Original Article

Modeling of Malaria Incidence in Nepal

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ARTICLE INFORMATION

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ABSTRACT

Background: Malaria is a major cause of morbidity and mortality in Nepal. The magnitude of malaria across the country is alarming and varies with location. Therefore, the present study aimed to model malaria incidence rates during 1998 to 2009 in Nepal.

Methods: Data for the study were obtained from Health Management Information System (HMIS), Ministry of Public Health. A negative binomial model was used to fit malaria incidence rates as a function of year and location and provided a good fit, as indicated by residual plots.

Results: In total, 83,345 cases of malaria were reported from 1998 to 2009. The mean incidence rate was 0.30 per 1000 population. The models show trends and spatial variations in disease incidence. There was decreasing trend in the incidence rates of malaria (1998-2004), followed by a more moderate upward trend until 2008, when the rate decreases again. Zero malaria incidences occurred in six districts including Humla, Jajarkot, Manang, Kathmandu, Bhakthapur and Solukhumbu districts for over twelve years. Higher incidence occurred in Kanchanpur, Kailali, Bardiya, Kavre, and Jhapa districts for the study period.

Conclusion: Malaria is still a public health problem in Nepal. This study showed a steady decreasing trend in malaria incidence but the numbers of cases are still very high. Higher rates were observed in Terai Region and border areas. These findings highlight the need for more systematic and effective malaria control measures on malaria burden areas of Nepal.

Introduction

Malaria remains a global problem with an over 600 million cases and over 2 million deaths each year worldwide [1]. It is endemic in 109 countries with about half of the world's population is at risk of malaria, particularly those living in lower-income countries [2]. In Nepal, malaria is major public health concerns in terms of mortality, morbidity and the subsequent overall impact on the national economy. It is estimated that about 74% (17.4 million) live in endemic areas. The disease is prevalent in the plains, foot- hills, forest, and forest- fringe of Terai and inner Terai valleys and distributed sporadically in hills, hill-mountain valleys [3]. The transmission is distinctly seasonal, with transmission limited to the warm and rainy summer months (June-September), hence malaria is unstable and epidemic-prone [3, 4].

The annual reports provide evidence that the magnitude of malaria across the country is high and varies with location. Malaria is prevalent in 67 districts of country with high endemicity in 12 districts and throughout the Terai from the far west to the eastern region [5]. There is also growing concern that the reservoir of malaria in

the Terai has become also affected by its neighboring country India. Malaria in Nepal occurred along the national borders particularly on the border to India [6]. The Terai region of Nepal has cross-border problems of communicable disease including malaria with the Indian states measuring a length of approximately 550 miles.

Malaria related problems have assumed a newer dimension in the recent decades. Epidemics are now even occurring in areas where transmission was thought to have been eliminated already. The migration of population, deforestation, inadequate resources increase in epidemic potential and neglect of epidemiology are other important factors responsible for changing epidemiological pattern of malaria. The situation is likely to be further aggravated by climate change. The climate variability and the breeding activity of anopheles are considered one of the important environmental contributors to malaria transmission in recent years[7].

Estimating the burden of malaria is highly needed for evidence based planning of malaria control. It is required for public health officials to evaluate disease incidence in the country. They need to investigate the regional and temporal pattern of disease so that necessary actions can be taken. Statistical modeling may applied investigating key issues related to disease incidence. The Poisson distribution and its extension to the negative binomial distribution to handle over-dispersion is a standard approach to modeling event count data.

The objective of our study was thus to identify the spatial patterns and trends of malaria incidences in Nepal with focused for border and non-border districts.

Methods

Study area and data source

Nepal is a landlocked country in the southern Asia, bordered on the north by Chinese Tibet and the Himalayas and by India to the east, south, and west. It has five development regions (eastern, central, western, mid western and far western), 14 zones, 75 districts. Based on topography, it is divided into three distinct

geographical regions areas; Mountain (7% of the population), Hill (43%) and Terai (50%), in decreasing altitude [8].

The information used, regarding cases notified between mid July 1998 to mid July 2009 were reviewed using Annual Reports of the Department of Health Services and data were obtained through Health Management Information System (HMIS). These data were available in computer files for each year comprising characteristics of the disease, location and year. These data were obtained in excel format and were then modified and entered into computer text files suitable for data cleaning and analysis.

Statistical methods

Poisson regression is commonly used for modeling the number of cases of disease in a specific population within a certain time. If λ_{jt} denotes the mean incidence rates for geographical location j and year t, an additive model with this distribution is expressed as

$$\ln(\lambda_{jt}) = \ln(P_j) + \mu + \alpha_j + \beta_t \quad (1)$$

In this model, P_j is the corresponding population at risk in 1000s of location j and the terms α_j and β_t represent location (border + non-border districts) and year effects that sum to zero so that μ is a constant encapsulating the overall incidence. Poisson models for disease counts are often over-dispersed due to clustering, in which case the negative binomial model is more appropriate [9]. The negative binomial model is an extension of the Poisson model for incidence rates that allows for the over dispersion that commonly occurs for disease counts. The variance of this distribution is $\lambda_{jt}(1 + \lambda_{jt}/\theta)$ with the Poisson model arising in the limit as $\theta \to \infty$ [10].

A characteristic of the Poisson distribution is that its mean is equal to its variance. If the observed variance is greater than the mean, the data are over-dispersed and the residual deviance plot will indicate that the model is not appropriate. After fitting the model to the data, to check the adequacy of the respective model, one usually computes a residual deviance for each cell. Thus, the deviance statistic for an

observation reflects its contribution to the over-all goodness of fit of the model. Plotting these residual deviances against corresponding quantiles for the normal distribution gives an indication of the adequacy of the fit of the model to the data. If the plot is approximately linear with unit slope, the fit is satisfactory [9]. In addition, it is also informative to plot observed counts and appropriately scaled incidence rates against corresponding fitted values based on the model.

The model also gives adjusted incidence rates for each factor of interest, obtained by sup-pressing the subscripts in Equation (1) corresponding to the other factors and replacing these terms with a constant satisfying the condition that the sum of the disease counts based on the adjusted incidence rates matches the total. Sum contrasts [9, 11] were used to obtain confidence intervals for comparing the adjusted incidence rates within each factor with the overall incidence rate. The R program was used for all statistical analysis, graphs, and maps [12, 13].
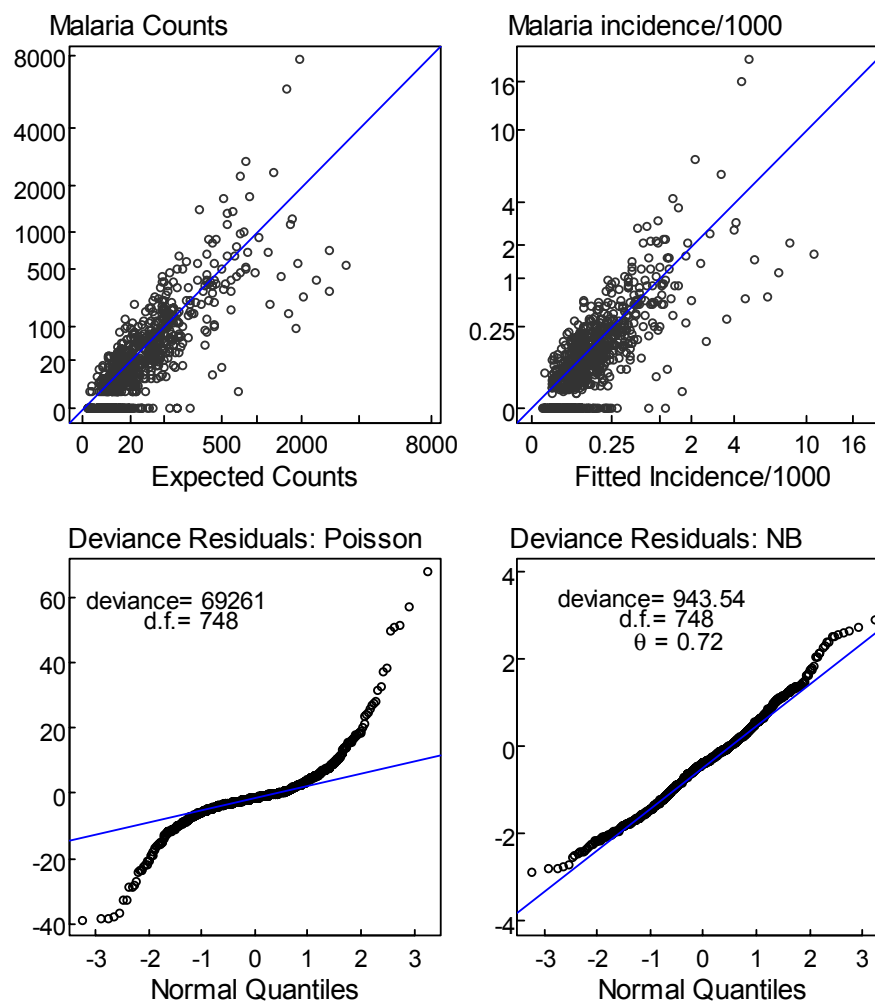

Figure 1: Diagnostic plots for Poisson and negative binomial models and plots of observed counts and   observed incidence against fitted values.

Results

The results of the model fitting are shown in Figure 1. The left and right upper panels show plots of observed counts and observed annual incidence rates per 1000 versus corresponding fitted values using the negative binomial mod-el. The left and right lower panels show plots of the deviance residuals against the normal quantiles based on Poisson model and negative binomial model. The dispersion parameter θ provides a way of improving the fit, by allowing for over-dispersion and thus reducing the residual deviance. Clearly, the residuals plot

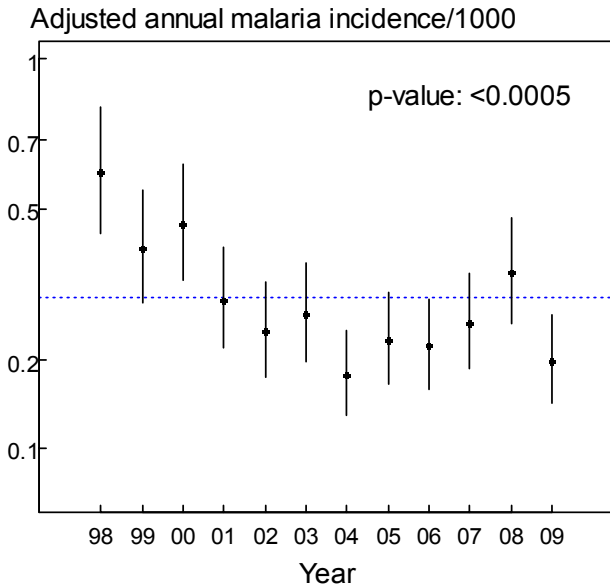from the negative binomial model fit the data well.

Adjusted annual malaria incidence/1000

Figure 2: Annual malaria incidence in Nepal

Figure 2 shows 95% confidence intervals of the trends of malaria incidence rates over pe-riod fitted by negative binomial model. The horizontal dotted line corresponds to the overall mean incidence rates of malaria (0.30 per 1000). There was decreasing trend in the incidence rates of malaria (1998-2004), followed by a more moderate upward trend until 2008, when the rate of decrease again accelerated.

Figure 3 shows 95% confidence intervals of annual malaria incidence rates by districts separated by border regions based on the negative binomial model. The dotted horizontal lines on graph represent the overall mean annual incidence rate (0.30 per 1000). Higher malaria incidences occurred in border districts.

Figure 4 shows a schematic map of the malaria incidence rates by districts by classifying districts as their confidence intervals (Figure 3) above the mean (darkest shade), below the mean (lightest shade), not evidently different from the mean (intermediate shade) and zero malaria case (no shade).
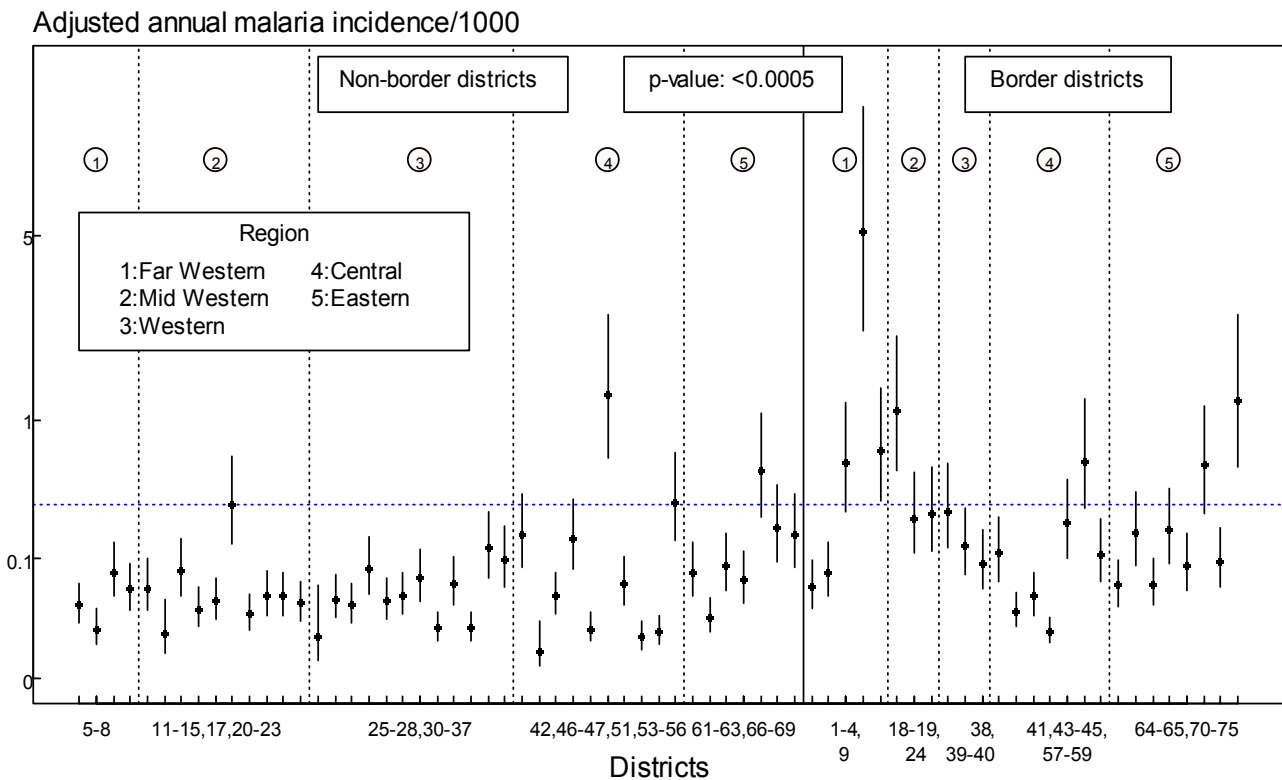
Adjusted annual malaria incidence/1000

Figure 3: Annual malaria incidence/1000 for non-border districts and border districts in 75 districts of Nepal

The map shows that zero malaria incidences occurred in six districts including Humla, Ja-jarkot, Manang, Kathmandu, Bhaktapur and Solukhumbu districts for over eleven years.

Similarly higher incidence occurred Kanchan-pur,Kailali, Bardiya, Kavre and Jhapa districts.
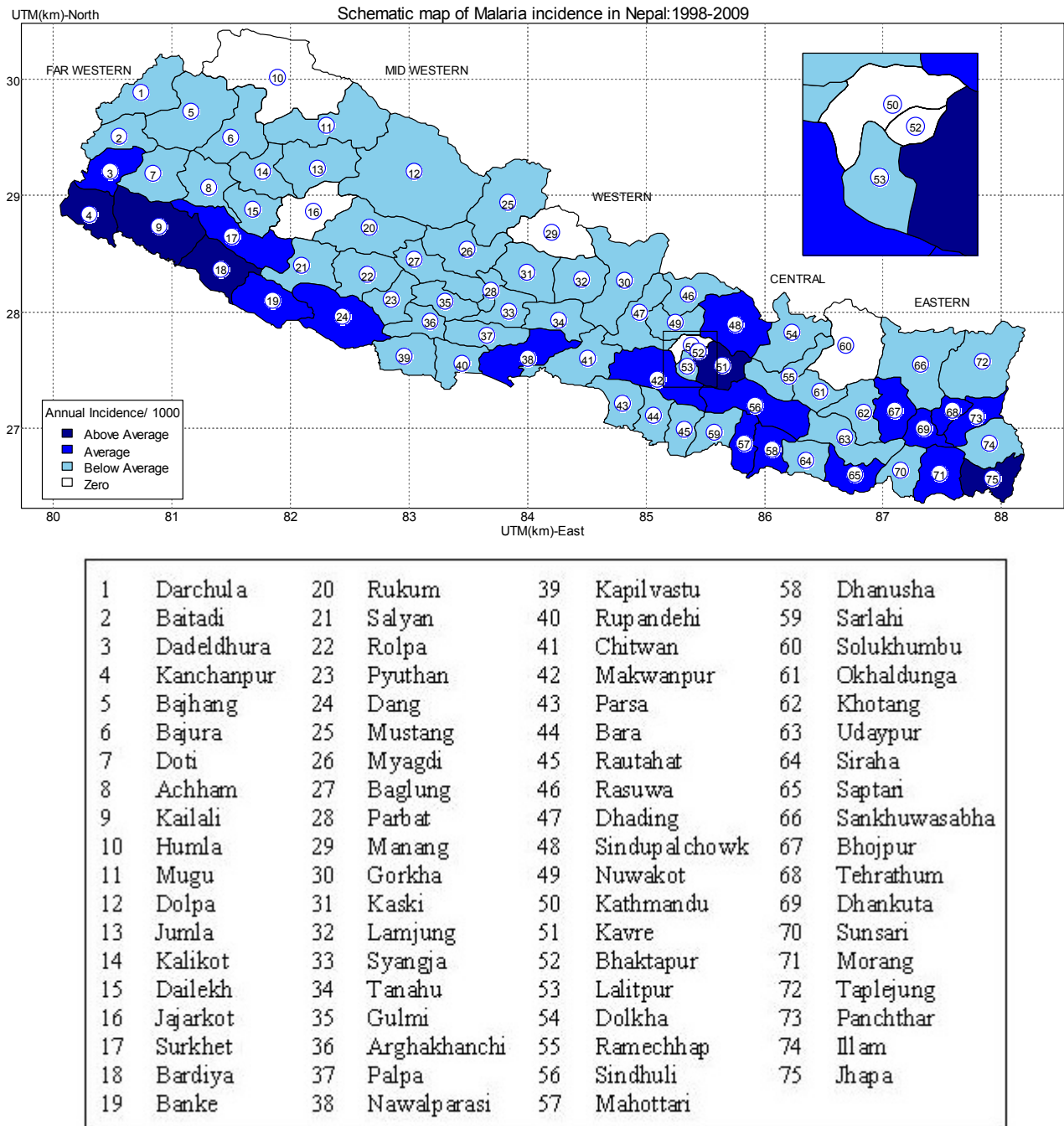

1	Darchula	20	Rukum	39	Kapilvastu	58	Dhanusha
2	Baitadi	21	Salyan	40	Rupandehi	59	Sarlahi
3	Dadeldhura	22	Rolpa	41	Chitwan	60	Solukhumbu
4	Kanchanpur	23	Pyuthan	42	Makwanpur	61	Okhaldunga
5	Bajhang	24	Dang	43	Parsa	62	Khotang
6	Bajura	25	Mustang	44	Bara	63	Udaypur
7	Doti	26	Myagdi	45	Rautahat	64	Siraha
8	Achham	27	Baglung	46	Rasuwa	65	Saptari
9	Kailali	28	Parbat	47	Dhading	66	Sankhuwasabha
10	Humla	29	Manang	48	Sindupalchowk	67	Bhojpur
11	Mugu	30	Gorkha	49	Nuwakot	68	Tehrathum
12	Dolpa	31	Kaski	50	Kathmandu	69	Dhankuta
13	Jumla	32	Lamjung	51	Kavre	70	Sunsari
14	Kalikot	33	Syangja	52	Bhaktapur	71	Morang
15	Dailekh	34	Tanahu	53	Lalitpur	72	Taplejung
16	Jajarkot	35	Gulmi	54	Dolkha	73	Panchthar
17	Surkhet	36	Arghakhanchi	55	Ramechhap	74	Illam
18	Bardiya	37	Palpa	56	Sindhuli	75	Jhapa
19	Banke	38	Nawalparasi	57	Mahottari		

Figure 4: Schematic map of annual malaria incidence rates in districts of Nepal

Discussion

Mosquito-borne diseases particularly malaria is becoming dreaded health problems in Nepal. This study applied statistical modeling of malaria incidence in Nepal from 1998 to 2009. When the dependent variable is the disease count, Poisson and negative binomial generalized linear models are usually considered most statistically appropriate. The Poisson distribution assumes events independent and does not account for clustering, over-dispersion, or serial correlation. A negative binomial GLM is an extension of the Poisson regression model that allows for over-dispersion. Poisson and Negative binomial models containing year and district as factors were fitted to the disease incidences. However, for these data the negative

binomial model fit the data as indicated by the residual plot.

Over the year 1998 to 2008, the incidence rate of malaria showed a fluctuating trend in Nepal, with increasing trend (2004-2008) followed by decreased in 2009. These findings were in consistent with WHO report and annual report on malaria, which shows decreasing, trends of malaria.

Zero incidences occurred in six districts as Humla, Jajarkot, Manang, Kathmandu, Bhakthapur and Solukhumbu districts for over twelve years. The findings were consistent with the annual reports. However, the malaria control programmes have identified these districts as the "malaria free" districts. Along with them, the Malaria control programmes have identified Mugu, Dopla, Mustang, and Rasuwa as the "malaria free" districts [5]. In our study, these districts also show the low incidences of Malaria over the period.

Higher incidence occurred in five districts including Kanchanpur, Kailali, Bardiya, Kavre and Jhapa district. Out of them, four districts occurred in Terai region and border regions. Thus, it can be concluded that malaria is more prevalent and prone in the Terai region and border regions. These findings were consistent with the annual report that prioritized these districts as endemic malaria districts in annual reports. The endemicity of malaria in Terai may be attributed to factors such as topography, climate, socio-economic status, heavy migration and cross boarder issues [5, 6]. The Terai region is characterized by hot and humid climate, high precipitation, and low socio-economic status that attributed to high malaria cases. A number of studies had found a strong correlation between malaria incidence rate and variations of environmental variables. In many studies, humidity, temperature and rainfall are considered major risk factors that affects the life cycle and breeding of mosquitoes [14, 15]. Study in Nepal indicates that rainfall during months of June, July and August influence the number of malaria cases which occur (after a certain time lag) during September, October, and November [16]. Besides this, Nepal also has an active migrant population moving frequently to malaria-risk areas of India for livelihood and they return home infected and easily transmit malaria. In addition, malaria-stricken patients from India are lined up at the government health centre to receive treatment in Nepal free medicines. Thus, it can be conclude that malaria is higher in boarder areas.

There are some limitations in our study. It is based on secondary data and we could not incorporate seasonal or months, which is considered as the one of the factors for malaria, due to unavailability of monthly-specific incidence data.

Conclusion

In general, the present study investigates the spatial patterns and trends of malaria incidences in Nepal in various districts. The results are illustrated by a thematic map showing both the districts with high incidence rates. Such maps can be used by public health authorities for applying preventive measures to control malaria outbreaks by focusing preventive measures according to priority in high, average, and low locations. These findings also highlight the endemic prone malaria areas in Nepal and the need for future intervention policies. It would be useful and appropriate to apply the statistical model to additional examples of disease incidence and disease forecasting.

Acknowledgments

Conflict of interest statement

The authors have no conflict of interests to declare.

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