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Geographical Information System and Geostatistical Modelling Approach for Spatial Risk Assessment of Tuberculosis Dynamics

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Abstract
This paper explores the scenario of tuberculosis (TB) dynamics and to evaluate risk factors contributing to local cases in Shah Alam using geographical information system (GIS) and geostatistical approach. This risk assessment is important to model the overall potential hazards factors that cause harm to local TB. Geostatistical model was applied to predict TB risk surface according to the existing locations of TB risk factors. The unknown points of risk TB locations were defined based on known points of the existing locations using GIS and logistic regression analysis. The risk map of TB has estimated 102 high risk localities in the study areas. Most the risk locations were concentrated around northern zone, central zone and a few areas around southern zone especially at 10 main sections of U17, U18, U19, U20, S7, S17, S18, S20, S27 and S28. Seven influential risk factors are identified to contribute to the local cases, including high risk group, Socio-economic status (SES), population, type of houses, human mobility, urbanisation, and distance to of factory. These results stimulate new attributes of risk factor and interpretation on the local disease phenomena. The combinations of GIS and geostatistical method have also demonstrated its geographical neighbourhood capabilities to predict local TB risk dynamics.

Keywords: *Geostatistics, GIS, Risk ssessment, Tuberculosis.*

I. INTRODUCTION

Health and environment are naturally connected within a spatial context and play key role in influencing human health risks as well as other health effects. The geo-graphic context of social (people), built and natural environment affect human health and well-being in ways that are relevant to health policy [8]. Health risk factors and the assessment were used to determine the source and outcome of the TB risk determinants and their associations in a local context.

In general, the context of transmission of tuberculosis (TB) can be explained through a typical traditional model of infection that describes the infectious disease result. It covers three main entities, namely external agent resources such as bacterium in human, a susceptible host of airborne and an environment which carry host and agent collectively. The model is vital as an ideal illustration to simplify the convoluted comprehension of dynamics of local TB risk factors.

Contributing risk factors of TB are good source to regulate the features of high-risk areas. Most of the studies focus on internal or human factors as suggested by WHO such as biomedical or clinical approach (screening for TB and prophylactic therapy) to diagnose latent TB infection. But, their inability to distinguish latent infection from disease and high

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operational costs makes them less than a suitable tool for use in the unindustrialized world. Human factors are also currently identified as the main indicators causing TB cases in Malaysia in particular in Selangor. In this manner, some initiatives need to be conducted to gather risk information in routine observation for TB infection [20].

In addition, the combination of these components will assess the genuine dimension of the risk among individuals and their environment. For example, the well-being of people who have poor genetic or biological factor, and low immunisation risk factors will be worsened if they were exposed to environmental risk factors (such as biophysical environment or geographical factors). The environ-mental factors include natural environment (such as air pollution and land cover) and built environment (healthcare technology capability, physical infrastructure, and housing or building condition).

Other contributing factors may include urbanisation, rural, population crowd, changes and density, neighbourhoods and others, and socio-economic and culture (such as education, income, employment, demographical characteristics, behaviour and human social lifestyle, habitat or settlement censuses, poverty, migrant population). Therefore, exploring the dynamics and risk factors of local TB cases is crucial aspect to be addressed in this study.

II. SPATIAL DYNAMICS OF TUBERCULOSIS: HUMAN, ENVIRONMENT AND DISEASE

A. Risk Factors of Tuberculosis

Submit Disease contraction among people and animal has an explicit relation to spatial environmental variation. This situation relates to health geography and is closely aligned with epidemiology. Health geography emphasizes on spatial interactions and patterns, while epidemiology is founded on the biomedical model and emphasizes on the biology of disease.

In tuberculosis (TB) transmission risk, the causation of transmission is a complex process and the approved models of disease causation need the exact relationship of variables and conditions before a disease occurs. But, the customary model of infection outlines that the result from the infectious association includes three elements of external agent, host and environment that carry the host and agent together.

The factors that decide the likelihood of Mycobacterium tuberculosis (MTB) transmission can be partitioned into a few epidemic stages from human body (internal factor) to human situations (external factor). As indicated by [6] and [20] inner or human dimension conditions are prevailing factors of powerlessness, while external or outside variables incorporate condition and exposure. Internal factor assumes a key job in emphasizing the movement from exposure to disease development among which the bacillary burden in the sputum and the closeness of a person to an irresistible TB case are the key indicators.

Likewise, endogenous factors lead in development from infection to active TB disease. In a human body, these are intrinsic factors (agent and host factors) related to the capacity of MTB present in the body and factors influence an individual's exposure, susceptibility, or response to a causative agent, including age, race, sex, socioeconomic status and behaviours which are only a portion of the many host factors which influence a person's likelihood of exposure.

Contributing risk factors of TB are good source to determine the characteristics of high-risk population and areas. However, most of the studies focus on internal or human factors as suggested by [25] such as biomedical or clinical approach (screening for TB and prophylactic therapy) to diagnose latent TB infection. But, their inability to discriminate latent infection from disease and high operative costs makes them less than a suitable device for use in the developing world. Similarly, human factors are also currently identified as the main indicators causing TB cases in Malaysia as in Selangor. Therefore, some effective initiatives can also be introduced to gather data of risk variables in routine observation for TB cases [20] and integrate these factors for precise risk assessment of TB. review.

B. Risk Assessment of Disease Using GIS and Geostatistics

Geographical information system (GIS) is a computerised based approach for gathering, managing, analysing and displaying geospatial data. GIS can reveal insight into data, useful information and smart decision making such as patterns, relationships and situations of disease dynamics. Geostatistical method is an interpolation technique in a spatial statistics of GIS environment used for deriving a surface using the numbers from the known locations to predict unknown location in a landscape of earth.

Recently, many researchers used a geostatistical modelling, analysis and mapping approach to map and understand the epidemic situation and disease pattern [1][2][3][4][11][15][22]. Reference [22] studied correlation between disease prevalence, population distribution and meteorological variables, and the characteristics of spatio-temporal clusters by supplementing a geostatistical analysis and spatio-temporal permutation statistic tools, the spatial variation of disease incidences can be mapped and analysed.

Geostatistical model or spatial interpolation method has technical capabilities to predict unknown values for any geographical point data of risk concentrations. Geo-statistical analysis needs two elementary inputs which are known or control points and an interpolation procedure [7] such as Kriging and Inverse Distance Weighting (IDW) interpolation. Principally, an IDW interpolation explicitly applies the concept that things which are close to one another are more alike than those that are farther apart. Interpolated points are estimated based on their distance from known values with influencing a power setting. Points that are nearer to measured values will be more affected than points that are more remote away.

Geostatistics offers better global predictions and more weight to 'neighbouring' observations compared to the regression technique [26]. Originally, this method-driven approach was used in geology and ecology. It was then expanded to other fields such as geography, social science and health. In the context of epidemiology and SES, some authors have increased interest in studying TB hotspots using geostatistical analysis [3][10][11][12][23][27]. Reference [27] demonstrated the advantages of geostatistical applications in disease mapping by providing the most accurate results of a continuous surface than multiple linear regression models. In Malaysia, a GIS or geostatistical analysis application is narrowed to a general mapping and descriptive statistics on TB distribution [1]. Recently a knowledge-driven GIS method and geo-statistical model had been attempted to map potential areas of Tuberculosis [3].

In the context of epidemiology and socioeconomic status, a number of authors had shown interest in studying TB hotspots using geostatistical analysis [10][13][27]. Reference [27] demonstrated the advantages of geostatistical applications in disease mapping by providing the most accurate results of a continuous surface than multiple linear regression models. In Malaysia, a geostatistical analysis application is limited as compared to only general mapping and descriptive statistics on TB distribution as practiced in some other countries [16][18][19]. Reference [1] has recently attempted a knowledge-driven GIS method to map potential areas of TB in Selangor, but this technique still requires further enhancement by combining statistical and geostatistical models for a significant result for determining potential high-risk areas of TB.

Geostatistical method applies Tobler’s theory and spatial diffusion for defining risk concentration of disease phenomenon. Tobler’s theory on geographical neighbourhood is the transmission of infectious diseases closely linked to the concepts of spatial and spatio-temporal proximity as described by Waldo Tobler’s theory (1970); everything is related to everything else, but near things are more related than distant things. This first law is the foundation of the fundamental concepts of spatial dependence and spatial autocorrelation and is utilised specifically for the inverse distance weighting method for spatial interpolation and to support the regionalised variable theory of kriging.

Examining disease visual map, together with the spatial pattern assessment in relations to potential risk factors as proved by Philosopher Karl Popper and John Snow, is an initial possible scientific investigation that shows the capability of geospatial for formulating theoretical hypotheses and supporting animal and human health policy developments. In addition, [5] pointed out that to make fairly abstract quantitative results easier to comprehend on widespread understanding of scientific evidence, map or visual methods can be particularly useful.

Concept of spatial diffusion on disease transmission is derived from 'diffuse' which means to disperse from a centre or to spread widely (Oxford English) including the activity of spread, transmission, and propagation homogeneously. The development of the diffusion is achieved by the main driving factors that endeavour to spread something in a system. In geography, [11] applied spatial diffusion phenomena in the spread of infectious disease, urban growth, wildfires spread, and effects of environments.

However, [11] emphasized that a comprehensive understanding of the mechanism of spread remains indefinable because of the dynamics in which a phenomenon initially situated at one point moves outward towards another location. In fact, the current information systems cannot represent the dynamic phenomena like spatial dispersion. The theory of spatial diffusion covers all procedures that add to moves, to relocation inside geographical space, and to backlash impacts created in this space by those moves.

III. DATA AND METHODS

A. Research Framework

A research framework of spatial epidemiological approach [9][21] are fundamentally adjusted and applied in this proposed geospatial model. The fundamental is vital to explore and describe the spatial pattern and risk factors of TB epidemics in Shah Alam, Selangor. Shah Alam is certainly a relevant area to be studied due to its environmental condition and active population growth and human mobility, particularly, people who are from other states (like Kuala Lumpur, Klang, and Sabah) and living in this city.

Geostatistical analysis is the main method applied in this study that requires two basic inputs which are known or control points and an interpolation method as in [7] such as Kriging and IDW in equation (1). Principally, an IDW interpolation explicitly implements the assumption that things which are close to one another are more alike than those that are farther apart. Interpolated points are estimated based on their distance from known values with influencing a power setting.

$$z_p = \frac{\sum_{i=1}^{n} \left(\frac{z_i}{d_i} \right)}{\sum_{i=1}^{n} \left(\frac{1}{d_i} \right)} \quad (1)$$

Where;

z = Value of Magnitude (e.g. elevation, risk and others)
d = Distance
p = Effect on the interpolated value (power)

B. Data and Software

The materials used in the study covers the TB cases, environmental data of TB risk factors, and spatial-statistical packages from ArcGIS and IBM SPSS Statistics 21. Primary data were particularly obtained from expert opinions (Staff from PKD, Petaling), while the main secondary data included cases from 2013 to 2015 obtained from MyTB system, and data linked to eight risk factors (see in Table 1) and base maps from local agencies.

C. Factor Selection, Database and Mapping

TB risk factors in this study were divided into three main indicators, namely, biophysical environment, human-population based environment, and organisational environment. Biophysical and human indicators have been suggested as the main factors in local study (see in Table 1).

All non-spatial data were transformed into spatial data using ArcGIS to become a database of TB in

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Shah Alam. The next steps include map digitizing, geocoding, mapping and data editing using Google Earth and ArcGIS (ArcMap). Geostatistical exploratory spatial data analysis (ESDA) and Data Analysis Tools in M. Excel menu were used to gain a deeper understanding of the TB data variations.

Indicators	Independent variables Using Continuous scale from 1 to 5 in surface or areal form
Natural environment of landscape (Biophysical and ecological environment)	Urbanisation-land use (Score_Urb)
	Types of house-settlement (Score_Hou)
	Distance to healthcare facilities (Score_Hea)
	Distance to industrial factory locations (Score_Fac)
Anthropogenic (Human and population)	Number of people in a house (Score_Peo)
	High risk groups (Score_Gro)
	Household income-Socio economic status, SES

Table 1: Potential Risk Factors of Tuberculosis in Shah

Standardisation and classification of TB risk scale were then carried out for spatial analysis. Attributes for each data were obtained from existing data sources except for TB cases, whereby the attributes were included with eight risk factors (as independent variables, IV of risk factor of TB), and one for total score of risk factors (as a dependent variable, DV) with their risk value. The table has standardised value of risk ranking from 1 to 5 since some original data were formed as categorical values. The higher range of value will lead to the higher risk of the factor.

D. Risk Assessment Analysis

Two main methods were used, namely GIS-Multi-Criteria Decision Making (GIS-MCDM) and Geostatistical Analyst. GIS-MCDM is a knowledge-driven method, a common approach to carry out risk evaluation of a disease [21]. The main part of the approach is the expert opinion through MCDM technique (such as Rank Sum) and a systematic review on the TB risk factors that used three main steps: i) Selection of risk factors, ii) Calculation of risk factor weights and iii) Eliciting local risk factors by using rank sum techniques as showed in equation (2) from 0 to 1.

$$W_j = \frac{n - r_j + 1}{\sum (n - r_k + 1)} \quad (2)$$

Where;
W_j = the normalized weight for the j^{th} criterion
n = the number of criteria under consideration (k=1,2,3…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 example, the number of people is the primary criterion added to nearby TB risk that is categorised as rank 1 and appointed the most elevated weight as 8. The social economic status (SES), the most reduced criteria are signified as rank 8 and appointed the least weight as 1. From this straight position, the standardised risk level can be computed.

The last step is compelling danger factors and hazard weight of nearby TB as indicated by expert's rank or MCDM technique. The estimations of standardised weight (Wj) were duplicated with each hazard factor and their aggregate of hazard values were resolved (as Total risk Rank [DV]) utilizing a Likert scale of 1 to 5; Scale 1 and 5 delineate the most minimal and the most astounding danger of the TB chance separately. The estimations of 1-5 were added to the TB geodatabase. The scale values were also added into logistic outcome using 1 (Yes Risk) and 0 (No Risk) for TB risk mapping using Inverse Distance Weighting (IDW) interpolation technique in geostatistics as shown in equation (3).

$$Y = \frac{1}{1 + \exp^{-(\beta_o + \beta_1 X_1 \ldots \beta m X m)}} \quad (3)$$

Where,
Y = the risk of disease incidence or the probability of an event (e.g., 1 for Yes and 0 No for TB risk)
β0 = intercept
βm = coefficient (the regression coefficients associated with the reference group)
Xm=explanatory or independent variables
exp-(β0+… βmxm) = Odds=likelihood of response for the –mth factor

IV. RESULTS AND DISCUSSION

A. Spatial Risk Factors of Local Tuberculosis

Table 2 explains that the odds of having TB disease in the location ("Risk =1" category) of human mobility is 3.654 times greater for more concentration time exposure as opposed to non-exposure in a building within 8 hours for 5 days. B expresses the extent in which logistics function influences the TB risk location (odds prediction). A nlocation of TB risk will also increase by 3.654 if families or individuals are living together (in the same house) with people who have TB disease for a particular time period.

The situation would become worse if the locality has also high-risk group (2.061), low income family (2.395), and other risk factors. The last parameter is the value of Exp (B) that influences the odds ratio predicted by the model and it can be deter-mined by the exponentiation of both sides of this expression or log (odds). For example, if the close proximity to factory's odds is 1.598, then the chance or magnitude of effect (odd ratio) is predictive of 4.942 (exp1.598 =4.942). This shows the model of potential TB risk location (1) which predicts that the odds of deciding to continue the potential location is 4.942 times higher for Yes-Risk than they are for No-Risk of the location.

Variables	Coefficient (ß) B	S.E.	Wald	Sig. (p)	Exp(ß)
Score_Urb	1.161	0.669	3.01	0.083	3.194
Score_Peo	2.061	0.655	9.887	0.002	7.853
Score_Hou	1.715	0.466	13.562	0	5.558
Score_Soc	2.395	0.697	11.819	0.001	10.97
Score_Gro	2.841	0.956	8.828	0.003	17.125
Score_Fac	1.598	0.386	17.168	0	4.942
Score_Mob	3.654	1.367	7.141	0.008	38.62
Constant	-46.807	11.331	17.065	0	0

a. Variable(s) added in step 1: Score_Urban, Score_Popul, Score_House, Score_SES, Score_Group, Score_Factory, Score_Mobility

Therefore, the outcome of the model demonstrates that chosen variables of TB patient were significantly connected with the likelihood of possibly the location of TB chance areas (p=0.008, Wald test). The outcome gives the coefficients of intercept = - 46.807 and risk factors with their coefficients. These coefficients were then simultaneously entered in the logistic regression equation (2) to predict the likelihood of risk model by converting odds to probabilities (Y=Odds/1+Odds or 1/1+exp-(β0+ β1x1 + …) that used for spatial modelling. It can be seen that human-based indicators are more leading factors than biophysical-based indicators.

B. Spatial Risk Mapping of Local Tuberculosis

Producing risk map is the primary step in any epidemiological analysis of disease to explore the pattern and spatial characteristics of TB dataset [21]. It is the simplest way to visualise and examine the disease event information in point data of TB cases. According to the District Health Office (PKD) of Petaling, 47 sections were selected to be monitored for the TB surveillance system, including Section S1 to S24 (central zone), Section U1 to U20 (northern zone, Section S27 and S28 (southern zone). Each value from the risk factor was interpolated to map the spatial variation and to explore the qualitative association between TB and risk factor, in a certain scale as shown in Fig. 1. Scale 1 shows the potential risk is very low, while 5 is very high.

Overall, after combining all factors from the three-year spatial pattern trend in the study area showed a medium random pattern with the total of 923 cases. Similar patterns also could be seen in each year's trend on the cases. This reveals that TB distribution was fairly well-distributed, but there was also some clustering concentration in the study areas (Fig. 1). The cases were focused at the northern zone (Section U17 to Section U20) and some were clustered at U5 and U13, while in the central zone, some cases were concentrated at Section S7, S17, S18, S19 and S24. Section S27 and S28 were also found as high-case areas at the southern zone. These sections recorded at least 10 cases for three consecutive years.

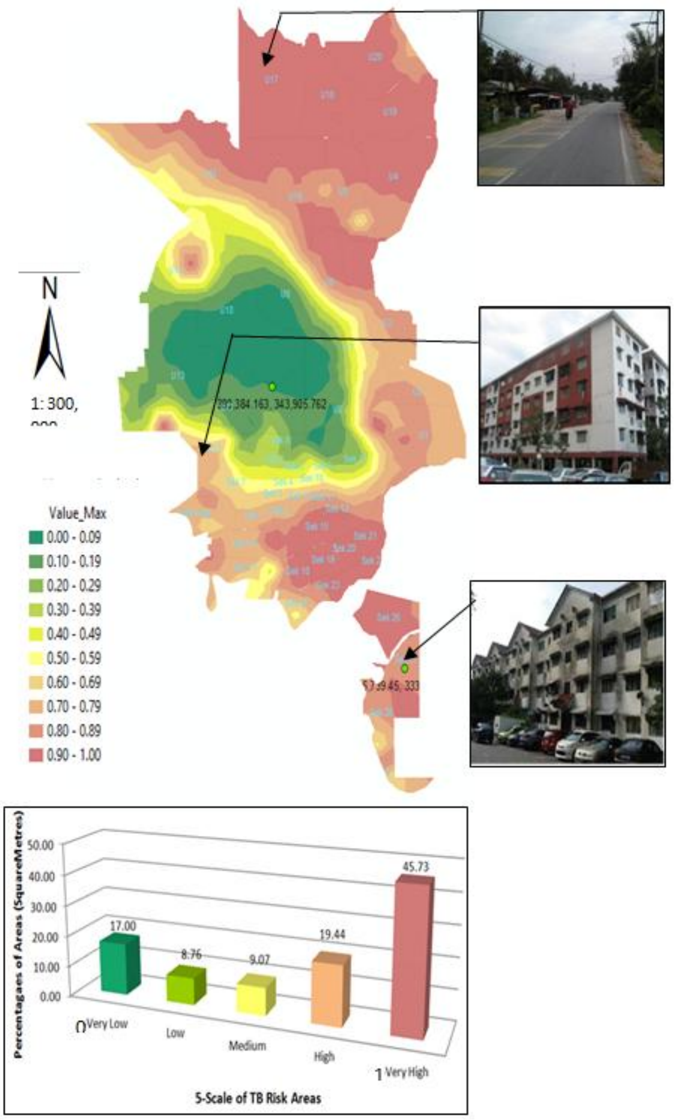

Fig. 1. Estimated Risk Map of TB Areas in Shah Alam using GIS and Geostatistics

The research proposed the zone that has potential risk of 65% potential risk spots. These estimated spots are additionally steady with findings obtained in the regression model where the study area has a medium-high hazard of TB epidemic. As projected, the hazard spots are scattered at northern zone, central zone and southern zone, with the likelihood of having risk degree of TB outbreak process.

GIS and geostatistical model can provide a holistic platform in identifying local risk factors and targeted areas for TB risk concentration. For example, the model has identified the risk sections in Shah Alam, and identified 102 high-risk localities. Although the general landscape characteristics of these risk localities have similarities in terms of risk factor influencing the local cases, there are some significant and new findings in this study that require utmost attention by local authorities i.e. the factor of industrial distance factors, human mobility pattern and medium-income status are possibly related with local TB cases. From this risk assessment, the health officers can conduct TB screening programmes at the sites for earlier identifying the potential TB risk persons.

With regards to the map validation, comparative parameters in the IDW technique and overlaying process or visual comparison were also made to examine the accuracy of the risk map. The accuracy is a fairly relevant result, indicating the actual cases as the cases are located in the potential risk areas. Specifically, the Root Mean Square Error (RMSE) is 0.274, showing an acceptable result on how closely your model predicts the measured values. However, some pockets of the risk areas also occur in low-risk areas due to other factors such as human mobility and uncertainty.

V. CONCLUSION

Combination of GIS and geostatistical model can provide a holistic platform in identifying local risk factors and targeted areas for TB risk concentration. The model has identified 102 high-risk localities at the risk sections in Shah Alam, including the sections of U17, U18, U19, U2, S7, S17, S18, S20, S27 and S28. Although the general landscape characteristics of these risk localities have resemblances in terms of risk factor shaping the local cases, there are some insightful findings in this study that require utmost attention by the local authorities, especially the factor of industrial factors, mobility pattern and income status are conceivably related with local TB cases. This proposed model has advantages for abstracting the complexities of real or complex structure system, phenomena of local TB transmission by providing a simplified map, statistical information and building an explanatory model. Geostatistics has demonstrated that the approach has a dynamic and a reliable characteristic be-cause of the geographical

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neighbourhood and predictive capabilities, fitting with the local TB transmission pathways. However, other techniques and stochastic method may also be considered for this study thus able to better model the significant phenomena of TB epidemics in the study area.

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