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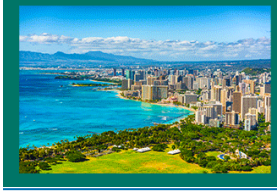

Comparison of Bayesian Spatio-temporal Models of Tuberculosis in Makassar, Indonesia

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Abstract. South Sulawesi province ranks sixth-highest in tuberculosis (TB) in Indonesia. Makassar ranks the highest in South Sulawesi. Spatio-temporal modelling can identify the areas with high risk as well as the temporal relative risk of disease. We analysed the tuberculosis cases data from Makassar City Health Office for 15 districts over seven years from 2012 to 2018. Seven models of Bayesian Spatio-temporal (BST) Conditional Autoregressive (CAR) were applied by using the measures of goodness of fit (GOF) namely, DIC and WAIC. The results showed that BST CAR localised model with G = 3 has the lowest DIC and BST CAR adaptive has the lowest WAIC. Based on the preferred model (Bayesian ST CAR localised with G=3), Panakukang district had the highest relative risk of TB in 2012, 2013, and 2014, while Makassar district had the highest relative risk of TB in 2015, 2016, and 2017. Mamajang had the highest relative risk of TB in 2018.

Keywords: Bayesian, Spatio-temporal Models, Tuberculosis, CAR, DIC, WAIC

1. Introduction

Makassar is the fourth largest city in Indonesia and the largest city in the Eastern Indonesia region. The area of Makassar is about 175.77 km^2 with 15 districts and 153 sub-districts[1,2]. The population of Makassar City in 2020 [2] was 1,489,011 people consisting of 737,146 men and 751,865 women, with a projected growth of 1.32 percent (1.43% growth for men and 1.36% for women) [1].

Since 2013, the number of people diagnosed with tuberculosis (TB) has increased in many countries. The first and second biggest contributors to TB on the global increase were India and Indonesia [3–5]. In India, notifications of people newly diagnosed with TB rose from 1.2 million (2013) to 2.2 million (2019) and from 331,703 (2015) to 562,049 (2019) in Indonesia [3]. South Sulawesi is the sixth province with the highest TB burden in Indonesia. In 2016, South Sulawesi had 7,139 cases of TB with 4,277 males. One study stated that Makassar had the highest rank of TB patients in South Sulawesi and Tallo district has the highest rank on TB cases in Makassar City [5].

Various research on modelling TB has been carried out in Indonesia, including time series analysis for predicting pulmonary TB in Ponorogo [6], spatial analysis of TB+ spread in Semarang [7], spatial analysis of TB in Cimahi Utama Village [8], spatial analysis pulmonary TB in Semarang [9], analysis of TB risk factors in Palembang [10], Generalized Space-Time Autoregressive (GSTAR) in pulmonary TB in DKI Jakarta [11], spatial logistic regression model to predict TB cases in Samarinda [12], and spatial distribution of TB in Kabanjahe District-Karo [13].

Several studies on TB have been conducted in Makassar, including the Local Indicators of Spatial Association (LISA) method [14], Susceptible-Infective-Treatment-Recovered (SITR) model [15], Susceptible-Infective-Recovered (SIR) Runge-Kutte model [16], Spatio-temporal approach of tuberculosis cases in Makassar [17], and descriptive research on the significant positive effect of

knowledge, attitudes, and behaviour TB patients on medication adherence in the work area of the Bangkala Health Centre Makassar City [18].

A Bayesian spatial and Bayesian Spatio-Temporal (BST) models have been used in several studies but they were applied in dengue cases, including the BST CAR localised model for DHF cases in Makassar City [19], Bayesian spatial survival model for DHF cases in Makassar [20,21], Bayesian spatial and Spatio-temporal for dengue fever cases [22], comparison of Bayesian Spatio-temporal CAR models for dengue fever cases in Makassar [23], and Bayesian Spatio-temporal model for modelling the effect of climatic factors on dengue cases in Makassar [24]. Among these studies, no study has discussed the Bayesian Spatio-temporal CAR model for TB in Makassar city.

Bayesian Spatio-temporal models for tuberculosis have been also conducted. A Bayesian Spatio-temporal assuming a Poisson distribution for the count data of TB in Ribeirão Preto, State of São Paulo, southeast Brazil has been evaluated [25]. Another study used one of the Bayesian Spatio-temporal CAR models for tuberculosis in India [26]. Another study has also been used to model socioeconomic risk factors for the population TB susceptibility using a hierarchical Bayesian Spatio-temporal model where the count data is modelled by using a negative binomial in the Sichuan province of China [27]. Bayesian Spatio-temporal models have not been explored yet for modelling TB in Makassar, Indonesia. Therefore, this study aims to compare seven Bayesian ST CAR models and choose the best model in modeling the relative risk of TB disease in Makassar City.

2. Methods

2.1. *Data*

The annual tuberculosis cases data were gathered from Makassar City Health Office from 2012 to 2018 for every district (15 districts) in Makassar city. Population data in every district is also used to calculate the expected number of tuberculosis cases. A total of 13163 TB cases were registered from 2012 to 2018. The number of TB cases in each district varies between districts and years ranging from 1035 cases (2013) to 3445 cases (2017). There is an increasing number of TB cases from 2013 (1035 cases) to 2017 (3445 cases) but then decreased in 2018 (1040 cases). The three highest number of TB cases (2012-2018) were Panakkukang (1740 cases), Tallo (1630 cases), and Rappocini (1334 cases), while the lowest number of TB cases were Sangkarrang Island (137 cases), followed by Wajo (235 cases), and Ujungpandang district (323 cases).

2.2. *Models*

Seven BST conditional Autoregressive (CAR) models were applied in modelling TB cases, namely BST CAR linear model [28,29], BST CAR ANOVA [30], BST CAR separated spatial [31], BST CAR Autoregressive (AR) [32], BST CAR Adaptive [33], BST CAR localised G=2, and BST CAR localised G=3 [34]. The tuberculosis counts were modelled using the common model of disease namely Poisson distribution as follows:

$$y_{ij} \sim Poisson(e_{ij}\theta_{ij})$$
$$log\ log\ (\theta_{ij}) = \varphi_{ij}$$

where y_{ij} is the number of TB cases in the i-th district and j-th time period, i=1, 2, …, n, j=1, 2, …, T; e_{ij} is the expected number of TB cases in the i-th district and and j-th time period. θ_{ij} is the relative risk of TB, and φ_{ij} is a latent variable for district i and time j considering one or more sets of Spatio-temporal random effects. A detailed explanation of the seven models is available in some papers [21,23,24]. The Spatio-temporal structure of these models are explained as follows:

a. ST CAR linear model consists of the intercept, spatial random effect for all time, temporal random effect for all areas, and the space-time interaction.
b. ST CAR ANOVA consists of spatial random effect for all time, temporal random effect for all areas, and the independent space-time interaction.
c. ST CAR separated spatial consist of separate spatial effects for each time and temporal effect for all areas.
d. ST CAR Autoregressive (AR) model consists of a spatial random effect for each time.

e. ST CAR adaptive model has the same model structure as STCAR AR but STCAR AR allows for localised spatial dependence.
f. ST CAR localised model consists of spatial random effect for each time and a cluster component .

All these distinct models are run using the package of CARBayesST [29] in R [35]. The GOF of these models was applied by using DIC and WAIC. The package of CARBayesST in R [29,35] was used to fit all models. The estimates of posterior were based on 15,000 MCMC samples collected after a burn-in of 10,000 samples.

3. Result and discussion

The descriptive analysis of the number of tuberculosis cases from 2012 to 2018 is given in Table 1. The results showed that the highest TB cases were in 2017 (3445 cases) and the lowest TB cases were in 2013 (1035 cases).

Table 1. Descriptive analysis of the number of tuberculosis for each year

	Mean	Median	1st Qu	3sr Qu	Min	Max	Sum
2012	76.07	59	40.50	108.50	0	159	1141
2013	69.00	60	41.00	94.50	10	144	1035
2014	99.87	82	69.50	144.50	15	205	1498
2015	150.93	120	80.00	228.50	27	328	2264
2016	182.67	153	95.50	257.50	36	387	2740
2017	229.67	186	118.00	325.00	34	483	3445
2018	69.33	72	40.00	96.50	15	153	1040

The highest number of TB cases was Panakukang district from 2014 to 2017, while the lowest number of TB cases was Sangkarrang district in almost all years. Tallo and Panakkung districts almost had the same number of TB cases in 2017 and 2018. These results are illustrated through the profile analysis in Figure 1.

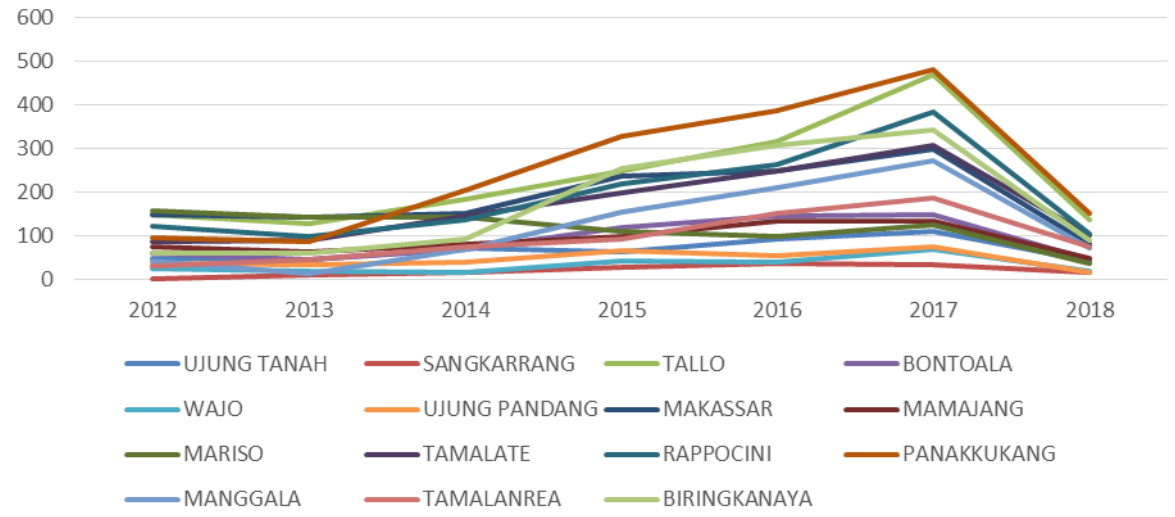

Figure 1. Profile analysis for the number of TB patients per sub-district.

A plot for the proportion between the number of TB cases and the total population in each district of Makassar city is given in Figure 2. This proportion provides information on the percentage of the population with TB patients' each-district from 2012 to 2018. The highest proportion occurred in Mariso district from 2012 to 2014, Makassar district from 2015 to 2017, and the highest proportion in 2018 was Ujungtanah district. Meanwhile, the Tamalanrea district has the lowest proportion of TB over the year.

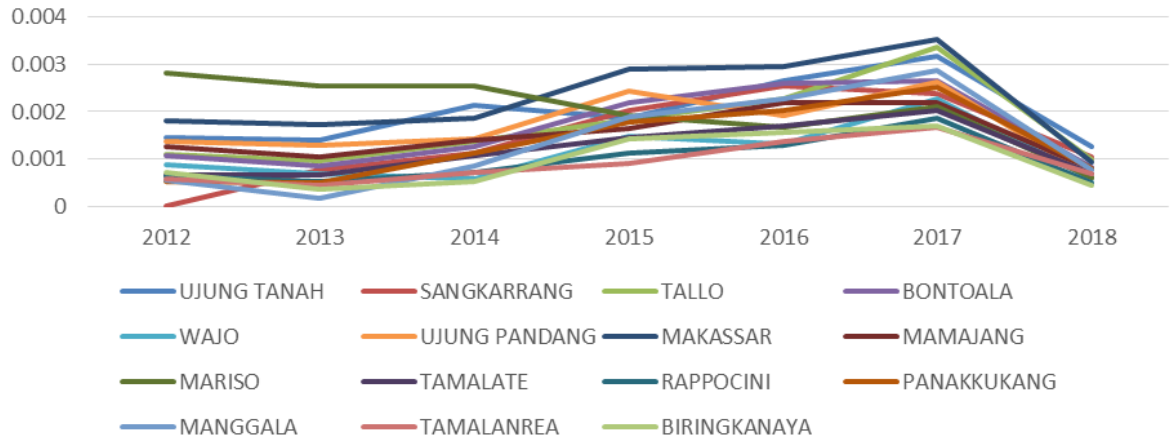

Figure 2. Profile analysis for the proportion of TB patients to the population

It can be seen from Table 1, Figure 1, and Figure 2 that the TB cases vary between districts and over years. The DIC and WAIC results for all seven Bayesain ST CAR models from 2012 to 2018 are given in Table 2.

Table 2. DIC and WAIC for all seven Bayesian ST CAR models

Model	DIC	WAIC
ST CAR linear	3159.36	4322.72
ST CAR Anova	879.52	866.67
ST CAR separated spatial	879.47	866.11
ST CAR AR	869.41	853.35
ST CAR adaptive	856.14	**846.56**
ST CAR Localized G=2	854.55	869.82
ST CAR Localized G=3	**837.87**	909.21

Based on Table 2, it is shown that the lowest DIC value (837.87) is the Bayesian ST CAR Localised with G=3 and the highest DIC (3159.36) is the Bayesian ST CAR linear model. Furthermore, the lowest WAIC value (846.56) is Bayesian ST CAR adaptive and the highest WAIC (4322.72) is Bayesian ST CAR linear model. Overall, Bayesian ST CAR Localised with G=3 is the preferred model in modeling the relative risk of TB cases in Makassar city. Based on the preferred model, the localised structure (LS), and the relative risk (RR) of TB cases in Makassar city from 2012 to 2018 for each district are given in Table 3. Furthermore, districts included in Group 1 and Group 2 under the Bayesian ST CAR localised G=3 model are given in Table 4.

Table 3. The localised structure (LS), and the relative risk (RR) of TB cases in Makassar city (2012-2018) for each district based on Bayesian ST CAR Localised with G=3

Districts	2012		2013		2014		2015		2016		2017		2018	
	LS	RR	LS	RR	LS	RR	LS	RR	LS	RR	LS	RR	LS	RR
Mamajang	2	1.11	2	1.12	2	1.54	2	1.47	2	2.00	2	2.40	2	**1.04**
Manggala	1	0.24	1	0.58	2	0.95	2	1.57	2	1.80	2	1.78	2	0.92
Mariso	2	0.85	1	0.70	2	1.03	2	1.37	2	1.74	2	2.56	1	0.74
Sangkarrang	2	0.82	2	0.73	2	0.93	2	1.61	2	1.95	2	2.02	2	0.68
Rappocini	1	0.65	1	0.48	1	0.45	2	1.16	2	1.07	2	1.71	1	0.48
Tamalate	2	1.03	2	1.01	2	1.09	2	1.72	2	1.48	2	1.99	1	0.51
Makasar	2	1.38	2	1.30	2	1.41	2	**2.10**	2	**2.23**	2	**2.67**	1	0.70
Ujungpandang	2	0.94	2	0.85	2	1.04	2	1.24	2	1.65	2	1.71	1	0.59
Panakukkang	2	**2.04**	2	**1.86**	2	**1.88**	2	1.43	2	1.28	2	1.61	1	0.47
Bontoala	1	0.38	1	0.39	1	0.57	2	0.83	2	0.99	2	1.20	1	0.41
Wajo	2	0.63	1	0.46	2	0.68	2	1.03	2	1.24	2	1.77	1	0.48
Ujungtanah	1	0.50	1	0.46	2	1.09	2	1.69	2	2.00	2	2.46	2	0.81
Tallo	1	0.28	1	0.14	1	0.40	2	0.91	2	1.16	2	1.47	1	0.40
Tamalanrea	1	0.25	1	0.33	1	0.53	1	0.63	2	1.07	2	1.26	1	0.50
Biringkanaya	1	0.26	1	0.26	1	0.38	2	0.99	2	1.16	2	1.25	1	0.34

Table 4. Districts included in Group 1 and Group 2 under the Bayesian ST CAR localised G=3 model

Year	Group 1	Group 2
2012	Manggala, Rappocini, Bontoala, Ujungtanah, Tallo, Tamalanrea, Biringkanaya	Mamajang, Mariso, Sangkarrang, Tamalate, Makasar, Ujungpandang, Panakukkang, Wajo
2013	Manggala, Mariso, Rappocini, Bontoala, Wajo, Ujungtanah, Tallo, Tamalanrea, Biringkanaya	Mamajang, Sangkarrang, Tamalate, Makasar, Ujungpandang, Panakukkang
2014	Rappocini, Bontoala, Tallo, Tamalanrea, Biringkanaya	Mamajang, Manggala, Mariso, Sangkarrang, Tamalate, Makasar, Ujungpandang, Panakukkang, Wajo, Ujungtanah
2015	Tamalanrea	All districts, exept Tamalanrea
2016	-	All districts
2017	-	All districts
2018	Mariso, Rappocini, Tamalate, Makasar, Ujungpandang, Panakukkang, Bontoala, Wajo, Tallo, Tamalanrea, Biringkanaya	Mamajang, Manggala, Sangkarrang, Ujungtanah

The relative risk of TB cases varies over the districts and years (Table 3). Based on the best model, Panakukang district had the highest relative risk of TB from 2012 to 2014, while Makassar district had the highest relative risk of TB from 2015 to 2017. Mamajang had the highest relative risk of TB in 2018. Bayesian ST CAR Localised with G=3 means that it is allowed to have a maximum of three clusters. Based on Table 3 and Table 4, under the preferred model, we can see that no year had three clusters, most years (2012, 2013, 2014, 2015, and 2018) had two clusters, but two years (2016 and 2017) had only one cluster.

4. Conclusion

In conclusion, our results depict that the ST CAR localised model with G = 3 had a better model fit based on DIC followed by the ST CAR localised with G = 2, and adaptive model (856.14). on the other hand, the ST CAR had the largest DIC and WAIC. Overall, it can be concluded that the best model in modelling the relative risk of TB cases in Makassar city from 2012 to 2018 is the ST CAR localised model with G = 3. The relative risk of TB varies over the districts and year. Based on the best model, Pangkukang district had the highest relative risk of TB in 2012, 2013, and 2014, while Makassar district had the highest relative risk of TB in 2015, 2016, and 2017. Mamajang had the highest relative risk of TB in 2018. It is recommended to explore a range of models as it gives different results. These results are based on the TB cases in Makassar city. It is acknowledged that different datasets may have different results. Providing more general insight into the performance of these Bayesian ST CAR models could be potential future work.

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