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การวิเคราะห์รูปแบบของโรคท้องร่วงเชิงพื้นที่ ด้วยกระบวนการสถิติสหสัมพันธ์เชิงพื้นที่ ในจังหวัดพะเยา ประเทศไทย

Analysis of Spatial Pattern of Diarrhea Incidence Based on Spatial Autocorrelation Statistics in Phayao Province, Thailand

Phaisarn Jeefoo[1]

บทคัดย่อ

โรคท้องร่วงเป็นโรคที่ได้สร้างปัญหาอย่างมากต่อการสาธารณสุขในประเทศไทย กระทรวงสาธารณสุขได้พยายามที่จะดูแลและควบคุมโรคนี้มาอย่างต่อเนื่อง บทความวิจัยนี้ได้ใช้ระบบสารสนเทศภูมิศาสตร์มาวิเคราะห์การแพร่กระจายเชิงพื้นที่และช่วงเวลาของโรคท้องร่วง วัตถุประสงค์หลักในการศึกษาครั้งนี้เพื่อตรวจสอบความสัมพันธ์โดยใช้สถิติเชิงพื้นที่แบบกว้างด้วยวิธี Global Moran’s I และแบบแคบด้วยวิธี Local Getis-Ord และกำหนดพื้นที่เสี่ยงจากการรายงานจำนวนผู้ป่วยโรคท้องร่วง ข้อมูลที่ใช้ในการศึกษาได้ใช้ข้อมูลระบาดวิทยาในจังหวัดพะเยา (รายงานจำนวนผู้ป่วยโรคท้องร่วงตั้งแต่ปี พ.ศ. 2552-2554) ผลการศึกษารูปแบบการแพร่กระจายตัวเชิงพื้นที่ช่วงระหว่างปี พ.ศ. 2552-2554 แสดงให้เห็นถึงรูปแบบการเกาะกลุ่มแตกต่างกันในแต่ละตำบล โดยตำบลทางด้านทิศตะวันออกของจังหวัดแสดงกลุ่มเสี่ยงต่อโรคที่มีความหนาแน่นในระดับมากที่สุด การสร้างแผนที่การเกาะกลุ่มนี้ได้แสดงแนวโน้มการแพร่กระจายของโรคเชิงพื้นที่ การศึกษาในครั้งนี้แสดงให้เห็นถึงสารสนเทศที่เป็นประโยชน์โดยเกี่ยวโยงกับรูปแบบการแพร่กระจายของโรคท้องร่วง

[1]Geographic Information Science, School of Information and Communication Technology, University of Phayao, 19 Moo 2, Mae-Ka, Muang, Phayao 56000, Thailand

E-mail: phaisarn.je@up.ac.th

ABSTRACT

Diarrhea is a major public health problem in Thailand. The Ministry of Public Health, Thailand, has been trying to monitor and control this disease for many years. This paper presents a GIS approach to analyze the spatial and temporal distributions of diarrhea epidemics. The major objective of this study was to examine spatial autocorrelation methodologies including Global Moran's I and Local Getis-Ord statistics and risk zone identification for reported diarrhea cases. Epidemiological data from Phayao province, Thailand (reported diarrhea cases for the years 2009-2011) was used for this study. The results revealed spatial diffusion patterns duringthe years 2009-2011 representing spatially clustered patterns with significant differences by sub-district. Sub-district on the East of the province reported higher incidences. The cluster mapping showed the spatial trend of diarrhea diffusion. This study presents useful information related to the diarrhea outbreak patterns in space and time.

คำสำคัญ: โรคท้องร่วง สถิติความสัมพันธ์เชิงพื้นที่ ระบบสารสนเทศภูมิศาสตร์ แผนที่การเกาะกลุ่ม จังหวัดพะเยา

Keywords: Diarrhea, Spatial autocorrelation statistic, Geographic Information Systems (GIS), Cluster mapping, Phayao Province

1. Introduction

Diarrhea diseases are a major public health problem in the developing world. Approximately 1.5 million children die from diarrhea diseases each year globally, which makes it the second most common cause of mortality in children under five (UNICEF/WHO, 2009: Wu et al., 2011). Diarrhea is a major public health problem in Thailand. The Ministry of Public Health (MOPH), Thailand, has been trying to monitor and control this disease for many years. The main objective of this study was to analyse the epidemic outbreak patterns of diarrhea in Phayao province, Northern Thailand, in terms of their geographical distributions and risk zone identification. The methodology and the results could be useful for public health officers to develop a system to monitor and prevent diarrhea outbreaks.

Diarrhea is the passage of three or more loose or liquid stools per day, or more frequently than is normal for the individual. It is most commonly caused by gastrointestinal infections (bacterial, viral and parasitic organisms). The infection is spread through contaminated food or drinking-water, or from person to person as a result of poor hygiene (Zwaneand Kremer, 2007). Diarrhea disease is an important cause of morbidity and mortality in many regions of the world, with more than 4 billion cases and 2.5 million deaths estimated to occur annually (UHNIS, 2007). It is widespread all over the world, and especially in developing regions such as Africa, Southeast Asia and the Eastern Mediterranean, where there is rapid population growth, increased urbanization, and limited safe water, infrastructure, and health systems (UNICEF/WHO, 2009).

In Thailand, diarrhea has been a major public health problem for many years (Chaikaew et al., 2009). In 2012, according to diarrhea surveillance data from the Thai Ministry of Public Health (MOPH), the total numbers of reported cases of diarrhea infections in Thailand were 1,013,225 cases and 37 deaths nationwide with the highest incidences occurring in Mae Hong Son, Phuket, Tak, Chiang Rai and Phayao provinces (Bureau of Epidemiology of Thailand, 2012).

Geographic information systems (GIS) are potentially powerful resources for community health for many reasons including their ability to integrate data from disparate sources to produce new information, and their inherent visualization (mapping) functions, which can promote creative problem solving and sound decisions with lasting, position impacts on people's live (Buckeridge et al., 2002; Gavin, 2002; Maged and Boulos, 2004; Jeefoo, 2012). Spatial analyses and statistics, such as spatial autocorrelation analysis, cluster analysis, temporal analysis, are commonly used to highlight spatial patterns of diseases and to test whether there is a pattern of disease incidence in a particular area (Cheng et al., 2011). Spatial autocorrelation is a measure of the similarity of objects within an area (Lee and Marion, 1994). Spatial autocorrelation is a powerful technique for the analysis of spatial patterning in variant values which has been successfully applied in locational geography (Premo, 2003). Spatial analysis has taken giant steps forward in the recent decade, and GIS software makes it possible to undertake a sophisticated visual approach to data analysis in medical issues (Gesler, 1986). However, most studies using GIS have relied on their mapping capabilities rather than performance of statistical analyses (Gilberg et al., 2003; Jia et al., 2008; Mathur et al., 2010). Only when GIS are combined with spatial analytical methods can the result provide a helpful tool in the study of public health issues (Gesler, 1986; Rezaeian et al., 2007). The use of the Getis statistic (Gi*) provides insights on the spatial ramifications of a spatial change to model input. Specifically, the location of significant Gi* values identified areas where the differences in leaf area index (LAI) and stand volume occur and are spatially clustered (Wulder et al., 2007). Local spatial autocorrelation indices are a decomposition of the global Moran I index (Flahaut et al., 2002). Hence, in this study spatial statistical analyses were used to investigate spatial temporal patterns of diarrhea cases in Phayao province from 2009 to 2011.

2. Materials and method

2.1 study area: Phayao province, Thailand

Phayao, a province in the northern part of Thailand (Figure 1), had chronic voluminous diarrhea and malabsorption, therefore Phayao was selected as the study area because of the high number of diarrhea cases. Phayao province comprises 9 districts, 68 sub-districts, and 766 villages. The province covers an area of 6,335 square kilometers with geographical location between 18°44’ N to 19°44’ N and 99°40’ E to 100°40’ E. The province has a population of about 470,000 people (Department of Province Administrator, 2011). It is mostly covered with forested mountain, with an approximate elevation of 380 meters about mean sea level. Methodology is summarized in the flowchart shown in Figure 2.

2.2 data preparation

2.2.1 diarrhea epidemiology data

Diarrhea cases data reported in years 2009 to 2011 was used in this study. The data was obtained from the Phayao Provincial Public Health Office (PPPHO), with regards to the number of reported apparent and confirmed diarrhea cases per sub-district and per day. After the first diarrhea cases were confirmed, all persons that had visited hospitals in Phayao province with the following symptoms: severe abdominal or rectal pain, blood in stool, black, tarry stools, fever, and signs of dehydration were considered as suspects of diarrhea infection and their cases reported to PPPHO who notify the Bureau of Vector Borne Disease (BVBD), MOPH. Data represented only the patients and were filled in the official form 506 by the PPPHO. The forms provided data for each patient’s address, gender, age, and the dates of the symptoms and for hospital consultation.

Figure 1. Study area, Phayao province northern of Thailand

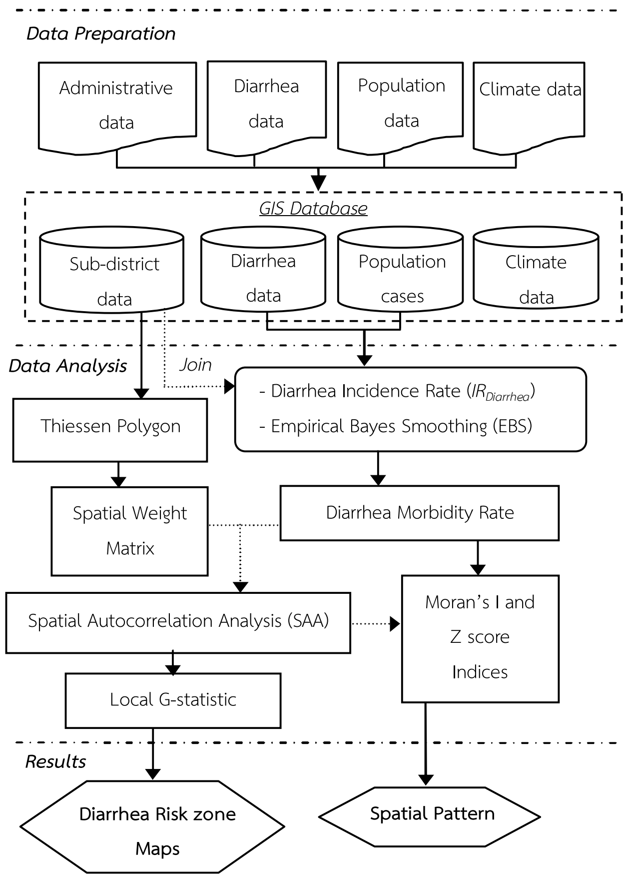


Figure 2. Flowchart of the methodology

2.2.2 administrative data

In this study, administrative data and population data for 68 sub-districts were collected from the Department of Provincial Administration, Thailand. Administrative boundaries were confirmed for accuracy by overlaying on high resolution QuickBird satellite images.

2.2.3 climate data

Monthly rainfall (mm.), relative humidity (%), and temperature (°C) for the years 2009-2011 were obtained from 8 weather stations of Thai Meteorological Department. Each station provides data for rainfall (mm), relative humidity (%), and minimum/maximum temperature (°C).

2.3 data analysis

2.3.1 general analysis

For each year, diarrhea incidence per year by gender (male and female) and age groups was analyzed. Moreover, the gender (male and female) and age groups (i.e. 0-5, 6-10, 11-15, 16-20,...,> 65 years) were also analyzed from 2009 to 2011 years.

2.3.2 temporal analysis

Monthly data with diarrhea cases and with climate data (rainfall, relative humidity, temperature) from years 2009 to 2011 was generated.

2.3.3 spatial pattern analysis

Mapping incidence is the first step in spatial analysis of a disease, but mapping, as always with any ratio, need to be made carefully. Sub-districts with a small number of inhabitants are more variable than Sub-districts with high numbers of inhabitants, and ratios may also reflect this difference in statistical variability. While a small population density occurs generally in large areas, mapping reinforces this difference and may give a false view of observed reality (Jeefoo et al., 2011). To overcome this problem, an empirical Bayes smoothing (EBS) method based on the idea of pooling information across villages was developed (Marshall, 1991). Essentially, rates were smoothed and thus stabilized by borrowing strength from other spatial units (Anselin, 2005). The diarrhea incidence rate ($IR_{Diarrhea}$) per year or per month were adjusted by EBS function and converted to the diarrhea morbidity rate by multiplying by 1,000 (Chaikaew et al., 2009). The diarrhea incidence rate ($IR_{Diarrhea}$) is a ratio of number of observed incidence cases (n_i) in each year divided by total population in each sub-district (p). More explicitly;

$$IR_{Diarrhea} = \frac{n_i}{p} \qquad (1)$$

The global spatial autocorrelation statistical method was used to identify characteristics of the global spatial pattern. The global Moran's I statistic measures the correlation among spatial observations, and allows to find the characteristics of the global pattern (clustered, dispersed, random) among sub-district (Jeefoo et al., 2011). The Moran's I statistic is calculated by;

$$I = \frac{N}{S_O} \sum_i \sum_j w_{ij} \frac{(x_i - u)(x_j - u)}{\sum_i (x_i - u)^2} \qquad (2)$$

Where *N* is the number of sub-districts; w_{ij} is the element in the spatial weight matrix corresponding to the observation pair *i, j*; and x_i and x_j are observations for areas *i* and *j* with mean *u* and

$$S_O = \sum_i \sum_j w_{ij} \qquad (3)$$

Since the weight are row-standardized $\sum w_{ij} = 1$, the first step in the spatial autocorrelation analysis is to construct a spatial weight matrix that contains information about the neighborhood structure for each location. Adjacency is defined as immediately neighboring administrative sub-district, inclusive of the district itself. Non-neighboring administrative sub-districts are giver a weight of zero (Tsai et al., 2009).

2.3.4 diarrhea risk zone maps

The local Gi* (d) statistic (local G-statistic) is used to test for statistically significant diarrhea local autocorrelation, for each year. The local Gi* (d) statistic is useful for determining the spatial dependence of neighboring observation (Getis et al., 2003;

Hinman et al., 2006). The local G-statistic can be written as follows (Getis and Ord, 1992; Wu et al., 2004; Feser et al., 2005).

$$G_i^*(d) = \frac{\sum_j w_{ij}(d)x_j - W_i\bar{x}}{s\sqrt{\frac{(nS_{1i}-W_i^2)}{(n-1)}}}, \text{ for all j} \quad (4)$$

Where x is a measure of the prevalence rate of each sub-district; w_{ij} is a spatial weight that defines neighboring administrative sub-districts j to i; W_i is the sum of weight w_{ij}, $\bar{x} = \frac{1}{n}\sum_j x_j \, S_{1i} = \sum_j w_{ij}^2, s^2 = \frac{1}{n}\sum_j x_j^2 - \bar{x}^2$.

Developing the spatial weight w_{ij} is the first step to calculating Gi* (d). The spatial weight matrix includes $w_{ij} = 1$. In this study, adjacency is defined using a first order queen polygon continuity weight file which has been constructed based on the sub-districts that share common boundaries and vertices. Non-neighboring administrative sub-districts are given a weight of zero. The neighbors of an administrative sub-district are defined as those with which the administrative sub-district shares a boundary. A sample 0/1 matrix is formed, where 1 indicates that the municipalities having a common border or vertex; 0 otherwise (Ceccatoand Person, 2002; Wu et al., 2004).

The local G-statistic includes the value in the calculation as *i*. Assuming that Gi* (d) is approximately normally distributed (GetisandOrd, 1992), the output of Gi* (d) can be calculates as a standard normal variant with as associated probability from the z-score distribution (MacKellar, 1993). Clusters with a 95 percent indicate significance level from a two-tailed normal distribution indicate significant clustering spatially, but only positively significant clusters (the z-score value greater than +1.65) are mapped.

2.4 software

Various software's, namely GeoDa (http://geodacenter.asu.edu/), ArcGIS (www.esri.com), and SPSS, were used in this study.

3. Results

3.1 spatio-temporal analysis of diarrhea

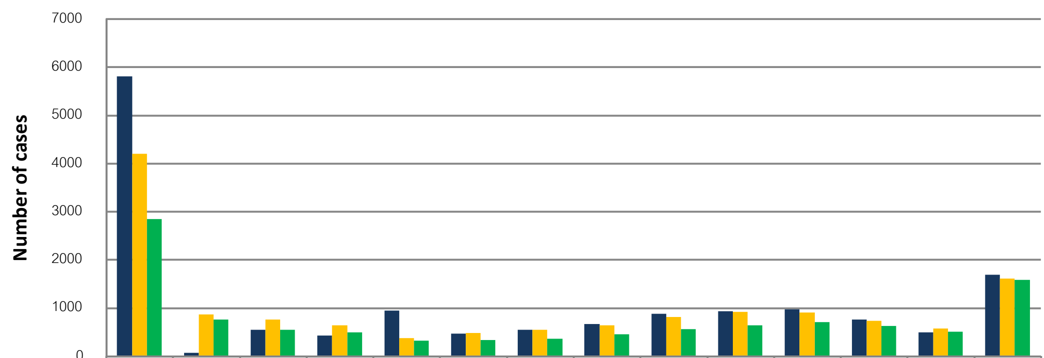
3.1.1 general analysis

Diarrhea occurred in most sub-districts of Phayao province, causing severe health problems. In 2009, the total number was 15,351 cases, which is the highest recorded incidence for the current decade. The lowest occurrence was in 2011 (10,901 cases). As shown in Table 1, in total 40,506 cases were reported, including 18,625 males and 21,881 females. During the highest diarrhea incidence in 2009, 7,147 male and 8,204 female patients were suspected cases. There were slightly more female patients (54.02%) than male patients.

Table 1. number of diarrhea cases classified by gender during the years 2009-2010.

Gender	Year			%
	2009	2010	2011	
Men	7,147	6,609	4,869	45.98
Female	8,204	7,645	6,032	54.02
Total	15,351	14,254	10,901	100.00

Source: Phayao Provincial Public Health Office (PPPHO)



	0-5y	6-10y	11-15y	16-20y	21-25y	26-30y	31-35y	36-40y	41-45y	46-50y	51-55y	56-60y	61-65y	> 65y
2009	5816	83	557	443	954	477	561	675	890	949	977	769	502	1698
2010	4216	880	774	654	389	488	563	651	824	932	920	748	589	1626
2011	2858	767	559	499	337	344	375	466	577	647	720	641	512	1599

Figure 3. Number of diarrhea cases classified by age groups during the years 2009-2011.

Disease distribution based on age of the patients was also determined (Figure 3). The highest incidence was in the 0-5 years age group with a percentage of 31.82% (12,890 cases), while incidence in the population older than 65 years age group was 12.15% (4,923 cases).

3.1.2 temporal analysis

The comparison of temporal distribution of diarrhea cases for years 2009 to 2011 is shown in Figure 4. The diarrhea temporal distribution in the whole province, with the highest incidence in the hot season, presented a similar trend every year. The disease patterns indicated critical months from March to June that is during the summer season. The worst incidence was reported in March 2009 with more than 1,600 cases. Diarrhea outbreaks generally occurred during the first part of the hot season, when relative humidity was higher than average. Rainfall, relative humidity, and temperature start to increase in May, consequently the diarrhea outbreaks reported during the months of March to July, having high relative humidity and temperature. Subsequently number of cases decrease in August to November when rainfall and temperature were at their highest, but temperature also showed a decrease. The numbers of diarrhea cases were very low level during the cold season and presenting peak during the summer season from March to June. Overall, the average monthly relative humidity (2009-2011) was 73.37%. The mean temperature was observed between 19°C to 31°C (2009-2011).

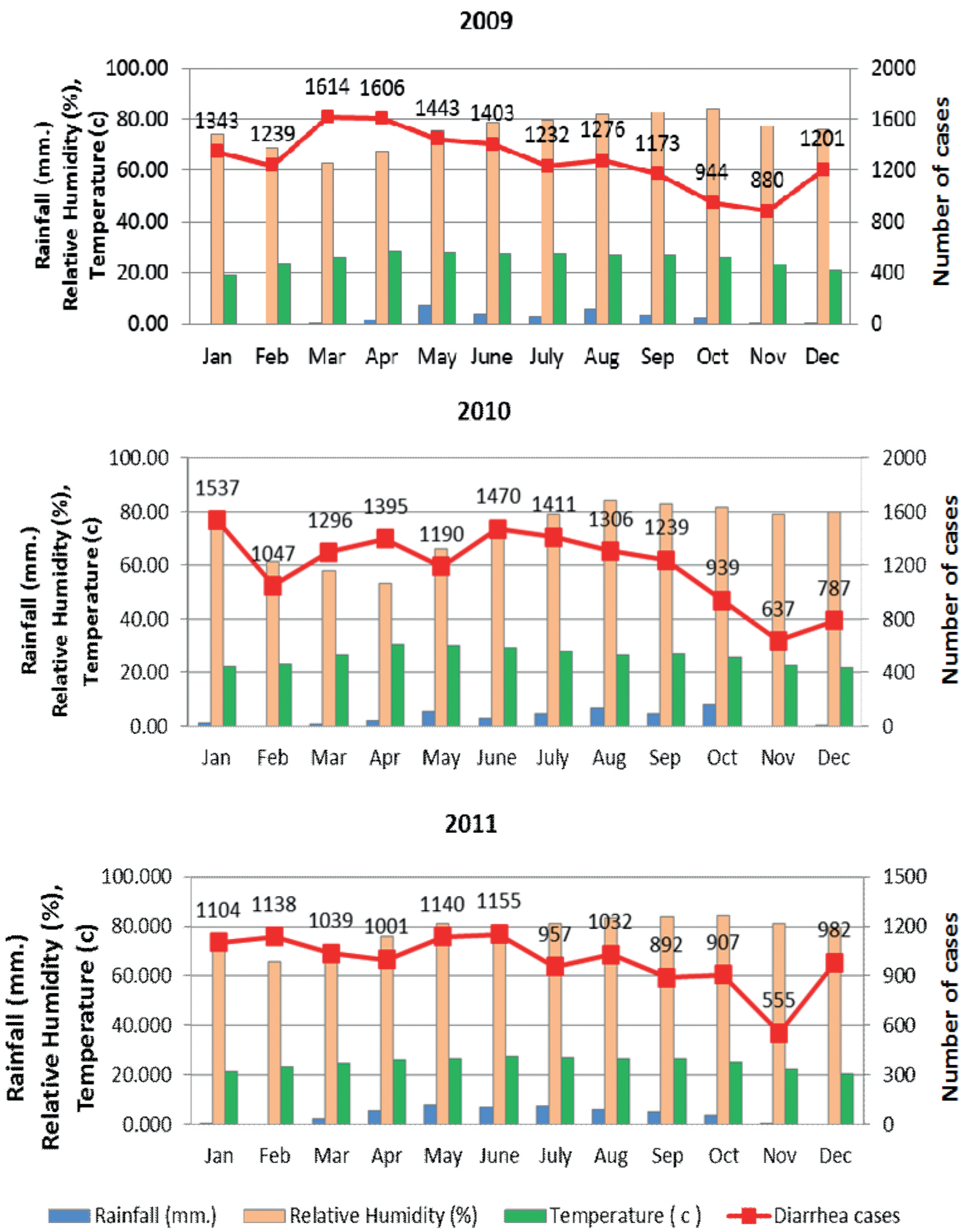


Figure 4. Monthly rainfall (blue color), relative humidity (ping color), temperature (green color)and the total number of diarrhea cases (line with symbols) in years 2009-2011.

3.2 spatial autocorrelation analysis

The results of the calculation of the global autocorrelation statistics for diarrhea incidence in years 2009 to 2011 in Phayao province are summarized in Table 2. The results of the global Moran's tests for all cases related to the 68 sub-districts are statistically significant (z-score greater than 1.65) and indicate spatial heterogeneity. The global spatial autocorrelation analysis with Moran index showed that the spatial distribution of diarrhea morbidity rate was clustered, for all years (2009-2011). This information is a major finding to suggest public health departments that diarrhea is occurring in cluster and not spread randomly throughout the province.

These locations may be considered as hotspots for future strategy to control. The highest of Moran's I and G-statistic (z-score) values were confirmed 0.69 and 11.21 respectively in the year 2011. It presented expected clustered pattern for an infectious disease, even at sub-district level.

This describes the methods for generating potential risk map of diarrhea cases by considering both the location and their attributes. Spatial cluster of diarrhea morbidity rate is covering Phayao province. The results are presented from 2009-2011 years. The map in sub-districts level with significant local indices of spatial association (p-value < 0.01) using the local Moran's I statistic represented the diarrhea risk map (Figure 5). The standardized values of diarrhea morbidity rate in each sub-district were displayed in spatial cluster plot, to contrast observed value with their spatial average (spatially averaged adjacent values), and to detect outliers. The clustered sub-district with high diarrhea morbidity rate (risk map) was found.

The potential risk maps of diarrhea diseases during 2009-2011 years were concentrated in the East part of the province (Pong, Chiang Kham, and Phu Sang districts). The highest risk zone were shown from 2010 and 2011years in Pha Chang Noi, Ngim, Oi, and KhunKhuan sub-districts (Z(I) = 1.96 to 2.58) of Pong district (red colored area).

Table 2. global spatial autocorrelation analysis of DMR

Year	Moran's I	Z(I)	Pattern
2009	0.68	11.01	Clustered
2010	0.52	8.45	Clustered
2011	0.69	11.21	Clustered

Note: Z(I) a value greater than 1.96 is statistically significant.

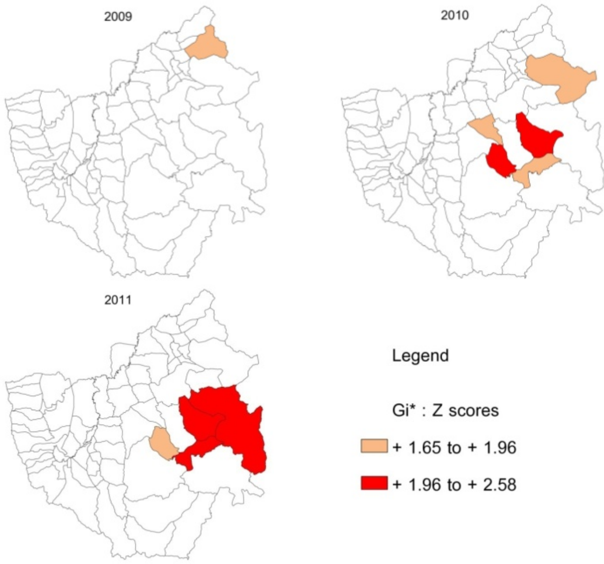


Figure 5. risk map of diarrhea potential risk from 2009-2011.

4. Discussion

Spatial epidemiological research has a long history, but epidemiology studies using GIS has emerged only recently. With the development of computer technology and spatial analysis methods, GIS is becoming more and more important. Monitoring and planning control measures for dengue epidemics have recently become vital to control disease outbreaks. This article aimed at providing useful information on diarrhea incidences and mapping their patterns of diffusion. Spatial autocorrelation analysis proved to be a valuable tool to analyze the spatial patterns change over time (Jeefoo et al., 2011).

This paper revealed useful information on age group and gender vulnerability to diarrhea. Incidence of diarrhea observed to be greater than expected in the 0 to 5 years old age group. Climate also plays important role and it was seen that diarrhea is generally prevalent in the province of Phayao during the months of March to July. Temporal analysis of climatic factors (rainfall, relative humidity, andtemperature) showed that diarrhea generally occurs when average temperatures increase, when the humidity is higher than average, and when the rainfall season has already started.

Using spatial analysis methods in GIS, the spatial patterns of diarrhea cases in Phayaoprovince from 2009–2011 were mapped and analyzed. The nature of spatial distribution was found to be clustered. Concerning the empirical Bayes smoothing (EBS) method, raw rates were used to estimate this underlying risk, which reduced differences in population size and in turn addressed variance instability and spurious outliers. In short, rate smoothing presented one way to address this variance instability (Meza, 2002). The study showed that spatial distribution patterns of diarrhea cases were significantly clustered, and identified the diarrhea risk zone area in Phayao province.The diarrhea risk zone analysis shows a cluster pattern in the East (Pong, Chiang Kham, and Phu Sang districts) of the study area, and also showed how the diarrhea occurrence locations of disease. Nevertheless, the limitation in the study was the diarrhea cases data. Due to administrative reorganization, some new sub-districts were formed and diarrhea cases data for these sub-districts was not available for earlier years.

5. Conclusion

Spatial autocorrelation calculation is useful for cluster mapping of diarrhea incidence. This study identified and mapped spatial distribution of diarrhea incidence, potential diarrhea risk based on diarrhea incidence and high risk population age groups. The methodology developed using GIS, spatial statistics have improved the understanding of disease outbreak patterns and its association with climate factors (rainfall, relative humidity, and temperature). I found a temporal and spatial correlation between summer seasons and diarrhea disease outbreaks for the East part of the province based on analysis of climate, population and epidemiology data obtained for the 2009-2011 period. Diarrhea spatial autocorrelation analysis and risk zone detection may provide useful information to support public health officers to control and predict diarrhea spread over critical risk areas only rather than for a whole province. In future it would be important to have regular daily analysis for several years to converge faster at outbreak locations and be prepared for preventive measures and focus on local scale or village level. The methodology is based on notions on general principles of geostatistics and has the potential for application for other epidemics.

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