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Local Spatial Knowledge for Eliciting Risk Factors and Disease Mapping of Tuberculosis Epidemics

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Abstract
Predicting risk areas of tuberculosis (TB) epidemics needs a proper understanding of the disease transmission process in identifying holistic risk factors. This study was performed to determine the causative factors triggering the epidemics in Shah Alam, Malaysia by utilising spatial analysis techniques and participation of local-expert knowledge or local spatial knowledge (LSK) approach. LSK approach was conducted to collect data on TB risk factors by combining experienced local experts' opinions, multi-criteria decision making (MCDM) analysis, and GIS mapping. The combination of experts participatory GIS and knowledge elicitation can generate a useful spatial knowledge framework for risk assessment of local epidemics.

Keywords: Local spatial knowledge, MCDM method, experts participatory GIS, tuberculosis.

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1.0 Introduction

Determining a risk factor framework contributing to local TB incidence is essentials knowledge for understanding a real phenomenon of local TB and to support detects missing cases on the ground. The incidence of the disease has a specific link with environmental factors and spatial variation. TB risk factor is typically associated with an individual condition as defined by the World Health Organization (WHO) as someone who has a weak immune system, living in a poor community, and other related human indicators. However, the risk for getting TB does not only depend on individual situations alone but also on the surrounding circumstances. TB risk factors are generally driven by anthropogenic or human indicators and natural environment indicators (Abdul Rasam et al., 2018; Wei et al., 2016; Sun et al., 2015).

In Malaysia, finding a holistic TB risk framework is probably a demanding task because every state or area may have their risk factors and dynamic distribution as occurred in China (Sun et al., 2015) and South Africa (Musenge et al., 2013). Therefore, a knowledge-driven (such as LSK, MCDM, and expert opinion) and data-driven methods (such as statistical method) are common methods used to conduct a risk assessment of diseases (Pfeiffer et al., 2008) and for environmental modelling (Sun et al., 2012; Stevens & Pfeiffer, 2011).

The data-driven method is a direct estimation of disease population size and it is easy to determine its relative risk abundance, but Wilkinson and Val Duc (2017) stated that a knowledge-driven method has its advantages because having spatially restricted relative to

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specific local areas. Mollison. (1995) also emphasised these types of understanding is required for ecological modelling with scientific values. Hence, LSK has been empirically applied for hazard management (Weichselgartner and Pigeon, 2015), and disease risk assessment (Stadler et al., 2013) in TB epidemiology (Rakotosamimanana et al., 2014; Abdul Rasam et al., 2016, Abdul Rasam et al., 2019).

Similarly, the information system of the Malaysian notified TB cases (MyTB system) are only obtained from patients record and secondary data, whereas in reality, the primary data from public participatory and actual site observation are also crucial to gain scientifically the knowledge of local TB transmission as in the real situation. This study carries out a local knowledge approach in a spatial or GIS environment to determine the influential TB risk factors and their infection risk rate in Shah Alam, Selangor. Currently, Shah Alam has diverse environments and socioeconomic status among the population that are possible factors related to TB epidemics.

2.0 A Review on Local Spatial Knowledge Approach in Disease Risk Management

Quantifying a precise causal association of a disease and its causal factors can be challenging work because of the multidisciplinary demands. It is required to use accurate techniques to control the disease. Knowledge-driven and data-driven methods are common approaches to conduct a risk assessment of diseases (Pfeiffer et al., 2008). The knowledge-driven method (such as local spatial knowledge, MCDM, and expert opinion) is formulated based on the human expert assumptions, while the data-driven method is the solving of the parameter estimation such as linear equation, polynomial and neural networks (Todorovski and Dˇzeroski, 2006).

Since both methods have strengths and limitations for risk estimation, some experts have integrated them for modelling a systematic environmental system and explaining dynamic phenomena (Sun et al., 2012; Stevens & Pfeiffer, 2011; Todorovski and Dˇzeroski, 2006). Similarly, Sun et al. (2012) and Stevens & Pfeiffer. (2011) provided an integrated knowledge model to effectively identify risk factors of the disease and to increase the capability of disease modelling method. The principal benefit of spatial knowledge (SK) or cognitive map in a physical environment is to act as a problem solver for finding routes and relative positions, better map interpretation, and adapt new geographic information (Abdul Rasam et al., 2020; Ishikawa and Montello, 2006; MacEachren, 1991; Kuipers, 1976)

Local spatial knowledge (LSK) is generated from incorporating local experts or community knowledge and spatial cognitive to collect data and decision-making plan for disaster risk management (Weichselgartner and Pigeon, 2015; Price et al., 2012; Botzen et al., 2009). For example, LSK was used to investigate the direct participation of local people in developing hazard mapping and risk management, creating awareness among a community by applying information technologies to protect risk areas (Price et al., 2012), and for disaster risk reduction policy. The roles of expert knowledge within a community can also be boosted by utilising interactive web-based workshops to inform landscape simulations of conservation scenarios. In the context of health and epidemiology, a spatial knowledge-based method is desired to map the areas suitable for disease spread through assessing the risk factors and their relative risk weights (Abdul Rasam et al., 2016; Abdul Rasam et al., 2017; Tran et al., 2016; Stadler et al., 2013; Cravey et al., 2001)

Besides, local spatial knowledge provides users with a practical mapping system according to data availability and meticulous knowledge. The similar concept of socio-spatial knowledge networks (SSKNs) is also introduced by Cravey et al., (2001) to identify key socio-spatial information and intervention strategies for preventing the onset of a certain disease. Stadler et al. (2013) adapted this cognitive approach to specifying data about study locales to inform strategies for disease prevention using community-based medical approaches.

The roles of spatial knowledge (SK) in TB epidemiology is much focused on gaining TB information among community using knowledge attitude and practice (KAP) (Rakotosamimanana et al., 2014) and comprehensive investigation of TB transmission. Abdul Rasam et al. (2016) operated the concept of SK by applying a GIS-MCDA method in determining TB risk factors and risk areas in Malaysia. This study hypothesised that local knowledge and spatial techniques have the potentials to answer the key question of what risk factors of TB are available towards developing a GIS-based model of high-risk TB locations in Malaysia.

3.0 Material and Method

The approach used in this study is a local spatial knowledge (LSK) derived from the knowledge-driven method. The approach applies a holistic risk assessment of TB factors for enhancing known knowledge-based risk factors with additional potential risk factors as supported by Sun et al. (2012). The architectural system of the approach is illustrated in Fig. 1, demonstrating the ways (black box) of identifying the risk factors, and then combines all steps to find the final local risk factors (grey box). The core of the approach is an expert interview through the MCDM method (Rank sum), comprehensive reviews, and spatial or GIS mapping that correspond to both local-expert knowledge and selected risk factors. It comprises of the components, inputs, and outputs to describe the analytical core of the system.

Input: Data Collection and Selection of Risk Factors. The information gathered on the knowledge-driven risk factor was obtained from the direct input of global literature review and local opinions through conducting scholarly review studies on the global TB epidemiology and interviews with selected experts as shown in Table 1. Inputs from the local health experts from PKD, Petaling were then compiled into a list of risk factor concepts, which are the relevant risk factors (Sun. et al., 2012). For example, local experts and existing guidelines from the Ministry of Health Malaysia (MOH) and World Health Organization (WHO) are synthesised to rank the local high-risk group of TB in a standardised risk scale (0 to 1). Scale zero and one indicate the lowest and the highest level of TB risks respectively. Table 1 is a list of selected risk factors that are proposed by Abdul Rasam et al. (2016), but with new elements added to the list that is the socioeconomic status (SES) and human mobility. These predictors were included in the TB GeoDatabase for risk assessment as individual-level spatial information. TB cases and land use maps were respectively obtained from the Selangor State Health Department, Petaling District Health Office, and Town and Country Planning Department, Selangor.

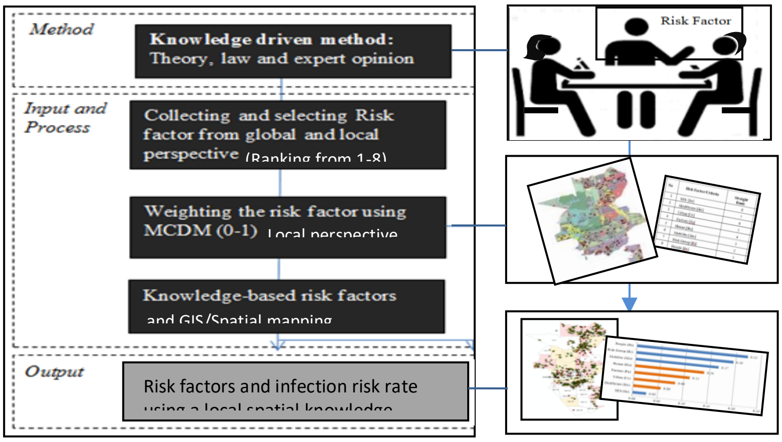

Fig. 1: A local spatial knowledge framework using a knowledge-driven method driven

Table 1: Potential risk factors of TB in Shah Alam using expert opinions

TB Risk Factors (description of variables)
[Ur] Urbanisation-land use (population and Physical Development)
[Ho] Types of house-settlement (cost, size, and condition)
[He] Shortest and direct distance to healthcare facilities (in metres)
[Fa] Shortest and direct Distance to factory locations (in metres)
[Pe] Number of people in a house
[Ri] High-risk groups (young and senior citizen, PTB, non-Malaysian, no BCG diabetics others)
[So] Socioeconomic status, SES (Income, job, education)
[Mo] Concentration of human mobility (Special/red flag cases such as HIV/AIDS other with their workplaces)

Process: Data Processing and Calculation of Risk Factor Weights. Although the study was conducted using secondary data from particular organisations, the risk data had been assigned values by combining primary inputs from expert opinions and literature. MCDA method (Malczewski, 2000; Chang 2011) analysis was implemented to rank the TB infection risk rate. Each criterion or risk factor was straightforwardly ranked (from 1 to 8) by selected experts and then the values or weight were standardised using rank-sum techniques as shown in equation (1) from 0 to 1. Four experts from the District Health Office of Petaling (PKD, Petaling) were interviewed to rank each criterion used. These local experts are chosen based on their real experience in directly handling TB cases during the site investigation and surveillance. Meanwhile, this Ratio Estimation (RE) ranking technique is the simplest and most popular method employed to quantify the importance of weights by positioning it in rank order.

$$W_j = \frac{n - r_j + 1}{\sum (n - r_k + 1)} \qquad (1)$$

Where;

W_j = the normalized weight for the j^{th} criterion

n = the number of criteria under consideration ($k = 1,2,3 \ldots n$) and

r_j = the rank position of the criterion

each of the criterion is weighted $(n - r_k + 1)$ and then normalized by the sum of all weights and that is $\Sigma (n - r_k + 1)$.

For instance, the population number is the main criterion that contributes to local TB risk that is denoted as rank 1 and assigned the highest weight as 8. Similarly, the socio-economic status (SES) is the lowest criterion is denoted as rank 8, and assigned the lowest weight as 1. From this straight rank, the standardised weights can be computed. Table 2 illustrates the list of risk factors and their weighted standardisation. Human mobility [Mo] as an example, which is ranked as 3 in the straight rank column, the weight value is calculated as 6 (i.e.8–3+1). Then, the weight value is divided by the total values of weight as showed in equation (1), which is to determine the standardised weight value of types of the house of 0.17. GIS data exploration was also conducted for examining the overall pattern and potential risk factors. ArcGIS (ESRI, Inc., Redlands, CA, USA) and Microsoft Excel used for spatial (GIS mapping) and non-spatial analysis (weighting calculation).

Table 2: Potential risk factors of TB in Shah Alam using expert opinion

No	Risk Factor/Criteria	Straight Rank	Weight $(n-r_j+1)$	Standardised Weight, W_j (0-1)
1	SES [Se]	8	1	0.03
2	Healthcare [He]	7	2	0.06
3	Urban [Ur]	6	3	0.08
4	Factory [Fa]	5	4	0.11
5	House [Ho]	4	5	0.14
6	Mobility [Mo]	3	6	0.17
7	Risk Group [Ri]	2	7	0.19
8	People [Pe]	1	8	0.22
	Total		**36**	**1.00**

Output: Eliciting Local Risk Factors: A comparative evaluation was conducted based on the risk factors ranks from local knowledge and GIS mapping of TB. The level of risk rank and weight of each selected risk factors were determined based on the MCDM result and expert opinion. The scale of knowledge-based risk factors used the value from 0 to 1. Meanwhile, GIS mapping and spatial descriptive analysis used to identify the spatial pattern and possible clustering of TB distribution and variation risk. This combination creates an inspired approach as a local-expert spatial knowledge for enhancing the process of decision making and TB control programmes in the country.

4.0 Results and Discussion

This section answers the main question of the study on what risk factors are affecting TB incidents and their specific infection risk rate in Shah Alam. Thus, a GIS mapping and knowledge-driven method have been integrated for developing a systematic local spatial knowledge (LSK) approach to describe the TB risk associations and their spread pattern as described in the following sub-section 4.1 and 4.2.

Infection Rate of TB Risk Factors. Fig. 2 local experts' opinions used to determine infection risk rate according to the local environments. The result showed that the human or population factor is selected as the main risk factor (0.61 or 61%), in the study. The factors include the number of population (0.22), the concentration of the high-risk group (0.19), and human mobility (0.17). But, the socioeconomic status, SES (0.3) is chosen as the lowest risk contributor only to the local factor since some of the cases also come from the medium and high- income family. The other core factors are grouped as ecology or biophysical environment (0.39 or 39%), including the types of houses (0.14), the distance of factory from the cases (0.11), land use type or urbanisation (0.08), and proximity to healthcare facilities from the house (0.06).

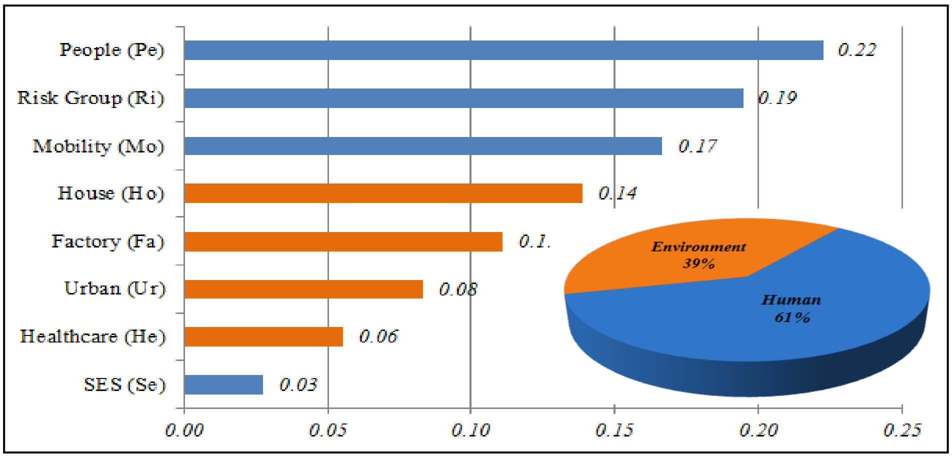

Fig. 2: Infection risk rate (0-1) of TB selected by the TB experts' opinion in Shah Alam. Human indicator (blue) is more dominant thanenvironmental or ecological indicators (orange)

The poverty (low SES) and healthcare accessibility factors seemed to be not the major factors contributing to TB risk in the study area due to Shah Alam is a progressive area, thus in general perspective, the population has access to good economic capacities and available healthcare facilities. Besides, the availability of public transportation is also an alternate solution for poor and marginalised communities to reach any facilities. The finding was slightly consistent with the spatial analysis of the human factors that have more influential effects than the environmental factors. These result showed that the combination of a local knowledge-driven method with spatial cognitive can help the decision-maker to identify the specific risk factors contributing to the disease in a certain area (Abdul Rasam et al., 2016; Tran et al., 2016; Stadler et al., 2013; Cravey et al., 2001).

This proposed framework of spatial knowledge approach can also increase the capability of disease risk factor identification and modelling in a GIS environment than the common method (Sun et al., 2012; Stevens & Pfeiffer, 2011), especially for adaptation of geographic information for guide person's actions in new ways (Ishikawa and Montello, 2006; MacEachren,1991; Kuipers, 1976). LSK as a knowledge-driven method could be combined with a data-driven method for explaining complex phenomena (Sun et al., 2012; Stevens & Pfeiffer, 2011; Todorovski and Dˇzeroski, 2006)

Risk Mapping of TB Concentration. Fig. 3 indicates the distribution of TB cases in Shah Alam using a GIS, containing 161 TB cases with eligible income data in 2015. The overall distribution of TB is medium randomness due to local spatial heterogeneous as occurred in China (Sun et al., 2015) and South Africa (Musenge et al., 2013). This descriptive analysis is important to qualitatively identify the possible spatial pattern, clustering, and variation risk of TB distribution.

Potential risk location concentrated in the northern zone (Section of U5, U17, U18, U19, and U20), central zone (Section S7 and S17 to S21), and a few at the south zone (Section 27). As expected earlier, these clustered locations have the characteristics of high-risk areas, especially as the focal points for human habitation and daily activities. It can be seen that the local TB occurrences in Shah Alam are likely driven by human indicators rather than biophysical environment indicators. These GIS findings could be used to support the next association study between risk factors and TB cases using a local-expert knowledge approach (e.g. MCDM and expert opinions).

Systematic reviews from global scholarly studies stated that eight risk factors had a possible correlation with the local TB risk transmission. The factors include two main indicators; human and environment. Human or internal factors cover the number of people (Zaragoza Bastida et al., 2012; Erazo et al., 2014), human mobility, risk group (WHO, 2015) and socioeconomic status (Yakam et al., 2014), while for environment or external factors comprise urbanisation (Harling & Castro, 2014), the distance of industrial factory, type of house, the distance of healthcare facilities. A comprehensive review from the global TB scenario is crucial steps since there are no standard reports to use as a single holistic risk factor in the world. The risk factors of each country or area are possibly driven by different predictors as well as their level of infection risk. These local risk factors of TB are used to determine influential risk factors and risk rates according to the local condition.

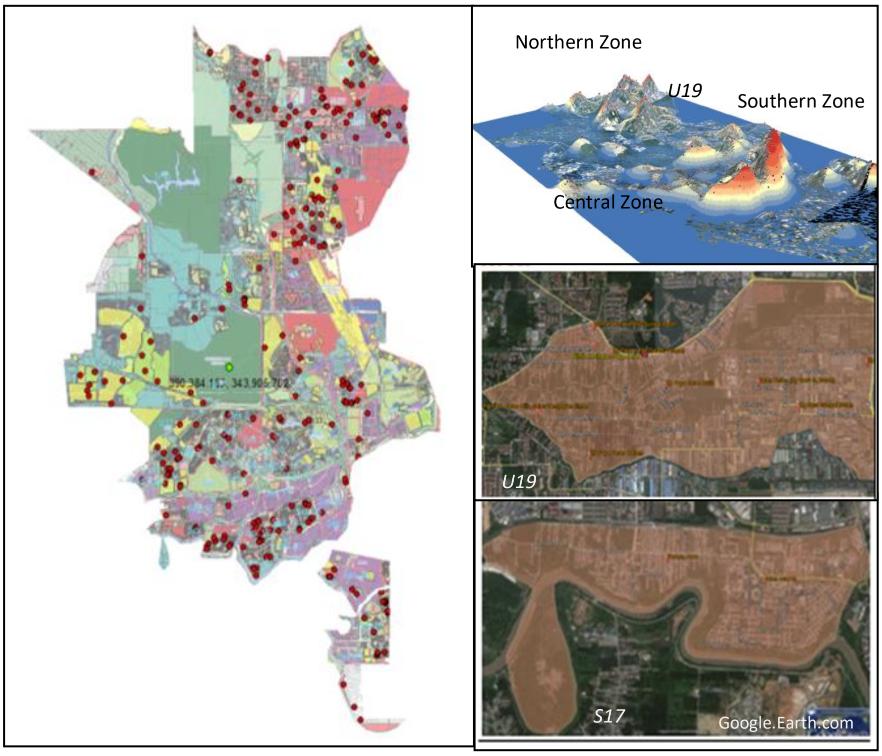

Fig. 3: Spatial Pattern of TB Distribution in Shah Alam, 2015, concentrating at a high density of population as occurred at Section U19 and S17.

5.0 Conclusion

This study is accomplished to explore the capabilities of the local-expert spatial knowledge (LSK) approach for eliciting TB risk factors in Shah Alam. The combination of technical components of a knowledge-driven method, GIS, and MCDM method has produced a systematic approach for insightful identification of the risk factors of diseases towards improving the prediction performance of the existing non-knowledge approaches. The result from the LSK has revealed that TB in Shah Alam Malaysia has been influenced by human or anthropogenic factors rather than ecological factors, particularly the density of people, concentration of high-risk groups in certain areas, the human mobility of confirmed risk people, and socioeconomic status (SES). The other potential factors are the types of houses, the distance of the industrial factory to TB cases, urbanisation, and distance to healthcare facilities. However, the integration of all these factors could trigger the environments and ultimately enable a neighbouring human and area to become an endemic or high-risk infection. In terms of methodological aspect, the LSK has successfully demonstrated its capabilities to find intuitive TB risk factors and mapping in the local context as demonstrated by previous studies. But, the participation of the public community, integrating quantitative assessment and geospatial innovation should also be considered in future research for exploring other roles of a participatory geoinformation approach in the Malaysian national TB control programme.

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