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Review Article

The role of Remote Sensing and GIS for spatial prediction of vector-borne diseases transmission: A systematic review

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ABSTRACT

There have been several attemps made to the appreciation of remote sensing and GIS for the study of vectors, biodiversity, vector presence, vector abundance and the vector-borne diseases with respect to space and time. This study was made for reviewing and appraising the potential use of remote sensing and GIS applications for spatial prediction of vector-borne diseases transmission. The nature of the presence and the abundance of vectors and vector-borne diseases, disease infection and the disease transmission are not ubiquitous and are confined with geographical, environmental and climatic factors, and are localized. The presence of vectors and vector-borne diseases is most complex in nature, however, it is confined and fueled by the geographical, climatic and environmental factors including man-made factors. The usefulness of the present day availability of the information derived from the satellite data including vegetation indices of canopy cover and its density, soil types, soil moisture, soil texture, soil depth, etc. is integrating the information in the expert GIS engine for the spatial analysis of other geoclimatic and geoenvironmental variables. The present study gives the detailed information on the classical studies of the past and present, and the future role of remote sensing and GIS for the vector-borne diseases control. The ecological modeling directly gives us the relevant information to understand the spatial variation of the vector biodiversity, vector presence, vector abundance and the vector-borne diseases in association with geoclimatic and the environmental variables. The probability map of the geographical distribution and seasonal variations of horizontal and vertical distribution of vector abundance and its association with vector-borne diseases can be obtained with low cost remote sensing and GIS tool with reliable data and speed.

Key words Ecological modeling; environmental variables; mapping; remote sensing and GIS; spatial prediction; vector-borne diseases transmission

INTRODUCTION

The application of remote sensing and GIS has been significantly developed over the past 25 years for ecological modeling with special emphasis on vectors and vector-borne diseases[1-91]. These studies were conducted on the appreciation of remote sensing and GIS applications to the study of vectors' biodiversity, vector presence, vector abundance and the vector-borne diseases with respect to space and time. This study was made for appreciation of remote sensing and GIS application to review and update the studies of ecological modeling of vector-borne diseases. The numbers of traditional, conventional, and modern scientific methods are being applied by the experts, specialists, or scientists working on vector-borne diseases control and who have contribution to the readily available references including text books and research articles. The traditional method of vector-borne diseases control is based on the empirical knowledge, however, it is most crude and the conventional method is laborious, expensive, erroneous, and time consuming. Whereas, by applying the remote sensing and GIS techniques for mapping vector habitats, vectors' presence, abundance and density, assessing the risk of vector-borne diseases, disease transmission, spatial diffusion, we can find the root cause of the disease infection, and source of infection. Perhaps, these techniques help us to assess disease affected age groups, sex, severity of the diseases, and the community at risk of infection. The areas exposed to the disease transmission are epidemiologically important for choosing the appropriate disease controlling methods. The sea change population and the corresponding environmental changes including the agricultural land use/land cover changes, urban sprawl and irregular growth of urban development and industrial growths are fueled to the development of suitable environment for vector-borne diseases outbreaks. Therefore, there is a need for the replacement of conventional methods for mapping and predicting the problematic areas with risk of disease transmission in the country[1-91]. The present attempt gives the detailed information on the classical studies of the past and the novel ideas of the present and the future role of remote sensing and GIS for understanding the spatial variation of the vector biodiversity, vector presence, vector abundance and the vector-borne diseases in association with geoclimatic variables[1-91].

Remote sensing data products

The low cost remote sensing data products are readily available for the educationalists and researchers. The visual interpretation and analysis of the multispectral and multitemporal satellite data products derived from the earth observation resource satellites [Landsat TM (Thematic Mapper) satellite, French Satellite Systeme Pour l'Observation de la Terre (SPOT), Indian Remote Sensing (IRS) LISS I, LISS II, LISS III and Panchromatic Imagery, IKONOS] and red and infrared colour aerial photographs and the meteorological satellites, National Oceanic and Atmospheric Administration's Advanced Very High Resolution Radiometer (NOAA-AVHRR) are used for delineating and mapping of mosquito breeding habitats and mosquito ecology. The unsupervised digital image processing of remote sensing data followed by the geoprocessing of supervised image analysis, geostatistical analysis of discriminant analysis, cluster analysis, and the regression analysis show the results of statistically significant relationship between the vector abundance, vector-borne diseases and the environmental variables[4, 7-10, 20-23, 25, 26, 28, 29, 31, 33-41, 44-52, 62-68, 73-91].

GIS Software platforms

There have been several attempts made in the area of remote sensing and GIS application for ecological modeling of vectors, vector-borne diseases and the geoclimatic and the environmental variables[1-13, 16-18, 20-25, 27-32, 35-38, 41, 44, 54, 56-60, 62-66, 69-76, 84-91]. A set of spatial analysis (Kriging, Co-Kriging, Universal Kriging, Block Kriging, Buffering, Map overlay analysis, Fussy analysis, K-means analysis, interpolations, etc) using the GIS platforms, namely ARC Info/ARC View, Map Info, Map Maker, EPIMAP, Pop Map, Surfer, Atlas GIS, Geo Statistics+, IDRSI, GRASS, Geographical Analysis Support System (GRASS), using GIS software support is used to assess the mosquitogenic conditions, mapping the vector habitats, vector abundance, larvae and adult density with 90% accuracy and create the buffer zones with 2.5 km radius around the breeding habitats describing where the area of maximum adult mosquito flight range of 2.5 km, the community is at the risk of vector-borne diseases transmission.[4, 8, 15, 21, 25, 29, 32-34, 39, 40, 41, 47, 53, 65, 66-69, 72-74, 76-79, 86-91].

Remote sensing and GIS for mapping vector-borne diseases

With the availability of multispectral, multi-temporal and real time satellite data products, GPS assisted geo-referenced epidemiological data are being integrated under the umbrella of the GIS software for mapping vector-borne diseases distribution. This technique has been significantly developed for the past 25years[4, 8, 15, 21, 25, 29, 32-34, 39, 40, 41, 47, 53, 65, 66-69, 72-74, 76-79, 86-91]. The remote sensing and GIS for mapping land use/land cover and changes over the period of time interval in association with vector habitats and mapping vector abundance are epidemiologically important for disease control[2, 20-23, 26, 29, 35-37, 40, 41, 52, 72-75]. The survival and longevity of infected mosquitoes and the prevalence of the disease are spatially determined and definitely controlled by the geoclimatic variables. The remote sensing of Landsat TM, IRS LISS I, LISS II, LISS III, IRS CARTOSAT, SPOT, IKONOS, NOAA-AVHRR, etc. are used to analyze vector habitats and mapping vector abundance. The remote sensing data sets and the geoclimatic environmental data are integrated with vector-borne disease data, and the epidemiological data for geostatistical analysis to generate the information where no information is available or the areas are at remote and difficult to reach locality, predicting and mapping vector-borne disease transmission risk areas using analyzed using GIS expert engine[4, 8, 15, 21, 25, 29, 32-34, 39-41, 47, 53, 65-69, 72-74, 76-79, 86-91].

The role of remote sensing sensors, and GIS in identifying and mapping the risk of malaria mosquito ecology and habitats, is to provide relevant surrogate information related to the spatial variation in meteorological and the environmental variables[1-13, 16-18, 20-25, 27-32, 35-38, 40, 41, 44, 53-59, 61-65, 68-75, 83-91]. The calibrated value of normalized difference vegetation index (NDVI) ranges (between –1 and + 1)[7, 10, 12, 20, 21, 38, 40, 41, 62, 85, 87-91]. The most reliable and real time high spatial resolution on land use/land cover information provides guideline for mapping the breeding habitats around the area of average flight range of adult mosquitoes in a 2.5 km radius buffer zone[11, 12, 20, 40]. The data on distance to livestock sheds and the human settlements from the surrounding area of perimeter of malaria mosquito breeding sources imported into the GIS expert engine are sufficient to predict high and low vector abundance and disease infection or transmission with overall accuracy of 90% and to classify the areas with 100% sensitivity. The use of colour-infrared (CIR) aerial photography to identify the larval habitat of the rice-field mosquitoes, and the mathematical relationships between the temperature suitability and mosquitoes surviving the incubation period and mapping the breeding habitats of the species facilitates assessment of the risk of contracting the diseases and also assists in control of the mosquito vectors[2, 5, 85].

Remote sensing and GIS for ecological modeling of vector abundance

The remote sensing-based land use/land cover classification of the satellite-based spatial analysis provide the information on the mosquitogenic conditions. The differences of spatial changes in mosquito density in close association with changes in the environmental variables including the water bodies and vegetation revealed positive correlation[40, 41, 73-76]. The satellite image processing classifier could possibly identify the mosquito breeding habitats with significant results of 75% and increase to 100% accuracy at the sites where potential larval habitats are ascertained by field checks or ground truth verifications[2, 20-23, 26, 29, 35-37, 40, 41, 52, 72-75]. Discriminant analysis could able to correctly distinguish between villages with high and low vector abundance, with an overall accuracy of 90%. Regression results have found both transitional swamp and unmanaged pasture proportions to be predictive of vector abundance during the wet season[2]. The image classification of the spectral signature of the satellite data can be imported into the GIS platform to create the buffer zones of the average adult mosquito flight range of 2.5 km radius around the breeding habitats for mapping the breeding habitats and describing the areas at risk of disease transmission[11, 12, 20, 40, 41]. The spatial agreement between the observed and predicted values of logistic regression model has 0.76% sensitivity and 0.78% specificity of larval index within a buffer around the trap location of rice-fields[38, 87-91]. The coefficient model of rainfall and temperature with the mosquito abundance is highly correlated with the normalized difference vegetation index (NDVI) of NOAA-AVHRR satellite. It is useful in the estimation of mosquito larval abundance and used to predict adult abundance 7 days in advance[18, 38, 59, 60] and is also useful for estimating *Anopheline* malaria vector mosquito abundance in the mosquito habitats of rice-fields using remote sensing spectral signatures[76, 77, 87-91].

Malaria risk assessment

The remote sensing and GIS are used over the past 25 years for identifying and mapping spatial and temporal distribution of malaria vector habitats and ecology. It could provide relevant surrogate information to identify villages at high risk for malaria transmission[4, 7-10, 20-23, 25, 26, 28, 29, 31, 33-40, 50, 53, 62, 63, 66-69, 73-80, 83-91]. Considering the maximum flight range of adult mosquito vectors[27-29], we can demonstrate the community exposure of malaria transmission in the buffer zone of villages where the distances are < 2.5 km from mosquito breeding sites[11, 12, 20, 40, 41, 87-91]. Soil moisture with vegetation cover information of the remote sensing and GIS-based model could predict the malaria transmission in advance[4, 11, 12, 21, 25, 31-33, 37, 57, 66, 75, 77-79, 88-91]. Remote sensing and GIS can be used for mapping the past, present and predicted future situation of malaria transmission in the country[4, 8, 12, 20, 22, 25, 28, 35, 36, 40, 41, 44, 45, 55-58, 64, 65, 70, 71].

Remote sensing and GIS have an important role in ecological mapping of *Anopheles* genus malaria vectors and their breeding habitats. Remote sensing of Landsat TM 7, Panchromatic and colour aerial photographs, IRS LISS I, LISS II, LISS III, Panchromatic, IKONOS, SPOT, NOAA-AVHRR data products and GIS spatial analysis are widely used for classifying and mapping of land use/ land cover categories and land use changes. Mapping the aquatic mosquito breeding habitats of *Anopheles* vector and the spatial relationship between the normalized differential vegetation index (NDVI) and the *Anopheles* genus malaria vector show statistical significance[7, 10, 12, 18, 20, 21, 38, 40, 41, 52, 62, 85, 88-91].

The application of remote sensing and GIS is used for gaining a better understanding of malaria distribution, mapping *Anopheles* genus malaria vector habitats, estimating the mosquito larvae abundance in the water bodies in and around the metropolitan city, and the malaria transmission dynamics at the local level[72-74]. The AVHRR of the NOAA and the European Meteorological Satellites (EUMETSAT) are used to estimate the land surface temperature (LST), atmospheric moisture, cold cloud duration (CCD) data for the measurement of temperature, atmospheric moisture and rainfall surfaces. Thus, remote sensing and GIS data are used for mapping short- and long-term climate changes and their impact on malaria vector abundance and the disease in the rural and hilly areas[2, 8, 21-23, 27, 36, 37, 52, 60, 70, 74, 76, 84, 88-91]. The relative abundance of the malaria vectors are directly controlled by the climate variables. The model can predict accurately the relative abundance of malaria vectors (*An. arabiensis* and *An. gambiae*) and r(s) = 0.745, p = 0.002) and the results used to map suitable climate zones for vector species and relative vector abundance proved very good agreement[1, 9, 21, 23, 24, 35, 44, 60, 62, 64, 76].

Mapping filariasis transmission risk

The remote sensing information derived from the calibrations of NDVI from the red and infra-red spectral DN values alone has insignificance with filariasis distribution, because there are complex of several phenomena influencing the filariasis transmission. However, soil moisture with vegetation cover information of the remote sensing false colour composite DN values from 145 to 158 are valuable and statistically significant[34, 67], whereas, GIS has the efficient utility value in the application of geostatistical modeling to generate a "filariasis transmission risk map", using the selected environmental variables. We can demonstrate the filariasis spatial pattern, quantified clustering and the potential of GIS application in vector-borne diseases epidemiology[27, 31, 33, 34, 39, 47, 66-68, 80]. The appreciation of GIS is for optimum allocation of the patients to the health service centres with <1 km distance coverage for filariasis morbidity management and control[39]. GIS is the rapid method for prediction and mapping the potential breeding habitats of *Culex* genus of filariasis vector in both urban and rural environments. GIS is also used to generate data for predicting the real picture of filariasis situation. A huge sample points are needed at < 10 km interval[68, 80], for classifying the areas correctly with the real situation of the filariasis transmission risk in the country. The results obtained showed > 93.4% accuracy and 100% sensitivity[66, 68, 80].

Ecological mapping of Japanese encephalitis (JE)

The breeding habitats of JE vector mosquitoes are found mainly in the areas where wet land agricultural practices with water resource projects are developed (paddy fields, sugarcane, plantain, etc.), and the epidemic of outbreaks has high significance with wet land cultivations[3, 6, 11, 14, 19, 45, 49, 54, 58, 59, 72, 76, 86]. The ecological modeling of JE transmission is best fitted with red and infrared spectral signature of the wetland agricultural land cover parcels of remote sensing data[11, 12, 19, 20, 22, 27, 40, 41, 49, 59, 85, 86]. The abundance, density, and the survival of JE vectors are highly associated with the climatic factors (i.e. temperature, rainfall, relative humidity, saturation deficiency), and the environmental variables including the land use/ land cover categories, the number of larval breeding sites, soil alkalinity, water temperature, turbidity, hardness of breading sources, etc. Remote sensing and GIS expert engine helps in understanding the spatial and the temporal aspects of JE vector larval habitats, adult mosquito density, and the abundance of adult mosquito peak seasons and JE epidemics in different parts of the country in close relationship with the geographical, climate and the environmental changes[3, 6, 11, 14, 19-20, 22, 27, 40, 41, 45, 49, 54, 58, 59, 72, 76, 86].

These factors are fueled for mosquito JE vector mosquito abundance and the disease outbreak in and around the buffer zone of 2.5 km of water resource projects and wetland cultivation areas[11, 12, 20, 41, 89-91]. The type of vegetation which surrounds the breeding sites (and thereby provides potential resting sites, sugar-feeding supplies for adult mosquitoes and protection from climatic conditions) may also be important in determining the abundance of mosquitoes associated with the breeding site[21, 40, 84, 87-90]. The maximum breeding and the high abundance of JE mosquito vectors (*Cx. tritaeniorhynchus, Cx. vishnui* and *Cx. pseudovishnui,* with *Cx. whitmorei* and *Cx. bitaeniorhynchus*) take place 4–6 wk after rice transplantation and the extensive epidemic of encephalitis occurred in most parts of the southern India, between the months of August and December[3, 6, 11, 14, 19, 20, 22, 27, 41, 45, 49, 54, 58, 59, 72, 76, 86].

Mapping dengue and chikungunya transmission risk

The aid of remote sensing and GIS, the estimation and the mapping of potential areas for the abundance of *Aedes* genus mosquito larvae and adults 7 days in advance and further study showed that the coefficient of meteorological variables of remote sensing is useful for the estimation of larval abundance and has significant correlation with NDVI of NOAA-AVHRR satellite data have limitation with low spatial resolution[18, 50]. However, it has the high temporal resolution and is very useful for the study of mosquito breeding, survival and population dynamics associated with climatic variables[49]. The appreciation of potential use of GIS to co-analysis of mosquito- borne diseases (dengue and malaria) and economic resources are considerably important[25]. However, the present study revealed that a remote sensing-based classification of residential areas with *Ae. aegypti* breeding locations in the residential environment shows insignificant correlation observed in the logistic regression analysis in associated colour infrared aerial photographs, and the ability of mapping and surveillance is limited. The appreciation of GIS application for mapping dengue and chikungunya transmission risk with conventional ground survey technique is most reliable tool for identifying *Ae. aegypti* breeding sites in the residential environment[18, 25, 50].

Mapping of Ross river virus transmission risk

The outbreak of Ross river virus disease and disease transmission risk is associated with immediately after heavy summer rainfall and the pattern of water under mangrove forest canopy. The GIS combined with the aerial remote sensing colour photographs on large-scale is used to identify the specific parts of the salt marsh in which larvae and eggs are abundant. The image analysis and the field ground truth survey was conducted for identifying and giving training sites to create the major temporary breeding sites and thus, mapping the breeding sites of Ross River Virus vector (*Cx. annulirostris*, *Ae. vigilax*) embedded on the colour photograph using image processing packages with accuracy of 87% and sensitivity of 100% [11, 91].

Ecological mapping of sand fly fever and leishmaniasis

The geoclimatic aspects related to the occurrence of visceral leishmaniasis, sand fly fever and cutaneous leishmaniasis are highly determined by the geoclimatic and the variables[7, 10, 13, 15, 21, 48]. The geographical and seasonal distribution of the major vectors *Phlebotomus martini* and *P. orientalis* of kala-azar (visceral leishmaniasis) is analyzed using GIS. The best fit for the distribution *of P. martini* is the dry season composite NDVI 0.07–0.38 and land surface temperature (LST) 22–33°C with a predictive value of 93.8%, and the best fit for *P. orientalis* is the wet season composite NDVI 0 to 0.34 and LST 23–34°C with a predictive value of 96.3%. The predictive climate model shows the best fit with the average altitude (12–1900 m), average annual mean temperature (15–30°C), annual rainfall (274–1212 mm), average annual potential evapotranspirations (1264–1938 mm) and readily available soil moisture (62–113 mm) for *P. martini*. Whereas, average altitude (200–2200 m), annual rainfall (180–1050 mm), annual mean temperature (16–36°C) and readily available soil moisture (67–108 mm), alluvial and black cotton soils dark coloured alkaline in nature (pH 7.2– 8.5), calcareous with chief inorganic constituents of silicon, iron and aluminium are most suitable for both *P. orientalis* and *P. papatasi*[7, 10, 13, 15, 21, 48].

The Landsat TM multispectral (band 3, 4 and 5) false colour composite images are used for identifying the potential sites and the proximity with 250 m perimeter of buffering zone for the occurrence of cutaneous leishmaniasis in the urban situation. The spatial correlation existed among the areas at risk of infection and the presence of creeks and relevant vegetations[15, 21, 48]. The use of climatic and remote sensing data shows the results of spatial agreements and the range of NDVI of satellite data highly determine the presence of the vectors. GIS was applied to generate the probable distribution of *P. papatasi*. The predicted map also provides the information on high, moderate and low risk of disease transmission where no survey was conducted/no information was reported[7,10]. The geographical distribution of *P. orientalis* and visceral leishmaniasis are directly controlled by the geo-climatic variables (altitude, mean annual temperature, mean annual rainfall, potential evapotranspiration, composite NDVI, readily available soil moisture, soil types and water logging potential, and terrain slope, annual mean maximum NDVI. The co-analysis of vectors and visceral leishmaniasis linked with environmental variables is significantly associated and the results found to have a significant association with the presence of the black cotton soils[13]. The geographical and seasonal distribution of *P. papatasi* is fully controlled by the geoclimatic variables (temperature and relative humidity). The range average composite NDVI indices produce the probability distribution map of sand fly vectors and relationship associated with visceral leishmaniasis disease[7, 10, 13, 15, 21, 48].

Remote sensing and GIS for schistosomiasis disease control

A GIS-based buffering zone boundary map of the neighbouring areas with proximity to snail breeding sites of irrigation canals, black cotton soils and the areas under wetland agricultural practices are identified as the most suitable environment for snail populations and thus, the areas are vulnerable at risk of schistosomiasis transmission[32, 87]. The meteorological satellite remote sensing derived temperature difference of LST and SST data is a guide for mapping of suitability of the environment for local snail hosts and schistosomiasis transmission risk at the local level[13, 52, 68]. The climate and environmental changes and their impact on the propagation of schistosomiasis vectors and the risk of transmission are addressed with aid of remote sensing and GIS. However, the applicability of the RS and GIS advanced technology is inaccessible in the underdeveloped countries in Africa where the problems of schistosomiasis transmission risk are very high[52]. These can be overcome, if the WHO/TDR and funding agency of other developed nations come forward for funding the research projects of RS and GIS technology and its applications to the schistosomiasis control. If succeeded, the RS and GIS-based models may perhaps provide useful information to a disease prediction model for disease control programme and also provide a baseline to the managers for the disease control, particularly in the underdeveloped countries[50, 51].

CONCLUSION

The 25 years of research articles were reviewed for the appreciation of remote sensing and GIS application for ecological modeling of vector-borne diseases. These factors are fueled to the abundance of *Anopheles* genus malaria vectors and *Culex* genus JE vector mosquitoes and disease outbreaks in and around the buffer zone of 2.5 km of water projects, wetland and cultivation areas. The type of vegetation which surrounds the breeding sites may also be important in determining the abundance of mosquitoes associated with the breeding sites. The predictive climate model shows the best fit with the average altitude (12–1900 m), average annual mean temperature (15–30°C), annual rainfall (274–1212 mm), average annual potential evapotranspirations (1264–1938 mm) and readily available soil moisture (62–113 mm) for *P. martini* and average altitude (200–2200 m), annual rainfall (180–1050 mm), annual mean temperature (16–36°C) and readily available soil moisture (67–108 mm), alluvial and black cotton soils dark coloured alkaline in nature (pH 7.2–8.5), calcareous with chief inorganic constituents of silicon, iron and aluminium most suitable for both *P. orientalis* and *P. papatasi*. The remote sensing and GIS-based predictive climate models produce the probability distribution map of sand fly vectors. The geographical distribution and seasonal variations of horizontal and vertical difference of vector abundance and vector-borne diseases are completely controlled by the environmental and geoclimatic variables[1-91]. The usefulness of the present day availability of the information derived from the satellite data including vegetation indices of canopy cover and its density, soil types, soil moisture, soil texture and soil depth is integrating these information in the expert GIS engine for the spatial analysis of other geoclimatic and geoenvironmental variables. The probability map of the geographical distribution and seasonal variations of horizontal and vertical distribution of vector abundance and vector-borne diseases is at a low cost remote sensing and GIS tool with reliable and speed.

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