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A BAYESIAN SPATIOTEMPORAL AUTOREGRESSIVE MODEL WITH CONSTANT AND TEMPORALLY VARYING COEFFICIENTS: AN APPLICATION TO HOTSPOT DETECTION OF CHILDHOOD TUBERCULOSIS IN BANDUNG CITY, INDONESIA

NENENG SUNENGSIH[1,*], I.G.N.M. JAYA[1,2]

[1]Department Statistics, Universitas Padjadjaran, Indonesia

[2]Faculty Spatial Science, Groningen University, The Netherlands

Abstract. The health reported data shows that the risk of tuberculosis among children aged 0-14 years is still a significant health problem in developing countries such as Indonesia in terms of case detection, control, and effective treatment. However, some information is available about the burden of tuberculosis and its risk factors (e.g., malnutrition, population density, healthy behaviours, and AFB smear-positive tuberculosis) which can be very useful. This study aimed to identify the hotspot of tuberculosis among children aged 0-14 years in Bandung city, Indonesia. Using Bandung health profile database of tuberculosis notification for 2016 – 2018, we estimated the burden of tuberculosis among children aged 0-14 years by districts. We estimate that incidence rates vary over space and time, with the hotspots centred in the western and central regions of Bandung city. Population density has a significant effect on burden tuberculosis among aged 0-14 years over districts.

Keywords: Bandung; tuberculosis; malnutrition; population density; healthy behaviors; AFB smear-positive tuberculosis.

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*Corresponding author

E-mail address: sunengsih@unpad.ac.id

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1. INTRODUCTION

Tuberculosis (TB) is an infectious disease caused by the bacillus Mycobacterium tuberculosis ([1], [2]). TB is a significant cause of ill health and death worldwide. It spreads when people who are sick with TB expel bacteria into the air via coughing. Following WHO report (2020), a quarter of the world's population is infected with M. tuberculosis. Anyone anywhere can be affected by TB, and most adults have a higher risk. But, children aged 0-14 years still have a high risk, particularly in developing countries.

Nevertheless, the research interest in childhood TB was limited. It is often regarded as unimportant because 95% of cases are sputum smear-negative with a low transmission rate [3]. However, the transmission rate within the community could arise if there is no serious attention to childhood TB, in developing countries, WHO estimated that 1.3 millions cases of TB and 450,000 death annually [3]. According to [3], the youngest children carry the most significant burden because they are more prone to develop severe extrapulmonary TB and likely develop the disease after being infected.

There are several problems in childhood TB prevention. Firstly, the diagnosis is much less accurate than adult and tracing. More than 50% of childhood TB cases will not be diagnosed in developing countries because of the lack of radiographic facilities [3].

Several factors thought to affect childhood TB, such as malnutrition, Acid-Fast Bacillus (AFB) smear TB (+), healthy behaviour, and population density ([4], [5]).

To control childhood TB transmission, the government needs to know how the risk factors can influence the incidence rate of childhood TB. The spatiotemporal model is the most popular in epidemiology that usually use to model disease data such as Dengue disease ([6]-[8]), Tuberculosis [9], Malaria [10], COVID-19 [11] etc.

This study considers a Bayesian spatiotemporal autoregressive model with constant and temporally varying coefficients to identify the hotspot area of childhood tuberculosis in Bandung city, Indonesia.

The structure of the remainder of this paper is as follows. Section 2 presents the method including test for spatiotemporal autocorrelation using spatial and spatiotemporal Moran's, introducing spatiotemporal autoregressive mode and summarizes its estimation by INLA. Section

3 applies the method to Bandung, Indonesia. Section 4 presents the conclusions.

2. METHOD

2.1 Test for spatiotemporal autocorrelation

The spatiotemporal autocorrelation of the dependent variable can be evaluated using an extension of Moran's I, called Moran's spatiotemporal autocorrelation statistic (MoranST). It is defined as [6]:

$$\text{MoranST} = \frac{nT \sum_{i=1}^{n}\sum_{t=1}^{T}\sum_{j=1}^{n}\sum_{s=1}^{T} \widetilde{w}_{(it,js)}(y_{it}-\bar{y})(y_{js}-\bar{y})}{\sum_{i=1}^{n}\sum_{t=1}^{T}\sum_{j=1}^{n}\sum_{s=1}^{T} \widetilde{w}_{(it,js)} \sum_{i=1}^{n}\sum_{t}^{T}(y_{it}-\bar{y})^2} \quad (1)$$

where $\bar{y}$ is the mean of the observed residuals y_{it} over T periods and n spatial units, and $\widetilde{w}_{(it,js)}$ is the weight accounting for the spatiotemporal autocorrelation between r_{it} and r_{js}, defined as [6]:

$$\widetilde{w}_{(it,jt')} = \begin{cases} w_{ij}, & \text{if } t = t' \\ 1, & \text{if } i = j \text{ dan } |t-t'| = 1 \\ 0, & \text{otherwise} \end{cases} \quad (2)$$

where w_{ij} is one if regions i and j are neighbours, and zero otherwise i.e.,.

$$w_{ij} = \begin{cases} 1 \text{ if } i \text{ and } j \text{ contiguous} \\ 0 \; otherwise. \end{cases}$$

Here we use queen definition of spatial weight matrix [2] [6].

A MoranST which is close to one indicates a strong positive spatiotemporal autocorrelation of the spatiotemporal residuals. A value close to zero indicates white noise.

2.2. Bayesian spatiotemporal autoregressive

In order to model incidence rate of childhood TB we consider spatiotemporal regression model. The most common model that usually used is spatiotemporal autoregressive model. Here, the spatiotemporal autoregressive model is extension of standard linear regression model. It allows observations of dependent variable y in area i $(i = 1, \dots, n)$ at time T $(t = 1, .., T)$ to depend on observations in neighboring areas j, $j \neq i$ and $t + 1$. The model takes form [2] [13]:

$$\boldsymbol{y} = \rho\widetilde{\boldsymbol{W}}\boldsymbol{y} + \boldsymbol{X\beta} + \boldsymbol{\varepsilon} \quad (3)$$

where $\boldsymbol{y} = (y_{11}, \dots, y_{nT})'$ denote an $(nT \times 1)$ vector of dependent variable, ρ is spatiotemporal autoregressive coefficients with $|\rho| < 1$, $\widetilde{\boldsymbol{W}}$ is $(nT \times nT)$ spatiotemporal weight matrix. It defines as follows (2). The $\boldsymbol{X} = (\boldsymbol{1}, \boldsymbol{x_1}, \dots, \boldsymbol{x_K})$ denote the design matrix which

is corresponding to vector of regression coefficient including intercept and slop coefficients $\boldsymbol{\beta} = (\beta_0, \beta_1, \ldots \beta_K)'$, with $\boldsymbol{\varepsilon}$ denotes an $(nT \times 1)$ vector of error term that follows zero-mean Gaussian distribution with constant variance $\sigma^2\boldsymbol{I}$ i.e., $\boldsymbol{\varepsilon} \sim \mathcal{N}(0, \sigma^2\boldsymbol{I})$ with $\boldsymbol{I}$ is an $(nT \times nT)$ identity matrix. Model (3) can be extended to cover constant (global) and temporally varying index as follows:

$$\boldsymbol{y} = \rho\widetilde{\boldsymbol{W}}\boldsymbol{y} + \boldsymbol{X_1}\boldsymbol{\beta_1} + \boldsymbol{X_2}\boldsymbol{\beta_2} + \boldsymbol{\varepsilon} \tag{4}$$

where $\boldsymbol{X_1} = (\boldsymbol{x_1}, \ldots, \boldsymbol{x_{K-R}})$ with $\boldsymbol{\beta_1} = (\beta_1, .., \beta_l)'$ are the covariates and its coefficients which constant over time, and

$$\boldsymbol{X_2} = \begin{bmatrix} x_{l+1,11} & 0 & \ldots & 0 \\ \vdots & \vdots & \ldots & \vdots \\ x_{l+1,n1} & 0 & \ldots & 0 \\ 0 & x_{l+1,12} & \ldots & 0 \\ \vdots & \vdots & \ldots & \vdots \\ 0 & x_{l+1,n2} & \ldots & 0 \\ 0 & 0 & \ldots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \ldots & x_{K,1T} \\ \vdots & \vdots & \ldots & \vdots \\ 0 & 0 & 0 & x_{K,nT} \end{bmatrix}_{(n \times \boldsymbol{K}T)} \quad \text{with } \boldsymbol{\beta_2} = \begin{bmatrix} \beta_{l+1,1} \\ \vdots \\ \beta_{l+1,T} \\ \vdots \\ \beta_{K,1} \\ \vdots \\ \beta_{K,T} \end{bmatrix}_{(l \times T)}$$

are the covariates and its coefficients which vary over time.

2.3. Bayesian approach

To estimate the parameter model (1) we may use Bayesian approach. Bayesian setting provide flexible alternative in order to obtain the standard error estimate of spatial autoregressive parameters model. The most popular Bayesian approach in recent year is Integrated Nested Laplace Approach (INLA). INLA provides an alternative to the simulation methods for running Bayesian inference. It is based on numerical approach. INLA be able to modeling general models that belong to exponential family.

$$\begin{gathered} \boldsymbol{y} \sim \text{Exponential Familiy} \\ \mu \sim \text{E}[y] \\ g(\mu) = \eta = \beta_0 + \sum_{k=1}^{K} \beta_k X_k + \sum_{l=1}^{L} f_l \end{gathered} \tag{5}$$

where f_l are random effects. INLA implemented in R-INLA. Although INLA can be used to

model many types of models, however, in practice there are still some models not implemented in R-INLA such as spatiotemporal autoregressive model. For the particular cases of Gaussian models, the spatiotemporal autoregressive model (3) can be rewritten as:

$$\boldsymbol{y} = \left(\boldsymbol{I}_{nT} - \rho\widetilde{\boldsymbol{W}}\right)^{-1}(\boldsymbol{X\beta} + \boldsymbol{\varepsilon}) \tag{6}$$

which is the basis for INLA formulation (5). In relation to INLA, the expression can be written as:

$$\boldsymbol{z} = \left(\boldsymbol{I}_{nT} - \rho\widetilde{\boldsymbol{W}}\right)^{-1}(\boldsymbol{X\beta} + \boldsymbol{\varepsilon}) \tag{7}$$

Where $\boldsymbol{z}$ is assumed as vector of nT random effects, $\boldsymbol{I}_{nT}$ is an identity matrix with dimension $\boldsymbol{I}_{nT}$, and the other components similar with definition in (3). With observations $\boldsymbol{y}$, than we have:

$$\boldsymbol{y} = z + \boldsymbol{e} \tag{8}$$

with $\boldsymbol{e}$ is a tiny error that introduce to fit the model. This error is assumed follow Gaussian distribution and do not appear in likelihood function. To apply Bayesian inference, we need a prior distribution for each parameter interest. We assign Gaussian vague prior for $\boldsymbol{\beta}$, i.e., $\boldsymbol{\beta} \sim MVN(\mathbf{0}, 10^6\boldsymbol{I}_{K+1})$, $logit(\rho) \sim N(0,10)$ and $\sigma^2 \sim Inverse\ Gamma(1,0.00005)$.

2.4. Bayesian model averaging with INLA

INLA can be used to estimate the wide class of the conditional models by setting some hyperparameters (ψ_d) to fixed values [14]. However, we cannot obtain the uncertainty of the hyperparameters (ψ_d). Following Gómez-Rubio et al. (2020), the uncertainty can be obtained using Bayesian model averaging (BMA). INLA does not provide direct function to BMA. Using some modifications, BMA can be done in INLA setting. For the spatial model, models are fit conditional on $\psi_d = (\rho, \lambda)$ so that $\psi_{-d} = (\beta, \sigma_\varepsilon^2)$, and σ_ε^2 is fixed to remove the Gaussian error term. The posterior of complete spatial model can be written as:

$$p(.|\mathcal{D}) = \int p(., \psi_d|\mathcal{D})d\psi_d = \int p(.|\mathcal{D}, \psi_d)p(\psi_d|\mathcal{D})d\psi_d \tag{9}$$

where $p(.|\mathcal{D}, \psi_d)$ denotes the conditional posterior marginal given ψ_d, while $p(\psi_d|\mathcal{D})$ is the joint posterior distribution of ψ_d and it can be written as:

$$p(\psi_d|\mathcal{D}) \propto p(\mathcal{D}|\psi_d)p(\psi_d) \tag{10}$$

Following Bivand et al. (2014) when ψ_d is unidimensional, numerical integration through a regular grid of K values $\left\{\psi_d^{(k)}\right\}_{k=1}^{K}$ can be used to estimate the posterior marginal $p(\psi_d|\mathcal{D})$. Then the posterior marginal of the reminder of the hyperparameter and latent effects can obtained as:

$$p(.|\mathcal{D}) \cong \sum_{k=1}^{K} p\left(.|\mathcal{D}, \psi_d^{(k)}\right) w_k \tag{11}$$

with weights w_k defined as:

$$w_k = \frac{p\left(\mathcal{D}|\psi_d^{(k)}\right) p\left(\psi_d^{(k)}\right)}{\sum_{k=1}^{K} p\left(\mathcal{D}|\psi_d^{(k)}\right) p\left(\psi_d^{(k)}\right)} \tag{12}$$

The posterior marginal $p\left(.|\mathcal{D}, \psi_d^{(k)}\right)$ now is expressed as a BMA using the conditional posterior marginal of all the fit models. Hyperparameter inference is based on the values $\left\{\psi_d^{(k)}\right\}_{k=1}^{K}$ and weight $\{w_k\}_{k=1}^{K}$. For example, for inference $\psi_{id}^{(k)} = \sum_{k=1}^{K} \psi_{di}^{(k)} w_k$

2.5. Model comparison criterion

2.5.1. Deviance information criterion (DIC)

$$DIC = \overline{D} + p_D \tag{13}$$

where $\overline{D}$ the posterior means of the deviance and p_D the effective number of parameter, i.e.,

$$p_D = E_{\boldsymbol{\psi}|y}[D(\boldsymbol{\psi})] - D\left(E_{\boldsymbol{\psi}|y}[\boldsymbol{\psi}]\right) = \overline{D} - D(\overline{\boldsymbol{\psi}})$$

2.5.2. Watanabe Akaike information criterion (WAIC)

$$WAIC = -2 \sum_{t=1}^{T} \sum_{i=1}^{n} \log E_{\boldsymbol{\psi}|y}\left[f(y_{it}|\boldsymbol{\psi})\right] + 2p_W \tag{14}$$

where

$$p_W = \sum_{t=1}^{T} \sum_{i=1}^{n} Var_{\boldsymbol{\psi}|y}\, log\left[f(y_{it}|\boldsymbol{\psi})\right]$$

The smaller DIC and WAIC correspond to the better model predictive performance.

2.6 Hotspot identification

Spatiotemporal hotspots are identified using exceedance probability criteria [15]. It is estimated as:

$$\widehat{\Pr}(\hat{y}_{it} > c|\mathbf{y}) = 1 - \int_{\hat{y}_{it} \leq c} p(\hat{y}_{it}|\mathbf{y})\, d\hat{y}_{it} \tag{15}$$

where $\int_{\hat{y}_{it} \leq c} p(\hat{y}_{it}|\mathbf{y})$ is the cumulative probability of fitted values $\hat{y}_{it}$ with threshold value c. It can be estimated using the Laplace approximation [16]

3. Modeling Childhood TB in Bandung City

3.1. Data Exploration

The data health data used in this study were obtained from Bandung health office and can be accessed from http://data.bandung.go.id/organization/dinas-kesehatan. It is comprehensive data set of childhood tuberculosis including incidence rate of childhood tuberculosis, malnutrition, healthy behaviour and population density. The statistics descriptive of each variable can be seen in Table 1. The highest incidence rate of childhood TB occurs in 2017 and lowest in 2018 (see Figure 1). It is consistent with malnutrition. The health behaviour index, population density and AFB smear-positive tuberculosis relatively constant over time. and their spatiotemporal distributions are presented in Figure 2.

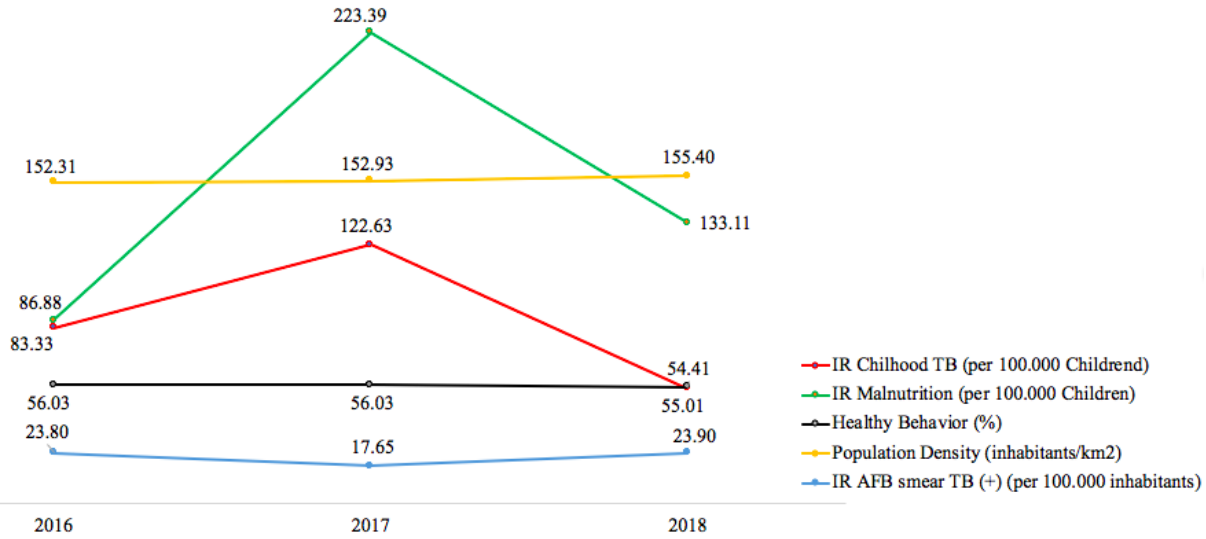

Figure 1. Temporal distribution of childhood TB, malnutrition, population density, healthy behaviors, and AFB smear TB (+)

Table 1. Statistics descriptive

Variables	Statistic	Year		
		2016	2017	2018
Childhood TB	Mean	83.33	122.63	54.41
	Min	17.10	15.53	6.71
	Max	211.70	252.21	141.02
Malnutrition	Mean	86.88	223.39	133.11
	Min	0.00	8.89	17.63
	Max	520.00	1100.63	862.34
Healthy Behavior	Mean	56.03	56.03	55.01
	Min	15.13	15.13	13.13
	Max	83.33	83.33	87.66
AFB smear TB (+)	Mean	23.80	17.65	23.90
	Min	5.33	1.92	9.75
	Max	49.03	37.34	48.59
Population Density	Mean	152.31	152.93	155.40
	Min	37.65	38.00	40.00
	Max	388.17	387.00	394.00

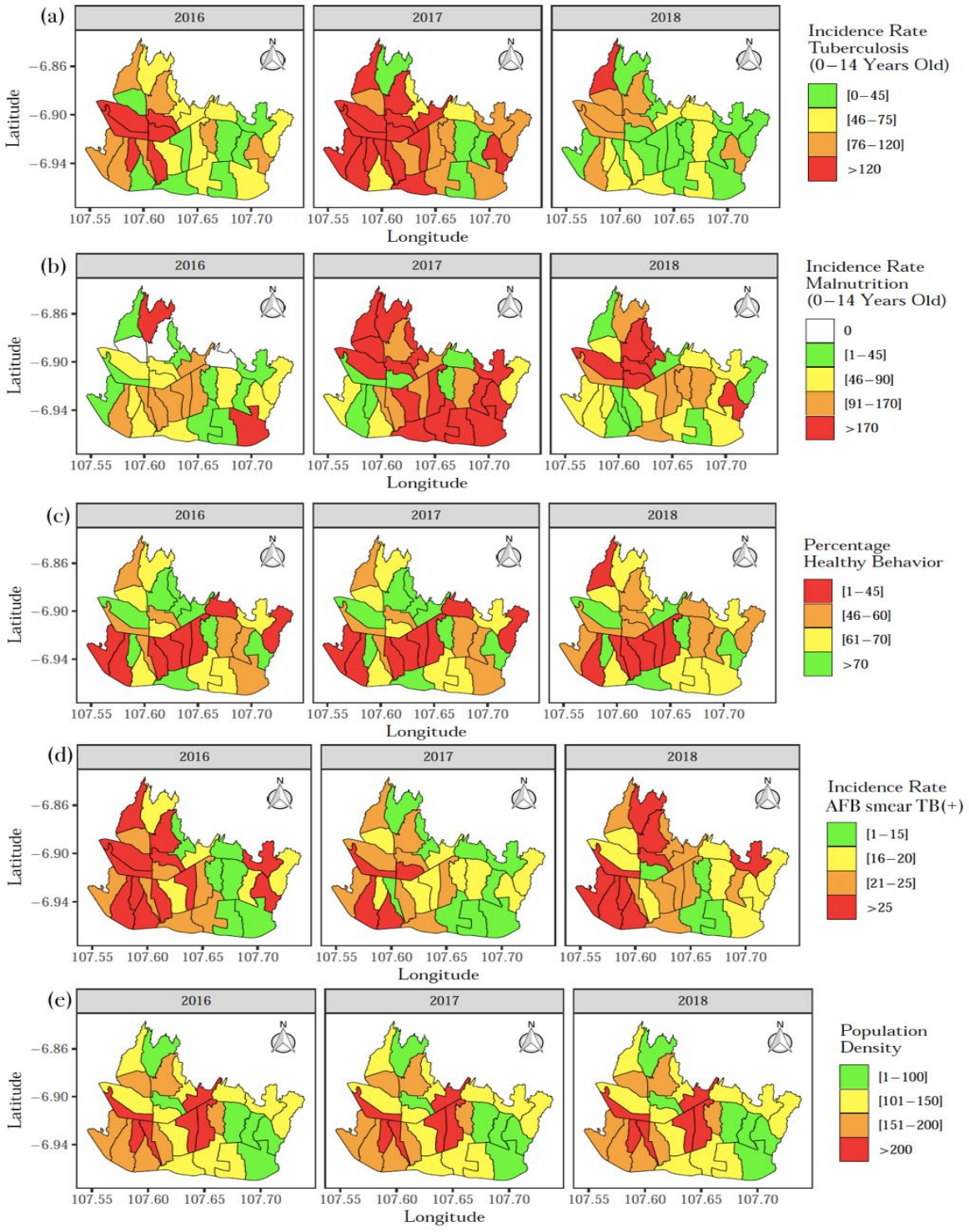

Figure 2. Spatiotemporal distribution of (a) incidence rate childhood TB, (b) incidence rate malnutrition, (c) percentage healthy behaviors, (d) AFB smear smear TB (+), and (c) population density, 2016-2018

Figure 2 (a) shows the incidence rate of childhood TB for 3 years (2016-2018). The incidence rate of childhood TB seems have spatiotemporal clusters. The data of incidence rate of malnutrition in Figure 2 (b) has a similar pattern with the incidence rate of childhood TB. It indicates there is a strong correlation between the incidence rate of childhood TB. The healthy behavior index seems to have a spatiotemporal pattern also. The index was almost similar over 3 years. Figure 2 (d) shows the spatiotemporal pattern of FBA smear TB (+) which is commonly found in adults. The last variable is population density (in Figure 2 (e)) shows there is a similar pattern of population density over 3 years. There is no variation in the population in Bandung city over 3 years.

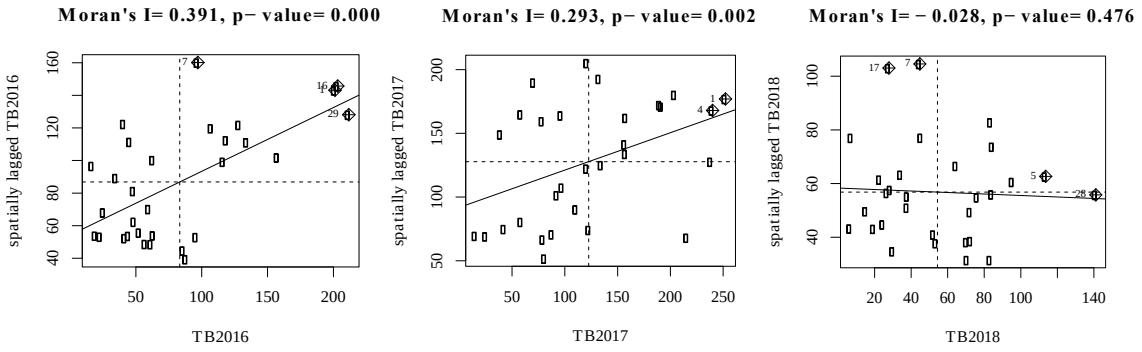

Figure 3. Spatial Moran's I for incidence rate of childhood TB

To evaluate the spatial autoregressive model is a good candidate model for a modeling incidence rate of childhood TB, we estimate the spatial Moran's I and spatiotemporal Moran's I. The spatial Moran's I have high positive values for the period 2016 and 2017. However, negative in 2018. We also considered spatiotemporal Moran's I. We found high positive spatiotemporal autocorrelation 0.494 (p-value =0.002) (see Figure 4). It indicates, there is a strong spatiotemporal autocorrelation in the incidence rate of childhood TB data.

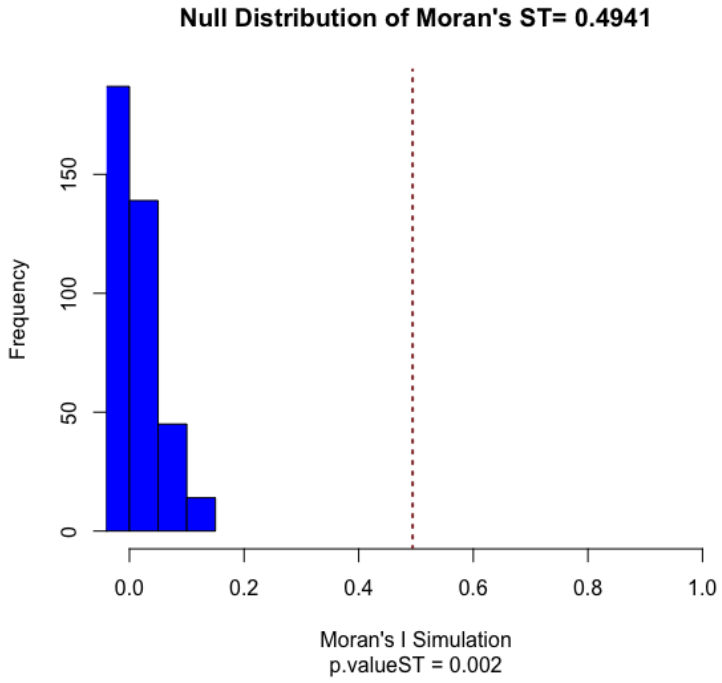

Figure 4. Spatiotemporal Moran's I

3.2. Spatial autoregressive model

We estimate two different models to find the best model for a modeling incidence rate of childhood TB with its risk factors. First, we assume the risk factors have a constant effect on the incidence rate of childhood TB, and second, we considered the constant and temporally coefficients model. We use deviance information criteria (DIC) and Watanabe Akaike information criteria (WAIC) to evaluate the model's predictive performance. The model that has the smallest values of DIC and WAIC will be selected as the best model to explain the effect of risk factors on the incidence rate of childhood TB.

Table 2. Model Comparison

Model	DIC	WAIC
M1: Constant	967.96	968.90
M2: Constant + Temporally varying	923.05	922.14

Table 2 shows the model comparison between the constant-coefficient model and the constant and temporally coefficients model. The second model has the smallest values of DIC and WAIC which indicates the best model is the model with constant and temporally varying coefficients.

The regression coefficients of first and second models are presented in Tables 3 and 4 respectively.

Table 3. Constant coefficients model

	mean	sd	0.025quant	0.5quant	0.975quant
Malnutrition	0.0242	0.0335	-0.0416	0.0241	0.0899
AFB smear TB(+)	-0.9621	0.8007	-2.5341	-0.9621	0.6087
Healthy behaviour	0.6016	0.7022	-0.7771	0.6015	1.9791
Population density	0.4267	0.2648	-0.0932	0.4267	0.9461
Autoregressive coefficient	0.5298	0.0333	0.4804	0.5245	0.6063

Table 4. Constant and temporally coefficients model

	mean	sd	0.025quant	0.5quant	0.975quant
Malnutrition	0.0077	0.0274	-0.0461	0.0077	0.0614
AFB smear TB(+)	0.4522	0.6982	-0.9185	0.4522	1.8218
Healthy behaviour	-0.0399	0.6351	-1.2868	-0.0399	1.2059
Population density (2016)	0.4591	0.2453	-0.0224	0.4591	0.9402
Population density (2017)	0.7253	0.2413	0.2515	0.7253	1.1987
Population density (2018)	0.2738	0.2376	-0.1928	0.2738	0.7399
Autoregressive coefficient	0.5153	0.0362	0.4517	0.5122	0.5932

The regression coefficients of the first and second models have the different sign of impact effects. In the theoretical framework, malnutrition, AFB smear TB(+), and Population density should have positive signs of impact effects, and Healthy behavior should have negative signs. The majority of the signs of impact effects of the first model (constant-coefficient) have wrong signs. Conversely, the model with constant and temporally varying coefficients has a correct sign of impact effects. The result describes that we have to be aware of the model specification to avoid making a wrong conclusion.

3.3 Identifying hotspot

To identify hotspot of the childhood TB in Bandung city, we estimate the posterior exceedance probability with two different thresholds 50 and 100 using the second model.

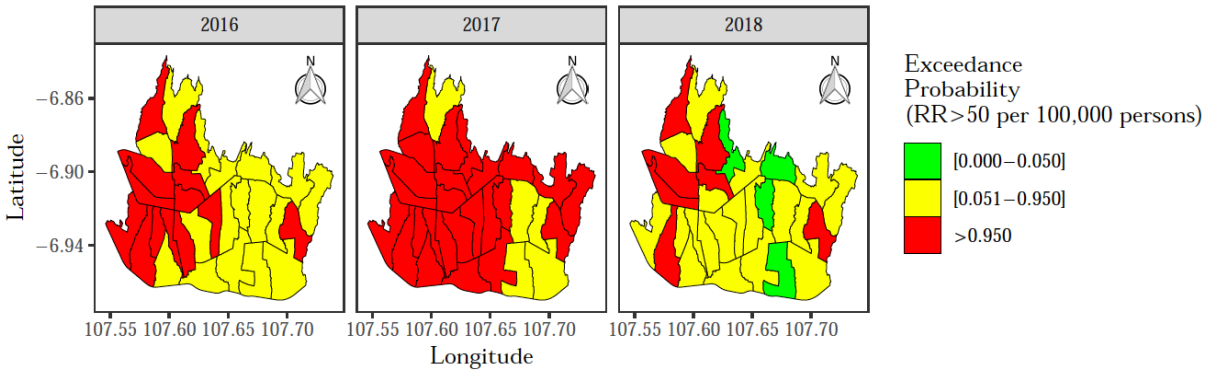

Figure 5. Posterior exceedance probability for $c = 50$

Using threshold $c = 50$, Figure 5 shows the hotspot area in 2016 are found in the northern and western areas of Bandung, and one area in the eastern area. While in 2017 the hotspot area spread to central and eastern Bandung. Majority of districts are categorized as a hotspot. In 2018, the number of hotspots decreased significantly.

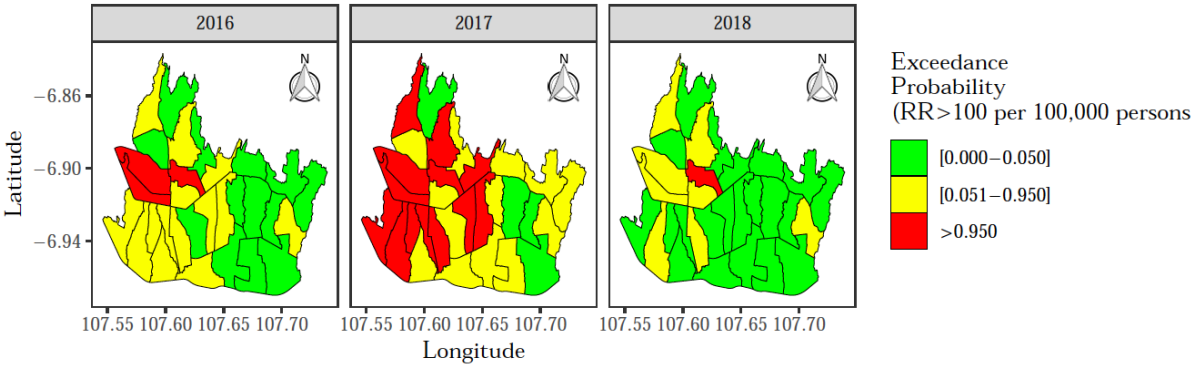

Figure 6. Posterior exceedance probability for $c = 100$

Using threshold $c = 100$, the hotspot area in 2016 are found in the northern and western areas of Bandung. The number of hotspots increased significantly in 2017. The hotspot area spread to the other western areas and central Bandung. Majority of districts are categorized as a hotspot. In 2018, the number of hotspots decreased significantly. Only one district was categorized as hotspot.

Different values of thresholds present different number of hotspot areas. The threshold $c = 50$ should be considered if the government have unlimited resources to control childhood TB and $c = 100$ for limited resources.

4. CONCLUSION

In this paper, a Bayesian spatiotemporal autoregressive model is employed to model spatiotemporal tuberculosis in children 0-14 years old. The models for the data at hand included two components: the first, covariates effects, and the second is an autoregressive effect with spatial autoregressive. We applied INLA using R-INLA for parameter estimation, providing the fast and flexibility to include constant and temporally coefficients. There are a few examples varying coefficients model ([8], [17]).

Our finding can be summarized as follows: we observed high differences between the constant-coefficient and mixed coefficients (constant and temporally varying coefficients) models. The Bayesian spatiotemporal autoregressive model with constant coefficients provides wrong coefficients. The regression coefficients have wrong sign effects with less predictive performance. By considering the mixed coefficients, the model much better with higher predictive performance. The malnutrition, population density, AFB smear TB (+) has a positive impact on tuberculosis, and the healthy behaviour index has a negative impact. It is consistent with the increasing incidence rate of malnutrition, population density, and AFB smear TB (+), leading to an increasing incidence rate of tuberculosis.

Furthermore, increasing the healthy behaviour index will decreasing the incidence rate of tuberculosis. The findings are significant because the constant coefficients model for covariate area statistical method is commonly employed to model incidence rate. We need to be careful to make a wrong model with the constant coefficients due to the temporal heterogeneity.

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CONFLICT OF INTERESTS

The authors declare that there is no conflict of interests.

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