

## Remote sensing applied to the analysis of spatial and temporal patterns of dengue incidence based on ecological and socio-economic and demographic factors in Sri Lanka

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### ABSTRACT

Dengue outbreaks are affected by biological, ecological, socio-economic and demographic factors that vary over time and space. These factors have been examined separately, with limited success, and still require clarification. The present study aimed to investigate the spatial and temporal relationships between these factors and dengue outbreaks in the northern region of Sri Lanka, in order to clarify the disease causes and to better target surveillance and control. Remote sensing (RS) data gathered from a plurality of satellites were used to develop an index comprising rainfall, humidity and temperature data. RS data gathered by ALOS/AVNIR-2 were used to detect urbanization, and a digital land cover map was used to extract land cover information. Other data on relevant factors and dengue outbreaks were collected through institutions and extant databases. The analyzed RS data and databases were integrated into geographic information systems, enabling both spatial association analysis and spatial statistical analysis. Our findings show that the combination of ecological factors derived from RS data and socio-economic and demographic factors is suitable for predicting spatial and temporal patterns of dengue outbreaks.

**Keywords:** dengue, ecological and socio-economic and demographic factors, Local Moran LISA statistics, spatial and temporal analysis

### 1. INTRODUCTION

Since the early 1960s, dengue has been an important vector-borne viral disease and a major cause of childhood fever burden in Sri Lanka, which has experienced a number of large epidemics over the past decade. In 2012, 44,456 dengue cases were reported, corresponding to a rate of 220 per 100,000 individuals. Approximately a quarter of reported cases occur in children under 15

years of age (Tam et al., 2013). Dengue is now considered to be hyperendemic in Sri Lanka, with detected co-circulation of multiple serotypes (Kanakaratne, 2009; WHO, 2011).

Dengue outbreaks are affected by biological, ecological, socio-economic and demographic factors that vary over time and space. Disease-promoting factors include 1) climate, such as rainfall, humidity and temperature (Canyon, 1999); 2) changes in

land cover, particularly rapid unplanned expansion of urbanization with inadequate housing and infrastructure (Gubler, 1997; Rodhain and Rosen, 1997; Lian, et al., 2006; Ooi and Gubler, 2008; Tran, et al. 2010; Gubler, 2011; WHO, 2012); and 3) high population density (Gubler, 1998).

Previous studies have identified a large number of biological, ecological and socio-economic and demographic factors that are considered to impact both susceptibility and exposure to spatial and temporal outbreaks of dengue in Sri Lanka. However, these factors have mainly been examined separately, with limited success. Further clarification is required.

The present study aimed to investigate the spatial and temporal relationships between these factors and outbreaks of dengue associated with mosquito breeding sites and habitats in northern Sri Lanka, in order to clarify the causes of the disease and to better target surveillance and control in this region.

## 2. MATERIAL AND METHODS

### 2.1 Conceptual Framework

Our conceptual framework highlights ecological factors (i.e., rainfall, humidity, temperature and land cover, including rapid unplanned expansion of urbanization) as well as socio-economic and demographic factors (i.e., population density) that impact vulnerability to dengue by creating conditions of susceptibility within human communities, of exposure to the vector, or proximity to breeding habitats.

### 2.2 Study Area

Dengue outbreaks in Sri Lanka are spatially heterogeneous. Investigating the spatial-temporal relationships between various factors and dengue outbreaks at the local level in Sri Lanka can help to better target surveillance and control.

Our study area was the northern region of Sri Lanka, consisting of twelve

Medical Officer of Health (MOH) divisions which are the health administrative divisions in Sri Lanka. Each MOH division has different geographic features—including agricultural fields, forested areas, wetlands, grassland, urban areas, etc.—as well as different social backgrounds. The climate in the region is tropical, with two monsoon seasons: namely north east monsoon from November to April, and south west monsoon from May to October.

### 2.3 Dengue Data

From the MOH divisions in Sri Lanka, we obtained the monthly numbers of clinically confirmed dengue cases from January 2010 through December 2013 in the twelve MOH divisions, and the annual numbers of clinically confirmed dengue cases from 2007 through 2013 in the same MOH divisions.

### 2.4 Rainfall, Humidity and Temperature

Rainfall data for the region were obtained using the Global Satellite Mapping of Precipitation (GSMaP) product, based on the combined MW-IR algorithm with a plurality of satellites: TRMM TMI, Aqua AMSR-E, GCOM-W AMSR2, DMSP SSM/I, DMSP SSMIS, NOAA-19 AMSU, MetOp-A AMSU and GEO IR. The GSMaP is drawn to the highest levels of precision and resolution in the world (Temporal resolution: 1 hour, Spatial resolution: Grid latitude-longitude of 0.1 degrees), and is published on a quasi-real-time basis with an approximately 4-hour lag from the time of satellite monitoring (JAXA, 2014; RESTEC, 2014). The monthly average rainfall from January 2010 to December 2013 and the annual average rainfall from 2007 to 2013 were obtained by processing the RS data, and converting this processed data into TIFF image data for spatial analysis in geographic information systems (GIS).

Humidity data were acquired from the Aqua/MODIS and Terra/MODIS data set. The MODIS instrument is operating on both



the Terra and Aqua spacecraft. It has a viewing swath width of 2,330 km, and views the entire Earth's surface every one to two days. Its detectors measure 36 spectral bands between 0.405 and 14.385  $\mu\text{m}$ , and it acquires data at three spatial resolutions: 250m, 500m and 1,000m (NASA, 2014). We obtained the monthly average humidity levels from January 2010 to December 2013, and the annual average humidity levels from 2007 to 2013 by processing the RS data, and converting this processed data into TIFF image data for spatial analysis in GIS.

Temperature data were also acquired from the Aqua/MODIS and Terra/MODIS data set. We obtained the monthly average temperatures from January 2010 to December 2013 and the annual average temperatures from 2007 to 2013 by processing the RS data, and converting this processed data into TIFF image data for spatial analysis in GIS.

## 2.5 Land Cover, Including Urbanization

A paper survey map was digitized to generate detailed land cover data, and the digital land cover map of this study area was used for spatial analysis in GIS.

The ALOS/AVNIR-2 data set was used to detect urbanization by conducting unmixing, which isolates the contribution of a specific material within the mixed pixel. This method identifies the locations of pixels that contain a given material, and reports the material pixel fraction, i.e., how much of the material is in each pixel. We selected eight material pixel fraction classes that report subpixel detections in material pixel fraction increments of 0.20. Pixels determined to have material pixel fractions of 20–29% belong to class 0.20–0.29, pixels with material pixel fractions of 30–39% belong to class 0.30–0.39, and pixels with material pixel fractions of 90–100% belong to class 0.90–1.00.

## 2.6 Population Density

We obtained annual population data for the respective MOH division from 2007 to 2013 from the Regional Epidemiological Unit, Jaffna. With this information combined with the area data by MOH division obtained from spatial analysis in GIS, we calculated the population density as a socio-economic and demographic factor. We also calculated the average value from a set of annual population density at the MOH division level to investigate the comprehensive trend of annual population density. This was used for both spatial association analysis and spatial statistical analysis.

## 2.7 Incidence Rates

To examine the spatial patterns of dengue disease, epidemic curves were produced by calculating the annual dengue incidence rate during the period 2007–2013. Annual incidence rates for each MOH division were calculated from the number of annual confirmed dengue cases, divided by the total population-years and then multiplied by 10,000. These rates were expressed as annual confirmed dengue cases divided by total population \* 10,000 people. The average annual incidence at the MOH division level was also calculated to determine the comprehensive trend of annual incidence. This was used for both spatial association analysis and spatial statistical analysis.

## 2.8 Spatial Analysis in GIS

A polygon layer that generates the twelve MOH divisions in the northern region of Sri Lanka was used for spatial analysis in GIS. TIFF image data on rainfall, humidity and temperature were integrated into GIS, and the pixel (i.e., raster) size was changed from 0.05 to 0.01. The polygon layer and the processed raster layer were overlaid. The values of a raster within the polygons were summarized, and the results were reported to excel tables.



The digital land cover map was integrated into GIS. The polygon layer and the digital land cover map layer were overlaid. The land cover data within the polygons were summarized and the results were reported to excel tables. The raster data on urbanization were integrated into GIS. The polygon layer and the raster layer were overlaid. Again, the values of a raster within the polygons were summarized, and the results were reported to excel tables.

The table of polygon layer attributes was joined with the excel tables containing data on ecological, socio-economic and demographic factors. This information was used for spatial association analysis and spatial statistical analysis.

We additionally calculated the average values from data on annual rainfall, humidity and temperature at MOH division level. This information was used to investigate the comprehensive trend of annual rainfall, humidity and temperature, and was used for both spatial association analysis and spatial statistical analysis.

## 2.8 Temporal Analysis

To examine temporal patterns, we used data on monthly dengue cases, rainfall, humidity and temperature during the period from January 2010 through December 2013. The moving average (MA) was calculated and visualized to examine the temporal climate trend associated with outbreak of dengue. We also calculated the average monthly values from data on monthly rainfall, humidity and temperature within the period to investigate the comprehensive trend and to be used for the chi-square test. The chi-square test was used to test monthly differences in dengue cases, rainfall, humidity and temperature across the study period. The statistical significance was set at 0.05.

## 2.9 Spatial Association Analysis

Univariate Local Indicators of Spatial Association (LISA) was applied to measure

the local spatial autocorrelation of dengue outbreak using GeoDa (Anselin, 1995; Anselin et al., 2006). LISA are statistics that measure spatial dependence and evaluate the existence of local clusters within the spatial arrangement of a given variable. They are based on a statistical index  $I$  developed by Moran to measure the global spatial autocorrelation of the overall data clustering in the area under investigation (Moran, 1950). Moran's  $I$  ranges from  $-1$  (negative spatial autocorrelation) to  $1$  (complete spatial dependence), with  $0$  indicating an absence of spatial dependence (i.e., random distribution) (Guessous et al., 2014).

Local spatial autocorrelation analysis was performed based on the Local Moran LISA statistics, which yields a measure of spatial autocorrelation for each individual location. The LISA statistic reveals five categories of spatial autocorrelation that appear on the cluster map legend: 1) not significant, 2) high-high, 3) low-low, 4) low-high and 5) high-low (Anselin, 2003; Singh et al., 2011). High-high and low-low represent positive spatial autocorrelation, and high-low and low-high represent negative spatial correlation (Anselin, 2003; Martinez et al., 2014). A finding of significant clustering at  $p < 0.05$  suggests that dengue incidence values are too similar across these neighboring provinces to have occurred by chance, providing significant evidence for rejecting the null hypothesis of spatial randomness (Martinez et al., 2014).

## 2.10 Spatial Statistical Analysis

The chi-square test was used to test the spatial association between ecological, socio-economic and demographic factors and dengue outbreak. The ecological, socio-economic and demographic factors were categorized into two levels: above average and below average. The threshold values for these levels were determined based on the average values for these factors from the results obtained with spatial analysis in GIS. Land cover differed among MOH divisions, with some MOH divisions showing



a total absence of a given land cover type. Regarding the land cover data, the threshold values for the levels were categorized as two-level based on the presence or absence of each land cover. The categorized data, dengue case and control (i.e., population minus dengue case) were used for the chi-square test. The statistical significance was set at 0.05.

As a second exploratory analysis, using the results from the chi-square test, we compared the differences in ecological, socio-economic and demographic factors between the areas of significant high-high clustering (i.e., endemic areas) and the areas of significant low-high clustering (i.e., non-endemic areas estimated to be controlled by some factors) as identified in the univariate LISA analysis.

### 3. RESULTS

#### 3.1 Results of Temporal Analysis

Humidity tends to rise in early January, remaining high during the dry season, and then declining with the increase in rainfall in early September. These changes are accelerated at lower temperature.

The distribution of monthly dengue cases indicated a strong seasonal pattern. Dengue case tended to increase after exponential increases or decreases in rainfall. The chi-square test results supported these tendencies. We observed significant monthly differences in dengue cases and rainfall ( $p < 0.01$ ), while humidity and temperature were not significant.

#### 3.2 Results of Spatial Association Analysis

The LISA cluster map shows two types of geographical clustering (high-high and low-high). The area of significant high-high clustering of the average values from a set of annual dengue incidences accounted for 8.3% and occurred in Nallur MOH division. The area of significant low-high clustering of the average values from a set of

annual dengue incidences accounted for 16.7% and occurred in Kopay and Tellipallai MOH divisions. The Moran's I statistic was  $-0.08$ , suggesting a random spatial pattern.

#### 3.3 Results of Spatial Statistical Analysis

The spatial statistical analysis revealed the dengue outbreak was significantly associated with ecological, socio-economic and demographic factors. Significantly more dengue cases were observed in MOH divisions (66.7%) with average annual rainfall of  $>1353$  mm compared to those with average annual rainfall of  $<1353$  mm ( $\chi^2 = 112.8$ ;  $p < 0.01$ ). Correspondingly, we also observed significantly more dengue cases in MOH divisions (66.7%) with average annual humidity of  $>39.62$  mm compared to those with average annual humidity of  $<39.62$  mm ( $\chi^2 = 55.6$ ;  $p < 0.01$ ). Moreover, significantly more dengue cases occurred in MOH divisions (58.3%) with an average annual temperature of  $>31.2^\circ\text{C}$  compared to those with an average annual temperature of  $<31.2^\circ\text{C}$  ( $\chi^2 = 104.7$ ;  $p < 0.01$ ).

Dengue occurrence was also significantly associated with the presence or absence of built-up area considered to represent urbanization ( $\chi^2 = 264.7$ ;  $p < 0.01$ ). The presence of built-up area in MOH divisions (33.3%) significantly influenced dengue occurrence, with significantly more dengue cases observed in MOH divisions (50.0%) that had a  $>18\%$  ratio of urbanization to MOH division area compared to those with a  $<18\%$  ratio of urbanization to MOH division area ( $\chi^2 = 40.7$ ;  $p < 0.01$ ). We also found significantly more dengue cases in MOH divisions (33.3%) with a population density of  $>1150$  compared to those with a population density of  $<1150$  ( $\chi^2 = 347.2$ ;  $p < 0.01$ ).

The chi-square test results showed Nallur MOH division to be a high-high



clustering area, with built-up land area and a higher population density, while Kopy and Tellipallai MOH divisions were low-high clustering areas lacking built-up land area and having lower population densities. These results suggest significant differences in the presence or absence of built-up area and higher population density between high-high clustering areas and low-high clustering areas. Presence of built-up area and higher population density could influence the dengue occurrence.

#### 4. CONCLUSION

Our present results showed that dengue outbreak was associated with rainfall, humidity, temperature, built-up area considered to represent urbanization, urbanization and higher population density. Furthermore, our analyses quantitatively indicated to what degree these factors influenced dengue occurrence. Our findings indicate that these factors impact vulnerability to dengue by creating conditions of either susceptibility within human communities or of exposure to the vector and proximity to breeding habitats.

The presently observed temporal association underlines the fact that rainfall, humidity and temperature (considered as ecological factors) can strengthen forecasting models. The spatial association found in our study highlights the fact that built-up area and urbanization (considered as ecological factors) and higher population density (a socio-economic and demographic factor) can also strengthen forecasting models. Spatial-temporal models must be developed and strengthened by incorporating ecological and socio-economic and demographic factors for further analysis.

Dengue transmission within Sri Lanka is spatially heterogeneous. Further research must focus on the whole island to improve the accuracy of spatial and temporal models. An integrated spatial-temporal prediction model using ecological and socio-economic and demographic factors could lead to substantial improvements in the

control and prevention of dengue by allocating the right resources to the appropriate places at the right time.

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