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A multi-factor malaria occurrence analysis in Sudan

Interaction between climate, conflict, and
health systems

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Division of Water Resources Engineering
Department of Building and Environmental Technology
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ChatGPT-5.5 was used during this study for language editing and text polishing, for the generation and refinement of Python scripts used in data acquisition, processing, analysis, and visualization, and for the development of automated workflows used to compile, process, and analyze the ReliefWeb humanitarian reporting database.

Abstract

Malaria remains a major public health concern in Sudan, where transmission is influenced by climate variability, environmental conditions, population displacement, conflict, and disruptions to healthcare services. Using ERA5 climate data, a Climate Suitability Index (CSI) was developed to evaluate the climatic suitability for *Plasmodium falciparum* transmission in Sudan between 2000 and 2024. Annual state level and population-weighted national CSI were computed and compared with national malaria occurrence data from the World Health Organization. Further analyses were conducted to assess the relationships between malaria occurrence, flooding, displacement, and disruptions to the health systems. A humanitarian malaria reporting database containing 273 Sudan specific reports from 2000 to 2024 was established from ReliefWeb reports to identify reported malaria drivers and interventions, and to support the quantitative analyses. The results suggested that the southern and southeast regions of Sudan exhibited consistently higher climatic suitability, while the hyper-arid northern regions exhibited lower suitability. CSI showed a stronger association with malaria occurrence when a one-year lag was considered, while flooding demonstrated a significant positive relationship with malaria occurrence in the same year. Humanitarian reporting database demonstrated the increasing impact of conflict, displacement, and disruptions to the health systems on malaria occurrence. The results support the integration of climate-based suitability monitoring with humanitarian and health system indicators to strengthen malaria preparedness, surveillance, and intervention planning in Sudan, while highlighting the need for improved availability and accessibility of subnational and long-term malaria occurrence data, longer-term health system capacity data, and state level displacement information to enable more robust analyses of the interactions between climate, conflict, displacement, and malaria occurrence.

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<i>Abbreviation</i>	<i>Full term</i>
<i>ACT</i>	Artemisinin-based Combination Therapy
<i>ACLED</i>	Armed Conflict Location & Event Data
<i>API</i>	Application Programming Interface
<i>CSI</i>	Climate Suitability Index
<i>DALY</i>	Disability-Adjusted Life Year
<i>DTM</i>	Displacement Tracking Matrix
<i>EIP</i>	Extrinsic Incubation Period
<i>ERA5</i>	Fifth Generation European Centre for Medium-Range Weather
<i>EWARS</i>	Early Warning and Response Surveillance System
<i>GADM</i>	Database of Global Administrative Areas
<i>GHO</i>	Global Health Observatory
<i>HDX</i>	Humanitarian Data Exchange
<i>HeRAMS</i>	Health Resources and Services Availability Monitoring System
<i>HSDU</i>	Health Service Delivery Unit
<i>HTML</i>	HyperText Markup Language
<i>IDP</i>	Internally Displaced Person
<i>IOM</i>	International Organization for Migration
<i>IRS</i>	Indoor Residual Spraying
<i>ITCZ</i>	Intertropical Convergence Zone
<i>ITN</i>	Insecticide-Treated Net
<i>JJAS</i>	June-July-August-September
<i>JMP</i>	Joint Monitoring Programme for Water Supply, Sanitation and
<i>JRC</i>	Joint Research Centre
<i>LLIN</i>	Long-Lasting Insecticidal Net
<i>MAP</i>	Malaria Atlas Project
<i>MENA</i>	Middle East and North Africa
<i>MSF</i>	Médecins Sans Frontières
<i>NMCP</i>	National Malaria Control Programme
<i>OCHA</i>	Office for the Coordination of Humanitarian Affairs
<i>PCA</i>	Permanent Court of Arbitration Area (Abyei PCA terminology datasets)
<i>PDF</i>	Portable Document Format
<i>PDR</i>	Parasite Development Rate
<i>Pf</i>	<i>Plasmodium falciparum</i>
<i>PfPR</i>	<i>Plasmodium falciparum</i> Parasite Rate
<i>Pv</i>	<i>Plasmodium vivax</i>
<i>PvPR</i>	<i>Plasmodium vivax</i> Parasite Rate

<i>RDT</i>	Rapid Diagnostic Test
<i>UN</i>	United Nations
<i>UNICEF</i>	United Nations Children's Fund
<i>WASH</i>	Water, Sanitation and Hygiene
<i>WHO</i>	World Health Organization
<i>WHO GHO</i>	World Health Organization Global Health Observatory
<i>WorldPop</i>	WorldPop Gridded Population Dataset

1. Introduction

1.1. Background on Malaria Occurrence

Despite decades of control initiatives, malaria continues to remain one of the most critical vector-borne diseases in the world and poses a serious threat to global public health. The World Health Organization (WHO) estimates that there were 263 million malaria cases and 597,000 malaria related deaths worldwide in 2023, with tropical and low-income regions continuing to bear a disproportionate share of the disease burden (WHO, 2024).

Malaria occurrence is influenced by the complex interaction of environmental, biological, socioeconomic, and health system factors (Smith et al., 2012; WHO, 2024). Climatic conditions such as temperature, rainfall, and humidity affect mosquito survival, breeding habitat availability, and parasite development, thereby influencing the potential for malaria transmission (Craig et al., 1999; Mordecai et al., 2013; Yamana & Eltahir, 2013). At the same time, access to healthcare, vector control interventions, population movement, conflict, and broader socioeconomic conditions can influence disease transmission, detection, treatment, and overall malaria burden. Consequently, malaria patterns often reflect the combined effects of multiple interacting factors rather than any single driver alone (WHO, 2024).

Climate variability and climate change are increasingly recognized as important drivers of malaria transmission dynamics. Changes in temperature and precipitation patterns can alter mosquito habitat suitability, survival rates, parasite development rates, and the duration of transmission seasons (Intergovernmental Panel on Climate Change, 2022). According to recent studies, climate change may significantly impact the distribution of malaria risk across Africa, increasing transmission suitability in some regions while decreasing it in others (Caminade et al., 2014; IPCC, 2022). However, the relationship between malaria and climate is complex and influenced by

interactions with healthcare accessibility, vector control interventions, population movement, conflict, and socioeconomic conditions (WHO, 2024).

Sudan represents a particularly important case study because it experiences substantial environmental variability alongside severe humanitarian challenges. With borders with the Central African Republic, Chad, Egypt, Eritrea, Ethiopia, Libya, and South Sudan, Sudan is situated at the intersection of Sub-Saharan Africa and the Middle East. Additionally, the two of the longest-lasting civil wars on the African continent happened in Sudan (World Bank, n.d.). The country spans diverse climatic zones that transition from desert and semi-desert environments in the north to savannah and semi-humid regions in the south, resulting in considerable spatial variation in rainfall, temperature, humidity, and hydrological conditions (The Republic of Sudan, 2023; World Bank Climate Change Knowledge Portal, n.d.). Previous studies have shown that malaria transmission in Sudan is influenced by environmental and ecological conditions, including climatic variability and water related factors that affect mosquito habitat availability and transmission suitability (Elagali et al., 2022). At the same time, ongoing conflict, population displacement, infrastructure destruction, and disruptions to healthcare delivery have created additional challenges for disease surveillance, prevention, and control efforts (WHO, 2025). Map of Sudan showing the country's 18 states is given in Figure 1.



Figure 1. Map of Sudan (Mappr, n.d.)

A number of studies have used mechanistic transmission frameworks, ecological suitability mapping, and statistical models to investigate the influence of climate on malaria transmission. Climate based suitability models have been successfully applied at continental and regional scales to identify areas favorable for malaria transmission and to assess how environmental conditions constrain the geographic distribution of malaria risk (Craig et al., 1999). At the same time, mechanistic transmission models derived from the Ross-Macdonald framework require detailed entomological and epidemiological parameters, including mosquito density, biting rates, survival rates, and parasite development characteristics, many of which are often unavailable in data scarce settings (Smith et al., 2012). Although climatic drivers of malaria transmission have been extensively studied, fewer studies have explicitly examined how climatic suitability interacts with conflict, displacement, flooding, and health system functionality within a single

analytical framework, particularly in unstable humanitarian settings. Consequently, there remains a need for transparent and reproducible approaches that can assess climatic suitability while accounting for the humanitarian and health system factors that may influence malaria occurrence.

To address this gap, this study develops a Climate Suitability Index (CSI), which was designed as a simplified climate explicit representation of the environmental factors that influence the transmission of malaria, for malaria transmission in Sudan. The study then evaluates the relationships between climate suitability, conflict, displacement, flooding, water and sanitation conditions, and health system functionality and malaria occurrence.

However, it should be acknowledged that malaria transmission is a complex process influenced by numerous interacting environmental, biological, socioeconomic, and health system factors. While this study incorporates several important drivers, it cannot capture all processes affecting malaria occurrence in Sudan.

1.2. Aim & Objectives

The project aims to investigate the effects of factors influencing malaria occurrence in Sudan, and to evaluate how data availability and quality influence the ability to assess malaria dynamics in a data limited, unstable and malaria endemic region. The project further aims to develop practical recommendations for the improvement of data collection in Sudan, while additionally providing a reproducible analytical framework that can support future research on malaria occurrence conducted in data limited and unstable regions.

Objectives of the study are as follows:

- To review the data availability on malaria occurrence in Sudan
- To investigate the potential influence of climatic and non-climatic factors on malaria occurrence, including conflict, health, and demographic conditions.

- To determine the methodological requirements for malaria occurrence analysis in data limited and unstable regions and to develop recommendations for improving data collection in Sudan.

1.3. Literature Review

A literature review on malaria in Sudan was conducted to identify the environmental, epidemiological, infrastructural, and humanitarian factors influencing disease occurrence, transmission, and vulnerability. Further, a conceptual framework linking climate, vector ecology, disease occurrence, population exposure, flooding, conflict, displacement, WASH conditions, health system functionality, and humanitarian efforts was developed from the literature review.

Main databases for the literature review were Scopus, PubMed, news sites, and reports from different humanitarian organizations, such as World Health Organization (WHO), Red Cross Climate Center, United Nations Children's Fund (UNICEF), and World Bank Group. Backward reference checking was used to find more research and reports.

Prior studies on malaria occurrence in Sudan investigated transmission from several perspectives, including routine surveillance modeling, national risk mapping, urban malaria, irrigation related transmission, displacement, climate change, and vector ecology. Collectively, these studies demonstrate that malaria transmission in Sudan is shaped by interactions among environmental suitability, water systems, population vulnerability, vector ecology, and health-system capacity rather than climate alone.

Elagali et al. (2022) made a significant contribution to malaria research in Sudan by modeling the spatiotemporal incidence of malaria across the country using routine surveillance data from the National Malaria Control Programme. Their study identified strong spatial heterogeneity in malaria transmission, with higher transmission occurring in irrigated and river adjacent regions

because of their proximity to mosquito breeding habitats. Persistent *Plasmodium falciparum* transmission was reported in Al-Gezira, Sennar, White Nile, Khartoum, Darfur, and South Kordofan, whereas Northern and Red Sea states generally exhibited lower transmission levels. The study also identified distinct seasonal dynamics between malaria species, reporting that *P. falciparum* transmission peaks after the rainy season, while *Plasmodium vivax* transmission increases mainly between March and May. In addition, *P. vivax* transmission was particularly important in Khartoum, Central Darfur, and Al-Gezira, supporting growing evidence that *P. vivax* is becoming an increasingly important malaria species in Sudan. Environmental covariates associated with malaria incidence included precipitation, aridity, tasseled cap brightness, which is a satellite derived indicator of land surface reflectance used to characterize environmental and land cover conditions, and potential evapotranspiration.

Earlier national level research by Noor et al. (2012) similarly highlighted the spatial variation of malaria risk in Sudan. Using community parasite prevalence surveys, their malaria risk mapping study showed that *P. falciparum* transmission was generally low to moderate across most of Sudan, although substantial regional differences existed. While the study primarily focused on parasite prevalence mapping rather than long-term environmental suitability, it provided an important national malaria risk profile for control planning and intervention prioritization.

Several studies emphasized the importance of irrigation systems and managed water environments in sustaining malaria transmission. Himeidan et al. (2005) investigated malaria epidemiology in New Halfa, an irrigated area in eastern Sudan, and found that permanent irrigation altered the seasonal pattern of malaria transmission. *P. falciparum* accounted for most positive cases, while *P. vivax* and mixed infections occurred at lower proportions. The study further reported seasonal variation in slide positivity rates, defined as the percentage of examined blood smears testing positive for malaria parasites, suggesting that irrigation systems may maintain mosquito breeding habitats beyond the normal rainfall season. These findings are consistent with Sudan's malaria epidemiological stratification, which recognizes distinct transmission settings including seasonal, riverine, irrigated scheme, urban, desert fringe, and emergency settings, reflecting the substantial ecological and socio

environmental heterogeneity of malaria transmission across the country (Elagali et al., 2022).

Urban malaria transmission has also been documented in Sudan. El Sayed et al. (2000) investigated malaria transmission in Khartoum and demonstrated that vector density varied seasonally, with lower densities observed during the dry season. Their findings showed that malaria transmission can persist in urban settings where local environmental conditions, poor drainage systems, informal settlements, and household water storage practices create suitable mosquito breeding habitats.

The role of social vulnerability and healthcare accessibility in malaria risk was highlighted in studies among displaced populations. Saeed and Ahmed (2003a) examined determinants of malaria among displaced people in Khartoum and found that malaria attacks were associated with factors including tribe, language, education, water source, and household food expenditure. The study demonstrated that socio-economic conditions, living environment, and access to basic services significantly influenced malaria risk among displaced communities. In a separate study, Saeed and Ahmed (2003b) investigated determinants of malaria mortality among displaced people and reported associations between malaria deaths and factors such as insufficient knowledge of malaria prevention and treatment, delayed healthcare seeking, and poor access to appropriate treatment. Together, these studies highlight that malaria vulnerability in Sudan is shaped not only by environmental conditions but also by socio economic status, education, access to water, health awareness, and healthcare accessibility.

Abdalla et al. (2007) assessed malaria incidence, mortality, and disability-adjusted life years (DALYs) in Sudan and reported that children under five years of age experienced the highest mortality and DALY burden. Their study also identified substantial underreporting of malaria episodes and deaths within the formal health system, indicating that routine datasets may underestimate the true malaria occurrence, particularly among vulnerable populations.

Recent studies further linked malaria transmission to humanitarian crisis conditions. Mohamed et al. (2021) analyzed malaria surveillance records from South Kordofan and documented epidemic malaria patterns during periods of humanitarian crisis, with major peaks observed in 2018 and 2019. Their

findings emphasized the importance of conflict, displacement, and disrupted health services in shaping malaria transmission dynamics in Sudan.

Studies on vector ecology additionally demonstrated the importance of local habitat conditions and hydrological processes in malaria transmission. Ageep et al. (2009) investigated the spatial and temporal distribution of *Anopheles arabiensis* in northern Sudan and found that larval habitats were strongly associated with riverside environments, although some breeding sites also occurred away from the river. The study suggested that mosquito abundance may increase during flood recession periods when declining river levels leave behind shallow stagnant pools and isolated edge-water habitats favorable for larval development. These findings highlight the importance of floodplain hydrology and water persistence in shaping vector abundance near river systems.

The species composition of malaria infection in Sudan has also been changing. Suliman et al. (2016) provided molecular evidence of a high proportion of *P. vivax* infections in the White Nile region, indicating that *P. vivax* may be more widespread and epidemiologically important than previously recognized. These findings are consistent with Elagali et al. (2022), who identified *P. vivax* as an emerging public health concern with seasonal dynamics distinct from *P. falciparum*.

Climate related studies further suggested that rainfall and temperature strongly influence malaria transmission in Sudan. Aal and Elshayeb (2011) reported that the spatial distribution of malaria broadly follows the rainfall distribution across Sudan, with higher transmission generally occurring in wetter central and southern regions. However, the study also noted that irrigation systems and riverine environments may sustain malaria transmission even in relatively dry areas. The authors additionally discussed projected climate-change impacts on temperature and future population exposure to malaria risk.

At the regional scale, Maher et al. (2024) reviewed climate change vulnerabilities and communicable diseases in the Eastern Mediterranean Region and identified Sudan among the countries exhibiting vulnerability to the health impacts of climate change. The review highlighted that rising temperatures, changing precipitation patterns, floods, droughts, and other climatic extremes can influence the occurrence and transmission of climate

sensitive communicable diseases, including malaria, across the region. Similarly, Al-Manji et al. (2025) reviewed mosquito-borne disease risk factors in the MENA region and found that geography, socio-economic status, age, and gender were among the most frequently examined determinants of disease vulnerability. These findings suggest that mosquito-borne disease risk is shaped not only by environmental conditions but also by demographic and socio-economic inequalities. Although these regional studies are less Sudan specific than the national studies discussed above, they reinforce the broader importance of climatic and social vulnerability in shaping mosquito-borne disease risk.

Overall, the literature from Sudan demonstrates that malaria transmission is spatially heterogeneous, seasonally variable, and strongly associated with rainfall patterns, irrigation systems, riverine habitats, displacement, and healthcare accessibility. However, most existing studies focus primarily on epidemiological mapping, localized field investigations, vector ecology, or social vulnerability, therefore examining isolated drivers of transmission rather than integrated multi driver interactions across long temporal scales, highlighting the need for more comprehensive Sudan focused analyses combining climatic, hydrological, environmental, and humanitarian factors.

1.4. Background on malaria

Malaria is a mosquito-borne disease caused by parasites of the genus *Plasmodium*. The disease is transmitted through the bites of infected female *Anopheles* mosquitoes and continues to cause substantial burden, especially in sub-Saharan Africa (WHO, 2024). Malaria is endemic in Sudan and poses a serious risk to the country's public health systems. The two main malaria parasite species reported in Sudan are *Plasmodium falciparum* (*Pf*) and *Plasmodium vivax* (*Pv*), with *Pf* accounting for approximately 89% of reported cases (WHO EMRO, n.d.). Malaria transmission is influenced by a combination of environmental, socioeconomic, and health system factors. In particular, mosquito survival, the availability of breeding habitats, and the transmission potential are influenced by climate factors like temperature, humidity, and rainfall (Mordecai et al., 2013).

2. Methods

2.1. Study Framework & Data Collection

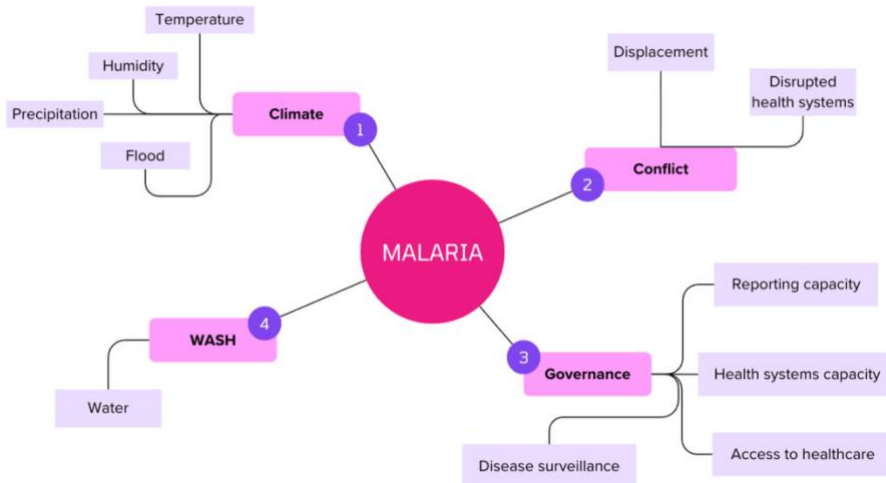


Figure 2. Conceptual map of factors influencing malaria occurrence, where pink boxes represent main factors influencing malaria occurrence and purple boxes represent components of those factors

A conceptual framework was developed from the literature review to illustrate the major factors influencing malaria occurrence in Sudan. The framework groups these factors into four interacting factors as climate, conflict, governance, and WASH. The climate factor includes temperature, humidity, precipitation, and flooding, which influence the environmental suitability for malaria transmission. The conflict factor includes displacement and disruption of health systems, while the governance factor encompasses health system capacity, access to healthcare, disease surveillance, and reporting capacity. The WASH factor represents drinking water infrastructure that may influence malaria risk. Together, these factors provide a conceptual basis for

understanding how climatic, environmental, humanitarian, and health system factors may interact to influence malaria occurrence. Governance related factors were primarily considered qualitatively in the interpretation of the results and discussion. These components were included because they influence both the detection and reporting of malaria cases and may affect the relationship between reported malaria occurrence and underlying transmission, particularly in conflict affected settings. Although information on health system functionality was available through HeRAMS, the limited temporal coverage of these data restricted their use in the broader quantitative analyses.

The conceptual framework in Figure 2 guided the selection of datasets and the design of the analytical workflow. The datasets, along with data source, spatial and temporal resolution, and their roles in the analysis are presented in Table 1. In the figure, main factors influencing malaria occurrence are given in pink boxes, while components of those factors are given in purple boxes. Based on the literature review, sociodemographic factors were also identified, however, due to data availability, they are not included in this study. Flood, WASH, health system capacity and access to healthcare, conflict, internally displaced persons (IDPs), reporting capacity, and disease surveillance factors served as a framework for interpretation. A state with high climatic suitability but low reported occurrence, for instance, might indicate limited access to care, underreporting, or interrupted diagnostic services, whereas a state with high occurrence and moderate suitability might indicate displacement, inadequate service availability, or concentrated vulnerable populations.

The analysis was restricted to Sudan's 18 states, therefore, Abyei PCA was excluded to maintain consistency among the datasets. Because of the disease occurrence data availability, the study period for the malaria occurrence and climate suitability index (CSI) analysis was set at 2000-2024. In order to avoid comparing climate suitability with years for which the associated malaria occurrence was unavailable, CSI outputs were aligned to the malaria occurrence dataset regardless of whether climate data was available after 2024. The JRC Global Surface Water monthly history product included flood data until 2021, but because their accessible reporting period is concentrated in 2023-2025, health system indicators were employed for recent conflict contextual analysis.

All analyses were implemented in Python, working through the ChatGPT 5.5 interface and using Visual Studio Code.

Table 1. Overview of data used in the analysis

Data theme	Data source	Spatial resolution used	Temporal coverage used	Role in analysis
Malaria occurrence	WHO Global Health Observatory (GHO)	National level	2015-2024	Primary confirmed disease occurrence
Climate	ERA5 / ERA5-Land reanalysis	Gridded climate data aggregated to admin-1 states	2000-2024	Primary input to CSI
Population	WorldPop gridded population rasters	Gridded rasters aggregated to admin-1 states	2000-2024, using anchor years 2000, 2005, 2010, 2015, 2020, and 2025 where available	Used to calculate malaria cases per 100,000 people and normalize IDPs
Flooding	European Commission Joint Research Centre Global Surface Water monthly history	Gridded satellite-derived surface water aggregated to admin-1 states	2000-2021	Used to examine flood exposure and its relationship with CSI and malaria occurrence
Health system capacity	WHO HeRAMS Sudan Baseline Report 2025 series	State level summaries extracted from report tables/figures	2023-2025 contextual period	Used to interpret health system vulnerability and service disruption
WASH	WHO/UNICEF Joint Monitoring Programme (JMP) and HeRAMS health-facility WASH indicators	National rural/urban/total for JMP; state level health facility WASH from HeRAMS where available	2003-2024 for JMP; 2025 for HeRAMS baseline	Used as contextual environmental health and health system service indicators
Displacement	Internal Displacement Monitoring Centre (IDMC) Global Internal Displacement Database (GIDD)	National level	2009-2024	Used to examine displacement driven vulnerability and population exposure
Conflict	WHO HeRAMS Sudan Baseline Report 2025 series; IDMC GIDD	State level summaries extracted from report tables/figures	2000-2024	Used to examine insecurity as a non-climatic vulnerability driver
Administrative boundaries	GADM Sudan admin-1 boundaries	Admin-1	Static boundary layer	Used for mapping, spatial aggregation, and state joins
Hydrography / river layer	Natural Earth or equivalent hydrographic layer used for map overlays	Vector line layer	Static mapping layer	Used for visualization of flood maps

3. Data Employed and Theory

3.1. Disease Occurrence Data

Observed malaria occurrence data were obtained from the World Health Organization Global Health Observatory (WHO GHO) as national confirmed malaria cases for Sudan, which were obtained from national malaria control programme (NMCP) reports compiled by WHO. Reported confirmed cases were primarily based on laboratory confirmed diagnoses and were corrected for known double counting between microscopy and rapid diagnostic tests (RDTs) when such information was available. The dataset includes all confirmed malaria cases regardless of origin (indigenous, imported, introduced, relapsing, or recrudescent) and includes infections caused by all malaria parasite species.

The annual number of confirmed cases of malaria was extracted and were available from 2015 to 2024. This national confirmed case dataset was used as the primary observed disease occurrence dataset because it is based on reported confirmed malaria cases rather than modeled subnational occurrence estimates.

To account for changes in population size over time, confirmed cases were normalized using the summed annual state population estimates:

$$\text{Confirmed cases per } 100,000_t = \frac{\text{Confirmed cases}_t}{\text{Population}_{\text{national},t}} \times 100,000 \quad (1)$$

where:

- $\text{Population}_{\text{national},t}$: sum of interpolated state populations in year t.

Confirmed cases were additionally normalized using annual national population estimates calculated as the sum of interpolated state level WorldPop populations, producing confirmed malaria cases per 100,000 population. In order to investigate potential delayed climatic impacts on malaria occurrence, both contemporaneous and one-year lagged relationships were evaluated.

An additional malaria occurrence dataset was obtained from Malaria Atlas Project from 2000 to 2024 as annual state level clinical case estimates for *Plasmodium falciparum* (*Pf*) and *Plasmodium vivax* (*Pv*), which are the two main parasite species for malaria in Sudan, and *Pf* is the dominant malaria parasite in Sudan accounting for approximately 89% of reported malaria cases, whereas *Pv* accounts for about 11% (Severe Malaria Observatory, n.d.; WHO EMRO, n.d.). Although occurrence estimates for both species were examined, the CSI was developed only for *Pf*. This decision was made because *Pf* represents the epidemiologically dominant species in Sudan and because the temperature-dependent transmission relationships required for mechanistic climate suitability modelling, including parasite development and vector-parasite interactions, are more extensively established and experimentally validated for *Pf* than for *Pv* (Mordecai et al., 2013). Consequently, *Pf* provided the most robust and defensible basis for constructing a climate-based suitability model for Sudan.

Because Sudan is categorized by MAP as a cartographic country, estimates of the country's malaria occurrence are generated using spatial statistical modeling rather than directly from comprehensive national surveillance systems. In order to establish continuous spatial and temporal malaria prevalence surfaces in cartographic countries, MAP utilizes a Bayesian model based geostatistical framework that integrates geolocated parasite prevalence surveys (*Pf*PR/*Pv*PR) with environmental covariates, intervention coverage, socioeconomic variables, and spatial-temporal correlation (Weiss et al., 2019; Battle et al., 2019).

National level *Pf* and *Pv* clinical case estimates from MAP were compared with confirmed malaria case records from the WHO GHO for the years 2015-2024 in order to further assess the consistency of national malaria occurrence patterns.

The MAP framework reconstructed malaria intervention coverage using information from WHO malaria reporting systems, national malaria control programme reports, household surveys, and other intervention datasets containing geographic information (Bhatt et al., 2015; Weiss et al., 2019; Weiss et al., 2025). However, because the intervention data generated by MAP are modeled estimates, they won't be used in this study.

3.2. Climate Suitability Index Development

3.2.1. Defining the index

To assess the relationship between climate and malaria occurrence, a Climate Suitability Index (CSI) was developed. Climate suitability indices combine information from multiple environmental variables into a single metric intended to represent the favorability of conditions for disease transmission. Recent studies have developed climate-based suitability metrics that integrate temperature, humidity, and precipitation to assess malaria transmission potential across large spatial scales (Brown et al., 2024). However, rather than directly applying an existing suitability metric, a new CSI was developed for this study to maintain a transparent connection to the Ross-Macdonald transmission framework and to represent the climate sensitive processes relevant to malaria transmission in Sudan.

In this study, the CSI was designed as a simplified climate explicit representation of vectorial capacity, derived conceptually from the classical Ross-Macdonald malaria transmission framework, which relates transmission potential to mosquito density relative to humans, mosquito biting rate, daily mosquito survival rate, parasite development rate and the extrinsic incubation period of the parasite (Smith et al., 2012). Application of the full Ross-Macdonald malaria transmission framework requires detailed information on mosquito abundance, mosquito-to-human ratios, biting rates, survival rates, parasite development rates, and other transmission related parameters that are not available at appropriate spatial and temporal scales across Sudan. Consequently, the CSI was developed to assess climatic suitability for malaria transmission by representing the principal climate sensitive components of the

Ross-Macdonald malaria transmission framework. Temperature was used to characterize mosquito biting rate and parasite development rate, relative humidity was used to represent moisture related effects on adult mosquito survival, and precipitation was used to represent the availability of aquatic breeding habitats.

The multiplicative structure of the CSI was adopted to maintain consistency with the conceptual basis of the Ross-Macdonald framework, in which transmission potential emerges from the interaction of multiple biological processes that act jointly rather than independently (Smith et al., 2012). In the original framework, factors such as mosquito biting rate, survival, and parasite development contribute multiplicatively to transmission potential, implying that unfavourable conditions in a single component can substantially constrain overall transmission. The CSI therefore combines temperature-dependent biting rate, temperature-dependent parasite development rate, humidity-related survival suitability, and rainfall-related habitat suitability using a multiplicative formulation. No additional weighting factors were applied because insufficient evidence was available to justify the relative importance of individual climatic drivers in Sudan, and the objective was to preserve the climate-based representation of the main transmission framework.

Although conceptually derived from the Ross-Macdonald framework, the CSI does not explicitly represent mosquito density, mosquito-to-human ratios, or human infection dynamics. Furthermore, unlike more complex contemporary malaria transmission models, it does not simulate mosquito population dynamics, larval development, intervention coverage, treatment access, human immunity, population movement, land use change, or socioeconomic determinants of transmission (Smith et al., 2012; Griffin et al., 2010; Mandal et al., 2011). Instead, it provides an assessment of environmental suitability for malaria transmission while maintaining relatively modest data requirements.

Due to the limited availability of spatially and temporally representative mosquito surveillance and transmission data, parameter values and functional relationships were not calibrated using Sudan-specific entomological observations. Instead, the CSI was constructed using biologically established relationships reported in other studies.

In the CSI, temperature controls the mosquito biting rate, PDR and temperature-controlled survival, relative humidity regulates adult mosquito survival through desiccation stress, whereas precipitation is used as a climatic proxy for the availability of aquatic breeding habitats required for mosquito reproduction ((Mordecai et al., 2013; Yamana & Eltahir, 2013; Craig et al., 1999).

The three-climate controlled biological mechanisms combined in the CSI are given in *Table 2*.

Table 2. Climate factors and the biological mechanisms they control in the CSI

Climatic factor	Mechanism
Temperature	Mosquito biting rate
	Parasite development rate (PDR)
	Temperature-dependent mosquito survival
Relative humidity	Adult mosquito survival through desiccation stress
Precipitation	Aquatic breeding habitat availability

Thus, the final CSI is represented as:

$$CSI(T, RH, P, species) = S_{bite}(T) \times S_{PDR}(T) \times S_{survival}(T, RH) \times S_{habitat}(P)$$

where:

- $S_{bite}(T)$: temperature-dependent biting rate from Mordecai et al. (2013),

- $S_{PDR}(T)$: temperature-dependent parasite development rate from Mordecai et al. (2013),
- $S_{survival}(T, RH)$: mosquito survival suitability derived from temperature and relative humidity from Yamana and Eltahir (2013),
- $S_{habitat}(P)$: rainfall suitability component representing the potential availability of mosquito breeding habitats based on monthly precipitation, following the rainfall suitability framework of Craig et al. (1999).

The ERA5-Land data were utilized for climate factors because they provide a physically consistent, long-term reanalysis of land-surface meteorological and hydrological variables at relatively high spatial and temporal resolution, making them suitable for environmental and climate related analyses (Muñoz Sabater et al., 2021). All climate variables were clipped to the Sudan study domain and aligned to a common grid. The CSI was then computed using daily temperature, relative humidity, and precipitation series. Seasonal aggregation was performed over June-September (JJAS), corresponding to the rainy season in Sudan (Red Cross Climate Center, 2024). Then, gridded CSI values were spatially averaged within admin-1 state polygons to determine state level CSI values.

3.2.2. Mosquito biting rate and Parasite development rate

Following Mordecai et al. (2013), who fitted a Briere thermal response function to experimental observations of temperature-dependent *Plasmodium falciparum* sporogonic development within malaria vector mosquitoes, mosquito biting rate and parasite development rate were represented using Brière thermal performance functions (Brière et al., 1999). These functions describe the nonlinear temperature dependence of biological traits, with performance increasing from a lower thermal threshold to an optimum before declining toward zero at an upper thermal limit. This formulation provides a biologically realistic representation of how temperature influences mosquito biting and parasite development rates.

$$S_{bite}(T) = c_a T(T - T_{0,a})\sqrt{T_{m,a} - T} \quad (2)$$

where:

- $S_{bite}(T)$: mosquito biting rate,
- c_a : fitted coefficient from experimental data,
- T : air temperature ($^{\circ}\text{C}$),
- $T_{0,a}$: lower developmental threshold,
- $T_{m,a}$: upper thermal limit.

The following values were used for biting rate function: $c_a = 2.03 \times 10^{-4}$, $T_{0,a} = 11.7^{\circ}\text{C}$, and $T_{m,a} = 42.3^{\circ}\text{C}$, based on Mordecai et al. (2013).

$$S_{PDR}(T) = c_{PDR}T(T - T_{0,PDR})\sqrt{T_{m,PDR} - T} \quad (3)$$

where:

- $S_{PDR}(T)$: parasite development rate,
- c_{PDR} : fitted coefficient from experimental data,
- T : air temperature ($^{\circ}\text{C}$),
- $T_{0,PDR}$: lower developmental threshold,
- $T_{m,PDR}$: upper thermal limit.

For *Falciparum* malaria, parasite development was modeled using the thermal response parameters of Mordecai et. Al. (2013), with $c_{PDR} = 1.11 \times 10^{-4}$, $T_{0,PDR} = 14.7^{\circ}\text{C}$, and $T_{m,PDR} = 34.4^{\circ}\text{C}$. These parameters were experimentally fitted to describe *P. falciparum* sporogonic development within *Anopheles* mosquitoes.

3.2.3. Mosquito survival probability

EIP, or the time required for parasite maturation inside the mosquito, together with mosquito survival, determines the probability that mosquitoes survive long enough to become infectious. Adult mosquito survival is a critical determinant of malaria transmission because mosquitoes must survive long enough for the parasite to complete its EIP. The approach of Yamana and Eltahir (2013), who suggested a survival formulation for *Anopheles gambiae* that depends on both temperature and relative humidity, was implemented to represent mosquito survival. Their analysis, which was tailored for the Sahel region of Africa, demonstrated that relative humidity has a significant impact on mosquito population dynamics and survival, particularly in arid environments where desiccation stress shortens the lifespan of adult mosquitoes (Yamana & Eltahir, 2013). Their formulation is especially relevant to Sudan because the country has hot, seasonally arid regions where rainfall may provide breeding habitats, but low air humidity can still limit adult mosquito survival.

The CSI survival term was developed as a combined temperature–humidity survival function in accordance with this logic:

$$S_{survival}(T, RH) = p_T(T)x(1 - S_{RH}(RH)) \quad (4)$$

where:

- $S_{survival}(T, RH)$: climate-dependent mosquito survival suitability,
- p_T : temperature-dependent survival component,
- $1 - S_{RH}$: relative-humidity stress modifier.

Yamana and Eltahir (2013) improved a previously developed temperature-dependent survival relationship by including relative humidity stress, calculated as:

$$p_T(T) = \exp\left(\frac{-1}{-4.4 + 1.31T - 0.03T^2}\right) \quad (5)$$

where:

- $p_T(T)$: baseline daily mosquito survival probability
- T : air temperature ($^{\circ}\text{C}$)

Under conditions of extreme heat or cold, this formulation results in decreased survival and higher survival at intermediate temperatures. In the script, survival values were clipped to a numerical range of 0.01–0.99 to avoid undefined values in the denominator when p_T approaches 0 or 1.

The relative humidity stress term was represented using the piecewise stress function:

$$S_{RH}(RH) = \begin{pmatrix} 1, & RH \leq RH_{low}; \\ \frac{RH_{high} - RH}{RH_{high} - RH_{low}}, & RH_{low} < RH < RH_{high}; \\ 0, & RH \geq RH_{high} \end{pmatrix} \quad (6)$$

where:

- S_{RH} : humidity stress term,
- RH_{low} : lower humidity threshold,
- RH_{high} : upper humidity threshold

Relative humidity (RH) was derived from temperature and dew point according to the Magnus equation:

$$RH = 100 \times \frac{\exp\left(\frac{17.625T_d}{243.04 + T_d}\right)}{\exp\left(\frac{17.625T}{243.04 + T}\right)} \quad (7)$$

where:

- RH: relative humidity (%),
- T: 2 m air temperature (°C),
- T_d : 2 m dewpoint temperature (°C).

The coefficients 17.625 and 243.04 °C are parameters of the improved Magnus approximation for saturation vapour pressure over water proposed by Alduchov and Eskridge (1996), which is commonly used in meteorological applications to estimate relative humidity from air temperature and dewpoint temperature.

In the CSI, RH_{low} and RH_{high} values were set to 5% and 42%, respectively (Yamana and Eltahir, 2013). Therefore, maximum humidity stress occurs in extremely dry conditions, the stress decreases linearly between 5% and 42% relative humidity, and no additional humidity stress is applied above 42%.

The survival term is a probability with an interval of 0 to 1. High mortality is indicated by values close to 0, while favorable survival conditions are indicated by values approaching 1. Even when the temperature remains favorable for transmission, this formulation allows survival to decline in dry atmospheric conditions.

3.2.4. Mosquito breeding habitats

The availability of aquatic breeding habitats required for mosquito reproduction and larval development was represented using the rainfall suitability framework proposed by Craig et al. (1999). Because direct observations of mosquito breeding habitat extent were unavailable, monthly precipitation was used to represent rainfall-driven habitat availability. Using a fuzzy climate suitability approach, Craig et al. (1999) identified approximately 80 mm month⁻¹ as a rainfall level associated with climatic conditions favorable

for sustained malaria transmission. This was operationalized in this study by a normalized linear suitability score, where rainfall suitability increases linearly from 0 to 1 with increasing monthly precipitation and reaches its maximum value at 80 mm month⁻¹. The resulting rainfall suitability function is given by:

$$S_{habitat}(P) = \begin{cases} 0 & P_m \leq 0 \\ P_m/P_{crit} & 0 < P_m < P_{crit} \\ 1 & P_m \geq P_{crit} \end{cases} \quad (8)$$

where:

- $S_{habitat}(P)$: rainfall suitability score
- P_m : monthly precipitation (mm month⁻¹)
- P_{crit} : critical rainfall threshold

Although mosquito breeding habitat availability is influenced by hydrological processes controlling the formation, persistence, and disappearance of surface water bodies (Bomblies et al., 2008; Bomblies, 2012), these processes were not included in the CSI. Instead, precipitation was used as a proxy for breeding habitat availability because hydrological observations required to represent these processes were unavailable. As a result, the rainfall suitability term represents potential habitat formation based on precipitation alone.

3.2.5. Model aggregation

In order to capture peak rainfall driven transmission conditions and reduce short term variability, daily and monthly CSI components were aggregated over June to September, which represents the rainy season in Sudan.

$$CSI_{seasonal} = mean(CSI_{daily \text{ for months June, July, August, September}})$$

CSI values were calculated at the state level and subsequently normalized using min–max scaling to a range of 0–1. The normalization was performed using the minimum and maximum raw CSI values across all state-year observations (2000-2024), allowing direct comparison of relative suitability across both states and years.

$$CSI_{norm} = \frac{CSI - CSI_{min}}{CSI_{max} - CSI_{min}} \quad (9)$$

The CSI was computed for only *Pf* because it is the dominant parasite species in Sudan (Severe Malaria Observatory, n.d.).

The observed confirmed malaria case numbers were available at the national level as rather than the state level. Therefore, the state level CSI were aggregated into a national annual CSI using population weighting. This method produces a national index that is comparable to national surveillance data while maintaining the state level climate suitability computation.

The national CSI was computed as follows for each year:

$$CSI_{national,t} = \frac{\sum_{i=1}^n (CSI_{i,t} \times Population_{i,t})}{\sum_{i=1}^n Population_{i,t}} \quad (10)$$

where:

- $CSI_{i,t}$: 0-1 min-max normalized CSI for state i and year t ,
- $Population_{i,t}$: interpolated state population for the same year,
- n : number of states included in the analysis.

The national population-weighted CSI time series was compared with WHO Global Health Observatory (GHO) national confirmed malaria cases for 2015-2024. Population weighting was used because national confirmed case counts

reflect disease occurrence among people rather than land area; therefore, highly populated states contribute more to the national exposure-weighted suitability estimate, while sparsely populated arid regions do not disproportionately influence the national CSI.

The relationships between national population-weighted CSI and national malaria occurrence data were assessed using Pearson and Spearman correlation analyses. Pearson correlation was used to assess linear associations between the annual national population-weighted CSI time series and annual malaria occurrence metrics, including confirmed malaria cases and confirmed cases per 100,000 population. Spearman rank correlation was additionally applied because malaria surveillance data from Sudan may be influenced by non-normality, reporting instability, and outliers associated with conflict related healthcare disruption.

3.2.6. Model assumptions

The following main assumptions were made in the CSI formulation:

- Despite not being calibrated using Sudan specific observations, climate parameters obtained from previous studies were assumed to be transferable to Sudan at the state level.
- Although local vector composition and ecology may differ, the same framework for climate-dependent mosquito transmission was applied to all Sudanese states under the assumption that major *Anopheles* mosquito vector communities respond to climate similarly at large spatial scales.
- The rainfall component assumes that monthly precipitation provides a reasonable approximation of breeding habitat availability and does not explicitly account for local hydrological processes, irrigation infrastructure, river dynamics, or direct observations of larval habitats.

- ERA5/ERA5-Land climate fields were assumed to adequately represent state level climatic conditions relevant to malaria transmission, including temperature, precipitation, and atmospheric moisture. Consequently, relative humidity derived from ERA5 temperature and dewpoint data was assumed to provide a reasonable representation of the moisture stress experienced by adult mosquitoes. While these datasets capture large-scale climatic variability, they may not fully resolve local microclimatic conditions, irrigation effects, urban water storage environments, or other small-scale habitat features that can influence mosquito ecology.
- June-September (JJAS) was assumed to represent the dominant seasonal transmission period across Sudan and was therefore used for seasonal aggregation of climate suitability.

3.3. Population Data

Population data were derived as gridded datasets available for the years 2000, 2005, 2010, 2015, 2020, and 2025, and aggregated to the state level. For each reference year, population counts were aggregated from raster cells to the state level using the administrative boundaries employed in this study.

Annual population estimates were reconstructed using exponential interpolation between consecutive reference years:

$$P(t) = P_0 \times \exp[r(t - t_0)] \quad (11)$$

where:

- $P(t)$: population in year t ,
- P_0 : population at the initial reference year t_0 ,

- r : annual population growth rate calculated between two consecutive reference years.

Growth rates for the years 2000-2005, 2005-2010, 2010-2015, 2015-2020, and 2020-2025 were computed independently for each state. The resulting growth rates were then used to estimate annual populations for the intervening years, producing a continuous state level population time series for 2000-2024 while preserving the original WorldPop estimates at each reference year.

The resulting annual state level population estimates were used to normalize malaria cases and IDP counts.

3.4. Flood Data

Flooding was conceptualized as influencing malaria transmission through both enhancing mechanisms and disruptive mechanisms. Flooding may increase mosquito breeding habitats by expanding surface water, while intense rainfall and flooding may also flush larval habitats and reduce larval survival under some conditions (Paaijmans et al., 2007). Floods may additionally damage infrastructure, displace populations, and disrupt malaria prevention and treatment services (World Health Organization, 2013).

Flood indicators were analyzed separately from the CSI because flood extent was not included in the CSI calculation. This allowed flooding to be examined as an independent environmental factor and enabled comparison between the spatial distribution of flooding and climatically suitable areas for malaria transmission.

Flood data were derived from the European Commission Joint Research Centre Global Surface Water monthly history product, which maps monthly surface water occurrence from Landsat observations and classifies each 30 m pixel as water or non-water on a monthly basis (Pekel et al., 2016). The data was available for 2000-2021.

Monthly flooded fractions were first calculated for each Sudanese state by dividing the number of pixels classified as water by the total number of pixels within the state boundary. Flooded area (km²) was then derived by multiplying the flooded fraction by the total state area obtained from the Sudan administrative boundary shapefile. National flooded area for each month was subsequently calculated by summing flooded areas across all states, while national flooded percentage was calculated by dividing the total flooded area by the total mapped area of Sudan. Because temporary floodwaters contribute to increases in observed surface water extent, this indicator was used as a proxy for flooding and potential mosquito breeding habitat availability. However, the indicator represents observed surface water extent rather than direct measurements of flood severity, depth, duration, exposure, or impacts. Consequently, major flood disasters may not always correspond to the largest flooded area estimates because the indicator measures surface water extent rather than flood severity, duration, exposure, or impacts.

Because WHO malaria occurrence data were only available as annual observations, monthly flood estimates were summarized using the maximum flooded area (km²) and maximum flooded fraction (%) observed during each year. These indicators represent the largest flood extent observed during a given year and were selected to provide annual measures of flood severity that could be compared directly with annual malaria occurrence estimates. The annual maximum was chosen rather than the annual mean because averaging monthly flood conditions would smooth short lived but potentially important flooding episodes and could mask the occurrence of extreme inundation events. In contrast, the annual maximum captures the most severe flooding conditions experienced during a given year, which are more likely to influence malaria transmission through the rapid expansion of surface-water habitats, population displacement, disruption of healthcare services, and other flood related impacts.

National annual maximum flooded area was compared with WHO national confirmed malaria occurrence estimates normalized per 100,000 population.

3.5. WASH Data

Household WASH indicators were obtained from the WHO/UNICEF Joint Monitoring Programme (JMP), including access to drinking water, sanitation, and hygiene services by rural, urban, and total population categories. However, only the water indicator was used to reflect environmental health conditions that may indirectly affect malaria vulnerability through water storage practices.

In order to produce globally consistent annual estimates of WASH service coverage, the WHO/UNICEF Joint Monitoring Programme collects data from nationally representative household surveys and censuses and utilizes standardized statistical modeling methods (WHO & UNICEF JMP, 2024).

The data were available from 2003 to 2024 for drinking water and sanitation, and from 2008 to 2024 for hygiene. JMP household drinking water services indicator was used for contextual interpretation of the relationship between WASH infrastructure and national disease occurrence rather than as direct state level predictors because they are predominantly national or rural/urban rather than state level.

State level health facility WASH data, such as hand hygiene indicators in health service delivery units, water availability, and sanitation availability, was also extracted from the WHO HeRAMS Sudan Baseline Report 2025, which covers the period from 2023 to 01 June 2025. However, they were not used in the analysis due to the limited temporal coverage.

3.6. Internally Displaced Persons Data

Internally displaced persons (IDPs) data was incorporated to represent displacement driven vulnerability. By increasing exposure in temporary shelters or densely populated areas, decreasing access to prevention and treatment, altering population distribution, and putting strain on host-community services, displacement can impact the malaria occurrence (Malaria Consortium, n.d.).

Internal displacement data used in this study were obtained from the Internal Displacement Monitoring Centre (IDMC), which maintains the Global Internal

Displacement Database (GIDD). IDMC gathers data on displacement from a variety of sources, including news media outlets, civil society organizations, United Nations agencies and other international organizations, national and subnational government institutions, and relevant global databases (IDMC, n.d.). The database distinguishes between displacement associated with conflict and violence and displacement associated with disasters. Sudan's conflict related internal displacement data were retrieved from the IDMC country profile and related GIDD databases and were used to characterize national displacement patterns during the study period.

Displacement information is also available through the International Organization for Migration Displacement Tracking Matrix (IOM DTM) reports and snapshots following the outbreak of conflict in 2023. However, because these data do not provide the same temporal coverage as the IDMC dataset, they were not used as the primary displacement data source in this study.

3.7. Health Systems Capacity Data

The World Health Organization's Health Resources and Services Availability Monitoring System (HeRAMS) Sudan 2025 baseline assessment provided state level data on health service delivery units (HSDUs). The health system capacity analysis was divided into two subsections as effects of conflict on health systems and WASH in HSDUs.

For the effects of conflict on health systems, only indicators that clearly and directly indicated conflict or insecurity were included in the analysis. These included equipment damage due to conflict, attack, or looting; building damage due to conflict, attack, or looting; inaccessibility due to insecurity; and non-functionality due to insecurity. These indicators were selected because they represent direct manifestations of conflict reported by health facilities themselves and can therefore be clearly linked to conflict related disruption. Other reported barriers, such as lack of staff and lack of supplies were not included as direct conflict indicators. Although conflict may contribute to these challenges through displacement of healthcare workers, disruption of supply

chains and broader deterioration of health system capacity, these relationships are indirect and cannot be quantified using the available HeRAMS data. WASH in HSDUs was investigated through the availability of essential WASH services.

Additionally, HeRAMS provided information on capacity of HSDUs, with the following indicators: the type, number, and proportion of HSDUs that were fully operational, partially operational, non-operational, non-reporting, or planned/closed where reported. Because it only covers a small period and state level occurrence data is not available, this data is not used in the analysis. However, this data can suggest substantial regional differences in healthcare service availability across Sudanese states, where larger numbers of operational HSDUs may have greater capacity to provide malaria diagnosis, treatment, surveillance, and prevention services, while states with fewer operational facilities may encounter greater challenges in maintaining healthcare access.

State level percentages reported by HeRAMS were extracted and visualized. The spatial patterns of health system disruption, infrastructure deterioration, and service availability in Sudan were investigated using these visualizations.

3.8. Conflict Data

Armed conflict and insecurity were factors included in the analysis because conflict is recognized as an important indirect driver of infectious disease occurrence through destruction of healthcare infrastructure, disruption of disease control programs, reduced healthcare accessibility, interruptions in medicine supply chains, weakened disease surveillance systems, and large-scale population displacement (Marou et al., 2024). Annual state level political violence events and fatalities and civilian targeting events and fatalities data by Armed Conflict Location & Event Data (ACLED) were available on Humanitarian Data Exchange (HDX) portal from 1997 to 2026 as indicators of conflict intensity across Sudanese states. However, as the effects of conflict on health systems and displacement are of interest, HeRAMS and IDPs data are more closely related to the scope of this study.

3.9. ReliefWeb Malaria Humanitarian Reports Database

A malaria specific humanitarian reporting database was constructed for Sudan for the period 2000-2024 using humanitarian reports retrieved from ReliefWeb and automated keyword-based text extraction procedures. The aim of the database was to identify malaria incidence information, malaria drivers, intervention activities, and humanitarian situations that could help interpret the quantitative analyses presented in this study. While the other datasets primarily provided quantitative indicators of malaria occurrence, climate, conflict, displacement, WASH conditions, and health system functionality, the humanitarian database provided additional contextual information on malaria occurrence and potential causes. ReliefWeb was selected as the primary retrieval platform because it provides a large and systematically maintained archive of humanitarian situation reports, operational updates, outbreak reports, weekly bulletins, humanitarian overviews, and emergency health reports from organizations such as the Office for the Coordination of Humanitarian Affairs (OCHA), the World Health Organization (WHO), Médecins Sans Frontières (MSF), and other humanitarian actors. Reports were obtained through the ReliefWeb API and supplemented with additional ReliefWeb PDF reports that were manually downloaded when necessary. Manual retrieval was required because some relevant reports were not captured through the API search results despite being available on the ReliefWeb platform. Only reports relevant to Sudan and containing explicit malaria related information were retained. Because Sudan shares name with the country South Sudan, additional filtering was applied to retain the reports that focused exclusively on South Sudan. The main stages of database construction, filtering, and evidence extraction are summarized in *Table 3*. Manual inspection of selected reports and extraction outputs was conducted during database development and validation to identify filtering, extraction, and classification issues. These inspections were intended to support refinement of the automated extraction procedures and were not a comprehensive review of all reports included in the database.

Table 3. Stages of ReliefWeb database development

Stage	Description	Purpose
1. ReliefWeb retrieval	Humanitarian reports were retrieved from ReliefWeb using the API, and additional relevant ReliefWeb PDF reports were manually downloaded.	Established the initial archive of humanitarian reporting from which malaria related information could be extracted.
2. Organization and source filtering	Retrieved records were filtered to retain reports produced by WHO, OCHA, and MSF, including situation reports, operational updates, humanitarian bulletins, outbreak reports, and epidemiological updates.	Focused the database on organizations that consistently report health conditions, outbreaks, humanitarian situations, and response activities relevant to malaria in Sudan.
3. Sudan relevance screening	Filename-based filtering, title-based filtering, body-text filtering, Sudan state-name matching, and South Sudan keyword exclusion were applied.	Reduced geographic misclassification and minimized inclusion of reports focused on South Sudan or broader regional contexts.
4. Malaria relevance filtering	Reports were screened for malaria related terminology including malaria, malarial, <i>Plasmodium</i> , <i>Anopheles</i> , mosquito, long-lasting insecticidal net (LLIN), indoor residual spraying (IRS), rapid diagnostic test (RDT), artemisinin-based combination	Ensured that retained reports contained explicit malaria related content rather than only general humanitarian information.

	therapy (ACT), vector control, and antimalarial related terms.	
5. Duplicate review	Publication year, reporting organization, and normalized report titles were used to identify potential duplicates. Suspected duplicates were reviewed before removal.	Reduced duplication while preserving reports that covered different locations or reporting periods despite similar titles.
6. Additional PDF integration	Additional ReliefWeb PDF reports were manually downloaded and processed using the same extraction, filtering, and classification procedures applied to API derived reports.	Improved coverage of Sudan malaria related humanitarian reporting.
7. Sentence level evidence extraction	Individual intervention, driver, malaria mention, and case count sentences were extracted and retained together with report metadata.	Increased transparency, enabled inspection of extracted evidence, and supported evidence level analyses rather than relying solely on report level classifications.
8. Driver identification and classification	Rule-based extraction combined malaria context, driver related terminology, and causal expressions such as “due to”, “because of”, “associated with”, and “resulting from”. Extracted sentences were classified into rainfall, flooding, displacement, conflict, sanitation, health system disruption, and	Identified reported factors potentially contributing to malaria transmission.

	endemicity/transmission categories.	
9. Intervention identification and classification	Rule-based extraction combined malaria specific intervention terminology with implementation language such as “distributed”, “provided”, “implemented”, and “conducted”. Extracted sentences were classified into LLINs/bed nets, IRS/vector control, diagnosis/testing, treatment/antimalarials, surveillance, health education/outreach, and distribution/supplies categories.	Identified malaria response activities and enabled temporal analysis of intervention reporting.
10. Malaria incidence extraction	Pattern-based extraction was used to identify sentences containing malaria case counts, outbreak totals, incidence information, mortality information, and population-at-risk estimates.	Provided supporting information on malaria occurrence.
11. Reporting period, state, and locality extraction	Rule-based extraction identified reporting periods, Sudan states, and localities from report texts.	Provided supporting temporal and geographic context for interpretation of reported malaria information.
12. Final database construction	Report metadata, malaria relevance flags, extracted evidence sentences, intervention classifications, driver classifications, case count information, reporting periods,	Produced the final dataset used for analysis of malaria related humanitarian reporting in Sudan.

	and geographic references were combined into the final database.
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To improve transparency and reproducibility, the final database retained individual evidence sentences rather than only report level classifications. Each extracted sentence was linked to the report title, publication year, source organization, and evidence category. This structure enabled inspection of individual classifications and facilitated temporal summaries of malaria reporting, drivers, and interventions. Because a single report could contain multiple relevant statements, sentence level evidence frequencies may exceed the number of reports containing a given theme.

Additional exploratory extraction of reporting periods, states, and localities was conducted to provide supporting temporal and geographic context. However, because humanitarian reports often contained complex layouts, tables, and fragmented PDF text, location extraction was considered supporting qualitative evidence rather than a complete spatial dataset. Consequently, extracted state and locality information should be interpreted as indicative rather than exhaustive.

Potential duplicates were identified using combinations of publication year, source, and normalized report title and were reviewed before removal. This approach was necessary because recurring humanitarian bulletins and outbreak updates often covered different reporting periods or geographic areas despite having similar titles.

Driver, intervention, and malaria case count information were identified using automated keyword and pattern-based sentence extraction procedures. The extraction scripts searched report texts for predefined malaria related keywords, contextual terms, and text patterns to identify potentially relevant evidence. Driver extraction combined malaria related context with environmental and humanitarian conditions and associated causal language, while intervention extraction combined malaria specific intervention terminology with implementation related language indicating that an activity had been carried out. Extracted sentences were classified into predefined driver and intervention categories. The keywords, classification criteria, and evidence categories used in the final extraction scripts are summarized in *Table 4*.

Table 4. Keywords used to identify different themes

<i>Theme</i>	<i>Category</i>	<i>Keywords used</i>
<i>Malaria relevance</i>	Malaria related content	malaria, malarial, Plasmodium, Anopheles, mosquito(es)
<i>Driver classification</i>	Rainfall / rainy season	rain, rainfall, rainy season
	Flooding / stagnant water	flood, stagnant water, standing water, breeding
	Displacement / IDPs	IDP, internally displaced, displacement, displaced
	Conflict / insecurity / access	conflict, insecurity, violence, access
	Poor sanitation / overcrowding	sanitation, overcrowd, poor hygiene, unsafe water
	Health system disruption	health facility, stock-out, shortage, health service
	Endemicity / transmission suitability	endemic, transmission, high risk, population at risk
<i>Intervention classification</i>	LLINs / bed nets	LLIN, ITN, insecticide-treated net, long-lasting insecticidal net, bed net, mosquito net, anti-malaria bed net
	IRS / spraying / vector control	indoor residual spraying, IRS, residual spraying, spraying of stagnant water, vector control, larviciding

	Diagnosis / testing	RDT, rapid diagnostic test, malaria diagnosis, diagnosis of malaria
	Treatment / ACTs / antimalarials	ACT, artemisinin, artemisinin-based combination therapy, antimalarial, anti-malarial, malaria treatment, treatment of malaria, malaria case management
	Surveillance / monitoring	malaria surveillance, malaria monitoring
	Health education / outreach	malaria awareness, malaria health education, malaria outreach
	Distribution / supplies	distribution, distributed, provided, supplied, delivered, procured, supported combined with malaria-specific intervention items such as LLINs, RDTs, ACTs, antimalarials, or malaria treatment supplies
<i>Implementation/action terms</i>	Intervention identification support	distributed, distribution, provided, supplied, delivered, deployed, procured, supported, implemented, conducted, carried out, intensified, launched, trained, training, treated, diagnosed, tested, sprayed, spraying

<i>Malaria incidence classification</i>	Quantitative malaria incidence reporting	Numerical expressions associated with malaria cases or infections, including confirmed malaria cases, suspected malaria cases, malaria infections, malaria incidence rate, mid-point estimate of cases, and phrases linking disease occurrence to reported case totals. Detection additionally required explicit numerical values (e.g., thousands, millions, or comma-separated case counts).
<i>False positive exclusions</i>	Examples removed from intervention classification	reporting units, reporting sites, surveillance data, EWARS reporting, food distribution, NFI distribution, non-food items, preventive health action, relief delivery, vaccination campaigns, measles, polio, supplementary feeding, plastic sheeting, jerry cans

Extracted intervention evidence was classified into intervention categories, while driver evidence was classified into environmental, conflict related, displacement related, WASH related, health system, and transmission related categories. Because classification was performed at the sentence level, categories were not mutually exclusive, and a single sentence could contribute to more than one intervention category. Consequently, category frequencies

should be interpreted as evidence frequencies rather than independent counts of intervention activities.

Finally, reports were screened for malaria case count information, including reported cases, mortality estimates, incidence information, and population-at-risk estimates. These records were retained together with relevant report metadata to support interpretation of malaria occurrence patterns. Because some humanitarian reports contained regional or multi-country summaries, a small number of extracted evidence sentences may occasionally reference neighboring countries despite Sudan focused filtering procedures.

Following API retrieval, integration of additional PDF reports, duplicate review, filtering, and post-processing, the final curated database contained 273 malaria related humanitarian reports covering Sudan between 2000 and 2024. Within this database, intervention evidence, driver evidence, and malaria case count information were reported in smaller subsets of reports, with some reports contributing to more than one evidence category. For each report, the database retained metadata including report title, publication year, source organization, document type, malaria relevance indicators, extracted driver and intervention evidence, driver and intervention classifications, and supporting location and document references where available. Although some extraction uncertainties remain, particularly for complex report layouts, multi country reports, and automated location extraction, the dataset was considered suitable for qualitative interpretation of humanitarian malaria reporting and temporal analysis of reported drivers and interventions.

4. Results and Discussion

4.1. Comparison of National WHO Confirmed Malaria Cases and National MAP Occurrence Estimates

Figure 3 shows the temporal evolution of national MAP Pf+Pv clinical cases and WHO confirmed malaria cases. The multi-year temporal pattern of both datasets was generally similar, especially between 2017 and 2022. The malaria

occurrence increased starting in 2015 and peaked between 2019 and 2021. While WHO confirmed malaria cases increased from approximately 0.6 million to nearly 1.7 million cases throughout the same period, MAP national Pf+Pv clinical cases increased from approximately 1.6 million cases in 2015 to over 3 million cases by 2021. Over the course of the investigation period, MAP estimates were continuously significantly higher than WHO confirmed cases, despite these similarities in temporal evolution. Since the two datasets represent essentially different epidemiological quantities, the higher occurrence estimated by MAP should be anticipated. While MAP clinical cases represent modeled estimates of the overall malaria occurrence, including potentially unreported and undiagnosed infections estimated through statistical spatial modeling frameworks, WHO GHO confirmed malaria cases rely on healthcare access, diagnostic availability, reporting infrastructure, and laboratory confirmation (Weiss et al., 2019; WHO, 2024). As a result, MAP estimates are expected to exceed surveillance based confirmed case records, especially in resource constrained and conflict affected countries like Sudan.

After 2022, the differences in the datasets became particularly noticeable. While MAP national malaria occurrence estimates remained almost unchanged in 2023, WHO confirmed malaria cases decreased considerably. The timing of this mismatch coincides with the escalation of conflict and humanitarian disruption in Sudan, which likely affected disease monitoring systems, diagnostic capacity, and healthcare access (WHO, 2024; UNOCHA, 2024). Therefore, rather than a real sudden decline in the malaria transmission, the post 2022 difference most likely reflects surveillance instability and reporting disruption.

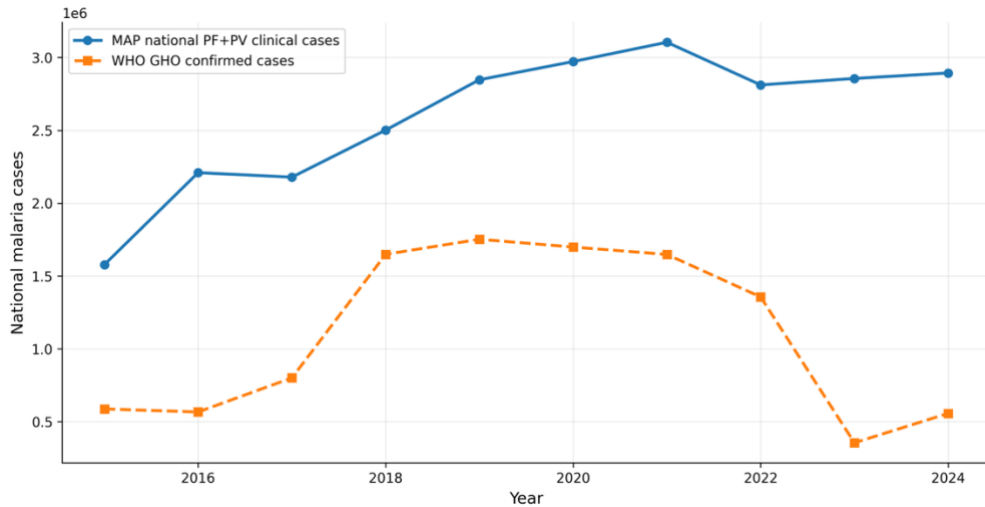


Figure 3. Temporal evolution of WHO and MAP malaria occurrence data

Standardized z-score anomalies were calculated independently for the MAP and WHO datasets in order to compare interannual variability regardless of variations in magnitude and units (Figure 4). The anomaly comparison showed relatively consistent positive anomalies in both datasets during 2018-2022, indicating that both datasets identified these years as periods of elevated malaria occurrence relative to their respective long-term trends. This agreement implies that both datasets captured generally similar large-scale temporal variability for the majority of the research period, despite significant differences in absolute magnitudes. The anomaly analysis did, however, also show a significant difference between 2023 and 2024, when MAP anomalies remained positive while WHO anomalies became sharply negative. This implies once more that disruptions to the healthcare system, reduced testing capacity, underreporting, and insufficient surveillance coverage may have had a significant impact on the WHO surveillance signal during later conflict affected years.

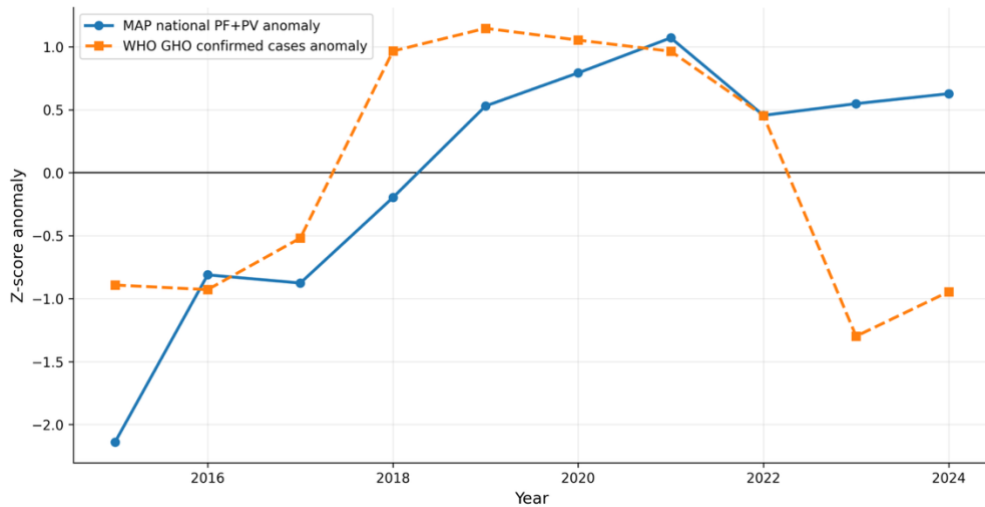


Figure 4. Standardized anomalies of WHO and MAP malaria occurrence data

Further, the relationship between MAP Pf+Pv clinical cases and WHO confirmed cases were evaluated using scatterplots, which revealed relatively low yearly agreement but slightly positive general relationships (Figure 5). A moderate Pearson correlation ($r \approx 0.48$) was observed in the raw case comparison, suggesting that years with higher MAP estimated occurrence typically corresponded with higher WHO confirmed occurrence. The corresponding Spearman rank correlation, however, remained low ($\rho \approx 0.20$), indicating that there were significant differences between datasets in the exact ordering of high and low occurrence years. The post-2022 divergence, in which WHO confirmed cases drastically decreased despite consistently high MAP occurrence estimates, had a significant impact on the comparatively low rank agreement.

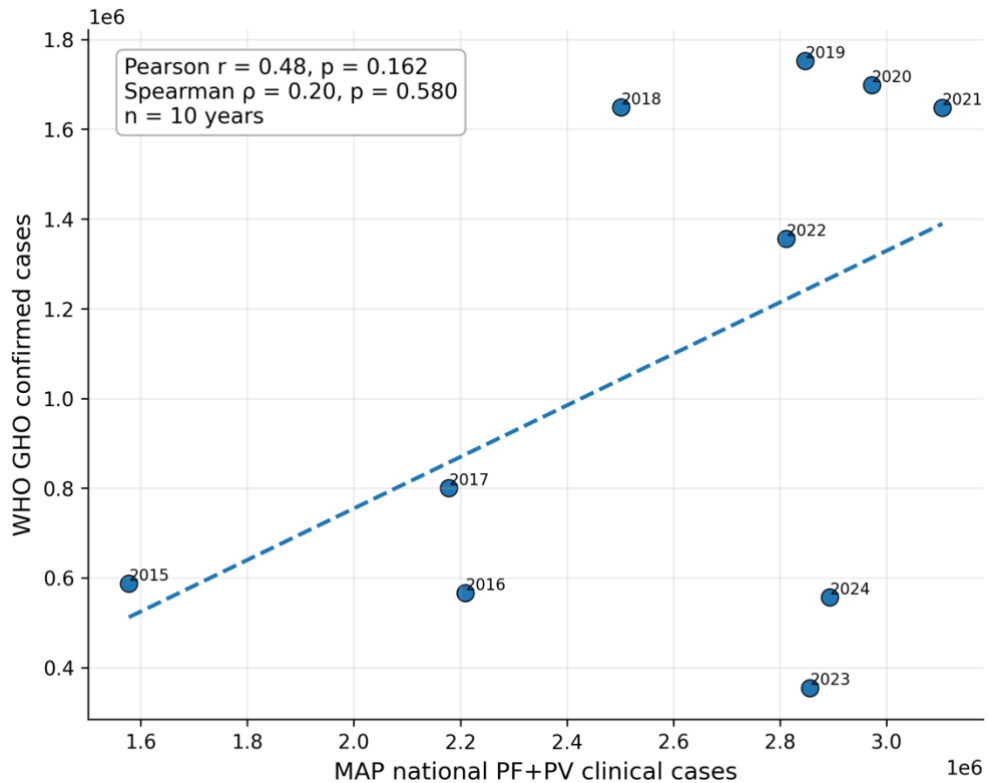


Figure 5. Agreement between WHO and MAP malaria occurrence data

The MAP national burden is further divided into *Pf* and *Pv* components in Figure 6. Throughout the study period, *Pv* provided a significantly lower number of all malaria cases, but *Pf* clinical cases dominated the national malaria burden. This result validates the CSI framework's primary focus on climate suitability of *Pf*, since *Pf* transmission is the main factor influencing Sudan's national malaria occurrence.

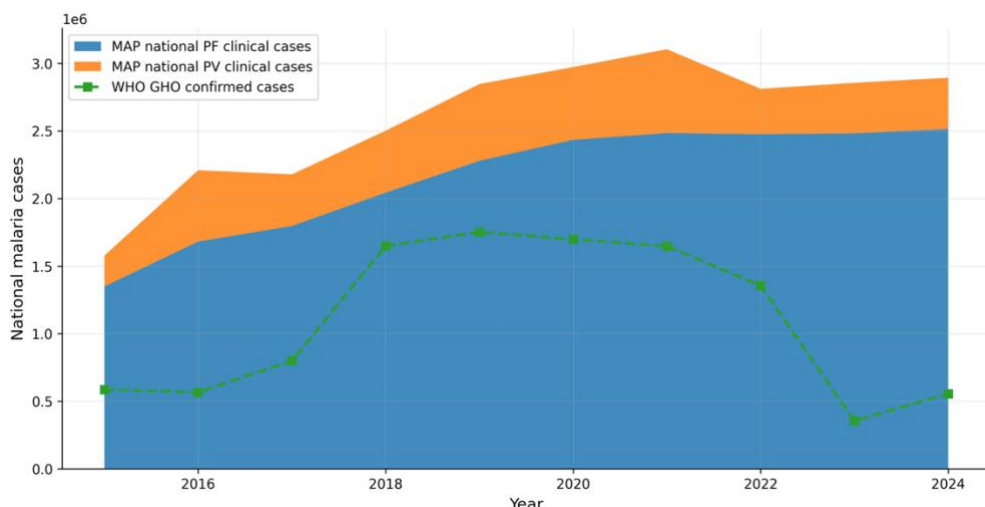


Figure 6. MAP Pf and Pv malaria occurrence components compared with WHO malaria occurrence

Overall, the comparison of WHO confirmed malaria cases and MAP national malaria occurrence estimates indicates that the two datasets capture similar broad temporal patterns in malaria occurrence, especially during relatively stable years, but differ significantly during conflict affected periods. The findings suggest that during periods of healthcare disruption and humanitarian crisis, the true malaria occurrence may be underestimated or incompletely captured by surveillance based confirmed case records alone. Further, these results emphasize how crucial it is to interpret malaria surveillance data in light of Sudan's conflict, humanitarian disruption, reporting stability, and health system functionality.

4.2. CSI and Malaria Occurrence

The state level spatial distribution of the CSI for *Pf* for the years 2000, 2008, 2016 and 2024 are demonstrated in Figure 7. Throughout the course of the study, *Pf* accounted for 89% of the malaria cases in Sudan (Severe Malaria

Observatory, n.d.). Hence, in the following sections of the study, the CSI only calculated for *Pf*.

Further, there was a distinct north-south gradient in climate suitability, with the southern and southeastern parts of the country, such as South Darfur, South Kordofan, Blue Nile, Sennar and White Nile, experiencing the highest suitability and the arid northern states, such as Northern, River Nile, and Red Sea, consistently experiencing the lowest.

Significant temporal variations were identified, but the overall spatial pattern remained mostly stable. Of the four years demonstrated, the mean national CSI increased between 2000 and 2016, peaking among the illustrated years in 2016 with a mean CSI = 0.458. In 2016, several southern and southeastern states had CSI values that were approaching the highest end of the normalized range, suggesting especially favorable conditions for malaria transmission. However, throughout the study period, the highest CSI values were observed in 2019 with mean CSI = 0.533. On the other hand, of the four years demonstrated, 2024 had lower average suitability (mean CSI = 0.404), with a noticeable decrease in the intensity of highly suitable areas. The lowest suitability throughout the study period was observed in 2022 (mean CSI = 0.358).

Additionally, some northern states showed slight increases in CSI compared to 2000, despite the overall decrease in overall national suitability in 2024. Northern, River Nile, and Red Sea, for instance, had slightly greater suitability scores in 2024 compared to the start of the study period, indicating regional changes in climate suitability although general national suitability declined.

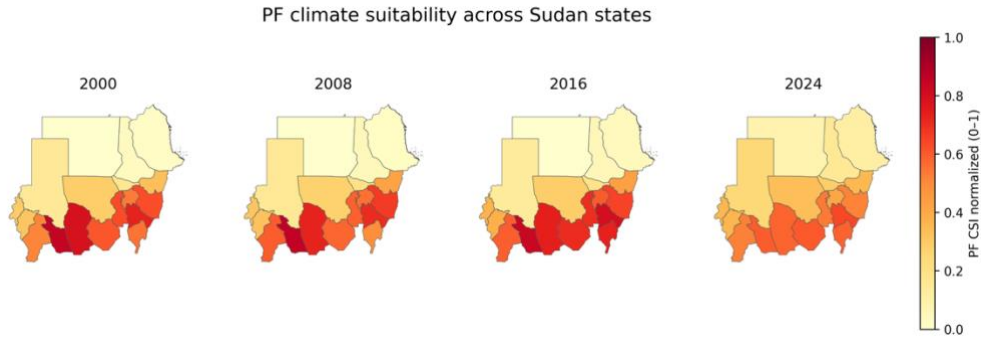


Figure 7. *Pf* CSI across Sudan states

The major climatic zones of Sudan are reflected in the strong north-south gradient observed in *Pf* climate suitability. While southern and southeast Sudan receive significantly more seasonal rainfall and humidity due to the northward migration of the Intertropical Convergence Zone (ITCZ), northern Sudan is characterized by hyper-arid desert conditions with very little rainfall and surface water availability. These wetter conditions lead to enhanced mosquito survival, formation of breeding habitats, and transmission of parasites (Red Cross Climate Centre, 2024; Craig et al., 1999). These environmental gradients were successfully replicated by the CSI, suggesting that the model accurately reflects the primary climatic effects on the potential for malaria transmission throughout the country. The higher CSI values observed in the wetter south and southeastern states is consistent with previous studies which reported that malaria transmission is strongly influenced by rainfall and temperature conditions (Craig et al., 1999; Mordecai et al., 2013).

The conclusion that interannual climatic variability significantly influences malaria transmission variability in Sudan is further supported by Z-score anomaly analyses (Figure 8), which also revealed that years with strongly positive CSI anomalies, particularly for 2018-2019, generally corresponded to elevated malaria occurrence anomalies. However, divergence between CSI anomalies and malaria occurrence anomalies emerged after 2019, when malaria occurrence remained elevated despite declining climate suitability. One possible explanation is the occurrence of widespread flooding during 2018-2021, including particularly large flood extents in 2019 and severe

flooding in 2020 (OCHA, 2020). Because the CSI does not represent flood extent, floodwater persistence, or other hydrological processes associated with the creation of mosquito breeding habitats, flooding may have contributed to sustaining malaria transmission despite lower CSI values.

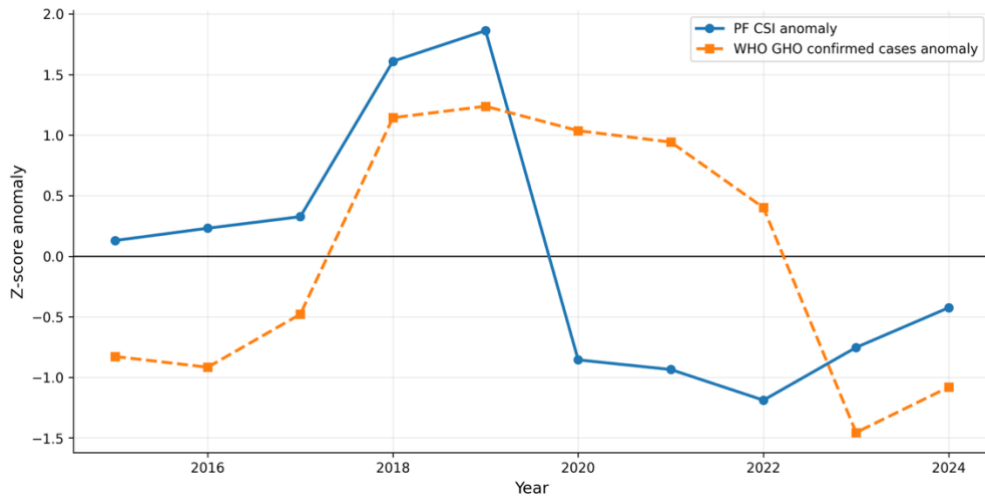


Figure 8. Standardized anomalies of Pf CSI and malaria occurrence

The national population-weighted CSI and malaria occurrence revealed moderate contemporaneous relationships, with Pearson $r=0.30$ and $p=0.403$ (Figure 9). Although the exact magnitudes varied, Spearman correlations were generally slightly stronger than Pearson correlations, suggesting that years with relatively higher climate suitability tended to correspond with relatively higher malaria occurrence years. The strongest relationship was observed for the one-year lagged analysis, where the CSI in year t showed a strong positive association with confirmed malaria cases per 100,000 population in year $t+1$ ($\rho \approx 0.70$, $p \approx 0.036$), while the corresponding Pearson correlation reached $r=0.57$ (Figure 10). These results suggest that climate suitability may influence malaria occurrence with delayed national scale effects rather than immediate responses.

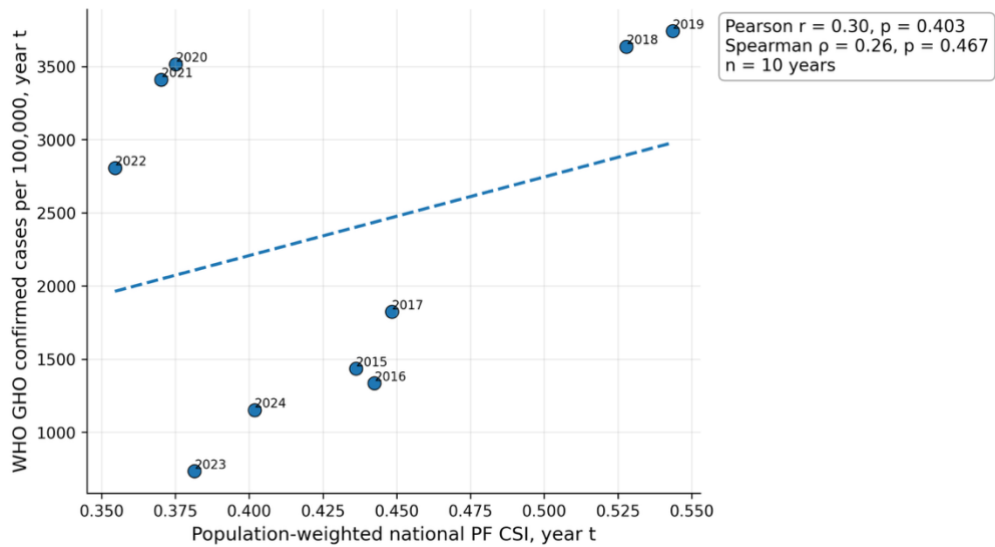


Figure 9. Same year correlation analysis between *Pf* CSI and malaria occurrence

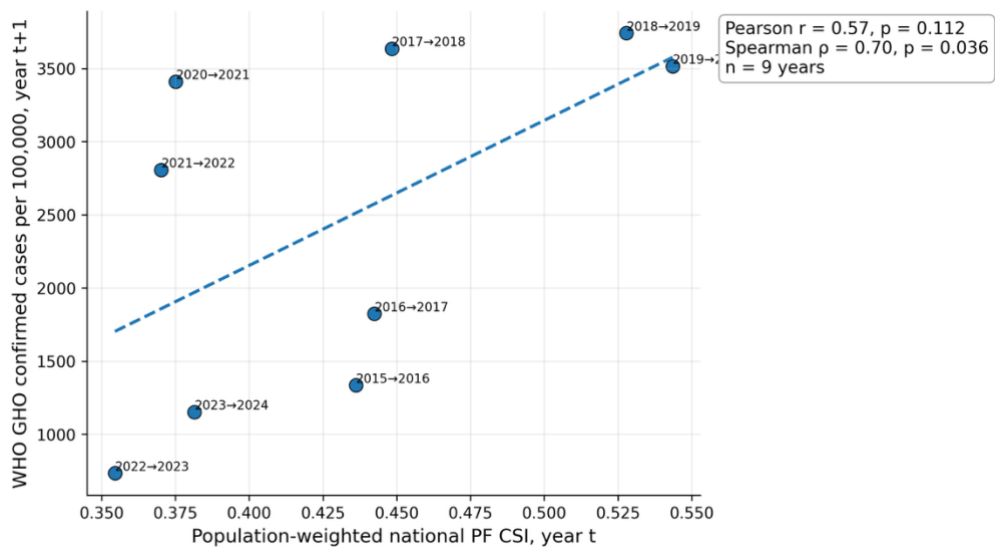


Figure 10. One-year lagged correlation analysis between *Pf* CSI and malaria occurrence

Overall, the results indicate that while climate suitability alone does not fully explain malaria occurrence dynamics in Sudan, the CSI captures significant large-scale interannual variability related to malaria occurrence potential. The stronger lagged relationships compared with contemporaneous associations indicate that climate effects may function through delayed ecological and epidemiological mechanisms, such as vector population growth, breeding habitat persistence, and transmission processes that develop over several months before being reflected in reported malaria cases.

4.3. Flood Data

There were significant variations in the malaria occurrence and flooded area relationship (Figure 11). For instance, although there was less flooding in 2018 than in 2020 and 2021, the malaria occurrence was higher, and while the flooded area was larger in 2016 than 2015, the malaria occurrence was lower. Of the years investigated, 2019 had the highest malaria occurrence of approximately 4,220 confirmed cases per 100,000 people, and the largest flooded extent of approximately 6,450 km² flooded area. Similarly, 2020 exhibited both severe flooding and increased malaria occurrence. On the other hand, both malaria occurrence and flood extent were lower in 2015 and 2016.

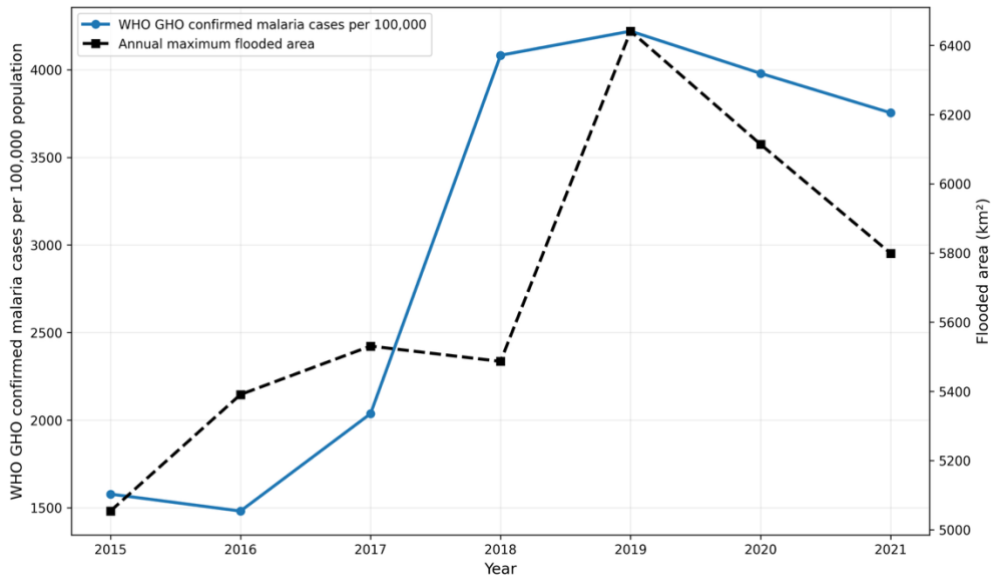


Figure 11. Temporal evolution of malaria occurrence and flooded area

Correlation analyses were conducted using both contemporaneous and one-year lagged relationships to examine if flooding was linked to malaria occurrence immediately or with a delayed effect. A significant positive correlation between the annual malaria occurrence and flood extent was observed in the contemporaneous analysis with Pearson $r=0.767$, $p=0.044$; Spearman $\rho=0.750$, $p=0.052$ (Figure 12). The one-year lagged relationship, on the other hand, was weaker with Pearson $r=0.635$, $p=0.175$; Spearman $\rho=0.486$, $p=0.329$. According to these results, there was a stronger correlation between the extent of the flood and the malaria occurrence in the same year as opposed to the subsequent year. This indicates that rather than having a long-term delayed effect that extends into the following year, flooding may mainly influence malaria transmission through relatively immediate mechanisms, such as the formation of temporary breeding habitats and increased vector abundance within the same transmission season. However, the variation in lagged results could also be due to the influence of other environmental, epidemiological, and humanitarian factors.

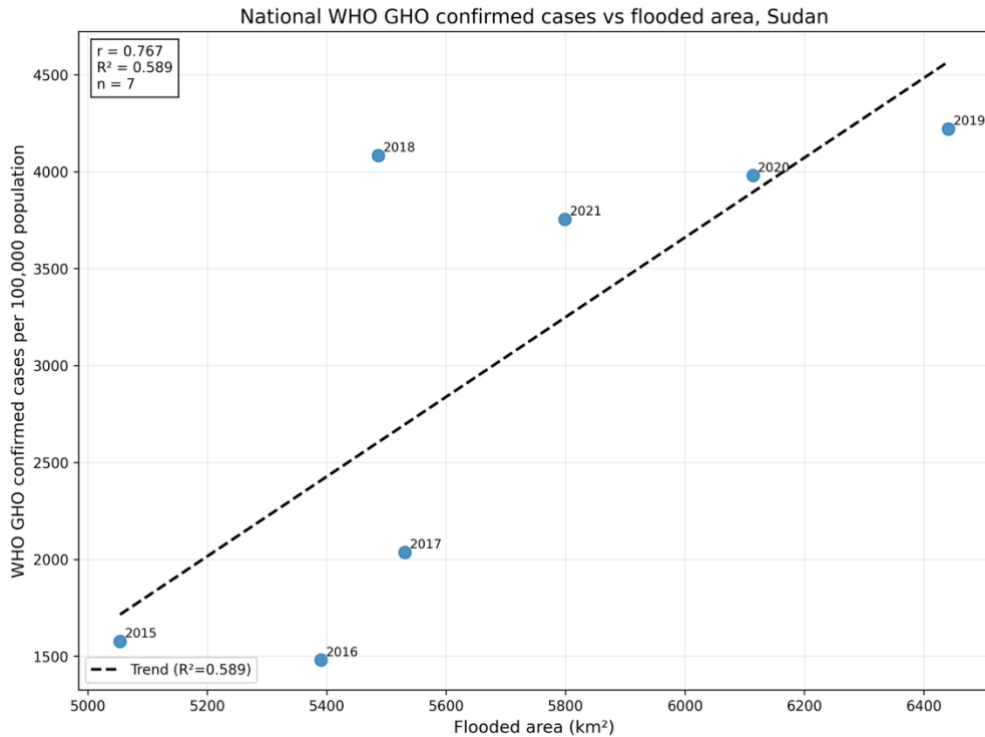


Figure 12. Same year correlation analysis of malaria occurrence and flooded area

In contrast, the CSI exhibited its strongest association with malaria burden when a one-year lag was applied. While this pattern may suggest that broader climatic suitability conditions influence malaria transmission through processes that develop over longer time periods, the difference between the flood and CSI lag structures should not be interpreted as definitive evidence of distinct transmission pathways. This variation in correlation between contemporaneous and lagged relationships for these factors could also be due to the influence of other environmental, epidemiological, and humanitarian factors. Consequently, the observed lag patterns are likely to reflect a combination of climatic influences and other interacting factors and should be interpreted as indicative rather than conclusive given the small sample size.

4.4. WASH Data

Drinking water indicators from JMP database revealed a gradual long-term improvement across total, urban, and rural populations (Figure 13). Over the study period, unimproved water use and surface water use continually decreased, while access to at least basic drinking water services increased steadily. For the total population, access to at least basic drinking water increased from 45.8% in 2003 to 64.9% in 2024, while unimproved water use declined from 24.6% to 1.8%. In rural areas, where reliance on unimproved and surface water sources was initially highest, the improvement was especially noticeable, with access to at least basic drinking water increasing from 37.4% to 59.6% over the study period. Compared to rural areas, urban areas showed lower reliance on unimproved or surface water sources and higher levels of access to basic drinking water, reaching approximately 74% by 2024. Improvements in drinking water services may influence malaria occurrence by reducing the need for household water storage, which can create artificial breeding habitats for mosquitoes. For example, a study in Sudan reported higher malaria risk among households relying on cart delivered water, partly due to water storage practices that provide suitable breeding sites for mosquitoes (Saeed & Ahmed, 2003). However, the extent to which improvements in drinking water access have reduced mosquito breeding habitats in Sudan cannot be assessed due to data limitations.

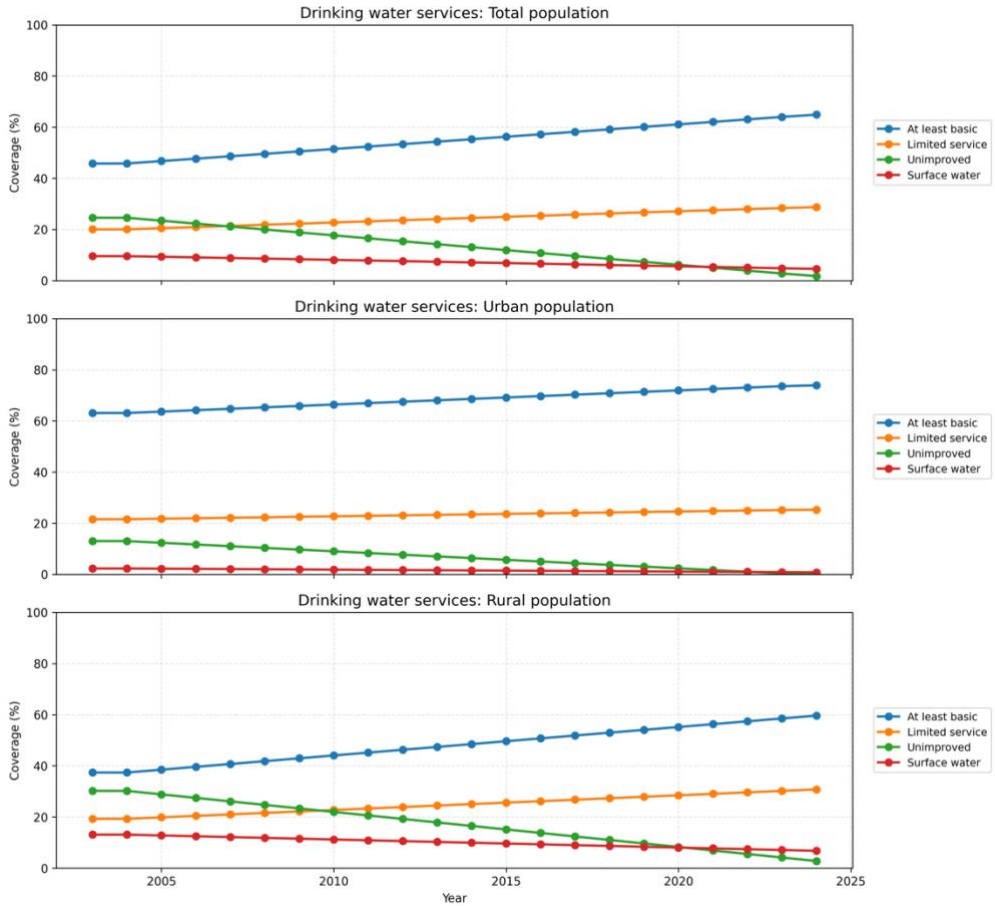


Figure 13. Drinking water services coverage in Sudan (data from JMP, 2026)

4.5. Internally Displaced Persons

The national IDPs and malaria occurrence time series revealed significantly different patterns before and after the outbreak of Sudanese civil war in 2023, as depicted in Figure 14. Conflict related internal displacement remained generally lower than 1,000 displacements per 100,000 people, whereas WHO

confirmed malaria occurrence remained quite high, ranging from approximately 1,500 to 4,000 cases per 100,000 people between 2015 and 2022. A substantial shift occurred in 2023 following the outbreak of armed conflict in April 2023. Conflict related internal displacement increased dramatically to approximately 12,500 displacements per 100,000 population, representing the highest value in the study period. In contrast, reported malaria cases declined sharply from approximately 2,750 cases per 100,000 population in 2022 to approximately 730 cases per 100,000 population in 2023. Further, while reported malaria cases increased slightly to approximately 1,100 cases per 100,000 people in 2024, they were still considerably below pre-conflict levels, whereas displacement remained high at approximately 7,800 displacements per 100,000 people in 2024.

The impact of conflict on health systems, surveillance, and case reporting is likely reflected in the significant decrease in reported malaria cases that coincided with the extraordinary increase in displacement in 2023. The outbreak of conflict in April 2023 resulted in large-scale population displacement and major disruptions to healthcare delivery, health infrastructure, and disease surveillance systems across Sudan, potentially reducing malaria case detection and reporting (WHO, 2026).

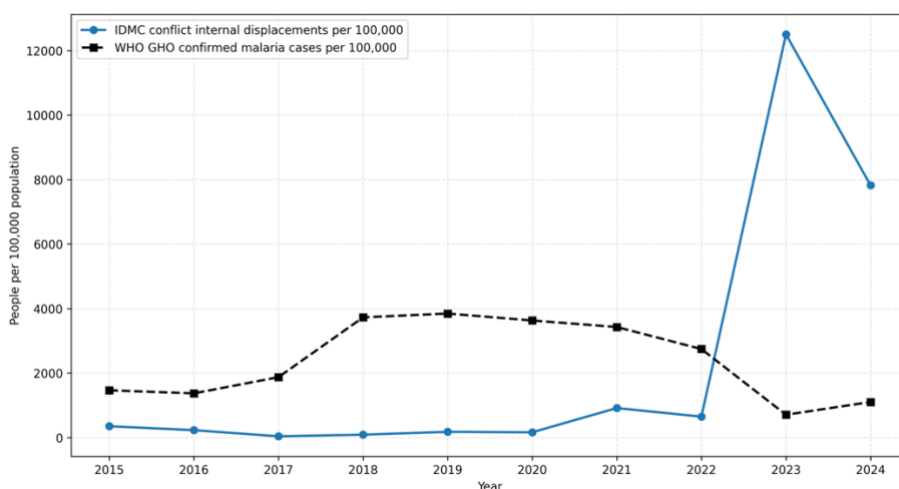


Figure 14. Temporal evolution of IDPs and malaria occurrence (IDMC, 2026)

4.6. Health Systems Capacity

4.6.1. Effects of Conflict on Health Systems

Nationally, 4,363 HSDUs were reporting out of 6,674 HSDUs targeted (HeRAMS, 2025). Among HSDUs reporting building damage, 56% identified conflict, attack, or looting as the cause, while 64% of HSDUs reporting equipment damage attributed the damage to conflict related causes. Additionally, 56% of HSDUs reporting accessibility limitations identified insecurity as the primary reason for inaccessibility, and 62% of HSDUs reporting functionality constraints identified a lack of security as a significant factor. These results from HeRAMS assessments reveal that conflict and insecurity were the main causes of Sudan's health system disruption, and that they have a significant direct influence on Sudan's health system's accessibility and functionality.

The percentage of HSDUs in Sudanese states that reported health system disruption due to conflict and security is shown in Figure 15. The most severe effects were observed in Khartoum, where the majority of HSDUs reported non-functionality due to lack of security, building damage due to conflict, equipment damage due to conflict, and accessibility limitations due to insecurity. Similarly, North Kordofan and North Darfur reported consistently high levels across all indicators, with over 80% of facilities impacted by extensive barriers due to insecurity and conflict related building and equipment damage. The concentration of health system disruption in Khartoum, North Darfur, and North Kordofan states was consistent with humanitarian assessments documenting severe conflict related insecurity, displacement, and humanitarian access constraints in these regions since 2023 (ACAPS, 2025; IOM, 2025).

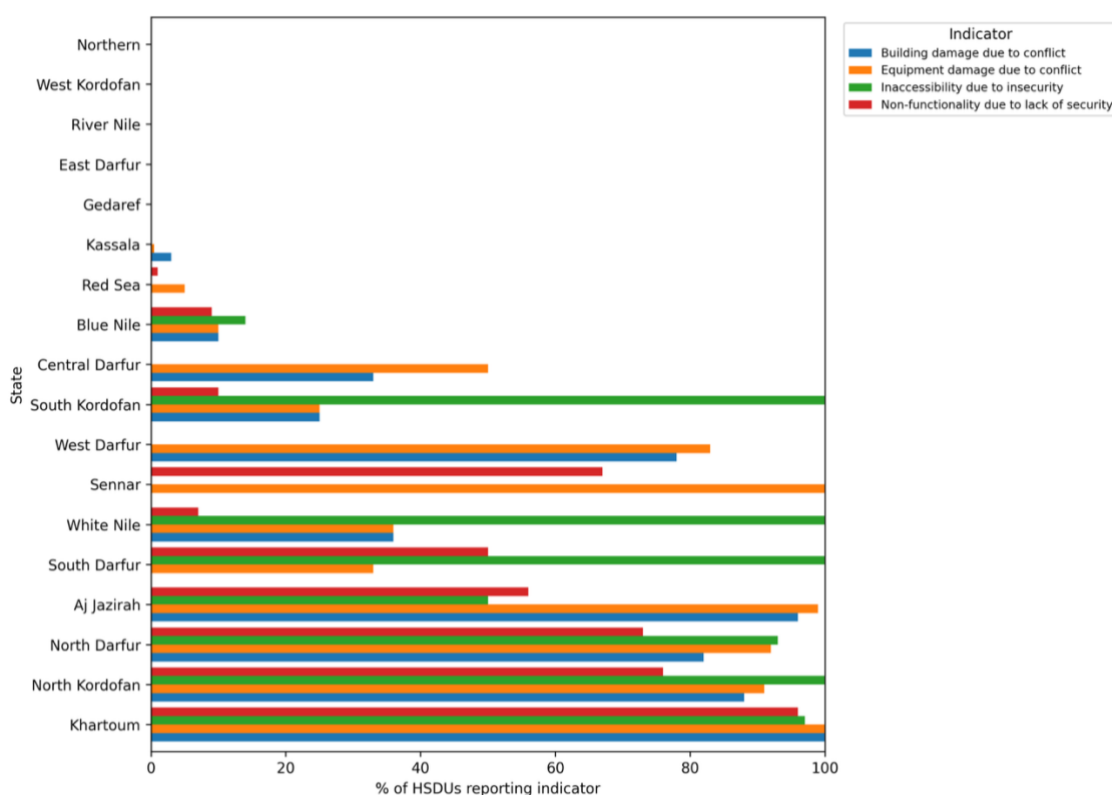


Figure 15. Conflict and security related disruptions in health systems by state (HeRAMS, 2025)

Aj Jazirah also demonstrated significant interruption, with over half of the facilities reporting operational constraints and insecurity, and between 95 and 100% reporting damage attributable to the conflict. Although there was less reported insecurity and security related non-functionality in West Darfur than in Khartoum, North Kordofan, and North Darfur, there was still significant conflict related damage, especially to buildings and equipment.

Several states showed a contrasting pattern, with limited physical damage but substantial insecurity related barriers. For instance, South Darfur, White Nile, and South Kordofan reported very high levels of inaccessibility due to insecurity, but comparatively low levels of conflict related building and equipment damage. This suggests that even in areas where direct physical

infrastructure destruction is less common, security conditions may have an impact on access to healthcare. On the other hand, conflict related disruption was not reported in River Nile, Gedaref, East Darfur, West Kordofan, and Northern.

The results indicate that health systems capacity is impacted by conflict in different ways, beyond simply through infrastructure destruction.

4.6.2. WASH in HSDUs

Numerous states reported significant barriers to water services availability in health systems. The most common barriers affecting the provision of water services in healthcare facilities were identified as lack of supplies, equipment, and financial resources.

4.7. ReliefWeb Malaria Humanitarian Reports Database

4.7.1. Overview of evidence records

At completion, humanitarian malaria reporting database consisted of 273 malaria relevant Sudan humanitarian reports for the period 2000-2024. The database was dominated by OCHA and WHO reports, with 136 OCHA reports, 123 WHO reports, and 14 MSF reports.

A total of 461 evidence records were generated by the final evidence level extraction, consisting of 197 intervention evidence records, 77 driver evidence records, and 187 malaria occurrence evidence records. The categories are not mutually exclusive, and a single sentence may contribute to more than one category when it contains information on malaria occurrence, drivers, or interventions.

Over the course of the study, reporting was inconsistent. With 51 reports, 2005 experienced the most significant reporting peak, followed by 25 reports in 2004, 20 reports in 2013, 19 reports in 2007, and 18 reports each in 2008 and 2009. Later years also demonstrated increased reporting activity, especially in 2023 (11 reports) and 2024 (13 reports). However, this pattern does not necessarily indicate a direct change in malaria occurrence, but rather variations in humanitarian reporting activity.

Only a small portion of the humanitarian reporting archive contained malaria incidence information. Nine reports included quantitative information about the malaria occurrence, such as reported cases, outbreak totals, mortality estimates, incidence data, or population-at-risk estimates. 6 of these were by OCHA, 2 by WHO, and 1 by MSF. Examples included 1,700 malaria cases reported in West Darfur during 2013, more than 1,000 cases and 7 associated deaths reported in West Darfur during 2016, 431,325 malaria cases and 23 deaths reported nationally during 2022, and more than 2.54 million malaria cases and 128 deaths reported across 16 states during 2024. Malaria incidence reporting was relatively rare when compared to intervention and driver evidence.

Figure 16 presents the number of unique reports containing extracted malaria occurrence evidence, intervention, and driver evidence by year. For the majority of the study period, malaria occurrence evidence was identified more frequently than either intervention or driver evidence. Malaria occurrence reporting peaked in 2007 to 2009, 2013, and 2024, highlighting periods when humanitarian reporting focused more on malaria. Intervention evidence generally followed a similar pattern to malaria related evidence, particularly during from 2007 to 2009, when nearly all reports that explicitly discussed malaria also contained descriptions of malaria control activities, such as LLIN distribution, vector control campaigns, diagnosis, and treatment. This suggests that malaria reporting during these years was strongly linked to ongoing response efforts rather than discussions of malaria occurrence alone. Driver evidence, on the other hand, was consistently less prevalent, suggesting that humanitarian reports documented responses to malaria more frequently than explanations of conditions that contribute to the malaria occurrence.

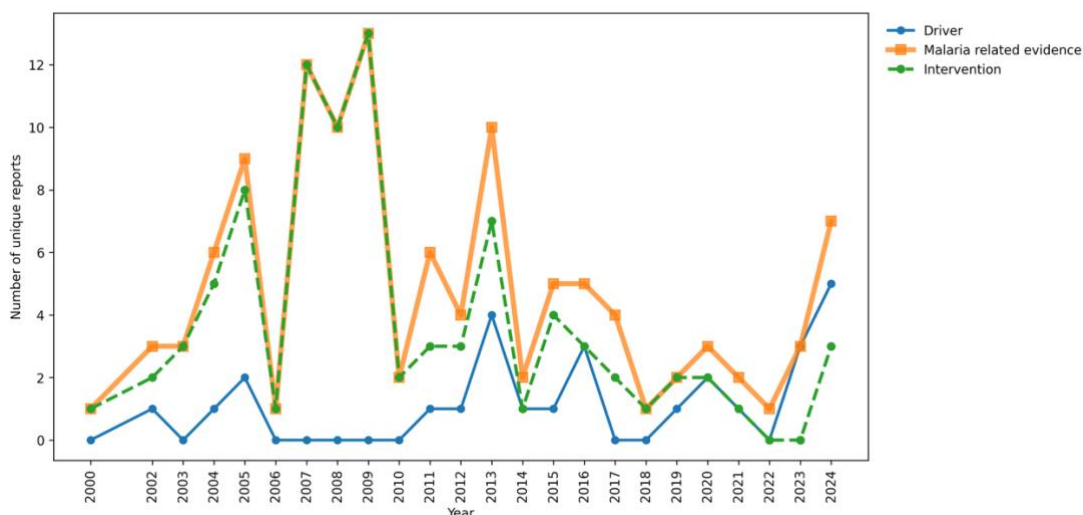


Figure 16. Reports with extracted evidence categories by year

197 intervention evidence sentences originating from 89 reports were identified as represented in Figure 17. LLINs/bed nets were the most common type of intervention evidence (71 sentence level mentions in 55 reports), followed by distribution/supplies (59 mentions in 50 reports), IRS/spraying/vector control (26 mentions in 22 reports), treatment/ACTs/antimalarials (21 mentions in 20 reports), and diagnosis/testing (18 mentions in 14 reports). The years 2009, 2007, 2013, 2008, and 2005 had the highest evidence for interventions.

LLIN distribution, vector control activities, diagnosis, and treatment representing the most frequently reported intervention categories is generally consistent with WHO malaria control recommendations, which identify vector control through LLINs and IRS together with rapid diagnosis and effective treatment as the core components of malaria prevention and control (WHO, 2025).

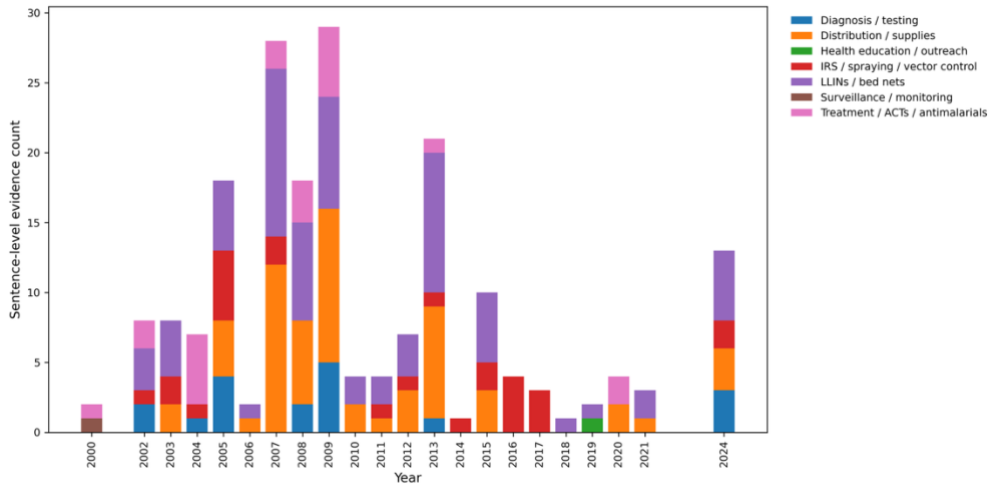


Figure 17. Intervention evidence categories by year

77 driver evidence records from 27 reports were identified as represented in Figure 18. Rainfall/rainy season was the most common driver category (18 sentence level mentions in 14 reports), followed by flooding/stagnant water (15 mentions in 13 reports), conflict/insecurity/access (14 mentions in 13 reports), displacement/IDPs (11 mentions in 8 reports), and endemicity/transmission suitability (9 mentions in 8 reports). Poor sanitation/overcrowding and health system disruption were less common, with 6 and 4 mentions respectively. The years 2024, 2016, 2023, 2020, and 2013 had the highest driver evidence.

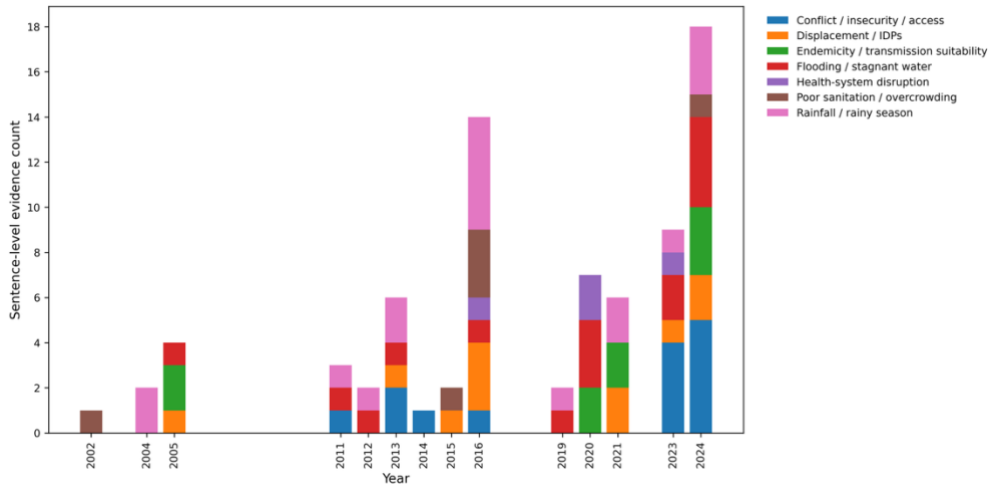


Figure 18. Driver evidence categories by year

Qualitative information from the humanitarian reporting archive shows that environmental factors, population displacement, conflict, and disruptions to health services are often highlighted in relation to malaria risk in Sudan. The extracted driver evidence's emphasis on rainfall, rainy season conditions, and flooding is consistent with the function that precipitation and surface-water accumulation have in establishing mosquito breeding habitats and influencing the dynamics of malaria transmission (Mordecai et al., 2013; Caminade et al., 2014).

Conflict, insecurity, displacement, and disruption of the health systems were also frequently mentioned in humanitarian reports, especially in recent years. Although these factors are unlikely to be direct biological drivers of malaria transmission, they may have an indirect impact on the disease occurrence through reduced access to healthcare, interruptions to disease control efforts, population displacement, overcrowding, disruptions to medicine supply chains, and inadequate surveillance systems (Marou et al., 2024). The increasing frequency of these themes during 2023-2024 is consistent with the deterioration of humanitarian conditions associated with the ongoing conflict in Sudan.

Intervention evidence was considerably more common than driver evidence throughout the reporting period. LLIN distribution, vector control activities, diagnosis, and treatment represented the most frequently reported intervention categories. This pattern is generally consistent with WHO malaria control recommendations, which identify vector control through LLINs and IRS together with rapid diagnosis and effective treatment as the core components of malaria prevention and control (WHO, 2025).

4.7.2. State level analysis of ReliefWeb database

A state level location extraction was carried out to determine the geographic distribution of humanitarian reporting related to malaria in order to supplement the analysis. The location extraction generated 822 state level evidence records. The higher number of records reflects the fact that many humanitarian reports discussed malaria related issues across multiple states simultaneously. Regardless of the number of locations mentioned, each relevant sentence was only counted once during the sentence level extraction. However, each state mentioned in a sentence was recorded separately through the geographic extraction process. For instance, a report describing the risks of malaria associated with flooding in North Darfur, South Darfur, and West Darfur would add three separate records to the state level database but only one driver evidence record to the sentence level database. As a result, rather than the quantity of separate evidence statements, the state level database shows the cumulative frequency with which specific states were associated with malaria related drivers, interventions, or malaria occurrences. Significant regional variability in reporting frequency was identified in the state level analysis. The frequently mentioned states were North Darfur, South Darfur, and West Darfur, followed by South Kordofan, Central Darfur, Blue Nile, East Darfur, and Khartoum.

These results indicate that humanitarian reporting on malaria was focused on a small number of states, especially in the Darfur region and parts of western and southern Sudan affected by the conflict. However, the structure, level of detail, and geographic detail of humanitarian reports varied significantly. While some reports only mentioned larger areas, villages, or national level

events, others specifically named the states that were impacted. Therefore, rather than being a direct indicator of the malaria occurrence or its humanitarian significance, the frequency with which a state appears in the location database indicates the availability of geographically explicit reporting. Because malaria related activities were documented at a more aggregated geographic level or because locations were not consistently identified within reports, it is likely that some states were underrepresented. Despite this uncertainty, the repeated appearance of North Darfur, South Darfur, West Darfur, Central Darfur, and South Kordofan across a large number of independent reports indicate that these states represented primary areas of malaria related humanitarian attention throughout the study period.

The location extraction's spatial patterns are consistent with the results of the HeRAMS, which reported significant health system disruption in several of these states.

On the other hand, these states were not necessarily those with the highest climatic suitability. Among Sudan's 18 states, South Kordofan ranked 7th in mean CSI, South Darfur 9th, Central Darfur 12th, West Darfur 13th, and North Darfur 15th. This indicates that non-climatic factors are more prominent for humanitarian reporting related to malaria.

4.8. Combined analysis of national malaria occurrence and potential drivers

Standardized annual anomalies of Sudan's malaria occurrence, climate suitability, flooding, and displacement are shown in Figure 19. Despite climate suitability being close to or slightly above average, malaria occurrence remained below the long-term mean from 2015 to 2017. During this period, flooding also remained below average, and displacement remained relatively stable and below the long-term mean. Malaria occurrence increased dramatically in 2018 and reached positive anomalies that continued until 2022, with the highest anomaly observed in 2019. Between 2017 and 2019, climatic suitability increased similarly, peaking in 2019. During this period, flooding also significantly increased, reaching its peak in 2019. In contrast,

displacement remained relatively stable during 2018-2020, whereas both climate suitability and flooding increased substantially over the same period. The simultaneous occurrence of significant climatic suitability, severe flooding, and above-average malaria occurrence in 2018-2020 suggests that favourable environmental conditions may have increased malaria transmission potential during this period.

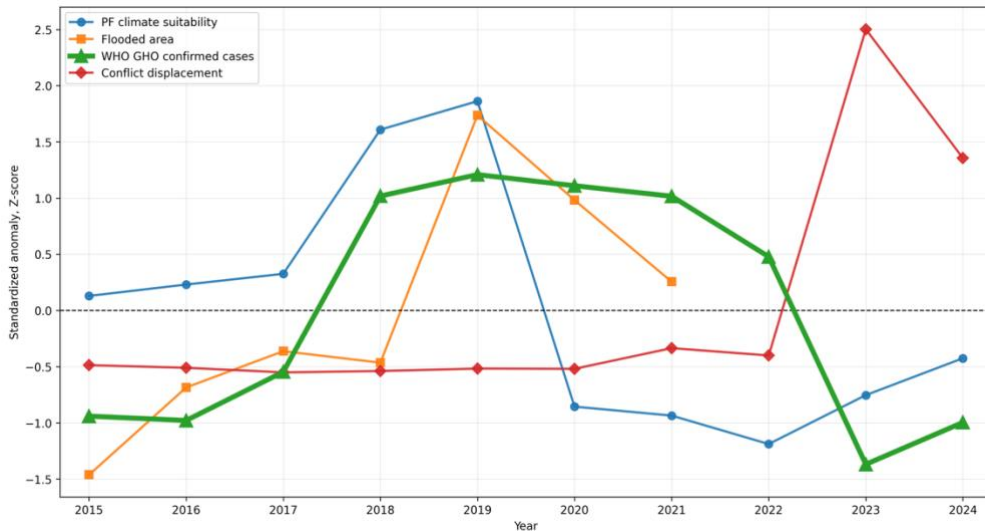


Figure 19. Combined temporal evolution of malaria occurrence, Pf CSI, flooded area, and IDPs.

Climate suitability decreased sharply after 2019 and remained below average from 2020 to 2024. On the other hand, malaria occurrence remained high through 2022 and decreased significantly in 2023. Additionally, although a decrease in flooding was observed after 2019, it remained above average until 2021, after which flood data were not available. Displacement remained relatively low until 2022 but increased sharply in 2023 and remained strongly above average in 2024, reflecting the major displacement crisis following the outbreak of conflict.

Figure 19 suggests that malaria occurrence cannot be attributed to a single factor but rather appears to be the result of the combined effects of flooding,

climate suitability, displacement, and broader humanitarian conditions. The highest malaria occurrence anomaly in 2019 coincided with the highest anomalies in both climate suitability and flooding, while displacement was still below average. This pattern is consistent with the correlation analyses that revealed positive associations between flooding and malaria occurrence and between climatic suitability and malaria occurrence, suggesting that favorable environmental conditions may contribute to increased transmission and subsequently influence observed occurrence. In addition, the ReliefWeb database identified flooding/stagnant water and rainfall/rainy season as the most frequently reported malaria drivers in 2019 and 2020, further supporting the interpretation that environmental conditions contributed substantially to the elevated malaria occurrence observed in 2019 and 2020.

The observations from the 2023 conflict period provide additional insight into the dynamics of malaria occurrence. Displacement reached its highest standardized anomaly in 2023 and remained strongly positive in 2024, while reported malaria occurrence dropped below the long-term average in both years. At the same time, climate suitability reached some of its lowest values during 2022-2023. Further context is provided by the ReliefWeb database, in which conflict was the most frequently reported driver in both 2023 and 2024, while flooding/stagnant water remained among the most frequently reported drivers in 2024. The displacement data further support this interpretation by showing a sharp increase in conflict related displacement in 2023 followed by persistently high displacement in 2024. However, the simultaneous decline in reported malaria occurrence suggests that conflict related disruption may have affected disease detection and reporting. Reductions in reported malaria occurrence in conflict affected areas may therefore reflect challenges related to disease surveillance, healthcare access, diagnosis, and reporting rather than real decreases in occurrence.

The ReliefWeb evidence also shows broader agreement with the climate suitability analysis beyond the peak years. Periods characterized by relatively high CSI values, including 2013, 2016, 2019, and 2020, frequently contained references to rainfall/rainy season conditions, flooding/stagnant water, and transmission suitability as contributors to malaria occurrence. These factors correspond closely to the climatic processes represented within the CSI, namely temperature-dependent transmission processes, humidity-related

mosquito survival, and rainfall-driven breeding habitat availability. Although the ReliefWeb evidence is qualitative and not available for every year, the recurring identification of environmentally related drivers during periods of elevated CSI provides additional support that the index captures climatic conditions relevant to malaria transmission in Sudan.

Overall, the combined anomaly analysis suggests that the 2018-2020 increase in malaria occurrence occurred during a period of elevated climatic suitability and flooding, which may have enhanced malaria transmission potential, whereas the 2023-2024 period was characterized by high conflict related displacement, major humanitarian disruption, and potential surveillance and reporting challenges.

5. Limitations

A major limitation of this study was the availability of malaria occurrence data only at the national level. The absence of state level occurrence data prevented quantitative comparisons between malaria occurrence and the state level climate suitability, flooding, displacement, humanitarian, and health system datasets. In addition, the available malaria occurrence dataset only covered a ten-year period (2015-2024), limiting the ability to evaluate longer-term relationships. Similar limitations were encountered for health system analyses, as the available HeRAMS dataset only covered approximately late 2023 to mid-2025. Flood data were only available until 2021, while displacement data were available primarily at national annual resolution. Although national WASH datasets were available for longer periods, subnational data were not available. The ReliefWeb evidence database provided valuable contextual information and enabled qualitative assessment of reported drivers and interventions for specific locations; however, as humanitarian reporting is not spatially, temporally, or thematically consistent, it should not be interpreted as a formal surveillance system. Additionally, an important characteristic of the CSI is that temperature influences multiple components simultaneously. Temperature affects both mosquito biting rate and parasite development rate through nonlinear Brière functions, each with different thermal thresholds.

Consequently, the overall response of the CSI to temperature is not linear and cannot be interpreted as a simple increase or decrease with warming.

An additional source of uncertainty arises from the integration of multiple datasets with differing spatial resolutions, temporal resolutions, methodologies, and reporting frameworks. Malaria occurrence was represented using WHO GHO confirmed malaria case data, which reflect laboratory confirmed cases detected through the health system and therefore depend on diagnostic availability, healthcare access, surveillance coverage, and reporting capacity. Climate suitability estimates were derived from gridded ERA5 climate data, while flooding indicators were based on 30 m satellite-derived surface water observations, population was estimated using data from WorldPop, and humanitarian indicators originated from humanitarian reporting databases. These datasets differ in their underlying assumptions, data collection methods, and sources of uncertainty. Furthermore, temporal coverage was not fully consistent across datasets, requiring some analyses to be restricted to overlapping periods. Aggregation of datasets to annual and state level scales likely reduced some spatial and temporal mismatches but may also have masked local variability.

6. Recommendations

Future analyses would benefit from improved access to state level malaria occurrence data and longer-term health system monitoring datasets. Monthly malaria occurrence data, where available, would enable more detailed investigation of seasonal relationships with climate suitability and flooding. Similarly, subnational displacement datasets at state level would allow closer examination of interactions between population movements and malaria occurrence. Longer-term monitoring of health systems functionality, accessibility, staffing, medicine availability, and service disruption would also improve the assessment of how health system conditions influence malaria occurrence and reporting. Access to intervention coverage data, including indicators such as insecticide-treated net distribution, indoor residual spraying coverage, malaria diagnostic testing, and treatment coverage, would further strengthen future analyses. These datasets may already exist within national

surveillance, reporting, and humanitarian monitoring systems but were not accessible for this study.

Future research could also improve the analytical framework developed in this study. Closer collaboration with national authorities, health agencies, and local stakeholders may improve data sharing and data accessibility, and support validation of the identified relationships. Access to higher resolution datasets would also enable the application of multivariable statistical approaches to evaluate the combined influence of climate suitability, flooding, conflict, displacement, WASH, health system capacity, and intervention coverage on malaria occurrence. In addition, the CSI could be further refined through calibration using locally available epidemiological, entomological, and ecological observations where such data become available. Such developments would strengthen future efforts to assess the combined influence of climate, flooding, conflict, displacement, health systems capacity, and WASH on malaria occurrence in Sudan.

7. Conclusion

To conclude, this study demonstrates the value of combining climate suitability, flooding, displacement, humanitarian reporting, and health system capacity to examine malaria occurrence in Sudan within a single analytical framework. A CSI was developed using temperature, rainfall, and humidity data and was subsequently evaluated alongside flood extent, displacement estimates, health system capacity, drinking water indicators, and a humanitarian malaria reporting database. The analyses indicated that the factors associated with malaria occurrence varied over time. In contrast to the post-2023 period, which was increasingly characterized by conflict related displacement, insecurity, and disruption of health systems, the high-occurrence period of 2018-2020 was characterized by increased climate suitability, extensive flooding, and predominantly environmental driver reporting in humanitarian reports. Additionally, the temporal associations between malaria occurrence, climate suitability, and flooding differed, with climate suitability exhibiting its strongest association with one-year lagged occurrence data, whereas flooding exhibited its strongest association within the same year. These findings suggest

that environmental and humanitarian factors may influence malaria occurrence through different mechanisms and timescales.

The study also highlighted important limitations related to data availability, accessibility, spatial resolution, and temporal coverage. The primary methodological constraint was that malaria occurrence data were available only as annual national level observations for 2015-2024, whereas climate suitability and flooding data were available as monthly state level and gridded datasets. Consequently, quantitative comparisons between malaria occurrence and the state level climate suitability, flooding, displacement, humanitarian, and health system datasets were not possible. In addition, the available malaria occurrence dataset only covered a ten-year period, limiting the assessment of longer-term relationships. Similar limitations were encountered for health system analyses from the HeRAMS dataset, while interpretation of the ReliefWeb database is limited by a lack of consistency in humanitarian reporting.

Future research would benefit from improved access to state and monthly level malaria occurrence data, while longer-term health system monitoring datasets state level displacement datasets, and intervention coverage information would allow more detailed assessments of the interactions between environmental, humanitarian, and health system factors. Such datasets would enable more detailed evaluations of the combined influence of climate suitability, flooding, conflict, displacement, WASH, health systems capacity, and malaria interventions on malaria occurrence. Future studies could also further refine the CSI through calibration using locally available epidemiological, entomological, and ecological observations, improving its applicability for malaria risk assessment in Sudan.

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APPENDIX

Yearly driver evidence summary

YEAR	DRIVER TYPE	SENTENCE COUNT
2002	Poor sanitation / overcrowding	1
2004	Rainfall / rainy season	2
2005	Displacement / IDPs	1
2005	Endemicity / transmission suitability	2
2005	Flooding / stagnant water	1
2011	Conflict / insecurity / access	1

2011	Flooding / stagnant water	1
2011	Rainfall / rainy season	1
2012	Flooding / stagnant water	1
2012	Rainfall / rainy season	1
2013	Conflict / insecurity / access	2
2013	Displacement / IDPs	1
2013	Flooding / stagnant water	1
2013	Rainfall / rainy season	2
2014	Conflict / insecurity / access	1
2015	Displacement / IDPs	1
2015	Poor sanitation / overcrowding	1
2016	Conflict / insecurity / access	1
2016	Displacement / IDPs	3
2016	Flooding / stagnant water	1
2016	Health-system disruption	1
2016	Poor sanitation / overcrowding	3
2016	Rainfall / rainy season	5
2019	Flooding / stagnant water	1

2019	Rainfall / rainy season	1
2020	Endemicity / transmission suitability	2
2020	Flooding / stagnant water	3
2020	Health-system disruption	2
2021	Displacement / IDPs	2
2021	Endemicity / transmission suitability	2
2021	Rainfall / rainy season	2
2023	Conflict / insecurity / access	4
2023	Displacement / IDPs	1
2023	Flooding / stagnant water	2
2023	Health-system disruption	1
2023	Rainfall / rainy season	1
2024	Conflict / insecurity / access	5
2024	Displacement / IDPs	2
2024	Endemicity / transmission suitability	3
2024	Flooding / stagnant water	4
2024	Poor sanitation / overcrowding	1
2024	Rainfall / rainy season	3

Yearly intervention evidence summary

YEAR	INTERVENTION TYPE	SENTENCE COUNT
2000	Surveillance / monitoring	1
2000	Treatment / ACTs / antimalarials	1
2002	Diagnosis / testing	2
2002	IRS / spraying / vector control	1
2002	LLINs / bed nets	3
2002	Treatment / ACTs / antimalarials	2
2003	Distribution / supplies	2
2003	IRS / spraying / vector control	2
2003	LLINs / bed nets	4
2004	Diagnosis / testing	1
2004	IRS / spraying / vector control	1
2004	Treatment / ACTs / antimalarials	5
2005	Diagnosis / testing	4
2005	Distribution / supplies	4

2005	IRS / spraying / vector control	5
2005	LLINs / bed nets	5
2006	Distribution / supplies	1
2006	LLINs / bed nets	1
2007	Distribution / supplies	12
2007	IRS / spraying / vector control	2
2007	LLINs / bed nets	12
2007	Treatment / ACTs / antimalarials	2
2008	Diagnosis / testing	2
2008	Distribution / supplies	6
2008	LLINs / bed nets	7
2008	Treatment / ACTs / antimalarials	3
2009	Diagnosis / testing	5
2009	Distribution / supplies	11
2009	LLINs / bed nets	8
2009	Treatment / ACTs / antimalarials	5
2010	Distribution / supplies	2
2010	LLINs / bed nets	2
2011	Distribution / supplies	1
2011	IRS / spraying / vector control	1
2011	LLINs / bed nets	2
2012	Distribution / supplies	3

2012	IRS / spraying / vector control	1
2012	LLINs / bed nets	3
2013	Diagnosis / testing	1
2013	Distribution / supplies	8
2013	IRS / spraying / vector control	1
2013	LLINs / bed nets	10
2013	Treatment / ACTs / antimalarials	1
2014	IRS / spraying / vector control	1
2015	Distribution / supplies	3
2015	IRS / spraying / vector control	2
2015	LLINs / bed nets	5
2016	IRS / spraying / vector control	4
2017	IRS / spraying / vector control	3
2018	LLINs / bed nets	1
2019	Health education / outreach	1
2019	LLINs / bed nets	1
2020	Distribution / supplies	2
2020	Treatment / ACTs / antimalarials	2
2021	Distribution / supplies	1

2021	LLINs / bed nets	2
2024	Diagnosis / testing	3
2024	Distribution / supplies	3
2024	IRS / spraying / vector control	2
2024	LLINs / bed nets	5

Parameter table for CSI

<i>Component</i>	<i>Parameter</i>	<i>Value</i>	<i>Description</i>	<i>Source</i>
<i>Mosquito biting rate</i>	c_a	2.03×10^{-4}	Brière scaling coefficient	Mordecai et al., 2013
	$(T_{min,a})$	11.7°C	Lower biting threshold	
	$(T_{max,a})$	42.3°C	Upper biting threshold	
<i>Pf parasite development</i>	(c_{Pf})	1.11×10^{-4}	Brière scaling coefficient	
	$(T_{min,Pf})$	14.7°C	Lower thermal development threshold	

<i>Humidity stress</i>	$(T_{max,Pf})$	34.4°C	Upper thermal development threshold	Yamana and Eltahir, 2013
	(RH_{low})	5%	Critical humidity threshold	
	(RH_{high})	42%	Humidity saturation threshold	
<i>Rainfall</i>	$P_{critical}$	80 mm/month	Rainfall suitability threshold	Craig et al., 1999