Journal of Applied Data Sciences
Vol. 4, No. 4, December 2023, pp. 466-479

Spatial Estimation of Relative Risk for Dengue Fever in Aceh Province using Conditional Autoregressive Method

Latifah Rahayu [1,*], Novi Reandy Sasmita[2], Wulan Farisa Adila[3], Zurnila Marli Kesuma [4], Rumaisa Kruba [5]

[1,2,3,4,5] *Department of Statistics, Faculty of Mathematics and Natural Sciences, Universitas Syiah Kuala, Darussalam, Banda Aceh and 23111, Indonesia*

(Received: October 16, 2023; Revised: November 21, 2023; Accepted: November 29, 2023; Available online: December 10, 2023)

Abstract

The study aims to comprehensively analyze the spatial distribution and varying risk levels of Dengue Hemorrhagic Fever (DHF) within Aceh Province. The primary objective is to identify and delineate regions within Aceh Province that demonstrate diverse probabilities of DHF occurrences. By investigating the discrepancies in DHF cases and population susceptibility across districts and cities, the research intends to facilitate strategic planning and targeted interventions for disease mitigation and control. Utilizing secondary data sourced from the Aceh Provincial Health Profile spanning 2016 to 2022, this study employs the Bayesian Conditional Autoregressive (CAR) prior model Besag-York-Mollie (BYM). This statistiThe research significantly contributes to enhancing our understanding of DHF distribution patterns and associated risks within Aceh Province. By employing a robust statistical model and analyzing secondary health profile data, the study offers valuable insights into identifying areas with varying levels of DHF risk. The findings are pivotal in guiding evidence-based decision-making for targeted interventions, resource allocation, and strategic planning aimed at mitigating the impact of DHF in high-risk regions. The study's outcomes highlight notable fluctuations in mortality due to dengue cases within Aceh Province, particularly evident in the peaks observed during 2016 and 2022. Furthermore, through the Bayesian CAR (BYM) model, the research identifies districts and cities with varying relative risk values for DHF occurrences. Notably, Sabang city emerges with the highest relative risk value of 3.54, signifying elevated susceptibility, while Bener Meriah district demonstrates the lowest relative risk at 0.2, indicating lower vulnerability to DHF. These findings provide critical insights into the heterogeneous DHF risk landscape across Aceh Province, informing targeted interventions and planning strategies to effectively address the disease burden.

Keywords: Dengue Fever, Bayesian Conditional Autoregressive, Besag-York-Mollie, Aceh Province.

1. Introduction

Health problems are a serious problem in the world. Infectious diseases are disease problems that are one of the factors or causes of death in the world [1][2]. Infectious diseases can be influenced by climate change and extreme environmental conditions. One of the most dangerous infectious diseases for the community is Dengue Hemorrhagic Fever (DHF); socioeconomic status, globalization, climate and temperature changes are highly involved in the spread of dengue fever and many scientists and healthcare professionals believe that dengue will continue to be on the rise especially when influenced by these factors. [3].

Dengue Fever is an infectious disease that can be fatal to those who become infected. Dengue fever is a disease transmitted by the Aedes aegypti mosquito. As reported by [4] , the global prevalence of Dengue Fever has exhibited a rapid increase in recent years. Current estimates suggest that approximately half of the world's population is at risk of developing dengue disease. An estimated modeling using a cartographic approach shows that approximately 390 million dengue fever infections occur annually worldwide, of which 96 million manifest clinically with acute severity [5]. Additional studies support the notion that approximately 3.9 billion individuals, constituting nearly half of the global population, are at risk of contracting the dengue virus [6].

The first dengue fever in Indonesia was found in the city of Surabaya in 1968 with 58 infected cases and 24 of them died. DHF cases have spread to all provinces in Indonesia, including Aceh province, which is located at the western tip of Indonesia. Aceh province is situated in a region characterized by a diverse climate, spanning from temperate to tropical zones. This climate makes it easy for Aedes mosquitoes to breed, so Aceh experiences many dengue cases every year. Aceh exhibits variations in the prevalence of DHF cases and the at-risk population across its districts and cities. As a result, the number of cases and population at risk of DHF varies. Therefore, it is important to plan which

*Corresponding author: Latifah Rahayu (latifah.rahayu@usk.ac.id)
DOI: https://doi.org/10.47738/jads.v4i4.141

districts and cities have a high chance of DHF.

Disease Mapping has gained prominence within the field of Spatial Epidemiology due to its increasing relevance and applications [7]–[9], . The main objective of Disease Mapping is to estimate the spatial pattern of disease risk in a unit area and to identify areas that have a high level of disease risk [10][11]. The simplest measure (parameter) in mapping disease is through the incidence rate. Incident Rate is the ratio between the number of people suffering from a disease and the total population at risk in a particular area. The Incidence Rate may yield less accurate results in areas with diverse populations, as it may fail to standardize risk across regions, potentially leading to errors in interregional comparisons. In addition, Dengue Fever (DHF) is an infectious disease spread by Aedes Aegypti and Aedes Albopictus mosquitoes which are vectors for the dengue virus. DHF disease occurs mostly during the rainy season because of the large amount of standing water that can be a breeding ground for mosquitoes. In disease mapping utilizing the Incidence Rate measure, spatial information is not integrated into the calculation, limiting its ability to account for spatial variability. Therefore, disease mapping requires an approach that incorporates spatial information into the modeling and estimates relative risk values.

One method that can be used to estimate the relative risk value of disease spread is to use the Bayesian Conditional Autoregressive (CAR). In the Bayesian CAR approach, the modeling takes into account the smoothing of the estimated value of the relative risk and includes spatial information to reduce the error of the estimated relative risk parameters so that a more reliable relative risk estimate is obtained. The term 'Bayesian' pertains to a smoothing model concept, whereas 'Conditional Autoregressive (CAR)' denotes a modeling approach that facilitates the inclusion of spatial information.

To determine which parts of Aceh Province are most vulnerable to DHF, a relative risk analysis of the spread of DHF is needed. A study used Bayesian CAR with the BesagYork-Mollie (BYM) model to estimate the relative risk [12]. Previously, a study used Bayesian CAR to compare the BYM model and localized model in a study to estimate the relative risk of air pollution [13]. The localized model had a smoother relative risk than the BYM model, according to the study. In disease mapping using the localized model, it is assumed that the number of dengue fever patients follows a Poisson random variable distribution, and the data exhibits a cluster structure. This model allows us to determine the risk level of dengue fever spread every year in each district in Aceh Province. Therefore, the objective of this study is to estimate the relative risk to determine which parts of Aceh Province have the greatest risk of DHF spread. The findings of the study allowed for the mapping of DHF in Aceh Province for each district, showing that Aceh Province is still highly vulnerable to the disease.

2. Literature Review

The CAR Model is used to analyze data in various fields such as demography, geography, economics and epidemiology. In the field of epidemiology, CAR models are usually used to explain observations that vary on a discrete index set of the number of disease cases in a region. By developing a smoothing model and incorporating spatial data into the model, the weakness of the SMR method for relative risk assessment can be overcome. Bayesian CAR is a disease mapping method that models relative risk by focusing on smoothing the estimated value of relative risk and incorporating spatial information with the aim of reducing the estimated error of relative risk parameters so as to obtain more reliable estimates of relative risk [14].

2.1 Besag-York-Mollie Model (BYM)

In calculating relative risk, the BYM model incorporates unstructured spatial random effects (correlated heterogeneity) and structured spatial random effects (uncorrelated heterogeneity) into a log-linear model. The inclusion of these spatial random effects allows the smoothing of relative risk at both global and local levels. The equation of the BYM model developed by [15] is as follows:

$$y_i \sim Poisson(e_i \theta_i) \tag{1}$$

$$\log \theta_i = \alpha + u_i + v_i \tag{2}$$

Where y_i is the number of disease cases in region i, e_i is expected number of disease cases in region i, θ_i is relative risk in region i, α is overall relative risk level, u_i is unstructured spatial random effects (uncorrelated heterogeneity) and v_i is structured spatial random effects (correlated heterogeneity).

Bayesian modeling requires specification of the prior distribution of each component [16][17]. The prior distribution for spatially structured random effects (uncorrelated heterogeneity) is independent of geographic location and is assumed to follow a normal distribution with mean zero and *variance* τ_v^2, or

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

The unstructured spatial random effects (correlated heterogeneity) are used for the clustering component, where the estimated risk in each region is influenced by neighboring regions. The equation can be written as follows:

$$\left[u_i \middle| u_j, i \neq j, \tau_u^2\right] \sim N(\bar{u_\iota}, \tau_u^2) \tag{4}$$

$$\bar{u_\iota} = \frac{1}{\sum_j \omega_{ij}} \sum_j u_j\, \omega_{ij} \tag{5}$$

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

where the prior mean of each u_i is defined as the weighted average of the other u_j. ω_{ij} is defined as the relationship between regions i and j. The precision parameters τ_v^2 and τ_u^2 control the amount of variability of random effects u and v, respectively.

In Bayesian model analysis, specifying the prior distribution for precision parameters τ_v^2 and τ_u^2 is essebsial. As suggested by [18], a gamma distribution with parameters (0.5, 0.0005) is recommended, as it provides a 99% probability coverage for both parameters. This prior selection minimizes the influence on relative risk inference.

2.2 The Markov Chain Monte Carlo

The Markov Chain Monte Carlo (MCMC) method is a sample simulation method that uses the properties of Markov chains to generate values that approximate the mean value of the posterior distribution [19]. Suppose that we have some distribution $\pi(x)$, $x \in E \subseteq R^p$, which is known only up to some multiplicative constant. We commonly refer to this as the target distribution. If π is sufficiently complex that we cannot sample from it directly, an indirect method for obtaining samples from π is to construct an aperiodic and irreducible Markov chain with state space E, and whose stationary (or invariant) distribution is $\pi(x)$. Sources for readers who may want to delve deeper into the MCMC method [2]. Then, if we run the chain for sufficiently long, simulated values from the chain can be treated as a dependent sample from the target distribution and used as a basis for summarizing important features of π. Many important implementational issues are associated with MCMC methods. These include (among others) the choice of transition mechanism for the chain, the number of chains to be run and their length, the choice of starting values and both estimation and efficiency problems.

In the Bayesian approach, the parameters used are not constant or are random variables that follow a distribution [20]. The description of these parameters is obtained through determining the posterior distribution [21]–[23].

One key algorithm within the MCMC method is the Gibbs Sampling technique, as explained by [24][25]. Gibbs Sampling simplifies complex calculations by generating random variables from the marginal distribution without the need for density calculations [26][27]. It focuses on identifying the univariate conditional distribution, involving only one variable to be determined [28][29].

2.3 Relative Risk

In basic epidemiologic calculations, Relative Risk (RR) is the ratio of the risk between exposed and unexposed groups in terms of the likelihood of the group developing a particular health problem or disease [30]. The number of times the risk of developing a disease in an exposed population is greater than in an unexposed population is shown as the relative risk.

The relative risk in each region is classified into five categories based on the relative risk classification system according to as follows:

a. $0 \leq \theta_i < 0.5$, meaning that the relative risk level of disease spread in region *i* is very low.
b. $0.5 \leq \theta_i < 1$, meaning that the relative risk level of disease spread in region *i* is low.
c. $1 \leq \theta_i < 1.5$, meaning that the relative risk level of disease spread in region *i* is medium.
d. $1.5 \leq \theta_i < 2$, meaning that the relative risk level of disease spread in region *i* is high.

e. $\theta_i \geq 2$, meaning that the relative risk level of disease spread in region i is very high.

Disease Mapping is a growing study in the world of Spatial Epidemiology. The main objective of disease mapping is to estimate the spatial pattern of disease risk in a unit area and to identify areas that have a high level of disease risk.

3. Method

3.1 Data Source

The type of data used in this study is secondary data sourced from the Aceh Health profile from 2016 to 2022. The research focused on 23 districts and cities in Aceh Province, covering a 7-year period from 2016 to 2022. During this timeframe, there were a total of 11,483 DHF cases.

3.2 Phases of Data Analysis

In this study, statistics is the primary method employed to warrant that the results are generalizable to a wider data [31][32]. Data processing in this study used R 4.3.1 software, OpenBugs 3.2.3 and QGIS 10.4. Initial analysis was carried out descriptively. The statistical approach employed in this study involves measures of central tendency and variability, which are integral components of descriptive statistical analysis [32]. This analysis was used to understand the essential characteristics of the data, and it provided basic information about the data [33][34].

In the simulation stage, the study determine the neighboring relationship between regions using a spatial weighting matrix with the Queen contiguity method and conduct relative risk analysis with the Bayesian Conditional Autoregressive (CAR) approach using the Besag-York-Mollie (BYM) prior model. In the stage of estimating relative risk, the study estimated the relative risk value in each region from the average sample generated using the Markov Chain Monte Carlo (MCMC) simulation process.

In the Gibbs Sampling algorithm, the value of each parameter or sample, namely $\Theta = \{\theta_i\}$ with $i = 1,2, \dots n$, is obtained from the results of the jth iteration which is denoted by $\theta_i^{(i)}$. According to [35], the Gibbs Sampling algorithm follows these steps: first, define a vector of initial sample values $\theta^{(0)} = \left(\theta_1^{(0)}, \theta_2^{(0)}, \dots, \theta_n^{(0)}\right)$; 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 $p\left(\theta_{(-i)}\right)$; last, iterate over each sample j times using the full conditional distribution for each sample. For clarity, the first iteration of this algorithm is:

Sample $\theta_1^{(1)}$ is obtained from $p\left(\theta_2^{(0)}, \theta_3^{(0)}, \dots, \theta_n^{(0)}\right)$.

Sample $\theta_2^{(1)}$ is obtained from $p\left(\theta_1^{(1)}, \theta_3^{(0)}, \dots, \theta_n^{(0)}\right)$.

Sample $\theta_3^{(1)}$ is obtained from $p\left(\theta_1^{(1)}, \theta_2^{(1)}, \theta_4^{(0)}, \dots, \theta_n^{(0)}\right)$.

$$\vdots$$

Sample $\theta_n^{(1)}$ is obtained from $p\left(\theta_1^{(1)}, \theta_2^{(1)}, \theta_3^{(1)}, \dots, \theta_{n-1}^{(1)}\right)$.

After running the iteration process for j times, $\theta_1^{(j)}, \theta_2^{(j)}, \dots, \theta_n^{(j)}$are obtained which approach the mean value of the posterior distribution. Furthermore, determining the convergence of relative risk parameters as validity through diagnostic plots of parameters in each district/city. This stage consist of three step; first, mapping the relative risk of DHF in Aceh Province based on the classification results obtained in each district/city. Second, determining the relative risk mapping from 2016 to 2022 in each district/city that has been grouped based on the classification results obtained in each district/city. Last, determine the relative risk mapping from 2016 to 2022 in each district/city that has been grouped based on its relative risk category.

ISSN 2723-6471

4. Results and Discussion

4.1 Statistics Descriptive

In the ongoing efforts to understand and improve health outcomes across various regions, studies focusing on prevalence and incidence rates of diseases are crucial. They provide insights into the effectiveness of current health interventions and identify areas in need of additional resources. The following table presents the findings from a comprehensive study conducted in different cities and districts, revealing significant data points on health-related measurements within these populations. The parameters captured include the minimum and maximum values observed, the mean and standard deviation indicating the average and variability of the data, and the interquartile range showing the middle spread of the values. Additionally, the population of each area is noted alongside the percentage of prevalence and the calculated incidence risk per 100,000 inhabitants. This data is vital for public health officials and policymakers as they strategize to address the healthcare needs of these communities.

Table 1. Descriptive analysis of dengue cases in Aceh province 2016-2022

No	City/District	Min	Max	Mean	SD	IQR	Population	Prevalence	Inciden Risk (per100k)
1	Simeulue	1	92	40.57	40.11	78	92,977	2%	44.14
2	Aceh Singkil	11	184	55.00	60.98	57	126,514	4%	44.71
3	Aceh Selatan	10	197	65.86	64.21	70	234,761	3%	27.85
4	Aceh Tenggara	4	47	19.14	14.40	18	220,860	1%	10.14
5	Aceh Timur	10	156	86.29	53.67	114	429,006	4%	20.28
6	Aceh Tengah	8	293	99.43	91.64	61	213,056	5%	48.57
7	Aceh Barat	9	133	70.29	46.49	84	201,682	4%	34.42
8	Aceh Besar	30	389	172.43	126.84	225	409,109	8%	41.42
9	Pidie	28	357	189.57	122.39	232	440,231	9%	43.14
10	Bireuen	34	410	185.71	143.25	235	443,874	9%	37.71
11	Aceh Utara	19	108	55.71	30.46	49	602,793	3%	9.14
12	Aceh Barat Daya	15	266	78.29	85.72	45	150,775	5%	52.71
13	Gayo Lues	0	34	7.29	12.12	8	96,126	0%	5.85
14	Aceh Tamiang	5	252	90.86	94.23	172	294,356	5%	31.42
15	Nagan Raya	11	68	28.29	18.75	14	168,392	2%	16.7
16	Aceh Jaya	5	50	24.43	19.33	37	92,892	2%	16.71
17	Bener Meriah	0	22	10.71	9.23	17	152,369	1%	7.34
18	Pidie Jaya	10	100	67.43	30.75	47	160,115	5%	44.28
19	Banda Aceh	19	366	189.00	130.81	246	257,635	9%	70.61
20	Sabang	4	88	46.29	26.28	32	35,076	2%	158.47
21	Langsa	18	453	132.14	146.94	88	183,386	7%	42.42
22	Lhokseumawe	47	280	107.00	79.75	62	195,186	8%	53.28
23	Subulussalam	4	36	12.00	11.50	13	83,273	1%	13.42

The average number of dengue cases in Aceh from 2016 to 2022 was 3,029 cases per year from 2016 to 2022. The highest prevalence of cases was found in Pidie, Bireuen, and Banda Aceh districts with 9% and the lowest prevalence was found in Gayo Lues district with 0% prevalence. The highest number of DHF cases was found in Pidie district, indicating that Pidie district has significant health problems and requires intensive prevention and treatment measures.

4.2 Spatial Analysis

Spatial relationships between regions are defined by adjacency, which reflects the relative positioning of spatial units within a given space. We employed the queen contiguity weight (based on the intersection of sides and corners) to establish neighboring relationships among the 23 districts and cities in Aceh Province, resulting in a 23×23 spatial weighting matrix. The map of Aceh Province with queen contiguity can be described in Figure 1.

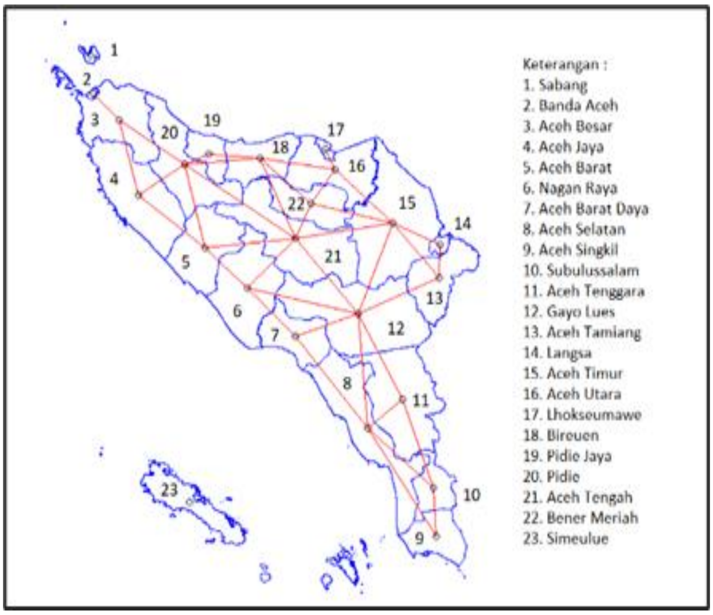


Figure 1. Map of neighborhood relations between districts/cities in Aceh

Figure 1 illustrates neighboring relationships among Aceh's districts and municipalities. Notably, Sabang City and Simeulue District, being islands, lack direct neighboring relationships with other districts or municipalities. Kabupaten Aceh Tengah stands out with seven neighboring districts. For detailed information on neighboring relationships, please refer to Table 1.

Table 2. Map of neighborhood relations between districts/cities in Aceh

No	Districts/ Cities	Neighbouring Districts/Cities	Sum of Neighbours
1	Sabang	-	0
2	Banda Aceh	Aceh Besar	1
3	Aceh Besar	Banda Aceh, Aceh Jaya, Pidie	3
4	Aceh Jaya	Aceh Barat, Pidie, Aceh Besar	3
5	Aceh Barat	Aceh Jaya, Nagan Raya, Pidie, Aceh Tengah	4
6	Nagan Raya	Aceh Barat, Aceh Barat Daya, Gayo Lues, Aceh Tengah	4
7	Aceh Barat Daya	Nagan Raya, Aceh Selatan, Aceh Tenggara, Gayo Lues	4
8	Aceh Selatan	Aceh Barat Daya, Aceh Singkil, Subulussalam, Aceh Tenggara	4
9	Aceh Singkil	Aceh Selatan, Subulussalam	2
10	Subulussalam	Aceh Selatan, Aceh Singkil, Aceh Tenggara	3
11	Aceh Tenggara	Aceh Barat Daya, Aceh Selatan, Subulussalam, Gayo Lues	4
12	Gayo Lues	Nagan Raya, Aceh Barat Daya, Aceh Tenggara, Aceh Tamiang, Aceh Timur, Aceh Tengah	6
13	Aceh Tamiang	Gayo Lues, Langsa, Aceh Timur,	3
14	Langsa	Aceh Tamiang, Aceh Timur	2
15	Aceh Timur	Gayo Lues, Aceh Tamiang, Langsa, Aceh Utara, Aceh Tengah, Bener Meriah	6
16	Aceh Utara	Aceh Timur, Lhoseumawe, Bireuen, Bener Meriah	4
17	Lhoseumawe	Aceh Utara	1
18	Bireuen	Aceh Utara, Pidie Jaya, Pidie, Aceh Tengah, Bener Meriah	5
19	Pidie Jaya	Bireuen, Pidie	2
20	Pidie	Aceh Jaya, Aceh Besar, Aceh Barat, Bireuen, Pidie Jaya, Aceh Tengah	6
21	Aceh Tengah	Aceh Barat, Nagan Raya, Gayo Lues, Aceh Timur, Bireuen, Pidie, Bener Meriah	7
22	Bener Meriah	Aceh Timur, Aceh Utara, Bireuen, Aceh Tengah	4
23	Simeulue	-	0

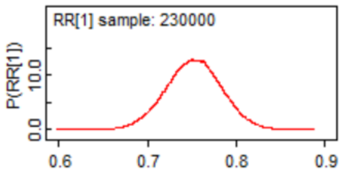
4.3 Relative Risk Estimation

The relative risk values for each district and municipality in Aceh are estimated using the Markov Chain Monte Carlo (MCMC) simulation process. One of the algorithms used in the MCMC method is the Gibbs Sampling algorithm. In

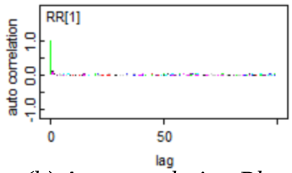
 ISSN 2723-6471

the Gibbs Sampling algorithm, the value of each parameter or sample, namely $\Theta = \{\theta_i\}$ with i = 1,2, ..., n, is obtained from the results of the jth iteration which is denoted by $\theta_i^{(i)}$. To obtain good estimation results, it is necessary to check the convergence of relative risk parameters as validity through parameter diagnostic plots in each district/city.

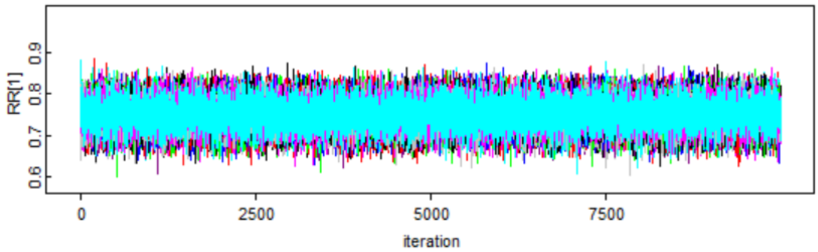
The final result of the risk estimation process is the relative risk value from the simulation results generated through the use of the Gibbs Sampling algorithm. By iterating 10,000 times, the diagnostic plot of relative risk parameters for each district/city in Aceh Province was obtained. Parameter diagnostic plots for several districts and cities can be observed in Figure 2 to Figure 6.



(a) Density Plot

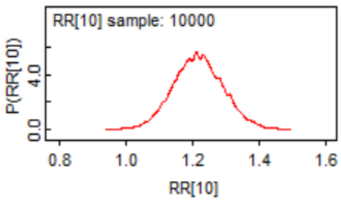


(b) Autocorrelation Plot

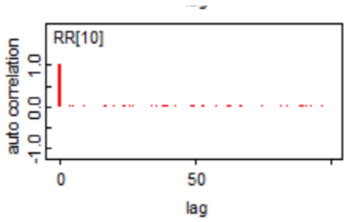


(c) History Plot

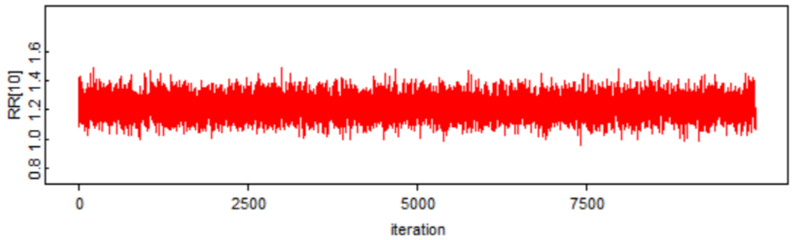
Figure 2. Diagnostic Plot of Relative Risk Parameters for Simeulue district



(a) Density Plot

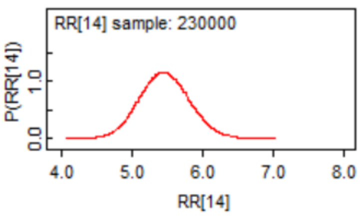


(b) Autocorrelation Plot

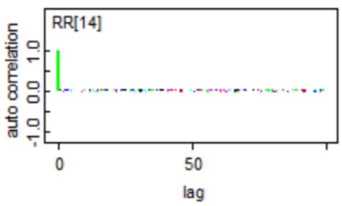


(c) History Plot

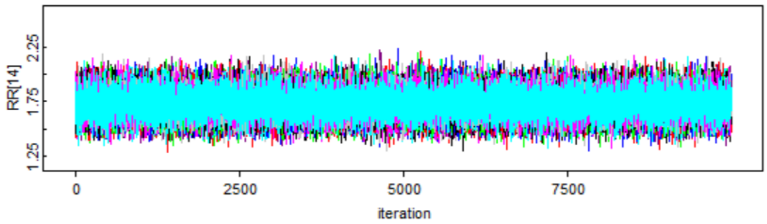
Figure 3. Diagnostic Plot of Relative Risk Parameters for Bireuen district



(a) Density Plot

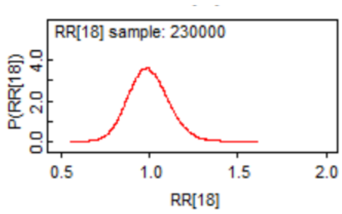


(b) Autocorrelation Plot

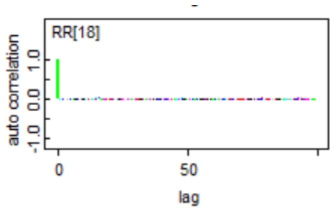


(c) History Plot

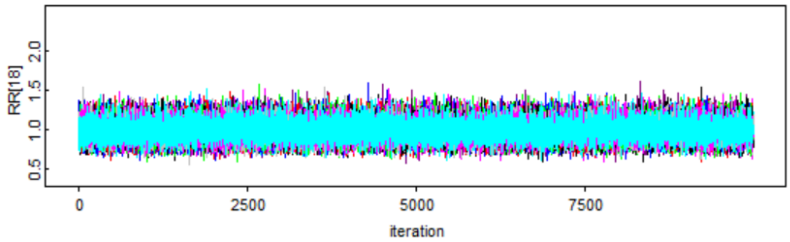
Figure 4. Diagnostic Plot of Relative Risk Parameters for Aceh Tamiang district



(a) Density Plot

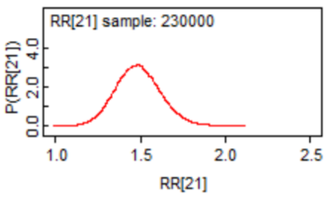


(b) Autocorrelation Plot

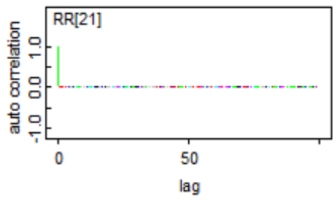


(c) History Plot

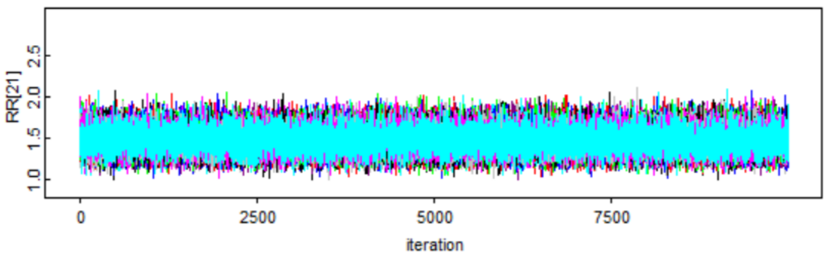
Figure 5. Diagnostic Plot of Relative Risk Parameters for Pidie Jaya district



(a) Density Plot



(b) Autocorrelation Plot



(c) History Plot

Figure 6. Diagnostic Plot of Relative Risk Parameters for Langsa City

The density plots shown in Figures 2(a) to 6(a) describe the posterior distribution pattern in each district and city. Based on the density plot figure, the distribution pattern of the sample values generated in each district/city has only one mode value and the pattern is close to a normal distribution so it can be said that the MCMC process meets the convergent properties [36].

The strong or weak correlation between sample values can be determined using the Autocorrelation plots shown in Figures 2(b) to 6(b). The autocorrelation plot for each district or city shows that the first lag is close to one and subsequent lags have values that decrease to close to zero. This result indicates that the resulting sample values do not have a strong correlation with each other. The result also implies that the correlation between the sample values generated in each district/municipality is in the posterior distribution region.

The results of the history plot in Figures 2 (c) to 6 (c) of the MCMC process in each district/city are stationary. There is no obvious trend or change in spread. We can also get a rough idea of how much dependence there is in the chain by counting large wiggles [37]. We can also get a rough idea of how much dependence there is in the chain byThis shows that each sample produced is in the domain interval that has a certain value. In addition, the history plot is found to be tight or fastly mixing and can capture all possible parameter values, so that the history plot has fulfilled the irreducible nature. The history plot also illustrates that the generated value is not in a certain periodicity, so it can also be said that the MCMC process carried out fulfills the aperiodic nature. In addition, the parameter value generated in state-i can return to state-i so that the resulting MCMC iteration process fulfills the recurrent nature. So it can be said that the relative risk parameter has converged at the 10,000th iteration.

The relative risk of each district/city classified into five categories according to the relative risk classification system by [38] is shown in Table 2.

Table 3. Relative risk of dengue fever in Aceh Province 2016-2022

Distric/ City	Relative Risk	Confidence Interval 95%	Category
Aceh Tamiang	5,46	4,81 - 6,16	Very high
Sabang	2,86	2,13 - 3,71	Very high
Aceh Tengah	2,83	2,52 - 3,17	Very high
Lhokseumawe	2,77	2,46 - 3,11	Very high
Aceh Selatan	1,67	1,44 - 1,91	High
Langsa	1,48	1,24 - 1,75	High
Bireun	1,21	1,08 - 1,36	High
Banda Aceh	1,16	0,98 - 1,35	High
Pidie Jaya	0,99	0,78 - 1,22	Moderate
Aceh Barat Daya	0,9	0,69 - 1,12	Moderate
Pidie	0,86	0,74 - 0,99	Moderate
Simeulue	0,75	0,69 - 0,81	Moderate
Subulussalam	0,75	0,69 - 0,81	Moderate
Aceh Timur	0,74	0,63 - 0,86	Moderate
Aceh Besar	0,72	0,61 - 0,84	Moderate
Aceh Barat	0,66	0,51 - 0,82	Moderate
Aceh Tenggara	0,45	0,33 - 0,59	Low
Aceh Utara	0,35	0,29 - 0,42	Low
Bener Meriah	0,27	0,16 - 0,40	Low
Nagan Raya	0,25	0,15 - 0,37	Low
Aceh Singkil	0,2	0,11 - 0,33	Low
Aceh Jaya	0,14	0,05 - 0,26	Low
Gayo Lues	0,08	0,02 - 0,18	Very low

There are several districts/cities in the very high relative risk category, namely Aceh Tamiang, Sabang, Central Aceh and Lhokseumawe. In the high relative risk category, there are four districts/cities, namely South Aceh, Langsa, Bireun, and Banda Aceh. In the medium relative risk category, there are eight districts/cities, namely Pidie Jaya, Southwest Aceh, Pidie, East Aceh, Aceh Besar, Simeulue, Subulussalam, and West Aceh. In the relatively low risk category, there are six districts/cities: Southeast Aceh, North Aceh, Bener Meriah, Nagan Raya, Aceh Singkil, and Aceh Jaya. Pidie Jaya, South Aceh, Sabang, Simeulue, Aceh Jaya, East Aceh, Nagan Raya. In the very low relative risk category is Gayo Lues District. The districts/cities of South Aceh, Langsa, Bireun, Banda Aceh, Sabang, Central Aceh, Lhokseumawe, and Aceh Tamiang are in the high and very high categories so that when compared to other districts and cities in Aceh, these districts and cities are more vulnerable to the risk of dengue transmission.

4.4. Mapping of the Relative Risk of DHF in Aceh Province

The relative risk mapping of DHF in Aceh Province was conducted using ArcGis 10.4 software. The map of the relative risk distribution of DHF in Aceh Province based on the estimation results using the BYM CAR model is presented in Figure 7:

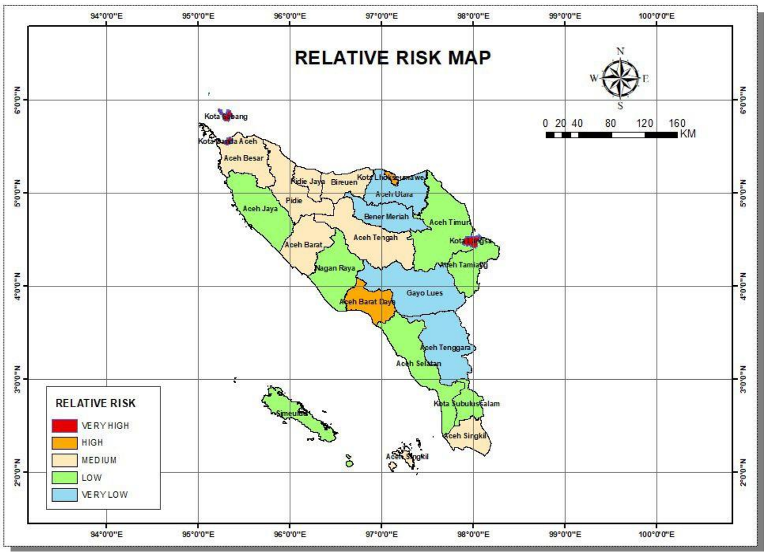


Figure 7. Map of the relative risk distribution of dengue fever in Aceh Province 2016-2022

Figure 7 displays the relative risk distribution map of DHF in Aceh for the years 2016-2022. The map reveals that regions with very low and low relative risk are predominantly situated in the southeastern part of Aceh, while those with moderate relative risk are concentrated in the northwestern part of Aceh. In contrast, districts/cities with high and very high relative risk appear to be scattered randomly.

4.5. Trend Analysis of the Relative Risk

To see the trend of increasing or decreasing relative risk each year in each district/city, the relative risk value was calculated separately for each year. Each district/municipality is grouped based on predetermined categories. The trend of relative risk in each category is presented in Figure 8.

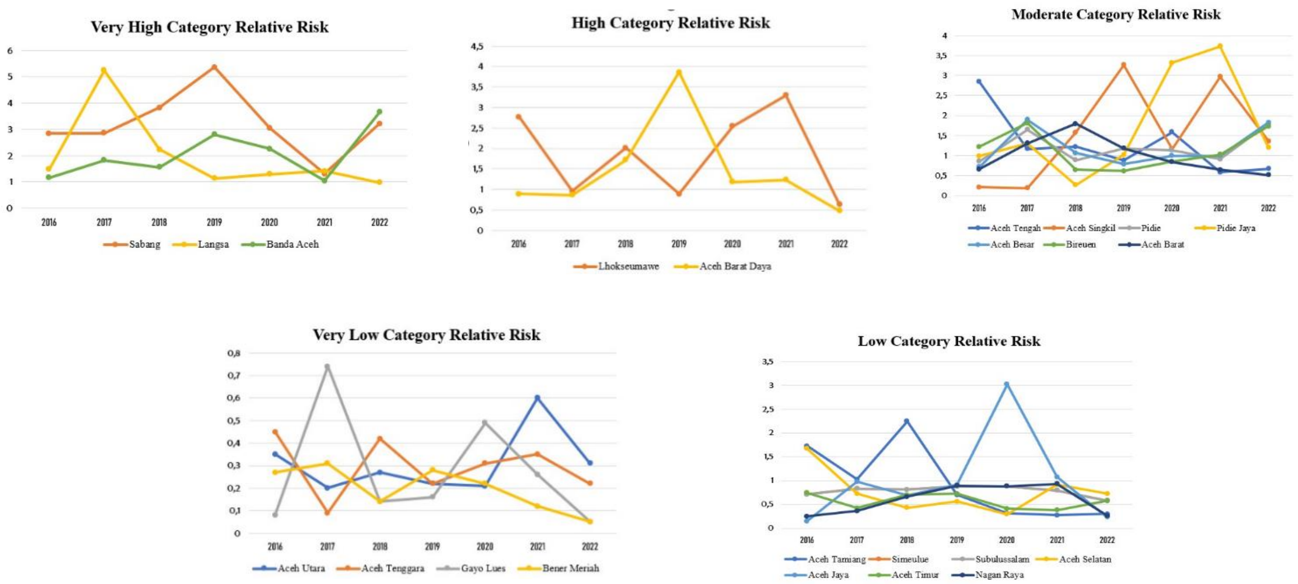


Figure 8. Trends in relative risk of districts/cities in Aceh by category

In the very high relative risk category, there are four districts/cities, namely Aceh Tamiang, Sabang, Central Aceh and Lhokseumawe. Based on the figure, Sabang City experienced a fairly high upward trend in relative risk in 2019. In 2019 and 2022, the relative risk in Aceh Tengah District decreased with a value below one. In the high relative risk category, there are four districts/cities, namely South Aceh, Langsa, Bireun and Banda Aceh. Langsa experienced a

ISSN 2723-6471

fairly high increase in the relative risk trend in 2017, while Aceh Tengah and Bireun districts showed a downward trend in relative risk in 2019 and 2020.

There are eight districts/cities in the moderate relative risk category. Southwest Aceh experienced a high increase in the relative risk trend in 2017. A decrease in the relative risk trend was seen in Pidie Jaya, while other districts/cities tended to fluctuate. There were six districts/cities in the low relative risk category. Aceh Singkil District showed a significant downward trend in relative risk in 2019. Aceh Jaya district experienced a fairly low decline in relative risk in 2016, but again experienced an increase in 2020. Nagan Raya and Aceh Jaya districts experienced an increasing trend of increasing risk in 2018, 2019 and 2021. Meanwhile, other districts experienced stable relative risk trends.

In the very low relative risk category, Gayo Lues is the sole district/city. While Gayo Lues District experienced a notable increase in relative risk in 2017, it remained relatively low. Consequently, the study observe that the relative risk value in Gayo Lues Regency tends to stabilize below the value of one.

While this study provides valuable insights into the spatial estimation of relative risk for Dengue Fever in Aceh Province, it is important to acknowledge certain limitations in our methodology and data. Firstly, the study relies on secondary data sourced from the Aceh Provincial Health Profile from 2016 to 2022, which may have inherent biases or inaccuracies. Secondly, the Bayesian Conditional Autoregressive (CAR) approach, though robust, is dependent on the assumptions of the Besag-York-Mollie (BYM) Model, which may not capture all spatial complexities. Furthermore, the Markov Chain Monte Carlo (MCMC) simulation process, essential for our analysis, has its limitations in terms of convergence and the accuracy of the estimated parameters.

5. Conclusion

Based on our analysis of the relative risk distribution map of Dengue Hemorrhagic Fever (DHF) in Aceh from 2016 to 2021, several key patterns and observations emerge. Regions with low and very low relative risk categories are predominantly situated in the southeastern part of Aceh, while those with moderate relative risk are concentrated in the northwestern part. In contrast, districts and cities with high and very high relative risks exhibit a more random distribution. Notably, Aceh Tamiang District, Sabang Municipality, Central Aceh, and Lhokseumawe Municipality demonstrate a comparatively higher vulnerability to DHF transmission within Aceh Province. Furthermore, our analysis reveals an increasing trend of high relative risk in Pidie Jaya District from 2016 to 2022. This evolving risk landscape underscores the dynamic nature of DHF transmission and the necessity for adaptive and timely intervention strategies to curb the escalating risk in certain areas. The identified patterns from our analysis offer invaluable insights for public health authorities, aiding in the formulation of proactive measures and tailored interventions to address the varying DHF risk levels across Aceh Province. By leveraging this knowledge, stakeholders can strategically allocate resources and implement focused interventions, ultimately contributing to a more effective and targeted approach in controlling and reducing the burden of DHF transmission.

6. Declarations

6.1. Author Contributions

Conceptualization: L.R. and N.R.S.; Methodology: N.R.S.; Software: L.R. and W.F.A; Validation: L.R. and N.R.S.; Formal Analysis: L.R. and N.R.S.; Investigation: W.F.A.; Resources: Z.M.K.; Data Curation: W.F.A.; Writing Original Draft Preparation: W.F.A. and L.R.; Writing Review and Editing: R.K. and Z.M.K.; Visualization: Z.M.K.; All authors, L.R., N.R.S., W.F.A., Z.M.K., and R.K., have read and agreed to the published version of the manuscript.

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 financial support for the research, authorship, and/or publication of this article from Universitas Syiah Kuala.

6.4. Institutional Review Board Statement

Not applicable.

ISSN 2723-6471

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

Acknowledgments

The author would like to thanks to Universitas Syiah Kuala funding for supporting this research and publication.

References

[1] L. D. Frenkel, "Infectious diseases as a cause of global childhood mortality and morbidity: Progress in recognition, prevention, and treatment," *Adv. Pediatr.* Res., vol. 5, no. 14, pp. 1–11, 2018, doi: 10.24105/apr.2018.5.14.

[2] N. R. Sasmita, M. Ikhwan, S. Suyanto, and V. Chongsuvivatwong, "Optimal control on a mathematical model to pattern the progression of coronavirus disease 2019 (COVID-19) in Indonesia," *Glob. Heal. Res. Policy*, vol. 5, no. 1, pp. 1-38, Dec. 2020, doi: 10.1186/s41256-020-00163-2.

[3] A. Sanyaolu, "Global Epidemiology of Dengue Hemorrhagic Fever: An Update," *J. Hum. Virol. Retrovirology*, vol. 5, no. 6, pp. 1–6, Oct. 2017, doi: 10.15406/jhvrv.2017.05.00179.

[4] World Health Organization (WHO)., *Dengue: Guidelines for Diagnosis, Treatment, Prevention and Control*. Genewa: WHO, 2009. [Online]. Available: https://www.ncbi.nlm.nih.gov/books/NBK143157/

[5] S. Bhatt *et al.*, "The global distribution and burden of dengue," *Nature*, vol. 496, no. 7446, pp. 504–507, Apr. 2013, doi: 10.1038/nature12060.

[6] O. J. Brady *et al.*, "Refining the Global Spatial Limits of Dengue Virus Transmission by Evidence-Based Consensus," *PLoS Negl. Trop. Dis.*, vol. 6, no. 8, pp. 1-15, Aug. 2012, doi: 10.1371/journal.pntd.0001760.

[7] L. Liu *et al.*, "Epidemiology for public health practice: The application of spatial epidemiology," *World J. Diabetes*, vol. 13, no. 7, pp. 584–586, Jul. 2022, doi: 10.4239/wjd.v13.i7.584.

[8] H. Sofyan *et al.*, "The state of diabetes care and obstacles to better care in Aceh, Indonesia: a mixed-methods study," *BMC Health Serv. Res.*, vol. 23, no. 1, pp. 1-7, Mar. 2023, doi: 10.1186/s12913-023-09288-9.

[9] Z. Kesuma, L. Siregar, E. Fradinata, and A. Fathinah, "Factors Affecting Stunting in Children under 5 Years of Age in Indonesia using Spatial Model," *Indian J. Public Health*, vol. 66, no. 3, pp. 264-268, Jul. 2022, doi: 10.4103/ijph.ijph_1989_21.

[10] G. Konstantinoudis, D. Schuhmacher, H. Rue, and B. D. Spycher, "Discrete versus continuous domain models for disease mapping," *Spat. Spatiotemporal. Epidemiol.*, vol. 32, no. 1, pp. 1-12, Feb. 2020, doi: 10.1016/j.sste.2019.100319.

[11] K. M. Zurnila, Hizir, R. Latifah, and U. Farazilla, "Spatial Distribution of Anemia Among Adolescents In Banda Aceh, Indonesia," *IOP Conf. Ser. Mater. Sci. Eng.*, vol. 506, no. 1, pp. 1-6, Apr. 2019, doi: 10.1088/1757-899X/506/1/012007.

[12] N. A. Samat and L. W. Mey, "Malaria Disease Mapping in Malaysia based on Besag-York-Mollie (BYM) Model," *J. Phys. Conf. Ser.*, vol. 890, no. 1, pp. 1-7, Sep. 2017, doi: 10.1088/1742-6596/890/1/012167.

[13] D. Lee, A. Rushworth, and S. K. Sahu, "A Bayesian localized conditional autoregressive model for estimating the health effects of air pollution," *Biometrics*, vol. 70, no. 2, pp. 419–429, Jun. 2014, doi: 10.1111/biom.12156.

[14] L. Raubenheimer, R. Southey, and Sarah E. Radlof, "Bayesian Disease Mapping: A Literature Review With an Application, Using WinBugs Software," *Stat. Optim. Inf. Comput.*, vol. 10, no. 3, pp. 829–857, Apr. 2022, doi: 10.19139/soic-2310-5070-1395.

[15] J. Besag, J. York, and A. Molli, "Bayesian image restoration, with two applications in spatial statistics," *Ann. Inst. Stat. Math.*, vol. 43, no. 1, pp. 1–20, Mar. 1991, doi: 10.1007/BF00116466.

[16] F. Yanuar and C. Saputri, "Bayesian inference for Pareto distribution with prior conjugate and prior non conjugate," *J. Mat. Stat. dan Komputasi*, vol. 16, no. 3, pp. 382-390, Apr. 2020, doi: 10.20956/jmsk.v16i3.8019.

[17] R. Idroes *et al.*, *A Genetic Algorithm to Determine Research Consultation Schedules in Campus Environment*," IOP Conf. Ser. Mater. Sci. Eng., vol. 796, no. 1, pp. 1-8, Mar. 2020, doi: 10.1088/1757-899X/796/1/012033.

[18] L. Bernardinelli, D. Clayton, C. Pascutto, C. Montomoli, M. Ghislandi, and M. Songini, "Bayesian analysis of space—time variation in disease risk," *Stat. Med.*, vol. 14, no. 21–22, pp. 2433–2443, Nov. 1995, doi: 10.1002/sim.4780142112.

[19] D. Vats, N. Robertson, J. M. Flegal, and G. L. Jones, "Analyzing Markov chain Monte Carlo output," *WIREs Comput. Stat.*, vol. 12, no. 4, pp. 1-8, Jul. 2020, doi: 10.1002/wics.1501.

[20] R. Idroes *et al.*, "Retention Index Prediction of Flavor and Fragrance by Multiple Linear Regression and the Genetic Algorithm," *Int. Rev. Model. Simulations*, vol. 12, no. 6, pp. 373-380, Dec. 2019, doi: 10.15866/iremos.v12i6.18353.

[21] M. van Oijen, "Deriving the Posterior Distribution," in *Bayesian Compendium*, Cham: Springer International Publishing, 2020, pp. 29–32. doi: 10.1007/978-3-030-55897-0_5.

[22] R. Idroes *et al.*, "Analysis of Temperature and Column Variation in Gas Chromatography to Dead Time of Inert Gas and N-Alkane Homologous Series Using Randomized Block Design," *IOP Conf. Ser. Earth Environ. Sci.*, vol. 364, no. 012020, pp. 1–7, 2019, doi: 10.1088/1755-1315/364/1/012020.

[23] R. Idroes *et al.*, "Application of Genetic Algorithm-Multiple Linear Regression and Artificial Neural Network Determinations for Prediction of Kovats Retention Index," *Int. Rev. Model. Simulations*, vol. 14, no. 2, pp. 137-145, Apr. 2021, doi: 10.15866/iremos.v14i2.20460.

[24] A. Terenin, S. Dong, and D. Draper, "GPU-accelerated Gibbs sampling: a case study of the Horseshoe Probit model," *Stat. Comput.*, vol. 29, no. 2, pp. 301–310, Mar. 2019, doi: 10.1007/s11222-018-9809-3.

[25] M. Agustia *et al.*, "Application of Fuzzy Support Vector Regression to Predict the Kovats Retention Indices of Flavors and Fragrances," in *2022 International Conference on Electrical Engineering and Informatics (ICELTICs)*, IEEE, vol. 1, no. 1, pp. 13–18, Sep. 2022. doi: 10.1109/ICELTICs56128.2022.9932124.

[26] T. Park and S. Lee, "Improving the Gibbs sampler," *WIREs Comput. Stat.*, vol. 14, no. 2, pp. 1-6, Mar. 2022, doi: 10.1002/wics.1546.

[27] Y. Nadia *et al.*, "Simple Combination Method of FTIR Spectroscopy and Chemometrics for Qualitative Identification of Cattle Bones," *IOP Conf. Ser. Earth Environ. Sci.*, vol. 364, no. 1, pp. 1-6, Nov. 2019, doi: 10.1088/1755-1315/364/1/012040.

[28] G. Zanella and G. Roberts, "Multilevel Linear Models, Gibbs Samplers and Multigrid Decompositions (with Discussion)," *Bayesian Anal.*, vol. 16, no. 4, pp. 1309–1391, Dec. 2021, doi: 10.1214/20-BA1242.

[29] A. Maulana, T. R. Noviandy, R. Idroes, N. R. Sasmita, R. Suhendra, and I. Irvanizam, "Prediction of Kovats Retention Indices for Fragrance and Flavor using Artificial Neural Network," *Proc. Int. Conf. Electr. Eng. Informatics*, vol. 1, no.1, pp. 1–5, Oct. 2020, doi: 10.1109/ICELTICs50595.2020.9315391.

[30] M. N. Mittinty and J. Lynch, "Reflection on modern methods: risk ratio regression—simple concept yet complex computation," *Int. J. Epidemiol.*, vol. 52, no. 1, pp. 309–314, Feb. 2023, doi: 10.1093/ije/dyac220.

[31] Azharuddin *et al.*, "Patient Satisfaction And Its Socio-Demographic Correlates In Zainoel Abidin Hospital, Indonesia: A Cross-Sectional Study," *Unnes J. Public Heal.*, vol. 12, no. 2, pp. 57–67, 2023, doi: 10.15294/ujph.v12i2.69233.

[32] D. Sasaki, H. Sofyan, N. R. Sasmita, M. Affan, and N. Nizamuddin, "Assessing the Intermediate Function of Local Academic Institutions During the Rehabilitation and Reconstruction of Aceh, Indonesia," *J. Disaster Res.*, vol. 16, no. 8, pp. 1265–1273, Dec. 2021, doi: 10.20965/jdr.2021.p1265.

[33] N. Earlia *et al.*, "Protective Effects of Acehnese Traditionally Fermented Coconut Oil (Pliek U Oil) and its Residue (Pliek U) in Ointment against UV Light Exposure: Studies on Male Wistar Rat Skin (Rattus novergicus)," *Sains Malaysiana*, vol. 50, no. 5, pp. 1285–1295, May 2021, doi: 10.17576/jsm-2021-5005-09.

[34] T. R. Noviandy *et al.*, “The Prediction of Kovats Retention Indices of Essential Oils At Gas Chromatography Using Genetic Algorithm-Multiple Linear Regression and Support Vector Regression,” *J. Eng. Sci. Technol.*, vol. 17, no. 1, pp. 306–326, 2022.

[35] S. P. Brooks, “Markov Chain Monte Carlo Method and Its Application,” *J. R. Stat. Soc. Ser. D (The Stat.*, vol. 1, no. 47, pp. 69–100, 1998, [Online]. Available: http://www.jstor.org/stable/2988428

[36] S. D. Hill and J. C. Spall, “Stationarity and Convergence of the Metropolis-Hastings Algorithm: Insights into Theoretical Aspects,” *IEEE Control Syst.*, vol. 39, no. 1, pp. 56–67, Feb. 2019, doi: 10.1109/MCS.2018.2876959.

[37] G. Fitzmaurice, *Handbook of Markov Chain Monte Carlo*. Boston, MA, U.S.A; Chapman and Hall/CRC, 2011.

[38] N. A. Samat and M. I. M. S.H, “Dengue Disease Mapping with Standardized Morbidity Ratio and Poisson-gamma Model: An Analysis of Dengue Disease in Perak, Malaysia,” *Int. J. Math. Comput. Sci.*, vol. 7, no. 8, pp. 1299–1303, 2013.