Spatial Stochastic Modeling of Adolescent and Under-Five Children Nutritional Status: A Case Study from Aceh, Sumatera Island, Indonesia

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Abstract

Purpose – The purpose of this study is to explore the concept of spatial modeling in adolescent and under-five children's nutritional status.

Design/Methodology/Approach – The indicator used to identify spatial autocorrelation is the Local Indicator of Spatial Association (LISA). LISA is a method of exploratory analysis of spatial data capable of detecting spatial relationships at the local level and its effects globally. Aplication of stochastic modeling in spatial nutrition identification mapping can be categorized into two cases based on spatial autocorrelation and non-spatial autocorrelation.

Findings – This results of this study indicate that there is no spatial autocorrelation in the adolescent nutritional dataset. The thematic map for anemia showed that that the highest number of anemia in adolescents was in KutaAlam sub-districts (48 people). Sub-districts that were second most common were Meuraxa, Jaya Baru, and Baiturrahman sub-districts. The fewest cases were found in Lueng Bata sub-district (12 people). There were no sub-districts affected by neighboring areas, in the case of adolescents' anemia in Banda Aceh. For the under-five nutritional data set, it shows that there are four factors that significantly affect spatial influence, which are malnutrition, chronic energy deficiency, woman of child-bearing age, proportion of family planning, percentage of households with PHBS and coverage of access to clean water.

Research Limitations/Implications – Anemia data were obtained with a school-based survey. Household survey would be better to implement in spatial analysis.

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Practical Implications – The comparison of the dataset with the two methods provides a simple example to implement special autocorrelation in practice.
Social Implications – The results contribute to a much better comparison in many cases in the nutritional field.
Originality/Value – This is the initial nutritional status of adolescents in Banda Aceh.

Keywords Spatial, mapping, spatial autocorrelation, adolescent, anemia

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1. Introduction

Practical decision problems for which optimal solutions are sought are subject to uncertainty in the problem data especially with spatial data. As transition, opportunities are arranged in a matrix called the transition probability matrix or transitinstochastics matrix. In general, stochastic analysis can describe the cause and effect relationship between one dependent variable with one or several independent variables called linear regression analysis (Draper & Smith, 2014). It ignores the spatial dependence so that data analysis for spatial data is a spatial regression analysis. The fundamental component of the spatial model is the matrix of the spatial weights as well as the transitional stochastic matrix, reflecting the relationship between one region and another. This aspect is important for study because inter-region certainly has different characteristics (Anselin, 1995).

Nutritional status is one of the measures indicating development in healthcare, and this is of special concern when it is focused on the nutritional condition of under-five children, which is seen from the parameter of body weight and height only (Gaetan & Guyon, 2010). Unfulfilled nutritional needs during this time can result in delayed sexual maturation and growth restriction. At this time, important nutrients should be given to prevent the occurrence of chronic diseases associated with nutrition in later adulthood. These diseases include cardiovascular disease, diabetes, cancer, and osteoporosis.

2. Method

2.1. Spatial and geostatistical data analysis

Spatial method is a method to get observational information that is influenced by the effect of space or location. Spatial data type consists of point data (point pattern analysis), which shows the location of a point, for example, latitude and longitude (longitude and latitude) and x and y axis. Data line (geostatistical data) and data area (polygons or lattice data) indicate the location of an area, such as a country, district, city, and so forth. Geostatistical techniques rely on stochastic models based on the theory of random functions (or random variables) to model the uncertainties associated with spatial estimation and simulation.

For example, Z (s) random variable is measured at n location point, with $S_1, S_2, \ldots, S_n$ and area $D \subset$ Rd. The random process is shown in n measurements:

$$Z = \{Z(s_1), Z(s_2), \ldots, Z(s_n)\} \tag{1}$$

And there is a random process $\{Z(s); s \in D,$ where D is fixed (nonrandom), but there are random states because it relates to the value of the variables measured in each location. Process Time series $\{Z(t); - \sim < t < \sim\}$ for the purple room process is determined by $\{Z(s, t); s \in D(t), t \in T,$ where Z, D, T is a geostatistical random beyond the interpolation problem, taking into account the phenomena studied in unknown locations as a set of correlated random variables.

2.2. Modeling of spastic stained pattern data

Spatial stochastic is a widely used tool for describing and analyzing the spatial pattern, i.e. how geographical objects occur and change in a location. It can also compare the pattern of these objects with the pattern of objects found in other locations. Some methods for detecting spatial patterns are quadrant analysis, kernel density estimation (K means), and nearest neighbor distance. These methods only analyze the spread of the location from a point but do not differentiate the point based on its attributes (Fradinata, 2012).

2.3. Index Moran's global and local indicator of spatial autocorrelation (LISA)

The Moran I Index can be used to identify local auto-correlation coefficients (local auto-correlation) or spatial correlations in each area studied.

Methods of analysis through the stages of exploration of data are thematic maps followed by spatial auto-correlation analysis, namely Moran's Global Index and LISA. The weights used are binary code and sideways (Rook contiguity) calculated using the Z test count statistics (Kesuma & Rahayu, 2017).

Moran's Global Index is based on the following equation:

$$I = \left[\frac{n}{\sum_i^n \sum_j^n w_{ij}}\right]\left[\frac{\sum_i^n \sum_j^n w_{ij}(y_i-\bar{y})(y_j-\bar{y})}{\sum_i^n (y_i-\bar{y})^2}\right] \tag{2}$$

I is the value of the Moran index, n is the number of observations, y is the mean value of yi from n location, yi is the value at the ith location, yj is the value at the jth location, and wij is the spatial weighted matrix element (Dolores Ugarte, 2011).

3. Results and discussion

Application of stochastic modeling in spatial nutrition identification mapping can be categorized into two cases based on spatial autocorrelation and non-spatial autocorrelation. In this case, it is important to note whether there is inter-regional spatial dependence. This spatial auto-correlation is one of the assumption tests that is used to know whether a spatial linear regression model between regions were correlated with the existence of dependence of one region with the surrounding area.

3.1. Case of adolescent nutrition in banda aceh city (non-spatial autocorrelation)

The phenomenon of growth in adolescence demands high nutritional needs. The high demand for energy and nutrients for adolescents are due to several factors such as changes and the increase of various dimensions of the body (weight and height), body mass and body composition, nutrient intake, etc. The case of anemia in adolescents is a nutritional problem in Kota Banda Aceh consisting of nine districts, which to date have not received special attention. Based on the number of respondents and cases of anemia in Banda Aceh city from a survey of adolescent nutritional status, data were recorded and presented in Table 1.

The descriptive analysis conducted in this study aims to see the spread of anemia and its relationship with the independent variables depicted in the thematic map of Banda Aceh city through GeoDa software. The thematic map is used descriptively to test the spatial autocorrelation locally and globally among sub-districts for cases of anemia in adolescents in Banda Aceh city, which is shown in Figure 1 as follows:

Based on Figure 1, it appears that the highest number of cases of anemia in adolescents was in KutaAlam sub-districts (48 people). Sub-districts with the second most common occurrence were Meuraxa, Jaya Baru, and Baiturrahman sub-districts. The fewest cases were found in Lueng Bata sub-district (12 people).

3.2. Spatial-weighted matrix for anemia in banda aceh

The spatial weighting matrix used for anemia cases in Banda Aceh can be determined based on the neighboring relationships among sub-districts in Kota Banda Aceh by drawing adjacent neighboring maps of software *R*.

Figure 2 shows the relationship between sub-districts in Kota Banda Aceh based on the border between sub-districts. Among them are Banda Raya Sub-district (1) adjacent to Jaya Baru sub-district (2), Lueng Bata sub-district, (3) and Baiturrahman sub-district (4). The results of the data from the above map were presented in Table 2. The spatial weighted matrix is formed according to Figure 2. The neighboring districts are assigned a value of 1, and the non-neighboring districts are given a value of 0.

3.3. Global spatial auto-correlation

Global spatial auto-correlation is done to find out whether there is a spatial relationship between the sub-districts for adolescent anemia cases in Banda Aceh city. This test is

Table 1. Number of Respondents and Cases of Anemia

Districts of Aceh Provinci	Total of Respondent	Anemia
UleeKareng	55	26
Banda Raya	71	30
Meuraxa	55	35
Lueng Bata	64	12
Kuta Raja	63	23
Jaya Baru	66	36
KutaAlam	114	48
Baiturrahman	65	38
Syiah Kuala	49	31
Average	**67**	**31**

Figure 1. Anemia Catches Tematic Map in Banda Aceh

performed by Moran's I test on equation (9). Based on testing using software R (Appendix 3, part 2), Moran's I score for adolescent anemia is -1.2163 (p-value = 0.2239 means p-value> $\alpha = 0.05$). This figure indicates that there is no spatial relationship between sub-districts in Kota Banda Aceh for anemia cases in adolescents. This means that each adjacent sub-district in Kota Banda Aceh has no similarity to cases of anemia in adolescents.

Based on Table 3, there is no single sub-district in Banda Aceh city that has spatial auto-correlation. This is indicated by the value of p-value $> \alpha = 0.05$. That is, no sub-districts are actually affected by neighboring areas in the case of anemia in adolescents in Banda Aceh city (Table 4).

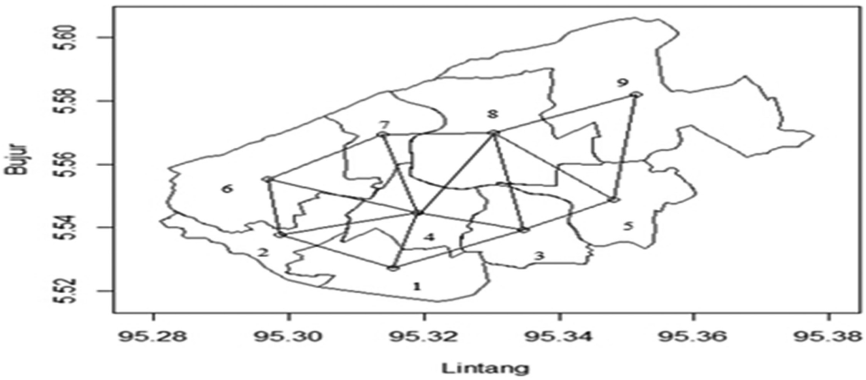

Figure 2.
Map of Neighboring Relationships between Districts

Code	The Name of Districs	Neighbors
1	Banda Raya	Jaya Baru, Lueng Bata, Baiturrahman
2	Jaya Baru	Banda Raya, Baiturrahman, Meuraxa
3	Lueng Bata	Banda Raya, Baiturrahman, UleeKareng, KutaAlam
4	Baiturrahman	Banda Raya, Jaya Baru, Lueng Bata, Meuraxa, Kuta Raja, KutaAlam
5	UleeKareng	Lueng Bata, KutaAlam, Syiah Kuala
6	Meuraxa	Jaya Baru, Baiturrahman, Kuta Raja
7	Kuta Raja	Baiturrahman, Meuraxa, KutaAlam
8	KutaAlam	Lueng Bata, Baiturrahman, UleeKareng, Kuta Raja, Syiah Kuala
9	Syiah Kuala	UleeKareng, KutaAlam

Table 2.
Name of Subscription in the City of Banda Aceh and the Area of the Neighbors

Code	Name of Districts	I_i	$E(I_i)$	Var(I_i)	$Z(I_i)$	P-Value
1	Banda Raya	0.0253	–0,125	0.2005	0.3357	0.3686
2	Jaya Baru	0.1807	–0,125	0.2005	0.6828	0.2474
3	Lueng Bata	–0.9271	–0,125	0.1322	–2.2065	0.9863
4	Baiturrahman	–0.2884	–0,125	0.0912	–0.5413	0.7059
5	UleeKareng	0.0361	–0,125	0.2005	0.3599	0.3595
6	Meuraxa	0.0578	–0,125	0.2005	0.4083	0.3415
7	Kuta Raja	–0.8096	–0,125	0.2005	–1.5291	0.9369
8	KutaAlam	–1.4747	–0,125	0.1322	–3.7128	0.9999
9	Syiah Kuala	0.0000	–0,125	0.3371	0.2153	0.4148

Table 3.
Test Result of Local Spatial Autocorizations

3.3.1. Case of nutrition of under-five children in sumatera Island (Spatial Auto-correlation). The prevalence of malnutrition and under-nutrition in infants on the island of Sumatra is still quite alarming. There are still some districts/cities with prevalence rates above the national prevalence rate (19.6%) and above the WHO standard rate (30%). That is, nutritional problems of children under five in Sumatra are quite serious (Draper & Smith, 2014). The spread of malnutrition and malnutrition prevalence in under-fives in eight provinces of Sumatra Island can be seen in Figure 3.

3.3.2. Spatial weighted matrix. Based on the distribution of malnutrition prevalence, Figure 4 shows a spatial weighted (W) matrix of 125 × 125. The method is used to determine the nearest neighbor k. In this study using the k-nearest neighbor's method, that is the method with the distance approach in equation (6). Given the wide coverage of the island of Sumatra, the nearest k number of k selected is $k = 4$ using trial and error, for $k = 4$ means

Table 4.
Prevalence Profile of Health Care in Sumatera Island

Distribution of Samples	Variable	$(-\mathbf{X})$	Districts/City Profile
BeratBadanLahirRendah (BBLR)	X_1	8.91	Nias, Aceh Barat Daya, Lingga
InisisaiMenyusuiDini (IMD)	X_2	20.15	Dumai, Natuna, Lebong
MakanPendamping ASI (MP-ASI)	X_3	48.25	Aceh Tenggara, Nagan Raya, KepulauanMeranti
ASI ekslusif	X_4	70.15	MusiRawas, OganIlir, MuaraEnim
Vitamin A	X_5	67.42	TanjungBalai, Padang Lawas Utara, Kota Medan
Balitaditimbang	X_6	51.31	Padang Lawas Utara, Nagan Raya, Mndling Natal
Imunisasi (X_7)	X_7	57.45	Nagan Raya, Samosir, Aceh Selatan
KunjungankonsultasiIbuHamil (K4).	X_8	54.16	LabuhanBatu Selatan, Nias, Nias Barat
KurangEnrgiKronisWntSbr (KEKWUS)	X_9	18.47	Nias Selatan, Nias Barat, GunungSitoli
PenggunaanKontrasepsi KB	X_{10}	9.8	PematangSiantar, Dairi, Kerinci
PerilakuHidupBersih&sehat (PHBS)	X_{11}	20.94	Nias Selatan, PakpakBharat,HumbangHasundutan
Air bersih	X_{12}	97	Padang Lawas, Batu Bara, TanjungJabungTimur
Sanitasi	X_{13}	55.41	KepulauanAnambas, Pesawaran, Nias Selatan

Source: Riskesdas (2013).

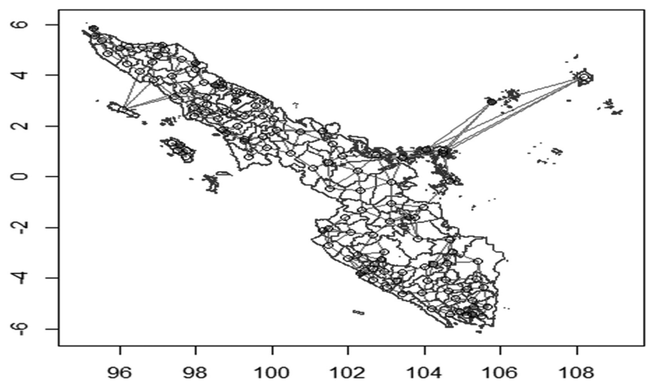

Figure 3.
k-Nearest Neighborhood Location

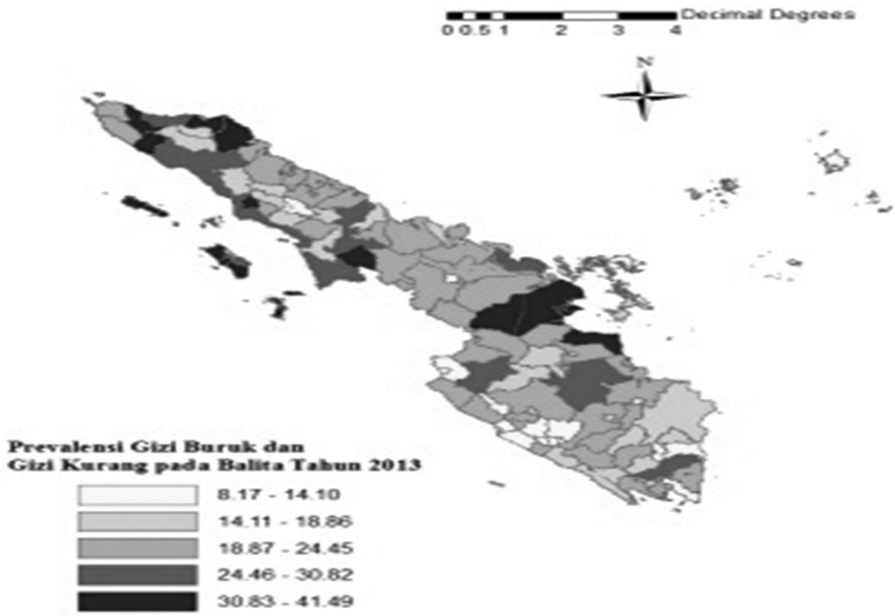

Figure 4. Prevalence Distribution of Poor Nutrition and Nutrition less in Sumatera Island

that each district/city will have four nearest neighbors, where the spatial-weighted matrix is formed according to the matrix equation W (5d), and the matrix is not symmetric with the size 125×125.

3.3.3. Modeling stochastic for the nutritional status of under-five children. Beginning with the data of prevalence of malnutrition and underweight nutrition in under-fives with the under-five condition, mother condition, and environmental condition for 125 regency/city profile in Sumatera Island consists of 13 causes (variable) as seen in Table 5.

The independent variables are divided into three categories, namely health under-five children, maternal health, and environmental health. The health of children under one of the sample distribution profiles can be seen in Figure 5. As representative, underweight infants and early breastfeeding treatment (IMD) are still approximately 40% located in the regency/municipality of Sumatra Island. Similarly, the maternal health profile shows that the constipation visits of complete pregnant women (K4) is still low (<30.9%) (Kesuma & Chongsuvivatwong, 2015). Furthermore, the family planning program is still uneven in North Sumatra Island. This is indicated by the number of districts with a low percentage of family planning (<5%), and even the highest percentage is only 36.21% (<50%) (Kesuma & Chongsuvivatwong, 2016). With regard to the health of the environment, access to clean

Test statistics	Value	*P*-Value
Lagrange multiplier (SAR)	5.4921	0.0191*
Lagrange multiplier (SEM)	3.0231	0.08208
Lagrange multiplier (SARMA)	5.5067	0.06371

Table 5. Lagrange Multiplier Test

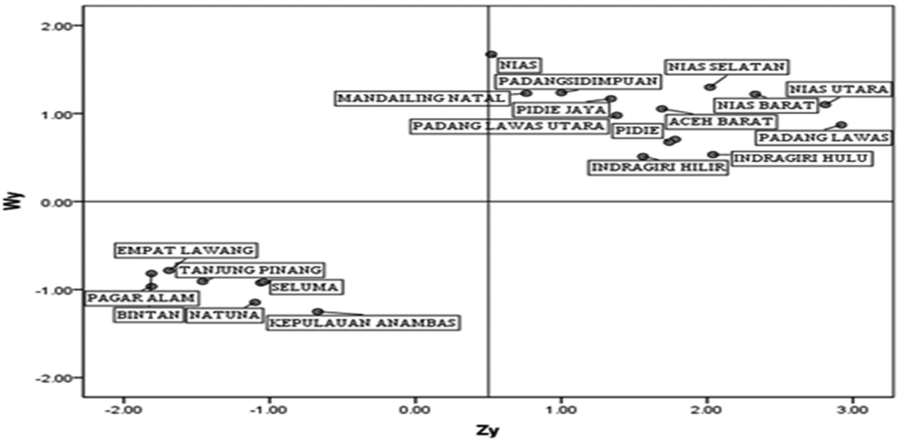

Figure 5.
Plot of Moran Directions Value of Standards of Sumatra Island

water access in 125 regencies/cities of Sumatra Island is 97%, and the average coverage of sanitation access on the island of Sumatra is 55.41%.

The spatial regression model consists of three models, namely the spatial autoregressive model (SAR), the spatial error model (SEM), and SARMA. However, other models can be used, such as the Lagrange multiplier test and the result of the Lagrange multiplier test. The SAR model for malnutrition and malnutrition cases in infants on the island of Sumatra can be written according to the following equation:

$$\hat{y}_i = 47,157 + 0,24335 \sum\nolimits_{j=1, j\neq i}^{125} w_{ij} y_j + 0,139X_9 - 0,370X_{10} - 0,136X_{11} - 0,254X_{12} \tag{3}$$

where y_i = prevalence of malnutrition and under-nutrition in under-fives in the 1st district/city for $i = 1, 2, ..., 125$. Yj is the prevalence of malnutrition and under-five nutrition in the junior districts / cities that are neighboring region i where $j = 1, 2, ..., 125$ and $j \neq i$. $X9$ is a prevalence of chronic energy deficiency in women of child-bearing age. $X10$ is the proportion of KB users, $X11$ is the percentage of households with PHBS, $X12$ is the coverage of access to clean water, wij is a 125×125 spatial weighted matrix and value $\rho = 0.24355$.

4. Conclusion

From the result, the calculation in Table 5 shows that four independent variables significantly spatially influence to the second case that is malnutrition and malnutrition prevalence in under-fives using $\alpha = 0.05$, that is chronic energy deficiency prevalence in woman of child-bearing age ($X9$), proportion of family planning ($X10$), percentage of households with PHBS ($X11$), and coverage of access to clean water ($X12$).

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