

Spatio-Temporal Variation of Malaria Incidence and Risk Factors in West Gojjam Zone, Northwest Ethiopia

Authors: Tegegne, Eniyew, Alemu Gelaye, Kassahun, Dessie, Awrajaw, Shimelash, Alebachew, Asmare, Biachew, et al.

Source: Environmental Health Insights, 16(1)

Published By: SAGE Publishing

URL: <https://doi.org/10.1177/11786302221095702>




BioOne Complete (complete.BioOne.org) is a full-text database of 200 subscribed and open-access titles in the biological, ecological, and environmental sciences published by nonprofit societies, associations, museums, institutions, and presses.

Your use of this PDF, the BioOne Complete website, and all posted and associated content indicates your acceptance of BioOne's Terms of Use, available at www.bioone.org/terms-of-use.

Usage of BioOne Complete content is strictly limited to personal, educational, and non - commercial use. Commercial inquiries or rights and permissions requests should be directed to the individual publisher as copyright holder.

BioOne sees sustainable scholarly publishing as an inherently collaborative enterprise connecting authors, nonprofit publishers, academic institutions, research libraries, and research funders in the common goal of maximizing access to critical research.

Spatio-Temporal Variation of Malaria Incidence and Risk Factors in West Gojjam Zone, Northwest Ethiopia

Eniyew Tegegne¹, Kassahun Alemu Gelaye², Awrajaw Dessie², Alebachew Shimelash¹, Biachew Asmare³, Yikeber Argachew Deml⁴, Yonas Lamore¹, Tegegne Temesgen¹, Biruk Demissie⁵ and Abraham Teym¹

¹Department of Environmental Health, College of Health Sciences, Debre Markos University, Debre Markos, Ethiopia. ²Institutes of Public Health, College of Medicine and Health Sciences, University of Gondar, Gondar, Ethiopia. ³Department of Human Nutrition, College of Health Sciences, Debre Markos University, Debre Markos, Ethiopia. ⁴Department of Biomedical Sciences, School of Medicine, Debre Markos University, Ethiopia. ⁵Department of Environmental Health, College of Health Science, Debre Tabor University, Debre Tabor, Ethiopia.

Environmental Health Insights
Volume 16: 1–10
© The Author(s) 2022
Article reuse guidelines:
sagepub.com/journals-permissions
DOI: 10.1177/11786302221095702



ABSTRACT

INTRODUCTION: Malaria is a life-threatening acute febrile illness which is affecting the lives of millions globally. Its distribution is characterized by spatial, temporal, and spatiotemporal heterogeneity. Detection of the space-time distribution and mapping high-risk areas is useful to target hot spots for effective intervention.

METHODS: Time series cross sectional study was conducted using weekly malaria surveillance data obtained from Amhara Public Health Institute. Poisson model was fitted to determine the purely spatial, temporal, and space-time clusters using SaTScan™ 9.6 software. Spearman correlation, bivariate, and multivariable negative binomial regressions were used to analyze the relation of the climatic factors to count of malaria incidence.

RESULT: Jabitenan, Quarit, Sekela, Bure, and Wonberma were high rate spatial cluster of malaria incidence hierarchically. Spatiotemporal clusters were detected. A temporal scan statistic identified 1 risk period from 1 July 2013 to 30 June 2015. The adjusted incidence rate ratio showed that monthly average temperature and monthly average rainfall were independent predictors for malaria incidence at all lag-months. Monthly average relative humidity was significant at 2 months lag.

CONCLUSION: Malaria incidence had spatial, temporal, spatiotemporal variability in West Gojjam zone. Mean monthly temperature and rainfall were directly and negatively associated to count of malaria incidence respectively. Considering these space-time variations and risk factors (temperature and rainfall) would be useful for the prevention and control and ultimately achieve elimination.

KEYWORDS: Spatio-temporal variation, malaria incidence, risk factor, West Gojjam, Ethiopia

RECEIVED: January 28, 2022. **ACCEPTED:** March 25, 2022.

TYPE: Ecological Public Health - Original Research

FUNDING: The author(s) disclosed receipt of the following financial support for the research, authorship, and/or publication of this article: All the necessary financial funding was covered by the Debre Markos University, College of Health Sciences but not involved in any of the research work.

DECLARATION OF CONFLICTING INTERESTS: The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

CORRESPONDING AUTHOR: Eniyew Tegegne, College of Health Sciences, Debre Markos University, Addis Ababa_Bahir Dar, Debre Markos, 269, Ethiopia. Email: eniyewtegegne@gmail.com

Introduction

Malaria is a common and life-threatening acute febrile illness in many tropical and subtropical countries, and is caused by 5 different parasites of protozoan species: *P. falciparum*, *P. malariae*, *P. ovale*, *P. vivax*, and *P. knowlesi*. It is transmitted by female *Anopheles* mosquitoes bite between dusk and dawn.¹ *P. falciparum* can be fatal if treatment is delayed.² Species other than *P. falciparum* result insignificant morbidity but are rarely life-threatening.^{3–6}

It is World Health Organization's (WHO) vision to see a world free of malaria by ensuring universal access to malaria prevention, diagnosis, and treatment, accelerating efforts toward elimination, transforming malaria surveillance, harnessing innovation and expanding research and strengthening the enabling environment. Despite interventions, gains achieved are fragile and unevenly distributed. The human toll of malaria remains high due to lack of robust, predictable, and sustained financing compounded by the difficulty in maintaining political

commitment and ensuring regional collaboration. Since 2014, investments in malaria control have declined in many high-burden countries. The second important challenge is biological: the emergence of parasite resistance to anti-malarial medicines and of mosquito resistance to insecticides.^{4,7}

Globally, there were an estimated 241 million malaria cases in 2020 in 85 malaria endemic countries, increasing from 227 million in 2019, with an estimated 228 million cases in 2020 (95% of cases globally) coming from the WHO African Region. More than 3 quarters (79%) of the US\$ 3.3 billion invested in 2020 benefited the WHO African Region. To reach over 80% coverage of currently available interventions, investment in malaria needs to increase substantially above the current annual spending of about US\$ 3.3 billion.⁸

In Ethiopia, more than 75% of the total area is malarious where over 63 million people live in these areas. Benshangul Gumuz, Gambela, Tigray, and Amhara Regional States are



Creative Commons Non Commercial CC BY-NC: This article is distributed under the terms of the Creative Commons Attribution-NonCommercial 4.0 License (<https://creativecommons.org/licenses/by-nc/4.0/>) which permits non-commercial use, reproduction and distribution of the work without further permission provided the original work is attributed as specified on the SAGE and Open Access pages (<https://us.sagepub.com/en-us/nam/open-access-at-sage>).
Downloaded From: <https://complete.bioone.org/journals/Environmental-Health-Insights> on 19 Apr 2024
Terms of Use: <https://complete.bioone.org/terms-of-use>

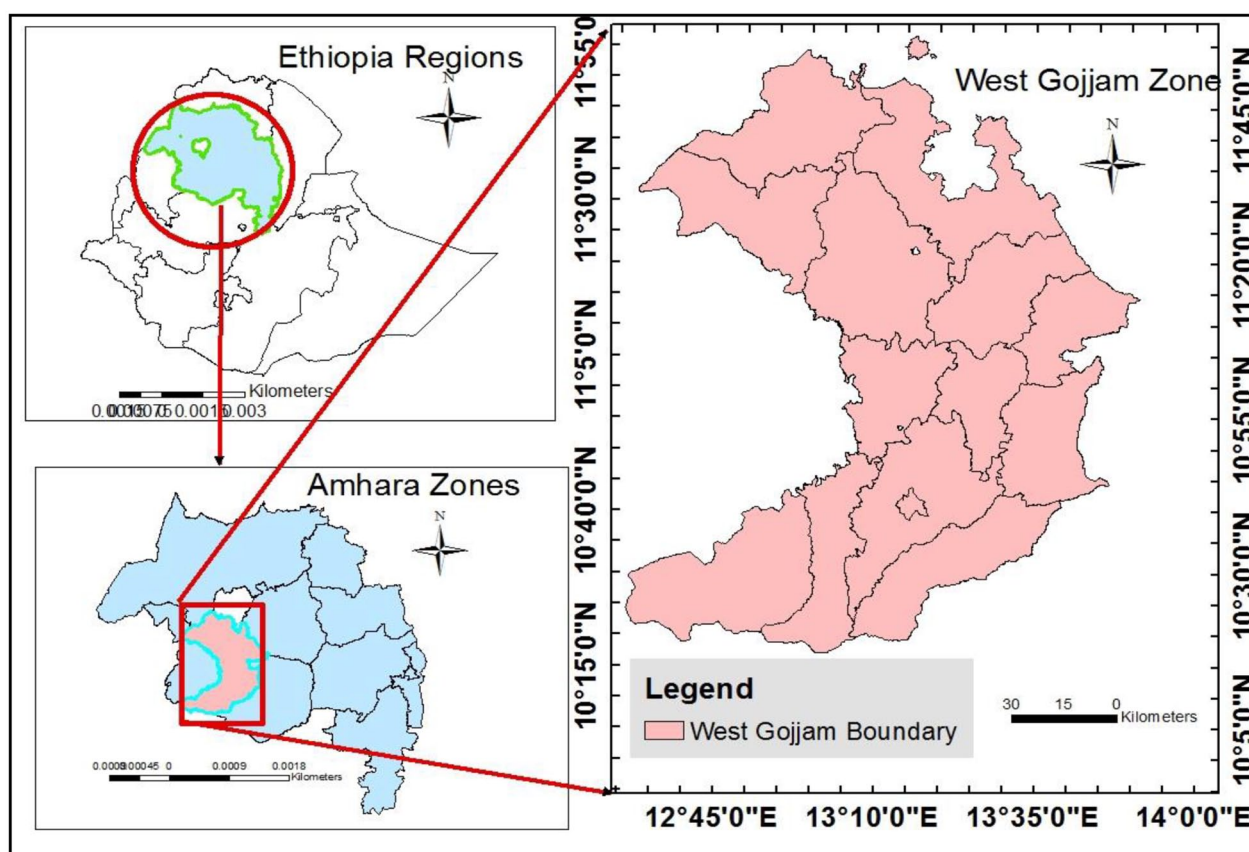


Figure 1. Map of the study area, West Gojjam.

among the regions with the highest proliferation of the disease.⁹ Ethiopian highlands were home to the majority of the country's population where the cooler climate serving as a natural buffer against malaria transmission. But now, a new data showed that increasing temperatures over the past 35 years are eroding this buffer, allowing conditions more favorable for malaria to begin climbing.^{10,11} There was a clear decrease in the malaria incidence rate and malaria death rate in Ethiopia, however, its incidence remained high: 19.8 cases per 1000 people in 2016,¹² which exceeds the WHO standard for pre-elimination.¹³

Malaria remains to be the major public health challenge in the Amhara Region.¹⁴ Among 10 zones and 3 town administrations of Amhara Region, West Gojjam Zone alone accounts for one-third of the malaria burden.¹⁵

Understanding the epidemiology and the disease pattern in time and space is indispensable to manage the disease proactively. Thus, the identification of geographical areas using geographic information systems and spatiotemporal statistical analyses has become indispensable for proper allocation and mobilization of resources. However, there is scanty of information on district level spatial, temporal, and spatiotemporal cluster evidence on malaria incidence and risk factors in West Gojjam Zone. Therefore, the this study was aimed to assess spatial, temporal, and spatiotemporal distribution patterns and risk factors associated to count of malaria incidence in West Gojjam Zone from 1 July 2013 to 30 June 2018.

Methods

Study area

The study was conducted in West Gojjam Zone. All districts were included and studied. West Gojjam is located in the Northwestern and north-central parts of Ethiopia. The average altitude of West Gojjam is 1920m above sea level. The mean annual rainfall in the West Gojjam is 1352.9ml, and the annual mean temperature ranges 12.9°C to 29.5°C.¹⁶ West Gojjam Zone alone accounts for one-third of the malaria burden of Amhara Region.¹⁵ The town of this zone is Finote Selam, which is 246 and 173 km far from Addis Ababa, the capital of Ethiopia, and the city of Amhara Region, Bahir Dar respectively. West Gojjam is bordered on the south by the Abay River which separates it from the Oromia Region and Benishangul-Gumuz Region, on the west by Agew Awi, on the northwest by North Gondar, on the north by Lake Tana and the Abay River which separates it from the South Gondar, and on the east by East Gojjam (Figure 1).

Study design and period

A retrospectively analysis was conducted from 1 July 2013 to 30 June 2018 using a malaria data obtained from the Amhara Public Health Institute and climatic data obtained from West Amhara Meteorology Agency. All districts were included in to the study without sampling. The temporal analyses were based on WHO epidemic weeks.

Data management and analysis

The malaria case data was received from the Amhara Public Health Institute on a formal basis. The data were collected from health facilities by passive surveillance in a weekly basis, and was accurate, complete and relevant to be researched. The malaria datasets were aggregated at a district levels and comprised information on malaria cases, type of parasites (*P. falciparum*, *P. vivax*), age category as (<5, 5-14, ≥15) and time of illness (week and year). Climatic data was obtained from West Amhara Meteorology Agency.

The spatial coordinates (the latitudes and longitudes) for each district were obtained from the Central Statistical Agency's polygon shape file. The spatial data were then created in ArcGIS10.2.2 for each district. The population data were used to calculate annual malaria incidence and used as known underlying population at risk to fit Poisson model. Population data was obtained from Central Gondar Zone Health Department.

A shape file with district boundaries and polygon shapes were obtained from the Amhara Region Central Statistical Agency (CSA) and each district was geo-referenced to its geographic centroid. Then, the spatial data was created in ArcGIS10.2.2 version software for each district.

Weekly and annual cumulative malaria incidences of each district were calculated and plotted to check the annual fluctuations of malaria transmission from 1 July 2013 to 30 June 2018. The number of malaria cases to the population at risk was used to calculate the monthly and annual cumulative malaria incidences during the specified period.

The discrete Poisson model: The discrete Poisson model was used because the number of cases in each location was Poisson distributed and the nature of the data was count,¹⁷ and the population was the combined number of person-years lived used to fit the Poisson model.

Purely spatial clusters: This spatial statistical analysis method employs the creation of a circular window that scans the entire study area. Since researchers recommend the maximum-size be no greater than 50%, that is a reported cluster can contain at most 50% of the total population at risk,¹⁸ so maximum cluster size used was 50% of the population at risk. The circle with the maximum likelihood ratio containing more cases than expected is identified as the most likely (primary) cluster.¹⁷ The *P*-value was estimated using Monte Carlo simulations,¹⁸ and a significance level of $\alpha < .05$ was used to test whether the cluster was significant.

Spatiotemporal clusters: The space-time scan statistic was employed to detect clusters in both space and time using a cylindrical window. Districts with a significant number of cases within the corresponding time were identified using a *P*-value that was determined using Monte Carlo simulations. For space-time analyses, the most likely cluster (primary) were identified using an iterative manner as described in Kulldorff,¹⁹ and *P*-value was generated using Monte Carlo simulations, and significance level of $\alpha < .05$.

Purely temporal clusters: Temporal scan statistics used a window that moved in 1 dimension only using the height of the cylindrical window as the time dimension. A *P*-value was generated using Monte Carlo simulations like spatiotemporal clusters. Like spatial and spatiotemporal clusters, a significance level of $\alpha < .05$ were used to identify a significant risk period. For purely temporal analyses, only the most likely cluster was reported. The scan was used to scan for areas/districts and times/periods with high rate malaria clusters.

Statistical analyses were performed and reported using Excel, SaTScan™ 9.6 and ArcGIS10.2.2 software. Excel spreadsheet was used to describe data by drawing line graphs. Spatial and spatiotemporal clusters were analyzed using SaTScan™ 9.6. ArcGIS 10.2.2 was used to plot significant spatial clusters, and to compute distribution pattern (Global Moran's I), and hot spot (Getis-Ord G_i^* statistic).

Correlation and regression analysis

Spearman's correlation, bivariate, and multivariable negative binomial regressions were performed to test the relationship between climatic factors and count of malaria incidence. Correlation analysis was done considering 0, 1, and 2 lag months of the climatic variables to count of malaria incidence. The multicollinearity between climate variables using the Variance Inflation Factor (VIF) was checked before the multivariable regression analysis and was found to be < 5 .

A bivariate negative binomial regression was performed to check the crude associations between the climatic factors and count of malaria incidence. Variables with *P*-value $\leq .2$ were entered into the final model. In the multivariable negative binomial regression model, adjusted Incidence Rate Ratio (IRR) with 95% Confidence Interval (CI) was calculated to identify the independent effect of each explanatory variable with the outcome variable. A significance level of .05 was considered for all statistical tests. Adjusted IRR with 90% CI was used to declare statistical significance by SPSS 20.

Ethical clearance

Ethical clearance was obtained from the Research and Ethical Review Board of Institute of Public Health, College of Medicine and Health Sciences, University of Gondar. Supportive letters were written to Amhara Public Health Institute, West Amhara Meteorology Agency, and Central Gondar Zone Health Department for retrieving data from records. All the information was kept confidential and no individual identifiers were collected.

Results

Distribution of malaria infections

A total of 342 947 malaria cases were reported from 1 July, 2013 to 30 June 2018 among 13 districts. *Plasmodium falciparum* 58.76% (201 510) was the dominant species compared to

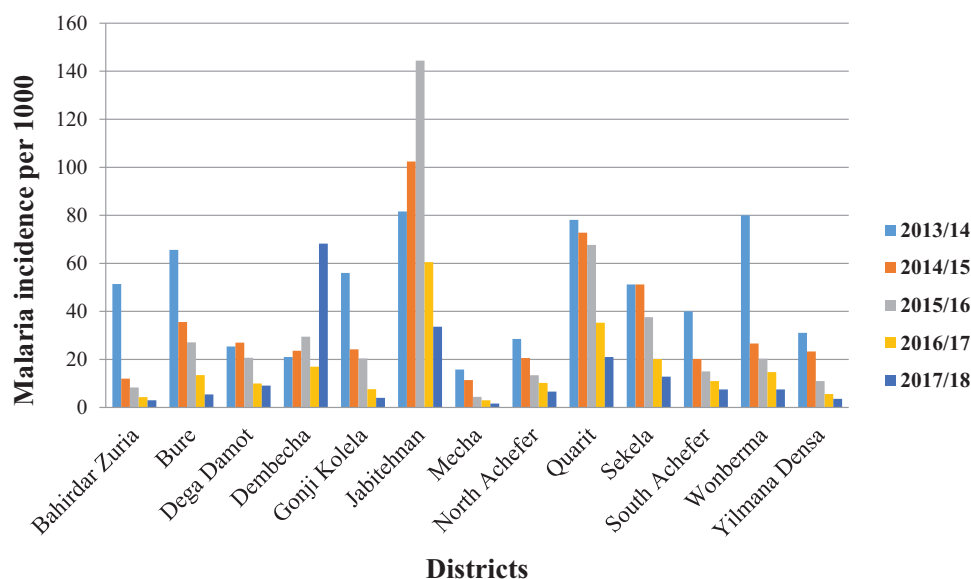


Figure 2. District level annual cumulative malaria incidence in West Gojjam, 1 July 2013 to 30 June 2018.

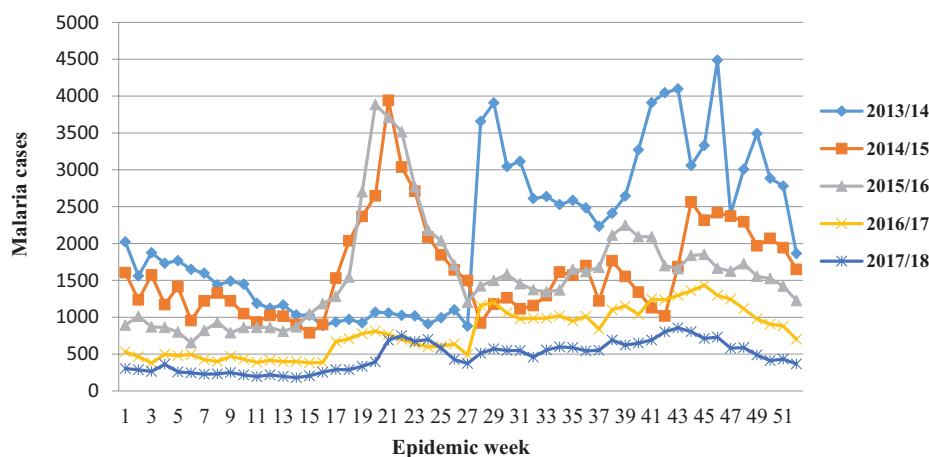


Figure 3. Temporal variation of malaria cases in West Gojjam, 1 July 2013 to 30 June 2018.

Plasmodium vivax 41.24% (141 437). The highest proportion, 69.33% (237 753) of the malaria cases, was accounted by ≥ 15 years of age, followed by 18.38% (63 049) which was accounted by 5 to 14 years of age. The < 5 accounted 12.29% (42 145) of malaria cases.

The average cumulative annual malaria incidence was 29.10 per 1000 population at risk, 2.91 in percent. The highest cumulative annual malaria incidence, 144.4 per 1000 population at risk occurred in Jabitenan district in 2015/16. Whereas, the lowest incidence, 3 per 1000 population at risk occurred both in Bahir Dar Zuriya and Mecha districts in 2017/18 and 2016/17 respectively (Figure 2).

Trends of malaria infections

There was a decreasing trend of malaria incidence, and showed weakly and seasonal variability. The period from 1 July 2013 to

30 June 2014 had been showing multiple weekly peaks of malaria case incidence.

There were 2 peak malaria seasons between 2014/15 and 2015/16. The first peak was from week 16 through week 28 and the second peak was from about week 37 to week 47. Fluctuating temporal trends of annual malaria incidence were observed throughout the study period (Figure 3).

Spatial pattern and spatial clusters

The global autocorrelation results depicted that the malaria incidence was clustered (Global Moran's $I=0.303613$, $P\text{-value}=.025485$) (Figure 4).

Malaria distribution was found to be clustered. Jabitenan ($LLR=59178.27$, $P<.001$), Quarit ($LLR=7821.767$, $P<.001$), Sekela ($LLR=843.9762$, $P<.001$), Bure ($LLR=81.49807$, $P<.001$), and Wonberma ($LLR=77.73337$, $P<.001$) districts

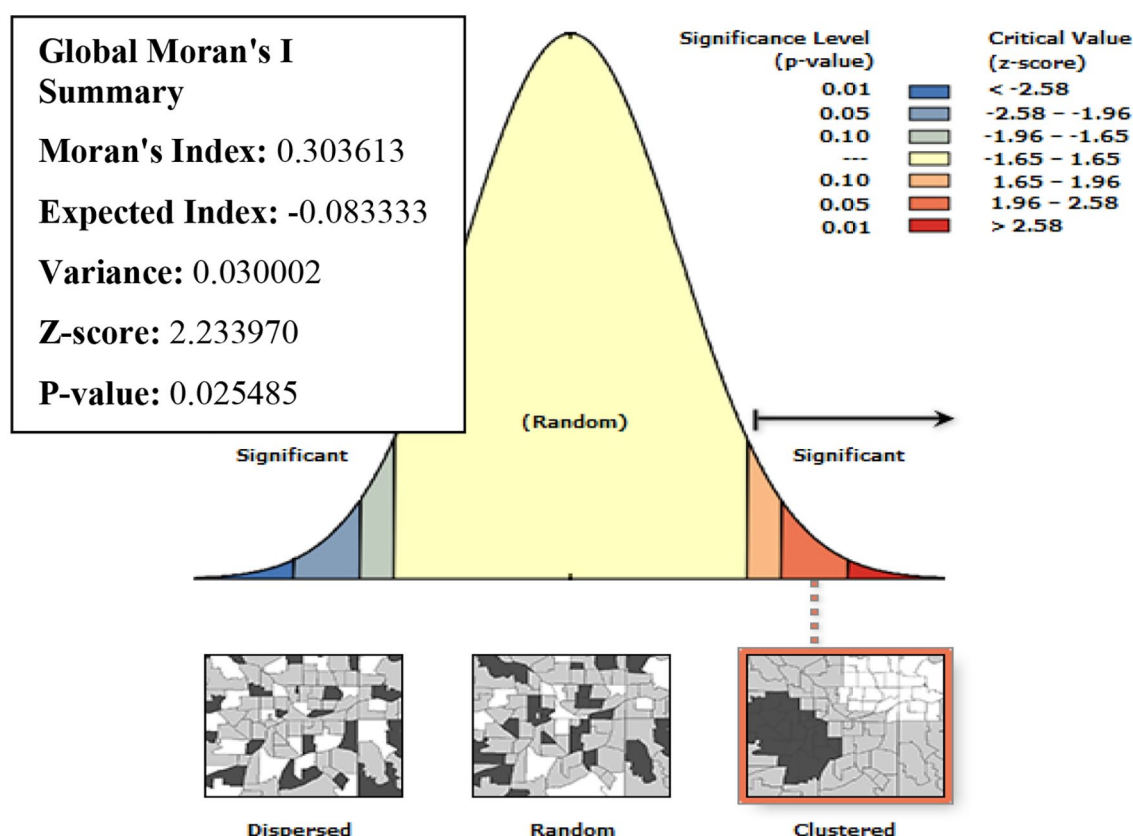


Figure 4. Spatial autocorrelation based on feature locations and attribute values (average cumulative annual malaria incidence) using the Global Moran's I statistic in West Gojjam, 1 July 2013 to 30 June 2018.

Table 1. Significant high rate spatial clusters of malaria in West Gojjam, 1 July 2013 to 30 June 2018.

SPATIAL CLUSTER	POP.	COORDINATES/RADIUS	OBS.*	EXP.*	RR	LLR
Jabitenan	255261	10.700600 N, 37.276100 E/0 km	107306	34136.29	4.12	59178.27
Quarit	132459	10.974000 N, 37.441100 E/0 km	36070	17713.88	2.16	7821.767
Sekela	160710	10.998700 N, 37.207900 E/0 km	27562	21491.82	1.31	843.9762
Bure	179122	10.541900 N, 37.048900 E/0 km	25883	23954.14	1.09	81.49807
Wonberma	124328	10.489000 N, 36.79970 E/0 km	18218	16626.53	1.1	77.73337

Abbreviations: POP., population; RR, relative risk; LLR, Log likelihood ratio; Obs.*, number of observed cases in a cluster; Exp.*, number of expected cases in a cluster. P-value < .001 for all clusters.

were high rate malaria clusters identified hierarchically (Table 1, Figure 5).

High rate temporal clusters

Based on annual aggregation, a significant temporal cluster was observed from 1 July 2013 to 30 June 2015 (LLR = 22448.54, $P < .001$) (Table 2).

Spatiotemporal clusters

Significant spatiotemporal malaria clusters were detected at Jabitenan from 1 July 2014 to 30 June 2016, Quarit and Sekela

between 1 July 2013 and 30 June 2015, Wonberma, Bure, Bahir Dar Zuriya, GonjiKolela, South Achefer, Yilmana Densa, and North Achefer between 1 July 2013 and 30 June 2014 and Dembecha between 1 July 2015 and 30 June 2016 (Table 3).

Spearman's correlation analysis

Correlation analysis was conducted to quantify the relationship between monthly malaria incidence to climatic variables at 0, 1, and 2 months lag. A significant positive correlation was found between monthly average temperature and the count of malaria incidence at 0, 1, and 2 months lag. The correlation coefficient decreased as the number of lags increased from 0 to 2 months.

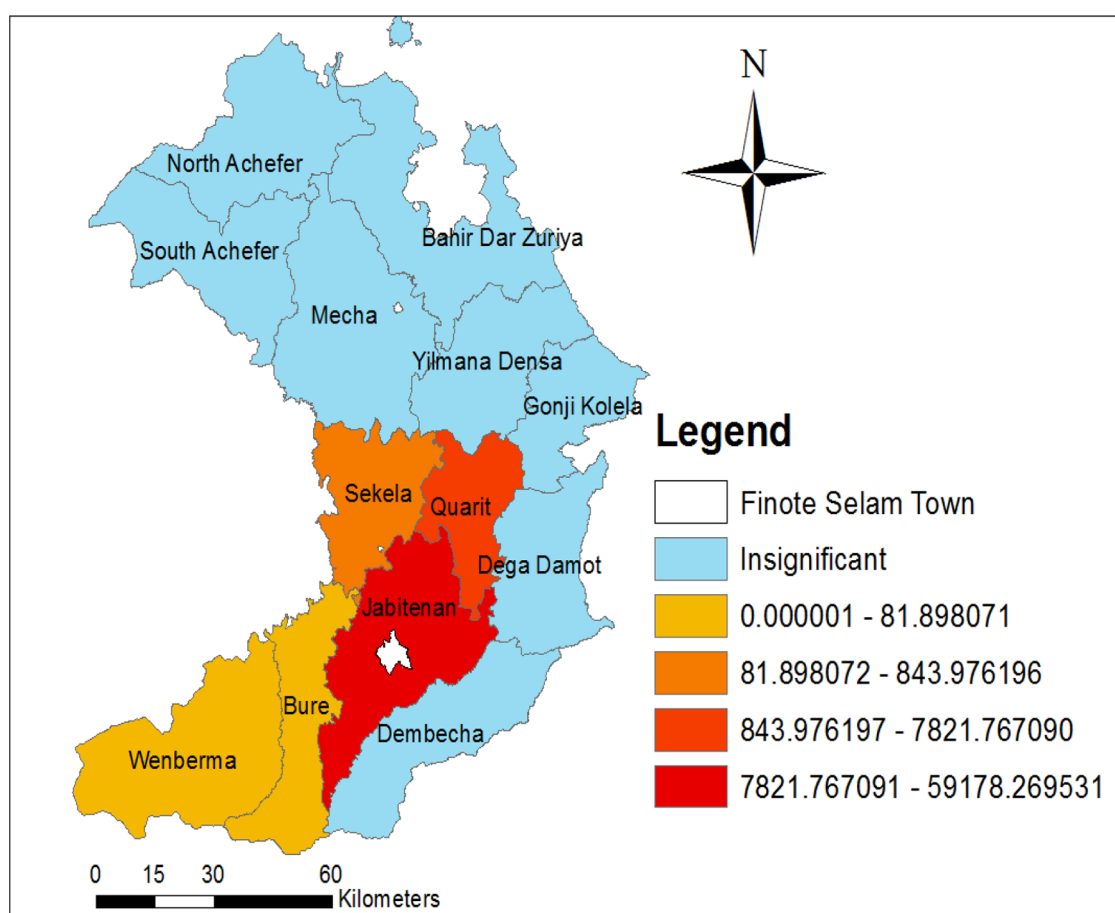


Figure 5. District level spatial clusters. Color identification of the clusters was ordered based on the value of likelihood ratio test statistic.

Table 2. Significant high rate temporal cluster of malaria in West Gojjam, 1 July 2013 to 30 June 2018.

TEMPORAL CLUSTER	OBS.*	EXP.*	RR	LLR	P-VALUE
2013/7/1 to 2015/6/30	195 144	133 649	2.07	22 448.54	.001

Abbreviations: RR, relative risk; LLR, Log likelihood ratio; Obs.*, number of observed cases in a cluster; Exp.*, number of expected cases in a cluster.

Monthly mean rainfall and number of monthly malaria cases showed a negative correlation at all lags (0, 1, and 2 months). All lag-months were significant and the correlation increased as the number of lags increased. Monthly mean relative humidity was negatively correlated with the number of malaria cases (ranged from $-.334$ to $-.347$) (Table 4).

Regression analysis

The multivariable negative binomial regression depicted that monthly average temperature, monthly average rainfall, and monthly average relative humidity were significantly associated with the rate of malaria incidence. There was a significant positive association between monthly average temperature and malaria incidence at all lag months. Monthly average rainfall and malaria incidence were negatively associated at all lag months. There was a significant negative relationship between relative humidity and malaria at 2 months lag.

There was a significant positive association between monthly average temperature (Adjusted IRR=1.301; 95% CI 1.212, 1.396) and the count of malaria incidence at 0 lag months. This means that 1°C rise in monthly average temperature increases count of malaria incidence by 30.1% (95% CI 21.2%, 39.6%). Monthly average rainfall (Adjusted IRR=0.998; 95% CI 0.996, 0.999) was negatively associated with a count of malaria incidence at 0 lag months. Besides, there was a significant positive association between monthly average relative humidity and count of malaria incidence (Adjusted IRR=1.021; 95% CI 1.009, 1.033) at 2 lag months (Table 5).

Discussion

Malaria incidence showed interannual variability across districts and survey years in West Gojjam zone from 1 July 2013 to 30 June 2018. Fluctuating seasonal and temporal trends of malaria incidence were observed. All districts reported malaria cases during the study period.

Table 3. Significant high rate spatiotemporal clusters of malaria in West Gojjam, 1 July 2013 to 30 June 2018.

SPATIOTEMPORAL CLUSTERS	TIME FRAME	OBS.*	EXP.*	RR	LLR	P-VALUE
Jabitenan	2014/7/1-2016/6/30	62712	13550.07	5.44	50789.1	<.001
Quarit	2013/7/1-2015/6/30	19476	6907.49	2.93	7857.882	<.001
Wonberma	2013/7/1-2014/6/30	9604	3214.69	3.04	4182.239	<.001
Bure	2013/7/1-2014/6/30	11284	4612.85	2.5	3489.048	<.001
Sekela	2013/7/1-2015/6/30	16051	8384.58	1.96	2845.244	<.001
Bahir Dar Zuriya	2013/7/1-2014/6/30	10981	5715.51	1.95	1946.236	<.001
Gonji Kolela	2013/7/1-2014/6/30	6627	3164.35	2.12	1453.762	<.001
South Achefer	2013/7/1-2014/6/30	6033	4032.82	1.5	435.6952	<.001
Yilmana Densa	2013/7/1-2014/6/30	7978	6868.12	1.17	87.03831	<.001
Dembecha	2015/7/1-2016/6/30	4529	4111.62	1.1	20.75957	<.001
North Achefer	2013/7/1-2014/6/30	6705	6297.32	1.07	13.16705	<.001

Table 4. Spearman correlation between the monthly counts of malaria incidence and mean monthly climatic variables in West Gojjam, 1 July 2013 to 30 June 2018, West Gojjam.

MONTHLY MEAN CLIMATIC VARIABLES	LAG-MONTHS	SPEARMAN'S R	P-VALUE
Temperature (°C)	0	.318	.01
	1	.284	.01
	2	.209	.01
Rainfall (mm)	0	-.195	.01
	1	-.311	.01
	2	-.332	.01
Relative humidity (%)	0	-.334	.01
	1	-.391	.01
	2	-.347	.01

In this study, the average annual cumulative malaria incidence was found to be 2.91%. Thus, the result was lower than studies in Northwest Ethiopia (30%),²⁰ Dabat district (9.7%),²¹ Southern Nations Nationalities and Peoples' Region (6.8%),²² Ethiopia's national malaria report of 2017 (4.5%),²³ Ethiopia's national malaria report of 2011 (43%), Ethiopia's national malaria report of 2014 (33%) of Tigray National Regional State.²⁴ Also, the incidence had shown a decreasing trend year after year. This variation might be due to the time of the study, which is after the first National Strategic Plans (NSP 2006-2010) and during the second 5-year National Strategic Plans for Malaria Prevention, Control, and Elimination,²⁵ and

endorsement of malaria elimination in 2016 using different surveillance mechanisms, and community mobilization.²⁶ As well, malaria control programs that the country has been carried out previously in collaboration with partners brought a good lesson in terms of training human power, provision of services, application of indoor residual spraying, improving surveillance activities and laid the foundation toward malaria reduction. The treatment, the controlling method, and the people awareness is improved now compared to the past.⁹

The average annual cumulative malaria incidence (2.91%) was similar to the study conducted in Ethiopia from 2001 to 2016 (2.9%),¹² but, it is still higher than the WHO pre-elimination standard (<1 case/1000 population at risk/year).¹³ Low level of knowledge, attitude and practice of the community toward malaria prevention and control,²⁷ difficulty of multiple mosquito breeding sites for environmental management, untimely performance of malaria control methods like indoor residual spraying of houses, and usually spraying after the outbreak begun, untimely replacement and not replacing Long Lasting Impregnated Nets at all, and the low practice of environmental management by the community and health extension workers might be the possible explanations for the observed level of average cumulative annual malaria incidence.¹⁵

Spatial clusters: Jabitenan, Quarit, Sekela, Bure, and Wonberma districts bordered with each other, and might be of having similar geographical parameters, such as altitude (below about 2000m above sea level according to the centroid of districts), weather conditions, and economic characteristics.²⁸ Since the importance of cluster analysis is to detect the aggregation of disease cases and to find evidence of risk factors on which prevention and control activities can be focused,²⁹ it

Table 5. Negative binomial regression analysis of the effect of climate variability on malaria in West Gojjam, 1 July 2013 to 30 June 2018.

MONTHLY MEAN CLIMATE VARIABLES	LAG-MONTHS	CRUDE IRR (95% CI)	ADJUSTED IRR (95% CI)
Monthly average temperature (°C)	0	1.325 (1.243, 1.412)***	1.301 (1.212, 1.396)***
	1	1.289 (1.212, 1.371)***	1.283 (1.198, 1.373)***
	2	1.250 (1.170, 1.335)***	1.274 (1.188, 1.367)***
Monthly average rainfall (mm)	0	0.997 (0.996, 0.997)***	0.998 (0.996, 0.999)*
	1	0.996 (0.995, 0.997)***	0.997 (0.95, 0.998)***
	2	0.996 (0.995, 0.997)***	0.995 (0.994, 0.997)***
Monthly average relative humidity (%)	0	0.973 (0.964, 0.981)***	
	1	0.974 (0.966, 0.983)***	
	2	0.986 (0.978, 0.994)**	1.021 (1.009, 1.033)***

Abbreviation: IRR, incidence rate ratio.

P*-value = .005. *P*-value = .001. ****P*-value < .001.

would be useful to apply priority intervention to identified these clusters.

Significantly a high rate of purely temporal malaria cluster was observed from 1 July 2013 to 30 June 2015 (LLR = 22 448.54, *P* < .001). There was a significant decrease in malaria incidence after this 2 year risk period. This might be due to the commencement of malaria elimination road map in Ethiopia by 2030 since 2016.²⁶

Spatiotemporal clusters were detected at Jabitenan from 1 July 2014 to 30 June 2016, Quarit and Sekela from 1 July 2013 to 30 June 2015, Wonberma, Bure, Bahir Dar Zuriya, GonjiKolela, South Achefer, Yilmana Densa, and North Achefer from 1 July 2013 to 30 June 2014, and Dembecha from 1 July 2015 to 30 June 2016. Space-time clusters from 1 July 2013 to 30 June 2015 might be explained by their occurrence preceding the endorsement of national malaria elimination road map.²⁶ Those space-time clusters which occurred after 30 June 2015 might be due to malaria intervention measures might not be taken, or might not been utilized correctly.^{27,30} The period was attributed by risk from hunger, disease, and lack of water due to El Niño, and these calamities in turn would exacerbate malaria incidence.³¹ El Niño conditions can cause a multiple of health problems. Above-average rainfall caused by El Niño can cause floods and increase diseases spread by mosquitoes, such as malaria, and the utilization of malaria control will be compromised during flooding.³² Thus, decision-makers and health managers need to follow up the implementation of interventions in a sustained way to prevent the cyclic resurgence of epidemics during environmental catastrophes through strong health systems, determined leadership, appropriate incentivization, an effective surveillance system, and regional collaborations.³³

A trend of seasonality in malaria was occurring more frequently from September to December and March to June based on the epidemic weeks. This finding is consistent with previous studies in the Northwest part of Ethiopia,^{20,30,34} which showed

climate factors significantly affected seasonal malaria incidence. Peak malaria transmission occurs between September and December in most parts of Ethiopia, after the main rainy season from June to July. Besides, some areas experience a second minor malaria transmission period from April to June, following a short rainy season from March to May with high maximum temperature.^{35,36} The rainy season ends leaving stagnant water collections, and during dry season rivers also start pooling and makes the environment favorable mosquito breeding.³⁷

Temperature was statistically significant and positively associated to count of malaria incidence in this study, which is in line with previous studies of Jimma town,³ and Amhara Region.³⁸ Besides, it is supported by a study done in Yunnan Province of China which showed that annual average temperature was positively associated with the malaria incidence rate.³⁹ Temporal correlation analysis between malaria and meteorological factors in Motuo County of China revealed that temperature was an important factor in the transmission of malaria.⁴⁰ Spatiotemporal data at a regional scale in highlands of Colombia and Ethiopia showed spatial distribution of the disease changes with the interannual variability of temperature which provided evidence for an increase in the altitude of malaria distribution in warmer years, which implies that climate change, without mitigation, will result in an increase of the malaria burden. Temperature is known to influence transmission intensity through its effects on growth of the mosquito and pathogen development within the vector.⁴¹

Rainfall to malaria incidence was found to be negatively correlated. This finding is in argument to previous studies of Chennai, India,⁴² Yunnan Province, China,³⁹ Motuo County, China,⁴⁰ and Jimma town.³ This might be due to the variation of strength of rainfall in different settings to erode and outflow mosquito breeding sites. Water collections that support vector breeding appear mainly after the rains. Hence, malaria transmission is highest immediately after the rainy seasons in

Ethiopia.⁴³ Because, the presence of high rainfall may not mean high malaria incidence as it causes overflow and erodes water collections and drain pooling rivers during dry season. Malaria starts getting higher immediately after the rainy season ends. Therefore, rainfall is a good indicator for malaria prevention and control activities in malaria endemic areas.

Relative humidity affects malaria transmission through its effect on the activity and survival of mosquitoes.⁴⁴ The relative humidity was found to be negatively correlated to count of malaria incidence in this study. This finding is not parallel to the study finding of Akure, Nigeria,⁴⁵ Motuo county, Tibet,⁴⁰ and Baluchestan, Iran.⁴⁶ This might be due to the effect of high relative humidity of the area above which the survival of mosquito vector will be declining. In the negative binomial regression analysis, relative humidity at 2 months lag was significantly associated to malaria incidence negatively. This might be due to the value of relative humidity regressed at 2 months lag be higher than the 0 lag and 1 month lag.

Conclusion

This study identified spatial, temporal, spatiotemporal clustering, and seasonal pattern of malaria incidence. There was also a decreasing temporal trend of malaria incidence. Mean monthly temperature and rainfall were directly and negatively associated to malaria incidence respectively at all lag months. Relative humidity was positively associated at 2 lag months. Considering these space-time variations and factors would be useful for the prevention and control, and ultimately achieve elimination targets in the area.

Limitations

The data were obtained from a passive surveillance system. This means that all clinical records did not fully capture the level of malaria transmission in the districts, because some people may not report to the formal governmental health institutions instead use either private clinics or traditional therapists or purchase drugs by their own. Data on individual, environmental, and institutional variables were not available for further factors analysis.

Acknowledgements

We are thankful to Amhara Public Health Institute, West Amhara Meteorological Agency, Amhara Region Central Statistical Agency, and Central Gondar Zone Health for giving data required for the study.

Author Contributions

Eniyew Tegegne conceived and initiated the study and made data available. All authors made major contributions to the study design, statistical analysis, and writing of the manuscript and approved the submitted version of the manuscript.

Availability of Data and Material

Authors present the data in the main paper.

Ethical Approval and Consent to Participate

Ethical clearance was obtained from Research and Ethical Review Committee of Institute of Public Health, College of Medicine and Health Sciences, University of Gondar. There were no individual participants in the study because it was secondary data/count of malaria which has no personal identifiers.

ORCID iDs

Eniyew Tegegne  <https://orcid.org/0000-0002-1915-2229>

Awrajaw Dessie  <https://orcid.org/0000-0001-5436-9936>

Abraham Teym  <https://orcid.org/0000-0001-5954-0923>

REFERENCES

1. WHO. World Malaria report 2014: summary. 2015. Accessed February 1, 2019. https://apps.who.int/iris/bitstream/handle/10665/160458/WHO_HTM_GMP/?sequence=8
2. Feng J, Xiao H, Liu J, Zhang L, Feng X, Xia Z. Towards malaria elimination: monitoring and evaluation of the “1-3-7” approach at the China–Myanmar border. *Am J Trop Med Hyg*. 2016;95:806–810.
3. Alemu A, Abebe G, Tsegaye W, Golassa L. Climatic variables and malaria transmission dynamics in Jimma town, South West Ethiopia. *Parasit Vectors*. 2011;4:30.
4. WHO. World malaria report 2018. 2018. https://scholar.google.com/scholarq=WHO.+World+malaria+report+2018.+2018.&hl=en&as_sdt=0&as_vis=1&oi=scholar
5. Pavli A, Maltezos HC. Malaria and travellers visiting friends and relatives. *Travel Med Infect Dis*. 2010;8:161–168.
6. Schumacher R-F, Spinelli E. Malaria in children. *Mediterr J Hematol Infect Dis*. 2012;4:e2012073.
7. WHO. Global technical strategy for malaria 2016–2030. 2015. Accessed February 2, 2019. https://apps.who.int/iris/bitstream/handle/10665/176712/9789241564991_eng.pdf?sequence=1
8. WHO. *World Malaria Report 2021*. WHO; 2021.
9. FMOH. Improved controlling methods help to reduce malaria: report from Government of Ethiopia. 2018. <https://reliefweb.int/report/ethiopia/improved-controlling-methods-help-reduce-malaria>
10. Fiondella F. Malaria risk increases in Ethiopian highlands as temperatures climb. 2017. Accessed January 1, 2019. <https://www.google.com/search?client=firefox-b-ab&q=Fiondella+F.+Malaria+Risk+Increases+in+Ethiopian+Highlands+as+Temperatures+Climb.+2017>
11. Scott M. Malaria risk zones expand to higher elevations in Ethiopian Highlands. 2017. Accessed February 1, 2019. <https://www.climate.gov/news-features/featured-images/malaria-risk-zones-expand-higher-elevations-ethiopian-highlands>
12. Taffese HS, Hemming-Schroeder E, Koepfli C, et al. Malaria epidemiology and interventions in Ethiopia from 2001 to 2016. *Infect Dis Poverty*. 2018;7:103.
13. WHO. Country classification by malaria elimination phase. 2012. https://www.google.com/search?q=WHO.+Country+classification+by+malaria+elimination+phase.&rlz=1C1CHBD_enET923ET923&coq=WHO.+Country+classification+by+malaria+elimination+phase.&aqs=chrome..69i57j33i160l2.1134j0j9&sourceid=chrome&ie=UTF-8
14. Emerson PM, Ngondi J, Biru E, et al. Integrating an NTD with one of “the big three”: combined malaria and trachoma survey in Amhara Region of Ethiopia. *PLoS Negl Trop Dis*. 2008;2(3):e197.
15. Kassa AW, Tamiru MA, Yeshanew AG. Assessment of control measures and trends of malaria in Burie-Zuria District, West Gojjam Zone, Amhara Region, North West Ethiopia. *Malar Res Treat*. 2015;2015:1–5.
16. Tadesse L, Suryabagavan KV, Sridhar G, Legesse G. Land use and land cover changes and soil erosion in Yezat watershed, North Western Ethiopia. *Int Soil Water Conserv Res*. 2017;5:85–94.
17. Kulldorff M. A spatial scan statistic. *Commun Stat Theory Methods*. 1997;26:1481–1496.
18. Kulldorff M, Nagarwalla N. Spatial disease clusters: detection and inference. *Stat Med*. 1995;14:799–810.
19. Kulldorff M. An isotonic spatial scan statistic for geographical disease surveillance. *J Natl Inst Public Health*. 1999;48:94–101.
20. Tadesse AA, Baraki AG, Gelaye KA. Spatial modeling, prediction and seasonal variation of malaria in northwest Ethiopia. *BMC Res Notes*. 2019;12:273.
21. Alemu K, Worku A, Berhane Y, Kumie A. Spatiotemporal clusters of malaria cases at village level, northwest Ethiopia. *Malar J*. 2014;13:223.

22. Bekele Dessie D. Spatial modelling of malaria prevalence and its risk factors in rural SNNPR, Ethiopia: classical and Bayesian approaches. *Am J Theor Appl Stat.* 2017;6:254.
23. USAID. Ethiopia malaria operational plan. 2017. <https://reliefweb.int/report/ethiopia/president-s-malaria-initiative-ethiopia-malaria-operational-plan-fy-2017>
24. Gerensea H, Teklay H. Pattern and trend of malaria morbidity and mortality in Tigray Region, Ethiopia from 2011. 2017. https://www.researchgate.net/profile/Gerensea-Hadgu/publication/316622651_Pattern_and_Trend_of_Malaria_Morbidity_and_Mortality_in_Tigray_Region_Ethiopia_from_201112-201415/links/59086c690f7e9b1d080f25f9/Pattern-and-Trend-of-Malaria-Morbidity-and-Mortality-in-Tigray-Region-Ethiopia-from-2011-12-2014-15.pdf?__cf_chl_tk=Mb6mK7wJ91YY_hPomn2kiq8niN3tcI3dRqUWBLmAqYA-1650445077-0-gaNycGzNCmU
25. Ethiopian Public Health Institute. Ethiopia National Malaria Indicator Survey 2015. 2016. Accessed June 3, 2019. <https://www.ephi.gov.et/images/pictures/download2009/MIS-2015-Final-Report-December-2016.pdf>
26. Gebrezgabier H. Ethiopia: AU endorses roadmap to eliminate malaria by 2030. 2017. Accessed June 3, 2019. <https://allafrica.com/stories/201607200560.html>
27. Aderaw Z, Gedefaw M. Knowledge, attitude, and practice of the community towards malaria prevention and control options in anti-malaria association intervention zones of Amahara national regional state, Ethiopia. *J Trop Dis.* 2013;1:118.
28. Azage M, Kumie A, Worku A, Bagtzoglou AC. Childhood diarrhea exhibits spatiotemporal variation in northwest Ethiopia: a SaTScan spatial statistical analysis. *PLoS One.* 2015;10:e0144690.
29. Mboera LE, Senkoro KP, Mayala BK, et al. Spatio-temporal variation in malaria transmission intensity in five agro-ecosystems in Mvomero district, Tanzania. *Geospat Health.* 2010;4:167-178.
30. Alemu K, Worku A, Berhane Y. Malaria infection has spatial, temporal, and spatiotemporal heterogeneity in unstable malaria transmission areas in north-west Ethiopia. *PLoS One.* 2013;8:e79966.
31. New York Times. Ethiopia El Niño emergency - fast facts. 2016. Accessed June 3, 2019. <https://reliefweb.int/report/ethiopia/ethiopia-cl-ni-o-emergency-fast-facts-june-2016>
32. Kovats RS, Bouma MJ, Hajat S, Worrall E, Haines A. El Niño and health. *Lancet.* 2003;362:1481-1489.
33. Shahandeh K, Basseri HR. Challenges and the path forward on malaria elimination intervention: a systematic review. *Iran J Public Health.* 2019;48:1004-1013.
34. Yeshiwondim AK, Gopal S, Hailemariam AT, Dengela DO, Patel HP, Dengela DO. Spatial analysis of malaria incidence at the village level in areas with unstable transmission in Ethiopia. *Int J Health Geogr.* 2009;8:5.
35. USAID. Ethiopian malaria operational plan. 2018. <https://d1u4sg1s9ptc4z.cloudfront.net/uploads/2021/03/fy-2018-ethiopia-malaria-operational-plan.pdf>
36. NNM Agency. Guide to the use of weather and climate information (WCI) for agricultural practices over selected district of Tigray, Ethiopia. National Meteorological Agency (NMA) of Ethiopia. 2017. Accessed June 1, 2019. <http://www.wmo.int/pages/prog/dra/raf/documents/Climate%20Guide%20for%20Tigray%20and%20SNNPR.pdf>
37. CDC. Factors that affect malaria transmission. Accessed June 2, 2019. <https://www.open.edu/openlearncreate/mod/oucontent/view.php?id=89&printable=1>
38. Midekisa A, Beyene B, Mihretie A, Bayabil E, Wimberly MC. Seasonal associations of climatic drivers and malaria in the highlands of Ethiopia. *Parasit Vectors.* 2015;8:339.
39. Yang D, Xu C, Wang J, Zhao Y. Spatiotemporal epidemic characteristics and risk factor analysis of malaria in Yunnan Province, China. *BMC Public Health.* 2017;17:66.
40. Huang F, Zhou S, Zhang S, Wang H, Tang L. Temporal correlation analysis between malaria and meteorological factors in Motuo County, Tibet. *Malar J.* 2011;10:54.
41. Siraj AS, Santos-Vega M, Bouma MJ, Yadeta D, Carrascal DR, Pascual M. Altitudinal changes in malaria incidence in highlands of Ethiopia and Colombia. *Science.* 2014;343:1154-1158.
42. Kumar DS, Andimuthu R, Rajan R, Venkatesan MS. Spatial trend, environmental and socioeconomic factors associated with malaria prevalence in Chennai. *Malar J.* 2014;13:14.
43. Woyessa A, Deressa W, Ali A, Lindtjörn B. Malaria risk factors in Butajira area, south-central Ethiopia: a multilevel analysis. *Malar J.* 2013;12:273.
44. Li T, Yang Z, Wang M. Temperature, relative humidity and sunshine may be the effective predictors for occurrence of malaria in Guangzhou, southern China, 2006–2012. *Parasit Vectors.* 2013;6:1-4.
45. Makinde OS, Abiodun GJ, Ojo OT. Modelling of malaria incidence in Akure, Nigeria: negative binomial approach. *GeoJournal.* 2021;86:1327-1336.
46. Mohammadkhani M, Khanjani N, Bakhtiari B, Tabatabai SM, Sheikhzadeh K. The relation between climatic factors and malaria incidence in Sistan and Baluchestan, Iran. *Sage Open.* 2019;9:2158244019864205.