Modeling and Mapping on Bayesian Spatio-Temporal CAR Localized for Poverty in Sulawesi Island, Indonesia

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Abstract. Spatial modeling can identify locations with high or low risk of disease effect, but it cannot explain the temporal shift in risk, which may be as relevant or more important. As a result, mapping modeling should consider both geographical and temporal components. Some research has utilized Bayesian Spatio-Temporal Conditional Autoregressive (BST CAR) models. However, no research has been conducted on using BST CAR Localized model for poverty on Sulawesi Island, Indonesia. This research aims to find the best BST CAR localized model for poverty in 81 regencies/cities on Sulawesi Island. The BST CAR localized model with different number of clusters G=2, G=3, and G=5 was used to model the relative risk (RR) of poverty in each of 81 regencies and cities. The results suggest that BST CAR Localized with G=2 is the best model for modeling the relative risk of poverty on Sulawesi Island. Variables such as Gender Development Index (IPG), Women's Income Contribution (SPP), Adjusted Per Capita Expenditure (PKD), and Human Development Index (IPM) have a significant impact on poverty. SPP has a positive influence on poverty, while the other three components have a negative impact.

Keywords: Bayesian Spatio-temporal Localized model, Relative risk, Sulawesi Island Poverty.

1 Introduction

Spatial data are classified into three types based on the types of data: area data (lattice data), geostatistical data, and point patterns [1–3]. Spatial models are frequently used in a variety of fields [4]. The Conditional Autoregressive (CAR) spatial Bayesian model is a mapping approach that takes into consideration the spatial interaction among small geographic areas within a region and incorporates the smoothing of relative risk (RR) estimates to produce more accurate RR estimations [5]. The Intrinsic CAR (ICAR), Besag-York-Molli (BYM), Localised, and Leroux models are among the spatial Bayesian CAR models [6]. The presence of spatial autocorrelation is the cornerstone of spatial analysis.

Spatial autocorrelation is the correlation between a variable and itself based on space or as a measure of similarity across objects in space. There is spatial autocorrelation when there is a systematic pattern in the distribution of a quantity. According to spatial

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autocorrelation, attribute values in certain places are connected to attribute values in neighboring regions [7]. Positive spatial autocorrelation and negative spatial autocorrelation are two potential outputs of autocorrelated data. Positive spatial autocorrelation suggests that close places with comparable values cluster together, whereas negative spatial autocorrelation implies that nearby locations with differing values disperse [8].

Several spatial models, including the empirical Bayes method and the full Bayesian GLMM, have been developed and adapted to poverty data. Roberto Benavent and Domingo Morales investigated bivariate target variables [9], particularly poverty proportions and gaps, which are affected by age, education, citizenship, and work position characteristics. Tomas Hobza, Yolanda Marhuenda Garca, and Domingo Morales González researched average earnings and poverty proportions [10].

Spatial modeling that includes spatial components can identify areas at high or low risk of disease impact. Still, it cannot explain the temporal change of risk, which may be as essential or more important. As a result, the involvement of both spatial and temporal components (spatio-temporal modeling) in mapping modeling must be considered. Using Bayesian methods can facilitate determining additional information, such as spatial and temporal structures, through prior distributions.

A Generalized Linear Mixed Model (GLMM) formulation can be applied in a Bayesian spatio-temporal CAR)model for integrating spatial and temporal dependencies in the data. The CAR model is a common technique for modeling geographical data in which an observation's value is determined by the values of neighboring observations [11]. The spatio-temporal CAR model can represent the combined variation in space and time by expanding this approach to add temporal dependencies [12].

A GLMM with spatial random effects for spatio-temporal data was implemented to develop disease maps using data on dengue fever incidence, with the response variable assumed to follow a Poisson distribution [13].

Bayesian Spatio-Temporal Conditional Autoregressive (BST CAR) models have been used in several studies. Three BST CAR models have been compared: the ST CAR localized model [14], which allows for the separation of regions into various groups, the ST CAR ANOVA model [15], and the ST CAR autoregressive (AR) model [16]. Their study will compare smoking rates among moms with and without confounders. There has also been research on BST CAR on DHF cases in Makassar with different priors [17–21], BST on TB cases in India [22], BST for Malaria in Rwanda [23], BST Graph for forecasting congestion [24], and BST for the ambient illness [25].

Other research used the BST CAR model applied to influential factors for Makassar DHF cases [20], TB in Makassar [26], and BST CAR localized for Makassar DHF cases. Based on the literature study, research that applies BST CAR Localized for poverty in Sulawesi Island, Indonesia, has not been carried out. This study aims to obtain the most appropriate BST CAR localized model for poverty in 81 regencies/cities on Sulawesi Island.

2 Methods

2.1 Study Area

Sulawesi Island has six provinces, 81 regencies, and cities. Those provinces are North Sulawesi, Central Sulawesi, South Sulawesi, Southeast Sulawesi, Gorontalo, and West Sulawesi. The North Sulawesi Province has 15 regencies or cities, the Central Sulawesi Province has 13 regencies or cities, the South Sulawesi Province has 24 regencies or cities, the Northern Sulawesi Province has 17 regencies or cities, Gorontalo Province has six regencies or cities, and West Sulawesi Province has six regencies or cities.

2.2 Data

The annual poverty cases in every six provinces with 81 regencies/cities were obtained from the online annual report of the Central Bureau of Statistics (BPS) from 2007 to 2022 by https://bps.go.id. The number of the population was also used to calculate the expected value of dengue fever cases.

2.3 Spatial Dependence

Moran's I Testing. Moran's Index (MI) is the most comprehensive indicator to assess the degree of spatial autocorrelation in ordinal or interval data (Blangiardo & Cameletti, 2015; MORAN, 1950). MI is calculated as the spatial covariation to total variation ratio. Moran's I values range between -1 and +1. The positive number represents positive spatial reliance, the negative value represents negative spatial dependence, and the 0 value represents no spatial dependence.
Moran's I statistics (Blangiardo & Cameletti, 2015) are formulated 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 denotes the number of locations, Y_i and Y_j are the observed values in position i and another place, respectively. ω_{ij} is the spatial connectivity/weight matrix, j, $\bar{Y}$ is the average of all the Y values over the n locations.
The binary spatial matrix using a first-order adjacency weight matrix is the most common for areal data, and it is defined (Carrijo & da Silva, 2017) as follows:

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

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

Relative Risk. The Standardised Incidence Ratio (SIR) is calculated by dividing the number of poverty (Y_i) cases with the number of expected cases in each area (E_i). The expected number of poverty cases is here calculated as the overall population for the entire Sulawesi Island Regency and City multiplied by the population at risk in each location (pop_i) and it is given as follows:

$$E_i = \frac{\sum_i Y_i}{\sum_i pop_i} pop_i$$

Usually, this would be calculated by age groups and summed together, but data by age were unavailable.
In estimating the relative risk (RR) across small areas, Bayesian methods such as Bayesian hierarchical models are preferred over raw SIRs as they can incorporate information from neighboring locations through prior distributions and adjust for covariates in the model.

2.4 Model Formulation

BST CAR localized model with G=2, G=3, and G=5 was used to model poverty's relative risk (RR) in every 81 regencies and cities in Sulawesi Island, Indonesia (Lee & Sarran, 2015). The number of poverty is assumed to be the Poisson distribution (Aswi & Sukarna, 2020; Lee & Sarran, 2015). The model can be written as follows:

$$y_{ij} \sim Poisson(E_{ij}\theta_{ij})$$
$$E_{ij} = \frac{\sum_i \sum_j y_{ij}}{\sum_i \sum_j n_{ij}} n_{ij}$$
$$log(\theta_{ij}) = \alpha + \varphi_{ij} + \lambda_{z_{ij}}$$

where

y_{ij} is the number of poverty in each area i = 1, 2, …, 81 and the time j = 1, 2, …, 6.

E_{ij} is the expected value calculated as the overall incidence rate for each case in each area i = 1, 2, …, 81 and the time j = 1, 2,…, 6 multiplied by the population at risk in each area.

n_{ij} is the total population in the i-th province (i = 1, 2, …, 81) and the j-th time (j = 1, 2,…, 6).

θ_{ij} is the relative risk in the i-th area (i = 1, 2, …, 81) and the j-th time (j = 1, 2,…, 6).

φ_{ij} and $\lambda_{z_{ij}}$ are smoothing components: φ_{ij} are spatial and temporal autocorrelation variations, while $\lambda_{z_{ij}}$ are clustering or constant intercept components.

φ_{ij} is a structured spatial random effect to be modeled with prior CAR as follows:

$$(\varphi_j|\varphi_{j-1}) \sim N(\rho_j\varphi_{j-1}, \tau^2 Q(W)^{-1}), j = 2, \dots ,6$$
$$\varphi_1 \sim N(0, \tau^2 Q(W)^{-1})$$

where

$$\rho_j \sim Uniform(0,1)$$

Hyperprior on the variance component τ^2 Inverse-Gamma IG (1, 0.01) was used as the default hyperprior in the CARBayesST package.

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

$f(z_{ij}|z_{i,j-1}) = \frac{\exp\left(-\delta\left[(z_{ij}-z_{i,j-1})^2+(z_{ij}-G^*)^2\right]\right)}{\sum_l \exp\left(-\delta\left[(l-z_{i,j-2})^2+(l-G^*)^2\right]\right)};$

$j = 2,3, \ldots, 8$

$f(z_{i1}) = \frac{\exp(-\delta[(z_{11}-G^*)^2])}{\sum_l \exp(-\delta(l-G^*)^2)}$

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

The value of G is usually determined by choosing a small and odd G (Lee & Lawson, 2016). The CARBayesST package version 3.3 (Lee et al., 2018) with R 4.3.2 is used in analyzing data. Selection of the best model is based on DIC, WAIC, and parsimony values by considering the number of regions included in a group.

3 Results and Discussion

3.1 Results

This study is conducted on the island of Sulawesi, divided into six provinces. These six provinces each have a different number of districts or cities, totaling 81 districts and cities on the island of Sulawesi. The number of people living in poverty in these 81 districts and cities from 2017 to 2022 is the response data for this study.

Figure 1 depicts the impoverished people in each district/city over six years. The number of impoverished people does not appear to fluctuate significantly from year to year (Figure 1). The number of locations (districts or cities) with more than 40,000 impoverished people is substantially lower than those below it. Every year, about 2,042,812 people live in poverty, with an average of 25,220 people in each area ranging from 4,300 to 83,660.

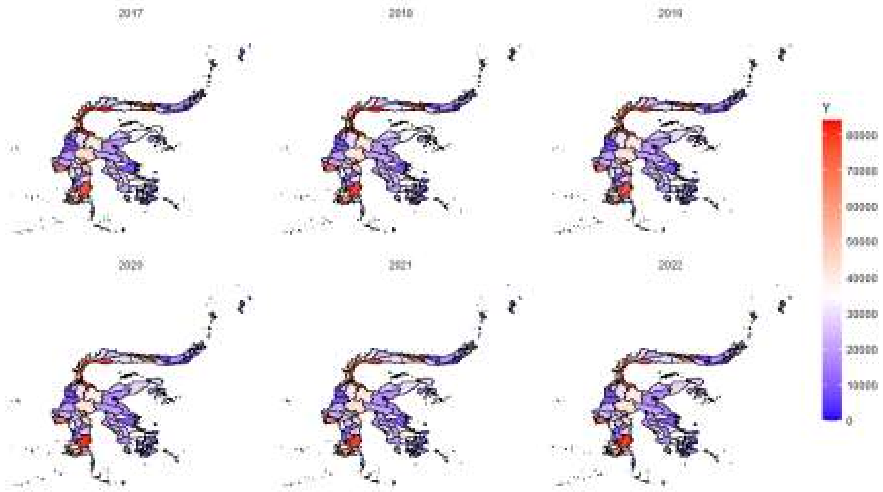

Fig. 1. The number of poor population per district/city from 2017 to 2022.

According to Figure 1, the Parigi Moutong District (ID=45) in Central Sulawesi had the largest number of impoverished people in 2017, 2018, and 2019, with counts of 82,880, 83,660, and 81,360. Furthermore, Bone District (ID=15) in South Sulawesi had the largest number of impoverished people in 2020, 2021, and 2022, with 81,330, 79,640, and 80,340, respectively. Bolaang Mongondow Timur District (ID=70) in North Sulawesi, on the other hand, has the fewest impoverished people, with 4,370, 4,300, 4,410, 4,300, 4,470, and 4,320 in 2017, 2018, 2019, 2020, 2021, and 2022, respectively.

3.2 Discussion

Compared to the models with G = 3 and G = 5, the Localised CAR model with G = 2 (Table 1) has the lowest DIC value of 6698.49 and the lowest WAIC value of 6555.55.

Table 1. CAR Localized G = 2, 3, dan 5 dilengkapi covariate, CI, DIC, WAIC

Model	Covariate	Credible Interval 2.5%	Credible Interval 97.5%	DIC	WAIC
CAR Localized G =2	IPG	-0.0268	-0.0261	**6698.49**	**6555.55**
	SPP	0.0139	0.0145		
	PKD	-0.1189	-0.1173		
	IPM	-0.1290	-0.1278		
CAR Localized G =3	IPG	-0.0261	-0.0248	6708.41	6572.71
	SPP	0.0132	0.0139		
	PKD	-0.1196	-0.1180		
	IPM	-0.1291	-0.1275		
CAR Localized G =5	IPG	-0.0261	-0.0242	6800.59	6746.32
	SPP	0.0135	0.0139		
	PKD	-0.1205	-0.1183		
	IPM	-0.1291	-0.1265		

The Bayesian Spatio-Temporal Conditional Autoregressive Localised model with G = 2 was employed to develop the poverty data model.

The Localised model with G = 2 (Table 1) shows that all variables significantly impact poverty. Covariates IPG, PKD, and IPM have a negative impact, and SPP positively affects poverty.

The Localised Structure (LS) and Relative Risk (RR) values for poverty cases in Sulawesi Island from 2017 to 2022 are given in Table 2.

Table 2. LS and RR values for each regency/city every year (2017–2022).

ID	KabKot	2017 LS	2017 RR	2018 LS	2018 RR	2019 LS	2019 RR	2020 LS	2020 RR	2021 LS	2021 RR	2022 LS	2022 RR
1	Boalemo	2	1.97	2	1.9	2	1.83	2	2.18	2	2.12	2	2.17
2	Bone Bolango	2	1.61	2	1.63	2	1.57	2	1.59	2	1.54	2	1.54

ID	KabKot	2017		2018		2019		2020		2021		2022	
		LS	RR	LS	RR	LS	RR	LS	RR	LS	RR	LS	RR
3	Gorontalo	2	1.86	2	1.87	2	1.77	2	1.7	2	1.67	2	1.68
4	Gorontalo Utara	2	1.74	2	1.74	2	1.65	2	1.57	2	1.5	2	1.52
5	Kota Gorontalo	1	0.51	1	0.52	1	0.53	1	0.63	1	0.64	1	0.63
6	Pohuwato	2	1.92	2	1.82	2	1.77	2	1.98	2	1.94	2	1.98
7	Majene	2	1.26	2	1.29	2	1.34	2	1.39	2	1.39	2	1.51
8	Mamasa	1	1.22	1	1.25	2	1.31	2	1.34	2	1.33	2	1.43
9	Mamuju	1	0.62	1	0.67	1	0.69	1	0.74	1	0.78	1	0.82
10	Mamuju Tengah	1	0.63	1	0.67	1	0.67	1	0.69	1	0.69	1	0.72
11	Mamuju Utara	1	0.44	1	0.42	1	0.42	1	0.42	1	0.43	1	0.47
12	Polewali Mandar	2	1.45	2	1.5	2	1.52	2	1.43	2	1.4	2	1.5
13	Bantaeng	1	0.88	1	0.87	1	0.88	1	0.86	2	0.88	1	0.87
14	Barru	1	0.88	1	0.85	2	0.84	1	0.78	1	0.8	2	0.8
15	Bone	1	0.93	1	1	1	0.99	1	1.02	1	0.97	1	1
16	Bulukumba	1	0.72	1	0.71	1	0.71	1	0.69	1	0.7	1	0.71
17	Enrekang	2	1.19	2	1.17	2	1.2	2	1.12	2	1.13	2	1.14
18	Gowa	1	0.77	1	0.74	1	0.75	1	0.76	1	0.74	1	0.75
19	Jeneponto	2	1.39	2	1.46	2	1.45	2	1.33	2	1.27	2	1.24
20	Kepulauan Selayar	1	1.21	1	1.24	2	1.27	2	1.25	2	1.2	2	1.21
21	Luwu	2	1.26	2	1.25	2	1.24	2	1.26	2	1.23	2	1.27
22	Luwu Timur	1	0.7	1	0.69	1	0.69	1	0.7	1	0.68	1	0.69
23	Luwu Utara	2	1.3	2	1.29	2	1.33	2	1.31	2	1.3	2	1.3
24	Makasar	1	0.42	1	0.41	1	0.42	2	0.49	2	0.51	2	0.51
25	Maros	1	1.01	2	0.97	2	0.97	2	0.89	1	0.84	1	0.85
26	Palopo	2	0.8	2	0.75	2	0.78	2	0.8	2	0.8	2	0.78
27	Pangkajene Dan Kepulauan	2	1.47	2	1.42	2	1.38	2	1.37	2	1.36	2	1.36
28	Parepare	1	0.52	1	0.53	1	0.52	1	0.53	1	0.51	1	0.52
29	Pinrang	1	0.77	1	0.83	2	0.83	2	0.83	1	0.81	2	0.82
30	Sidenreng Rappang	1	0.49	1	0.49	1	0.47	1	0.48	1	0.46	1	0.48
31	Sinjai	1	0.84	1	0.87	1	0.9	1	0.85	1	0.81	1	0.83
32	Soppeng	1	0.75	1	0.7	1	0.7	1	0.74	1	0.72	1	0.73
33	Takalar	1	0.84	1	0.85	1	0.86	1	0.85	1	0.8	1	0.82
34	Tana Toraja	1	1.14	1	1.19	1	1.2	1	1.02	1	1.01	1	1.01
35	Toraja Utara	1	1.3	2	1.25	1	1.2	1	1.07	1	1.05	1	1.04
36	Wajo	1	0.67	1	0.7	1	0.67	1	0.73	1	0.68	1	0.71
37	Banggai	1	0.83	1	0.86	1	0.76	1	0.74	1	0.81	1	0.78
38	Banggai Kepulauan	2	1.44	2	1.47	2	1.45	2	1.41	1	1.31	2	1.32
39	Banggai Laut	2	1.46	2	1.53	2	1.49	2	1.46	2	1.51	2	1.47
40	Buol	2	1.5	2	1.51	2	1.48	2	1.39	2	1.57	2	1.52
41	Donggala	2	1.65	2	1.7	2	1.8	2	1.74	2	1.66	2	1.66
42	Morowali	2	1.31	2	1.34	2	1.34	2	1.34	2	1	2	0.86
43	Morowali Utara	2	1.42	2	1.45	2	1.47	2	1.41	2	1.48	2	1.44
44	Palu	2	0.61	2	0.62	2	0.67	2	0.68	2	0.74	2	0.72
45	Parigi Moutong	2	1.59	2	1.63	2	1.62	2	1.58	2	1.7	2	1.72
46	Poso	2	1.54	2	1.57	2	1.52	2	1.54	2	1.66	2	1.65
47	Sigi	1	1.14	1	1.18	2	1.26	1	1.24	2	1.18	2	1.12
48	Tojo Una-Una	2	1.64	2	1.72	2	1.67	2	1.64	2	1.52	2	1.5
49	Toli-Toli	1	1.2	1	1.28	1	1.28	1	1.29	2	1.39	2	1.37
50	Bau-Bau	1	0.76	1	0.71	1	0.71	1	0.71	2	0.81	1	0.79
51	Bombana	1	1.11	1	1.03	1	1.03	1	1	1	1.27	2	1.29
52	Buton	1	1.21	1	1.28	1	1.33	1	1.32	1	1.19	1	1.14
53	Buton Selatan	1	1.45	1	1.4	1	1.43	1	1.41	1	1.2	1	1.18

ID	KabKot	2017		2018		2019		2020		2021		2022	
		LS	RR	LS	RR	LS	RR	LS	RR	LS	RR	LS	RR
54	Buton Tengah	2	1.67	1	1.4	2	1.54	2	1.53	1	1.24	1	1.15
55	Buton Utara	2	1.41	2	1.4	2	1.4	2	1.41	2	1.37	2	1.33
56	Kendari	1	0.45	1	0.44	1	0.43	1	0.43	2	0.54	2	0.54
57	Kolaka	2	0.96	2	0.91	2	0.9	2	0.9	2	1.36	2	1.32
58	Kolaka Timur	2	2.04	2	1.87	2	1.93	2	1.95	2	1.63	2	1.61
59	Kolaka Utara	2	1.47	2	1.34	2	1.28	2	1.3	2	1.5	2	1.49
60	Konawe	2	1.41	2	1.26	2	1.2	2	1.22	2	1.22	2	1.21
61	Konawe Kepulauan	1	1.63	1	1.64	2	1.68	2	1.7	2	1.56	2	1.42
62	Konawe Selatan	1	1.01	1	1.03	1	1.05	1	1.08	1	1.13	2	1.14
63	Konawe Utara	2	1.26	2	1.33	2	1.33	2	1.35	2	1.32	2	1.28
64	Muna	2	1.34	2	1.24	2	1.24	2	1.27	2	1.37	2	1.39
65	Muna Barat	1	1.47	1	1.33	2	1.38	2	1.37	2	1.34	2	1.35
66	Wakatobi	2	1.47	2	1.4	2	1.44	2	1.44	2	1.33	2	1.3
67	Bitung	1	0.6	1	0.63	1	0.63	1	0.63	1	0.62	1	0.61
68	Bolaang Mongondow	1	0.72	1	0.71	1	0.72	1	0.73	1	0.75	1	0.72
69	Bolaang Mongondow Selatan	2	1.28	2	1.28	2	1.3	1	1.22	1	1.2	1	1.14
70	Bolaang Mongondow Timur	1	0.56	1	0.57	1	0.59	1	0.49	1	0.49	1	0.47
71	Bolaang Mongondow Utara	1	0.8	1	0.81	1	0.82	1	0.82	1	0.77	1	0.72
72	Kepulauan Sangihe	2	1.07	2	1.11	2	1.09	2	1.05	2	1.02	2	1
73	Kepulauan Talaud	1	0.88	1	0.89	1	0.96	1	0.94	1	0.86	1	0.81
74	Kotamobagu	1	0.53	1	0.56	1	0.56	1	0.57	1	0.6	1	0.56
75	Manado	1	0.49	1	0.51	1	0.54	1	0.57	2	0.58	1	0.56
76	Minahasa	1	0.71	1	0.68	1	0.7	2	0.72	2	0.74	1	0.7
77	Minahasa Selatan	1	0.88	1	0.88	2	0.91	1	0.82	1	0.81	1	0.8
78	Minahasa Tenggara	2	1.34	2	1.31	2	1.3	2	1.18	2	1.11	2	1.08
79	Minahasa Utara	1	0.67	1	0.66	1	0.68	1	0.64	1	0.63	1	0.59
80	Siau Tagulandang Biaro	1	0.94	1	0.93	1	0.94	1	0.83	1	0.82	1	0.77
81	Tomohon	1	0.58	1	0.56	1	0.55	1	0.6	1	0.6	1	0.58

Table 2 illustrates the position of each district or city in terms of its LS (localized structure) and RR (relative risk) values. Both values are essential for evaluating the relative risk associated with particular poverty circumstances and studying the grouping of districts/cities. Table 3 depicts the number of districts or cities based on their LS values for each year.

Table 3. The number of areas for each LS from 2017 to 2022.

Localized Structure	2017	2018	2019	2020	2021	2022
LS = 1	46	45	37	39	37	36
LS = 2	35	36	44	42	44	45

Table 3 depicts the number of districts or cities established as LS = 1 or LS = 2 for each year (2017–2022). Figure 2, however, displays the trend or pattern of changes in the number of areas each year for LS=1 and LS=2.

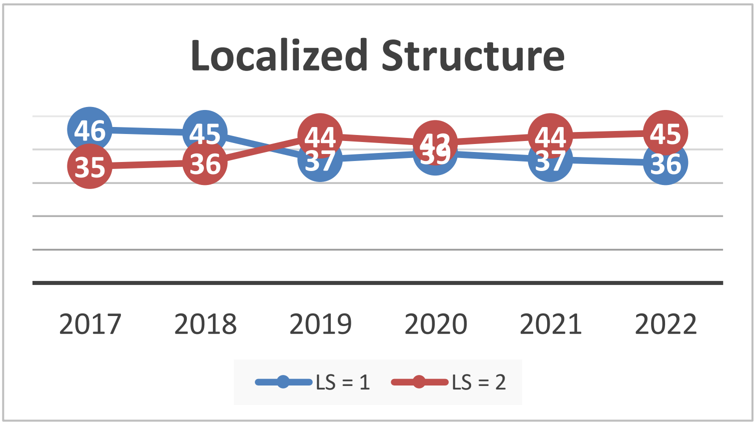

Fig. 2. Trend localized structure from 2017 to 2022.

Figure 3 depicts that the number of areas in LS = 2 from 2017 to 2022 increases, whereas LS = 1 decreases. It means that areas with a high risk of poverty increase from time to time.

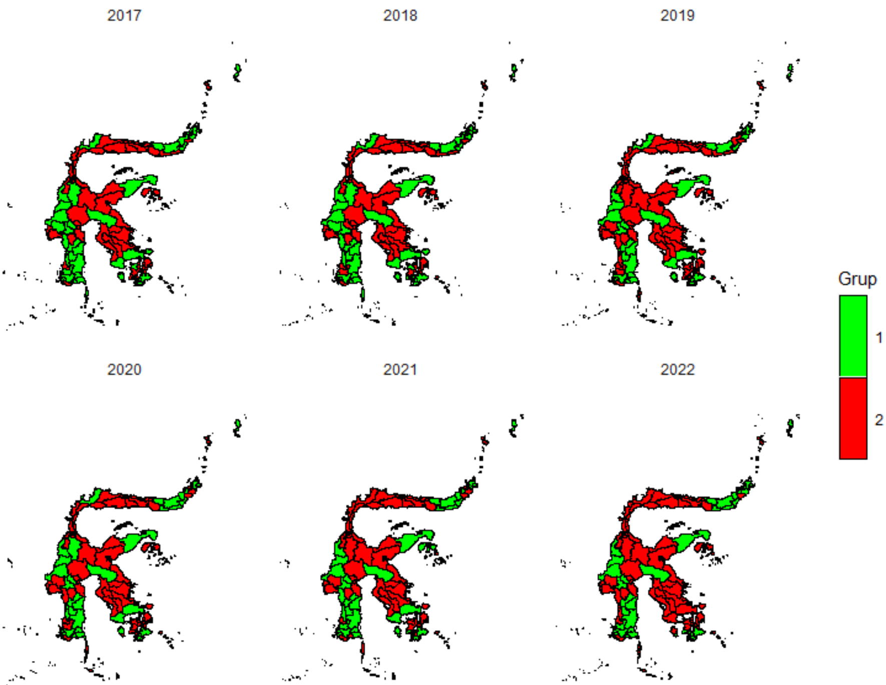

Fig. 3. LS per kabupaten/kota dari 2017 sampai 2022.

Furthermore, Figure 3 shows that red areas reflect places with a higher relative risk (LS = 2), and green areas (LS = 1) have a reduced risk.

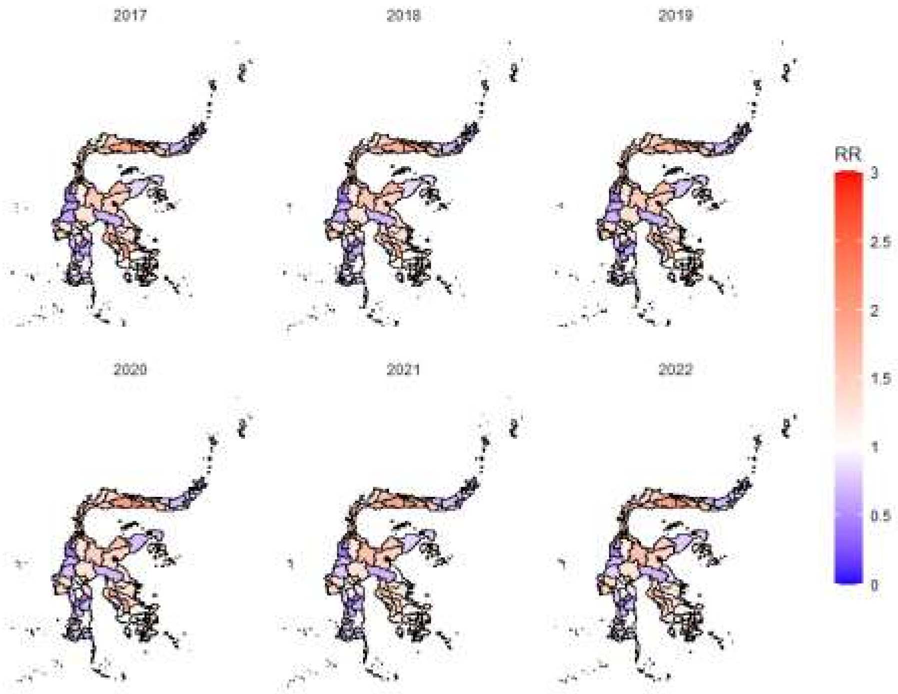

Fig. 4. Value of RR for each area from 2017 to 2022.

Figure 4 illustrates that the number of regions with high RR values is greater than that of locations with low RR values (less than 1).

According to Figure 4 and Table 2, most areas in Group 1 belong to areas in the provinces of South Sulawesi, West Sulawesi, and North Sulawesi. As a result, areas with low relative risk values are dispersed over South Sulawesi, West Sulawesi, and North Sulawesi. Areas in Southeast Sulawesi, Central Sulawesi, and Gorontalo provinces have high relative risk values from 2017 to 2022.

In 2020, the district of Boalemo had the greatest relative risk rating (RR=2.18)

4 Conclusion

This study concludes that the covariates of the Gender Development Index (IPG), Women's Income Contribution (SPP), Adjusted Per Capita Expenditure (PKD), and Human Development Index (IPM) have a significant influence on the poverty level in each regency/city throughout Sulawesi Island. SPP positively influences poverty, while the other three components have a negative impact.

Based on the DIC and WAIC values, the Bayesian Spatio-Temporal Conditional Autoregressive Localized model with G = 2 outperforms the models with G = 3 and G = 5.

From 2017 to 2022, the trend of LS = 2 (high-risk group) indicates a rising tendency.

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