Linking Climate Variability and Malaria Trends: A Case Study on Southern Mozambique

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1. Project summary

This summer, I set out to explore how climate patterns influence malaria trends in Southern Mozambique, with a focus on Maputo Province. I began by working with follow-up and case notification data, then shifted to studying historical precipitation and temperature records to understand long-term patterns. As the project progressed, I narrowed in on more recent years, integrating climate drivers such as precipitation, the Indian Ocean Subtropical Dipole (IOSD), and ENSO to see how they related to malaria incidence.[1]

Analysis showed that precipitation had a generally positive relationship with malaria incidence, particularly at short time lags, though the strength of this relationship varied. IOSD stood out — a one standard deviation increase corresponded to an estimated 0.4 additional malaria cases per 1,000 population. ENSO, in contrast, did not show a strong or consistent signal in the data.

It is worth noting that my background is not in climatology, and most of the work done, plots obtained, and analysis done were done for the first time. I used aid from both research specialists on campus and AI to better understand these climate data sets. As such, while this is not a polished, publication-ready study, it reflects an important first step in building climate-linked malaria early warning capacity. More importantly, it's been a deep learning experience in climate data processing, spatial analysis, and the complexities of linking environmental conditions to health outcomes.

2. Introduction

Malaria continues to be one of the most persistent public health challenges in sub-Saharan Africa, responsible for significant morbidity and mortality despite decades of control efforts. In Mozambique, the disease remains endemic, with transmission patterns influenced by a complex interplay of environmental, climatic, and socio-economic factors. The southern provinces — including Maputo, Gaza, and Inhambane — experience distinct wet and dry seasons, which shape vector breeding cycles and, ultimately, malaria transmission dynamics.

Recent research has shown that climatic variables such as precipitation, temperature, and large-scale ocean–atmosphere oscillations (e.g., El Niño–Southern Oscillation [ENSO] and Indian Ocean Subtropical Dipole [IOSD]) can influence malaria incidence with time-lagged effects.[1] Understanding these relationships at a provincial scale is crucial for developing timely, data-driven interventions that can anticipate and respond to outbreaks.

This report builds on previous work linking climate variability and malaria transmission by focusing on the Maputo Province over the past five years. The analysis integrates malaria incidence data with high-resolution climate datasets, exploring lagged relationships between climatic drivers and disease trends. While this study does not aim to provide a publishable epidemiological model, it offers valuable insights for operational decision-making, strengthening Goodbye Malaria's capacity to leverage climate information in program planning and community-level response.

3. Methods

Study-Area

Analysis focused on Maputo Province, Mozambique (7 districts) from January 2020 to the most recent available month in 2025 (monthly resolution).

Malaria-Data

Monthly case counts provided by Goodbye Malaria were converted to incidence per 1,000 population using an assumed population of 2.5 million for Maputo Province:

$$Incidence = \frac{Cases}{2,500,000} \times 1000$$

Where mapping required, district values were averaged to a province-wide monthly series.

Climate Data

- **Precipitation:** CHIRPS monthly (~0.05°). Cropped to Maputo Province, masked to land, and aggregated to provincial means.
- **Historical climatology:** WorldClim used for long-term seasonal context.

- **Other variables (exploratory):** ERA5-Land monthly temperature, dew point, wind, soil moisture, solar radiation,

All rasters were reprojected to WGS84 (EPSG:4326) and time-aligned to the first of each month.

Climate Indices

- **ENSO:** NOAA ONI v5 (3-month Niño 3.4 SST anomaly). Each seasonal value assigned to a representative month for merging with malaria and precipitation series. Effects reported per +1 ONI unit.
- **IOSD:** Calculated from ERA5 SSTs as the difference between western (20°S–10°S, 50–70°E) and eastern (20°S–10°S, 90–110°E) box averages. Effects reported per +1 SD of the IOSD index.

Data-Processing

All −9999 values set to NA. Monthly series joined on date. No smoothing or detrending applied. Analyses performed on copies of the main data frames to preserve originals.

Statistical-Analysis

Lagged linear regressions tested relationships between climate variables at month t and malaria incidence at t + 0…6 months:

$$Incidence_{t+k} = \alpha + \beta X_t + \epsilon$$

- Precipitation effects scaled per +100 mm.
- IOSD effects scaled per +1 SD.
- ENSO effects per +1 ONI unit.
- Outputs included β, 95 % CI, p-value, and R^2. Correlations were also computed for comparison.

Visualization

- Time series of malaria incidence.
- Precipitation–incidence dual-axis plots by year.

- Spatial CHIRPS maps with fixed color scales for seasonal context.

Software

- **Acquisition:** Python (VS Code) — CDSAPI for ERA5, HTTP for ONI, CHIRPS direct downloads.
- **Processing/analysis:** R 4.x (tidyverse, terra, tmap, ggplot2, ggpubr) and Python 3.11 (rasterio, geopandas, matplotlib).
- **CRS:** EPSG:4326 for all spatial layers.

Limitations
The 5-year window limits power, particularly for ENSO (low variability in this period). Models did not adjust for interventions, mobility, or other covariates.

4. Results

4.1 Malaria Incidence trends

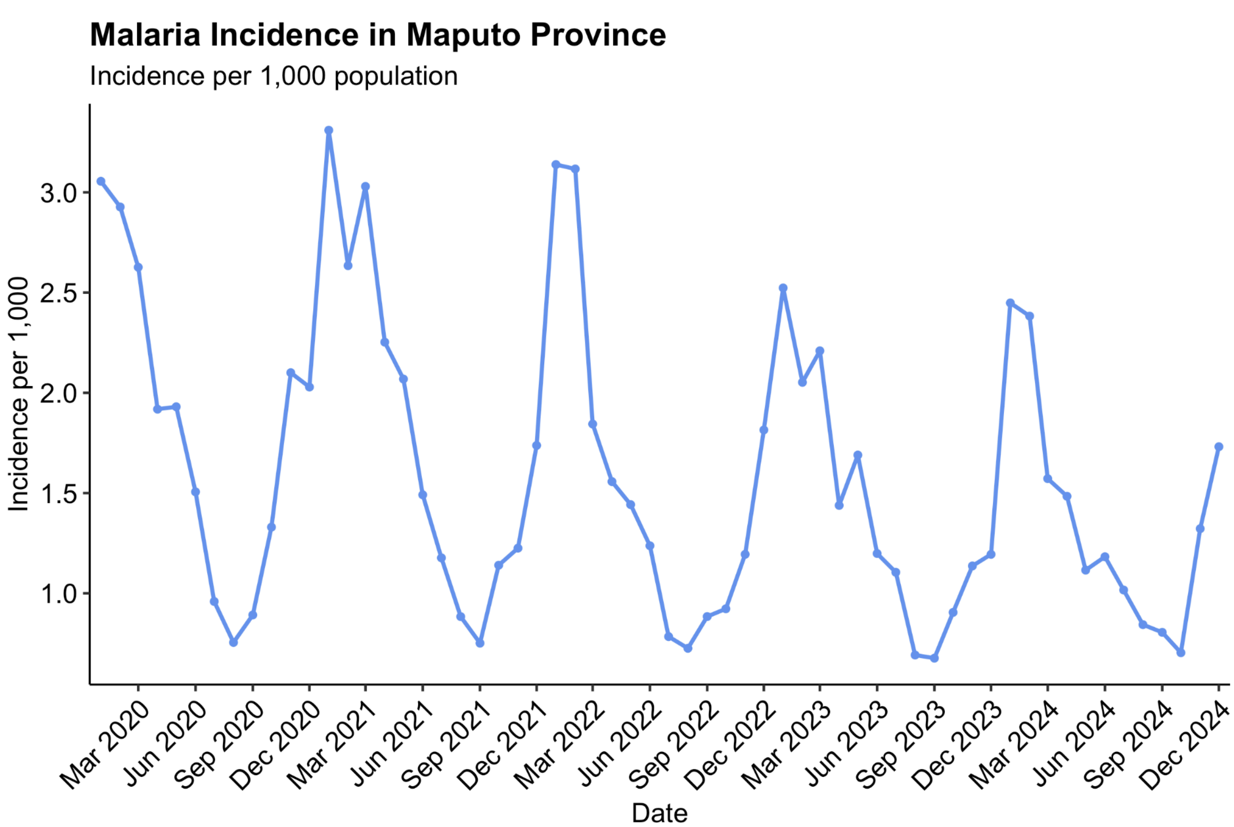


Figure 1: Malaria Incidence in Maputo Province

Malaria incidence in Maputo Province was calculated and plotted to examine monthly trends from 2020–2024. **Peak transmission seasons consistently occurred between December and April, with 2020–2021 recording the highest average incidence levels.** From 2022 onward, peak magnitudes were generally lower than in earlier years. Across all years, June to October marked the lowest incidence period.

4.2 Precipitation Analysis

Historic Precipitation

Historically, Southern Mozambique receives substantial annual precipitation, with the coastal belt—particularly areas along Inhambane, Gaza, and Maputo provinces—often recording over 800 mm per year. WorldClim v2.1 historical climate data (1970–2000) show a distinct spatial gradient, where coastal and low-lying districts experience significantly higher rainfall compared to inland areas. **The wet season typically spans from December to March, with January, February, and December consistently being the wettest months across most regions.**

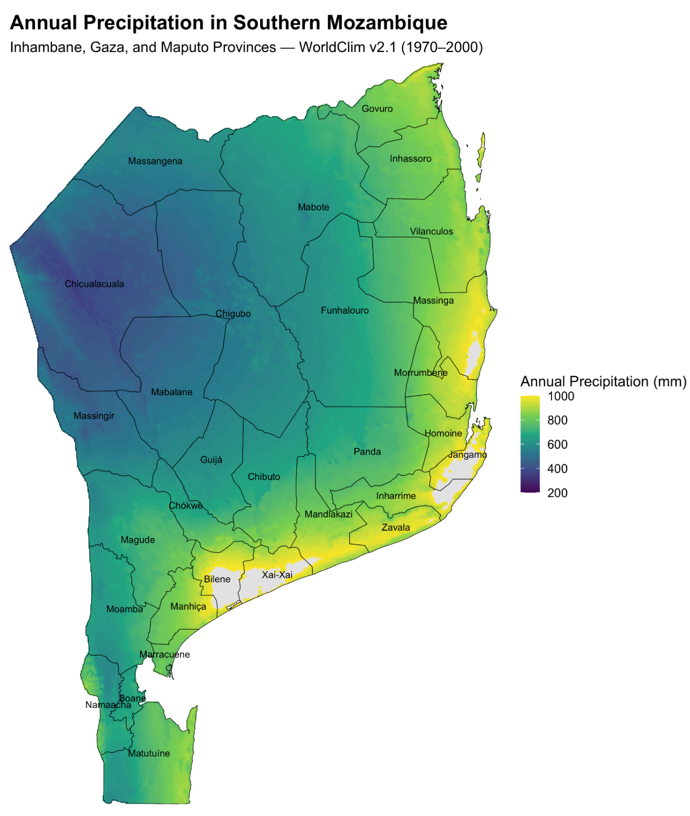


FIgure 2: Historic Annual Precipitation in Southern Mozambique

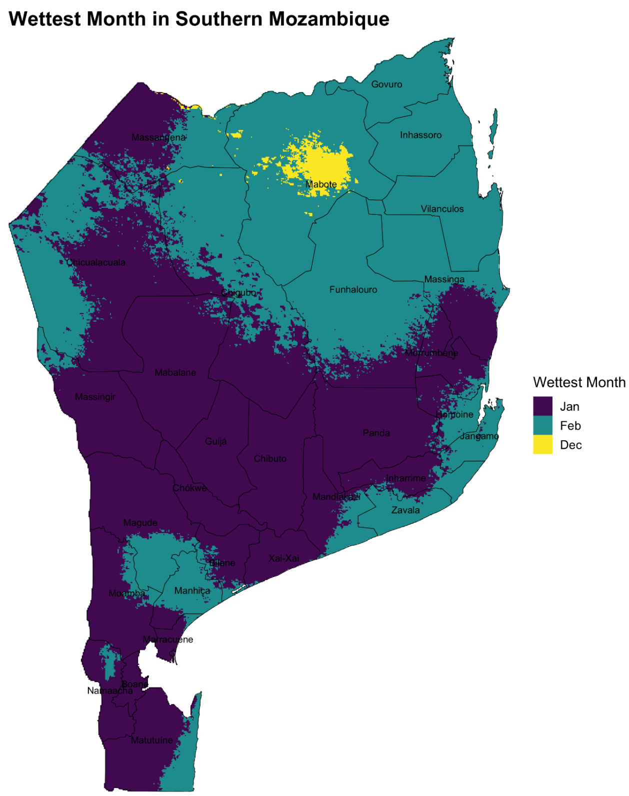


Figure 3: Historic Wettest Months in Southern Mozambique

Recent Precipitation

Recent CHIRPS precipitation records (2020–2024) reveal considerable interannual variability in both rainfall totals and distribution across months. While the general wet season timing remains consistent, peak rainfall amounts vary sharply from year to year. For example, February 2023 recorded exceptionally high rainfall in the Maputo Province, largely driven by Cyclone Freddy's landfall. In contrast, years such as 2022 showed lower peak values and a more gradual onset of the wet season.

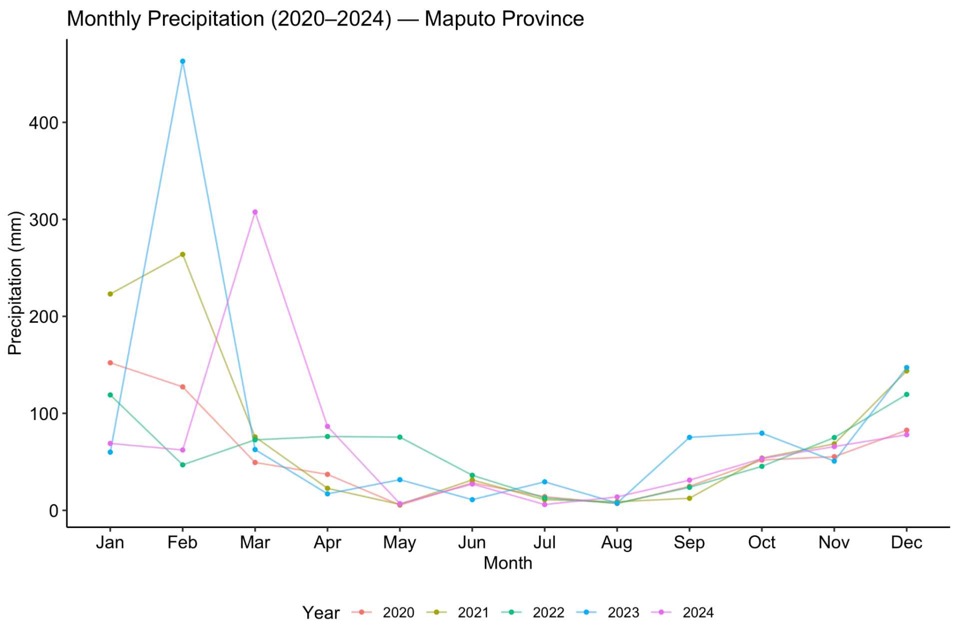


Figure 4: Monthly Precipitation in the Maputo Province

Relationship Between Precipitation and Malaria Burden

Monthly precipitation data for Maputo Province was overlaid with annual malaria case counts, revealing consistent seasonal patterns and a clear temporal alignment between rainfall peaks and subsequent malaria surges.

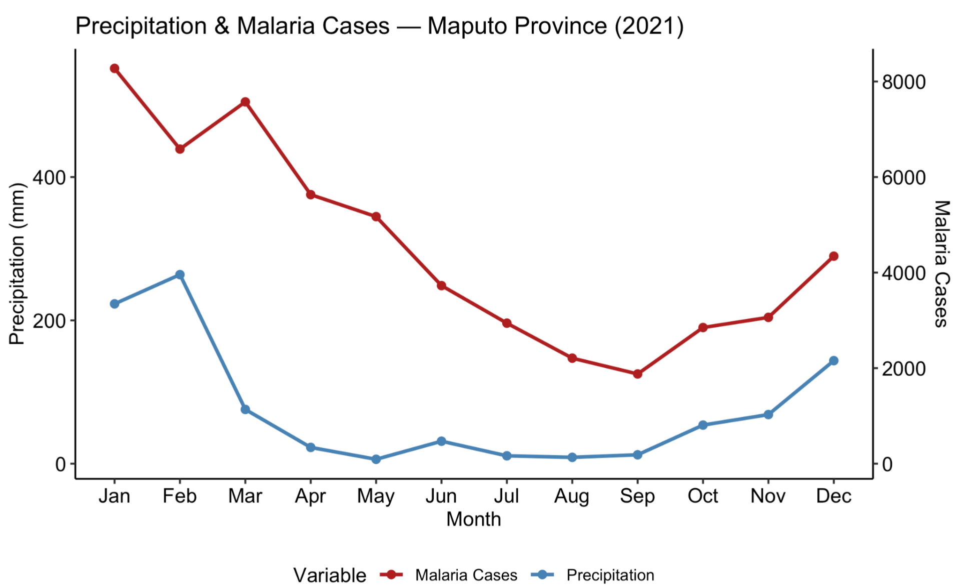


Figure 5: Monthly Precipitation and Malaria Cases in 2021(Figures for each year can be found in Section 7)

To refine this relationship, incidence rates (cases per 1,000 people, assuming a population of 2.5 million) were also plotted alongside precipitation trends.

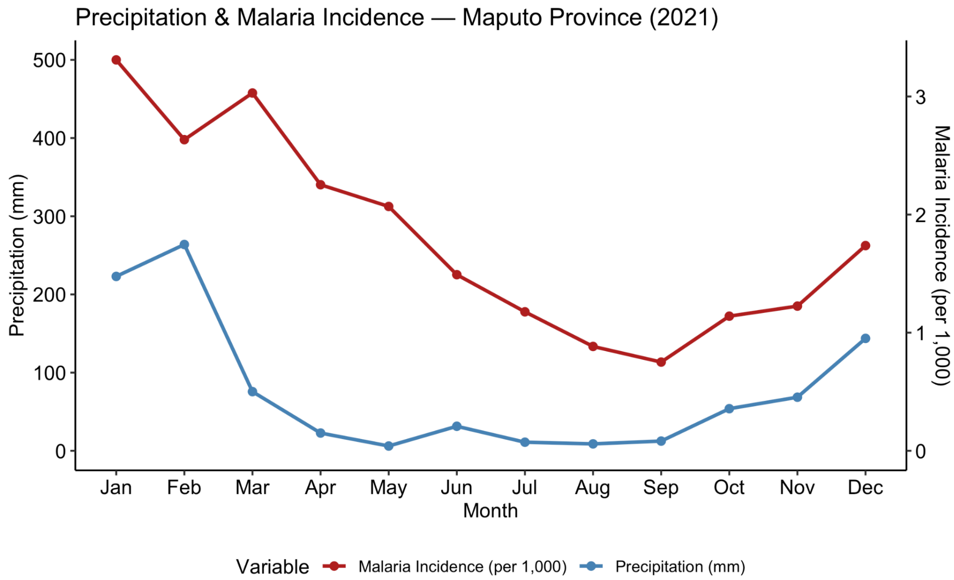


Figure 6: Monthly Precipitation and Malaria Incidence in 2021(Figures for each year can be found in Section 7)

From 2020–2024 in Maputo Province, precipitation follows a clear wet–dry seasonal cycle — high rainfall early in the year (January–March), a sharp decline during the mid-year dry season (May–September), and a gradual rise toward year's end.
Malaria incidence generally lags behind rainfall peaks, often remaining high for several months after the rainy season begins, then declining through the dry season before starting to rise again near year-end.

Lagged correlation analysis showed the strongest positive associations within a 0–2 month lag window. Across the study period (2020–2024), the correlation between precipitation and malaria cases peaked at:

- 2020: 0-month lag = 0.80, 1-month lag = 0.89, 3-month lag = 0.73, 4-month lag = 0.43
- 2021: 0-month lag = 0.65, 1-month lag = 0.88, 3-month lag = 0.85, 4-month lag = 0.82
- 2022: 0-month lag = 0.61, 1-month lag = 0.88, 3-month lag = 0.73, 4-month lag = 0.01
- 2023: 0-month lag = 0.33, 1-month lag = 0.62, 3-month lag = 0.26, 4-month lag = 0.72
- 2024: 0-month lag = 0.30, 1-month lag = 0.32, 3-month lag = 0.15, 4-month lag = 0.14

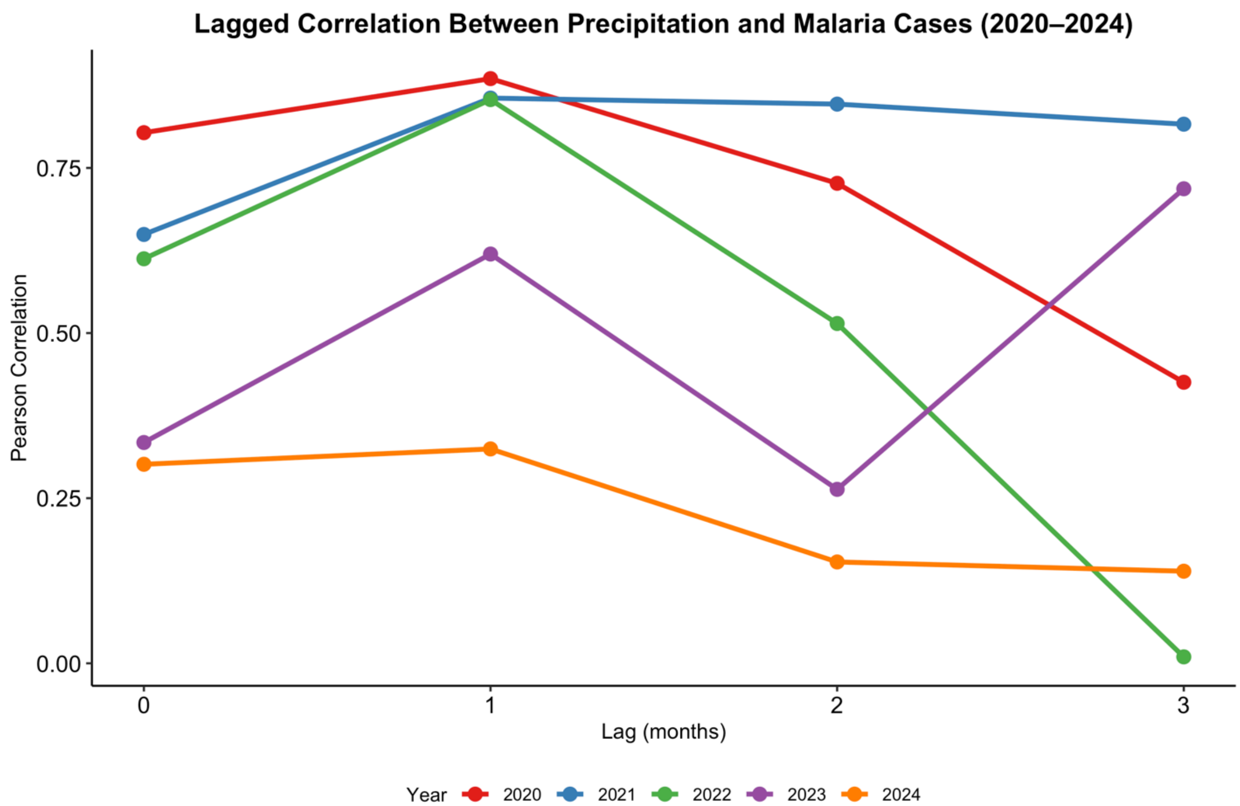


Figure 7: Lagged Correlation Between Precipitation and Malaria Cases.

The year 2023 showed a deviation in the trend for the drop in correlation as the lag months progressed.

Lagged linear regression further supported these findings, with model estimates indicating an average increase of **~0.4 malaria cases per 1,000 people for every 100mm increase in precipitation during this 0–2 month period**. Beyond a 2-month lag the regression slopes dropped sharply, with several years showing near-zero or negative values by 3–4 months.

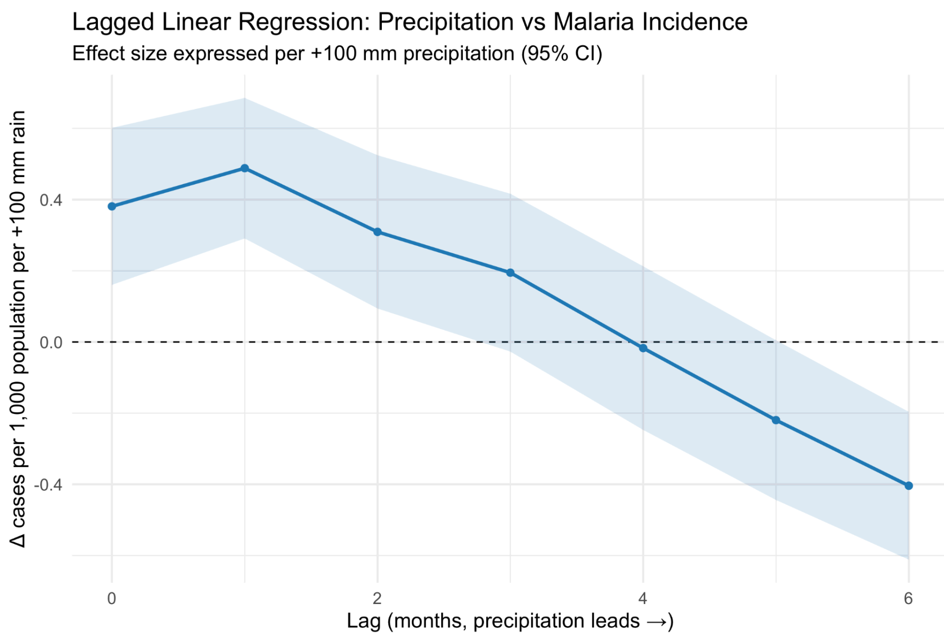


Figure 8: Lagged linear regression plot of Precipitation vs Malaria incidence

4.3 ENSO and IOSD

Indian Ocean Subtropical Dipole (IOSD) Analysis

Trends in precipitation and malaria incidence have been associated with large-scale climate drivers such as the El Niño–Southern Oscillation (ENSO) and the Indian Ocean Subtropical Dipole (IOSD). To explore IOSD influence, phases were overlaid on annual precipitation–malaria plots using a ±0.4 °C threshold to classify positive (red), negative (blue), and neutral (gray) phases.

In 2023, positive IOSD phases dominated early in the year, coinciding with higher precipitation peaks and early malaria case counts, followed by a neutral mid-year phase. In contrast, 2022—characterized by lower rainfall—was marked by a prolonged negative IOSD phase, with intermittent neutral periods, aligning with reduced precipitation and a delayed malaria rise.

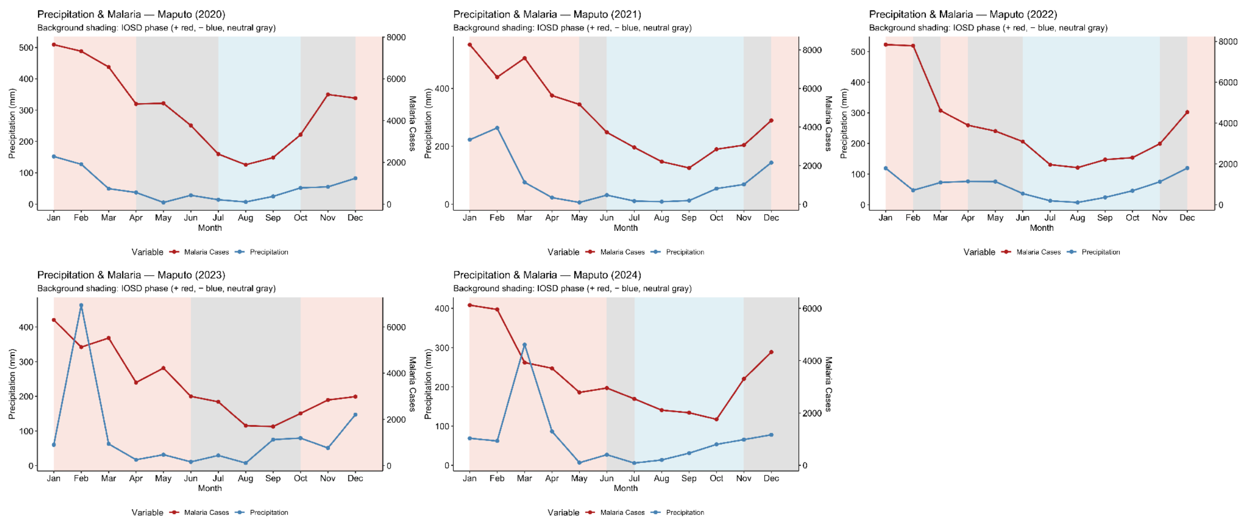


Figure 9: IOSD phases overlaid on 2020-2024 Monthly Precipitation and Malaria cases plot in Maputo

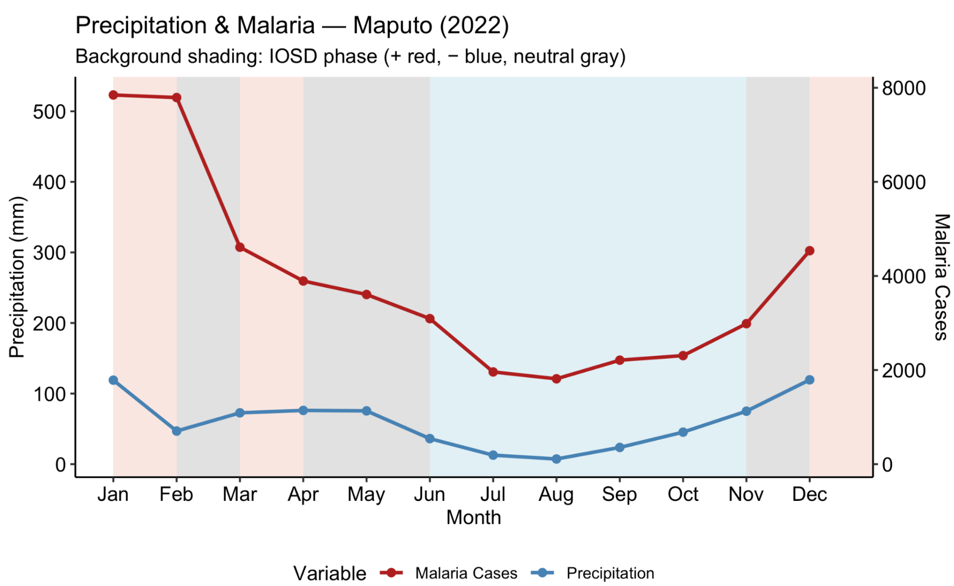


Figure 9: IOSD phases overlaid on 2022 Monthly Precipitation and Malaria cases plot in Maputo(Individual plots in Section 7)

Lagged Pearson Correlation Between IOSD and Malaria Cases

To quantify the relationship between IOSD phases and malaria dynamics, monthly IOSD index values were lag-correlated with malaria case counts in Maputo Province. The IOSD index was calculated from NOAA OISSTv2 sea surface temperature anomalies, with a ±0.4 °C threshold used to classify phase in earlier plots. For this correlation analysis, the monthly IOSD time series and malaria case counts were first standardized (z-score normalization) to remove scale differences.

Pearson correlation coefficients were then computed at monthly lags from 0–6 months, where a positive lag indicates that IOSD values lead malaria cases by that number of months. This approach helps capture potential delayed climate–health linkages, such as precipitation or temperature anomalies induced by IOSD influencing mosquito breeding and malaria transmission dynamics over subsequent months.

Results show the strongest positive correlations at 0–2 month lags (r ≈ 0.4–0.55), suggesting that positive IOSD phases may be associated with increased malaria cases within the following two months. Correlations turn negative at lags beyond 4 months, indicating a possible reversal in climate influence over longer timescales.

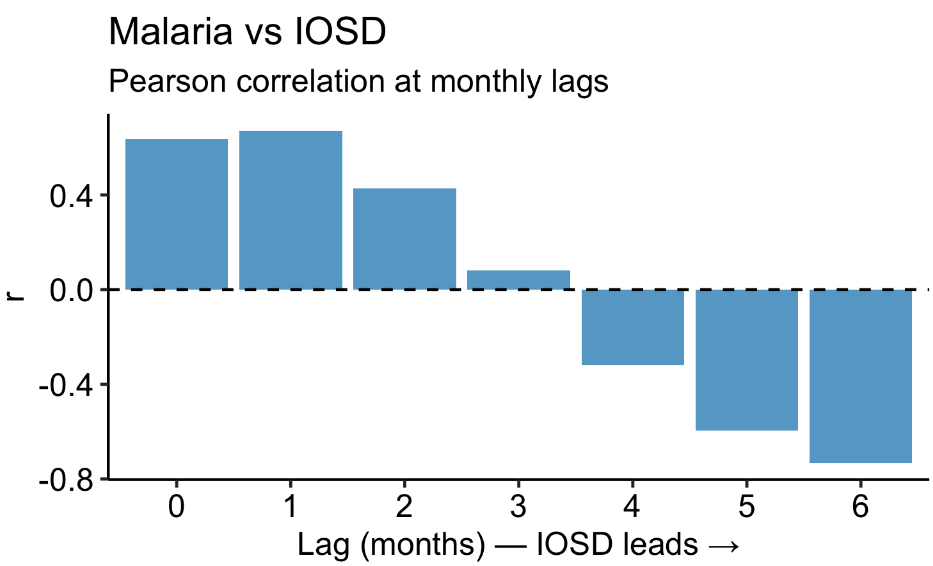


Figure 10: Malaria vs IOSD lagged Pearson correlation

ENSO Influence on Precipitation and Malaria

ENSO (El Niño–Southern Oscillation) describes recurring ocean–atmosphere patterns in the tropical Pacific that shift between **warm (El Niño), cool (La Niña),** and neutral phases, influencing rainfall and temperature patterns worldwide.

From 2020–2024 in Maputo, the relationship between ENSO phases and malaria cases appears inconsistent. While some years fit expectations—such as wetter conditions during La Niña (2021–2022) and drier conditions during El Niño (2020, 2023, 2024)—the magnitude of these effects and their influence on malaria incidence vary considerably. **For instance, the prolonged La Niña in 2022 did not produce a clear spike in cases, while the strong El Niño in 2023 coincided with only modest declines in precipitation and relatively stable malaria trends.**

This variability is reinforced by the lagged Pearson correlations between ENSO (ONI index) and malaria cases, which remain weak and negative ($r \approx -0.10$ to -0.25) across lags of 0–6 months. These results suggest that while ENSO may contribute to climate conditions relevant for malaria transmission, it is not a strong standalone predictor for Maputo. Other drivers—such as the Indian Ocean Subtropical Dipole (IOSD), local hydrology, and intervention measures—likely play a more dominant role in shaping malaria dynamics in this region.

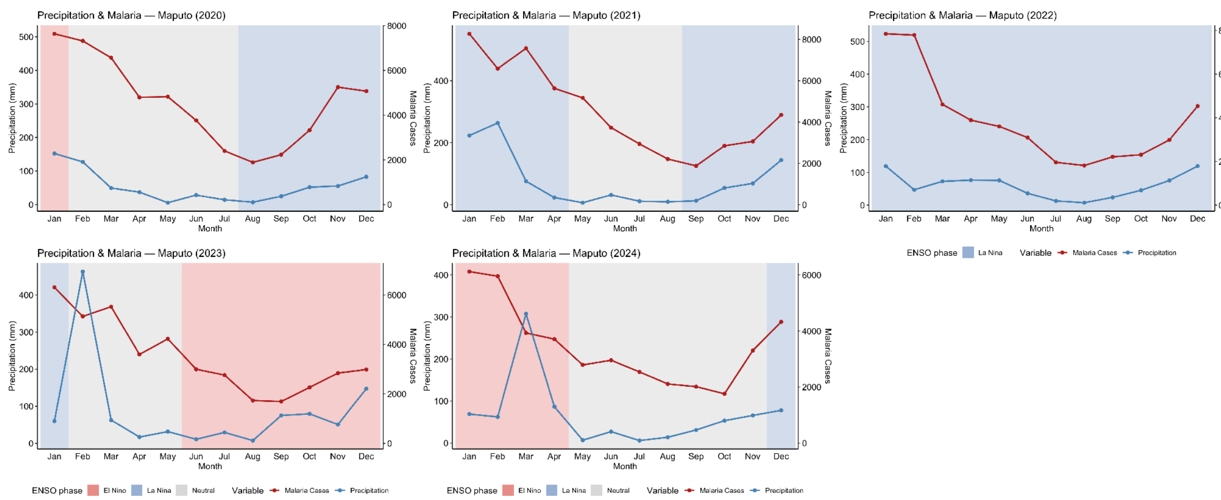


Figure 9: ENSO phases overlaid on 2022 Monthly Precipitation and Malaria cases plot in Maputo(Individual plots in Section 7)

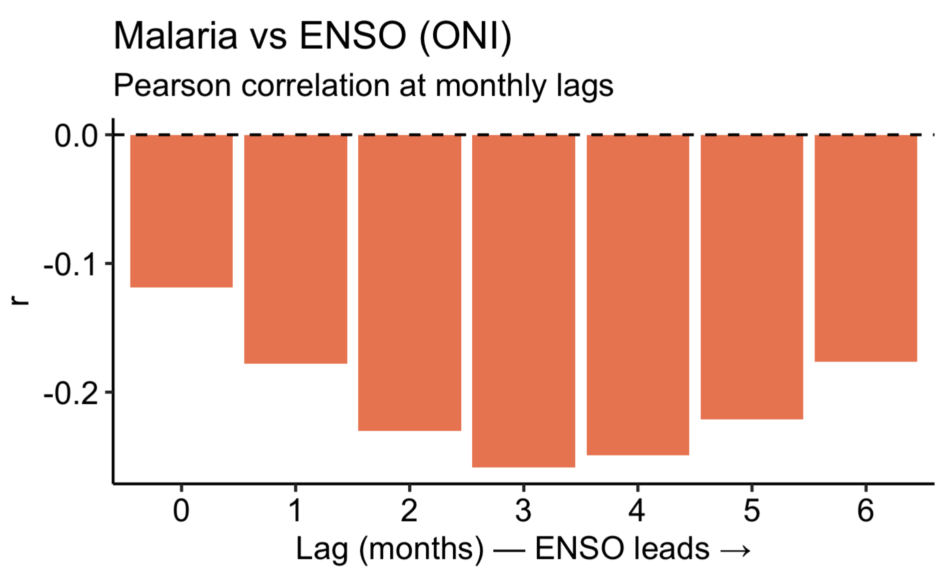


Figure 10: Malaria vs ENSO lagged Pearson correlation

Lagged Linear Regression: ENSO & IOSD vs Malaria Cases

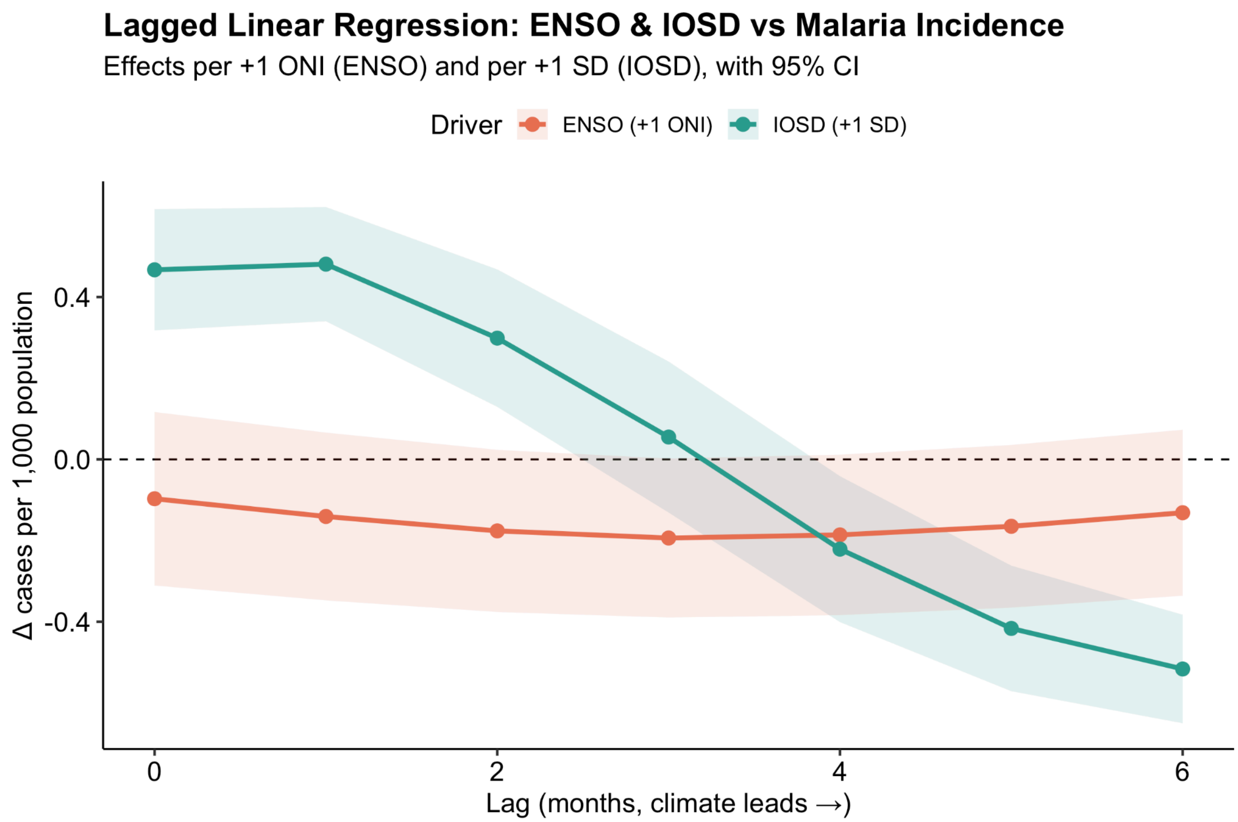


Figure 11: Lagged Linear Regression of ENSO and IOSD with Malaria incidence

This analysis examined how monthly ENSO (ONI) and IOSD anomalies influence malaria incidence in Maputo at lags of 0–6 months.

IOSD: Positive anomalies (+1 SD) were linked to substantial increases in malaria incidence at short lags (0–2 months, ~+0.45 cases per 1,000 population), with effects declining steadily and turning negative by 4 months. This suggests IOSD's influence is rapid and seasonally dependent.

ENSO: A +1 ONI (El Niño–like) was weakly associated with slightly lower malaria incidence across all lags (~–0.05 to –0.15), with narrow variation and no clear reversal.

Takeaway: IOSD appears to be a stronger and more immediate driver of malaria variability in Maputo than ENSO, with the clearest signal occurring within the first 2 months.

5. Discussion

5.1 Linking Climate Variability to Malaria Risk

Previous studies across southern Africa have identified strong links between large-scale climate drivers and malaria transmission dynamics. A seasonally lagged modelling framework found that sea surface temperature (SST) anomalies in the Indian Ocean and Pacific Ocean can influence rainfall, temperature, and humidity patterns in southern Mozambique, thereby creating conditions favourable (or unfavourable) for malaria transmission.1

In particular, El Niño–Southern Oscillation (ENSO) events — typically measured by the Oceanic Niño Index (ONI) — have been associated with altered rainfall timing and magnitude in the region. Positive ONI anomalies (El Niño–like conditions) can suppress summer rainfall in southern Mozambique, reducing mosquito breeding habitats, while negative anomalies (La Niña–like) tend to enhance precipitation and humidity.

The Indian Ocean Subtropical Dipole (IOSD), measured as SST gradients in the southwestern Indian Ocean, has also been highlighted as a potential driver of interannual variability. A positive IOSD phase is often linked to enhanced summer rainfall over southern Mozambique, creating wetter conditions favourable for Anopheles mosquito proliferation and potentially increasing malaria incidence.

5.2 Potential Mechanisms Affecting Malaria Incidence

Malaria transmission is sensitive to climatic conditions through several pathways:

1. **Rainfall** – Sustained precipitation creates breeding habitats for mosquito vectors. However, excessive rainfall can wash away larvae, leading to nonlinear relationships.
2. **Temperature** – Warmer temperatures can accelerate the mosquito life cycle and parasite development rate (up to an optimal threshold), potentially shortening the extrinsic incubation period.
3. **Humidity** – High humidity extends mosquito survival, increasing the likelihood of parasite transmission.
4. **Indirect Socioeconomic Effects** – Extreme events linked to ENSO or IOSD (e.g., flooding, drought) can disrupt healthcare access, vector control measures, and housing stability, amplifying disease risk.

Both ENSO and IOSD influence these variables in different ways and at different timescales. Understanding their lagged effects is essential for early-warning systems that allow public health programs to pre-position interventions.

5.3 Interpreting This Study's Findings

In our Maputo Province dataset (2020–2024):

- **IOSD** showed a clear positive relationship with malaria incidence at short lags (0–2 months), with effects declining and reversing by ~4 months. This pattern suggests IOSD-linked rainfall and humidity anomalies may rapidly influence mosquito breeding and transmission potential, but the signal diminishes as other factors (seasonal decline, interventions, environmental changes) take over.
- **ENSO** displayed a weak, consistently negative association with incidence across all lags. This aligns with studies suggesting that El Niño–like conditions reduce rainfall in southern Mozambique, thereby suppressing mosquito populations — but the relationship here was statistically weak.
- The contrast between the strong IOSD signal and weak ENSO signal in this dataset may reflect **regional climate dominance**, with the southwestern Indian Ocean playing a greater role in interannual rainfall variability over southern Mozambique than Pacific SST anomalies.

Implications:

These findings suggest that **IOSD anomalies could be used as a short-term predictive indicator** for malaria risk in Maputo, especially in the December–February period when rainfall is highest. ENSO, while globally important, appears to have less local predictive power in this dataset.

This study adds to what we know about climate and malaria by showing how large-scale climate drivers like ENSO and IOSD link with local precipitation and malaria cases in Southern Mozambique. The lagged effects we found highlight why timing matters — and why local studies are critical for building accurate, region-specific early warning systems instead of relying only on global patterns. These insights can help shape malaria control strategies, like timing vector control or resource deployment around climate forecasts.

6. Conclusion

This study examined the influence of large-scale climate drivers — **ENSO (ONI)** and **IOSD** — on malaria incidence in Maputo Province from 2020 to 2024, using lagged correlation and regression analyses. The results reveal that IOSD exhibits a stronger and more immediate association with malaria incidence than ENSO, with positive IOSD anomalies linked to higher case counts within 0–2 months. In contrast, ENSO signals remained consistently negative and relatively weak across all lags.

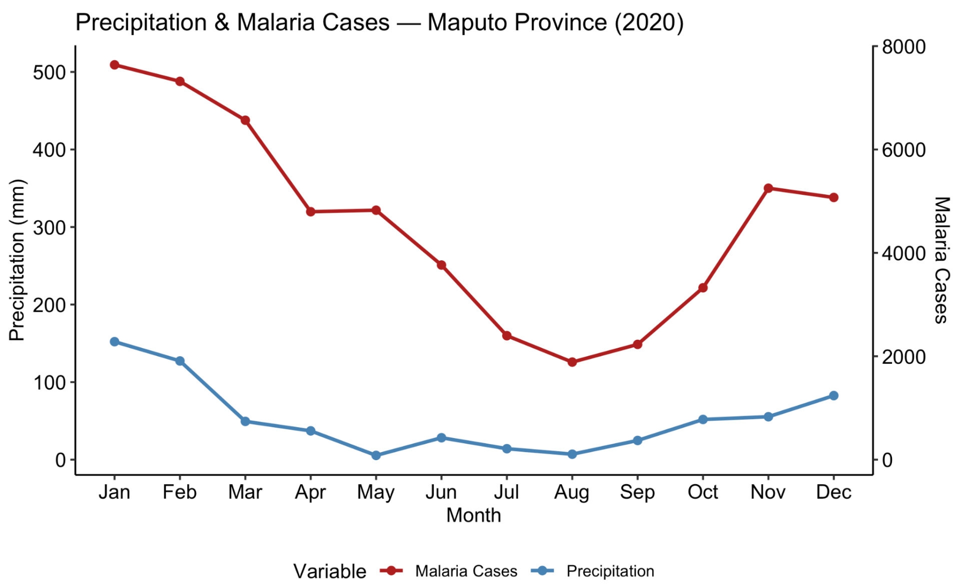
These patterns suggest that, in southern Mozambique, **regional ocean–atmosphere variability in the southwestern Indian Ocean may exert a more direct influence on malaria transmission dynamics** than Pacific-based ENSO events. The strong short-term IOSD signal supports the potential for its inclusion in **early-warning frameworks**, enabling health agencies to anticipate and respond to elevated malaria risk before peak transmission seasons.

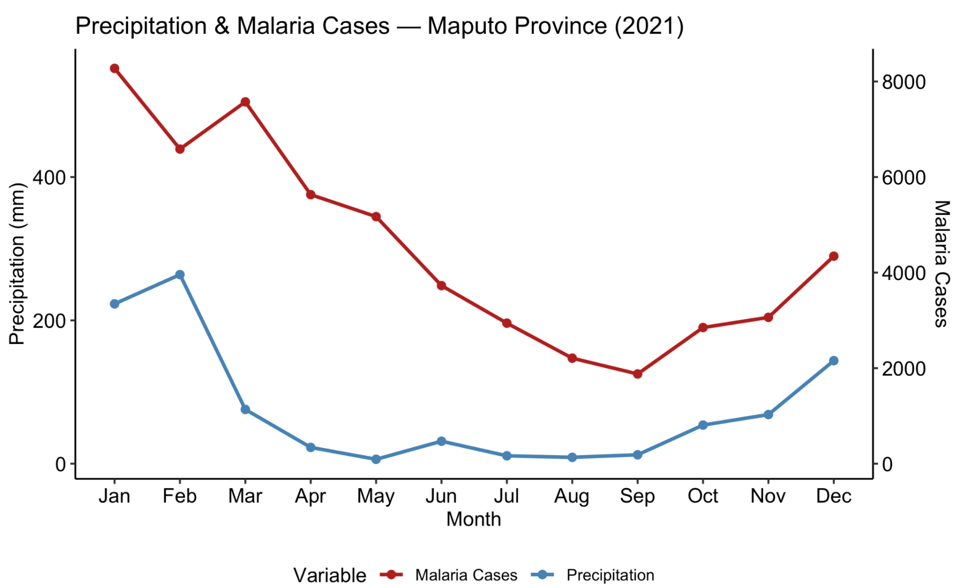
However, these findings are based on a relatively short time series and a single province. **Longer datasets, finer spatial coverage, and integration with entomological and intervention data** are needed to confirm these relationships and understand their variability across different ecological zones.

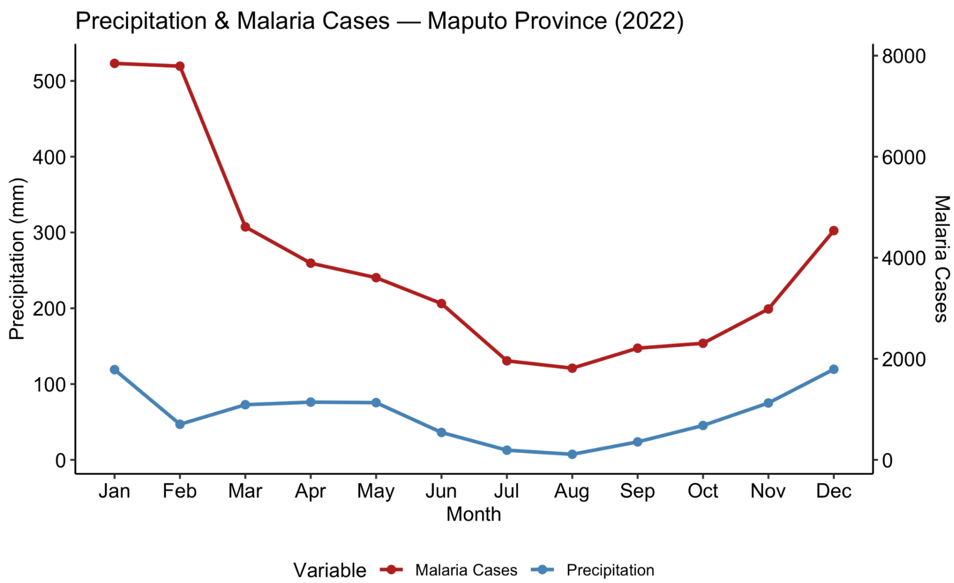
By incorporating both local climate monitoring and large-scale climate indices into malaria surveillance systems, Mozambique's malaria control programs could move toward **climate-informed public health strategies** — a critical step in mitigating the impact of climate variability on one of the country's most persistent health challenges.

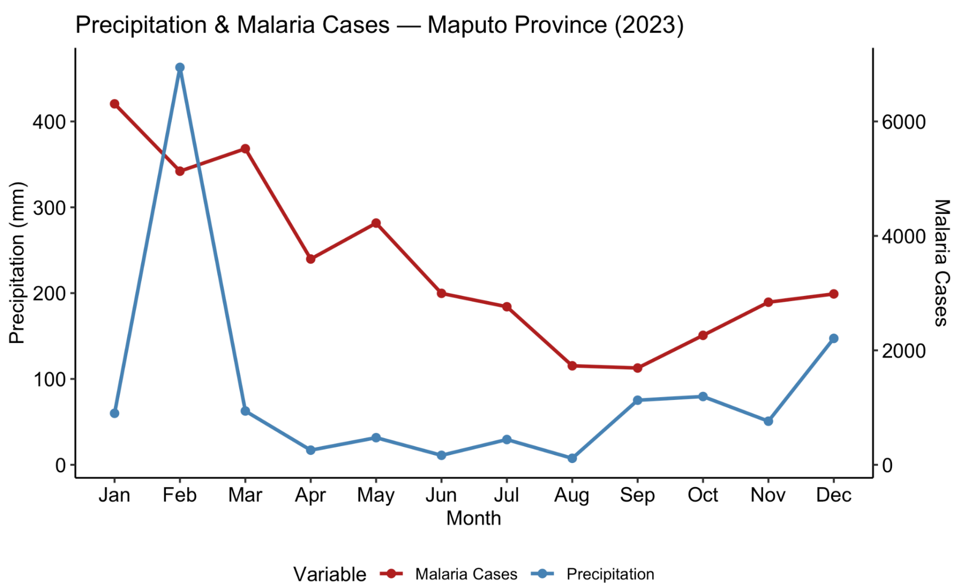
7. Appendix

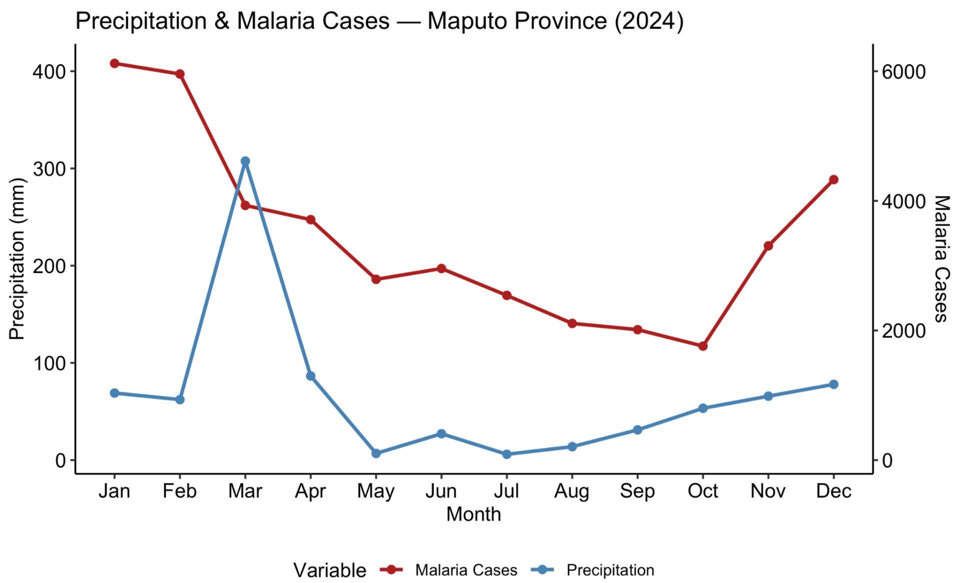
7.1 Precipitation and Malaria Cases:



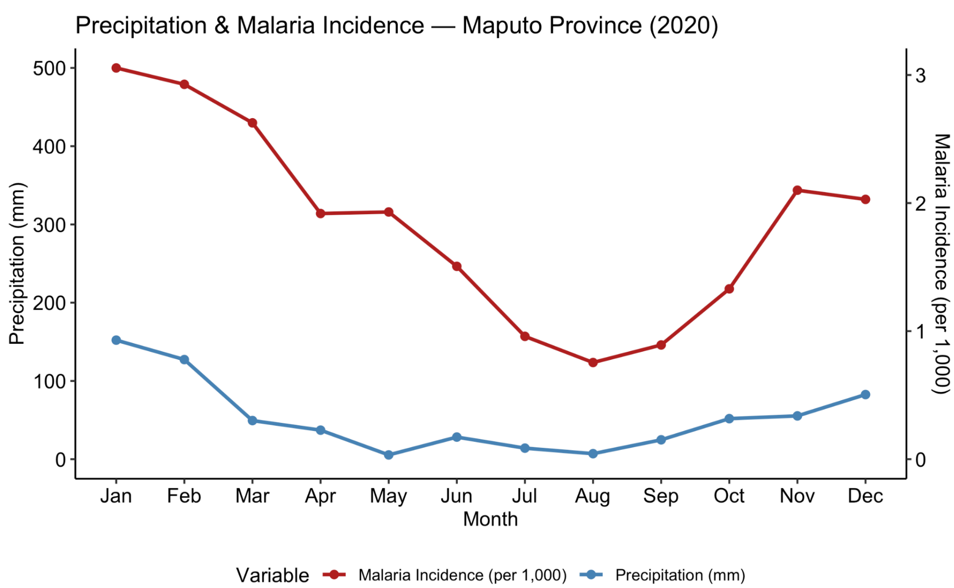


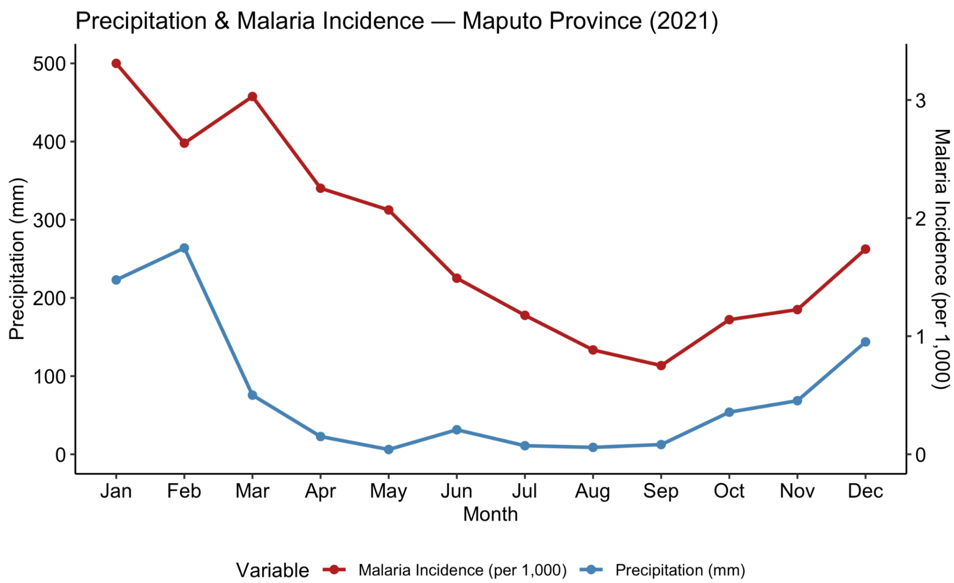

Precipitation & Malaria Cases — Maputo Province (2022)
Precipitation (mm)
Malaria Cases
0
100
200
300
400
500
0
2000
4000
6000
8000
Jan Feb Mar Apr May Jun Jul Aug Sep Oct Nov Dec
Month
Variable
Malaria Cases
Precipitation

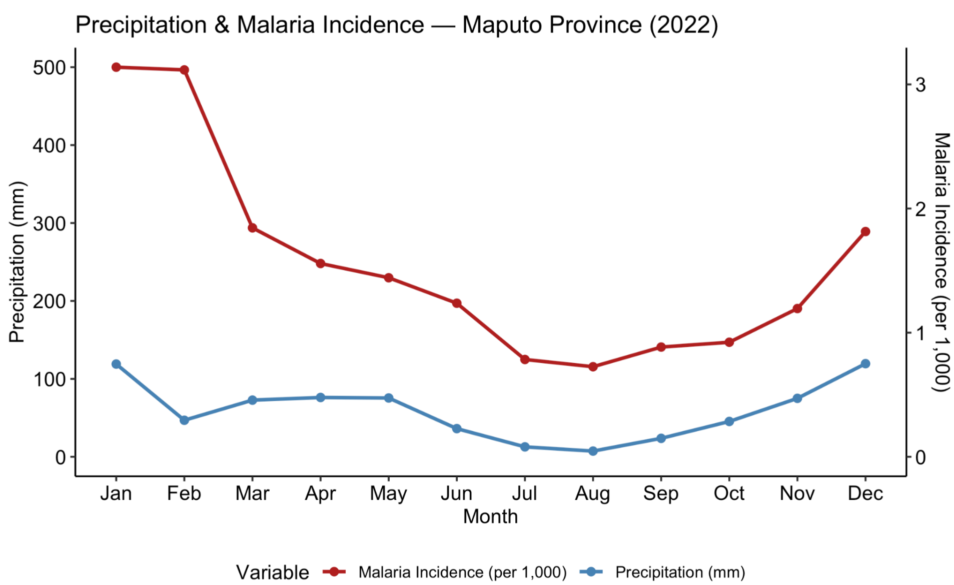

Precipitation & Malaria Cases — Maputo Province (2023)
Precipitation (mm)
Malaria Cases
0
100
200
300
400
0
2000
4000
6000
Jan Feb Mar Apr May Jun Jul Aug Sep Oct Nov Dec
Month
Variable
Malaria Cases
Precipitation

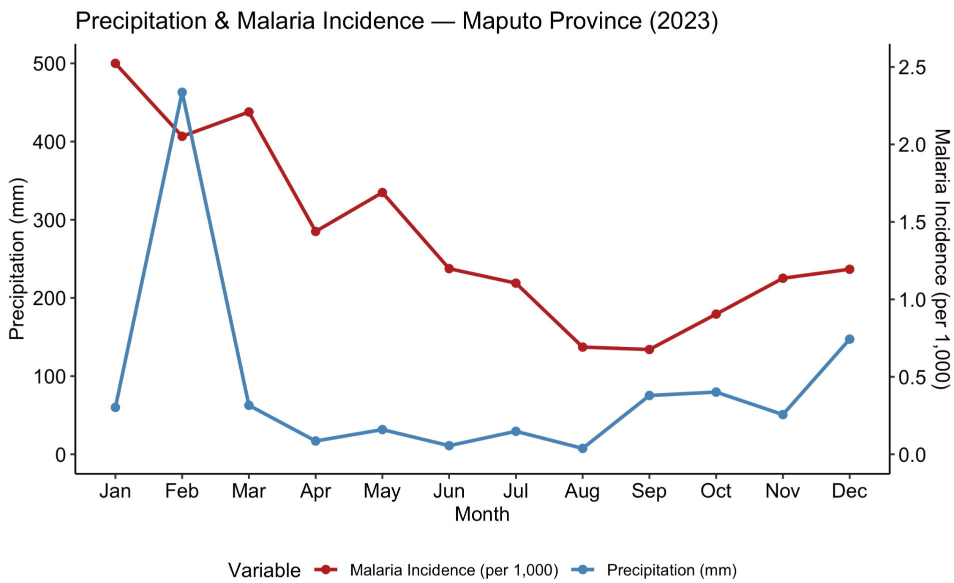


7.2 Precipitation and Malaria Incidence:




Precipitation & Malaria Incidence — Maputo Province (2021)
Precipitation (mm)
Malaria Incidence (per 1,000)
Month
Jan Feb Mar Apr May Jun Jul Aug Sep Oct Nov Dec
Variable
Malaria Incidence (per 1,000)
Precipitation (mm)


Precipitation & Malaria Incidence — Maputo Province (2022)
Precipitation (mm)
Malaria Incidence (per 1,000)
Month
Jan Feb Mar Apr May Jun Jul Aug Sep Oct Nov Dec
Variable
Malaria Incidence (per 1,000)
Precipitation (mm)



Precipitation & Malaria Incidence — Maputo Province (2023)
Precipitation (mm)
Malaria Incidence (per 1,000)
0
100
200
300
400
500
0.0
0.5
1.0
1.5
2.0
2.5
Jan
Feb
Mar
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May
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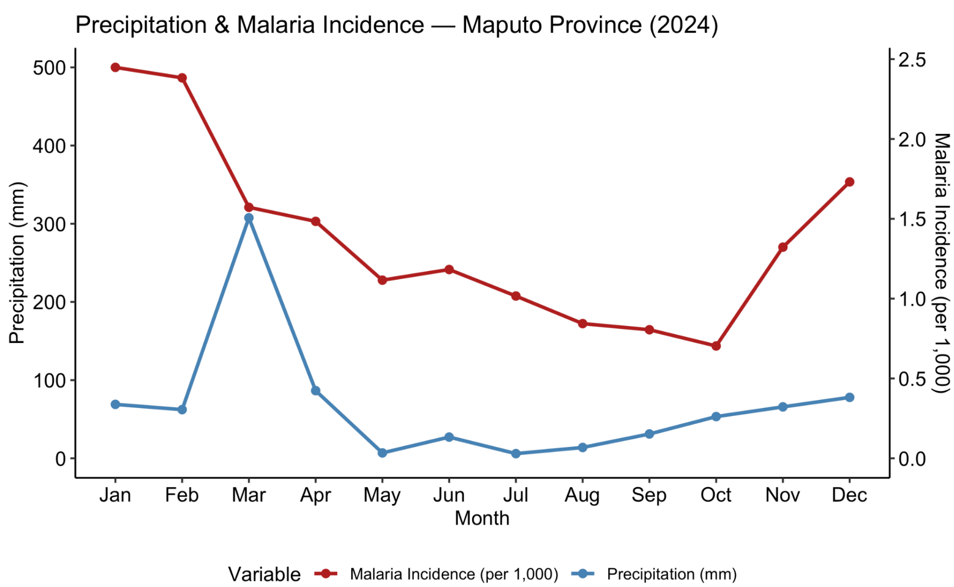
Jul
Aug
Sep
Oct
Nov
Dec
Month
Variable
Malaria Incidence (per 1,000)
Precipitation (mm)



Precipitation & Malaria Incidence — Maputo Province (2024)
Precipitation (mm)
Malaria Incidence (per 1,000)
0
100
200
300
400
500
0.0
0.5
1.0
1.5
2.0
2.5
Jan
Feb
Mar
Apr
May
Jun
Jul
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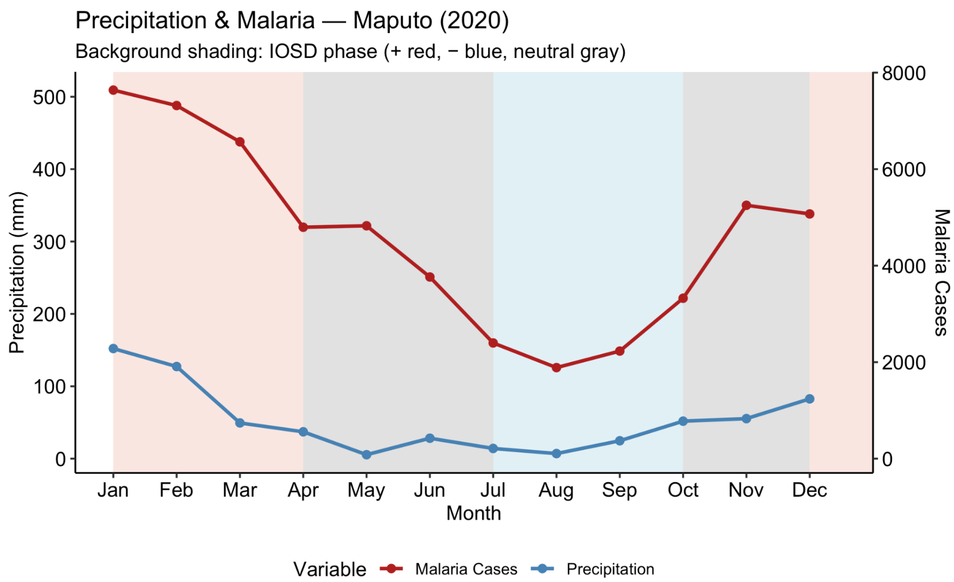
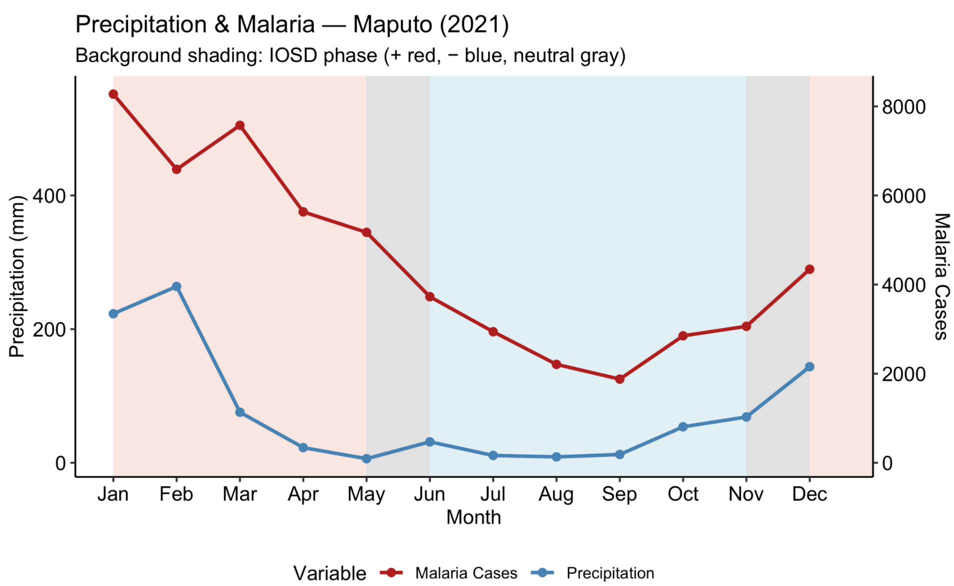
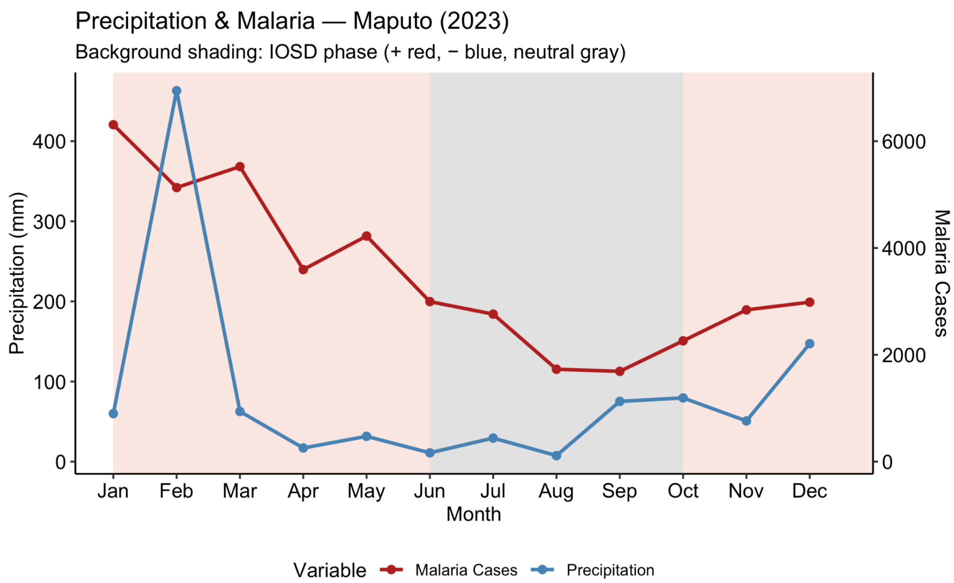
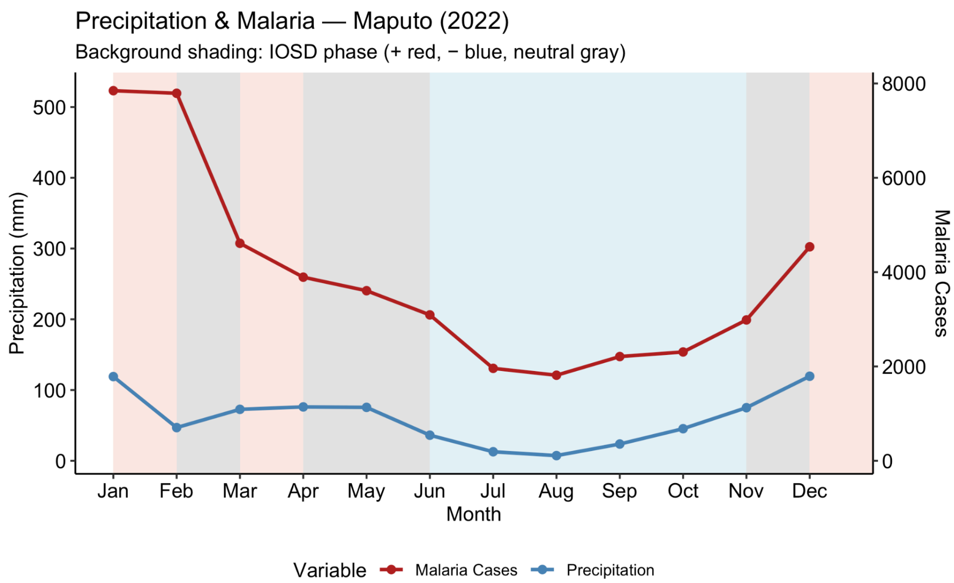
Oct
Nov
Dec
Month
Variable
Malaria Incidence (per 1,000)
Precipitation (mm)

7.3 IOSD and Precipitation + Malaria plots:

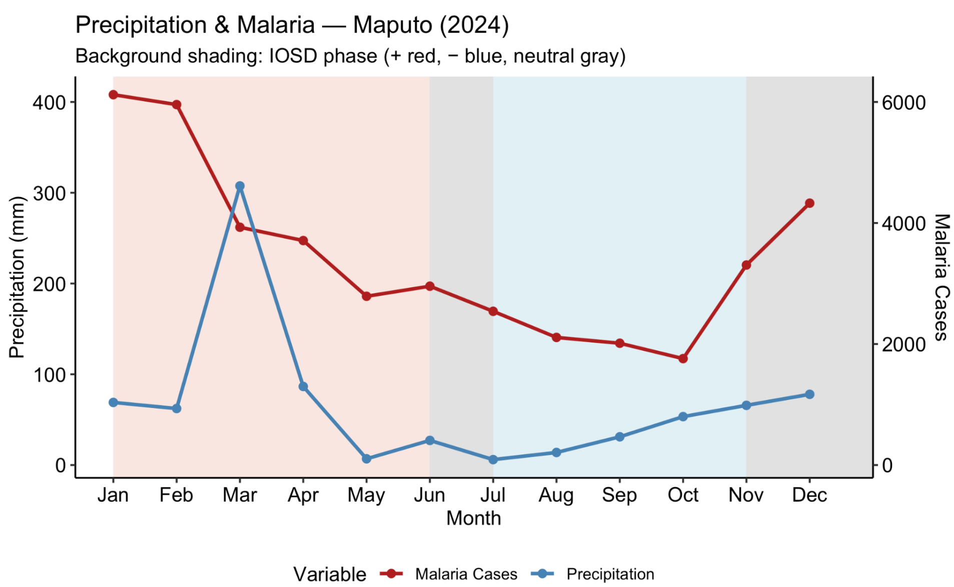





Precipitation & Malaria — Maputo (2023)
Background shading: IOSD phase (+ red, − blue, neutral gray)
Precipitation (mm)
400
300
200
100
0
Malaria Cases
6000
4000
2000
0
Jan
Feb
Mar
Apr
May
Jun
Jul
Aug
Sep
Oct
Nov
Dec
Month
Variable
Malaria Cases
Precipitation

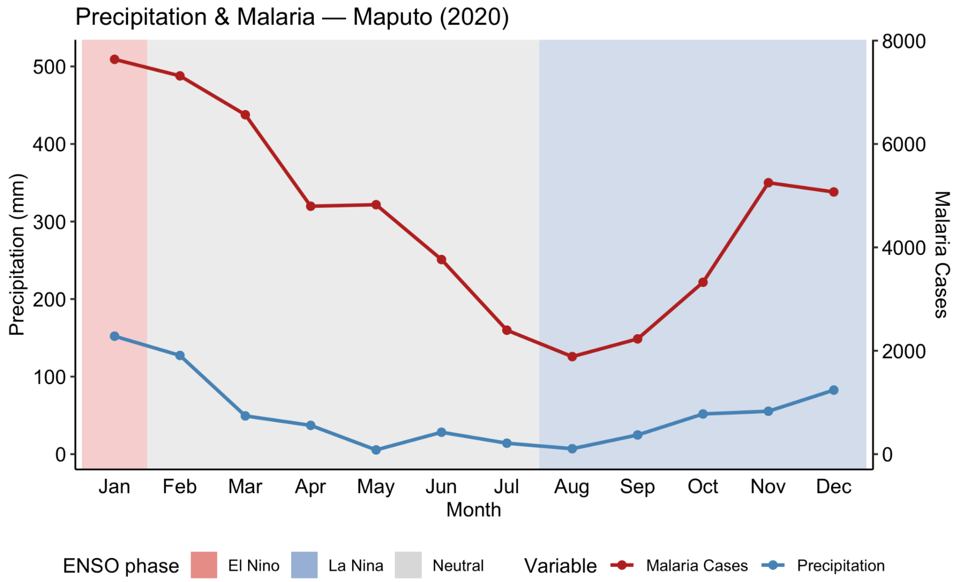


Precipitation & Malaria — Maputo (2022)
Background shading: IOSD phase (+ red, − blue, neutral gray)
Precipitation (mm)
Malaria Cases
0
100
200
300
400
500
0
2000
4000
6000
8000
Jan
Feb
Mar
Apr
May
Jun
Jul
Aug
Sep
Oct
Nov
Dec
Month
Variable
Malaria Cases
Precipitation

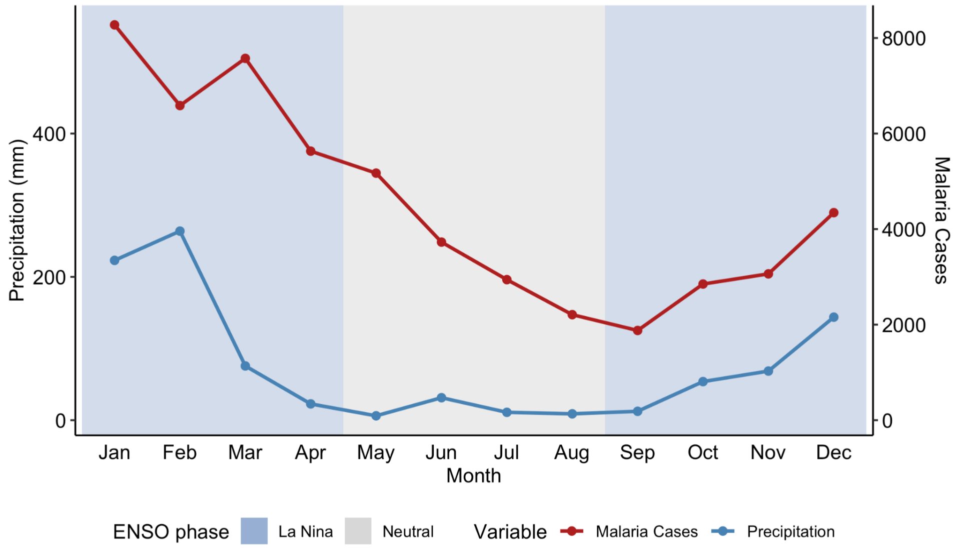


Precipitation & Malaria — Maputo (2024)
Background shading: IOSD phase (+ red, − blue, neutral gray)
Precipitation (mm)
Malaria Cases
0
100
200
300
400
0
2000
4000
6000
Jan
Feb
Mar
Apr
May
Jun
Jul
Aug
Sep
Oct
Nov
Dec
Month
Variable
Malaria Cases
Precipitation

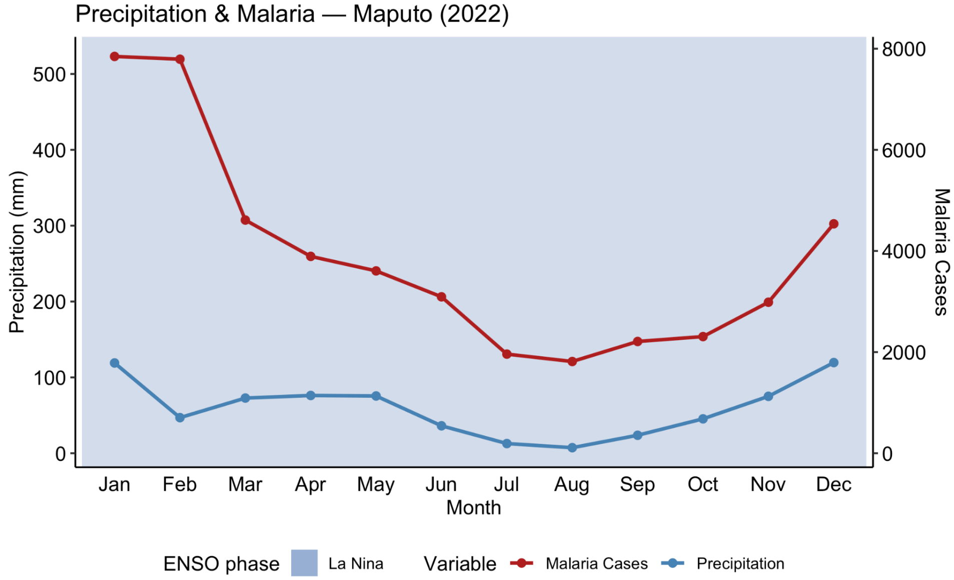
7.4 ENSO and Precipitation + Malaria plots

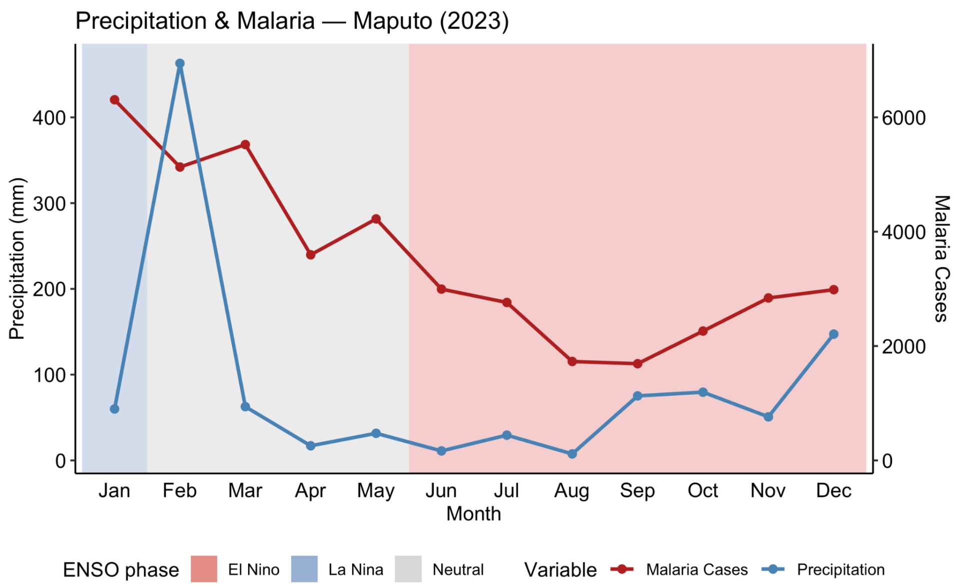


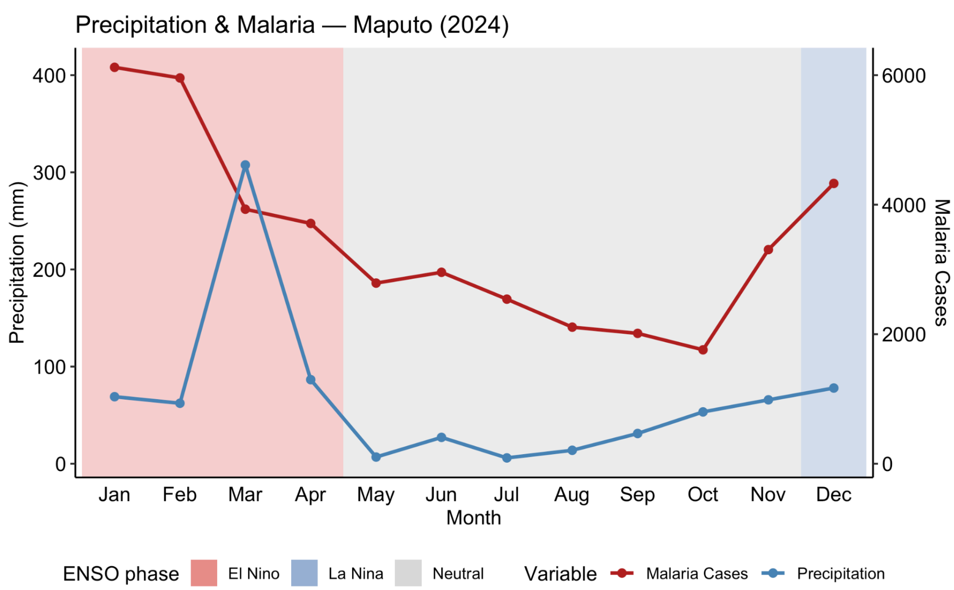
Precipitation & Malaria — Maputo (2021)



Precipitation & Malaria — Maputo (2022)




Precipitation & Malaria — Maputo (2023)
Precipitation (mm)
0
100
200
300
400
Malaria Cases
0
2000
4000
6000
Jan
Feb
Mar
Apr
May
Jun
Jul
Aug
Sep
Oct
Nov
Dec
Month
ENSO phase
El Nino
La Nina
Neutral
Variable
Malaria Cases
Precipitation


Precipitation & Malaria — Maputo (2024)
Precipitation (mm)
0
100
200
300
400
Malaria Cases
0
2000
4000
6000
Jan
Feb
Mar
Apr
May
Jun
Jul
Aug
Sep
Oct
Nov
Dec
Month
ENSO phase
El Nino
La Nina
Neutral
Variable
Malaria Cases
Precipitation

7.5 LInear regression tables

ENSO and IOSD

Driver	Lag	effect	ci_lo	ci_hi	p.value	r.squared	scale_note
ENSO (+1 ONI)	0	-0.09692188255280150	-0.3104652688733940	0.1166215037677910	0.367358883831862	0.014031753012192000	per +1 ONI
ENSO (+1 ONI)	1	-0.14064419390840900	-0.3470994847359450	0.06581109691912730	0.17788401332869400	0.031615117140852400	per +1 ONI
ENSO (+1 ONI)	2	-0.17615943787191700	-0.37573821004762900	0.02341933430379440	0.08247903612900090	0.05287711140606790	per +1 ONI
ENSO (+1 ONI)	3	-0.19370325703779900	-0.389419377854464	0.002012863778865340	0.05232025622856190	0.06675280162664820	per +1 ONI
ENSO (+1 ONI)	4	-0.18603867721524700	-0.3835850900920990	0.011507735661605400	0.06439157284009850	0.061928000970668100	per +1 ONI
ENSO (+1 ONI)	5	-0.16484617687866600	-0.36507496141706800	0.03538260765973500	0.10458931202036200	0.04893192896397960	per +1 ONI
ENSO (+1 ONI)	6	-0.1313924776072370	-0.3356068084578350	0.07282185324336190	0.20238411493386100	0.03106017590830690	per +1 ONI
IOSD (+1 SD)	0	0.46704642071115300	0.31788726560284700	0.6162055758194590	4.91178812218105E-08	0.4038130245233610	per +1 SD (SD=0.916)
IOSD (+1 SD)	1	0.48101396784015800	0.34045586959582200	0.6215720660844940	5.59510068489017E-09	0.4517153959703250	per +1 SD (SD=0.924)
IOSD (+1 SD)	2	0.2987178263473700	0.12958145389812100	0.4678541987966190	8.18631126313981E-04	0.1826894999832820	per +1 SD (SD=0.932)
IOSD (+1 SD)	3	0.05505409700296970	-0.13079995799276800	0.24090815199870700	0.5551849269160150	0.006366687062091800	per +1 SD (SD=0.937)
IOSD (+1 SD)	4	-0.2210732719510850	-0.4006140453130710	-0.041532498589098500	0.016758232454431600	0.10141205465688100	per +1 SD (SD=0.935)

IOSD (+1 SD)	5	-0.41643905270191900	-0.5708979278341850	-0.2619801775696530	1.55628296327813E-06	0.35557200514036900	per +1 SD (SD=0.933)
IOSD (+1 SD)	6	-0.5163588637961250	-0.6499001987928290	-0.3828175287994220	3.0646337036814E-10	0.5365517552416000	per +1 SD (SD=0.934)

Precipitation

estimate	p.value	conf.low	conf.high	r.squared	Lag	Driver	beta_per100	ci_low_per100	ci_hi_per100
0.0038106224206626500	0.0010303229276073100	0.0016038968034334600	0.006017348037891830	0.17081440216437400	0	Precipitation	0.381062242066265	0.16038968034334600	0.6017348037891830
0.00488349132176847	6.86749481542141E-06	0.0029091088771264400	0.006857873766410500	0.3008857621119990	1	Precipitation	0.48834913217684700	0.2909108877126440	0.6857873766410500
0.003093765927372260	0.005654670056493660	9.40388172071451E-04	0.005247143682673080	0.12885548696549000	2	Precipitation	0.3093765927372260	0.09403881720714510	0.5247143682673080
0.0019475165286282100	0.08404656113850100	-2.70622323911361E-04	0.004165655381167780	0.05329095790233780	3	Precipitation	0.19475165286282100	-0.027062232391136100	0.4165655381167780
-1.72205242563418E-04	0.881185049657832	-0.00247117441227437	0.002126763927147530	4.1747242845157E-04	4	Precipitation	-0.017220524256341800	-0.247117441227437	0.2126763927147530
-0.0021958795208033600	0.054966493207324000	-0.0044401776592809200	4.84186176742001E-05	0.06774345716637570	5	Precipitation	-0.21958795208033600	-0.44401776592809200	0.004841861767420010
-0.004039503813580000	2.74141261025182E-04	-0.006115957368705540	-0.0019630502584544600	0.22663809438630800	6	Precipitation	-0.40395038135800000	-0.6115957368705540	-0.19630502584544600

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Bibliography

1. Ikeda, T. *et al.* Seasonally lagged effects of climatic factors on malaria incidence in South Africa. *Sci Rep* **7**, 2458 (2017).
2. Wu, Y. *et al.* Describing interaction effect between lagged rainfalls on malaria: an epidemiological study in south–west China. *Malaria Journal* **16**, 53 (2017).
3. Abiodun, G. J. *et al.* Investigating the Resurgence of Malaria Prevalence in South Africa Between 2015 and 2018: A Scoping Review. doi:10.2174/1874944502013010119.