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Bayesian Spatio-Temporal Conditional Autoregressive Modelling of Factors Affecting Pneumonia Cases in Indonesia

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ABSTRACT
The Bayesian Spatio-Temporal Conditional Autoregressive (BST CAR) method is a statistical approach used to analyze data with both spatial and temporal components. While the BST CAR model has been widely applied in various studies, no research has yet explored using the BST CAR Localized model for pneumonia cases in Indonesia. This study aims to identify and model the factors influencing pneumonia incidence in Indonesia using the BST CAR Localized framework. The data analyzed in this study comprise the number of pneumonia cases in Indonesia from 2018 to 2022, along with several variables hypothesized to influence the incidence. The results indicate that the BST CAR Localized model with G=3 provides the best fit for modeling the relative risk of pneumonia cases across Indonesia. Significant factors affecting pneumonia incidence include the percentage of exclusively breastfed infants, the percentage of infants with complete basic immunization, and the percentage of the population living in poverty.

KEYWORDS
Pneumonia, Bayesian Method, Spatio Temporal CAR.

1. INTRODUCTION

Spatial statistics is a methodological approach used to analyze spatial data [1]. Spatial analysis refers to the process of integrating location, distance, and area with both geographic and quantitative data, methods, and techniques to identify spatial patterns [1]. Spatial data modeling frequently depends on the relationships between neighboring locations, leading to spatial dependencies across regions. The first law of geography, proposed by W. Tobler, posits that "everything is related to everything else, but near things are more related than distant things". This concept, known as the spatial effect, reflects the variations in environmental and geographical characteristics across observation areas, suggesting that each observation may exhibit distinct spatial patterns [2].

One statistical method commonly used to identify the factors influencing disease incidence spatially and temporally is Bayesian Spatio-Temporal Conditional Autoregressive (BST CAR) modeling. The BST CAR method is designed to analyze data with both spatial and temporal components. A key advantage of the CAR model lies in its ability to map disease incidence by modeling relative risk and incorporating spatial information, thereby reducing estimation errors. To date, numerous studies have applied the CAR method across various contexts [3]. This model assumes that observations are correlated with their neighboring observations, with the strength of the correlation diminishing as the distance between observations increases [4].

According to data from the Ministry of Health (2021), the incidence of pneumonia in children under the age of five has decreased by 34.8% in Indonesia [5]. This decline may be attributed to the Covid-19 pandemic, which led to a reduction in the number of children visiting healthcare facilities for symptoms such as coughing and shortness of breath. Pneumonia remains a significant global health issue for children, with high morbidity and mortality rates. Each year, approximately 2 million children worldwide die from pneumonia, a figure surpassing death from AIDS, malaria, and measles. In Indonesia, pneumonia ranks among the five leading causes of death in children [6]. According to the World Health Organization [7], pneumonia in children under five is an acute respiratory infection that affects the lungs, restricting oxygen supply due to the alveoli being filled with pus and fluid.

A study on pneumonia cases was conducted using the geographically weighted generalized poisson regression (GWGPR) method in west Java Province [8]. The study identified that significant factors influencing pneumonia cases in toddlers included the percentage of vitamin A coverage and the percentage of individuals practicing clean and healthy living behaviors. Several other studies have applied the spatio-temporal conditional autoregressive method where the CARBayesST package is designed to fit CAR-type spatio-temporal models for area unit data [9]. The package facilitates the incorporation of various models and focuses on aspects of space-time modeling, such as estimating overall spatial and temporal trends and identifying groups of area units with high values. Another relevant study found that low socioeconomic status, low maternal education, and maternal anemia at the zonal level were strongly associated with child anemia in Ethiopia [10]. The study emphasized the need to enhance women's education, improve their socioeconomic status, and reduce maternal anemia to decrease the prevalence of childhood anemia in the country.

Several studies have applied BST CAR Localized modeling in various research fields. For instance, a study on poverty modeling across Sulawesi Island, Indonesia, demonstrated that covariates such as the Gender Development Index, Women's Income Contribution, Adjusted Per Capita Expenditure, and Human Development Index significantly affected poverty levels [11]. The study further reported that the BST-CAR Localized model with G = 2 provided a better fit compared to models with G = 3 and G = 5, as indicated by lower DIC and WAIC values. Additionally, BST CAR Localized modeling has been employed to analyze dengue fever incidence in Makassar, where the BST CAR Localized model with G = 3, incorporating average humidity, was found to yield the best model performance [12]. It has also been employed in modeling stunting cases in Indonesia [13]. A review of existing research reveals that no studies have been conducted on the application of the BST CAR Localized model to analyze factors influencing pneumonia cases across provinces in Indonesia. The objective of this study is to apply the BST CAR Localized model to identify factors affecting pneumonia cases in Indonesia and to estimate the relative risk of pneumonia cases.

2. LITERATURE REVIEW

Spatial analysis involves processing, modeling, and interpreting data related to geographic or spatial locations on the Earth's surface [14]. The primary objective of spatial analysis is to understand and explore the geographic relationships between objects, phenomena, or entities within a given area [15]. Spatial analysis is generally categorized into three main groups: visualization, exploration, and modeling. Visualization facilitates the interpretation of spatial analysis results, exploration processes spatial data using statistical methods, and modeling predicts spatial patterns by integrating spatial and non-spatial data sources. To assess spatial effects, it is essential to measure the location of spatial data.

Location information can be obtained from two primary sources. The first is the neighborhood relationship, which defines the relative position of one spatial unit in relation to another. Maps are commonly used to determine these relationships, as spatial units in proximity are expected to exhibit a high degree of spatial dependence compared to those located farther apart. The second source is distance, which provides location information within a specific space based on latitude and longitude. This data allows for the calculation of distances between points in space, with spatial dependence generally expected to decrease as distance increases [16].

2.1 Moran Spatio Temporal Index

The Spatiotemporal Moran Index is used to analyze the patterns of spatial and temporal variables over time. It serves as a measure of spatiotemporal autocorrelation, quantifying the degree of coherence within the data across both space and time [17]. The calculation of the spatio-temporal Moran Index can be expressed as follows:

$$I_{st} = \frac{n\sum_i \sum_j w_{ij}\left(x_{it}-\bar{x}_t\right)\left(x_{jt}-\bar{x}_t\right)}{\sum_i \sum_j w_{ij}\left(x_{it}-\bar{x}_t\right)^2} \tag{1}$$

Description:
I_{st}: spatiotemporal Moran index

n: number of spatial units in the analysis
x_{it}: value of the variable at unit i at time t
x_{jt}: value of the variable at unit j at time t
$\bar{x}_t$: mean value of the variable at time t
w_{ij}= spatial weight matrix between units i and j
$\sum$: summation over all relevant spatial units (i and j) and time periods (t).

The hypotheses for the Spatiotemporal Moran Index are as follows:
$H_0 : I_{st} = 0$ (indicating no spatiotemporal autocorrelation)
$H_1 : I_{st} \neq 0$ (indicating the presence of spatiotemporal autocorrelation)

$$Z_{calculated} = \frac{I_{st} - E\left(I_{st}\right)}{\sqrt{var\left(I_{st}\right)}} \tag{2}$$

Description:
$E\left(I_{st}\right)$: Expected value of the Spatiotemporal Moran Index
$var\left(I_{st}\right)$: Variance of the Spatiotemporal Moran Index
Test Criteria:
The null hypothesis H_0 is rejected if $|Z_{calculated}| > Z_{\frac{\alpha}{2}}$ or if the p-value is less than α.

2.2 Bayesian Spatio Temporal Conditional Autoregressive (BST CAR) Localized Model

In this study, the BST CAR Localized model was employed to estimate the relative risk (RR) of pneumonia across 34 provinces in Indonesia. The number of pneumonia cases is assumed to follow a Poisson distribution [18], [19]. The model is expressed as follows:

$$\begin{aligned} y_{ij} &\sim Poisson\left(E_{ij}\theta_{ij}\right) \\ E_{ij} &= \frac{\sum_i \sum_j y_{ij}}{\sum_i \sum_j n_{ij}} n_{ij} \\ log\left(\theta_i\right) &= \alpha + \varphi_{ij} + \lambda z_{ij} \end{aligned}$$

where, y_{ij} represents the number of pneumonia cases in region $i = 1,\ 2,\ \ldots,\ 34$ and time $j = 1,\ 2,\ \ldots,\ 5$. E_{ij} is the expected value, calculated by multiplying the total incidence rate for each case in region $i = 1,\ 2,\ \ldots,\ 34$ and time $j = 1,\ 2,\ \ldots,\ 5$ by the number of people at risk in each region. n_{ij} denotes the total population in the i-th province ($i = 1,\ 2,\ \ldots,\ 34$) and j-th time period ($j = 1,\ 2,\ \ldots,\ 5$). θ_{ij} represents the relative risk in the i-th region ($i = 1,\ 2,\ \ldots,\ 34$) and j-th time period ($j = 1,\ 2,\ \ldots,\ 5$). φ_{ij} and λz_{ij} are the smoothing components; φ_{ij} represents the autocorrelation between temporal and spatial variations, while λz_{ij} is the clustering component or constant intercept. α indicates the overall level of relative risk; φ_{ij} is modeled as a structured spatial random effect with CAR priors, as follows:

$$\begin{aligned} \left(\varphi_i|\varphi_{j-1}\right) &\sim N\left(\rho_j\varphi_{j-1}, \tau^2 Q(W)^{-1}\right), \quad j = 1,\ 2,\ \ldots,\ 5 \\ \varphi_i &\sim N\left(0,\ \tau^2 Q(W)^{-1}\right) \end{aligned} \tag{3}$$

where,
$\rho_j \sim Uniform\left(0,1\right)$

The hyperprior on the τ^2 Inverse-Gamma IG (1, 0.01) variance component is used as the default hyperprior in the CARBayesST package;

$\lambda_k \sim Uniform(\lambda_{k-1}, \lambda_{k+1})$ for $k = 1,\ 2,\ \ldots,\ G$.

$$\begin{aligned} (Z_{ij}|Z_{i,j-1}) &= \frac{exp\left(-\delta\left[(Z_{ij}-Z_{i,j-1})^2(Z_{ij}-G^*)^2\right]\right)}{\sum_l exp\left(-\delta\left[(Z_{ij}-Z_{i,j-1})^2(Z_{ij}-G^*)^2\right]\right)};\ \ j=1,\ 2,\ \ldots,\ 5 \\ f\left(Z_{ij}\right) &= \frac{exp\left(-\delta\left[(Z_{11}-G^*)^2\right]\right)}{\sum_l exp\left(-\delta(l-G^*)^2\right)} \end{aligned} \tag{4}$$

where $\delta \sim Uniform(1,10)$ and the value of δ is the penalty parameter.

3. METHODOLOGY

The secondary data used in this study were obtained from the official website of the Indonesian Ministry of Health, specifically from the Indonesian Health Profile publications for the years 2018–2022, which provide data on pneumonia cases across all provinces in Indonesia. Additionally, data were sourced from the website of the Central Statistics Agency (BPS). The variables analyzed include the number of pneumonia cases (Y) as the dependent variable. The independent variables considered as potential influencing factors are percentage of infants exclusively breastfed (X_1), percentage of infants fully immunized (X_2), dan percentage of population living in poverty (X_3).

3.1 Bayesian Spatio Temporal Conditional Autoregressive (BST CAR) Localized Model

The research was conducted through a systematic series of procedures. First, the research problems were clearly formulated to define the scope and objectives of the study. Relevant references were then gathered to support both the methodological framework and the selected case study. Subsequently, the variables required for analysis were identified and defined, followed by the collection of all necessary data. The data were analyzed using the BST-CAR Localized method to capture spatial and temporal dependencies. Based on the analysis results, the best-fitting model was selected to ensure robust inference. Finally, conclusions were drawn from the findings, and a comprehensive research report was prepared to summarize the entire study process and outcomes. Selecting the best model based on the analysis results.

4. RESULT & DISCUSSION

Descriptive Analysis The descriptive statistics for the number of pneumonia cases are presented in **Table 1**.

Table 1. Descriptive Statistics of Pneumonia Cases

Year	Average	Minimum	Maximum
2018	14863	427	131382
2019	13769	17	104866
2020	9113	0	76929
2021	8184	281	74071
2022	11374	209	101967

Based on **Table 1**, the lowest average number of pneumonia cases occurred in North Sulawesi Province in 2018, 2021, and 2022, while Papua Province had the lowest in 2019 and 2020. Conversely, the highest number of pneumonia cases was reported in West Java Province in 2018, 2019, and 2022, and in East Java Province in 2020 and 2021.

4.1 Percentage of Infants Exclusive Breastfeeding

The descriptive statistics for the percentage of exclusively breastfed infants are presented in **Table 2**. Based on the table, the lowest average percentage of exclusively breastfed infants was observed in North Sumatera Province in 2018, in Bangka Belitung Province in 2019, in Central Kalimantan Province in 2020, and in Gorontalo Province in both 2021 and 2022. In contrast, the highest percentage of exclusively breastfed infants was recorded in North Maluku Province in 2018, in Papua Province in 2019, in Yogyakarta Province in 2020, and in West Nusa Tenggara Province in both 2021 and 2022.

Table 2. Descriptive Statistics of the Percentage of Infants Exclusive Breastfeeding

Year	Average	Minimum	Maximum
2018	45.43	25.69	64.28
2019	64.37	39.64	79.05
2020	66.49	52.98	78.93
2021	68.88	52.75	81.46
2022	69.21	53.60	79.69

4.2 Percentage of Infants Fully Immunized

The descriptive statistics for the percentage of fully immunized infants are presented in **Table 3**.

Table 3. Descriptive Statistics of the Percentage of Infants Fully Immunized

Year	Average	Minimum	Maximum
2018	87.19	66.20	102.30
2019	85.21	29.60	102.99
2020	89.09	50.90	104.20
2021	78.55	41.80	99.40
2022	80.87	42.70	100.00

Based on **Table 3**, the lowest average percentages of fully immunized infants were recorded in North Kalimantan Province in 2018, Papua Province in 2019, and Aceh Province from 2020 to 2022. In contrast, the highest percentages were observed in South Sumatra Province in 2018, Central Java Province in 2019, Bali Province in 2020 and 2021, and South Sulawesi Province in 2022. These findings indicate considerable regional disparities in immunization coverage across provinces and over time, highlighting areas that may require targeted public health interventions to improve vaccination uptake.

4.3 Percentage of the Population Living in Poverty

The descriptive statistics for the percentage of the population living in poverty are presented in **Table 4**.

Table 4. Descriptive Statistics of the Percentage of the Population Living in Poverty

Year	Average	Minimum	Maximum
2018	10.61	3.55	27.43
2019	10.46	3.47	27.53
2020	10.78	4.45	26.80
2021	10.43	4.60	27.40
2022	10.29	4.50	26.80

The spatio-temporal Moran index is a measure of spatio-temporal autocorrelation that quantifies the degree of spatio-temporal coherence in the data. The results of the spatio-temporal Moran index calculation are presented in Table 5.

Table 5. Testing the Spatio-Temporal Moran Index

Year	Moran's I Statistic	p-value
2018	0.5329004	4.696492e-05
2019	0.4359885	1.050302e-03
2020	0.3294764	8.393504e-03
2021	0.3598471	3.623596e-03
2022	0.4538335	5.814894e-04

Based on Table 5, the p-values for 2018 to 2022 are all smaller than $\alpha = 0.05$, suggesting that spatial autocorrelation exists among the provinces in Indonesia.

4.4 Best Model Selection

The optimal model is selected based on the smallest DIC and WAIC values. **Table 6** presents the results of the BST CAR Localized modeling for four models: G = 2, G = 3, G = 4 and G = 5.

Table 6. DIC and WAIC Values for the CAR Localized Model

Model	Covariate	2.5%	97.5%	DIC	WAIC
CAR Localized G = 2	X_1+	0.0027	0.0110	2075.8709	2053.8021
	X_2+	0.0023	0.0166		
	X_3	-0.0493	-0.0290		
CAR Localized G = 3	X_1+	0.0028	0.0088	2062.1887	2030.3587
	X_2+	0.0096	0.0205		
	X_3	-0.0224	-0.0055		
CAR Localized G = 4	X_1+	0.0058	0.0090	2083.6863	2080.1237
	X_2+	0.0102	0.0242		
	X_3	-0.0308	-0.0117		
CAR Localized G = 5	X_1+	-0.0042	0.0068	2107.2288	2165.9396
	X_2+	0.0017	0.0209		
	X_3	-0.0367	-0.0128		

Based on **Table 6**, it can be concluded that the optimal model in this study is the CAR localized model with G = 3, as it exhibits the lowest DIC (2062.1887) and WAIC (2030.3587) values. The model demonstrated convergence for the parameters τ^2, δ and ρ making it suitable for modeling pneumonia cases in Indonesia. Additionally, Table 4.6 indicates that the Credible Intervals (CI) values for the CAR localized model with G = 3 do not contain zero suggest that the predictor variables X_1, X_2, and X_3 significantly affect the response variable. Both X_1 and X_2 have a positive effect on pneumonia cases, while X_3 has a negative effect on pneumonia cases in Indonesia.

The results revealed that the proportions of infants who were exclusively breastfed and fully immunized were positively related to the number of pneumonia cases, whereas the poverty rate was negatively related. While these findings may seem counterintuitive, they likely reflect underlying differences in healthcare accessibility, diagnostic capability, and data reporting systems across regions. Provinces with well-established health infrastructures may report higher pneumonia incidence due to enhanced disease surveillance and case detection, which are typically associated with greater breastfeeding and immunization coverage. In contrast, the negative association between poverty and pneumonia may result from underreporting in low-resource settings where access to healthcare and reliable data systems remains limited. Another plausible explanation involves unobserved confounding factors that were not incorporated into the model. Environmental and socioeconomic variables, including air quality, urbanization, access to clean water, sanitation, and population density, may have influenced the observed associations. Failure to control for these variables could result in misleading interpretations of the direction and magnitude of the effects. The results of the parameter convergence check for the BST CAR Localized model with G = 3 are presented in **Figure 1** to **Figure 3**. The results of the Relative Risk (RR) and Localized Structure (LS) values for pneumonia cases in Indonesia from 2018 to 2022, based on the best model, the BST CAR Localized model with G = 3, are presented in **Table 7**.

According to **Table 7**, several regions in Indonesia in 2022 exhibited high relative risk values (RR ¿ 1), including South Kalimantan, West Nusa Tenggara, Banten, Jakarta, East Java, West Java, Central Sulawesi, North Kalimantan, Bangka Belitung, and Gorontalo. The highest relative risk value was observed in South Kalimantan (RR = 1.9546), while the lowest relative risk value was found in North Sulawesi (RR = 0.0570). Based on these findings, the spatial distribution of relative risk (RR) values is visualized in **Figure 4**, highlighting areas with higher and lower pneumonia risk across Indonesia.

This study is limited by the lack of comprehensive covariate data at finer spatial scales, such as the district or sub-district levels, as well as by the absence of more recent observations. Access to a more up-to-date and detailed dataset with additional explanatory variables would enhance the ability to capture underlying spatial and temporal patterns, thereby improving the

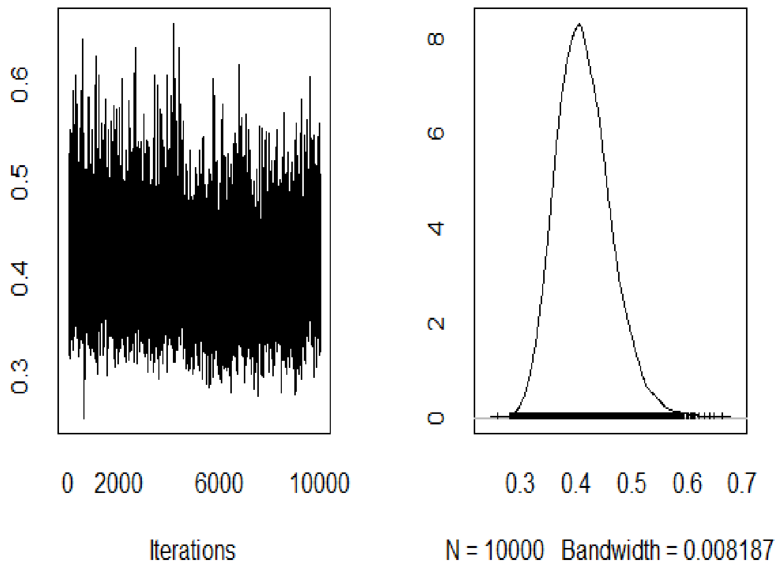

Figure 1. History Iteration Plot and Density Plot for the Parameter τ^2 Based on the CAR Localized Model with G = 3

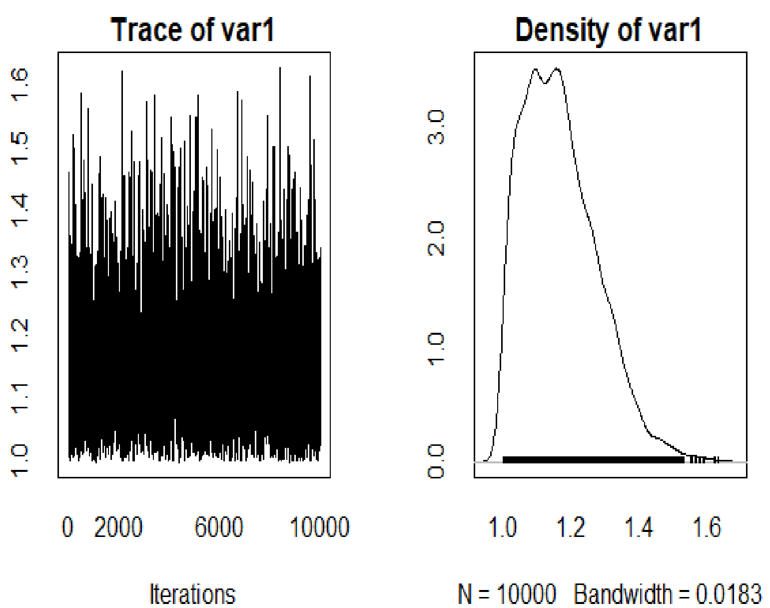

Figure 2. History Iteration Plot and Density Plot for the Parameter δ Based on the CAR Localized Model with G = 3

timeliness and relevance of the findings. Furthermore, the pneumonia data were available only on an annual basis, which may have reduced the precision of group classification and the robustness of the estimated associations. Another limitation lies in the use of a single prior distribution. Given that Bayesian methods were employed, conducting a sensitivity analysis is recommended, as prior selection may influence the results. Future research should also consider combining related covariates and exploring alternative model specifications to identify the most appropriate framework for analysis.

5. CONCLUSION

The results suggest that the BST CAR Localized model with G=3 offers the best fit for estimating the relative risk of pneumonia cases in Indonesia. Significant determinants of pneumonia incidence include the proportion of exclusively breastfed infants, the percentage of infants who have received complete basic immunization, and the proportion of the population living in poverty.

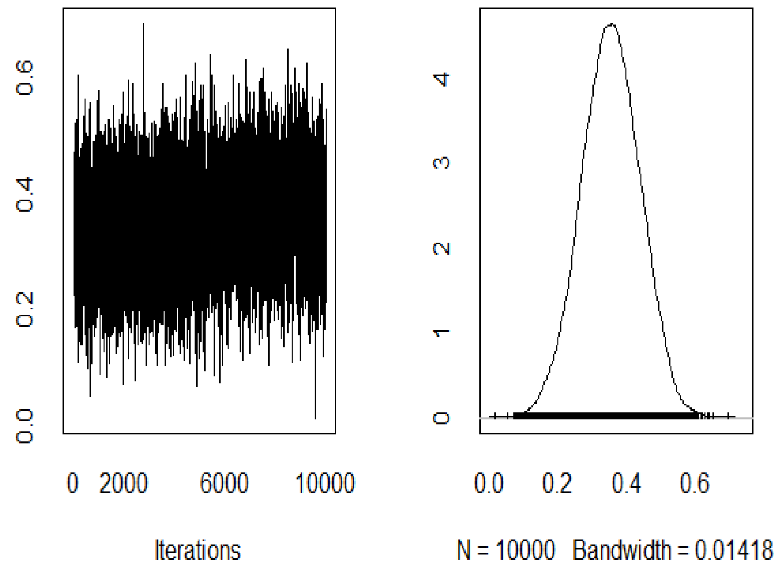

Figure 3. History Iteration Plot and Density Plot for the Parameter ρ Based on the CAR Localized Model with G = 3

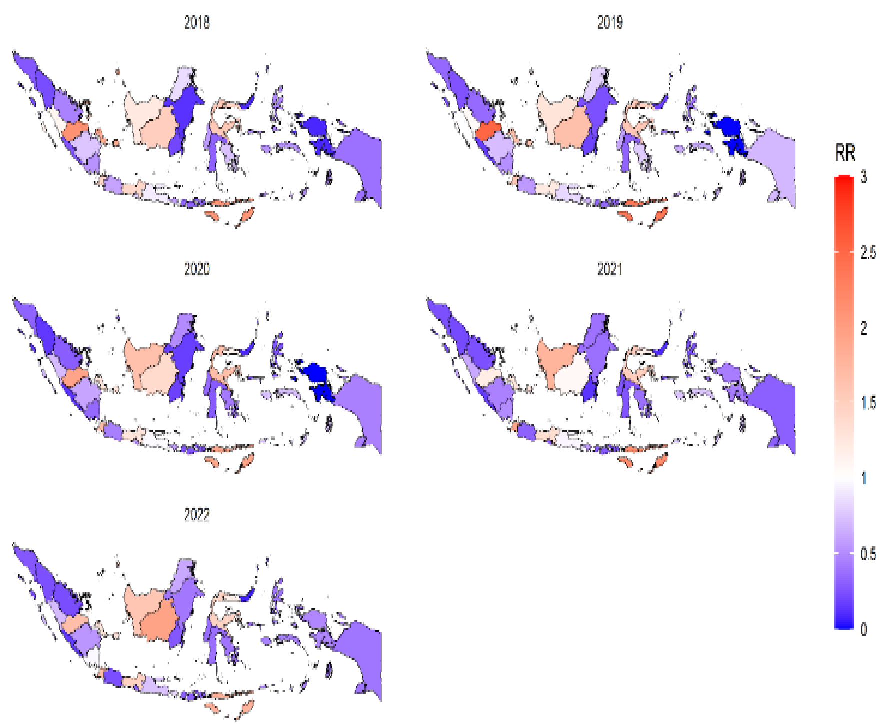

Figure 4. Map illustrating the relative risk (RR) of pneumonia cases in Indonesia (2018-2022).

South Kalimantan exhibited the highest relative risk of pneumonia (RR = 1.9546) followed by Nusa Teggara Barat in 2022, whereas North Sulawesi recorded the lowest relative risk (RR = 0.0570).

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Table 7. LS and RR Values for Each Province in Indonesia from 2018 to 2022

No.	Province	2018		2019		2020		2021		2022	
		LS	RR	LS	RR	LS	RR	LS	RR	LS	RR
1	Aceh	2	0.2733	2	0.3501	2	0.3229	2	0.2422	3	0.2746
2	Bali	2	0.5795	2	0.6665	2	0.5947	2	0.5806	3	0.8522
3	Bangka-Belitung	3	1.8737	3	1.6211	3	1.2859	3	1.2581	3	1.2755
4	Banten	3	1.4086	3	1.5763	3	1.6979	3	1.9111	3	1.7185
5	Bengkulu	2	0.2577	2	0.1599	2	0.1291	2	0.1588	2	0.1483
6	Gorontalo	3	1.4491	3	1.4601	3	1.1265	3	1.1807	3	1.1625
7	Irian Jaya Barat	2	0.6141	3	0.7748	3	0.9908	2	0.2862	3	0.6413
8	Jakarta Raya	3	2.1208	3	2.5158	3	1.9410	3	1.1927	3	1.6733
9	Jambi	2	0.6051	2	0.5631	2	0.4445	2	0.3185	2	0.2367
10	Jawa Barat	3	1.4168	3	1.2195	3	1.2739	3	1.3493	3	1.4719
11	Jawa Tengah	3	0.9228	3	0.8295	3	0.9803	3	0.9596	3	0.7385
12	Jawa Timur	3	1.2289	3	1.2818	3	1.6496	3	1.7754	3	1.5965
13	Kalimantan Barat	2	0.2065	2	0.1930	2	0.1875	2	0.1327	2	0.2722
14	Kalimantan Selatan	3	1.5091	3	1.6599	3	1.3817	3	1.0683	3	1.9546
15	Kalimantan Tengah	2	0.1239	2	0.2427	2	0.1705	2	0.3829	2	0.4164
16	Kalimantan Timur	2	0.8554	3	0.8114	2	0.4993	2	0.3912	2	0.6263
17	Kalimantan Utara	3	1.9606	3	1.1349	3	0.4045	3	0.9386	3	1.3153
18	Kepulauan Riau	2	0.5309	2	0.5120	2	0.3495	2	0.5032	3	0.9705
19	Lampung	2	0.5353	3	0.6436	2	0.7285	3	0.7527	2	0.4547
20	Maluku Utara	2	0.4847	2	0.3847	2	0.2539	2	0.2488	2	0.4006
21	Maluku	2	0.3240	2	0.3562	2	0.2642	2	0.2912	2	0.3096
22	Nusa Tenggara Barat	3	2.0822	3	2.3693	3	1.9241	3	2.1663	3	1.8039
23	Nusa Tenggara Timur	2	0.3861	3	0.6941	2	0.4522	2	0.3067	2	0.4031
24	Papua	2	0.0856	1	0.0016	1	0.0003	3	0.4397	3	0.4825
25	Riau	2	0.4546	2	0.3565	2	0.2969	2	0.2410	2	0.2319
26	Sulawesi Barat	3	0.5677	2	0.6199	2	0.3477	2	0.2708	2	0.3629
27	Sulawesi Selatan	2	0.3195	2	0.3304	2	0.2914	2	0.2617	2	0.3767
28	Sulawesi Tengah	3	1.5619	3	1.5802	3	1.6706	3	1.5138	3	1.4582
29	Sulawesi Tenggara	3	0.7400	3	0.7808	2	0.4257	2	0.3857	2	0.4002
30	Sulawesi Utara	2	0.0909	2	0.1719	2	0.0916	2	0.1049	2	0.0570
31	Sumatera Barat	3	1.0962	3	1.0620	3	0.7045	3	0.6315	3	0.7065
32	Sumatera Selatan	2	0.7537	2	0.7164	2	0.6107	2	0.4573	3	0.5482
33	Sumatera Utara	2	0.2274	2	0.2579	2	0.1479	2	0.2196	2	0.2404
34	Yogyakarta	3	0.8244	3	1.0182	2	0.5546	2	0.3108	2	0.3201

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