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Landscape epidemiology: An emerging perspective in the mapping and modelling of disease and disease risk factors

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ABSTRACT

Landscape epidemiology describes how the temporal dynamics of host, vector, and pathogen populations interact spatially within a permissive environment to enable transmission. It also aims at understanding the vegetation and geologic conditions that are necessary for the maintenance and transmission of a particular pathogen. The current review describes the evolution of landscape epidemiology. As a science, it also highlights the various methods of mapping and modeling diseases and disease risk factors. The key tool to characterize landscape is satellite remote sensing and these data are used as inputs to drive spatial models of transmission risk.

1. Introduction

Disease occurrence and transmission is an interaction of person, place and time. Person and time had been the focus of most researches. Little has been based on the place *i.e.* geographical location of disease occurrence. The emergence and spread of infectious diseases in a changing environment require the development of new methodologies and tools for risk assessment, early warning signs and policy-making.

Landscape epidemiology aims at understanding the vegetation and geologic conditions that are necessary for the maintenance and transmission of a particular pathogen. The term “landscape epidemiology” was first coined by a Russian parasitologist in 1966[1]. Pavlovsky’s historical concept of landscape epidemiology consists of three basic observations: first, diseases tend to be limited geographically; second, this spatial variation arises from underlying variations in the physical (abiotic) and/or biological (biotic) conditions that support the pathogens and its vector and reservoir; and third, if these abiotic and

biotic conditions can be delimited on maps, then both the contemporaneous risk and future change in risk can be predictable.

Key environmental factors such as temperature, rainfall, humidity, vegetation which influence the development, activity and longevity of pathogens, vectors and zoonotic reservoir of infection and their interaction with human can be sensed by remote sensing technology. Geographic information system (GIS) modeling is routinely used to perform risk assessment for the mitigation of these diseases.

2. Remote sensing and landscape epidemiology

Remote sensing (RS) enables scientists to study the biotic and abiotic components of the earth surface. RS essentially measures energy reflected or emitted in distinct and specific electromagnetic spectrum, using sensors usually onboard satellites. They are used to monitor and observe the earth’s landscape. The epidemiological applications of RS and GIS have been reviewed extensively[2–5].

Since the launch of ERTS-1 (Earth Resources Technology Satellites) in 1972, National Aeronautics and Space Administration (NASA’s) Center for Health Applications

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Aerospace Related Technologies (CHAART) has initiated programs aimed at integrating these technologies into the areas of forestry, agriculture, geology and public health. The worsening health conditions around the world and the significant advancement in computer processing, improvement in data acquisition, reduced hardware and software cost and the development of computer based GIS technology have led to the launching of programs that aim at integrating RS/GIS into health applications by CHAART.

To better apply these technologies and satellite–sensor capabilities, NASA–CHAART developed a website to evaluate sensors for health applications. They defined 16 groups of physical factors that could be used for both research and in practice. Each of these factors is essentially an environmental variable that might have a direct and indirect bearing in the survival of pathogen, vectors, reservoir or host. These factors (biotic and abiotic) may also affect many types of non–vector borne diseases such as water borne diseases. Examples of these factors include soil moisture, wetlands, vegetation and crop type and sea surface temperature. All these factors can be sensed by a sensor mounted on a satellite imagery used for landscape epidemiology. Some of the links between these factors and various diseases as developed by CHAART are listed in

Table 1.

Two approaches used for mapping diseases are the correlation of host distribution with climatic data or correlation with landscape. Most human studies using RS have focused on data obtained from 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). In many of these studies, remotely sensed data were used to derive three variables: landscape structure, vegetation cover and water bodies. Table 2 contains examples some researches conducted using remote sensing.

3. Approaches used in disease mapping

3.1. Spatio–temporal/dynamic approach

This kind of map is used for retrospective purposes to understand the spread pattern and rate of spread of diseases. This approach was employed to research the spatiotemporal transmission of hand, foot and mouth disease in China^[4]. It was also used to describe the “travelling wave” in epidemics

Table 1
Potential links between remotely sensed factors and disease.

Factor	Disease	Mapping opportunity
Vegetation/crop type	Chagas disease	Palm forest, dry and degraded woodland habitat for triatomines
	Leishmaniasis	Thick forests as vector/reservoir habitat in Americas
	Malaria	Breeding/resting/feeding habitats, crop pesticides vector resistance
	Schistosomiasis	Agricultural association with snails, use of human fertilizer
	Trypanosomiasis	<i>Glossina</i> habitat (forests, around villages, depending on species)
	Yellow fever	Reservoir (monkey) habitat
Deforestation	Yellow fever	Migration of infected human workers into forests where vectors exist
		Migration of disease reservoirs (monkeys) in search of new habitat
Forest patches	Yellow fever	Reservoir (monkey) habitat, migration routes
Flooding	Malaria	Mosquito habitat
	Schistosomiasis	Habitat creation for snails
Permanent water	Malaria	Breeding habitat for mosquitoes
	Onchocerciasis	<i>Simulium</i> larval habitat
	Schistosomiasis	Snail habitat
Wetlands	Cholera	<i>Vibrio cholerae</i> associated with inland water
	Malaria	Mosquito habitat
	Schistosomiasis	Snail habitat
Soil moisture	Helminthiasis	Worm habitat
	Malaria	Vector breeding habitat
	Schistosomiasis	Snail habitat
Canals	Malaria	Dry season mosquito–breeding habitat; ponding; leaking water
	Onchocerciasis	<i>Simulium</i> larval habitat
	Schistosomiasis	Snail habitat
Human settlements	Diseases	Source of infected humans; populations at risk for transmission in general
Ocean color	Cholera	Phytoplankton blooms, nutrients, sediments
	Red tides	
Sea surface temperature	Cholera	Plankton blooms (cold water upwelling in marine environment)
Sea surface height	Cholera	Inland movement of <i>Vibrio</i> –contaminated tidal water

Source: Beck *et al.*, 2002[6].

Table 2

Research using remote sensing data to map disease vector.

Disease	Vector/reservoir	Location	References
Hydatid disease	Dogs	China	[7]
Malaria	<i>Anopheles</i> spp.	Burkina Faso	[8,9]
Schistosomiasis	<i>Oncomelania hupensis</i>	China	[10,11]
Dengue	<i>Aedes aegypti</i>	Bangkok	[12,13]

of measles in England and Wales^[15]. Similarly, a dynamic map, a visual–analytic method for exploring spatio–temporal disease patterns was employed by Castronovo *et al* to determine the spatio–temporal pattern of spread of *Salmonella* in the US^[16].

Dynamic mapping is a practical visual–analytic technique for public health practitioners and has an outstanding potential in providing insights into spatio–temporal processes such as revealing outbreak origins, percolation and travelling waves of the diseases, peak timing of seasonal outbreaks, and persistence of disease clusters^[16].

3.2. Static risk map

This map is used to characterize ecological risk of infection. Ecological risk refers to the probability of exposure to an infection in the absence of active preventive measures.

However, irrespective of the entity mapped, the most common procedure for creating a risk map is as follows^[4]: 1) construct a distribution map for vector, reservoir or disease; 2) use RS data and GIS to characterize the distribution of abiotic conditions and sometimes vegetations that might influence the vector or reservoir; 3) select RS variables that are most strongly associated with the distribution of the vector, reservoir or disease; 4) project the distribution of the identified RS variable to either areas or future times to make predictions; 5) guide the methodology of interventions, such as pesticide application or vaccination.

4. Limitations with disease mapping approaches

The limitations with disease mapping approaches are as following: 1) disease or incidence is more closely correlated with abundance of pathogen–infected vectors other than simple presence of vector; 2) discrepancies between risk and infection, such as immunity and use of preventive measures; 3) poor and inconsistent standards of case reporting *e.g.* under reporting or over–reporting of disease; 4) discrepancies between location where infection was obtained and where the disease was reported.

5. Approaches used for modelling diseases and disease risk factors

The major approach for epidemiological modeling in

GIS is the ecological niche modeling (ENM). This concept was originated by Joseph Grinnell^[17]. His idea was that the ecological niche of specie is the set of conditions under which the specie can be maintained without migration. This is used to characterize the distribution of species(s) across a landscape. A more comprehensive discussion of the concept is provided elsewhere^[18,19]. Applications of ENM include understanding ecology of diseases, characterizing the distributional areas of species, anticipating high risk area with changing climate and identifying unknown vectors, host or areas of potential pathogen invasion.

However, other methods of modeling which are statistically based and could be targeted at the vector, environmental factors or incident cases as described by Eisen *et al*^[20] are divided into two which includes: spatial risk interpolation models and space–time risk models.

5.1. Spatial risk interpolation models

5.1.1. Spatial risk models

This is a GIS–based statistical model used to estimate vector presence or abundance, or vector–borne diseases (VBD) case presence or incidence, within a particular geographical area. Model outputs typically are displayed in map format. Basic spatial modeling approaches include: a) interpolation based on spatial dependence in vector or VBD data and b) extrapolation based on associations between vector or VBD data and environmental or socioeconomic predictor variables. Importantly, this allows for the development of continuous risk surfaces that include locations where surveillance data are lacking and the level of risk therefore it is not known prior to the modeling exercise. Coupled with demographic data, such risk surfaces can be used to assess the number of individuals or the proportion of a human population that is potentially at risk for exposure to vectors and vector–borne pathogens. Another benefit is the potential to reveal spatial heterogeneity in risk patterns at fine scales relevant for practical prevention and control activities.

5.1.2. Spatial risk interpolation models

Spatial dependence for vector abundance or VBD case count or incidence is frequently observed at fine spatial scales. For example, areas with high vector abundance or high disease incidence often border on other areas with high vector abundance or high disease incidence, and the similarity in the response variable decreases with increasing distance. In such instances, kriging or other types of interpolation models are used to produce smooth

interpolated maps of the response variable.

5.2. Space–time risk models

This model is used to explore spatial clustering of vectors or VBD cases and is useful for identifying changing risk patterns. This is especially relevant for VBDs such as dengue, which is characterized by outbreaks with rapidly building dengue case numbers and explosive spread within affected areas. Space–time modeling may aid in identifying underlying factors that regulate the spread of vectors or the occurrence of VBD cases and may be more sensitive than purely spatial or temporal models in detecting local outbreaks. Therefore, outputs of these models may be used as early–warning systems and could guide vector control or surveillance activities.

6. Conclusion

The climate of the world is changing owing to global warming, which would have an effect on the ecological niche of vectors, reservoirs and human cases. The scientific community has a relative consensus that epidemics and pandemics would worsen by changing global climate. With current RS technologies, we can measure key environmental parameters and hence provide global coverage of changing environmental conditions. Successful predictive modeling of disease and the establishment of early warning system can be achieved using RS and GIS technology. Satellite imaging may be critical for effective disease prediction and thus future mitigation of epidemics and pandemic diseases can be predicted.

Conflict of interest statement

We declare that we have no conflict of interest.

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