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Since 2002

Projecting Malaria Incidence Based on Climate Change Modeling Approach: A Systematic Review

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Abstract

BACKGROUND: Climate change will affect the transmission of malaria by shifting the geographical space of the vector.

AIM: The review aims to examine the climate change modeling approach and climatic variables used for malaria projection.

METHODS: Articles were systematically searched from four databases, Scopus, Web of Science, PubMed, and SAGE. The PICO concept was used for formulation search and PRISMA approach to identify the final articles.

RESULTS: A total of 27 articles were retrieved and reviewed. There were six climate factors identified in this review: Temperature, rainfall/precipitation, humidity, wind, solar radiation, and climate change scenarios. Modeling approaches used to project future malarial trend includes mathematical and computational approach.

CONCLUSION: This review provides robust evidence of an association between the impact of climate change and malaria incidence. Prediction on seasonal patterns would be useful for malaria surveillance in public health prevention and mitigation strategies.

Introduction

Malaria is a life-threatening disease caused by *Plasmodium* parasites. It is transmitted to people through the bites of infected female *Anopheles* mosquitoes, called “malaria vectors.” There are five parasite species that cause malaria in humans, and two of these species – *Plasmodium falciparum* and *Plasmodium vivax* – pose the largest threat. Malaria is a public health burden; however, it is preventable and curable. In 2019, there were an estimated 229 million cases of malaria globally [1]. The estimated number of malaria mortality was 409,000 in 2019. Children aged under 5 years are the most vulnerable group affected by malaria. In 2019, they accounted for 67% (274,000) of all malaria deaths internationally. The World Health Organization (WHO) African Region (AFR) carries a disproportionately high share of the global malaria burden. In 2019 alone, the region was home to 94% of malaria cases and mortality. In 2018, *P. falciparum* accounted for 99.7% of estimated malaria cases in the WHO AFR, 50% of cases in the WHO South-east Asia Region, 71% of cases in the Eastern Mediterranean and 65% Western Pacific. *P. vivax* is the most prevalent parasite in the WHO Region of America, representing 75% of all malaria cases [1]. Total funding for malaria control and elimination reached an estimated US$ 3 billion in 2019. Subsidies from governments of endemic nations amounted to US$ 900 million, representing 31% of total aid.

Climate plays a crucial role in malaria transmission, particularly in tropical countries. Factors such as land use, population growth, urbanization, migration, and high economic development also contribute to malaria transmission [2]. Climate change will directly affect the information of vector-borne disease by shifting the vector’s geographical space, increasing reproduction and biting rate, and shortening the pathogen’s incubation period [3]. Other factors such as temperature, rainfall, and humidity may influence the population of *Anopheles* and malaria incidence [4], [5]. Warmer temperatures can reduce the sporogonic cycle duration; hence, mosquitoes will be more infective and spread widely [6]. Temperature suitable for mosquitoes lifespan ranges from 16°C to 36°C with life sustainability equal to 90%. A higher proportion of mosquitoes in the incubation period in temperature varies from 28°C to 32°C [7]. Rainfall does not affect parasites directly; however, it plays an important part in malaria spread. Rain will form stagnant water as breeding place for *Anopheles.* High rainfall increases humidity and prolong age of adult mosquitoes [2].

At present, there are developments of conceptual models or modeling in controlling malaria transmission. Mathematical modeling of malaria is the best method to synthesize information, measure uncertainty, and extrapolate knowledge [8]. Modeling of malaria used as a climate factor has been undertaken in countries such as Nigeria, Bangladesh, Brazil, Kenya, Ethiopia, China, West Africa, Burundi, and Bhutan [2]. Numerous studies employ either mechanistic or statistical modeling frameworks that have investigated climatic change effects on the distribution and intensity of malaria risk in different situations. In some studies, an association was established between climatic change and the exacerbation of the risk while in others, the climatic effect was not established. However, instead, the increasing malaria burden was attributed to other factors such as drug resistance, failure of vector control operations, and changes in land use [9]. Interpretations of results from studies that employed a statistical modeling framework are often limited by the absence of good quality data caused by the weak and fragmented nature of national health information systems in malaria-endemic countries [10]. Other than that, heterogeneity exists in the projection approach in terms of no standardized settings used to predict the future incidence of malaria.

It is essential to address the high uncertainties of climate predictions by estimating the impact of climate change over the predictions by current climate models used for predicting the re-emergence of malarial incidence in endemic and non-endemic countries. Since there are not many articles that study the temporal projection of malaria incidence based on climatic variables, hence with the advent of this review, it is hoped that the results will build an understanding of the association between climatic variables and malaria transmission in terms of epidemiological evidence. Therefore, this review examines the climate change modeling approach and climatic variables used for malaria projection.

Methodology

The review protocol – PRISMA

The PRISMA review protocol guided this study. PRISMA, otherwise known as Preferred Reporting Items for Systematic Reviews and Meta-analyses, is explicitly designed for systematic reviews and meta-analyses [11]. PRISMA aims to prompt researchers to source the correct information with an accurate level of detail. Based on this review protocol, the researchers started their systematic literature review by formulating appropriate research questions. Next, the researchers began the systematic search that consists of three main sub-processes: Identification, screening (inclusion and exclusion criteria), and eligibility. Next, the researchers appraise the quality of the selected articles using the mixed methods appraisal tool (MMAT) Version 2018 [12] to ensure the quality of the articles for reviewing. Finally, the researchers explore in detail the data that were extracted for analysis and validation.

Formulation of the research question

The formulation of the research question for this study was based on PICO. PICO is a tool that assists authors in developing a relevant research question for the review. It is based on three main concepts: Population or problem, interest, and context/outcome [13]. Based on these concepts, the researchers have included the three main aspects in the review, namely, community (Population), climate change modeling approach and climatic variables (Interest), and projection of malaria incidence (Context/Outcome), which guided the researchers to formulate their main research question "What are the climate change modeling approach and climatic variables used for malaria projection?"

Systematic searching strategies

There are three main processes in the systematic searching strategies process: Identification, screening, and eligibility (Figure 1).

Identification

Identification is a process to enrich the keywords by identifying the synonyms and their variation during article searching in the databases. The search

Table 1: Keywords search used in the identification process

Database	Search string
Scopus	TITLE-ABS-KEY (["climate change*" OR "global warming" OR "climate emergenc*" OR "climate crisis" OR "global heating" OR "weather crisis" OR "extreme weather" OR "temperature" OR "humid*" OR "precipitation" OR "rainfall"] AND ["malaria incidence" OR "malaria epidemiology"] AND ["project*" OR "forecast*" OR "estimate*" OR "prediction" OR "calculation" OR "expectation" OR "prognosis" OR "computation" OR "extrapolation"])
Web of Science	TS = (["climate change*" OR "global warming" OR "climate emergenc*" OR "climate crisis" OR "global heating" OR "weather crisis" OR "extreme weather" OR "temperature" OR "humid*" OR "precipitation" OR "rainfall"] AND ["malaria incidence" OR "malaria epidemiology"] AND ["project*" OR "forecast*" OR "estimate*" OR "prediction" OR "calculation" OR "expectation" OR "prognosis" OR "computation" OR "extrapolation"])
PubMed	(["climate change*" OR "global warming" OR "climate emergence*" OR "climate crisis" OR "global heating" OR "weather crisis" OR "extreme weather" OR "temperature" OR "humid*" OR "precipitation" OR "rainfall"] AND ["malaria incidence" OR "malaria epidemiology"] AND ["project*" OR "forecast*" OR "estimate*" OR "prediction" OR "calculation" OR "expectation" OR "prognosis" OR "computation" OR "extrapolation"])
SAGE	(["climate change*" OR "global warming" OR "climate emergence*" OR "climate crisis" OR "global heating" OR "weather crisis" OR "extreme weather" OR "temperature" OR "humid*" OR "precipitation" OR "rainfall"] AND ["malaria incidence" OR "malaria epidemiology"] AND ["project*" OR "forecast*" OR "estimate*" OR "prediction" OR "calculation" OR "expectation" OR "prognosis" OR "computation" OR "extrapolation"])

string was developed and enhanced using Boolean operators and phrase searching, as shown in Table 1. The systematic literature search was conducted in May 2021 involved four primary databases: Scopus, Web of Science, PubMed, and SAGE, which resulted in the retrieval of 276 records. These four databases were selected because of their availability and accessibility in our organization. There were 91 duplicate records found and removed. The records were exported from the databases and arranged for screening in an Excel sheet.

Screening

The title and abstract of each record were examined for relevance and screened based on specific criteria by MB, SSSS, SPC, and MHB. This screening process excluded 107 articles, while the remaining 78 articles retrieved full text for eligibility. The inclusion criteria for article selection were: (1) Published in 2012–2021, (2) full original article, (3) written in English, and (4) observational study. In addition, articles that are not original, such as systematic review, conference proceedings, book chapters and reports, were excluded from the study. Any disagreement on article selection was resolve through discussion.

Eligibility

Four independent reviewers screened the potentially relevant articles for eligibility. MB, SSSS, SPC, and MHB reviewed the full-text articles and kept a log of the reason for the article excluded from the study. A total of 51 articles were excluded in view of absence of future prediction periods (n = 37), the articles were focus on spatial prediction only (n = 6), focus on vector distribution prediction (n = 5) and article related to model validation study (n = 3). Subsequently, the remaining articles proceeded for quality appraisal.

Quality appraisal

The remaining articles from the eligibility process need to be examined to ensure that the quality of methodology is free from any bias [14]. MMAT for the systematic review of non-randomized studies was used by MB, SSSS, SPC, and MHB to ensure the value of diverse study designs in a review. The authors focused on the 25 criteria that cover five categories of the articles. For the articles to be included in the review, all authors must mutually agree. Any disagreement was discussed between them before deciding on the inclusion or exclusion of the articles for the review. Thus, all the remaining 27 articles were eligible for review.

Data extraction and analysis

This study relied on the qualitative aspect of the article related to environmental factors and their effect on malaria disease. The present study selected the qualitative technique, while the authors read the 27 articles thoroughly, particularly in abstract, results, and discussions. Data extraction was conducted by MB, SSSS, SPC, and MHB based on the research questions. It denotes that any data from the reviewed studies that can answer the research questions were extracted and placed in a table. Subsequently, the researcher performed a systematic analysis that identified findings based on efforts related to noting patterns and themes, clustering, counting, noting similarities, and relationships within the extracted data [15]. This analysis is considered the most suitable in synthesizing a mixed research design (integrative) [16]. Furthermore, it is explained as a descriptive method that reduces the data in a flexible model that merges with other data analysis techniques [17].

The first step of systematic analysis is to generate findings. The authors had identified all the patterns that emerged among all reviewed articles' extracted data in the process. Next, any similar or related extracted data were pooled in as a characteristic, and eventually, six findings were created. The development of these findings was done using this technique in a group consisting of authors with the characteristics of the results. During the development of the findings, authors discussed any inconsistencies, thought, puzzles, or ideas associated with the interpretation of the data until the point of agreement on the adjustment of the developed findings.

Results

Background of the selected articles

A total of 27 studies were included in this systematic review (Figure 1). Descriptive summary of included studies concerning publication year, study location, and setting is shown in Tables 2 and 3. All eligible studies were conducted in various countries, including Afghanistan, China, Ethiopia, Ghana, India, Iran, Kenya, Republic of Korea, Mali, Mozambique, Uganda, and other African countries. When categorized into the WHO regions, 16 of the studies were performed in the AFR, five studies from the South-east Asian region and three studies from Eastern Mediterranean Region and Western Pacific Region, respectively. The analyzed articles were published in the year 2012–2021. These quantitative studies resumed cross-sectional study design with time-series analysis for prediction of the future malaria cases. However, the baseline period trend across all studies was not uniform, renders it difficult to compare the projection results. Two studies used 2001–2009 as baseline period while another two studies used 2005–2015, but the rest of the studies varied in their baseline period selection. The duration

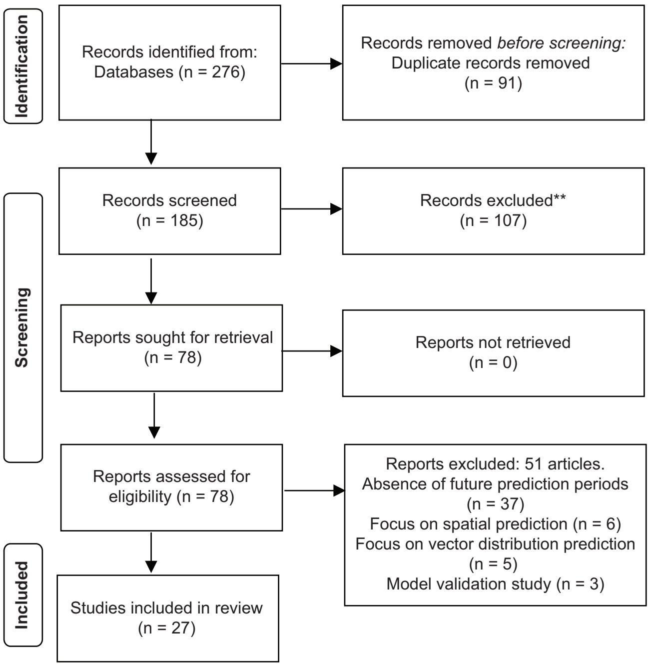

Figure 1: The PRISMA flow diagram

of the baseline period (in years) used for the future prediction in all of the studies ranging from <5 years to more than 25 years. The availability and completeness of the meteorological information and climate change scenarios contributed significantly to the modeling approach of the projection studies.

Table 2: Descriptive summary of included studies (n = 27)

Characteristic	Frequencies (%)
WHO regions	
AFR	16 (59)
SEAR	5 (19)
EMR	3 (11)
WPR	3 (11)
Publication year	
2012–2016	15 (56)
2017–2021	12 (44)
Duration of the baseline period (years)	
<5 years	1 (4)
5–10 years	14 (52)
11–15 years	4 (15)
16–20 years	3 (11)
21–25 years	3 (11)
More than 25 years	2 (7)
Study design	
Cross-sectional	27 (100)

AFR: African region, SEAR: South-east asian region, EMR: Eastern mediterranean region, WPR: Western pacific region.

Climate factors variable

The climate factors variables employed in these studies mainly consist of surface temperature (26 studies), rainfall/precipitation (19 studies), relative humidity (11 studies), wind (four studies), and solar radiation (two studies). In addition, four studies considered the additional factor of the geographical vegetation index, whereas a study includes topographic depression as variables to fit the prediction modeling of malaria cases. However, the selection of environmental factors other than climate studied in each article is primarily dependent on multifactorial and will not be discussed further in this review.

Climate change scenarios

Two studies conducted in the East AFR and the Republic of Korea used representative concentration pathway (RCP) 8.5 and RCP 4.5 as the climate change scenarios to drive the future prediction of malaria both regionally and nationally. However, as the Intergovernmental Panel on Climate Change (IPCC) produced, the climate change scenarios resembled the gradual simulation increase of temperature at the global level by up to 2100 (IPCC 2014). Therefore, limited usage of climate change scenarios may indirectly impact the consistency of the future prediction periods and malaria trends.

Modeling approach

Several types of models are used to project the future malaria trend based on the mathematical and computational approach [18]. In the 27 studies that projected malaria's future nationally or regionally, 23 used a mathematical modeling approach and the other four used computational methods. Studies that performed autoregressive integrated moving average (11 studies), regression analyses (five studies), the Liverpool Malaria Model (three studies), general additive modeling (two studies), generalized linear Poisson modeling (one study), and polynomial distributed lag time-series regression (one study) were categorized into the mathematical approach. Meanwhile, the HYDREMATS model, Ross-Macdonald model, Waikato environment for knowledge analysis model, and SLIM model utilizes complex computational approaches based on machine learning analysis.

Discussion

Despite predicting the malaria incidence in a particular population and place using multiple methods of environmental modeling, there are still other challenges that need to be overcome in reducing malaria incidence. The literature suggested that human intervention factors such as insecticide-treated bed nets and the complexity of multi-species vectors contribute significantly to malaria transmission [19], [20], [21]. In addition, the human host mobility for work and home, mass migration of workers for better socioeconomic condition, education on protective measures against malaria infection, and nutritional status of vulnerable groups have collectively impacted the dynamicity of morbidity and mortality rate of malaria [20], [21], [22], [23]. Besides the climate change effect that has tremendously cause a large-scale increase in malaria incidence, the housing structures, land use, and access to healthcare are often missed in modeling studies [23], [24].

Table 3: Characteristics of included studies

ID	Authors (year)	Country	Baseline study period	Future prediction period	Prediction Modelling Involved	Accuracy of Modelling	Factors/Climatic Variables Involved	Results/Outcome	Conclusion
1	(Ateba *et al*. 2020)	Mali	2012–2017	40-weeks based incidence	Functional Generalised Spectral Additive model	Adjusted R square = 67.3%	Rainfall, average air temperature, humidity in the ground surface, wind speed	Malaria incidence per 1000-persons week	Geo-epidemiological approach using functional models is useful to health managers to allocate resource for epidemic outbreak control and management
2	(Anwar *et al*. 2016)	Afghanistan	2005–2015	12 months	ARIMA Model	R square = 0.897	Precipitation, surface relative humidity, enhanced vegetation index, surface air temperature	Malaria cases per 1000 outpatients	Vegetation is correlated with malaria cases in Afghanistan, hence, vegetation seems to be a better predictor of malaria
3	(Ermert *et al*. 2012)	Africa	1960–2000	2001–2050	Liverpool Malaria model	None	Surface temperature, rainfall, p. Falciparum infection rate	Infectious bite per human per year	The model confirms the impact of altered temperature and precipitation under future climate on spread of malaria
4	(Saha *et al*. 2020)	India	1995–2016	annual	ARIMA Model	None	Temperature, rainfall, relative humidity	Malaria incidence per year	ARIMA model has prospect for the future prediction of malaria in India
5	(Bouma *et al*. 2016)	Ethiopia	1966–1980	August 2016 – July 2017	Regression analysis	R square = 0.6	Sea surface temperature	Malaria cases per annum	El-Nino related global warming as a climate signal that translates into large scale of malaria incidence
6	(Dabaro *et al*. 2021)	Ethiopia	2010–2017	monthly forecast of 2030	ARIMA model	None	Rainfall and temperature	Malaria incidence	Rainfall was positively correlated with the malaria incidence while the temperature was negatively correlated
7	(Darkoh *et al*. 2017)	Ghana	2002-2015	2016–2020	ARIMA model	None	Rainfall and temperature	Malaria incidence	There is an association of temperature and malaria incidence
8	(Le *et al*. 2019)	Kenya	2008–2013	S2 & S3 (future)	SLIM Model	R square = 0.93−0.96	1. Daily precipitation 2. Mean daily air temperature 3. Mean annual evapotranspiration 4. Topographic depression 5. Soil characteristics 6. Vegetation cover	Trend of malaria incidence	This work can be applied to analyze the impacts of environmental changes on other mosquito-borne diseases in particular and vector-borne diseases in general.
9	(Leedale *et al*. 2016)	East African Community (EAC) region	1980–2005	Future slices (2016-2085)	1. LMM 2. Vector-borne Disease Community Model of International Centre for Theoretical Physics Trieste (VECTRI)	None	1. Rainfall 2. Temperature 3. Precipitation	Malaria transmission (vector survival probability)	These scenarios will still be undermined by the possibility of bio-technological break throughs (e.g. The development of cost-efficient vaccines and novel control techniques) that might occur during the following decades.
10	(Nath and Mwchahary 2012)	India	2001–2010	12 monthly seasonal oscillation	SARIMA models	r = 0.689	1. Rainfall 2. Temperature 3. Relative humidity	Malaria incidence rates (MIR)	1. Climatic variables are not instantaneous facilitator of malaria transmission 2. The implicit association between the two makes it difficult to develop a tool for forecasting malaria incidence based on individual influences of the climatic variables
11	(Macleod and Morse 2014)	Africa	1871–2010	12 months	LMM	None	1. Temperature 2. Precipitation	Malaria incidence	A tailor-made visualization may help to simply communicate quantified key modelling uncertainties, and the work described here is the first step toward the creation of such a tool
12	(Midekisa *et al*. 2012)	Ethiopia	2001–2009	1–3 months	SARIMA Models	None	1. Rainfall 2. Actual evapotranspiration 3. Land surface temperature 4. Vegetation indices	Malaria incidence	Malaria risk indicators such as satellite-based rainfall estimates, LST, EVI exhibited significant lagged associations with malaria cases in the Amhara region and improved model fit and prediction accuracy
13	(Mohapatra *et al*. 2021)	India	2002–2017	Monthly	WEKA	None	1. Rainfall 2. Temperature 3. Relative humidity	Malaria incidence	The climate is an extremely complex factor to predict, and the results provided promising signals for predicting future malaria incidents

(Contd...)

Table 3: *(Continued)*

ID	Authors (year)	Country	Baseline study period	Future prediction period	Prediction Modelling Involved	Accuracy of Modelling	Factors/Climatic Variables Involved	Results/Outcome	Conclusion
14	(Mopuri *et al*. 2020)	India	2001–2016	January 2015–December 2016	SARIMA Models	R squared = 0.85	1. Mean temperature 2. Rainfall 3. Normalised Difference Vegetation Index 4. Wind speed	Malaria incidence	The predictive results indicate that the models help for better understanding the disease transmission mechanism and can also assist in malaria intervention and control programs
15	(Moukam Kakmeni *et al*. 2018)	Africa	2000–2010	2050 (future climate)	The Ross–Macdonald model	None	Temperature	Predicted value R nought	The findings in this research could constitute a realistic basis for understanding the interactions and complexities between the disease (malaria), its vectors and the parasites
16	(Ostovar *et al*. 2016)	Iran	2003–2009	Weekly and monthly	ARIMA	Weekly model (R2 = 0.863), monthly model (R2 = 0.424)	Rainfall, temperature, relative humidity	Malaria incidence	Statistical models can be with a MEWS to predict malaria incidence, while the time-series model also has acceptable accuracy.
17	(Sewe *et al*. 2017)	Kenya	2003–2012	2013	General additive modelling framework	R2 in General Additive Model (GAM) 1-month lead = 0.44 2-month lead = 0.37 3-month lead = 0.16 GAMBOOST 1-month lead = 0.71 2-month lead = 0.56 3-month lead = 0.50	Land surface temperature, precipitation, normalised difference vegetation index	Monthly Malaria admissions at a district hospital.	GAMBOOST model with a lead time of 1 month proved to have the best accuracy to predict monthly admissions at a district hospital. The use of boosting regression in GAM models can be beneficial in early warning systems to improve predictions.
18	(Sheikhzadeh *et al*. 2017)	Iran	2005–2015	2019–2025	Regression analysis	Not included	Mean of monthly temperature, monthly precipitation, monthly humidity, monthly highest temperature, and socioeconomic (education and wealth).	Monthly incidence of locally transmitted vivax and falciparum malaria.	Socioeconomic and climatic variables are most important contributors to malaria transmission.
19	(Yamana and Eltahir 2013)	West africa	1980–1999	2080–2099	Simulation based on Hydrology, Entomology and Malaria Simulator (HYDREMATS) model and General Circulation model.	Not included	Rainfall, temperature, wind speed, wind direction and radiation	Vectorial capacity	Findings emphasise the importance of rainfall in determining how climate change would affect malaria transmission in the future climates. Result predicted there is no major rise in malaria prevalence in Africa region
20	(Zinszer *et al*. 2015)	Uganda	2006–2013	Weekly forecast over a 52-week forecasting period	ARIMA model with exogenous variable (ARIMAX)	The accuracy of the models varied widely between the sites. Large relative error measures (200%).	Rainfalls, LST, EVI	Number of confirmed malaria	Clinical data such as drug treatment could be used to improve the accuracy of malaria predictions in a highly endemic setting when coupled with environmental predictors
21	(Ferrão *et al*. 2017)	Mozambique	2006–2014	3.5 months in advance prediction	ARIMA model and regression model - box-cox	R-square in this study was 0.725, implying that 72.5% of the variance in malaria occurrence can be explained by variance in the predictive variables	Temperature, relative humidity, wind speed, visibility, and precipitation	His model is robust and, can predict the expected number of malaria cases 3.5 months in advance	A seasonal pattern was observed in malaria occurrence in Chimoio with peaks during weeks 1–12 (January to March)
22	(Gao *et al*. 2012)	China, Anhui province	1990–2009	1–2 months	PDL time-series regression	The modelling results show that 92%, 93% and 90% of the variance in malaria transmission was accounted for by rainfall in the northern, middle and Southern Anhui Province,	Temperature, RH, rainfall and The MEI	Impact of rainfall on malaria follows lag of 1–2 months	A significant association between malaria transmission and rainfall in Anhui Province
23	(Goswami *et al*. 2012)	Northeast India	2006–2010	2 years prediction	genesis model of malaria epidemiology	Cant tell	Daily temperature, rainfall and humidity	12 districts follow independent patterns of annual cycle and inter annual variability of epidemiology	Inclusion of the three meteorological variables, with the expressions for exposure and transmission, can accurately represent observed epidemiology over multiple locations and years

(Contd...)

Table 3: ***(Continued)***

ID	Authors (year)	Country	Baseline study period	Future prediction period	Prediction Modelling Involved	Accuracy of Modelling	Factors/Climatic Variables Involved	Results/Outcome	Conclusion
24	(Karuri and Snow 2016)	East African coast	1990–2011	2 months	AR model of order two can be used to forecast the malaria hospital burdens over the subsequent 12 months.	Not mention	Temporal association between monthly paediatric malaria hospital admissions, rainfall, and Indian Ocean Sea surface temperatures	The proportion of paediatric admissions to KDH due to malaria can be forecast by a model which depends on the proportion of malaria admissions in the previous 2 months	Surveillance data can build time-series prediction models which can be used to anticipate seasonal variations in clinical burdens of malaria and aid the timing of malaria vector control.
25	(Kim *et al*. 2019)	Limpopo, South Africa	1998–2015	1–2 weeks prediction	MEWS, GLM and autoregressive integrated moving average (ARIMA) time series model	Correlation coefficient r>0.8 for 1-2 weeks ahead forecast	Temperature and precipitation	Malaria incidence	The prediction model showed good performance for the short-term lead time, and the prediction accuracy decreased as the lead time increased but retained fairly good performance
26	(Kim *et al*. 2012)	Korea	2001–2009	7-week prediction	Generalised linear Poisson models and DLNM were used for Akaike. information criterion.	Not mention	Effects of temperature, relative humidity, temperature fluctuation, duration of sunshine, and rainfall	An increase in temperature, relative humidity and sunshine was associated with increase in malaria incidence	Lagged estimates of the effect of rainfall on malaria are consistent with the time necessary for mosquito development and P. Vivax incubation
27	(Kwak *et al*. 2014)	Korea	2001–2011		CNCM3 climate model	coefficient of determination R is 0.852	The effect of time lag between malaria occurrence and mean temperature, relative humidity, and total precipitation	An increase of malaria occurrence before rainy season in summer using climate change scenario and CNCM3 climate model	There is a strong correlation between malaria occurrence and monthly average temperature, relative humidity, and precipitation data are analyzed with time lag effect between malaria occurrences

*ARIMA: Autoregressive integrated moving average, SARIMA: Seasonal autoregressive integrated moving average, PDL: Polynomial distributed lag, RH: Relative humidity, LST: Land surface temperature, EVI: Enhanced vegetation index, MEI: Multivariate ENSO Index, GAMBOOST: General Additive Model with boosting, LMM: Liverpool malaria model, SLIM: Stochastic lattice-based integrated malaria, MEWS: Malaria early warning system, GLM: Generalized linear model, DLNM: Distributed lag non-linear models

Climate change models of malaria provide a quantitative method of considering the impact of climate variables on malaria transmission. Several climatic variables have been identified in this study: Temperature, rainfall, precipitation, humidity, wind direction, and solar radiation. Among the climate-change scenarios used for climate modeling and research are the IPCC Fifth Assessment Report (AR5) in 2014 that include the RCP 2.6, 4.5, 6, and 8.5 projected for the year 2100 [25]. The variation of the mosquito population in both aquatic and adult stages is highly dependent on climatic factors. The largest total mosquito population is found to correspond to the highest air temperature and rainy seasons. Simulations obtained from projected climate scenarios show that the elevated CO_2 condition increases the habitat index for mosquito reproduction, which leads to a higher density of vectors, thus leading to an increase in malaria incidence. Unlike the high CO_2 condition, the rise in air temperature has two distinct effects on malaria dynamics. First, temperature affects the development of malaria as the parasite does not develop below 18°C and over 40°C [26]. Second, higher air temperature reduces soil moisture, thus decreasing the habitat index for the *Anopheles* vector. Furthermore, higher air temperature non-linearly shortens the life cycles of *Anopheles* and *Plasmodium*. Although, under high air temperature increase, non-linear effects of air temperature are stronger than the impacts of soil moisture decrease on vector abundance, resulting in more significant changes of malaria incidence [21]. A study carried out in India by Mopuri shows that peak transmission of malaria occurs during the South-west monsoon (June to September). Whereas mean temperature, average wind speed, relative humidity, and normalized difference vegetation index have significantly correlated with malaria cases in different seasons. The Visakhapatnam district contains heterogeneous climatic conditions and different altitudinal variations that favor the vectors and parasites, thus lead to high transmission of malaria [27]. Furthermore, Siraj *et al*. predicted that a 1°C increase in daily mean temperature would result in three million additional malaria cases in the unstable transmission highlands of Africa [28].

Since the formulation of AR5, RCP 4.5 is described by the IPCC as an intermediate scenario [29]. For the climate change scenario, the future carbon dioxide concentration scenario was used as the boundary condition of the climate model and many different situations were assumed and applied. The RCP scenario is the most studied; however, only two studies in this review used it [30], [31]. According to the IPCC, RCP 4.5 requires that CO_2 emissions start declining by approximately 2045 to reach roughly half of the levels of 2050 by 2100. It also requires that methane emissions (CH_4) stop increasing by 2050 and decline somewhat to about 75% of the CH_4 levels of 2040 and that sulfur dioxide emissions decline to approximately 20% of those of 1980–1990 [29]. Analysis of simulated data using RCP 4.5 shows that the trend of malaria incidence will gradually increase [30]. The predictive results indicate that the modeling helps better understand the disease transmission mechanism and assist in malaria intervention and control programs.

Recent studies have shown that state-of-the-art modeling approach ensemble prediction systems can make a skilfull forecast of climatological variables to anticipate the emerging malaria trend [30], [32], [33]. However, the specific climate factors used in respective geographic settings to integrate the modeling approach contribute to the heterogeneity in future malaria prediction [18], [34], [35]. Despite the increasing use of complex mathematical modeling and mechanistic multi-model, there is no observed systematic pattern in the future prediction period among the included studies. This could be explained by utilizing different time serial intervals, baseline periods, and covariates within each modeling approach yielded distinct forecasts of malaria trends over one another [36], [37], [38]. There is no universal modeling approach to date that can fit all the countries given the dynamicity of climate change behavior.

Modeling outcomes can vary depending on the epidemiological characteristics of the malaria diseases, encompassing the agent, host, and environment [37], [38], [39]. A centralized reference data platform that allows for sharing climatological parameters would enable researchers to calibrate future malaria prediction based on comparable and standardized metrics [26], [37], [38], [40]. However, the review noted inconsistency in computation of climate factors variable into the modeling approach that is ultimately limited by the availability of information at the national or subnational level [41], [42]. This makes the future prediction of malaria under the simulation of climate change alone is challenging without uniform calibration [43], [44].

Strengths

This review highlights the current public health issues on re-emerging malaria compounded with the flexible climate change behaviors. It identifies future research areas on the incorporation of non-climatic predictors of malaria. Besides, the review finds cautious interpretation when utilizing any type of modeling approach due to the heterogeneity. Future projection of malaria is direly essential to aid in the planning and mitigation strategies by the stakeholders; hence, the need for the scientific consensus on data potentially used in the modeling.

Limitations

There are several limitations to this review. Most of the articles found do not holistically fulfill the inclusion criteria of temporal prediction of malaria incidence based on climatic variables. Hence, it was challenging to search for quality papers to be included in the systematic appraisal. Besides that, the habitat index was estimated only from open topographic depressions, limiting the applicability of the proposed model in urban areas [21]. However, malaria can also occur in urban. Furthermore, modeling can be extended using statistical techniques to analyze the uncertainty of small-size anthropogenic factors on the dynamics of malaria in the cities. In addition to that, the dynamics of malaria caused by multi-species vectors are not considered. Although *Anopheles* is the primary vector involved, malaria transmission in many other places is influenced by the population dynamics of other numerous vector species.

Furthermore, human hosts are assumed to be immobile in most of the modeling projections. However, it has been shown that mass migration may contribute to malaria infection dynamics, especially at scales that exceed the limits of mosquito dispersal [22]. Another limitation is that very few studies use IPCC's standardized climate change scenario to predict malaria incidence. One of the strengths of using the IPCC AR5 climate model is its ability to predict climate over a longer time or glacial year. The disadvantage is that it only considers the natural Earth systems and not the interaction between humans and nature.

Conclusion and Recommendations

This review provides robust evidence of an association between the impact of climate change and malaria incidence. There are growing numbers of research that forecast malaria incidence based on climate factor variables, but limited studies utilize the climate change scenarios in future malaria prediction. In addition to the future forecasts, accounting for alternative climate factor variables, the benefit would come from considering climate change scenarios and other non-climatic drivers such as the presence/absence of malaria vectors, population growth, and deforestation as crucial factors triggering malaria transmission. This would strengthen projection realism and act as a podium for academics and policy makers' consensus on provisions to mitigate future malaria. With all the limitations and strengths discussed, multiple methods of using the statistical method and predicting models must fit in the study. The local context of the disease where the variability of the malaria vector, the malaria parasite, and even the climate variability is different from place to place. Having the local knowledge of seasonal patterns would be helpful to apply to these prediction methods of malaria disease, which could help strengthen the public health intervention in terms of mitigation strategies.

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Author Contributions

All authors contributed to the design and implementation of the research, analysis of the results, and writing of the manuscript.

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