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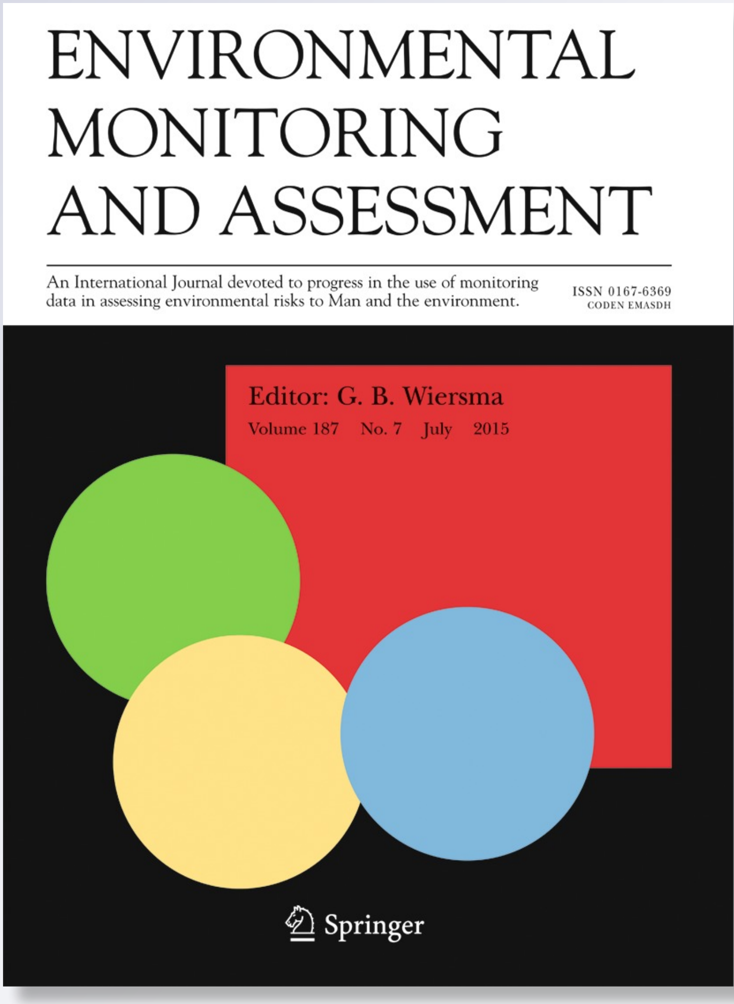

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Abstract One of the features of medical geography that has made it so useful in health research is statistical spatial analysis, which enables the quantification and qualification of health events. The main objective of this research was to study the spatial distribution patterns of malaria in Rawalpindi district using spatial statistical techniques to identify the hot spots and the possible risk factor. Spatial statistical analyses were done in ArcGIS, and satellite images for land use classification were processed in ERDAS Imagine. Four hundred and fifty water samples were also collected from the study area to identify the presence or absence of any microbial contamination. The results of this study indicated that malaria incidence varied according to geographical location, with eco-climatic condition and showing significant positive spatial autocorrelation. Hotspots or location of clusters were identified using Getis-Ord Gi* statistic. Significant clustering of malaria incidence occurred in rural central part of the study area including Gujar Khan, Kaller Syedan, and some part of Kahuta and Rawalpindi Tehsil. Ordinary least square (OLS) regression analysis was conducted to analyze the relationship of risk factors with the disease cases. Relationship of different land cover with the disease cases indicated that malaria was more related with agriculture, low vegetation, and water class. Temporal variation of malaria cases showed significant positive association with the meteorological variables including average monthly rainfall and temperature. The results of the study further suggested that water supply and sewage system and solid waste collection system needs a serious attention to prevent any outbreak in the study area.

Keywords Geostatistical modeling · Hotspots · Global Moran's *I* test statistics · Ordinary least square (OLS) regression analysis · Land use classification · Epidemiological studies

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Introduction

During the past century, despite the fact that many infectious diseases have been brought under control due to substantial advancement in public health measures and biomedical sciences, there still has been increase in the spread of emerging and re-emerging infectious diseases (Jones et al. 2008), which happens to be the major cause of death and disability around the globe along with the other old ones (Cohen 2000; Morens et al. 2004).

Around the globe, morbidity and mortality are mainly caused by the water-associated infectious diseases (Murray and Lopez 1997; Fenwick 2006; Lewin et al. 2007). According to a careful estimate; infectious diseases such as diarrheal diseases, trachoma, hookworm infections, ascariasis, schistosomiasis, and trichuriasis, which are caused by water, sanitation, and hygiene (WSH), attribute to approximately 4.0 % of global deaths and almost 5.7 % of disease burden

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(in DALYs) (Pruss et al. 2002; Kosek et al. 2003; Lewin et al. 2007).

Malaria, one of serious waterborne infectious disease, is caused by Plasmodium which is a protozoan genus and is a vector-borne disease. There are four malaria parasite species in humans, namely *Plasmodium falciparum*, *Plasmodium vivax*, *Plasmodium malaria*, and *Plasmodium ovale.* Female mosquitoes of the genus Anopheles are the carriers of the parasite and transfer it from person to person. The transmission can be seasonal, depending on the dynamics of the vector population (Autino et al. 2012). Although many advances have been made in mosquito control and in the treatment of the disease, malaria remains a significant public health issue, with over 200 million cases reported in 2010, of which 5 % were reported in Eastern Mediterranean Region, 13 % were reported in South East Asia and 81 % were reported in Africa. WHO reported 106 countries at risk of malaria transmission in malaria report 2011. The exposure of the population to malaria parasite has decreased during the last century, but due to the increased population of the world living in malaria-endemic regions, the absolute number of people exposed to the disease increased from 0.8 billion in 1900 to 3.3 billion in 2010 (Hay et al. 2010; World Malaria Report 2011). However, there has been a decrease in malaria cases from 24 million to 216 million between 2005 and 2010. In addition, the mortality rate due to malaria reduced by 26 % between 2000 and 2010.

Causes of waterborne diseases such as malaria in Pakistan include lack of potable water, current situation of drinking water in Pakistan (which according to the survey conducted by National Institute of Health is very poor and the statistics reveal that 87 % of water in Rawalpindi and 75 % in Islamabad are not suitable for human utilization), and insufficient sanitation facilities available in Pakistan which tend to be poor due to lack of proper management (Fawell and Nieuwenhuijsen 2003).

In determining the global burden of waterborne diseases, inadequate surveillance data is a very big problem. Generally, in developing countries, disease cases are not informed to a centralized surveillance system because most of the waterborne diseases remain unidentified misdiagnosed (Mitchell 2009). Disease surveillance and outbreak analysis are vital to make sure effectual control and prevention of waterborne disease outbreaks. Clear identification of the infections source might be a challenge from surveillance point of view as for many pathogens of interest, water is not the only exposure way. Additionally, the disease may be primary illness or secondary (Takasawa 2006).

Nowadays, GIS applications are used by almost all sectors of life particularly for their planning activities. In medical sciences, the usability of GIS extends with the expansion of epidemiological applications which is quite evident in the field of medical geography. Medical geography is the integration of GIS with epidemiological study though in Pakistan use of GIS in epidemiological studies is a recent advancement. Human geography has a branch of Medical geography which deals with the geographic characteristics of health and health-care facilities by carrying out studies on geographical allocation and causes of diseases associated with natural, environmental, manmade interactions, the proportion of inhabitants under threat, and the health-care facilities provided in areas as a whole. Medical geographers used two approaches: geographical epidemiology and spatial analysis of health planning and allocation of health facilities to achieve their goals (Dogru et al. 2007). Epidemiologists are helped by GIS technology because it enables them to understand the different phenomenon very easily and interfere in it quickly. Furthermore, epidemiologist better understand the epidemiological problems by using GIS because it helps in presenting the statistical data graphically by using maps. Thus, studies' results can be easily understood by the public in making their opinion (Dogru et al. 2007).

In recent years, integration of geospatial sciences and medical geography undergo a substantial development particularly regarding the application implementation for health-care services and epidemiology. GIS use has considerably improved the value of the studies with its capabilities in collecting, storing, organizing, and manipulating the spatial data. Moreover, numerous tools for performing spatial analysis (overlay, buffer, network, proximity, and etc.), programming environment to modify extended existing logarithms and to generate new analysis tools, and visualization and mapping tools to display the results of analysis make GIS as an essential tool in medical geography researches. Various studies on the spatial distribution of waterborne diseases have been conducted in the past by using GIS tool throughout the world (Satoshi et al. 2008; Yeshiwondim et al. 2009; Chaikaew et al. 2009; Srivastava et al. 2009).

Study area

The study area of this research work was Rawalpindi district (Fig. 1.). Rawalpindi means abode of Rawals, a jogi tribe. The District Rawalpindi derives its name from "Rawalpindi City" which is also its headquarter town. District Rawalpindi is situated in the north, north-western part of Pakistan. The west side of the district is adjacent to Attock district, north of the district is covered by Islamabad, the capital, Haripur and Abbotabad and of Khyber Pakhtun-Khwah province. Jehlum and Chakwal district lie to the south of Rawalpindi district. Rawalpindi district comprises of an area of 5286 km^2 and has the 42nd position with respect to the total area of Pakistan (USAID and PAIMAN 2005).

Rawalpindi district is divided into seven tehsils administratively namely, Murree, Kahutta, Kotli Sattian, Gujar Khan, Kallar Syedan, Taxila, and Rawalpindi. District and tehsil councils are formulated by elected representatives of 114 rural and 54 urban union councils accounting to a total number of 168 (USAID and PAIMAN 2005).

Total population of the district is 4,786,392, with annual growth rate is 2.75 %. The population density of the district is 905 persons/km^2. Tehsil-wise population distribution is given in Fig. 2. Majority of the district population are living in urban areas (53 %), while 47 % population is living in rural areas. Female population of the district is 51 % (2,253,348), while male population is 49 % (2,160,082).

The public health sector of District Rawalpindi includes 4 tehsil headquarter hospitals (THQ), 10 rural health centers (RHC), 98 basic health units (BHU), and 66 dispensaries. Three public sector tertiary care hospitals work in addition to those mentioned above.

Objectives

Study focused on investigation and categorization of the burden of water-based infectious disease in health facilities; analyze the spatial pattern and diffusion of water-based infectious disease cases by incorporating epidemiological and statistical techniques into a GIS system; application of pixel-based approach to image classification to identify environmental risk variables by using ERDAS Imagine and to identify vulnerable at-risk specific locations and congregate groups of populations in order to implement the preventive measures.

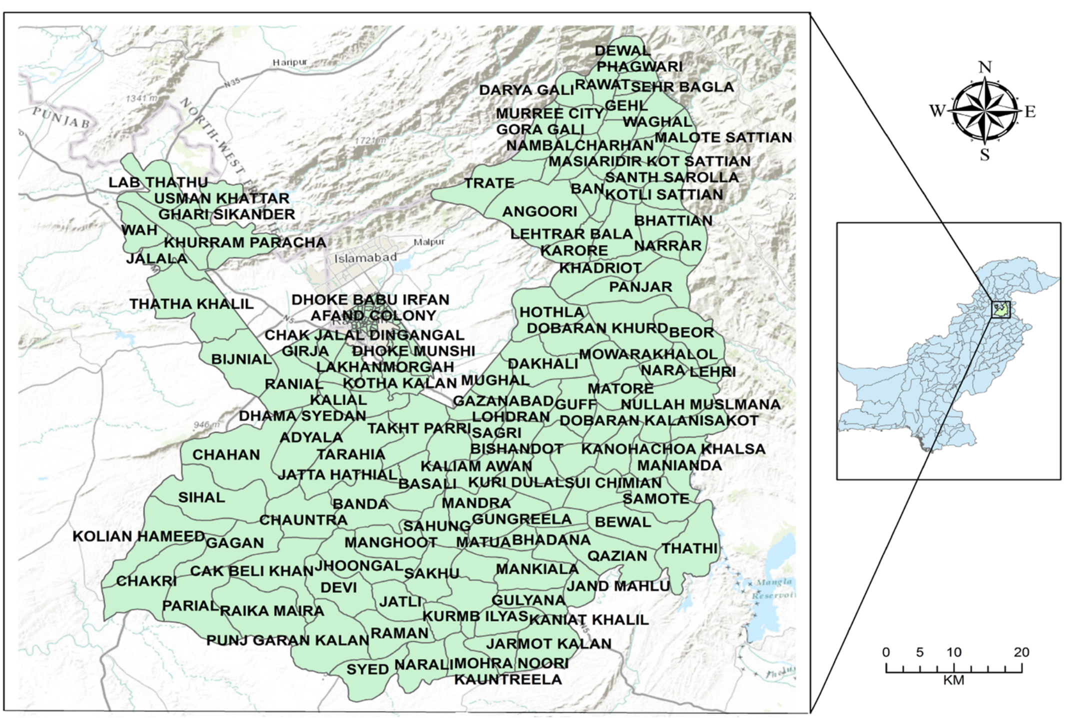

Fig. 1 Map of study area

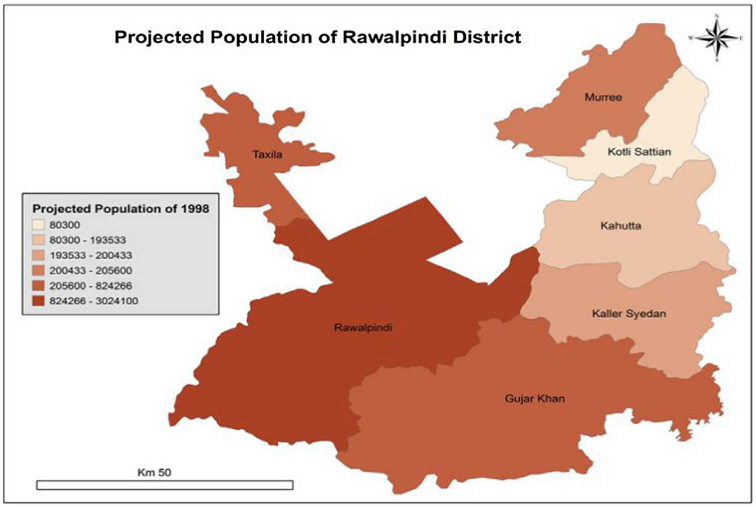

Fig. 2 Tehsil-wise projected population of Rawalpindi district

Materials and methods

For the purpose of this study, disease cases data reported during the years 2010 to 2012 was used, obtained from the Rawalpindi District Health Office (DHO). The data regarding suspected malaria cases was collected on per month basis for 3 years at BHU, RHC, GRD, maternal and child health centers (MCHC), and THQ hospital level from district Rawalpindi.

The location data of the health facilities including BHU, RHC, GRD, MCH, and THQ hospital of Rawalpindi were collected using GPS by visiting all these places. GPS data was collected using a Trimble Nomad 900 receiver. Latitude and longitude were both recorded for each location manually on paper and within the physical memory of the receiver. The accuracy of each recording was checked by importing the coordinates into Google Earth™ to see if they cartographically matched the satellite image.

The disease patient's data was imported into ArcGIS Version 10 in database format. Geographic data, which included the geographic coordinates for each health facility, was also imported into ArcGIS Version 10. Epidemiological data was merged with the geographic data so that each individual was assigned geographic coordinates according to his or her respective family number. The spatial and attribute data bases were then integrated through Arc GIS and over laid on base map to generate the spatial distribution map of malaria disease. SPOT image of 2012 for analyzing the land use was purchased from SUPARCO.

Monthly rainfall (mm), relative humidity (percent), and temperature (°C) from 2010–2012 were collected from Islamabad Meteorological Department. The climate data from 2010 to 2012 was generated along with the monthly data with disease cases. Subsequently, the analysis was done for temporal patterns of disease cases and incidence. Moreover, correlation between malaria disease cases and monthly means of climatic data (temperature, rainfall, and relative humidity) was analyzed for each month. A classic Pearson correlation coefficient was used in order to assess the correlation.

Spatial analysis

Standard deviational ellipses, global Moran's *I* statistic, space-time cluster analysis, hotspot detection, and ordinary least square (OLS) were performed in ArcGIS software.

Standard deviational ellipses

In spatial analysis, the first step is to map the incidence of that disease. Standard deviational ellipse (SDE) was used to map the directional distribution trend of disease spread during the 3 years. SDE measures whether features are farther from a specified point in one direction than in another (Ebdon 1991). In order to compare the global position and extent of the disease between the years, SDE parameter for each year was calculated.

Global Moran's I statistic

Global Moran's I statistic measures the correlation among the spatial observations and allows to find the characteristics of the global pattern (clustered, dispersed, random) among health facilities (Boots and Getis 1998; Fang et al. 2006). This statistical test compares the values of neighboring locations, and a strong positive spatial autocorrelation (clustered) is indicated when the neighboring units over the whole study area have similar values. If neighboring units have very dissimilar values, then the statistics indicates strong negative spatial autocorrelation (dispersed). The possible range of values for Moran's I index is from −1 and 1. 'Z' value is calculated to assess whether the observed clustering/dispersing is statistically significant or not. When the Z score indicates statistical significance, a positive Moran's I index value indicates tendency towards clustering while a negative Moran's I index value indicates tendency towards dispersion.

Space-time cluster analysis

Space-time clustering can be identified at those times or in those locations when, over limited time periods and within small locations, excess cases of a disease are observed but cannot be explained in terms of general excesses (Si et al. 2008). It is critical to understand and predict the spatial and temporal dynamics of disease outbreak at different scales in order to prevent and control the disease. GIS software and improved analysis techniques provide opportunities to study and model spatio-temporal dynamics of disease outbreak (Cummings et al. 2004; Kan et al. 2008; Eisen and Lozano-Fuentes 2009). Tracking analysis was chosen to find reasons of diseases spread in space and time and to create map to analyze the time dimension the disease spread (Zhong et al. 2005). Spreading pattern of disease cases of malaria was analyzed in space-time dynamics using animations.

Hotspot detection

Detecting hot spots is a valuable method of identifying areas with larger or smaller than expected concentrations of events. Hotspot detection can still be useful if global pattern is not clustered. Spread of an infectious disease can be influenced by the clusters of the cases that occur randomly. Getis-Ord Gi* statistics identifies different spatial clustering patterns like hot spots, high-risk, and cold spots over the entire study area with statistical significance. The statistic returns a Z score for each feature in the dataset. For statistically significant negative Z score, smaller value of Z score shows more intense clustering of low values (cold spots). For statistically significant positive Z score, larger value of Z score shows more intense clustering of high values (hot spots). High-risk areas are at lower significance level in comparison to hot spots.

Ordinary least square

Ordinary least squares (OLS) were performed in ArcGIS software. According to Hutcheson (2011), the ordinary least squares (OLS) regression is a generalized linear modeling and is used to model a dependent variable. This method is a major technique to analyze data is the basis of many other techniques (for example generalized linear models and ANOVA). As such, OLS regression is used in a wide variety of fields. The OLS method can be applied to appropriately coded categorical variables and to single or multiple explanatory variables. At the basic level, the relationship between a response variable (y) and an explanatory variable (x) may be represented using a line of best fit, where y is predicted to some extent by x. In assessing the model's performance, six indicators allow the researcher the necessary feedback to determine whether or not the analysis was successful: model performance, explanatory variables in the model, model significance, the Koenker (BP) statistic, model bias and spatial autocorrelation.

Image classification

Five image titles covering the entire study area were obtained in 2012. Radiometric, sensor, and geometric correction have been applied to the data. It is a 16-bit data and consists of an image file, metadata file, a browse image file, and unusable data mask (UDM) file. It has a UTM projection and WGS84 Horizontal datum system. The images were firstly mosaicked into one large image using ERDAS Imagine 2011 and the study area of interest from the large image.

A pixel-based approach (supervised classification) was used in classifying the image. The image classification process apportions the pixels of an image to exact spectral behavior of the ground data. Depending on the data file values of the pixels, they are sorted into finite number of categories of data or individual classes. A pixel is assigned to a class corresponding to a certain criteria, if it satisfies a set of criteria. This process converts image data to thematic data. The land use/land cover of the study area was classified to identify water reservoirs using SPOT image of 2012 using maximum likelihood algorithm.

The results of the image classification were validated in order to assess their accuracy. For this study, random sampling scheme was used to select 70 points (pixels) from the classification output and compared with the reference data. Comparison was done by creating error matrix. The image classification and accuracy assessment were done in ERDAS Imagine 2011. The classification map is given in Fig. 3.

Results and discussion

Data collected from January 2010 to December 2012 from District Health Office of Rawalpindi showed total patients of malaria reported in 3 years gradually decreased from 2010 to 2012 (Table 1).

General analysis

Data related to malaria cases was collected from January 2010 to December 2012 from District Health Office shown in Table 2. Highest number of malaria cases was reported in 2010. In Rawalpindi, 10,205 cases were reported in 2010, 9351 cases in 2011, and 8068 cases in 2012. Reported malaria cases in Gujar Khan in year 2010 were 9292 and 8687 and 7855 in 2011 and 2012, respectively. In Kahutta Tehsil, 3945 malaria cases reported in 2010, 5681 cases in 2011, and 3349 cases in 2012. Reported malaria cases in Kaller Syedan in year 2010 were 1987 and 2108 and 1834 in 2011 and 2012, respectively. In Kotli Sattian, 1139 cases were reported in 2010, while 1017 and 749 cases in 2011 and 2012, respectively. Reported cases in 2010 in Murree Tehsil was 5244, while 3572 and 2899 cases in 2011 and 2012, respectively. In Taxila Tehsil, the reported number of cases in 2010 was 2058, while for year 2011 and 2012,

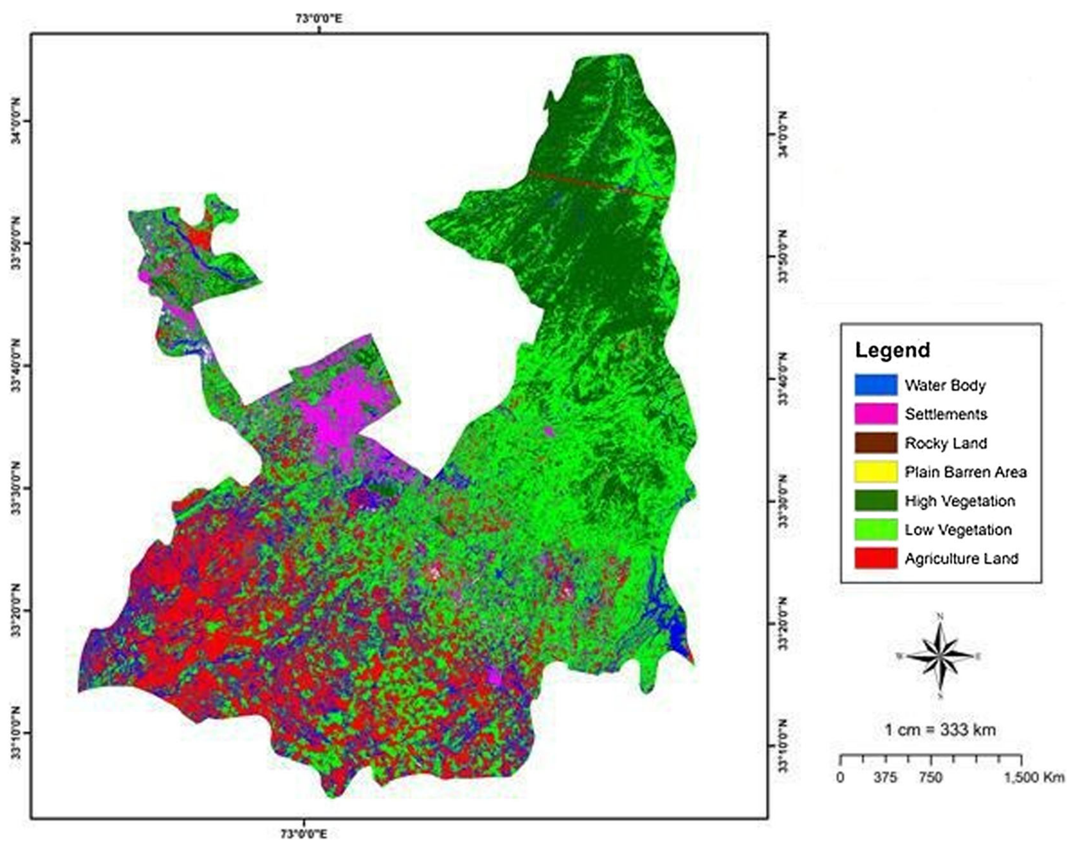

Fig. 3 Land use map created from Spot 5 Image

Table 1 Malaria patients reported in Rawalpindi district during 2010–2012

Waterborne disease	2010	2011	2012
Malaria	33,870	32,331	26,222

the reported cases were 1915 and 1468, respectively. Overall, the incidence of malaria cases decreased from 2010 to 2012 in Rawalpindi district. Maximum decline was seen in Murree Tehsil, i.e., 45 %, while the lowest was observed in Kaller Syedan Tehsil, i.e., 8 %.

Temporal analysis

Relationship of climatic variable including average monthly temperature, rainfall, and precipitation with the malaria cases is represented in Fig. 4.

Seasonal variation of meteorological variables including average temperature and rainfall and relative humidity showed a positive association with the malaria incidence. Incidence rate was low in winter and increased in summers. Maximum incidence was observed in the monsoon period including August, September, and October. Bi-variable correlation analysis of malaria cases in relation to independent meteorological variables including average monthly temperature, rainfall, and relative humidity were shown in Table 3. Analysis indicated that temperature (coefficient = 0.808, P = 0.000), rainfall (coefficient = 0.906, P = 0.000), and relative humidity (coefficient = 0.716, P = 0.000) showed the positive association with number of malaria cases.

Table 2 Malaria cases reported in Rawalpindi district during 2010–2012

Tehsil	Suspected malaria			% change
	2010	2011	2012	
Rawalpindi Tehsil	10,205	9351	8068	−20.94
Gujar Khan Tehsil	9292	8687	7855	−15.46
Kahutta Tehsil	3945	5681	3349	−15.10
Kallar Syedan Tehsil	1987	2108	1834	−7.70
Kotli Sattian Tehsil	1139	1017	749	−34.24
Murree Tehsil	5244	3572	2899	−44.71
Taxila Tehsil	2058	1915	1468	−28.66
Rawalpindi district	33,870	32,331	26,222	−22.58

Spatial distribution of malaria cases

Incidence rate of malaria per 1000 people was calculated for the study areas as shown in Fig. 5. The spatial distribution of the proportion of malaria incidence in the study area is depicted in Fig. 6. In 2010, the highest incidence was observed, while the lowest was in 2012. In general, a higher proportion of malaria incidence was observed in the central (Gujar Khan and Rawalpindi Tehsil) part of the study area.

Standard deviational ellipses

The result of the directional distribution analysis for health facilities for each year is presented in Fig. 7. Both urban and rural areas were observed within the SDE for each year (Rawalpindi Tehsil, Taxila Tehsil, Kahutta Tehsil, Kaller Syedan Tehsil, Murree Tehsil, and Kotli Sattian Tehsil) of the Rawalpindi district. A standard deviational ellipse (SDE) model was used to better understand the geographical distribution of malaria cases among the health facilities for three consecutive years. Similar global distribution pattern of cases was observed for each year, with no significant differences in Rawalpindi, Gujar Khan Murree, and Kaller Syedan Tehsil (Fig. 7). In case of Kahutta, the global pattern for the year 2011 was concentrated as compared to 2010 and 2012. For Kahutta Tehsil, ellipses for the year 2012 and 2011 were slightly more northward, while for year 2010, the ellipses were more towards southward direction. In Taxila, the global distribution of malaria cases in years 2010 and 2011 was more confined, while in 2012, ellipse is slightly widespread and move towards south westward direction.

The ellipse area for malaria cases was largest in 2010 and decreased in the subsequent years for Kaller Seydan, Murree, and Taxila Tehsil. While for Rawalpindi and Gujar Khan Tehsil, ellipse area was maximum in 2011. In case of Kahutta and Kotli Sattian, lowest ellipse area was observed in 2011. Similar is the cases with X stdDist and Y stdDist. There was no significant change in the means center location for three consecutive years for Rawalpindi, Gujar Khan, Murree, Taxila, and Kaller Seydan Tehsil. While in Kahutta, mean center position for the year 2012 and 2011 was slightly more northward, while for year 2010, the ellipses more towards southward direction.

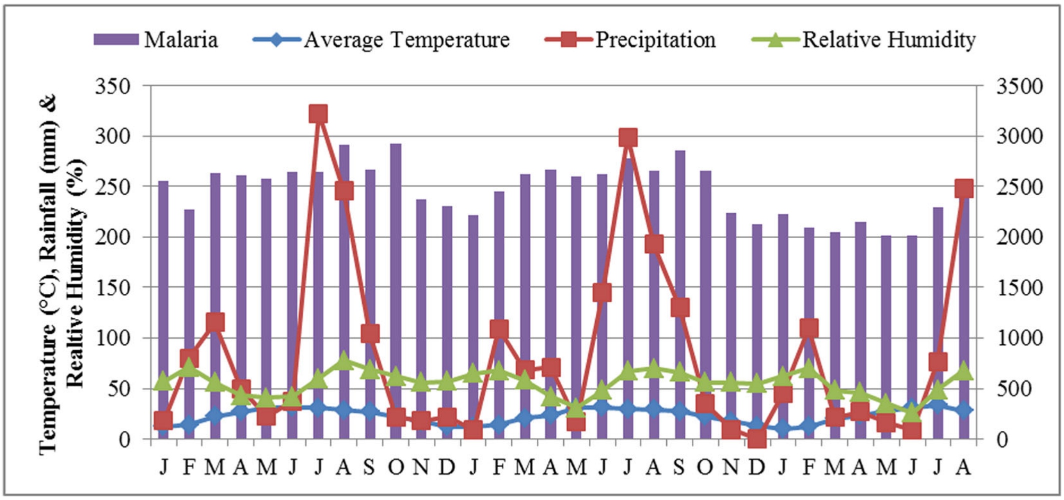

Fig. 4 Monthly rainfall, temperature, and total number of malaria cases in year 2010–2012

Global spatial autocorrelation analysis

Moran's autocorrelations statistic (I), weighted for 2010, 2011, and 2012, was 0.39 (Z score = 2.8, P = 0.01), 0.33 (Z score = 1.91, P = 0.05), and 0.22 (Z score = 1.72, P = 0.05), respectively. Thus, based on Moran's autocorrelation statistic, malaria cases in each year of the study were significantly ($P < 0.05$) spatially clustered as shown in Table 4. In addition, this clustering was strongest in 2010 and was reduced in subsequent years.

Moran's autocorrelations statistic (I), weighted for monthly averages of 2010–2012 as shown in Table 5. Based on Moran's autocorrelation statistic, malaria cases in each year of the study were significantly ($P < 0.05$) spatially clustered as shown in Table 5. In addition, this clustering was strongest in July and January and was reduced in subsequent months.

Table 3 Pearson correlation between climate factor and malaria cases in time series, 2010–2012

Variables	Coefficients			
	Malaria	Temperature	Rainfall	Relative humidity
Malaria	1			
	0.000			
Temperature	0.808**	1		
	0.000	0.000		
Rainfall	0.906**	0.521**	1	
	0.000	0.000	0.000	
Relative	0.716	0.209*	0.032	1
Humidity	0.00	0.039	0.112	0.000

*$P < 0.05$; **$P < 0.01$

Hotspot analysis

Figure 8 indicated hotspot identification for malaria using Getis-Ord Gi* statistic by each year from 2010 to 2012 in Rawalpindi district. The Z score outcomes as calculated by the Gi*(d) statistic are categorized as clusters or non-clusters at the 5 % significance level. Hotspots for malaria cases were mostly seen in central and south western part of the study area in 2010 and 2012. While in 2011 some part of Kahutta and Kotli Sattian were also included in the hotspots.

Figure 9 showed the monthly distribution of hotspots of malaria in Rawalpindi district. Hotspots were more concentrated in south western part of the study area in January to March, while the trend shift to North Eastern part of the study area in May and June. While in July to December, hotspots mostly concentrated in the central part of the study area.

Ordinary least square regression analysis

OLS model was used to identify the possible risk factors of malaria cases in Rawalpindi district. The dependent variable in the model was number of malaria cases, while the independent variables include population, literacy ratio, distance from the water channels, and population density. This model explained the 49 % of the

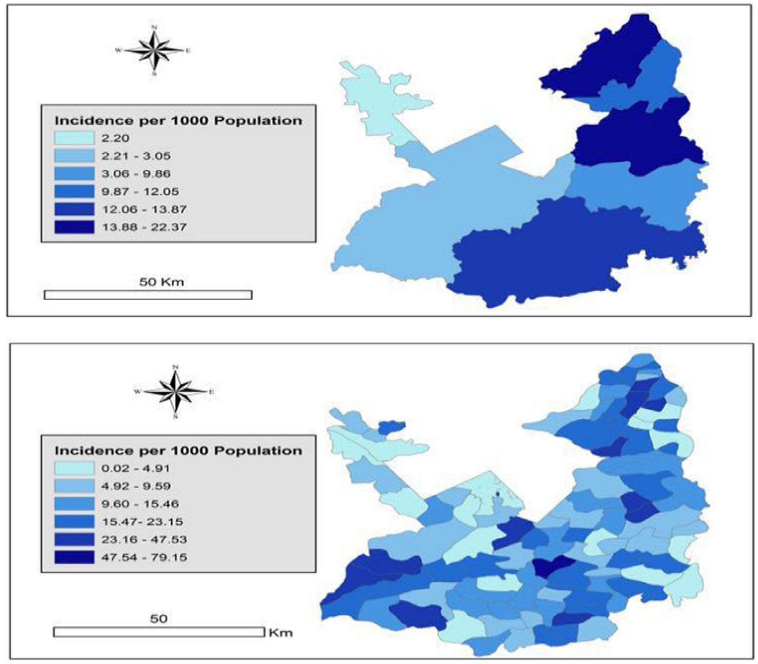

Fig. 5 Malaria incidence rate in Rawalpindi district

malaria cases variation in the study area and met all the OLS model requirements. This model indicated that increase in population, population density, lower female education, and proximity to water channel increased the risk of malaria. OLS regression analysis showed that malaria had negative and significant association with the population and population density, which means that as the population and population density increases, the chances of acquiring the diseases also increase.

These interrelated elements were selected due to their influence on health in homes, public places, communities as well as in physical environment. The total population

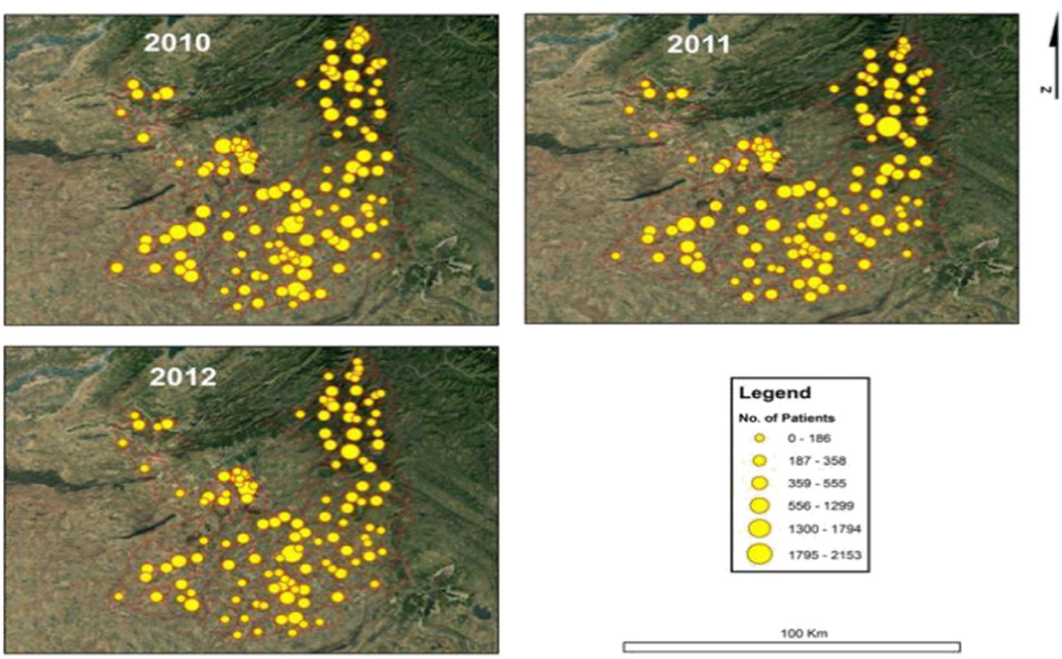

Fig. 6 Spatial distribution of malaria cases in Rawalpindi district 2010–2012

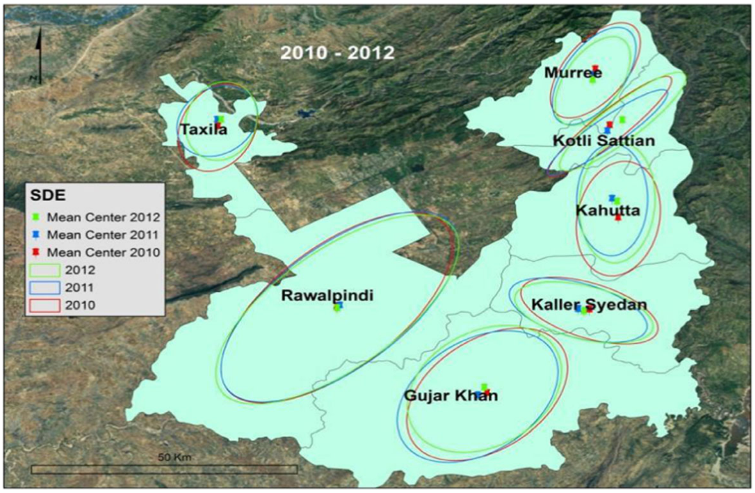

Fig. 7 Distribution of standard deviational ellipses for each year

and population density has been mentioned earlier in the study area section. In Rawalpindi district like the rest of the country, significant gender gaps in literacy were observed in spite of the large percentage of females in total population of the district, i.e., 51 %. The literacy rate for females and males was observed to be 67 and 86 %, respectively (GoP 2011). Moreover, the water and sanitation conditions of the district were even worse. According to a survey, the use of proper treated water was 13 %, proper disposal of waste water was 56 %, while proper disposal of solid waste was 25 % (GoP 2010). Therefore, the proximity to water channel was one of the major contributors in increasing the risk of malaria.

Kazembe et al. (2006a, b) reported high malaria risk in the low-lying areas along the lake shores. Ernst et al. (2006) observed a strong association between proximity to forest, altitude and population density, distance to swap, and malaria incidence. Hakre et al. (2004) identified a statistically significant relationship between the malaria incidence villages and proximity to vegetation and river in Belize, Central America. High malaria risk was reported in areas close to hydrographic networks, households with low socioeconomic and education levels, and congested areas in Ouagadougou Burkina-Faso (Baragatti et al. 2009). Omumbo et al. (2005) identified urbanization as a predictor of malaria prevalence. Moffett et al. (2007) identified the growing population density as major factor in determining the malaria risk in Africa. Grillet et al. (2010) ordinary least squares (OLS) regression models indicated that lower elevations, greater population density, and proximity to aquatic habitats cause disease persistence in northeastern Venezuela.

The health sector in Rawalpindi district is facing enormous health problems. This is due to changing lifestyle, urbanization, ecological, and other factors. Besides, health problem service delivery/managerial issues are also hindering the access and quality of health services to the population. Management problems are

Table 4 Global spatial autocorrelation statistics of malaria cases for 2010–2012

Year	Moran's *I*	*Z* score	*P* value	Pattern
2010	0.39	2.8	0.01	Clustered
2011	0.33	1.91	0.05	Clustered
2012	0.22	1.72	0.05	Clustered

Table 5 Global spatial autocorrelation statistics of malaria cases on monthly basis

Month	Moran's *I*	*Z* score	*P* value	Pattern
January	0.34	3.35	0.01	Clustered
February	0.24	1.68	0.1	Clustered
March	0.32	1.56	0.05	Clustered
April	0.3	1.68	0.01	Clustered
May	0.28	1.68	0.05	Clustered
June	0.28	1.74	0.05	Clustered
July	0.42	3.12	0.01	Clustered
August	0.32	1.69	0.05	Clustered
September	0.22	1.68	0.01	Clustered
October	0.45	1.98	0.05	Clustered
November	0.31	2.32	0.05	Clustered
December	0.31	1.72	0.05	Clustered

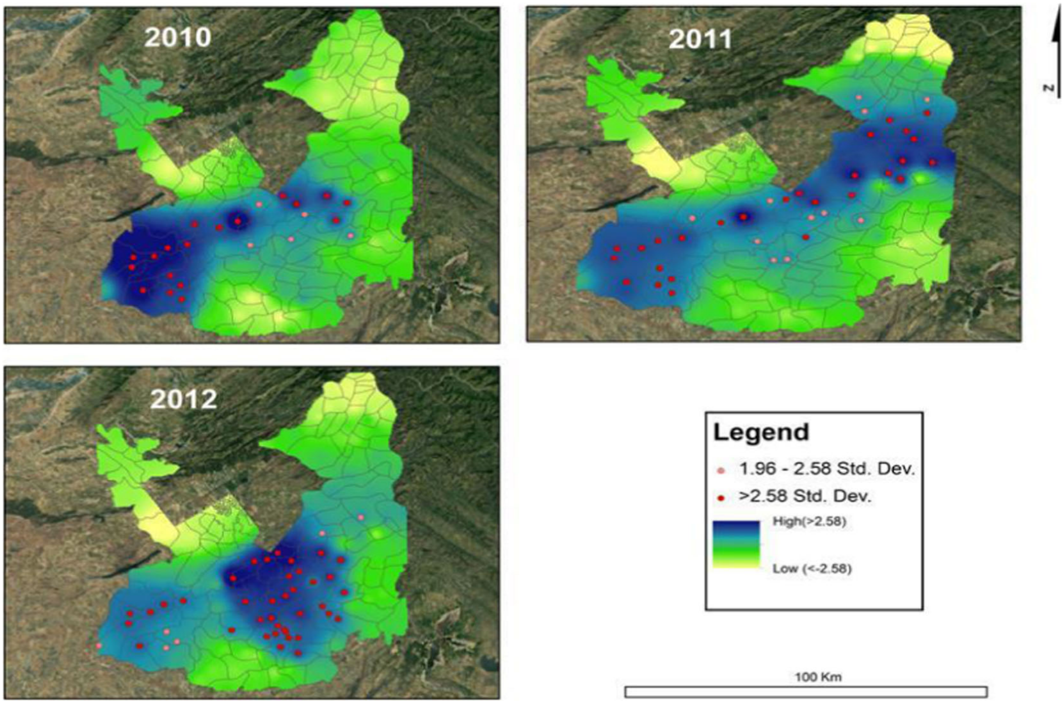

Fig. 8 Mapping of malaria hot spots, high-risk, and cold spots using Getis-Ord G* statistics during 2010 - 2012 in Rawalpindi district

result of deficiency/lack of resources; these problems range from administrative to financial issues and cause hindrance in the smooth delivery of health services in the district (GoP 2010). Poverty remains a serious concern for the district with average per capita income Rs. 1729 per month (PAIMAN 2005). Along with the poor financial conditions, shortage of human resources, lack of accountability, political interference, lack of capacity-building mechanism for managers, and deficient supervision/monitoring are a few factors which need immediate action with renewed and additional efforts at both district as well as provincial level in order to meet Millennium Development Goals (MDGs) by the end of 2015 (GoP 2010). In order to achieve the MDGs, the government of Punjab has adopted Minimum Service Delivery Standards (MSDS) as strategic framework, but the working and implementation of these standards are again hindered by political situation of the area.

Land use classification

Land use classification map was created in order to identify the land use of the nearby areas of hotspots. Land use and hot spot overlay analysis was conducted to identify possible land use type majorly associated with the disease cases. Malaria and land use overlay analysis indicated that land use mostly relate with low vegetation, agriculture, and water bodies land cover class as shown in Fig. 10.

Climate change

Correlation analysis of meteorological variable and malaria cases showed a significant relationship. During the warmer season, the incidence of malaria increased and similar was the case with rainfall and humidity. Graves et al. (2009) reported a statistically significant relationship between monthly rainfall and malaria incidence. Kazembe (2007) also identified a relationship of malaria cases with meteorological variables. Xiao et al. (2010) also confirmed a strong association between malaria incidence and meteorological variables in Hainan, China. Kazembe et al. (2006a, b) examined spatial clustering of malaria risks in northern Malawi. The results obtained indicated a clear spatial pattern of malaria incidence and high transmission rate during the wet season. Abellana et al. (2008) also identified the high malaria transmission rate in wet season in Mozambique. Ali et al. (2008) reported that malaria incidence was positively associated with maximum temperature and

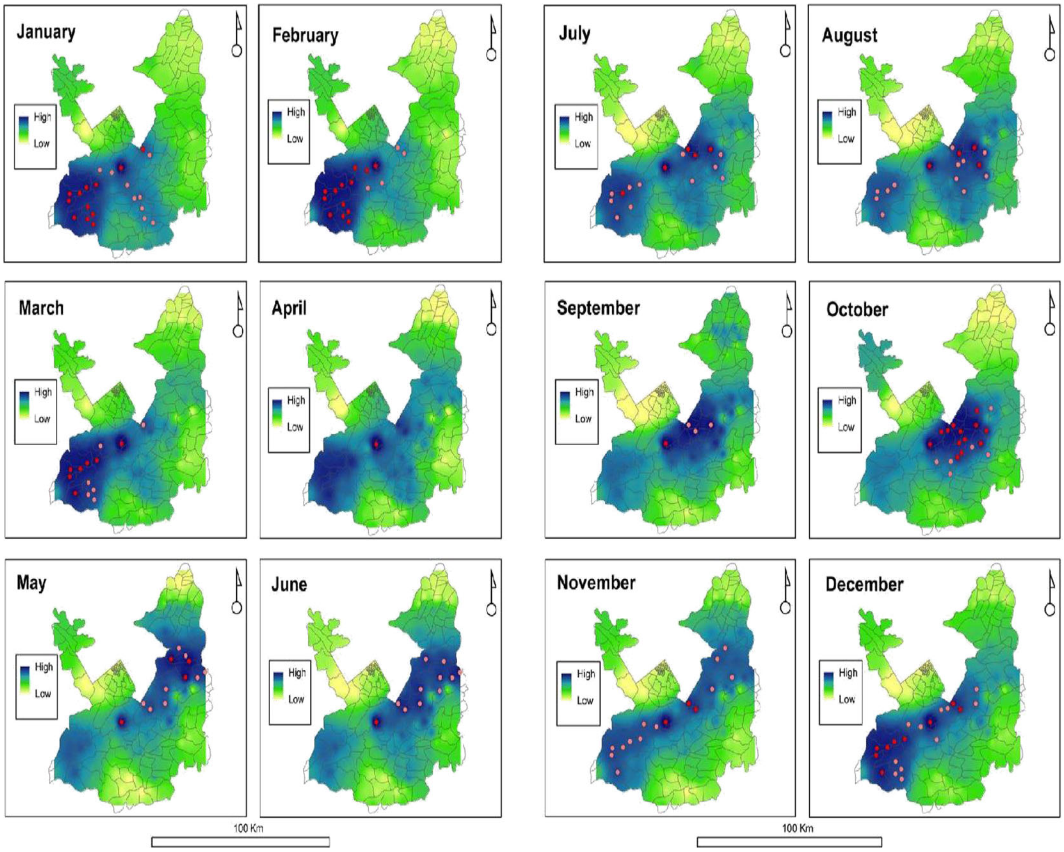

Fig. 9 Mapping of malaria hot spots, high-risk, and cold spots using Getis-Ord G* statistics during January–December in Rawalpindi district

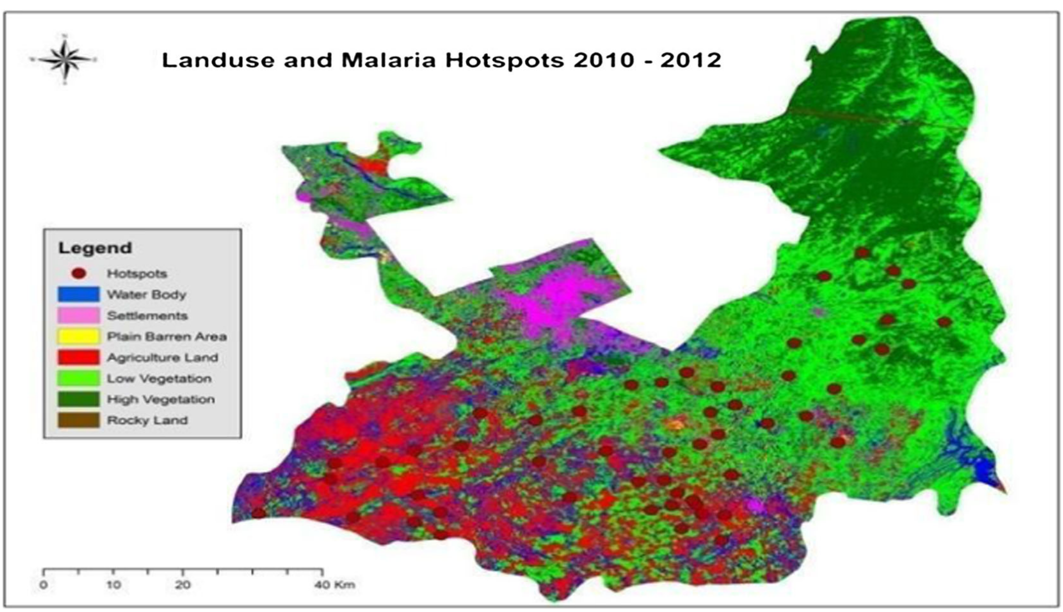

Fig. 10 Land use and malaria cases hotspots

mean relative humidity in Iran. Ingrid et al. (2009) indicated that proximity to vector breeding site, maximum and minimum temperature, and rainfall were positively associated with malaria incidence in Adama, Ethiopia.

Seasonal variation of incidence of malaria clearly indicated their dependency on the meteorological variable. This intensified the importance of climate change. As climate change could increase the disease burden associated with infectious waterborne diseases (McMichael et al. 1996; IPCC 2008) especially for vulnerable populations around the world, given the linkages between weather and infectious gastrointestinal illnesses (IGI), as well as changes already experienced in location, timing, intensity, and duration of precipitation and temperature patterns. Many studies associated periods of heavy rainfall with increased levels of pathogens in drinking water sources (Skerrett and Holland 2000; Schijven and Husman 2005).

Similarly changes in atmospheric and/or water temperatures can also increase the risk of waterborne disease. Generally, pathogen growth is temperature dependent (Prescott et al. 1996; Hall et al. 2002). Increased ambient temperatures were also correlated with various waterborne disease outbreaks in developing (Hoge et al. 1993; Madico et al. 1997; Fleury et al. 2006; Hashizume et al. 2007; Hashizume et al. 2008) and developed countries (Fleury et al. 2006).

Much has also been written on the potential effects of long-term climate change and global warming on malaria (McMichael and Martens 1995; Martens et al. 1995; Tanser et al. 2003). Rainfall has often been associated with malaria due to the creation of standing pools of water, which are prime mosquito breeding grounds (Small et al. 2003; Dahal 2008). Prolonged rainy season in turn increase the duration of malaria transmission season. On a daily and hourly scale, minimum and maximum ambient temperatures can place powerful limitations on parasite (Detinova 1962) and vector survival (Jepson et al. 1947).

The study results therefore indicated towards the applicability of the research for true depiction of health conditions of any city in developing countries facing health situations similar to those that prevail in the current study's scenario. The study further highlights the significance of such analyses in socioeconomic terms as the population existing in such localities usually belongs to lower class or lower middle class which are deprived of the basic necessities of life. Furthermore, in such localities, health becomes the most neglected component, yet the most important for governments to improve the living conditions of these people. Governments therefore need such kind of studies for their policy/decision making. Moreover, the application and comparison of different analyses can provide more accurate results and can be undertaken by the decision making authorities for contingency planning. Hence, this study can be used as a reference at both national as well as international level where almost similar conditions prevail.

Conclusion and recommendations

This study describes the spatial pattern of malaria distribution in Rawalpindi district using routinely collected individual patient morbidity data from health-care facilities. It further provides in-depth and accurate analysis of the disease incidence by employing a combination of techniques where mostly such studies usually involve only one or two techniques. It not only gives overview of applications but also a kind of comparison among all techniques used in this study for spatial and temporal surveillance of malaria. The results of this study showed that the temporal variation in the incidence of malaria in Rawalpindi district exhibits a significant dependence on meteorological variables. The global Moran's *I* test statistics show significant clustering (spatial autocorrelation) of malaria in the study area. Hotspots or location of clusters were identified using Getis-Ord Gi* statistic. High malaria incidence was observed in central part of the study area. OLS regression models indicated that 49 % of the malaria cases variation was due to population, literacy ratio, distance from the water channels, and population density in the study area. Image classification also facilitates to create a relationship of land cover class and disease cases. Based on the results obtained, the study concludes that these techniques could successfully be applied for all kinds of infectious diseases and recommends that interventions should be made by the relevant organizations in high-risk areas to provide GIS-based surveillance.

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