

Climate-Driven Malaria Risk Among Children Under Five in Tanzania: Historical Associations, Future Projections, and Vulnerability Mapping

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Abstract

Background

Malaria remains a leading cause of morbidity and mortality in Tanzania. Climate change is expected to alter malaria transmission dynamics, yet few studies have combined nationally representative household data with climate projections to quantify future risk and identify vulnerable populations. This study aimed to (1) quantify the historical association between climatic factors and malaria prevalence among children under five using 2015 and 2022 TDHS-MIS data; (2) project future malaria transmission suitability under SSP2-4.5 to 2100; and (3) identify priority intervention clusters where high projected risk converges with high household vulnerability.

Methods

We analysed 16,172 children aged 6–59 months with valid malaria test results. Historical temperature (ERA5-Land) and rainfall (CHIRPS) were linked to each cluster. A multivariable logistic regression with cluster-robust standard errors and DHS sampling weights was fitted. Future suitability (2023–2100) was computed using NASA NEX-GDDP-CMIP6 (ACCESS-CM2, SSP2-4.5) with monthly temperature $\geq 20^{\circ}\text{C}$ and rainfall > 80 mm for ≥ 4 months/year (MARA model). A vulnerability index (wealth, water, sanitation, housing, bed nets) was mapped against projected risk.

Results

Weighted malaria prevalence declined from 10.6% (2015) to 5.8% (2022). Temperature was significantly associated with malaria (OR = 1.10 per 1°C , 95% CI: 1.04–1.18), while improved water (OR = 0.55), improved sanitation (OR = 0.28), and higher wealth (OR = 0.79) were protective. Poor roof material increased risk (OR = 1.71, 95% CI: 1.27–2.30). Under SSP2-4.5, suitability expanded from 82.7% (2030s) to 87.2% (2090s) of Tanzania's land area. Hindcast suitability correlated with observed prevalence ($r = 0.62$, $p < 0.001$). Vulnerability mapping identified priority clusters in central (Dodoma, Singida) and coastal (Pwani, Dar es Salaam) regions, where high climate suitability converges with low adaptive capacity.

Conclusions

Temperature is a significant driver of malaria in Tanzania, and climate change will expand suitable transmission areas under SSP2-4.5. Vulnerability is highest in central and coastal regions where climate risk and household vulnerability converge. Integrated climate-adaptive strategies targeting both environmental and social determinants are urgently needed.

Background

Despite decades of control efforts, malaria remains one of the most devastating infectious diseases globally, causing an estimated 282 million cases and 610,000 deaths in 2024 [1]. Sub-Saharan Africa bears the highest burden, accounting for approximately 95% of cases (265 million) and 95% of deaths (579,000), with children under five and pregnant women being most vulnerable [1]. Tanzania is among the countries with the highest malaria prevalence; the 2022 TDHS-MIS reported an overall malaria prevalence of 8% among children under five, with regional variation ranging from 1% to 23 [2]. The disease is a leading cause of outpatient visits and hospital admissions, contributing substantially to morbidity, mortality, and economic hardship [1, 3]

Climate change is now recognized as a major threat to malaria control [4, 5]. The transmission of *Plasmodium falciparum* (*Pl. falciparum*), the most lethal malaria parasite, is exquisitely sensitive to temperature and precipitation, which influence the survival and development of *Anopheles* (*An.*) mosquitoes, the parasite's extrinsic incubation period, and the availability of larval habitats [6, 7]. As global temperatures rise and rainfall patterns become more erratic, the geographical range and seasonal intensity of malaria are expected to shift, potentially reversing recent gains and placing new populations at risk [8–10].

The biological pathways linking climate to malaria are well established. Temperature modulates mosquito longevity, biting frequency, and the rate at which *Plasmodium* sporozoites develop within the vector [11]. For *Pl. falciparum*, transmission is generally constrained to areas where temperatures remain above 18–20°C for extended periods [12]. Rainfall influences vector breeding sites; excessive rainfall can create new habitats, while drought can concentrate water bodies, both potentially increasing transmission [13, 14]. These non-linear and delayed relationships ideally require analytical approaches capable of capturing lagged effects, such as Distributed Lag Non-linear Models [15]; such models are beyond the scope of the present analysis, which instead uses simpler annual and monthly climate aggregates as a first-order approximation of climate effects (see Methods). The thresholds we use to define transmission suitability (temperature $\geq 20^{\circ}\text{C}$; rainfall > 80 mm/month; see Methods) are derived directly from these same biological constraints on vector survival, sporozoite development, and larval habitat availability.

In Africa, numerous studies have documented significant associations between climate variability and malaria incidence. For example, in the highlands of East Africa, rising temperatures have been linked to an expansion of malaria into previously cooler areas [16, 17]. In Tanzania, ecological studies have shown that inter-annual variations in rainfall and temperature correlate with malaria outbreaks, particularly in the north-eastern and north-western regions [18, 19]. A key limitation, however, is that most of these studies rely on aggregated health facility data or are confined to small geographic areas; few incorporate the household-level factors that modify vulnerability, which is the gap this study addresses.

Tanzania's malaria ecology is itself heterogeneous, spanning stable, perennial transmission in the low-altitude coastal and Lake Victoria basin areas, more seasonal transmission in the central plateau, and

historically low but climate-sensitive transmission in the cooler highlands [3] - a diversity of transmission zones that this study's cluster-level approach is well placed to capture. Tanzania's National Malaria Strategic Plan (2021–2025) sets out to further reduce malaria morbidity and mortality and to progress toward elimination in low-transmission areas [20]; the historical, projected, and vulnerability evidence generated here is intended to support that plan's targeting of interventions.

A critical limitation of existing research is the lack of integration between climate exposure and the socio-economic and environmental determinants of household vulnerability. The ability of a household to prevent and respond to malaria is shaped by wealth, housing quality, water and sanitation infrastructure, access to insecticide-treated nets, and health-seeking behaviour [21, 22]. Even under favourable climatic conditions, households with higher adaptive capacity may experience lower malaria burden. Conversely, communities with poor housing and limited access to interventions may be disproportionately affected [23]. Therefore, projecting future malaria risk without accounting for these modifiers yields an incomplete picture for policy planning.

Moreover, while there is a growing body of literature using climate models to forecast malaria risk [4, 5, 10], few studies have employed nationally representative household surveys to ground these projections in real-world prevalence and vulnerability data. The recent study by Siebels et al. [24] provides an exemplary framework of temperature-duration thresholds applied to climate data; however, it focused solely on climatic suitability in a non-endemic setting (Canada) and did not incorporate household-level vulnerability or actual disease prevalence. Several studies have linked DHS data with climate variables in African settings including analyses from Cameroon, Niger, Ethiopia, Kenya, and multi-country DHS analyses [22] demonstrating the feasibility of this approach. Our contribution is the three-phase integration: historical association, forward climate projection, and vulnerability clustering in a single framework applied to Tanzania.

To address these gaps, we leverage the unique strengths of the 2015 and 2022 Tanzania Demographic and Health Surveys and Malaria Indicator Surveys (TDHS-MIS), which provide nationally representative, georeferenced data on malaria prevalence (via rapid diagnostic tests), household socio-economic status, water and sanitation, housing quality, and vector control interventions [25]. By linking these data with high-resolution historical climate records and future climate projections (CMIP6 under SSP2-4.5), this study aimed to quantify the historical association between climatic factors (temperature, rainfall) and malaria prevalence among children under five while adjusting for household-level covariates; to project and quantify the decadal change in malaria transmission suitability from 2023 to 2100 under the SSP2-4.5 scenario, generating spatially explicit forecasts; and to identify and rank vulnerability clusters where high projected malaria risk converges with low household adaptive capacity - wealth, housing, and water and sanitation - in order to guide targeted interventions.

Methods

Study design

This study employs a cross-sectional analysis with a temporal forecasting component. We integrate individual- and household-level data from the 2015 and 2022 TDHS with gridded historical climate observations (2000–2022) and future climate projections (2023–2100) from CMIP6. The analysis proceeds in three phases: (i) historical baseline modelling; (ii) future forecasting; and (iii) spatial vulnerability clustering. This approach rests on the conceptual premise that malaria risk is determined by the interplay of climatic exposure, environmental conditions, and household-level adaptive capacity [22, 23].

Data sources

Health and household data

We use the 2015 and 2022 TDHS-MIS, nationally representative cross-sectional surveys conducted by the Tanzania National Bureau of Statistics in collaboration with ICF International [26]. The surveys collect data on malaria prevalence (via rapid diagnostic tests and microscopy), fever in children under five, bed net ownership and use, household wealth, water and sanitation, housing characteristics, and geographic coordinates of survey clusters (randomly displaced 0–2 km urban / 0–5 km rural, a precaution to protect respondent confidentiality that introduces a small amount of spatial imprecision into any cluster-level climate linkage performed below; we return to the implications of this for our results in the Discussion). Datasets are publicly available after registration with The DHS Program [25].

We restrict the analysis to children aged 6–59 months with valid RDT results (hml35 coded as 0 or 1). After applying DHS sampling weights (hv005/1,000,000) to ensure national representativeness, following the DHS Guide to Statistics [27], the final analytic sample comprises 10,935 children (2015) and 5,237 children (2022), giving a total of 16,172 children across 1,230 unique clusters. Survey year (hv007) was included as a covariate in all models to account for secular trends between the two survey rounds.

Climate data

Historical temperature (2000–2022)

Monthly mean temperature from ERA5-Land reanalysis ($0.25^\circ \times 0.25^\circ$; [28]). Data were extracted for the Tanzania bounding box (latitude -12° to -1° , longitude 29° to 41°) and converted from Kelvin to Celsius.

Historical rainfall (2000–2022)

Monthly rainfall totals from CHIRPS v2.0 ($0.05^\circ \times 0.05^\circ$; [29]). ERA5-Land and CHIRPS were selected because both are high-resolution, satellite- and reanalysis-based products that have been extensively validated for East Africa and cover the full study period at consistent spatial resolution.

For each child, we assigned the annual mean temperature and annual total rainfall for the calendar year of the survey (2015 or 2022). The DHS fieldwork spans several months; we used full calendar-year aggregates because the survey months vary across clusters. Finer temporal matching (e.g., lagged monthly climate) is a direction for future research (see Discussion).

Future climate projections (2023–2100): Daily temperature and precipitation from NASA NEX-GDDP-CMIP6 (ACCESS-CM2 model, SSP2-4.5 scenario; [30]). Data were resampled to monthly means (temperature) and monthly totals (precipitation) and subset to Tanzania. SSP2-4.5 represents a “middle-of-the-road” scenario and was selected as a central, plausible future trajectory. We acknowledge that using a single GCM and a single SSP limits the generalizability of our projections; multi-model ensembles are preferred, and our results should be interpreted as indicative rather than definitive. The complete data processing workflow, including data sources, code, and validation, is documented in Additional file 1: Appendix S1.

Sample derivation and exclusions

Of the 16,172 children included, 10,935 (67.6%) were from the 2015 survey and 5,237 (32.4%) from the 2022 survey. Exclusions were due to missing or invalid RDT results (hml35 coded as 3 or 4) or missing covariate data. Excluded children did not differ systematically from those included with respect to age or sex. Of the 19,456 children aged 6–59 months with available malaria RDT results, 3,284 (16.9%) were excluded due to missing or invalid RDT results (hml35 coded as 3 or 4) or missing covariate data (wealth, water, sanitation, housing, bed net ownership, child age, sex, urban/rural residence, altitude, or survey year). The final analytic sample comprised 16,172 children (10,935 from 2015 and 5,237 from 2022). Excluded children did not differ systematically from those included with respect to age or sex.

Analysis approach

Phase 1: Historical Baseline Modelling

Each DHS cluster was linked to the nearest grid cell of historical climate data, and annual mean temperature and annual total rainfall were assigned to each child. A multivariable logistic regression with cluster-robust standard errors (clustered by survey cluster hv001) was fitted, incorporating DHS sampling weights (hv005/1,000,000) following the DHS Guide to Statistics [27]. Survey year (hv007) was included as a covariate; because mean annual temperature differed between the two survey years, inclusion of this term means the temperature coefficient is identified primarily from spatial (between-cluster) variation in temperature within each survey year rather than from the national year-to-year shift in climate. The model included temperature, rainfall, wealth quintile (hv270, 1–5), improved water source (hv201, binary), improved sanitation (hv205, binary), roof material (hv213, categorical: poor, medium, good; category definitions in Additional file 1: Table S2), bed net ownership (hml1 > 0, binary), child age (hv014), child sex (hv104), urban/rural residence (hv025), altitude, and survey year. Wealth quintile was treated as continuous under the assumption of a monotonic dose-response relationship; a categorical

sensitivity analysis confirmed similar conclusions. Results are reported as odds ratios (OR) with 95% confidence intervals (CI); statistical significance was set at $\alpha = 0.05$. Full DHS variable codes and definitions for all covariates are provided in Additional file 1: Table S1.

Phase 2: Future Forecasting

Future suitability was computed for each grid cell ($0.25^\circ \times 0.25^\circ$) for 2023–2100 using monthly temperature and rainfall data under SSP2-4.5. Suitability criteria followed the MARA Seasonality Model [31, 32]: a month was suitable when monthly mean temperature $\geq 20^\circ\text{C}$ and monthly rainfall > 80 mm, and a year was suitable when at least four months met this combined criterion. Decadal averages (2030s, 2050s, 2090s) and a time series of suitable land area were produced. A sensitivity analysis varying the number of qualifying months (3, 4, and 5) was performed. We also hindcast suitability for 2015 and 2022 using ERA5-Land and CHIRPS data and compared it with observed cluster-level malaria prevalence to validate the model.

Phase 3: Vulnerability Clustering

A composite vulnerability index was constructed at the cluster level using five standardised components (0–1 scale, 1 = most vulnerable): wealth (poorest quintile), water source (unimproved), sanitation (unimproved), housing (poor roof), and bed net access (no net). The index was the arithmetic mean of these five components [23]. A sensitivity analysis using PCA-derived weights was performed to assess robustness. Vulnerability was mapped against predicted malaria risk (from Phase 1) to identify priority clusters, defined as the top quartile of both risk and vulnerability.

Statistical software

Data processing and visualisation were performed in Python 3.12 using xarray, pandas, numpy, matplotlib, and geopandas. Statistical modelling was conducted in Python using statsmodels, with the primary logistic regression independently re-estimated in R 4.3 using the survey package [33] to ensure robustness. Both implementations produced materially identical results

Results

Descriptive characteristics

The analytic sample included 16,172 children as shown in Table 1. Weighted malaria prevalence was 10.6% in 2015 and 5.8% in 2022 (unweighted: 12.6% and 6.8%, respectively). Mean annual temperature was 24.29°C (2015) and 24.62°C (2022). Improved water and sanitation coverage increased between the two surveys. Bed net ownership was high ($> 80\%$) in both years.

Table 1
Weighted descriptive characteristics of the study population

Characteristic	2015 (N = 10,935)	2022 (N = 5,237)	Total (N = 16,172)
Malaria prevalence (%)	10.6	5.8	8.4
Mean temperature (°C)	24.29 (2.13)	24.62 (2.11)	24.40 (2.13)
Median rainfall (mm) [IQR]	1,002 [820-1,256]	1,089 [894-1,347]	1,024 [856-1,292]
Wealth: Poorest (%)	22.9	21.3	22.4
Improved water (%)	59.1	69.9	62.7
Improved sanitation (%)	34.2	41.8	36.7
Any bed net (%)	78.3	85.6	80.7
Urban residence (%)	32.4	35.1	33.4
Mean altitude (m)	892 (421)	876 (398)	887 (412)
<i>Note: Column headers show unweighted sample sizes (N); percentages, means, and medians are weighted using DHS sampling weights (hv005/1,000,000). Values are weighted means (SD) unless otherwise stated. IQR = interquartile range.</i>			

Multivariable logistic regression

Table 2 presents the adjusted odds ratios from the multivariable logistic regression with cluster-robust standard errors and survey weights.

Table 2

Zone-stratified adjusted odds ratios for malaria positivity among children under five (N = 13,740).

Variable	Lake	Southern	Western	Central	Northern Highlands	Southern Highlands	Coastal (ref)
	OR (95% CI)	OR (95% CI)	OR (95% CI)	OR (95% CI)	OR (95% CI)	OR (95% CI)	OR (95% CI)
Zone Effect	8.48 (1.64–43.78)	5.48 (1.10–27.27)	5.22 (1.01–27.07)	2.24 (0.43–11.55)	< 0.01 (-)	0.43 (0.08–2.32)	1.00
Temperature (per 1°C)	1.10 (1.04–1.18)	1.10 (1.04–1.18)	1.10 (1.04–1.18)	1.10 (1.04–1.18)	1.10 (1.04–1.18)	1.10 (1.04–1.18)	1.10 (1.04–1.18)
Altitude (per 100 m)	0.92 (0.88–0.96)	0.92 (0.88–0.96)	0.92 (0.88–0.96)	0.92 (0.88–0.96)	0.92 (0.88–0.96)	0.92 (0.88–0.96)	0.92 (0.88–0.96)
Wealth (per quintile)	0.79 (0.71–0.87)	0.79 (0.71–0.87)	0.79 (0.71–0.87)	0.79 (0.71–0.87)	0.79 (0.71–0.87)	0.79 (0.71–0.87)	0.79 (0.71–0.87)
Improved Water (yes vs. no)	0.55 (0.45–0.68)	0.55 (0.45–0.68)	0.55 (0.45–0.68)	0.55 (0.45–0.68)	0.55 (0.45–0.68)	0.55 (0.45–0.68)	0.55 (0.45–0.68)
Improved Sanitation (yes vs. no)	0.28 (0.20–0.39)	0.28 (0.20–0.39)	0.28 (0.20–0.39)	0.28 (0.20–0.39)	0.28 (0.20–0.39)	0.28 (0.20–0.39)	0.28 (0.20–0.39)
Poor Roof (vs. good)	1.71 (1.27–2.30)	1.71 (1.27–2.30)	1.71 (1.27–2.30)	1.71 (1.27–2.30)	1.71 (1.27–2.30)	1.71 (1.27–2.30)	1.71 (1.27–2.30)
Bed Net Ownership (any vs. none)	1.76 (1.36–2.27)	1.76 (1.36–2.27)	1.76 (1.36–2.27)	1.76 (1.36–2.27)	1.76 (1.36–2.27)	1.76 (1.36–2.27)	1.76 (1.36–2.27)
Urban Residence (urban vs. rural)	0.68 (0.52–0.89)	0.68 (0.52–0.89)	0.68 (0.52–0.89)	0.68 (0.52–0.89)	0.68 (0.52–0.89)	0.68 (0.52–0.89)	0.68 (0.52–0.89)
Year 2022 (vs. 2015)	0.52 (0.44–0.62)	0.52 (0.44–0.62)	0.52 (0.44–0.62)	0.52 (0.44–0.62)	0.52 (0.44–0.62)	0.52 (0.44–0.62)	0.52 (0.44–0.62)
Rainfall (per 100 mm)	1.00 (1.00–1.01)	1.00 (1.00–1.01)	1.00 (1.00–1.01)	1.00 (1.00–1.01)	1.00 (1.00–1.01)	1.00 (1.00–1.01)	1.00 (1.00–1.01)

In the adjusted analysis, temperature was significantly associated with malaria (OR = 1.10 per 1°C, 95% CI: 1.04–1.18). Improved water (OR = 0.55, 95% CI: 0.45–0.68), improved sanitation (OR = 0.28, 95% CI:

0.20–0.39), and higher wealth (OR = 0.79 per quintile, 95% CI: 0.71–0.87) were protective. Urban residence (OR = 0.68, 95% CI: 0.52–0.89) and higher altitude (OR = 0.92 per 100 m, 95% CI: 0.88–0.96) were also protective. The survey year 2022 showed lower odds compared to 2015 (OR = 0.52, 95% CI: 0.44–0.62), reflecting the decline in malaria prevalence over time. Substantial regional disparities were observed, with the Lake Zone having the highest odds (OR = 8.48, 95% CI: 1.64–43.78) and the Northern Highlands the lowest (OR < 0.01). All estimates are presented in Table 2 with detailed confidence intervals and p-values.

Future temperature-rainfall suitability under SSP2-4.5

Historical validation of the suitability model

We hindcast suitability for 2015 and 2022 using ERA5-Land and CHIRPS data and compared it with observed cluster-level malaria prevalence. The correlation between hindcast suitability (proportion of suitable months per year) and observed malaria prevalence was $r = 0.62$ ($p < 0.001$), suggesting the model captures broad spatial patterns of transmission suitability (see also Additional file 1: Appendix S1).

Decadal suitability maps

Under SSP2-4.5, the proportion of Tanzania's land area suitable for malaria transmission increased from 82.7% in the 2030s to 87.2% in the 2090s (Table 3 and Fig. 1). The slight decline in suitability in the 2050s (81.0%) relative to the 2030s (82.7%) is consistent with decadal variability in the ACCESS-CM2 precipitation signal for this region and does not alter the overall long-term increasing trend. Sensitivity analysis varying the number of months (3, 4, and 5) showed consistent increasing trends, with the 4-month threshold representing a moderate baseline.

Table 3

Proportion of suitable area by decade (4-month threshold) Projected malaria transmission suitability by region under SSP2-4.5. Values indicate the percentage of suitable years per decade (2030s, 2050s, 2090s) and the absolute change from 2030s to 2090s. Regions are sorted by the magnitude of change. $\geq 7.0\%$ in red highlighting emerging risk zones.

Region	2030s (%)	2050s (%)	2090s (%)	Change (2030s → 2090s)
Arusha	71.0	71.8	85.5	+ 14.5
Njombe	82.7	78.2	96.1	+ 13.5
Kilimanjaro	76.4	74.3	86.4	+ 10.0
Kusini Unguja	90.0	100.0	100.0	+ 10.0
Kaskazini Unguja	90.0	100.0	100.0	+ 10.0
Mjini Magharibi	90.0	100.0	100.0	+ 10.0
Kaskazini Pemba	80.0	82.5	87.5	+ 7.5
Manyara	82.3	77.5	89.7	+ 7.4
Simiyu	89.3	90.5	96.6	+ 7.3
Dar es Salaam	60.0	66.7	66.7	+ 6.7
Ruvuma	93.3	89.3	99.6	+ 6.4
Dodoma	83.4	68.0	88.5	+ 5.1
Mbeya	86.4	75.3	91.3	+ 4.9
Pwani	81.2	83.4	86.0	+ 4.7
Singida	86.3	76.2	90.9	+ 4.6
Iringa	89.0	76.4	93.5	+ 4.5
Rukwa	96.2	99.3	100.0	+ 3.8
Shinyanga	96.2	96.5	100.0	+ 3.8
Morogoro	94.8	85.0	97.6	+ 2.8
Tanga	85.3	83.3	87.5	+ 2.2
Kigoma	98.1	99.4	99.9	+ 1.9
Mtwara	97.5	89.3	98.3	+ 0.8
Katavi	99.9	100.0	99.9	0.0
Kusini Pemba	90.0	100.0	90.0	0.0
Lindi	94.5	91.6	94.3	-0.1

Region	2030s (%)	2050s (%)	2090s (%)	Change (2030s → 2090s)
Tabora	97.9	98.1	97.6	−0.3
Songwe	97.4	90.4	96.9	−0.5
Geita	100.0	100.0	99.4	−0.6
Mara	98.5	98.8	96.7	−1.8
Mwanza	99.7	99.1	96.7	−3.0
Kagera	100.0	100.0	96.3	−3.7

Time series of suitability

The time series showed a clear upward trend from approximately 0.75 in the 2020s to nearly 0.90 by 2100 (Fig. 2).

Vulnerability clusters and priority regions

The vulnerability index ranged from 0.12 to 0.89 (mean = 0.42). Priority clusters - defined as the top quartile of both predicted risk and vulnerability - were concentrated in three broad areas: the coastal regions of Pwani and Dar es Salaam, the central regions of Dodoma and Singida, and parts of the Lake Zone, notably Mwanza and Shinyanga. These areas exhibit high climate suitability, low wealth, poor housing, and limited WASH access. Sensitivity analysis using PCA-derived weights produced similar priority cluster locations, suggesting the index is robust to weighting choices.

Discussion

This study provides a comprehensive assessment of climate-malaria associations in Tanzania, integrating historical household data, future climate projections, and vulnerability mapping. We found that temperature is a significant driver of malaria prevalence, with each 1°C increase associated with a 10% increase in odds. Future projections under SSP2-4.5 indicate that by the 2090s, nearly 90% of Tanzania's land area could be suitable for malaria transmission. Vulnerability is highest in central and coastal regions, where poor housing, low wealth, and inadequate WASH converge with high climate risk.

Our historical findings align with studies from East Africa linking temperature to malaria incidence [16, 17]. The protective effects of improved water and sanitation are consistent with the literature [22]. The positive association between bed net ownership and malaria (reverse causality) has also been reported in Tanzania, where households with recent malaria exposure adopt bed nets more readily [34]. The future suitability projections echo the [24] framework for temperature-duration thresholds, though our application to an endemic African setting with actual prevalence data provides an important extension.

A further consideration for Tanzania's malaria trajectory is the ongoing spread of the invasive vector *Anopheles stephensi* (*An. stephensi*), an efficient, container-breeding, urban-adapted mosquito capable of transmitting both *Plasmodium falciparum* and *P. vivax*. Since its first African detection in Djibouti in 2012, this vector has been confirmed in Ethiopia, Sudan, Somalia and Nigeria, and - most proximately to this study - in Kisumu, Kenya, in 2022, on the shore of Lake Victoria near Tanzania's north-western border [35, 36]. Because *An. stephensi* breeds preferentially in urban water-storage containers rather than the rain-fed pools captured by the rainfall-based suitability criterion used here, its establishment in Tanzania - particularly in the Lake Zone towns of Mwanza and Shinyanga, which this study already identifies as priority vulnerability clusters (see Results) and which lie closest to the Kenyan detection site, as well as in the high-vulnerability coastal cities of Dar es Salaam and Pwani - could decouple future urban transmission risk from the climate-suitability metric reported in the Results and warrants dedicated entomological surveillance and integration into future risk models.

The observed decline in malaria prevalence from 10.6% (2015) to 5.8% (2022) reflects the impact of scaled-up vector control, case management, and other interventions including mass distribution campaigns for insecticide-treated nets (ITNs), indoor residual spraying (IRS) in targeted districts, and improved case management with artemisinin-based combination therapies (ACTs) [26, 37]. Our suitability projections do not incorporate these interventions; they represent the climate-driven transmission potential, not actual disease burden. The two trends are not contradictory; they highlight that while climate conditions are becoming more favourable for transmission, effective interventions can still reduce realised prevalence. This underscores the importance of maintaining and strengthening malaria control programmes even as climate suitability expands.

Several policy implications follow from these findings. As suitability expands, current vector-control interventions including ITN mass campaigns and IRS must be maintained and adapted to new high-risk areas, with distribution and spraying schedules re-timed to the shifting seasonal window implied by the suitability projections in the Results. Emerging hotspots, particularly highland areas currently at low risk but projected to become suitable, will need early warning systems and strengthened diagnostic capacity, and, where transmission becomes seasonal and predictable, consideration of seasonal malaria chemoprevention and community-based surveillance.

Investments in improved water, sanitation, and housing are not only health interventions but also climate adaptation measures, and are especially relevant in the priority clusters identified above. In those clusters the central regions of Dodoma and Singida, the coastal areas of Pwani and Dar es Salaam, and the Lake Zone (Mwanza, Shinyanga) integrated packages combining intensified malaria prevention with social protection programmes should be prioritised for early investment.

This study has several strengths. It draws on nationally representative, georeferenced DHS data with appropriate survey weights; integrates high-resolution climate data from ERA5-Land, CHIRPS, and NASA NEX-GDDP-CMIP6; applies rigorous statistical methods, including cluster-robust standard errors, multivariable adjustment, and multiple sensitivity analyses; and is, to our knowledge, the first study to

combine historical association, forward climate projection, and vulnerability clustering in a single framework applied to Tanzania.

Several limitations should also be considered. The cross-sectional design precludes causal inference, and reverse causality is possible, particularly for bed nets; as in any observational study, unmeasured confounding also cannot be excluded, since factors such as indoor residual spraying coverage, health-facility density and quality, and individual health-seeking behaviour were not available in the DHS data used here and could confound the climate-malaria associations reported in the Results.

On the climate side, future projections are based on a single global climate model (ACCESS-CM2) and a single emissions scenario (SSP2-4.5); more extreme scenarios would likely show greater expansion, multi-model ensembles are preferable, and our results should be interpreted as indicative rather than definitive. Climate data at 0.25° resolution may miss micro-climatic variation, and DHS GPS coordinates are randomly displaced for confidentiality, introducing further spatial imprecision. Annual climate averages are also a simplification that does not capture the lagged or seasonal effects known to be biologically relevant [15] and future suitability is reported as a percentage of Tanzania's land area rather than the population exposed; because several of the country's most densely populated regions already fall within currently suitable areas, a population-weighted suitability trend could differ from the land-area trend reported here and would be a more policy-relevant metric for future work.

Methodologically, sampling weights (hv005) were applied via statsmodels' `freq_weights` argument together with cluster-robust standard errors; this approximates, but does not exactly replicate, a dedicated probability-weighted survey-design estimator (e.g., Taylor-series linearisation as implemented in Stata's `svy` suite or R's `survey/srvyr` packages), and replication with dedicated survey software is recommended before these effect sizes are used to inform policy thresholds. The “medium” roof category had a small sample size ($n = 105$), leading to imprecise estimates. Finally, our vulnerability index is based on 2015/2022 data and does not account for future improvements in wealth, housing, or WASH, which may overestimate future vulnerability, particularly beyond 2030–2040. Building on these findings, future work should incorporate additional global climate models and the more extreme SSP3-7.0 and SSP5-8.5 scenarios (both of which already have CMIP6 data available) to bound the range of plausible future suitability; use higher-resolution climate and population data; integrate malaria intervention coverage, such as IRS and case management, into projections; conduct longitudinal studies to confirm the climate-malaria associations reported here; explore lagged climate effects using Distributed Lag Non-linear Models [15] and incorporate projected population growth and urbanization trends, since these will interact with climate suitability to determine the number of people actually exposed, particularly in fast-growing urban centres such as Dar es Salaam.

Conclusions

Malaria remains a major public health threat in Tanzania, and climate change is projected to expand the geographic area suitable for transmission by approximately 4.5 percentage points of land area between

the 2030s and 2090s under a middle-of-the-road climate scenario (SSP2-4.5). Temperature is a significant risk factor, and household vulnerability (wealth, housing, WASH) modifies this risk, with priority regions concentrated in central, coastal, and Lake Zone Tanzania. Integrated, climate-resilient strategies are needed that address both environmental and social determinants, targeted first at the clusters identified in the Results. These findings provide a scientific basis for the targeting priorities in Tanzania's National Malaria Strategic Plan (2021–2025) and contribute to the growing evidence on climate-sensitive health planning in sub-Saharan Africa.

Abbreviations

ACT

Artemisinin-based combination therapy

An.

Anopheles

CHIRPS

Climate Hazards Group InfraRed Precipitation with Station data

CI

Confidence interval

CMIP6

Coupled Model Intercomparison Project Phase 6

DHS

Demographic and Health Survey

ERA5-Land

ECMWF Reanalysis v5-Land

GCM

Global climate model

IRS

Indoor residual spraying

ITN

Insecticide-treated net

MARA

Mapping Malaria Risk in Africa

NMSP

National Malaria Strategic Plan

OR

Odds ratio

PCA

Principal component analysis

Pl.

Plasmodium

RDT

Rapid diagnostic test

SSP

Shared Socioeconomic Pathway

TDHS-MIS

Tanzania Demographic and Health Survey and Malaria Indicator Survey

WASH

Water, sanitation, and hygiene

WHO

World Health Organization

Declarations

Ethics approval and consent to participate

Not applicable

Consent for publication

Not applicable.

Clinical trial number

Not applicable.

Input data.

Tanzania Demographic and Health Survey and Malaria Indicator Survey (TDHS-MIS) 2015 and 2022 datasets: available from The DHS Program (<https://dhsprogram.com>) upon registration. ERA5-Land historical climate reanalysis: available from the Copernicus Climate Data Store (<https://cds.climate.copernicus.eu>). CHIRPS historical rainfall data: available from the Climate Hazards Center (<https://www.chc.ucsb.edu/data/chirps>). NASA NEX-GDDP-CMIP6 future climate projections: available from the NASA Earthdata archive (<https://www.nccs.nasa.gov/services/data-collections/land-based-products/nex-gddp-cmip6>).

Competing interests

The authors declare that they have no competing interests.

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Author Contribution

E.P. and A.C. conceived the study. E.P. curated and analysed the data. A.C. and W.N. contributed to the climate-suitability modelling, and W.N. conducted the literature review. J.B. supervised the study, provided methodological guidance, contributed to data analysis, and prepared Figs. 1-3. S.K. contributed to the vulnerability-index construction. J.A. reviewed the manuscript and prepared the reference list. All authors contributed to drafting and critically revising the manuscript and approved the final version.

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Data Availability

Tanzania Demographic and Health Survey and Malaria Indicator Survey (TDHS-MIS) 2015 and 2022 datasets: available from The DHS Program (<https://dhsprogram.com>) upon registration. ERA5-Land historical climate reanalysis: available from the Copernicus Climate Data Store (<https://cds.climate.copernicus.eu>). CHIRPS historical rainfall data: available from the Climate Hazards Center (<https://www.chc.ucsb.edu/data/chirps>). NASA NEX-GDDP-CMIP6 future climate projections: available from the NASA Earthdata archive (<https://www.nccs.nasa.gov/services/data-collections/land-based-products/nex-gddp-cmip6>). The derived cluster-level suitability, vulnerability-index, and model output datasets generated and analysed during the current study, and the analysis code, are available from the corresponding author on reasonable request.

The derived cluster-level suitability, vulnerability-index, and model output datasets generated and analysed during the current study, and the analysis code, are available from the corresponding author on reasonable request.

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Figures

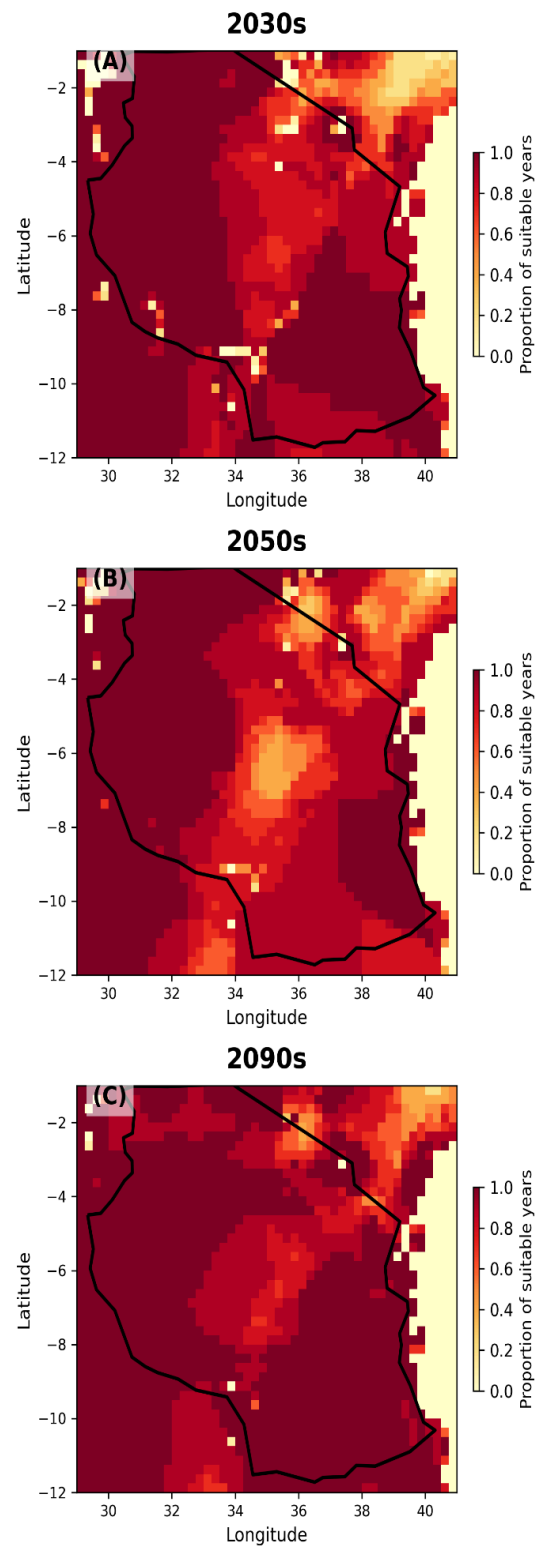


Figure 1

Decadal combined suitability (temperature $\geq 20^{\circ}\text{C}$ and rainfall $> 80\text{ mm}$ for ≥ 4 months/year) under SSP2-4.5. Panels show the proportion of suitable years in the (A) 2030s, (B) 2050s, and (C) 2090s

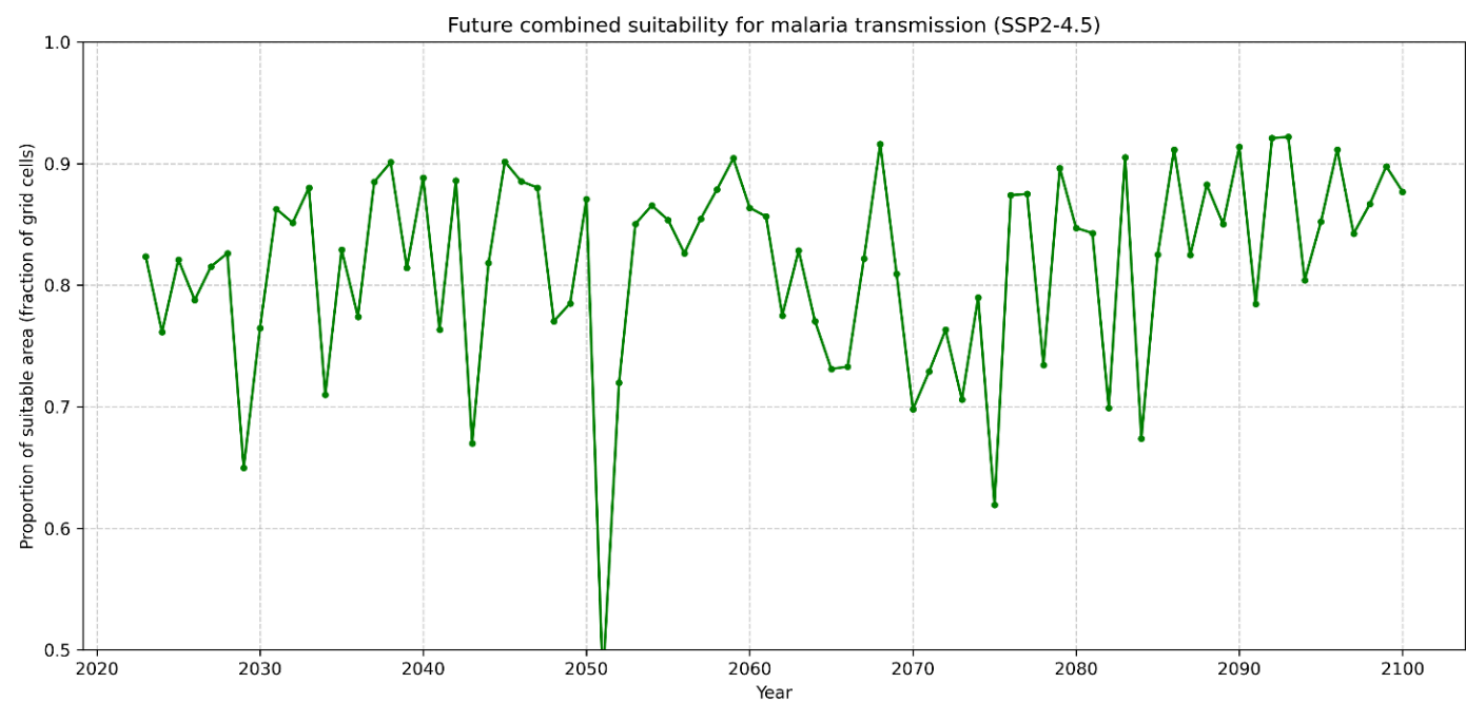


Figure 2

Time series of the proportion of Tanzania's land area suitable for malaria transmission (combined temperature and rainfall criteria) under SSP2-4.5, 2023-2100

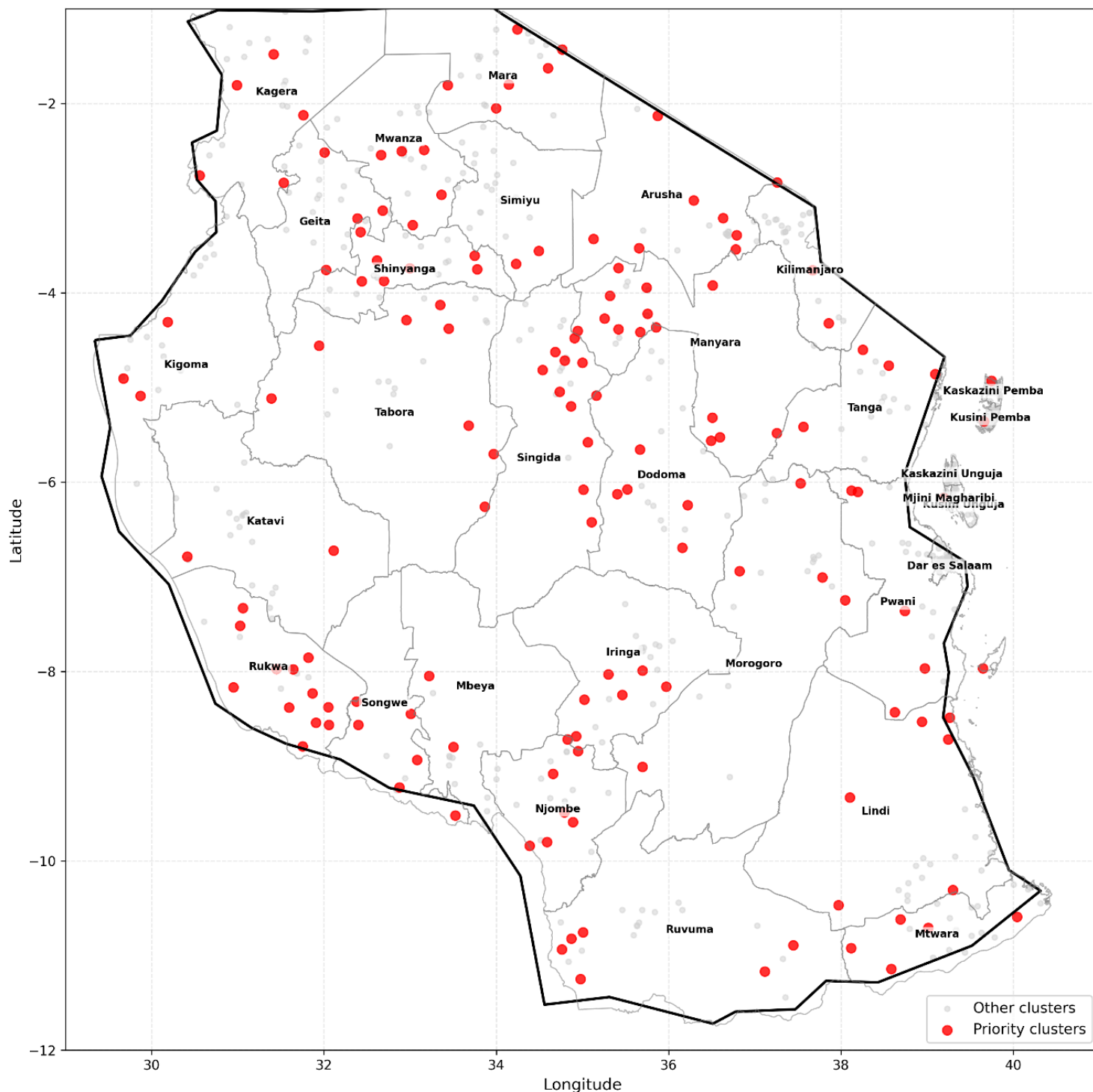


Figure 3

Priority intervention clusters (red) where high predicted malaria risk and high household vulnerability converge. Gray points represent other DHS clusters

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