities in the more recent period (b), but again, the coastal parts of Sofala and Inhambane Provinces experienced the most pronounced differences of 2 mm and 6 mm per day, respectively.

Figure 17. Average rainfall intensity: (a) 1981–1999; (b) Difference between 1981–1999 and 2000–2014



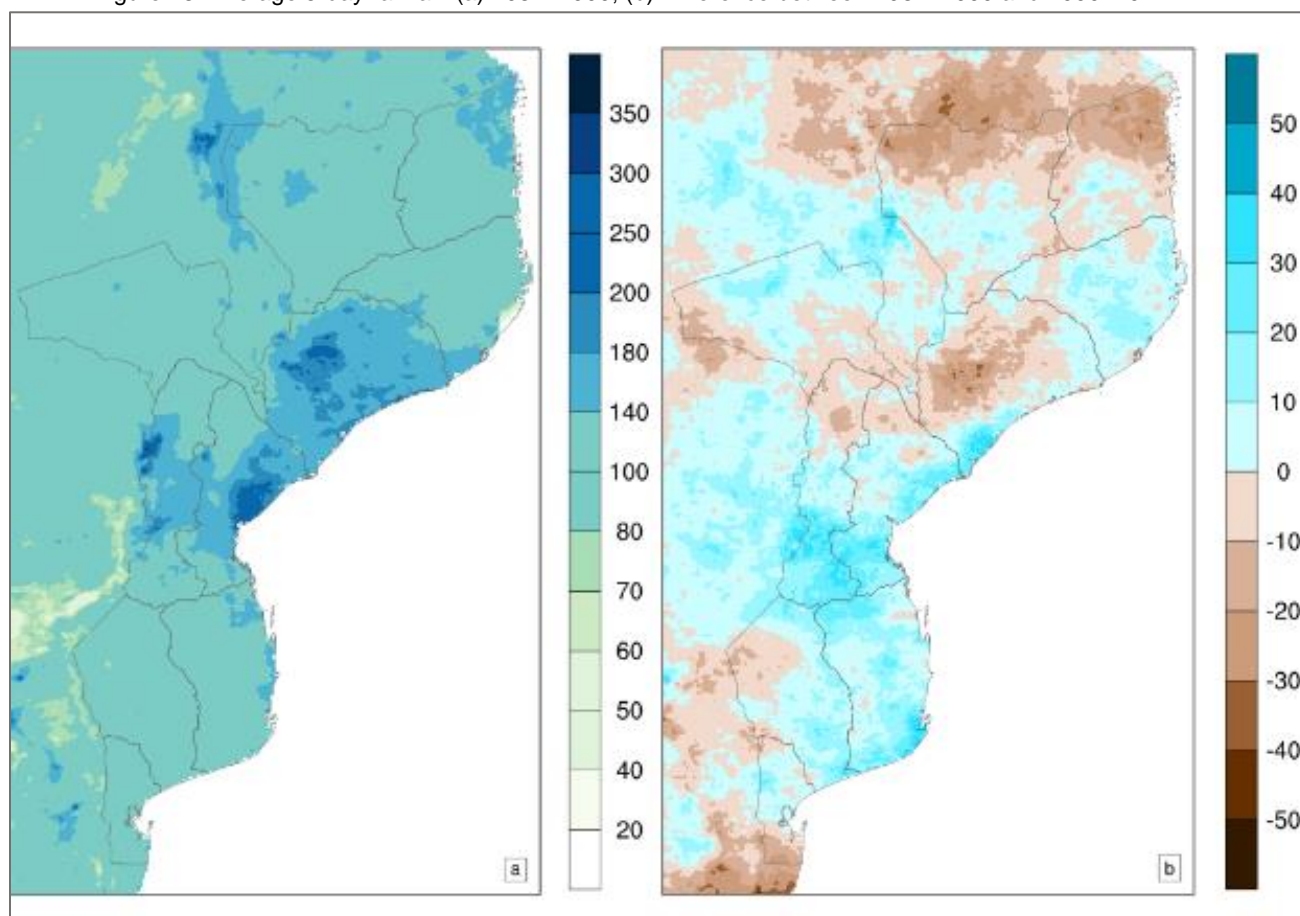
Note: Rainfall in mm/day.

Source: CHIRPS dataset.



Figure 18 shows that in the earlier period, the highest average maximum 5-day rainfall occurred in parts of Zambezia, Sofala, and Manica Provinces, with up to 250 mm of rainfall experienced over a 5-day period. Figure 18 (b) does not reflect as strong a difference between the two periods. The differences shown correlate well with the differences in total average rainfall seen in Figure 14.

Figure 18. Average 5-day rainfall: (a) 1981–1999; (b) Difference between 1981–1999 and 2000–2014



Note: Rainfall in mm/day  
Source: CHIRPS dataset.

## DISCUSSION

A comparison of the two periods, 1981–1999 and 2000–2014, shows some important differences in the long-term versus current climate of Mozambique:

- **Mean temperature increased across the country.** Temperatures showed a more linear trend than rainfall. The increase in mean temperature across Mozambique over the periods was clear.
- **Due to the high interannual variability of rainfall, the two periods of analysis were not long enough to deduce statistically significant trends.** It is possible, however, to highlight differences between the two periods that may have bearing in further analysis of climate and health links for the second period where health records are available.

- **The more recent period was wetter than the earlier period.** The results across all five rainfall indices are in general agreement on this point. However, this is not the case across the whole country. In particular, Zambezia Province experienced lower rainfall in the more recent period compared with the earlier period. This difference was confirmed by the complementary rainfall indices of consecutive dry days, heavy rain days, and average maximum 5-day rainfall. To deduce whether these observed differences were attributable to any trend in rainfall, it would be necessary to analyze a longer period of observed data.
- **Rainfall differences between the two periods are not likely large enough to significantly alter a climate and health analysis.** However, given the changes in temperature between the two periods, it is imperative that climatological values for the second period are used to represent recent climate across Mozambique, especially considering that the availability of climate records is limited to recent years. Use of a longer climatological period would risk misattribution of climate and health relationships.

## CLIMATE CHANGE IN MOZAMBIQUE

A synthesis of available evidence on projected climate changes of relevance to health programming is summarized in Table 3. A detailed analysis follows.

Table 3. Projected changes in climate across Mozambique

Rainfall
<ul style="list-style-type: none"> <li>• Rainfall will continue to vary. While no statistically significant rainfall changes are projected, the current delayed start and earlier end to the rainy season in the northern region will likely continue and the intensity of single rainfall events is likely to increase.</li> </ul>
Temperature
<ul style="list-style-type: none"> <li>• Temperature will continue to rise by approximately 1°C over the next 20 years and by 3°C to 5°C by the end of the 21st century.</li> <li>• An increase in the number of days exceeding 35°C and a decrease in the number of nights below 25°C will occur.</li> <li>• The difference between the daily maximum and minimum temperatures, called the diurnal temperature range, will increase.</li> </ul>

### SOURCES AND LIMITATIONS OF THE DATA

#### Global Climate Models (CMIP5)

The primary sources of information on large-scale changes to the global climate are Global Climate Models (GCMs) and more specifically, coupled Atmosphere-Ocean Global Climate Models (AOGCMs). AOGCMs simulate responses to changing atmospheric concentrations of greenhouse gases, mostly carbon dioxide and methane, and other emissions, including sulfates and black carbon. AOGCMs simulate both ocean dynamics and atmospheric dynamics and many modern models also simulate vegetation and other land surface processes and feedbacks. These more sophisticated models are called Earth System Models.

AOGCMs involved in the CMIP5 (Coupled Model Intercomparison Project Phase 5) experiment operate at relatively low spatial precision. This means that they simulate average conditions over fairly large spatial areas. For example, a typical AOGCM member of CMIP5 would simulate

an area of 200 km x 200 km as a homogenous area with no variations in rainfall, temperature, or wind across that area. Clearly, such low resolution is unable to accurately represent the complexity of the microclimates within that area but can capture large-scale shifts in circulation patterns and processes. Therefore, CMIP5 GCM data are not suitable for direct use in local-scale climate change assessment and impact modeling. For this, GCM data have to be appropriately downscaled (see below). In spite of this, it is important to look at GCM output in conjunction with downscaled data because of the uncertainties introduced by downscaling. By comparing both, we look at multiple sources of evidence, and their qualitative agreement increases confidence in the projections. If GCM projections agree with downscaled projections, then there is increased confidence in the projected changes. If the two approaches contradict each other, it suggests that the downscaling is capturing local-scale dynamics not represented in the GCMs. Such contradictions need to be considered intelligently and interpretation of results needs to be balanced by expert judgment on the plausibility of projected changes. This comparison is presented later in this report.

#### **TECHNICAL INFORMATION: THE COUPLED MODEL INTERCOMPARISON PROJECT**

The Coupled Model Intercomparison Project (CMIP) was established under the World Climate Research Program by the Working Group on Coupled Modelling. The goal was to provide a standard experimental protocol for studying the output of coupled Atmosphere-Ocean GCMs to facilitate model improvement through better model quality control and a better understanding of model behavior (Meehl et al., 2000). The output of phase three of CMIP was used extensively in the Intergovernmental Panel on Climate Change's (IPCC) Fourth Assessment Report (AR4; IPCC, 2007). The fifth phase of the Coupled Model Intercomparison Project (CMIP5) is the latest set of coordinated climate model experiments (Taylor et al., 2012).

#### **Self-Organizing Map-based Downscaling (SOMD)**

Through the process of “downscaling,” it is possible to produce future projections of climate change for a finer spatial resolution. Downscaling assumes that the local climate is primarily a function of the large-scale climate modified by some local factors, such as topography, continentality, and proximity to oceans and lakes. Two types of downscaling techniques are available: dynamical and empirical/statistical. Dynamical downscaling uses the same principles as global climate modeling in that the physical process such as wind flows, cloud formation, and rainfall mechanisms in the regional atmosphere are explicitly simulated for the region. Statistical downscaling does not attempt to simulate physics but rather uses historical observations of weather and associated wind and moisture patterns to construct a model relating large-scale weather patterns to local-scale weather. The analysis presented here uses a statistical downscaling method called Self-Organizing Map-based Downscaling (SOMD), developed at the Climate System Analysis Group (CSAG) (Hewitson & Crane, 2006). This is a leading empirical downscaling technique for Africa and provides meteorological station-level (or gridded) projections of change.

A few assumptions included in this methodology are that:

- The main driver for the local climate is large-scale climate. Although this method does capture the dominant forcing of the local climate, some processes may still be unresolved.
- GCMs are good enough to accurately simulate the large-scale climate. If the GCM fails to do so, the errors will propagate through the downscaling process. Similarly, if the quality of the observation data used to derive the statistical relationship is poor, this will negatively affect the projections.
- The relationship between the large-scale drivers and local climate will be the same in the future as in the past. This is likely of greatest concern for long-term projections, whereas near-term projections often assume climate stationarity (wherein the near-future climate dynamics will be the same as the past).

#### TECHNICAL INFORMATION: HOW TO INTERPRET SPATIAL PLOTS

The spatial anomaly plots show the observed climatology (1986–2005) in the upper left-hand panel followed by projections of change (from the observed) across each of the subset of CMIP5 models, for 2040–2065 for Representative Concentration Pathway (RCP) 8.5. The hashing on the maps indicates where the projected change is statistically significant (hashing is more predominant in the temperature indices).

#### Modeling uncertainties

All future projections of climate include a range of uncertainties. It is important to understand that the climate is changing; however, a range of uncertainty arises in the magnitude of change because of limitations in our scientific understanding of the climate system and hence methods used to project future climate. As spatial scales become finer, more uncertainties are introduced into the modeling, and the range of possible climate response therefore widens.

Projecting future climate is a complex subject and the focus of much work worldwide. Progress is being made on understanding the underlying sources of uncertainty and how best to manage them. Sources of uncertainty include:

- *Natural variability*: It is not possible to accurately define the limits of natural variability due to the relatively short time historical records have been kept, and because the climate system is chaotic. This source of uncertainty cannot effectively be reduced, meaning that users need to evaluate a range of possible futures.
- *Future emissions*: The range of possible societal development pathways will have significant impacts on greenhouse gas emissions and other environmental forcing factors. Two dominant emissions scenarios used in planning are Representative Concentration Pathway 4.5 (RCP 4.5) and Representative Concentration Pathway 8.5 (RCP 8.5). RCP 4.5 represents an emissions pathway that stabilizes before 2100, with emissions peaking around 2040. RCP 8.5 represents a high-emissions future where emissions continue to increase (Moss et al., 2010).
- *Uncertainty in the science*: Gaps persist in the current knowledge and understanding of the dominant physical processes controlling the regional climate system and how these processes might change in the future.
- *Structural uncertainty*: Tools and methods are imperfect, and their application is sometimes inappropriate.

- *Observational uncertainties*: Inaccurate information may be used as input into the climate modeling and used to test the results.

Some uncertainty issues can be addressed through continual improvement of the science. However, some uncertainty will always remain. The best way to understand the possible range of projected changes is to combine as many models as reasonably possible under one emissions pathway. What results is a range of likely change. This allows the user to have a more defensible projection of the direction of change, even though the size of the projected change is less certain.

For the reasons stated above, where we provide projections of change in this report, we incorporate a subset<sup>3</sup> of GCMs used in the latest IPCC report (CMIP5). This shows the spread of projections across the models, rather than taking a best-guess approach.

## FUTURE PROJECTIONS OF CHANGE FOR MOZAMBIQUE

For simplicity, a selection of plots is shown here to illustrate the projected changes in climate for Mozambique. A more comprehensive set of plots, including both CMIP5 and SOMD anomalies and climatologies and for both RCP 4.5 and RCP 8.5, will be published in a separate appendix.

The research team, which included health experts, decided to focus on the SOMD RCP 8.5 plots. These are shown here (except when the GCM plots are shown for comparison).

### TECHNICAL INFORMATION: HOW TO INTERPRET PLUME PLOTS

Estimates of uncertainty resulting from natural variability are represented by shaded areas surrounding the projected values. The significance of the projected changes (i.e., when the changes exceed the bounds of what was experienced in the past) is highlighted by a change in color from blue to orange. This allows for some estimation of when in the future it is likely that the projections are operating under a climate that is distinctly different from the one currently experienced.

## COMPARISON OF GCM AND DOWNSCALED PROJECTIONS

The differences between projections derived from GCMs versus those derived from the SOMD method are illustrated in Figure 19 - Figure 31, and are summarized below:

- As expected, their projected changes differ because the downscaling is designed to better represent local-scale responses to large-scale circulation forces. Downscaling not only adds spatial detail but can also (and generally does) alter large-scale projected changes.
- The most marked differences between the two sets of projections are for rainfall, as it is the rainfall response that downscaling typically alters the most. Typically, downscaled temperature projections will exhibit local-scale detail not present in the GCM-based projections, but the large-scale mean response should be very similar to the GCM-based projections.

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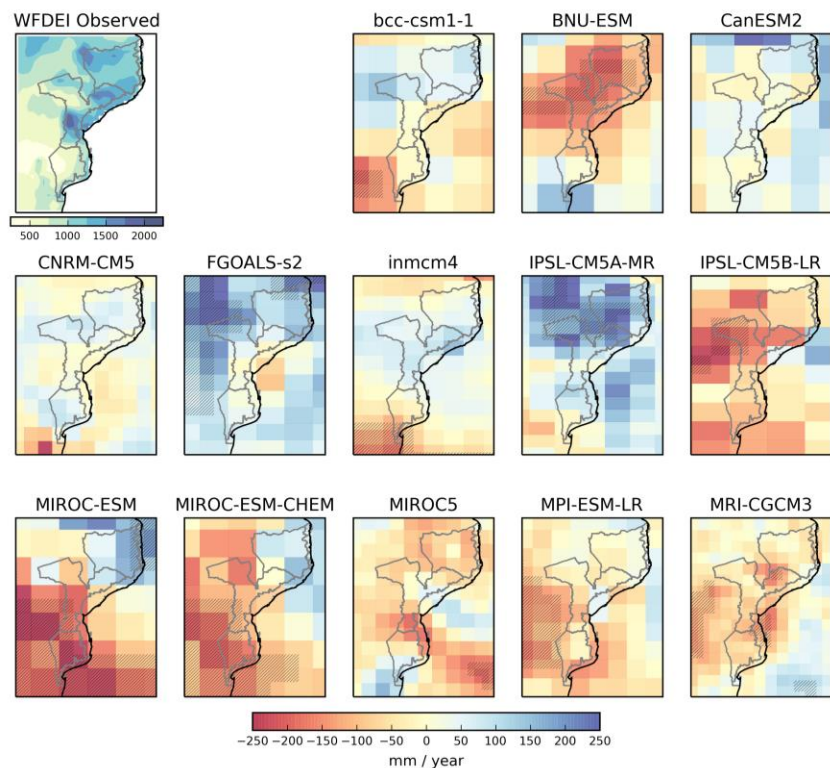
<sup>3</sup> The subset of models consists of all models that provide daily time resolution surface and atmospheric thermodynamic variables required for downscaling.

- On the whole, across Mozambique, the SOMD downscaling (Figure 20) introduces a greater tendency toward a drier future compared with the GCM-based projections (Figure 19), which are fairly split between increased and decreased rainfall. Significant decreases only emerge toward the end of the century. It is difficult within the scope of this work to unpack the causes behind this difference in signal, but the most defensible argument would be that the SOMD downscaling is responding to the increasing dominance of the subtropical high-pressure system suppressing convection and/or moisture transport off the ocean. As the GCMs are unable to represent convection explicitly, it is possible that they fail to translate this large-scale circulation response into a reduction in rainfall. However, without further analysis, we cannot conclude that the downscaled projections are necessarily more correct or defensible, and so both GCM and downscaled projections should be considered plausible. In this case, strong contradictions do not arise between the GCM rainfall projections and the SOMD projections, as both show a possibility of increased and decreased rainfall over all regions. Certainly, within the next 20- to 30-year timeframe, no strongly significant rainfall changes are projected by either method, and rainfall variability will almost certainly be dominated by natural variability through this time period.
- The count of days exceeding 50 mm of rainfall (Figure 21 and Figure 22) differs between the two projection methods. For this parameter, the GCMs show significant increases toward the end of the 21st century, particularly for the northern region. The SOMD projections fail to show this, likely because it is such a rare event (only one to two times per year) that the statistical modeling used in the SOMD approach is unable to capture it. This is a common limitation of statistical approaches and a strength of dynamical approaches. As this statistic has been highlighted as predictive of malaria incidence in some areas, particular attention is placed on these differences below.
- The two methods agree very well with regard to temperature-related projections (Figure 23 and Figure 24). The only difference is that the SOMD method shows marginally reduced uncertainty toward the end of the century. For the time period of relevance here, no difference arises in the projected changes for temperature.

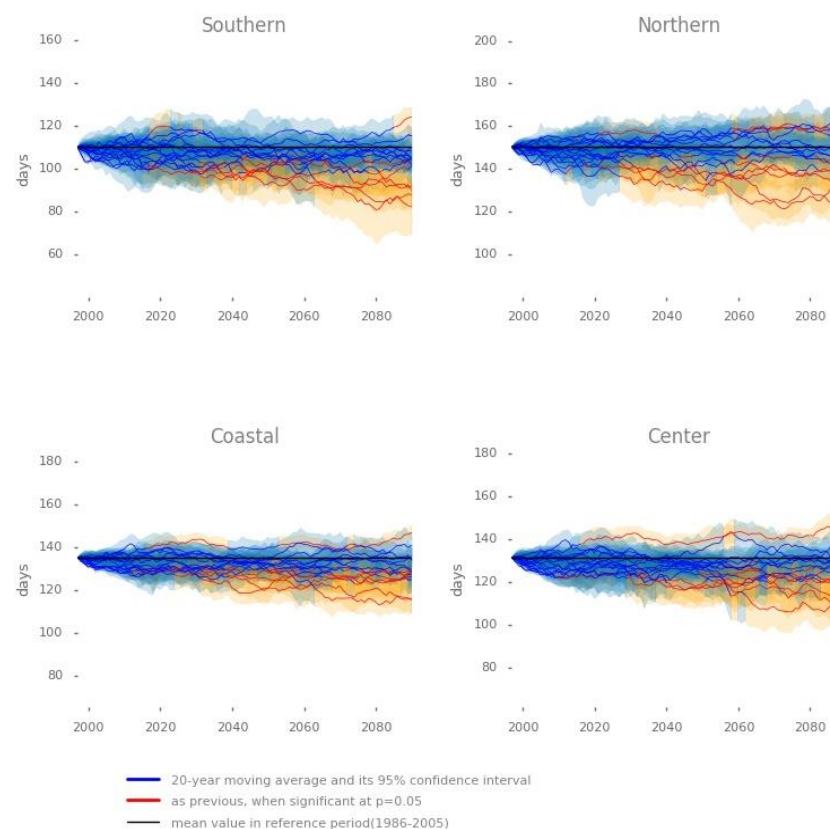


Figure 19. Projected change in rainfall derived from Global Circulation Models under RCP 8.5 (worst-case scenario), 2046–2065

**a) Future anomalies in annual pr totals**



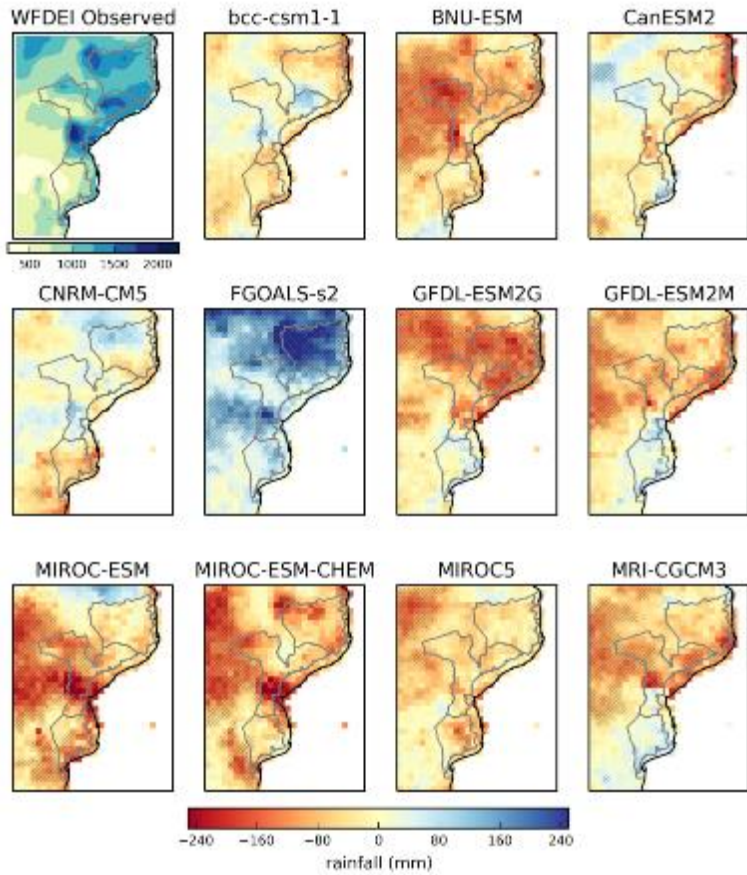
**b) Temporal evolution of rain days in a year with rain > 1 mm/day**



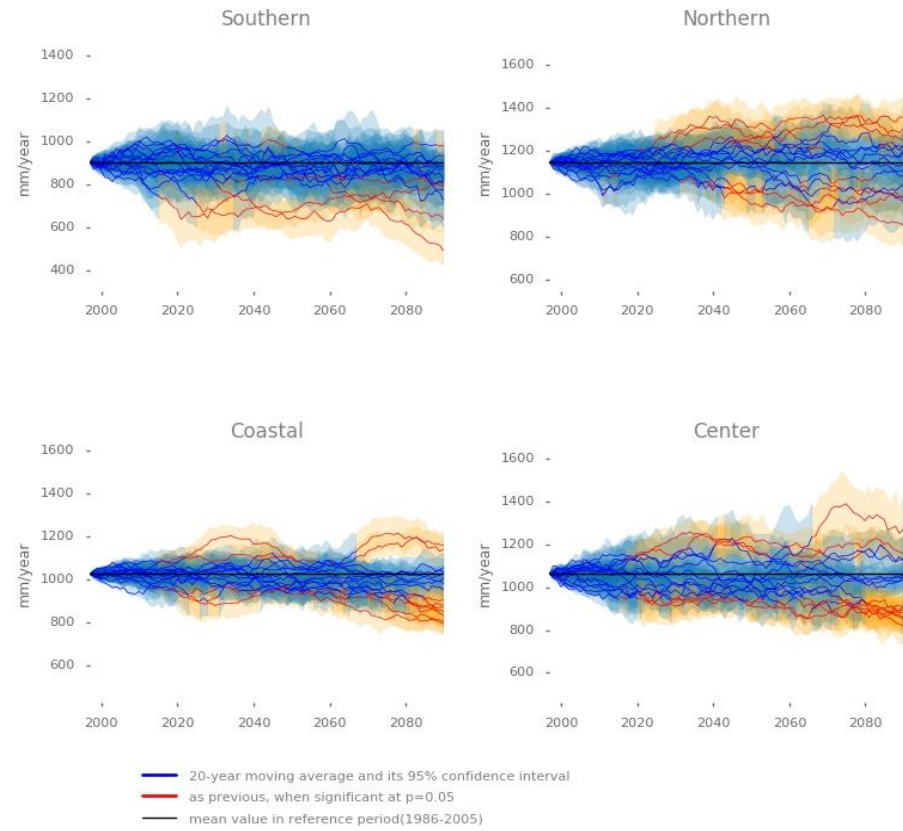
Note: a) CMIP5 GCM future change in annual rainfall under RCP 8.5 (2045–2065 minus 1986–2005) of average annual total rainfall. Top left plot on left is the observed climatology from historical observed data (WFDEI) (1986–2005). b) Time series of CMIP5 GCM projections of the same variable for each of the regions described in this report based on GCM CMIP5 multimodel ensembles (RCP 8.5).

Figure 20. Rainfall projections derived from the Self-Organizing Map-based Statistical Downscaling method under RCP 8.5 (worst-case scenario), 2046–2065

**a) Future anomalies in annual pr totals**



**b) Temporal evolution of total annual rainfall**

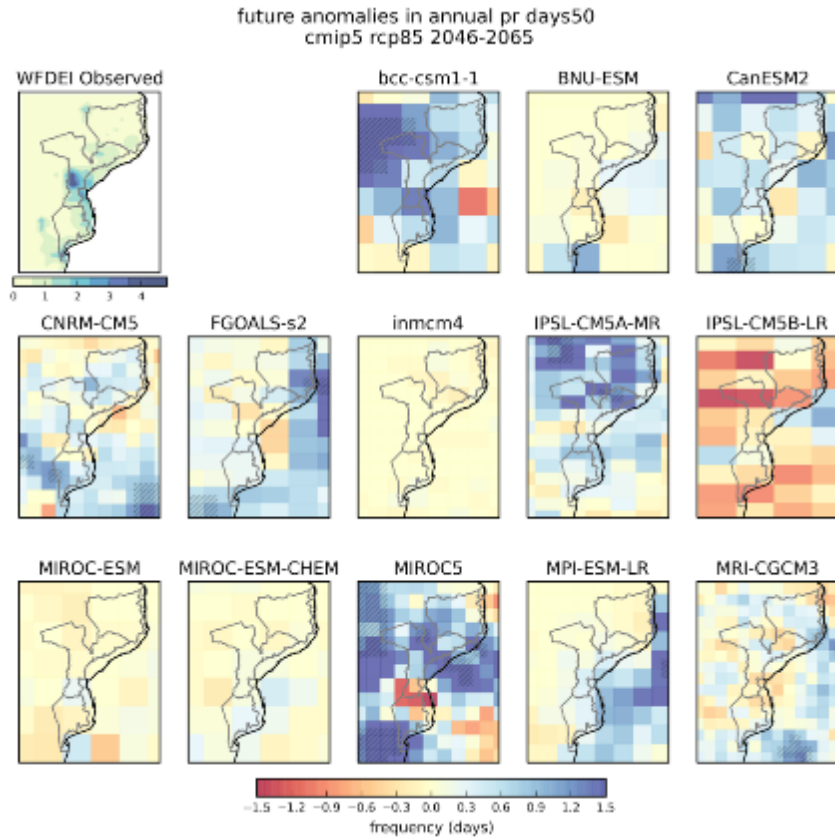


Note: a) SOMD downscaled future anomalies (2046–2065 minus 1986–2005) of average annual total rainfall (RCP 8.5). Top left plot is the observed climatology from WFDEI (1986–2005). b) Time series of SOMD projections of the same variable for each of the regions described in this report based on GCM CMIP5 multimodel ensembles (RCP 8.5).

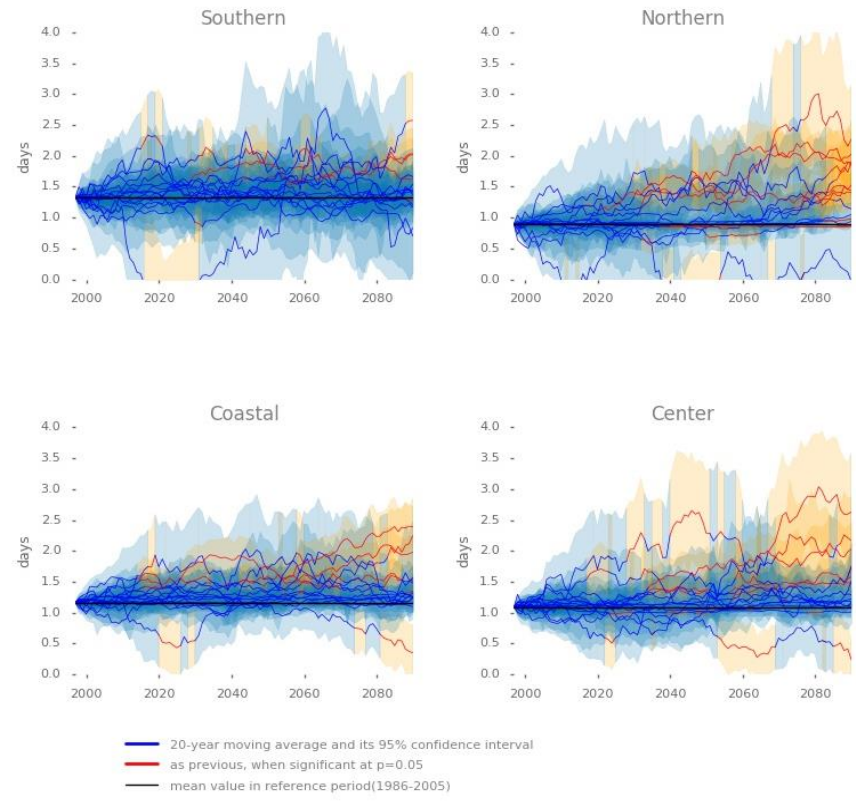


Figure 21. Projected changes in number of days exceeding 50 mm rainfall derived from Global Circulation Models (CMIP5), 2046–2065

**a) Future anomalies in annual pr days50**



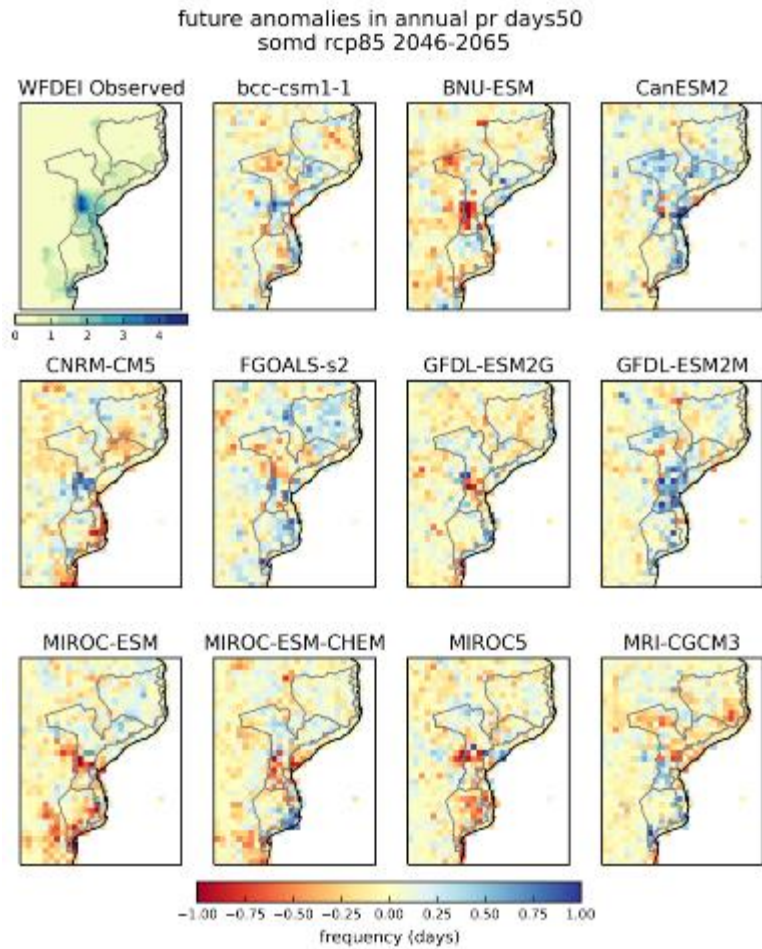
**b) Temporal evolution of rain days in a year with rain > 50 mm/day**



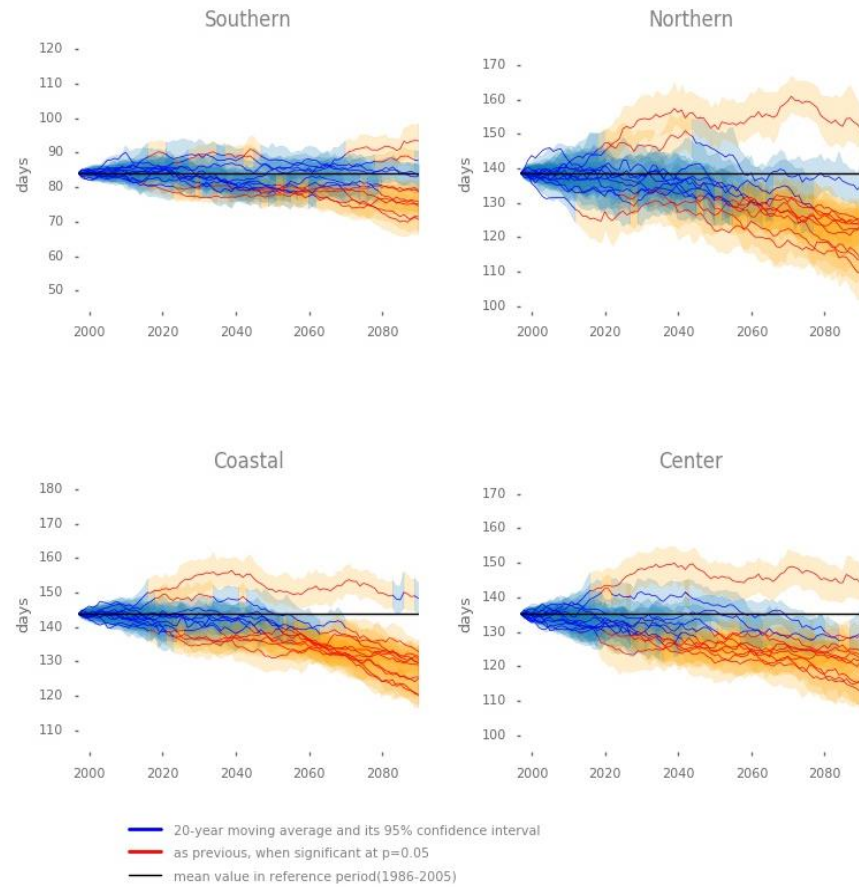
Note: a) CMIP5 GCM future anomalies (2046–2065 minus 1986–2005) of annual days exceeding 50 mm rainfall (RCP 8.5). Top left plot is the observed climatology from WFDEI (1986–2005). b) Time series of CMIP5 GCM projections of the same variable for each of the regions described in this report based on GCM CMIP5 multimodel ensembles (RCP 8.5).

Figure 22. Projected changes in number of days exceeding 50 mm rainfall derived from downscaled data, 2046–2065

**a) Future anomalies in annual pr days50**



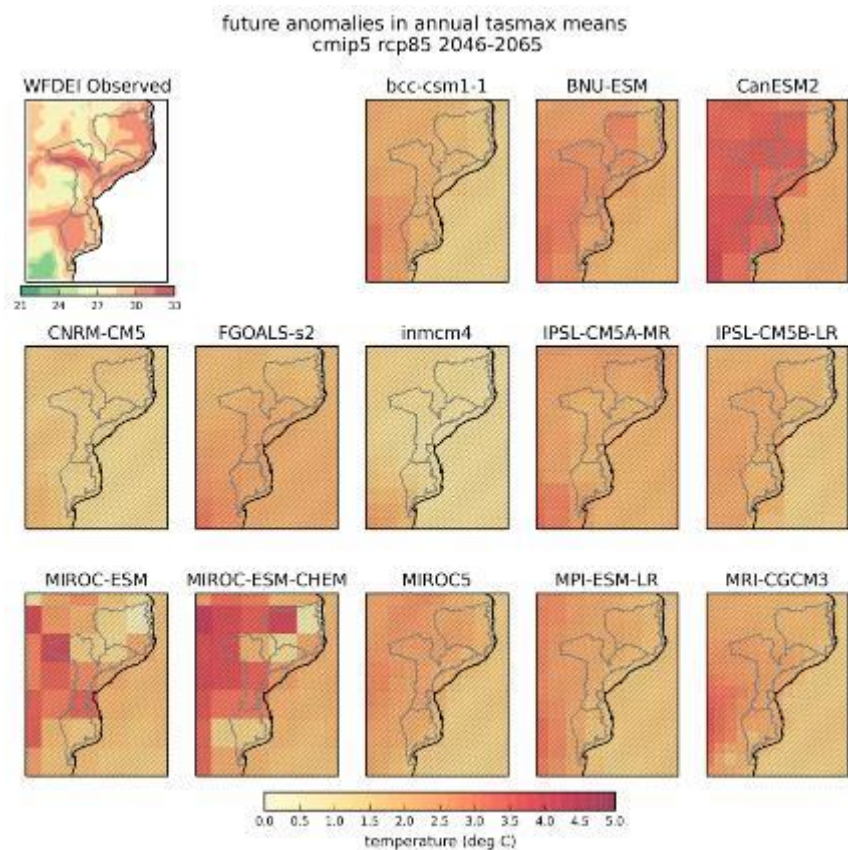
**b) Temporal evolution of rain days in a year with rain > 50 mm/day**



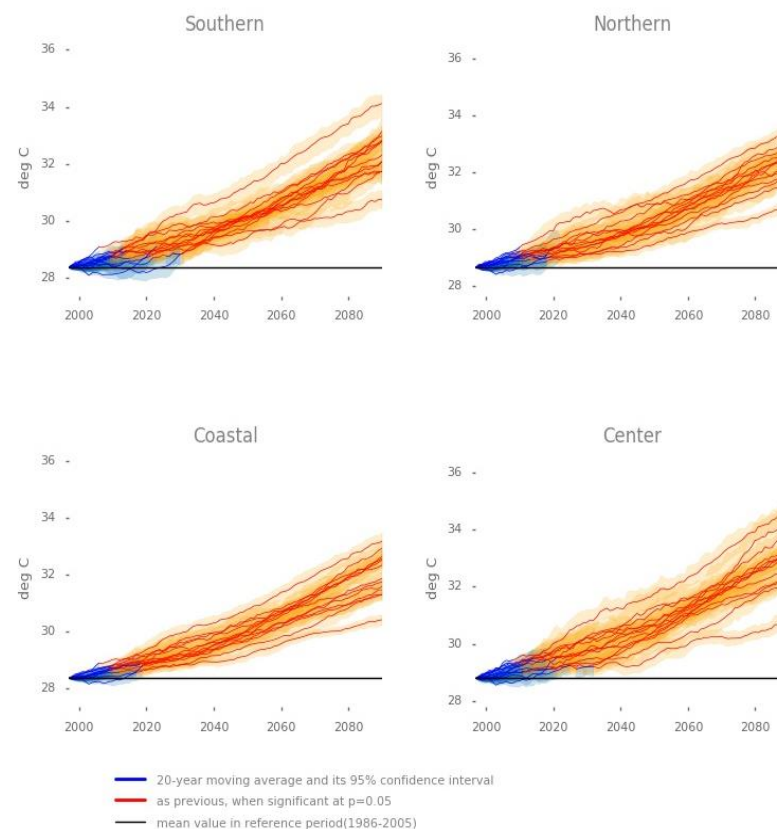
Note: a) SOMD downscaled future anomalies (2046–2065 minus 1986–2005) of annual days exceeding 50 mm (RCP 8.5). Top left plot is the observed climatology from WFDEI (1986–2005). b) Time series of SOMD projections of the same variable for each of the regions described in this report based on GCM CMIP5 multimodel ensembles (RCP 8.5).

Figure 23. Future temperature projections derived from Global Circulation Models (CMIP5), 2046–2065

**a) Future anomalies in annual tasmax means**



**b) Temporal evolution of yearly mean of daily maximum temperature**

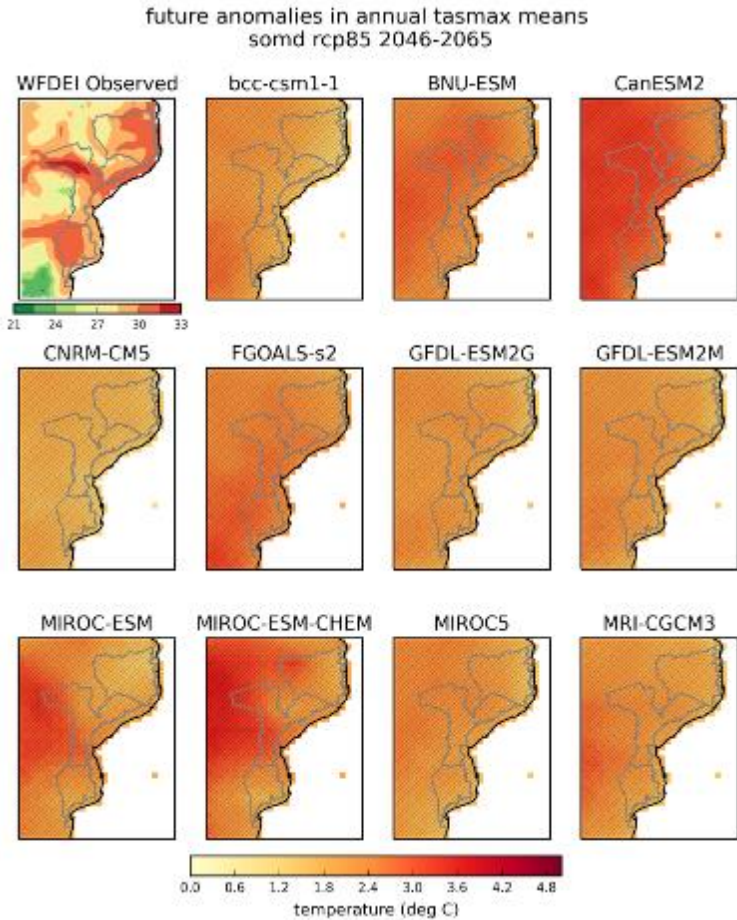


Note: a) CMIP5 GCM future anomalies (2046–2065 minus 1986–2005) of average annual mean maximum temperature (RCP 8.5). Top left plot is the observed climatology from WFDEI (1986–2005). b) CMIP5 GCM projections of annual mean maximum temperature for each of the regions, based on the GCM CMIP5 multimodel ensemble (RCP 8.5).

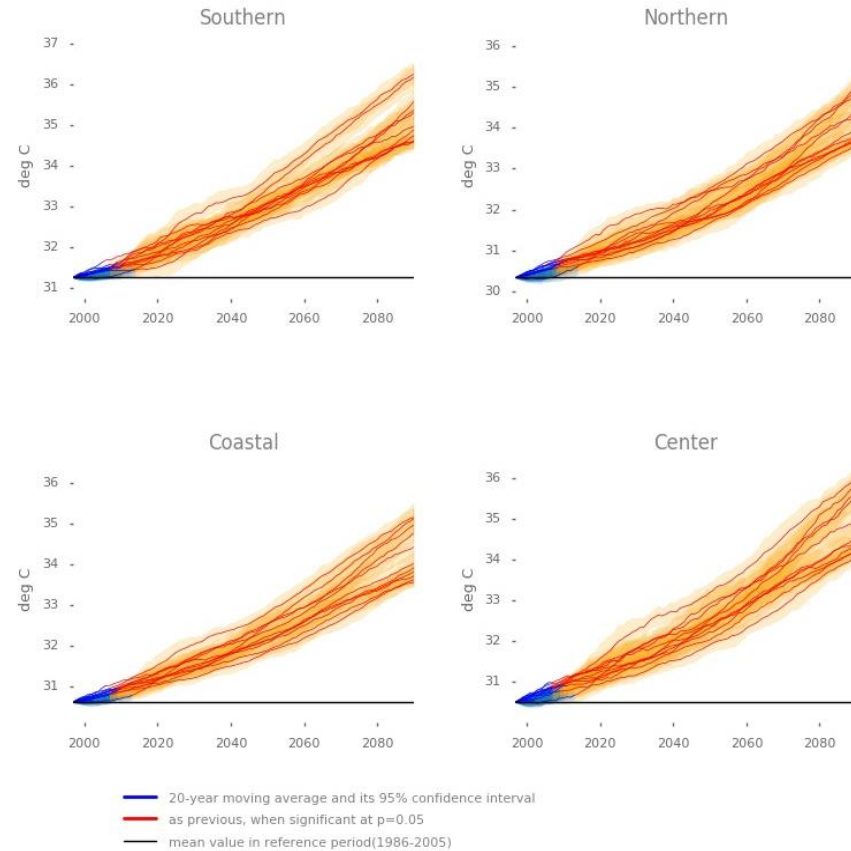


Figure 24. Maximum temperature projections derived from downscaled data, 2046–2065

**a) Future anomalies in annual tasmax means**



**b) Temporal evolution of yearly mean of daily maximum temperature**



Note: a) SOMD downscaled future anomalies (2046–2065 minus 1986–2005) of average annual mean maximum temperature (RCP 8.5). Top left plot is the observed climatology from WFDEI (1986–2005). b) SOMD downscaled projections of annual mean maximum temperature for each of the regions based on the GCM CMIP5 multimodel ensemble (RCP 8.5).

## **ANNUAL AVERAGE DOWNSCALED PROJECTIONS, 2046 - 2065**

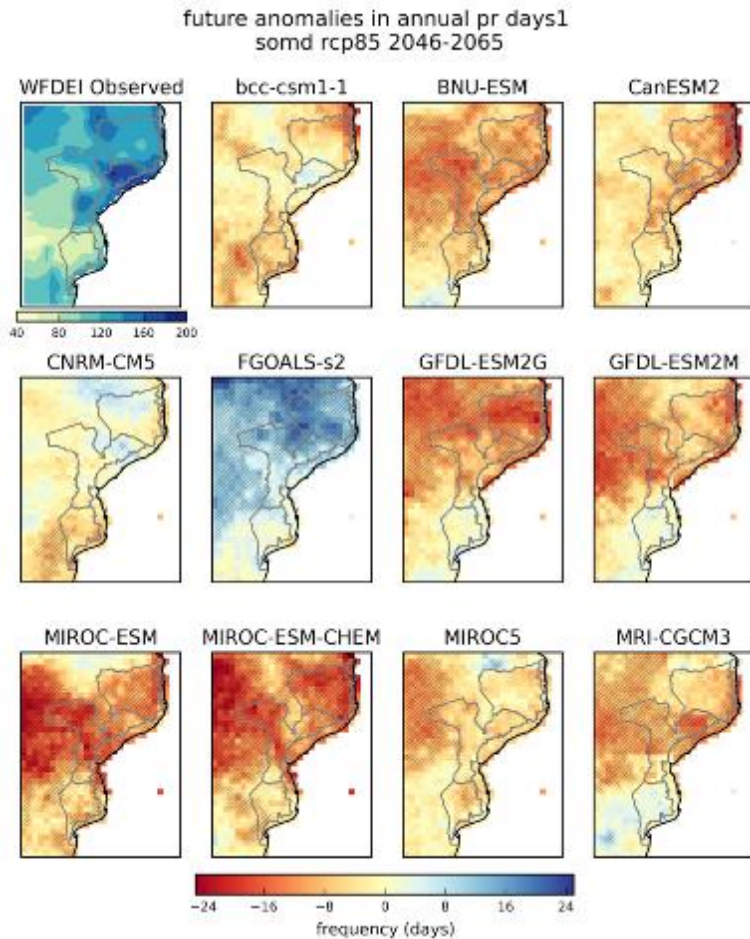
Projections of wet days (days > 1 mm) (Figure 25) show consistent decreases across most models in the SOMD ensemble across the whole country. Mean daily rainfall (average amount of rain on wet days) (Figure 26) shows very little signal of change. These two statistics combined indicate a general message of drying over the country, which is supported by the projected changes in total rainfall (Figure 20). Projected changes in extremes do not show expected increases, but the differences between the SOMD and GCM projections of extremes were discussed in the previous section. As a result, while the SOMD's projected changes in days exceeding the 90th percentile and days exceeding 50 mm do not show increases, it is likely that such increases will occur, particularly in the northern region (Figure 27).

Projected changes in temperature are clear, and for the next 20 to 30 years, there is relatively little uncertainty. Average temperatures will very likely increase by around 1°C in the next 20 years and by 3°C to 5°C by the end of the 21st century (Figure 23). The result is a dramatic increase in the number of days exceeding 35°C (Figure 29) and a decrease in the number of nights below 25°C (Figure 30), both thresholds/parameters identified as relevant for malaria transmission/incidence.

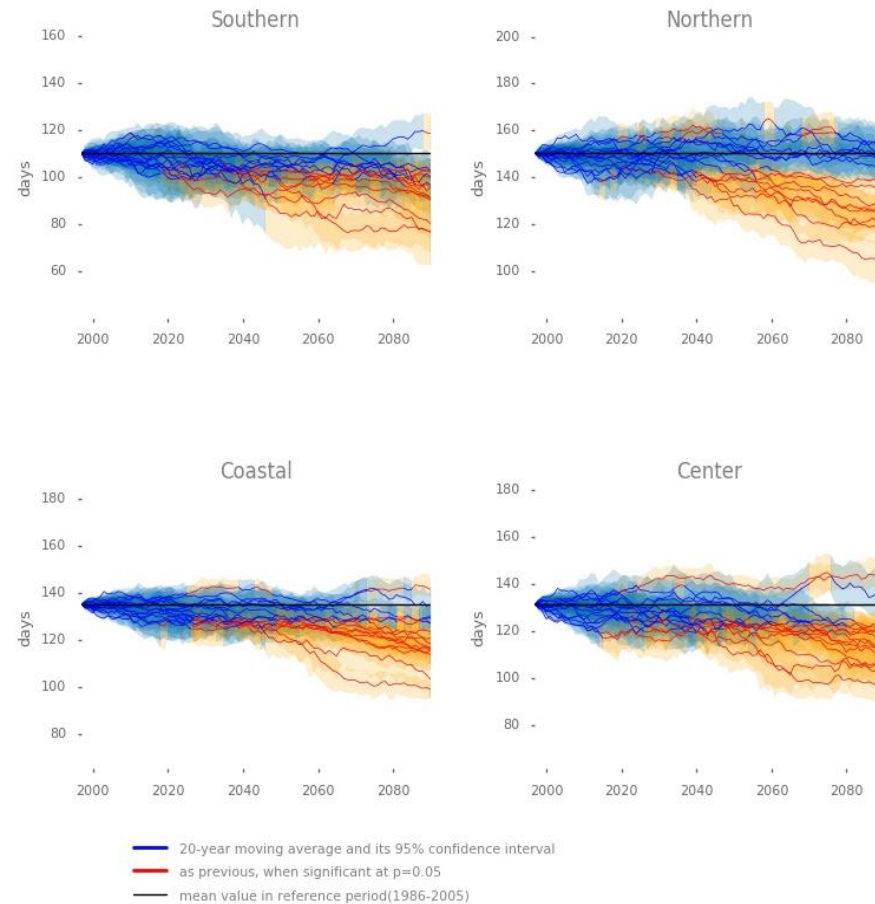
The mean diurnal temperature range is also projected to increase (Figure 28). This could be a result of a more rapid increase in maximum temperatures compared with minimum temperatures (Figure 31), but it could also be a result of reduction in cloud cover during certain periods, which can allow for greater nighttime cooling.

Figure 25. Projections of rain days above 1 mm derived from Global Circulation Models under RCP 8.5 (worst-case scenario), 2046–2065

**a) Future anomalies in annual pr days1**



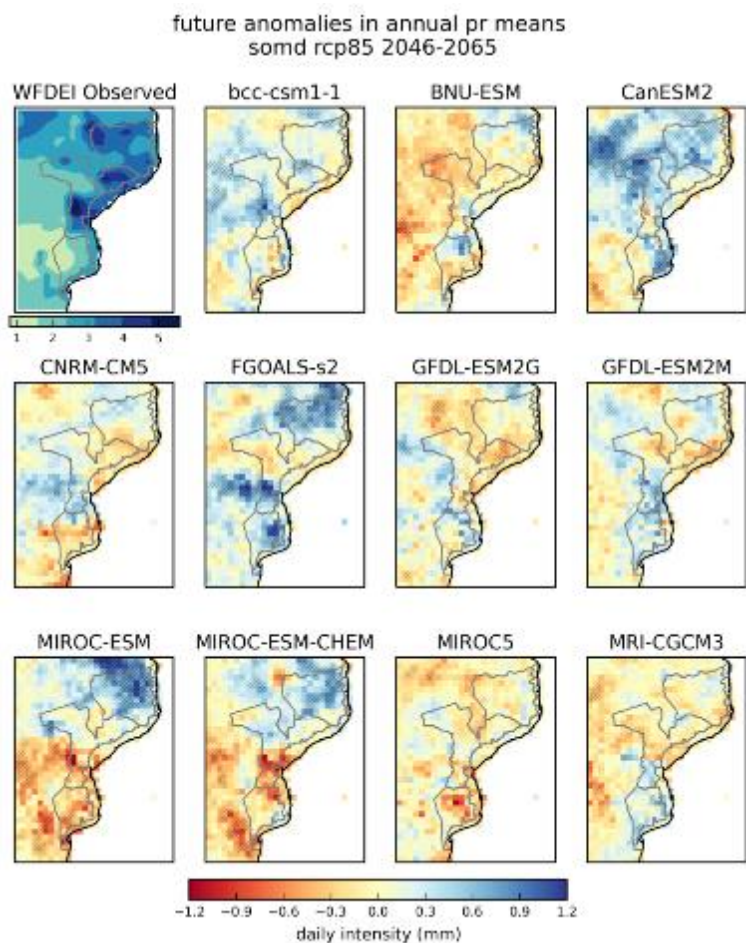
**b) Temporal evolution of rain days in a year with rain > 1 mm/day**



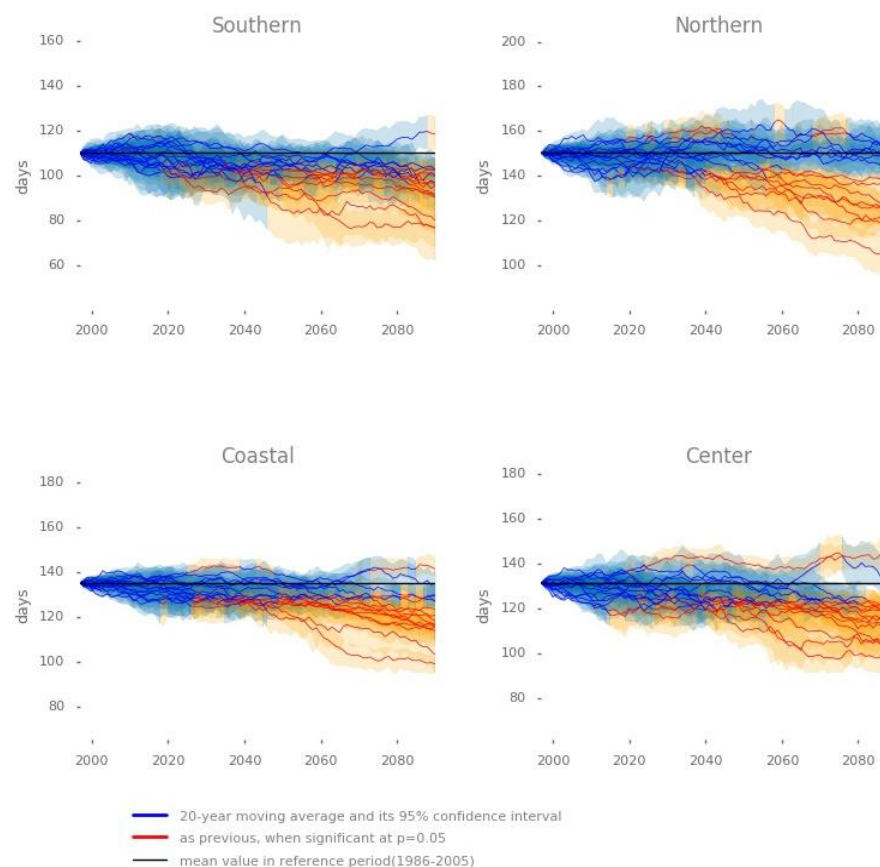
Note: a) SOMD downscaled future anomalies (2046–2065 minus 1986–2005) in the average annual frequency of rain days above 1 mm (RCP 8.5). Top left plot is the observed climatology from WFDEI (1986–2005). b) Time series of SOMD projections of the same variable for each of the regions described in this report based on GCM CMIP5 multimodel ensembles (RCP 8.5).

Figure 26. Annual rainfall projections derived from Self-Organized Map-based Statistical Downscaling method under RCP 8.5 (worst-case scenario), 2046–2065

**a) Future anomalies in annual pr means**



**b) Temporal evolution of mean daily rainfall in a year**

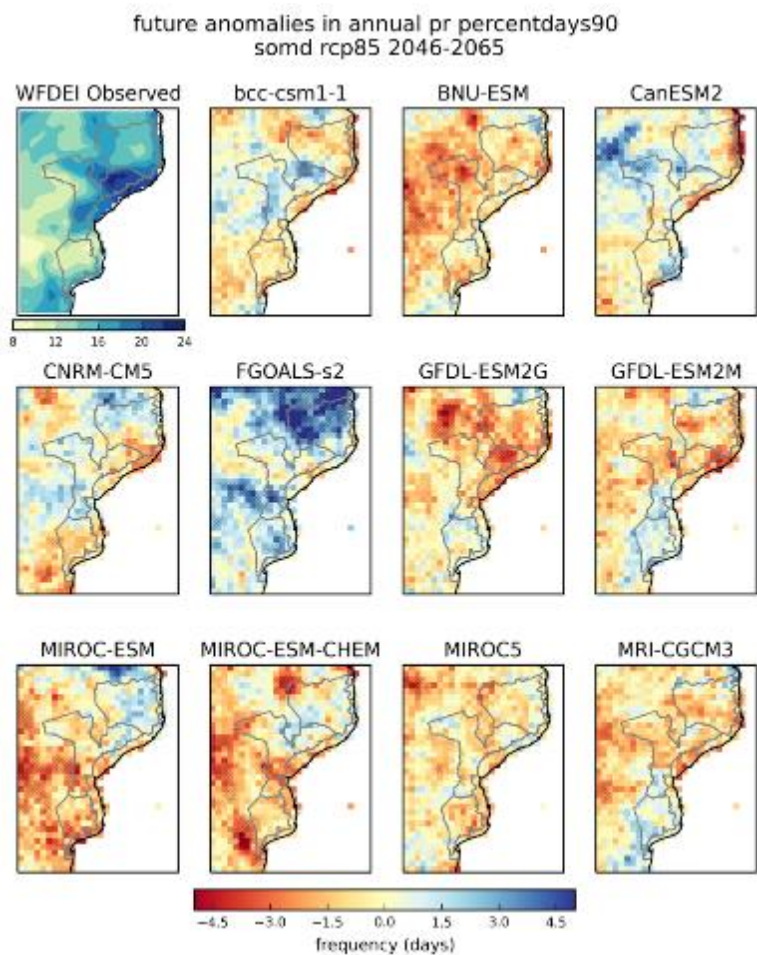


Note: a) SOMD downscaled future anomalies (2046–2065 minus 1986–2005) of average annual mean daily rainfall (RCP 8.5). Top left plot is the observed climatology from WFDEI (1986–2005). b) Time series of SOMD projections of the same variable for each of the regions described in this report based on GCM CMIP5 multimodel ensembles (RCP 8.5).

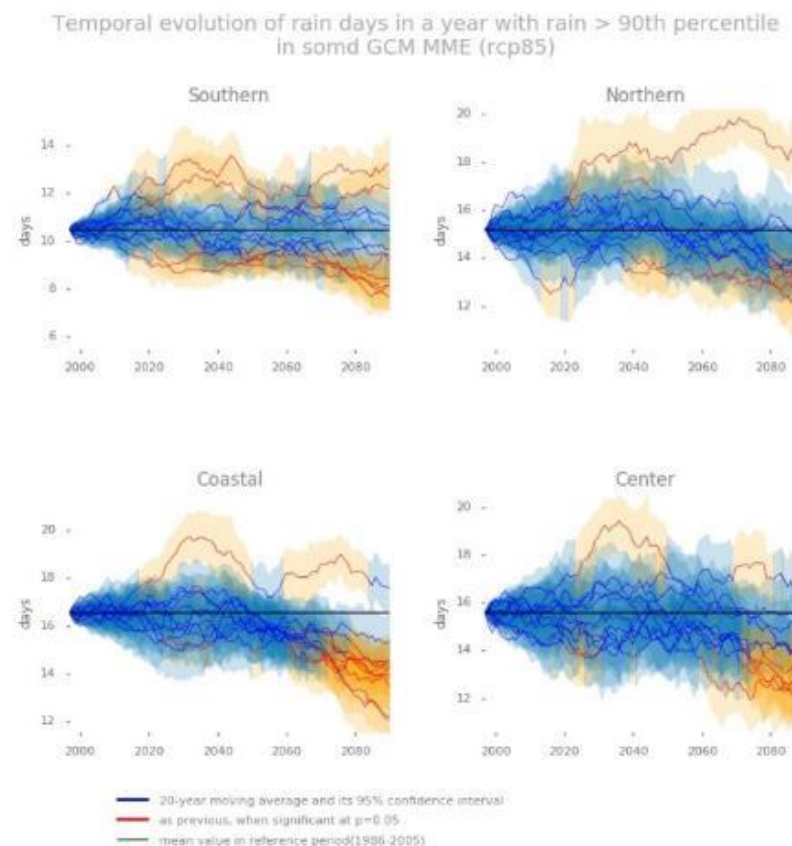


Figure 27. Rain day projections derived from Global Circulation Models under RCP 8.5 (worst-case scenario), 2046–2065

**a) Future anomalies in annual pr percentdays90**



**b) Temporal evolution of rain days in a year with rain > 90<sup>th</sup> percentile**

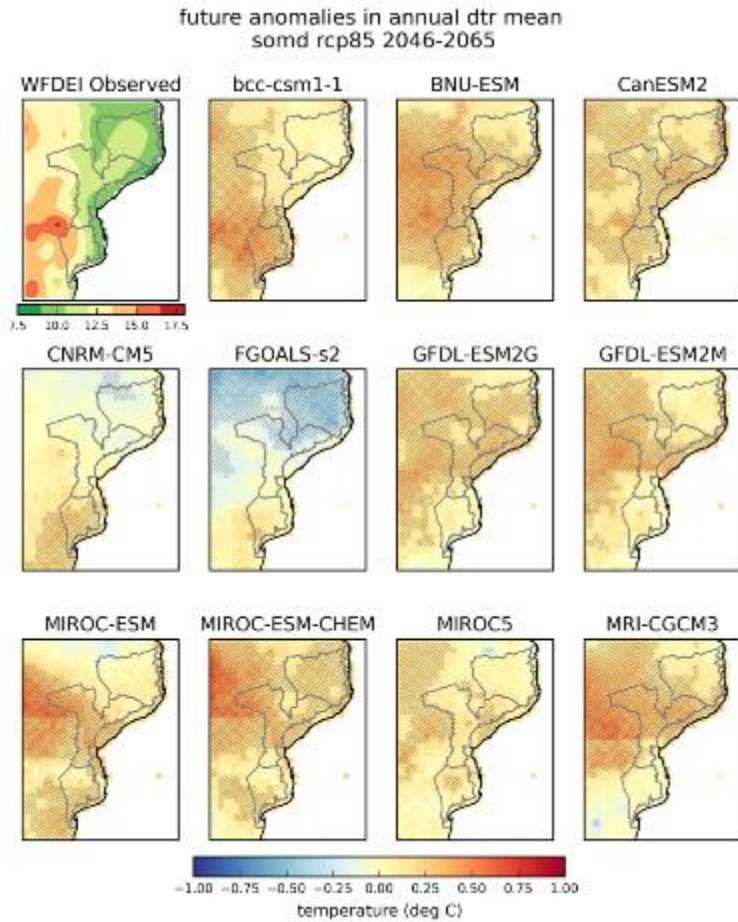


Note: a) SOMD downscaled future anomalies (2046–2065 minus 1986–2005) of average annual frequency of rain days above the historical period 90th percentile (RCP 8.5). Top left plot is the observed climatology from WFDEI (1986–2005). b) Time series of SOMD projections of the same variable for each of the regions described in this report based on GCM CMIP5 multimodel ensembles (RCP 8.5).

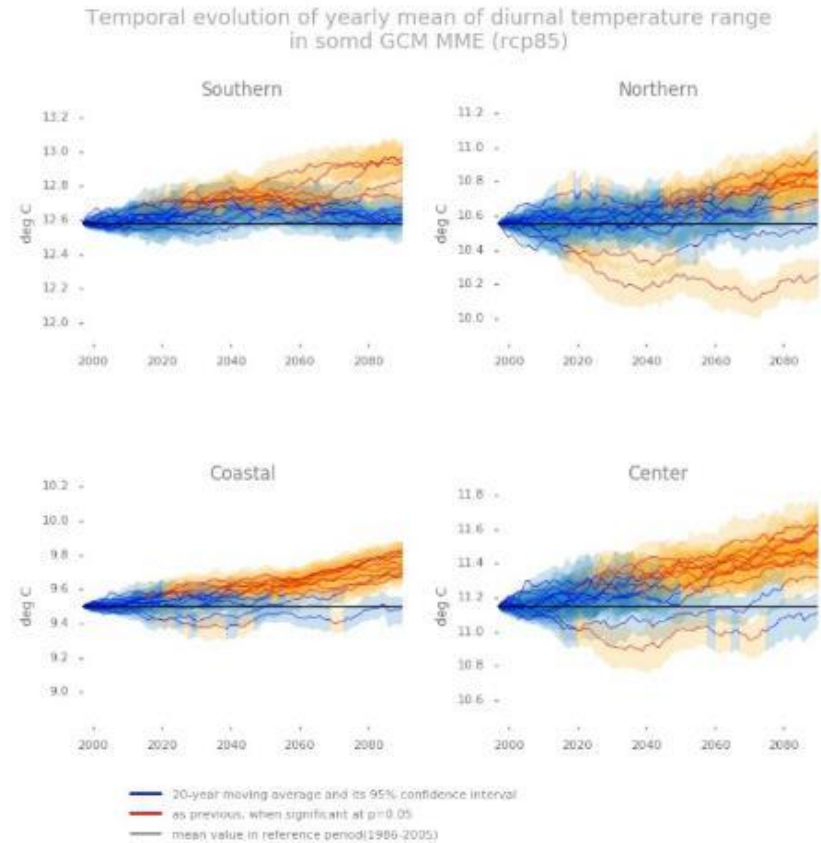


Figure 28. Diurnal temperature range projections derived from Global Circulation Models under RCP 8.5 (worst-case scenario), 2046–2065

**a) Future anomalies in annual dtr mean**



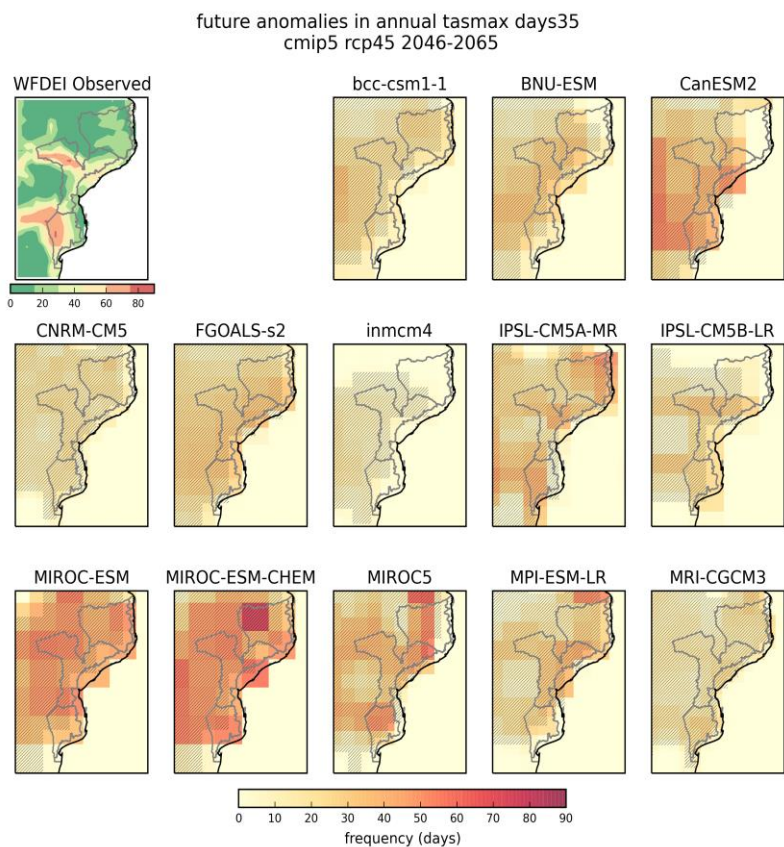
**b) Temporal evolution of yearly mean of diurnal temperature range**



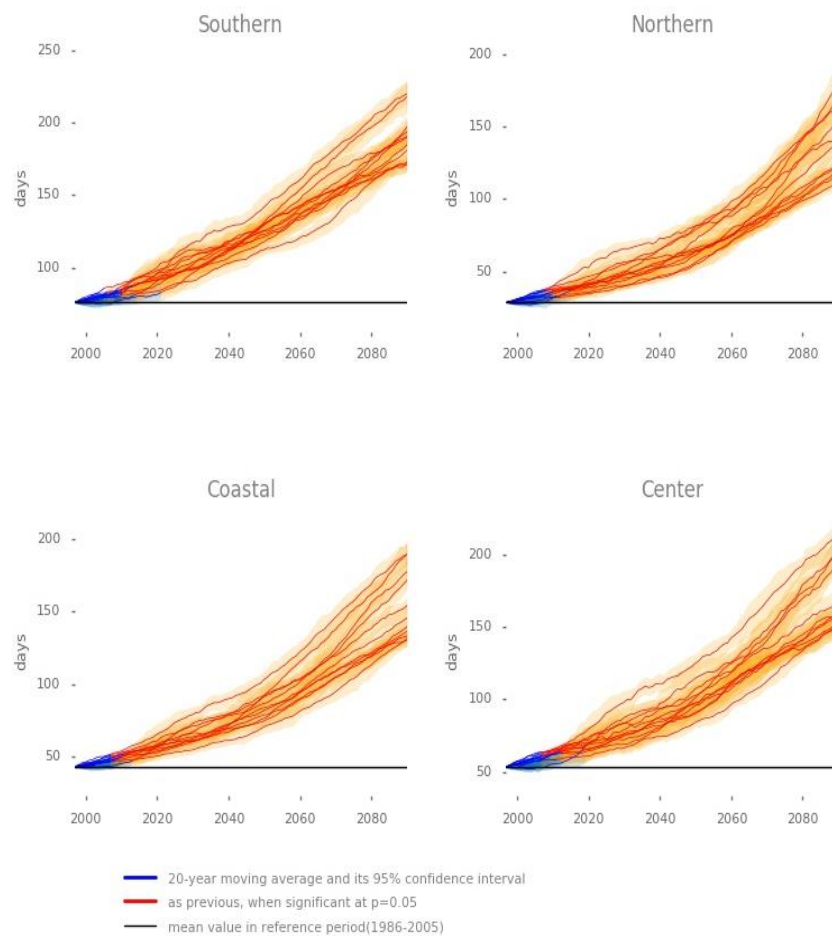
Note: a) SOMD downscaled future anomalies (2046–2065 minus 1986–2005) of average annual mean daily temperature range (RCP 8.5). Top left plot is the observed climatology from WFDEI (1986–2005). b) Time series of SOMD projections of the same variable for each of the regions described in this report based on GCM CMIP5 multimodel ensembles (RCP 8.5).

Figure 29. Projections of days over 35°C derived from Global Circulation Models under RCP 8.5 (worst-case scenario), 2046–2065

**a) Future anomalies in annual tasmax days35**



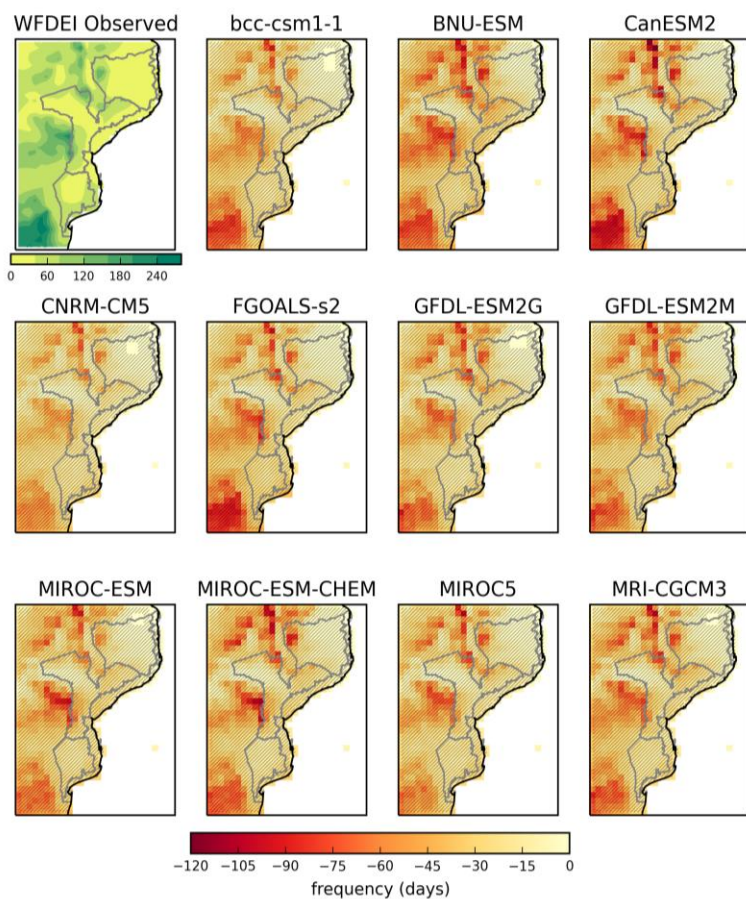
**b) Temporal evolution of number of days with tmax>35 deg in a year**



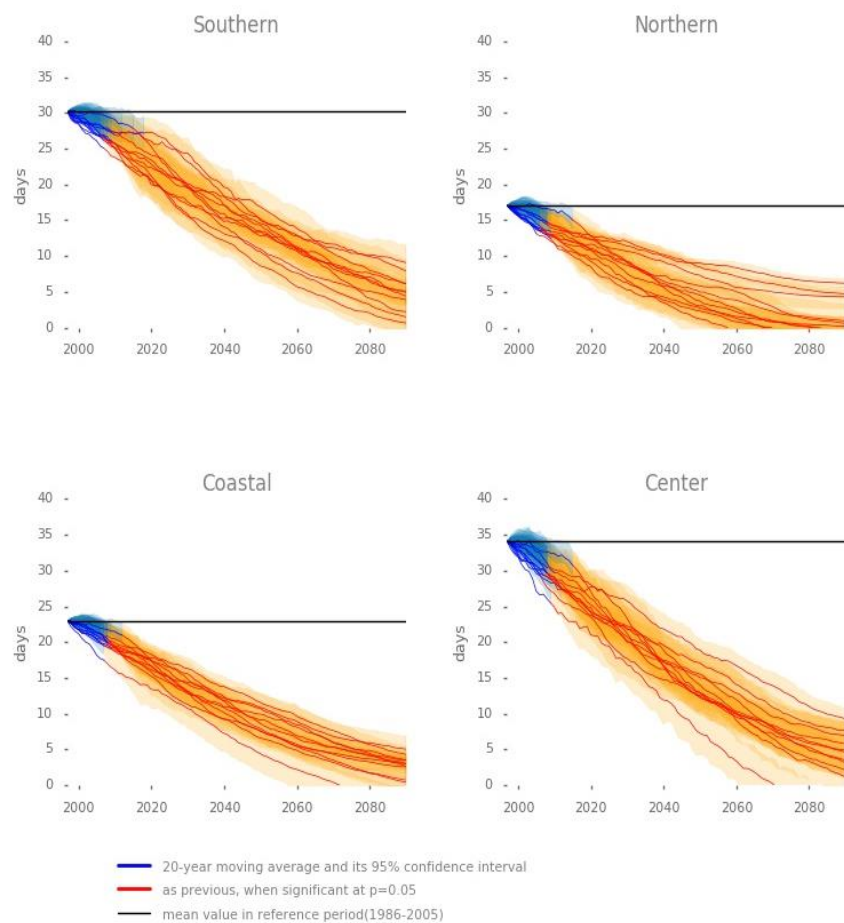
Note: SOMD downscaled future anomalies (2046–2065 minus 1986–2005) of average annual frequency of days above a maximum temperature of 35°C (RCP 8.5). Top left plot is the observed climatology from WFDEI (1986–2005). b) Time series of SOMD projections of the same variable for each of the regions described in this report based on GCM CMIP5 multimodel ensembles (RCP 8.5).

Figure 30. Projections of days below 25°C derived from Global Circulation Models under RCP 8.5 (worst-case scenario), 2046–2065

**a) Future anomalies in annual tasmax daysbelow25**



**b) Temporal evolution of number of days with tmax < 25 deg in a year**

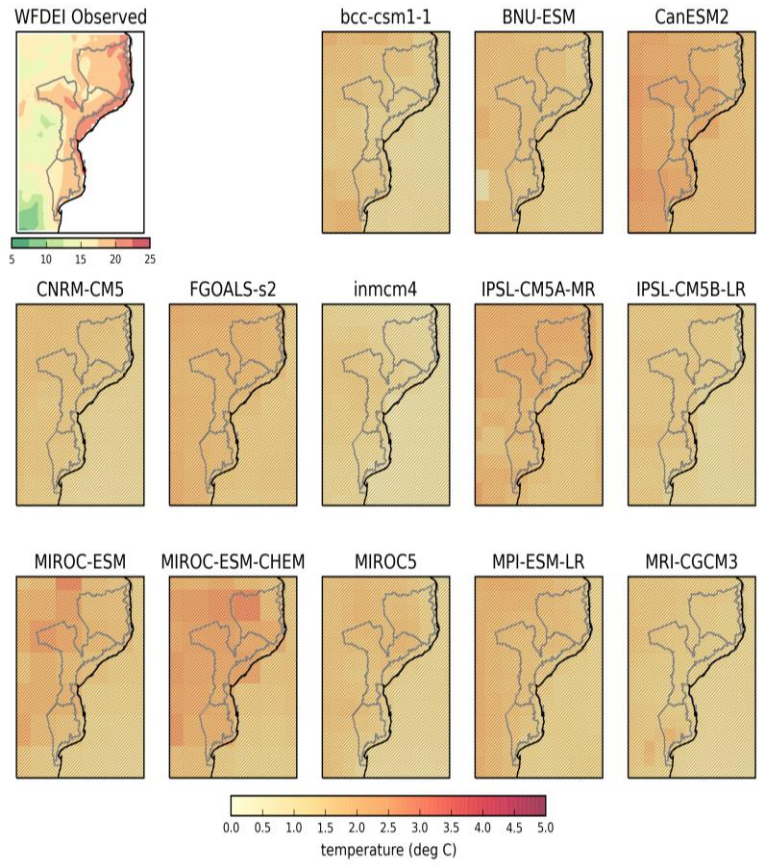


Note: SOMD downscaled future anomalies (2046–2065 minus 1986–2005) of average annual mean minimum temperature (RCP 8.5). Top left plot is the observed climatology from WFDEI (1986–2005). b) Time series of SOMD projections of the same variable for each of the regions described in this report based on GCM CMIP5 multimodel ensembles (RCP 8.5).

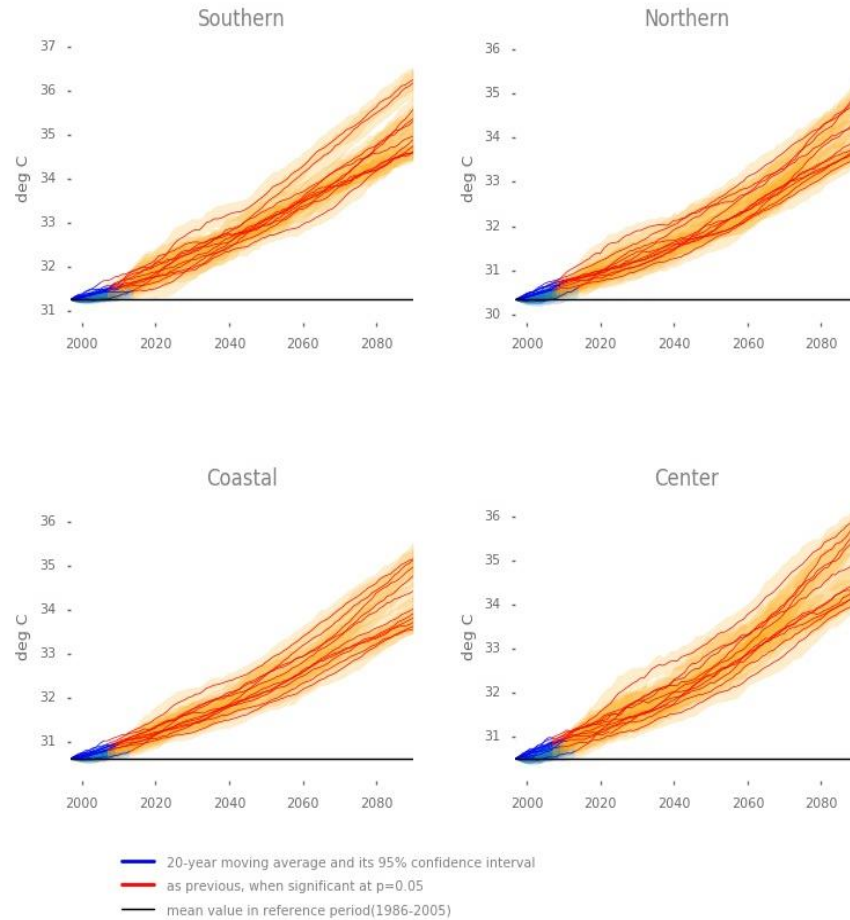


Figure 31. Projected average minimum temperature derived from Global Circulation Models under RCP 8.5 (worst-case scenario), 2046–2065

**a) Future anomalies in annual tasmin means**



**b) Temporal evolution of yearly mean of daily minimum temperature**



Note: SOMD downscaled future anomalies (2046–2065 minus 1986–2005) of average annual lowest minimum temperature (RCP 8.5). Top left plot is the observed climatology from WFDEI (1986–2005).

## SEASONAL DOWNSCALED PROJECTIONS ANALYSIS

Many diseases, including malaria and diarrheal diseases, have strong seasonal cycles related to climate and weather conditions. Other factors, such as changing agricultural activities and the seasonal cycle of food availability, can enhance this seasonal cycle. This means that during some periods of the year, climate conditions are not conducive to the spread of the disease. A key concern with climate change impacts is whether climate change will lengthen the period of the year during which diseases can develop and be transmitted. For example, areas where spring and autumn are now too cold for the reproduction of malaria vectors may become more suitable in the future. In these areas, increases in temperatures may not impact midsummer malaria incidence but may result in a longer season, extending into both spring and autumn, during which malaria incidences occur. In some cases, malaria might shift from being a seasonal disease burden to a year-round burden.

For the seasonal analysis, a selection of plots (Figure 32–Figure 38) was chosen based on the climate indices that had the most effect on malaria incidence in each of the regions. Based on findings of the malaria analysis, this analysis focuses on the following variables in each region:

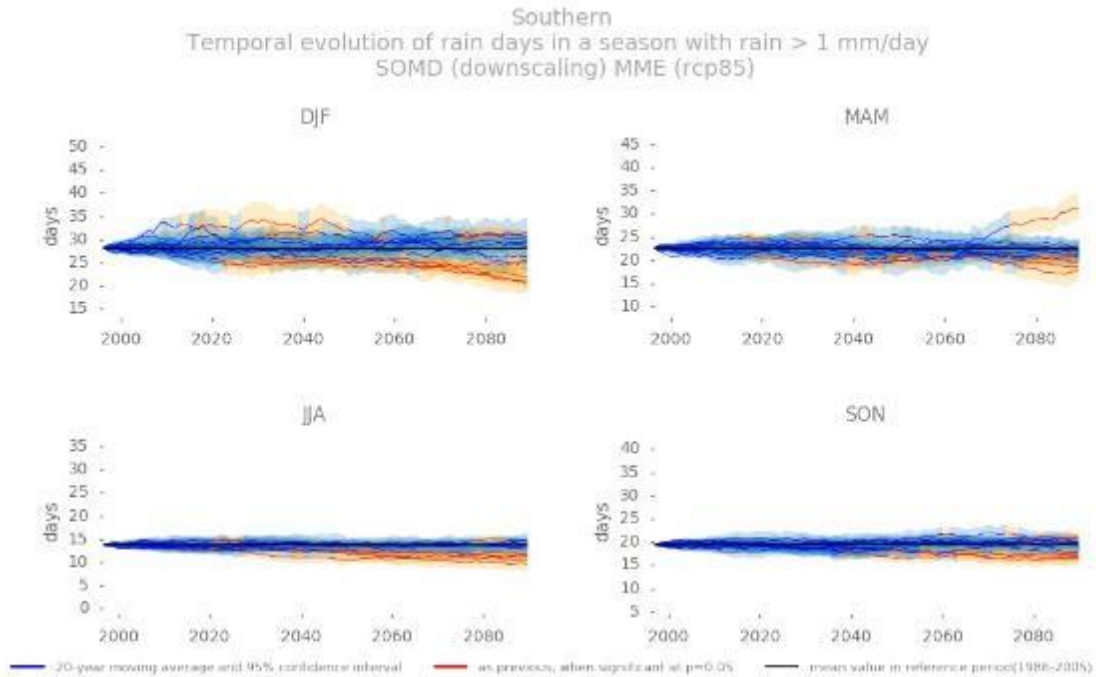
- *Southern, coastal and central:* rainfall days over 1 mm and mean maximum temperature (Figures 32, 33, 34 and 35)
- *Northern and coastal:* rainfall days over 1 mm and number of days with maximum temperature greater than 35°C (Figure 36, 37 and 38)

As noted, most vector-borne diseases, including malaria, have optimum environmental windows in which transmission is maximal. The projected changes over Mozambique therefore suggest a complex impact on malaria transmission/incidence. In some areas, for example in the northern region (Figure 38), increasing temperatures during some periods of the year (December–February) may rise above the ideal threshold for malaria, resulting in a decrease in transmission during this period. It is likely, though, that this effect will be minimal because high temperatures may only slow transmission rather than radically stop it.

In the southern region (Figure 33), increasing temperatures in winter, spring, and autumn may promote more transmission in the future compared with the present when these periods may be too cool to be optimal. However, in this case rainfall may be insufficient in the southern region during winter to promote transmission (Figure 32). It is likely that projected rainfall changes are not significant enough to impact malaria transmission, as most changes are relatively small. The only significant threat may be increased frequency of extreme rainfall events that cause flooding and can have multiple health implications. GCM projected increases in very heavy rainfall events, particularly in the north of the country, should not be ignored, as such changes are well supported both theoretically and in some observational studies. However, most impacts on malaria are likely to be temperature-related.

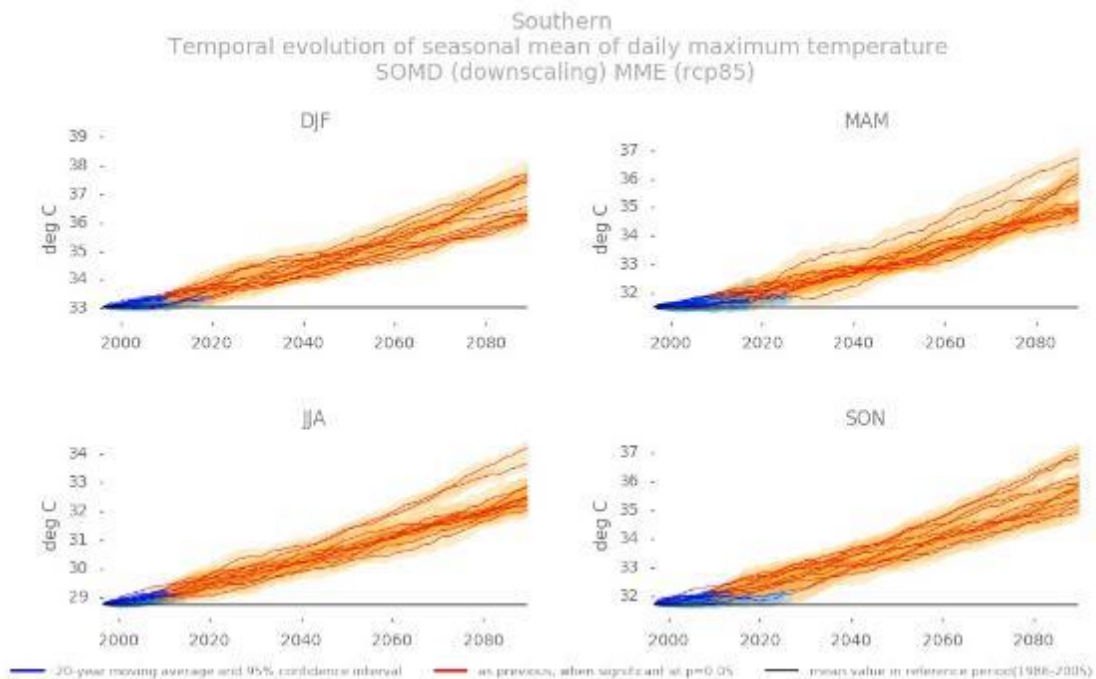
That said, a multivariate health analysis model is required to make robust statements about changing health risks. Those made here are speculative because they are based primarily on climate projections.

Figure 32. Projected change in days with at least 1 mm of rain/day for 2046–2065 under RCP 8.5 for the southern region



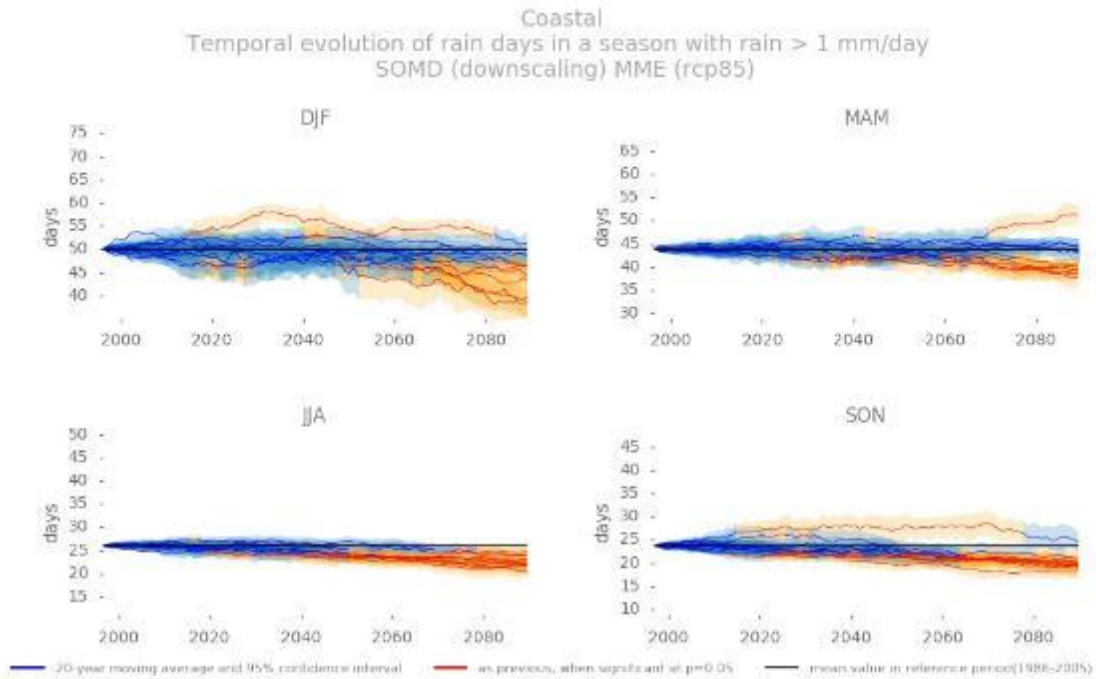
Note: SOMD downscaled temporal evolution of rain days in a season with rain greater than 1 mm/day, for the southern region, based on the GCM CMIP5 multimodel ensemble (RCP 8.5).

Figure 33. Projected change in seasonal mean of daily maximum temperature for 2046–2065 in the southern region



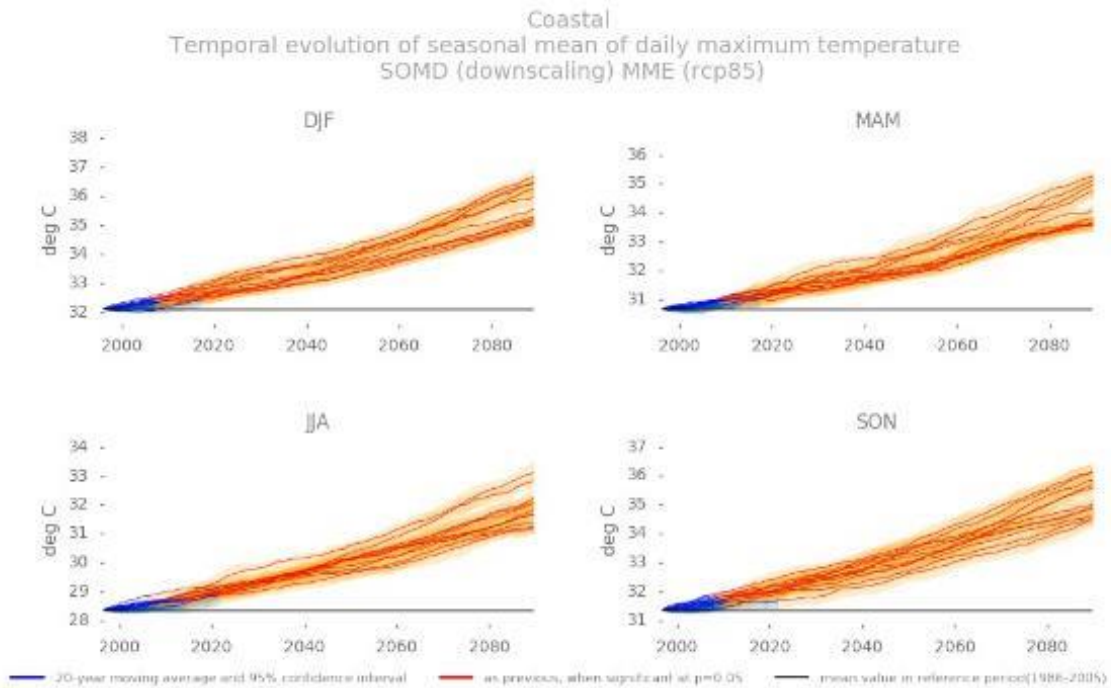
Note: SOMD downscaled temporal evolution of seasonal mean of daily maximum temperature for the southern region based on the GCM CMIP5 multimodel ensemble (RCP 8.5).

Figure 34. Projected change in days with at least 1 mm of rain/day by 2046–2065 for the coastal region



Note: SOMD downscaled temporal evolution of rain days in a season with rain greater than 1 mm/day for the coastal region based on the GCM CMIP5 multimodel ensemble (RCP 8.5).

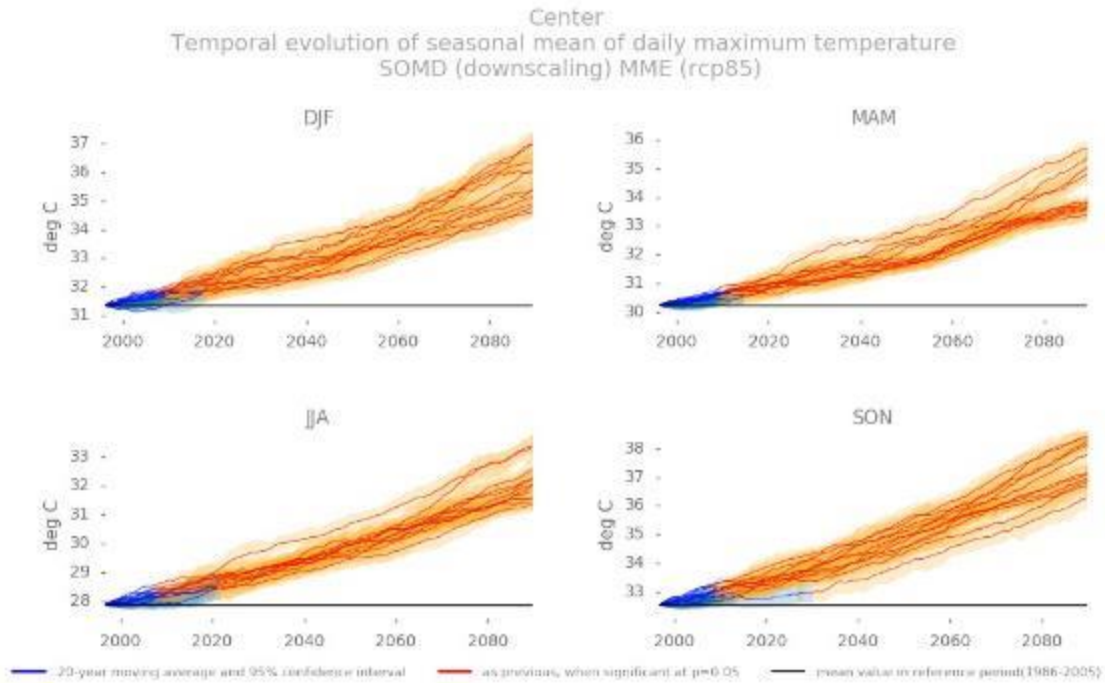
Figure 35. Projected change in seasonal mean of daily maximum temperature by 2046–2065 for the coastal region



Note: SOMD downscaled temporal evolution of seasonal mean of daily maximum temperature for the coastal region based on the GCM CMIP5 multimodel ensemble (RCP 8.5).

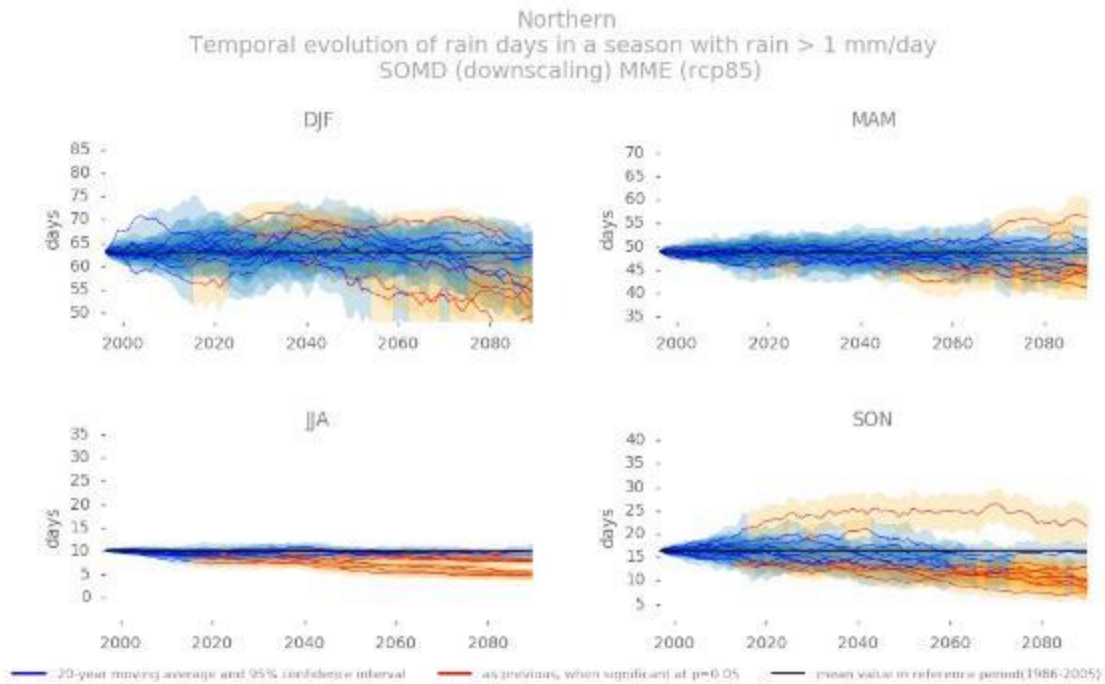


Figure 36. Projected change in seasonal mean of daily maximum temperature by 2046–2065 for the central region



Note: SOMD downscaled temporal evolution of seasonal mean of daily maximum temperature for the central region based on the GCM CMIP5 multimodel ensemble (RCP 8.5).

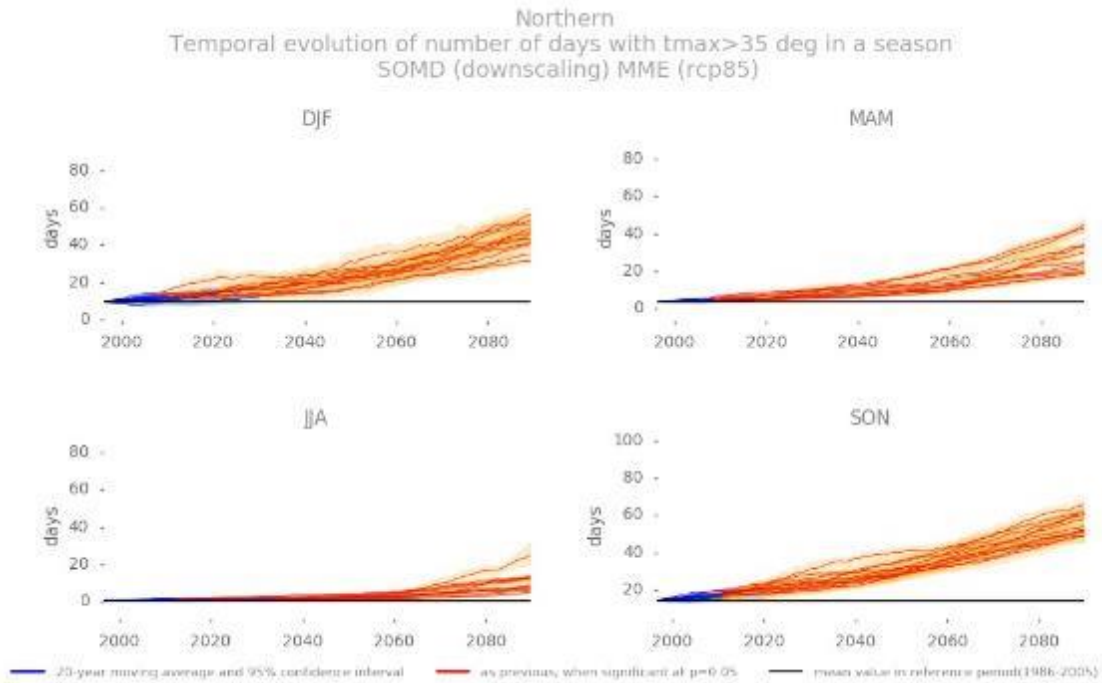
Figure 37. Projected change in days with at least 1 mm of rain/day by 2046–2065 for the northern region



Note: SOMD downscaled temporal evolution of rain days in a season with rain greater than 1 mm/day for the northern region based on the GCM CMIP5 multimodel ensemble (RCP 8.5).



Figure 38. Projected change in days above 35°C by 2046–2065 for the northern region



Note: SOMD downscaled temporal evolution of number of days with maximum temperature greater than 35°C for the northern region based on the GCM CMIP5 multimodel ensemble (RCP 8.5).

## II. CURRENT AND FUTURE RISKS FROM DIARRHEAL DISEASE AND MALARIA

### KEY MESSAGES

#### Current Risks

- Rainfall and maximum and minimum temperature all influence the incidence of malaria and diarrheal disease.
- Diarrheal disease burdens vary regionally, with higher incidence in the southern region, where rainfall is limited.
- Diarrheal disease incidence shows a seasonal pattern, with peaks occurring toward the middle-to-late part of the rainy season (February/March) and the lowest incidence corresponding to the cool, dry, winter months of June to August.
- Overall, maximum temperature and the number of wet days in a week are associated with outbreaks of diarrheal disease in Mozambique, with significant associations in all regions.

#### Future Risks

- As climate change increases temperatures and changes the hydrological cycle, the burden of diarrheal disease in Mozambique is expected to increase without additional health system interventions. These projected additional cases of diarrheal disease are potentially preventable using the increasing skill in forecasting temperature and precipitation over seasonal timescales.
- As temperatures continue to rise, and given the strong statistical link between the increased number of days above 35°C, malaria incidence is expected to increase in previously unsuitable regions such as those in the higher elevation regions of northern Tete and western Niassa Provinces near the border with Malawi. Malaria risks are likely to remain consistent across the rest of the country.
- Since no strongly significant rainfall changes are projected for the next 20 years, precipitation variability will continue to contribute to malaria incidence through this time period, which will translate into continued malaria risks.
- The increased variability in precipitation, as well as the complicated relationship between malaria and temperature, mean that malaria transmission will likely be more variable and unpredictable in the future.

With a wide range of health outcomes sensitive to weather, climate variability and climate change present current and future risks to health in Mozambique. Climate change could increase or decrease future health burdens, though the expectation is that those burdens are likely to increase in coming decades as a result of high underlying vulnerability. Changes in temperature and rainfall may alter the geographic range, pathogenicity, seasonality, and survival of disease-causing pathogens while also increasing human exposure and jeopardizing the infrastructure necessary to prevent disease transmission (Carlton et al., 2016). This section explores the causal pathways linking climate to diarrheal diseases and malaria in Mozambique and examines the relationship between historical health facility data collected by the MoH and satellite-derived rainfall and temperature variables.

Furthermore, knowledge is limited about the threats to future health outcomes in Mozambique by current climate variability, extreme weather events, and projected climate changes. Detailed information on how these dynamics manifest at regional and local scales—and what can be done to mitigate their impacts—is also limited, despite the importance of this information in designing responses.

This section seeks to address that knowledge gap by presenting the evidence base for projected changes in climate for the country and regionally. By building on the statistical relationships identified in Section II, it also examines the potential impact of these changes on disease risk in the future. The analysis aims to inform future programming by predicting burden or providing early warning of increasing burden. Emphasis is placed on determining future climate risks from the relevant findings from the diarrheal disease and malaria analyses. These are summarized below:

- Rainfall and maximum and minimum temperature all influence the incidence of malaria and diarrheal disease.
- Relevant rainfall indices include: the count of rain days, rain days greater than 50 mm, and mean rainfall per rain day.
- Maximum temperature-derived indices of relevance include: days greater than 35°C and days below a maximum temperature of 25°C.
- Lowest minimum temperature of the coldest night during the week and diurnal temperature range are relevant to disease burden.
- In all cases, different lag relationships were identified, ranging from zero lag for temperature indices, a 4-week lag for extreme rainfall events, and a 4-week lag for wet days.

In general, the northern parts of Mozambique receive, on average, a greater total annual rainfall (approximately 1,500–2,000 mm/year) than the southern areas (approximately 300–500 mm/year), while the driest areas of the country lie in the interior of Gaza Province in the south. These differences result in malaria risk being most significant in the coastal, central, and northern regions. Rural areas also have a higher incidence, likely reflecting rural populations' limited access to preventive measures or differences in behavior.

This dynamic is most likely reflective of the threshold nature of malaria. Different climate profiles in different areas are closer to or further from the thresholds required for malaria transmission. The northern region is likely too warm on average, so an increase in mean maximum temperature and temperatures over 35°C will further reduce malaria incidence. Similarly, the southern region is likely too dry on average, but anomalously high rainfall allows for incidences of malaria. In other words, different areas have different constraints on malaria incidence, but deviations from mean climate can temporarily remove these constraints, allowing transmission and higher incidence. Spatial variations also occur in diarrheal disease incidence, though all regions have a diarrheal disease peak around February.

Although the above climatic indices were identified as having an effect on the incidence of disease, anomalies to this finding still arise, which may be due to nonclimate-related factors not accounted for in this analysis. This caveat should be recognized when interpreting the results of the future climate analysis presented below.

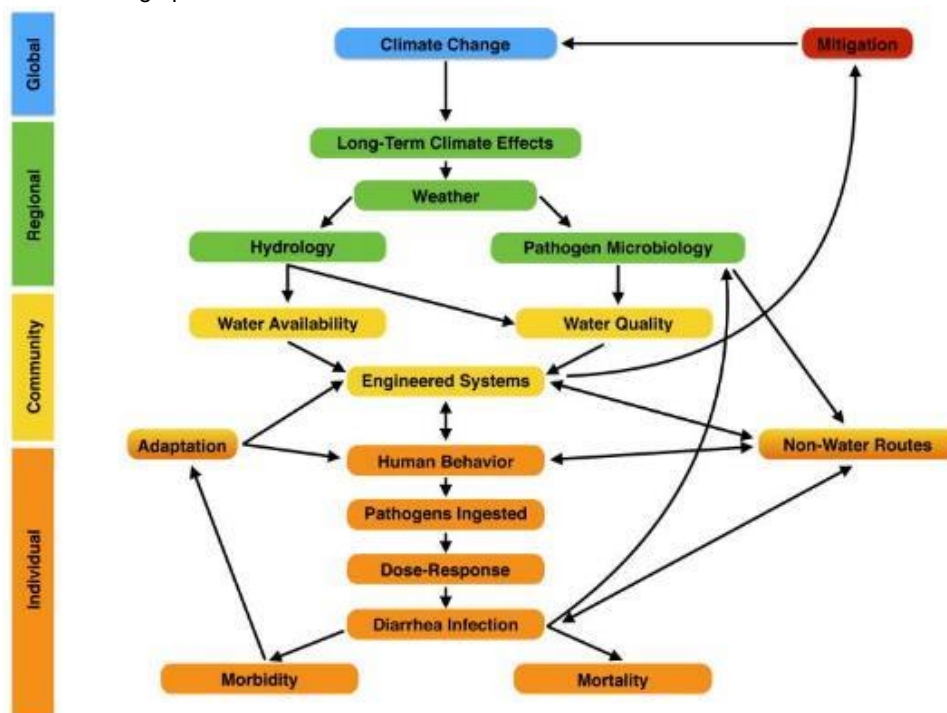
For the purposes of this report, both annual and seasonal statistics are included. The component of seasonality is seen as critical to identifying peak risk timeframes for disease prevalence and how these may change in the future.

## **DIARRHEAL DISEASE AND WEATHER ASSOCIATIONS**

Diarrheal diseases are climate-sensitive and of significant concern in Mozambique. Diarrhea is usually a symptom of a bacterial, viral, or parasitic infection in the intestinal tract. Infection is spread through contaminated food or drinking water, or from person to person because of poor hygiene (fecal–oral transmission). Three clinical types of diarrhea are recognized: acute watery diarrhea that lasts hours to days (includes cholera); acute bloody diarrhea (also called dysentery); and persistent diarrhea. Interventions to prevent diarrhea include access to safe drinking water, improved sanitation, and handwashing with soap. Worldwide, nearly 90 percent of diarrhea-associated deaths are due to unsafe water, inadequate sanitation, and poor hygiene. Diarrheal diseases are the second leading cause of death worldwide in children under the age of five years, causing 760,000 childhood deaths every year.

The causal pathways between weather/climate and diarrheal disease are complex, as shown in Figure 39. Water may become polluted during flooding events by contamination with fecal matter or during periods of increased temperature by pathogen proliferation. Cases of bacterial diseases (e.g., salmonella, campylobacter, and *Escherichia coli*) are positively correlated with temperature and heavy rainfall (Kolstad & Johansson, 2011; Smith et al., 2014). Despite diarrhea being a leading cause of morbidity and mortality in Africa, the quality of evidence on climate and diarrheal diseases in sub-Saharan Africa is considered very low (Smith et al., 2014).

Figure 39. Climate change potential to affect the burden of diarrheal disease in low- and middle-income countries



Source: Mellor et al. (2016).

Studies of clinical or self-diagnosed diarrheal illness report diverse associations with weather variables (Table 4) (Alexander et al., 2013; Azage et al., 2015; Bandyopadhyaya et al., 2012; Bonkougou et al., 2013; Carlton et al., 2016; Oloukoi et al., 2014; Rabassa et al., 2014; Tornheim et al., 2010). Studies vary depending on the pathogen considered, but they report both dry and wet seasonal peaks associated with diarrheal disease.

Table 4. Associations between weather and diarrheal disease in African countries

Country/region of study	Diarrheal disease and weather associations	Author
Ethiopia	Disease peaks in the months preceding the two rainy seasons.	Azage et al., 2015
Kenya	Disease peaks one to two months after heavy rains.	Tornheim et al., 2010
Botswana	Disease peaks follow a bimodal cyclical pattern, with peaks in the wet and dry season.	Alexander et al., 2013
Sub-Saharan Africa	Shortage of rainfall in the dry season and an increase in average maximum temperature are associated with disease peaks.	Bandyopadhyaya et al., 2012
Nigeria	Disease peaks in the dry season.	Oloukoi et al., 2014
Nigeria	Disease peaks as a result of rainfall shocks (10% increase in rainfall over historical volumes).	Rabassa et al., 2014
Global	A positive association exists between ambient temperature and disease.	Carlton et al., 2016

Compared with middle-income regions, low-income regions are expected to experience larger increases in the burden of diarrheal disease with more variable weather, climate variability, and climate change. These regions will, in many cases, have higher exposure to climate-related hazards, such as extreme rainfall or temperature events, and they have low capacity to manage those hazards. Africa is particularly vulnerable because it is already facing weather conditions conducive to the spread of diarrheal disease that climate change is expected to exacerbate (Smith et al., 2014). Kolstad and Johansson (2011) estimated that by the end of the 21st century, climate change would lead to over a 22 percent increase in the relative risk of diarrhea in southern Africa.

In Mozambique, diarrheal disease is the fourth leading cause of death and disability. Lack of sanitation and hygiene is responsible for the spread of diarrheal diseases (the poorest 20 percent of the population is four times more likely to practice open defecation, for example, than the wealthiest 20 percent). There is also an underlying vulnerability to disease, particularly of children who are malnourished and suffering from hunger.

## SUMMARY OF RESULTS

Building on prior research, this analysis sought to estimate risks specific to the Mozambique health and climate context.

The analysis was conducted in two parts:

- Analysis of 10 years of diarrheal disease case-reporting in the context of rainfall and temperature data. This analysis identified trends related to seasonal variations of weather and the incidence of diarrheal disease.
- This information was used to model health outcomes based on potential future variations in rainfall and temperature. These models were developed at national and regional scales and accounted for vulnerability of the populations.

The analysis of historical cases and climate data identified these trends:

- All regions appeared to have their biggest annual disease peaks around late February and early March, the end of summer, when some of the warmest temperatures of the year occur. Typically, tropical cyclones and the year's heaviest rainfalls occur in this period.
- While all regions have similar peaks, the seasonality of weather and disease varied by region.
  - *Northern region*: bimodal disease peaks each year around February and October, with diarrheal disease peaking during week 4 of the year.
  - *Central region*: bimodal disease peaks each year around February and October, but with disease peaks in week 8 of the year.
  - *Coastal region*: one pronounced disease peak in late February/early March, with disease peaks in week 8 each year.
  - *Southern region*: a slight peak around week 12 but less variability throughout the year and no pronounced disease trough.
- All four regions appeared to have their lowest mean disease counts in the middle of the year, corresponding with the cool, dry, winter months of June, July, and August, when the monthly mean temperature often drops below 20°C. The northern region appeared to



have the earliest trough, beginning in May, while the other regions appeared to have their lowest disease burdens a month or two later.

- The coastal region had the highest average number of weekly reports of diarrheal disease, at 68.32 cases. The southern region, however, had a significantly high weekly diarrheal disease count given its smaller population, with an average of 40.35 cases per week.
- The burden of disease was similar in the northern, central, and coastal regions, with 15 to 20 cases per 100 people, but far higher in the southern region, at nearly 32 cases per 100 people. The southern population may be particularly sensitive because rainfall there is normally limited.

In addition to the climate factors, socioeconomic status, behavioral and cultural practices, overall health, sanitation and hygiene, and other factors affect susceptibility to disease. To account for this vulnerability, the model incorporated two proxy measures: 1) number of people per medical clinic, and 2) poverty.

The two models used for the second part of the analysis considered national (Model A) and regional (Model B) scales, with varying inputs related to rainfall, temperature, and vulnerability. Statistically significant results are detailed below.

Model A estimated that at the national scale:

- **Rainfall:** For every additional day in a given week with more than 1 mm rain, an estimated 1.04 percent increase in diarrheal disease occurs at a 4-week lag, controlling for time, average high temperature, and region.
- **Temperature:** For every additional 1°C increase in the hottest day of the week, diarrheal disease increased 1.13 percent at a 4-week lag. However, while the rainfall modeling showed the highest incidence of disease at a 4-week lag, the highest increase in disease and temperature was observed at no lag, with the model estimating an increase in disease of 3.64 percent.

Model B estimated that at the regional scale:

- One additional wet day (a day receiving at least 1 mm of rainfall) resulted in a 1.86 percent, 1.37 percent, and 2.09 percent increase in diarrheal disease in the northern, central, and southern regions, respectively.
- Coastal region disease patterns appeared to be the least affected by rainfall: an additional wet day resulted in a 0.63 percent increase in disease counts. This difference was likely due to the unique weather patterns of coastal land.
- All regions exhibited a statistically significant increase in diarrheal disease for each 1°C increase in the maximum temperature, with the increase varying widely by region.
- While the coastal region's diarrheal disease burden had the smallest association with an additional wet day, it was the most sensitive to an increase in the maximum temperature. It was estimated that for every additional degree increase in the maximum temperature, diarrheal disease counts increased by nearly 6 percent in the coastal region.

*People per clinic:* Among districts with the fewest people per clinic, one more wet day per week was associated with 1.23 percent more cases of diarrheal disease. Among districts with the most people per clinic, one additional wet day was associated with 2.12 percent more cases of diarrheal disease. These results suggest that living in districts with more people per clinic may lead to increased vulnerability to weather’s impact on diarrheal disease.

*Poverty:* Among districts with the lowest poverty level, each additional wet day increased diarrheal disease counts by 1.08 percent. Among districts with the highest poverty level, each additional wet day increased diarrheal disease counts by 2.07 percent. This suggests that those living with higher levels of poverty are likely to have less access to safe water and improved sanitation, putting these populations at greater risk of diarrheal disease.

## ANALYSIS IN DETAIL

### Objectives

Based on published associations between weather patterns and diarrheal disease, the association between diarrheal disease counts and the number of wet days and maximum temperature was modelled. Specifically, the relationship between the number of wet days (rainfall > 1 mm) in a given week and weekly total cases of diarrheal disease reported in Mozambique from 1997 through 2014 was assessed. Temperature was modeled as the highest single temperature observation in the week in degrees Celsius for the same timeframe.

### Data

A time series analysis was conducted to estimate how weekly total diarrhea case counts vary by temperature and rainfall during the preceding weeks. This approach is often used in environmental epidemiology. The data are structured with weekly aggregate counts of total cases from reporting at the district level. Weather variables include weekly averages and totals at the district level. Variables in the dataset are defined in Table 5.

Table 5. Names, definitions, and units of variables used in the analysis of diarrheal disease

Variable	Definition	Unit
<b>Total cases</b>	Total number of diarrhea cases (all ages) reported in a given week by each district	Cases
<b>Tmax_mean</b>	Mean of the daily maximum temperatures during the week	°Celsius
<b>Tmax_max</b>	Highest maximum temperature during the week (i.e., the maximum temperature of the hottest day)	°Celsius
<b>Tmax_min</b>	Lowest minimum temperature of the coolest day during the week	°Celsius
<b>Tmin_mean</b>	Mean of the daily nighttime minimum temperatures during the week	°Celsius
<b>Tmin_max</b>	Highest temperature of the hottest night during the week	°Celsius
<b>Tmin_min</b>	Lowest minimum temperature of the coldest night during the week	°Celsius
<b>Wet Day</b>	Number of days during the week receiving at least 1 mm of rain	Days
<b>Precip_max</b>	Maximum single daily rainfall volume during the week	mm
<b>Precip_total</b>	Total volume of rainfall during the week	mm

### Diarrheal disease data

The outcome of interest was weekly diarrheal disease case counts reported by each district to the Mozambique MoH reportable disease registry from 1997 to 2014. These years were chosen because, on average, district reporting exceeded 90 percent. Individual districts were included in the analysis if their reporting exceeded 85 percent during all the weeks of follow-up treatment, which included clinical visits and tests.

### Overview of case data

Diarrheal cases were reported on average in 50 out of 52 weeks each year of follow-up. There were more than 7.3 million reported cases of diarrheal disease in the districts of study for 1997–2014. The highest weekly diarrhea case count in the dataset was 2,033, observed in the tenth week of each year, when disease reports commonly peak. The lowest value of 0 occurred in weeks when a given district reported no diarrhea cases for treatment. Counts of 0 occurred more frequently in the years prior to 2000.

The mean weekly maximum temperature was 29.45°C, and the mean daily minimum temperature was 18.94°C during follow-up. The average week received a mean of 17.59 mm of rain over 1.23 days, though total rainfall had a minimum of 0 mm and a maximum of 398.33 mm during the highest rain volume week. Within a given week, the highest volume of rain in one day had a mean of 8.47 mm, and the highest volume of rain received in one day was 169.26 mm. The descriptive statistics showing the range of values for each variable are displayed in Table 6.

Table 6. Univariate descriptive statistics: total reported diarrhea cases each week and weather covariates

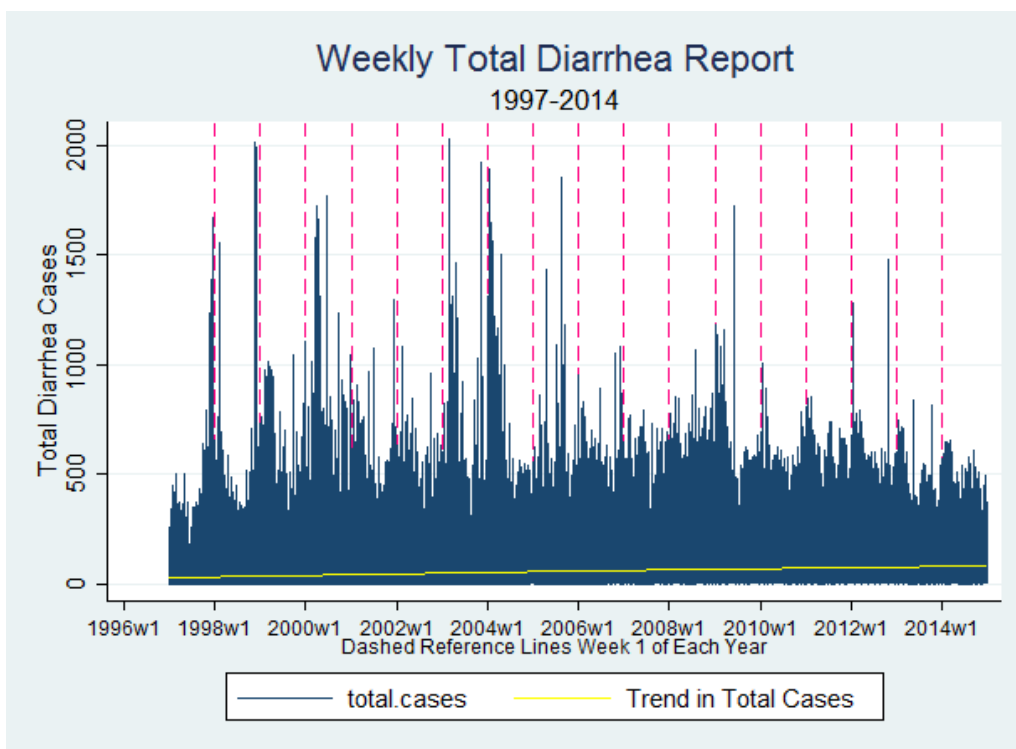
Variable	N	Mean	Standard deviation	Minimum	Maximum
Total cases	126,118	58.08	80.86	0.00	2,033.00
Tmax_mean	126,056	29.45	2.94	14.24	41.64
Tmax_max	126,056	32.50	3.45	15.05	45.25
Tmax_min	126,056	26.39	3.15	11.21	38.29
Tmin_mean	126,056	18.94	3.46	6.48	26.50
Tmin_max	126,056	20.58	3.21	9.64	29.28
Tmin_min	126,056	17.21	3.84	1.28	25.73
Wet day	126,118	1.23	1.91	0.00	7.00
Precip_max	126,118	8.47	14.40	0.00	169.26
Precip_total	126,118	17.59	32.71	0.00	398.33

**Note:** Total cases = total number of diarrhea cases reported in a given week by each district; tmax\_mean = mean of the daily maximum temperatures during the week; tmax\_max = highest maximum temperature during the week; tmax\_min = lowest minimum temperature of the coolest day during the week; tmin\_mean = mean of the daily nighttime minimum temperatures during the week; tmin\_max = highest temperature of the hottest night during the week; tmin\_min = lowest minimum temperature of the coldest night during the week; wet day = number of wet days

during the week (1 mm threshold); precip\_max = maximum single daily rainfall volume during the week (mm); precip\_total = total volume of rainfall during the week (mm).

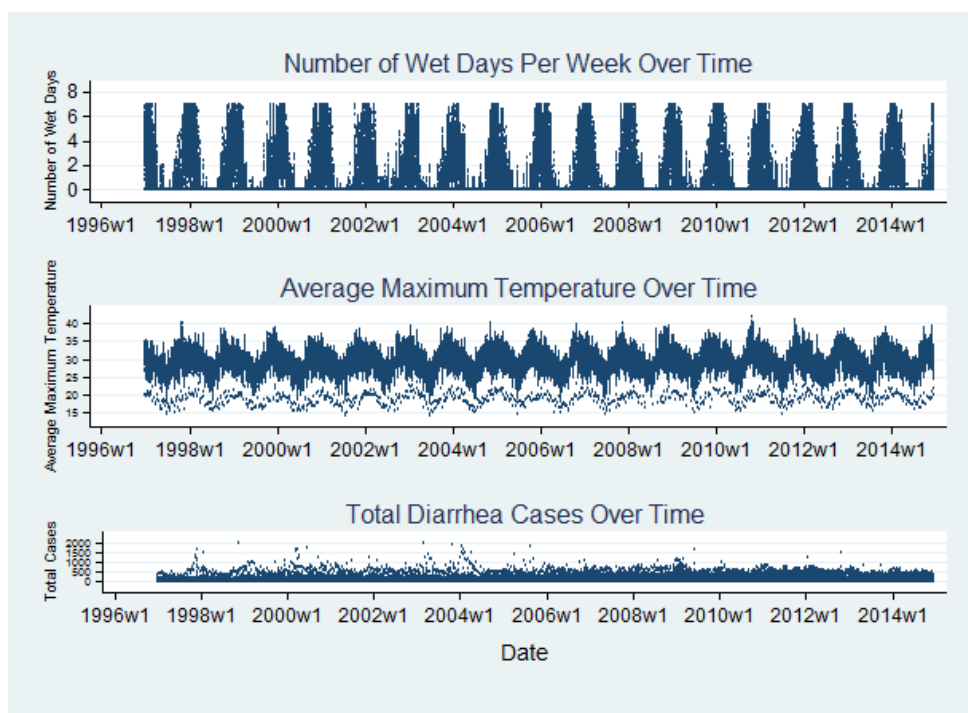
Weekly diarrhea case counts over the 18 years of follow-up for all districts are shown in Figure 40. The pink dashed lines mark the first week of each calendar year. The highest total weekly diarrhea counts were typically clustered following the first of each year. The mean weekly number of cases reported in 1997 was 24.45, whereas the mean weekly number of cases reported in 2014 was 63.14. The fitted yellow line shows the increasing trend of total diarrhea cases reported weekly. Figure 41 shows the pronounced seasonality of the weather predictors of interest and diarrheal disease over the years of follow-up.

Figure 40. Weekly reported diarrhea cases during the 18 years of follow-up



Note: Pink lines indicate the first week of each year. Yellow line shows the trend in case counts over time.

Figure 41. Time series data from 1997-2014



Regional weather summary statistics are provided in Table 7. As noted, the national summary statistics average over significant heterogeneity.

Table 7. Regional summary statistics of weather variables

Region	tmax_mean	tmax_max	tmax_min	tmin_mean	tmin_max	tmin_min	precip_days 1mm	precip_max	precip_total
Northern	29.35	32.60	26.08	18.09	19.98	16.13	1.29	8.58	18.63
Central	29.57	32.70	26.54	20.06	21.54	18.46	1.01	8.74	16.18
Coastal	29.19	31.43	26.78	18.83	20.19	17.36	1.62	8.50	20.87
Southern	29.95	34.34	25.61	17.44	19.71	15.11	0.82	7.10	11.39
							Red values are the highest mean of four regions		
							Blue values are the lowest mean of the four regions		

Finding include:

- The northern region experiences relatively high rainfall volume, though it is much less variable compared to the other regions. The northern region also experiences the northeast monsoons.
- The central region experiences some of the highest low temperatures in the country and high rainfall volume and variability, with both intense drought and above-average rainfall that can cause flooding along river basins.



- The coastal region's climate is characterized by high rainfall and northeast monsoons. On average, this region has the most wet days per week and highest rainfall volume per week.
- The southern region experiences the most climate variability: it averages the highest high temperatures and lowest low temperatures. The southern region is both the driest region and has higher rainfall variability than the rest of country, experiencing periods of intense drought and above-average rainfall.

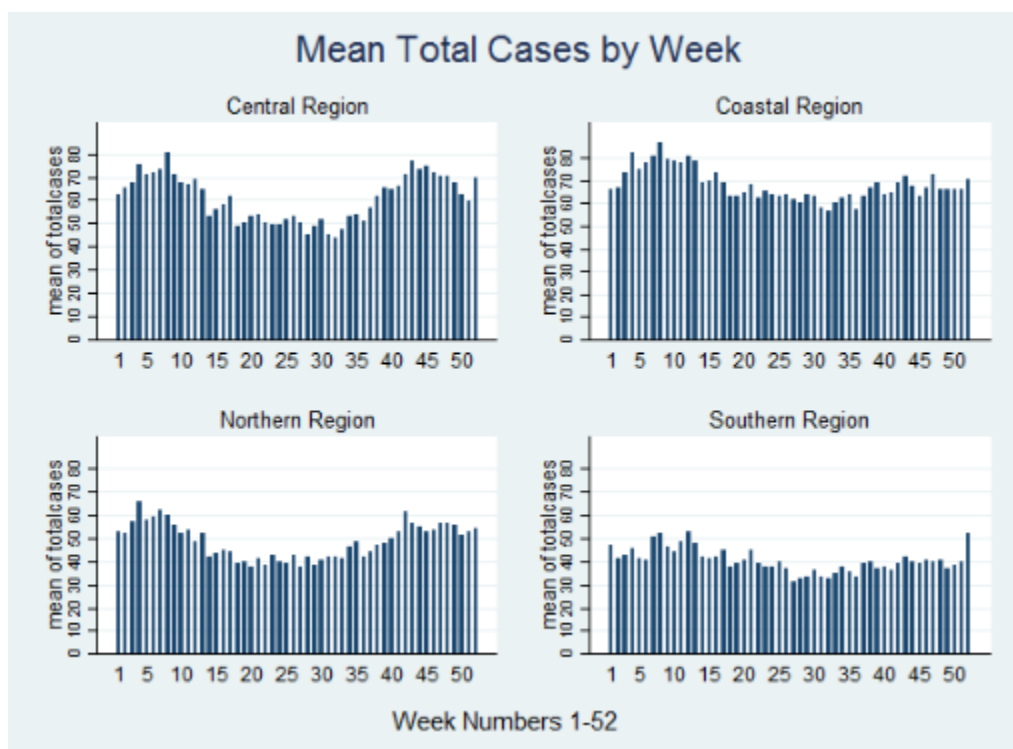
### **Regional seasonality**

All regions appeared to have their biggest annual disease peaks around late February and early March (Figure 42). February marks the end of the summer months (December, January, and February), when some of the warmest temperatures of the year occur. This season is also associated with tropical cyclones and the heaviest rainfall.

While all regions had similar peaks, the seasonality of weather and disease varied by region. The northern region exhibited strong seasonality, with bimodal disease peaks occurring around February and October of each year. Overall, diarrheal disease peaked during week 4 in the northern region. Similar to the northern region, the central region exhibited pronounced seasonality, with bimodal disease peaks occurring around February and October of each year. Averaging over all years, the central region experienced disease peaks in week 8 of the year. The coastal region had one pronounced disease peak in late February/early March and a less prominent peak, if it is a peak at all, later in the year, with disease peaks in week 8 each year. Lastly, the southern region had the least seasonality, with a slight peak around week 12 but less variability throughout the year and no pronounced disease trough.

All four regions appeared to have their lowest mean disease counts in the middle of the year, corresponding with the cool, dry, winter months of June, July, and August, when the monthly mean temperature often drops below 20°C. The northern region appeared to have the earliest trough beginning in May, while the other regions appeared to have their lowest disease burdens a month or two later.

Figure 42. Seasonality of disease by week and region



Based on the number of recorded observations in the dataset and 2014 population estimates (Table 8), the coastal region had the most districts and highest population of all the regions, with over 9.2 million people. The southern region had the fewest districts and smallest population, at just over 1 million people.

Table 8 averages over considerable seasonality to estimate one weekly average number of cases reported. As shown, the southern region experienced a disproportionately high number of weekly diarrheal disease counts given its small population size.

Table 8. Regional diarrheal disease summary statistics and population estimates

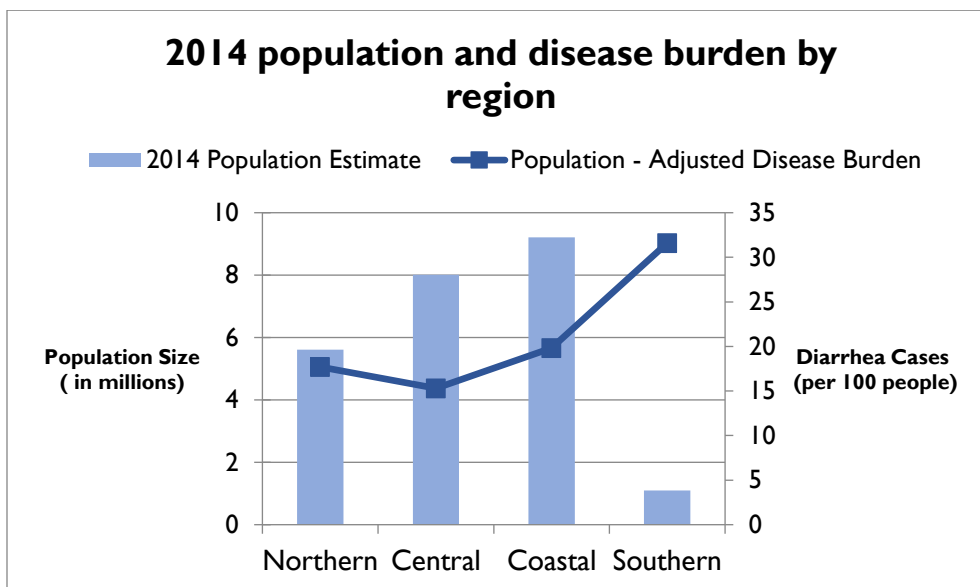
Region	Number of observations in the dataset	Average number of cases per week over follow-up	Maximum cases in a given week	Minimum cases in a given week	2014 population estimate
Northern	34,555	48.65	2,014	0	5,604,764
Central	32,113	60.94	2,033	0	8,014,718
Coastal	45,821	68.32	1,894	0	9,209,851
Southern	13,567	40.35	852	0	1,092,420

The diarrheal disease variable is a count, not a rate. Thus, it is necessary to understand population size when interpreting the regional burdens of disease because the size of the denominator (e.g., population) affects the rate of disease. The coastal region had the highest

average *number* of weekly reports of diarrheal disease cases at 68.32 and the largest population, more than eight times larger than the southern region, which reported an average of 40.35 cases per week.

The burden of disease is relative to population size in 2014, the year for which population estimates were available (Figure 43). Dividing each region’s number of reported cases in 2014 by its population yielded a population-adjusted number of cases per year per region. This is not a measure of incidence because individuals can experience more than one episode of diarrheal disease annually. The results indicate that the burden of disease was similar in the northern, central, and coastal regions, 15 to 20 cases per 100 people, but far higher in the southern region, at nearly 32 cases per 100 people. Relative to its population size, the southern region had a far higher burden of diarrheal disease, indicating increased vulnerability. The population in the southern region may be particularly sensitive because rainfall there is normally limited.

Figure 43. Population-adjusted disease burden by region



#### *Weather/meteorological data*

Temperature data are daily remotely sensed values, averaged each week. Rainfall data come from the CHIRPS dataset, which contains daily rainfall data derived from a combination of satellite, re-analysis, and weather station rainfall data gridded to 0.05 x 0.05-degree spatial resolution. The primary climate drivers are: 1) number of wet days in a week, defined as the number of days in a week (0–7) for which rainfall meets or exceeds 1 mm; and 2) the maximum temperature during the week in degrees Celsius.

## **METHODS**

### **Rainfall**

Rainfall was chosen as a key variable of interest because studies in similar settings found rainfall to be a predictor of diarrheal disease, with both high and low rainfall associated with increased numbers of cases (Alexander et al., 2013; Hashizume et al., 2007; Tornheim et al.,

2010). The transmission pathways through which rainfall causes increases in diarrheal disease are broad and complex.

In Africa, flooding is associated with increased diarrheal disease prevalence (IPCC, 2007; Kandiji et al., 2006). Rainfall variability can also cause periods of water scarcity and drought that can increase diarrheal disease through a variety of pathways, including increased consumption of compromised or unsafe water and reduced hygienic practices (Bandyopadhyay et al., 2012). Rainfall runoff and flooding can also lead to human exposure to pathogens by flushing pathogens from environmental reservoirs into freshwater supplies (Hashizume et al., 2007; Alexander et al., 2013; Singh et al., 2001). Overall, diarrheal disease peaks are associated with the dry and wet seasons, below-average rainfall, heavy rains, and rainfall shocks (Alexander et al., 2013; Azage et al., 2015; Bandyopadhyay et al., 2012; Bonkougou et al., 2013; Oloukoi et al., 2014; Rabassa et al., 2014; Tornheim et al., 2010).

The ensuing analyses were designed to elucidate associations between number of wet days and diarrheal disease in Mozambique. Other rainfall variables were not available in the CHIRPS dataset.

To estimate short-term, or less than seasonal, associations between weekly case counts of diarrheal disease and lagged number of wet days, a time series analytic strategy was applied (Bhaskaran et al., 2013) using a generalized linear model (GLM) that assumes that weekly case counts follow a Poisson distribution (Zhou et al., 2011; Gasparrini & Armstrong, 2010). The model accounts for overdispersion, or an observed variance that exceeds the expected number of weekly diarrheal cases, as is common with disease count data (Gasparrini & Armstrong, 2010).

A common statistical method to control for seasonality and long-term trends was applied, called a cubic spline for time with four knots per year (Peng et al., 2006; Hashizume et al., 2007; Singh et al., 2001). By filtering out trends that dominate in the data and trends that change slowly over time, we examined short-term variation of total cases and explanatory factors on the timescale of interest. Temperature was controlled for using a cubic spline and no lag (Hashizume et al., 2007; D'Souza et al., 2004; Naumova et al., 2006).

Increases in the number of cases of diarrheal disease are often not concurrent with the timing of the weather driver; a delay often occurs between the predictor (e.g., wet days) and the health outcome. This is due to delays related to the incubation period of the waterborne pathogen and the time between when an individual begins to develop a diarrheal disease and when he/she seeks medical care (Alexander et al., 2013). Rainfall typically affects diarrheal disease with a lag of four to eight weeks (Alexander et al., 2013; Hashizume et al., 2007; Tornheim et al., 2010).

A lag was entered into the model to account for these delayed effects and temporal dependency between the exposure event and outcome. Consistent with prior research and to allow for pathogen incubation, illness presentation, and the subsequent clinical visit requirement to be

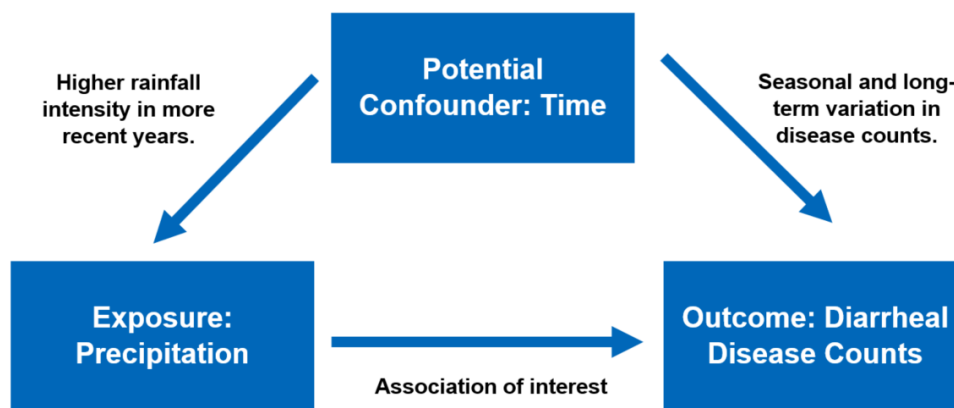
included as a case count, the wet days variable was lagged by four weeks using a distributed lag model (Bhaskaran et al., 2013).

Confounders are variables associated with both the outcome and the exposure of interest. If no adjustment is made, they can bias a modeled association of interest. Time, temperature, and region were confounders of our association of interest.

### *Time*

The descriptive analyses below highlight the temporal associations with diarrheal disease, because disease counts vary across the weeks seasonally (medium-term trends) and years (long-term trends) of follow-up. Failing to account for these variables in the analysis would obscure the association at the timescale of interest: weeks. Most of the country experienced higher rainfall intensity in more recent years compared with earlier years. Figure 44 is a depiction of the association between time and the variables of interest in the form of a directed acyclic graph, or DAG. DAGs are commonly used to evaluate confounding. If a causal, or “directed”, association (depicted with an arrow) exists between the potential confounder and both the exposure and outcome, then that variable must be adjusted for to estimate the true association between the exposure of interest and outcome. Otherwise, the confounder influences the estimates. Without controlling for confounding, it may not be possible to ascertain the true association of interest.

Figure 44. Directed acyclic graph (DAG) depicting the confounding influence of time on the impact of rainfall on diarrheal disease



### *Temperature*

All models were adjusted for average maximum temperature because research has shown that increased temperatures alone could increase diarrheal disease rates.

### *Region*

A regional variable was incorporated in each model by either adjusting for or stratifying by it. Research and the exploratory analyses below show that diarrheal disease counts vary from region to region. Further, each region has a different climate profile. There is strong evidence that rainfall intensity varies spatially in Mozambique. The northern parts of the country receive appreciably more annual rainfall than the southern parts, and the driest parts of the country are in the southwest.

Time, temperature, and region were included in the models to remove confounding that could affect the estimated associations of interest.

This analysis was conducted at two geographic scales (Table 9):

- Nationally, quantified as the number of wet days and diarrheal disease counts (Model A); these analyses estimated one countrywide association.
- Regionally, estimating the association for each region (Model B).

Table 9. Rainfall-related model components

<b>Model A (National)</b>	<b>Model B (Regional)</b>
4-week lagged number of wet days, the predictor of interest	4-week lagged number of wet days, the predictor of interest
Spline for time to adjust for long-term (annual) and medium-term (seasonal) time trends	Spline for time to adjust for long- and medium-term time trends
Smoothing spline for temperature	Smoothing spline for temperature
Regional variable to adjust for regional-level variation	District variable to adjust for district-level variation

The components of Model B included the first three variables in Model A, stratified by region (Table 9). These analyses consider the spatial variation in rainfall in Mozambique, estimating the association between the number of wet days and diarrheal disease counts within each region. The model included a variable for district number for reasons similar to the regional variable inclusion in Model A: inclusion of a district variable adjusts for each region's widespread variation in rainfall and diarrheal disease cases.

### *Maximum temperature*

The association between the week's highest maximum temperature and diarrheal disease was subsequently examined using a similar method. Seasonal changes include temperature variations. Carlton et al.'s (2016) global systematic review of temperature and diarrheal disease found all-cause diarrheal disease and bacterial diarrhea to be positively associated with ambient temperature. The meta-analysis estimated a 7 percent increase in all-cause diarrheal disease for each degree Celsius increase in temperature. Bandyopadhyaya et al.'s (2012) examination of temperature and childhood diarrhea in 14 sub-Saharan African countries found that a 1°C increase in the average maximum temperature increased diarrhea prevalence by 1 percent.



One causal pathway for high temperatures to increase diarrheal disease is by increasing pathogen proliferation in food and water sources (Singh et al., 2001; D'Souza, et al., 2004).

The same time series analytic strategy used to examine rainfall was applied to the temperature analyses. However, rather than controlling for temperature, it was adjusted with a cubic spline for the number of wet days. Time, region, and district were included in the models in the same format as for the models exploring rainfall.

Similar to rainfall, a lagged relationship with temperature and diarrheal disease was included that considered environmental changes, pathogen exposure, incubation, and disease presentation. Studies have used temperature lags ranging from zero to eight weeks when examining all-cause diarrheal disease (Carlton et al., 2016). Bandyopadhyaya et al. (2012) and Alexander et al. (2013) used a 4-week lag for their studies of temperature and diarrheal disease in sub-Saharan Africa and Botswana, respectively. Thus, temperature was lagged four weeks in the analysis.

Based on these modifications, Models A and B examined the temperature associations at the national and district level, respectively (Table 10).

**Table 10. Temperature-related model components**

Model A (National)	Model B (Regional)
4-week lagged maximum temperature, the predictor of interest	4-week lagged maximum temperature, the predictor of interest
Spline for time to adjust for long-term (annual) and medium-term (seasonal) time trends	Spline for time to adjust for long- and medium-term time trends
Smoothing spline for number of wet days	Smoothing spline for number of wet days
Regional variable to adjust for regional-level variation	District variable to adjust for district-level variation

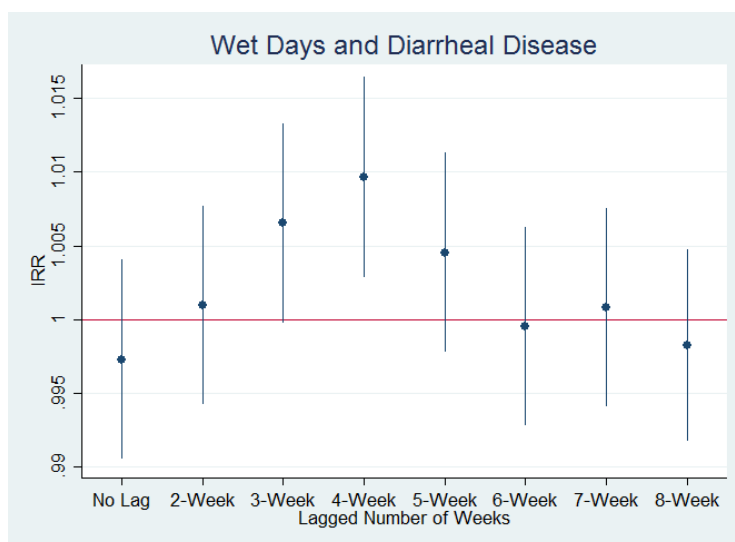
Model B included a regional variable to take into account the sizeable variation in temperature in each region of Mozambique. The northern and central regions generally experience higher average temperatures. Temperature was included as a lagged variable and rainfall was transformed to a smoothing spline to remove its effects and allow focus on temperature's impact on diarrheal disease.

## RESULTS IN DETAIL

### *Rainfall Model A*

Model A estimated a single association between rainfall and diarrheal disease across considerable heterogeneity due to the variation of both diarrheal disease burden and weather within Mozambique. Nevertheless, Model A estimated that for every additional wet day in a given week, an estimated 1.04 percent increase occurs in diarrheal disease, controlling for time, average high temperature, and region (95 percent confidence interval (CI) 0.42 percent–1.66 percent). This finding is statistically significant ( $p=0.001$ ). The a priori decision to use a 4-week lagged association confirms that our data agree with existing studies: the 4-week lag had the strongest association between wet days and diarrheal disease (Figure 45).

Figure 45. Association between number of wet days and diarrheal disease counts



Note: Estimated incidence rate ratios (with 95% confidence intervals) for 0–8-week lags, controlling for time, average maximum temperature, and region.

### Rainfall Model B

Model B found evidence of a larger association between wet days and diarrheal disease in the northern, central, and southern regions (Table 11). One additional wet day resulted in a 1.86 percent, 1.37 percent, and 2.09 percent increase in diarrheal disease in these three regions, respectively. The coastal region disease patterns appeared to be the least affected by rainfall: an additional wet day resulted in a 0.63 percent increase in disease counts. This difference was likely due to the unique weather patterns of coastal areas. All of these findings were significant at  $p < 0.05$  (Figure 46).

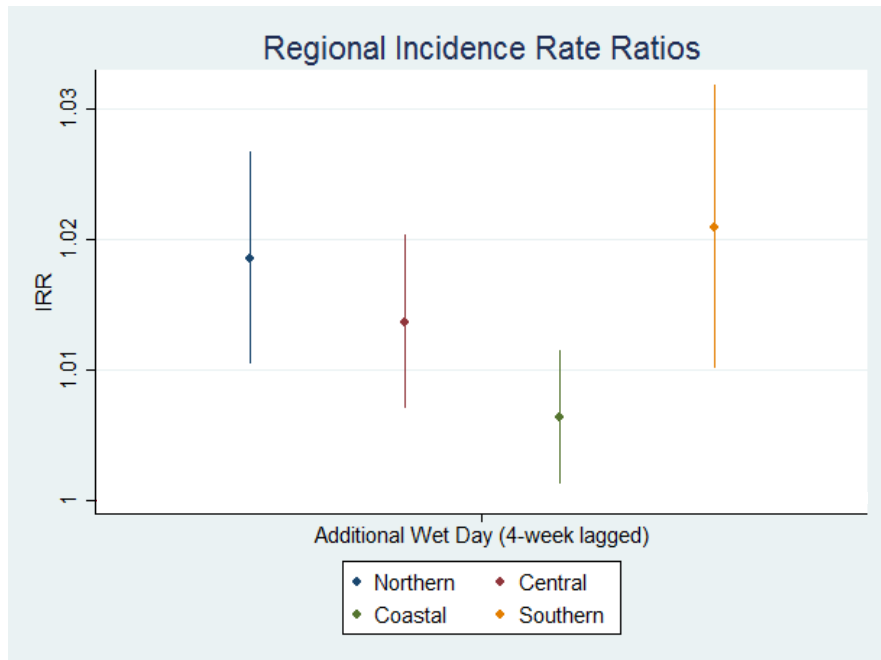
Table 11. GLM Model B results showing incidence rate ratio (IRR) by region

Number of Wet Days (4-week lagged): Model B				
Region	IRR*	95% CI LL	95% CI UL	p value
<b>Northern</b>	1.0186	1.0105	1.0267	<0.001
<b>Central</b>	1.0137	1.0070	1.0204	<0.001
<b>Coastal</b>	1.0063	1.0011	1.0114	0.016
<b>Southern</b>	1.0209	1.0101	1.0318	<0.001
*Controlling for time, average high temperature, and district				

Note: CI = confidence interval; LL = lower limit; UL = upper limit.

The results estimate a region-specific association between number of wet days (rainfall >1 mm) lagged and weekly total cases of diarrheal disease reported in Mozambique, 1997–2014.

Figure 46. Incidence rate ratios (IRRs) and 95% confidence interval bars for the four regions for each additional wet day



Note: Lagged four weeks and controlling for time, average maximum temperature, and district.

### Maximum Temperature Model A

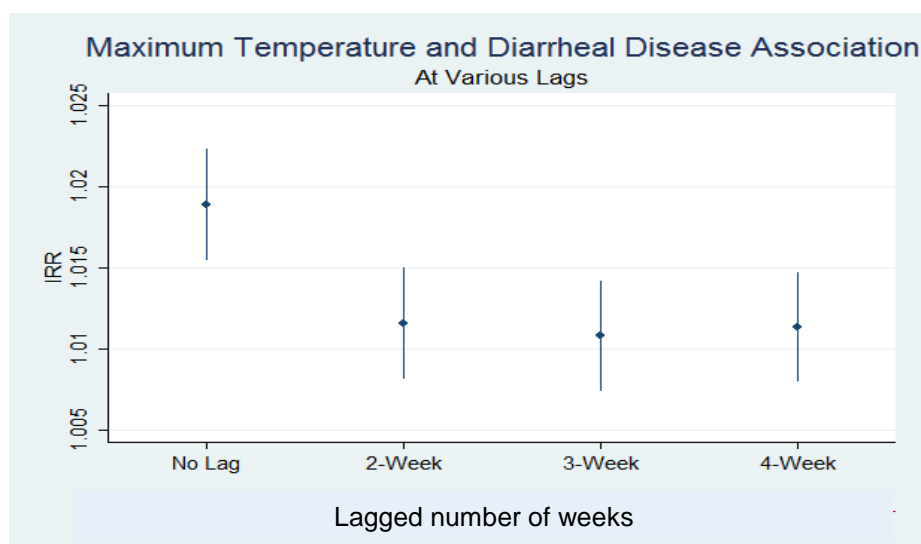
Examining maximum temperature as the predictor of interest, Model A estimated that for every additional 1°C increase in the hottest day of the week, diarrheal disease increased 1.13 percent (95 percent CI: 0.80–1.47 percent) at a 4-week lag, controlling for time, rainfall, and region. This finding was statistically significant ( $p < 0.001$ ).

While the decision was to examine the association at a 4-week lag, the strongest association was at no lag (i.e., during the concurrent week). Selecting a single lag for a variety of pathogens with differing incubation periods is challenging. Ideally the lag most relevant for each pathogen would be included in the model. However, the diarrheal disease surveillance system does not routinely capture the pathogen responsible for each case. Based on the literature, a 4-week lag was expected to be most strongly associated with disease counts. Others hypothesize, however, that pathogen transmission may happen simultaneously with increased temperatures because increased fly activity may amplify transmission (Alexander et al., 2013).

Figure 47 shows the associations at various lags, when all of the lagged terms are included in the model simultaneously.

Due to the strength of the association observed at no lag, an exploratory analysis was performed that removed all lagged temperature variables from the model. A 1°C increase in the highest maximum temperature during the week of interest increased diarrheal disease by 3.64 percent (95 percent CI: 3.35–3.93 percent,  $p < 0.001$ ).

Figure 47. National association between maximum temperature and diarrheal disease counts



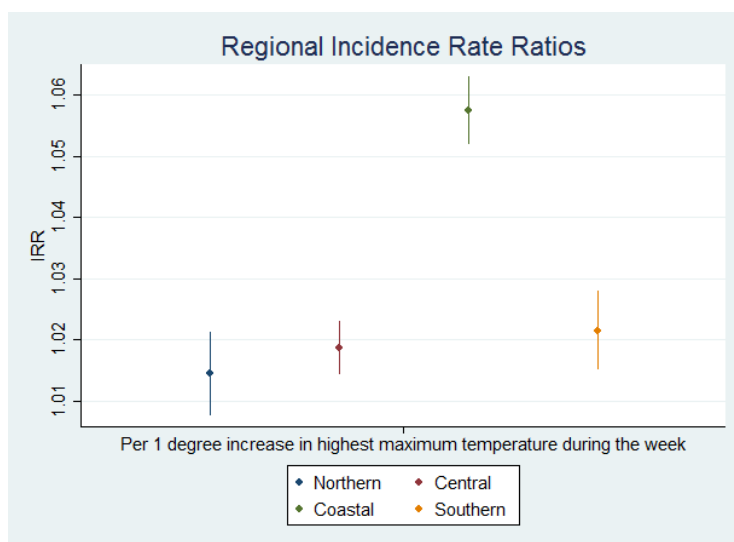
Note: Estimated incidence rate ratios (with 95 percent confidence intervals) for 0–4-week lag, controlling for time, average maximum temperature, and region.

### *Maximum Temperature Model B*

Based on the results from Model A, Model B was fit without any lags. All regions exhibited a statistically significant increase in diarrheal disease for each 1°C increase in the maximum temperature, with the increase varying widely by region.

Figure 48 and Table 12 display the IRRs and 95 percent CIs by region. The IRRs were 1.45, 1.87, and 2.15 in the northern, central, and southern regions, respectively. While the coastal region's diarrheal disease burden had the smallest association with an additional wet day, it was the most sensitive to an increase in the maximum temperature. It was estimated that for every additional degree increase in the maximum temperature, diarrheal disease counts increased by nearly 6 percent in the coastal region (95 percent CI: 5.18–6.29 percent). A range of reasons explain why this might be the case, including behavioral changes when weather gets warmer that increase transmission of diarrheal diseases and specifics of the replication rate and transmission cycle for the pathogens. Information on causative pathogens is required to better understand this.

Figure 48. Regional association between maximum temperature and diarrheal disease counts



Note: These rates are based on a 1°C increase in highest maximum temperature, controlling for time, average maximum temperature, and region.

Table 12. GLM Model B results for maximum temperature

Maximum Temperature: Model B				
Region	IRR*	95% CI LL	95% CI UL	p value
Northern	1.0145	1.0077	1.0213	<0.001
Central	1.0187	1.0144	1.0230	<0.001
Coastal	1.0574	1.0518	1.0629	<0.001
Southern	1.0215	1.0151	1.0280	<0.001
*Controlling for time, average high temperature, and district				

Note: Incidence rate ratio (IRR) by region estimating a region-specific association between the highest maximum temperature and weekly total cases of diarrheal disease reported in Mozambique, 1997–2014. CI = confidence interval; LL = lower limit; UL = upper limit.

## DIARRHEAL DISEASE UNDER A CHANGING CLIMATE

The previous section outlined projected changes in the climate of Mozambique. These included changes in the number of wet days at an annual timescale, averaged over the period 1986–2005 and the future period 2046–2065, using the RCP 8.5 emission scenario for 11 climate models as described in Section II of this report.<sup>4</sup> Projections were based on a GCM and downscaled data analyzed on an annual and seasonal timescale. Both approaches showed a possibility of increased or decreased rainfall over all regions, indicating large uncertainties about the possible future burdens of diarrheal disease in a warmer climate. The following sections

<sup>4</sup> RCP 8.5 is a scenario with continued high emissions of greenhouse gases such that atmospheric concentrations of carbon dioxide equivalents reach more than 1,350 parts per million in 2100.

outline the relationship between historical and projected burdens from diarrheal disease and malaria due to key climate parameters.

### NUMBER OF WET DAYS PER WEEK

The differences in estimates between the time periods of the annual number of wet days were expressed as negative or positive values depending on the direction of change. Table 13 shows the average, minimum, and maximum of the 11 downscaled projections for the number of wet days. Each region’s projection shows a substantial range, with positive and negative values. Because there is no objective measure to choose one climate model over another, the average of the models was used to calculate expected changes in diarrheal disease with climate change.

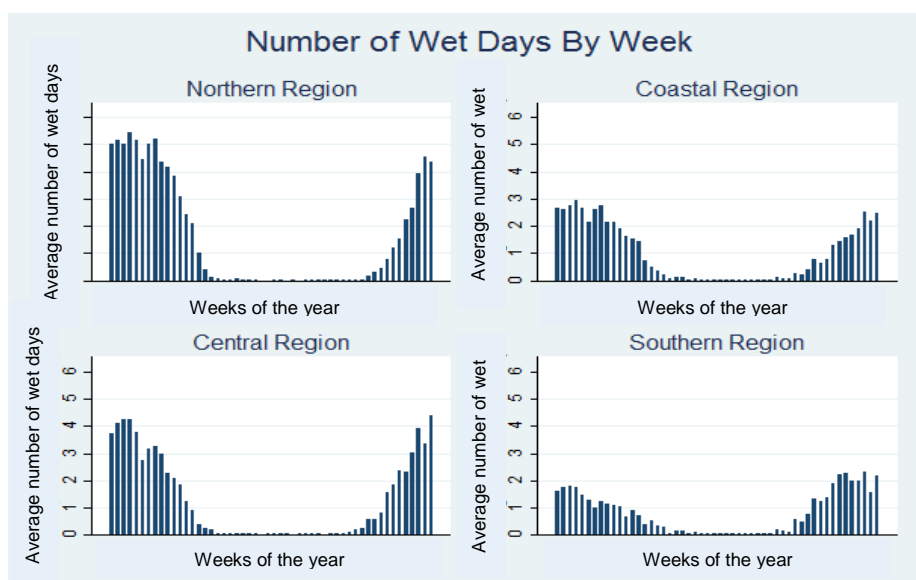
Table 13. Change in number of wet days per year, 1986–2005 and 2046–2065

Region	Average	Minimum	Maximum
Northern	-6.30	-14.52	9.27
Central	-5.71	-11.39	5.96
Coastal	-6.25	-15.51	14.75
Southern	-2.52	-6.43	3.10

Note: Average, minimum, and maximum of 11 downscaled projections for the change in number of wet days in Mozambique’s four regions between 1986–2005 and 2046–2065.

Heavy rainfall and warm temperatures characterize Mozambique’s summer months of December, January, and February, although this varies slightly by region (Figure 49). Applying the expected proportion of the average reduction in the number of wet days to each region’s 13 wettest weeks, Table 14 summarizes the estimated percent reduction in diarrheal disease and total number of cases per week during the wettest weeks, based on model projections.

Figure 49. Average number of wet days by week



Note: The x axis lists the weeks of the year from 1 to 52



Table 14. Diarrheal disease during the 13 wettest weeks, 1986–2005 and 2046–2065

Region	Projected % decrease in disease per week	Total number of cases averted per week
Northern	0.61	12.64
Central	0.41	9.59
Coastal	0.18	6.35
Southern	0.31	1.87

Note: Projected percent change and total decrease in number of cases per region during its 13 wettest weeks, based on 11 downscaled projections for the average change in number of wet days between 1986–2005 and 2046–2065.

The method used for these calculations, as applied to the northern region, is as follows:

1. Determine weeks with the majority of wet days and quantify the percent
  - Over all the years of follow-up, the northern region experienced 56,108 total wet days, 38,418 (68.5 percent) of which occurred during weeks 1–8 and 48–52 (time periods selected in an attempt to capture the wettest weeks).
2. Distribute the proportion of the projected change that will apply to these weeks
  - The 11 projections averaged to predict 6.30 fewer wet days each year. Allocating that projection to the 13 wettest weeks, we expect  $0.685 \times 6.30$ , or 4.32 fewer wet days during the 13 wettest weeks.
3. Calculate the number of fewer wet days per week expected during these weeks
  - Calculate the expected weekly decrease in the number of wet days to enable application of our IRR to the weekly timescale. Thus  $4.32/13 = 0.33$  fewer wet days per week are expected during the time period of interest.
4. Apply the IRR to calculate expected change in disease burden during the rainy weeks
  - Multiply the calculated IRR of 1.86 percent for the northern region by the expected reduction in the number of wet days per week (0.33). The result is  $1.86 \times 0.33 = 0.61$  (0.61 percent fewer cases per week).
5. Apply the percent above to quantify the total number of cases (added or averted, depending on the direction of change)
  - To estimate the total number of diarrheal disease cases averted per week from the projected decrease in the number of wet days, calculate the total number of cases that occurred during those weeks in the northern region over all years of follow-up and divide by 18 to get the average number per year:  $484,795 \text{ cases total}/18 = 26,933 \text{ cases}$ .
  - Divide the result by 13 to get the estimated number of cases per week during the rainy season:  $26,933/13 = 2,072 \text{ cases per week}$ .
  - Applying the estimate established of 0.61 percent fewer cases per week, the expectation is that 12.64 fewer cases of diarrheal disease per week will occur in the northern region.

## 6. Interpretation

- During the primary rainy season (or wettest weeks of the year) in the northern region, the projected decrease in the number of wet days will result in 0.61 percent or 12.64 fewer diarrheal disease cases per week during the 2046–2065 time period.

This same methodology was also applied to the other three regions, with the following results:

As in the northern region, 68.5 percent of wet days occur during weeks 1–8 and 48–52 in the central region. Distributing the projected 5.71 fewer wet days over this time, 3.91 fewer wet days would occur during the rainy season in the central region, resulting in 0.30 fewer wet days per week and 0.41 percent fewer cases of diarrheal disease during the wettest 13 weeks of the year. This would mean 9.59 fewer cases per week in 2046–2065.

In the coastal region, 60.1 percent of wet days occur during the aforementioned 13 weeks. The projections suggest 3.76 fewer wet days during this time period, or 0.29 fewer wet days per week. This would result in 0.18 percent fewer cases of diarrheal disease per week, or 6.35 cases reduced per week.

The southern region has different seasonality than the other regions, with the majority of rainfall occurring in the final eight weeks of the year. Weeks 1–5 and 45–52 account for 58.1 percent of annual wet days. Applying the projections would result in 0.15 fewer wet days per week, and 0.31 percent fewer cases of diarrheal disease per week, or 1.87 fewer cases.

All climate models are equally probable, and using only the average may lead to underpreparedness for climate change impacts. The same method used above was applied to the maximum projected change in number of wet days per year. The same 13 weeks determined above to be the wettest in each region were used for this analysis.

Applying the maximum projection, we expect that during each region's 13 wettest weeks, 0.91 percent, 0.42 percent, 0.43 percent, and 0.29 percent more diarrheal disease cases would arise in the northern, central, coastal, and southern region, respectively. This would result in 18.86, 9.82, 15.16, and 1.75 more cases per week in 2046–2065 in each respective region.

### **MINIMUM LOW TEMPERATURES**

Projections were available for weekly minimum temperatures in 2046–2065 (maximum temperature projections were not available). To use these projections, the associations between the observed lowest low temperatures and cases of diarrheal disease over 1997–2014 were analyzed, using the same methods as for maximum temperature.

The projected lowest low temperatures in a given week were calculated using the same models, methods, and number of wet day projections (Table 15). The ranges were much smaller, and all models projected an increase in the minimum temperature.

Table 15. Change in lowest minimum temperature (°C), 1986–2005 and 2046–2065

Region	Average	Minimum	Maximum
Northern	2.39	1.94	2.85
Central	1.94	1.45	2.38
Coastal	2.17	1.83	2.70
Southern	2.09	1.49	2.66

Note: Average, minimum, and maximum of 11 downscaled projections for the change in lowest minimum temperature (in degrees Celsius) in Mozambique’s four regions between 1986–2005 and 2046–2065.

Table 16 shows the projected percent changes in diarrheal disease for each 1°C increase in the minimum temperatures of the week in the three regions in which the minimum low temperature was significantly associated with diarrheal disease. Applying the averages of the models to the IRRs for each region, 3.27 percent, 2.37 percent, and 1.84 percent increases in diarrheal disease are projected in the northern, central, and coastal regions, respectively. In the southern region, the minimum temperature was not significantly associated with diarrheal disease.

Table 16. Change in lowest annual minimum temperature (°C) and diarrheal disease, 1986–2005 and 2046–2065

Region	IRR	Projected change in temperature	Increase in diarrheal disease projected
Northern	1.37	2.39 °C	3.27%
Central	1.22	1.94 °C	2.37%
Coastal	0.85	2.17 °C	1.84%

Note: Average, minimum, and maximum of 11 downscaled projections for the change in lowest minimum temperature in Mozambique’s four regions between 1986–2005 and 2046–2065. Note that the southern region is not shown as the change in minimum temperature was not significantly associated with diarrheal disease incidence there.

## MALARIA AND WEATHER ASSOCIATIONS

Malaria is a major health problem in Mozambique and is significantly affected by climate (Figure 50). Transmission intensity, risk of infection, and prevalence of the disease are all impacted by both rainfall and temperature, largely through the impacts on the mosquito vector (Egbedewe-Mondzozo et al., 2011) but also through human host and parasite interactions.

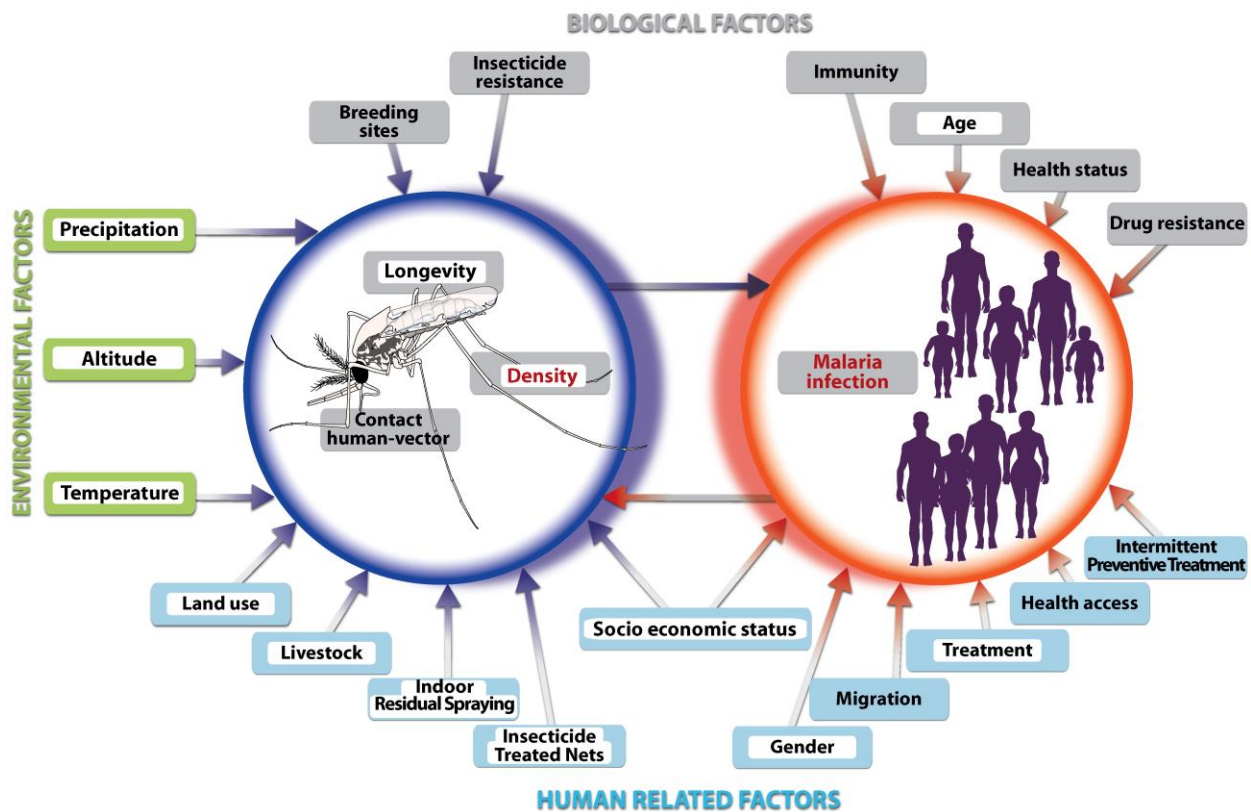
The relationship between malaria transmission and climate is complex: climate can impact the transmission of malaria by affecting the parasite’s and the mosquito’s lifecycle, the human host, or any combination of the three. Predicting how changes in rainfall or temperature might affect transmission geographically requires detailed knowledge of all other related factors, including number of breeding sites, vector species distribution, infection rates, and more. Many of these are difficult if not impossible to measure empirically (Parham & Michael, 2010).

A variety of studies have examined the future impact of climate change on malaria transmission worldwide (Parham & Michael, 2010; Caminade et al., 2014) and specifically on Africa (Tompkins & Caporaso, 2016). Most of these studies used mathematical modeling to address

the lack of measured or observed values for all parameters (such as malaria transmission intensity, length of transmission season, entomological inoculation rate, larval growth rates, larvae and adult mortality, frequency of adult feeding, etc.) and found that the expected changes in the climate over the next several decades will lead to more people at risk of malaria. Caminade et al., (2014) predicted an increase in transmission intensity (through increased biting rates and reduced pathogen development) in Mozambique, along with longer transmission seasons.

Based on these conclusions, it is likely that the malaria profile in Mozambique will change. To prepare for the changes, knowledge is required on how disease incidence may evolve with the changing climate. A first step in this process is to understand the historical relationship between climate and malaria incidence. This information can be used in conjunction with climate models to identify populations at increased risk for future high malaria burden.

Figure 50. Impact of weather, climate variability, and climate change on malaria



Note: The impact of climate on malaria is manifested in three main ways: through biological, environmental, and human-related factors, all of which end up affecting the mosquito vector, the parasite, and the human host.

Source: Protopopoff N., Van Bortel W., Speybroeck N., Van Geertruyden J-P., Baza D., D'Alessandro U., et al. (2009).

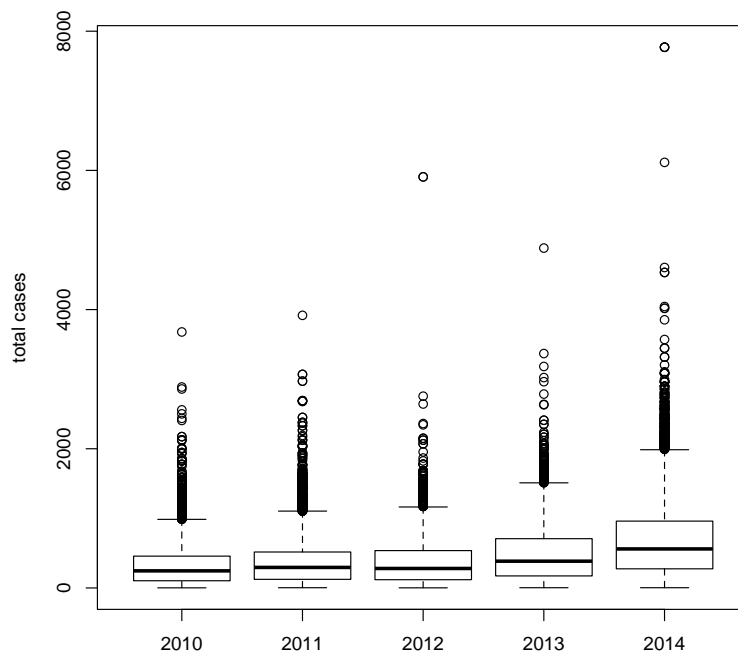
Mozambique has some of the highest levels of malaria incidence in the world. Malaria is regularly among the leading causes of morbidity and mortality in the country. The entire country is at risk, though transmission tends to be higher in the northern region than in the southern

region. The transmission season typically begins in late December or early January, peaks between February and April, and ends in May. Malaria control efforts in Mozambique can be broadly grouped into two categories:

- *Case management*: testing and treating patients with malaria, which has tended to be uniform across the country and consistent over the past several years; and
- *Vector control*: indoor residual spraying (IRS) and distribution of long-lasting insecticide-treated nets (LLINs), practices that have varied considerably by time and location since 2010, with IRS applied sporadically and LLINs only reaching significant numbers of people in 2013.

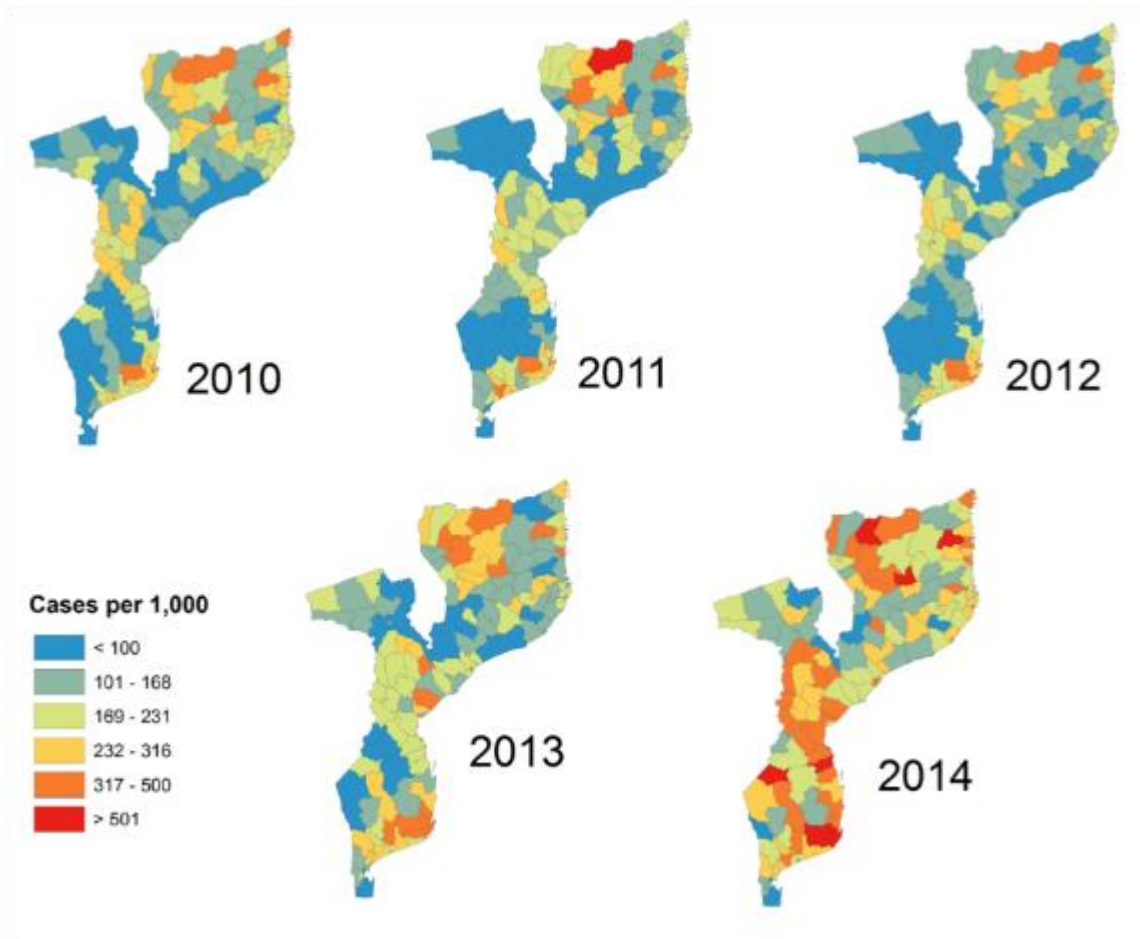
Figure 51 shows the total malaria cases by year from 2010 to 2014 for all districts across Mozambique. As the graph shows, malaria cases remained steady between 2010 and 2012, then increased rapidly between 2013 and 2014. Previous investigations were conducted by the President’s Malaria Initiative (PMI), an effort by the U.S. government to reduce malaria-related mortality by 50 percent across 15 high-burden countries in sub-Saharan Africa through a rapid scale-up of four proven and highly effective malaria prevention and treatment measures. In Mozambique the PMI examined various potential causes for this increase, for example, interventions and reporting rates, and concluded that changes in weather may have been responsible for the increase. The increase was not uniform across the country, with Niassa (northern region), Manica (central region), and Inhambane (coastal/southern regions) Provinces having the most districts with increased cases reported during this time (Figure 52).

Figure 51. Total reported malaria cases, 2010–2014



Note: Total number of malaria cases reported per year. Whiskers indicate the 90<sup>th</sup> percentiles and the line within each box indicated the median value. All other dots are outliers.

Figure 52. Reported malaria cases per 1,000 population by district, 2010–2014



Source: Mozambique's weekly epidemiological bulletin.

## SUMMARY OF RESULTS

The analysis considered the years 2010 to 2014 with the aim of uncovering why malaria incidence rose between 2013 and 2014. To determine statistical relationships between variations in temperature and rainfall and the incidence of malaria, a four-step process was used to determine the most appropriate variables and lag times for the final model. This preliminary analysis also considered whether to include nonclimate variables such as region, land cover, and population density. Ultimately, only region was included.

### National findings

The model results included the following:

- Among the weather variables, days below 25°C was most highly predictive of malaria incidence. For each day per week below 25°C, malaria incidence declined by 3 percent.
- Other temperature and rainfall variables were significant. A 1°C increase in minimum temperature and a one-day increase in days with at least 1 mm or 50 mm rainfall resulted in a 2 percent increase in malaria incidence.



- However, climate variables did not fully explain the rise in malaria incidence in 2013 and 2014. To explore this, the model was run splitting the datasets into two periods: 2010 to 2012 and 2013 to 2014. These results showed that for the two time periods, nearly all the weather variables had similar associations. The exception was days with at least 50 mm rainfall. From 2010 to 2012, a one-day increase in days with at least 50 mm rainfall in a week led to a 7 percent increase in malaria incidence. In comparison, from 2013 to 2014, days above 50 mm rainfall led to a 2 percent decrease in malaria incidence.
- Between the two time periods, the early increase may have been the result of more rainfall leading to more breeding sites, while the later decline was the result of extreme rainfall that washed breeding sites away. This is backed up by the significant increase in days with at least 50 mm rainfall and total rainfall during the study period.
- To further explore the two time periods, control interventions were included in the model. They were based on a five-level index representing varying intensity of IRS and LLIN interventions. The districts with one to two years of IRS combined with a subsequent LLIN campaign saw a 36 percent reduction in malaria incidence compared with districts with no IRS or LLINs. This suggests that even when variation in weather is taken into account in the model, vector control interventions succeed in controlling malaria.

## Regional findings

To account for the potential interaction between region and vector control intervention, models were created for each of the four regions. The results include the following:

- The biggest variation among the weather variables was in days with at least 50 mm rainfall. In the northern region, a one-day increase in days with at least 50 mm rainfall resulted in a 95 percent reduction in malaria incidence, while in the southern region, a one-day increase in days with at least 50 mm rainfall led to a 100 percent increase in malaria incidence.
- In addition, the region-specific models suggest that climate anomalies could play an important role in malaria incidence. For example, average rainfall is highest in the northern region, resulting in more permanent, year-round breeding sites. Extreme rainfall events could therefore be expected to lead to the destruction of existing breeding sites and, consequently, the decrease in malaria described above. Conversely, in the southern region, the driest part of the country, permanent year-round breeding sites are less common. Extreme rainfall events are more likely to lead to the creation of new breeding sites rather than elimination of existing ones. This may account for the observed increase in malaria incidence.
- In addition, the model showed that increased vector control had differing impacts in different parts of the country, with interventions more effective in the northern and central regions than in the southern and coastal regions.

## ANALYSIS IN DETAIL

### Objectives

The objective of this part of the study was to use statistical techniques to examine the role that predictor variables such as environmental and demographic factors, climate, and weather play in malaria incidence (or outcome). Once a formal statistical relationship between the predictor variables and the outcome is established, future climate profiles can be used to project how malaria incidence may change under a changing climate, thereby helping to identify populations that might be at risk for increased malaria incidence in the future.

## Data

Weekly malaria case counts were obtained from Mozambique's BES. Climate indices used were weekly averages or sums of daily remote-sensed data. Because the impact of weather on malaria cases is delayed due to the time needed for development of both the mosquito and the parasite in the mosquito, it was necessary to implement a lag between the weekly weather data and the malaria case data. For malaria, this lag is normally between two and eight weeks for temperature and rainfall, though individual lags for each weather variable were identified to maximize the accuracy of the final statistical model. These variables are described below and in Table 17.

In addition to the variables listed in Table 17, other variables known or thought to be potentially related to malaria transmission were considered. These included: percentage of land covered by water; percentage of land above 500 meters (m), 1,000 m, and 1,500 m; the number of people covered per health facility; and population density. Although these and other variables such as enhanced vegetation index were found to be significantly associated with malaria in previous studies, the studies used point estimates of malaria prevalence and vegetation indices from these same points. Because this study used district-level estimates of malaria cases, all environmental variables were aggregated to the district level. For variables such as elevation and vegetation indices with many different measures for one district, the significance of the indices was lost upon district-level aggregation, as can be seen by the elevation measures in.

Table 17. Names, definitions, and units of variables used in the analyses of malaria

Variable	Definition	Unit
<b>Incidence</b>	Total number of malaria cases (all ages), per 1,000 people, reported in a given week by each district	Cases
<b>Tmax_mean</b>	Mean of the daily maximum temperatures during the week	Celsius
<b>Tmax_max</b>	Highest maximum temperature during the week (i.e., the maximum temperature of the hottest day)	Celsius
<b>Tmax_min</b>	Lowest minimum temperature of the coolest day during the week	Celsius
<b>Tmin_mean</b>	Mean of the daily nighttime minimum temperatures during the week	Celsius
<b>Tmin_max</b>	Highest temperature of the hottest night during the week	Celsius
<b>Tmin_min</b>	Lowest minimum temperature of the coldest night during the week	Celsius
<b>Days above 35°C</b>	Number of days above 35°C during the week	Days
<b>Days below 25°C</b>	Number of days below 25°C during the week	Days
<b>Precip_days1mm</b>	Number of wet days during the week, using a 1-mm threshold for wet	Days
<b>Precip_days50mm</b>	Number of days with 50 mm or more of rainfall during the week	Days
<b>Precip_max</b>	Maximum single daily rainfall volume during the week	mm
<b>Precip_total</b>	Total volume of rainfall during the week	mm

## Methods

To model the association between environmental factors and health outcomes, a time series analysis was conducted using generalized linear mixed models (GLMMs). Weekly malaria cases adjusted for district population were used as the outcome variable. Demographic, environmental, and weather variables, including weekly averages and totals at the district level from preceding weeks, were used as the predictor variables. To account for the correlation among observations from the same districts over time, a random effect to estimate the within-district variation was also included. All quantitative variables were first plotted against the malaria rates using cubic smoothing splines to verify that all trends were linear.

A four-step process was used to determine the statistical relationships between the predictor and outcome variables:

1. Determine the correlation between different climate indices. Because collinear variables in a multivariable statistical model can negatively affect the model's performance, it was important to identify any collinearity between the climate indices.
2. Determine which climate indices and fixed effects (nonclimate variables such as region, land cover, population density, etc.) are most strongly related to malaria cases through simple correlation plots. The idea was to avoid having to test too many variables to determine proper lags (Step 3) and to avoid putting too many variables in the final model.
3. Determine the most appropriate lags for variables identified in Step 2 as most strongly correlated with malaria cases. This was done through single-variable regression analysis: lags presenting the highest Z-scores were selected for inclusion in the final model.
4. Perform multivariable regression with a GLMM using the above selected variables and lags. This model also included an offset for district population, a fixed effect to take into account the repeated measures from districts over time, as well as a variable for region, week of the year (transformed using sine/cosine to account for the seasonality in malaria transmission, year (2011 to 2014), and urban/rural areas. For the final model, only variables with  $p$  values less than 0.05 were included.

## RESULTS

### Variables selected for multivariable analysis

Following the results of Steps 1 to 3, the climate indices included in the multivariable analysis were: Tmin\_min, days with at least 1 mm precipitation, days with at least 50 mm precipitation, diurnal temperature range (tasdtr), days above 35°C, and days below 25°C. Based on results from single-variable regression analysis (Step 3):

- A 2-week lag was used for tasdtr, days above 35°C, and days below 25°C
- A 4-week lag was used for Tmin\_min and days with at least 50 mm precipitation
- An 8-week lag was used for days with at least 1 mm precipitation

The averages of each variable included in the final model are shown by region in Table 18. Significant differences by region can be seen, particularly in the rainfall indices and days below 25°C. These results further justify the inclusion of region in the models.

Table 18. Weekly averages for weather variables in the full model, 1979–2014

Region	Tmin_min	Days 1 mm precip	Days 50 mm precip	Days above 35 °C	Days below 25 °C	Diurnal temp range
Northern	17.39	1.67	0.01	0.64	0.23	10.28
Central	16.33	1.35	0.02	1.00	0.56	11.13
Southern	15.27	0.85	0.02	0.92	0.86	12.50
Coastal	18.52	1.08	0.04	0.62	0.43	9.47
Mozambique	17.25	1.29	0.03	0.77	0.45	10.47

### National results for full model

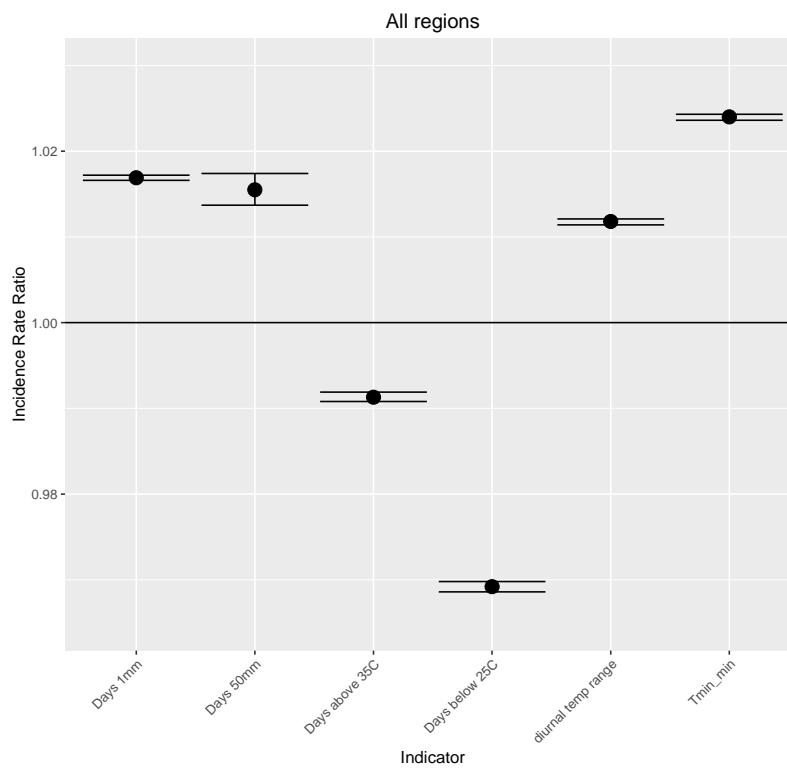
Table 19 and Figure 53 show the results of the full model using malaria incidence as the outcome variable. The results show the IRR for each predictor variable, which is the percent change expected in malaria incidence with a one-unit change in the predictor variable. Each table shows the IRR, along with the lower and upper limits of the confidence interval (CI LL and CI UL), as well as the *p*-value. Each figure compares the IRR for weather variables, to compare the impact of each variable on malaria incidence. Among the weather variables, days below 25°C was most highly predictive of malaria incidence. For each day per week below 25°C, a 3 percent decrease in malaria incidence occurred. Tmin\_min and days with at least 1 mm and 50 mm rainfall were also significantly associated with malaria cases. A 1°C increase in Tmin\_min and a one-day increase in days with at least 1 mm or 50 mm rainfall resulted in a 2 percent increase in malaria incidence.

It is important to note that although weather variables included in the final model were statistically significant, the effect sizes were relatively smaller than expected. This is reiterated by the large effect size of years 2013 and 2014. The fact that year was still a significant predictor of malaria incidence when weather was accounted for means that the factors included in the model were not sufficient to explain the increase in incidence seen in 2013 and 2014. Interestingly, region was not significant, meaning that all the variation in malaria incidence among the regions was explained by weather or year.

Table 19. Final model output from GLMM using malaria incidence as the outcome variable

	IRR	p value
<b>Intercept</b>	0.00	<0.001
<b>Sin(week)</b>	1.26	<0.001
<b>Cos(week)</b>	0.92	<0.001
<b>Tmin_min</b>	1.02	<0.001
<b>Days 1mm</b>	1.02	<0.001
<b>Days 50mm</b>	1.02	<0.001
<b>Days above 35°C</b>	0.99	<0.001
<b>Days below 25°C</b>	0.97	<0.001
<b>Diurnal temp range</b>	1.01	<0.001
<b>Year 2012 (ref 2011)</b>	1.03	<0.001
<b>Year 2013 (ref 2011)</b>	1.02	<0.001
<b>Year 2014 (ref 2011)</b>	1.37	<0.001
<b>Year 2015 (ref 2011)</b>	1.92	<0.001

Figure 53. Incidence rate ratio (IRR) for climate indices in the full model



Note: Incidence Rate Ratios depict the incidence of malaria with a one-unit increase in the climate variable compared with the baseline) and the six climate variables most significantly correlated with malaria at the weekly time-scale:

days 1mm – the number of days receiving at least 1 mm of rain; days 50mm – the number of days within a week when at least 50 mm of rain was received; days above 35C – the number of days during a given week when temperatures exceeded 35 degrees Celsius; days below 25C– the number of days during a given week when temperatures fell below 25 degrees Celsius; diurnal temperature range – the difference between the daily maximum temperatures and daily minimum temperatures; and Tmin-min – the lowest minimum temperature of the coldest night during the week. Incidence rates above 1.0 suggest a positive correlation between malaria and the variable. For example, as the number of days with rain (number of wet days) and days with at least 50 mm of rain increase, malaria incidence rates increase. The same is true for diurnal temperature range and minimum temperatures. Rates below 1.0 suggest a negative relationship between malaria and the indicator. For example, with increases in the number of days above 35 degrees Celsius (e.g., as hotter temperatures occur) and the number of days below 25 degrees Celsius (as minimum temperatures increase), incidence is reduced.

### National results for year-specific models

Because the increase in cases in 2013 and 2014 was not fully explained by the climate variables, the database was divided into two datasets: one for the years 2010–2012, and the other for 2013–2014. The analyses described above for the full model were then performed for each dataset individually, and the results compared.

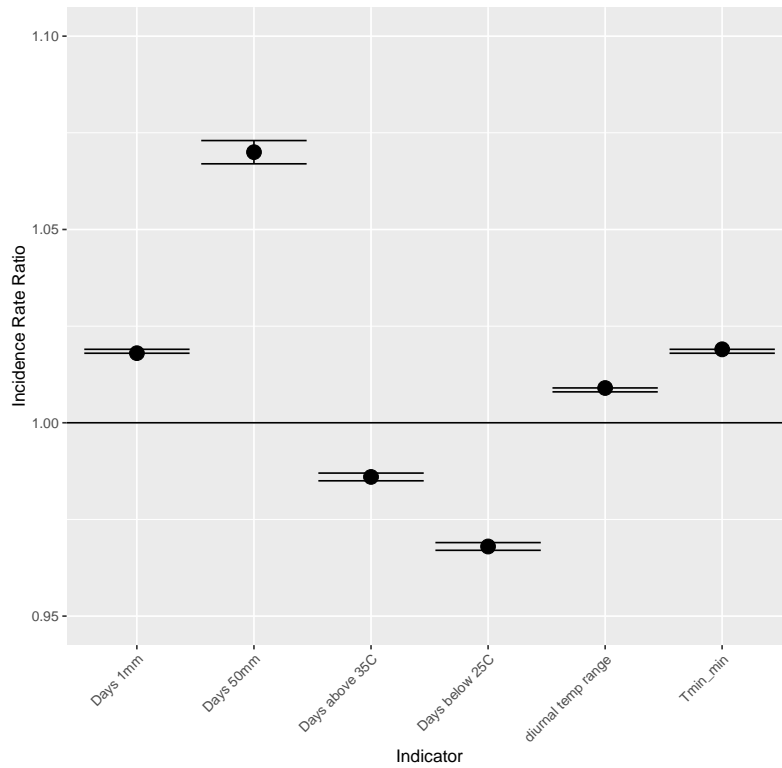
Table 20, Figure 54, and Figure 55 show the results of the GLMM using incidence for the years 2010–2012. For nearly all the weather variables, the associations with incidence were similar in the two time periods. Most of these associations were minor, with days below 25°C and Tmin\_min having the strongest association with malaria incidence in 2010–2012 and 2013–2014, respectively. The exception was days with at least 50 mm rainfall. From 2010 to 2012, a one-day increase in days with at least 50 mm rainfall in a week led to a 7 percent increase in malaria incidence. In comparison, from 2013 through 2014, days above 50 mm rainfall was negatively associated with malaria incidence: a one-day increase in days with at least 50 mm rainfall led to a 2 percent decrease in malaria incidence. Figure 56 shows the mean number of days with at least 50 mm rainfall by year, as well as the mean monthly malaria incidence (red line) by year. Both indices show similar trends (increase in 2011, decrease in 2012, followed by an increase in 2013 and 2014. The mean number of days with at least 50 mm rainfall was significantly lower from 2010–2012 than in 2013–2014 (0.028 vs 0.034, respectively;  $p < 0.001$ ).

Table 20. Final model output using malaria incidence for Model 1 (2010–2012) and Model 2 (2013–2014)

	IRR		CI LL		CI UL		p value	
	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2
<b>Intercept</b>	0.00	0.00	0.00	0.00	0.00	0.00	<0.001	<0.001
<b>Sin(week)</b>	1.24	1.27	1.23	1.27	1.24	1.27	<0.001	<0.001
<b>Cos(week)</b>	0.94	0.90	0.94	0.89	0.94	0.90	<0.001	<0.001
<b>Tmin_min</b>	1.02	1.03	1.02	1.03	1.02	1.03	<0.001	<0.001
<b>Days 1mm</b>	1.02	1.01	1.02	1.01	1.02	1.01	<0.001	<0.001
<b>Days 50mm</b>	1.07	0.98	1.07	0.97	1.07	0.98	<0.001	<0.001
<b>Days above 35°C</b>	0.99	0.99	0.99	0.99	0.99	0.99	<0.001	<0.001
<b>Days below 25°C</b>	0.97	0.98	0.97	0.98	0.97	0.98	<0.001	<0.001
<b>Diurnal temp range</b>	1.01	1.01	1.01	1.01	1.01	1.01	<0.001	<0.001
<b>Year 2011 (ref: 2010)</b>	1.02	-	1.02	-	1.02	-	<0.001	-
<b>Year 2012 (ref: 2010)</b>	1.02	-	1.01	-	1.02	-	<0.001	-
<b>Year 2014 (ref: 2013)</b>	-	1.40	-	1.40	-	1.40	-	<0.001

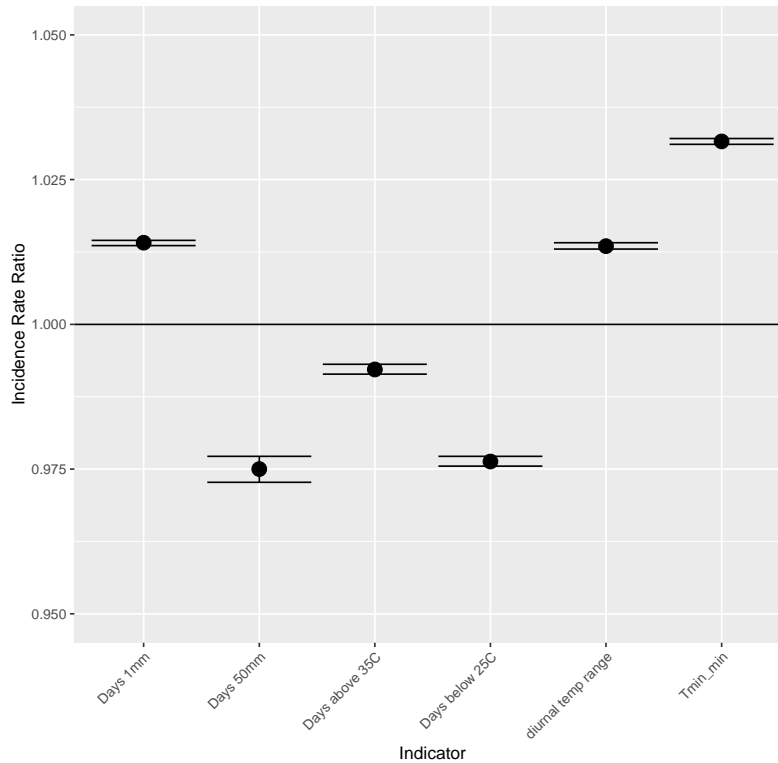


Figure 54. Incidence rate ratio for climate indices in GLMM, 2010–2012



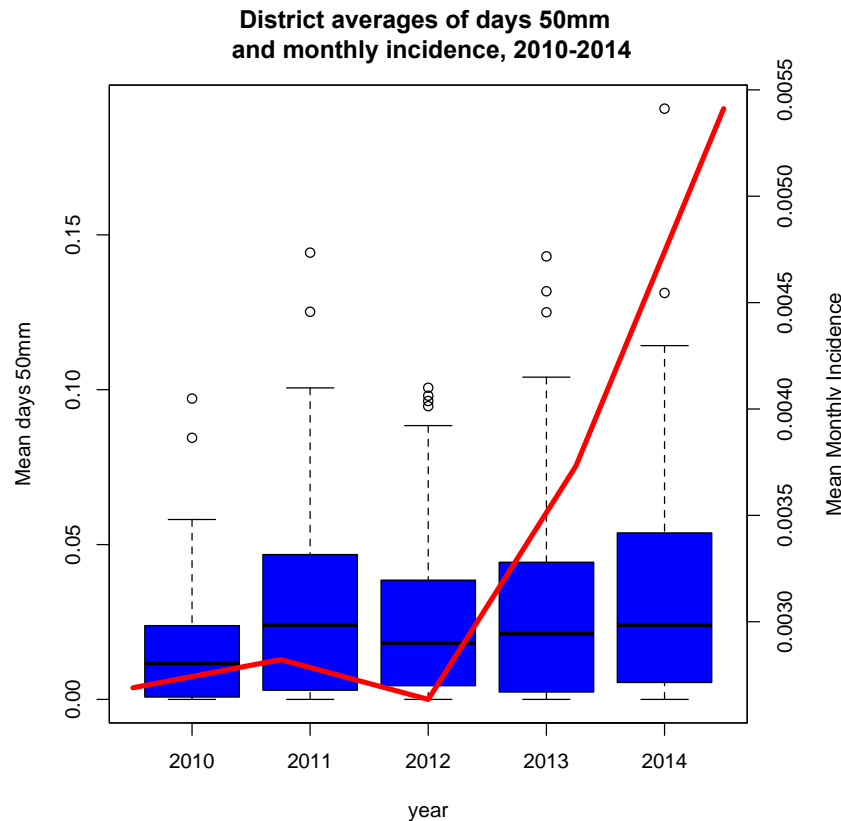
Note: Incidence Rate Ratios depict the incidence of malaria with a one-unit increase in the climate variable compared with the baseline) and the six climate variables most significantly correlated with malaria at the weekly time-scale: days 1mm – the number of days receiving at least 1 mm of rain; days 50mm – the number of days within a week when at least 50 mm of rain was received; days above 35C – the number of days during a given week when temperatures exceeded 35 degrees Celsius; days below 25C – the number of days during a given week when temperatures fell below 25 degrees Celsius; diurnal temperature range – the difference between the daily maximum temperatures and daily minimum temperatures; and Tmin-min – the lowest minimum temperature of the coldest night during the week. Incidence rates above 1.0 suggest a positive correlation between malaria and the variable. For example, as the number of days with rain (number of wet days) and days with at least 50 mm of rain increase, malaria incidence rates increase. The same is true for diurnal temperature range and minimum temperatures. Rates below 1.0 suggest a negative relationship between malaria and the indicator. For example, with increases in the number of days above 35 degrees Celsius (e.g., as hotter temperatures occur) and the number of days below 25 degrees Celsius (as minimum temperatures increase), incidence is reduced.

Figure 55. Incidence rate ratio for climate indices in GLMM, 2013–2014



Note: Incidence Rate Ratios depict the incidence of malaria with a one-unit increase in the climate variable compared with the baseline) and the six climate variables most significantly correlated with malaria at the weekly time-scale: days 1mm – the number of days receiving at least 1 mm of rain; days 50mm – the number of days within a week when at least 50 mm of rain was received; days above 35C – the number of days during a given week when temperatures exceeded 35 degrees Celsius; days below 25C– the number of days during a given week when temperatures fell below 25 degrees Celsius; diurnal temperature range – the difference between the daily maximum temperatures and daily minimum temperatures; and Tmin-min – the lowest minimum temperature of the coldest night during the week. Incidence rates above 1.0 suggest a positive correlation between malaria and the variable. For example, as the number of days with rain (number of wet days) and days with at least 50 mm of rain increase, malaria incidence rates increase. The same is true for diurnal temperature range and minimum temperatures. Rates below 1.0 suggest a negative relationship between malaria and the indicator. For example, with increases in the number of days above 35 degrees Celsius (e.g., as hotter temperatures occur) and the number of days below 25 degrees Celsius (as minimum temperatures increase), incidence is reduced.

Figure 56. Mean days with at least 50 mm rainfall and monthly malaria incidence, 2010–2014



### Incorporation of malaria control programs

Because the full climate model did not fully explain the increase in malaria incidence between 2013 and 2014, coverage of malaria interventions was incorporated into the analysis. To merge climate data with monthly intervention data, monthly averages for all weather indices included in the final model were calculated. For intervention data, an index incorporating coverage of both LLINs and IRS during the period of 2010 to 2014 was calculated. This index had five levels:

- Group 1: no IRS, pre-/no LLIN campaign
- Group 2: 1–2 years IRS, pre-/no LLIN campaign
- Group 3: 3–4 years IRS, pre-/no LLIN campaign
- Group 4: no IRS, post-LLIN campaign
- Group 5: 1–2 years IRS, post-LLIN campaign

As mentioned, IRS coverage has been variable since 2010, with only four districts in Zambezia Province sprayed every year during this time. Large-scale distributions of LLINs began in 2012, resulting in increased coverage beginning in 2013. As with the previous model, a GLMM was run, this time including the intervention index.

Table 21 and Figure 57 show the model results when incorporating intervention coverage. In this model, coverage with LLINs and/or IRS explains more of the variation in malaria incidence

than do the weather variables. Districts in intervention Group 5 (1–2 years of IRS and post-LLIN campaign) had a 36 percent reduction in malaria incidence risk compared with districts with no IRS or LLINs. Taken together, these results show the success of vector control interventions in controlling malaria, even while taking into account variation in weather.

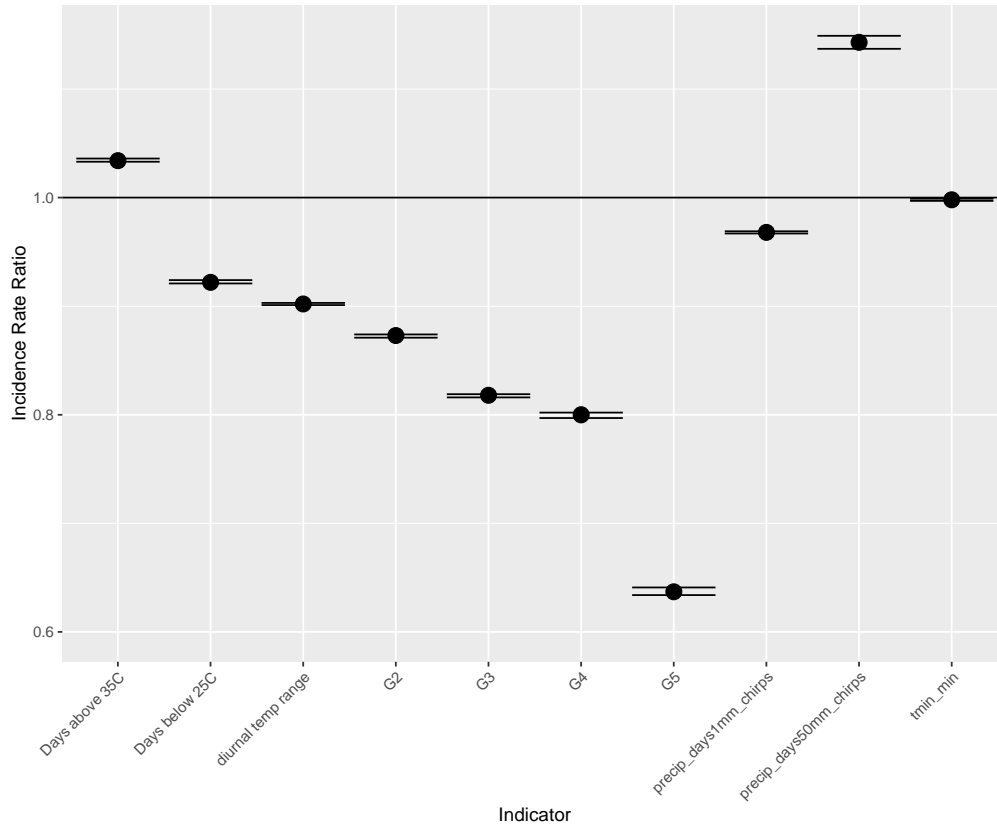
Table 21. Model results (incidence rate ratios) for the joint climate–intervention model

	IRR	CI LL	CI UL	p value
Intercept	0.06	0.06	0.06	<0.001
Sin(month)	1.24	1.24	1.24	<0.001
Cos(month)	0.91	0.91	0.91	<0.001
Tmin_min	1.00	1.00	1.00	<0.001
Precip_days1mm_chirps	0.97	0.97	0.97	<0.001
Precip_days50mm_chirps	1.14	1.14	1.15	<0.001
Days above 35°C	1.03	1.03	1.04	<0.001
Days below 25°C	0.92	0.92	0.92	<0.001
Diurnal temp range	0.90	0.90	0.90	<0.001
Group 2 (ref: Group 1)	0.87	0.87	0.87	<0.001
Group 3 (ref: Group 1)	0.82	0.82	0.82	<0.001
Group 4 (ref: Group 1)	0.80	0.80	0.80	<0.001
Group 5 (ref: Group 1)	0.64	0.63	0.64	<0.001
Year 2011 (ref: 2010)	1.03	1.03	1.03	<0.001
Year 2012 (ref: 2010)	0.99	0.98	0.99	<0.001
Year 2013 (ref: 2010)	1.27	1.27	1.27	<0.001
Year 2014 (ref: 2010)	1.71	1.71	1.72	<0.001
Coastal (ref: South)	0.67	0.67	0.67	<0.001
Central (ref: South)	0.68	0.68	0.68	<0.001
Northern (ref: South)	0.62	0.62	0.62	<0.001

Note: CI—confidence interval; LL—lower limit; UL—upper limit.

All weather indices remained significant at the  $p < 0.001$  level, though a number of the indices did change the direction of their association: a one-day change in days with at least 1 mm rainfall went from leading to a 2 percent increase in malaria incidence to leading to a 3 percent decrease, while a one-day increase in days above 35°C went from leading to a 1 percent decrease in incidence to leading to a 3 percent increase in incidence when intervention coverage was taken into account. Among the weather indices, diurnal temperature range and days with at least 50 mm rainfall had the strongest association with incidence in the intervention model: a 1°C increase in diurnal temperature range led to a 10 percent decrease in malaria incidence, while an increase of one day with at least 50 mm rainfall led to a 14 percent increase.

Figure 57. Incidence rate ratio (IRR) plots for weather and intervention indices  
Climate-Vector Control IRRs

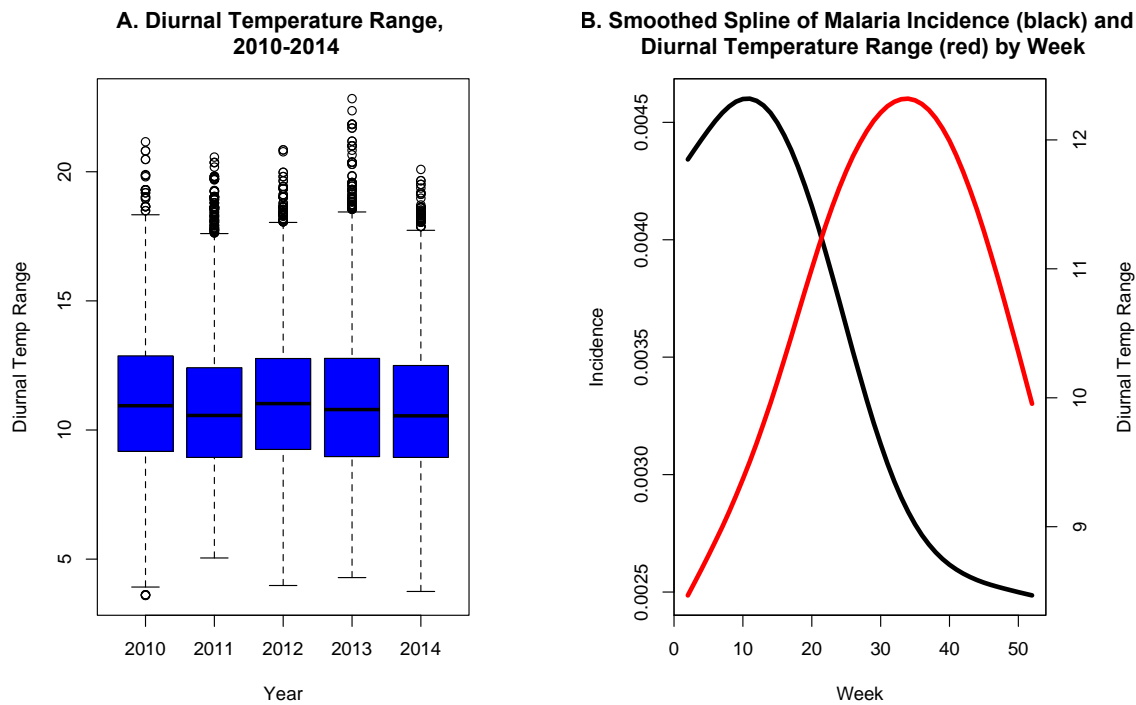


Note: Incidence Rate Ratios depict the incidence of malaria with a one-unit increase in the climate variable compared with the baseline) and the climate and vector control variables most significantly correlated with malaria at the weekly time-scale.

Figure 58 shows the variation in average daily diurnal temperature range by year (a) and by week (b) in comparison to malaria incidence. Although no significant variation is seen in daily diurnal temperature range from 2010 to 2014, a clear negative relationship exists between weekly diurnal temperature range and weekly malaria incidence: diurnal temperature range peaks around weeks 35 to 40, with the lowest values around week 0, in comparison to malaria incidence, which peaks around week 10 and has the lowest values around weeks 45 to 50.

Interestingly, when intervention data were included in the full model, region became a significant predictor of malaria incidence, suggesting an interaction between region and intervention, and consequently that the interventions had differing effects in different parts of the country.

Figure 58. (a) Average daily diurnal temperature range by year; (b) Smoothed weekly malaria incidence (black) and smoothed weekly average daily diurnal temperature range (red)



### Regional analysis of climate and intervention data

To account for the potential interaction between region and vector control intervention, separate models for intervention and weather variables were created for each region. Table 22 shows the results of all four models (northern, central, southern, and coastal) and highlights the variation in the impact of both weather and vector control intervention on malaria incidence across the country. The biggest variation among the weather variables was in days with at least 50 mm rainfall: in the northern region, a one-day increase in days with at least 50 mm rainfall resulted in a 95 percent reduction in malaria incidence, while in the southern region a one-day increase in days with at least 50 mm rainfall led to a 100 percent increase. Similarly, increased vector control had differing impacts in different parts of the country: northern districts in Group 5 had a 59 percent reduction in malaria risk compared with northern districts in Group 1, while southern districts in Group 5 had a 5 percent increase in malaria risk compared with southern districts in Group 1. In other words, based on these results, vector control interventions were more effective in the northern and central regions than in the southern and coastal regions.



Table 22. GLMM (incidence rate ratio) results for region-specific models for both weather and vector control coverage

	Northern IRR CI (LL, UL)	Central IRR CI (LL, UL)	Southern IRR CI (LL, UL)	Coastal IRR CI (LL, UL)
<b>Intercept</b>	0.11 (0.10,0.11)	0.76 (0.73,0.80)	0.04 (0.04,0.05)	0.03 (0.02,0.03)
<b>Sin(month)</b>	1.26 (1.25,1.27)	0.88 (0.87,0.88)	0.93 (0.92,0.94)	1.31 (1.31,1.31)
<b>Cos(month)</b>	1.20 (1.19,1.21)	0.70 (0.70,0.71)	0.59 (0.58,0.59)	0.93 (0.93,0.93)
<b>Tmin_min</b>	0.89 (0.89,0.90)	0.96 (0.96,0.96)	1.02 (1.02,1.03)	1.01 (1.01,1.01)
<b>Precip_days1mm_chirps</b>	1.07 (1.06,1.07)	1.07 (1.07,1.07)	1.10 (1.10,1.11)	0.90 (0.90,0.90)
<b>Precip_days50mm_chirps</b>	0.05 (0.05,0.06)	1.87 (1.84,1.89)	2.00 (1.96,2.04)	1.11 (1.10,1.12)
<b>Days above 35°C</b>	0.87 (0.86,0.87)	0.96 (0.96,0.96)	0.89 (0.89,0.90)	1.04 (1.04,1.04)
<b>Days below 25°C</b>	0.93 (0.93,0.93)	1.00 (1.00,1.00)	1.02 (1.01,1.02)	0.93 (0.92,0.93)
<b>Diurnal temp range</b>	0.98 (0.98,0.99)	0.74 (0.73,0.74)	0.85 (0.85,0.85)	0.93 (0.93,0.93)
<b>G2</b>	0.75 (0.75,0.76)	0.61 (0.61,0.62)	1.35 (1.34,1.35)	0.90 (0.90,0.90)
<b>G3</b>	0.98 (0.97,0.99)	0.88 (0.88,0.89)	1.26 (1.25,1.26)	0.73 (0.73,0.73)
<b>G4</b>	0.99 (0.98,0.99)	0.97 (0.96,0.98)	1.61 (1.59,1.63)	0.69 (0.69,0.70)
<b>G5</b>	0.41 (0.40,0.41)	0.42 (0.41,0.43)	1.05 (1.04,1.07)	0.60 (0.60,0.61)
<b>Year 2011</b>	0.91 (0.91,0.92)	0.90 (0.90,0.91)	1.32 (1.30,1.33)	1.07 (1.07,1.07)
<b>Year 2012</b>	0.80 (0.80,0.81)	0.87 (0.87,0.88)	1.11 (1.10,1.12)	1.09 (1.08,1.09)
<b>Year 2013</b>	1.08 (1.07,1.09)	1.03 (1.02,1.03)	1.80 (1.79,1.82)	1.37 (1.37,1.38)
<b>Year 2014</b>	1.35 (1.34,1.36)	1.41 (1.41,1.42)	2.14 (2.13,2.16)	1.84 (1.84,1.85)

Note: CI – confidence interval; LL – lower limit; UL – upper limit.

## Discussion

Taking the results of all models together, climate clearly had an impact on malaria incidence in Mozambique between 2010 and 2014. When considering the results of the model including only the weather variables, days below 25°C was the most significant predictor of malaria incidence. Although this indicator remained a strong predictor of incidence when the periods of 2010 to 2012 and 2013 to 2014 were considered separately, days with at least 50 mm rainfall became the most significant predictor of incidence in these two models. However, days with at least 50 mm rainfall was positively associated with incidence from 2010 to 2012, then negatively associated with incidence in 2013 to 2014. Interpretation of these differing relationships is difficult, although a clear and significant increase occurs in the average number of days with at least 50 mm rainfall during the two time periods. It is possible that the positive association from 2010 to 2012 was the result of more rainfall leading to more breeding sites for the vector, and the negative association the result of too much rainfall leading to breeding sites being washed out. This is backed up by the significant increase in days with at least 50 mm rainfall and total rainfall during the study period.

Incorporation of malaria vector control coverage helped explain some of the remaining variation in malaria incidence seen when weather variables were considered alone, though the fact that most districts only received LLINs and/or IRS beginning in 2013 complicated the ability to discern statistically significant relationships. When considered together with weather variables, coverage with LLINs and at least one year of IRS appeared to protect against malaria incidence,

though this relationship was not significant due to reasons discussed earlier. Coverage with LLINs alone appeared to be positively associated with malaria incidence, though more data that would allow a better comparison of incidence before and after introduction of LLINs would likely change the outcome.

Weather variables were also significant predictors of incidence when vector control intervention coverage was included in the model. In particular, days with at least 50 mm rainfall was a strong predictor of malaria incidence: more days with at least 50 mm rainfall led to a lower malarial incidence. If these rainfall events are significant enough, they can also result in flooding that displaces people and communities, which could prevent people sick with malaria from seeking care at health facilities, thus resulting in an artificial decrease in malaria cases.

The region-specific models incorporating both weather and vector control coverage suggest that deviation from the normal climate could play an important role in malaria incidence. For example, average rainfall is highest in the northern region, resulting in more permanent, year-round breeding sites. The southern region is significantly drier than the northern region, and receives the lowest average rainfall of all regions in the country. Permanent year-round breeding sites are less common and extreme rainfall events are more likely to lead to the creation of new breeding sites rather than eliminating existing ones; consequently, the observed increase in malaria incidence.

## **MALARIA UNDER A CHANGING CLIMATE**

To help identify areas and populations potentially at risk for future increased malaria transmission due to climate change, 11 climate models (as discussed in Section II of this report) were considered to get estimates of key climate indices in Mozambique in 2030. For each model, the estimated weekly change in 2030 was calculated for each index, and the median value for all indices was then used to determine the expected percent change from the 1979–2014 average (Table 23). Of note: the climate variable most consistently associated with malaria transmission (days with at least 50 mm rainfall) is not expected to change much in most of the country. The exception is in the southern region, where a nearly 300 percent decrease in the number of days with at least 50 mm rainfall in a given week is expected by 2030.

These predicted changes in rainfall are all expected to have a moderately negative impact on malaria transmission; that is, based on projected changes in this one variable, less malaria transmission is expected throughout the country, with the possibility of a significant decrease in the southern region. Conversely, the climate variables expected to change most significantly by 2030 (days above 35°C and below 25°C) were not strongly associated with malaria transmission.

Nonetheless, the projected changes in these variables would be expected to have a balancing effect on malaria transmission, meaning that a significant change in transmission would not be expected.

The impact of vector control interventions on future malaria transmission patterns is more difficult to discern because of the unclear impact of intervention coverage on malaria incidence during 2010–2014, as well as the uncertainty around future coverage of these interventions. Based on Mozambique’s Integrated Vector Control Strategy, it is safe to assume that the entire country will have universal coverage of LLINs, and IRS will be used in combination with LLINs in selected areas. Based on this, it is reasonable to expect at least a moderate impact of vector control interventions on malaria transmission, which would lend further support to the idea of a general future decrease in malaria transmission.

Table 23. Projected weekly changes in climate indices by 2030

Region	Tmin_min	Days 1mm precip	Days 50mm precip	Days above 35C	Days below 25C	Diurnal temp range
Northern	2.07 (12%)	-0.17 (-10%)	0.002 (17%)	43.68 (132%)	-14.81 (-125%)	0.08 (1%)
Central	2.42 (15%)	-0.16 (-12%)	-0.005 (-21%)	55.05 (105%)	-23.52 (-80%)	0.20 (2%)
Southern	2.08 (14%)	-0.08 (-10%)	-0.055 (-284%)	59.98 (126%)	-18.55 (-41%)	0.11 (1%)
Coastal	1.98 (11%)	-0.12 (-11%)	0.020 (53%)	48.05 (150%)	-16.26 (-73%)	0.13 (1%)

Note: Projected average weekly changes (and percent change from 1979–2014 average) in key climate indices by 2030 (median of 11 climate models).

## DISCUSSION

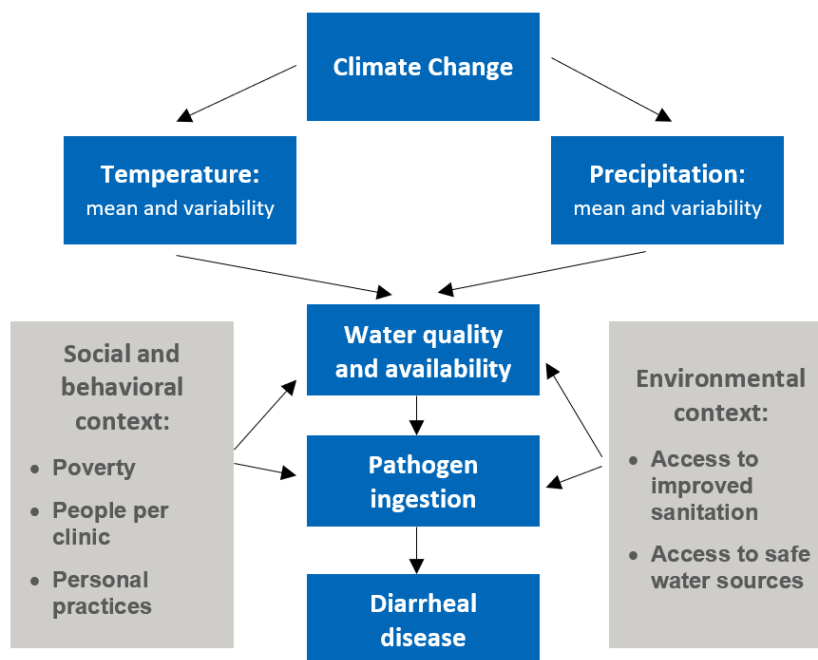
### OVERVIEW

The pathways between weather, climate variability, and climate change and health outcomes are often complex and indirect, making attribution challenging. Climate change may not be the most important driver of climate-sensitive health outcomes over the next few decades, but it could be significant past midcentury. It is a stress multiplier, putting pressure on vulnerable systems, populations, and regions. The following discussion offers insights into the changing dynamics of diarrheal disease and malaria under projected changes in climate.

### DIARRHEAL DISEASE

Climate change will continue to increase maximum temperatures and heavy rainfall events, suggesting that Mozambique can expect to see additional cases of diarrheal disease if no additional interventions are implemented (Figure 59). The magnitude and pattern of future burdens of diarrheal disease will depend on the magnitude and patterns of changes in weather and climate in the four regions of Mozambique.

Figure 59. Overview of the pathways between climate change and the burden of diarrheal disease in Mozambique



The large range and uncertainty in climate projections for Mozambique offer several potential evolutions to the changing dynamic of diarrheal disease. Given an increase in heavy rainfall events, as suggested for the northern and central regions, cases of diarrheal disease are also likely to increase. However, projections for the coastal and southern regions tend to oscillate around a central value that suggests little change in annual rainfall, leading to a constant or potential decline in diarrheal disease incidence for these regions. Nevertheless, future disease burden will also depend on the rate of population increase, the effectiveness of efforts to increase access to safe water and improved sanitation, and other interventions to prevent contamination of food and water with disease-causing pathogens. Existing uncertainty and the potential interactions between weather variables preclude examination of the combined effects of multiple weather drivers on diarrheal disease.

Overall, maximum temperature and the number of wet days in a week are associated with outbreaks of diarrheal disease in Mozambique. Significant associations exist in all regions for temperature and for rainfall. With climate change increasing temperatures and changing the hydrological cycle, the burden of diarrheal disease in Mozambique is expected to increase without additional health system interventions.

In the northern, central, and southern regions, one additional wet day in a week increased the incidence of diarrheal disease by 1.86 percent, 1.37 percent, and 2.09 percent, respectively. These numbers, while fairly small, are statistically significant and represent a burden on health systems to treat these additional cases. In the northern, central, coastal, and southern regions, an increase in the maximum temperature increased the incidence of diarrheal disease by 1.45 percent, 1.87 percent, 5.74 percent, and 2.15 percent, respectively. Together, these analyses

suggest that without implementing additional interventions, the number of cases of diarrheal disease is expected to increase over coming decades (Table 24).

These additional cases of diarrheal disease are potentially preventable using the increasing skill in forecasting temperature and rainfall over seasonal timescales. Having advance warning (e.g., an early warning and response system) that temperatures are expected to be higher or that a week is expected to be wetter than normal would provide valuable time to put interventions in place, such as increasing access to oral rehydration in health care centers and increasing education on appropriate use and handling of water (such as boiling drinking water) and sanitation practices that can reduce transmission of diarrheal pathogens. Developing and deploying such an early warning system would increase population resilience to outbreaks of diarrheal disease over coming decades.

Climate projections are consistent that maximum and minimum temperatures will increase across this century. The projected changes in rainfall are less consistent, with many models suggesting that intense rainfall days could decrease by midcentury and other models suggesting the opposite. If heavy rainfall declines, then rainfall would become a less important driver of the magnitude and pattern of diarrheal diseases in Mozambique. At the same time, temperature could become more important over this century without increased access to safe water and improved sanitation, and other interventions to reduce fecal–oral transmission of diarrheal disease pathogens.

Table 24. Estimated percent change in diarrheal disease using historical data and projections

	Historical Association		Projected Change <sup>∞</sup>	
	One additional wet day*	One-degree C increase in maximum temperature**	During 3 wettest months	One-degree C increase in minimum temperatures
<b>National</b>	1.04	3.64	--	--
<b>Northern</b>	1.86	1.45	-0.61	3.27
<b>Central</b>	1.37	1.87	-0.41	2.37
<b>Coastal</b>	0.63	5.74	-0.18	1.84
<b>Southern</b>	2.09	2.15	-0.31	--

Note: \* 4-week lag, \*\* concurrent week, <sup>∞</sup> using the mean of climate change projections

Better understanding is needed of the pathogens associated with outbreaks of diarrheal disease in Mozambique so that interventions can be most effectively targeted. Large numbers of pathogens can cause diarrheal disease, and not all are associated with temperature and rainfall. For those pathogens affected by weather variables, the specific association varies by pathogen. For example, two reviews of African rotavirus trends found seasonal peaks during the dry season (Cunliffe et al., 1998; Waggie et al., 2010). In contrast, several Africa-based studies found cryptosporidium peaks during the rainy season (Siwila et al., 2011; Tellevik et al., 2015). Knowing which pathogens are associated with outbreaks of diarrheal disease in particular time periods in Mozambique would identify more specific associations between weather variables

and pathogens. This would lead to more precise estimates of the impacts of climate variability and climate change that could be used to increase the effectiveness of prevention programs.

## **MALARIA**

The relationship between climate and malaria in Mozambique is too complex to provide detailed predictions. Taken together, the results suggest that excess rainfall has decreased malaria incidence, though this relationship varies by region of the country. In general, it appears that a more variable climate over the past several years in part led to the observed increase in reported malaria cases. More vector control coverage also appears to be associated with a decrease in malaria incidence, though there was not enough data to show a significant relationship with the decrease in incidence. Finally, key climate indices that had strong associations with malaria incidence are expected to change significantly over the next decades, meaning that the malaria profile will also likely change.



# III. USING WEATHER AND CLIMATE INFORMATION TO IMPROVE HEALTH SYSTEM RESILIENCE

## KEY MESSAGES

Reducing and managing the magnitude and pattern of health risks will require modifying current policies and programs and implementing new ones to explicitly consider climate variability and change.

Adaptation actions should focus on building more resilient health systems, reducing overall vulnerability, and developing specific system capacities by investing in several entry points, including: 1) information systems, 2) leadership and governance foundations, and 3) risk management.

The projected additional cases of diarrheal disease and potential increase in malaria risks in higher-elevation areas are potentially preventable using seasonal weather forecasts and targeted responses. For example, creating an early warning and response system that enables advance warning when temperatures are expected to be higher or when weeks are expected to be wetter than normal would provide valuable time for decision makers to put interventions in place. Developing and deploying such an early warning system would increase population resilience to outbreaks of disease over the coming decades.

Examples of specific interventions include:

- *Diarrheal disease*—modify supply chain flows to guarantee timely delivery of critical oral rehydration stocks to local health care centers; and, as described above, increase education on appropriate use and handling of water (such as boiling drinking water) and sanitation practices that can reduce transmission of diarrheal pathogens.
- *Malaria*—improve disease surveillance throughout the entire country, implement a system to detect unexpected rises in cases, and build awareness of the population and health workers in areas prone to outbreaks and where transmission is expected to be more variable due to climate change.

## THE IMPORTANCE OF CONTINUED INVESTMENT IN MALARIA

Malaria risk in particular is expected to increase throughout the country as a result of climate change, though the complicated relationship between climate and malaria makes it difficult to predict exactly how significant and where those changes will be. The expected increase in climate variability will also result in more variability and unpredictability in malaria transmission. This has the potential to affect the acquisition of disease immunity, resulting in outbreaks with more severe disease and more deaths. There is, therefore, an impetus to ensure that surveillance systems are in place to forecast the likelihood of outbreaks before they occur, if possible, and to respond to them before they become widespread. In a larger context, climate variability reaffirms the need to continue to invest in elimination and control efforts in Mozambique, because these will likely become more challenging due to the expected changes in climate.

## NATIONAL RESPONSE

As previously noted, current challenges to development mean that Mozambique has high vulnerability to climate variability and climate change, including high levels of poverty, high infant and maternal mortality, high burdens of undernutrition, malaria, and diarrheal disease, low expenditure on health systems, and very low levels of education. Climate change is projected to make these conditions more common as temperatures rise and rainfall becomes more variable, with resulting declines in soil moisture. The USAID Feed the Future program is targeting investments in Nacala, Nampula, and Zambezia Provinces to increase the low levels of production and lack of dietary diversity that result in some of the highest rates of child stunting in the world. Because undernutrition, diarrheal disease, and malaria interact, aligning climate change adaptation pilot projects with these investments could increase resilience in vulnerable individuals, particularly children and women.

Mozambique's climate change action is guided by the country's National Climate Change Adaptation and Mitigation Strategy (ENAMMC) and the Action Plan for Poverty Reduction (PARPA). These documents outline strategic priorities and specifically mention health risks and the importance of early warning, as well as strengthening the capacity to prevent and control the spread of vector-borne diseases. Tackling the challenges of understanding and responding to climate risks in the health sector means working across disciplines and organizations. Collaboration between government ministries that track key population vulnerability indicators, health, weather, and other environmental variables is essential. Furthermore, these ministries need to continue to build partnerships with organizations outside the Government of Mozambique that work on health and climate issues.

This close collaboration is at the heart of Mozambique's climate and health observatory, established under the auspices of the INS in 2016 with the goal of providing information to aid decision making around health issues. The observatory is Mozambique's first community of practice for health professionals and reflects the importance of cross-agency and cross-departmental work and the need for evidence-based policy and decision making. By working together with other agencies, it takes advantage of existing academic and state-based public health investments.

The Government of Mozambique has demonstrated a strong commitment to addressing the needs of its population and achieving the Sustainable Development Goals (SDGs). The PARPA 2011–2014 aims at pursuing inclusive economic growth and reducing poverty and vulnerability by focusing on three general objectives: increased production and productivity in the agriculture and fisheries sectors, employment creation, and human and social development. Good governance, macroeconomics, and sound public financial management are the supporting pillars for achievement of these objectives.

Many of the identified strategies are highly relevant to reducing current vulnerability and to increasing resilience to future health risks. Explicitly including climate variability and climate change into the next Poverty Reduction Strategy Paper (PRSP, or PARPA in Portuguese) would help protect population health as the climate changes. The goal should be to ensure that policy and program choices made today will be robust in a future climate.

#### **A CLIMATE AND HEALTH OBSERVATORY FOR MOZAMBIQUE**

Fluctuations in climate lead to extremes in temperature, rainfall, flooding, and droughts. These climate extremes create ideal ecological conditions for the promotion of disease transmission. Tackling the challenges of understanding and responding to climate risks in the health sector means working across disciplines and actors: implicitly forging collaboration between governmental ministries that track key population vulnerability indicators, health, weather, and other environmental variables and building partnerships with external bodies working on health issues.

This close collaboration is at the heart of Mozambique's Public Health Observatory, established in 2016 with the explicit goal of providing information to aid decision making around health issues. To do this, the observatory assembles, analyses, reviews, and synthesizes all available data (e.g., meteorological, demographic, nutritional, and health) for the country. Combining this information, the observatory seeks to understand the relationship between disease and global environmental change with the aim of using this knowledge to provide warnings with sufficient lead time to reduce the possibility of an outbreak.

The observatory is Mozambique's first community of practice for health professionals and reflects the importance of cross-agency and cross-departmental work and the need for evidence-based policy and decision making. By working together with other agencies, it takes advantage of existing academic and state-based public health expertise to provide relevant and up-to-date information for those who require it.

#### **Key areas of focus include:**

- Building the awareness of the public and policy makers of the risks posed by climate variability and change.
- Understanding and communicating past trends in climate and short-term forecasts to health care professionals.
- Exploring methods and tools to support the incorporation of climate information into health planning, with a focus on working with information that is already available (short-term), and an additional focus on using long-term climate change projections.

## RECOMMENDATIONS

Reducing health risks will require modifying current policies and programs and implementing new ones to explicitly consider climate variability and climate change. Adaptation actions should focus on building more resilient health systems, reducing overall vulnerability, and developing specific system capacities by investing in several entry points, including: 1) information systems, 2) leadership and governance foundations, and 3) risk management. Specific actions that align with Mozambique's 2014–2019 Health Sector Strategic Plan, which prioritizes primary health care, equity, and better quality of services, are detailed below.

### INFORMATION SYSTEMS

Improved analysis can inform the extent to which a specific option is likely to be needed and where and when implementation would be more effective. Because there are drivers other than weather and climate for these health outcomes, such as the status and quality of infrastructure and irrigation schemes, developing additional research and analyses in collaboration with other sectors could provide critical information and perspectives. The factors that these sectors are monitoring could be relevant to climate change and useful to monitor and evaluate. Examples of adaptation strategies are presented in Table 25. Specific actions are to:

- *Support research.* Mozambique will be better prepared to aid its citizens through improved understanding of past trends and future projections of climate and their relationship to health outcomes. The analysis presented here is one of a handful of studies available on the relationship between climate change and variability and disease incidence for Mozambique. More research is needed to understand the climate–disease relationship and to identify practices that will more effectively manage risk as the climate changes. Building on the results of this study, for example, a statistical evaluation of the relationship between ENSO events and disease outbreak could help to define thresholds of risk based on changing sea surface temperatures, informing the design of early warning systems, particularly in the southern region. Additionally, exploring the associations between weather and vector-borne diseases such as dengue could offer insights on improved diagnosis and response, particularly in the coastal region.
- *Improve epidemic detection and response.* Exploring technological options for improving health data collection, such as SMS-based forms sent directly by health post workers, could facilitate the timely flow of information and responses. Such systems could improve early warning by detecting changes in disease incidence more quickly and in time for people to respond promptly to an outbreak. This information would be useful in regions where mosquitos could not previously survive, such as in the higher-elevation areas of northern Tete and western Niassa Provinces near the border with Malawi.
- *Deploy early warning systems.* Having advance (early) warning that temperatures are expected to be higher or that a week is expected to be wetter than normal, and therefore that incidence rates may increase, as noted above, would provide valuable time to put interventions in place. Information on sea surface temperatures indicative of ENSO events, available four to six months in advance, could offer a window of opportunity for response efforts, particularly in areas where research indicates a strong association between events and disease outbreaks.
- *Build awareness.* Communicate to the public and policy makers the risks of climate variability and climate change, as well as options for disease control, prevention, and treatment.

Table 25. Examples of health adaptation options related to science and analysis

Adaptation strategy	Vector-borne disease	Water- / foodborne disease	Undernutrition
<b>Prevention</b>	<ul style="list-style-type: none"> <li>Expand the scope of diseases monitored, and monitor at the margins of current geographic distributions of disease</li> <li>Establish early warning systems when data are sufficient and a robust enough association exists between environmental variables and health outcomes</li> <li>Increase use of insecticide-treated bed nets</li> </ul>	<ul style="list-style-type: none"> <li>Expand the scope of diseases monitored, and monitor at the margins of current geographic distributions</li> <li>Expand access to safe water and improved sanitation</li> <li>Supplement with vitamin A where needed</li> <li>Strengthen food and water quality control</li> </ul>	<ul style="list-style-type: none"> <li>Perform seasonal nutritional screening in high-risk communities</li> <li>Scale up integrated food security, nutrition, and health programming in fragile zones</li> <li>Increase dietary diversity and access to micronutrients</li> </ul>
<b>Control</b>	<ul style="list-style-type: none"> <li>Enhance disease surveillance systems during high-risk seasons/periods</li> <li>Increase use of larvicidal and insecticidal spraying</li> </ul>	<ul style="list-style-type: none"> <li>Enhance disease surveillance systems during high-risk seasons/periods</li> <li>Improve infection control procedures to prevent spread of illness</li> </ul>	<ul style="list-style-type: none"> <li>Enhance surveillance during high-risk seasons/periods</li> </ul>
<b>Treatment</b>	<ul style="list-style-type: none"> <li>Enhance diagnostic and treatment options in high-risk regions/periods</li> <li>Increase access to health facilities and use of appropriate drugs</li> </ul>	<ul style="list-style-type: none"> <li>Enhance diagnostic and treatment options in high-risk regions/periods</li> <li>Increase access to health facilities and use of oral hydration and appropriate drugs</li> </ul>	<ul style="list-style-type: none"> <li>Enhance diagnostic and treatment options in high-risk regions/periods</li> <li>Increase access to health facilities</li> </ul>
<b>Public education</b>	<ul style="list-style-type: none"> <li>Promote public health awareness on climate change impacts, disease control, prevention, and treatment</li> </ul>	<ul style="list-style-type: none"> <li>Promote public health awareness on climate change impacts, sanitation and hygiene, and treatment</li> </ul>	<ul style="list-style-type: none"> <li>Promote public health awareness on climate change impacts, undernutrition, prevention, and treatment</li> </ul>
<b>Capacity</b>	<ul style="list-style-type: none"> <li>Improve health care facilities, staffing</li> </ul>	<ul style="list-style-type: none"> <li>Improve health care facilities, staffing</li> </ul>	<ul style="list-style-type: none"> <li>Improve health care facilities, staffing</li> </ul>
<b>Knowledge generation</b>	<ul style="list-style-type: none"> <li>Estimate relationships between weather/climate variables and health outcomes</li> <li>Project health risks over the next few decades, taking into consideration climate and development</li> <li>Enhance surveillance of Anopheles and Aedes sp. mosquitoes</li> <li>Enhance integrated surveillance of malaria<sup>5</sup></li> </ul>	<ul style="list-style-type: none"> <li>Estimate relationships between weather/climate variables and health outcomes</li> <li>Project health risks over the next few decades, taking into consideration climate and development</li> <li>Enhance integrated surveillance of water- and foodborne diseases</li> </ul>	<ul style="list-style-type: none"> <li>Estimate relationships between weather/climate variables and undernutrition</li> <li>Project health risks over the next few decades, taking into consideration climate and development</li> <li>Enhance integrated surveillance of undernutrition, including stunting and wasting</li> </ul>

## LEADERSHIP AND GOVERNANCE FOUNDATIONS

The health risks posed by climate variability and climate change will require leadership and strategic planning that can articulate and operationalize coordinated responses across various ministries and sectors. Since climate change is a relatively new issue, current policies and programs have probably been developed without consideration of the effect of climate change on the magnitude and pattern of health outcomes. Efforts are underway in many countries to implement policies and programs to prepare for, cope with, respond to, and recover from the hazards associated with a changing climate (see box). Doing so would reduce the current burdens of climate-sensitive health outcomes, such as malaria and diarrheal disease, by adding new dimensions to control programs. Many opportunities exist for improving understanding of current and future climate-related risks and for managing those risks by piloting and testing programs and scaling up best practices. Climate-sensitive health policies and programs should take into account that the health risks of climate change are a function of:

- Hazards such as changing rainfall patterns and increases in the frequency, intensity, and duration of heat events;
- The populations exposed to those hazards; and
- The vulnerability of exposed populations.<sup>6</sup>

### POTENTIAL COLLABORATION WITH ONGOING ACTIVITIES

- The Famine Early Warning Systems Network (FEWS NET) offers best practices for developing, implementing, monitoring, and evaluating early warning systems that could be helpful for health-related systems (<http://www.fews.net/>).
- A consortium of international organizations and bilateral development partners launched Climate Risk & Early Warning Systems (CREWS) in December 2015. The goal is to increase the capacity for multihazard early warning systems to generate and communicate early warnings and risk information for hazardous hydro-meteorological and climate events in least-developed countries and small island developing states. It may be possible to develop pilot projects in collaboration with CREWS that focus on health ([http://www.diplomatie.gouv.fr/en/IMG/pdf/crews-flyer\\_eng\\_cle0fa357.pdf](http://www.diplomatie.gouv.fr/en/IMG/pdf/crews-flyer_eng_cle0fa357.pdf)).

Recommendations to support leadership and governance mechanisms are listed below.

- *Enhance cross-sectoral governance and collaboration.* Negotiate sharing agreements that could contribute to improved epidemic detection systems and ultimately support the development of early warning systems. Disease surveillance systems could benefit from being coupled with climate and weather information to build the evidence base on links between disease and climate.
- *Develop capacity within the health system.* Mozambique's doctor-patient ratio is among the lowest in the world, and climate variability and climate change may increase local demand for services. The country already faces chronic shortages of skilled staff and low productivity stemming from poor working conditions. Health workers work long

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<sup>5</sup> Per the WHO: "Surveillance can be defined as 'ongoing systematic collection, collation, analysis and interpretation of data and the dissemination of information to those who need to know in order that action may be taken' – Information for Action." Source: <http://www.who.int/countries/eth/areas/surveillance/en/>

<sup>6</sup> Vulnerability is determined by individual physiological factors, demographic structure, and other factors, and, as noted above, the ability of individuals and institutions to prepare for, cope with, respond to, and recover from the exposure



hours, and may also be required to conduct additional support activities beyond caring for patients. Systems for tracking, motivating, and retaining staff need strengthening. While health workers may recognize that climate extremes such as droughts and floods impact health, they often have limited access to climate information that would modify their treatment and diagnosis plans. Important areas of investment in capacity development include:

- Training professional staff on the health risks posed by climate change.
- Training professional staff to differentially diagnose diseases based on early warning signs (using climate information) of health risks.
- Building capacity to incorporate climate information into decision making. Beyond the development of the country's health information system, the ability to use data for decision making needs to be improved. The health information system and its subsystems need to produce comprehensive, timely, and accurate data for policy makers. During decision making, reforms and improvements should consider the use of weather and climate information and decentralization of health service delivery.

## RISK MANAGEMENT

Risk management generally involves a portfolio of actions to reduce and transfer risk and to respond to events, as opposed to a singular focus on any one action or type of action. In Mozambique, this will require investments that:

- *Advance integrated risk monitoring.* Surveillance systems are crucial for disease control programs. The country's health information system tracks weekly and monthly reports of disease incidence, but faces recording challenges that result in important health information gaps, including improper diagnoses and reporting inconsistencies. The system initially collects data using paper-based methods and does not report in real time, which means that delays across the information chain at the national level, including in analysis and feedback, can limit monitoring and response options.
- *Promote climate-smart health programming.* Policy makers should ensure that the information available on climate and disease impacts is used in the planning of resources and supply chain management.
- *Strengthen public health services and facilities.* Most health care facilities operate off-grid and require alternate fuel supplies to support lighting, refrigeration, and sterilization, and they must collect medical commodities from district depots if supplies are unreliable. Furthermore, many of these facilities are located long distances from district storage facilities and are only accessible via unpaved roads that are challenging to travel on, especially during the rainy season.
- *Support emergency preparedness and management.* Establishing contingency plans to deploy surge support, both for staff and supplies, to areas where disease risks may rise in light of forecasts, could make supply chains more resilient to shocks.

Carrying out these recommendations can reduce current vulnerability to weather and climate variability and help to manage future health risks from climate change. Policy and program choices made today will enable resilience in a future climate.

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