CHAPTER II
REVIEW OF LITERATURE

This chapter carries the review works on relevant literature on the research theme. Here, a good number of works have been referred to. In order to present the review works in a systematic format, some related and relevant themes have been identified and according to these themes the literature is reviewed briefly. The relevant themes under which review works are discussed are (i) malaria transmission (ii) factors favouring malaria (iii) deforestation and malaria (iv) malaria epidemiology and entomology with reference to India and North-East India (v) deforestation in Sonitpur district (vi) applications of GIS and remote sensing in malaria study (vii) other methods of malaria study (viii) challenges and strategies for malaria control and (ix) forecasting and predicting malaria.

(i) Malaria transmission

While the malaria parasite is the true agent of infection, the female Anopheles mosquito is the agent of transmission. The environment of malaria occurrence is considered from three aspects - physical, biological and socio-economic conditions. Movements of people in a variety of forms and at a variety of scales play an important role in the malaria equation of parasites—vectors—people (Prothero, 2001). He discussed about the transmission of malaria, spreading infection and exposing non-immune people to risk of infection. Mundada et al. 2012, have underline the various factors influenced by human activities and natural
calamity that have great bearing on mosquitogenic conditions leading to increased potential for malaria transmission. They highlighted that natural transmission of malaria depends on the presence of, and relationship between the three basic epidemiological factors: the agent, the host and the environment.

In a study carried out by Markwardt et al. 2008, regarding outbreak of malaria among children in Tong Pha Phum district of Kanchanaburi, Thailand the evidence of exposure and transmission patterns confirmed the relationship of malaria to: (i) migration of infected individuals into the area, (ii) increased human presence due to the deforestation and plantation activities, (iii) the lack of self-protection from mosquito-bites when in the forests, and (iv) changing activity patterns of villagers.

(ii) Factors favouring malaria

Climate change is affecting the global pattern of vector borne diseases. Warmer climatic conditions have been responsible for direct increase in mosquito and the vector reproduction, biting, and pathogen transmission despite shortening mean daily survivorship. Changes in temperature, rainfall and humidity have created opportunities for emerging diseases in new area. Climate change is a new emerging threat to health, particularly in the context of vector-borne diseases (Dhiman et al. 2008). Lieshout et al. (2004) in their research article proposed that environmental conditions play an important role in the transmission dynamics of malaria, as the parasite has to pass its developmental cycle in the mosquito. The three main climatic factors that affect malaria transmission and distribution, as they
suggested are temperature, precipitation and relative humidity. It was also mentioned that temperature affects the developmental period related to different stages of a mosquito’s lifecycle - blood feeding rate, gonotrophic cycle (physiological process consisting of digestion of blood-meal and development of ovaries) and longevity. As temperature increases, the rate of digestion of blood-meal increases, which in turn accelerates ovarian development, egg laying, reduction in gonotrophic cycle and a greater frequency of feeding on hosts, thereby increases the probability of transmission. It takes about 10 days for an egg to reach the adult stage of an anopheline mosquito at an optimum temperature of 28 °C. At lower temperature, the duration gets prolonged while at increased temperature the duration is reduced. However, at more than 40 °C, mortality occurs in adult mosquitoes. The minimum temperature required for development of *Plasmodium vivax* parasite in anopheline mosquitoes ranges from 14.5°C to 16.5 °C, while for *Plasmodium falciparum* it ranges from 16.5°C to 19 °C (Lieshout et al. 2004). However, the best conditions for development of the malaria parasite, as suggested by them, are 20–30 °C temperature and 60% relative humidity (RH). The distribution and seasonal transmission of malaria is affected by climate, as both vector and parasite are sensitive to temperature.

To understand the likely influence of climate change on vector production and malaria transmission in India, a study was carried out by Bhattacharya *et al.* (2006). Based on some transmission window criteria, the most endemic malaria prone regions emerge as the central and eastern Indian regions of the country covering Madhya Pradesh, Jharkhand, Chhattisgarh, Orissa, West Bengal and Assam in the current climatic conditions. Under the future climate change
conditions in 2050s, it is projected that malaria is likely to persist in Orissa, West Bengal and southern parts of Assam bordering north of West Bengal. However, it may shift from the central Indian region to the south-western coastal states of Maharashtra, Karnataka and Kerala. Also the northern states, including Himachal Pradesh and Arunachal Pradesh, Nagaland, Manipur and Mizoram in the North-East may become malaria prone.

The peak density of An. fluvialis was observed in the post-monsoon months whereas the abundance of An. dirus was observed throughout the study period with population peak in monsoon season (Baruah et al. 2007). An. minimus, which is a species of hill and foothills occupying ecotone zones, closure to the forest is being considered as the major vector of malaria in NE region of India. An. minimus was found more abundant during the wet season compared with the dry and hot seasons in Thailand (Chareonviriyaphap et al. 2003). The density of malaria vectors was influenced by rainfall pattern in a study carried out to observe the seasonal prevalence of malaria vectors in Sonitpur district of Assam (Baruah et al. 2007). Anopheles minimus, an important malaria vector of South East Asia has reappeared in the Singhbum hills, East-Central India where deforestation and DDT residual spraying had reportedly eliminated it during the Malaria Eradication Programme. The study carried out by Jambulingam et al. (2005) shows that the environmental conditions favour the existence of the species and was one of the possible reasons for its reappearance.

Ecological changes due to canal irrigation for agriculture, increased water logging due to seepage from canals and inadequate drainage have resulted in
creation of extensive mosquitogenic condition. Further, deforestation, rapid urbanization, industrialization and extensive use of insecticides in agriculture and public health may also have contributed towards changes in the ecosystem and in the prevalence of mosquito vectors. Research suggests that irrigation for rice cultivation increases the production of *Anopheles gambiae*, the main vector of malaria in Mali and their abundance is highly variable across villages and seasons (Duik-Wasser *et al.* 2007).

Ecological disturbances exert an influence on the emergence and proliferation of malaria and zoonotic parasitic diseases. Any environmental change, whether occurring as a natural phenomenon or through human intervention, changes the ecological balance and context within which disease hosts or vectors and parasites breed, develop, and transmit disease (Patz *et al.* 2000).

In North-East India, rice is the staple food and in many parts, particularly in the foothill region, paddy is grown at the risk of malaria infection (Dev *et al.* 2003a). They also suggested that, *An. minimus* breeding was recorded throughout the year in slow flowing streams with grassy banks while *An. dirus* (the monsoon species) breeds in pools and rain water collections in deep jungles. Malaria is prevalent during all months of the year and there is a peak between May to September marking the high transmission period. Pattern of seasonal prevalence of *An. dirus* related to the proliferation of its breeding habitats during rainy season and their scarcity during dry season in the forest-fringed areas (Prakash *et al.* 1997).
Malaria which is a local and focal disease is not only caused by ecological factors, but also by some important local factors such as socio-economic, socio-cultural and behaviour patterns of the community which plays a major role in disease transmission (Dassh et al. 2009). Malaria burden is linked with poverty (Malaney et al. 2004). Likewise Dev et al. (2004) pointed out that as much as 36% of the total population of Assam is estimated to be living below the poverty line, and the risk factors for malaria are much concentrated in these marginalized population groups.

Pattanayak et al. (2006) discussed the close association of deforestation, malaria and poverty and stressed on using transdisciplinary research to develop more effective policies to control malaria, protect forest and alleviate poverty. The behavioural and socio-economic factors associated with avoiding mosquitoes and preventing malaria in urban environments in Kenya was observed by Macintyre et al. (2002). The analysis showed that people from wealthier and more educated households were more likely to sleep under a net.

A study on the prevalence of malaria during the agricultural season suggests that the risk of disease varies according to the characteristics of the house and the house environment (Guthmann et al. 2001). A multi-factorial risk factor analysis study was designed by Kirby et al. (2008) to highlight important spatial, compound and mosquito control-related parameters that affect house entry of malaria vectors in Gambia. The study demonstrated that the risk of malaria transmission was greatest in rural areas, where large numbers of people sleep in houses made of mud blocks, where the eaves (lower edge of a roof) were open.
Education status of a mother in a family is an important aspect in determining malaria cases. In a study in rural Kenya by Noor et al. (2006), stress was given on mother’s education determining children malaria cases. Children's use of nets purchased from the retail sector was shown to be closely correlated with mother's education, with only 14.4% of children of uneducated mothers using nets compared with 32.7% of those whose mothers had education up to secondary level and above.

(iii) Deforestation and malaria

The investments of billions of dollars in policies worldwide have been made to slowdown deforestation, eradicate malaria, and foster economic development. About one third of the world’s population live in malaria-infected areas related to deforestation. Deforestation continued at the rate of 16 million hectares annually throughout the last decade, and about half the world’s population live on less than US$2 per day (Pattanayak et al. 2006). It is widely recognized that tropical deforestation can change the regional climate significantly. The seasonal and spatial fluctuations in the precipitation anomalies caused by the tropical deforestation are linearly related to seasonal and spatial variability in the differences of the reflected radiation (Berbet and Costa, 2003). They, in their research also found that the decrease in the precipitation over the deforested area is proportional to the reflected radiation increment, consistent with the results of Dirmeyer and Shukla (1994), Zeng and Neelin (1999) and Kanae et al. (2001). Ermert et al. (2011) simulated model based estimates for the present climate (1960 to 2000) with observed data for the spread of malaria in Africa that project that
climate changes driven by greenhouse-gas and land-use changes will significantly affect the spread of malaria in tropical Africa well before 2050. Similarly, Reiter (2001) pointed out the 1935 malaria epidemic in Sri Lanka which killed 1,00,000 people came after two exceptionally dry years. Vittor et al. (2009) too suggested that various landscapes and ecologic features associated with deforestation are positively associated with mosquito larval breeding sites and therefore causing malaria in Amazon.

Changes in habitat ecology of mosquito and human behaviour patterns in deforested regions influence the transmission of malaria and deforestation has therefore, increased the risk of malaria transmission in sub-Saharan (Uneke, 2009). The reason behind is that mosquitoes are highly sensitive to environmental changes, and because of deforestation their survival, density and distribution are dramatically influenced by small changes in environmental conditions.

Deforestation in the Amazon rainforest has been linked to the rise in malaria prevalence (Singer and Castro, 2001; Castro et al. 2006; Vasconcelos et al. 2006; Yasuoka and Levins, 2007). Its associated ecologic alterations are conducive to *An. darlingi* larval presence that increases malaria risk in Peruvian Amazon (Vittor et al. 2009).

Afrane et al. (2008) investigated the effects of deforestation on microclimates and sporogonic development of *Plasmodium falciparum* parasites in *Anopheles gambiae* mosquitoes in an area of the western Kenyan highland prone to malaria epidemics. The results showed that deforested sites had higher temperatures and relative humidities, and the overall infection rate of mosquitoes
increased compared with that in forested sites. Changes of micro-climates due to
deforestation lead to more rapid sporogenic development of \textit{P. falciparum} and to a
marked increase of malaria risk.

Land use changes have been suggested as one of the major causes for
malaria epidemics in the African highlands. A study conducted by Afrane \textit{et al.}
(2006) investigated the effects of deforestation-induced changes in indoor
temperature on the survivorship and reproductive fitness of \textit{Anopheles gambiae} in
an epidemic prone area in the western Kenya highlands. Significant increase in net
reproductive rate and intrinsic growth rate for mosquitoes in the deforested area
suggest that deforestation enhances mosquito reproductive fitness, increasing
mosquito population growth potential in the western Kenya highlands. Mosquitoes
that were prevalent in houses in the deforested area recorded a 64.8–79.5\% higher
fecundity than those in houses located in the forested area. The vectorial capacity
of \textit{An. gambiae} was estimated at least 106\% and 29\% higher in the deforested area
than in the forested area in dry and rainy seasons respectively.

Olson \textit{et al.} (2010) has established the relation between deforestation and
malaria in Brazil. Cumulative percent of deforestation was calculated for the
spatial catchment area of each health district by using 60 × 60–meter resolution-
classified imagery. The cross-sectional study showed that malaria incidence across
health districts in 2006 as positively associated with greater changes in percentage
of cumulative deforestation within respective health districts. The results revealed
that a 4.3\% change in deforestation from August 1997 through August 2000 was
associated with a 48\% increase of malaria incidence.
Deforested sites had an *Anopheles darlingi* biting rate that was more than 278 times higher than the rate determined for areas that were predominantly forested in the Peruvian Amazon (Vittor *et al.* 2006). A year-long study of the primary malaria vector in the Amazon, *An. darlingi* fed on humans was carried out to observe the impact of tropical rain-forest destruction on malaria. The results indicate that *An. darlingi* displays significantly increased human-biting activity in areas that have undergone deforestation and development associated with road construction works. Impact of deforestation and agricultural development on anopheline ecology and malaria epidemiology was studied by Yasuoka and Levins (2007). The study suggested the possibility of predicting potential impacts of future deforestation on vector density by using information on types of planned agricultural development and the ecology of local anopheline species.

Epidemiological situation of forest malaria in central Vietnam was studied by Erhart *et al.* (2005) to measure malaria endemicity and identify important risk factors. Mapping of parasite rate and *Plasmodium falciparum* seroprevalence showed a patchy distribution, suggesting that risk factors other than remoteness and forest proximity modulated the human-vector interactions. This was confirmed by the results of the multivariate-adjusted analysis, showing that forest work is a significant risk factor for malaria infection which gets further increased by staying in the forest overnight.

**Malaria epidemiology and entomology in India and North-East India**

India contributes about 70% of malaria in the South East Asian Region as per WHO report 2010. The high burden populations are ethnic tribes living in the
forested pockets of the states like Orissa, Jharkhand, Madhya Pradesh, Chhattisgarh and the North-Eastern states which contribute bulk of morbidity and mortality due to malaria in the country (Dash et al. 2008). In India, there are more than 533 tribes, comprising 8% of the total population contributing 30% of total malaria cases, 60% of total *Plasmodium falciparum* cases and 50% of malaria deaths in the country (Singh et al. 2003, ICMR Bulletin, 2004).

Lal et al. (2004) describes the overall situation of malaria in India by giving more emphasis on vectors and parasites. They indicated that there are about 400 species of anopheline mosquitoes throughout the world, but only 60 species are vectors of malaria. In India, 9 species out of 45 anopheline species have been accused as malaria vectors. The primary vectors of rural and urban malaria are *An. culicifacies* and *An. stephensi* respectively. *An. dirus* is considered as the most important vector of malaria in the entire South-East Asia and is distributed in wet forest areas in North-East India, western ghats in south-western peninsular India and in Andaman Islands. Further, *An. minimus* and *An. fluviatilis* are also responsible malaria vectors in North-Eastern states of India (ICMR Bulletin, 1998).

Dash et al. (2007) illustrated an update on recent advances in the field of vector biology, particularly recognition of sibling species, methods for their identification, differential bionomics of members of species complexes and vector control options currently available. In India, so far only *An. minimus* sub species has been reported from North-Eastern states, Singhbhum hills and West Bengal. In India *An. minimus* sub species is an endophilic and endophagic species with highly
anthropophilic behaviour. It is an efficient malaria vector mainly in North-Eastern states and it is also one of the important mosquito vectors found in Assam responsible for causing malaria (Dev, 1996a). As suggested by Prakash et al. (1996a) *An. minimus* is prevalent throughout the year with high densities between March and August. It usually feeds throughout the night with pronounced feeding between 2100 hrs and 0400 hrs. It prefers to rest indoors on the lower half of the walls and its distribution is usually patchy in the village with some houses being preferred for resting. The Dirus Complex is mainly prevalent in the forest and forest-fringe areas and its members are vectors in India. *An. dirus* is a primary vector of malaria available in North-Eastern states of India (Dutta et al. 1996, Das and Baruah, 1985).

The capacity of the vector to transmit malaria is the interaction between the environment, both natural and man-made and genetically determined characteristics. There are four species of human malaria parasites *Plasmodium vivax, falciparum, malariae* and *ovale*. In India, 60% to 65% of the infections of malaria are due to *P. vivax* and 35% to 40% due to *P. falciparum*. Only few cases of *P. malariae* have been reported from Orissa and Karnataka (Lal et al. 2004).

Malaria is a major public health illness in Assam that contributes >5% of the reported cases in the country annually (Dev et al. 2006). 103 of 156 Primary Health Centres (PHC) in Assam are identified as being high risk for malaria, nearly 65% of total population (Statistical hand book, 2003; Dev et al. 2004). They also highlighted that transmission of the malaria pathogen is persistent, and is maintained mostly by *Anopheles minimus*. Other vectors in this region are *An.
dirus and An. fluviatilis. The populations of border areas are considered to be at greater risk and believed to be infectious reservoirs or persistent transmission of malaria due to intermixing of non-immune and immune population at border areas (Dev et al. 2004).

Malaria is very common in North-East India due to the predominance of P. falciparum parasite (Rahman, 1981; Jana-kara et al. 1995; Prakash et al. 1996b; Das et al. 1997; Bagchi, 2010) development of parasite resistant to chloroquine (Barkakati and Narasimham, 1992; Gogoi et al. 1995; Sharma, 2000; Dev et al. 2003b; Dua et al. 2003) efficient anthropophagic vectors and congenial climatic conditions. Difficult terrain, hilly forest, inadequate infrastructure coupled with development of chloroquine resistance in P. falciparum in Assam is aggravating the situation (Sehgal et al. 1973).

The worst affected districts are Cachar, Darrang, Goalpara, Hailakandi, Karbi-Anglong, Kokrajhar, Lakhimpur, Dima-Hasao and Sonitpur (Dev et al. 2006). The hilly districts of Karbi-Anglong and Dima-Hasao were worst affected, reporting Annual Parasitic Index (API), a criterion which is considered to be a sensitive malarialometric indicator for residual spray interventions against vector populations, was more than 12. These were also the districts having more than one interstate border and higher concentration of tribal natives (> 50%) and population densities were the least (< 100 km²). The districts of Dibrugarh, Sibsagar and Jorhat were affected the least reporting the lowest API (0.02–0.1) also ones with the highest proportion of literates (> 70%) against the state average of 64%. Malaria burden is linked with poverty. As much as 36% of the total population of
Assam is estimated to be living below the poverty line, and the risk factors for malaria are much concentrated in these marginalised population groups.

Epidemiological and entomological studies undertaken in forest-fringed villages and a tea estate in Sonitpur, Assam to assess the malaria situation by Das et al. (2004, 2007) and Dev (1996b) reflects the high vector density with high parity rate, poor socio-economic conditions, lack of awareness, poor sanitation and congenial atmosphere for mosquito proliferation has aggravated the malaria situation in border areas of the district. They also pointed out about vast ecological changes occurred due to deforestation in Sonitpur, in recent years, that has created enormous mosquitogenic conditions favouring vector longevity and rapid multiplication. They also suggested the predominance of \textit{P. falciparum}, presence of asymptomatic carriers of the parasite in the community, \textit{Pf} resistance to antimalarials and \textit{An. minimus} for the perennial transmission of malaria in the district of Sonitpur.

A review paper by Dhiman (2010) gave emphasis on military malaria on North-East India. The problem is worst for military and paramilitary forces deputed in all the states of North-East India as the forces are deployed for a short time generally from non malarious regions and thus become highly vulnerable to acquire the malaria infection. Potential malaria vectors with very high vectorial capacity and high slide positivity rate in civil population manifold the chances of infection. The malaria- attributable morbidity and mortality amongst troops of India Army units deployed in Assam was studied by Pardal et al. (2009). It was validated that the parasitic load of malaria in Assam is high as compared with other
parts of the country and new settlers and migrates like troops are more vulnerable to malaria.

(v) Deforestation in Sonitpur

The deforestation causing habitat destruction is one of the major causes for the human-elephant conflict in Sonitpur district of Assam as advocated by Saikia et al. (2007). The loss of dense forest in the order of 43216 hectares (1994-2007) was the underlying cause of human-elephant conflict in Sonitpur. Dense forest declined from 14% in 1994 to 6% by 2007. A work accomplished by Srivastava et al. in 2002 states that an overall loss of 232.19 km$^2$ of forests was noticed in the Sonitpur District between 1994 and 2001. The study highlights the deforestation and encroachment into the moist deciduous and other forest areas in Sonitpur District of Assam. The time series analysis of satellite imagery was carried out for the years 1994, 1999 and 2001 and the loss of forest cover was found to be more pronounced between 1999 and 2001 than between 1994 and 1999. In another study by Kushwaha and Hazarika (2004) put the pathetic condition of the forest cover in Sonitpur district of Assam and Kameng district of Arunachal Pradesh. The overall habitat loss was found to be 344 km$^2$ between 1994 and 2002. The average annual rate of deforestation was worked out to be 1.38%, which was much higher than the national average. The rate of deforestation was highest between 1999 and 2002.

(vi) Application of GIS and remote sensing in malaria studies

Effective control measures for malaria requires evidence-based utilisation of data resources and proper techniques. Characterizing spatial patterns of risk
through maps is an important tool to guide control programmes (Kazembe et al. 2006) which can be achieved using geoinformatics techniques. Goodchild (2009) in an article explained the present scenario and the future scope of the application of Geoinformatics. Remote sensing (RS) and Geographic Information Systems (GIS) have become powerful tools to study many health related aspects like vector borne diseases, water borne diseases, environmental health, modeling exposure to electromagnetic fields, quantifying lead hazards in a neighborhood, TB transmission patterns, prevalence, monitoring and control programs for onchocerciasis, child pedestrian injury, cancer distribution, diffusion of HIV-AIDS etc. Application of GIS and Remote Sensing technologies for assessing and monitoring malaria risk was well recommended by Ceccato et al. 2005. Bergquist (2001) in a review article strongly urged for using the applications of remote sensing, GIS and GPS that promises improved planning and management in the control of endemic diseases.

The use of remote sensing, GIS, and spatial statistics in the study and control of arthropod vectors of disease has increased greatly in recent years (Thomson et al. 1997; Tran et al. 2008; Lowther et al. 2009). Through combination of field data, satellite image analysis, and GIS modeling, Bogh (2007) developed a high-resolution map of malaria entomological inoculation rates (EIR) in Gambia, West Africa. The analysis was based on the variation in exposure to malaria parasites experienced in 48 villages in 1996 and 21 villages in 1997. The extent of overall change in the vegetation classes and the magnitude among classes and the degree of spatial variation in deforestation can be estimated with the help of remote sensing technique.
Remotely sensed data was used to map the incidence of Q fever, a bacterial infection, in the vicinity of Cayenne, French Guiana (Tran et al. 2002). Eisen (2006) carried out a supervised classification model based on remote sensing data from multi-seasonal Landsat TM 5 images to identify the key habitat in Mendocino County where humans are exposed to *Ixodes pacificus* nymphs which are the primary vectors to humans of *Borrelia burgdorferi*, the etiological agent of Lyme disease. Data relating to mosquito incorporated into a GIS environment along with remotely sensed satellite imagery were used by Sithiprasasna et al. (2005) to determine if remote sensing data could be used to estimate mosquito habitats. They found that the immature collections of *Anopheles* were significantly correlated with landuse. They established that classified remotely sensed data could potentially be used to estimate the distribution of immature and adult mosquito populations. Anopheline mosquitoes that depend on fresh and brackish water in the early stages of their life cycle make them particularly tractable to be studied by remote sensing (Duik-Wasser et al. 2007).

In a study carried out by Rahman (2006) in Bangladesh, epidemiologic data of malaria cases were correlated with satellite-based vegetation health (VH) indices to investigate if they can be used as proxy for monitoring malaria epidemics. The vegetation condition index (VCI) and the temperature condition index (TCI) which estimate moisture and thermal conditions respectively were assessed using correlation and regression analysis. During cooler months (November–March), when mosquitoes are less active the correlation was low. It increased considerably during the warm and wet season (April–October), reaching TCI index value of 0.7 in early October and VCI index value of −0.66 in mid
September. The results of this study showed that AVHRR-based VH indices can be used as proxy for numerical estimation of the number of malaria cases. Malaria endemic areas in the Indochina Peninsula using NDVI tool of remote sensing was used and correlated by Nihei et al. (2002). The outcome maps with NDVI values between +0.3 and +0.4 matched the *Plasmodium falciparum* distribution. NDVI and satellite based rainfall estimates are routinely used to identify areas prone to malaria (Hay et al. 1998).

Forest density and its validation by NDVI analysis in a part of Western Himalaya, India using remote sensing and GIS techniques was carried out by Kumar and others (2007b). The forest density output was verified by Normalized Difference Vegetation Index (NDVI) analyses and positive correlation (r=0.99) between NDVI values and forest density confirms the accuracy of the results. D.R. Fastring and J.A. Griffith (2009) focused on to decide, if the remotely-sensed metric, NDVI and ground-collected decadal climatological variables were useful predictors of future malaria outbreaks in an epidemic-prone area of Nairobi, Kenya. They collected data of 36 dekadal (10-day) periods for the variables like rainfall, temperature and NDVI along with yearly documented malaria admissions in 2003 for Nairobi, Kenya and finally linear regression models were built. Rainfall was taken as it increases the activities of mosquito for laying eggs in standing water and NDVI was taken so as to confirm the availability of water to the plants. Malaria cases were correlated with the variables and results showed that NDVI and other climatological variables had a close relation in determining malaria cases. But, the limitation of the study is that the number of malaria cases may vary as the other factors like education, socio-economic status, infrastructural
development, government policies etc. also influence the occurrence pattern thus may distract the prediction value.

NDVI was used for filovirus outbreaks which is restricted to tropical Africa. A study on five filovirus outbreaks for which time series of remotely sensed data (NDVI values) were available and the reservoir-to-human index case transmission timing and location are known was carried out by Lash et al. (2008). The outbreaks were found to be associated with either behavioural shift in a vertebrate host or changes in viral population dynamics. Lui and Chen (2006) studied the relationship of remote sensing normalized differential vegetation index (NDVI) with *Anopheles* density and malaria incidence rate and concluded that remote sensing NDVI can serve as a sensitive evaluation index of *Anopheles* density and malaria incidence rate.

Irrigated rice fields provide an ideal breeding habitat for *An. freeborni*, the western malaria mosquito throughout California. It was determined that early-season rice canopy development as monitored using remotely sensed data could be used to distinguish between high and low mosquito producing rice fields (Wood *et al*. 1991, 1992). Duik-Wasser *et al*. (2004, 2006) in a research article tried to determine whether remotely sensed data could be used to identify rice-related malaria vector breeding habitats in an irrigated rice growing area near Niono, Mali. They showed that optical remote sensing can reliably identify potential malaria mosquito breeding habitats from space.

Remote sensing-based biomass estimation approaches and a discussion of existing issues influencing biomass estimation are valuable for further improving
biomass estimation performance (Lu, 2006). A methodology to monitor forest cover using IRS-1C Wide Field Sensor (WiFS) data was demonstrated by Roy and Joshi (2002). It avoids illumination differences and has a better temporal resolution. NOAA Advanced Very High Resolution Radiometer (AVHRR) data have also found considerable acceptance for land cover studies at the regional level.

The application of remote sensing in malaria studies has some limitations. Jacob et al. (2005) in a research article tried to find out probable mosquito larval habitat sites using remotely sensed satellite images, but failed to find such suitable areas. The cause explained by them suggests that the image do not show adequate spatial information for remote visual detection of mosquito larval habitats due to inadequate display of surface features. It shows the limitation of remote sensing data in detecting small larval habitats.

GIS in health has many applications and tremendous potential in a variety of ways, e.g. planning, monitoring, resource management, cost effective interventions. GIS was used to monitor and highlight diseases like kala azar (Thomson et al. 1999), tuberculosis DOTS strategy (Tanser and Wilkinson, 1999), HIV heterogeneity and proximity (Tanser et al. 2000), sleeping sickness surveillance (Cattand et al. 2001), malaria (Kleinschmidt et al. 2001), dengue (Chadee et al. 2005), intestinal schistosomiasis (Kabatereine et al. 2004).

GIS technique has been used earlier for malaria risk assessment at various levels. Mapping of *P. vivax* and *P. falciparum* malaria incidence distribution helped in the assessment of malaria risk in Sri Lanka (Briet et al. 2003). GIS was
used to stratify malaria risk and disease incidence in Africa (Booman et al. 2009). In India, GIS based studies have been carried out to understand malaria epidemiology, risk factors and identification of malaria hot spots (Srivastava et al. 2004, 2009; Daash et al. 2009). GIS was also used to map the distribution of potentially important malaria vectors to formulate species specific control measures (Srivastava et al. 2001, 2005). The GIS can be applied in malaria control programme in many ways from simple mapping of malaria incidence to sophisticated risk models.

A GIS-based Malaria Information System (MIS) for malaria research and control in South Africa was discussed by Martin et al. 2002, who felt that GIS-based MIS provides accurate, timely and relevant information for decision-making and research. They hold the opinion that it is a powerful tool that can be used to assist in the control of environmental diseases where spatial analysis is essential to focus scarce resources, improves the efficacy of control and decrease the burden of disease. Hay et al. (2004) used GIS to overlay historical maps of malaria risk to create a single global distribution map of malaria risk which illustrated range of risk changing from 1900 to 2002.

Sipe and Dale (2003) in a review article discussed the challenges in using geographic information systems (GIS) to understand and control malaria. They talked about how GIS is being used in malaria research and control like the mapping malaria incidence/prevalence, relationships between malaria incidence/prevalence and other potentially related variables and modelling malaria risk. They also described some softwares being used by researchers and
professionals like ArcGIS, Mapinfo, EpiInfo/Epimap and HealthMapper. The limitations in using GIS as discussed by them are lack of qualified staff, data limitations, financial implications of hardware and software, understanding of applications by decision-makers, misinterpretation of result, lack of software to perform spatial analysis, lack of software controlled by outsiders and over dominance by GIS technocrats.

Recent applications of GIS and GPS in malaria control have been reported in India, Madagascar, Thailand and Kenya. In India, the objective was to develop a model to assist planning and implementation of a suitable malaria control programme. The location of disease occurrence and information on specific vectors were analyzed using GIS permitting the development of appropriate preventive action (Srivastava et al. 2003). In Madagascar, application of GIS has been applied to detect areas at high-risk for malaria outbreak and used in malaria surveillance with the objective of anticipating areas with a concentrated distribution of *An. funestus* (Rakotomanana et al. 2001; Romi et al. 2002). Similarly, in Thailand, GIS and GPS have permitted real-time monitoring and forecasting of the distributions of four malaria species so that control measures may be conducted before mosquitoes emerge as adults and transmit disease (Sithiprasasna et al. 2003).

In an annual report of NIMR (2005), the GIS was used to study the malaria situation of Jodhpur area of Rajasthan. Vas Dev (2009) in his article in ICMR Bulletin recommended the application of GIS where tools were field tested for establishing distribution of vector species and targeting interventions for effective control, and for saving costs. Dassh et al. (2009) focussed on building spatial
infrastructure for geographic information as it is becoming an important concept for spatial analysis tools which provide excellent means for visualization and analysis of data, revealing trends, dependencies and inter-relationships leading to identification of high risk areas. The study also emphasized spatial analysis tools in decision making and utilising the limited resources in a cost effective manner for disease control. Ali et al. (2004) strongly supported the use of GIS and integrated remote sensing and GPS for mapping health information. They used IKONOS satellite imagery that allows them to construct an accurate household GIS database in Karachi, Pakistan, which included the size and orientation of the houses and later merged with health data for spatial analysis of disease.

Geoinformatics comprising Geographical Information System (GIS) and Global Positioning System (GPS) was widely used in a study carried out by Hightower et al. (1998) in Kenya for finding out the epidemiological situation of malaria. GIS was used to predict distribution of *An. dirus* in different parts of India in a study carried out by Srivastava et al. (2001). The study suggested that the large areas in North-East are favourable for *An. Dirus*. Another study by Srivastava et al. (2004) in Mewat district of Haryana illustrated malaria epidemicity using remote sensing and GIS. Five easily recognizable malaria areas, namely irrigation command areas, catchment/non-catchment, mining, urban and flood-prone areas were mapped for delineation of malaria prevalent areas at macro level and identification of their eco-epidemiological characteristics.

In order to predict the distribution of *An. minimus*, a malaria vector commonly found in forest fringe areas, GIS was used to support precision surveys
for malaria control (Srivastava et al. 2005). With the application of GIS for delineating favourable areas for An. minimus precision surveys can be conducted. They pointed out the favourable conditions for the vector based on forest, altitude, temperature, rainfall and soil conditions. Srivastava et al. (2006) observed that the malaria risk was mainly linked with proximity of the house to the forest edge and source of water. People living close to breeding sites are at higher risk of malaria than people living further away. Risk maps of malaria can be prepared based on the location of houses relative to streams and rivers that are potential breeding sites for the malaria vector (Hoek et al. 2003). Another study carried out by Srivastava et al. (2009) focused on the application of GIS for the management of malaria in forested areas and tribal belts of Madhya Pradesh. An information management system based on GIS using district and block wise malaria data was effectively used to highlight hot spots of malaria for formulating prompt and focused malaria control strategy. Out of total 48 districts consisting of 313 blocks, based on certain criteria GIS identified 58 blocks falling in 25 districts as hot spots. The criteria for identifying blocks/districts as hot spots are considered as (a) 100% Pf in any year in (2000 – 2005), (b) Consistently >30% Pf and (c) Pf > 70% in 2005. Since P. falciparum is responsible for mortality due to malaria and also is indicative of fresh transmission, Pf% cases were considered for identifying the hot spots.

However, there are other criteria based on which malaria hot spots can be identified. These conditions are mentioned in the recommendations of National Malaria Eradication Programme (NMEP) supported by WHO. According to NMEP, an area can be of malaria high risk based on certain conditions which are -

Condition I: Doubling of Slide Postivity Rate (SPR) during the last three years
provided the SPR in second or third year reaches 4% or more, Condition II: Where SPR does not show the doubling trend as above but the average SPR of the last three years is 5% or more and Condition III: *P. falciparum* proportion is 30% or more provided the SPR is 3% or more during any of the last three years.

(vii) Other methods of malaria study

Database management system for the control of malaria was strongly recommended by Mutry *et al.* (2006). They laid more emphasis on the collection of detailed information about the disease for suitable implementation of mosquito control strategies. A surveillance study was conducted by Bautista *et al.* (2006) to examine the micro geographic variation of malaria incidence in periods with high or low incidence, identify malaria high-risk areas, and analyse the presence of spatial and spatial-temporal clusters of malaria in Northern Peruvian Amazon. The study suggested that modest targeted control efforts directed at identified high-risk areas may have significant impact on malaria transmission in the region.

A computerized based management system was used in South Africa for indoor residual spraying operation which maintained huge information that allowed malaria programme management and field supervisors to monitor spraying coverage, insecticide consumption and application rates on an ongoing basis (Booman *et al.* 2003). Moreno-Sanchez *et al.* (2007) recommended the use of web-based multimedia GIS system for use in a public health context using Open Source Software and Open Specifications. They have stated that globalization was contributing to the blurring of borders making irrelevant distinctions between
domestic and international health problems and urged for cross-border and global health spatial information systems (CBHSIS) required to address the new global health challenges. They highlighted the technological and sociocultural–political issues important in successful collaboration across borders and cultures and in the creation of interoperable CBHSIS.

Robertson et al. (2010) discussed the various methods used for space-time disease surveillance. They emphasized on statistical tests and model based approaches for space-time disease surveillance and such methods are space–time interaction, cumulative sum (cusum) methods, scan statistics, generalised linear mixed models, bayesian models and models of specific space–time processes.

Spatial patterns of disease and local characteristics can be examined visually and simultaneously using graphics called micromaps that links statistical information to an organised set of small maps in order to explore and communicate patterns in the outcome variables related covariates, geographic locations and the associations among them (Pickle and Caar, 2010). There are three basic types of disease maps corresponding to certain types of data. These are dot maps for point (or case-event) data, choropleth maps for regional data (also called lattice- or census-tract data), and lastly isopleth maps for geostatistical data (also called point measurements) representing spatially continuous phenomena at a limited number of sampling locations (Berke, 2004). Interpolation of the regional estimates overcomes the areal-bias problem and the resulting isopleth maps are easier to read than choropleth maps which is easily communicable to map users.
A study carried out by Allena and Shellito, (2008) dealt with the abundance and patterns of mosquito vectors of West Nile virus in Chesapeake, Virginia, USA using light trap collection data and a Landsat-7 Enhanced Thematic Mapper digital image for spatial interpolation and geostatistical mapping of the abundance of 24 species of mosquitoes capable of transmitting West Nile virus to humans. Spatial interpolation techniques including inverse distance weighting, ordinary kriging and co-kriging geostatistics were used to estimate the vector dominance (Allena and Shellito, 2008). Population interpolation techniques revealed the most accurately indicated distributions for generating burden of disease estimates to help guide priority setting in international health financing (Hay et al. 2005).

(viii) Challenges and strategies for malaria control

Collection of epidemiological data and accuracy of data is utmost important for making decisions for long term projects and policies. There was evidence of time-based variations of malaria cases due to reporting delays contributing to false alerts of outbreaks (Chilundo et al. 2004). The potential use of malaria incidence data routinely collected from endemic regions for disease control and research has increased with the availability of advanced computer-based technologies, but will depend on the quality of the data itself (Abeysekera et al. 1997). There is an imperative need for better reporting system for evidence-based targetting of interventions, and to save operational costs (Greenwood, 2004). The challenges and opportunities for malaria control in India as explained by Dash et al. (2008) lie in insecticide resistance in vectors, drug resistance in human, lack of information on true disease burden, regular outbreaks in some urban, rural and large project
areas, lack of trained manpower and infrastructure at grass root level, diagnosis of malaria in remote areas, counterfeit drugs, population migration and impact of climate change on malaria. Similarly Bagchi and Kar (2008) too discussed about the problems and management in Assam.

There are more asymptomatic cases of malaria which may occur throughout the year. Risk analysis suggests that the greatest risk factor in acquiring malaria depends on place of residence and not on occupation, including those associated with forest activities such as charcoal making (Saul et al. 1997).

In view of growing problem of insecticide resistance in mosquito vectors and environmental concern, a non-insecticidal community based integrated malaria control strategy was launched in rural areas of Nadiad Taluka of Kheda district in central Gujarat, with focus on elimination of mosquito breeding places, introduction of larvivorous fishes, health education and community participation (Malaviya et al. 2006). The whole concept was found to have enormous community acceptance and proved effective in reducing the mosquito population and malaria incidence.

A work by Agrawal (2008) on Plasmodium falciparum control strategy has stressed on World Health Organization (WHO) announcement of Roll Back Malaria (RBM) with an aim to reduce 50% deaths due to malaria by 2010. He has discussed on interventions by National Malaria Control Programme and its modification in India. He has also stressed on mosquito control by using Insecticide-treated nets (ITNs) and Indoor residual spraying (IRS). Both the measures suggested by him were effective for vector control that ultimately
reduces the load of malaria in a particular area. ITNs can reduce the number of under-five deaths from all causes by about 20% and clinical episodes of malaria by about half. It also improved the health of children and pregnant woman. Use of DDT as IRS in malaria control registered outstanding success in all parts of world. But DDT has lost its effectiveness in malaria control subsequently. This is partly due to six decades of spraying resulting in physiological resistance to DDT in mosquitoes. Other measures that he suggested are intermittent preventive treatment during pregnancy, prompt and effective management of malaria also depends on measures like antimalarial therapy, different drug treatment strategies for low and high risk areas, different drug policies in different drug resistant areas and controlling malaria in urban settings etc. Resistance to chloroquine in *P. falciparum* is a widespread phenomenon in Southeast Asia (Kondrashin, 1992). In India it was first documented in Karbi-Anglong district of Assam in the year 1973 (Prasad, 2009).

Mosquito larval control may prove to be an effective tool for incorporating into Integrated Vector Management (IVM) strategies for reducing malaria transmission. Environmentally safe microbial larvicides can significantly reduce larval abundance in the natural habitats and could be a useful tool for inclusion in an IVM programme. In a study carried out by Chaturvedi et al. (2009) in malaria endemic zones of two districts of upper Assam, individual characteristics of patients including social indicators, area of residence and distance of health service centres have been considered with respect to the patients initial and final choice of service providers. The popular use of self-medication and traditional system of
treatment, especially in remote areas may be the main cause of delay in diagnosis of malaria and it is a big issue.

(ix) **Forecasting and predicting malaria**

GIS-based prediction of malaria risk in Egypt was done using environmental variables to differentiate between high and low risk of malaria (Hassan *et al.* 2003). Discriminant models correctly classified 96.3% of the risk categories and indicated that the most important predictor of risk was hydrogeology. GIS spatial analysis indicated that the high malaria risk was associated with a unique environmental envelope of biotic (presence of both efficient malaria vectors) and abiotic (hydrogeology and soil) variables.

Development of temporal modelling for forecasting and prediction of malaria infections using time-series and ARIMAX analyses incorporating climatic factors such as temperature, humidity and rainfall can be done by using statistical tool (Wangdi *et al.* 2010). Time series analysis was performed by them on monthly malaria cases from 1994 to 2008 in seven malaria endemic districts of Bhutan. The time series models derived from a multiplicative seasonal Autoregressive Integrated Moving Average (ARIMA) was deployed to identify the best model using data from 1994 to 2006. The best-fit model was applied for each individual district and the overall endemic areas were selected and the monthly cases from January to December during 2009 and 2010 were forecasted. In developing the predictive model, the monthly reported malaria cases and the meteorological factors were analysed using data during 1996-2008 for the seven districts.
Mabaso et al. (2006) used Bayesian negative binomial models for spatio-temporal analysis of the relationship between annual malaria incidence and selected climatic covariates at a district level in Zimbabwe from 1988 to 1999. The study revealed a spatially varying risk pattern that was not attributable only to climate. Only years characterized by extreme climatic conditions may be important for developing climate based Malaria Early Warning System and also for delineating areas prone to climate driven epidemics.