ISSN 2723-6471

Spatial Estimation for Tuberculosis Relative Risk in Aceh Province, Indonesia: A Bayesian Conditional Autoregressive Approach with the Besag-York-Mollie (BYM) Model

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(Received: March 11, 2024; Revised: March 20, 2024; Accepted: April 4, 2024; Available online: May 17, 2024)

Abstract

Tuberculosis (TB) remains a significant public health challenge globally, with Indonesia being the second-highest country in TB cases worldwide. Aceh Province has one of the highest TB incidence rates in Indonesia. This study aims to estimate and map the spatial distribution patterns of TB relative risk across districts in Aceh Province, Indonesia, to reveal significant variations. The study employed an ecological time-series study design, utilizing the Bayesian Conditional Autoregressive (CAR) approach with the Besag-York-Mollie (BYM) model for spatial estimation and mapping of TB relative risk. TB case data and population data for 23 districts/cities in Aceh Province from 2016 to 2022 were analyzed. Spatial analysis was used to estimate and map TB's relative risk, aiding in identifying areas with higher transmission risks. The results showed that the relative risk of TB varied across districts/cities in Aceh Province over the study period. However, Lhokseumawe and Banda Aceh consistently exhibited high to very high relative risks over the years. In 2022, Lhokseumawe City and Banda Aceh City had the highest relative risks by 2.26 and 2.17, respectively, while Sabang City and Bener Meriah District had the lowest by 0.43 and 0.32, respectively. This study provides valuable insights into the heterogeneous landscape of TB risk in Aceh Province, which can inform targeted interventions and planning strategies for effective TB control. Using the Bayesian CAR BYM model proved effective in estimating and mapping TB's relative risk, highlighting areas requiring prioritized attention in TB prevention and control efforts.

Keywords: Tuberculosis, Relative Risk, Bayesian Conditional Autoregressive, Besag-York-Mollie Model, Aceh Province

1. Introduction

Global health issues pose a significant concern, with infectious diseases being a contributing factor to mortality worldwide [1]. TB an infectious disease, remains among the most challenging global health problems [2]. TB is caused by the bacterium Mycobacterium Tuberculosis, and the lungs are the main target of the disease [3]. TB causes severe infection and impaired respiratory function. The spread of TB mainly occurs through direct contact with people with low immunity through infected droplets in the air [4]. TB is mainly preventable and cured. But in 2022, TB killed nearly twice as many people as HIV/AIDS and was the second most common infectious agent worldwide, after coronavirus disease (COVID-19). Each year, more than 10 million people still contract tuberculosis. All member states of the United Nations (UN) and the World Health Organization (WHO) have agreed that immediate action is needed to stop the worldwide tuberculosis epidemic by 2030 [5]. Furthermore, there were 7.5 million newly diagnosed cases of TB worldwide in 2022. At 7.1 million in 2019, above the pre-COVID baseline and up from 5.8 million in 2020 and 6.4 million in 2021, this is the most prominent figure since WHO started global TB monitoring in 1995 [5]. The figure in 2022 most likely includes a sizable backlog of patients who had TB in prior years but whose diagnosis and treatment were postponed due to COVID-related interruptions that hampered their ability to receive and provide medical care [6].

TB is a deadly disease and one of the leading causes of death, especially in developing countries. It is estimated that 1.3 million people will die from TB by 2022 [5]. Although TB is one of the leading causes of death worldwide, TB control efforts continue to face challenges. Several factors affect TB control, including limited resources, inadequate

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DOI: https://doi.org/10.47738/jads.v5i2.185

health infrastructure, and many other prioritized health issues [7]. Since 1947, WHO has made various efforts to control TB. These efforts include using TB drugs and developing service and management programs for TB control to developing the directly observed treatment shortcourse (DOTS) strategy [8].

As a developing country, Indonesia is the second country with the largest TB cases in the world after India [5]. TB cases have spread to all provinces in Indonesia, including Aceh Province, which is located at the western tip of Indonesia. Aceh Province is one of the highest TB incidence rates in Indonesia. The reported coverage of TB suspects receiving standardized TB care in Aceh in 2022 was 36.12%, with a total of 10,896 TB cases. Based on the Aceh Health Profile Report, the cure rate of bacteriologically confirmed pulmonary tuberculosis was 26.8%, the complete treatment rate of all tuberculosis cases was 74.7%, the success rate of all tuberculosis cases was 89.2%, and the number of deaths of tuberculosis cases from data reported during tuberculosis treatment in Aceh province was 3.9% [9]. The incidence of TB in Aceh Province is relatively high due to several factors, such as lack of access to health facilities, poverty levels resulting in limited access to care, and other factors. Aceh Province has varied geographical conditions, from lowlands to mountainous areas, affecting TB's spread. Despite lower population density in mountainous areas, access to health facilities is limited compared to flat areas. In addition, there is significant variation in the number of TB cases and populations at risk across districts in Aceh, with some areas recording high levels of cases and risk and others lower. Therefore, calculating the relative risk of TB in districts/cities is important to understand the variation in the relative risk of TB and identify high-risk areas.

A method often used in epidemiology and public health to evaluate the relative risk of disease in a given population is the standardised morbidity ratio (SMR). SMR is the ratio between the number of disease cases in a population and the expected number of cases in a population [10]. SMR method, an extension of the Poisson regression model, is reliable for areas with large sample sizes but fails to address overdispersion. Overdispersion is the calculation of excessive relative risk, so a more valid approach is needed in estimating the relative risk number [11]. The weakness of SMR in relative risk estimation can be overcome by modeling smoothing and incorporating spatial information into the statistical model. CAR is a statistical technique in disease mapping that models relative risk by taking into account the smoothing of the estimated value of relative risk and incorporating spatial information to reduce the error of the estimated relative risk parameters so that more reliable relative risk estimates will be obtained [12]. Furthermore, CAR is also one of the methods that can overcome overdispersion problems by selecting appropriate prior parameters in disease mapping [11].

Disease mapping is a growing study in spatial epidemiology, and it is used to assess the status of an area with disease incidence [13]. One way to see the location of disease distribution is to use spatial analysis [14]. It aims to categorize diseases to examine potential environmental hazards to the population [15]. The assessment of relative risk using the SMR method has been carried out by [16] to see the variation in the risk of TB disease in Indonesia. This study used a large sample size, namely the number of TB cases in Indonesia, so accurate and significant SMR values could be produced. Next, a study used SMR to examine the relationship between healthcare resources and mortality in 3,360 Japanese cities [17]. However, this study used a smaller sample size, namely the number of TB cases in each district/city in Aceh Province, so the estimated relative risk based on the SMR method was less reliable and allowed overdispersion. Therefore, the CAR method is an optimal alternative for estimating relative risk by incorporating spatial information into the model.

This approach was used successfully in a study to identify provinces in Turkey with a high risk of death from respiratory diseases [18]. In addition, a study has also successfully estimated the disease relative risk of dengue fever for districts in Aceh Province [19]. Previous, a study conducted research on TB cases in Banyumas Regency by comparing three models, namely the bayesian conditional autoregressive besag-york-mollie (CAR-BYM), generalised poisson (GP) and negative binomial (NP) models. Based on the performance evaluation metric through the study's root means square error (RMSE), it was decided that Bayesian CAR-BYM produced the most accurate accuracy to become the best model [20]. Based on this basis, the CAR BYM model was used in this study. A similar study has been conducted to identify and map the relative risk area of malaria disease spread in Malaysia through relative risk estimation generated from the CAR BYM model. The result is that the BYM CAR model can estimate the relative risk of malaria disease in Malaysia well [21]. Furthermore, this study aims to provide a concise overview of the objectives and methodologies, focusing on estimating the relative risk of TB across districts in Aceh Province, Indonesia, using the Bayesian CAR approach

with the BYM model, and mapping the distribution patterns of TB relative risk. The study results can offer insights into potential variations in TB relative risk within Aceh Province.

2. Literature Review

2.1. CAR

CAR is a disease mapping technique that models relative risk by considering the smoothing of estimated relative risk values. CAR distributions have been used to account for spatial autocorrelation in small areal data [22]. This method incorporates spatial information by reducing the error of the estimated relative risk parameters to obtain a more reliable relative risk value [23]. This method can also overcome overdispersion problems with the selection of appropriate priors. CAR models are the first-order gaussian markov random field (GMRF) models on a 2 dimensional plane [24]. Furthermore, in Bayesian CAR, the term Bayesian refers to smoothing models, while CAR refers to models allowing spatial information into modeling.

2.2. BYM

Prior distributions must be specified for the precision parameters τ_v^2 and τ_u^2 in calculating the Relative Risk. It is followed by consideration of the gamma distribution (0.5, 0.0005), which yields a probability of 99% for both parameters. It is then incorporated into the BYM model developed by [25], which is formulated as follows:

$$y_i \sim \text{Poisson}\,(E_i\theta_i) \tag{1}$$

$$\log(\theta_i) = \mu + v_i + u_i \tag{2}$$

The expected value of yi is denoted by $E_i\theta_i = \mu$, which is obtained by multiplying the total population at risk by the probability of one case in each district. To obtain μ, the BYM model without covariates can solve this problem. In estimating the relative risk, Bayesian modeling requires the specification of the prior distribution by combining the structured random effect (v_i) with the spatially unstructured random effect (u_i) into a log-linear model [26]–[28]. In the Bayesian CAR BYM model, the structured random effect (v_i) accounts for spatial correlation among neighboring areas, while the unstructured random effect (u_i) captures area-specific variations. The model is expressed as $\log(\theta_i) = \mu + v_i + u_i$, where θ_i is the relative risk for area i, μ is the overall mean, v_i is the spatially structured random effect, and u_i is the unstructured random effect.

For the structured random effect (v_i), it is geographically independent and assumed to be normally distributed with mean equal to zero and variance τ_v^2:

$$v_i = N(0, \tau_v^2) \tag{3}$$

In unstructured random effects (u_i), the parameter value of a region is influenced by the average value of neighboring calculated areas using the formulation:

$$[u_i[u_j, i \neq j, \tau_v^2] \sim N(\bar{u}_i, \tau_v^2) \tag{4}$$

with the average of the i-th neighborhood

$$\bar{u}_i = \frac{1}{\sum_j \omega_{ij}} \sum_j u_j\, \omega_{ij} \tag{5}$$

$$\tau_i^2 = \frac{\tau_u^2}{\sum_j \omega_{ij}} \tag{6}$$

In the Bayesian approach, a simulation method is required to produce a value approximating the posterior distribution's mean value [29]. In this study, the method used is the monte carlo markov chain (MCMC) method, a combination of the monte carlo and markov chain methods. Monte carlo is a method for approximating a value obtained from the results of iterations or repetitions and the average results of several simulations.

2.3. Markov Chain Monte Carlo

The MCMC method is a sample simulation method using Markov chain properties to produce a value approximating the posterior distribution's mean value [6]. In the Bayesian framework, the parameters utilized are variable and do not remain constant; instead, they are modeled as random variables that adhere to a specific distribution [30]–[32]. The parameters' description is acquired by determining the posterior distribution [33]–[35]. With the observed data denoted by $y = y_i$ and the relative risk value $\theta = \theta_i$, to find the value of θ_i, we first need to find the value of $\theta_i|y$ through the following equation:

$$p(\theta_i|y) = \iiint \dots \int p(\theta_1, \theta_2, \dots, \theta_n|y)\, d\theta_{(-i)} \quad (7)$$

This equation represents the calculation of the posterior probability $p(\theta_i|y)$ of parameter θ_i based on data y in Bayesian statistics. The double integral is used to integrate all parameters except $\theta_{(-i)}$ from the joint probability distribution $p(\theta_1, \theta_2, \dots, \theta_n|y)$ to obtain the posterior probability distribution for θ_i. Monte Carlo is a method for approximating a value obtained from iterations and averaging results from multiple simulations. The MCMC method was chosen for its ability to efficiently sample from complex posterior distributions in Bayesian models, particularly when dealing with high-dimensional parameter spaces and intricate spatial dependencies, making it well-suited for the Bayesian CAR BYM model used in this study.

2.4. Relative Risk

Relative risk is the ratio of the risk of developing a particular disease or health condition between exposed and unexposed groups. Relative risk indicates how often the risk of developing a disease in the exposed population is compared to the unexposed population [7]. In its development in spatial epidemiology, relative risk is used in disease mapping to identify locations at high risk of disease. The relative risk of disease spread in each district/city was classified into five categories: 1) $0 \leq \theta_i < 0{,}49$, meaning the relative risk of disease spread in region i is very low; 2) $0{,}5 \leq \theta < 0{,}99$, meaning the relative risk of disease spread in region i is low; 3) $1 \leq \theta_i < 1{,}49$, meaning that the relative risk of disease spread in region i is moderate; 4) $1{,}5 \leq \theta_i < 1{,}9$, meaning that the relative risk of disease spread in region i is high; and 5) $\theta_i \geq 2$, meaning that the relative risk of disease spread in region i is very high [19], [21]. These categories help in identifying areas with different levels of TB transmission risk, guiding targeted TB control efforts to prioritize regions with higher risk levels for interventions such as enhanced surveillance, vaccination campaigns, and improved access to healthcare services.

3. Method

3.1. Desain Study and Data Source

In this study, statistical analysis is used to ensure that the findings can be applied to a broader dataset [36], [37], [38]. This study used an ecological time series study. In health statistics fields such as biostatistics and epidemiology, ecological time-series study analyses health data over time within a given population or area. This study design aims to identify relationships, detect trends, and inform public health interventions by examining temporal patterns of disease rates in relation to certain factors. The study collects longitudinal data at regular intervals to understand how health indicators change over time and identify factors that influence population health dynamics. Furthermore, the data for this study consisted of the number of TB cases and the total population of 23 districts/cities in Aceh Province sourced from the Aceh Health Profile report from 2016 to 2022.

3.2. Stages of Data Analysis

Data analysis was performed using Rstudio 4.2.2, OpenBugs 3.2.3 and QGIS 3.28.3 software. Rstudio 4.2.2 served as the primary platform for data preprocessing and statistical analysis. It was used to organize and clean the TB case data and population data, as well as to perform initial descriptive analyses such as calculating means, standard deviations, and interquartile ranges. OpenBugs 3.2.3 was utilized to implement the Bayesian CAR BYM model for spatial analysis. It was used to run MCMC simulations to estimate the parameters of the model and to obtain the posterior distributions of the relative risk values for each district. OpenBugs allowed for the incorporation of spatial autocorrelation and overdispersion in the model, providing more accurate and reliable estimates of TB relative risk. QGIS 3.28.3 played a

 ISSN 2723-6471

crucial role in the spatial visualization and mapping of the TB relative risk across Aceh Province. It was used to create thematic maps that display the distribution patterns of TB relative risk, highlighting areas with higher transmission risks. QGIS facilitated the interpretation of the results by providing a geographical context, allowing for the identification of high-risk districts that require targeted interventions for effective TB control.

Furthermore, initial analysis was carried out descriptively using the maximum value, minimum value, mean, standard deviation, and interquartile to provide an overview of the centeredness and variation of the data. These analyses were used to understand the essential characteristics of the data and the information in the data [39]–[41]. In the simulation stage, this study uses a spatial weighting matrix with the Queen Contiguity method to determine the neighborhood relationship between regions. It conducts relative risk analysis using the Bayesian CAR approach with the BYM prior model to estimate the relative risk value in each area from the average sample generated through the MCMC simulation process with the Gibbs Sampling algorithm.

In the Gibbs Sampling algorithm, the value of each parameter or sample, namely $\Theta = \{\theta_i\}$ with i = 1,2, ... n, is obtained from the j[th] iteration's results, denoted by $\theta_i^{(i)}$. According to [19], [29], the steps of the Gibbs Sampling algorithm are as follows: First, determine a vector of initial sample values $\theta^{(0)} = (\theta_1^{(0)}, \theta_2^{(0)}, \dots, \theta_n^{(0)})$; second, find the full conditional distribution for each sample, i.e. the conditional distribution of $\theta_i; i = 1, 2, \dots, n$ given all samples other than θ_i and denoted as $p(\theta_i|\theta_{(-i)})$; finally, iterate over each sample j times using the full conditional distribution for each sample. For more details, the first iteration of this algorithm is:

$$\text{the sample } \theta_1^{(1)} \text{ is obtained from } p\left(\theta_1 \middle| \theta_2^{(0)}, \theta_3^{(0)}, \dots, \theta_n^{(0)}\right). \quad (8)$$

$$\text{the sample } \theta_2^{(1)} \text{ is obtained from } p\left(\theta_2 \middle| \theta_1^{(1)}, \theta_3^{(0)}, \dots, \theta_n^{(0)}\right). \quad (9)$$

$$\vdots$$

$$\text{the sample } \theta_n^{(1)} \text{ is obtained from } p\left(\theta_n \middle| \theta_1^{(1)}, \theta_2^{(1)}, \theta_3^{(1)}, \dots, \theta_{n-1}^{(1)}\right). \quad (10)$$

After iterating j times, we obtained $\theta_1^{(j)}, \theta_2^{(j)}, \dots, \theta_n^{(j)}$ that approached the mean value of the posterior distribution. Next, the convergence of relative risk parameters through parameter diagnostic plots will be evaluated to determine the validity of the results in each district/city using density plots, autocorrelation plots, and history plots. Next, there are two stages in the subsequent step. Firstly, the tuberculosis (TB) relative risk in Aceh Province was calculated using data from each district/city. Secondly, determining relative risk mapping from 2016 to 2022 in districts/cities grouped based on their relative risk category. The Gibbs Sampling algorithm iteratively updates each parameter θ_i in the model by sampling from its conditional distribution given the current values of all other parameters, thus generating a sequence of samples that approximate the posterior distribution. This process is repeated for a large number of iterations to ensure convergence to the target distribution.

4. Result and Discussion

4.1. Descriptive Statistics

Table 1 presents a descriptive analysis of TB cases and population data in Aceh Province from 2016 to 2022. The Table showed the trend of TB cases in Aceh Province from 2016 to 2022, providing a clearer picture of the situation and aiding in understanding the significance of the study. This table aims to provide insights into the distribution and variation of TB cases across different districts/cities within the province, as well as the corresponding population figures.

 ISSN 2723-6471

Table 1. Descriptive analysis of TB cases and Population in Aceh Province 2016-2022

		Tuberculosis					Population				
No	**Districts/cities**	**Min**	**Max**	**Mean**	**SD**	**IQR**	**Min**	**Max**	**Mean**	**SD**	**IQR**
1	Simeulue	80	203	158.28	47.30	79	90,291	97,524	93,304	2,359.23	3,504
2	Aceh Singkil	67	228	161.42	59.86	113	116,712	130,787	124,523	43,084.87	7,799
3	South Aceh	246	755	397.71	168.30	134	228,603	248,511	235,948	6,438.27	6,188
4	Southeast Aceh	58	347	163.85	93.97	113	204,468	228,308	218,005	74,376.75	16,658
5	East Aceh	370	818	541.77	160.60	242	419,594	448,347	432,794	10,175.97	18,878
6	Central Aceh	136	266	178.85	42.67	42	200,412	222,673	212,360	7,719.82	13,763
7	West Aceh	184	311	238.28	50.10	105	194,712	215,294	203,045	7,258.89	12,192
8	Aceh Besar	326	483	390.71	55.48	90	390,037	436,212	411,645	140,581.20	24,303
9	Pidie	463	1,147	669.71	246.04	317	425,974	458,330	440,270	148,099.70	12,377
10	Bireuen	418	876	739.14	154.11	119	436,418	483,716	453,016	17,999.13	33,020
11	North Aceh	175	1,282	865.00	380.47	576	583,350	636,641	607,554	269,263.40	25,915
12	Southwest Aceh	18	658	327.42	220.43	117	143,312	155,966	150,385	4,581.56	9,320
13	Gayo Lues	105	226	176.42	40.17	50	89,500	103,131	96,192	47,495.42	8,913
14	Aceh Tamiang	150	573	370.85	143.73	192	282,921	304,273	294,201	100,340.90	14,485
15	Nagan Raya	123	385	212.28	90.56	124	158,223	173,393	167,126	5,456.52	9,718
16	Aceh Jaya	101	212	151.71	37.98	66	87,622	97,338	92,468	3,465.41	6,410
17	Bener Meriah	23	107	70.14	28.02	42	13,989	16,869	153,233	67,346.14	18,816
18	Pidie Jaya	65	199	137.85	651.29	93	151,472	165,397	159,166	4,757.71	7,976
19	Banda Aceh	379	1,115	739.42	253.03	416	244,689	280,231	260,085	11,777.01	17,422
20	Sabang	9	48	26.71	13.59	20	33,622	43,208	37,710	4,213.87	8,037
21	Langsa	241	485	342.57	103.24	198	16,882	19,263	180,803	79,597.01	14,858
22	Lhokseumawe	293	861	530.42	209.43	351	188,713	213,107	198,283	67,960.07	15,806
23	Subulussalam	72	416	197.85	106.80	71	77,084	95,199	84,597	6,510.90	12,026

The descriptive analysis of TB cases and population data in Aceh Province from 2016 to 2022 offers valuable insights for public health planning and intervention. The table 1 illustrates the variability in TB burden across different districts/cities, with a wide range of minimum and maximum TB cases recorded. For instance, South Aceh exhibits a relatively high TB burden with a maximum of 755 cases, whereas Sabang reports a maximum of only 48 cases. The mean values further highlight the districts with average TB cases, such as East Aceh with a mean of 541.77 cases, and Sabang with a mean of 26.71 cases. The standard deviation (SD) and interquartile range (IQR) metrics provide additional context on the variability of TB cases within each district. A higher SD, as seen in North Aceh (380.47), indicates greater fluctuations in TB case numbers over the years, whereas a lower SD, like in Simeulue (47.30), suggests more stable case counts. The IQR values help to understand the spread of the middle 50% of the data, with smaller IQRs indicating more consistency in TB case counts.

Comparing the TB case data with population figures reveals important patterns. Districts with larger populations, such as Banda Aceh and Aceh Besar, tend to have higher absolute numbers of TB cases. However, when considering the TB cases relative to population size, districts like North Aceh and Pidie stand out with higher TB case counts per capita, indicating a more pronounced TB burden in these areas. The implications of this analysis are multifaceted. Districts with both high TB case counts and high variability (e.g., North Aceh) may require more dynamic and responsive healthcare strategies to manage TB effectively. These areas might benefit from increased funding for TB control programs, enhanced surveillance systems, and targeted community outreach efforts to improve TB detection and treatment adherence. On the other hand, districts with lower and more consistent TB case counts (e.g., Sabang) might focus on maintaining their TB control measures and preventing any potential increase in TB incidence.

 ISSN 2723-6471

4.2. Spatial Analysis

In this study, the spatial effect that describes the weight of a region is considered based on neighboring areas with surrounding areas determined by Queen Contiguity. The spatial effect determined by Queen Contiguity is a fundamental concept in various research domains, particularly in spatial analysis and geographic studies [42]. Researchers have applied Queen Contiguity in diverse contexts. In the realm of public health, Queen Contiguity has been applied to analyze the spread of diseases

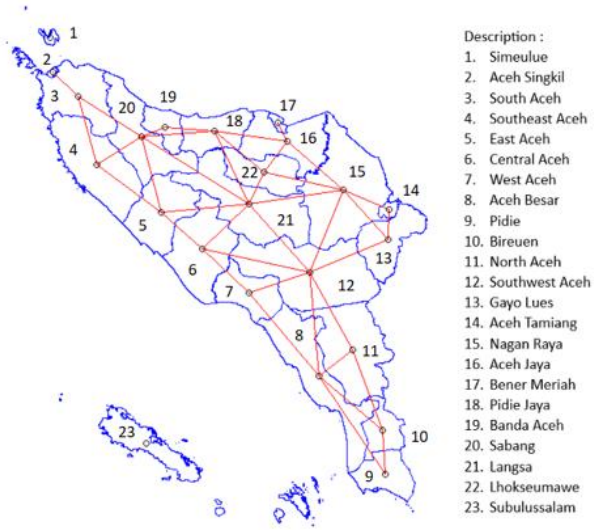

Figure 1. Map of neighborhood relations between districts/cities in Aceh Province

The connected red straight lines in figure 1 show the neighborhood relationship of each district or city. Neighboring regions have a weighting matrix with a value of 1, and non-neighboring regions have a value of 0 [43]. Furthermore, the number of neighbourhoods of each district/city which illustrates the relationship between districts/cities in Aceh Province is shown in table 2.

Table 2. Neighborhood relations between districts/cities in Aceh Province

No	Districts or cities	Neighboring districts or cities	Neighbors
1	Sabang	-	0
2	Banda Aceh	Aceh Besar	1
3	Aceh Besar	Banda Aceh, Aceh Jaya, Pidie	3
4	Aceh Jaya	West Aceh, Pidie, Aceh Besar	3
5	West Aceh	Aceh Jaya, Nagan Raya, Pidie, Central Aceh	4
6	Nagan Raya	West Aceh, Southwest Aceh, Gayo Lues, Central Aceh	4
7	Southwest Aceh	Nagan Raya, South Aceh, Southeast Aceh Tenggara, Gayo Lues	4
8	South Aceh	Southwest Aceh, Aceh Singkil, Subulussalam, Southeast Aceh	4
9	Aceh Singkil	South Aceh, Subulussalam	2
10	Subulussalam	South Aceh, Aceh Singkil, Southeast Aceh	3
11	Southeast Aceh	Southeast Aceh, South Aceh, Subulussalam, Gayo Lues	4
12	Gayo Lues	Nagan Raya, Southeast Aceh, Southeast Aceh, Aceh Tamiang, East Aceh, Central Aceh	6
13	Aceh Tamiang	Gayo Lues, Langsa, East Aceh	3

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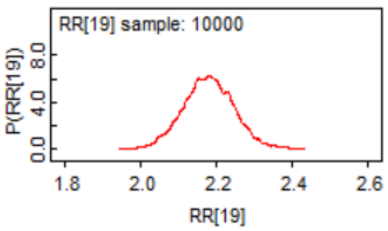
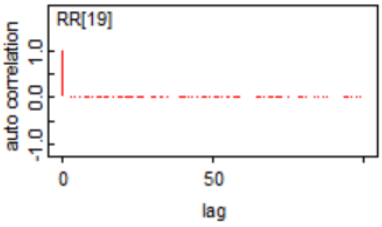
14	Langsa	Aceh Tamiang, East Aceh	2
15	East Aceh	Gayo Lues, Aceh Tamiang, Langsa, North Aceh, Central Aceh, Bener Meriah	6
16	North Aceh	East Aceh, Lhokseumawe, Bireuen, Bener Meriah	4
17	Lhokseumawe	North Aceh	1
18	Bireuen	North Aceh, Pidie Jaya, Pidie, Central Aceh, Bener Meriah	5
19	Pidie Jaya	Bireuen, Pidie	2
20	Pidie	Aceh Jaya, Aceh Besar, West Aceh, Bireuen, Pidie Jaya, Central Aceh	6
21	Central Aceh	West Aceh, Nagan Raya, Gayo Lues, East Aceh, Bireuen, Pidie, Bener Meriah	7
22	Bener Meriah	East Aceh, North Aceh, Bireuen, Central Aceh	4
23	Simeulue	-	0

4.3. Relative Risk Estimation

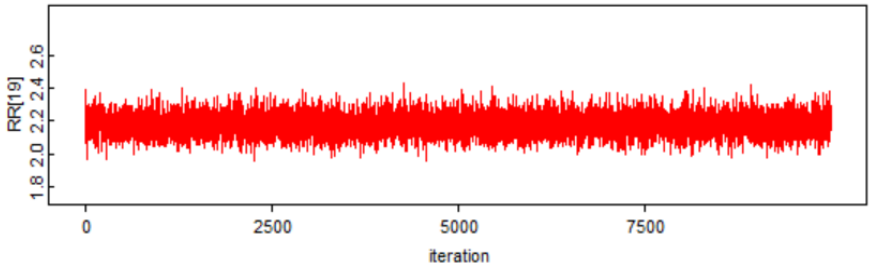
The parameter estimation process was carried out using OpenBUGS software. The results are the relative risk values of the simulation results generated using the Gibbs Sampling algorithm. To get good parameter for estimation results, it is necessary to check the convergence of each parameter. The review of the convergence of each parameter can be seen based on the diagnostic plot of the estimated parameter results. Spatial parameter estimates are obtained through the posterior distribution, with parameter sampling performed using the MCMC method with Gibbs Sampling. The results obtained in the Bayesian CAR method with the BYM model must fulfill 3 Markov chain properties, namely irreducible, aperiodic, and recurrent. These properties can be seen from the history, autocorrelation, and density plot results. Before estimating parameters, the convergence of spatial parameters will be shown through the plot results of the values obtained at each iteration with 10,000 iterations.



(a) Density Plot



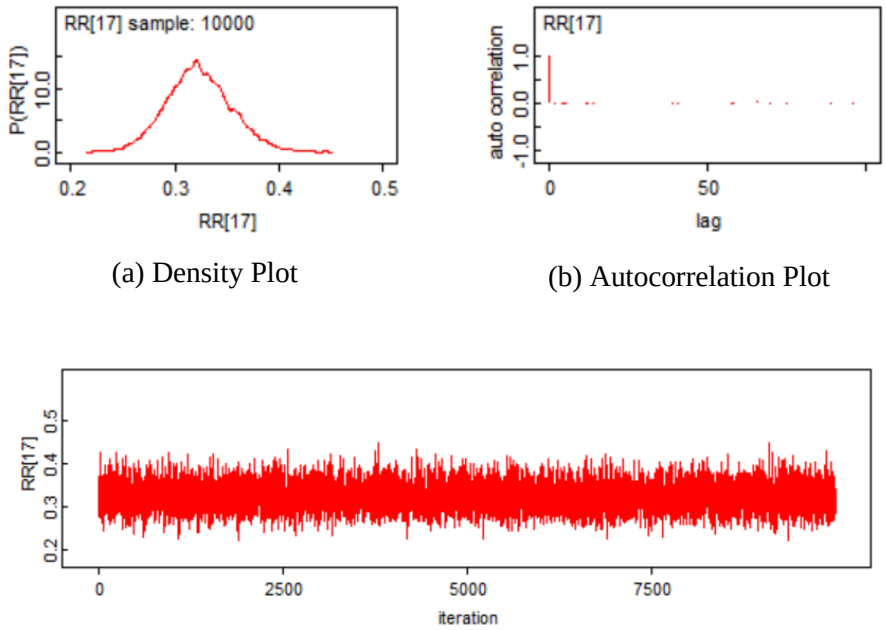
(b) Autocorrelation Plot



(c) History Plot

Figure 2. The diagnostic plot of relative risk parameters of Lhokseumawe City

 ISSN 2723-6471



(a) Density Plot

(b) Autocorrelation Plot

(c) History Plot

Figure 3. Diagnostic plot of relative risk parameters of Bener Meriah District

For instances of the analysis results, Lhokseumawe City and Bener Meriah District were chosen to show that the results for 23 districts/cities fulfilled 3 Markov chain properties. Based on the density plot in figure 2 (a) and 3(a), the distribution of sample values generated in each district/city tends to approach the normal distribution. The distribution pattern close to the normal distribution indicates that the MCMC process has good convergent properties [44]. Based on the autocorrelation plot in figure 2 (b) and figure 3 (b), it can be seen that the first lag approaches the value of one, and the subsequent lags decrease towards zero. It indicates a weak correlation between the generated sample values [45]. Next, the results of the history plot of the MCMC process on 2 (c) and 3 (c) carried out in each district/city are stationary. Furthermore, its figure aids readers in knowing of visualizing the spatial distribution patterns of TB relative risk across the province at iteration time.

All generated samples fall within a specific domain interval. Furthermore, the history plot demonstrates rapid mixing and the ability to capture all potential parameter values, thereby satisfying the irreducibility criterion. The plot also indicates that the generated values do not exhibit any particular periodicity, meaning the MCMC process adheres to the aperiodic property. Additionally, the parameter value produced in state-i can return to state-i, ensuring that the MCMC iteration process meets the recurrence criterion. Therefore, the relative risk parameter has reached convergence by the 10,000th iteration [45].

4.4. Relative Risk Trend Analysis

The analysis of the relative risk of TB in Aceh Province from 2016 to 2021, as depicted in table 3, presents a comprehensive narrative of the epidemiological landscape in the region. In 2016, Banda Aceh, with a relative risk of 2.73, was identified as the highest-risk district, setting a precedent for the following years. It was closely followed by other districts, such as Gayo Lues and Lhokseumawe, which also exhibited high relative risks. On the other hand, North Aceh and Southwest Aceh displayed much lower relative risks, indicating a varied distribution of TB risk across the province.

 ISSN 2723-6471

Table 3. The relative risk of TB in districts/cities of Aceh Province 2016-2022

No	Districts/cities	Relative Risk					
		2016	2017	2018	2019	2020	2021
1	Simeulue	0.92	0.89	0.82	0.90	0.72	0.83
2	Aceh Singkil	1.60	1.38	0.89	1.04	0.55	0.41
3	South Aceh	1.29	1.03	1.01	0.97	0.88	1.29
4	Southeast Aceh	1.19	0.56	0.25	0.38	0.20	0.56
5	East Aceh	1.10	0.70	0.54	0.81	0.99	1.12
6	Central Aceh	0.95	0.49	0.51	0.53	0.65	0.53
7	West Aceh	1.11	0.75	0.74	0.91	0.96	0.66
8	Aceh Besar	0.97	0.67	0.77	0.60	0.63	0.63
9	Pidie	1.30	0.80	0.70	1.12	0.99	1.22
10	Bireuen	1.13	1.16	1.18	1.12	1.25	1.17
11	North Aceh	0.35	1.53	1.33	0.90	0.93	0.82
12	Southwest Aceh	0.18	0.74	1.98	0.84	1.12	1.22
13	Gayo Lues	2.58	1.53	1.03	1.31	0.78	1.20
14	Aceh Tamiang	0.63	0.73	1.21	0.90	0.65	1.14
15	Nagan Raya	1.20	0.80	0.66	1.06	0.55	0.83
16	Aceh Jaya	0.14	1.09	1.27	1.40	1.20	0.95
17	Bener Meriah	0.63	0.30	0.09	0.29	0.46	0.32
18	Pidie Jaya	0.83	0.78	0.70	0.78	0.32	0.41
19	Banda Aceh	2.73	2.19	1.81	2.29	1.10	1.67
20	Sabang	0.50	1.01	0.50	0.60	0.38	0.32
21	Langsa	1.70	1.06	1.49	1.42	0.98	1.28
22	Lhokseumawe	2.24	1.18	2.19	1.79	1.14	2.13
23	Subulussalam	0.92	0.89	0.82	0.90	0.72	0.83

Over the years, a dynamic pattern emerged, with some districts showing notable fluctuations in their relative risk levels. For instance, Aceh Singkil's relative risk significantly decreased from 1.60 in 2016 to 0.41 in 2021, demonstrating substantial progress in TB control. Similarly, Southeast Aceh's relative risk dramatically dropped from 1.19 in 2016 to 0.20 in 2020, highlighting the effectiveness of interventions in the area. By 2021, the landscape of TB risk had evolved further. Banda Aceh remained a high-risk district, while Lhokseumawe experienced an increased relative risk, becoming the highest-risk area that year. In contrast, districts like Bener Meriah and Aceh Jaya showed consistent improvements in TB control, with relatively low risks.

The comparative analysis reveals distinct patterns across the province. High-risk districts such as Banda Aceh and Lhokseumawe require sustained attention and targeted interventions to control the spread. Meanwhile, districts like Aceh Singkil and Southeast Aceh have shown significant improvements and serve as examples of successful TB control efforts. Fluctuations in relative risk levels in districts like South Aceh emphasize the need for continuous monitoring and adaptable strategies to address the changing dynamics of TB. Additionally, consistently low-risk districts like Bener Meriah demonstrate the effectiveness of TB control measures and highlight the potential for maintaining low TB incidence.

Table 4 presents the relative risk of TB in different districts of Aceh Province in 2022, providing valuable insights into the regional distribution of TB risk. Lhokseumawe and Banda Aceh emerge as high-risk areas, with relative risk values of 2.26 and 2.17, respectively, categorizing them as very high-risk districts. These findings suggest a concentrated burden of TB in these districts, warranting targeted interventions to mitigate the spread of the disease. In contrast, districts such as Sabang and Bener Meriah exhibit very low relative risks of 0.43 and 0.32, respectively, indicating successful TB control measures. These districts serve as examples of effective TB control strategies that can be replicated in other regions.

Table 4. The relative risk of TB cases in Aceh Province in 2022

No	Districts/Cities	Relative Risk	Confidence Interval (95%)	Category
1	Lhokseumawe	2.260	2.112 - 2.413	Very High
2	Banda Aceh	2.179	2.053 - 2.308	Very High
3	South Aceh	1.600	1.488 - 1.716	High
4	Pidie	1.301	1.228 - 1.378	Moderate
5	Langsa	1.263	1.154 - 1.378	Moderate
6	Nagan Raya	1.121	1.012 - 1.234	Moderate
7	Gayo Lues	1.103	0.965 - 1.251	Moderate
8	Bireuen	0.995	0.931 - 1.063	Low
9	East Aceh	0.952	0.888 - 1.019	Low
10	Simeulue	0.874	0.850 - 0.898	Low
11	Subulussalam	0.874	0.850 - 0.898	Low
12	Southwest Aceh	0.858	0.758 - 0.962	Low
13	North Aceh	0.835	0.784 - 0.887	Low
14	Southeast Aceh	0.768	0.690 - 0.851	Low
15	Aceh Singkil	0.760	0.658 - 0.869	Low
16	Aceh Tamiang	0.756	0.688 - 0.827	Low
17	Aceh Jaya	0.754	0.637 - 0.880	Low
18	West Aceh	0.721	0.641 - 0.806	Low
19	Central Aceh	0.607	0.537 - 0.681	Low
20	Aceh Besar	0.535	0.487 - 0.586	Low
21	Pidie Jaya	0.519	0.444 - 0.600	Low
22	Sabang	0.433	0.309 - 0.577	Very Low
23	Bener Meriah	0.323	0.265 - 0.386	Very Low

the findings from table 4 underscore the importance of targeted, evidence-based interventions to reduce the burden of TB in Aceh Province. Public health authorities can make significant strides toward achieving TB control targets in the region by addressing the specific needs of high-risk areas and building on the successes of low-risk districts.

4.5. Relative Risk Mapping of TB in Aceh Province

The mapping of the relative risk of TB in Aceh Province was conducted. Figure 4 presents the distribution of TB and its relative risk in Aceh Province, as estimated using the BYM CAR model.

 ISSN 2723-6471

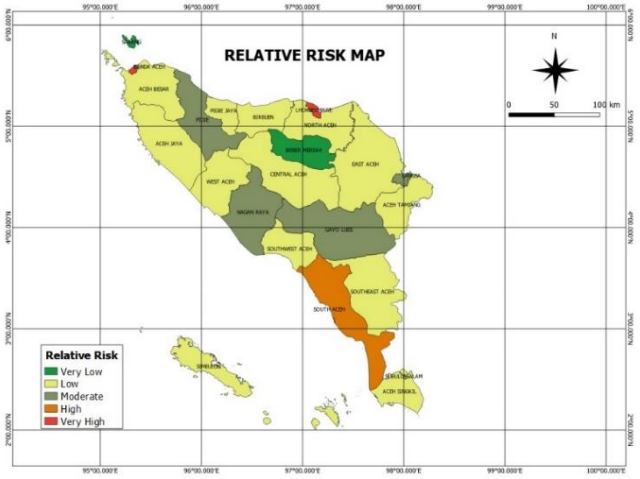


Figure 4. Map of relative risk distribution of TB cases in Aceh Province 2022

Figure 4 shows map of the relative risk distribution of TB cases in Aceh Province in 23 districts/cities in 2022, showing that areas with very high and high relative risk are marked in red and orange colors, namely Lhokseumawe City, Banda Aceh City, and South Aceh District. There are four districts/cities with a moderate category marked with dark brown color: Pidie District, Langsa City, Nagan Raya District, and Gayo Lues District. In contrast, areas with relatively low and very low risk are colored yellow and green.

Furthermore, the chosen Bayesian CAR approach with BYM model, has several strengths and limitations. One of the main strengths of this methodology is its ability to incorporate spatial autocorrelation in the estimation of relative risk, which is crucial for disease mapping studies where the risk of disease in one area may be correlated with the risk in neighboring areas. The Bayesian framework of the CAR BYM model allows for the incorporation of prior knowledge and uncertainty in the model parameters, leading to more robust and reliable estimates. Additionally, the BYM model effectively addresses the issue of overdispersion commonly encountered in disease count data, providing more accurate estimates of relative risk. However, the methodology also has limitations. The computational complexity of the Bayesian CAR BYM model, particularly when implementing MCMC simulations, can be challenging and time-consuming. This complexity requires a good understanding of Bayesian statistics and computational techniques. Additionally, the choice of prior distributions and hyperparameters in the Bayesian framework can significantly influence the results, requiring careful consideration and sensitivity analysis.

5. Conclusion

Based on the estimation of the TB relative risk using the Bayesian CAR BYM model applied to TB case data and population data spanning from 2016 to 2022, it shows variations in the level of risk in each district/city. Banda Aceh City had the highest risk in 2016 at 2.73, while Bener Meriah District had the lowest risk in 2018 at 0.09. In 2022, Lhokseumawe City and Banda Aceh City showed higher risk, while Sabang City and Bener Meriah District had lower risk. Based on our findings, we recommend targeted TB control strategies in high-risk districts such as Lhokseumawe and Banda Aceh, including enhanced surveillance, community awareness programs, and improved access to diagnostic and treatment services.

This variation underscores the importance of tailored interventions to address the unique risk profiles of each district/city. The result also highlights the need for continuous monitoring and surveillance of TB trends to identify emerging hotspots and implement timely interventions. Effective TB control strategies should strengthen healthcare systems, improve access to TB diagnostics and treatment, and enhance public awareness about TB prevention and control measures. These insights empower public health authorities to develop effective, tailored TB control strategies for each district, playing a vital role in the overall reduction of TB incidence in the province. Implementing continuous monitoring and surveillance of TB trends in resource-constrained settings like Aceh Province poses challenges, including limited healthcare infrastructure, workforce shortages, and financial constraints. Addressing these challenges requires a collaborative effort involving government, non-governmental organizations, and international partners to

strengthen healthcare systems and ensure sustainable TB surveillance and control. Furthermore, future study directions include exploring the socio-economic and environmental factors contributing to the spatial distribution of TB risk in Aceh Province and evaluating the effectiveness of the recommended targeted interventions in reducing TB incidence.

6. Declarations

6.1. Author Contributions

Conceptualization: N.R.S., M.Z., and L.R.; Methodology: N.R.S. and M.Z.; Software: M.Z., and L.R.; Validation: S.M. and R.K.; Formal Analysis: L.R. and N.R.S.; Investigation: M.A.; Resources: Z.M.K.; Data Curation: S.M.; Writing Original Draft Preparation: N.R.S. and M.A.; Writing Review and Editing: N.R.S and M.Z; Visualization: M.A.

6.2. Data Availability Statement

The data presented in this study are available on request from the corresponding author.

6.3. Funding

The authors received no financial support for the research, authorship, and/or publication of this article.

6.4. Institutional Review Board Statement

Not applicable.

6.5. Informed Consent Statement

Not applicable.

6.6. Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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