Factors Affecting the Covid-19 Risk in South Sulawesi Province, Indonesia: A Bayesian Spatial Model

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ABSTRACT – **The transmission of Coronavirus diseases 2019 (Covid-19) grows continuously around the world. Although a number of researches of modelling Covid-19 cases have been conducted, there was limited research implementing the Bayesian Spatial Conditional Autoregressive (CAR) model. Factors affecting the Covid-19 risk especially population density and distance to the capital city have been studied, but the results are inconsistent and limited research has been done in Indonesia. This study aims to assess the most appropriate Bayesian spatial CAR Leroux models and examine factors that affect the risk of Covid-19 in South Sulawesi Province. Data on the number of Covid-19 cases (19 March 2020 - 31 January 2022), population density, and distance to the capital city were used for every 24 districts. Several criteria were used in choosing the most appropriate model. The results depict that Bayesian spatial CAR Leroux with hyperprior IG (1, 0.01) model with the inclusion of population density were preferred. It is concluded that a factor that significantly affects the number of Covid-19 cases is population density. There was a positive correlation between the population density and Covid-19 risk. Makassar city has the highest relative risk (RR) among other districts while Bone has the lowest RR of Covid-19.**

Keywords– **Poisson, Bayesian, Spatial, Conditional Autoregressive (CAR)**

I. INTRODUCTION

The transmission of Coronavirus diseases 2019 (Covid-19) grows continuously across the globe. The first Covid-19 case in Indonesia was reported on March 2, 2020. It was reported that Indonesia has 4,353,370 confirmed Covid-19 cases, 4,140,454 people recovered, and 144,320 people died by January 31, 2022 [1]. In South Sulawesi province, as many as 111,244 confirmed Covid-19 cases with 107,859 recovered, and 2,245 people died were reported by January 31, 2022.

Several efforts to combat the spread of Covid-19 have been carried out, for example through disease modeling. Previous studies regarding Covid-19 modelling have been done. One study has shown that there is a significant positive relationship between the daily counts of confirmed Covid-19 cases and the human mobility index by using the generalized additive model (GAM) [2]. The effect of population density on the spread of Covid-19 has been studied. Exploratory analysis has been used to investigate the association of population density and the spread of Covid-19 at a county level in Brazil [3]. They found that population density affects the Covid-19 incidence. Extreme bounds analysis (EBA) has been used to investigate the relationship between population density and the number of Covid-19 cases as well as the number of deaths in 172 countries excluding Indonesia [4]. They concluded that population density has a significant positive effect on the number of Covid-19 cases, but there is no association between the number of death and population density.

An ordinary least squares (OLS) regression and a negative binomial regression (NBR) models were used to assess the influence of density and connectivity on the covid-19 outbreak in Korea [5] and concluded that residential density and connectivity are statistically significant in the spread of Covid-19. The association of population density and basic reproduction number in the United States using linear mixed models has been done [6]. They found that dense areas escalate contact rates which is the key for Covid-19 transmission. Arbel et al. [7] studied the effect of population density and socioeconomic factors on infection rates of Covid-19 in Israel using the logit model and conclude that the infection of Covid-19 increased the levels of population density. In contrast, Agnoletti et al. [8] used a linear regression model and found that the association of density and the spread of Covid-19 in Italy was not significant. The association of Covid-19 cases and the population density, as well as the distance from the virus epicenter, have been done by using linear regression in Iranian provinces [9]. However, these researches have not implemented the Spatial models.

Spatial models have been used to model Covid-19 cases. By using the spatial error model (SEM), the spatial autoregressive model (SAR), and the spatial autoregressive combined model (SAC), Ehlert [10] reported that employment density and population density were positively correlated with the mortality rates of Covid-19 in German. SEM was also used by Wand and Li [11] and found that population density is the key in the Covid-19 spread and it alone accounted for up to 76% of cumulative Covid-19 cases in the U.S.

Bayesian spatial models have been used to model Covid-19 cases [12-14]. However, these researches have not implemented the Bayesian Spatial Conditional Autoregressive (CAR) model. Recently, Whittle and Diaz [15] used a Bayesian spatial CAR Besag, York & Mollié (BYM) to assess the association between the number of positive Covid-19 and socioeconomic factors in New York City and concluded that there is a statistically significant association between the number of Covid-19 cases and population density, household income, race, and children under the age of 18 years. Furthermore, the Bayesian spatial CAR localised model without the inclusion of covariates has been used in modelling the relative risk of Covid-19 in South Sulawesi Selatan [16]. Aswi et al [17] used Bayesian spatial CAR Leroux models in modeling the relationship between the Covid-19 risk and the population density as well the distance to the capital city in Makassar. They found that the correlation between the distance to the capital city and Covid-19 risk was negative, but the association between the relative risk of Covid-19 and population density was not statistically significant.

While a number of researches assessing the impact of population density and distance to the capital city have been done, the results are inconsistent and limited research has been done in Indonesia, especially in South Sulawesi Province. This study aims to assess the most appropriate Bayesian spatial CAR Leroux models in modelling the number of Covid-19 cases without and with covariates namely the distance to the capital city and population density in South Sulawesi Province and examine factors that affect the risk of Covid-19 in South Sulawesi Province

II. MATERIAL AND METHODS

A. Study Area

South Sulawesi Province has 21 districts, namely Selayar Island, Bantaeng, Bulukumba, Barru, Bone, Jeneponto, Takalar, Gowa, Sinjai, Maros, Pangkep, Soppeng, Wajo, Sidrap, Pinrang, Enrekang, Tana Toraja, Luwu, Luwu Utara, Luwu Timur, Toraja Utara, three cities, namely Makassar, Palopo and Pare-Pare and 310 subdistricts. The area of South Sulawesi Province is 46717.48 km^2 with a population of roughly 9,073,500 in 2020. Selayar Island has the lowest population (approximately 137,100), while Makassar has the highest population (approximately 1,423,900) in 2020 [18]. The population density of South Sulawesi Province is 198.27 people per km^2 in 2020. Makassar city and Luwu Timur have the highest and the lowest population density, respectively [18]. Makassar is the capital city of South Sulawesi Province. Luwu Timur has the longest distance (565 km) to the capital city (Makassar city), but Gowa has the shortest distance from Makassar (11 km) [19].

B. Data

Data on the number of confirmed cases of Covid-19 (19 March 2020 -31 January 2022) for every 24 districts/cities were used in this study obtained from the official website "Ministry of Health of the Republic of Indonesia" https://infeksiemerging.kemkes.go.id/ and https://m.andrafarm.com/_andra.php?_i=daftar-co19-kota&noprovkot=28&corke=768&urut=2&asc=01100000000#Tabel%20Corona. Data on the number of the population gathered from the Badan Pusat Statistik [18] were also used to calculate the expectation of count data. Population density data in each district/city [18] and the distance to the capital city of South Sulawesi Province data [19] were also used as the covariates. Data on the number of confirmed Covid-19, population density, and distance to the capital city for each district/city are given in Appendix 1.

C. Spatial Autocorrelation

Moran's I is the widest indicator used to measure the degree of spatial autocorrelation [20] in ordinal or interval data. Moran's I is computed as the ratio of spatial covariation to the total variation. Moran's I values range from -1 to +1. The positive value indicates positive spatial dependence, while the negative value indicates negative spatial dependence, and the 0 value indicates no spatial dependence.

Moran's I statistics is calculated as follows:

$$I = \frac{n \sum_{i=1}^{n} \sum_{j=1}^{n} \omega_{ij} (Y_i - \bar{Y})(Y_j - \bar{Y})}{\sum_{i=1}^{n} \sum_{j=1}^{n} \omega_{ij} (Y_i - \bar{Y})^2}$$

n is the number of locations, Y_i and Y_j are the observed value in the particular location i and another location j, $\bar{Y}$ is the average of all the Y values over the n locations, ω_{ij} is the spatial connectivity/weight matrix.

As Moran's I tend to underestimate spatial autocorrelation for a few areas [21-23], a modified Moran's I (MMI) was developed [21] to detect spatial dependence which works even for a few areas. A comparison of Moran's I and MMI has been conducted [21, 23]. MMI statistics are calculated as follows:

$$I_{\text{Mod}} = \frac{\sum_{i=1}^{n}(Y_i - \bar{Y})(\sum_{j=1}^{n} w_{ij} Y_j - \bar{Y})}{\left[\sum_{i=1}^{n}(Y_i - \bar{Y})^2\right]^{1/2} \left[\sum_{i=1}^{n}\left(\sum_{j=1}^{n} w_{ij} Y_j - \bar{Y}\right)^2\right]^{1/2}}$$

The binary spatial matrix using first-order adjacency weight matrix is the most common for areal data and it is defined as follows:

$$w_{ij} = \begin{cases} 1 & \text{if areas } i \text{ and } j \text{ share a boundary} \\ 0 & \text{otherwise.} \end{cases}$$

There are three distinct forms of spatial adjacency matrix: queen contiguity, rook contiguity, and bishop contiguity [24]. Queen contiguity is implemented in this study as it can improve the model fit [25].

D. Model formulation

In this paper, the Bayesian spatial CAR Leroux model [26] was used to estimate the risk of Covid-19 and examine factors that influenced the Covid-19 risk without and with covariates (the distance of each district to the provincial capital and population density). The population density of each district is calculated as the ratio of the number of populations in each area to the corresponding area.

Bayesian spatial CAR Leroux model consists of spatial structured random effect (u_i). The Covid-19 cases in the ith location (y_i) were modelled using a Poisson distribution with a log link function as the most widely used for disease mapping [27] and it is given as follows:

$$y_i \sim \text{Poisson}(E_i\theta_i) \text{ for i = 1, 2, 3, …, 24 locations}$$

$$log(\theta_i) = \alpha + \beta_1 X_1 + \beta_2 X_2 + u_i$$

E_i and θ_i are the expected counts and the relative risk in the ith location, respectively. α is the overall level of relative risk and β_1 and β_2 are the coefficient of the covariates. The spatial structured random effect is modelled using an intrinsic conditional autoregressive (CAR) prior as follows:

$$(u_i|u_j, i \neq j, \tau_u^2) \sim N\left(\frac{\sum_j u_j\omega_{ij}}{\sum_j \omega_{ij}}, \frac{\tau_u^2}{\sum_j \omega_{ij}}\right)$$

ω_{ij} is the spatial weight matrix defined using binary spatial matrix and first-order adjacency weight matrix. A sensitivity analysis was performed by using five hyperpriors on the variance component τ_u^2, that is Inverse-Gamma (IG): IG (shape=1, scale=0.01) as the default hyperprior of CARBayes, IG (1, 0.1), IG (0.1, 0.1), IG (0.5, 0.05), and IG (0.5, 0.0005). A set of combination model formulations were used to examine the most appropriate model in modeling the Covid-19 cases without and with covariates included and five hyperpriors on the variance component τ_u^2.

Model parameters were estimated using the CARBayes package version 5.2.5 [28] in R software version 4.1.2 [29]. The posterior quantities for each parameter were based on 20,000 iterations with 12,000 Markov Chain Monte Carlo (MCMC) samples collected after a burn-in of 8,000 samples. Visualization of MCMC trace and density plots were used for checking the MCMC convergence.

E. Comparing Models

The goodness-of-fit of model formulation and combination of covariates was compared using the Deviance Information Criterion (DIC) [20], Watanabe Akaike Information Criterion (WAIC) [21], MMI [17, 18] for the residual, and 95% posterior credible interval (CI) does not contain zero. A smaller value of DIC and WAIC, as well as a closer to zero of MMI for residual, indicates a better model fit. R code used in this study is available upon request.

III. RESULTS AND DISCUSSION

A. Descriptive Analysis

A total of 111,244 confirmed Covid-19 cases in the Province of South Sulawesi (March 19, 2020- January 31, 2022) were identified with a mean (4,593), median (2,366), and variance (92,804,323). The first three highest number of confirmed Covid-19 cases are Makassar (49,149 cases), Gowa (8,685 cases), and Luwu Timur (4,940 cases). In contrast, the first three lowest numbers of confirmed Covid-19 cases are Enrekang (784 cases), Selayar (1,226 cases), and Toraja Utara (1,235 cases).

The number of populations in South Sulawesi in 2020 is about 9,073,800. Makassar (1,423,900), Bone (801,800), and Gowa (765,800) are the first three highest number populations. However, Selayar (137,100), Pare-Pare (151,500), and Barru (184,500) are the first three lowest numbers of populations.

Makassar has the highest population density (8100.80) followed by Pare-Pare (1524.76), and Palopo (746.13), while Luwu Timur has the lowest population density (42.73), followed by Luwu Utara (43.04), Luwu (121.86), and Enrekang (126.08). Makassar is the capital city of South Sulawesi Province. Luwu Timur has the longest distance to the capital city (565 km), followed by Luwu Utara (440 km) and Palopo (376 km). In contrast, Gowa has the shortest distance from Makassar (11 km), followed by Maros (30 km), and Takalar (45 km).

B. Morans'I and Modified Morans' I

The values of Morans'I statistics, expectation and variance for observed data are 0.0556, -0.0435, and 0.0023, respectively with Z-score = 2.045 and p-value = 0.0204. Given a Moran's I value of observed data of 0.056 with a Z-score of 2.089, the null hypothesis stating no spatial autocorrelation is rejected. This indicates that the areal pattern for Covid-19 cases is statistically significant with a positive spatial autocorrelation. MMI value is 0.038.

C. Bayesian Spatial CAR Leroux models

The plot of the neighborhood matrix using the binary spatial matrix with first-order adjacency weight matrix and queen contiguity can be seen in Figure 1.

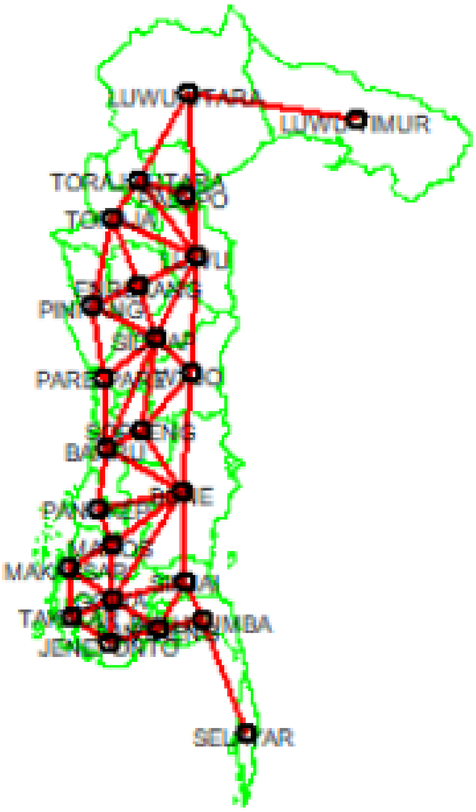

Figure 1. A plot of neighborhood matrix

The results of Bayesian Spatial CAR Leroux models for all five different hyperpriors without and with covariates (population density and distance to the provincial capital) for confirmed Covid-19 cases from March 19, 2020, to January 31, 2022, are given in Table 1.

Table 1. The values of DIC, WAIC, MMI for residual, and posterior Credible Interval for each model

Hyperpriors		Models	DIC	WAIC	MMI for residual	Posterior Quantities for Covariates	
						2.5%	97.5%
IG (1, 0.01)	M1	Without Covariate	287.80	291.28	-0.57	-	-
	M2	Density*	**287.25**	**292.31**	**-0.08**	**0.15**	**0.29**
	M3	Distance*	287.27	293.38	-0.44	-0.42	-0.39
	M4	Density* + Distance	287.79	293.00	-0.74	0.04 -0.16	0.37 0.15
IG (1, 0.1)	M5	Without Covariate	287.27	289.69	-0.72	-	-
	M6	Density*	288.31	297.63	-0.11	0.08	0.36
	M7	Distance	287.61	290.83	-0.10	-0.27	0.05
	M8	Density* + Distance	287.84	292.96	-0.25	0.37 -0.01	0.65 0.25
IG (0.1, 0.1)	M9	Without Covariate	287.48	289.21	-0.39	-	-
	M10	Density*	287.32	291.50	-0.14	0.22	0.45
	M11	Distance*	287.69	291.51	-0.54	-0.48	-0.18
	M12	Density* + Distance*	287.38	294.47	-0.09	0.39 0.09	0.55 0.34
IG (0.5, 0.05)	M13	Without Covariate	287.61	291.41	-0.42	-	-
	M14	Density*	287.37	291.73	-0.51	0.07	0.18
	M15	Distance*	**286.66**	**289.52**	**-0.11**	**-0.29**	**-0.14**
	M16	Density* + Distance*	286.41	290.01	0.23	0.28 0.16	0.51 0.29
IG (0.5, 0.0005)	M17	Without Covariate	288.01	293.04	-0.48	-	-
	M18	Density*	**286.89**	**289.68**	-0.45	0.23	0.43
	M19	Distance	**286.62**	**287.49**	-0.57	-0.31	0.007
	M20	Density* + Distance	287.48	294.41	-0.006	0.33 -0.10	0.67 0.02

$*$ 95% posterior CI for the coefficient does not contain zero.

The results from Table 1 show that the M15 model, that is, Bayesian Spatial CAR Leroux model with hyperprior IG (0.5, 0.05) with the incorporation of distance to the capital city has the lowest DIC (286.66) and it is indistinguishable from the M19 model with hyperprior IG (0.5, 0.0005) with the incorporation of distance to the capital city (DIC=286.62) as well as from hyperprior IG (0.5, 0.0005) with the incorporation of population density (DIC=286.89). It has a relatively similar result with the M2 model with hyperprior IG (1, 0.01) with the incorporation of population density (DIC=287.25).

M19 model, that is, a model with hyperprior IG (0.5, 0.0005) with the incorporation of distance to the capital city has the lowest WAIC (287.49) and it has a relatively similar result with hyperprior IG (0.5, 0.05) with the inclusion of distance (WAIC =289.52) and with hyperprior IG (0.5, 0.0005) with the inclusion of population density (WAIC =289.68). Even though M18 and M19 models have the lowest DIC and WAIC, the value of MMI for residuals is relatively high, -0.45 and -0.57, respectively. The MMI for residual using the M15 model with hyperprior IG (0.5, 0.05) with the inclusion of distance to the capital city is closer to zero (- 0.11) than the M19 model (- 0.57). The M2 model has the lowest MMI for residual (-0.08) and it has relatively similar DIC and WAIC with the M15 model.

All five models (M2, M6, M10, M14, and M18) indicated that population density was considered significant as the 95% posterior CI for the coefficient does not contain zero. The estimation of the posterior median for population density is positive indicating that there is a positive relationship between the population density and the number of Covid-19 cases. It means that the higher the population density in an area, the greater the chance of being infected with Covid-19.

On the other hand, only three out of five models (M3, M11, M15) found that distance to the capital city was considered significant (model with hyperprior IG (1, 0.01), IG (0.1, 0.1), and IG (0.5, 0.05)). The estimation of the posterior median for distance to the capital city is negative indicating that there is a negative relationship between the distance to the capital city and the number of Covid-19 cases. It indicates that the closer a district/city is to the capital city, the greater the risk of being infected with Covid-19.

Table 2. The Relative Risk using the preferred Model

ID	Districts	RR
1	Barru	0.73
2	Bone	0.26
3	Bulukumba	0.38
4	Enrekang	0.29
5	Gowa	0.93
6	Jeneponto	0.48
7	Luwu Timur	**1.37**
8	Luwu Utara	0.86
9	Luwu	0.31
10	Makassar	**2.84**
11	Maros	0.86
12	Palopo	**1.25**
13	Pangkep	0.7
14	Parepare	**1.47**
15	Pinrang	0.33
16	Selayar	0.74
17	Sidrap	0.41
18	Sinjai	**1.19**
19	Soppeng	0.84
20	Takalar	0.63
21	Toraja Utara	0.39
22	Toraja	**1.11**
23	Wajo	0.35
24	Bantaeng	0.54

Furthermore, three models with the inclusion of both the population density and the distance to the capital city (M4, M8, and M20) was not significant (model with hyperprior IG (1, 0.01), IG (1, 0.1), and IG (0.5, 0.0005)), while using the other two hyperpriors suggested that the inclusion of both population density and the distance to the capital city were significant.

Based on the best model selection criteria used in this paper (DIC, WAIC, MMI for residuals and 95% CI does not contain zero), the preferred model in modelling Covid-19 is Bayesian spatial CAR Leroux with hyperprior IG (1, 0.01) model with the incorporation of population density (M2). It has been found that there was a positive correlation between the population density and Covid-19 risk. This importance of population density is similar to some studies [4, 6, 7, 11, 15]. The relative risk (RR) values for each district/city and the RR map based on the preferred model are given in Table 2 and Figure 1, respectively.

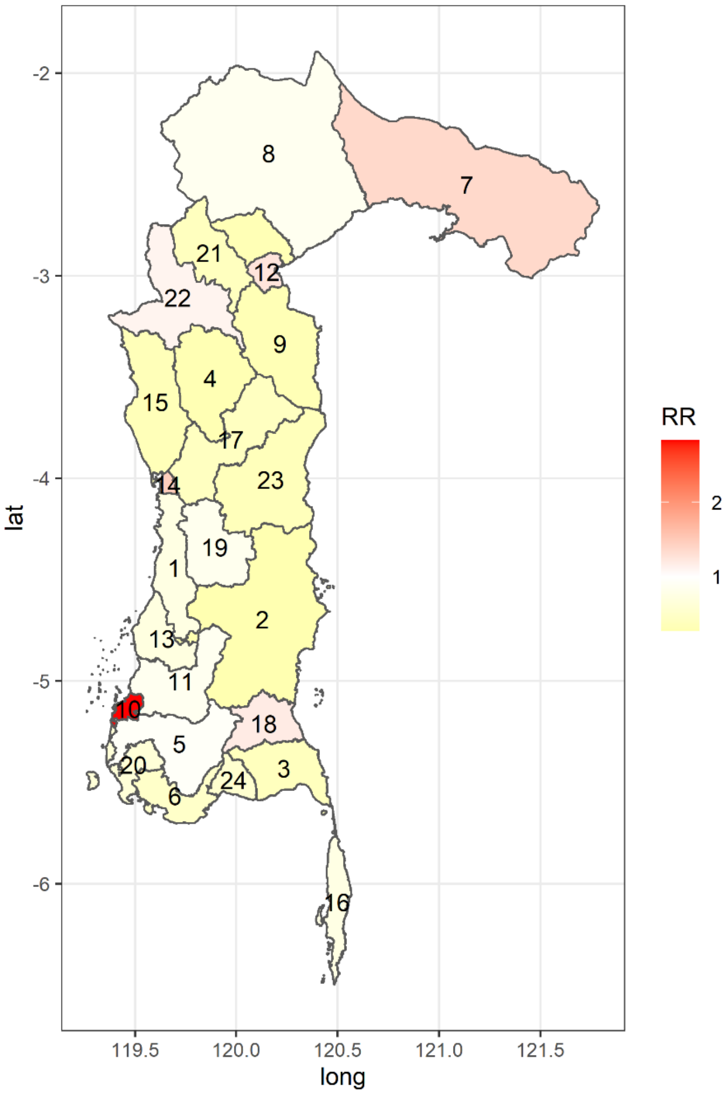

Figure 1. The RR map of Confirmed Covid-19 Cases for Each District in South Sulawesi Province

The results from Table 2 depict that Makassar city has the highest RR among other districts (2.84), followed by Pare-Pare city (1.47), Luwu Timur (1.37), Palopo city (1.25), Sinjai (1.19), and Toraja (1.11), while Bone has the lowest RR of Covid-19 (0.26), followed by Enrekang (0.29), Luwu (0.31), Pinrang (0.33), Wajo (0.35) and Bulukumba (0.38). From Appendix 1, it is seen that Makassar city has also the highest population density, followed by Pare-pare city, and Palopo city, while Luwu Timur has the lowest population density, followed by Luwu Utara, Luwu, and Enrekang.

South Sulawesi Province has three cities (Makassar, Pare-Pare, and Palopo) and 21 districts. These three cities are areas that have a high risk of infected Covid-19 and are the most three densely populated cities. A possible interpretation is that in densely populated cities, people are more likely to interact with each other. However, Luwu Timur is the third-highest relative risk of confirmed Covid-19 but has the lowest population density. This may be because Luwu Timur is a neighbor to Morowali Utara (Central Sulawesi Province) categorized as an area with high risk.

IV. CONCLUSION

Overall, the preferred model in modelling Covid-19 in South Sulawesi province is the Bayesian spatial CAR Leroux with hyperprior IG (1, 0.01) model with population density incorporated. Population density has been found as one of the factors that affect the Covid-19 risk. There was a positive correlation between the population density and Covid-19 risk. Makassar city, the highest population density, has the highest relative risk (RR) among other districts while Bone has the lowest RR of Covid-19 followed by Enrekang. This finding is beneficial for the policy maker as it may help for future planning to save our cities against the threat of Covid-19 or other infectious diseases. It is recommended that in denser areas more stringent policies may be required. Considering other models as well as other covariates could be possible future work.

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Appendix 1

ID	Districts	Covid-19 cases	Density	Distance
1	Barru	1635	157.02	102
2	Bone	2574	175.87	174
3	Bulukumba	2026	378.99	153
4	Enrekang	784	126.08	236
5	Gowa	8685	406.64	11
6	Jeneponto	2329	444.58	91
7	Luwu Timur	4940	42.73	565
8	Luwu Utara	3379	43.04	440
9	Luwu	1381	121.86	326
10	Makassar	49149	8100.8	0
11	Maros	4090	241.97	30
12	Palopo	2803	746.13	376
13	Pangkep	2928	310.87	51
14	Parepare	2703	1524.76	155
15	Pinrang	1608	206	182
16	Selayar	1226	151.71	263
17	Sidrap	1587	169.91	188
18	Sinjai	3769	316.45	220
19	Soppeng	2404	172.99	192
20	Takalar	2290	531.06	45
21	Toraja Utara	1235	226.74	328
22	Toraja	3803	136.69	310
23	Wajo	1604	151.26	242
24	Bantaeng	1297	496.97	123