Gouri Sankar Bhunia
Pravat Kumar Shit

Geospatial Analysis of Public Health

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Gouri Sankar Bhunia
Department of Science and Technology
Bihar Remote Sensing Application Centre
Patna, Bihar, India

Pravat Kumar Shit
Department of Geography
Raja Narendra Lal Khan Women's College
Midnapore, West Bengal, India

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Dedicated to beloved teachers and parents

Preface

Medical geography is incredibly a dynamic sub-discipline of geography which is conventionally related to the spatial aspects of disease ecology and healthcare management. With the expansion of geospatial technology, medical geography has been transformed to formulate several measurements from far above the earth surface and create dozen of maps of disease and health events within a short period. In this book, we look forward to achieve geographical aspects in public health research and analyze geographical distribution of population exposed to threats and health outcomes and to tackle public health problems. This book will be supportive in providing a blueprint of the dimensions of spatial distribution of diseases and the associated environmental health control measures.

The book has been structured into seven well-organized chapters. The introductory portion of this book will contain data collection, data organizations, data standardizations, and the description of the complications innate in interpreting semantics. In an effort to provide some common background in Chaps. 1 and 2, we have provided an overview of spatial issues in public health, an introduction to typical analytical methods in epidemiology, and also an introduction to basic issues in geographical science. In Chap. 3, we unite notions of conceptual aspects of geographical information system and its usefulness in public health events. Spatial and temporal pattern of disease distribution has also been analyzed with suitable example. Chapter 4 describes the use of spatial statistics through exploration of methods, contests, and techniques associated with mapping disease data. In Chap. 5, we have provided an introduction to image processing techniques and methods for the analysis of spatial data and extend them to a particular issue of identifying disease cluster which is often needed in public health. In Chap. 6, we have analyzed the risk assessment of disease distribution in terms of public health. Finally, in Chap. 7, we have provided several issues and challenges of policy implementation undertaken to control the diseases using space technology. Throughout, we provide the case studies to illustrate the application of the methods which is well described in the text. Additional learning tools like maps, charts, figures, and tables have been provided throughout the text for better understanding.

This book provides a conceptual framework for the future researchers on geomedical application using remote sensing and GIS technology. The information in this book will be of immense significance for professionals, epidemiologists as well as to the amateur environmental scientists. This book directs and facilitates students of human geography to get a critical look at the theories and practices that jointly embrace GIS. We therefore hope that the book will be useful both as a standard reference and as a source of new research questions and hypotheses.

Midnapore, West Bengal, India

Gouri Sankar Bhunia
Pravat Kumar Shit

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Midnapore, West Bengal, India

Gouri Sankar Bhunia
Pravat Kumar Shit

About This Book

Present book provides a research based study on vector borne disease in India through geospatial technology. The studies focused on the infectious disease i sub-tropical and ho humid environment. The present book also gathers creative research on geomedical applications using remote sensing and GIS technology. In this book, we have analyzed the basic concept and role of remote sensing, GIS and vector borne disease. Also, the present book represents the modern trends of geospatial technology in infectious disease risk assessment with appropriate illustration, statistical modelling and examples. This book comprises with spatial data, GIS, and spatial statistics to describe and interpret distributions of health related outcomes in public health problems.

Chapters 1 and 2, provides an overview of spatial issues in public health, an introduction to typical analytical methods in epidemiology, and an introduction to basic issues in geographical science. In Chap. 3, we have merged the ideas of geography and statistics through exploration of methods, challenges, and approaches associated with mapping disease data. In Chap. 4, have provide an introduction to image processing techniques and methods for the analysis of spatial data and extend them to a particular issue of identifying disease cluster which is often in interest in public health. Chapter 5 described about the ecological pattern and its associated with the vector borne disease pattern. In Chaps. 6 and 7 focused on the disease risk analysis and health-care planning policy. Finally, we have discussed several issues and challenges of policy implementation undertaken to control the diseases using space technology.

Contents

About the Authors

Gouri Sankar Bhunia received his Ph.D. from the University of Calcutta, India, in 2015. His Ph.D. dissertation work focused on environmental control measures of infectious disease (visceral leishmaniasis or kala-azar) using geospatial technology. His research interests include kala-azar disease transmission modeling, environmental modeling, risk assessment, data mining, and information retrieval using geospatial technology. He is Associate Editor and on the editorial boards of three international journal in Health GIS and Geosciences. He worked as a '*Resource Scientist*' in Bihar Remote Sensing Application Centre, Patna (Bihar, India). He is the recipient of the *Senior Research Fellow (SRF)* from Rajendra Memorial Research Institute of Medical Sciences (ICMR, India) and has contributed to multiple research programs kala-azar disease transmission modeling, development of customized GIS software for kala-azar 'risk' and 'non-risk' area, and entomological study.

Pravat Kumar Shit received his Ph.D. in Geography (Applied Geomorphology) from Vidyasagar University (India) in 2013, M.Sc. in Geography and Environment Management from Vidyasagar University in 2005, and PG Diploma in Remote Sensing & GIS from Sambalpur University in 2015. He is Assistant Professor in the Department of Geography, Raja N. L. Khan Women's College (Autonomus), Gope Palace, Midnapore, West Bengal, India. His main fields of research are soil erosion spatial modeling, badland geomorphology, gully morphology, water resources and natural resources mapping, and modeling and has published more than 45 international and national research articles in various renowned journals. His research work has been funded by the University Grants Commission (UGC), India. He is Associate Editor and on the editorial boards of three international journals in geography, and earth environment science.

Abbreviations

ABER	Annual Blood Examination Rate
AHP	Analytical Hierarchy Process
AIDS	Acquired Immune Deficiency Syndrome
ANN	Artificial Neural Network
API	Annual Parasite Index
AVHRR	Advanced Very-High-Resolution Radiometer
CR	Consistency Ratio
DTM	Digital Terrain Model
EID	Emerging Infectious Disease
GIS	Geographical Information System
GPI	Global Polynomial Interpolation
GPS	Global Positioning System
HIV	Human Immunodeficiency Virus
IDW	Inverse Distance Weighted
IRT	Inside Room Temperature
LPI	Local Polynomial Interpolation
LST	Land Surface Temperature
LULC	Land Use–Land Cover
ME	Mean Error
MODIS	Moderate Resolution Imaging Spectroradiometer
MSS	Multispectral Scanner System
MXL	Maximum Likelihood
NDVI	Normalized Difference Vegetation Index
NNA	Nearest Neighbour Analysis
NOAA	National Oceanic and Atmospheric Administration
NPP	Net Primary Productivity
NRDMS	National Resource Data Management System
NVBDCP	National Vector Borne Disease Control Programme
PCA	Principal Components Analysis
PF	*Plasmodium falciparum*

RBF	Radial Basis Function
RDVI	Re-normalized Difference Vegetation Index
RMSE	Root Mean Square Error
RS	Remote Sensing
SAM	Sandflies Abundance Mapping
SAVI	Soil-Adjusted Vegetation Index
SDE	Standard Deviation of Ellipse
SFR	Slide Falciparum Rate
SIMS	Summary Index of Malaria Surveillance
SPOT	France's Système Pour l'Observation de la Terre
SPR	Slide Positivity Rate
TIN	Triangulated Irregular Network
TM	Thematic Mapper
VL	Visceral Leishmaniasis
WGS	World Geodetic Survey
WHO	World Health Organization
WI	Wetness Index

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Chapter 1
Introduction to Geoinformatics in Public Health

1.1 Introduction

Medical geography or health geography is a branch of human geography that focuses on the terrestrial aspect in the study of health prominence and the banquet of diseases. Additionally, it provides an idea of the location of individual health as well as its geographical distribution and its association with environmental factors. The concept of medical geography was first introduced by Hippocrates (5th–4th Century BCE). People have also been conscious of the development of disease dissemination through geographic regions for eras even during times when aetiology of infectious diseases was anonymous (e.g., the Black Death/plague, 1346–51 AD pandemic), which was conceded along trade paths from China to Europe. At present, medical geography has a lot of applications as well. Mapping plays an enormous role in this field. Maps are produced to demonstrate historic epidemics like the 1918 influenza or Google Flu Trends across the United States or Malaria, Leishmaniasis across the entire world. Medical geographers and public health professionals determine health strictly in terms of signs of illness such as morbidity and mortality. However, understanding of disease spreading may well be the most interesting and intriguing research area within the entire discipline of human geography.

Medical geography concerns about three main themes: disease ecology, health care delivery and environment and health. Disease ecology encompasses the investigation of infectious disease (e.g., malaria, filaria, leishmaniasis and HIV/AIDS) comprehending the geographical distributions of weather associated phenomenon, biotic and cultural portents interrelated with disease, along with the demographic, political and economic hurdles to assenting change. The research of health care provision embraces geographical measures of health care conveyance and patient activities and encompasses differences like discrepancies in health (health prominence and ease of contact), and de-institutionalization of the mentally ill. Environment and health is a comparatively novel emphasis for health

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geographers that appeals geography's long ritual in environmental hazards investigation along with health geography. Although the portraying of infection data can be comparatively straightforward, understanding geographically referenced disease data can occasionally be puzzling, mainly for non-infectious and chronic diseases (e.g., coronary heart disease and diabetes mellitus). Geographers have certain hindrances to be overawed to collect data. However, the leading problem is allied with the footage of a disease's location and the subsequent problem is connected with the precise identification of that disease.

1.2 Spatial Data for Public Health

Today's public health information is an embryonic field which emphasizes on the solicitation of information science and technology to public health rehearsal and investigation. Public health determinations have been based on the use and exploration of spatial data for several decades. Generally, public health varies from particular health because it exclusively depends on the health of people who are reluctant to expose it and the restriction of administrative framework. In 1854, Dr. Snow used a hand-drawn map to investigate the geographical location of London's cholera epidemic (Tuthill 2003). Snow assumed that cholera was spread through public water supplies, and determined the broad street pump as the outmost probable source of the cholera epidemic.

Data in a geographical contiguity is more prospectful to be predisposed by analogous factors and consequently pretentious in a similar manner. In 1890, Palm accomplished a study on geographical situation of rickets in an industrial urban area that had a cold and wet climate. Moreover, Florence Nightingale studies patient statistics and visualizes the reasons of mortality to establish that soldiers during Crimean war were suffering from disease connected to contaminations in hospitals circumstances and stimulate sanitary practices in medical amenities which consequently sustains millions of lives. Nevertheless, this historical remark can be of immense significance in demarcating patterns of the disease. Spatial analysis in public health not only pertains to geographical location of disease distribution but also to the structure and environmental conditions of a population.

1.3 Basic of Epidemiological Data

The examination of public health data usually comprises the concepts and tools of epidemiology demarcated by MacMahon and Pugh (1970) as the study of the dissemination and contributing factors of disease frequency. In most cases, the analyses of epidemiological data are based on annotations of disease incidence in a population of people "at risk". Normally, we want to narrate incidence patterns between groups of people suffering various levels of acquaintance to some factors having a putative influence on a person's risk of disease. Experimental studies endeavor to control all reasons that may adapt the connotations under study while observational studies cannot. Additionally, experimental investigations randomize consignment of the disputes of interest to investigational units to lessen the effect of any hysterical allied variable that may jiggle the relationship under study. In an observational study investigator detect issues of variable interest without conveying treatments to the subjects.

There are several ways by which the incidence of disease may be enumerated. The frequently used events of incidence and prevalence count both newly emergent and existing cases of the disease.

The general outcomes for epidemiologic investigations are as follows:

- *Mortality*: Mortality is the state of being mortal or liable to death; whereas the mortality rate governs the number of deaths in a particular population.
- *Illness*: Illness determines a disease is an exact abnormal state, a disorder of an erection or function that disturbs part or all of an organism. It can be determined through the physical signs, laboratory test etc.
- *Discomfort*: It is the sensation of infuriation, inflammation, or pain that, though not severe, is irritating. However, it reduces the capability to do normal activities.
- *Destitution*: Destitution is an unfortunate state in which a person is deficient in somewhat significant—like wealth, food, employment, companionship, or even hope.

1.4 Measures of Disease Frequency

Epidemiology is about recognizing associations between exposures and outcomes. To determine any association, the exposure and outcomes are first to be calculated in a quantitative approach. Then rates of occurrence are measured or calculated. These measures are referred "*measures of disease frequency*". Epidemiological measures of disease frequency are of five types:

- *Count*: Measures the number of population that meets the case definition. Calculating the extent of disease occurrence with a count is simple and helpful for definite purposes. It is more supportive to have a denominator under the count that indicates the size of the study population. For example, 20,000 cases of Kala-azar in Bihar in 2015.
- *Proportion*: Proportion determines the part of population affected by the disease. Proportions, also acknowledged as fractions are often stated as percentage that ranges from 0 to 1 or 0–100%. It can be calculated as:

$$A/(A + B)$$

where, A is population who meets the case definition.
B is the study population who does not meet the case definition and is at risk.

- *Ratio*: A ratio is simply one number divided by another. It is not dependent upon time. It is a measure of disease frequency. A ratio does not necessarily imply any particular relationship between the numerator (e.g., case definition) and the denominator (e.g. study population). For example, male-female ratio of Kala-azar disease in Bihar is 1:1.92.
- *Rate*: A rate is also one number divided by another, but the rate is reliant on time. It determines ratio over a certain period of time. An epidemiological rate will contain the following: disease frequency (numerator), unit of population size, and the time period during which the event occurred.

For example: 14 cases per 1000 per year
There are several ways to determine the disease rates, like:

– *Incidence rate* (*IR*)—Incidence rates calculate the occurrence of new cases of disease in a population. Conversely, incidence rates take into explanation the amount of the time that each individual persisted under surveillance and at risk of developing the outcome under study. It can be calculated as

$$IR = \frac{Number\ of\ new\ cases\ of\ disease\ during\ a\ specific}{Population\ at\ risk\ during\ this\ time\ period}$$

– *Prevalence rate* (*PR*)—It is directly related to the duration of disease. It can be determined as follows:

$$prevalence = incidence * average\ duration$$

Prevalence depends on the incidence rate (r) and the period of disease (T). Such as, if the incidence of a disease is low but the period of disease is lengthy, the prevalence will be high relative to the incidence. On the other hand, if the incidence of a disease is high and the period of the disease is short, the prevalence will be low relative to the incidence (Hennekens and Buring 1987). There are two collective estimation of prevalence rate:

(i) *Point prevalence*—Prevalence of a situation of interest at a exact time. It can vary from 0 to 100%. It can be measured from a cross sectional survey data by calculating the % with a particular disease on a particular date.

(ii) *Period prevalence*—Prevalence measured over an interval of time. It is the proportion of individual with a particular disease at any time during the interval. It can be calculated as

$$PR = \frac{All\ new\ and\ pre\text{-}existing\ cases\ during\ a\ given\ time\ period}{Population\ during\ the\ same\ time\ period} \times 10^n$$

- *Risk*: Risk is the proportion of individuals in a population (initially free of disease) who develop the disease within a specified time interval. Unwin defined risk is "*the probability that event will occur*".

  For example: 0.014 cases per person/year
  There are several ways to measure the risk, like:

- *Absolute risk* = incidence rate
- *Relative risk* = measure the strength of association between disease and without disease
- *Attributable risk*—Measure the ratio of disease in a population that can be attributed to the exposure.

The incidence risk assumes that the entire population at risk at the beginning of the study period has been followed for the specified time period for the development of the outcome under investigation.

1.5 Role of Remote Sensing in Public Health

Remote sensing (RS) refers to science and technologies that observe atmospheric and ground-based features from a distance. RS can identify features from remote-space, near-space, aerial, and terrestrial vantage points. Earth observation satellite allows us to quantify physical, chemical and biological factors (environmental occurrences and events) almost every place on the earth. Comprehensive supervision of the earth configuration, in both its natural and anthropological aspects, necessitates facts and figures that are timely, of known feature, durable and universal. RS provides such information and pays to refining our understanding of how the environment influences public health and welfare (Table 1.1 and Fig. 1.1). In medical geography, satellites such as Landsat's Multispectral Scanner (MSS) and Thematic Mapper (TM), the National Oceanic and Atmospheric Administration (NOAA)'s Advanced Very High Resolution Radiometer (AVHRR), and France's Système Pour l'Observation de la Terre (SPOT), can provide information about vegetation cover, landscape, structure, and water bodies in almost any region of the

Table 1.1 Use of remote sensing technology in some important vector borne disease application

Disease	Vector/ reservoir	Location	Satellite/sensor	Methods/software	Remarks	Reference
Malaria	*An. albimanus*	Chiapas, Mexico	Aerial photos	Visual interpretation	Surrounding breeding sites of *An. albimanus* adult abundance were located at low elevations in flooded unmanaged pastures	Rodriguez et al. (1996)
	Anopheles albimanus	Tapachula, Chiapas, Mexico	LANDSAT (TM)	Multi-temporal satellite data	Using two remotely sensed landscape elements, the discriminant model was able to successfully distinguish between villages with high and low *An. albimanus*	Beck et al. (1997)
	Anopheles spp.	Gambia	NOAA (AVHRR), METEOSAT	Normalized difference vegetation index (NVDI) and Cold-Cloud Duration (CCD)	Processed to produce proxy ecological variables which have been extensively investigated for monitoring changes in the distribution and condition of different natural resources, including rainfall and vegetation	Thompson et al. (1996a, b)
	An. punctimaluca	Belize	SPOT (XS)	Discriminant function analysis, Canonical discriminant analysis	Habitat analysis and classification resulted in delineation of habitat types of mosquito defined by dominant life forms and hydrology	Rejmankova et al. (1998)
	An. subpictus	Lombok Island, Indonesia	JERS (optic)	Visible and near infrared radiometer to detect waterbodies, Overlay	Remote Sensing (RS), a Global Positioning System (GPS) and a Geographic Information System (GIS) were used to analyze relationship between *Anopheles subpictus* larval densities and environmental parameters	Anno et al. (2000)
	Anopheles spp.	Africa	LANDSAT (MSS, TM), SPOT, NOAA (AVHRR)		Investigating malaria epidemiology and assisting malaria control	Hay et al. (1998)
	Anopheles dints, Anopheles minimus	Assam, North-Eastern			Identified nature of the breeding ground for mosquitoes and their spreading patterns are not so complex as generally expected	Jeganathan et al. (2001)
	Anopheles spp.	Tanzania, Uganda, and Kenya/Africa	NOAA (AVHRR)	Discriminant analysis, multi-temporal meteorological satellite	The study identified land surface temperature as the best predictor of transmission intensity. Rainfall and moisture availability as inferred by Cold Cloud Duration (CCD) and the normalized difference vegetation index (NDVI), respectively, were identified as secondary predictors of transmission intensity	Omumbo et al. (2002)
		Kenya	RADARSAT 1	Land use/land cover analysis; texture analysis (eCognition software)	Object-oriented approach to image classification is taken in order to circumvent some of the limitations of traditional pixel-based classification of radar imagery	Kaya et al. (2002)

(continued)

Table 1.1 (continued)

Disease	Vector/reservoir	Location	Satellite/sensor	Methods/software	Remarks	Reference
	Plasmodium vivax	Republic of Korea	IKONOS, Landsat	Supervised classification, cost comparison of chemoprophylaxis; PCI remote sensing software (PCI Geomatics, Richmond Hill, Ontario, Canada)	To determine whether an accurate estimate of the area covered by mosquito larval habitats	Masuoka et al. (2003)
	Aedes aegypti	Puntarenas, Costa Rica	ASTER, quickbird	Land cover analysis, artificial neural network (ANN); Idrisi Kilimanjaro software (J. R. Eastman, Clark University, Worcester, MA. 2004)	Developed for sampling specific mosquito larval habitats using GIS technology and high-resolution satellite imagery	Troyo et al. (2007)
	Anopheles gambiae	India	IRS WiFS	Land cover analysis, NDVI	Use of red and infra-red IRS WiFS multispectral data for land use/land cover mapping on 1:25,000 scale, and to map the malaria, and JE vector breeding habitats with spatial consistency	Palaniyandi (2014)
	P. falciparum	Mangalore, India	Landsat TM	Land use/land cover analysis; unsupervised classification, ENVI software v4.6 (ITT Visual Information Solutions, Boulder, CO, USA)	Detecting land cover changes and assesses their relationship with the burden of malaria	Mohan and Naumova (2014)
RRV (Ross River Virus)	*Culex annulirostris*	Brisbane, Australia	Colored aerial photos	MicroBRIAN image processing package	A rapid technique is being developed and assessed to identify urban breeding sites of *Culex annulirostris*	Dale and Morris (1996)
Lyme disease	*Ixodes scapularis*	Chappaqua and Armonk, Westchester	LANDSAT (TM)	Tasseled cap transformation index	A Geographic Information System (GIS) was used to spatially quantify and relate the remotely sensed landscape variables to Lyme disease risk category	Dister et al. (1997)
	Ixodes scapularis	Wisconsin, USA	NOAA (AVHRR)	NDVI, overlay	A Geographic Information System (GIS) was used to map distributions of human Lyme disease cases, ticks, and degree of vegetation cover	Kitron and Kazmierczak (1997)
	Ixodes scapularis	Wisconsin, Illinois, Michigan, USA	LANDSAT (TM)	Discriminant analysis, overlay	Environmental data were gathered at a local level (i.e., micro and meso levels), and a Geographic Information System (GIS) was used with several digitized coverages of environmental data to create a habitat profile	Guerra et al. (2002)
	Ixodes scapularis	Northeast to Southeast USA	NOAA (AVHRR)	Geostatistics, NDVI	Geostatistics (cokriging) was used to model the cross-correlated information between satellite-derived vegetation and climate variables and the distribution of the tick	Estrada-Peña (1998)

(continued)

Table 1.1 (continued)

Disease	Vector/ reservoir	Location	Satellite/sensor	Methods/software	Remarks	Reference
Leishmaniasis	*Phlebotomus papatasi*	Saudi Arabia, Iran, Israel/Southeast Asia	NOAA (AVHRR)	NDVI	A computer model was developed using the occurrence of *P. papatasi* as the dependent variable and weather data as the independent variables	Cross et al. (1996)
	Lutzomyia spp.	Lagoinha, São Paulo, Brazil	LANDSAT (TM)	–	An area is characterized which may prove to be a macro-habitat for vectors, reservoirs and etiological agents	Miranda et al. (1998)
	Phlebotomus orientalis	Sudan/Africa	NOAA (AVHRR)	Logistic regression model, Normalized Difference Vegetation Index and land surface temperature	To estimate the probability of the presence of *P. orientalis* at each collecting site as a function of climatic and environmental variable	Thompson et al. (1999)
	Lutzomyia longipalpis	Teresina, Piauí, Brazil	LANDSAT (TM)	Spherical covariance structure, Spatial autocorrelation, NDVI (IDRISI software)	Demonstrate a method for modeling spatial autocorrelation within a mixed model framework, using data on environmental and socioeconomic determinants of the incidence of visceral leishmaniasis (VL) in the city of Teresina, Piauí, Brazil	Werneck and Maguire (2002)
	Phlebotomus argentipes	Vaishali district (Bihar, India)	IRS-1C LISS III	NDVI, supervised classification (ERDAS imagine v9.3)	Identify risk-prone areas of Kala-azar through GIS application tools	Sudhakar et al. (2006)
	Phlebotomus argentipes	Vaishali district (Bihar, India) and Lohardaga district (Jharkhand)	IRS-1C LISS III	NDVI, supervised classification (ERDAS imagine v9.3)	Identify the association between environmental factors and vector distribution	Paul et al. (2006)
	Phlebotomus argentipes	Northeastern Gangetic Plain,	NOAA (AVHRR)	Supervised classification (ERDAS imagine v9.3, ArcGIS v9.2)	The relationship between the incidence of VL and certain physio environmental factors was explored, using a combination of a geographical information system (GIS), satellite imagery, and data collected "on the ground"	Bhunia et al. (2010a, b)
	Phlebotomus argentipes	Vaishali district, Bihar, India	SRTM, Landsat 5 TM	DEM, NDVI (ERDAS imagine v9.3, ArcGIS v9.2)	To study the relationship between the incidence of Kala-azar and topography and vegetation density	Bhunia et al. (2010a, b)
	Phlebotomus argentipes	Vaishali district, Bihar, India	Landsat 5 TM	NDPI, nearest neighbour analysis, radial basic function interpolation (ERDAS imagine v9.3, ArcGIS v9.2)	Delineating the potential hydrological relationship between the vector and Kala-azar transmission, the associations between inland water bodies, sand fly prevalence, and Leishmania infections	Bhunia et al. (2011)

(continued)

Table 1.1 (continued)

Disease	Vector/reservoir	Location	Satellite/sensor	Methods/software	Remarks	Reference
	Phlebotomus argentipes	Vaishali district in Bihar, India, and Lohardaga district in Jharkhand, India	IRS-LISS III, LISS IV	NDVI, supervised classification (maximum likelihood algorithm), spatial analysis, factor analysis (ERDAS imagine v9.3, ArcGIS v9.2)	Delineate the suitable habitats of the VL vector, *P. argentipes* density in relation to environmental characteristics between different ecosystems was assessed in endemic (Bihar) and non-endemic (Jharkhand) Indian states	Kesari et al. (2011)
	Phlebotomus argentipes	Muzaffarpur district (Bihar, India)	Landsat 5 TM	SAVI, WI, LST, and supervised classification (maximum likelihood algorithm) (ERDAS imagine v9.3, ArcGIS v9.2)	Examining relation with the environmental factors and vector distribution in a Kala-azar endemic region in Bihar, India	Bhunia et al. (2012a, b, c)
	Phlebotomus argentipes	Vaishali and Muzaffarpur districts (Bihar, India)	AVHRR, MODIS, Landsat TM, LISS IV	Thematic maps and satellite supervised classification (ERDAS imagine v9.3, ArcGIS v9.2)	Examining the relationship between LULC classes and their suitability for vector habitats in areas endemic for Kala-azar at different spatial scale	Bhunia et al. (2012a, b, c)
Flariasis	*Culex pipiens*	Nile River Delta/Africa	NOAA (AVHRR)	TeraScan software to determine dTs, Overlay method	Correlation between Bancroftian filariasis distribution and diurnal temperature differences in the southern Nile delta	Thompson et al. (1996a, b)
Trypanosomiasis	*Glossina spp.*	Kenya/Africa	LANDSAT (TM)	Spectral bands of Landsat TM, multiple regression	Satellite imagery, Geographic Information Systems (GIS) and spatial statistics provide tools for studies of population dynamics of disease vectors in association with habitat features on multiple spatial scales	Kitron et al. (1996)
	Glossina spp.	Côte d'Ivoire and Burkina Faso/Africa	NOAA (AVHRR)	Temporal Fourier-processed surrogates for vegetation, temperature and rainfall derived from meteorological satellites	The application of remotely-sensed, satellite data to the problems of predicting the distribution and abundance of tsetse flies in West Africa	Rogers et al. (1996)
	Glossina spp.	Southern Africa	NOAA (AVHRR)	Linear discriminant analysis, maximum likelihood classification	Study about the distribution of *Glossina morsitans* centralis, *Glossina morsitans* and *Glossina* pallidipes using a range of multivariate techniques applied to climate and remotely sensed vegetation data	Robinson et al. (1997)
	Glossina tachinoides	Togo/Africa	NOAA (AVHRR), METEOSAT	0.125° raster or grid-based Geographic Information System data used	Addresses the problem of generating tsetse distribution and abundance maps from remotely sensed data, using a restricted amount of field data	Hendrickx et al. (1999)
	Glossina spp.	Africa	NOAA (AVHRR)	Multi-temporal satellite data; temporal fourier analysis; biological, process-based models	Descriptions of the different components of transmission, from the parasites to the affected hosts, eventually developed to include geographical dimensions	Rogers (2000)
	Glossina spp.	Burkina Faso/Africa	LANDSAT (TM) SPOT			De La Rocque et al. (2001)

Source de Moraes Correia et al. (2004), Cad. Saúde Pública, Rio de Janeiro, 20(4):895–896; Bhunia et al. (2013), ISRN infectious disease

NDVI normalized difference vegetation index, *WI* wetness index, *SAVI* soil adjusted vegetation index, *LST* land surface temperature, *NDPI* normalized difference pond index, *IRS* Indian remote sensing system, *LISS* linear imaging self-scanning, *TM* thematic mapper, *AVHRR* advanced very high resolution radiometer, *MODIS* moderate resolution imaging spectrora diometer

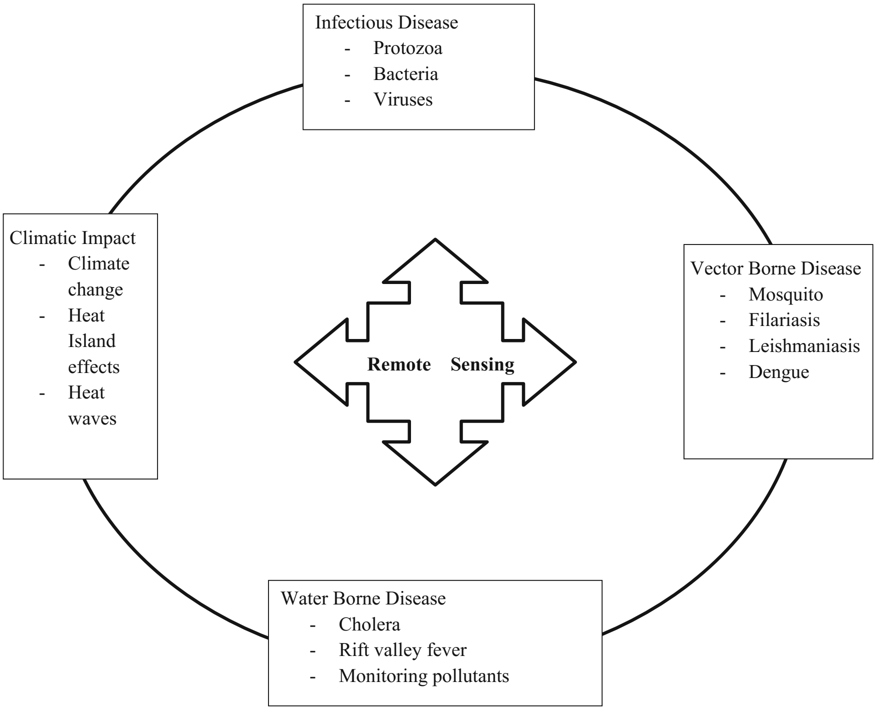

Fig. 1.1 Schematic diagram of remote sensing application in public health

globe—information that can be extremely valuable in health research that examines environmental factors in disease dissemination (Beck et al. 2000).

For example, when considering the association between climate and vector borne diseases, the succeeding associations among the distribution and life cycle of the vector, outbreaks of the disease, the impact on endemicity and the socio-economic drivers of the diseases should be measured. To generate a climatological record that can be likened to the above components of a disease, remote sensing and GIS is extremely relied upon. Current enhancement in spatial and temporal resolution of climatic variables has permitted for more healthy investigations of the connection of climate and diseases.

Remote Sensing has been used to predict cholera outbreaks in Bangladesh that is based on large-scale oceanic algal blooms (Ali et al. 2002); to identify snail habitat for schistosomiasis control in China (Guo-Jing et al. 2002); to predict the distribution of urinary schistosomiasis in Tanzania using land surface temperature (LST) and the normalized difference vegetation index (NDVI) (Brooker 2002); to map the distribution of intestinal schistosomiasis in Uganda using AVHRR (Kabatereine et al. 2004); to assemble a household-GIS database for health lessons in Karachi, Pakistan, by high resolution IKONOS imagery where GPS receivers failed because of structural barriers such as tall buildings (Ali et al. 2004); to quantify areas of reduced risk of hantavirus pulmonary syndrome in the United States using Landsat Thematic Mapper imagery (Glass et al. 2000); to envisage intestinal schistosomiasis infection in school children in the Côte d'Ivoire (Raso et al. 2005); to risk map VL in Sudan using NDVI and climate data (Elnaiem et al. 2003); to anticipate malaria epidemics in sub-Saharan Africa using climatic variables to predict vector habitat (Rogers et al. 2002); to determine small-area clustering of malaria in Nandi District, Kenya via land cover types recovered from the Digital Landsat Enhanced Thematic Mapper+ (ETM+) (Brooker et al. 2004); and to identify environmental factors that could predict Ascaris infections in South Africa (Saathoff et al. 2005).

The use of Remote Sensing techniques to map vector distribution and disease risk has evolved considerably during the last two decades. The complexity of methods range from using simple correlations between spectral signatures from different land use/land cover types and species abundance (Sithiprasasna et al. 2005) to complex techniques that link satellite-derived seasonal environmental variables to vector biology (Rogers et al. 2002). An assessment of different modeling approaches for mapping vector and vector-borne diseases is discussed by Rogers (2006). An outline of the accessibility of environmental satellite data for mapping infectious diseases can be found in Hay et al. (2006).

Role of Remote Sensing data in disease epidemiology involves retrieving environmental variables that characterize the vector ecosystem such as land cover, temperature, humidity or vapor pressure, and precipitation. However, measuring meteorological and climate variables near the surface is more tricky, and repeatedly, empirical methods were employed (Rogers 1991). The Normalized Difference Vegetation Index (NDVI), which exploits the strong contrast in the reflectance of vegetation in the red and near infrared wavelengths, is a commonly used index to characterize vegetation dynamics (Townshend and Justice 1986). An amalgamation of vegetation indices, surface reflectance, and temperature measurements have been used by epidemiologists to model vector ecosystems (Rogers et al. 2002).

Multispectral, microwave or thermal satellite imagery cannot be employed to monitor sand fly or vectors in a straight line from space, but can be used to recognize the favourable environment or breeding places. Remote Sensing technologies, which allow the mapping of environmental variables, have already been used in different epidemiological studies (Bhunia et al. 2010a, b), but so far only rarely deal with vector borne disease. Few studies are available that include the extraction of environmental indicators like meteorology, vegetation and altitude etc. (Sudhakar et al. 2006). Nieto et al. (2006) developed an ecological niche model to delineate the distribution and potential risk zone of Visceral leishmaniasis (VL).

1.6 Geographic Information Systems (GIS) in Public Health Research

The application of geographic information systems (GIS) to public health exercise has prodigious prospective for enlightening our understanding of the ecology and reasons of complex health problems, and for managing the policy and appraisal of effective population based programs and policies. According to Bill (1999) a Geographic Information System (GIS) is a computer-supported system consisting of hardware, software, data and the consequent applications. By means of GIS, data can be digitally recorded and edited, stored and reorganized, shaped and analyzed as well as presented in an alphanumerical and graphic mode. In its definition the (World Health Organization (WHO) 1999) states another essential: the trained staff. The spatial dimension of health and health care has been being noted since ancient times (Picheral 1994). There are three different types of geographic-epidemiological studies: disease mapping, ecological studies and migrant studies (English 1992). The

Table 1.2 Important analyzing methods of Geographical Information System (GIS)

Method	Description	Reference
Data base query	Identification of objects on the basis of user-defined selection terms	Huang et al. (2012)
Geometrical calculations	All functions carrying out calculations on the basis of geometry: distances, longitudes, areas, angles, differences in altitude etc.	Keegan and Dushoff (2014)
Overlay, clip, merge	Using these techniques new variables can be calculated, for instance, to check which measurement points are within a certain area	Achu (2008)
Buffering	Construction of zones (buffer) of determined dimension by points, lines and areas	Palaniyandi (2012)
Density estimation	Estimation of spatial density of geometric objects on the basis of user-defined conditions (e.g. Kernel estimation)	Hollingsworth et al. (2015)
Interpolation	Estimation of missing data on the basis of space-related relations and distribution of known data (e.g, Kriging); smoothing methods; construction of smoothed (generalized) patterns of attribute data (surfaces) (e.g., surface trend analysis)	Diuk-Wasser et al. (2010)
Analysis of space-related distribution	Check of space-related data in view of correlation and cluster by using visualization methods and geo-statistical methods (auto-correlation, Moran's coefficient, Nearest Neighbor Procedure etc.)	Ratmanov et al. (2013)
Modeling and simulation	Development of models and scenarios on the basis of geometric and attribute data, in particular tempo-spatial distribution- and spreading models etc.	Shah and Gupta (2013)

functionalities of GIS include the following selected aspects (Table 1.2) that are provided by the different scientists and researchers' worldwide (Clarke et al. 1996).

There are noteworthy methodological concerns which must be addressed so as to confirm that map yields are interpretable and not ambiguous. GIS can abridge vast extents of tabular data into convincing visual maps that can offer prevailing intuitions and engross the attention of policy makers and the public. GIS has been utilized to map the national distribution of lymphatic filariasis in Nepal (Sherchand et al. 2003); to invent threat maps of lymphatic filariasis in Africa based on climactic variation (Lindsay and Thomas 2000); to unmask the profound heterogeneity of malaria risk in magisterial districts of South Africa (Booman et al. 2000); to predict the spatial distribution of Schistosomiasis in Tanzania for use in a national mass drug treatment control program (Clements et al. 2006); to model patterns of African Trypanosomiasis in southern Cameroon (Muller et al. 2004); to expand models integrating livestock biomass, tsetse flies, farming systems, clinical disease, and land use for the control of African Trypanosomiasis (Hendricks et al. 2001); to establish the spatial outline of African Trypanosomiasis in Cote D'Ivoire using GPS and ground-collected information on households, agriculture, and vegetation (Courtin et al. 2005); to envisage community predominance of Onchocerciasis in the Amazon (Carabin et al. 2003); to map the global distribution of trachoma and Trichiasis (Polack et al. 2005); to identify areas of high risk for Giardiasis in Canada (Odoi et al. 2003); to determine the spatial distribution of visceral leishmaniasis infection in Africa and India (Bhunia et al. 2010a, b); and to construct a disease atlas of helminth infection in sub-Saharan Africa (Brooker et al. 2000).

The potential of GIS has yet to be revealed in at least two areas: a thematic one (i.e., policy making) and, suitably enough, a geographical under-developed region (Table 1.3). GIS applications related to Kala-azar have been introduced and used in, for example, the surveillance and monitoring of diseases (Kalluri et al. 2007), in environmental health (Bhunia et al. 2010a, b), quantifying environmental hazards and their influence on public health (Salomon et al. 2006), and for policy and planning purposes (Clements et al. 2006). In India, for example, GIS systems have been used in vector control research (Bhunia et al. 2012a, b, c) for studying and mapping of non-communicable diseases (Raban et al. 2009). The application of GIS in a public health circumstance can be a resource intensive activity, demanding a substantial speculation.

1.7 Statistical Methods for Spatial Data in Public Health Research

Statistical data analysis is now the most consistent and recognized set of tools to evaluate spatial datasets. Yet the solicitation of statistical practices of spatial data appearances is an imperative challenge, as conveyed in Tobler's (1969) first law of

Table 1.3 Use of Geographic Information System (GIS) in some important vector borne disease application

Disease	Location	Methods/software	Remarks	Reference
Malaria	Sub-Saharan Africa	Orthograph, aerial photograph, MapInfo software (version 4, MapInfo Corporation, New York, USA); Bentley and Intergraph software products (Symmetry Systems Inc., New York, USA) and Global Positioning System (Optron Precise Positioning Solutions, Johannesburg, South Africa)	Provides an example of how a geographical information system can contribute to the planning of malaria control programmes	Booman et al. (2000)
	South Africa	Geographical Information System based Malaria Information System	To process data timeously into a usable format is discussed, as well as its relevance to malaria research, appropriate malaria control measures, tourism, and social and economic development	Martin et al. (2002)
	Indonesia	Literature survey	Discussion of strategies that can be used to overcome some of problems like technological problems accurate data on the disease and how it is reported; basic environmental data and demographic data	Sipe and Dale (2003)
	Sub-Saharan Africa	Overlay and spatial analysis (ArcView version 3.2)	To relate stability of malaria transmission to biologic characteristics of vector mosquitoes throughout the world	Kiszewski et al. (2004)
	Valle del Cauca, Colombia	Malaria Climatic Convenience Index (MCCI), Malaria Natural Convenience Index (MNCI), Malaria Risk Transmission Index (MRTI)	To develop a methodology for mapping malaria risk, which integrates physical variables such as temperature, precipitation and geomorphologic features with related aspect to human being, which in this study will be recognized as anthropic variables	Rincón-Romero and Londoño (2009)

(continued)

Table 1.3 (continued)

Disease	Location	Methods/software	Remarks	Reference
	Orissa, India	Overlay, index model Arc/View	Identifies the risk factors associated with high malaria transmission and focused intervention based on geomorphological parameters, land use, soil type, water bodies and drainage network	Daash et al. (2009)
	Laos	NAVSTAR satellite system; KASHMIR 3D Version 8.0.9 Beta; Mandara for Windows Version 9.10	Geographic Information System (GIS) maps were developed using the data collected in an active case detection survey	Shirayama et al. (2009)
	Developing countries	Literature survey	Focuses on how advances in mapping, Geographic Information System, and Decision Support System technologies, and progress in spatial and space-time modeling, can be harnessed to prevent and control these diseases	Eisen and Eisen (2010)
	Bangladesh	PubMed database	Recent progress of malaria mapping in Bangladesh with GIS, GPS, and RS, and identified potential future applications and contributions of geospatial technologies to eliminate malaria in the country	Kirk et al. (2015)
RRV (Ross River Virus)	Leschenault estuary, WA, (south-west Australia)	Buffer zone, Spatial analysis	Investigate the relationship between risk of Ross River virus (RRV) infection and proximity to mosquito-breeding habitat surrounding a tidal wetland ecosystem	Vally et al. (2012)
	Australia	Principal Component Factor analysis, K-means cluster analysis; Spatial distribution analysis	To assess the relationship between socio-environmental variability and the transmission of RRV using spatio-temporal analysis	Hu et al. (2005)
	Australia	Spatial analysis; Principal Component Factor analysis and regression, chi-square tests	Spatial distribution was investigated using census data at the suburb level	Muhar et al. (2000)

(continued)

Table 1.3 (continued)

Disease	Location	Methods/software	Remarks	Reference
Lyme disease	USA	Risk model, logistic regression analysis	Identify and locate residential environmental risk factors for Lyme disease	Glass et al. (1995)
	United States	Risk model and spatial analysis, ARC/INFO and ArcView GIS (ESRI, Redlands, CA), Trimble Geoexplorer (Trimble Navigation, Ltd., Sunnyvale, CA)	To determine the distribution of *I. scapularis* in the upper Midwest based on data from Wisconsin, northern Illinois, and the Upper Peninsula of Michigan, and to explain the environmental factors that facilitate or inhibit the establishment of *I. scapularis*	Guerra et al. (2002)
	Ontario	Multi-Criterial Decision Making Model, Spatial analysis	Spatial distribution of endemic tick populations at the dissemination area (DA) level and the potential role of white-tailed deer in the spatial expansion of Lyme ticks; and determine the relationship between the tick *B. burgdorferi* bacterium and deer establishment	Chen et al. (2015)
Leishmaniasis	Vaishali district (Bihar, India)	Inverse distance weightage, Geostatistics, hotspot, spatial autocorrelation (ArcGIS software v 9.0)	Investigated the spatio-temporal patterns and hotspot detection for reporting Kala-azar cases in Vaishali district based on spatial statistical analysis	Bhunia et al. (2013)
	Muzaffarpur district (Bihar, India)	Spatial analysis and standard deviation of ellipse, spatial statistics (ArcGIS v9.2)	Examining disease distribution in a Kala-azar endemic region in Bihar, India	Bhunia et al. (2012a, b, c)
	Muzaffarpur district (Bihar, India)	Database queries, spatial analysis (ArcGIS v9.2)	The spatial distribution of reported Kala-azar cases in the 4 study periods of Muzaffarpur district, Bihar, India	Malaviya et al. (2011)

(continued)

Table 1.3 (continued)

Disease	Location	Methods/software	Remarks	Reference
	Venda Nova, Belo Horizonte, Minas Gerais, Brazil	Literature based study	The use of an automated database allied with geoprocessing tools may favor control measures of VL, especially with regard to the evaluation of control actions carried out	Saraiva et al. (2011)
	Iran	Global clustering methods including the average nearest-neighbour distance, Moran's I, general G indices and Ripley's K-function	To analyse yearly spatial distribution and the possible spatial and spatio-temporal clusters of the disease to better understand spatio-temporal epidemiological aspects of ZCL in rural areas of an endemic province	Mollalo et al. (2014)
	Brazil	Digital database, spatial analysis, overlay	Produce distributional maps of the phlebotomine vectors of American cutaneous leishmaniasis and superimpose these data with American cutaneous leishmaniasis disease records for the historical periods	Shimabukuro et al. (2010)
Filariasis	Nigeria	Spatial analysis of geographically referenced data	Focuses on how the use of Geographical Information System (GIS) can be harnessed for surveillance, prevention and control of LF and malaria	Okorie et al. (2014)
	Sri Lanka	Digital database and spatial analysis	To develop a site directed Geographic Information System (GIS) map of Lymphatic Filariasis (LF)	Wijegunawardana et al. (2012)
	Andhra Pradesh, India	Spatial database generation, GPS (ArcGIS Engine-9.2)	To present a spatial mapping and analysis of filariasis data over the historical period	Upadhyayula et al. (2012)

(continued)

Table 1.3 (continued)

Disease	Location	Methods/software	Remarks	Reference
Trypanosomiasis	Kenya	Database generation and spatial analysis, Global Positioning System (GPS), MapInfo Software	To map the spatial and temporal distribution of SS and determine possible risk factors associated with the disease	Rutto and Karuga (2009)
	Zambia	Spatial analysis, Buffering, multivariate (maximum likelihood) analysis	To identify areas where intervention is most likely to be technically, economically, socially and environmentally sustainable	Robinson et al. (2010)
	Africa	Georeferencing, Database generation	Mapping the distribution of human African trypanosomiasis in time and space	Simarro et al. (2010)
	Zambia	Decision-tree approach combined with a multiple-criteria evaluation (MCE)	To show how remotely sensed and other environmental data can be combined in a decision support system to help inform tsetse control programmes in a manner that could be used to limit possible detrimental effects of tsetse control	Symeonakis et al. (2007)

geography: “everything is related to everything else, but near things are more related than distant things”. Statistical analysis which covenants with geographically referenced data is designated as the science of spatial statistics. Standard statistical approaches undertake independence of observation. When employing this method to examine spatially interrelated data, the standard error of the covariate parameters is undervalued so the statistical significance is overemphasized. Spatial statistical procedures integrate spatial association along with the way of geographical contiguity is defined. Proximity further is governed by the geographical information that can be obtainable at areal/regional level or at point location level.

- Areal unit data are gathered over adjoining units (countries, state, districts, and survey zones) which divide the entire study region. Proximity in span is demarcated by their adjacent structure.
- Point referenced data are composed at stationary locations (household, villages) over an incessant study region.

However the contiguity in spatial statistical data is determined by the remoteness between sample locations. The crucial part of probabilities stimulates the practice of statistical methods to examine public health data and the usage of geostatistical approaches to

- Apprise various rate perceived from various geographical areas,
- Discrete arrangement from noise,
- Recognize disease clusters, and,
- Evaluate the connotation of latent exposures.

Furthermore, these methods permit to enumerate ambiguity in our assessments, forecasts, and maps and make available the practicalities for statistical inferences with spatial data.

GIS software and tools can be employed to generate covariates for inclusion in statistical model and to envisage the output from statistical models. Spatial statistics deliver regions modeling and extrapolations method for portraying interfaces from geographically referenced data. Geostatistics offers body of approaches for spatial smoothing and for accenting for spatial covariates in appearing spatial surface.

GIS based statistical models are employed to assess vector incidence or profusion within a specific geographic area. Basic spatial modeling methods comprise—interpolation based on spatial dependence in vector and extrapolation based on relations between vector data and environmental or socio-economic predictor variables. For instance, zones with high vector profusion or maximum disease occurrence often occupy on other areas with high vector abundance or high disease incidence, and the resemblance in their influencing variable losses with growing space. In these cases, kriging or supplementary categories of interpolation models are employed to create smooth interpolated maps of the influencing factors (Bunnell et al. 2003; Diuk-Wasser et al. 2010). GIS based extrapolation model, software is first employed to excerpt geographically categorical data for environmental variables of interest for the point locations or physical areas where the data were composed. Afterward, a prognostic model is established in a statistical software package and the model calculation is then useful in the GIS. For example, using the Raster Calculator in ArcGIS, continuous spatial surfaces were developed that present a estimated risk of exposure to vectors or vector borne pathogen (Craig et al. 2008; Honório et al. 2009).

1.8 Global Positioning System (GPS) in Public Health Research

Hand-held GPS is a technology developed by the United States Department of Defense that uses a constellation of 24–32 medium earth orbiting satellites to pinpoint a user's location, speed, direction, and time (King et al. 2004; Strom 2002). Re-developed for civilian use under the issue of Ronald Reagan in 1983, GPS today is utilized in a variety of geospatial applications, from superior computer cartography to aboard consumer automobile navigation systems (Pellerin 2006). Mention may be made of Tran et al. (2008)'s use of GPS to identify and map larval and adult populations of *Anopheles hyrcanus* to examine the potential of re-emergence of malaria in Southern France; Zeilhofer et al. (2007)'s identification of habitat suitability of *Anopheles darlingi*, a vector of malaria, with GPS around hydroelectric plants in Mato Grosso State, Brasil; and Dwolatzky et al. (2006)'s accomplishment of GPS into a personal digital assistant (PDA) for health care workers to locate remote home sites of tuberculosis cases in support of a tuberculosis control programme in South Africa.

1.9 Conclusion

At present, medical geography has a number of uses as well. Technological progresses continue with medical improvements. Meanwhile, the geographical dissemination of the disease is still a large substance of significance however; mapping plays an enormous role in the field. Although, geographers have some difficulties to be overawed when collecting data, the prime problem is allied with recording a disease's location. The earlier report suggested that social disparities and environmental factors are more lean towards key determinants of discriminations in health than access to health care. With growing interest in health GIS, the epidemiological method, assumed in the field of geography of disease relied increasingly on the statistical modeling of the geographical dissemination of diseases and their distribution in time and space. These methods allow health related information to be exhibited, and enable the visualization and monitoring of infectious disease. Uses of Remote Sensing and Geographic Information Systems are quickly gaining recognition as effective means to answer complex, ecological questions in health endorsement, public health, medicine, and epidemiology (Miranda and Dolinoy 2005; Foody 2006). The optimal use of RS and GIS will require not only continued innovation in technology and application but also something that is not yet visible: a continuous flow of information between disciplines and across borders, focusing on the end of the result.

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