TECHNICAL REPORT

THE INFLUENCE OF CLIMATE ON MALARIA INCIDENCE IN MALAWI

A RETROSPECTIVE ANALYSIS

February 2020

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Cover Photo: Chisomo Mdalla. June 2017. A young boy in Lilongwe shows off malaria medicine received through the U.S. Presidents Malaria Initiative.

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United States Agency for International Development

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ACRONYMS

CI	Confidence interval
CMIP5	Coupled Model Intercomparison Project Phase 5
DCCMS	Department of Climate Change and Meteorological Services
IRR	Incidence rate ratio
ITN	Insecticide treated net
NMCP	National Malaria Control Programme
RCP	Representative Concentration Pathway
WFDEI	Watch Forcing Data ERA - Interim

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EXECUTIVE SUMMARY

This report outlines the results of a study comparing historical rainfall and temperature data with malaria incidence. and explores the future risks from a warming climate for malaria burdens in Malawi. The study provides country-specific insights that contribute to the growing knowledge base of causal links between weather, climate, and malaria in sub-Saharan Africa.

Malaria control is a long-standing governmental priority, and vector control has been a cornerstone of the government's efforts. Within the Health Sector Strategic Plan II (2017-2022), the country's fourth strategic plan for malaria, Malaria Strategic Plan (MSP) 2017-2022, aims to reduce malaria incidence by at least 50 percent from a 2015 baseline of 386 per 1,000 population to 193 per 1,000, and malaria deaths by at least 50 percent from 23 per 100,000 population to 12 per 100,000 population by 2022. Understanding how, when, and under what circumstances climate variability and change impact health outcomes could offer insights on how to achieve these goals under a changing climate.

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 Malawi. Malawi's 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 the nature or distribution of these impacts. Improved knowledge of current associations between malaria, weather, and climate is needed to formulate evidence-based policies and programs. At the same time, there is an increasing call for the establishment of early warning systems informed by in-country research findings. This presents an opportunity to improve the health of Malawi's communities by better understanding the role that weather and climate play in health, particularly for infectious diseases like malaria.

OBJECTIVE OF THE STUDY

The principal objective of this work is to build a scientific knowledge base to support informed decision-making and investments in the malaria elimination efforts in Malawi. The findings will help to shape the Ministry of Health's (MoH) preparedness and response to emerging climate risks. To achieve this objective, the relationship between climate and malaria was examined using current weather, climate, and health data.

STUDY METHODOLOGY

For this study, two separate, related analyses were conducted. A statistical analysis of climate and malaria was conducted at the regional scale, dividing the country intofive geographic regions with similar climate parameters including:

- **Central East** (Region) – Dowa, Kasungu, Nkhotakota, Ntchisi, Salima (Districts)
- **Central West** – Dedza, Lilongwe, Mchinij, Ntcheu (Districts)

- **North** – Chitipa, Karonga, Likoma, Mzimba, Nkhala Bay, Rumphi (Districts)
- **South East** – Balaka, Blantyre, Machinga, Mangochi, Mulanje, Phalombe, Zomba (Districts)
- **South West** – Chikwana, Chiradzulu, Mwanza, Neno, Nsanje, Thyolo (Districts)

Historical weather data (temperature and rainfall), matched with malaria incidence data, were analyzed to correlate weather and malaria incidence for each region. A separate climate analysis was conducted for Malawi's three climatic zones, examining both historical weather data and using downscaled climate projection data to predict future malaria incidence. Together, these analyses provide the basis for the study insights and recommendations.

WEATHER AND CLIMATE VARIABILITY IN MALAWI

Analysis of climate trends allows us to 1) understand that historical climate variability and change may have contributed to malaria incidence, and 2) past trends may reveal a climate change "fingerprint," allowing us to better predict malaria incidence in the future.

Current daily rainfall and temperature data were sourced from WATCH Forcing Data ERA Interim (WFDEI), which is the only dataset that provides both precipitation and temperature at a daily scale over the southern African region. Additionally, the WFDEI provides a long and relatively up-to-date record and their ability to capture reality on the ground (skill of the variables) are consistent both through space and time which makes it suitable for trend analysis at the regional level.

The following key messages on rainfall and temperature from these data are summarized in Table ES1.

Table ES1: Climate trends in Malawi with respect to temperature and rainfall

OBSERVED CLIMATE TRENDS	
Parameter	**Observed climate trends**
Temperature	• Mean, maximum, and minimum temperatures all rose between1979 and 2016, by approximately 0.53 to 0.60°C. • Trends in daily maximum and minimum temperatures are similar to daily mean temperature in terms of trend and magnitude of change, pointing to an increase of 0.16 to 0.17°C per decade across all regions. • Higher elevation areas of Northern Malawi may become marginally or moderately suitable for malaria because of increasing temperatures, where temperatures may have been too cool several decades ago.
Rainfall	• While there appear to be reductions in annual rainfall totals, these were not statistically significant results. • While the number of rain days per year appears to be increasing, these were not statistically significant results. • The country receives ample rainfall, so it is unlikely that malaria is moisture-constrained in Malawi and, therefore, historical rainfall trends or variability would not be strong drivers of observed changes in malaria prevalence. However, seasonality of malaria may change in drier areas alongside changes in weather patterns. • The large interannual variability shows that both droughts (1991/92, 1993/94) and floods (1997 and 2003) occur in Malawi.

CLIMATE AND MALARIA INCIDENCE IN MALAWI

The relationship between malaria transmission and climate is complex: climate can impact the transmission of malaria by affecting the malaria parasite life cycle, the mosquito's life cycle and behavior, the human host's vulnerability, or any combination of the three. Predicting how changes in precipitation or temperature might affect transmission geographically requires detailed knowledge about a complex set of other drivers involved in transmission, including the number of breeding sites, vector species distribution, and infection rates, many of which are not yet fully understood or directly impacted by temperature and precipitation.

This report examines the relationship between (a) historical weather data (average monthly rainfall and average minimum monthly temperature) and (b) monthly reported total cases for each of Malawi's five regions in Malawi from January 2010 to September 2016. Malaria seasonality is very similar across all five regions, with year-to-year variability. All regions have the lowest malaria incidence in August of each year. Most regions exhibit strong seasonality, with approximately 2–3 times the number of cases in the peak of the season, January, as compared with August.

HISTORICAL CLIMATE AND MALARIA ASSOCIATIONS

Key findings for the analysis comparing temperature, rainfall, and malaria incidences are presented below.

- For each 1 mm increase in mean daily precipitation, childhood (**under 5**) malaria increased in the South East by 1.7 percent and South West by 2.3 percent, and in the North, all one month later.
- For each 1°C increase in daily minimum temperatures, malaria cases increase in the South East by 3.8 percent 2 months later.
- For malaria in people **over 5 years of age** in the South East and South West, each 1 mm increase in daily mean precipitation increases malaria incidence by 1.6 percent with a 2-month lag. The increase for the South West is 3.3 percent.

CLIMATE CHANGE IN MALAWI

An ensemble of 19 Regional Climate Model (RCM) projections from the Coordinated Regional Climate Downscaling Experiment (CORDEX) over the African Domain is used to examine how climate is projected to change across Malawi under two Representative Concentration Pathways: (RCP) 4.5 and 8.5 are presented. RCP 8.5 represents a weak mitigation future, while RCP 4.5 represents a much more aggressive mitigation future though still not in line with the 2016 Paris Agreement objectives, which aims to limit temperature increase to 1.5ºC. Key insights from this analysis are noted below.

TEMPERATURE

- Daily and yearly temperatures (average, maximum and minimum) will rise and these increases are statistically significant even as early as the 2020s.
- Average temperatures will increase between 1.5 to 6 ºC by 2100 under all scenarios evaluated.

- Maximum temperatures are projected to rise between 1-7 ºC by 2100.
- The warming rate is similar across all regions with no one region projected to warm faster than another.

RAINFALL

- Most models project a decrease in the number of rain days per year before the 2050s, representing an opposite direction of change in the trends observed.
- Projected changes in total and monthly rainfall are uncertain, and there is no agreement in the sign of the change between models, some show statistically significant increases and others statistically significant decreases.
- Seasonally, most models show a statistically significant reduction in rain days, with the worst-case scenario (RCP 8.5) pointing to a potentially later start in the rainy season across all regions in Malawi.

MALARIA IN A HOTTER CLIMATE IN MALAWI

Areas of malaria suitability were mapped in a model combining future temperature change projections and current knowledge about the life cycles of malaria-carrying mosquitoes and the malaria parasite. Malaria suitability was examined across two future time periods: the 2030s (representing the period between 2015 and 2044), and the 2060s (representing the period between 2045 and 2074). Details of the methodological approach are available in the Shifting Burdens, Malaria Risks in a Hotter Africa technical report. Key messages from this analysis are noted herein:

- An estimated 14 million people in 2010 were living in areas of risk for 1 or more months of transmission suitability in Malawi. Of these, one-third (4.8 million, 35 percent) live in areas suitable for seasonal (7-9 months) transmission.
- In all projected future scenarios, the largest portion of people at risk (ranging 46-77 percent) are at seasonal (7-9 months) risk, suggesting a shift toward more seasonal transmission risk from the baseline.

INSIGHTS AND RECOMMENDATIONS

Addressing the changing risk profile of malaria due to temperature increases combined with other drivers will require modifying current interventions and programs, and potentially implementing new programs, that can adapt and respond to changing climate conditions. With these challenges come opportunities for improving observations, surveillance, and responses, including detailed geographic targeting, optimizing strategies (i.e., finding the right combination of vector and case management), and aligning interventions to changing seasonality.

MEETING ELIMINATION TARGETS

Eliminating malaria is the goal of all development partners working in Africa (WHO 2015). Understanding how temperature may change the seasonality of malaria in Southern Africa, particularly for new areas at risk of malaria transmission or areas where the length of the season may shorten or extend, can inform malaria programs and policy and help reach the goal of elimination. In areas where the months of malaria suitability decrease, opportunities will arise to focus resources on making surveillance and response systems increasingly sensitive and focused to identify, track, and respond to malaria cases and any remaining transmission foci (e.g., infected mosquitoes or affected patients). Elimination efforts informed by these analyses could better target resources to reduce the potential burden of additional cases through timely treatment and preventive measures to avoid disease spread in exposed populations, such as the distribution of bed nets or indoor residual spraying.

ADAPTING TO CHANGING EPIDEMIOLOGY AND INCORPORATING NEW TOOLS

There are many examples across sub-Saharan Africa where investments have improved malaria control strategies. These gains, however, could be compromised if future investments do not consider the role of rising temperatures in changes to epidemiology. This analysis offers critical insight with respect to these risks, and especially how c*urrent management and control interventions may need to be reviewed and revised to account for likely changes in malaria incidence.* This information offers an opportunity to lengthen the investment timeframe (seasonal to year-round, or vice versa), optimize vector control, and improve case management, by providing the evidence base to support these actions. Targeted and concentrated surveillance at the edge of malaria's range, for example, presents an opportunity to focus on potential epidemic outbreaks as they happen and can reduce the risk of new outbreaks.

IMPROVING A COUNTRY'S CAPACITY FOR COLLECTING AND USING INFORMATION

Understanding how rising temperatures could impact vector ranges, and thus have the potential to alter disease dynamics, is an important step to build the knowledge base to evaluate the impact of climate on malaria incidence and to inform investments.

This analysis indicates that as temperatures rise, even within the next 11 years (by the 2030s), important changes are anticipated in *Anopheles* transmission suitability. Importantly, temperature-driven changes in vector dynamics are themselves mediated by direct and indirect environmental and societal factors, such as changes to ecosystems and land use that may reduce or increase the vulnerability of certain groups to malaria risks.

Public health observatories, many already operational around the world, can analyze health data in the context of other climate and environmental parameters (health observatories are virtual platforms that can link health systems to weather data). These observatories can pave the way for the timely use of remotely derived weather and climate information to inform investments and strategies in malaria control.

BUILDING CAPACITY IN HEALTH SYSTEMS

In order for malaria programming and health services to respond to climate risks, investments need to be made in building the skills and capacity of health workers to understand and address the health risks posed by climate. These include:

- ***Training health workers on the links between health and climate change*** to improve their understanding and increase capacity to address changing climate risks. Establishing health early warning systems—as an extension of the analytic work that a health observatory can provide—educational and advisory systems for disseminating clinical guidelines, and even the guidance offered by community health workers, will all require building awareness of the risks and responses available to address climate factors. USAID/AFR, for example, has developed a one-week training course on climate and health issues.

- ***Leveraging information technology*** such as GIS (geographic information system) and other tools to integrate information from various sectors and sources in order to rapidly evaluate the potential risks from specific weather events to a country, region, or health post.
- ***Streamlining supply chain management***, especially in countries where malaria control interventions have been successful, to guarantee the delivery of commodities and services for remote and mobile populations.
- ***Ramping up research*** on applied, regionally responsive health services for a future of climate change. To date, there is a clear lack of service-oriented research to drive regional health service development for climate change, with potentially serious adverse implications for future control efforts.

STRATEGIC BUDGETING AND EARLY AND TARGETED PLANNING

One of the core operating principles of many malaria intervention programs and for the President's Malaria Initiative (PMI) is prioritizing high-risk populations for malaria interventions. Based on this report, temperature may play a role in putting large percentages of populations within countries, and in the region overall, at risk of both seasonal and endemic malaria.

In many instances, information on projected temperature increases is criticized because it cannot address immediate disease planning needs. However, much like preventive medicine, which aims to promote long-term well-being, planning 10–12 years and even further into the future when fighting malaria can save lives and money over the long term and promote sustainable elimination efforts. For example, if we know that temperature is likely to increase malaria burden in a certain country or region where there is currently little investment to fight malaria, including in some Southern Africa countries, an investment in surveillance and prevention now could prevent the need for large, immediate, crisis-driven investments in the future.

BACKGROUND

Malaria is a serious and sometimes fatal disease caused by a protozoan parasite, *Plasmodium*, that commonly infects certain types of *Anopheles* mosquitoes that feed on humans. People who get malaria are often very ill for several days with high fever, shaking chills, and flu-like illness. Left untreated, they may develop severe complications and potentially die. In 2017, an estimated 217 million cases of malaria occurred worldwide, compared with 239 million cases in 2010 (WHO 2018). Most of these cases (92 percent) were in the World Health Organization Africa Region (AFRO), with five countries accounting for nearly half of all malaria cases worldwide: Nigeria (25 percent), Democratic Republic of the Congo (11 percent), Mozambique (5 percent), India (4 percent), and Uganda (4 percent). The ten highest—burden countries in Africa reported increases in cases of malaria in 2017 compared with 2016. Worldwide, there was no significant progress between 2010 and 2017 in reducing the burden of malaria; the number of cases remains at 59 per 1,000 population (WHO 2018). Nevertheless, detection and treatment efforts appear to be working to reduce burdens. In 2017, for example, there were an estimated 435,000 deaths from malaria globally, compared with 607,000 in 2010 (WHO 2018). Children under five years of age are the most vulnerable group, accounting for 61 percent of all deaths. AFRO countries accounted for 93 percent of malaria deaths. Over 90 percent of these deaths are from the parasite *Plasmodium falciparum*, the most severe of the five species of *Plasmodium*.

An estimated $3.1 billion was invested in malaria control and elimination globally in 2017, an amount slightly higher than for 2016, with nearly three—quarters ($2.2 billion) spent in AFRO countries (WHO 2018). Governments of endemic countries contributed 28 percent of total funding, with most of this funding invested in national malaria programs. The US was the largest international source of malaria financing, providing $1.3 billion (42 percent). About $6.6. billion in annual funding is needed to meet targets to reduce malaria deaths and cases by >90 percent by 2030 (Patouillard et al. 2017; World Health Organization and Global Malaria Programme 2015).

Like many countries in Africa, critical knowledge of the health risks associated with climate variability and climate change is lacking in Malawi. 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 risks in the Malawi's regions is needed to formulate evidence-based policies and programs. Working from first principles of transmission dynamics of infectious diseases and informed by the current literature, this report examines climate effects on malaria in Malawi.

STRUCTURE OF THE REPORT

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

Climate and Malaria Incidence in Malawi explores the causal pathways linking climate to malaria in Malawi 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 threefold: to understand the role that historical temperature and rainfall played in disease incidence, to explore the role of scientific information in understanding climate and malaria links, 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.

Climate Change in Malawi examines state of the art projections for climate in Malawi and how this will translate into rising temperatures across the country by the 2030s and 2060s.

Malaria in a Hotter Climate in Malawi *models how projected rising temperatures will impact malaria seasonality across Malawi.*

Insights and Recommendations concludes the report with insights and lessons to respond to the changing profile of malaria in Malawi as climate continues to change.

GEOGRAPHIC SCOPE OF THIS STUDY

To account for Malawi's varied climate, malaria data in Malawi is typically divided into five regions with similar climate parameters prevailing in each region (Figure 1)., The average population for these five regions for the study period is noted in Table 1.

Figure 1: Regions of analysis for historical malaria and climate data

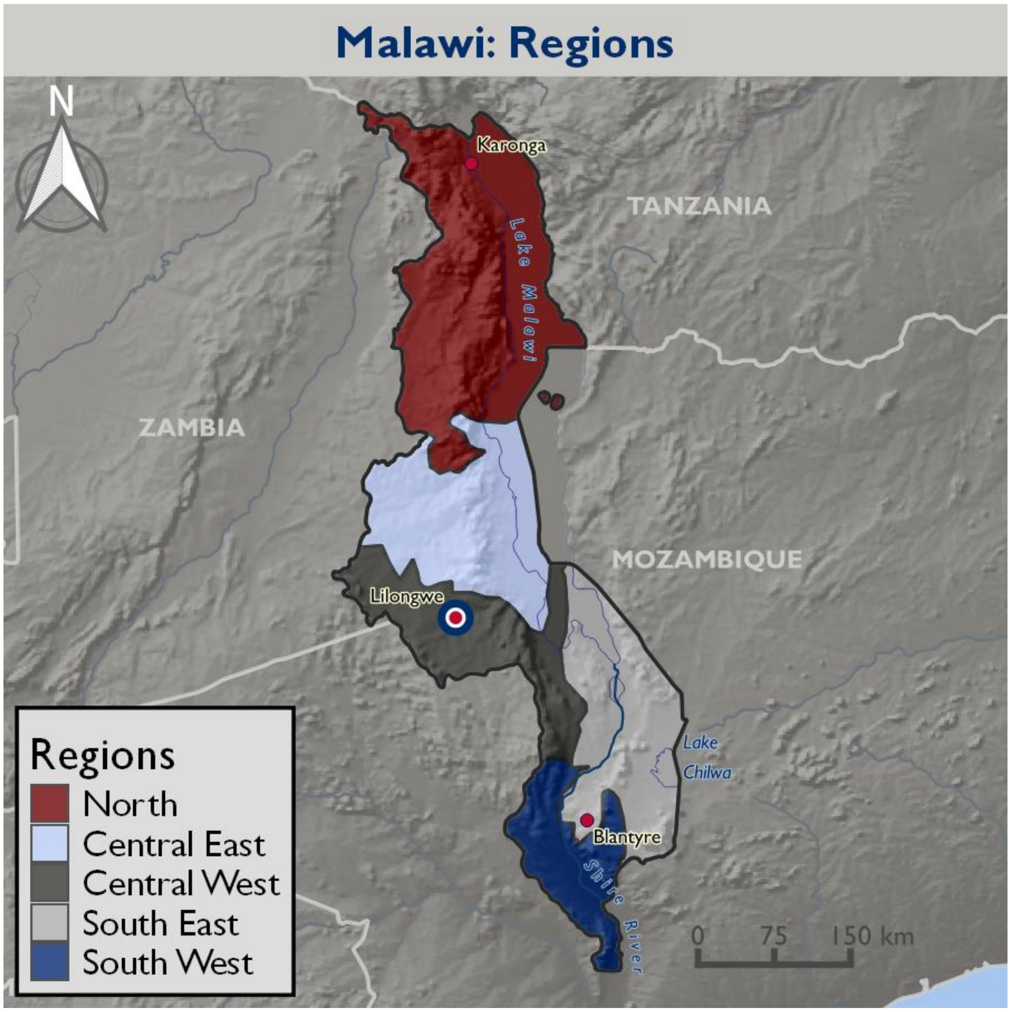


Table 1: Regions, number of districts within each region, and average population (January 2010 – September 2016_)

Region	Number of districts	Average population during study period
Central East	5	2,480,448
Central West	4	4,098,954
North	5	3,056,470
South East	7	4,633,546
South West	7	1,940,309

WEATHER AND CLIMATE VARIABILITY IN MALAWI

KEY MESSAGES

- Mean, maximum, and minimum temperatures all rose between 1979 and 2016 by approximately 0.53 to 0.60°C over the 35-year period.
- Three climatological regions in Malawi are recognized based on rainfall: a wetter north, the relatively drier Shire highlands and Rift Valley region, and the wet northern plateau.
- The country receives ample rainfall, so it is unlikely that malaria is moisture-constrained in Malawi and, therefore, historical rainfall trends or variability would not be strong drivers of observed changes in Malaria prevalence. However, seasonality of malaria may change in drier areas alongside changes in weather patterns.

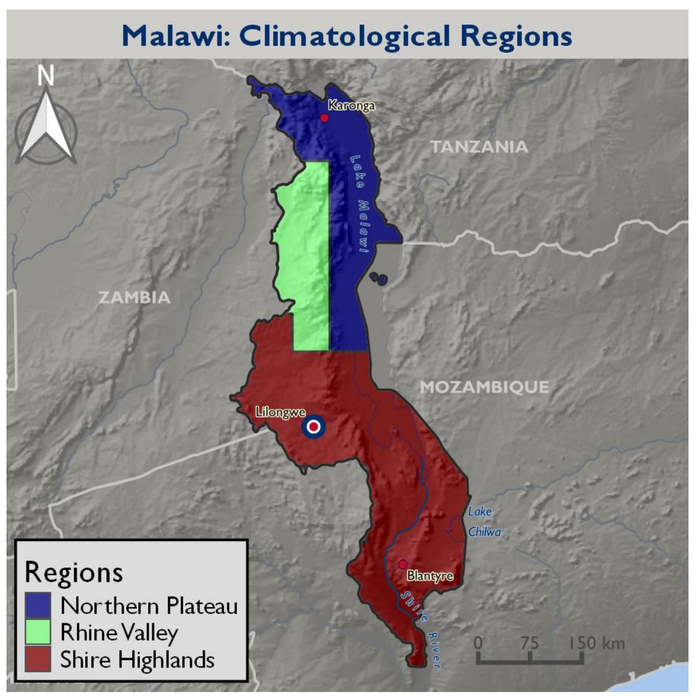
INTRODUCTION AND CONTEXT

This section provides a succinct interpretation of the climate information for use in establishing the relationship between weather and malaria in Malawi. Climate data for the country is typically divided into Malawi's three recognized climatological regions based on rainfall characteristics: Northern Plateau (blue), Shire Highlands (green), and the Rift Valley (red) (Figure 2).

THE CLIMATE OF MALAWI

The climate of Malawi is dominated by the position of the Inter-Tropical Convergence Zone (ITCZ) (which forms the boundary between the north-easterly monsoon and south-easterly trade winds) and the subtropical high-pressure belt associated with the descending branch of the meridional Hadley circulation. The southerly position of the ITCZ during the austral summer results in the country experiencing a single rainy season extending from November to April. Dominance of subtropical high-pressure systems in winter from May to September results in dry and often cool conditions. Typically, the rainy season begins earliest in the south and onset is progressively later further north. Rainfall distribution is not uniform across the

Figure 2: Regions of climatological analysis



country (Figure 3), as local variations in topography and the influence of Lake Malawi contribute to some notable spatial variability in its seasonal characteristics.

The country's three climatological (rainfall) regions differentiate between a wetter north-eastern region (the northern plateau) with a mean annual rainfall of 1,369 mm per year, and the drier Shire Highlands and Rift Valley region with mean annual rainfall figures of 1031 and 1017 mm per year, respectively (Figure 4). In the northern plateau the wettest month is March, whereas in the Shire Highlands and Rift Valley the wettest month is typically January (
Figure 4).

Temperatures in all regions show hot summers and colder winters with a mean difference between summer and winter of about 5°C (Figure 3). The Shire Highlands are generally cooler than the other two regions and exhibit less interannual variability in temperature (Figure 5).

Figure 3: Mean annual rainfall (left) and mean annual temperature (right) over Malawi

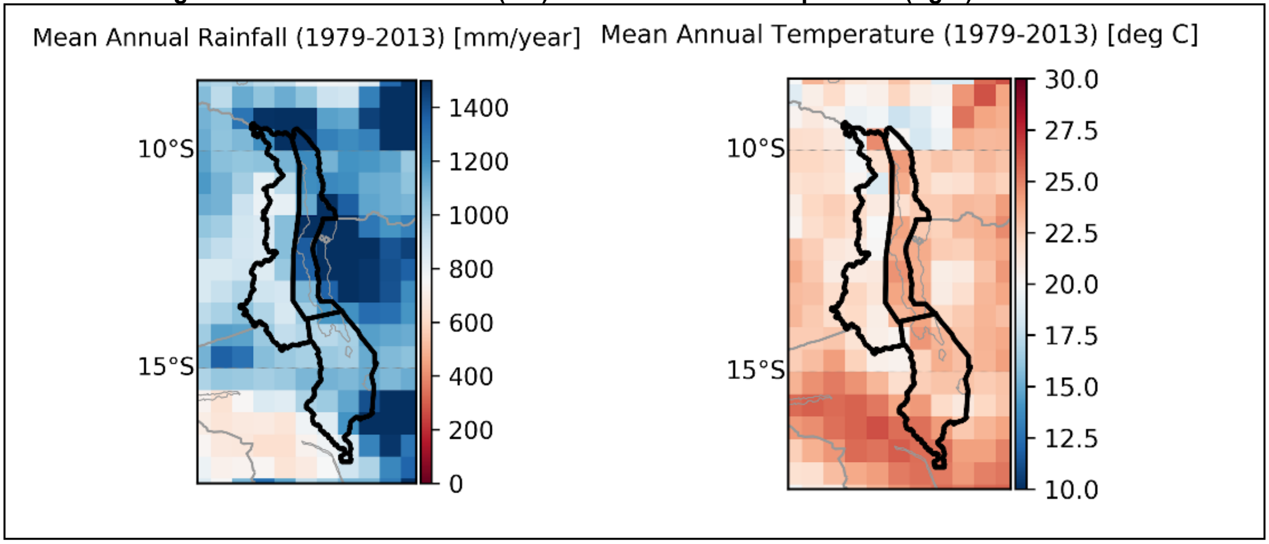
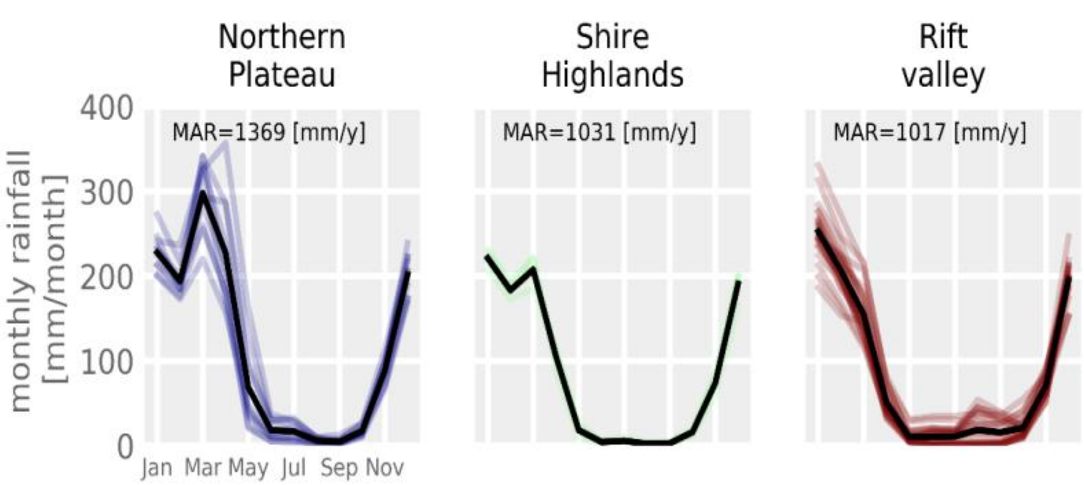
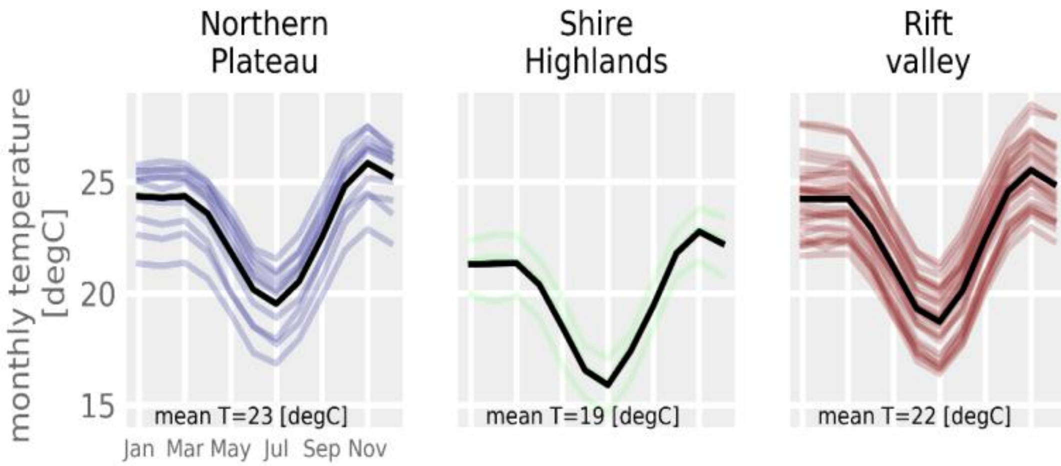


Figure 4: Rainfall regions based on rainfall climatology for the period 1979-2016.



Note: Each line represents an individual grid box, and the bold black line is the average.

Figure 5: Seasonal cycle of temperature for the period 1979–2016 by regions



Note: Each line represents an individual grid box, and the bold black line is the average.

CLIMATE TRENDS

The analysis of climate trends can be useful in understanding:

- How climate variables have varied through the past decades as this may help explain observed impacts such as increasing malaria incidence or decreasing crop yields. However, the links between climate variables and nonclimate variables is often complex and involves many nonclimate drivers. Trend analysis should therefore be used as a first step in exploring historical changes in climate—sensitive variables.

- How past trends could exhibit a climate change “fingerprint” that points at projected changes into the future. For example, almost all land locations globally have experienced a systematic and significant increase in temperature over the past 100 years. Coupled with knowledge of climate science, climate modeling can be used to explain the extent to which these past changes are responses to increasing greenhouse gas emissions. The alignment between observed trends and modeled past and future trends offers increased confidence in future projected changes.

While temperature trends are relatively easily explained by climate change, trends in precipitation- related statistics are often more complex. One important reason is that precipitation naturally varies far more from year to year than temperature and many locations exhibit not only strong year—to—year variability, but also decade or longer drier or wetter periods (e.g. the Sahel drought in the second half of the 20th century). Given a relatively short observation record, particularly in developing countries, it is often not possible to determine if a linear trend analysis is indicating a long-term systematic precipitation trend possibly driven by climate change or is merely a consequence of natural variability. While the data used here cover a substantial period of time, i.e., 35 years from 1979-2016, it is difficult to attribute the long-term trends in precipitation illustrated in to climate change, as these could also be part and parcel of decadal variability in the “tails” of the time series.

Interpretation of historical climate trends for precipitation should therefore be cautiously conducted where climate variables exhibit high natural variability, and in combination with analysis of climate model simulations and projected changes. This allows for judgments to be made on the strength of the evidence for a particular long-term change. Where low natural variability in the observed precipitation record is evident, and the direction of trend in the historical record matches that of the projected direction of change, then it gives us more confidence in the long-term projection.

Observed trends to several climate statistics (temperature, rainfall, and the number of "wet days"1) of potential relevance to malaria prevalence in Malawi are explored below. Here we offer a brief overview of the relative importance of these variables to malaria transmission:

- ***Temperature*** is known to be a strong limit on malaria transmission, though the dynamics are potentially complex. As such, we include an analysis of mean, maximum, and minimum daily temperatures.
- Total ***rainfall*** offers an indication of moisture availability, an important limit on malaria transmission.
- The ***number of wet days*** is important because heavy rainfall followed by long dry periods may limit moisture availability.

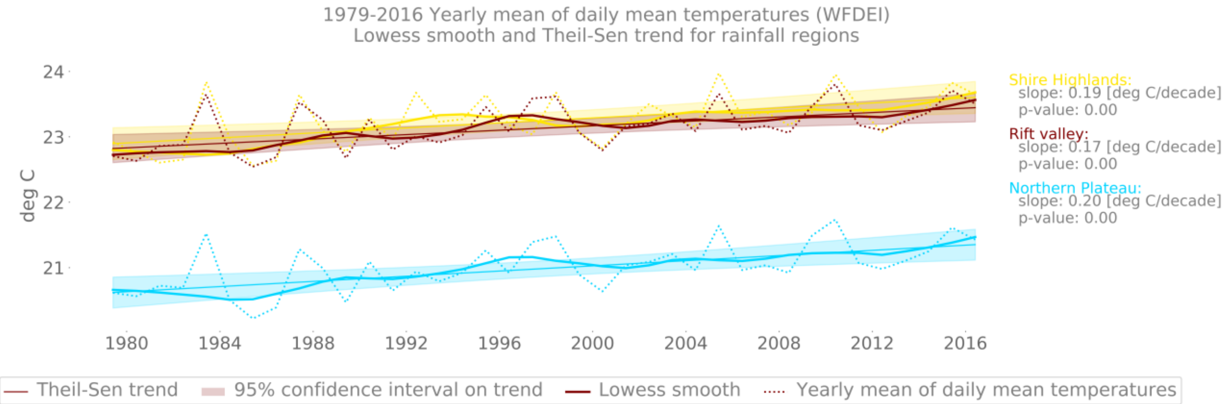
Temperature

Observed trends in daily mean temperature by region point to an increase in mean daily temperatures between 0.53 and 0.6°C over the 35-year period between 1979 and 2016 and are statistically significant (Figure 6). Trends in daily maximum and minimum temperatures track daily mean temperature in trend and magnitude of change, pointing to an increase of 0.16 to 0.17°C per decade across all regions (Figures 7 and 8). Interannual variability in the yearly averaged maximum temperature record is higher than for the minimum temperature record, maximum temperatures tracking more closely to rainfall values, with periods of higher rainfall corresponding to lower maximum temperatures.

Anopheles mosquito suitability is constrained by both very high temperatures and very low temperatures. Rising temperatures can shift the boundaries between areas of optimal (endemic or seasonal) suitability and limited (marginal or moderate) suitability. In particular, rising temperatures in the mountainous areas of Western Malawi may allow malaria to occur more readily at higher elevations for more months of the year where temperatures may have previously been too cool.

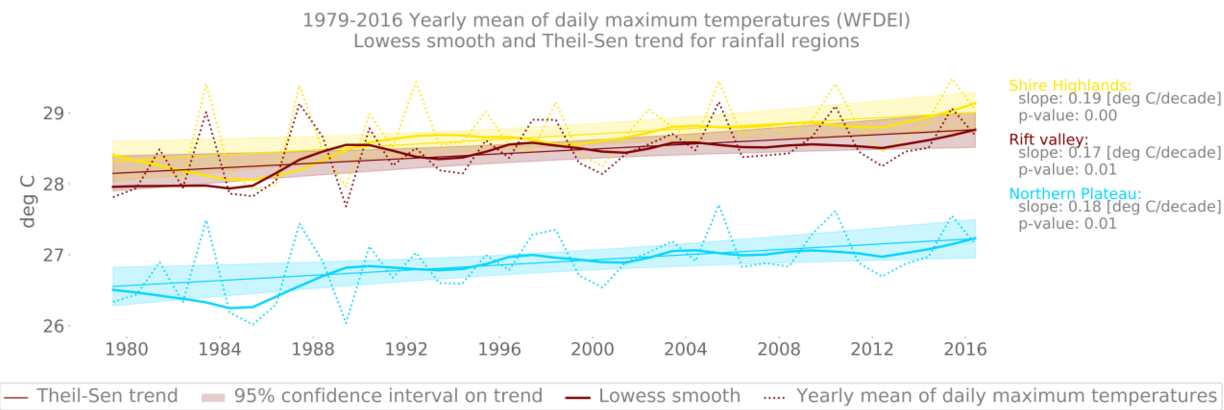
[1] Wet Days are traditionally measured by the days with rainfall greater than 1 mm.

Figure 6: Yearly mean of daily mean temperature and for the period 1979–2016



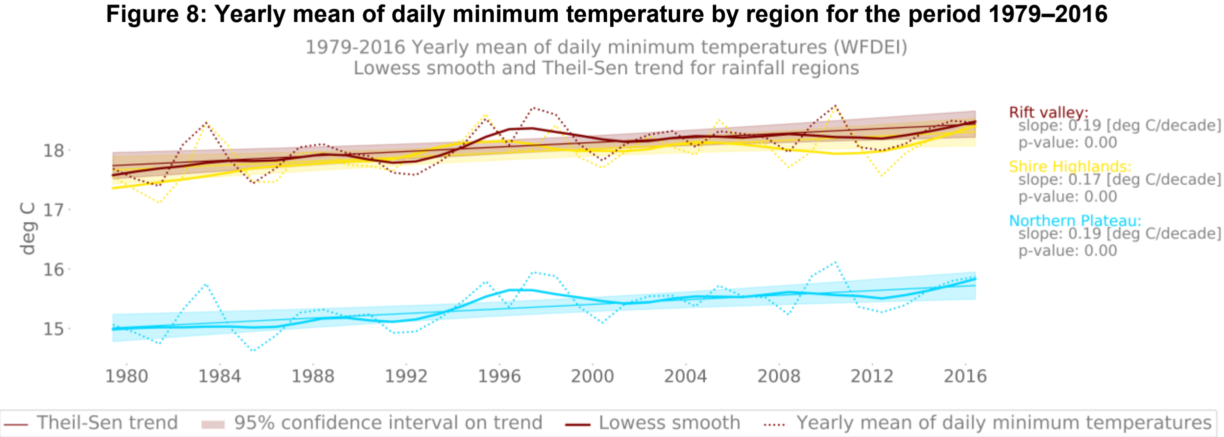
Note: Trends are considered statistically significant when p values (appearing in the legend) are less than 0.05, which nominally suggest that the trend is not due to chance but reflects a climate change influence. Where p values are greater than 0.05, it is difficult to attribute this to climate change and could be rather a function of natural variability.

Figure 7: Yearly mean of daily maximum temperature by region for the period 1979–2016



Note: Trends are considered statistically significant when p values (appearing in the legend) are less than 0.05, which nominally suggests that the trend is not due to chance but reflects a climate change influence. Where p values are greater than 0.05, it is difficult to attribute this to climate change and could be rather a function of natural variability.

Figure 8: Yearly mean of daily minimum temperature by region for the period 1979–2016



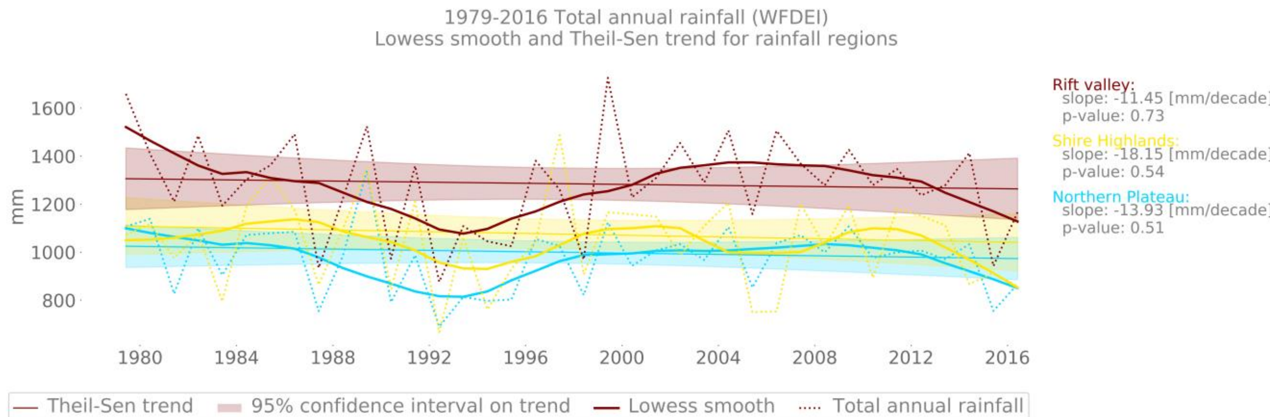
Note: Trends are considered statistically significant when p values (appearing in the legend) are less than 0.05, which nominally suggests that the trend is not due to chance but reflects a climate change influence. Where p values are greater than 0.05, it is difficult to attribute this to climate change and could be rather a function of natural variability.

Rainfall

All three regions show a reduction in total annual rainfall between 1979 and 2016 (
Figure 9). However, these trends are not statistically significant, so, while important, it is not possible to attribute this trend to climate change. The large interannual variability in the record reflects the droughts of 1991/92, 1993/94, as well as the flood years of 1997 and 2003. Trends in the number of rain days per year (Figure 10) are positive, suggesting an increase in the total number of rain days in all regions. These weren't statistically significant results, and there is a large interannual variability.

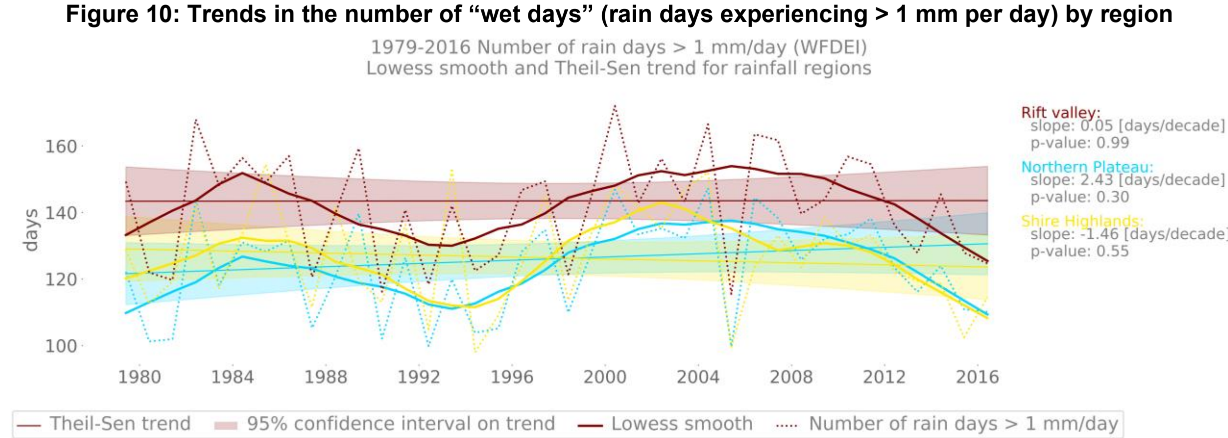
The country receives ample rainfall so it is unlikely that malaria is moisture-constrained in Malawi, and, therefore, historical rainfall trends or variability would not be strong drivers of observed changes in malaria prevalence. However, seasonality of malaria may change in drier areas with rising temperatures and increased evapotranspiration. These implications are subject to the outcome of the in-depth malaria incidence data analysis in Section III.

Figure 9: Trends in total annual rainfall by region



Note: Trend lines are shown as solid, with interannual variability in dotted lines. The large interannual variability in the record reflects the droughts of 1991/92, 1993/94 as well as the flood years of 1997 and 2003. Trends are considered statistically significant when p values (appearing in the legend) are less than 0.05, which nominally suggests that the trend is not due to chance but reflects a climate change influence. Where P values are greater than 0.05, it is difficult to attribute this to climate change, and could be rather a function of natural variability.

Figure 10: Trends in the number of "wet days" (rain days experiencing > 1 mm per day) by region



Note: Trend lines are shown as solid, with interannual variability in dotted lines. The large interannual variability in the record reflects the droughts of 1991/92 and 1993/94 as well as the flood years of 1997 and 2003. Trends are considered statistically significant when p values (appearing in the legend) are less than 0.05, which nominally suggests that the trend is not due to chance but reflects a climate change influence. Where p values are greater than 0.05, it is difficult to attribute this to climate change and could be rather a function of natural variability.

METHODS OF ANALYSIS

The WATCH Forcing Data ERA Interim (WFDEI) gridded dataset was used in the analysis (Weedon et al. 2014). These data provide observational temperature and rainfall data from 1979 to 2013. It contains eight meteorological variables at 0.5°C spatial resolution at 3-hourly or daily time resolution over the period 1979–2013. The WATCH WFDEI data are derived from the ERA-Interim climate reanalysis simulations, which are simulations with a global climate model that assimilates observations of certain large-scale atmospheric variables. In the process of generation of WATCH WFDEI, the underlying reanalysis variables are bias corrected (i.e., systematic differences are removed) to observations. In case of rainfall and temperature variables, bias correction is done to the Climate Research Unit (Harris 2014) gridded observed climate estimate data. The variables examined in this report were: daily precipitation and daily minimum, mean, and maximum temperature.

This dataset was selected since it was the only dataset that provided both daily precipitation and temperature data over the southern African region. Additionally, the WFDEI provides a long and relatively up-to-date record based on ERA-Interim climate reanalysis data and the ability of the data to capture reality on the ground (skill of the variables) are consistent through both space and time, which makes it suitable for trend analyses at regional levels.

What is a climate reanalysis dataset?

A climate reanalysis gives a numerical description of the recent climate, produced by combining models with observations. It contains estimates of atmospheric parameters such as air temperature, pressure, and wind at different altitudes, and surface parameters such as rainfall, soil moisture content, and sea-surface temperature. The estimates are produced for all locations on earth, and they span a long time-period that can extend back by decades or more. Climate reanalyse generate large datasets that can take up several petabytes of space.

Source: European Centre for Medium-Range Weather Forecasts 2020.

UNCERTAINTIES

While it is clear that temperatures will continue to rise across the world as greenhouse gas concentrations increase, projecting future climate change is uncertain. The sources of uncertainty are wide ranging but primarily involve:

- *Natural variability:* The climate system varies naturally (not as a result of global warming) on wide ranging time scales. Global phenomena such as the El Nino Southern Oscillation (ENSO) and others cause significant global and regional temperature shifts and regional rainfall changes. Multiyear or even decadal droughts also occur naturally. So some shifts in climate, even over multidecade periods, are just due to semirandom variability and not climate change. The same is true within climate model simulations of future climate. It is impossible to know if a climate model simulation is projecting a change in rainfall because of global warming or because it randomly simulated a particularly dry period. This source of uncertainty varies through time, being very dominant in the near future and decreasing into the far future as the changes driven by global warming become stronger. See Hawkins (2009) for a useful description.

- *Observational uncertainties*: Observations inform model parameters and model validation as well as providing baseline references against which to measure climate change. In many areas of the world, surface primary observations (weather stations) are declining in density and data availability, leading to increased uncertainty.

Of the above sources of uncertainty, natural variability is difficult to model and therefore hard to incorporate into the analysis. Observational uncertainties can be reduced through significant investment in climate and weather observation platforms as well as promoting open data access. Structural (model) and emissions uncertainty can be improved, but reducing the uncertainty requires making assumptions and potentially introducing new errors. For example, we can assume a single emissions pathway to reduce emissions uncertainty. Or we can attempt to identify better or worse climate models and so eliminate them and their associated projections from consideration. In some cases, this can reduce the range of projected changes, but not always. Regardless, removing models means that we risk not considering the projected changes simulated by that model. We need to be confident in our assumptions and comfortable with the increased risk of being wrong.

THE MANY OBSERVATIONAL CLIMATE DATASETS AVAILABLE

There is not one "best" gridded observed dataset for the southern African region or any region of the world. All datasets differ in the number of variables included, their spatial and temporal resolution, the length and period of record, and the ease with which the data can be accessed and used. Some datasets are more suitable for analysis of how the climate changes over space or time, while others provide a better representation of absolute values of the climate. There is always a trade-off, and users needs to select the most suitable dataset for their needs.

Considering multiple emissions scenarios and as many climate models as possible is a conservative and safe starting point. That is the approach we have taken in this analysis by drawing on the CMIP5 model ensemble and analyzing both RCP 4.5 and RCP 8.5 emissions experiments.

CLIMATE AND MALARIA INCIDENCE IN MALAWI

KEY MESSAGES

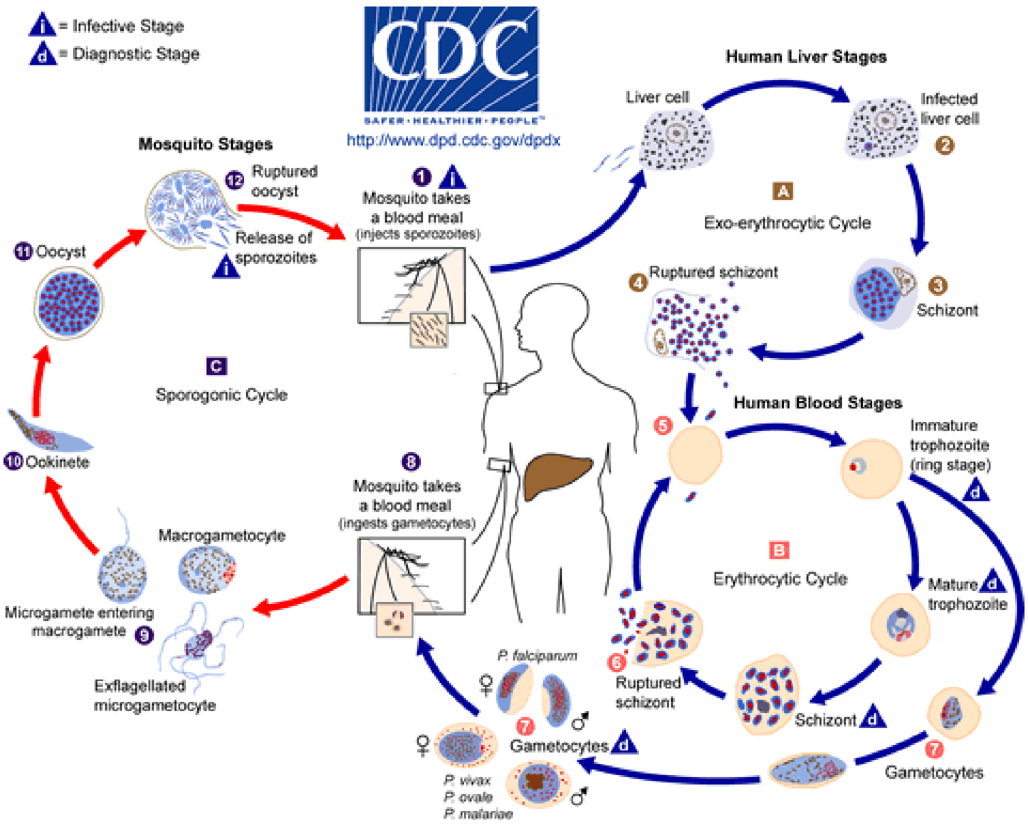
- Associations between temperature and/or precipitation and cases of malaria can reveal patterns that can be used alongside climate data and weather forecasts to provide information about the timing of seasonal disease outbreaks.
- Despite considerable progress and investments in prevention and control, malaria remains a leading cause of morbidity and mortality in Malawi. In 2017, there were an estimated 4.3 million cases and 7,100 deaths in a population of 18.6 million (WHO 2018).
- Malaria incidence in the South East/South West increases with normal rainfall, with a 1.6 percent/3.3 percent increase in malaria incidence, respectively, with each 1 mm increase in mean daily precipitation, with a 2-month lag.
- The results suggest that a combination of temperature and precipitation for the South East and South West regions could be used to forecast the timing of malaria outbreaks with at least a 1- to 2-month lead time.

MALARIA AND WEATHER ASSOCIATIONS

Environmental variables such as temperature, rainfall, and humidity help determine the geographic range of the *Anopheles* mosquitoes, affect the incidence of malaria by changing the duration of the mosquito and parasite life cycles, and influence human, vector, or parasite behavior (Gubler et al. 2001). Malaria transmission is also climate-sensitive in that weather variables affect the three stages of the malaria parasite life cycle: two stages while in humans and one stage in the vector, *Anopheles.* The causal pathways between weather/climate and malaria are complex, as shown in Figure 11.

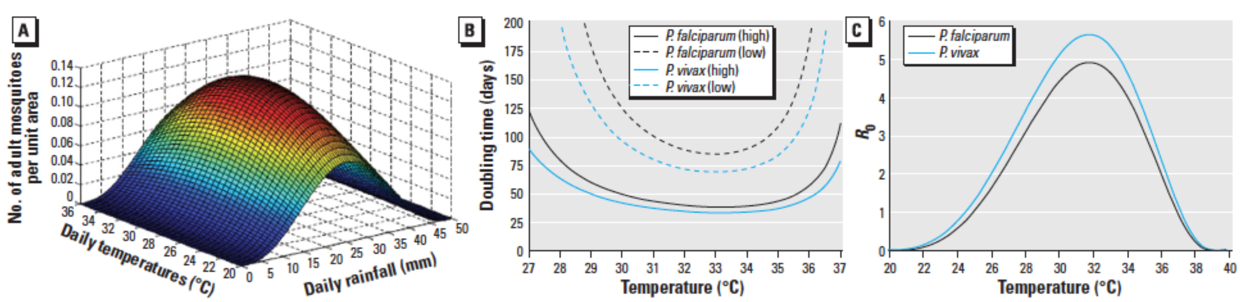
Temperature, humidity, rainfall, and wind speed affect the incidence of malaria (Figure 12), either through changes in the duration of mosquito and parasite life cycles or influences on human, vector, or parasite behavior (Parham and Michael 2010). A key parameter is the basic reproduction number, called R_0, a metric for malaria transmission suitability quantifying the expected number of secondary cases generated per infectious human introduced into an otherwise susceptible population. The statistical formula to determine the basic reproduction model includes temperature and rainfall for R_0.

Figure 11: The malaria life cycle



Source: CDC

Figure 12: Associations between temperature and rainfall on mosquito populations and *Plasmodium* species dynamics



Note: The mean number of mosquitoes per unit area as a function of temperature and rainfall (A); and the estimated doubling time of *P. falciparum* and *P. vivax*, with high and low referring to vector density values (the number of mosquitoes per humans) (B); and the dependence of R_0 on temperature for *P. falciparum* and *P. vivax* (C)

Source: Parham and Michael 2010

Understanding these dynamics can increase the efficiency and effectiveness of malaria control programs. For example, associations between temperature and/or precipitation and cases of malaria can reveal patterns that can be used alongside climate and weather forecasts to provide information about the timing of seasonal disease outbreaks. Further, some recent control tools, such as Seasonal Malaria Chemoprevention and RTS,S/AS01 malaria vaccine (see box below), need to be deployed in the regions where they are most needed. Understanding how climate may impact both number of incidence and the intensity of malaria infection between regions within a country is relevant for decision making, especially with limited resources (Greenwood 2017).

RECENT MALARIA CONTROL TOOLS

- **Seasonal malaria chemoprevention** is defined as the intermittent administration of full treatment courses of an antimalarial medicine to children in areas of highly seasonal transmission during the malaria season. The objective is to prevent malarial illness by maintaining therapeutic antimalarial drug concentrations in the blood throughout the period of greatest malarial risk.
- **RTS,S/AS01 (RTS,S)** is the world's first malaria vaccine that has been shown to provide partial protection against malaria in young children. The vaccine acts against *Plasmodium falciparum*, the deadliest malaria parasite globally and the most prevalent in Africa. The vaccine has been recommended by WHO for pilot introduction in selected areas of 3 African countries. It will be evaluated for use as a complementary malaria control tool that could be added to (and not replace) the core package of WHO-recommended preventive, diagnostic, and treatment measures. '

Source: WHO 2017 and WHO 2020

MALARIA IN MALAWI

Despite considerable progress and investments in prevention and control, malaria remains a leading cause of morbidity and mortality in Malawi. In 2017, there were an estimated 4.3 million cases and 7,100 deaths in a population of 18.6 million (WHO 2018). Malaria transmission occurs throughout the year in most areas and the entire population is at risk of the disease. The 2017 Malaria Indicator Survey reported that 24 percent of children 6–59 months of age tested positive for malaria by microscopy; the rate varied from 11 percent in the North region to 26 percent in the Central East, Central West, South East, and South West regions. This was despite increasing trends in access to and use of insecticide treated nets (ITNs). Overall, 68 percent of children under the age of five slept under an ITN the night before the survey (regional range: 62–72 percent) and within two weeks before the survey, 96 percent with fever were given an antimalarial drug. Annual malaria prevalence in Malawi decreased from 33 percent in 2014 to 24 percent in 2017. In children under the age of 5, prevalence decreased from 43 percent in 2010 to 24 percent in 2017. In 2017, Malawi accounted for 2 percent of the global cases of malaria and 10 percent of all cases within East and Southern Africa.

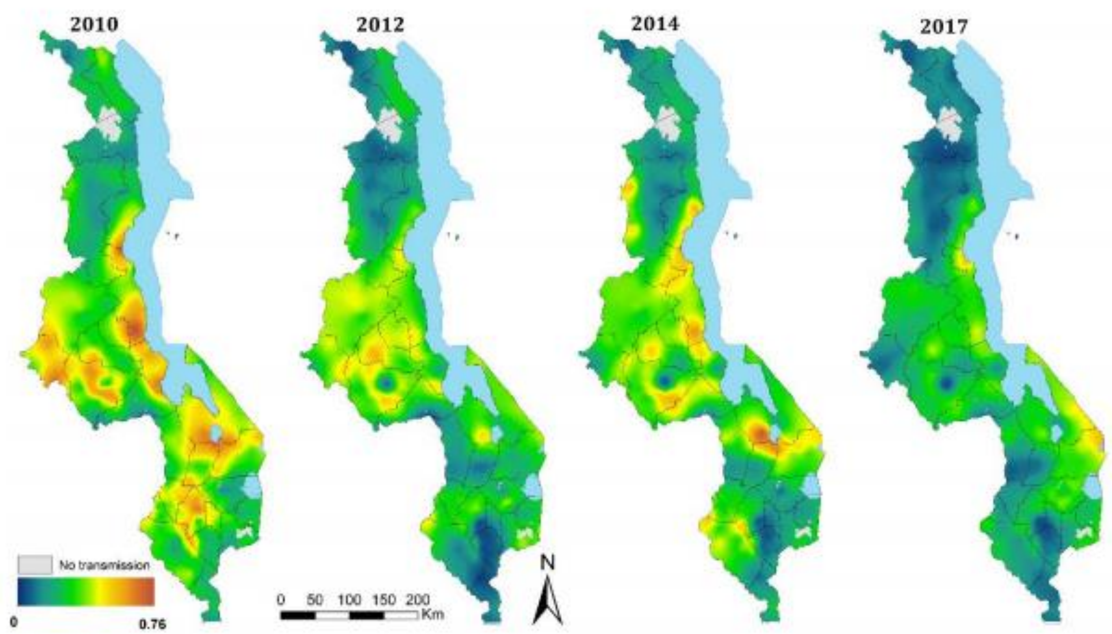
Malaria is now the sixth leading cause of death in Malawi, after HIV/AIDS, neonatal disorders, lower respiratory tract infections, tuberculosis, and diarrheal disease (IHME 2019). Malaria ranked third in 2007. Malaria is the fourth leading cause of premature deaths.[2]

[2] Premature deaths occur before the age that is considered "natural," in this case, 75 years of age.

Malaria control is a long-standing governmental priority, with vector control as a cornerstone of the government's efforts to control malaria. Vector control activities include the provision of insecticide-treated bed nets (ITN) and indoor residual spraying. In 2017, 82 percent of households owned at least one ITN, and 42 percent of households had at least one ITN for every two people.

Plasmodium falciparum is the most severe and the most common form of malaria in Malawi and the most common vector is *Anopheles funestus*, although *An. Gambiae ss* and *An. Arabiensis* may predominate in some areas at certain times of the year (Figure 13).

Figure 13: Plasmodium falciparum prevalence in Malawi



Notes: Continues predicted PfPR2-10 estimates for Malawi in 2010, 2012, 2014 and 2017. Ranging from yellow (low) to red (high) through intermediary prevalence (blue). Grey masks show areas unable to support stable transmission.: Source: (Gething, Patil, and Hay 2010)

Within the Health Sector Strategic Plan II (2017-2022), the country's fourth strategic plan for malaria, Malaria Strategic Plan (MSP) 2017-2022, aims to reduce malaria incidence by at least 50 percent from a 2015 baseline of 386 per 1,000 population to 193 per 1,000 and malaria deaths by at least 50 percent from 23 per 100,000 population to 12 per 100,000 population by 2022. Most of the $135 million spent on health comes from development assistance ($91 million); $26 million comes from government health spending. The President's Malaria Initiative (PMI) proposed budget for 2018 is $20 million, covering entomological monitoring and insecticide resistance management; ITNs; indoor residual spraying; malaria in pregnancy; case management; health systems strengthening and capacity building; social and behavioral change communication; surveillance, monitoring, and evaluation; and operational research. The other key development partner is the Global Fund to Fight AIDS, Tuberculosis, and Malaria. The National Malaria Control Programme also receives technical assistance from UNICEF, WHO, Save the Children, and United Purpose. Understanding how, when, and under what circumstances climate variability and change impact health outcomes could offer insights on how to achieve these goals under a changing climate.

OBJECTIVES

The goal of the analyses is to describe how temperature and rainfall have historically impacted malaria by region in Malawi. This included a review of the incidence of malaria across the country at the highest possible level of resolution—in this case, the regions defined below—as well as a statistical analysis of the relationship between malaria and weather variables documented to impact malaria incidence (Parham and Michael 2010).

METHODS

Based on published associations between weather patterns and malaria, the association between malaria disease counts and the average temperature and precipitation was modeled. Specifically, the relationship between rainfall and average minimum temperature was modeled for a month and monthly reported total cases by each of the five regions in Malawi from January 2010 to September 2016. The statistical evaluation of the associations between weather variables and malaria cases was conducted at a regional scale and aligned with malaria case data stratified by age, adjusting for seasonality using a lagged generalized linear model (GLM) assuming a Poisson distribution as described below.

INPUT DATA

A time series analysis was conducted to estimate how monthly malaria case counts (under 5 and over 5) vary by temperature and rainfall during the preceding weeks. This approach is often used in environmental epidemiology. The data are structured with monthly aggregate counts of total cases from reporting at the district level. Weather variables include monthly averages and totals at the district level. Variables in the dataset are defined in Table 2.

Table 2: Climate and health variables evaluated

Variable	Definition
region	5 regions containing districts (range: 4 – 7 districts per region)
district	28 administrative districts
date	Date, monthly
mal_u5	HMIS malaria cases under 5
mal_over5	HMIS malaria cases over 5
mean_monthly_rain	Monthly average of daily rainfall (mm)
mean_monthly_tmin	Monthly average of daily minimum temperatures (°C)

Study Period: January 2010 – September 2016.

MALARIA CASE DATA

Clinical and confirmed monthly malaria counts over the 81 months from January 2010 through September 2016 were reported via the Health Management Information System form 15 (HMIS-15). Malaria data were received as monthly reports of under-5 malaria cases and 5-and-over malaria cases at the district level (Table 3). Counts were aggregated to the regional level for analyses. Reporting rates were low between April 2011 through June 2012 and missing values were derived using an average of counts the year before (2010) and after (2013) the large missingness event, stratified by district and by month to preserve seasonality.

Table 3: District level (n=28) malaria variable summary statistics over the 81 months

Malaria Cases	Mean	Median	Minimum	Maximum	Missing reports
Under 5 years	6801	5396	12	53990	2
Over 5 years	8153	6903	26	55110	3

Definitions: Mean - Average *district's* monthly malaria case count, Median - Median *district's* monthly malaria case count, Min - Lowest *district's* monthly malaria count, Max - Highest *district's* monthly malaria count, Missing - Number of missing district monthly reports out of 336 possible monthly reports per year.

WEATHER DATA

Malaria transmission depends on various climatic variables, including precipitation, temperature, and humidity. Although there are nonclimate factors such as population, land use, and human immunity status that also influence transmission, this analysis examines only the relationship between climate and malaria incidence, as a first and critical step in determining the association between climate and malaria incidence. The rationale for considering rainfall and temperature parameters, as well as their seasonality in this analysis is described below.

- *Precipitation:* Precipitation data are sourced from WATCH Forcing Data ERA Interim (WFDEI) gridded dataset (Weedon et al. 2014). Daily rainfall volume (mm) was provided from January 1, 1979, through December 31, 2016, at the subdistrict level to align with available malaria incidence data.
- *Temperature:* Temperature data are sourced from WATCH Forcing Data ERA Interim (WFDEI) gridded dataset (Weedon et al. 2014). Daily temperature estimates (°C) were similarly provided from January 1, 1979, through December 31, 2016, at the subdistrict level.

The temperature and precipitation variables were aggregated to monthly values to match the monthly case data.

1. Precipitation modeled as the average rainfall (mean_monthly_rain)
   a. To produce monthly regional rainfall estimates, subdistrict daily rainfall volumes within each month were averaged.
2. Temperature modeled as the average minimum temperature (mean_monthly_tmin)
   a. Produced by averaging each region's subdistrict daily minimum air temperatures within each month.

Rainfall

Rainfall is a predictor of malaria transmission (cf. Parham and Michael 2010) as it can alter the availability of *Anopheles* larval habitat. Modeling studies have shown that rainfall controls malaria endemicity and influences vector abundance (Parham and Michael 2010). Higher *Anopheles* density and biting rates have been observed during the rainy seasons when compared with the dry season (Coleman 2009). This is likely due to an abundance of mosquito breeding sites in the rainy season, which allow larvae to develop. In some situations, rainfall can lead to flooding that washes away larval breeding sites.

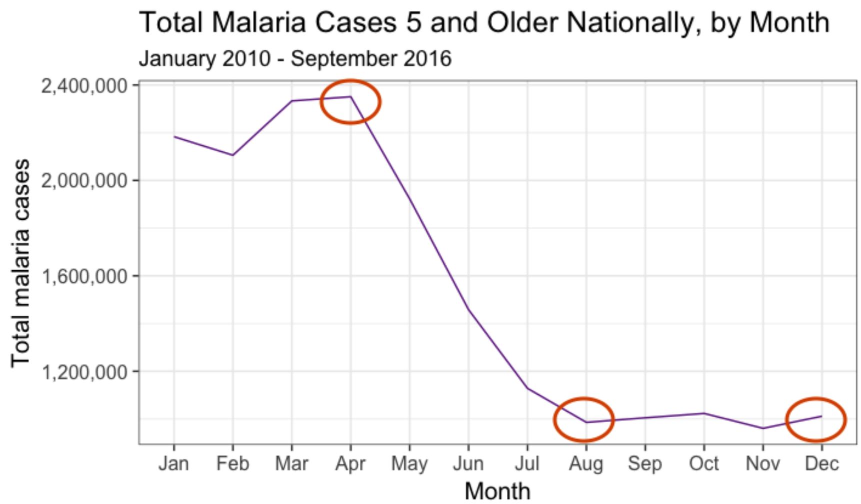
Temperature

As previously discussed, temperature is critical to the mosquito life cycle and the parasite's intrinsic incubation rates. Higher temperatures increase larvae mutation and survival. At temperatures below 16°C, parasite development within the mosquito is halted (Craig et al. 1999). Vector survival is also dependent on temperature. Between 16°C and 36°C, the daily vector survival is about 90 percent (Craig et al. 1999 or Patz and Olson 2006). Several studies have suggested that minimum temperature is the most significant meteorological factors involved in malaria transmission (Alemu et al. 2011, Bouma 2003, Loevinsohn 1994, and Rogers and Randolph 2000). In an Ethiopia-based study of malaria transmission, minimum temperature was most strongly positively correlated with malaria while maximum temperature was negatively correlated, both were significantly associated with malaria at a 1-month lag (Alemu et al. 2011).

Seasonality

Anopheles mosquitoes lay their eggs in water, and malaria transmission is often seasonal, peaking during or following the rainy season (Parham and Michael 2010). Seasonality's long-term pattern dominates the data and our interest lies in the short-term association between weather and malaria. Seasonal patterns were controlled for with a natural cubic spline. Splines are smoothing functions that can control for the confounding effects of seasonality's longer-term variation by modeling these patterns smoothly with joined curves that cover the time period of interest (Gasparrini and Armstrong 2010). Logical breaks, or knots, dictate how flexible the curve will be by specifying how many cubic curves are used. Knots were placed in April, August, and December of each year (shown in Figure 14) to allow flexibility at each of these points where seasonal changes were observed in the data. This spline's flexible way of fitting the model will also control for trends not explained by precipitation and temperature and for which we may not have data. This may include other time-varying factors such as population size or the number of facilities reporting case counts to their district.

Figure 14: Locations of knots in analyses using natural cubic splines



ANALYSIS IN DETAIL

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

A common statistical method to control for seasonality and long-term trends was applied, called a cubic spline for time with three 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 by using a cubic spline and a lag of 2 months (Hashizume et al. 2007; D’Souza et al. 2004).

Increases in the number of cases of malaria are often not concurrent with the timing of the weather driver; a delay often occurs between the predictor (e.g., average temperature) and the health outcome. Delays may be related to the mosquito life cycle, the incubation period of the malaria pathogen, and the time between an individual beginning to develop the disease and seeking medical care to be diagnosed (Alexander et al. 2013). Including lags and shifting exposures in the model accounts for this delayed effect and explores the association between a prior month’s weather and the current month’s malaria.

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 district were confounders of the association between malaria cases and precipitation.

In summary, model components include:

- Malaria under/over 5 years of age (case counts) as the outcome variable
- Precipitation, lagged 1 month
- Temperature, lagged 2 months (adjusted for 1-month lag)
- District indicator
- Spline for time

RESULTS

OVERVIEW OF MALARIA CASE DATA

On average, throughout the country, 6,801 cases of malaria under age 5 and 8,153 cases of malaria over age 5 were reported each month during the study period. The data were only missing 2 and 3 monthly reports over the study period's 81 months, for malaria under 5 and over 5, respectively. The highest district-level reports for a given month were 53,990 in April 2010 and 55,110 in March 2016, for malaria under 5 and over 5, respectively. The results of descriptive analyses are summarized in the following figures and tables.
The data record shows that between January 2010 and September 2016 (6 years, 9 months or 81 months total), there were:

- 15,411,736 total reported malaria cases in people under 5 years old
- 18,467,137 total reported malaria cases in people over 5 years old

Of the approximately 33 million reported cases of malaria in the five regions of study between January 2010 and September 2016, the highest case counts were reported in the South East region, which hosts the largest population (over 4.6 million people) and registered over 4.4 million cases of malaria in people under 5 years old (Table 4) and over 5.4 million malaria cases in people 5 years and older (Table 5).

ANNUAL MALARIA STATISTICS

Malaria in children under 5 years old

The evolution of malaria in children under 5 years old shows a pattern of both increases and decreases across the years analyzed. These statistics point to a higher number of cases between 2010 and 2011, with a reduction occurring between 2012 and 2013, and a subsequent increase in the number of cases between 2014 and September 2016, though the changes were not significant. The increase is consistent with observed malaria trends in other parts of Africa (WHO 2018).

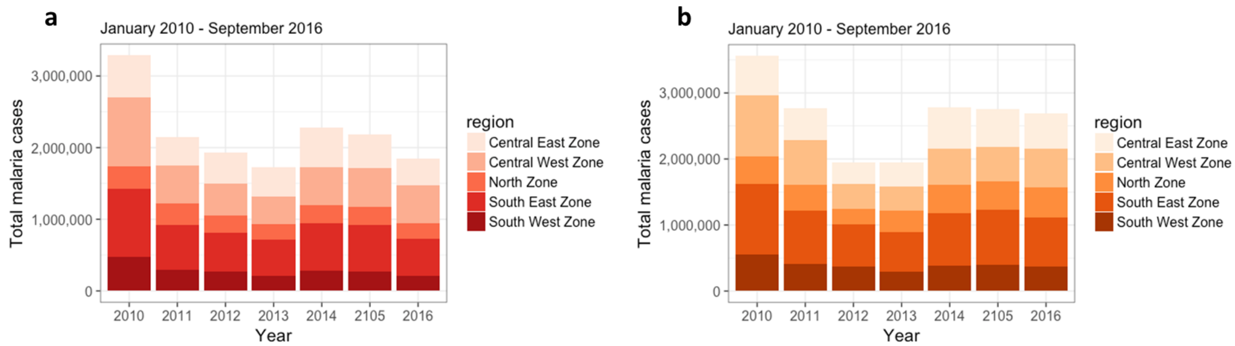
Table 4: Malaria cases among children under 5 years old, by year, including the region-level mean, median, and maximum number of cases for monthly reports

Year	Total Mal	Mean	Median	Min	Max
2010	3,287,125	54,790	54,820	22,430	118,900
2011	2,144,462	35,740	35,790	1,652	94,150
2012	1,937,234	32,290	30,250	13,280	68,570
2013	1,728,579	28,810	26,590	11,330	70,750

2014	2,282,651	38,040	31,830	13,660	84,790
2015	2,186,224	36,440	29,470	12,780	70,380
2016	1,845,461	41,010	31,640	8,528	99,290

A regional perspective is offered in Figure 15, again for the number of malaria cases by year for children under 5 years of age and over five years of age. As the figure shows, the South West and North regions have historically registered the lowest numbers of cases, while the South East bears the greatest burden of malaria cases. Population alone can't explain these results. Although the South East has the largest population, the North and South West have similar numbers of cases but with very different population sizes (the North has about 33 percent more people than the South West).

Figure 15: Total malaria cases among a) children under 5 years old, and b) 5 years of age and older by year and region of analysis



Malaria in persons 5 years of age and older

A similar pattern of outbreak followed by a decrease and then a subsequent increase is apparent in the malaria cases for persons 5 years of age and older, both at the district (Table 5) and the regional level (Figure 15)

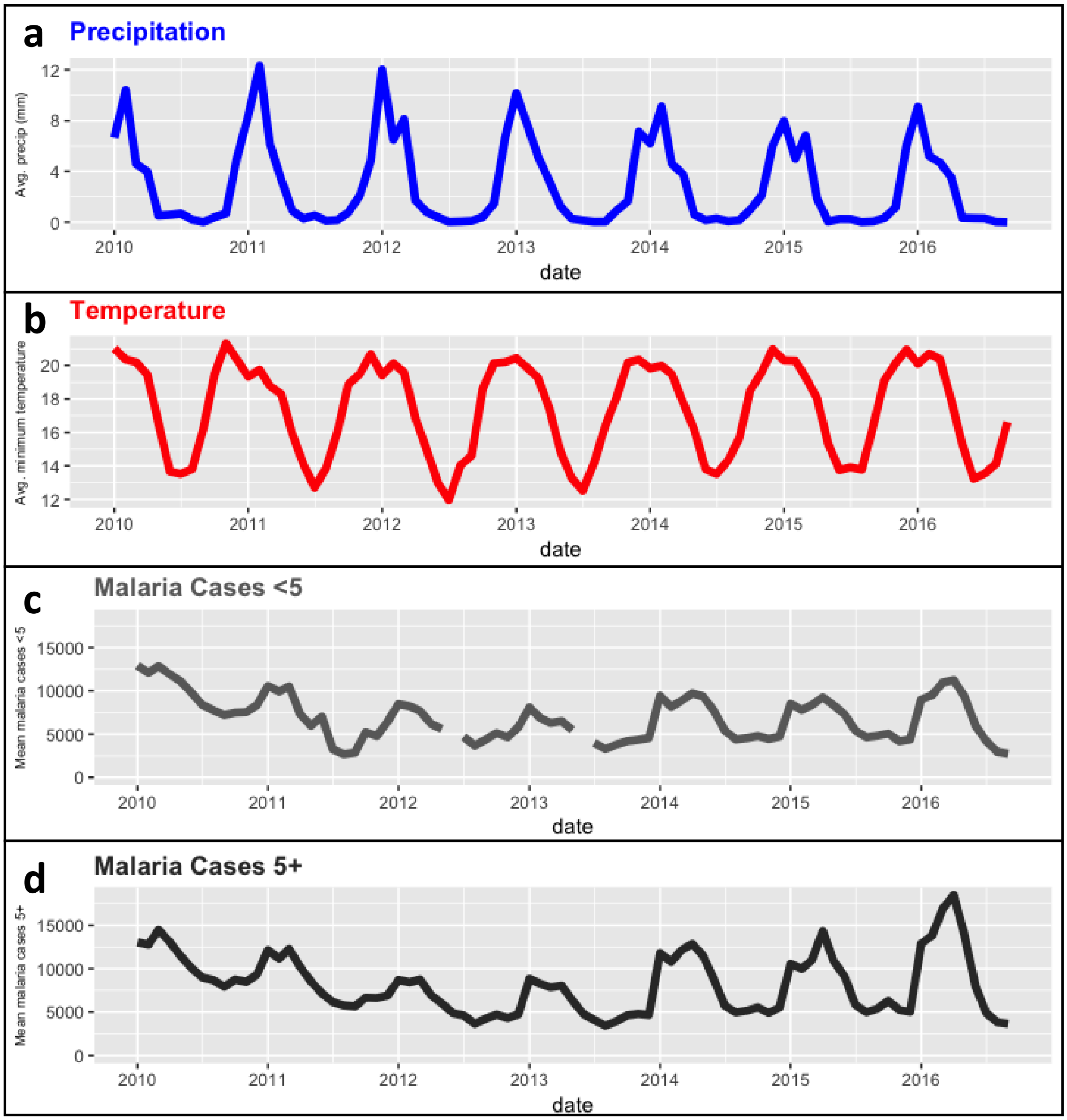
Table 5: Malaria cases among people 5 years and older, by year, including the region-level mean, median, and maximum number of cases for monthly reports

Year	Total Mal	Mean	Median	Min	Max
2010	3,559,023	59,320	55,760	29,630	125,500
2011	2,770,286	46,170	44,650	17,720	100,800
2012	1,952,523	5,828	4,901	135	24,070
2013	1,943,399	5,801	5,213	148	24,890
2014	2,786,881	8,294	7,246	212	38,450
2015	2,759,495	8,213	7,352	92	40,020
2016	2,695,530	10,700	8,464	256	55,110

MONTHLY MALARIA STATISTICS

Figure 16 shows precipitation, temperature, and malaria cases by age group (less than 5 years and 5 years and older over the period 2010-2016). Precipitation shows the expected seasonal pattern, with a high year-to-year variability. Visually, the annual peak in malaria cases tends to occur during months with higher amounts of precipitation (January – April). A similar pattern is observed for temperature, with a suggestion that temperatures rise just before a peak in malaria cases. This is expected because there is a lag between warmer temperatures and malaria transmission (see Figure 16). The time series also show the clear seasonality of cases. The number of malaria cases were higher in 2010–2011, then fell for the next two years, before rising again in 2014–2016.

Figure 16: Time series plots for outcomes and exposures of interest over the study period, including a) precipitation, b) temperature, c) malaria cases in children less than 5 years of age and d) malaria cases in children 5 years and older



January 2010 - September 2016

Seasonal patterns are apparent for both age groups, though the timing is shifted by age group as shown in Table 6 and Figure 17. Among children under 5, malaria cases peak in January with the lowest counts in August each year, on average. Peaks correspond to the highest rainfall values experienced during the season (January) and lowest values during the dry period (August), suggesting a high degree of sensitivity to the rainy season dynamics for children under 5. Among those 5 and over, malaria cases peak slightly later, toward the end of the rainy season (April), with the lowest counts corresponding to the start of the rains in November each year.

Figure 17: Total malaria cases in children under age 5 and 5 and older, by month, January 2010 – September 2016

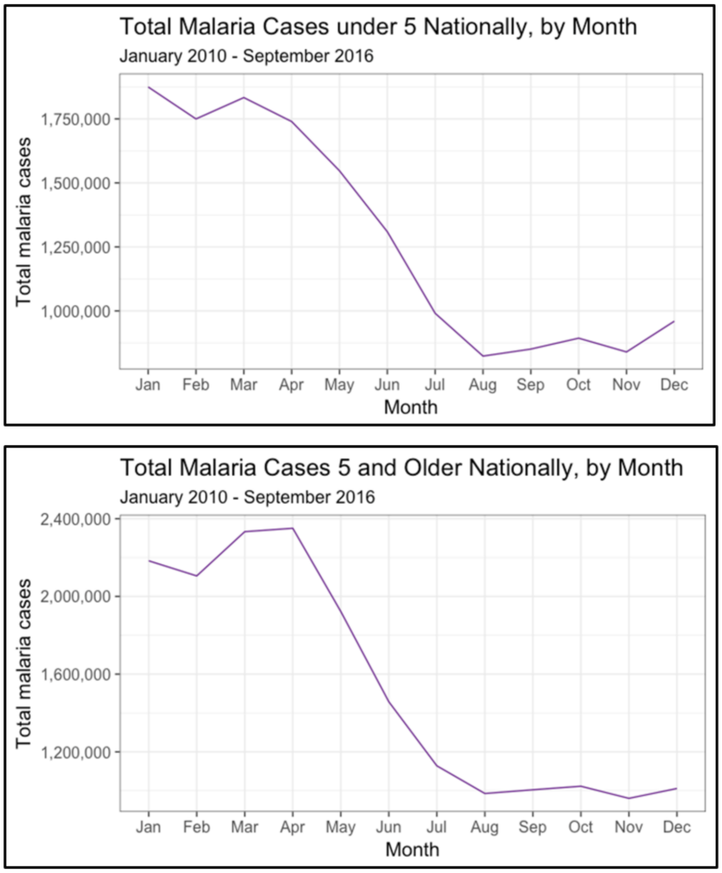


Table 6: Total malaria cases reported during each month of the study period by age group

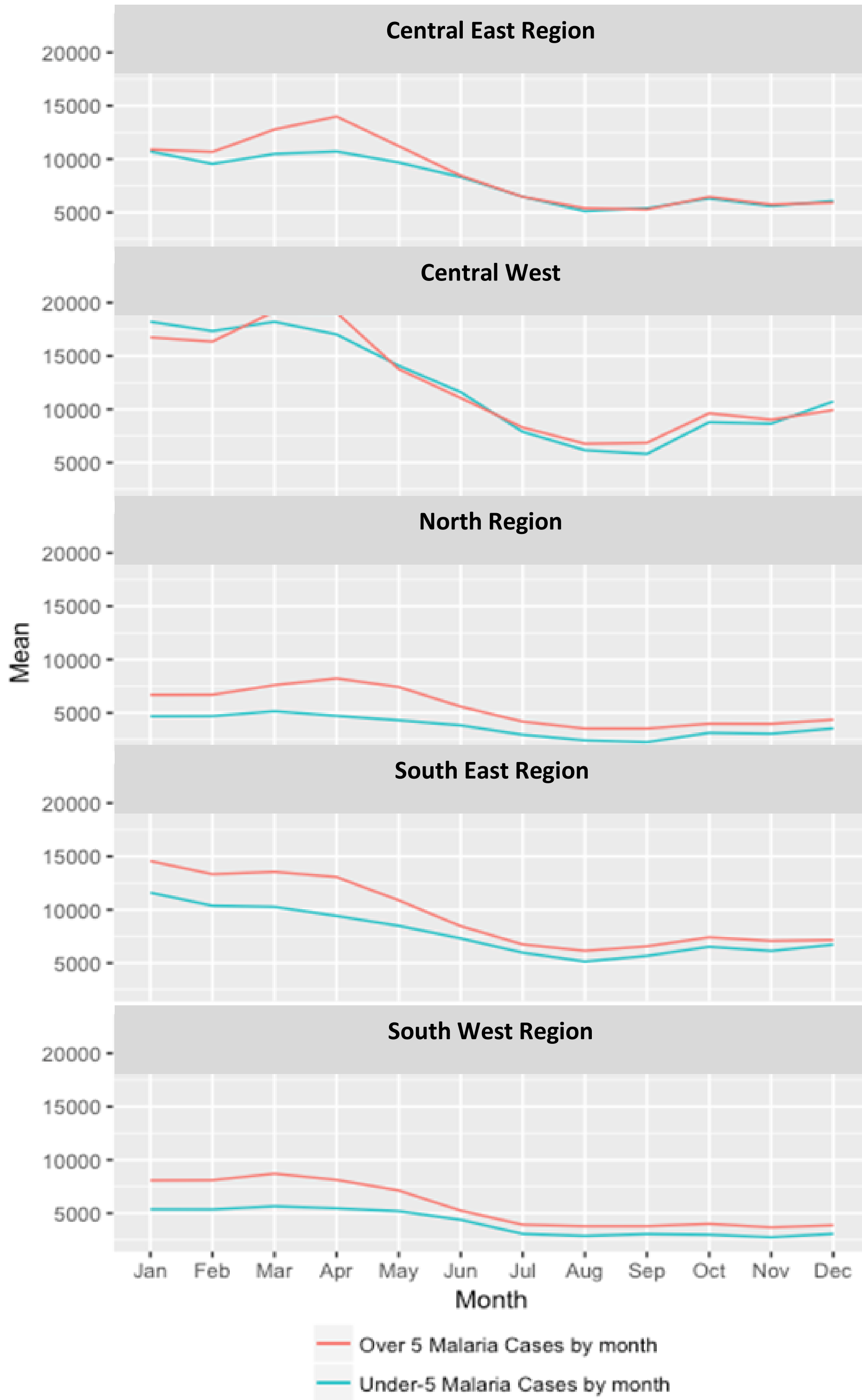
Month	Malaria <5 years	Malaria 5+ years
January	1,874,735	2,183,421
February	1,749,809	2,105,490
March	1,833,151	2,333,351
April	1,739,628	2,350,799
May	1,547,173	1,922,378
June	1,309,194	1,457,905
July	990,694	1,128,144
August	823,478	985,680
September	850,908	1,004,849
October	893,480	1,023,017
November	839,718	960,620
December	959,771	1,011,485

Note: Yellow highlights the highest values, green highlights the lowest values.

REGIONAL SEASONALITY

Malaria seasonality is very similar across the five regions, with year-to-year variability. All regions have their lowest counts in August of each year on average (Figure 18). Most regions exhibit strong seasonality, with approximately 2–3 times the number of cases in the peak of the season as compared with August. This is especially prominent in the Central West region, which decreases from more than 15,000 cases per month on average in March and April to nearly 5,000 cases on average in August.

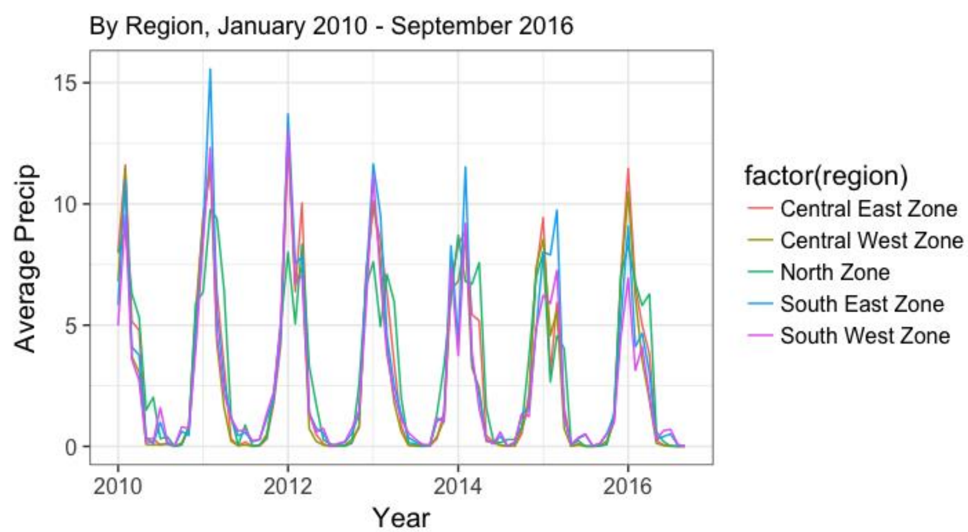
Figure 18: Mean malaria reports by month in each region, stratified by age

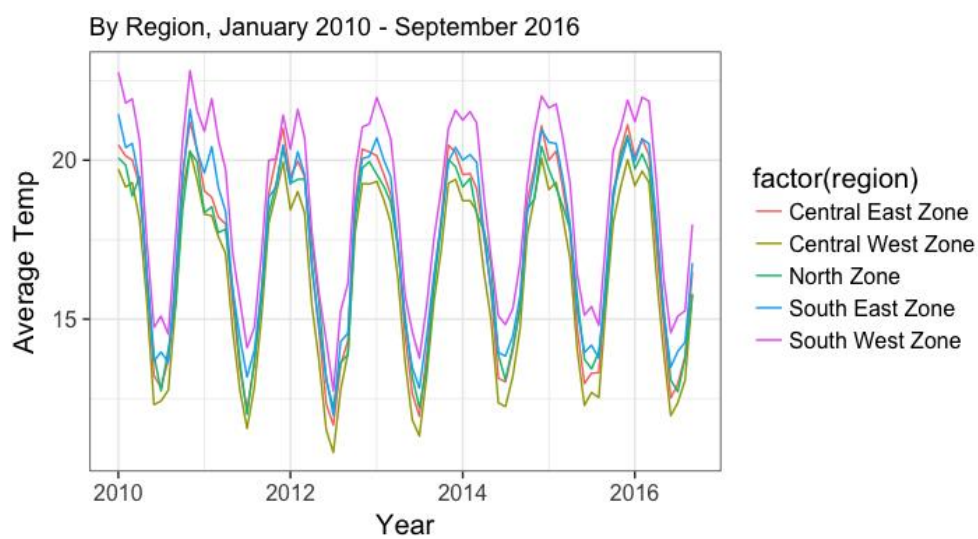


In general, the South West region experiences the highest summer maximum temperatures (about 22°C) and the highest minimum temperatures (about 15°C) in the winter (Figure 31). The Central West region has nearly the opposite pattern, experiencing lower maximum temperatures in the summer (about 19°C) and the lowest minimum temperatures in the winter (about 12°C), although, as the values show, the differences between these regions are not large. The temperature patterns for the other regions fall between these two.

Precipitation is strongly seasonal, with the highest rainfall around December to January (Figure 19). In general, the South East region receives more precipitation than the other regions, although that was not the case in 2016.

Figure 19: Mean precipitation and Mean temperature by region, January 2010 – September 2016





STATISTICALLY SIGNIFICANT ASSOCIATIONS BETWEEN MALARIA AND WEATHER VARIABLES

The associations between weather variables and malaria incidence were conducted using incidence rate ratios (IRRs) and mean daily precipitation and minimum temperature. These are summarized in the subsequent tables, under which:

- IRRs denote the change in malaria cases for each 1 mm difference in mean daily precipitation and each 1°C difference in mean monthly Tmin.
- Std Err is standard error.
- The lower (L) and upper (U) 95 percent confidence intervals (CI) also are shown
- Note that mean precipitation is lagged 1 month, adjusted for unlagged precipitation and temperature, and mean Tmin is lagged 2 months, adjusted for a 1-month lag, unlagged Tmin, and precipitation.

An interpretation example of these tables is presented below.

- Malaria 5 and over South West Region Precipitation—IRR = 1.033: When mean daily minimum temperature (2-month lag) is held constant, the model estimates that, for each 1 mm difference (increase or decrease) in mean daily rainfall during the month prior, there is a 3.3 percent (95 percent CI: 1.7 – 4.8 percent) difference (concurrently increased or decreased) in malaria case counts among people 5 years of age and older, controlling for seasonality and district, with the group with higher rainfall having higher malaria case counts.

Table 7 shows statistically significant relationships between mean daily precipitation and childhood malaria in children under 5 years old in the South East and South West, with a 1.7 percent increase in malaria in the South East for each 1 mm increase in mean daily precipitation, with a 2-month lag. The increase for the South West is 2.3 percent. Malaria decreases in the North with an increase in temperature. When mean daily temperature increases (2-month lag), there is a statistically significant increase in malaria in the South East of 3.8 percent. All other results are nonsignificant.

Table 8 shows statistically significant relationships between mean daily precipitation and malaria in people 5 years of age and over in the South East and South West, with a 1.6 percent increase in malaria in the South East for each 1 mm increase in mean daily precipitation, with a 2-month lag. The increase for the South West is 3.3 percent. All other results for temperature and precipitation are nonsignificant.

Table 7: Malaria analyses in children under 5 years of age.

Predictor	Region	IRR*	Percentage change	Std. Err.	95 percent CI L	95 percent CI U
Mean daily precipitation	Central East	1.012		0.010	0.993	1.031
	Central West	1.013		0.013	0.987	1.040
	North	0.960		0.015	0.933	0.989
	South East	1.017	1.7 percent	0.006	1.005	1.029
	South West	1.023	2.3 percent	0.008	1.008	1.039
Mean daily Tmin	Central East	1.026		0.027	0.974	1.081
	Central West	1.008		0.025	0.960	1.059
	North	1.025		0.023	0.980	1.073
	South East	1.038	3.8 percent	0.017	1.003	1.074
	South West	1.035		0.020	0.995	1.076

Table 8: Malaria analyses in persons 5 years of age and older

Predictor	Region	IRR*		Std. Err.	95 percent CI L	95 percent CI U
Mean daily precipitation	Central East	1.007		0.010	0.987	1.026
	Central West	1.017		0.015	0.988	1.047
	North	0.980		0.015	0.951	1.009
	South East	1.016		0.006	1.005	1.028
	South West	1.033		0.008	1.017	1.048
Mean daily Tmin	Central East	1.027		0.026	0.975	1.081
	Central West	0.979		0.028	0.926	1.034
	North	1.019		0.024	0.972	1.068
	South East	0.996		0.018	0.963	1.031
	South West	1.029		0.018	0.994	1.065

CLIMATE CHANGE IN MALAWI

KEY MESSAGES

Temperature

- Daily and yearly temperatures (average, maximum and minimum) will rise and these increases are statistically significant even as early as the 2020s.
- Average temperatures will increase between 1.5 to 6 ºC by 2100 under all scenarios evaluated.
- Maximum temperatures are projected to rise between 1-7 ºC by 2100.
- The warming rate is similar across all regions with no one region projected to warm faster than another.

Rainfall

- Most models project a decrease in the number of rain days per year before the 2050s, representing an opposite direction of change in the trends observed.
- Projected changes in total and monthly rainfall are uncertain, and there is no agreement in the sign of the change between models, some show statistically significant increases and others statistically significant decreases.
- Seasonally, most models show a statistically significant reduction in rain days, with the worst-case scenario (RCP 8.5) pointing to a potentially later start in the rainy season across all regions in Malawi.

APPROACH

An ensemble of 19 Regional Climate Model (RCM) projections from the Coordinated Regional Climate Downscaling Experiment (CORDEX) over the African Domain are used. The ensemble is made up of five Regional Climate Models (CLMcom-CCLM4-8-17, DMI-HIRHAM5, KNMI-RACMO22T, MPI-CSC-REMO2009 and SMHI-RCA4) where each model was driven by up to nine different Global Climate Models from the CMIP5 project using the historical, the RCP 4.5 and RCP8.5 experiments.

The CORDEX project provides daily maximum and minimum temperature. This has been converted to daily mean temperature and processed to form monthly climatologies for the historical period (1986-2005) and future period (2020-2039) under the RCP 4.5 and RCP 8.5 emission scenarios. These models have some biases in their temperatures (some models are warmer or cooler than reality), therefore future anomalies rather than the absolute values projected by the models were used. The future anomalies were calculated by differencing the future climatologies from the historical climatology. These anomalies were then added to the WFDEI -SRTM observed climatology. The spatial resolution of the CORDEX data was ~50 km, therefore the data were regridded to the 0.05-degree resolution of the WFDEI SRTM dataset using bicubic interpolation. It is important to note that this process is not the same as the process of interpolation of historical data that included elevation as a co-variate. Here, temperature anomalies (future-past change) rather than temperature itself are interpolated. Unlike with air temperature, there is no basis to consider that temperature anomalies are related to surface elevation. As a result, elevation is not considered as a co-variate here.

Climate model projections from Couple Model Intercomparison Project (CMIP5) are presented below. Both Representative Concentration Pathways (RCP) 4.5 and 8.5 are presented. RCP 8.5 represents a weak mitigation future, while RCP 4.5 represents a much more aggressive mitigation future though still not in line with the 2016 Paris Agreement objectives, which aims to limit temperature increase to 1.5ºC. The CMIP5 ensemble are global models with varying spatial resolutions and hence varying representations of the significant topography and water bodies of Malawi and so their ability to capture local scale process is limited. However, one would expect them to represent regional shifts in moisture transport, sea surface temperatures (SSTs), and large-scale rainfall changes.

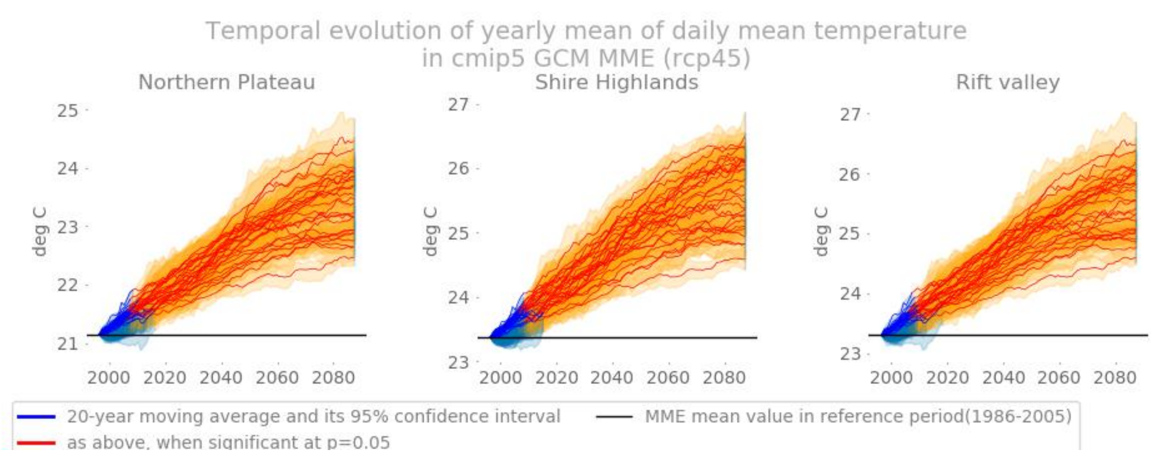
INTERPRETING PLUME PLOTS

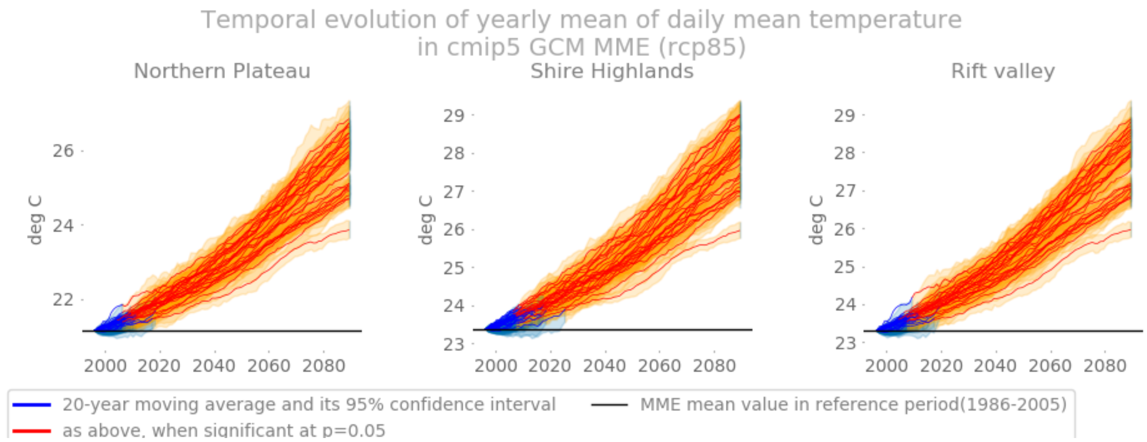
The solid straight line is the mean value of the reference period (1986-2005) based on the WFDEI data. Each thin colored line represents the change from the reference period from 2005 of a single model realization with its 95 percent confidence interval. The 95 percent confidence interval provides a range of values that are 95 percent likely to encompass the true value and so provides a statistical measure of confidence that the result is realistic. Each line represents a 20-year running mean as a departure from the reference period. When a line changes from blue to red this means, at that time, the change from the reference period becomes statistically significant for that model. If a line tracks below the reference period, that model is projecting a drier climate for the region compared to the reference period, and if it changes from blue to red, the change is statistically significant.

TEMPERATURE

Differences between the baseline and projected yearly mean of daily mean temperature are statistically significant for all three climatological (rainfall) regions under both RCPs as early as the 2020s (Figure 20). The magnitude of the increase of daily mean temperature under RCP 4.5 is between 1.5 and 3.5 ºC and under RCP 8.5 the warming is between 3 and 6 ºC by 2100.

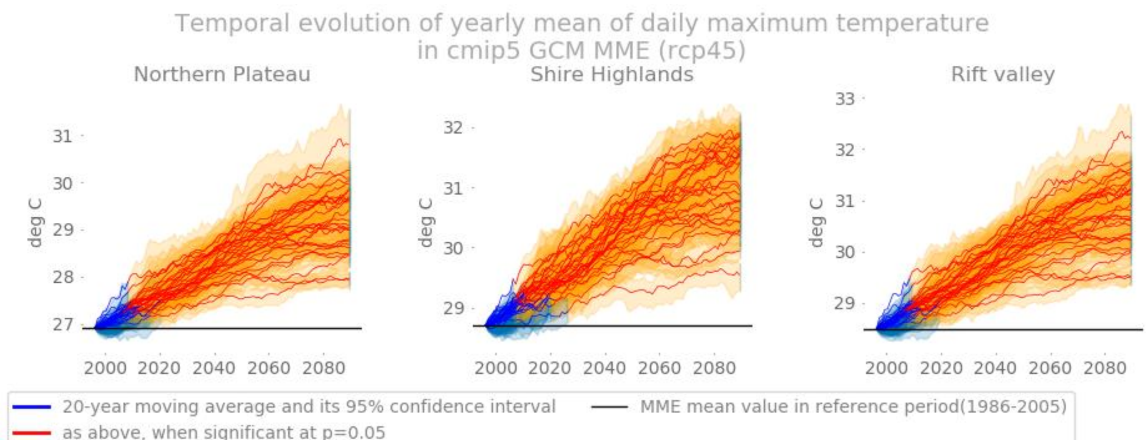
Figure 20: Projected changes in the yearly mean of daily mean temperature between 2005-2100 under RCP 4.5 (top) and RCP 8.5 (bottom).

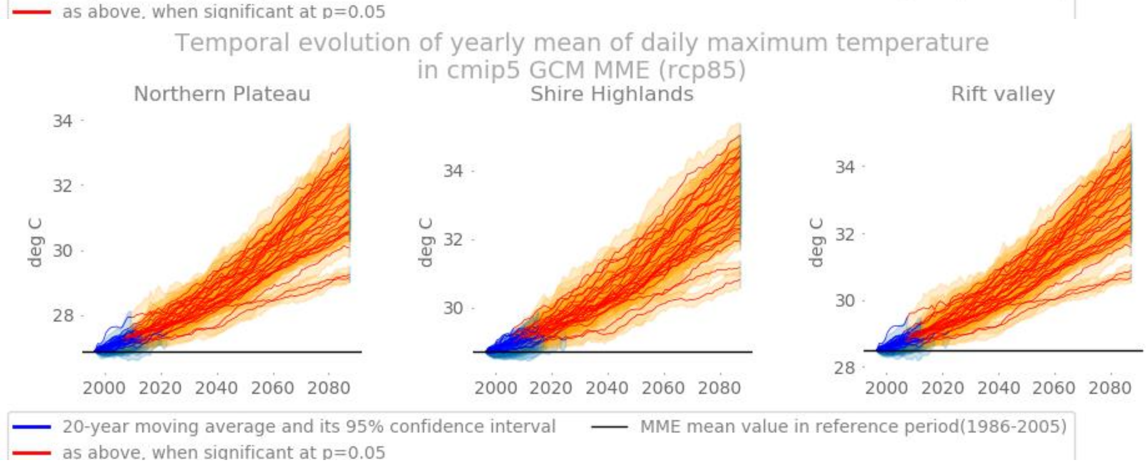




Statistically significant increases in the yearly mean of daily maximum temperature are also projected for all three regions under both RCPs well-before the middle of the century (Figure 21). The magnitude of the increase of daily maximum temperature under RCP 4.5 is between 1 and 4 ºC and under RCP 8.5 the warming is between 2 to 7 ºC by 2100.

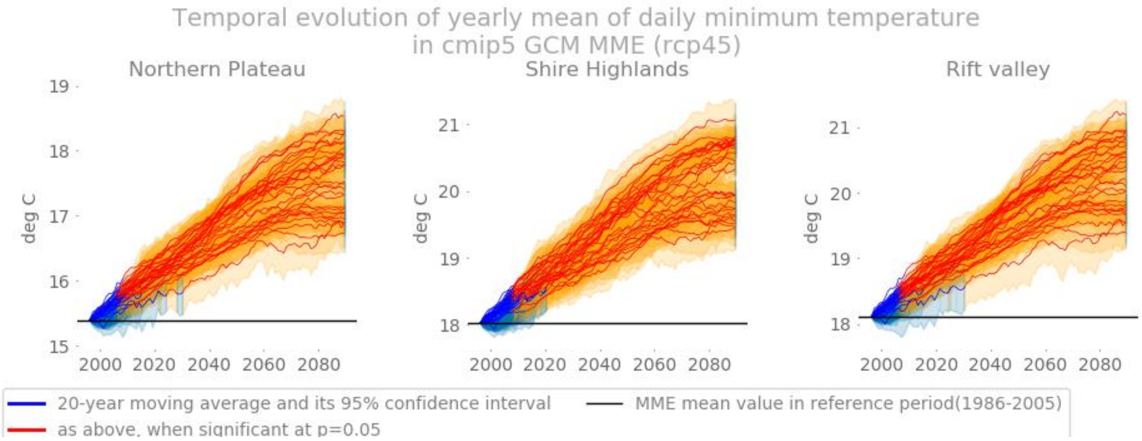
Figure 21: Projected changes in the yearly mean of daily maximum temperature between 2005-2100 under RCP 4.5 (top) and RCP 8.5 (bottom).

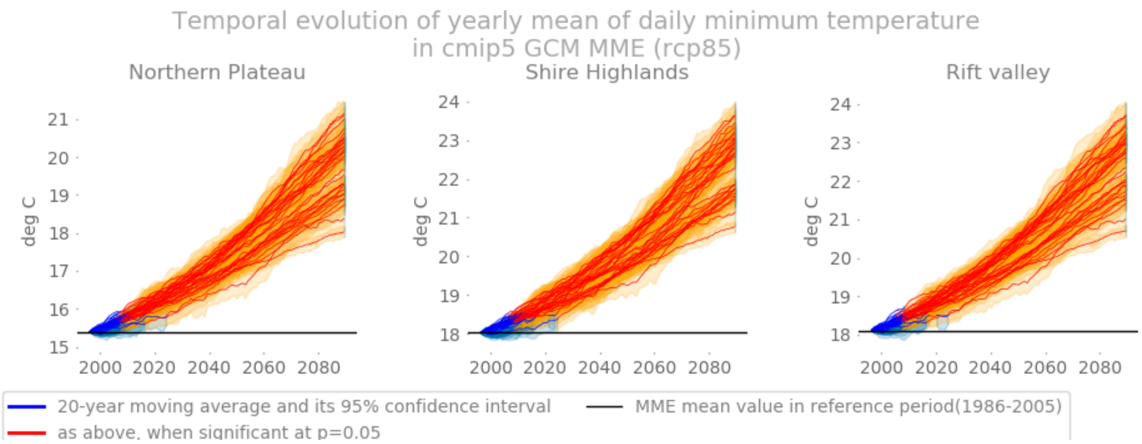




The warming rate is similar across all three regions with no one region projected to warm faster than another. Similarly, projected increases in the yearly mean of daily minimum temperature (Figure 22) are significantly different from the reference period before the middle of the century with between 1 and 3 ºC increase under RCP 4.5 and 2.5 to 6 ºC increase under RCP 8.5.

Figure 22: Projected changes in the yearly mean of daily mean minimum temperature between 2005-2100 under RCP 4.5 (top) and RCP 8.5 (bottom).

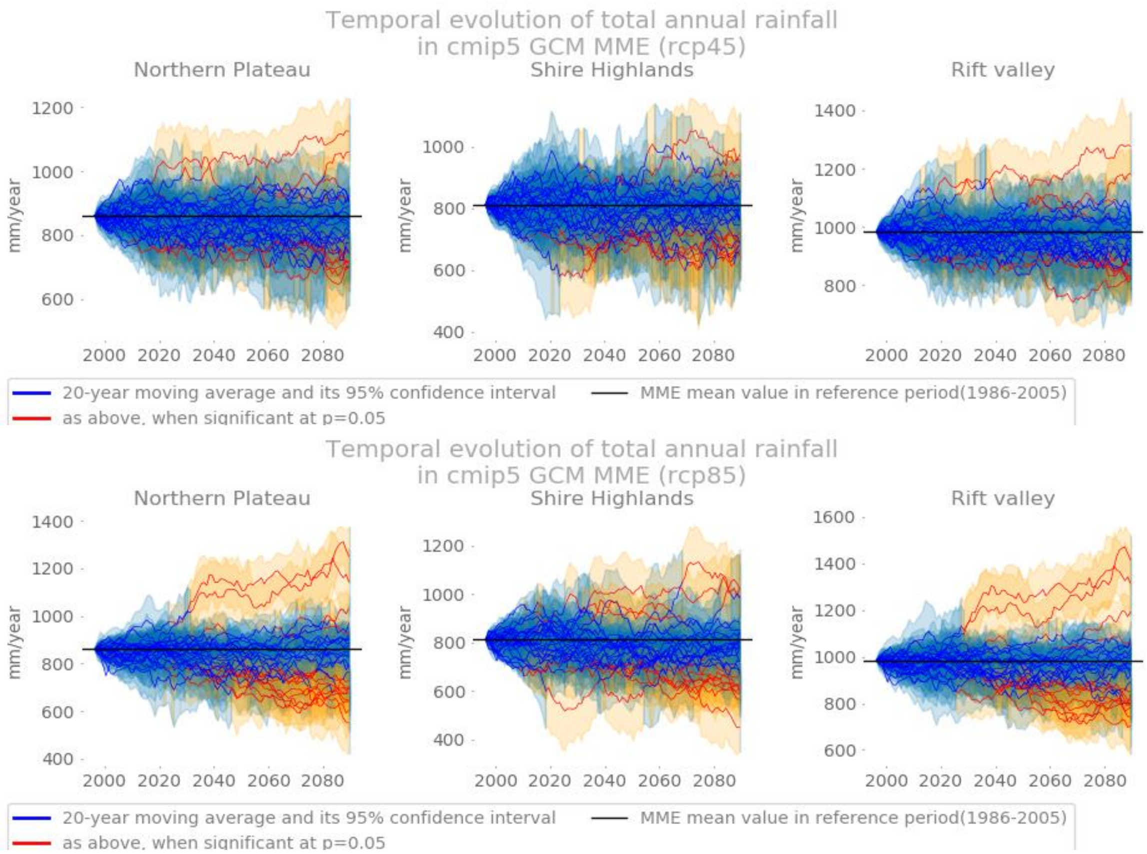




ANNUAL RAINFALL

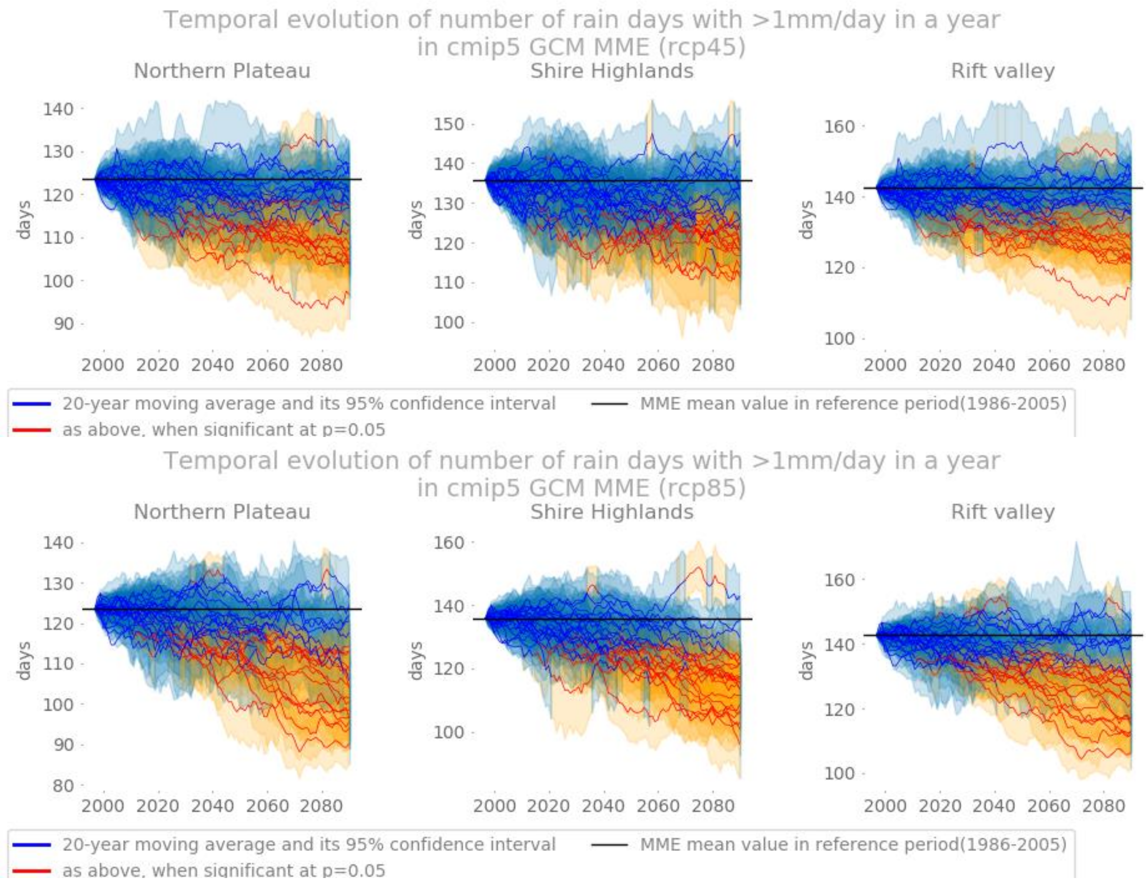
Across the ensemble of models, relatively few models show statistically significant changes in total annual rainfall before mid-century in RCP 4.5, although this number increases under RCP 8.5 (Figure 23). However, in all three regions under both RCPs there is no agreement in the sign of the change between models, some show statistically significant increases and others statistically significant decreases. Other models indicate no change in total annual rainfall until 2100. The projected change in total annual rainfall is therefore uncertain.

Figure 23: Projected changes in total annual rainfall between 2005-2100 under RCP 4.5 (top) and RCP 8.5 (bottom).



While projected changes in total rainfall are uncertain, most models project a decrease in the number of rain days per year before mid-century in both RCPs (Figure 24). Under RCP 8.5 a larger number of models show statistically significant changes and project a larger decrease in the number of rain days. Interesting this represents the opposite direction of change from the trend analysis for the same variable, although the historical trend of increasing rain days is not statistically significant.

Figure 24: Projected changes in number of rain days between 2005-2100 under RCP 4.5 (top) and RCP 8.5 (bottom).



SEASONAL RAINFALL

As rain days (days with rainfall greater than 1mm) are a significant predictor of malaria transmission, it is considered important to disaggregate the annual projections into seasonal projections of change. Furthermore, the rainy season is of most relevance to malaria. This incorporates the months of September, October, November (SON) and December, January, February (DJF). These two seasons are shown in Figure 25 and Figure 26 for RCP 4.5 and 8.5 respectively.

Under RCP 8.5 (Figure 26), most models show a statistically significant decrease in rain days in the SON and DJF period by the end of the century. However, this decrease in seasonal rain days is not clearly present under RCP 4.5 (Figure 25). The drying present in both seasons under RCP 8.5 indicates a possible drying of the entire rainy season, including a potentially later start to the rainy season in all three regions. This drying becomes statistically significant by mid-century.

Figure 25: Projected seasonal changes in number of rain days between 2005-2100 under RCP 4.5 in September, October, November (SON) (top) and December, January, February (DJF) (bottom)

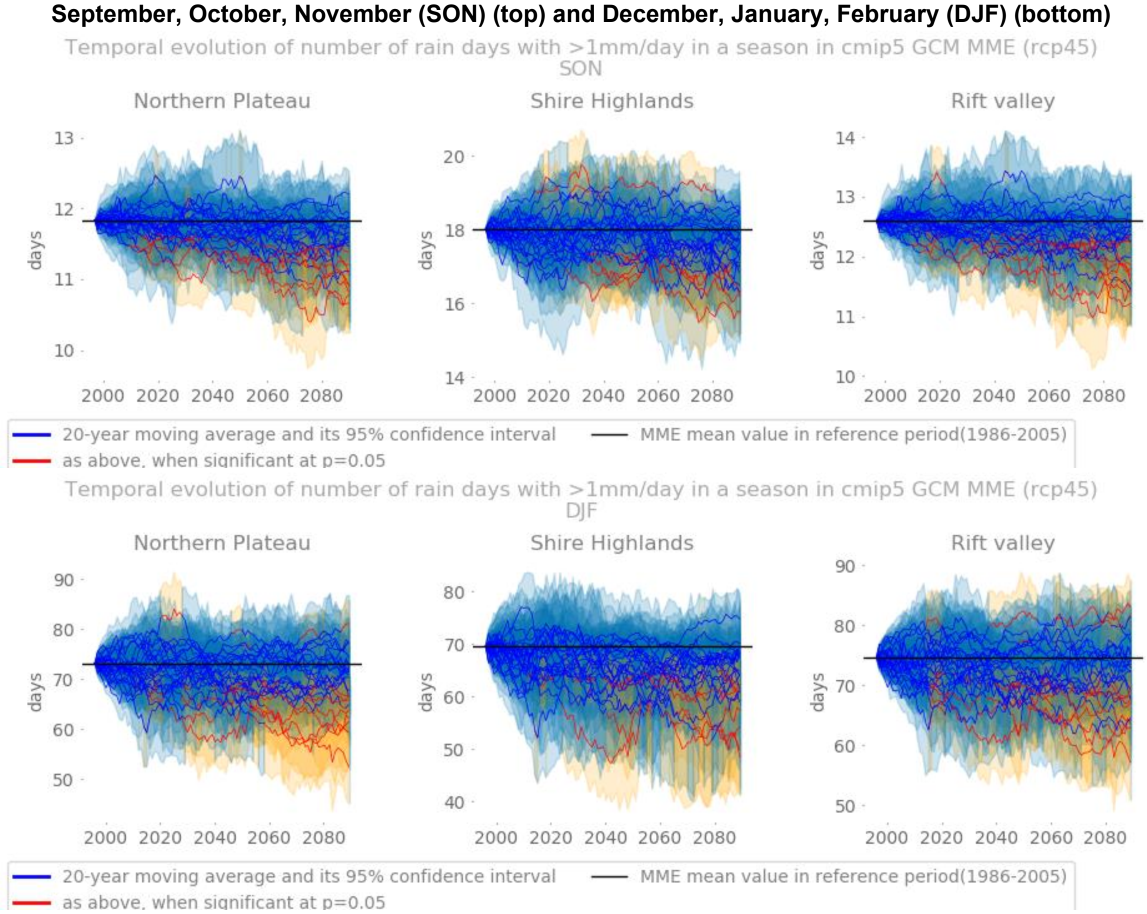
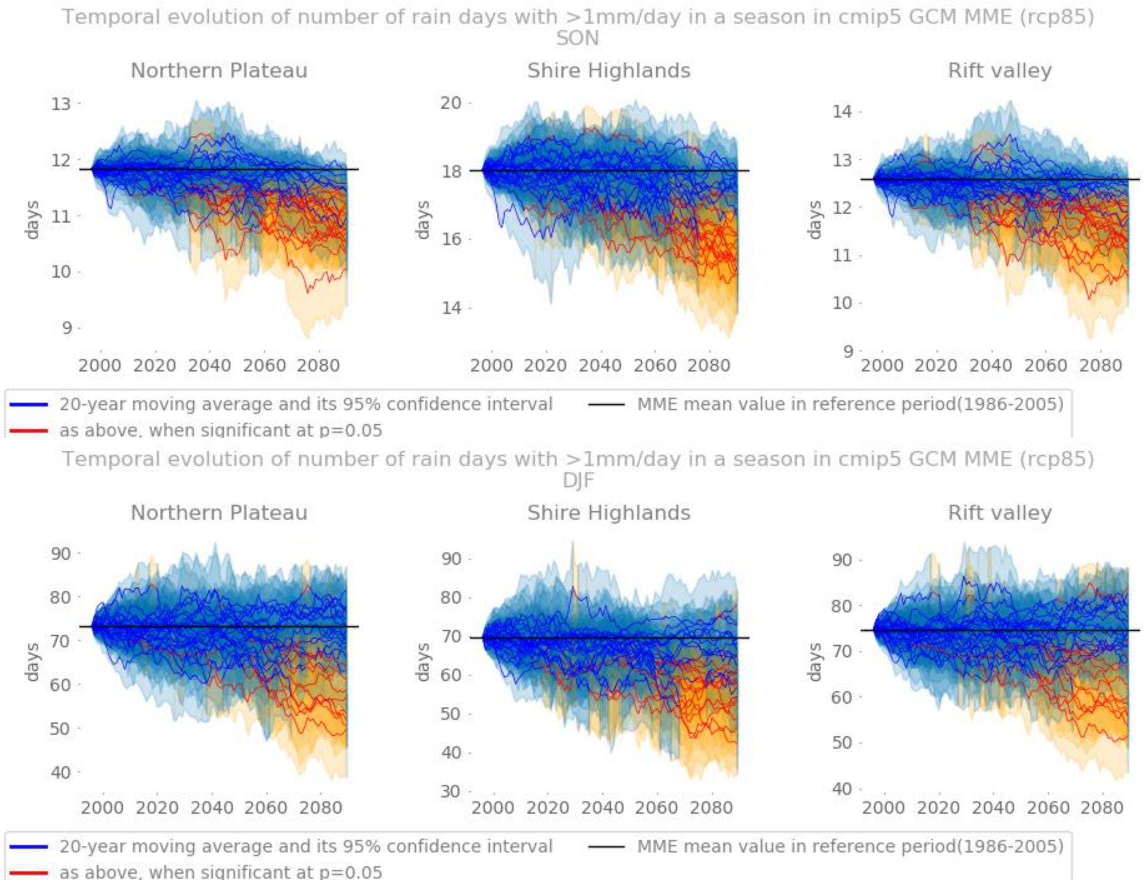


Figure 26: Projected seasonal changes in number of rain days between 2005-2100 under RCP 8.5 in September, October, November (SON) (top) and December, January, February (DJF) (bottom)



A better understanding of the skill and value of information resulting from climate modelling will inform climate inputs into disease modelling initiatives, ultimately helping to inform health programming and policies. This contributes towards the goal of disease elimination by informing modification of current interventions and programs and implementing new ones that can adaptively respond to changing climate conditions

MALARIA IN A HOTTER CLIMATE

KEY MESSAGES

- An estimated 14million people in 2010 were living in areas of risk for 1 or more months of transmission suitability in Malawi. Of these, a third (4.8 million, 35 percent live in areas suitable for seasonal (7-9 months) transmission.
- In all projected future scenarios, the largest portion of people at risk (ranging 46-77 percent are at seasonal (7-9 months) risk, suggesting a shift toward more seasonal transmission risk from the baseline.

Shifts in both the areas and populations exposed to malaria risks will require a change in the portfolio of responses to address those risks. Many countries with a high burden of malaria already have weak surveillance systems and are not able to assess disease distribution and trends, making it difficult to optimize responses and respond to outbreaks. The following analysis offers insights for programming decisions by exploring six scenarios of changing suitability. Not all potential scenarios of change were evaluated; rather, these scenarios highlight the changing profile of risk across the region but could be expanded to include other shifts, such as from endemic or seasonal to marginal or moderate suitability.

METHODS

Areas of malaria suitability were mapped in a model combining future temperature change projections and current knowledge about the life cycles of malaria-carrying mosquitoes and the malaria parasite. Malaria suitability was examined across two future time periods: the 2030s (representing the period between 2015 and 2044), and the 2060s (representing the period between 2045 and 2074). Details of the methodological approach are available in the [Shifting Burdens: Malaria Risks in a Hotter Africa report].

Figure 27: Summary of Analysis Parameters

Mosquito species: *Anopheles gambiae*

Malaria pathogen: *Plasmodium falciparum*

Climate models: Two reginal climate models representing the range of possible outcomes within the available models – a ‘hotter’ and a ‘cooler’ model

Climate projections: RCP 4.5 and RCP 8.5

Time period: 2030s and 2060s

The analysis of vector suitability considering future temperature projections is based on an empirical modeling methodology (see box below). The method of Ryan et al. (2015) is extended, applying the model from (Mordecai et al. 2013) to climate model layers (described in

Input Data below). All calculations are conducted in R [3.5.0], using the “raster,” “rgdal,” “sp,” and “maptools” functions, and mapped output is produced in ArcGIS (Version 10.5.1).

INPUT DATA

- CORDEX Experiment information under two Representative Concentration Pathways (RCPs)—RCP 4.5 and RCP 8.5—for two future time periods: the 2030s and the 2060s (see box). Two future climate models were selected for comparison to represent the range of possible outcomes within the available regional climate models – a ‘hotter’ future using WFDEI_SRTM_AFR-44_CNRM-CERFACS-CNRM-CM5_rcp45_r1i1p1_SMHI-RCA4_v1 and a ‘less hot’ future with the tair_mon_mean_clim_WFDEI_SRTM_AFR-44_MOHC-HadGEM2-ES_rcp45_r1i1p1_CLMcom-CCLM4-8-17_v1 Model as described in Shifting Burdens: Malaria Risks in a Hotter Africa.
- Countries of Africa are derived from a shapefile of the database of Global Administrative Areas (GADM). The Southern African region is defined based on a previous report Shifting Burdens: Malaria Risks in a Hotter Africa.
- To exclude arid areas that preclude *Anopheles* development, the Moderate-Resolution Imaging Spectroradiometer (MODIS)-derived normalized difference vegetation index (NDVI) values for 2016 and 2017 are used to create an “aridity mask,” as described below.
- Population data used as input to the calculations are derived from the SSP2 Shared Socioeconomic Pathways project (Jones and O’Neill 2016). Baseline calculations used 2010 data, while projected populations are extracted from the 2030 and 2050 layers as explained in the methodology below.

EXAMINING IMPACTS FROM FUTURE TEMPERATURE RISE USING SCENARIOS

To explore how the planet might change in the future, considering emissions, climate, environmental change, and vulnerability, the Intergovernmental Panel on Climate Change uses scenarios, termed Representative Concentration Pathways (RCPs).

These include: RCP 4.5 and RCP 8.5. The numbers refer to radiative forcing, a measure of the impact of greenhouse gases in the atmosphere on the Earth’s normal energy balance.

This information is translated through models of climate dynamics and used to project increases in temperature because of increased greenhouse gases.

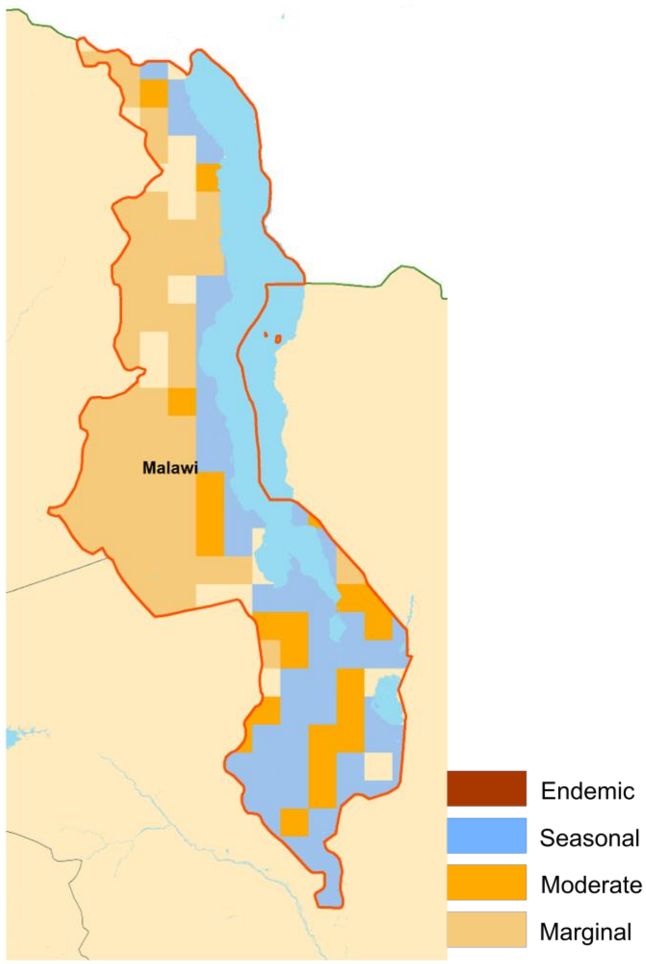
MODEL DESCRIPTION

Malaria transmission suitability model. Using the mechanistic model mentioned above (Mordecai et al. 2013, Mordecai et al. 2017), R_0, the metric for transmission suitability, scaled from 0 to 1, is described in quantiles. The top quantile (top 25 percent) of the curve is selected to represent the range of temperature in which transmission suitability is expected. This conservative measure of the overall temperature curve is used because it was previously shown to correspond visually to existing maps of ongoing transmission, under current temperatures (Ryan et al. 2015). Using this “most suitable” quantile, this temperature range is incorporated into projections of suitability, as described in the following sections.

RESULTS

The regional patterns of malaria suitability in Malawi point to seasonal transmission concentrated in the Shire basin and along the shores of lake Malawi, with Moderate and Marginal suitability in the other regions of the country (Figure 28). In the baseline of 2010 used, an estimated 14 million people were living in areas of risk for 1 or more months of transmission suitability in Malawi, with around a third (4.8 million, 35 percent) living in areas suitable for seasonal (7-9 months) transmission.

Figure 28: Current suitability for temperature driven malaria transmission in Malawi



PROJECTED CHANGES IN DETAIL

Shifts in both the areas and populations exposed to malaria risks will require a change in the portfolio of responses to address those risks. The following analysis offers insights for programming decisions by exploring three scenarios of changing suitability. Not all potential scenarios of change were evaluated; rather, these scenarios highlight the changing profile of risk across Malawi. The three scenarios of changing suitability are described below, and the findings summarized in Table 9, Figure 29, and Figure 30.

New areas of malaria suitability

1. Where and when are new areas of seasonal suitability going to emerge where malaria was previously unsuitable? How many people are at risk from this change?

Areas where the malaria season will be extended

2. Where and when will seasonal areas become endemic? How many people are at risk from this change?
3. Where and when will moderately or marginally suitable areas become seasonal? How many people are at risk from this change?

Table 9: Detailed results of projected changes examined including projected population growth

Change in suitability	Where will this happen?	How many people are at risk?
New areas of seasonal malaria suitability	By the 2030s, in the southern region near the Shire valley and the central rift valley region. By the 2060s, extending throughout the rift valley and into the north.	Under the hotter scenario, in 2060, and at RCP 8.5, we see 815,449 people newly at seasonal (7-9 months) of risk where there is currently no suitability; however, in all other future climate scenarios there are no novel seasonal areas arising.
Areas where malaria season will be extended (seasonal → endemic)	In the northern region.	We find that only under RCP 8.5 in 2030 and 2060 for the cooler future scenario are there changes from seasonal to endemic areas in Malawi; in 2030, this creates novel risk for 26,617 people, and in 2050, for 33,094 people. (Figure 29).
Areas where malaria season will be extended (moderate/marginal → seasonal)	Most changes in Malawi occur in this category, for reference on spatial changes, see Figure 29	• Under the 'cooler' future scenario, the total number of people living in areas of seasonal (7-9 months) transmission will rise to between 25.1 and 25.2 million in 2030 (RCP 4.5 and RCP 8.5), and to 39 million in 2060. • Under the 'hotter' future scenario, this will rise to 25.5 million people at risk by 2030, and 39.5 million by 2060. In all projected future scenarios, the largest portion of people at risk (ranging 46-77 percent) are at seasonal (7-9 months) risk, suggesting a shift toward more seasonal transmission risk from the baseline.

Figure 29: Areas currently moderate or marginally suitable (1-6 months) which become seasonally suitable (7-9 months) under RCP 4.5 and RCP 8.5 for 2030's and 2060's time horizons, for A. a less hot future; and B. a hotter future

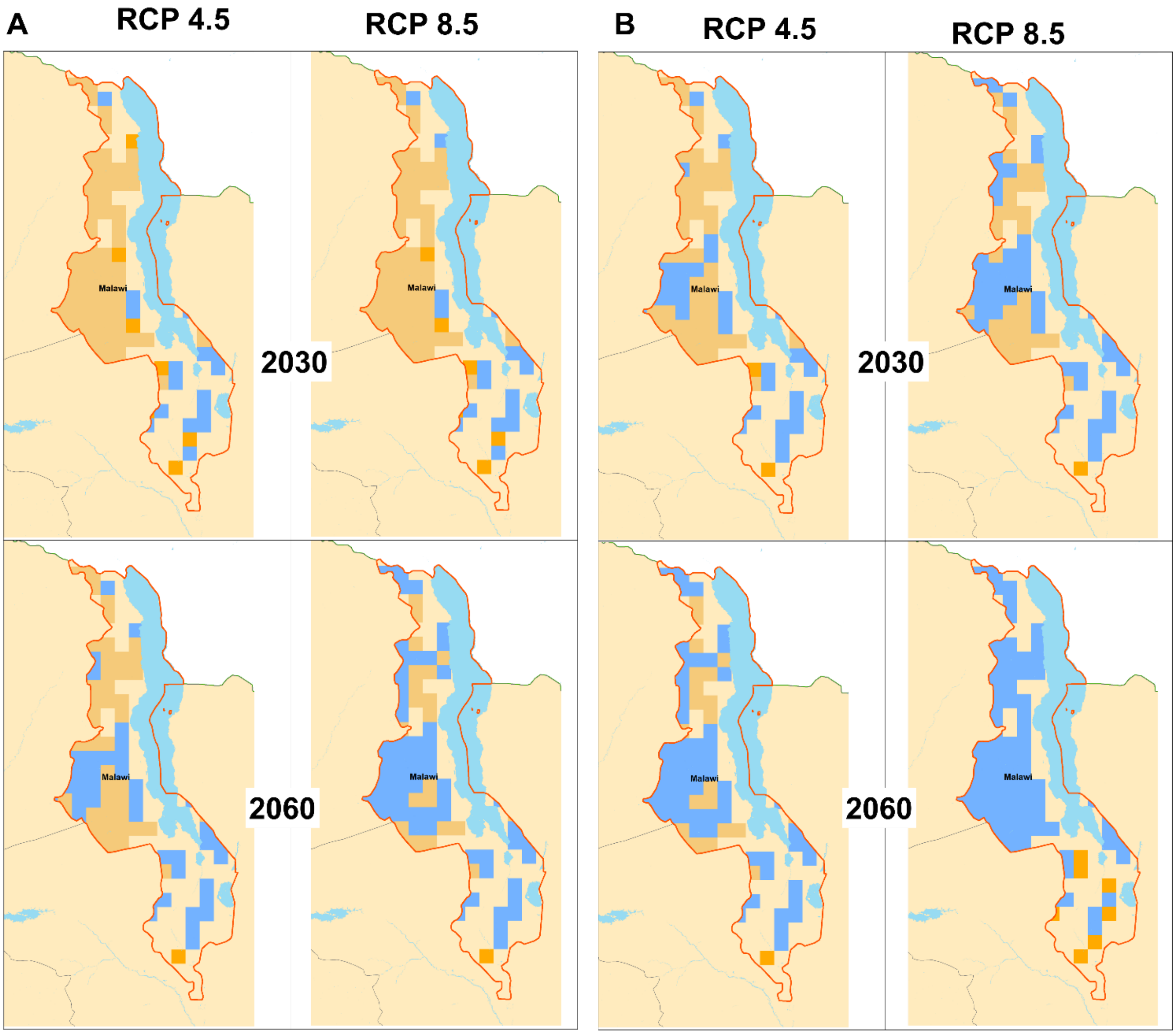
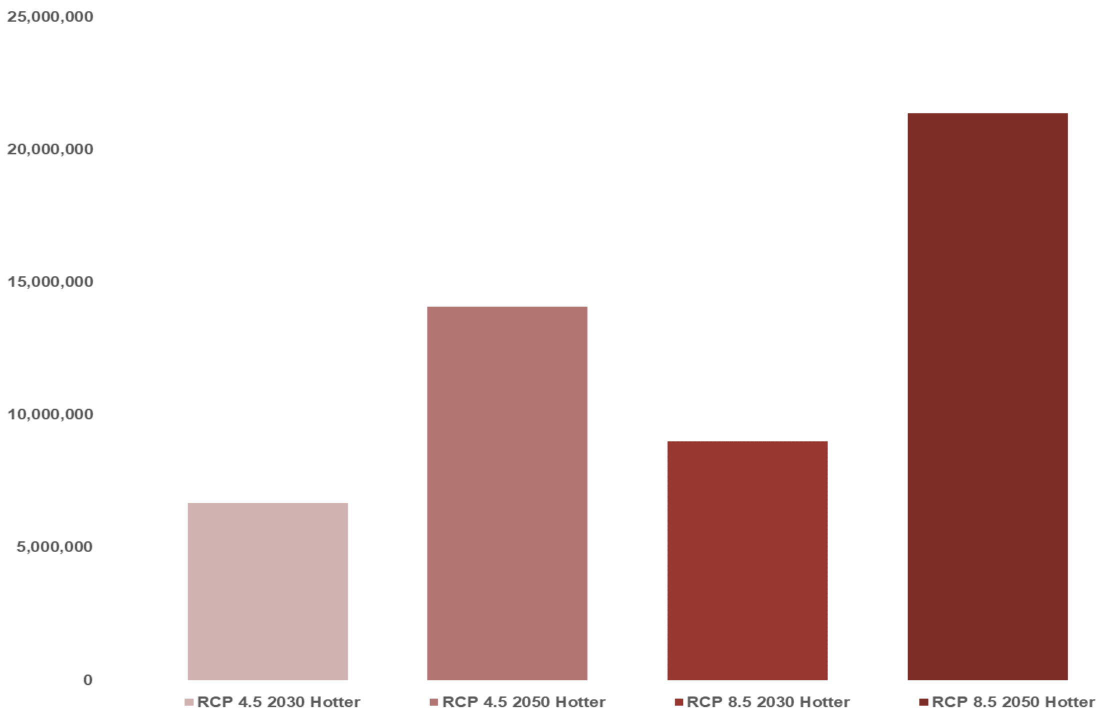
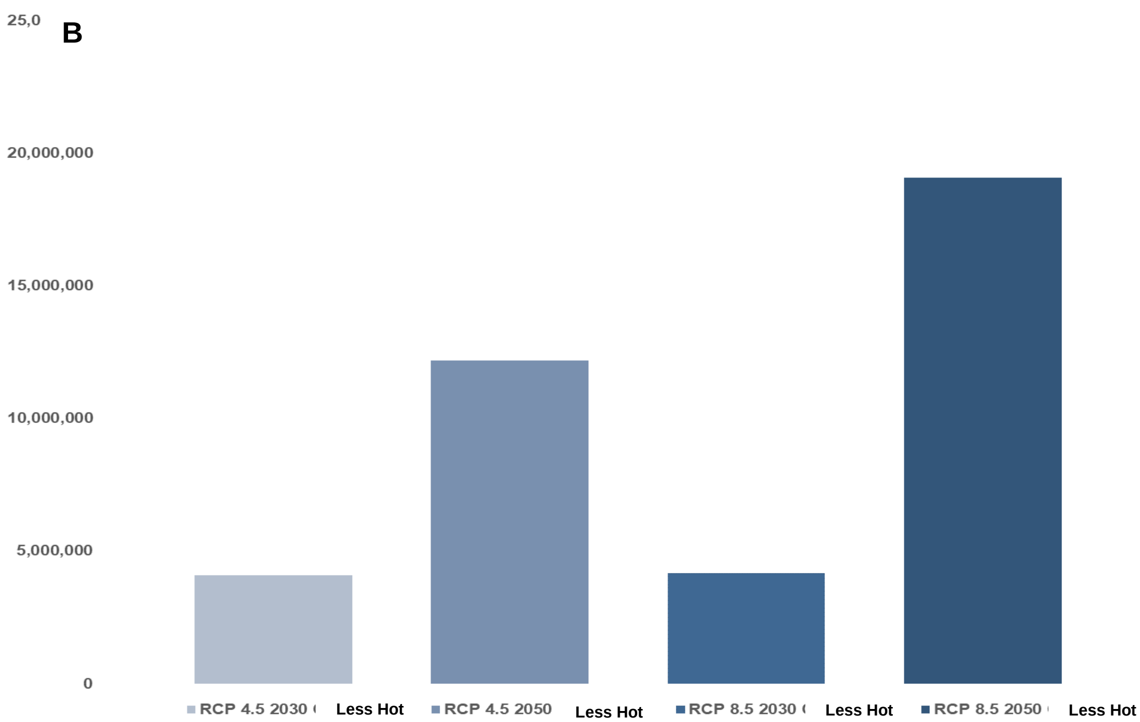


Figure 30: Number of people newly at risk as moderate and marginal (1-6 months) become seasonally suitable for transmission (7-9 months), for RCP 4.5 and 8.5, in the 2030's and 2060's time horizons, for A. the hotter model; and B. the less hot model

A



B



INSIGHTS AND RECOMMENDATIONS

With malaria as the third most common cause of death in Malawi (Malawi National Health Sector Strategic Plan 2017-2022), it is important that Malawi's health policies and planning consider the possibilities of shifting malaria suitability under a changing climate. Neither the National Health Policy (2012) nor the Health Sector Strategic Plan mention climate or climate change or any associated risks to malaria or other climate/weather-related diseases such as cholera.

INSIGHTS FROM THE ANALYSIS

The analyses show the seasonality of malaria in Malawi, with most cases occurring in the Jan-Apr period for both children and adults. The analyses also show an overall decline in malaria cases, but the decline is not continuous, with some years showing an increase in the number of cases. These results are consistent with what is reported in the 2017 Malaria Indicator Survey (NMCP 2017).

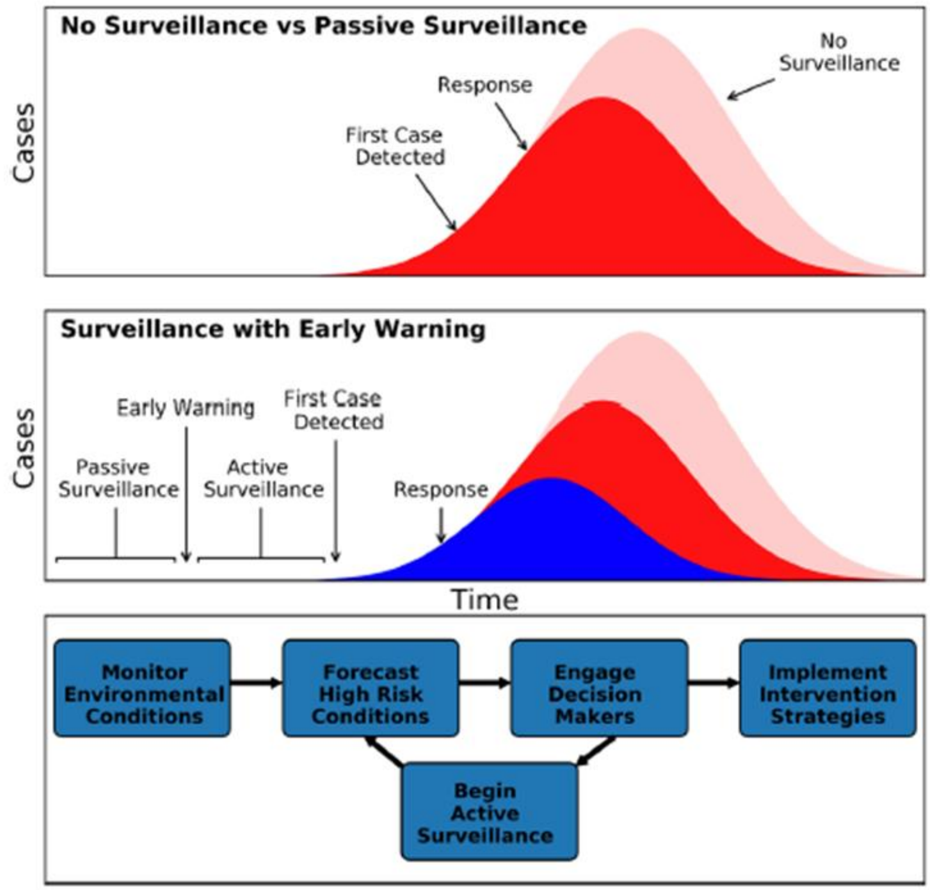
The statistical analyses showing associations between malaria and mean daily temperature and precipitation offer insights on the role of weather driving malaria caseloads. Although the incident rate ratios are relatively small, there are statistically significant associations for children under five between temperature and malaria in the South East, and between precipitation and malaria in the South East and South West, with incidence increasing as both temperatures and precipitation increase. There also is a significant association between mean daily precipitation and malaria in people 5 and older in the same regions (South East and South West). Furthermore, because the malaria data are monthly counts, it is highly likely that the actual associations are stronger because the within month variability of weather variables and outcomes cannot be analyzed.

Figure 31 shows how early warning systems combined with surveillance can provide longer lead times for control programs (Morin et al. 2018). The figure shows the theoretical epidemic curve representing no surveillance (pink curve) compared with passive surveillance[3] (red curve) and response (top panel). Integrating an early warning system (blue curve, middle panel) shows the possible improvement in the timeliness of surveillance, detection, and response. When only using passive surveillance (top panel), the first cases are detected only after enough transmission leads ill individuals to seek medical attention and get tested for the pathogen, and health care providers report positive results. An early warning system, with forecasts of high-risk conditions, provides additional time to plan, organize, and initiate screening or active

[3] Passive surveillance is the regular reporting of disease data by all institutions that see patients (or test specimens) and are part of a reporting network. There is no active search for cases. It involves passive notification by surveillance sites; reports are generated and sent by local staff.

surveillance, reducing the number of cases overall and the magnitude of the outbreak. This also can reduce the time between detection and response. The steps and connections within an early warning system are shown in the bottom panel.

Figure 31: A theoretical view of how early warning systems could reduce disease loads



Source: Morin et al. 2018

The results suggest that a combination of temperature and precipitation for the South East and South West regions could be used to forecast the timing of malaria outbreaks with at least a 1- to 2-month lead time. Such an early warning system could increase the effectiveness, efficiency, and timeliness of malaria control efforts, which is particularly important given the recent increase in the number of cases and the significant progress needed to reach the goals for reducing the burden of malaria by 2030.

RECOMMENDATIONS

Addressing the changing risk profile of malaria due to temperature increases combined with other drivers will require modifying current interventions and programs, and potentially implementing new programs, that can adapt and respond to changing climate conditions. With these challenges come opportunities for improving observations, surveillance, and responses, including detailed geographic targeting, optimizing strategies (i.e., finding the right combination of vector and case management), and aligning interventions to changing seasonality. Some of the implications for action and decision-making of this research are discussed below.

MEETING ELIMINATION TARGETS

Eliminating malaria is the goal of all development partners working in Africa (WHO 2015). Understanding how temperature may change the seasonality of malaria in Southern Africa, particularly for new areas at risk of malaria transmission or areas where the length of the season may shorten or extend, can help inform malaria programs and policy and help reach the goal of elimination. In areas where the months of malaria suitability decrease, surveillance and response systems should be strengthened to identify, track, and respond to malaria cases and any remaining transmission foci (e.g., infected mosquitoes or affected patients). Elimination efforts informed by these analyses could better target resources to reduce the potential burden of additional cases through timely treatment and prevention, such as the distribution of bed nets or indoor residual spraying.

ADAPTING TO CHANGING EPIDEMIOLOGY AND INCORPORATING NEW ANALYTICAL TOOLS

There are many examples across sub-Saharan Africa where investments have shown marked progress in malaria control strategies. These gains, however, could be compromised if future investments do not consider the role of rising temperatures in changes to epidemiology. This analysis offers critical insight with respect to these risks. Especially how current management and control interventions may need to be reviewed and revised to address likely changes in malaria incidence. This information offers an evidence base to support lengthening the investment timeframe (seasonal to year-round, or vice versa), optimizing vector control, and improving case management. Targeted and concentrated surveillance at the edge of malaria's range, for example, presents an opportunity to focus on potential epidemic outbreaks as they happen and can reduce the risk of new outbreaks.

IMPROVING A COUNTRY'S CAPACITY FOR COLLECTING AND USING INFORMATION

Significant progress has been made to improve data and information available for malaria programming, management, and evaluation via investments in strengthening routine disease reporting and health management information systems. Nevertheless, challenges remain, including the need to increase reporting rates and shorten the time before reporting data are available to inform planning and monitoring to near real-time.

Understanding how rising temperatures could impact vector ranges, and thus have the potential to alter disease dynamics, is an important first step in building the knowledge base to evaluate the impact of climate on malaria incidence and to inform investments. This analysis indicates that as temperatures rise, even within the next 11 years (by the 2030s), important changes are anticipated in transmission suitability. For example, in some areas in the northern part of the Southern Africa region, temperatures are expected to exceed the thermal limit of mosquitoes' tolerance, reducing the months of malaria suitability. At the same time, some areas of Southern Africa will become newly viable for Anopheline survival, raising the risks to people living there. Importantly, temperature-driven changes in vector dynamics are themselves mediated by direct and indirect environmental and societal factors. The same temperature changes that affect vector dynamics also influence changes to ecosystems, land use, and other factors that may reduce or increase the vulnerability of certain groups to malaria risks. The bottom line is that the environmental and social factors that define malaria incidence and risk are complex.

New methods of data collection, integration, and analysis will help explain the complex links between these factors. Public health observatories, many already operational around the world, offer a mechanism for analysis of health data in context with other climate and environmental parameters, paving the way for the timely use of remotely derived weather and climate information to inform investments and strategies in malaria control. In general terms, health observatories are virtual platforms that can link health systems to weather data, supporting health policies and planning. According to the WHO (2016), the purpose of health observatories "vary but the major objectives are: monitoring health situations and trends, including assessing progress toward agreed-upon health-related targets; producing and sharing evidence; and, supporting the use of such evidence for policy and decision making." Integrating weather data and climate analysis is consistent with these overarching objectives.

Establishing a health observatory in countries where PMI is working could help scale up interventions, fine-tune investments focused on improving the timeliness and completeness of surveillance during critical periods, *and:*

- *Build a community of practice on malaria*—Communities of practice beyond traditional PMI partners could explore the links between environmental parameters of interest (including weather and climate) and strategic and programmatic decisions that need to be made in a malaria program.
- *Further research on critical questions that remain about using climate information to inform malaria planning*—This research includes, but is not limited to, understanding more fully the links between increased temperature, changing rainfall patterns, extreme weather events, and malaria incidence; determining specific climatic thresholds of concern for surveillance; and improving analytic tools to visualize cross-sectoral information.
- *Formalize interdepartmental links and data sharing* —To further research and monitoring to better understand climate and weather impacts on epidemiology, it is essential to have access to historical climate and trend information, together with the health data related to past events. Furthermore, most government agencies lack the mandate to coordinate interactions between the many stakeholders in the health sector. Improved communication and coordination across the sector will facilitate more widespread use and understanding of the information available for planning.

BUILDING CAPACITY IN HEALTH SYSTEMS

In order for malaria programming and health services to respond to climate risks, investments need to be made in building the skills and capacity of health workers to understand and address the health risks posed by climate. These include:

- ***Leveraging information technology*** such as GIS and other tools to integrate information from various sectors and sources in order to rapidly evaluate the potential risks from specific weather events to a country, region, or health post.
- ***Streamlining supply chain management***, especially in countries where malaria control interventions have been successful, to guarantee the delivery of commodities and services for remote and mobile populations.
- ***Ramping up research*** on applied, regionally responsive health services for a future of climate change. To date, there is a clear lack of service-oriented research to drive regional health service development for climate change, with potentially serious adverse implications for future control efforts.

STRATEGIC BUDGETING AND EARLY AND TARGETED PLANNING

One of the core operating principles of many malaria intervention programs and for PMI is prioritizing high-risk populations for malaria interventions. This analysis indicates that temperature may play a role in putting large percentages of populations within countries, and in the region overall, at risk of both seasonal and endemic malaria.

In many instances, information on projected temperature increases is criticized because it cannot address immediate disease planning needs. However, much like preventive medicine, which aims to promote long-term well-being, planning 10–12 years and even further into the future when fighting malaria can save lives and money over the long term and promote sustainable elimination efforts. For example, if we know that temperature is likely to increase malaria burden in a certain country or region where there is currently little investment to fight malaria, including in some Southern Africa countries, an investment in surveillance and prevention now could avoid the need for large, immediate, crisis-driven investments in the future.

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