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The Influence of Climate Variables on Malaria Incidence in Vanuatu

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Abstract: Malaria, a climate-sensitive mosquito-borne disease, is widespread in tropical and subtropical regions, and its elimination is a global health priority. Malaria is endemic to Vanuatu, where elimination campaigns have been implemented with varied success. In this study, climate variables were assessed for their correlation with national malaria cases from 2014 to 2023 and used to develop a proof-of-concept model for estimating malaria incidence in Vanuatu. Maximum, minimum, and median temperatures; diurnal temperature variation; median temperature during the 18:00–21:00 mosquito biting period (VUT); median humidity; and precipitation (total and anomaly) were evaluated as predictors at different time lags. It was found that maximum temperature had the strongest correlation with malaria cases and produced the best-performing linear regression model, where malaria cases increased by approximately 43 cases for every degree (°C) increase in monthly maximum temperature. This aligns with similar findings from climate–malaria studies in the Southwest Pacific, where temperature tends to stimulate the development of both *Anopheles farauti* and *Plasmodium vivax*, increasing transmission probability. A Bayesian model using maximum temperature and total precipitation at a two-month time lag was more effective in predicting malaria incidence than using maximum temperature or precipitation alone. A Bayesian approach was preferred due to its flexibility with varied data types and prior information about malaria dynamics. This model for predicting malaria incidence in Vanuatu can be adapted to smaller regions or other malaria-affected areas, supporting malaria early warning and preparedness for climate-related health challenges.

Keywords: climate variability; vector-borne diseases; malaria; temperature; precipitation; Vanuatu

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1. Introduction

Climate change impacts are expected to exacerbate human health challenges and risks worldwide, particularly in their influence on many infectious diseases [1]. Pacific Island Countries (PICs) have increased vulnerability to climate change and a significant presence of tropical diseases, such as malaria, cholera, and those classed as neglected tropical diseases like dengue and chikungunya [2,3]. Climatic conditions in PICs tend to enhance the transmission of tropical diseases and are projected to increasingly challenge public health systems and impact hard-to-reach populations [4]. Opportunities to support resilience and adaptability to climate-related infectious diseases are a public health priority.

Pathways to achieve this should work to integrate communities and existing infrastructure to form a functional surveillance framework [5].

Malaria, a mosquito-borne infectious disease, is widespread in tropical and subtropical regions including Africa, Asia–Pacific, and South America. The global burden of malaria is influenced by existing inequities and environmental and socioeconomic conditions, and is largely concentrated in populations experiencing intersecting human health threats [6,7]. However, there has been an overall decline in global malaria incidence and deaths since 2000, a reduction in malaria in endemic areas, and a growing number of countries being certified as malaria-free [7]. Still, progress is sensitive to shocks, which have the potential to disrupt access to preventative resources and threaten elimination efforts.

Vanuatu, like other PICs, is particularly susceptible to malaria, largely due to favourable climatic conditions, the high frequency of extreme weather and climate events (EWCEs), and relative geographic isolation, which influences healthcare-associated costs [8,9]. Climate change is expected to exacerbate this vulnerability, acting as an amplifier for existing issues that compound the burden of disease [10,11]. Rising sea levels and changes in temperature, precipitation, and frequency or severity of EWCEs can compromise food security, access to sanitation and water, and functionality of healthcare facilities [12–14]. A large portion of healthcare infrastructure in Vanuatu is coastally distributed and therefore susceptible to multi-hazards from tropical cyclones (TCs). More frequent EWCEs can heighten the need for emergency services, increasing demand from already-strained infrastructure [9,15]. Even without the increased impacts from EWCEs, projected changes for climatic conditions indicate that the climate of Vanuatu will remain within suitable ranges for malaria transmission [9].

In Vanuatu, malaria is transmitted via the mosquito vector *Anopheles farauti* [16]. *An. farauti* is a coastally distributed species, with a spread that largely overlaps with Vanuatu's human population, contributing to high vector exposure risk for much of the population [17–20]. Of the five species of *Plasmodium* parasite that cause malaria in humans, *Plasmodium falciparum* and *Plasmodium vivax* have historically had the highest presence in Vanuatu [21,22]. Currently, *P. vivax* is the dominant malaria strain in Vanuatu [21,23]. Vanuatu has sustained efforts against malaria, launching a variety of elimination and control campaigns over the span of decades, with diverse scale and methods [24–26].

In 2022, the Vanuatu Ministry of Health declared an outbreak in parts of the country, a surge coming after decades of elimination progress [27]. Prior to this, Torba province was a promising target for elimination programmes, following the success of Tafea province declaring elimination in 2017 [28]. However, cases surged in 2022, due to limited healthcare capacity and disruptions to elimination programmes attributed to COVID-19 [5]. While Vanuatu's commitment to control measures and disease surveillance has shown success and restricted malaria distribution to isolated foci, the persistence of *An. farauti*, possibility of compounding hazards, and necessity of inter-island travel mean that national elimination remains challenging [15,29]. Additionally, Vanuatu uses a rapid surveillance approach to malaria, a system that may be limited in capturing distribution in low-transmission and hard-to-reach areas [30]. Continued risk awareness and predictive models developed from climate–malaria interactions are important for promoting elimination efforts.

Major phases of the malaria transmission cycle and its general population dynamics can be influenced by climate variables [31]. Mosquito- and parasite-related traits that interact to influence transmission rate are susceptible to changes in temperature, relating to development, behaviours, and population density [32]. These lifecycle stages influenced by temperature can contribute to greater numbers of infectious adult mosquitoes [33,34]. Precipitation largely impacts the habitat availability for *An. farauti* breeding, and as such is more irregular in its impact on malaria transmission between regions and seasons [35,36]. In Vanuatu, there has been a positive association found between rainfall and case numbers, where rainfall may produce transient habitats, expanding the range of *An. farauti* mosquitoes [37]. In regions where precipitation is more consistent and permanent bodies of water are more readily available, rainfall anomalies are less of a driver for malaria incidence [38]. Humidity, associated with both temperature and precipitation, can also influence malaria incidence [39,40].

Studies from the Southwest Pacific vary in climate–malaria associations. In Papua New Guinea, malaria incidence has been shown to be influenced by temperature and rainfall conditions [35]. This relationship varies regionally, largely based on altitude and vegetation, but increased rates of malaria tend to be observed in provinces with higher annual temperatures and rainfall. Similarly, in the Solomon Islands, Smith et al. (2017) found a strong region-specific correlation between rainfall and malaria [38]. While not endemic for malaria, research on Australian *An. farauti* populations observed a temperature-related change to biting behaviours, where biting activity was more consistent at warmer overnight temperatures over 25 °C [40]. This study, and another in the Solomon Islands, also found higher humidities associated with greater biting and resting densities [39,40]. While these studies provide an indication of which climatic conditions are likely to be significant, specific environmental factors make it difficult to extrapolate to Vanuatu [41]. The climate influence on region-specific social and infrastructure-related impacts of malaria transmission further complicate disease dynamics [10,42].

A model incorporating climate influence on mosquito–parasite interactions and region-specific information can form the basis for malaria forecasting. The potentially lagged relationship between these climate drivers and malaria incidence can be developed into a functional early warning system (EWS) [43,44]. Functioning EWSs for vector-borne diseases should be integrated into existing community practices and health infrastructure to strengthen preparedness for climate-related impacts. As Vanuatu has varying topography, health facilities, and malaria incidence rates, an EWS should be developed specific to this context.

The approach outlined in this study seeks to recontextualise climate and malaria incidence in Vanuatu in the past decade and contribute to developing a usable EWS and analyse a wider range of climate variables and relationships. This study aims to investigate how climate variables correlate with malaria incidence in Vanuatu from 2014 to 2023. Additionally, this study aims to use these findings to develop a proof-of-concept malaria model. This will provide a framework to develop a predictive EWS based on climate variables to support adaptive health decision-making. With climate variability growing in intensity and compounding infectious disease risk, findings that support outbreak resilience and preparedness are crucial.

2. Materials and Methods

Study Area: Vanuatu is a republic that forms an archipelago of 83 islands with ranging elevation in the Southwest Pacific (Oceania), spanning over 1000 km from about 12° S to 22° S (Figure 1). Inter-annual and inter-decadal climate variability is influenced by the El Niño–Southern Oscillation (ENSO) and the South Pacific Convergence Zone [45]. There is low seasonal variation in temperature, where mean monthly temperatures vary by 4 °C, but variation across the country and during seasons is evident [46]. The annual precipitation ranges from approximately 1000 mm to 4000 mm, influenced by latitude and large-scale climate drivers like ENSO; typically, Vanuatu experiences higher rainfall during La Niña years compared to El Niño years. The wet season (November–April) tends to have higher temperatures and rainfall compared to the dry season (May–October) [47].

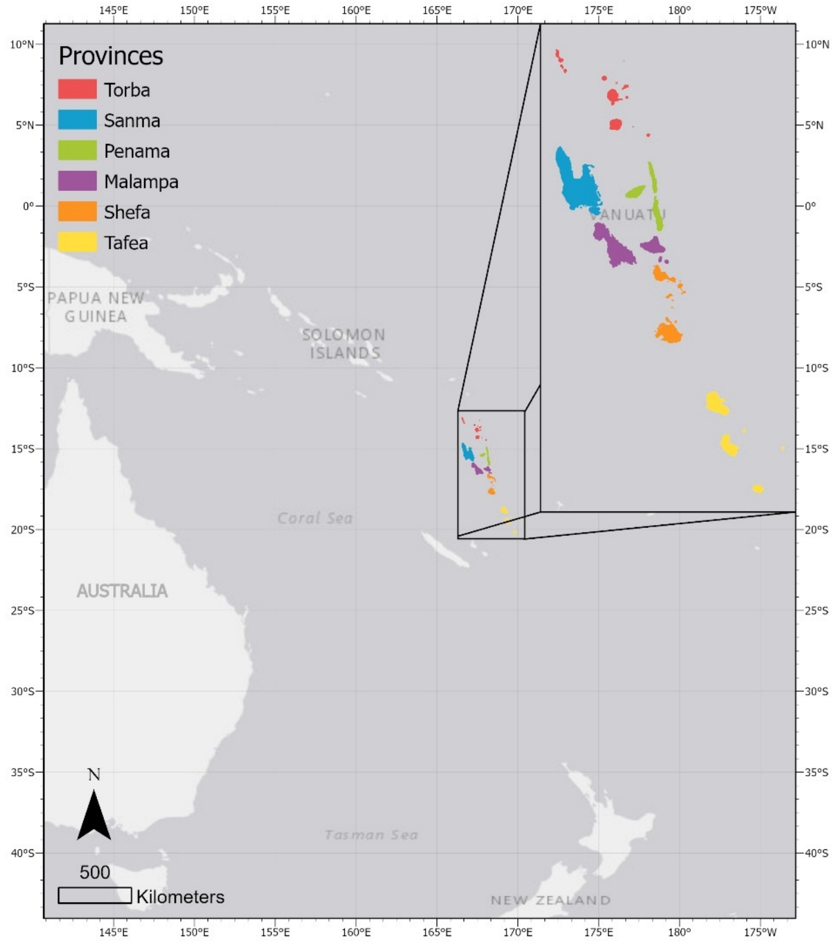


Figure 1. Map of Vanuatu with labelled provinces, showing neighbouring countries.

Across the six provinces, Vanuatu has a predominantly coastally distributed health network of six provincial hospitals and a range of health centres, dispensaries, and community-supported aid posts, with varying diagnostic and treatment capacities [15,23]. Malaria is considered endemic to Vanuatu, with the vector *An. farauti* specifically classed as endemic to every province, leaving provinces susceptible to spikes or resurgences in malaria transmission. One province (Tafea) has been declared malaria-free, and has maintained this state since 2017 [23,48]. This study covers malaria distribution across all Vanuatu provinces.

Malaria Data: The Health Information Systems unit of the Vanuatu Ministry of Health (MoH) manages and stores health data on health facility, provincial, and national scales. The MoH provided anonymised malaria case data for the period of 2014–2023 inclusive. Cases were reported from individual health facilities, recorded from the date treatment began, which were aggregated to a national scale on a monthly basis.

Variables: Variable selection was based on the prior literature, with a particular focus on research conducted in PICs, involving *An. farauti* and *P. vivax*, and using a statistical model approach. While Vanuatu is somewhat different in its geography compared to other PICs, similarities in climatic conditions and vector distribution were still considered to gain an understanding of relevant and promising variables. Variable selection based on the previous literature is described, and Table 1 shows a summary of variables and data sources.

Table 1. Climate variables and data sources used in analysis.

Variable	Data Type	Source	Resolution	Dates
Temperature (maximum, minimum, median, peak biting, diurnal)	Hourly 2 m air temperature	ERA5	0.25°	1/7/2013–31/12/2023
Humidity (median)	Hourly relative humidity at 1000 hPa	ERA5	0.25°	1/7/2013–31/12/2023
Precipitation (total, anomalous)	Three-hourly gauge-adjusted satellite re-analysis precipitation data	MSWEP V2	0.1°	1/7/2013–31/12/2023

All climate variables used were aggregated in latitude–longitude grids over the area of Vanuatu, with subsequent aggregation and analysis using Python (3.11.7) libraries Geopandas (0.14.4) and Matplotlib (3.6.3). Across climate datasets, there were differences in spatial and temporal resolution, but to reflect monthly malaria data, each variable was aggregated to monthly and national values. To ensure that only land data were included, a shapefile of Vanuatu's country boundaries, sourced from Humanitarian Data Exchange (2018), was applied to the grids prior to resampling [49]. All variables were resampled at lags from zero to six months (for example, a one-month lag in precipitation compares total precipitation from 1 to 31 December 2013 to malaria cases from 1 to 31 January 2014) and were assigned the final date of each calendar month to align with malaria data (VUT).

Temperature: In this study, five temperature variables were selected for investigation. Maximum, minimum, and median temperatures are often found to have high significance in malaria dynamic studies, attributed largely to an influence on mosquito and parasite life-cycle factors, such as extrinsic incubation period (EIP) and gonotrophic cycle length [31,50]. Diurnal temperature variation, which is the difference between the maximum and minimum daily temperatures, was chosen to capture fluctuation, and has been reported to influence parasite dynamics [32,41]. Peak biting temperature was selected for observations in the prior literature, showing its influence on mosquito biting and resting dynamics, likely having a shorter-term effect on malaria incidence [40]. In this study, peak biting time has been defined as 18:00–21:00 (VUT). Median peak biting time (subsequently referred to as 'peak biting') captures the median temperature during the period when *An. farauti* is expected to be most active. This has not been identified as a variable in previous Pacific-based predictive models. The European Centre for Medium-Range Weather Forecasts Reanalysis Version 5 (ERA5) data were used for calculating temperature-related variables [51]. ERA5 uses reanalysis combining model data with observations to form a global gridded dataset at 0.25° resolution at hourly intervals.

Humidity: Humidity, while potentially having high collinearity with both precipitation and temperature, was chosen as a variable of interest. Median humidity has previously been shown to influence biting rates and mosquito growth dynamics [39,40]. For humidity variables, ERA5 relative humidity datasets were used. For aggregation, relative humidity data at 1000 hPa were used.

Precipitation: Precipitation has varied associations with malaria incidence and has a more physical impact on malaria incidence by moderating larval habitat availability. Total precipitation, measuring the sum precipitation over a month, has previously been used to indicate larval habitat availability [35,36,38]. Precipitation anomaly, calculated by comparing monthly rainfall within the study period to a 30-year baseline (1991–2020), may be more indicative of rainfall experienced accounting for seasonality [52]. All precipitation variables were resampled and aggregated based on data sourced from Multi-Source Weighted-Ensemble Precipitation (MSWEP V2), a global precipitation dataset that provides sub-daily precipitation estimates at a 0.1° resolution [53]. MSWEP V2 merges satellite, reanalysis, and gauge observations into estimates, enhancing performance in a variety of regions. Precipitation is measured in mm per day.

Correlation Analysis: For each climate variable lagged from zero to six months, Spearman correlation matrices were created, using SciPy (1.11.4). These describe potential collinearity between variables, and those with the highest correlation with malaria cases. For subsequent regression analysis, multivariate models were compared, with a preference for variables showing higher correlation with malaria cases, and lower collinearity with other variables. As the strongest correlations were observed at zero-, one-, and two-month lags, only these variables were further examined for regression analysis.

Regression Analysis: To understand the potentially predictive relationship between climate and malaria in Vanuatu, regression analysis using generalised linear modelling (GLM) single and multiple regression was performed, using StatsModels (0.14.0). Gaussian GLM regression was used to indicate which variables had the strongest predictive relationship with malaria cases, and to determine if the combination of multiple variables had improved predictability. Collinearity was measured by variance inflation factor (VIF), with a score of VIF < 5 being sufficient.

Bayesian Modelling: Bayesian modelling was used to produce predictive models with specific distribution methods for each variable chosen, developed using PyMC (5.15.1). Malaria cases were modelled using a negative binomial distribution, which accounts for overdispersion in non-zero count data. Precipitation variables were modelled using a gamma distribution, suitable for continuous, positively skewed data. Temperature variables were modelled assuming a normal distribution. Posterior probability combines this prior information, and results were summarised and visualised, comparing modelled malaria cases to observed. Models were compared using highest density intervals (HDIs) and Leave-One-Out (LOO) Cross-Validation. The modelled Equation (1), modified for time lags, is as follows:

$$\begin{gathered} Y_m \sim \text{Negative binomial } (\mu, \alpha) \\ \mu_m = \text{intercept} + \beta_1 \times \text{maximum temperature} + \beta_2 \times \text{total precipitation} \end{gathered} \tag{1}$$

where Y is the number of malaria cases for the month m, and β_1 and β_2 are the coefficients for maximum temperature and total precipitation, respectively.

3. Results

3.1. Descriptive Analysis

There is spatial and temporal heterogeneity between provinces, both in climatic conditions and malaria incidence over the study period. There is variation in precipitation experienced by each province (Figure 2).

Typically, northern provinces experience higher annual rainfall, ranging upwards of 3000 mm, while southern islands receive closer to 2000 mm. There is inter-annual variation in the total precipitation across Vanuatu; e.g., in 2022, all provinces experienced higher annual rainfall than in 2017. A summary table of climate variable descriptions across the study period is included in Appendix A.

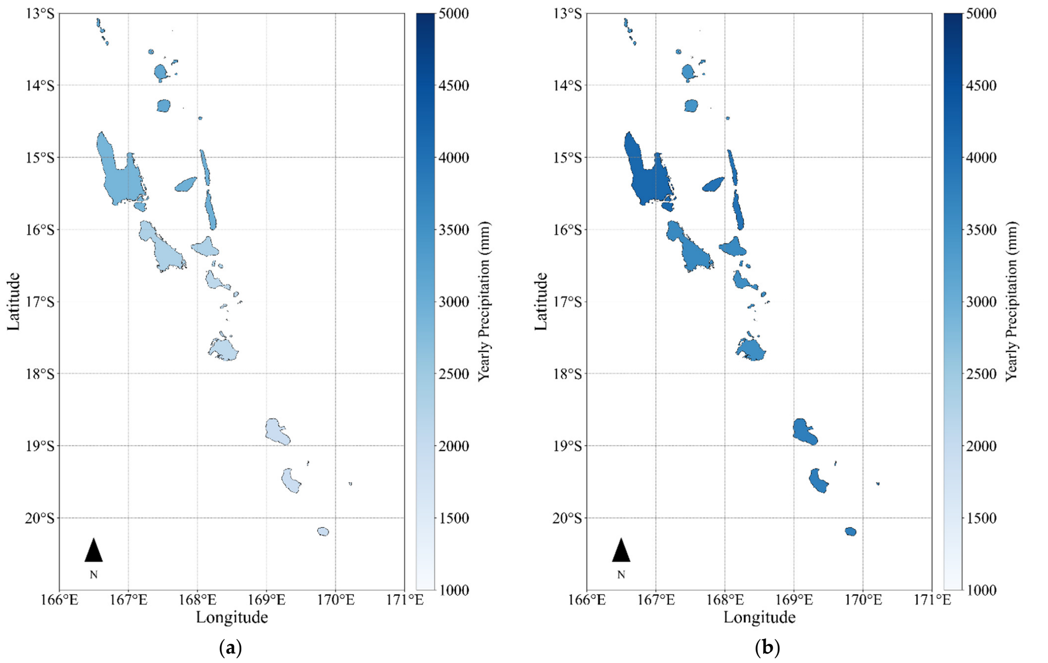


Figure 2. Total annual precipitation (mm) aggregated for each Vanuatu province for (**a**) 2017 and (**b**) 2022.

Figure 3a,b shows the transmission of malaria proportional to the population of each province, where the annual parasite index (API) represents malaria cases per 1000 population, in 2017 and 2020, respectively. Malampa and Sanma (refer to Figure 1 for the locations of provinces) show the highest API over both years, though the population of Sanma is larger by approximately 20,000 people and therefore has a higher total case count. In 2017, both provinces had an API higher than 10, decreasing in 2020 from 13.7 to 3.4 in Malampa, and 10.9 to 4.6 in Sanma. Torba had the highest API in 2022, increasing from no malaria incidence in 2017 to an API of approximately 23 in 2022.

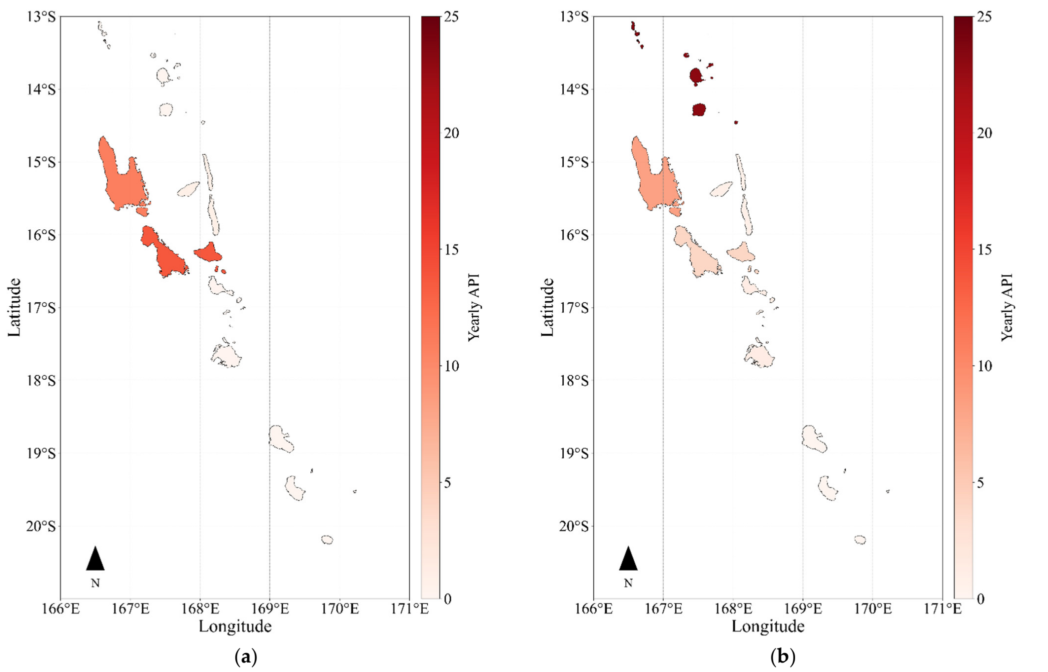


Figure 3. Annual parasite index measured in total reported cases per 1000 population in each Vanuatu province for (**a**) 2017 and (**b**) 2022.

Malaria cases were found to show a seasonality in Vanuatu, peaking from February to April during the latter half of the wet season, and were at their lowest from August to October, towards the end of the dry season (Figure 4). Throughout the study period, there was an overall decline in cases, until spikes in 2022, peaking in 2023.

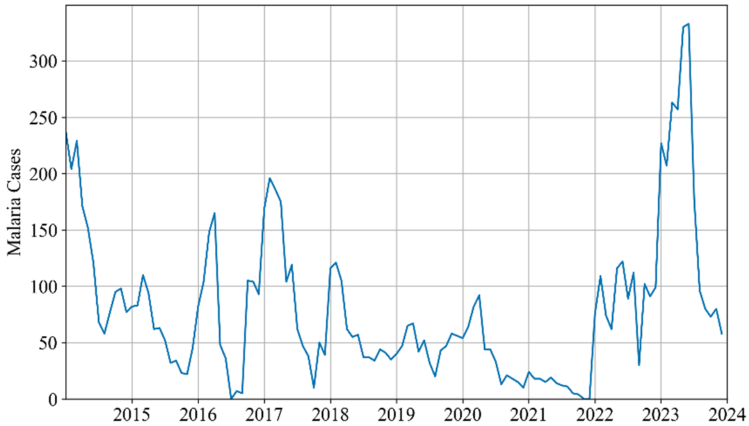


Figure 4. Monthly national malaria cases for Vanuatu from 2014 to 2023 inclusive.

3.2. Correlation Matrices

Across time lags from zero to four months (where lag refers to the time difference between prior climate conditions and malaria case numbers), climate variables were shown to have a positive relationship with malaria incidence, with the exception of diurnal temperature. Maximum temperature had the strongest overall correlation across time lags, highest at a one-month lag (rho = 0.52, $p < 0.001$), as shown in Table 2. This was followed by median temperature and median peak biting temperature (both with values of rho = 0.50, $p < 0.001$), showing moderately positive correlation. Higher temperatures and humidity and rainfall levels within a moderate range of conditions experienced in Vanuatu were correlated with increased malaria incidence.

Table 2. Spearman correlation matrix comparing climate variables at a one-month lag to Vanuatu monthly malaria cases, showing variable medians (Med), interquartile ranges (IQRs), and rho values (−1.0 < rho < 1.0). Significance (p values) are included in parentheses if $p > 0.05$.

	Variable	Med	IQR	1	2	3	4	5	6	7	8
1.	Cases	62	69.25								
2.	Max Temperature	27.14	1.25	0.52 *							
3.	Min Temperature	23.00	1.88	0.46 *	0.96 *						
4.	Med Temperature	25.54	1.80	0.50 *	0.99 *	0.97 *					
5.	Peak Biting	25.17	1.72	0.50 *	0.98 *	0.96 *	0.99 *				
6.	Diurnal Temperature	4.20	0.84	−0.31 *	−0.69 *	−0.83 *	−0.74 *	−0.75 *			
7.	Med Humidity	80.51	6.37	0.33 *	0.70 *	0.71 *	0.72 *	0.75 *	−0.65 *		
8.	Precipitation Anomaly	−29.11	141.95	0.05 (0.57)	0.09 (0.31)	0.07 (0.45)	0.09 (0.32)	0.14 (0.12)	−0.14 (0.13)	0.53 *	
9.	Total Precipitation	192.31	219.94	0.35 *	0.65 *	0.64 *	0.66 *	0.69*	−0.55 *	0.86 *	0.74 *

* $p < 0.05$.

The strongest positive correlations were all found at a one-month lag, with the exception of precipitation anomaly (rho = 0.05, $p = 0.57$) and diurnal temperature variation, which had a moderately negative correlation with malaria cases (rho = −0.31, $p < 0.05$). Correlations between climate variables and malaria became weaker and less statistically significant between three- and six-month lags (Appendix B). Precipitation anomaly was the only variable to show no correlations with malaria that reached statistical significance ($p > 0.05$), a variable that may not capture rainfall seasonality. Zero- and two-month lagged matrices can be found in Appendix B.

The variables showing the strongest correlation with malaria cases at zero-, one-, and two-month lags were selected for single and multiple linear regression analysis. For multiple regression analysis, variables showing the least collinearity (temperature and precipitation) were preferred.

3.3. Generalised Linear Model Regression Analysis

The best-performing univariate regression model used one-month lagged maximum temperature, indicating that for every one degree (°C) increase in maximum monthly temperature, within the study period temperature range, malaria cases would increase by 42.51 (±6.92). The maximum temperature (Max T) model had the lowest Akaike information criterion (AIC) at 1321.56, indicating the best comparative fit and was statistically significant. Table 3 shows the non-standardised variables and results for the best-performing model of each time lag.

Table 3. Summary table of the best-performing Gaussian single linear regression model comparing Vanuatu monthly malaria cases and temperature variables at each time lag.

Time Lag (Months)	Variables	Coefficient	0.025 CI *	0.975 CI	Standard Error	P > ∣z∣	AIC **
Zero	Max T	31.75	17.28	46.22	7.38	0.00	1337.37
One	Max T	42.51	28.94	56.08	6.92	0.00	1321.56
Two	Max T	38.30	24.34	52.27	7.13	0.00	1328.56

* Confidence interval; ** Akaike information criterion.

The best-performing multivariate regression model used one-month lagged variables, with an AIC value of 1323.35. In a multivariate model using maximum monthly temperature and total monthly precipitation, maximum temperature had a stronger relative impact on malaria cases than precipitation at all time lags (Table 4). Precipitation had relatively low explanatory power in any multivariate model (coefficient of −0.02 in the one-month lagged model) and had low significance ($p > 0.05$). Maximum temperature and total precipitation had low VIF scores (VIF < 5), indicating low multicollinearity.

Table 4. Summary table of the best-performing Gaussian multivariate linear regression model comparing Vanuatu monthly malaria cases and paired temperature–precipitation variables at each time lag.

Time Lag (Months)	Variables	Coefficient	0.025 CI *	0.975 CI	Standard Error	P > ∣z∣	AIC **	VIF ***
Zero	Max T Precipitation	27.47 0.04	9.33 −0.06	45.62 0.13	9.26 0.05	0.00 0.44	1338.76	3.30
One	Max T Precipitation	44.90 −0.02	27.76 −0.11	62.05 0.07	8.75 0.04	0.00 0.65	1323.35	3.32
Two	Max T Precipitation	34.97 0.03	17.27 −0.06	52.66 0.12	9.03 0.05	0.00 0.55	1330.19	3.38

* Confidence interval; ** Akaike information criterion; *** variance inflation factor.

3.4. Bayesian Modelling

Models at all lags using maximum temperature and total precipitation showed model convergence and model fit, though the two-month lagged model showed slightly better fit (LOO = −640.77) (Table 5). Each model similarly showed increases in malaria cases for each unit increase in the temperature and precipitation variables, with proximal highest density intervals. Each unit increase in two-month lagged maximum temperature (°C) and total precipitation (mm), respectively, increases malaria cases by 1.39 (94% HDI 0.89, 1.93) and 0.19 (94% HDI 0.11, 0.28). Markov chain Monte Carlo diagnostic parameters of effective sample size (ESS) bulk and tail indicate sufficient sampling and convergence of chains.

Table 5. Summary table of the coefficients, 94% highest density intervals, Markov chain Monte Carlo performance and model performance for Bayesian models comparing monthly maximum temperature and total precipitation to monthly national malaria cases at each time lag.

Time Lag (Months)	Variable	Mean	94% HDI *	ESS ** Bulk	ESS Tail	LOO ***
Zero	Intercept	0.07	(−1.77, 1.96)	2467.0	2313.0	−644.72
	Temperature	1.68	(1.12, 2.23)	1661.0	1766.0	
	Precipitation	0.16	(0.08, 0.24)	1595.0	1967.0	
One	Intercept	0.06	(−1.77, 1.97)	2051.0	2280.0	−642.69
	Temperature	1.52	(0.96, 2.12)	1654.0	1904.0	
	Precipitation	0.18	(0.10, 0.27)	1864.0	1826.0	
Two	Intercept	0.03	(−1.86, 1.94)	2196.0	2346.0	−640.77
	Temperature	1.39	(0.89, 1.93)	1879.0	1957.0	
	Precipitation	0.19	(0.11, 0.28)	1956.0	1587.0	

* 94% highest density interval; ** effective sample size; *** Leave-One-Out Cross-Validation.

The posterior predictive plot for the two-month lagged model qualitatively indicates good model fit (Figure 5). The data predicted by the model follow a similar distribution type as the observed cases for the study period. Figure 6 further shows a qualitative visualisation of predictive capacity of the model, plotting mean effects of two-month lagged climate variables with the observed malaria cases of the study period.

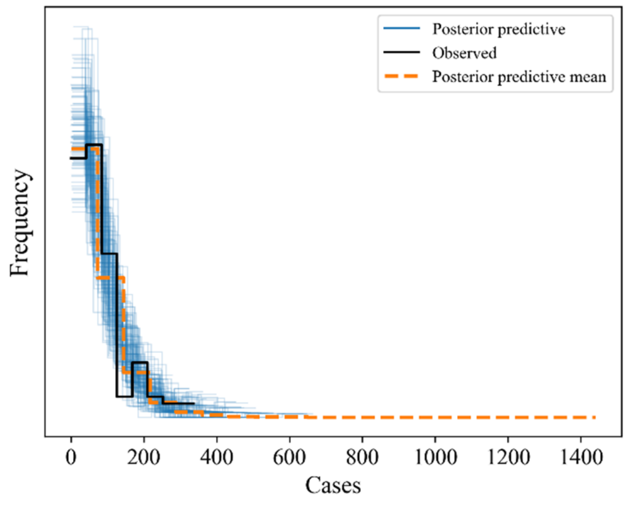
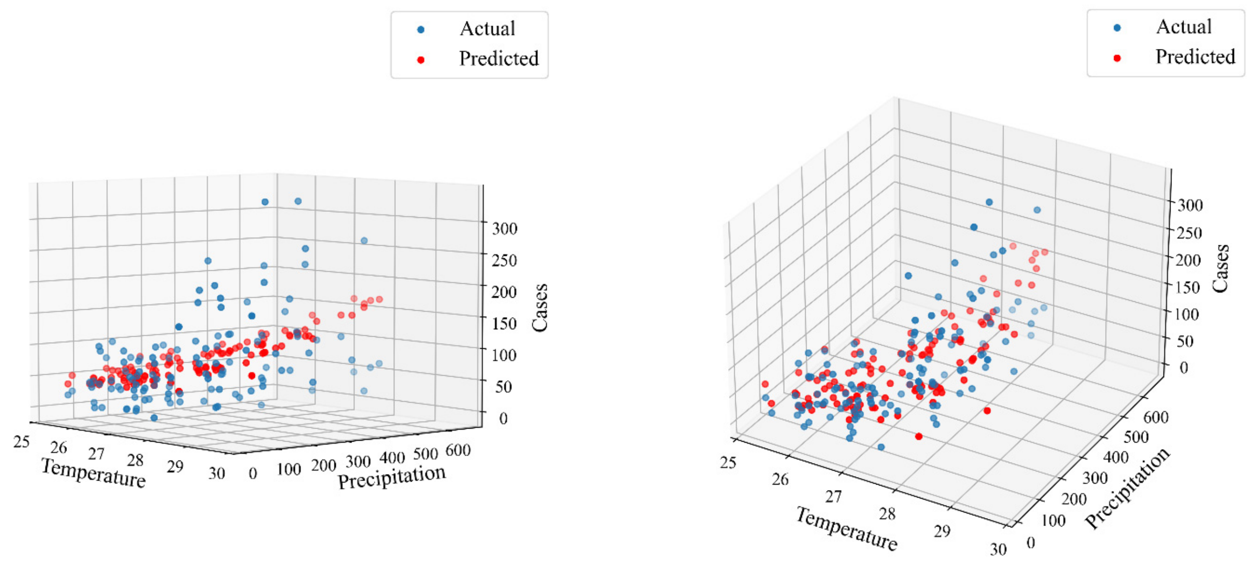


Figure 5. Posterior plot showing observed national malaria cases and Bayesian model-predicted cases from 2014 to 2023. The predictive model is based on monthly maximum temperature and monthly total precipitation from two months prior.

A mixed Bayesian model using two-month lagged maximum temperature and total precipitation appears to predict malaria cases within a plausible range. Within the probabilistic plot, the predicted and observed cases occupy a similar range, and share similar areas of higher density. There is more variability in the observed cases than predicted, with limited prediction for periods of especially high or low incidence.



(a) (b)

Figure 6. Two angles of a 3D scatterplot comparing observed national malaria cases and Bayesian model-predicted cases 2014–2023 for (**a**) side view and (**b**) top view. The predictive model is based on monthly maximum temperature and monthly total precipitation from two months prior.

4. Discussion

4.1. Malaria Incidence

Malaria incidence is influenced by a range of climate, geographical, and socioeconomic factors that vary greatly between regions, and as such, effective surveillance and prevention measures should be specific. Variation in climate and malaria burden across regions, and even within islands, will affect risk, but geographical and socioeconomic factors are likely to also be impactful [2].

Variation in climate factors and malaria burden across islands means that the effectiveness of a generalised approach to surveillance and control is likely limited. Vanuatu experiences higher levels of rainfall in the northern islands (Figure 2). Rainfall impact on malaria can be highly specific to environmental conditions, an association that can vary on a fine spatial scale. Research in Papua New Guinea found differing associations with rainfall and malaria across study locations, largely based on differences in topography [35,36]. Similarly, research focused on northern Guadalcanal in the Solomon Islands speculated that the negative association between rainfall and malaria observed in the low-lying flat plains may not apply in regions with more rugged terrain and less-permanent waterways [38]. Physical factors such as altitude and distance from waterways have been studied in the Southwest Pacific, generally showing a negative association with malaria incidence [35,54,55].

Social determinants and historical presence of malaria transmission differ regionally. Malampa and Sanma, as shown in Figure 3, have the highest overall rates of transmission across the study period. Despite the *An. farauti* vector being present in all islands, rates of malaria differ widely across Vanuatu [16]. Malampa, Penama, and Tafea have similar population sizes yet varied API, which, in the case of Tafea, is attributed to successful specialised elimination campaigns [56]. Torba, also showing low API, had elimination campaign progress over the past decade, until spikes in 2022 [5,26].

Before disruptions to malaria-specific healthcare and programmes following COVID-19 outbreaks in Vanuatu in 2022, there was a national downward trend in yearly incidence, shown in Figure 4 [7,26]. This was likely due to successful control efforts over the period, rather than climate influence [5,15]. Elimination progress and malaria programme funding (largely from government and the Global Fund), or disruptions to these services, were not quantified in this study [23]. Other social factors, such as population density, travel between islands, and community risk perception, are also potential drivers in Vanuatu [22,26,29]. Future research could attempt to incorporate social determinants into climate-based predictions. Additionally, EWCEs and competing public health crises may all contribute to variable risk, and may be quantified in further research [5,57]. Environmental (EWCEs and geographical variation) and socioeconomic drivers not addressed by climate variables may be critical to malaria transmission in the Southwest Pacific, and should be considered in modelling and planning.

4.2. Correlation and Regression Analysis

Of all climate variables, temperature-related variables had the highest correlation with malaria incidence. Influence of temperature has been linked to a wider number of lifecycle stages and behavioural factors [31,43]. Maximum temperature and median temperature showed the highest correlation at all time lags. In this study, diurnal temperature variation was the only variable to show a negative correlation with malaria cases at all time lags. As the daily temperature fluctuation increases, particularly at higher temperature ranges (26–30 °C), malaria incidence tends to decrease, related to slowed rates of parasite maturation and reduced mosquito populations [32,33]. At a finer resolution, this effect may be more observable.

Median peak biting temperature and median temperature performed similarly to each other and likely capture similar influences on malaria dynamics [39,58]. In future research, peak biting temperature will likely be discarded in preference for median temperature. Studies in the Southwest Pacific region, namely in Papua New Guinea, the Solomon Islands and Vanuatu, generally found positive associations between temperature and malaria [24,35,47]. Relative humidity performed similarly to total precipitation but had a higher collinearity with temperature variables. While higher relative humidities have been associated with increased resting and biting densities, this effect has also been associated with temperature variables [39,40].

Precipitation anomaly is another key variable of interest, showing variation in correlation across studies in the Southwest Pacific [17,59,60]. The correlation found in this study was weak and did not reach statistical significance, which may be related to the importance of seasonal precipitation in malaria transmission rather than variation within those seasons [38]. Precipitation anomaly may be a strong variable when accounting for periods of EWCEs, such as TCs or droughts, and may be re-investigated with particular case studies, such as periods where EWCEs may have impacted malaria healthcare systems in Vanuatu, or in neighbouring countries [56,61,62].

Precipitation variables would likely benefit from more detailed descriptions of the physical environment malaria is being modelled within [35,38]. Comparatively, the effect of temperature is further removed from the physical environment [33,41,58]. However, the influence of both variables on malaria incidence has been previously shown to differ when accounting for altitude [35,54,60]. This is typically through a negative association between increased altitude and temperature, and the impact of topography on region-specific rainfall patterns. As the climate data were aggregated to a national scale, this effect has not been captured in correlation analysis or modelling.

Regression models taking the best-performing variables showed slightly better performance at a one-month lag. All six models (considering univariate and multivariate) had AIC values in a close range and performed similarly. This is likely due to a reliance on maximum temperature as a driver of malaria incidence, reducing the relative explanatory power of total precipitation despite it having moderate correlation with malaria incidence. Both variables are on different scales, where one °C change in temperature (modelled to increase cases by 44.90) is more significant than one mm change in total precipitation, so scaling may improve the influence of precipitation in further modelling. Alternatively, the Gaussian GLM approach assumes the same data distribution for malaria cases, temperature, and precipitation, which may limit precipitation performance as a variable.

4.3. Bayesian Model for Malaria Prediction

Although the relationship between temperature, precipitation, and malaria incidence has been established, the extent to which a GLM distribution accurately model relationships may be limited [35]. In comparison, Bayesian models allow for more flexibility in distributions, using different distributions and unique information for each variable [63]. This model incorporated a Negative Binomial distribution for malaria cases, suitable for overdispersed count data, and a Gamma distribution for skewed, continuous precipitation data. The developed model indicates that precipitation and temperature, using appropriate distributions, can to some extent predict malaria incidence (Figure 6). The model produced showed a similar distribution of predicted malaria cases to observed cases, showing a promising proof of concept for a malaria EWS in Vanuatu.

Similarly to the GLMs, total precipitation had less influence on malaria cases in the model than maximum temperature but did have an effect, more so than in the GLMs (ranging from 0.16 to 0.19 at different time scales). All models had similar performance, but the two-month lagged model had an LOO value slightly closer to zero and was used in further visualisation (Table 5).

The model has limited prediction at the extremes of malaria incidence in the dataset, though this would be expected to improve using data with higher spatial resolution. The proof-of-concept model predicts malaria incidence using monthly values aggregated to a national scale, which does not account for region-specific climate conditions and malaria burden. Therefore, a provincial model would likely be more indicative of climate–malaria relationships and have improved predictive performance.

When considering a smaller-scale model, the prior distributions suitable for national datasets may not be applicable. Each province may have different variables driving malaria incidence and showing higher predictive skill, requiring further model experimentation. A Bayesian approach to climate-based malaria predictions also incorporates uncertainty in predictions, which has applications for provincial risk mapping. The uncertainty indicated by the model can further inform health decision-making, showing risk levels in both low- and high-transmission scenarios [35,54].

4.4. Modelling an Early Warning System

When comparing zero-, one-, and two-month lagged climate variables, all three lagged models performed similarly, with the two-month lag model having a slightly better model fit. This similar performance, particularly between the one- and two-month lagged models, may indicate that there is an optimal lag value between these two periods. Further research may incorporate weekly values to find the optimal lagged relationship that is not set to a calendar month.

For an EWS, a one- or two-month lag provides a lead time for practical control methods to be enacted, while maintaining a level of accuracy in prediction. Multi-month incidence forecasts may struggle with limited accuracy and may be more prone to unpredictable changes such as EWCEs [64]. While a six-month outlook may provide information for long-term planning, an EWS of two to six weeks would be useful to re-distribute resources and implement control methods, maintaining a higher degree of certainty in predictions. For Vanuatu, this provides valuable lead time to target high-risk foci and implement existing preparedness measures, such as active and passive case detection, and maintaining

LLIN distribution [23]. Recommendations from past malaria programmes reaffirm the importance of community engagement and participation, where local community members are informed and involved in malaria control and decision-making [26,48]. In a review of Vanuatu's malaria programmes, it was acknowledged that a large proportion of outbreaks and active foci are concentrated in remote or hard-to-access areas [23,65]. These areas are frequently less accessible for healthcare seeking and intensive to reach and survey, contributing to discrepancy in access to diagnostics and care [23,30]. As disproportionate transmission rates are often observed remotely, advanced warning using a Bayesian climate-based model can aid in providing targeted healthcare and reduce malaria burden [30].

The EWS aims to indicate baseline malaria risk to inform decision-making and preparedness measures in advance of high-risk periods. This EWS is intended to supplement adaptive frameworks to enhance community resilience and contribute towards climate-associated risk awareness in Vanuatu.

4.5. Limitations and Future Directions

While results of this study for Vanuatu are novel and contribute towards developing a malaria EWS, the data resolution impacts the accuracy of relationships that may be found between the tested climate variables and malaria. In particular, the monthly time scale may impact the predictive relationships found between climate variables and malaria, and useful, finer resolution relationships may have been overlooked. As such, higher-frequency data would be beneficial in clarifying these effects and improving model predictions.

The spatial resolution, aggregating data to national variables, has likely oversimplified climatic and malaria conditions used in the model. This aggregation does not account for local malaria locations of concentrated malaria burden, or local geographical features, altitude in particular, which are likely to influence temperature and precipitation on a smaller scale. Even a provincial-scale aggregation may limit these variables, particularly for larger provinces like Sanma and Malampa. Future research using higher-resolution spatial data, with a focus on integrating local topographical information, would likely improve the model's ability to account for island-specific variation, specifically the interactions between altitude, temperature, and precipitation. This resolution would also aid in targeted planning, with better predictions of local malaria burden.

The model also has limited predictive ability in potential future scenarios of worsened malaria burden, EWCEs, or progress towards elimination. The model presents a risk probability that does not capture unexpected hazards like EWCEs or competing disease outbreaks. Future research, at a finer resolution, should compare models, accounting for potential differences in key drivers between regions, and incorporate social determinants of malaria transmission for more refined analysis. This study can contribute towards a malaria EWS, providing findings relating climate variables in Vanuatu to malaria incidence. This can inform decision-making and malaria strategies, supplementing preparedness and adaptive frameworks for climate-associated health threats in Vanuatu.

5. Conclusions

This study aimed to assess correlations and predictive relationships between climate variables and malaria incidence in Vanuatu to enhance disease early warning, using national malaria case data from 2014 to 2023. This was developed as a proof-of-concept predictive model using key climate variables: maximum, minimum, and median temperature; diurnal temperature variation; median temperature between 18:00 and 21:00; precipitation—total and anomaly; and relative humidity. These variables were aggregated to monthly national values and compared for their usefulness in a predictive malaria model.

This study was conducted in the context of climate vulnerability in Pacific Island Countries and how it compounds infectious disease risk. The prior literature has established relationships between climate variables and malaria and used this to develop early warning systems (EWSs), yet there is less research specific to the context of Vanuatu, a country susceptible to extreme weather and climate events (EWCEs) and endemic malaria. This study contributes towards an EWS integrated into existing infrastructure and health decision-making, providing one- to two-month lead time for systems to prepare for periods of high malaria risk. Climate change and disease are compounding issues that disproportionately affect regions susceptible to EWCEs, and preparedness measures need to become increasingly tailored and adaptive.

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Conflicts of Interest: The authors declare no conflicts of interest.

Appendix A

Table A1. Summary table of climatic variables.

Climatic Variable	Mean	Standard Deviation	Minimum	Maximum
Max Temperature	27.06	0.79	25.15	28.87
Min Temperature	22.76	1.11	20.35	24.93
Med Temperature	25.33	1.04	22.95	27.68
Peak Biting	24.95	1.04	22.64	27.07
Diurnal Temperature	4.42	0.57	3.60	5.76
Med Humidity	79.77	3.97	67.83	86.19
Precipitation Anomaly	−17.24	113.28	−336.15	336.07
Total Precipitation	223.63	152.88	21.94	659.55

Appendix B

Table A2. Spearman correlation matrix showing the correlation between each climate variable at each lag (zero to six months) with national monthly malaria cases. Significance (p values) are included in parentheses if $p > 0.05$.

	Month Lag						
Variable	**Zero**	**One**	**Two**	**Three**	**Four**	**Five**	**Six**
Max Temperature	0.43 *	0.52 *	0.44 *	0.27 *	0.04 (0.67)	−0.20 *	−0.35 *
Min Temperature	0.34 *	0.46 *	0.42 *	0.29 *	0.07 (0.44)	−0.17 (0.06)	−0.35 *

Table A2. *Cont.*

Variable	Month Lag Zero	One	Two	Three	Four	Five	Six
Med Temperature	0.41 *	0.50 *	0.43 *	0.27 *	0.04 (0.69)	-0.19 *	−0.34 *
Peak Biting	0.39 *	0.50 *	0.43 *	0.27 *	0.05 (0.62)	-0.18 *	−0.34 *
Diurnal Temperature	−0.14 (0.14)	−0.31 *	−0.40 *	−0.38 *	−0.22 *	0.01 (0.95)	0.20 *
Med Humidity	0.28 *	0.33 *	0.33 *	0.21 *	0.03 (0.77)	−0.17 (0.07)	−0.25 *
Precipitation Anomaly	0.05 (.59)	0.05 (0.57)	0.14 (0.12)	0.09 (0.32)	0.11 (0.23)	0.04 (0.68)	0.12 (0.21)
Total Precipitation	0.34 *	0.35 *	0.36 *	0.21 *	0.06 (0.50)	−0.15 (0.11)	−0.20 *

* $p < 0.05$.

References

1. Calvin, K.; Dasgupta, D.; Krinner, G.; Mukherji, A.; Thorne, P.W.; Trisos, C.; Romero, J.; Aldunce, P.; Barrett, K.; Blanco, G.; et al. IPCC, 2023: Climate Change 2023: Synthesis Report. In *Contribution of Working Groups I, II and III to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*, 1st ed.; Core Writing Team, Lee, H., Romero, J., Eds.; Intergovernmental Panel on Climate Change (IPCC): Geneva, Switzerland, 2023.
2. Opeskin, B. Malaria in Pacific Populations: Seen but Not Heard? *J. Pop. Res.* **2009**, *26*, 175–199. [CrossRef]
3. World Health Organization. Ending the Neglect to Attain the Sustainable Development Goals: A Road Map for Neglected Tropical Diseases 2021–2030. Available online: https://www.who.int/publications/i/item/9789240010352 (accessed on 31 October 2024).
4. Hosking, R.; Smurthwaite, K.; Hales, S.; Richardson, A.; Batikawai, S.; Lal, A. Climate Variability and Water-Related Infectious Diseases in Pacific Island Countries and Territories, a Systematic Review. *PLoS Clim.* **2023**, *2*, e0000296. [CrossRef]
5. United Nations Development Programme Annual Report 2023: A Malaria Free Vanuatu. Available online: https://www.undp.org/pacific/publications/annual-report-2023-malaria-free-vanuatu (accessed on 29 October 2024).
6. *State of Inequality HIV, Tuberculosis and Malaria*; World Health Organization: Geneva, Switzerland, 2021.
7. World Health Organization World Malaria Report. 2023. Available online: https://www.who.int/publications/i/item/9789240086173 (accessed on 2 October 2024).
8. The Lancet Regional Health—Western Pacific Water, Climate Change, and Health in the Western Pacific Region. *Lancet Reg. Health West. Pac.* **2023**, *32*, 100753. [CrossRef]
9. World Health Organization Health and Climate Change: Country Profile 2020: Vanuatu. Available online: https://www.who.int/publications/i/item/WHO-HEP-ECH-CCH-20.01.03 (accessed on 29 October 2024).
10. Smith, K.R.; Woodward, A.; Campbell-Lendrum, D.; Chadee, D.D.; Honda, Y.; Liu, Q.; Olwoch, J.M.; Revich, B.; Sauerborn, S. Human Health: Impacts, Adaptation, and Co-Benefits. In *Climate Change 2014: Impacts, Adaptation, and Vulnerability. Part A: Global and Sectoral Aspects. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*; IPCC: Cambridge, UK; New York, NY, USA, 2014.
11. Ebi, K.L.; Vanos, J.; Baldwin, J.W.; Bell, J.E.; Hondula, D.M.; Errett, N.A.; Hayes, K.; Reid, C.E.; Saha, S.; Spector, J.; et al. Extreme Weather and Climate Change: Population Health and Health System Implications. *Annu. Rev. Public Health* **2021**, *42*, 293–315. [CrossRef] [PubMed]
12. McIver, L.; Kim, R.; Woodward, A.; Hales, S.; Spickett, J.; Katscherian, D.; Hashizume, M.; Honda, Y.; Kim, H.; Iddings, S.; et al. Health Impacts of Climate Change in Pacific Island Countries: A Regional Assessment of Vulnerabilities and Adaptation Priorities. *Environ. Health Perspect.* **2016**, *124*, 1707–1714. [CrossRef] [PubMed]
13. Filho, W.L.; Scheday, S.; Boenecke, J.; Gogoi, A.; Maharaj, A.; Korovou, S. Climate Change, Health and Mosquito-Borne Diseases: Trends and Implications to the Pacific Region. *Int. J. Environ. Res. Public Health* **2019**, *16*, 5114. [CrossRef] [PubMed]
14. Kuleshov, Y.; McGree, S.; Jones, D.; Charles, A.; Cottrill, A.; Prakash, B.; Atalifo, T.; Nihmei, S.; Seuseu, F.L.S.K. Extreme Weather and Climate Events and Their Impacts on Island Countries in the Western Pacific: Cyclones, Floods and Droughts. *Atmos. Clim. Sci.* **2014**, *4*, 803–818. [CrossRef]
15. Vanuatu Ministry of Health National Strategic Plan for Malaria Elimination 2021–2026. Available online: https://www.nab.vu/sites/default/files/documents/Health%20-%20National%20Strategic%20Plan%20for%20Malaria%20Elimination%202021-2030NSP2020_final_281020.pdf (accessed on 3 November 2024).
16. Lum, J.K.; Kaneko, A.; Taleo, G.; Amos, M.; Reiff, D.M. Genetic Diversity and Gene Flow of Humans, *Plasmodium falciparum*, and *Anopheles farauti s.s.* of Vanuatu: Inferred Malaria Dispersal and Implications for Malaria Control. *Acta Trop.* **2007**, *103*, 102–107. [CrossRef] [PubMed]

17. Bugoro, H.; Hii, J.; Russell, T.L.; Cooper, R.D.; Chan, B.K.; Iro'ofa, C.; Butafa, C.; Apairamo, A.; Bobogare, A.; Chen, C.-C. Influence of Environmental Factors on the Abundance of Anopheles Farauti Larvae in Large Brackish Water Streams in Northern Guadalcanal, Solomon Islands. *Malar. J.* **2011**, *10*, 262. [CrossRef]
18. Reiff, D.M.; Kaneko, A.; Taleo, G.; Amos, M.; Lum, J.K. Population Structure and Gene Flow of *Anopheles farauti s.s.* (Diptera: Culicidae) Among Ten Sites on Five Islands of Vanuatu: Implications for Malaria Control. *J. Med. Entomol.* **2007**, *44*, 601–607. [CrossRef]
19. Sinka, M.E.; Bangs, M.J.; Manguin, S.; Chareonviriyaphap, T.; Patil, A.P.; Temperley, W.H.; Gething, P.W.; Elyazar, I.R.; Kabaria, C.W.; Harbach, R.E.; et al. The Dominant Anopheles Vectors of Human Malaria in the Asia-Pacific Region: Occurrence Data, Distribution Maps and Bionomic Précis. *Parasites Vectors* **2011**, *4*, 89. [CrossRef] [PubMed]
20. Andrew, N.L.; Bright, P.; de la Rua, L.; Teoh, S.J.; Vickers, M. Coastal Proximity of Populations in 22 Pacific Island Countries and Territories. *PLoS ONE* **2019**, *14*, e0223249. [CrossRef]
21. Idris, Z.M.; Chan, C.W.; Mohammed, M.; Kalkoa, M.; Taleo, G.; Junker, K.; Arcà, B.; Drakeley, C.; Kaneko, A. Serological Measures to Assess the Efficacy of Malaria Control Programme on Ambae Island, Vanuatu. *Parasites Vectors* **2017**, *10*, 204. [CrossRef]
22. Watanabe, N.; Kaneko, A.; Yamar, S.; Leodoro, H.; Taleo, G.; Tanihata, T.; Lum, J.K.; Larson, P.S. Determinants of the Use of Insecticide-Treated Bed Nets on Islands of Pre- and Post-Malaria Elimination: An Application of the Health Belief Model in Vanuatu. *Malar. J.* **2014**, *13*, 441. [CrossRef] [PubMed]
23. Vanuatu Ministry of Health; United Nations Development Programme Mid-Term Review of the Malaria Elimination Programme: Vanuatu. Available online: https://pirmccm.org/wp-content/uploads/member-files/Funding%20Requests/2024-2026%20Funding%20Request/Malaria%20Funding%20Request/11.3%20VAN%20MTR%20%20Malaria%20Programme%20Mid-Term%20Review.pdf (accessed on 3 November 2024).
24. Chaves, L.F.; Kaneko, A.; Taleo, G.; Pascual, M.; Wilson, M.L. Malaria Transmission Pattern Resilience to Climatic Variability Is Mediated by Insecticide-Treated Nets. *Malar. J.* **2008**, *7*, 100. [CrossRef] [PubMed]
25. Kaneko, A.; Taleo, G.; Kalkoa, M.; Yaviong, J.; Reeve, P.A.; Ganczakowski, M.; Shirakawa, C.; Palmer, K.; Kobayakawa, T.; Björkman, A. Malaria Epidemiology, Glucose 6-Phosphate Dehydrogenase Deficiency and Human Settlement in the Vanuatu Archipelago. *Acta Trop.* **1998**, *70*, 285–302. [CrossRef] [PubMed]
26. Atkinson, J.-A.M.; Fitzgerald, L.; Toaliu, H.; Taleo, G.; Tynan, A.; Whittaker, M.; Riley, I.; Vallely, A. Community Participation for Malaria Elimination in Tafea Province, Vanuatu: Part I. Maintaining Motivation for Prevention Practices in the Context of Disappearing Disease. *Malar. J.* **2010**, *9*, 93. [CrossRef] [PubMed]
27. *Vanuatu Malaria and Measles Situation Report 1 to 27 July 2022*; Vanuatu Ministry of Health: Port Vila, Vanuatu, 2022; pp. 1–7.
28. *Case Study: Successful Elimination of Malaria, Tafea Province, Vanuatu*; Vanuatu Ministry of Health: Port Vila, Vanuatu, 2019; pp. 1–14.
29. Sekine, S.; Chan, C.W.; Kalkoa, M.; Yamar, S.; Iata, H.; Taleo, G.; Kc, A.; Kagaya, W.; Kido, Y.; Kaneko, A. Tracing the Origins of Plasmodium Vivax Resurgence after Malaria Elimination on Aneityum Island in Vanuatu. *Commun. Med.* **2024**, *4*, 91. [CrossRef] [PubMed]
30. Wangdi, K.; Pasaribu, A.P.; Clements, A.C.A. Addressing Hard-to-Reach Populations for Achieving Malaria Elimination in the Asia Pacific Malaria Elimination Network Countries. *Asia Pac. Policy Stud.* **2021**, *8*, 176–188. [CrossRef]
31. Beck-Johnson, L.M.; Nelson, W.A.; Paaijmans, K.P.; Read, A.F.; Thomas, M.B.; Bjørnstad, O.N. The Effect of Temperature on Anopheles Mosquito Population Dynamics and the Potential for Malaria Transmission. *PLoS ONE* **2013**, *8*, e79276. [CrossRef]
32. Paaijmans, K.P.; Blanford, S.; Bell, A.S.; Blanford, J.I.; Read, A.F.; Thomas, M.B. Influence of Climate on Malaria Transmission Depends on Daily Temperature Variation. *Proc. Natl. Acad. Sci. USA* **2010**, *107*, 15135–15139. [CrossRef] [PubMed]
33. Beck-Johnson, L.M.; Nelson, W.A.; Paaijmans, K.P.; Read, A.F.; Thomas, M.B.; Bjørnstad, O.N. The Importance of Temperature Fluctuations in Understanding Mosquito Population Dynamics and Malaria Risk. *R. Soc. Open Sci.* **2017**, *4*, 160969. [CrossRef]
34. Ohm, J.R.; Baldini, F.; Barreaux, P.; Lefevre, T.; Lynch, P.A.; Suh, E.; Whitehead, S.A.; Thomas, M.B. Rethinking the Extrinsic Incubation Period of Malaria Parasites. *Parasites Vectors* **2018**, *11*, 178. [CrossRef] [PubMed]
35. Cleary, E.; Hetzel, M.W.; Siba, P.M.; Lau, C.L.; Clements, A.C.A. Spatial Prediction of Malaria Prevalence in Papua New Guinea: A Comparison of Bayesian Decision Network and Multivariate Regression Modelling Approaches for Improved Accuracy in Prevalence Prediction. *Malar. J.* **2021**, *20*, 269. [CrossRef]
36. Imai, C.; Cheong, H.-K.; Kim, H.; Honda, Y.; Eum, J.-H.; Kim, C.T.; Kim, J.S.; Kim, Y.; Behera, S.K.; Hassan, M.N.; et al. Associations between Malaria and Local and Global Climate Variability in Five Regions in Papua New Guinea. *Trop. Med. Health* **2016**, *44*, 23. [CrossRef]
37. Gilbert, M.; Brindle, R. El Niño and Variations in the Prevalence of *Plasmodium vivax* and *P. falciparum* in Vanuatu. *Trans. R. Soc. Trop. Med. Hyg.* **2009**, *103*, 1285–1287. [CrossRef] [PubMed]
38. Smith, J.; Tahani, L.; Bobogare, A.; Bugoro, H.; Otto, F.; Fafale, G.; Hiriasa, D.; Kazazic, A.; Beard, G.; Amjadali, A.; et al. Malaria Early Warning Tool: Linking Inter-Annual Climate and Malaria Variability in Northern Guadalcanal, Solomon Islands. *Malar. J.* **2017**, *16*, 472. [CrossRef]

39. Pollard, E.J.M.; Russell, T.L.; Apairamo, A.; Burkot, T.R. Unique Fine Scale Village Spatial-Temporal Distributions of Anopheles Farauti Differ by Physiological State and Sex. *Parasites Vectors* **2019**, *12*, 558. [CrossRef] [PubMed]
40. Chow, W.K.; Beebe, N.W.; Ambrose, L.; Pickering, P.; Cooper, R.D. Seasonal Assessment on the Effects of Time of Night, Temperature and Humidity on the Biting Profile of *Anopheles farauti* in North Queensland, Australia Using a Population Naive to Malaria Vector Control Pressures. *Malar. J.* **2023**, *22*, 85. [CrossRef]
41. Mordecai, E.A.; Caldwell, J.M.; Grossman, M.K.; Lippi, C.A.; Johnson, L.R.; Neira, M.; Rohr, J.R.; Ryan, S.J.; Savage, V.; Shocket, M.S.; et al. Thermal Biology of Mosquito-Borne Disease. *Ecol. Lett.* **2019**, *22*, 1690–1708. [CrossRef] [PubMed]
42. Parham, P.E.; Waldock, J.; Christophides, G.K.; Hemming, D.; Agusto, F.; Evans, K.J.; Fefferman, N.; Gaff, H.; Gumel, A.; LaDeau, S.; et al. Climate, Environmental and Socio-Economic Change: Weighing up the Balance in Vector-Borne Disease Transmission. *Philos. Trans. R. Soc. Lond. B Biol. Sci.* **2015**, *370*, 20130551. [CrossRef]
43. Fouque, F.; Reeder, J.C. Impact of Past and On-Going Changes on Climate and Weather on Vector-Borne Diseases Transmission: A Look at the Evidence. *Infect. Dis. Poverty* **2019**, *8*, 51. [CrossRef]
44. Reiner, R.C.; Geary, M.; Atkinson, P.M.; Smith, D.L.; Gething, P.W. Seasonality of Plasmodium Falciparum Transmission: A Systematic Review. *Malar. J.* **2015**, *14*, 343. [CrossRef] [PubMed]
45. Santoso, A.; Mcphaden, M.J.; Cai, W. The Defining Characteristics of ENSO Extremes and the Strong 2015/2016 El Niño. *Rev. Geophys.* **2017**, *55*, 1079–1129. [CrossRef]
46. World Bank Group Climate Risk Country Profile: Vanuatu. Available online: https://climateknowledgeportal.worldbank.org/sites/default/files/country-profiles/15825-WB_Vanuatu%20Country%20Profile-WEB.pdf (accessed on 31 October 2024).
47. Gree, S.; Smith, G.; Chandler, E.; Harold, N.; Begg, Z.; Kuleshov, Y.; Malsale, P.; Rittman, M. *Climate Change in the Pacific 2022 Historical and Recent Variability, Extremes and Change*; Pacific Community (SPC): Suva, Fiji, 2022.
48. Malaria and other Vector Borne Diseases Control Program Vanuatu: Annual Program Report. 2022. Available online: https://pirmccm.org/wp-content/uploads/member-files/Funding%20Requests/2024-2026%20Funding%20Request/Malaria%20Funding%20Request/11.4%20VAN%202022%20Malaria%20Program%20Annual%20Report_.pdf (accessed on 1 November 2024).
49. Humanitarian Data Exchange Vanuatu—Subnational Administrative Boundaries—Humanitarian Data Exchange. Available online: https://data.humdata.org/dataset/cod-ab-vut (accessed on 5 November 2024).
50. Paaijmans, K.P.; Read, A.F.; Thomas, M.B. Understanding the Link between Malaria Risk and Climate. *Proc. Natl. Acad. Sci. USA* **2009**, *106*, 13844–13849. [CrossRef] [PubMed]
51. Hersbach, H.; Bell, B.; Berrisford, P.; Hirahara, S.; Horányi, A.; Muñoz-Sabater, J.; Nicolas, J.; Peubey, C.; Radu, R.; Schepers, D.; et al. The ERA5 Global Reanalysis. *Q. J. R. Meteorol. Soc.* **2020**, *146*, 1999–2049. [CrossRef]
52. Bugoro, H.; Iro'ofa, C.; Mackenzie, D.O.; Apairamo, A.; Hevalao, W.; Corcoran, S.; Bobogare, A.; Beebe, N.W.; Russell, T.L.; Chen, C.-C.; et al. Changes in Vector Species Composition and Current Vector Biology and Behaviour Will Favour Malaria Elimination in Santa Isabel Province, Solomon Islands. *Malar. J.* **2011**, *10*, 287. [CrossRef]
53. Beck, H.E.; Wood, E.F.; Pan, M.; Fisher, C.K.; Miralles, D.G.; van Dijk, A.I.J.M.; McVicar, T.R.; Adler, R.F. MSWEP V2 Global 3-Hourly 0.1° Precipitation: Methodology and Quantitative Assessment. *Bull. Am. Meteorol. Soc.* **2019**, *100*, 473–500. [CrossRef]
54. Reid, H.; Vallely, A.; Taleo, G.; Tatem, A.J.; Kelly, G.; Riley, I.; Harris, I.; Henri, I.; Iamaher, S.; Clements, A.C. Baseline Spatial Distribution of Malaria Prior to an Elimination Programme in Vanuatu. *Malar. J.* **2010**, *9*, 150. [CrossRef] [PubMed]
55. Jeanne, I.; Chambers, L.E.; Kazazic, A.; Russell, T.L.; Bobogare, A.; Bugoro, H.; Otto, F.; Fafale, G.; Amjadali, A. Mapping a Plasmodium Transmission Spatial Suitability Index in Solomon Islands: A Malaria Monitoring and Control Tool. *Malar. J.* **2018**, *17*, 381. [CrossRef] [PubMed]
56. Chan, C.W.; Iata, H.; Yaviong, J.; Kalkoa, M.; Yamar, S.; Taleo, G.; Isozumi, R.; Fukui, M.; Aoyama, F.; Pomer, A.; et al. Surveillance for Malaria Outbreak on Malaria-Eliminating Islands in Tafea Province, Vanuatu after Tropical Cyclone Pam in 2015. *Epidemiol. Infect.* **2017**, *145*, 41–45. [CrossRef] [PubMed]
57. Natuzzi, E.S.; Joshua, C.; Shortus, M.; Reubin, R.; Dalipanda, T.; Ferran, K.; Aumua, A.; Brodine, S. Defining Population Health Vulnerability Following an Extreme Weather Event in an Urban Pacific Island Environment: Honiara, Solomon Islands. *Am. J. Trop. Med. Hyg.* **2016**, *95*, 307–314. [CrossRef]
58. Paaijmans, K.P.; Cator, L.J.; Thomas, M.B. Temperature-Dependent Pre-Bloodmeal Period and Temperature-Driven Asynchrony between Parasite Development and Mosquito Biting Rate Reduce Malaria Transmission Intensity. *PLoS ONE* **2013**, *8*, e55777. [CrossRef]
59. Betuela, I.; Maraga, S.; Hetzel, M.W.; Tandrapah, T.; Sie, A.; Yala, S.; Kundi, J.; Siba, P.; Reeder, J.C.; Mueller, I. Epidemiology of Malaria in the Papua New Guinean Highlands. *Trop. Med. Int. Health* **2012**, *17*, 1181–1191. [CrossRef] [PubMed]
60. Park, J.-W.; Cheong, H.-K.; Honda, Y.; Ha, M.; Kim, H.; Kolam, J.; Inape, K.; Mueller, I. Time Trend of Malaria in Relation to Climate Variability in Papua New Guinea. *Environ. Health Toxicol.* **2016**, *31*, e2016003. [CrossRef] [PubMed]
61. Chase, J.M.; Knight, T.M. Drought-Induced Mosquito Outbreaks in Wetlands. *Ecol. Lett.* **2003**, *6*, 1017–1024. [CrossRef]

62. Iese, V.; Kiem, A.S.; Mariner, A.; Malsale, P.; Tofaeono, T.; Kirono, D.G.C.; Round, V.; Heady, C.; Tigona, R.; Veisa, F.; et al. Historical and Future Drought Impacts in the Pacific Islands and Atolls. *Clim. Change* **2021**, *166*, 19. [CrossRef]
63. Basáñez, M.-G.; Marshall, C.; Carabin, H.; Gyorkos, T.; Joseph, L. Bayesian Statistics for Parasitologists. *Trends Parasitol.* **2004**, *20*, 85–91. [CrossRef]
64. Kim, Y.; Ratnam, J.V.; Doi, T.; Morioka, Y.; Behera, S.; Tsuzuki, A.; Minakawa, N.; Sweijd, N.; Kruger, P.; Maharaj, R.; et al. Malaria Predictions Based on Seasonal Climate Forecasts in South Africa: A Time Series Distributed Lag Nonlinear Model. *Sci. Rep.* **2019**, *9*, 17882. [CrossRef] [PubMed]
65. Tynan, A.; Atkinson, J.-A.; Toaliu, H.; Taleo, G.; Fitzgerald, L.; Whittaker, M.; Riley, I.; Schubert, M.; Vallely, A. Community Participation for Malaria Elimination in Tafea Province, Vanuatu: Part Ii. Social and Cultural Aspects of Treatment-Seeking Behaviour. *Malar. J.* **2011**, *10*, 204. [CrossRef]