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RESEARCH

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Spatial analysis and mapping of malaria risk areas using geospatial technology in the case of Nekemte City, western Ethiopia

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Abstract

Background Malaria is a major public health issue in Nekemte City, western Ethiopia, with various environmental and social factors influencing transmission patterns. Effective control and prevention strategies require precise identification of high-risk areas. This study aims to map malaria risk zones in Nekemte City using geospatial technologies, including remote sensing and Geographic Information Systems (GIS), to support targeted interventions and resource allocation.

Methods The study integrated environmental and social factors to assess malaria risk in the city. Environmental factors, including climatic and geographic characteristics, such as elevation, rainfall patterns, temperature, slope, and proximity to river, were selected based on experts' opinions and literature review. These factors were weighted using the analytic hierarchy process according to their relative influence on malaria hazard susceptibility. Social factors considered within the GIS framework focused on human settlements and access to resources. These included population density, proximity to health facilities, and proximity to roads. The malaria risk analysis incorporated hazard and vulnerability layers, along with Land use/cover (LULC) data. A weighted overlay analysis method combined these layers and generate the final malaria risk map.

Results The malaria risk map identified that 18.2% (10.5 km^2) of the study area was at very high risk, 18.8% (10.9 km^2) at high risk, 30.4% (17.8 km^2) at moderate risk, 19.8% (11.5 km^2) at low risk, and 12.6% (7.3 km^2) at very low risk. A combined 37% (21.4 km^2) of Nekemte City was classified as at high to very high malaria risk, highlighting key areas for intervention.

Conclusions This malaria risk map offers a valuable tool for malaria control and elimination efforts in Nekemte City. By identifying high-risk areas, the map provides actionable insights that can guide local health strategies, optimize resource distribution, and improve the efficiency of interventions. These findings contribute to enhanced public health planning and can support future regional malaria control initiatives.

Keywords GIS, Malaria, Nekemte, Remote sensing, Risk

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Introduction

Malaria, a mosquito-borne infectious disease, is caused by *Plasmodium* parasites entering the bloodstream through the bite of infected female *Anopheles* mosquitoes [1]. It poses a significant global health threat. Over 212 million cases were reported worldwide in 2015, with the majority occurring in Africa [2]. The World Health Organization (WHO) recorded 229 million malaria cases in 2019, and of these, there were 409,000 deaths in 87 endemic countries, and 67% of these occurred in children under five years [3]. Among the four malaria parasites in humans, *Plasmodium falciparum (Pf)* and *Plasmodium vivax* are the most common. Pf causes the vast majority of cases in Africa and other regions [3, 4]. Sub-Saharan Africa, particularly the eastern and southern plateaus, bears the brunt of malaria's impact, affecting countries like Ethiopia, Kenya, Eritrea, Uganda, Tanzania, Burundi, and Rwanda [5, 6]. The region carries a disproportionately high burden, accounting for the majority of global malaria cases and deaths [7, 8].

Malaria is a major public health threat in Ethiopia, causing a significant number of outpatient visits, hospitalizations, and deaths [6, 9–11]. Transmission of the disease is seasonal in most regions, with periods of low activity punctuated by outbreaks. Variations in altitude, rainfall patterns, and population movement all contribute to the diverse patterns and intensity of malaria transmission across the country [9]. Ethiopia's diverse geography, with elevations ranging from below sea level to over 4,220 m, creates suitable breeding grounds for malaria across roughly 75% of its landmass [11, 12]. This exposes approximately 60% of the population, or over 50 million people, to the risk of infection, particularly those residing in areas below 2,000 m [9].

Integrating Geographic Information Systems (GIS) and remote sensing (RS) offers a powerful approach for both monitoring environmental factors that favor malaria transmission and assessing disease risk in human populations [13–15]. GIS manages and analyzes geospatial data, allowing for precise mapping, monitoring, visualization, retrieval, and modeling [16–18]. This translates to detailed maps of vector mosquito diversity, disease prevalence, transmission dynamics, and spatial spread of malaria. Generally, these geospatial technologies, including GIS, RS, and Global Positioning System (GPS), provide rapid assessment capabilities for malaria-endemic areas. This ultimately leads to new insights into the complexities of malaria transmission and epidemiology [19].

Numerous studies in Ethiopia have delved into malaria's status, transmission dynamics, prevalence, and risk factors, often using regression models [4, 5, 10, 11]. Despite these efforts, limited research employs advanced technologies like GIS and RS to model malaria risk areas, especially in the western Oromia region's Nekemte city. This gap highlights the need for more sophisticated methods to enhance malaria control and prevention strategies in these understudied areas, potentially leading to better-targeted interventions and improved public health outcomes.

Malaria poses a significant health challenge in Nekemte City, leading to high morbidity and mortality rates, as well as substantial economic burdens. The widespread occurrence of malaria in this region has led to numerous hospital admissions, straining local healthcare facilities. The disease disproportionately affects children under five and pregnant women, contributing to elevated child and maternal mortality rates. Malaria prevalence is high in the study area, with no risk analysis conducted, and the vulnerable regions remain unidentified based on environmental and socio-economic factors. Addressing this issue requires adopting cost-effective and efficient preventive and control measures, as prevention proves more economically viable than treatment in the long term [14]. The primary focus of this research study is to investigate the spatial distribution of malaria risk in Nekemte City, located in western Ethiopia. This study addresses a critical gap in the intersection of geospatial technology, disease mapping, and malaria control strategies, particularly in underserved and data-scarce regions. While malaria remains a global health challenge, much of the research and intervention efforts are concentrated in well-studied areas of sub-Saharan Africa, often overlooking the complex, localized dynamics of transmission in regions such as western Ethiopia. This gap is significant because malaria transmission is influenced by a combination of local environmental, socio-economic, and behavioral factors that require context-specific solutions.

This study makes several novel contributions that extend beyond the local context of Ethiopia. First, researchers demonstrate the application of advanced geospatial techniques, such as GIS, RS, and spatial modeling, in low-resource settings—an approach that can be adapted to other malaria-endemic regions with similar epidemiological profiles. Second, the research provides actionable insights for malaria control programs in Ethiopia and other regions facing similar challenges, such as parts of East Africa, Central Africa, and South Asia. Third, by integrating geospatial data with environmental, demographic, and behavioral factors, researchers propose innovative malaria control strategies that move beyond generalized interventions, offering more precise, context-specific solutions. The study also contributes to global malaria elimination efforts by enhancing risk mapping and surveillance in under-researched areas, helping to prioritize resources, improve vector control, and address drug-resistant strains. Moreover, the study explores the role of environmental and climatic variability in malaria transmission, providing insights into how climate change may influence risk in regions with similar geographic characteristics. Finally, researchers highlight the global impact of data-driven decision-making, showcasing how localized, real-time data can improve malaria control programs and serve as a model for other regions with limited access to such resources. By addressing these interconnected issues, this research aims to offer a comprehensive framework for malaria control and contribute to global efforts to reduce the burden of this preventable disease.

The study aims to explore how geospatial technologies can be utilized to map out areas with varying degrees of malaria risk within the city. It is expected that certain parts of the city may have higher levels of malaria risk due to specific environmental and socio-economic factors. By employing geospatial technologies to analyze these factors, a comprehensive map can be created to identify areas with different levels of malaria risk, ranging from very high to very low transmission risk. The ultimate objective of this research is to provide valuable insights that can inform policymakers, governmental organizations, non-governmental organizations (NGOs), and targeted malaria control interventions in the city to develop cost-effective and timely strategies for malaria prevention and control, with the overarching goal of reducing malaria prevalence in the area.

Materials and methods

Study area

This study was conducted within Nekemte City, located in the Oromia regional state, approximately 328 km west of Ethiopia's capital, Addis Ababa. Nekemte stands out as one of Ethiopia's rapidly growing and heavily populated cities. Geographically, it spans from 9°1′18′′ N to 9°7′ 12′′ N latitude and 36°29′50′′ E to 36°33′ 246′′ E longitude (Fig. 1). Nekemte City comprises seven kebeles viz; Bake Jama, Burka Jato, Kaso, Bakanisa Kase, Cheleleki, Darge, and Sorga. These kebeles represent the smallest administrative divisions within the city. These kebeles are vital for malaria control and prevention as they provide detailed local knowledge and facilitate the implementation of health interventions. Areas like Darge, Bake Jama, Kaso, Cheleleki, and the Bakanisa Kase regions are noted for their high incidence of malaria. The temperature ranges from 21 to 27 °C, with an altitude from 1956 to 2252 m above sea level, creating suitable conditions for malaria in the study area, as high temperatures and low elevations are conducive to malaria occurrence. The

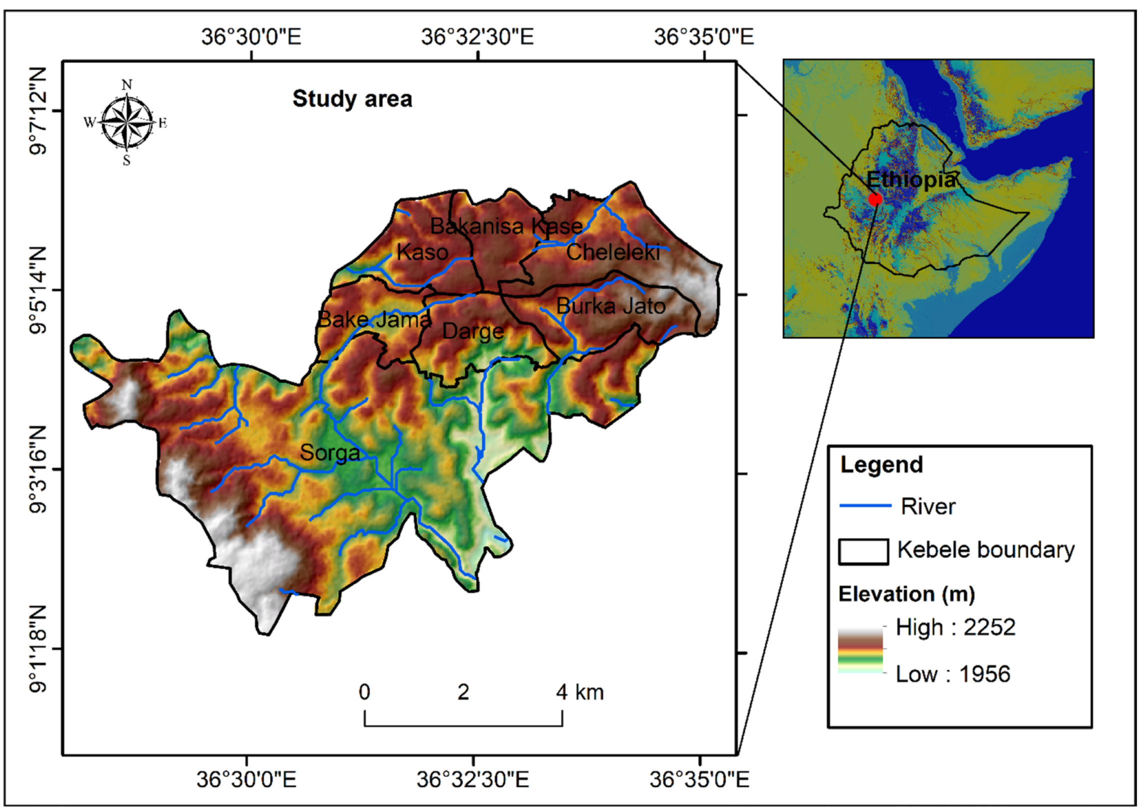

Fig. 1 Location map

area has an average annual rainfall of 2,240 mm, most of which falls during the wet season from June to September. The city exhibits five major Land use/cover (LULC) types, including grassland, vegetation, settlement areas, farmland, and water bodies. Among these LULC types, malaria transmission affects water bodies and settlement areas the most.

Data used

This study utilized various datasets to analyze malaria risk factors in the study area. Landsat 8 OLI/TIRS imagery for January 2023 and Shuttle Radar Topography Mission (SRTM) Digital Elevation Model (DEM) data with a 30-m spatial resolution were downloaded from the United States Geological Survey website (https://earthexplorer.usgs.gov/). Kebele (smallest administrative unit) boundaries for 2024 were acquired from the Nekemte City Land Administration Office. Rainfall data for 2011–2020, was retrieved from the Climatic Research Unit version 4 with high-resolution gridded data, 0.5°×0.5° (https://crudata.uea.ac.uk/cru/data/hrg/cru_ts_4.06/). The study area shapefile for 2021 and population density for 2016 data were accessed from the EthioGIS map server website (https://www.ethiogis-mapserver.org/). Malaria incidence data for July 2023-January 2024, along with the locations of two health centers, 61 clinics, and two hospitals within the study area, were obtained from the Nekemte City Health Office. Temperature data for January 2023-December 2023, was downloaded from the NASA POWER website (https://power.larc.nasa.gov/data-access-viewer/). The data obtained, including their source and function, are detailed in Table 1.

Malaria risk identification algorithm

"Risk" refers to potential negative consequences arising from a specific natural event. In other words, Simply put, it is the chance of acquiring a specific disease within a certain period of time [9]. It can be calculated by multiplying hazard, vulnerability, and elements at risk. Following [9, 18], this study employs the Risk computation model formula to map malaria-risk zones. These models direct the integration of vulnerability, hazard, and elements at risk (LULC) to pinpoint malaria-prone regions. By combining these factors, we can thoroughly evaluate and map malaria risk, allowing for targeted interventions and effective resource allocation to reduce the disease's impact.

$$\text{Malaria Risk Area} = \text{Elements at Risk} \times \text{Hazard} \times \text{Vulnerability}$$

"Hazard" represents the likelihood of a potentially harmful event, like malaria transmission, occurring within a specific timeframe and geographical area. It's determined by evaluating environmental conditions favorable for malaria transmission, considering various environmental and physical factors. The hazard of malaria was evaluated by examining the appropriateness of environmental conditions for malaria transmission, considering factors like slope, temperature, rainfall, elevation, and proximity to rivers [20]. "Elements at risk" encompass various factors within a given area, such as population density, economic activities, public services, and infrastructure. In the context of malaria and its mosquito vectors, there is a connection between land cover and vector density, as well as between vector density and the risk of disease [9]. LULC is a crucial risk factor, with changes in water bodies, agriculture, and urbanization significantly influencing the incidence, intensity, and spread of malaria. The closer one is to a water body, the higher the risk of malaria exposure, and vice versa [21]. "Vulnerability" refers to the susceptibility of specific elements or populations to the harmful effects of malaria, based on the event's magnitude. According to [22], malaria vulnerability is affected by demographic

Table 1 Data and their source with their respective function

Data	Source of data	Function
SRTM DEM	USGS	Slope, proximity to the river, and elevation map
Population density	EthioGIS map server	Population density map
Nekemte City shapefile	EthioGIS map server	Study area
Rainfall	Climatic Research Unit version 4	Rainfall map
Landsat 8 OLI/TIRS	USGS	LULC map
Temperature	NASA POWER	Temperature map
Road	EthioGIS map server	Proximity to road map
Kebele boundary	Nekemte City Land Administration Office	To overlay with the result
Location of health centers, clinics, and hospitals	Nekemte City Health Office	Proximity to the health station
Malaria incidence data	Nekemte City Health Office	To compare with the malaria risk map

characteristics, access to healthcare facilities, and socio-economic conditions. The researcher utilized proximity to health stations, roads, and population density measures to develop a malaria vulnerability map for the study area [20]. Figure 2 demonstrates the step-by-step presentation of the comprehensive methodology utilized in this study.

Weight assignment for parameters

The Analytic Hierarchy Process (AHP) is a powerful tool in multi-criteria decision-making (MCDM). It uses hierarchical structures to break down complex problems and relies on expert judgment to establish priority scales. This approach is particularly helpful in MCDM because it allows us to determine the relative importance, or weights, of different criteria [23]. According to [24], the AHP was employed to determine the weight of each factor contributing to malaria hazards. This involved a three-step process: Initially, creating a matrix for pairwise comparisons of each of the input parameters. Next, establish the relative weights for each parameter. Finally, consistency must be ensured throughout the comparison process (Fig. 3).

In this study, we aimed to evaluate various factors (Temperature, elevation, proximity to river, rainfall, and slope) influencing mosquito breeding and habitat suitability. Since these factors have varying degrees of influence, assigning weights to each criterion was crucial. We integrated insights from decision-makers and relevant literature [12, 19, 23, 24] to assign weights using the AHP model. Table 2 presents the weights assigned to the various factors affecting malaria hazard control. We calculated the consistency ratio to ensure precision, resulting in a value of 0.0215. Since the consistency ratio is below the threshold of 0.1, the assigned weights for the parameters are considered acceptable [25]. All factors were grouped into five categories using standard classification schemes, specifically the Jenks natural break classification method in ArcGIS software, as the researchers anticipated five zones of malaria risk susceptibility. These

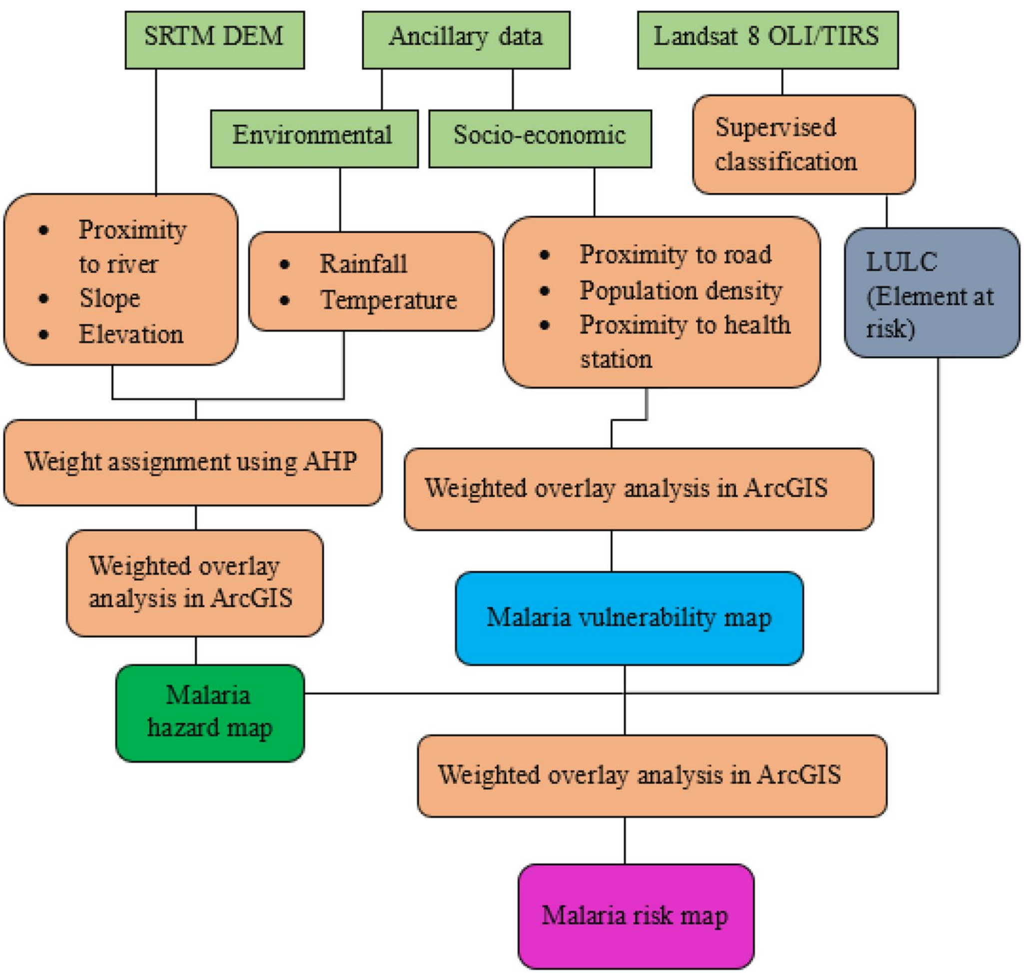

Fig. 2 Methodological flowchart of the study

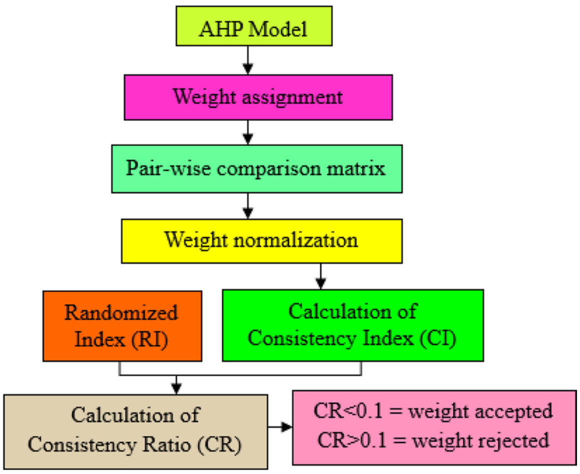

Fig. 3 Steps of the AHP

Table 2 Reclassification of malaria hazard controlling factors

Factors	Class	Rank	Hazard	Weight	Influence
Elevation (m)	2165–2256	1	Very low	0.37	37
	2114–2165	2	Low		
	2077–2114	3	Moderate		
	2038–2077	4	High		
	1956–2038	5	Very high		
Temperature (°C)	21–22	1	Very low	0.25	25
	22–23	2	Low		
	23–24	3	Moderate		
	24–25	4	High		
	25–27	5	Very high		
Slope (degree)	14–28	1	Very low	0.17	17
	10–14	2	Low		
	7–10	3	Moderate		
	4–7	4	High		
	0–4	5	Very high		
Proximity to river (m)	760–1243	1	Very low	0.13	13
	526–760	2	Low		
	336–526	3	Moderate		
	160–336	4	High		
	0–160	5	Very high		
Rainfall (mm)	2266–2294	1	Very low	0.08	8
	2248–2266	2	Low		
	2229–2248	3	Moderate		
	2211–2229	4	High		
	2186–2211	5	Very high		

factors were divided into sub-factors based on their level of susceptibility to malaria risk. Each sub-factor was assigned a rank from 1 to 5 (very low, low, moderate, high, and very high) according to its susceptibility level. The most susceptible sub-factor was given the highest rank of "5," while the least susceptible sub-factor was assigned the lowest rank of "1" [14].

Analysis

Relationship of environmental factors with malaria hazard

a) Elevation Altitude plays a significant role in determining the distribution of malaria in Ethiopia [6]. Altitude is a crucial factor affecting malaria transmission because it strongly influences temperature, which in turn impacts mosquito breeding duration during their life cycle [12]. Elevation data in the study area, extracted from an SRTM DEM using ArcGIS tools, varied from 1956 to 2252 m and was divided into five categories using standard classification schemes, namely Jenks natural break classification methods: 1956–2038, 2038–2077, 2077–2114, 2114–2165, and 2165–2256 m (Fig. 4a). The classified elevation map was then reassigned ranks based on its association with malaria incidence. Adopted by [14], lower elevation zones were prioritized with higher rankings due to their suitability for the malaria life cycle, while higher elevations received lower ranks (Table 2).

b) Temperature Numerous scholars have incorporated temperature as a primary factor in mapping malaria hazard zones [9, 12]. Malaria incidence and transmission typically occur in environments with higher temperatures [6]. A temperature map was prepared from collected temperature data in the ArcGIS environment and varied from 21 to 27 °C, as depicted in Fig. 4b. Under high temperatures, the duration of the egg, larval, and pupal stages is reduced, which accelerates the turnover rate. This also impacts the length of the saprogenic cycle of the parasite within the mosquito host, meaning that as temperatures rise, the saprogenic cycle duration shortens [9]. The classification of temperature values depends on the connection between temperature and malaria occurrence [12]. Consequently, higher temperature values were assigned the highest rank, and vice versa (Table 2).

c) Slope Slope, another topographic factor potentially influencing the formation of mosquito larval habitats, represents the rate of land elevation change over a given distance, impacting the stability of aquatic habitats [20]. Previous studies have demonstrated an inverse correlation between slope and mosquito abundance [26]. The study calculated the slope of the area from the SRTM DEM employing spatial analysis functions within ArcGIS, varying between 0 and 28 degrees, and segmented into five categories using Jenks natural break classification methods: 0–4, 4–7, 7–10, 10–14, and 14–28 (Fig. 4c). Subsequently, these slope categories were defined based on their association with malaria occurrence [26] (Table 2).

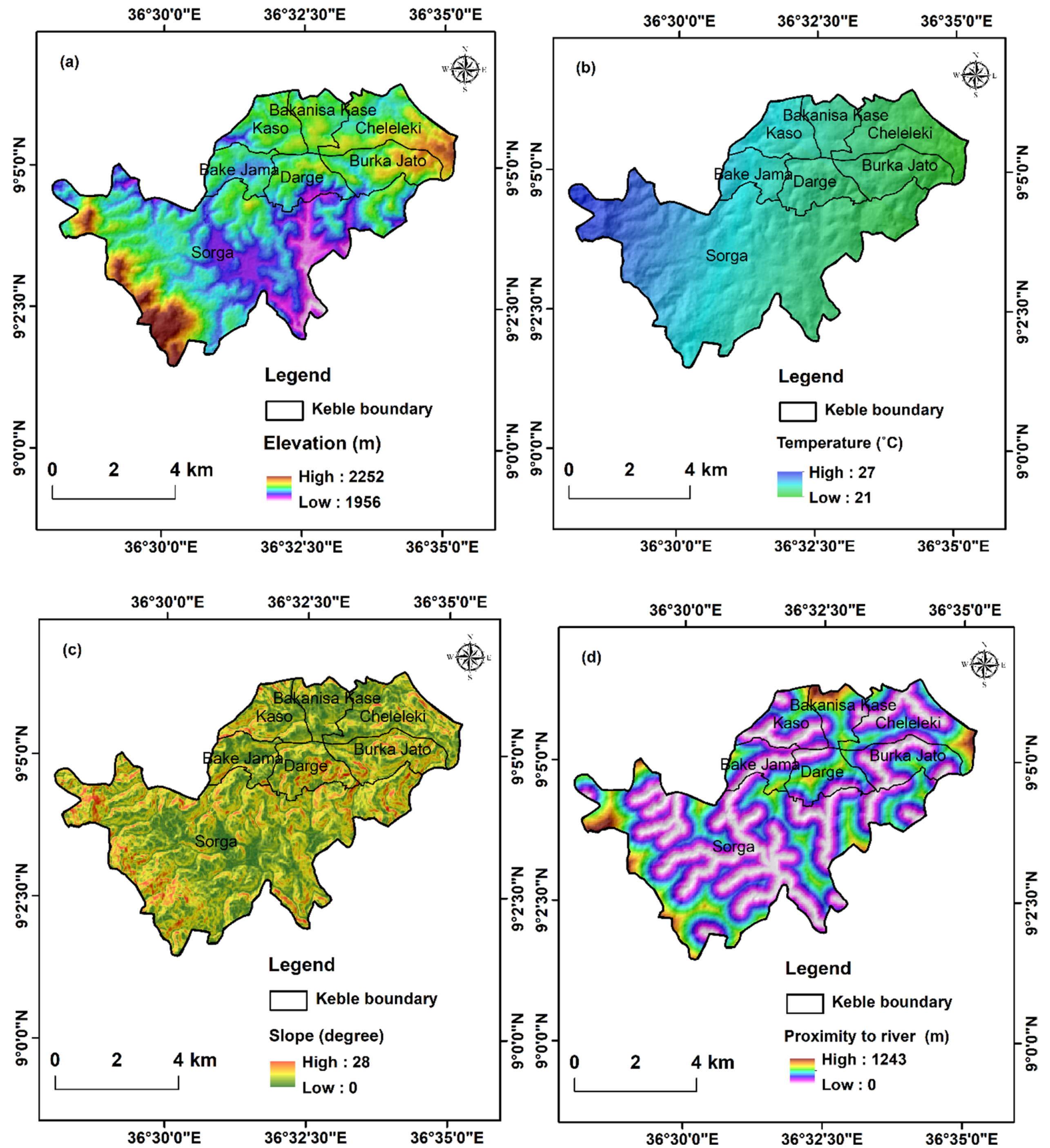

Fig. 4 Maps of environmental and socio-economic factors

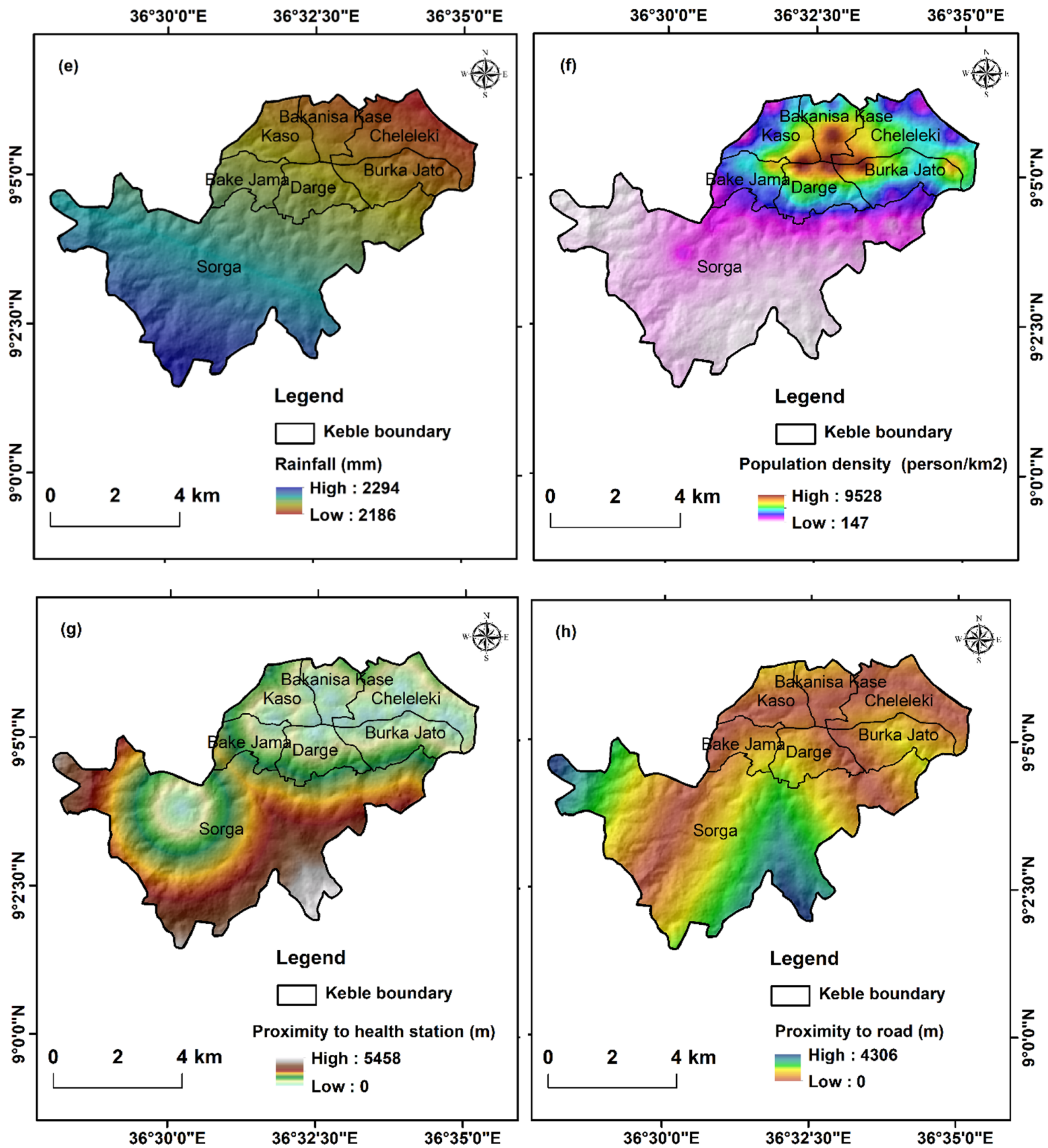

Fig. 4 continued

d) Proximity to rivers Water bodies play a significant role in malaria transmission. They act as breeding grounds for mosquitoes that carry the malaria parasite [26]. Therefore, the presence and proximity of water sources are important indicators of malaria risk. In this study, the Euclidean distance was used to the nearest river as a measure of malaria risk.

River data for the study area was obtained from the SRTM DEM and processed using the ArcGIS environment. Euclidean distance analysis was performed on the river data to calculate the distance from the river for each location. These distances ranged from 0 to 1243 m and were categorized into segments using natural break grading methods: 0–160 m, 160–336 m, 336–526 m, 526–760 m, and 760–1243 m (Fig. 4d). Finally, these distance categories were linked to mosquito prevalence rates to assess the correlation [26] (Table 2).

e) Rainfall Rainfall patterns highly influence the distribution of malaria [27]. During periods of heavy rainfall, breeding sites may be disrupted due to excessive water, which can flush away mosquito eggs and larvae, reducing mosquito populations and consequently lowering malaria incidence. Regions with moderate rainfall and low variability are likelier to have stable breeding habitats than areas with frequent and intense rainfall [27]. The study interpolated rainfall data through the Inverse Distance Weighting method in the ArcGIS framework, spanning values from 2186 to 2294 mm and divided into intervals using Jenks natural break classification methods: 2186–2211, 2211–2229, 2229–2248, 2248–2266, and 2266–2294 mm (Fig. 4e).

Relationship of socio-economic factors with malaria vulnerability

a) Population density Population density, calculated as the number of people per square kilometer, is a known vulnerability factor for malaria. Densely populated areas tend to have higher malaria incidence rates [20]. In the study area, population density ranged from 147 to 9528 people/km^2. This data was categorized into five zones for analysis using standard classification schemes, namely Jenks natural break classification methods: 147–1287, 1287–2906, 2906–4635, 4635–6548, and 6548–9528 people/km^2 as illustrated in Fig. 4f and Table 3.

b) Proximity to the health station Healthcare facilities in a specific area are crucial for patient treatment, raising awareness, and implementing preventive measures [12]. Lack of nearby healthcare facilities or their distant location leads to accessibility challenges and increased treatment costs. Consequently, individuals residing close to healthcare facilities are at an advantage compared to those living farther away [15]. The proximity to health stations was calculated using the Euclidean Distance tool in the ArcGIS environment. The range spanned from 0 to 5458 m and was divided into five intervals using natural break classification methods: 0–1091, 1091–2183, 2183–3275, 3275–4366, and 4366–5458 m (Fig. 4g, Table 3).

c) Proximity to the road Proximity to roads was considered a controlling factor for vulnerability, as individuals near roads are safer compared to those residing farther away. To create a vulnerability map, distances to roads were calculated using the Euclidean Distance tool (Fig. 4h). Distance from the road of the study area varied from 0 to 4306 m and was reclassified into five classes (Table 3).

Element at risk factors

LULC was considered an element at risk affected by malaria occurrence [20]. LULC data for the study area was obtained from Landsat 8 imagery. Supervised classification using maximum likelihood classification was

Table 3 Reclassification of malaria vulnerability controlling factors

Factors	Class	Rank	Vulnerability	Weight	Influence
Population density (person/km^2)	147–1287	1	Very low	0.50	50
	1287–2906	2	Low		
	2906–4635	3	Moderate		
	4635–6548	4	High		
	6548–9528	5	Very high		
Proximity to health station (m)	0–1091	1	Very low	0.30	30
	1091–2183	2	Low		
	2183–3275	3	Moderate		
	3275–4366	4	High		
	4366–5458	5	Very high		
Proximity to road (m)	0–591	1	Very low	0.20	20
	591–1266	2	Low		
	1266–2043	3	Moderate		
	2043–2921	4	High		
	2921–4306	5	Very high		

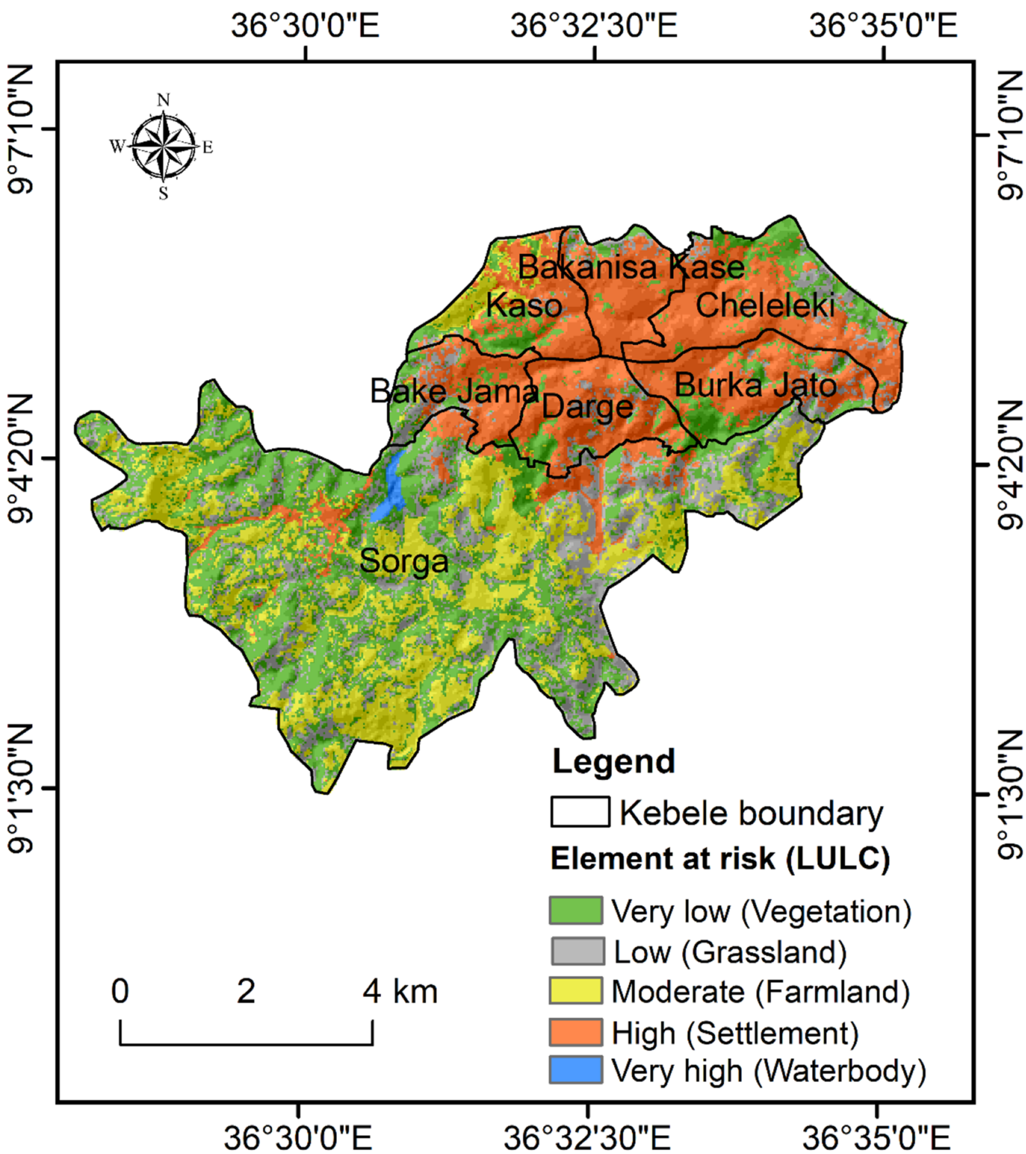

Fig. 5 Element at risk map

employed to classify LULC in ERDAS IMAGINE 2014. Major LULC types identified included grassland, vegetation, settlement areas, farmland, and water bodies (Fig. 5). All LULC classes were reassigned into five groups based on their vulnerability to malaria risk. Consequently, water bodies were designated a value of 5 due to their high susceptibility to malaria risk, while vegetation was given a value of 1, indicating very low susceptibility to malaria risk [19, 24] (Table 6).

Results and discussion

Malaria risk controlling factors

Malaria risk areas were identified using a weighted combination of three parameters: malaria hazard (30%), malaria vulnerability (30%), and element at risk (40%). Each parameter was assigned weight with experts' help and a literature review [19, 24].

Malaria hazard layer

In the ArcGIS environment, the factors influencing the occurrence of malaria hazards were combined to delineate the malaria hazard zones of Nekemte City.

$$\begin{aligned}&\text{Malaria hazard area}\\&= (\text{Temperature} \times 0.25) + (\text{Rainfall} \times 0.08)\\&+ (\text{Slope} \times 0.17) + \big(\text{proximity to river} \times 0.13\big)\\&+ (\text{Elevation} \times 0.37)\end{aligned}$$

The resulting malaria hazard index values ranged from 132 to 476. The final malaria hazard map classified the study area into five risk levels: very low (132–248),

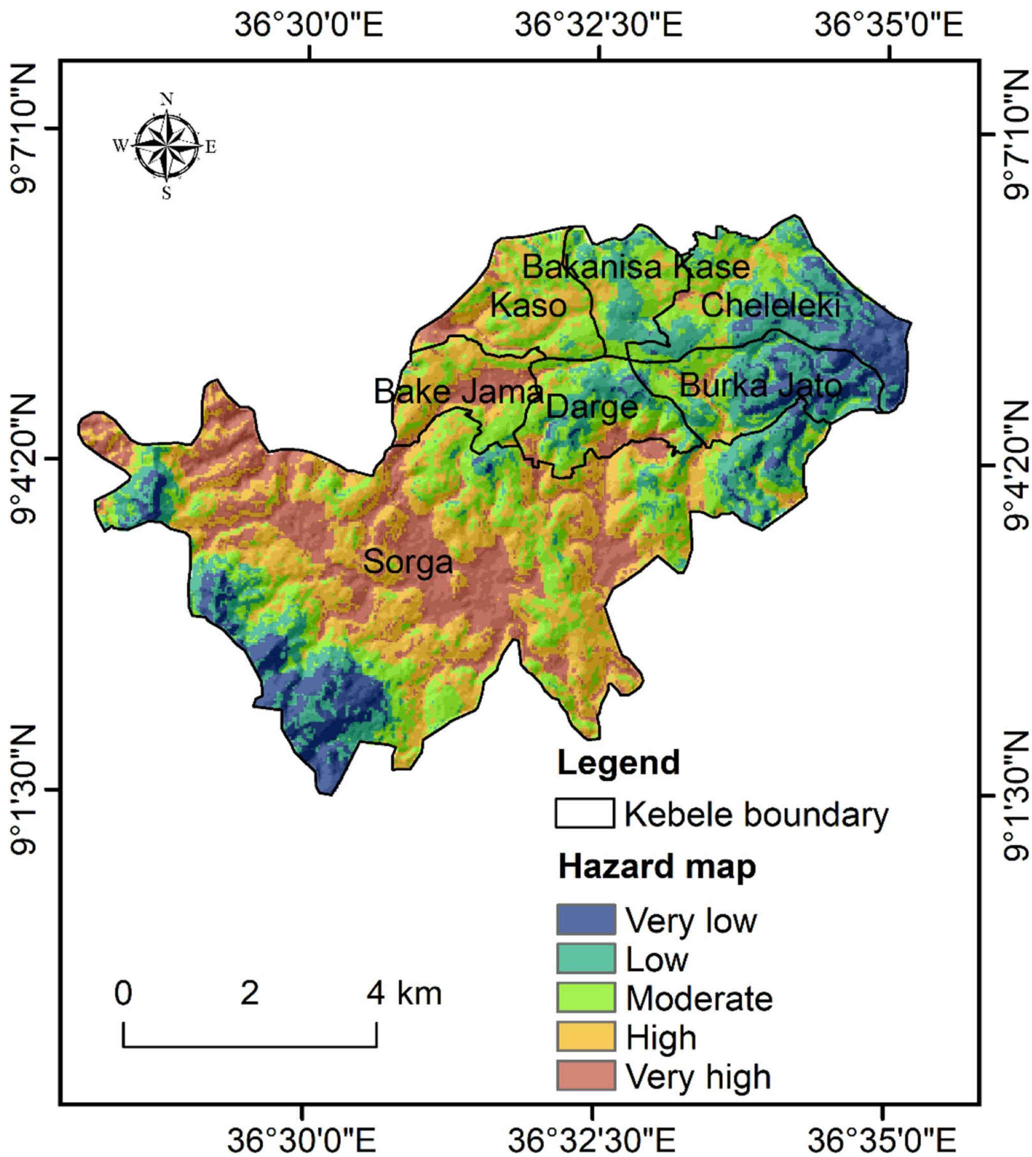

Fig. 6 Malaria hazard map

low (248–295), moderate (295–335), high (335–379), and very high (378–476) hazard (Fig. 6). Areas with high hazard encompassed roughly 16.6 km^2 (28.8% of the total area), while very high hazard zones covered approximately 10.1 km^2 (17.4%) (Table 4, Fig. 8). Notably, these high-risk zones encompassed the current Kebeles (administrative units) within the study area, including Sorga, Bake Jama, Kaso, and Darge. Factors like high temperature, gentle slopes, and low elevation likely contribute significantly to the high malaria hazard in these areas. Conversely, low malaria hazard zones cover around 10.4 km^2 (18%), while very low hazard zones span 5.8 km^2 (10%) (Table 4). These areas are often found in regions such as the eastern parts of Cheleleki and Borka Jato kebeles and the southwestern parts of Sorga kebele (Fig. 5). High elevation, low

Table 4 Malaria hazard classes and their areal coverage

Malaria hazard classes	Rank	Risk level	Area (km^2)	Percentage
Very low	1	Very low	5.8	10
Low	2	Low	10.4	18
Moderate	3	Moderate	14.8	25.7
High	4	High	16.6	28.8
Very high	5	Very high	10.1	17.4

temperatures, steep slopes, and high rainfall characterize these regions.

Malaria vulnerability layer

The malaria vulnerability zones map for the study area was generated by combining three thematic layers (population density, Proximity to health stations, and Proximity to roads) using the weighted overlay analysis. The significance assigned to each factor was determined based on expert opinions and existing literature [20].

$$
\begin{aligned}
&\text{Malaria vulnerability area} \\
&= (\text{Population density} \times 0.50) \\
&+ (\text{Proximity to health station} \times 0.30) \\
&+ (\text{Proximity to road} \times 0.20)
\end{aligned}
$$

The analysis resulted in a malaria vulnerability map with five categories: very low, low, moderate, high, and very high vulnerability zones (Fig. 7). Significantly, over half (50.9%) of the study area falls within the high and very high vulnerability zone ranges. These zones encompass 28.8 km^2 (49.7%) and 0.7 km^2 (1.2%) of the total area, respectively (Table 5, Fig. 8). This indicates that a substantial portion of the study area is at risk for malaria transmission. Factors such as greater distance

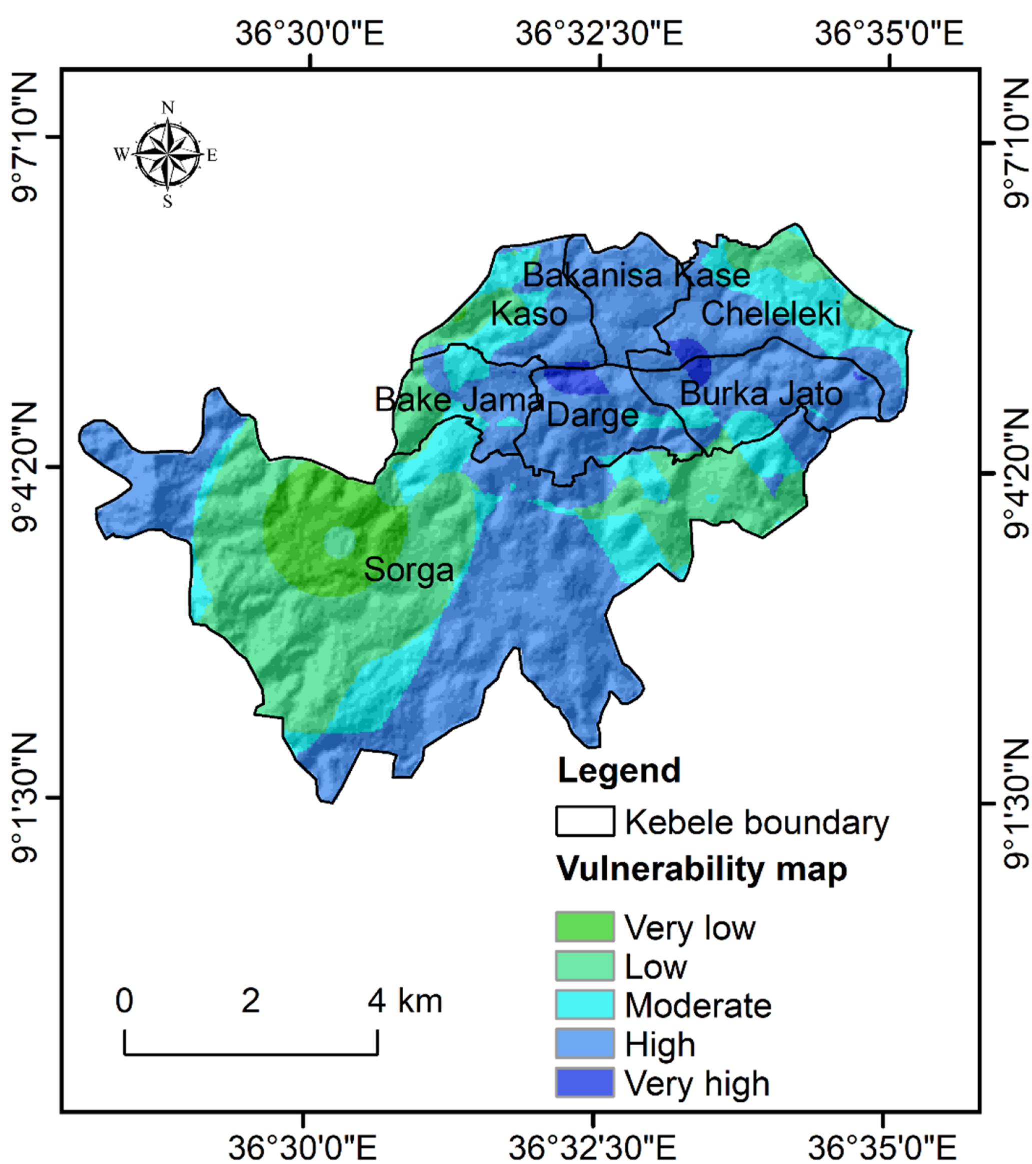

Fig. 7 Malaria vulnerability map

Table 5 Malaria Vulnerability classes and their areal coverage

Malaria vulnerability classes	Rank	Risk level	Area (km^2)	Percentage
Very low	1	Very low	3.3	5.8
Low	2	Low	15.8	27.3
Moderate	3	Moderate	9.2	15.8
High	4	High	28.8	49.7
Very high	5	Very high	0.7	1.2

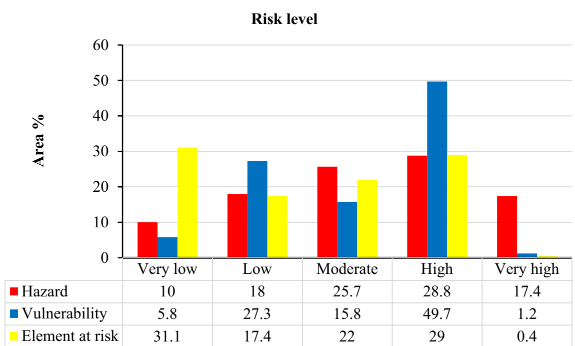

Fig. 8 The area of malaria hazard, vulnerability, and element at risk in percentage

from health stations and lower proximity to roads with high population density are likely significant contributors to the high to very high malaria vulnerability in these areas. As indicated in Table 5, approximately 15.8 km^2 (27.3%) and 3.3 km^2 (5.8%) of the study area fall into the low and very low malaria vulnerability zones, respectively. These areas are characterized by very low population density and proximity to health stations.

Element at risk

There is a connection between LULC and the density of malaria-carrying mosquitoes and between mosquito density and disease risk in the context of malaria transmission [26]. Water bodies are identified as high-risk areas due to stagnant water, ideal for egg-laying and larval development, fostering rapid population growth and increasing disease transmission risk. Settlement regions, both urban and rural, with gardens, are considered to have a high incidence of malaria (Fig. 5), because stagnant water in gardens creates breeding grounds for mosquitoes, boosting the local mosquito population and elevating the risk of malaria transmission. Out of the entire area, 0.4% was categorized as having a very high risk of malaria, 29% as high risk, 22% as moderate risk, 17.4% as low risk, and 31.1% was classified as having a very low incidence of malaria, contributing to the overall assessment of malaria risk and mosquito breeding potential (Table 6; Fig. 8).

Table 6 Malaria-risk/susceptibility areas due to LULC and areal coverage

Element at risk (LULC)	Rank	Risk level	Area (km^2)	Percentage
Vegetation	1	Very low	18	31.1
Grassland	2	Low	10.06	17.4
Farmland	3	Moderate	12.7	22.0
Settlement	4	High	16.8	29
Waterbody	5	Very high	0.24	0.4

Identified malaria risk area

Through the utilization of GIS, RS, and the integration of the AHP approach, three key factors (hazard layer, vulnerability layer, and malaria at risk) were aggregated to identify areas at risk of malaria within Nekemte City. These factors were amalgamated in the ArcGIS environment to generate a malaria risk map for the city. The resulting map, illustrating different malaria risk zones, was classified into five categories (very high, high, moderate, low, and very low-risk zones) through the natural break classification method (Fig. 9). Each risk zone encompasses a distinct area within the city. For instance, the very high-risk zone covers 18.2% of the area, the high-risk zone covers 18.8%, the moderate-risk zone comprises 30.4%, the low-risk zone includes 19.8%, and the very low-risk zone represents 12.6% of the total study area (Table 7, Fig. 10). This analysis reveals that over a third of the study area, totaling 37%, is classified as high to very high-risk malaria zones. These high to very high malaria risk zones are predominantly located in Darge, Bake Jama, Bakanisa Kase, Kaso, and western parts of Cheleleki kebeles and are linked to the concentration of elevated malaria hazard and vulnerability, along with water bodies and settlement areas. On the other hand, 32.4% of the study area is categorized as low to very low-risk malaria zones. These areas are primarily found in the northeastern parts of Cheleleki and the southwest and northeast parts of Sorga kebeles. The presence of vegetation with lower malaria hazard and vulnerability factors contributed to the designation of these areas as very low to low malaria risk zones.

Discussion

The application of GIS, RS techniques, and the AHP approach in mapping malaria risk areas offers a comprehensive understanding of the spatial distribution of malaria risk within Nekemte City. AHP is a

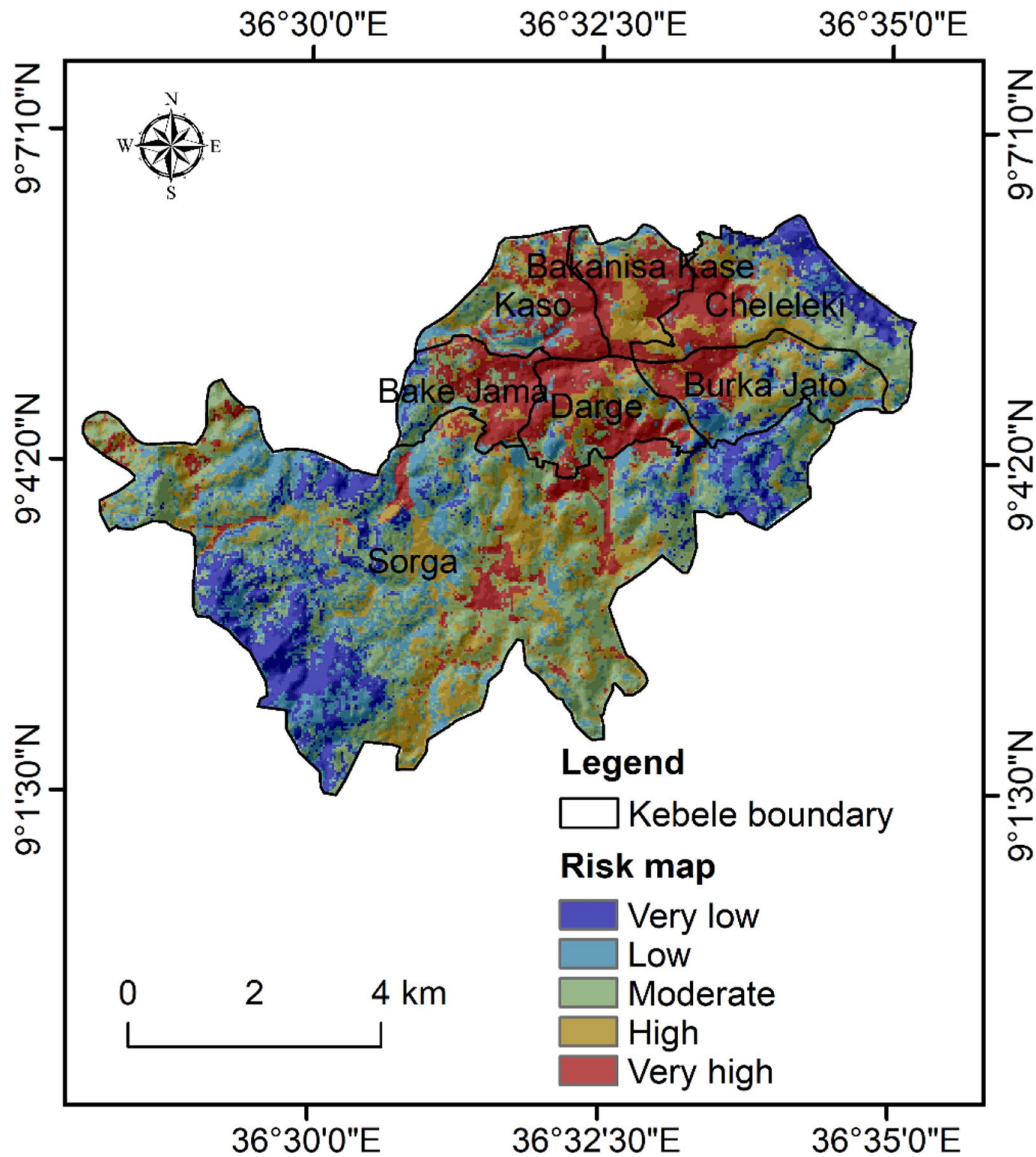

Fig. 9 Malaria risk map

Table 7 Malaria risk classes and their areal coverage

Malaria risk classes	Area (km^2)	Percentage
Very low	7.3	12.6
Low	11.5	19.8
Moderate	17.8	30.4
High	10.9	18.8
Very high	10.5	18.2

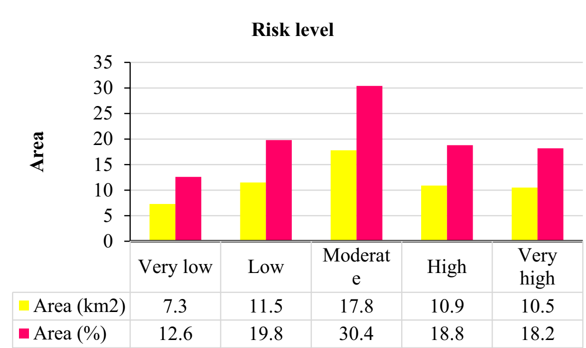

Fig. 10 Areal coverage of malaria risk zones

decision-making approach that employs hierarchical structures to represent problems, utilizing expert judgments to establish priority scales [28]. According to

Saaty [25], AHP proves effective in complex health scenarios, improving the optimization of resource allocation and intervention strategies. For instance, describing and decomposing complex psychosocial and behavioral interventions [29], diagnosing periprosthetic joint infection in Medicare patients [30], predicting the health economic performance of non-fusion surgery in adolescent idiopathic scoliosis [31], and a rapid cardiovascular diseases classifier [32]. This method is extensively applied in multi-criteria decision-making to determine the necessary weightings for factors in malaria risk management [33]. The malaria risk mapping for the study area was conducted by utilizing the malaria hazard layer, which is determined by natural conditions and elements at risk, such as LULC and the malaria vulnerability layer.

The malaria hazard layers were created by analyzing environmental factors like temperature, elevation, slope, proximity to rivers, and rainfall [20]. These factors were selected based on expert opinions and literature [19, 24]. Because the influence of each factor on controlling malaria hazards is not equal, the AHP method was used to assign appropriate weights to each factor [23, 31]. The element at risk layer was established by categorizing the LULC image file based on the malaria susceptibility of each LULC class [9, 12]. The LULC is directly related to the malaria burden through its impact on breeding sites and on the adult mosquito survival rate and dispersal [9]. According to Moha [20], areas with water bodies are highly susceptible to malaria incidence due to stagnant water, which is ideal for egg-laying and larval development, as well as rapid population growth, which increases the risk of disease transmission. Abdulahi [12] also noted that the expansion of settlements in urban areas can lead to a rise in malaria incidence. The vulnerability layer was developed by calculating the distance from the existing health station distribution points, proximity to roads, and population density of the study area [20]. The generation of a malaria risk map through the amalgamation of these key factors (elements at risk, malaria hazard and malaria vulnerability layer), enables a detailed classification of the city into distinct risk zones, ranging from very high to very low risk categories. Such nuanced delineation allows for targeted interventions and resource allocation based on the specific risk levels of different regions within the city [14].

The identification of high-risk areas, within a Kebeles such as Darge, Cheleleki, Bake Jama, Kaso, and Bakanisa Kase, highlights the importance of considering local environmental and socio-economic factors in assessing malaria vulnerability. Certain areas within Kebeles, like Cheleleki, Sorga, Darge, Bakanisa Kase, and Burka Jato, fall into the high malaria risk category. Factors like high temperatures and specific geographic features contribute to the elevated risk observed in these regions. According to [34], conducted in Chimoio, Mozambique, areas with high to very high malaria risk are predominantly characterized by dense populations, low rainfall, numerous perennial rivers with gentle slopes, high temperatures, and moderate to low elevations. These conditions create an optimal environment for the proliferation of the malaria parasite. Similarly, in the present study, areas with higher temperatures, gentle slopes, and lower elevations are the main contributors to high malaria risk [35, 36].

According to [6], which was conducted in the northwestern highlands of Ethiopia, and [33], which was conducted in Didesa District, South West Ethiopia, areas rated as very low to low malaria risk are characterized by sparse population density, high rainfall, absence of rivers, steep slopes, forested regions, lower temperatures, and higher elevations. All of these factors create an environment that is minimally suitable for the growth of malaria parasites. Similarly, this study area's lower to very low malaria risk map is highly associated with vegetation, higher elevation, low population density, steep slopes, and high elevations [9, 14, 19]. The research indicates that while the traditional AHP method is effective in the initial stages of malaria hazard mapping, it has limitations, such as subjectivity in pairwise comparisons, which can lead to potential bias; scalability issues as the number of criteria increases, making the process cumbersome; and the rank reversal issue, which can unpredictably change decision outcomes. Therefore, it has been suggested to enhance the original AHP by integrating advanced techniques like AHP with fuzzy AHP [37], FAHP-FCA [38], as well as fuzzy set theory and machine learning methods [39]. Another drawback of this study is the lack of sufficient malaria incidence cases for comparison. To address this, researchers used data from July 2023 to January 2024. High malaria cases in regions like Darge, Cheleleki, Kaso, and Bakanisa Kase indicate that the study's findings accurately reflect real conditions, aiding effective malaria control and eradication efforts. The malaria risk zones identified in Nekemte City align closely with findings from studies conducted in other regions, such as Dire Dawa City Administration in eastern Ethiopia [20], Bahir Dar City in Ethiopia [35], and Busia County in Kenya [36].

Conclusion and recommendation

The study's primary objective was to identify and map malaria risk areas in Nekemte City, using geospatial technologies such as GIS and RS to enhance the management and control of malaria vectors. The study findings revealed that malaria distribution is mainly influenced by various environmental and socio-economic factors, which significantly contribute to the occurrence and transmission of this vector-borne disease. A weighted overlay analysis tool has been utilized to integrate the thematic layers to identify malaria risk zones. The risk map divided the study area into five zones: very high, high, moderate, low, and very low risk. The findings indicate that over one-third of the city falls into the high to very high malaria risk categories. These high to very high-risk areas are predominantly situated in Kebeles, such as Darge, Cheleleki, Kaso, and Bakanisa Kase, due to their association with settlement areas, higher malaria vulnerability, and higher malaria hazard. This research confirmed that the method used in the study successfully integrated socio-economic and environmental factors to map malaria risk areas.

By actively involving stakeholders, utilizing precise risk assessments, and implementing a comprehensive strategy for malaria control, Nekemte City can effectively address the malaria challenge and enhance public health outcomes in the area. According to the study's findings, the following four recommendations are suggested:

1. Health Interventions: Prioritize the provision of anti-malaria drugs, distribution of bed nets, and house spraying in collaboration with NGOs, with a focus on areas identified as high-risk in the region.
2. Community Awareness and Education: Conduct targeted awareness training sessions on malaria prevention, especially in high and very high-risk areas, to empower communities with knowledge on preventive measures.
3. Environmental Management: Implement measures to drain swamps and stagnant water bodies to reduce mosquito breeding habitats, particularly in areas close to such environments.
4. Comprehensive Approach: Include additional factors like household income, housing conditions, and community awareness levels in future assessments to refine malaria risk prediction models and enhance the accuracy of intervention strategies.

Author contributions

Dechasa Diriba: writing—original draft, visualization, software, methodology, investigation, formal analysis, conceptualization. Shankar Karuppannan: Visualization, Supervision, Formal analysis, Writing—review and editing. Teferi Regasa: Writing- reviewing and editing. Melion Kasahun: Writing -reviewing and editing. All authors have read and agreed to the final version of the manuscript.

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Availability of data and materials

The data sets generated and / or analyzed during the current study are available from the corresponding author on a reasonable request.

Declarations

Ethics approval and consent to participate

Not applicable.

Consent for publication

The research is scientifically consented to be published.

Competing interests

The authors declare no competing interests.

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