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Multivariate spatial M-models on sexually transmitted infections in West Java

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Abstract

HIV and hepatitis B & C are sexually transmitted infections (STIs) that are still a serious health problem in Indonesia, especially in West Java province which has recorded a high number of cases in recent years. However, many previous studies still use a univariate approach that has not considered the interrelationships between diseases or spatial interrelationships between regions. This paper use Bayesian multivariate spatial M-models approach with three types of spatial priors to investigate interrelationships between HIV and hepatitis B & C and its spatial factors. Models with fixed effect components and spatial random effects based on regional neighborliness. Inference is performed using integrated nested Laplace approximation (INLA). Factors that significantly influence the distribution of HIV and hepatitis B & C are mostly similar, such as the number of villages on mountain slopes, the number of poor people, and the unemployment rate. Average education also influenced hepatitis B & C. Variables from the tourism dimension had no significant effect. Spatial patterns show similarities in the distribution of relative risk of both diseases, with strong and significant correlations. High-risk areas are generally located in urban. Multivariate spatial models showed strong associations between HIV and hepatitis B & C, with similar factors and distribution patterns.

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INTRODUCTION

Sexually transmitted infections (STIs) are a significant and growing global health problem. These diseases are transmitted through sexual contact and are caused by infectious agents such as bacteria, viruses, parasites, and fungi (Garcia et al., 2026). According to the World Health Organization (WHO), there are approximately one million new STI cases every day globally. The most common STIs include HIV and hepatitis B & C. By 2022, about 39 million people will be living with HIV/AIDS worldwide, up from 37.7 million in 2020 (*UNAIDS., 2026*.). Meanwhile, hepatitis causes about 1.3 million deaths, with 83% caused by hepatitis B and 17% by hepatitis C (*Global Hepatitis Report 2024: Action for Access in Low- and Middle-Income Countries., 2024.*). This is an increase from 1.1 million deaths from hepatitis in 2019, making it the second highest cause of death from infectious diseases after COVID-19.

In Indonesia, STIs are also a serious concern, especially HIV and hepatitis. In 2020, the Indonesian Ministry of Health estimates that there will be 543,100 people living with HIV (PLHIV), decreasing to 526,841 by 2022. However, this figure remains high. Meanwhile, around 20 million Indonesians are estimated to suffer from hepatitis, with the highest prevalence in hepatitis B. By 2022, there will be 50,744 hepatitis B positive pregnant women, causing 35,757 babies to be born to infected mothers. This shows that STIs are still an important problem in Indonesia.

West Java province is the focus of attention as it is one of the provinces with the highest number of STI cases. In 2020, West Java ranked second for the number of PLHIV, and rose to first place in 2022. The province also ranks second in the number of pregnant women infected with hepatitis B, with 6,779 cases. Several factors are thought to influence the spread of STIs in this area including socio-cultural, economic, educational, and environmental aspects (Newmyer et al., 2022; Septiana et al., 2021). Risky sexual behaviors such as LGBT and promiscuous sex, global cultural influences, poverty, and low education levels contribute to the spread of the disease. To fully understand this phenomenon, a more complex analytical approach is needed. Univariate analysis is often used in epidemiology, but it only looks at one variable at a time without considering interactions between factors. In the case of STIs, which are influenced by multiple factors and can occur simultaneously, a multivariate approach is much more relevant (Mwange et al., 2023). These analyses allow understanding of the relationships between variables as well as the interactions between different causes of disease. In a spatial context, it is also important to analyze interdependencies between regions. Methods such as conditional autoregressive (CAR) allow us to model the effects of geographic location, thus identifying high-risk areas more precisely.

This study aims to analyze the spatial patterns and factors affecting the simultaneous spread of HIV and hepatitis B & C in West Java using the multivariate spatial M-model approach. Although there have been many studies on HIV and hepatitis separately, no one has integrated them in a comprehensive spatial multivariate model, especially in Indonesia. This study fills this gap by using claims data from the Indonesian Social Security Administration (BPJS Kesehatan), which has not been widely used in similar studies. The analysis was conducted on 27 districts/cities in West Java for the period 2023. The spatial model used includes iCAR, pCAR, and BYM2 priors, with estimation conducted through the efficient integrated nested Laplace approximation (INLA) method. In addition to making methodological contributions, this study is expected to provide evidence-based policy recommendations, assist in mapping high-risk areas, and support the achievement of Sustainable Development Goals (SDGs) target 3.3, namely ending the epidemic of infectious diseases such as HIV and hepatitis by 2030.

This paper is organized as follows. The next section presents the research methodology, including the dataset, modeling variables, and a brief overview of Bayesian multivariate spatial M-models and the INLA approach. The subsequent section reports the results, highlighting significant variables affecting the response and the mapping of relative risk for sexually transmitted diseases. This is followed by a discussion of the findings, particularly the characteristics of high-risk areas. The final section concludes the study and provides recommendations for future research.

METHOD

Dataset

The variables used in the study are divided into Dependent and Independent. The dependent variable of this research is the number of HIV and hepatitis B & C cases. The dependent variable data is obtained from BPJS by submitting at the link https://data.bpjs-kesehatan.go.id/bpjs-portal/action/homedataset.cbi. While there are 10 independent variables which are divided into 3 dimensions, namely topography, sociodemography, and tourism which can be seen in Table 1. This dimensional division aims to reduce the intervening effect of variables that cannot be handled by multicollinearity between variables. In addition, the division of dimensions is intended to make the research more focused in analyzing each dimension. Data on independent variables were obtained from the Indonesian Central Bureau of Statistics (BPS).

Table 1. Research Variables

Variable	Dimension	Symbol	Unit	Source
HIV	Disease	Y_1	People	BPJS
Hepatitis B & C		Y_2	People	BPJS
Number of Mountain Slope Villages	Topography	X_{Slope}	Village	BPS
Number of Coastal Villages		X_{Coast}	Village	BPS
Area Height		X_{Height}	MSL	BPS
Distance to Provincial Capital		$X_{Captial}$	KM	BPS
Number of Poor	Sociodemographic	X_{Poor}	People	BPS
Number of female job seekers		X_{Femjob}	People	BPS
Unemployment Rate		X_{Un}	People	BPS
Average years of education		X_{Edu}	Year	BPS
Number of Tourist	Tourism	X_{Tour}	People	BPS
Number of hotel and inn		X_{Hotel}	Unit	BPS

Bayesian Multivariate Spatial M-Models

Multivariate models provide better risk estimates than the old univariate models. Let Y_{ij}, e_{ij}, and r_{ij} symbolize the observed number of events, expected number of events, and relative risk of occurrence in the i-th region in the j-th case, respectively.

$$Y_{ij}\,|r_{ij} \sim \text{Poisson}\big(\mu_{ij} = e_{ij} . r_{ij}\big), \tag{1}$$

$$\log \mu_{ij} = \log e_{ij} + \log r_{ij}\,, \tag{2}$$

with

$$\log\big(r_{ij}\big) = \alpha_j + \textstyle\sum_{k=1}^{n} \beta_{jk} x_{ik} + \theta_{ij}\,, \tag{3}$$

where the specific intercept for each event is denoted as a. The regression coefficient for the k-th covariate is denoted as βk. Finally, the spatial random effect is denoted as θ, which contains the set of effects for each event, i.e. θ, which represents the spatial random effect for each location at the j-th event. The dependency within and between events is represented through the covariance matrix of the spatial random effects. The following prior distribution with Gaussian kernel $p(\theta) \propto \exp(-\frac{\tau}{2}\theta'\Omega_\theta\theta)$ is assumed for θ with precision matrix

$$\boldsymbol{\Omega}_\theta = (\boldsymbol{\Sigma}_b^{-1} \otimes \boldsymbol{I}_n) Blockdiag\big(\boldsymbol{\Omega}_1, \ldots, \boldsymbol{\Omega}_J\big), \tag{4}$$

where $\boldsymbol{M}$ is the square root of the symmetric and positive definite JxJ between-case covariance matrix $\boldsymbol{\Sigma_b}$ (between-case covariance), i.e. $\boldsymbol{\Sigma_b} = \boldsymbol{M'M}$, with $\Sigma_b \sim Wishart\,(J, \sigma^2 \boldsymbol{I_J})$, and $\boldsymbol{\Omega_j}$ is the spatial precision matrix for the jth event case. All elements of the covariance matrix between event cases $\boldsymbol{\Sigma_b}$ are unknown and must be estimated. The symbol $\boldsymbol{\Omega_j}$ can be the precision matrix of the iCAR, pCAR or BYM2 priors. The different characteristics of each prior can be seen in **Error! Reference source not found.**.

Table 2. Spatial Prior Differences

Prior	Ω_j
iCAR	$D_w - W$
pCAR	$D_w - \lambda W$
BYM2	$\lambda(D_w - W)^{-1} + (1-\lambda)I_n$

$W = (w_{il})$ in Table 2 is a representation of the spatial adjacency matrix, where $w_{il} = 1$ indicates the neighbor relationship between the i-th and l-th areas and 0 otherwise, $D_w = \text{diag}(w_{1+}, \dots, w_{n+})$, where the diagonal element w_{i+} indicates the number of neighbors for the i-th area, λ is a spatial dependence parameter, and I_n is an identity matrix of dimension n (MacNab, 2022).

INLA (Integrated Nested Laplace Approximation)

INLA is a numerical method used to perform Bayesian inference in complex hierarchical models, especially in latent Gaussian models (Berild et al., 2022; Martino & Riebler, 2020; Van Niekerk et al., 2023). INLA was developed as an alternative to the Monte Carlo Markov Chain (MCMC) method which is commonly used in Bayesian analysis but requires long computation time and large resources (Rue et al., 2009). INLA offers a more efficient solution by using the Laplace Approximation approach to calculate the posterior distribution of the model parameters. This process includes an integrated assessment of the posterior distribution through a layered approach, allowing researchers to significantly reduce computational complexity.

RESULTS

Best Model Selection

This section compares the modeling results with different spatial priors. The comparison is based on the RMSE value, as presented in **Error! Reference source not found.**. Based on the results of the table, during the observation period of the study, the best model generated in each dimension is BYM2. This is evident from the RMSE value of BYM2 which is consistently the smallest in each year in each dimension analyzed. The results of this best model will be analyzed in more depth in the study to explore more comprehensive insights related to the spread and risk factors of both diseases.

Table 3. RMSE Value

Dimensions	Model	Year
		2023
Topography	iCAR	1.243
	pCAR	1.178
	BYM 2	1.138
Sociodemographics	iCAR	1.242
	pCAR	1.184
	BYM 2	1.146
Tourism	iCAR	1.551
	pCAR	1.433
	BYM 2	1.270

Significance of Variables

This section will identify variable significance tests of various dimensions over 2023. Each unit number represents the effect on case 1 (HIV) or case 2 (hepatitis B & C). For example, X_{Slope1} represents the effect of the slope variable on case 1 (HIV). **Error! Reference source not found.** shows the results of the significance test of the topographic dimension variable during the study period. Spatial regression models can also be formed from the mean coefficients in the table. For example, the HIV relative risk regression model on the topographic dimension:

$$\log(r_{i1}) = -0.23992 - -0.00405X_{Slope\ i1} - 0.01285X_{Coast\ i1} + 0.00065X_{Height\ i1} + 0.00607X_{Captial\ i1} + \theta_{i1}, \quad (5)$$

while in hepatitis B & C:

$$\log(r_{i2}) = 0.66312 - 0.00379X_{Slope\ i2} - 0.02129X_{Coast\ i2} - 0.00035X_{Height\ i2} - 0.00104X_{Captial\ i2} + \theta_{i2.} \quad (6)$$

In year of observation, the number of villages on mountain slopes again showed a significant negative effect on both diseases.

Table 4. Significance of Topography Dimension Variables

Variable	Mean (95% Credible Interval) Year 2023
α_1	-0.23992 (-2.014, 1.410)
α_2	0.66312 (-0.676, 2.059)
X_{Slope1}	-0.00405 (-0.008, -0.0002)
X_{Slope2}	-0.00379 (-0.007, -0.001)
X_{Coast1}	-0.01285 (-0.044, 0.018)
X_{Coast2}	-0.02129 (-0.046, 0.002)
$X_{Height1}$	0.00065 (-0.001, 0.003)
$X_{Height2}$	-0.00035 (-0.002, 0.001)
$X_{Captial1}$	0.00607 (-0.010, 0.023)
$X_{Captial2}$	-0.00104 (-0.015, 0.012)

Table 1. Significance of Sociodemography Dimension Variables

Variable	Mean (95% Credible Interval) Year 2023
α_1	**0.77098 (-2.211, 3.610)**
α_2	**-2.27869 (-4.894, 0.092)**
X_{Poor1}	**-0.00149 (-0.006, 0.003)**
X_{Poor2}	**-0.00204 (-0.006, 0.002)**
X_{Fem1}	**-0.00009 (0.000, 0.000)**
X_{Fem2}	**0.00003 (0.000, 0.000)**
X_{Un1}	**0.21531 (-0.010, 0.451)**
X_{Un2}	**-0.0199 (-0.227, 0.184)**
X_{Edu1}	**-0.18453**

Variable	Mean (95% Credible Interval)
	Year
	2023
	(-0.520, 0.154)
X_{Edu2}	0.27543 (0.0002, 0.577)

Table 5 shows the significance test results of the variables in the sociodemographic dimension during the study period. The average years of education variable shows a significant positive effect on hepatitis B & C, indicating a shift in risk factors from economic to educational aspects. **Error! Reference source not found.** shows the results of the significance test of the tourism dimension variables. During the observation, the variables of the number of tourists and the number of hotels did not show a significant influence on the two diseases studied.

Table 2. Significance of Tourism Dimension Variables

Variable	Mean (95% Credible Interval)
	Year
	2023
α_1	0.33498 (-0.237, 0.893)
α_2	0.20545 (-0.308, 0.686)
X_{Tour1}	0 (0.000, 0.000)
X_{Tour2}	0 (0.000, 0.000)
X_{Hotel1}	0.00032 (-0.003, 0.004)
X_{Hotel2}	-0.00042 (-0.003, 0.002)

Relative Risk

The results of the relative risk mapping for HIV and hepatitis B & C in West Java can be seen in Figure 1. The mapping shows that the distribution of relative risk for both diseases show a similar pattern. This indicates that most regions have interrelated risk characteristics, influenced by the same environmental, social, or demographic factors. This pattern indicates a spatial relationship between the spread of the two diseases, so that most areas with a high risk of one disease tend to have a high risk of the other disease as well. This finding is also reinforced by the results of the Pearson Relative Risk correlation test of the two diseases, with a correlation value of 0.499, which indicates a strong positive relationship between the two diseases. The mapping shows that the pattern of risk distribution is relatively random. Many areas with relatively high risk are surrounded by areas with low to medium risk. This is reinforced by the Moran test results, where HIV has an I = -0.054 with a p-value = 0.764, while hepatitis B & C has an I = -0.0008 with a p-value = 0.46. These two test results indicate that the pattern of relative risk distribution is dispersed. In addition, the p-value is greater than 0.05 (p-value>0.05) for both diseases indicating that the spatial effect of regional neighborliness does not significantly affect the relative risk in an area.

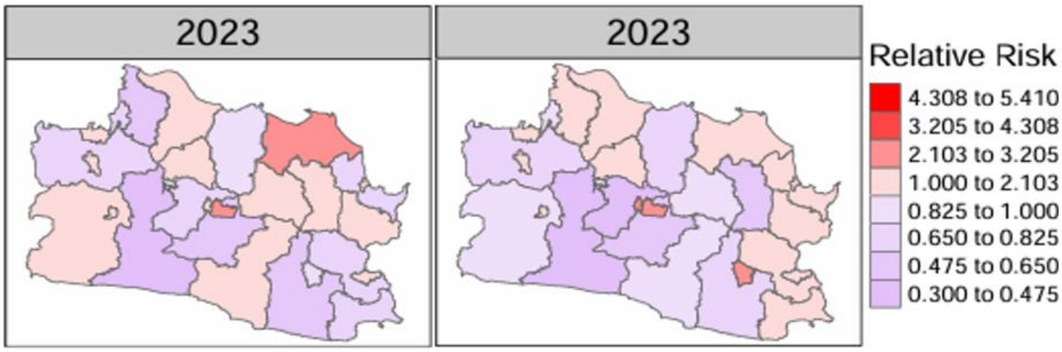

Figure 1. Relative Risk Mapping of HIV (left) and hepatitis B & C (right)

DISCUSSIONS

The finding of BYM2 as the best model is in line with previous research showing that with the number of areas around 25, the BYM2 model is the best choice (Jahan et al., 2022). This finding is further strengthened by another study which states that when the data has low autocorrelation and the number of regions is around 25, BYM2 remains the most suitable model (Aswi et al., 2020). A structure that combines structured and unstructured effects, the BYM2 model can accommodate diversity in the data, including in conditions where regions do not show a clear pattern of autocorrelation. This flexibility makes it an excellent model for handling various spatial data characteristics. It is expected that the selection of the best model based on the RMSE metric can strengthen the prediction accuracy and provide more reliable results in relative risk modelling.

Throughout the study period, the variable number of villages on mountain slopes consistently had a significant negative association with hepatitis B & C and HIV infection. This phenomenon can be explained by several factors. First, people living in rural areas, especially in mountainous regions, generally still live a traditional lifestyle with strong social and religious values. This culture contributes to the low level of risky sexual behavior among the population, both in mountainous and coastal areas (Sukardi, 2015). In addition, limited access to health information and medical services in rural areas contributes to low levels of awareness of the risks of sexually transmitted infections. Many individuals may be infected but undiagnosed due to lack of understanding and limited access to health facilities. These factors may indirectly lead to lower case numbers in the observed data, despite the fact that there are still individuals who are infected but not recorded. Thus, the significant negative association between the number of villages on mountain slopes and hepatitis B & C and HIV infection rates may not be solely due to low risk of transmission, but also due to limitations in data collection and diagnosis in these areas. This suggests the need for a more comprehensive approach to understanding risk factors for sexually transmitted diseases in different geographical settings, including efforts to increase awareness and access to health services in rural areas.

The positive effect of unemployment rate on hepatitis B & C and HIV could be due to psychosocial stress and hopelessness that encourage individuals to engage in sex work. This can lead to risky behaviors, such as injecting drug use and unsafe sexual intercourse (Abdullah et al., 2022; Nagelhout et al., 2017). In addition, unemployed individuals tend to have limited access to preventive health services and health education, which increases vulnerability to infections. Meanwhile, the negative effect of poverty on hepatitis B & C may be due to underreporting. The poor often have limited access to health services, so cases of infection may go undiagnosed or unrecorded in the health reporting system. In addition, people with low economic conditions are less likely to engage in drug use and nightlife activities that require high costs (Afrian Novia Kartikasari, 2022).

The significant mean level of education in the last year can be explained by social engagement among highly educated individuals, who may be more susceptible to certain risk factors. Individuals with higher levels of education tend to have wider social networks and lifestyles that may increase their risk of developing these two diseases, especially in urban areas. Higher education is also often followed by greater income, which allows access to risky behaviors or habits such as drug use, nightlife and promiscuous sex that are relatively expensive (Hidayati, 2024). In addition, individuals with higher education are usually more aware of their health conditions, making them more likely to be diagnosed, which contributes to the increased number of cases recorded.

This is related to the fact that most tourists visiting West Java do not engage in risky sexual activities. Most of the tourist destinations in this area are more geared towards family and children's tourism, both in cities and districts, which tend not to be associated with risk factors related to sexually transmitted diseases. In addition, the number of hotels used in this observation refers to officially registered hotels that have strict regulations and supervision systems regarding lodging licenses. Risky sexual activities are more likely to occur in lodging places that are not officially registered, such as illegal lodging, uncontrolled nightspots, or free boarding houses that do not meet licensing standards. Therefore, while the number of hotels may reflect the level of accessibility of lodging, not all types of accommodation support or are directly related to risky behaviors that can increase disease transmission.

The effect of spatial proximity has no significant effect on the spread of both diseases because the spread is limited to sexual spread, not as easily as through touch or airborne droplets. Mobilization of individuals from one area to another for sexual activities is minimal, if not non-existent. In addition, on the relative risk map, Hepatitis B and C appear to have a lower risk than HIV. This is due to the level of knowledge and understanding of the community that focuses more on HIV than Hepatitis B and C (Dehghani et al., 2020; Mehndiratta et al., 2022). As a result, HIV is more frequently recognized and identified. However, it is possible that the number of Hepatitis B and C cases is higher, but many individuals are unaware of the infection.

High relative risk areas tend to be found in urban areas. For example, areas with the highest relative risk of HIV include Sukabumi City, Bogor City, Cirebon City, and Bandung City. Meanwhile, for hepatitis B & C, a similar pattern is seen in the same urban areas, with the addition of Tasikmalaya City and Cimahi City. The high relative risk in urban areas may be closely related to the lifestyle of urbanites who are more prone to risky sexual behavior. Major factors contributing to the high risk in urban areas include promiscuity, especially among teenagers, which is often not accompanied by education on sexual health. The circulation of illicit drugs, such as drugs, also worsens the situation, especially for users who inject unsterilized drugs, which is one of the channels of transmission of the virus. In addition, the increasing number of deviant sexual behaviors, such as unsafe LGBT, also contributes to the risk. This phenomenon is exacerbated by the proliferation of nightlife venues in urban areas, which often serve as locations for risky sexual activities. Urban areas are also the center of various high migration activities, both from villages to cities and between regions. This migration allows the movement of individuals with risky behaviors, thus expanding the spread of the disease. In addition, the lack of supervision in some lodging places, as well as the lack of access or utilization of available reproductive health service facilities, hampers early detection of cases in the community. All these factors make urban areas potentially higher relative risks for HIV and hepatitis B and C than other areas. Future studies could explore additional factors such as marine resource sustainability, fisheries, and renewable ocean-based energy to further enhance the understanding of the blue economy. Expanding the model with multiscale approaches and global perspectives could provide a more comprehensive view of how spatial and temporal factors affect BEI. Additionally, using alternative variable selection methods could uncover other significant factors, further improving the accuracy and robustness of future models. Research focused on strengthening maritime infrastructure and aligning blue economy development with national defense and environmental sustainability goals would also be valuable for ensuring long-term economic and ecological resilience.

CONCLUSIONS

Analysis using multivariate spatial M-models shows that most of the variables that have a significant effect on both diseases are similar. These variables include slope, poor population, unemployment rate. In addition, the length of education also has a significant effect only on hepatitis B and C. Meanwhile, the tourism dimension variable has no significant effect. The distribution pattern of the relative risk of the two diseases also shows a similar pattern, where areas with a high risk of one disease tend to have a high risk of other diseases as well. This is consistent with the strong and significant correlation between the two diseases. The distribution of risk is random and dispersed, in accordance with the results of Moran's I test which shows a dispersed pattern, where spatial neighborliness does not have a significant influence on the spread of disease. Areas with high risk are generally located in urban areas, which is thought to be related to the lifestyle of urbanites who are more susceptible to both diseases.

Further research is recommended to expand the scope of the study beyond West Java Province to include other regions in Indonesia or even on a national scale, in order to obtain more robust generalizations of the results. Additionally, incorporating variables from various dimensions such as individual behavior, access to health services, population mobility, as well as cultural and health policy factors is crucial for providing a more comprehensive understanding of the determinants of HIV and hepatitis B & C transmission. The use of more diverse methodological approaches, such as spatio temporal models or the integration of machine learning with spatial statistical models, is also recommended to improve prediction accuracy and the ability to explore data patterns. Furthermore, future research may consider using data with higher resolution (e.g., at the subdistrict or individual level) and longer time periods to capture the dynamics of risk changes in greater detail. Finally, integrating research findings with evidence based policy approaches and fostering cross sectoral collaboration particularly in the health and defense sectors is expected to provide more practical contributions to efforts to control infectious diseases in Indonesia.

AUTHORS' CONTRIBUTIONS

All authors made significant contributions to this study. AA was responsible for the conceptualization of the study and the preparation of the initial draft of the manuscript. Author SA was involved in data collection and processing. RNR performed the formal analysis and developed the methodology and models. DHP contributed to the validation of the results and the presentation of visualizations. AR supervised the entire research process, managed project administration, and reviewed and refined the manuscript. All authors have read, revised, and approved the final version of the manuscript for publication.

CONFLICT OF INTEREST

The authors declare that they have no conflict of interest regarding the publication of this manuscript.

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